Online Malware Classification with System-Wide System Calls in Cloud IaaS

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Abstract—Accurately classifying malware in an environment allows the creation of better response and remediation strategies by cyber analysts. However, classifying malware in a live environment is a difficult task due to the large number of system data sources. Collecting statistics from these separate sources and processing them together in a form that can be used by a machine learning model is difficult. Fortunately, all of these resources are mediated by the operating system's kernel. User programs, malware included, interacts with system resources by making requests to the kernel with system calls. Collecting these system calls provide insight to the interaction with many system resources in a single location. Feeding these system calls into a performant model such as a random forest allows fast, accurate classification in certain situations. In this paper, we evaluate the feasibility of using system call sequences for online malware classification in both low-activity and heavy-use Cloud IaaS. We collect system calls as they are received by the kernel and take n-gram sequences of calls to use as features for treebased machine learning models. We discuss the performance of the models on baseline systems with no extra running services and systems under heavy load and the performance gap between

Index Terms—Malware Classification, Cloud Computing Security, Dynamic Malware Analysis, Machine Learning

I. Introduction

The rapid infrastructure churn of modern cloud systems requires a fast, scalable malware classification system that provides actionable intelligence that can be used for rapid remediation. In this work, we attempt to design a malware classification system that is able to run on features collected in real time from a running, online Linux system. Our primary motivation is collection performance: feature collection must not interfere with the processes on the system that are required for business value. Our chosen primary features, system calls, are more difficult to collect than simpler summary statistics like performance metrics or network flows, but their granularity and breadth of information are wonderful aids when classifying malware [1].

Malware analysis is broadly divided into two disciplines: static and dynamic. Static malware analysis deals with malware at rest. Static analysis inspects malware files without executing them. This makes static analysis a safe method of analysis because malware cannot damage an analysis machine or network. Modern malware creation techniques can often

evade static analysis by hiding parts of the executable or disguising control flow. The ease of disguising malicious code from static analysis is the greatest weakness of static analysis.

Dynamic analysis studies malware during and after execution. Unlike static analysis, the malware is actively executed and its effects on the system are studied. Much more information about a piece of malware can be collected during dynamic analysis. Since executable sections must be available for the malware to run, dynamic analysis defeats packing strategies that would evade static analysis. Further, network, memory, and file activity on the system can be observed to investigate what parts of the system the malware is affecting.

Malware is often destructive so care must be taken to create a network where damage that may be caused by the malware is reversible and contained to a well-monitored and segmented part of the network. Malware may attempt to detect if it is running in a sandbox or being monitored and alter its behavior to avoid analysis. Careful design of the execution environment can reduce the malware's ability to detect that it is being inspected. Online dynamic analysis is a specific dynamic technique where the malware is not run in a simulated environment but rather a real, internet connected system. This allows malware to connect to internet resources if those are required for its operation. While this gives the best view into the behavior of the malware, it is the most dangerous method of analysis, as giving malware access to the internet potentially allows it to spread and infect vulnerable systems. We have specifically designed our experiments and environments to leverage online analysis to replicate real enterprise installations that may be targeted by malware authors.

II. MOTIVATION

We chose to perform malware classification over detection because it gives greater insight into the threat and scale of possible damages for an infection. Simple spam tools or adware may not dictate the same measure of response that a cryptolocker or remote access Trojan would. Our specific dynamic analysis implementation is intended to detect a compromised system by inspecting system-wide features. While one process may be easier to classify, doing classification for every process on a system would quickly become impossible. Therefore, we observe features from the entire system at once. This has the

TABLE I RELATED WORKS COMPARED

Reference	Ana	lysis	1	ures	ML	Technique	Domain	P	Platforr	n
	Classification	Detection	System Calls	Other	Traditional	Deep Learn.	Online	Linux	Android	Windows
Canzanese et al. [2]	✓		✓		✓					✓
Babenko and Kirillov [3]	✓		✓			✓				✓
Canfora et al [4]	✓		✓		✓		✓		✓	
Alsulami and Mancoridis [5]	✓			✓		✓				✓
Das et al [6]		✓	✓			✓		✓		
Chandramohan et al [7]		✓	✓		✓					✓
Dawson et al [8]		✓	✓		✓			✓		
Azmandian et al [9]		✓		✓						✓
Our approach	✓		✓		✓		✓	✓		

additional benefit of being able to detect the compromise of existing benign processes on the system. "File-less" malware is malicious code that is somehow injected into the process of an already running process. This avoids malware detection if the detection is observing only new processes or has already flagged the compromised process as benign.

We chose to target online Linux systems because of the current and likely future popularity for the GNU/Linux-based operating systems in cloud computing. Cloud environments are increasingly popular for enterprise use because of their scalability, price efficiency, and availability. As their popularity increases, these systems are increasingly being targeted by malware authors seeking to compromise them.

Our choice of model and features were also driven by practical considerations. While modern neural models have shown great promise for security work, their high resource requirements during training and the high number of samples required to effectively train them makes them difficult to implement without considerable infrastructure investment. Traditional machine learning models require less training data and can be effectively trained on consumer-grade CPU hardware, and their performance has been proven to be acceptable for security tasks [10], [11].

The main contributions of this work are:

- We evaluate the feasibility of using traditional machine learning models for classifying malware from behavior in a custom whole-system system-call sequence data set from simulated cloud IaaS systems.
- We show this approach is effective for low-activity cloud systems, but is less effective when systems are under heavy load and generating many system calls.

III. RELATED WORK

Malware detection and classification are wide and active disciplines. To narrow the field of peers, we will compare our work to only those other works that are attempting *dynamic* analysis. While there is a plethora of static malware analysis research, static and dynamic analysis methods are distinct enough that static analysis is not comparable to our work.

Static analysis analyzes the attributes of malware files while dynamic analysis is focused on observing the behavior of a malware during its execution. We compare our work to only those other works that are also observing malware behavior. We would be particularly interested in comparing our work to other work where the malware is not sand-boxed and is able to run as it would "in the wild" on compromised systems, but such research is understandably difficult to find due to the dangers of running malware on live systems.

There is a large body of work on malware detection with various sources of dynamic features collected at run-time. We can make useful comparisons here to data collection and processing because these are largely similar between detection and classification tasks. Reference [8] uses VM introspection tools to collect system calls from a VM running below the context of the monitor system. Reference [7] provides an insightful method to process raw system calls into a format better suited for machine learning.

A. System Call Collection

Reference [6] is perhaps the most similar in concept to our own, also collecting Linux system calls. This work, however, is only concerned with single isolated systems and does not classify malware, only detects it. Reference [2] collects system calls for malware classification, but does so on hosts running the Windows operating system that are not connected to the internet.

Several malware detection works focus on the Android mobile operating system. While Android applications are packaged and managed differently than mainline GNU/Linux distributions, the similarities in the platforms make Android security research valuable contributors to our own work. Reference [4] uses system call sequences collected from Android program execution to detect malware. Their approach uses n-grams of system calls and the counts of those n-grams as features for a support vector machine. Similar to our work, the authors in this work wanted a realistic environment for malware to execute. To this end, they executed their malware

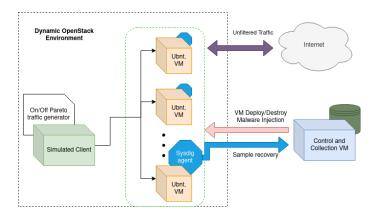


Fig. 1. The OpenStack Environment where the malware was examined

and benign data sets on a physical Android phone instead of using Android emulators.

IV. DATA COLLECTION METHODOLOGY

A. Experiment Environment

A primary goal of this research is to design malware classification that works in real environments. All of the malware experiments were carried out on real Linux cloud servers with unrestricted internet access. The experiments were hosted on an OpenStack* instance graciously provided by the University of Texas at San Antonio[†]. OpenStack provides a free and powerful cloud infrastructure platform like those that are popular in industry and as targets for malware authors. This OpenStack platform emulates production cloud environments with full Linux systems. This provides some important advantages for malware analysis over safer methods like sandboxing or emulation; the systems used in this research are just like those in the wild that malware will be written to infect. These systems likely pass most network and sandboxdetection evasion methods in malware so that the potentially hidden behavior of the executable can be captured.

Malware behavior collection experiments were performed in two stages across the same environment. The environment, shown in Figure 1, is a number of target virtual machines (VMs) running fully-patched Ubuntu 18.04 on OpenStack, each with its own network connection and public IP address. To collect malware behavioral data, each target machine was run for ten minutes. For the first five minutes, the machine ran unaltered. After approximately five minutes (some randomness was used to prevent malware from always executing at the same time in the traces), the controller node copies in and executes a malware executable. At ten minutes the target is destroyed and replaced by a new target and the experiment continues. In the first stage of experiments, no software other than what is required for the Ubuntu 18.04 image was running. In the second stage, the server was running an Apache web server hosting a WordPress site while simulated traffic was generated from the controller node.

TABLE II ALL CLASSES FROM THE 4,180 FINAL SAMPLES

Class	Count	Used
trojan	2299	✓
virus	616	✓
backdoor	382	✓
rootkit	253	✓
miner	226	✓
grayware	142	✓
worm	142	✓
none	87	
ransomware	21	
downloader	7	
bot	3	
hoax	2	

To efficiently collect the system calls from the live systems, we needed a kernel-level solution that did not interrupt process execution. The utility <code>sysdig‡</code> provides this functionality. System call collection is done in kernel at call time and is completely transparent to the calling process. Performance overhead is low enough to be acceptable in our experiments here, with no measured impact to application response.

During test execution on the targets, sysdig was run to collect all system calls sent to the kernel from all processes. The output of each system call record was retrieved from the target machine, labeled with the hash of the malware executable used, and stored for later use. Results were stored as-is in the proprietary sysdig binary output file because of its compact size and completeness.

B. Executable Sample Selection and Curation

A major share of the work behind this research was collecting and curating a suitable malware set that provided good samples that ran in our selected environment and had enough class diversity to perform useful classification. Initially, the academic dataset from VirusTotal§ was explored, but it was found to be poorly balanced. While the samples in the VirusTotal dataset were appropriate for our systems and were functional, the majority of them (>80%) were Mirai or Mirai variants. Additional samples from MalShare and VirusShare[¶] were added to increase the numbers of other classes. After removing duplicates and selecting only x86-64 binaries, from more than 10,000 total samples we selected 4,180 samples that were functional. These classes are shown in Table II and those used in our experiments are check-marked. These classes were sufficient as a base for our final class selection described in Section V.

V. MACHINE LEARNING CLASSIFICATION

A. Classes

Our malware samples were not labeled by the providers. To determine a reasonable classification, we examined the

^{*}www.openstack.org

[†]www.utsa.edu

[‡]https://github.com/draios/sysdig

[§]https://www.virustotal.com/

[¶]https://www.malshare.com/ and https://virusshare.com/

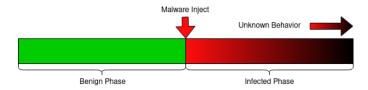


Fig. 2. Behavior over time of the experiments

combined output of the various engines behind VirusTotal with AVClass^{||} [12][13], a tool written to determine family and class labels from VirusTotal scan results.

VirusTotal uses several engines and scanners to determine what a malware file is. At the time of writing, VirusTotal claimed over 70 anti-virus scanners and services. VirusTotal has an available API where an executable can be uploaded and VirusTotal will distribute the sample to all of those engines and return a report containing reports from each engine. These reports are not standardized; each AV vendor engine has their own reporting syntax and semantics. This creates a difficulty for determining accurate class labels for a piece of malware since it may be reported as different classes by different vendors, and each vendor may use a different term or label for the same class. While this makes determining proper labels more difficult, it is not impossible. Fortunately, AVClass can parse these VirusTotal API results and determine proper class labels.

Semantics have a large influence on malware classification. The classes in Table II are labels created to describe malware based on some behavior that it exhibits. Some classes may have overlap in the behavior that they describe. In our data, we find the classes trojan, virus, and backdoor. Since the classification labels obtained from AVClass are sourced by consensus from many sources, the class labels are particularly likely to differ among the various engines based on the perspectives of those that wrote them. The trojan class in particular was found by the authors of [13] to have often been used as a 'catch-all' class when a better classification could not be made. This has some impact on our classification work.

The classes in Figure II are the total set present in all the malware selected. Obviously, the low-numbered classes are not usable for training a machine learning model, so they are dropped along with the 'none' class samples that AVClass was not able to determine a class for. This left the seven classes trojan, virus, backdoor, rootkit, miner, grayware, and worm. We did not pursue family attribution in this work, as we found that AVClass could not produce confident family labels for enough of our dataset.

B. Model Selection

In testing, we found random forests to be accurate classifiers that were easy to train on our data. Other work has also found decision tree models to be among the fastest and most accurate among traditional machine learning models for security work [10][11]. The particular tree model we found to be most fast

TABLE III
REDUCED SET OF 35 SYSTEM CALLS

read	write	creat
open	openat	unlink
chdir	access	utime
chmod	ftruncate	rename
getdents	fstat	fstat64
fadvise64	execve	rt_sigaction
rt_sigprocmask	kill	tgkill
sched_yield	send	bind
connect	recvfrom	poll
epoll_create	select	ioctl
brk	mmap	mmap2
munmap	mprotect	

and effective was LightGBM**, a gradient-boosting tree-based model.

C. Feature Processing

The raw features extracted from the malware experiments were the list of system calls made to the kernel during our execution periods. We decided to perform machine learning analysis using a random forest fed n-grams of system calls from the sequence. This approach has been accurate [14] and showed good and efficient results in our work.

There was some experimentation done to determine a proper feature space. First, we did not consider every possible combination of calls but only those that were present in all of our experiment runs. Second, to reduce the number of n-grams calculated, we performed the experiments with a limited number of system calls. Limiting the number of calls collected drastically reduces the number of possible n-gram features. Some detail is lost with the discarded calls of course, but careful selection of the retained calls still gives a good view of system activity. Based on [6] and observations from our dataset, we determined a short list of system calls that implicate security affecting behavior such as file interaction or network communication. These calls are listed in Table III.

While malware injection happens at approximately the same time in each malware experiment, there is a lot of uncertainty in how active the malware is. This has bearing on how n-gram features are extracted. Each malware binary in our final experiment set is confirmed run when it is injected, so features around the midpoint of the execution time will likely contain malware activity. The execution period before malware injection is also certain; the only activity during this period is related to the the baseline services we installed on the execution VMs. As time progresses past malware injection, however, behavior becomes more uncertain. Figure 2 shows the phases of the experiments. Features sampled farther and farther from malware injection may or may not actually contain any malware behavior and there is no way to determine this in our feature set.

We experimented with dividing the ten-minute experiment periods into time slices to reduce the amount of time covered

https://github.com/malicialab/avclass

^{**}https://lightgbm.readthedocs.io/en/latest/index.html



Fig. 3. Performance on the baseline experiment set with no background services running

by each system call sequence extraction. We tested model performance when all system calls from the 10 minutes were collected together and when the experiment was divided into three, five, and ten slices of equal length. Dividing into ten slices of a minute each was found to give a good balance of model efficacy and extraction performance. Larger slices were less accurate due to the number of non-malware calls increasing and smaller slices were less efficient because feature extraction had to be performed many more times.

We also had to develop a strategy to handle the uncertainty of malware behavior in the latter half of the experiments. The malware is on the system at this time so this time period cannot be considered benign, but the malware may not be active during the entire period and so may not show in the collected features. Labeling that period as a malware class will likely lead to poor classification both during training and classification. We withhold these time slices in training and separate them during classification and reporting.

VI. RESULTS

A. Result Methodology

A notable effort was made to determine the suitability of class labels in our dataset. As mentioned in section V-A, [13] discussed the semantic meaning behind certain anti-virus labeling with a focus on the trojan label. In Figure 3, it can be observed that several samples belonging to other classes are improperly classified as trojans. Our belief is that this is not due to a lack of model performance, but due to the differences among anti-virus vendors when selecting class labels. If a particular vendor cannot determine a proper class for a piece of malware, it may default to assigning it

TABLE IV
CLASSIFICATION PERFORMANCE PER-SLICE FOR MINUTE-LONG SLICES
OF 3-GRAM FEATURES ON BASELINE DATA. THE BOLDED ROW IS THE
ONLY SLICE IN WHICH MALWARE IS CERTAINLY ACTIVE

Minute	Label	Accuracy	Precision	Recall	F1
1	Benign	100.00	NA	NA	NA
2	Benign	99.09	NA	NA	NA
3	Benign	99.18	NA	NA	NA
4	Benign	99.74	NA	NA	NA
5	Benign	98.83	NA	NA	NA
6	Malicious	94.30	0.98	0.90	0.95
7	Malicious	33.57	0.86	0.25	0.39
8	Malicious	55.54	0.83	0.30	0.40
9	Malicious	41.82	0.84	0.28	0.41
10	Malicious	64.48	0.82	0.34	0.44

TABLE V

CLASSIFICATION PERFORMANCE PER-SLICE FOR MINUTE-LONG SLICES
OF 3-GRAM FEATURES ON APPLICATION DATA. THE SLICES AFTER
MALWARE INJECTION HAVE BEEN REMOVED

Minute	Label	Accuracy	Precision	Recall	F1
1	Benign	100.00	NA	NA	NA
2	Benign	100.00	NA	NA	NA
3	Benign	99.67	NA	NA	NA
4	Benign	100.00	NA	NA	NA
5	Benign	100.00	NA	NA	NA
6	Malicious	74.92	0.45	0.27	0.30

TABLE VI DETECTION (BINARY CLASSIFICATION) RESULTS FOR BOTH DATA SETS

Data set	Accuracy	Precision	Recall	F1
Baseline	1.00	1.00	1.00	1.00
Application	98.19	.97	.97	.97

to the trojan class. Additionally, the described behavior of some of these classes is quite similar. In particular, the classes trojan, rootkit, and backdoor may be reasonably used to describe malware that establishes an illicit backdoor connection to an infected machine. The final class name for samples from these classes is somewhat arbitrarily determined by malware research vendors.

To measure our models' performance, we use four evaluation^{††} metrics: accuracy, precision, recall, and F1 score. Our preferred measure of performance is the model's F1 score. F1 measures the relationship between *precision* and *recall*. Precision measures the number of samples that correctly belong to the predicted class and recall measures how many samples of a class were correctly assigned that class. The F1 score is the harmonic mean of precision and recall.

Note that Tables IV and V report NA values for precision, recall, and F1 for time slices that only have one class (benign) present, as having no true positives and false positives or negatives yields zeros in the denominators of the equations. Since we do not label samples in these slices as a positive malicious class, these metrics are difficult to report.

$$\begin{array}{l} ^{\dagger\dagger}Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, Precision = \frac{TP}{TP+FP}, \\ Recall = \frac{TP}{TP+FN}, F1-score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \end{array}$$

B. Results Discussed

Our experiments have determined that this approach is valid for determining the class of a piece of malware on a quiet system, but the approach as implemented is not as effective for classification of malware on a system under heavy load.

The results in Table IV shows classification performance on the baseline experiments where the malware is running on a system with no additional configuration after installation. These results indicate that the model has effectively learned to classify these samples based on patterns in their system call usage. There is no malware running on the system until it is injected at the half-way point, so all time slices prior to this point are labeled benign. The time slice where malware is injected and all following slices are labeled as the class to which the malware belongs. While time slices after the inject are labeled as the injected malware class, the malware is not certain to take any action during this period and may not leave any evidence of its presence. The performance metrics for these slices are therefore low. The majority of slices after the inject slice are identified by the model as benign, indicating that the malware was likely not active.

Table V displays the results of classification for the data collected while a web-server application was active and stress tested on the test machines; see section IV-A for experiment details. Clearly the results are much worse. This is attributable to the massive increase in the number of system calls observed on the data sets collected during the baseline and application experiments. The number of features doubles from the baseline to the application dataset. The increase in system calls made by the web service increases the chance that the system calls made by the malware will be dispersed through the benign calls and difficult to pick out.

Despite the inability to accurately classify malware in the application dataset, detection works well. Table VI displays the results when all malicious classes are combined into a single malicious class. While the main purpose of this work is to classify malware on these sequences, the results here do indicate that there is enough feature difference to make conclusions about malware behavior. Additional feature processing or model development may accurately classify malware while system call intensive applications are running on the system and is left for further work.

VII. CONCLUSION AND FUTURE WORK

In this work we described a system for attempting to determine the class of malware infecting a system by observing the all system calls made to the kernel. This approach is feature efficient because only a single feature feed needs to be collected from the kernel instead of separate feeds from every process. This work has shown to be effective at determining what class of malware a system is infected with by observing all system calls made to the kernel when other activity on the system is low. Future work should continue feature testing and processing to identify ways to improve the performance on systems with high amounts of other activity. The detection performance we achieved does indicate that

there is enough information in the system call sequences to make some observations on malware activity, so this should be explored further.

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