

Crypto-ransomware Detection through Quantitative API-based Behavioral Profiling

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Abstract. With crypto-ransomware's unprecedented scope of impact and evolving level of sophistication, there is an urgent need to pinpoint the security gap and improve the effectiveness of defenses by identifying new detection approaches. Based on our characterization results on dynamic API behaviors of ransomware, we present a new API profiling-based detection mechanism. Our method involves two operations, namely consistency analysis and API-contrast-based refinement. We evaluate it against a set of real-world ransomware and also benign samples. We effectively detect all ransomware executions in consistency analysis and reduce the false positive case in refinement. We also conduct in-depth case studies on the most informative API for detection with context.

Keywords: Ransomware · Data security · System security.

1 Introduction

Crypto-ransomware extorts money from victims by encrypting their files. It first appeared in 1989 and has had a resurgence recently. In 2017, WannaCry hit around 230,000 computers across 150 countries, causing a loss of \$4 billion [21]. The notorious Colonial Pipeline hack affected nearly half of the U.S. east coast gas supply and roughly \$5 million was paid for recovery in May 2021 [44]. Japan's largest port was hit by a Russian-based ransomware attack and was unable to operate for two days in July 2023 [1]. In 2021, REvil demanded \$50 million from Acer and \$70 million from Kaseya, which created a new high in history. Further, Babuk stole 250GB of sensitive data, including home address and financial data, from the D.C. Police Department [18]. Solely in Q4 of 2021, 34 variants of ransomware were observed [24]. 37% organizations reported being attacked by ransomware in 2021 and the average cost of recovering was \$1.85 million [39]. Even worse, on average, only 65% of data was recovered after the ransom payment [39]. One possible reason for this low recovery rate is file corruption.

Many efforts have been made to defend against ransomware attacks. However, in successful ransomware attacks, 77% of victims are running up-to-date endpoint protection, implying inadequacy in current solutions in practice [40]. There have also been academic solutions proposed to detect ransomware threats.

Monitoring the file system is a widely used approach [16, 17, 22, 28, 35, 42]. Hardware performance [10, 30], API call occurrence [8, 15, 20], and network activities [6, 7, 13] could also reveal the malicious purpose of a program.

Despite these research advances, the current literature does not have any work that focuses on in-depth Application Programming Interface (API) usage-based detection. Existing file system-based solutions (e.g., UNVEIL [22] and ShieldFS [16]) focus on low-level file system activities. API-based approaches could be alternative detection methods taking advantage of fine-grained program behavior information with less requirement for system modifications. Current API-based detection works [8, 15] mostly rely on machine learning classification. In-depth analyses of execution patterns could also complement and strengthen the detection. To close this gap, we aim to answer the following important research questions:

RQ1: What are the quantitative ransomware API invocation behaviors? How do they systematically compare with benign software? (Section 2)

RQ2: How to quantify the unique ransomware API usage patterns for detection? How to ensure good classification? (Section 3)

RQ3: How well does API profiling-based detection work? For commercial defense, what are the ransomware behaviors that trigger detection? What are the security gaps? (Section 4)

For such API-based detection, the challenge one would encounter is formulating the execution pattern in a manner that enables clear differentiation from benign processes, avoiding false alarms and missed detections. To overcome this difficulty, we propose a new two-stage API-based approach, which is capable of accurately separating ransomware execution from benign processes, based on two key findings. Specifically, ransomware has a highly repetitive execution pattern and shows a significant API invocation contrast compared to benign. We first distinguish ransomware execution by modeling the distinct repetitive execution patterns using a consistency analysis-based algorithm. Then, the positive cases are further refined by our API contrast score, which is computed from the API usage variation between ransomware and benign. Taking advantage of this multi-stage design, we achieve good separation between the two types of samples.

We summarize our experimental findings below.

- **API-usage profiling.** We quantitatively analyze the behaviors of ransomware samples through two sets of experiments. We first manually inspect 54 real-world ransomware samples from 35 families, including the notorious WannaCry, Sodinokibi, Babuk, and the most active ransomware families in 2021, LockBit, Mespinoza, and Hive, with a focus on encryption activities. We find that ransomware has a distinct file access behavior pattern during execution. We further collect the occurrence frequency of 288 Windows APIs from 348 ransomware samples. We discover differences in API occurrences and invocation frequencies between benign and ransomware executions, which is beneficial for improving detection accuracy. We leverage these for computing the API contrast score.

- **API-based classification.** Based on our observation of API usage, we invent a new two-stage detection mechanism, consisting of consistency analysis and refinement operations. In consistency analysis, we use multiple mathematical methods to capture the unique ransomware execution features, focusing on the fundamental encryption nature. In refinement, we further examine the positive cases by an API contrast score to filter wrongly classified cases. We further provide in-depth case analysis of API usage contrast with attack context.
- **Evaluation.** We conduct two sets of experimental evaluations. First, we carry out a feasibility assessment of our detection approach against 29 sets of execution traces. The results show that our consistency analysis effectively catches all malicious execution. Specifically, Manhattan-based consistency, frequency-weighted consistency, and Euclidean-based consistency show optimal performance, generating only one false positive case. With the assistance of refinement, this false alarm is reduced at the next classification stage. Second, we extensively evaluated three types of commercial defenses. Through our experiments, we found that the success rate of commercial decryptors is low (1 success out of 6), suffering from low generality across variants of ransomware. Anti-virus software detects only generic malicious behaviors, being insensitive to core ransomware encryption. Malware scanners use signature-based detection and miss unknown or obfuscated samples. The observations reveal that behavioral detection is necessary and our new API-based approaches can help strengthen ransomware-specific protection.

The rest of the paper is organized as follows. **Section 2** reports our findings on ransomware API-based behavioral characteristics, with systematic comparison to benign software. **Section 3** describes our new two-stage detection prototypes based on API usage patterns. **Section 4** evaluates our detection method and various commercial tools. **Section 5** talks further through our insights, **Section 6** discusses related academic works, and **Section 7** concludes the work.

2 Characterization of Ransomware API Usage

In this section, we present our findings on the ransomware API usage pattern and detailed analyses. With a comparison to benign software behaviors, we find that API usage and frequency are informative in terms of revealing malicious behaviors. We build our detection algorithms, which are presented in Section 3, based on these findings.

2.1 Encryption and File Access Behaviors

To take a close look at the file encryption behaviors, we analyze cryptographic and file-related API usage and call frequency of ransomware samples.

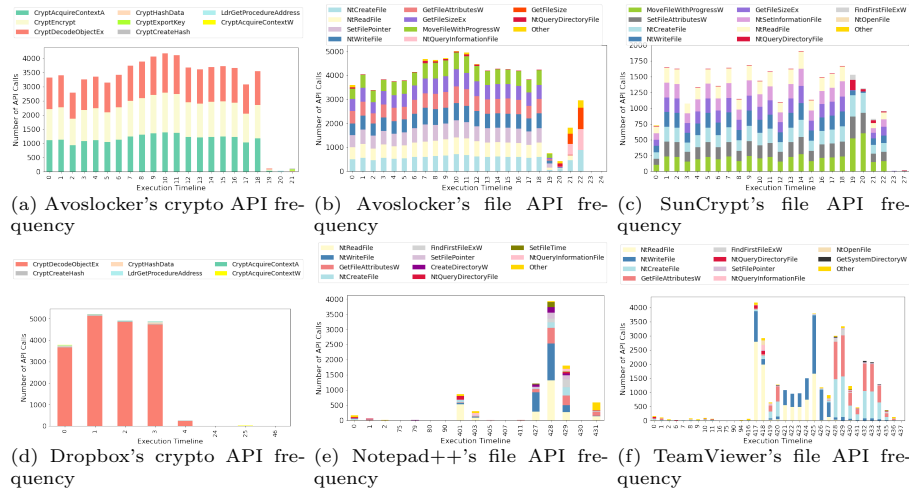


Fig. 1: API call statistics of executing ransomware samples (top) and benign software (bottom). The x-axis is the timestamp during execution and the y-axis shows the number of calls. If no call is made during a second, then it is not shown in the figures. Ransomware uses intensive crypto and file API calls during execution with a distinctive pattern. The same colors represent the same APIs across subfigures.

Experimental Setup 1 We first describe the setting for our encryption behavior characterization, referred to as setup 1.

Ransomware samples. We collect 262 ransomware samples from Malware-Barzaa⁴ and VirusShare⁵. Among these samples, we find 54 of the samples (from 35 distinct families) provide more meaningful traces for manual analysis. The SHA256 hashes of the 54 samples are shown in Table 14 in the appendix, which can help find the exact samples.

Analysis environment. We set up an isolated environment for safely executing ransomware samples using Cuckoo Sandbox (v2.0.7)⁶, with VirtualBox (v6.1)⁷ as the hypervisor and Windows 7 as the guest system. We use 4 CPUs and 4096 MB memory for the VM. We install several applications, including Chrome, Adobe PDF Reader, NotePad++, and LibreOffice, to make the environment more realistic. We also put random files under several directories, such as disk C, Documents, and Downloads for ransomware to encrypt. Each execution starts with a clean system image. To avoid VM escape, we use a different host system (Ubuntu 21.04). We also set up a fake internet service using INetSim⁸. Lastly, to minimize the risk of spreading, we disconnect the machine from the internet.

⁴ <https://bazaar.abuse.ch/browse/>

⁵ <https://virusshare.com/>

⁶ <https://cuckoosandbox.org/>

⁷ <https://www.virtualbox.org/>

⁸ <https://www.inetsim.org/>

Report and API analyses. For each successful execution, the Cuckoo sandbox generates a report in JSON format, from which we extract data for analysis. We conduct API call frequency analyses based on the reported API calls.

Comparison with benign software samples. We download the top popular Windows applications from a range of different categories from software.informer⁹ or the software’s official website. We use 38 samples from 12 categories for manual analysis (Table 15 in the appendix). We run the benign samples in the Cuckoo sandbox the same way we run ransomware samples and collect the execution reports for analysis. Among those samples, we use the ones with intensive file access behaviors in the evaluation of our detection.

Characterization Findings on Encryption Behaviors Our characterization study identifies interesting encryption behaviors.

CryptoAPI frequency. Some ransomware samples make intensive CryptoAPI calls, in the order of thousands, during execution. We show AvosLocker as an example in Figure 1a. It uses the API sequence `CryptAcquireContextA`, `CryptDecodeObjectEx`, `CryptEncrypt` for encryption. The number of calls to each of the three APIs is similar, adding up to around 4,000 calls per second.

Ransomware file access. Similar to crypto-related calls, file access frequency is also in the order of thousands per second. The peaks of calls are around 5000 and 1900 calls per second for AvosLocker and SunCrypt (Figures 1b and 1c), respectively. By examining the directory paths touched through calls to `NtCreateFile`, `NtWriteFile`, and `NtOpenFile`, we notice that these samples start traversing the directory at `C://` and then go into child directories. MountLocker even searches disks through `a://` to `z://`. AvosLocker accesses 780 unique directories during the execution, SunCrypt accesses 180, and MountLocker accesses 2,236 in our testbed. The three families use a similar combination of 6 to 7 file-related APIs repetitively during the encryption process. The combination includes APIs to create files, read files, write files, query file size or information, and set file pointers. The number of each API being called every second is somewhat evenly distributed, with no absolute dominance.

Comparison with benign samples. To contrast with ransomware behavior, we also analyze the execution of 38 benign software samples. The top API categories of the majority of benign samples include system, registry, and miscellaneous, varying from ransomware behavior. However, there are a few exceptions. Dropbox (Figure 1d) makes over 3500 crypto-related calls per second in the first four seconds of execution, with a peak of over 5000 calls per second. The difference is in the composition of the API calls made. While AvosLocker uses a combination of three CryptoAPIs with relatively even distribution, the vast majority of calls made by Dropbox are to a single CryptoAPI, i.e., `CryptDecodeObjectEx`.

Moreover, some benign samples also make a notable amount of file-related calls, as shown in Figures 1e (Notepad++) and 1f (TeamViewer). By examining

⁹ <https://software.informer.com/System-Tools/>

the composition and call patterns, one can easily tell the benign usage pattern is rather random, varying from program to program.

In summary, Ransomware shows a distinguishable repetitive file-access API pattern throughout the execution. We further analyze the distinction between ransomware behavior and intensive benign file access in-depth. The results show that this unique pattern can be quantified to help classify malicious from benign execution. Our detection method is presented in Section 3.

2.2 API Occurrence Contrast Analysis

In another characterization study, we conduct a contrast analysis of 288 APIs, comparing their occurrences and usage frequencies in ransomware and benign programs.

Experimental Setup 2 We collect 348 ransomware samples from Malware-Barzaa. The samples are from 37 families. For benign samples, we collect 330 of them from software.informer. We use the same sandbox setting in this experiment and the JSON report for API analysis. The virtual machine has 4 CPUs and 8192 MB of memory. We refer to this setting as setup 2.

Characterization Findings on Contrast Analysis We observe some APIs are used more commonly by ransomware than benign software. For instance, `WriteConsoleW` is used by 50% of ransomware samples we measure, while only occurs in the execution traces of 5% of benign samples. We show a list of such APIs in Table 1. Moreover, even if some APIs occur in a similar number of ransomware and benign software, the call frequency could vary substantially. For example, `NtWriteFile` is used by a comparable number of ransomware (333 samples) and benign programs (328 samples). However, ransomware samples make, on average, 40554 calls during execution, which is around 8 times compared to benign (5031 on average). More examples of such APIs are shown in Table 2. Comparably, there are also a set of APIs that are more commonly observed during benign executions. A list is presented in Table 3.

The invocation patterns of specific APIs vary between ransomware and benign programs. This API usage contrast is useful for building new detection. Later, we show how they aid detection in Section 3.1.

3 New API-profiling Based Classification Method

This section presents our new API-based detection mechanism for identifying ransomware threats (**RQ2**).

3.1 Our Detection Algorithms

Our method consists of two main operations: *i*) **consistency-based classification** and *ii*) **refinement using API contrast score**. In consistency-based

Table 1: List of APIs that significantly more prevalent in ransomware when compared to benign. The percentage is calculated by (number of ransomware that calls this API / 348) for ransomware and (number of benign programs call this API / 330) for benign programs.

	API	% RW	% Benign
1	NtOpenDirectoryObject	65%	32%
2	CoInitializeSecurity	59%	26%
3	MoveFileWithProgressW	57%	29%
4	WriteConsoleW	50%	5%
5	Process32NextW	49%	11%
6	CreateToolhelp32Snapshot	49%	12%
7	Process32FirstW	48%	11%
8	CryptEncrypt	18%	0%
9	CryptExportKey	15%	3%
10	CryptGenKey	10%	0%

Table 2: List of APIs that are comparably prevalent in ransomware and benign but have a much higher frequency in ransomware execution. RW stands for ransomware. RW freq mean is the average call frequency based on all ransomware samples that use this API. # RW is the number of ransomware samples that used this API and # benign is the number of benign programs that used this API. The call frequency is collected during a 300-second execution period for each sample.

	API	RW freq mean	Benign freq mean	# RW / # Benign
1	CryptCreateHash	159568.5	12.6	48 / 63
2	NtWriteFile	40554.4	5031.2	333 / 328
3	NtReadFile	33883	11532.1	324 / 329
4	SetFilePointerEx	7472	179.8	240 / 247
5	NtAllocateVirtualMemory	4839.2	1602.5	342 / 330
6	NtFreeVirtualMemory	4599.4	579.9	331 / 330
7	NtCreateFile	4564.3	1292.2	340 / 329
8	FindFirstFileExW	2666.1	963.6	281 / 308
9	CryptAcquireContextA	2170.6	16.1	50 / 60
10	GetFileType	1149.9	226.7	240 / 257
11	SetFileAttributesW	1105.6	103.1	152 / 115
12	NtDeviceIoControlFile	682.1	71.9	243 / 193
13	RegDeleteValueW	245.3	13.8	137 / 150
14	OpenSCManagerW	90.8	4.5	191 / 180
15	GetUserNameExW	34.3	6.5	133 / 166
16	OpenServiceW	23.6	7.6	174 / 140
17	NtOpenThread	14.3	4	170 / 164
18	CoCreateInstanceEx	6	2	126 / 96

Table 3: List of APIs that significantly more prevalent in benign software when compared to ransomware. The percentage is calculated by (number of ransomware that calls this API / 348) for ransomware and (number of benign programs that call this API / 330) for benign programs.

	API	% RW	% Benign		API	% RW	% Benign
1	RemoveDirectoryA	0%	53%	14	FindResourceW	16%	98%
2	NtDeleteKey	1%	94%	15	GetFileInformationByHandle	16%	82%
3	GetSystemDirectoryA	3%	57%	16	DrawTextExW	17%	100%
4	FindResourceA	5%	63%	17	GetCursorPos	17%	98%
5	NtReadVirtualMemory	9%	74%	18	SearchPathW	17%	98%
6	SendNotifyMessageW	10%	96%	19	SetFileTime	18%	97%
7	FindWindowW	12%	90%	20	GetVolumePathNameW	18%	80%
8	SetEndOfFile	12%	81%	21	SizeofResource	20%	99%
9	GetKeyState	13%	97%	22	NtCreateKey	20%	97%
10	GetTempPathW	13%	76%	23	FindResourceExW	21%	100%
11	GetFileVersionInfoW	14%	88%	24	OleInitialize	23%	87%
12	GetFileVersionInfoSizeW	15%	88%	25	GetForegroundWindow	24%	100%
13	RegCreateKeyExA	15%	65%	26	EnumWindows	24%	96%

classification, we quantify the ransomware execution patterns according to their API repetition patterns. We build several consistency-based mathematical models for classification. Then, in the refinement operation, we compute API contrast scores to further improve the detection accuracy.

Consistency-based classification. We present multiple computational methods, with varying complexity, for summarizing ransomware’s API invocation behavioral patterns. These methods are for the first stage of our detection.

Consistency-based detection. We design four consistency metrics to quantify the variation during the execution. We treat the API composition for a short execution time period as a vector and compare the vector with a previous period. Small variations between vectors suggest more consistency. Specifically, the metrics are Cosine-based consistency (equation 1), Manhattan-based consistency (equation 2), frequency-weighted consistency (equation 3), and Euclidean-based consistency (equation 4):

$$1 - \frac{c \bullet p}{\|c\| \|p\|} \quad (1) \quad \sum_{i=1}^n |c_i - p_i| \quad (2)$$

$$\sum_{i=1}^n f_i |c_i - p_i| \quad (3) \quad \sqrt{\sum_{i=1}^n (c_i - p_i)^2} \quad (4)$$

c is the vector representing the current execution window, p is the vector representing the previous execution window, and f is the vector representing the frequency of top APIs. When calculating the scores, we consider the top 10 file API and use 3-second and 1-second windows for the previous and current, respectively. All of those parameters can be adjusted at the time of application.

As the names suggest, Manhattan-based and Euclidean-based consistency use Manhattan and Euclidean distance to compute the difference between execution periods. The smaller the score, the more consistent the execution. Frequency-

weighted consistency is a variation of the Manhattan distance that each element is weighted by the frequency. That is, the top frequent API takes a larger part in the score. Lastly, cosine-based consistency is calculated based on the cosine similarity between the two vectors representing previous and current execution. Because the more similar the vectors are, the closer to 1 the cosine similarity is, we use 1 minus cosine similarity here to be consistent with other metrics (i.e., smaller values represent more consistency). For all four consistency algorithms, the smaller the value, the more malicious the program is.

Evenness-based detection. In this method, we analyze the frequency distribution of multiple top APIs together. This method aims to capture the ransomware feature that the API usage composition of each epoch is relatively evenly distributed during its execution. We develop two evenness-related metrics to quantify the execution pattern, namely normalized evenness (equation 5) and squared evenness (equation 6):

$$\sum_{i=1}^n \frac{|API_i - avg|}{avg} \quad (5) \quad \sum_{i=1}^n (API_i - avg)^2 \quad (6)$$

avg is the average of top API usage, n is the number of top APIs used. The evenness is first calculated for each small execution period and then averaged to present the whole execution.

Changepoint-based detection. In this method, we count notable changes using Bayesian Online Changepoint Detection (BOCD) [2] to separate malicious and benign traces. BOCD is designed to identify abrupt changes in sequential data. Ideally, ransomware execution should have fewer changepoints due to the constant pattern.

As a baseline, we also implement a single API distribution approach, whose detection is based on the frequency distributions of top file APIs, such as `NtWriteFile`, `NtReadFile`, and `NtCreateFile`, using the Poisson distribution, Wilcoxon rank sum test, and Jensen-Shannon (JS) divergence. The equation for computing JS divergence is as follows:

$$JS(P \parallel Q) = \frac{1}{2} * KL(P \parallel M) + \frac{1}{2} * KL(M \parallel P) \quad (7)$$

where

$$M = \frac{1}{2} * (P + Q) \quad (8)$$

and KL is the KL divergence that

$$KL(P \parallel Q) = \sum_{x \in \mathcal{X}} p(x) \log\left(\frac{p(x)}{q(x)}\right) \quad (9)$$

When computing a divergence score for a ransomware sample, P represents the API distribution of the specific sample and Q represents the overall benign distribution. Vice versa for benign.

Refinement using API contrast score. The refinement operation – the second stage of our detection – builds on leveraging the API occurrence variation between ransomware and benign programs. In refinement, our screening is centered on API contrast scores, explained next. **First**, with the labeled dataset, we perform a comparative counting analysis to compute a contrast score for each distinct API. This training process also organizes the APIs into three distinct sets, based on their occurrences and invocation frequencies in ransomware and benign execution. The three sets are *i)* likely ransomware API set \mathbb{R} , which contains APIs that often occur in ransomware, but rarely in benign programs, *ii)* likely benign API set \mathbb{B} , which contains APIs that commonly appear in benign, but less often in ransomware, and *iii)* co-occurring API set \mathbb{O} , which consists of APIs used by both types of samples, but with a much lower call frequency in benign execution. This assignment is based on relative or pre-defined thresholds, as shown in Equation 10. **Second**, we compute the single contrast score C_i for each API_i following Equation 10. **Finally**, during the testing phase, given the profile of an unknown execution, we compute the total contrast score for all n occurrences of APIs in the profile, i.e., $\sum_{i=1}^n C_i$, with deduplication (each distinct API will only be counted once).

$$C_i = \begin{cases} 1, API_i \rightarrow \mathbb{R}, & \text{if } \frac{occr_i^R}{occr_i^B} \geq \tau_1 \\ -1, API_i \rightarrow \mathbb{B}, & \text{if } \frac{occr_i^R}{occr_i^B} \leq \tau_2 \\ 1, API_i \rightarrow \mathbb{O}, & \text{if } \frac{occr_i^R}{occr_i^B} \in (\tau_2, \tau_1) \wedge \frac{freq_i^R}{freq_i^B} \geq \tau_3 \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

In Equation 10, set \mathbb{R} contains APIs occurring highly frequently in ransomware, but rarely in benign, \mathbb{B} contains APIs associated with benign software, but not with ransomware, and set \mathbb{O} contains APIs that occur in both, $occr_i^R$ is the count of ransomware samples in which the execution traces include the occurrence of API_i , and $occr_i^B$ is the count of benign samples whose traces include the occurrence of API_i .

$freq_i^R$ is the average call frequency of API_i in \mathbb{O} 's ransomware execution, $freq_i^B$ is the average call frequency of API_i in \mathbb{O} 's benign samples. In our implementation, τ_1 is set to 2, τ_2 is set to 3, and τ_3 is set to 2 (i.e., the call frequency exceeds the average benign call frequency by at least two times). The frequency limit used for each API in set \mathbb{O} can be found in Table 11 in the appendix. Because we already consider file-related APIs in the previous classification stage, we only include non-file APIs in the refinement. The lists of APIs in each set are in Tables 10, 11, and 12, respectively, in the appendix.

4 Evaluation

In this section, we present the evaluation results of our two-stage detection approach, first on consistency-based classification, then on API contrast-based refinement. Our evaluation is conducted on real-world samples from 15 distinct

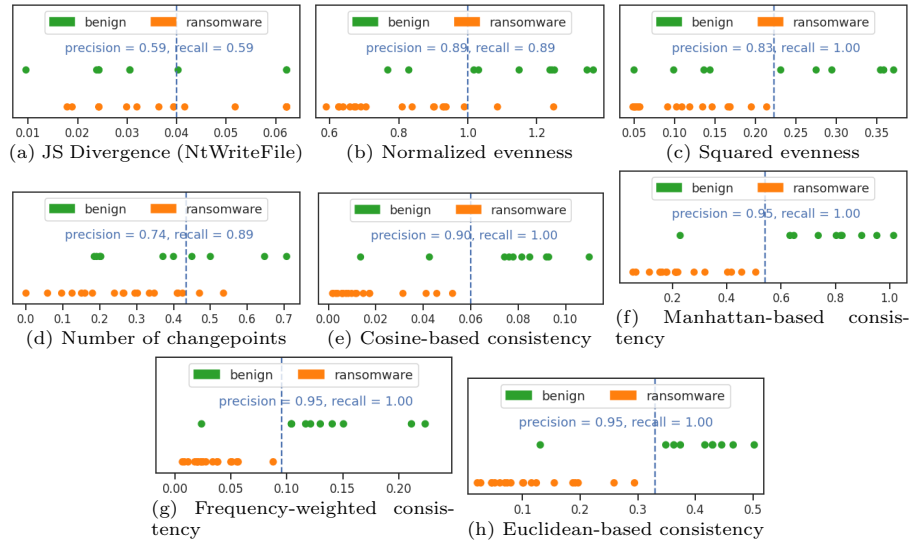


Fig. 2: Classification results using different methods and models. Each green dot (top row) represents a benign software sample and each orange dot (bottom row) represents a ransomware sample. The dotted blue line is a boundary for helping understand how well the separation is. The precision and recall shown in the figures are based on the chosen boundary and are in terms of the ransomware class.

ransomware families. Then, we provide an in-depth analysis of the top important APIs with attack context as case studies. Finally, we demonstrate the performance of the commercial defense, identifying the security gap.

4.1 Evaluation of Classification Models

We first present the classification results based on various mathematical models. Consistency-based algorithms show the best performance. The results of classifying 19 ransomware samples and 10 benign programs with notable amounts of file activities are shown in Figure 2.

Single API distribution. Using only the distribution of a single API (i.e., baseline), we observe the scores for ransomware and benign samples are highly overlapping, implying the inadequacy of this model. An example of JS divergence of NtWriteFile’s distribution is shown in Figure 2a.

Evenness and the number of changepoints. As shown in Figures 2b, 2c, and 2d, the evenness and changepoint metrics worked better than relying on single API distribution. We can see the trend that most ransomware samples are on the left side in the figure while benign samples have relatively larger values in both cases. However, there are still no clear boundaries between them and there exists room for improvement.

Consistency. When considering the consistent execution pattern, there is a clear separation between ransomware and benign samples. All ransomware sam-

ples have a relatively small value, gathering on the left side of the figure (Figures 2e, 2f, 2g, and 2h). Specifically, Manhattan-based consistency, frequency-weighted consistency, and Euclidean-based consistency show optimal performance. With a proper threshold, they accurately catch all ransomware cases with only one false positive. Cosine-based consistency has slightly a lower precision of 0.9. The false positive case that appeared in all four settings is Git, which has a period of execution with high consistency, shown in Figure 3. In summary, the consistency in ransomware file-access API usage helps to identify the threats from benign intensive file accesses.

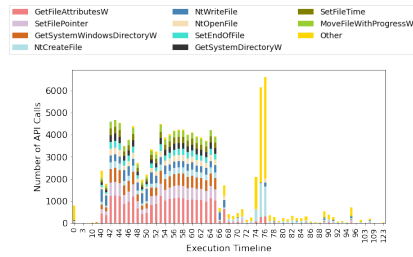


Fig. 3: Git’s file API frequency (false positive)



Fig. 4: API contrast scores of ransomware and benign samples.

4.2 Evaluation of API Contrast-based Refinement

We aim to evaluate the effectiveness of API-contrast refinement, specifically how much it can further improve the detection accuracy of consistency-based classification. The API patterns are distilled from samples from setup 2 and tested on setup 1. When considering only the top ransomware API score (i.e., only using APIs in sets \mathbb{R} and \mathbb{O} , as described in Section 3.1), all benign samples have a lower score, ranging from 0 to 4. Git, the false positive case generated by all four consistency algorithms, only has a score of 2, helping reduce the possibility of being malicious. Another false positive case produced by the cosine-based consistency is PaintNet, which hits none of these rules and gets a 0. On the other hand, ransomware samples have relatively high scores with a maximum of 11. The scores for all samples are listed in Table 4.

Comparably, for the top benign API score (i.e., only using APIs in set \mathbb{B}), the benign samples tend to cluster within the range of -7 to -17 (Table 4). The false positive sample, Git, has a score of -17, which is the lowest among all samples, implying benignness. However, the scores of ransomware are rather spread out, with a lower bound of -15, overlapping with the benign range.

The API contrast score, which takes advantage of both scores discussed above, demonstrates the most promising performance. All benign samples have a score of at most -7, gathering at the lower area (in blue) in Figure 4. Git has a

Table 4: API scores calculated based on the usage of top ransomware APIs and top benign APIs. The calculation process is described in Section 3.1. RW stands for ransomware. Ransomware API score is calculated based on APIs in sets \mathbb{R} and \mathbb{O} . Benign API score is calculated based on APIs in set \mathbb{B} . API contrast score is the final score, shown in Figure 4, from adding benign score to ransomware score. The lower the final score, the more likely the sample is benign.

Sample	RW API Score	Benign API Score	API Contrast Score	Sample	RW API Score	Benign API Score	API Contrast Score
Hive (47db)	8	-7	1	DoejoCrypt (e044)	0	0	0
LockBit (a2ad)	8	-15	-7	Mydoom (dd28)	0	-3	-3
LockBit (dec4)	7	-15	-8	Sage (ac27)	2	-5	-3
LockFile (2a23)	3	-11	-8	SunCrypt (759f)	3	0	3
Ryuk (9eb7)	1	0	1	Chrome	1	-10	-9
Ryuk (40b8)	7	-3	4	Git	2	-17	-15
Sodinokibi (9b11)	5	-12	-7	Notepad++	0	-14	-14
Sodinokibi (fd16)	6	-12	-6	TeamViewer	4	-17	-13
VirLock (7a92)	9	-2	7	Bitdefender	2	-12	-10
VirLock (f4b1)	11	-4	7	PaintNet	0	-7	-7
MountLocker (5eae)	3	-1	2	iCloud	0	-10	-10
Karma (6c98)	0	0	0	OneDrive	1	-16	-15
AvosLocker (7188)	6	-4	2	Skype	2	-16	-14
AvosLocker (f810)	6	-4	2	ScreenSplit	3	-14	-11
Dharma (dc5b)	9	-10	-1				

score of -15, falling in the range of benign. Filtering all positive predictions from Manhattan-based with a threshold of -10, the benign case Git is separated out while the decision on all ransomware cases remains unchanged, helping further boost the precision. The refinement outcome is the same for frequency-weighted and Euclidean-based consistency metrics.

On top of the consistency-based classification, the API contrast score helps further evaluate the risk and reduce false positives. However, this stage of detection could be evaded by sophisticated attacks. We acknowledge and discuss the limitations of it in Section 5.

4.3 Feature Importance Analysis

To further investigate the most informative APIs for revealing ransomware behaviors, we conduct a feature importance analysis based on a random forest model (using setup 2). The trained model achieves 0.99 ransomware class recall and precision using API call frequencies during the whole execution. We then manually analyze the top 29 APIs (Table 6 in the appendix) with their usage context and compare with benign application statistics. Next, we present a few detailed case studies of the APIs, differentiating the usage between ransomware and benign samples.

Persistence (NtDeleteKey). We observe that the lack of registry key deletion is a feature of ransomware maintaining persistence after the attack. Windows registry is a database that keeps important information related to the operation of the system and services running in the system.

- **Ransomware:** Ransomware creates a registry value in the “Run” subkey for auto-launching after the system reboots. In our experiments, we observed that 343 ransomware samples called `NtOpenKey` and 71 called `NtCreateKey`, whereas only 4 called `NtDeleteKey`.
- **Benign:** On the opposite, most benign software calls `NtDeleteKey` at the end of execution to delete any registry keys they opened (via `NtOpenKey`) or created (via `NtCreateKey`). Among 330 benign applications that called `NtCreateKey`, 319 of them called `NtOpenKey`, and 310 called `NtDeleteKey`. A few exceptions of benign applications also exist, such as Norton and Viber, which launch at Windows startup and thus keep their registry keys.

Kernel security driver access (`DeviceIoControl`). Our experiments show that ransomware often uses control code “3735560”, which is related to the kernel security driver, when calling `DeviceIoControl` API. `DeviceIoControl` is used by programs to interact with device drivers in the system. Sending a specific control code will cause the corresponding driver to perform corresponding actions.

- **Ransomware:** 149 out of 348 ransomware samples invoked `DeviceIoControl` during execution. Among those samples, 79% samples used 3735560 (0x390008 in hexadecimal) for control code, in which 0x39 corresponds to the macros “`IOCTL_KSEC_RANDOM_FILL_BUFFER`”, or “`IOCTL_KSEC_RNG_REKEY`”. “KSEC” stands for Kernal SECurity. The driver contains security and crypto-related functions, which are potentially used by ransomware samples for encryption key generation.
- **Benign:** 321 out of 330 benign software invoked `DeviceIoControl`. Only 40% of them used control code 3735560. The majority of benign samples invoked the API with code 589916 (0x9005C) and 590016 (0x900C0), with 0x9 referring to the file system (`FILE_DEVICE_FILE_SYSTEM`).

Besides, foreground-related API invocation differences may also serve as useful features for classification. For example, ransomware checks currently active program less frequently than benign ones, mainly for anti-analysis purposes. Only 82 ransomware samples (24%) used the `GetForegroundWindow` API, among which around 70% of samples belong to only a few families (i.e., LockBit, Stop, Ryuk, and Venus). In benign scenarios, We observe 329 benign applications invoked `GetForegroundWindow`. Another helpful API is `DrawTextExW`, which is for front-end formatting. Only 59 of 348 ransomware samples (17%) call `DrawTextExW` with low frequency. On contrast, 329 out of 330 benign samples make use of it, with an average call of 2256 times and a high of 49000.

4.4 Comparison with Benign File Operations

In this section, we compare several intensive file operations for benign purposes with ransomware. Benign software can also be designed to handle a significant amount of file operations, such as backup. To investigate how to differentiate such

benign behaviors from ransomware, we manually run a set of file operations using the 7zip file manager. The operations we perform include compressing, copying, moving, encrypting, extracting, and deleting. Each operation is performed on 1000 to 3000 files in at least 3 distinct directories. The encryption algorithm used is AES-256.

While some file operations have a repetitive execution period, they can be distinguished from malicious behaviors in a few ways (Figure 5 in the appendix). Copying (Figure 5b) and moving (Figure 5c) a large number of files show a few repetitive execution windows. However, the API composition is simpler during these periods, consisting of only 3 APIs, while typical ransomware execution uses 6 to 10. For extracting files (Figure 5e), the vast majority of calls were made to a single API, namely `NtWriteFile`. The execution process of compression (Figure 5a) and encryption (Figure 5d) has a 2-stage pattern, calling `NtOpenFile` and `NtQueryDirectoryFile` first for preparation and then using `NtReadFile`, `NtCreateFile`, and `GetFileInformationByHandle` for the operations. Deleting also has this 2-stage feature with the usage of a different set of APIs (Figure 5f). The repetitive period lasts longer in the case of deletion, but the call frequency is also lower for each second.

On the other hand, when looking at the top ransomware and benign API usage scores (described in Sections 3.1 and 4.2), we can also distinguish the file operations from malicious behaviors. The highest ransomware API score among all 6 operations is 1 (out of 18), suggesting the benignness. None of the operations used any of the top prevalent ransomware APIs. Only 2 of them exceed the frequency threshold of `RegDeleteValueW`. Furthermore, when looking at the top benign APIs, the scores range from -13 to -14, falling in the cluster of benign programs (benign scores are shown in Table 4).

In summary, with further inspection, it is possible to separate benign file accesses from malicious ransomware behaviors. However, execution patterns depend on the implementation of specific programs and ransomware could evolve to mimic benign behaviors. Therefore, while being helpful, those observations might not generalize to all cases.

4.5 Evaluation of Commercial Defense

We describe results from the experimental evaluation of decryptors, antivirus software, and malware scanners for **RQ3**. Besides success rates, we report ransomware behaviors that raise alarms. The experimental setup of the following evaluation can be found in the appendix.

Crypto Decryptors. Decryption is a ransomware-specific recovery strategy that aims to recover files without payment. Generally, it works by inspecting the encryption algorithm and inferring the key. Strategies include finding implementation flaws of encryption functions, brute forcing the key in a certain scope, and monitoring the key generation.

Among the 6 decryptors we test, only the decryptor for Alcatraz successfully recovers the files. The decryptor requires a pair of original and encrypted files for

Table 5: Evaluation results of 8 commercial antivirus software. # detection before execution: number of samples that are blocked before the malware executes. # detection during execution: number of samples that execute but get terminated during execution. # completely rolled back: among the attacks that started, the number of those being completely rolled back to the state with no trace of infected files. # failed: number of attacks the tool failed to generate alerts or make a reaction. Empty means zero. Ransomware simulators are software that mimics ransomware behaviors for security evaluation purposes. Blocked and detected are reactions taken by antivirus software. – represents no reaction.

Antivirus software	real ransomware samples				ransomware simulators		our script			
	# detection before execution	# detection during execution	# completely rolled back	# failed	RanSim	QuickBuck	File raverse	File encryption	Ransom note dropping	Volume shadow deletion
Antivirus A	20				Blocked	Blocked	–	–	–	–
Antivirus B	20				Blocked	Blocked	–	–	–	–
Bitdefender	19	1	1		Passed all scenarios	Blocked	–	–	–	Detected
Malwarebytes	17	3	3		Blocked	Blocked	–	–	–	–
Kaspersky	12	7	5	1	Blocked	Blocked	–	–	–	–
McAfee	16			4	Blocked	Blocked	–	–	–	–
Norton	18			2	Blocked	Detected marco simulation	–	–	–	–
360	offline	3		17	Failed all scenarios	–	–	–	–	–
	online	20			Blocked	Blocked	–	–	–	Detected

cracking the password and finds the password in seconds. To minimize the effect of randomness and confirm the effectiveness, we run the attack three times. For each attack, the decryptor crack the password in 12119, 3724, and 4879 tries, respectively. Alcatraz first appeared in 2016 and uses AES-256 with Base64 encoding for encryption. It is computationally infeasible to brute force the AES-256 key as the key space is 2^{256} [36]. Therefore, we suspect that there might be a design flaw in Alcatraz’s encryption function that the decryptor uses as a shortcut to search for the correct key. This low success rate of recovery further necessitates early detection.

Commercial Antivirus Software. We test the antivirus software with real ransomware samples and simulations of ransomware behaviors. First, we report their effectiveness and analyze the features (static or behavioral) used for detection based on their reactions. The results are summarized in Table 5.

Detection before execution. All 8 commercial tools detect and block the majority of threats before they start execution and make any modifications to the system. They do so by moving the executable file to quarantine or prohibiting it from execution. It is likely that they run a signature matching similar to the malware scanners. Antivirus tools A, B, and 360 (online) detect all malware executables immediately upon decompression, suggesting that they have up-to-date malware databases. Bitdefender, Malwarebytes, Kaspersky, McAfee, and Norton block 19, 17, 12, 16, and 18 samples, respectively, before execution (Table 5).

Detection during execution. We execute a sample to test behavioral detection if it is not blocked by scanning. Bitdefender and Malwarebytes catch all

threats they missed before execution and completely roll back the malicious behaviors, with no signs of infection left in the system. Kaspersky successfully detects all 7 attacks missed earlier and revokes 5 of them. In the other two cases, a few infected files are left in the system but all original data is accessible. This shows that antivirus software has real-time behavioral detection to catch ongoing threats.

While all other attacks are terminated with no additional information, Bitdefender gives two warnings before the remediation of the Cerber ransomware attack starts. One of the firewall rules is triggered first, followed by the discovery of an infected file, which is the ransom note in this case.

Failed cases. Kaspersky, McAfee, and Norton miss 1, 4, and 2 attacks, respectively. One special case is the Hive sample, which Kaspersky and McAfee miss. It runs in the background but no attack behaviors are observed in 10 minutes. In all other cases, a large number of files are encrypted, but no warning or action is triggered. In an offline setting, 360 only catches 3 out of 20 threats, implying cloud computation for detection.

Detection on ransomware-like behaviors. We further investigate the ability of antivirus software to detect various ransomware-like behaviors by running simulations. Most of them block public simulators as real malware. A few exceptions include Bitdefender, which passes all RanSim scenarios, Norton, which detects the macro simulation, and 360 (offline), which has no reaction at all. Emulating various ransomware behaviors, we find that antivirus software only reacts to the deletion of volume shadow copy, which is a backup copy of computer volume. Intensive encryption and file access do not invoke any warning.

Commercial Malware Scanners. We also evaluate the efficacy of general-purpose malware scanners. We find that the scanners’ detection capability could be significantly weakened by simple obfuscation, i.e., compression with passwords. Therefore, dynamic behavioral detection is necessary to complement the protection.

Malware scanners provide pre-execution scanning, an early layer of protection against infection. Our experiments show that the majority of the scanners can effectively identify the threat in plain executable files. On average, 56 out of over 70 scanners raise an alert. However, the detection capability significantly reduces on password-protected samples. When compressed with the simple password “infected”, WannaCry triggers three alarms, which is the most among the 54 samples. In the complex password setting, 37 out of 54 samples completely evade detection, i.e., marked as safe by all scanners. This result suggests that the scanners are likely signature-based and have very limited detection capability against unknown and obfuscated samples. Full results are shown in Table 13 in the appendix. Obfuscating a malicious sample with encryption requires little effort but significantly increases the chance of escaping. However, forcing breaking advanced encryption algorithms is impossible and should not be the goal of a malware scanner. One possible approach to strengthen security is to warn the user that the file is encrypted and suggest further scanning.

We summarize our experimental findings as follows:

- Ransomware has extremely high crypto API and file API usage frequency during execution, up to 5,000 times a second, with a unique high repetition pattern throughout the execution process, which we leverage for detection.
- The usage patterns of specific APIs exhibit disparities between ransomware and benign programs. This variation helps our classification further evaluate the risk.
- Our feasibility study shows that our two-stage API-based classification achieves perfect precision and recall in differentiating ransomware execution from benign. Our consistency-based detection, capturing the unique ransomware file API usage features, effectively recognizes all malicious execution during evaluation (1.0 recall), with only 1 false alarm. The API contrast score, as a second step, successfully filters the false positives (1.0 precision).
- For commercial defense, the efficacy and comprehensiveness of decryptors are very limited, with only 1 out of 6 tested decryptors successfully recovering infected files. Malware scanners use static signature-based detection. 69% complex password-protected ransomware samples evade the detection of all 70 malware scanners tested. Anti-virus software detects generic malware behaviors, overlooking the most essential ransomware encryption actions.

5 Discussion and Limitations

Detecting core ransomware-specific features. Static signature-based detection, while effective in catching known malware samples, falls short in detecting any variants. According to VirusTotal, the samples we studied stayed unknown for up to 211 days in the wild (Table 8 in the appendix). Packing is also a widely used technique in malware [3, 14, 26], found in 35 out of 54 samples we examined (Table 14 in the appendix). Different ways of packing also create different hash signatures. Both situations render the signature matching useless. However, ransomware shows distinguishing features during execution. Thus, behavioral monitoring is necessary to prevent them from bypassing detection.

Further, for behavioral detection, although there are many prevalent features in ransomware executions, such as prevention of recovery, none of them is required for launching an attack and keeping the data hostage, i.e., not the core behaviors of ransomware and can evolve at any time. However, in our experiments, none of the antivirus software reacts to intensive encryption or file modification. SonicWall reports that [38], on average, 9.7 ransomware attacks are attempted every business day for a company running in the US. Although generic detection catches many threats, with such a huge base number, even a small escape rate could cause big problems.

Our detection focuses on identifying the unique execution pattern during the rapid encryption of data. This feature holds for the majority of current

ransomware, as encryption is the core of ransomware and slower procedures increase the likelihood of detection and termination. Our method may miss newly emerged samples that exhibit significantly different functionalities, which is a limitation shared by feature-based detection approaches. However, because encryption is the fundamental nature of crypto-ransomware and is not easily discardable, we believe that it will remain a key feature of ransomware attacks.

Moreover, it is worth noting that different techniques and implementations can be used to achieve a single function, resulting in different traces for analysis. Strategies built using specific traces may not generalize well to other malicious samples or families. In our consistency analysis, we address this issue by distilling the core repetitive patterns from the execution. This enables the identification of the encryption process utilizing diverse API combinations.

Limitations. Our work has several limitations due to the usage of sandbox and VM. The sandbox cannot catch the dynamically resolved APIs and I/O through memory mapping, resulting in several reports with only a few records, even when we observe numerous infected files in the system. We were also unable to retrieve the memory access behaviors, which will be our future work. In many reports, hundreds of records have exactly the same timestamp, making it impossible to calculate the inter-arrival time of some API sequences. Thus, we only report the call frequencies per second. In some cases, the time interval between the first and last API call in the report exceeds the total execution time. In these cases, we omit the exceeding part.

For our second stage API contrast score, despite being helpful, it considers only non-file APIs and should not be used alone. The reason is that some behaviors, while common, are not essential for launching a ransomware attack. The hackers can selectively discard or incorporate specific functions to bypass this detection stage. Like other detection works relying on specific API usage, the effect of system updates and environment changes needs to be carefully handled. The core part of our detection is the first stage where we extract the underlying pattern of ransomware encryption. It is worth mentioning that every detection solution has limitations and the risk to be bypassed by evolving malicious behaviors. Additionally, we manually set the thresholds for selecting APIs in our implementation. Different thresholds or other selection criteria should also be explored in the future to enhance the effectiveness.

Another limitation of our work is that we need to carefully consider the runtime overhead associated with the deployment of our work. API monitoring may notably slow down the program execution. Optimization of the deployment is a further challenge that should be explored.

6 Related Work

Besides the download-and-run black-box commercial tools, a plethora of academic solutions has also been proposed. These proof-of-concept frameworks provide interesting insights and promising directions for reinforcing ransomware defenses. In this section, we summarize and discuss various related works. We

only theoretically compare our approaches with existing works due to the unavailability of code and details of the experimental environment configuration.

Several detection approaches using kernel-level filesystem activities [16, 17, 22, 28, 35, 42] have been developed. UNVEIL [22] extracts the I/O access pattern of program execution and matches it with typical ransomware file access patterns. ShieldFS [16] offers additional functionality that rolls back any detected malicious behaviors. Further, CryptoDrop [35] detects the transformation of the file system through file extension changes and program input and output similarity. Our detection, while also concentrating on file behaviors, distinguishes itself in the usage of API. API tracing provides more fine-grained information on program execution and does not require low-level system modification for deployment.

API-based classification [8, 15, 20, 23] has also shown promising performance in detecting ransomware execution at different stages. Kok et al. [23] and Coglio et al. [15] propose early-stage detection leveraging machine learning models. Kok et al. collect all API invocation activities before encryption and use a random forest model for classification. With an elevated level of advancement, Coglio et al. develop a more sophisticated neural network for detecting early-stage ransomware activities with a focus on evasion APIs. Complementary to the existing work, our new method provides more in-depth file API usage analyses during the ransomware encryption phase. We extract a unique repetitive execution pattern beyond plain traces in the first stage analysis, enhancing the resilience to specific software implementation changes. The findings can be combined with existing machine learning approaches in the future to form multi-layered defenses.

Additionally, hardware performance metrics [10, 30, 43], network activities [6, 7, 13], kernel-level provenance data [4], access control [27], query sequences [37], and N-grams features from opcodes [46, 47] can help identify ransomware as well. Recovering strategies for getting data back have also been developed, such as SSD and external storage-aided recoveries [11, 19, 34, 45].

Ransomware surveys. Works have also been done on summarizing the knowledge of ransomware and its defenses. Sultan et al. [41] summarize ransomware’s evolution since the late 1990s. Al-rimy et al. [5] categorize different ransomware. Moussaileb et al. [29] and Olaimat et al. [31] study Windows and Android ransomware, respectively. Alwashali et al. [9] survey on Ransomware-as-a-Service (RaaS). Works have also surveyed detection and mitigation strategies [5, 9, 12, 25, 29, 32, 33]. Our work adds insights into both dynamic ransomware behaviors and the effectiveness of defenses in practice through experiments.

7 Conclusion

Our detection focuses on profiling ransomware-specific API behaviors, including repetitive API invocations related to file systems and encryption. Our two-step detection solution leverages API usage consistency and contrast API usage is new and has shown to be promising in identifying ransomware with low false positives. We also report new insights from our in-depth API case studies and

the evaluation of commercial defenses, which previously have not been reported in the literature. Ongoing work is focused on addressing overhead-related deployment challenges.

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Appendix

Experimental setup for commercial defense evaluation:

Evaluation of malware scanners. We test over 70 commercial malware scanners available on VirusTotal ¹⁰. All scanners are general purpose malware scanners in a black-box manner (i.e., the algorithm used is unknown). For each sample we scanned, the number of available scanners slightly varies (Table 13 in the appendix). We test the scanners in three settings. First, we use them to scan the plain executable file (.exe). Second, we scan the compressed file with a simple password “infected”. This password is used as a convention for sharing malware samples. Lastly, we make compressed files with a random, complex password (i.e., DDfA3WFxcPMUrsA) to test scanners’ ability to detect obfuscated samples.

Evaluation of commercial antivirus software. We test 8 different commercial antivirus software that provides protection against ransomware, namely Antivirus A (anonymized), Antivirus B (anonymized), Bitdefender, Malwarebytes, Kaspersky, McAfee, Norton, and 360 Total Security (Table 9 in the appendix). We anonymize antivirus tools A and B following their user terms and conditions. All 8 antivirus software are generic for all types of malware with ransomware detection feature. We conduct three series of experiments. We first evaluate them with 20 real ransomware samples from 20 families active from 2015 to 2020 (marked in Table 14 in the appendix). Each sample is compressed with the password “infected” at the beginning. We decompress the sample and if the antivirus had no reaction, we then execute it. The machine is disconnected from the internet during all real ransomware execution to prevent spreading. Because 360 Total Security perform poorly in the offline setting, we add an online setting for it, in which we only decompress the samples without executing them. Second, we use two publicly available ransomware simulators to test more attack scenarios. RanSim¹¹ simulates 23 ransomware attack scenarios. Quickbuck¹² simulates several typical ransomware behaviors. Lastly, we also use our own script to further test the behavioral detection because most antivirus tools block public simulators as malware, giving them no chance to execute. Our script simulates behaviors such as iterating and encrypting files, appending random or known ransomware file extensions, deleting volume shadow copies, and dropping ransom notes. Those ransomware-like behaviors can be run separately or together. The script is in Python 3.8. To mimic real ransomware, we statically link the crypto libraries

¹⁰ <https://www.virustotal.com/gui/>

¹¹ <https://www.knowbe4.com/ransomware-simulator>

¹² <https://github.com/NextronSystems/ransomware-simulator>

used (PyAesCrypt¹³ and Cryptography¹⁴) so that no external dependencies are needed. All tests were run on a Windows 7 VM with 2 CPUs and 4096 MB memory. The machine was reversed to initial image after each test.

Evaluation of crypto decryptors. Decryptors can help recover encrypted data without paying ransom after an attack. However, not all ransomware families have decryptors available. For the ransomware samples we successfully run, we found decryptors for 6 of them on the NO MORE RANSOM website¹⁵. Different decrypting tools require different information, such as uploading the ransom note or providing file pairs (i.e.unencrypted and encrypted) for key cracking.

Table 6: Top 29 important APIs for identifying ransomware execution from feature importance analysis based on a random forest model.

API		API		API	
1	RegEnumKeyExW	11	SearchPathW	21	NtQueryKey
2	CreateDirectoryW	12	SetFileTime	22	NtQueryValueKey
3	DrawTextExW	13	SendNotifyMessageW	23	NtSetValueKey
4	CoInitializeEx	14	GetSystemMetrics	24	CreateActCtxW
5	NtDeleteKey	15	GetKeyState	25	GetSystemTimeAsFileTime
6	SHGetFolderPathW	16	NtCreateKey	26	GetSystemWindowsDirectoryW
7	GetFileInformationByHandleEx	17	LoadResource	27	SetErrorMode
8	GetForegroundWindow	18	GetDiskFreeSpaceExW	28	GetFileVersionInfoSizeW
9	NtQueryAttributesFile	19	EnumWindows	29	NtOpenMutant
10	DeviceIoControl	20	RegOpenKeyExW		

Table 7: List of decryptors we test. SHA-256 column shows the first 4 digits of the ransomware sample that generates the encrypted files. File extension is the extension appended by ransomware after encryption. Trend Micro tool is designed for decrypting files infected by multiple families. Different families can be selected before decryption.

Ransomware family	SHA-256	File extension	Decryptor provider	Requirements	Success	Notes
Alcatraz	9185	.alcatraz	Avast	A pair of files	Yes	
Babuk	eb18	.doydo	Avast		No	
Jigsaw	9074	.v316	Trend Micro		No	
Ragnarok	db8b	.ragnarok_cry	Emsisoft	Ransom note	No	Ransom note file is not supported by decryptor
Sodinokibi	fd16	.031j2adrq8	BitDefender	Internet access	No	
Xorist	fb54	.locks	Trend Micro	A pair of files	No	Not able to proceed after adding file pair

¹³ <https://github.com/marcobellaccini/pyAesCrypt>

¹⁴ <https://github.com/pyca/cryptography>

¹⁵ <https://www.nomoreransom.org/en/decryption-tools.html>

Table 8: Days the specified ransomware stayed unknown. The SHA-256 column shows the first 4 digits of the sample hash. The days unknown represent the length between they are first seen in the wild and first submitted to ViruaTotal.

Ransomware Family	SHA 256	First Seen in the Wild	First Submission	Days Unknown
Alcatraz	9185	2016-10-05	2016-10-05	0
LockFile	2a23	2021-04-19	2021-08-24	127
MedusaLocker	0abb	2021-01-09	2021-08-08	211
Mespinoza	4dc8	2021-01-05	2021-01-05	0
Phobos	265d	2021-04-09	2021-08-23	136
Ryuk	9eb7	2020-11-20	2021-03-10	110
Xorist	fb54	2021-01-04	2021-01-04	0

Table 9: Version information of antivirus software tested.

	Version/Build	License		Version/Build	License
Antivirus A	N/A	N/A	Kaspersky	21.3.10.391 (h)	30-day trail
Antivirus B	N/A	N/A	McAfee	16.0 R31	30-day trail
Bitdefender	26.0.18.75	30-day trail	Norton	22.22.4.11	30-day trail
Malwarebytes	4.5.10.200	14-day trail	360	10.8.0.1465	free

Table 10: List of top ransomware APIs used in API contrast score (set \mathbb{R}).

API			
CoInitializeSecurity	Process32FirstW	WriteConsoleW	CryptEncrypt
CreateToolhelp32Snapshot	Process32NextW	CryptGenKey	CryptExportKey

Table 11: List of co-occurring APIs used in calculating the API contrast score (set \mathbb{O}). The frequency limits are calculated based on the observed frequency and the duration of execution. We set them to be double the average benign frequency. Because the execution time is 600s for setup 1 samples and 300s for setup 2 samples, we further double the value when applied on setup 1 samples.

API	Threshold	API	Threshold
NtAllocateVirtualMemory	6412	RegDeleteValueW	56
NtFreeVirtualMemory	2320	GetUserNameExW	28
OpenSCManagerW	20	CoCreateInstanceEx	8
OpenServiceW	32	CryptAcquireContextA	64
NtOpenThread	16	CryptCreateHash	52

Table 12: List of top benign APIs used in calculating the API contrast score (set \mathbb{B}).

API			
NtDeleteKey	GetCursorPos	GetForegroundWindow	FindResourceExW
EnumWindows	SizeofResource	GetFileVersionInfoSizeW	FindResourceA
GetKeyState	OleInitialize	GetFileVersionInfoW	RegCreateKeyExA
DrawTextExW	FindWindowW	SendNotifyMessageW	
FindResourceW	NtCreateKey	NtReadVirtualMemory	

Table 13: Evaluation commercial malware scanners. Simple password and complex password columns show the scanning results for simple and complex password-compressed files (.zip), respectively. Number before the slash is the number of successful detections. Number after is the number of total scanners available for this sample. This number varies slightly for each sample. Last row shows the average number of detection on 54 samples. The samples are uploaded for scanning in May 2022 and December 2022.

Ransomware Family	SHA256	Plain File	Simple Password	Complex Password	Ransomware Family	SHA256	Plain File	Simple Password	Complex Password
7ev3n	000e	56/71	0/62	0/62	Mespinoza	4dc8	61/69	1/58	0/59
	0047	62/71	0/64	0/61		44f1	57/69	1/58	0/61
	0084	57/70	0/62	0/62		af99	58/69	1/57	0/58
Alcatraz	9185	52/70	1/61	0/61	MountLocker	5eae	56/69	1/59	0/59
AvosLocker	7188	48/64	2/59	1/59	Phobos	9dde	52/68	1/58	1/59
	f810	51/66	1/57	0/58		265d	58/67	2/58	1/58
Babuk	eb18	54/67	1/58	0/59		8710	62/70	2/59	1/61
BlackBasta	9a55	52/70	1/62	1/62	Ragnarok	db8b	52/69	1/61	0/59
	7883	60/70	1/62	1/62	Ryuk	9eb7	61/68	1/60	0/59
Cerber	0cd2	49/69	1/57	0/58		40b8	58/68	1/58	0/60
Dharma	dc5b	52/68	0/62	0/62	Sage	ac27	65/71	0/62	1/62
DoejoCrypt	e044	56/72	0/62	0/64	SatanCryptor	dd28	56/71	0/64	0/62
HelloKitty	fa72	59/69	1/57	0/60	Snatch	edad	53/69	1/57	0/61
Hive	47db	49/69	1/58	0/59	Sodinokibi	9b11	61/68	1/58	0/58
Jigsaw	9c74	48/67	2/58	1/61		fd16	60/70	1/57	0/61
	3ae9	59/68	1/62	1/62	Sugar	1d4f	52/67	1/57	0/60
	df04	56/72	1/62	1/62	SunCrypt	759f	58/72	1/62	1/62
Karma	6c98	55/68	2/58	1/58	TellYouThePass	7697	47/68	2/61	1/59
LockBit	a2ad	55/70	1/58	0/61	TeslaCrypt	4de6	61/71	0/61	0/62
	dec4	59/69	1/58	0/57	Venus	d609	61/72	0/62	0/62
LockFile	2a23	53/68	1/58	0/57		ee03	61/72	0/62	0/64
Lorenz	1264	49/68	2/57	1/58		59b0	58/72	0/61	0/64
	a0cc	53/69	2/59	1/61	VirLock	7a92	60/67	1/59	0/50
	cdc2	55/69	1/57	0/60		f4b1	63/71	1/59	0/61
MarraCrypt	be88	60/71	0/62	0/62	VoidCrypt	4b78	53/71	0/62	0/60
MedusaLocker	0abb	49/67	1/59	0/59	WannaCry	ed01	60/67	3/59	2/59
	f5fb	51/68	2/59	1/59	Xorist	fb54	62/71	1/59	0/59
					average		56	0.96	0.33

Table 14: The full SHA-256 hashes of the ransomware samples we measure. The exact samples can be found using the hashes. Year is the (possible) compilation time from the executable file. 1969 and 2010 might be intentional for anti-analysis reasons. Entropy is the file entropy calculated by Detect it Easy (DiE). A sample is packed if the entropy is over 6.5. Samples marked with yes in the used for evaluation column are used for testing antivirus software.

Ransomware Family	Compiled Year	SHA256	entropy	if packed	Used for evaluation
7ev3n	2016	000ec059ab4eafd2591449c6581b34748d3f90ef1688b9ec6daf5ab58d5da73	6.40 (80%)		
	2016	0047aed5ba539ab2e56e78d47b0ae8673d4f221bf5106987f66437e6eb0978ba	6.38 (79%)		
	2016	0084af770e99180fcd6c778c513d36384cf4b3ff24d0f8bc62ecaa76651be616	6.40 (80%)		
Alcatraz	2016	918504ede26bb9a3aa315319da4d3549d64531afba593bfad71a653292899fec	6.48 (81%)		
AvosLocker	2021	718810b8eeb682fc70df602d952c0c83e028c5a5bfa44c506756980caf2edeabb	6.63 (82%)	yes	yes
	2021	f810deb1ba171cea5b595c6d3f816127fb182833f7a08a98de93226d4f6a336f	6.63 (82%)	yes	
Babuk	2021	eb180fcc43380b15013d9fe42e658fc6f6c32cf23426ef10b89bc6548d40523b	5.73 (71%)		yes
BlackBasta	2022	9a55f55886285eef7ffabd55c0232d1458175b1d868c03d3e304ce7d98980bc	6.62 (82%)	yes	
	2022	7883f01096db9bcf090c2317749b6873036e27ba92451b212b8645770e1f0b8a	6.62 (82%)		
Cerber	2015	0cd28b912cf4d9898a6f03c4edfd73d1d90faf971ad84b28c6c254408ad7630f	7.86 (98%)	yes	yes

Ransomware Family	Compiled Year	SHA256	entropy	if packed	Used for evaluation
Dharma	2017	dc5ba84e57cf8d8dfcb8fb2de6f842786428fc46c34d8a3e02c8119bbd9f7584	7.23 (90%)	yes	
DoejoCrypt	2021	e044d9f2d0f1260c3f4a543a1e67f33fcac265be114a1b135fd575b860d2b8c6	6.99 (87%)	yes	
HelloKitty	2020	fa722d0667418d68c4935e1461010a8f730f02fa1f595ee68bd0768fd5d1f8bb	5.98 (26%)		yes
Hive	1969	47dbb2594cd5eb7015ef08b7fb803cd5adc1a1fbc4849dc847c0940f1ccace35	6.06 (75%)		yes
Jigsaw	2020	9c748a69c48b79e6422b3bea1766e415de5532cb7ba2b9673d5a51163e6c1df2	7.98 (99%)	yes	yes
	2016	3ae96f73d805e1d3995253db4d910300d8442ea603737a1428b613061e7f61e7	7.68 (95%)	yes	
	2020	df049efbfa7ac0b76c8daff5d792c550c7a7a24f6e9e887d01a01013c9caa763	7.61 (95%)	yes	
Karma	2021	6c98d424ab1b9bfba683eda340fef6540ffe4ec4634f4b95cf9c70fe4ab2de90	5.87 (73%)		yes
LockBit	2021	a2ad5cc5045a1645f07da7eab14ba13eb69ab7286204f61ba6a4226bfade7f17	6.68 (83%)	yes	yes
	2021	dec4ca3a0863919f85c2a1a4a7e607e68063a9be1719ccb395353fe4a2d087e5	6.68 (83%)	yes	
LockFile	2021	2a23fac4cfa697cc738d633ec00f3be93ba22d2498f14dea08983026fdf128a	7.92 (98%)	yes	yes
Lorenz	2021	1264b40feaa824d5ba31cef3c8a4ede230c61ef71c8a7994875deefe32bd8b3d	6.26 (78%)		yes
	2021	a0ccb9019b90716c8ee1bc0829e0e04cf7166be2f25987abbc8987e65cef2e6f	6.31 (78%)		
	2021	edc2070fd8116f1df5c8d419189331ec606d10062818c5f3de865cd0f7d6db84	6.27 (78%)		
MarraCrypt	2020	be88512c9250a558a3524e1c3bbd0299517cb0d6c3fb749c22df32033bf081e8	7.40 (92%)	yes	
MedusaLocker	2021	f5fb7fa5231c18f0951c755c4cb0ec07b0889b5e320f42213cbf6bbbe499ad31	5.57 (69%)		
	2021	0abb4a302819cdca6c9f56893ca2b52856b55a0aa68a3cb8bdcd55dcc1fad9ad	5.57 (69%)		
Mespinoza	2020	4dc802894c45ec4d119d002a7569be6c99a9bba732d0057364da9350f9d3659b	6.65 (83%)	yes	yes
	2021	44f1def68aef34687bfacf3668e56873f9d603fc6741d5da1209cc55bdc6f1f9	6.65 (83%)	yes	
	2020	af99b482eb0b3ff976fa719bf0079da15f62a6c203911655ed93e52ae05c4ac8	6.65 (83%)	yes	
MountLocker	2020	5eae13527d4e39059025c3e56dad966cf67476fe7830090e40c14d0a4046adf0	4.00 (50%)		yes
Phobos	2020	9dde984b21a00bc3307c28bd81f229500b795ce4e908b6f8cb5fbd338b22b8e1	3.38 (42%)		yes
	2020	265d1ae339e9397976d9328b2c84aca61a7cb6c0bca9f2f8dc213678e2b2ad86	6.97 (87%)	yes	
	2020	8710ad8fb2938326655335455987aa17961b2496a345a7ed9f4bbfcb278212bc	6.70 (83%)	yes	
Ragnarok	2020	db8b499d613b604a439bca37c3be2f578bdfcde1b2271eccbcf22db85996e785	6.73 (84%)	yes	
Ryuk	2021	9eb7abf2228ad28d8b7f571e0495d4a35da40607f04355307077975e271553b8	6.42 (80%)	yes	yes
	2020	40b865d1c3ab1b8544bcf57c88edd30679870d40b27d62feb237a19f0c5f9cd1	5.11 (63%)		
Sage	2017	ac2736be4501b8c6823ebcf7241ceda38c3071418fb43c08b30f54f1a45d07e0	6.54 (81%)	yes	
SatanCryptor	1969	dd286a4d79d0f4c2b906073c7f46680252ca09c1c39b0dc12c92097c56662876	7.91 (98%)	yes	
Snatch	1969	edade6616334f3d313ac3ea7c3e432d8d9461cddad8e2ec3a94ffdc6e336a94e	7.89 (98%)	yes	yes
Sodinokibi	2021	9b11711efed24b3c6723521a7d7eb4a52e4914db7420e278aa36e727459d59dd	6.14 (76%)		yes
	2021	fd164c4c121371f94cfd3a034ad8cf8edc7c0f7141a8f4c9da1683d41b212a87	6.76 (84%)	yes	

Software	File Name	SHA-256	# Alerts
Steam	SteamSetup.exe	874788b45dfc043289ba05387e83f27b4a046004a88a4c5ee7c073187ff65b9d	0/69
TeamViewer	teamviewer_setup.exe	e463f3a11c4eafc698906876d610702fc9227a65183a30104579d8912ecdefe4	1/68
Tree Size	TreeSizeFree Setup.exe	4de19445df877ef4df981fbeat9440cf4a8832a284ea0e753ff1e7dd41dc10fa	0/69
WhatsApp	whatsappsetup.exe	8aefba89a391331d8d3ad08f988c2a5ba0d69d04069f03a3121a01573da7be6c	0/66
WinRAR	winrar-x32-611.exe	59276c49519ebd5194b95622c1c81d4b2c45d14eb6b07ea6d9f2b37c9c7bbf93	1/68
WinZIP	winzip26-home.exe	a9ed6c5db282c4d42f4fd232627dab25b2f777b561a0065998a82b9e668d9f70	1/69
Zoom meeting	zoominstallerfull.exe	cdb3a3b20d65db7e51e345aa32075bc37b99cd8de86c5df950409bd56168da53	5/66
NetBean IDE	apache-netbeans-13-bin-windows-x64.exe	a06ea580a2bfe50bdc8c9791fed5c6032ce8330b16e0c6c5dbf6c9e1c931dc9e	0/61
Bitdefender	bitdefender_avplus_v10.exe	b973f4fe1f3bb9de06abd2f615d2f47c3c52810ee09d17255a6ba3c0a65eb801	0/65
Dev-C++	dev-cpp_5.11_tdm-gcc_4.9.2_setup.exe	faad96bbcc51f115c9edd691785d1309e7663b67dcfc7c11515c3d28c9c01f	1/67
Evernote	Evernote-10.48.4-win-ddl-ga-3760-5f4dcc5719-setup.exe	a81ec8d119abaaf31cb46125f50c0089f054d085ca3b1f6927b48f3be40e9de	0/66
Google Drive	GoogleDriveSetup.exe	2cb39f4b8e640944c83e7ee34f0f886b58df23fa4141c225714cd6646b96575	0/67
Grammarly	grammarlysetup.exe	368e252f2e066bda82b8524c4ac939e5728154a334b991153a4fbc3a2320f14	0/69
iCloud	iCloudSetup.exe	4cfd20d13cdce2b5c435f2ddaf4ee4c81d976461846bf3b954e8af6bcdeb9f7	0/67
KeePass password safe	keepass-2.52-setup.exe	da403bc2e91132d1c1e0c49f585441e4cd430c8195ca8af38adc2ea300de52cb	0/71
MalwareBytes	mbsetup.exe	057ac0f95e80abc5c73d9aefbc4e5e1bb778c2c154bf65c35435a34cdfa3da94	0/72
Microsoft Teams	microsoft-teams-1-5-00-28567.exe	dcca2a974c673e21f3b5b11cee955fb20b14903c3218cef3b9d2b061cc8a0c30	0/61
OneDrive	OneDriveSetup.exe	83d2429a8568ee4ea0ed002c0897560c6b0a3e0b2a66f72a4149a521d461c6e7	0/71
Paint.Net	paint.net.4.0.21.install.exe	088a02864e8daf807584fdd14ba3ed191979db0af301a318e7c1e8fc4c03dcdbd	3/68
QuickTime	quicktimeinstaller.exe	56eff77b029b5f56c47d11fe58878627065dbeacbc3108d50d98a83420152c2b	0/66
Skype	Skype-8.90.0.405.exe	d073e31487c5584f12b263d0372288c049a1d316a75151801bb7e6ebb39766b1	0/69
Slack	SlackSetup.exe	0682a25eae6bfe3bc42e949aa4af0274c983690b726922217befb02d8e2f5306	0/69
Screen Split	SS_Setup_6-57.exe	78a9ba1748686eccc181e97151c813acc92edcd35c05a673f24823ae0bb2a8ec	0/66
Mozilla Thunderbrid	Thunderbird Setup 91.3.1.exe	39a502318a8b10bc25d9547b9c48fb646f7083d7161a4da7cee48ceabe77c65e	0/53
WordWeb	wordweb10.exe	27142582b89e0fa2ca6a9d5036eccc3bde140109aa9632f9b5eac30933a082080	1/70

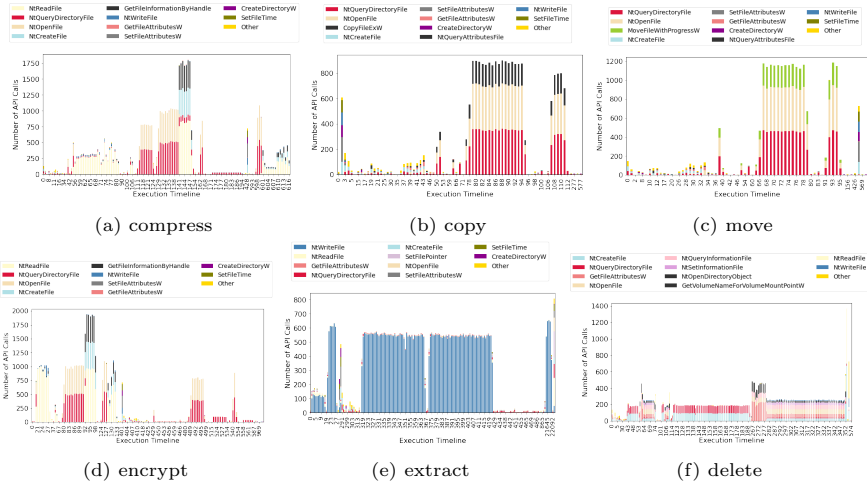


Fig. 5: File-related API call statistics of benign file operations (performed using the 7zip file manager). The same colors represent the same APIs across subfigures.