Malicious Linux Binaries: A Landscape

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Abstract. *Linux applications are finding their role on important computer systems. As their use grow, they become target for malware. Therefore, understanding the security impacts of malware infections on them is essential to allow system hardening and countermeasures development. In this paper, we evaluate malicious ELF binaries to present a landscape of current threats. We discuss the challenges and pitfalls of analyzing samples on this platform and compare the identified behaviors to the ones presented by other platforms' samples.*

1. Introduction

Fighting malware is currently a major security task for incident response teams, as this kind of threat is responsible for a myriad of damages, from privacy leaks to financial losses [TrendMicro 2017]. To provide proper countermeasures, understanding samples behavior is essential.

Recently, `Linux` systems have grown their market share [Itsfoss 2017], being present as back-end of many services. As it brings new, benign opportunities, it makes this environment target for malicious actors. Therefore, understanding the impact of `Linux` malware is essential to protect modern computer systems.

Previous work on `Linux` malware was guided by sandbox development [A 2015, 0x71 2016], thus not presenting a panorama of existing threats. Existing landscapes are limited to the Android ecosystem [Lindorfer et al. 2014], thus leaving other contexts underexplored. In this work, we evaluate `Linux` malware samples to present a panorama of their behaviors. Our goal is to understand their impact over systems as a whole, thus allowing more precise and effective incident response.

This work is organized as follows: in section 2, we present related work; in section 3, we present our assumptions and methods; in section 4, we present the threat landscape; in section 5, we discuss the impact of our findings; finally, we draw our conclusions in Section 6.

2. Related Work

The first step for analyzing `Linux` malware is to adopt a sandbox solution. In the literature, many solutions were proposed, such as a `Linux` version of Cuckoo Sandbox [0x71 2016]. In this work, we developed our own solution based on the use of `Linux` built-in tracing tools, such as `strace`, an approach also adopted by other sandbox solutions, such as Limon [A 2015].

A drawback of most solutions is to rely only on generic characteristics, such as the performed API calls. Few solutions consider OS particularities, such as the ELF (Executable and Linkable Format) format and `Linux` internal structures [Damri and Vidyarthi 2016, Shahzad et al. 2011]. In this work we considered these in our analysis, covering for instance, the `passwd` and `shadow` files, structures not present in other OS.

Based on the sandbox results, most solutions adopt classification approaches [Asmitha and Vinod 2014, KA and P 2014] to distinguish malicious from benign applications. Although important for individual sample analysis, these do not provide insights

regarding the whole malware scenario. In this sense, our work contributes for better understanding the whole context.

Previous work addressed the malware landscape issue on other platforms. Lindorfer et al. [Lindorfer et al. 2014] surveyed the Android ecosystem. Bayer et al. [Bayer et al. 2009] surveyed the `Windows` one. This work extends these for the `Linux` scenario.

During the development of this work, we were noticed of the publication of a `Linux` malware survey [Cozzi et al. 2018], thus being this the closest work to ours so-far. As a significant distinction, our work digs into more details about x86 samples' behavior during dynamic analysis, thus complementing it.

3. Methodology

3.1. Dataset Description

To provide a comprehensive evaluation of `Linux` binaries, we collected samples from distinct sources. In total, this study considers 5,680 unique ELF binaries—identified by their MD5—crawled from `MalShare`[1], `VirusTotal`[2] and `VirusShare`[3].

A noticeable `Linux` characteristic is its multi-platform support: the collected ELF samples cover 8 distinct architectures, as shown in Figure 1.

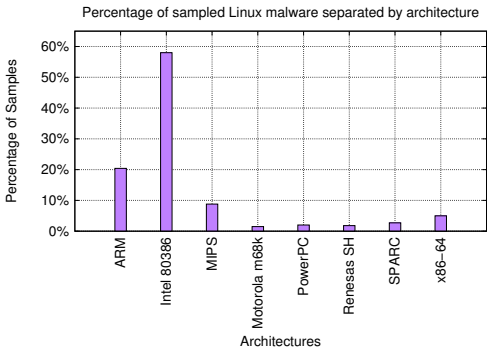

Figure 1. ELF binaries by architectures. `x86` and `ARM` are the most prevalent architectures.

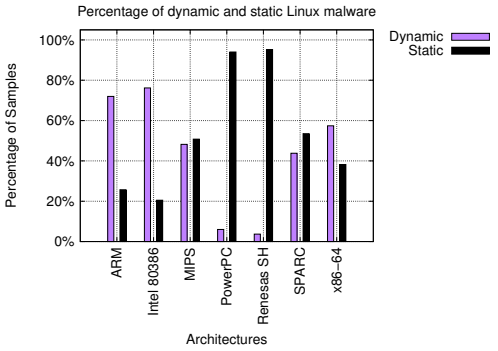

Figure 2. Binary linking methods by architecture. Most architectures present a significant number of both static and dynamic linked binaries.

We observe that the most prevalent architectures are `Intel x86`, found in most desktop computers and servers, and `ARM`, often found in mobile phones and tablets. Besides that, we observe a diversity on the remaining platforms, thus showing the heterogeneity of the `Linux` ecosystem, which covers a myriad of embedded systems, from co-processors to `IoT` devices.

The ELF heterogeneity is observed not only in the target platform but also in the binaries themselves, Figure 2 presents how samples of each architecture are linked[4]—statically or dynamically. Whereas some architectures present a higher rate of statically linked samples, other presents higher rates of dynamically linked ones. The linking project decision is not only tied to environment characteristics but also to evasion attempts, as statically linked libraries cannot be traced by some analysis solutions (`ltrace`).

In addition to linking methods, malware creators also adopt distinct project decisions regarding the distributed object file, as shown in Figure 3. Whereas executables are prevalent in most

[1] `malshare.com` [2] `virustotal.com` [3] `virusshare.com` [4] Unavailable info for m68k.

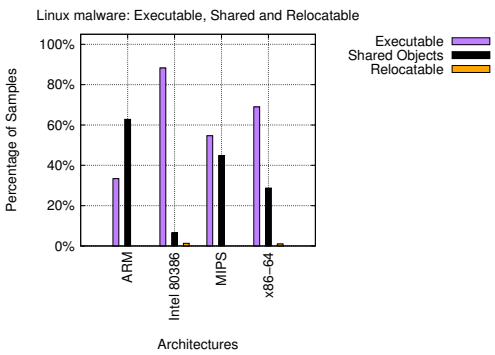

Figure 3. Object file formats. Samples are distributed both as executables and libraries.

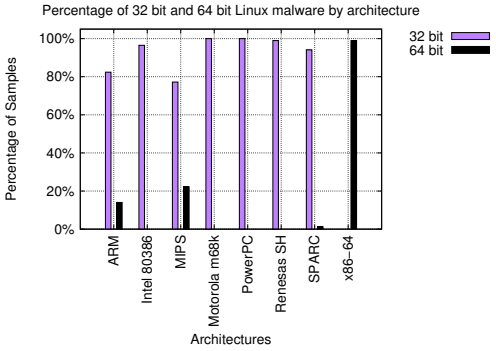

Figure 4. Percentage of 32-bit and 64-bit binaries by architecture. 32-bit binaries are prevalent.

platforms, shared objects (libraries) also appear in significant rates. Leveraging executables is interesting for malware creators as it enables users infecting themselves by directly running the objects. Shared objects, in turn, allow attackers to inject their payloads in any other binary in the form of a library. Finally, shared objects are also employed to allow code modularization, a strategy employed in malware to bypass detection methods.

The most homogenous characteristic in our ELF dataset are binaries word size (32 or 64 bits). As presented in Figure 4, almost all architectures present higher rates of 32 bit samples, as was the standard until few years ago. Modern samples, however, are already compiled as 64 bits.

3.2. Analysis Methods

First, all samples were submitted to `VirusTotal` to retrieve anti-virus detection rates and label information; secondly, static analysis was performed, by disassembling (using `objdump`) all files and retrieving header information; finally, dynamic analysis was performed to evaluate samples' behavior and capture network traffic. As samples may be equipped with anti-analysis techniques, the strategy presented in Table 1 was employed.

Table 1. Analysis techniques. Adopted strategy to handle evasive samples.

Technique	Tool	Evasion	Countermeasure
Static analysis	*objdump* *file* *strings*	obfuscation	Dynamic analysis
Dynamic analysis	*ltrace*	Static compilation	*ptrace* step-by-step
	ptrace	*ptrace* check	binary patching
	strace	Long *sleep*	*LD_PRELOAD*
	LD_PRELOAD	Injection blocking	Kernel *hooks*

As static analysis procedures may be defeated by obfuscation, we also submitted samples to dynamic analysis procedures. Dynamic analysis may be performed in a series of ways [Gebai and Dagenais 2018]. In our evaluation, we leveraged `strace` for system call inspection and `ltrace` for function call inspection.

Dynamic analysis, however, may also be defeated in diverse ways: i) `ltrace` analysis may be avoided by the use of static libraries, as it handles only dynamic ones. These samples are analyzed in more details through step-by-step instruction tracing by using `ptrace`, which is able to dig into samples despite their linking mode; ii) `Ptrace` analysis in turn, may be defeated by `ptrace` checks. In this case, the check may be removed by using a binary patching procedure; iii) `ltrace`

and `strace` may be evaded by a long `sleep`, aimed to trigger a timeout on the sandbox. Such cases are handled by the injection of a library—through `LD_PRELOAD`—to hook the `sleep` function so it immediately returns; iv) the `LD_PRELOAD` method may be blocked by some samples. Such cases may be inspected by a kernel driver which hooks API calls to log them.

In addition to anti-analysis-armored samples, other particular behaviors were considered, as shown in Table 2.

Table 2. Handling suspicious behaviors. Adopted strategy to keep log files safe.

Behavior	Action	Countermeasure	Method
Evidence removal	delete logs	log access	*syslog/audit*
Ransomware	delete files	shadow copy	*inotify*

Some samples present the evidence removal behavior, deleting the stored logs. For these cases, a logging mechanism was implemented to register such occurrences and thus characterize the samples as evidence removers. Ransomware samples also may damage the filesystem by encrypting all files, including the collected logs. Therefore, a shadow copy of files using `inotify` was implemented, thus keeping all original files safe.

All aforementioned analysis procedures were conducted on a network-isolated, virtual machine-based sandbox solutions running *Ubuntu 16*. The samples were individually analyzed by up to 3 minutes and the clean system state was restored through snapshots after each execution.

4. Linux Malware Landscape

4.1. Static Features

We initially submitted all samples through static analysis procedures to get general insights about how samples look like. We first retrieved (via `objdump`) the linked function calls to understand which behaviors the samples were supposed to present. For such, we classified the obtained functions in categories, according to the behaviors defined in [Grégio et al. 2015].

The `Network` category encompasses functions responsible for allowing samples to communicate through the Internet, thus enabling malicious content download and information exfiltration. The `Evasion` category encompasses functions which can be used to thwart an analysis procedure thus keeping samples undetected. It covers functions used to modularize malware code and the ones used to finish and/or block other processes execution. The `Environment` category encompasses functions which allows environment fingerprinting, such as retrieving username information. Such information can be used for evasion and/or for infection accountability. The `Removal` category encompasses functions related to anti-forensics produces, thus allowing the sample to cover its track. Finally, the `Timing` category encompasses functions which allows the sample to measure the spent time while processing. Such information can be used for evasion procedures, as the samples may detect the performance overhead imposed by an analysis solution. Figure 5 shows how often samples of each architecture link functions from one or more of these categories.

We notice that attempting to establish a network connection is the most prevalent suspicious behavior among all architectures, being it present in over 25% of the entire dataset samples. Attempts to evade analysis procedures are also frequent, either in the form of analysis termination or in the form of overhead measurement. Environment information was collected in fewer samples, which indicates such information is not being used for evasion in a broad way but for other purposes, such as information leaking, according to each samples specific goal.

The identified prevalent use of network capabilities is an even more significant result when we consider it is a lower bound, because `objdump` only identifies function entries present in the dynamic symbol table. Therefore, function calls from statically linked and obfuscated samples were not retrieved. Figure 6 shows the rate of samples whose dissasembly attempts failed. Omitted architectures are due to lack of `objdump` support.

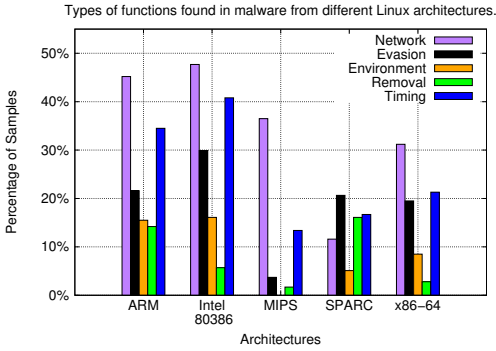

Figure 5. Malware behavior prevalence by malware architectures. We observe that network functions are prevalent.

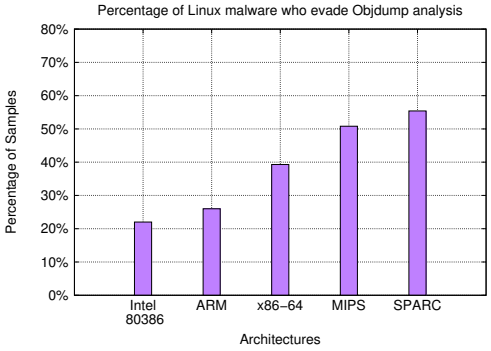

Figure 6. Percentage of malware that failed to disassembly. Some architectures aren't present because of lack of objdump support.

After identifying the high use of network functions, we queried (via `strings` [5]) network-related information embedded in the binary. By matching the retrieved strings with regular-expressions patterns, we identified information about IP addresses, URLs and E-mail contacts. The ratio of samples presenting network-related strings and the fraction of distinct strings are present in Figure 7.

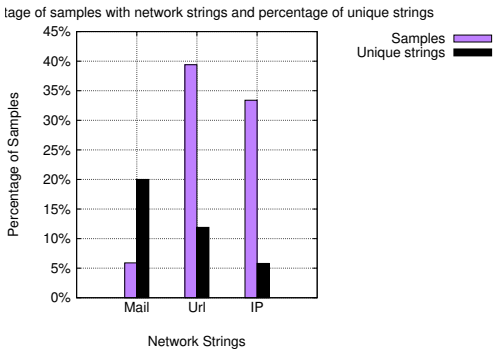

Figure 7. Network-Related Strings. Percentage of samples with network-related strings and the fraction of unique strings.

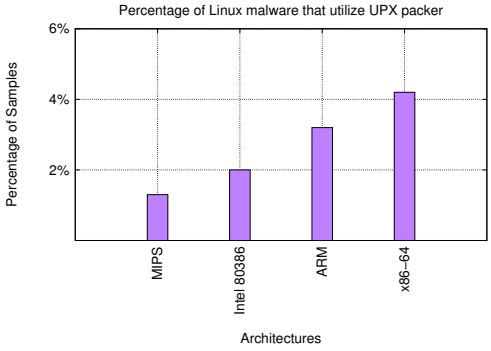

Figure 8. Percentage of UPX-packed samples. Few samples are packed. 64-bits samples are the most packed ones.

Among all identified strings, we found suspicious IP and URL addresses, including local and remote hosts, of which many are related to shell script downloads. We also identified embedded Email addresses, which are probably related to phishing campaigns. As for functions, embedded strings can also be hidden by packer-based obfuscation. Figure 8 shows the rate of samples leveraging `UPX`[6], a popular open-source packing solution.

To confirm our findings about the intense network usage, we checked how AVs label the samples. Figure 9 shows labels attributed to all samples by the *Kaspersky* AV. Among all 10 attributed labels, the three more prevalent ones (*Exploits, Virus* and *Backdoor*) account for 60% of all samples.

The high presence of *Backdoor* samples explains the high linkage rate of network-related functions—presented in the Figure 5—, as *Backdoors* make use of network connection to allow the external attackers to remotely access the infected system.

[5] man strings [6] `upx.github.io`

The prevalent labels also explain the low rate of `UPX` packed samples, as presented in Figure 8. *Exploits*, which represent nearly 25% of all samples tend to present low obfuscation rates due to their nature. These aren't self-contained applications which unpack themselves, but payloads which are injected into third processes to cause these to behave maliciously.

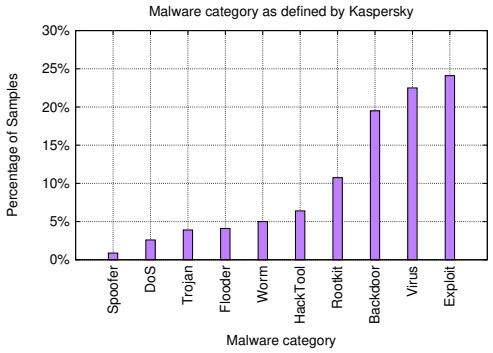

Figure 9. AV labels according Kaspersky AV. We observe a prevalence of exploits and network-related threats.

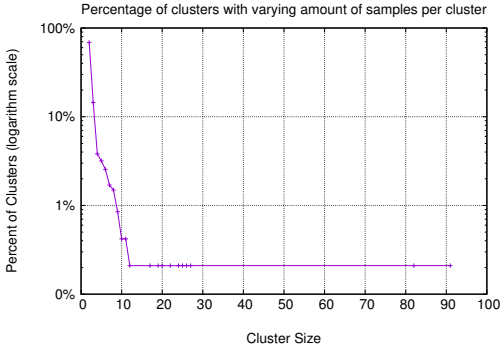

Figure 10. Samples variants clustering. Smaller clusters (up to 5 samples) are prevalent. Largest cluster has 91 samples.

Given many samples present similar behaviors, we checked whether these samples were independently developed or were variants of the same original code. To perform such check, we computed the fuzzy hash of all samples using `SSDeep`[7] with a 90% threshold. Further, all samples were matched against each other. Figure 10 shows the identified distinct clusters, their sizes and the number of samples on each. We discovered that most samples are located in the smaller clusters. On the other hand, many clusters hold at least 1 large variant family; the largest variant family presented 91 samples.

4.2. Dynamic Analysis & Behaviors

Whereas static analysis is useful to determine several features, it is subject to be defeated by obfuscation. To overcome such limitation, we submitted samples to dynamic analysis. As dynamic analysis procedures require effectively running the samples, we limited our evaluation to inspect Intel x86 and x64 ones, as they can be run in common machines without emulation. Each sample was executed up to 3 minutes, being terminated by a timeout. Their termination signals rates are presented in Figure 11.

We first observe that ≈15% of samples were terminated due to a segmentation fault error. It happens due to malware-environment incompatibilities, such as distinct library versions, nonexistent peripheral communication attempts or lack of a required resource.

Another portion of ≈15% of samples were terminated due to `timeout`[8] expiration. It happens when a sample enters on an infinite loop or keep a long time waiting a resource. Most samples were terminated by the usual `SIGTERM` signal. Fewer samples handled and ignored this signal, being forcibly terminated by the `SIGKILL` one.

We also discovered a small fraction (≈3%) of samples making use of the `SIGKILL` signal to terminate their own processes. It happens mostly due to evasion attempts, as a child process may detach itself from a debugger after killing its own father.

As for static analysis, we classified system calls into behaviors. Figure 12 shows the fraction of samples presenting each one of these behaviors.

[7] `ssdeep-project.github.io` [8] man timeout

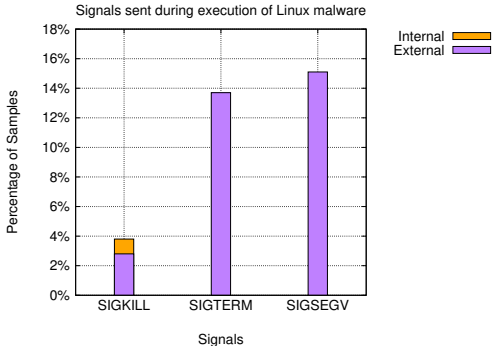

Figure 11. Observed Signals during execution. Most samples terminated prior timeout expiration. Few samples exhibited inter-process interactions.

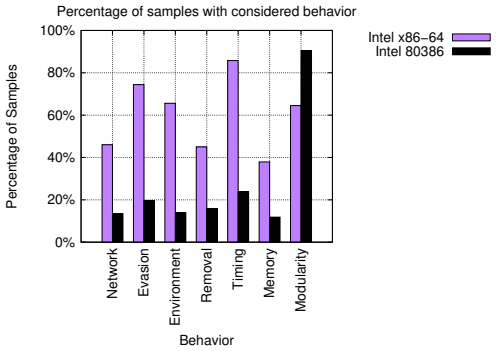

Figure 12. Malware behavior prevalence. Modularity is the prevalent behavior. Evasion and Timing are also significant.

We observe that many samples implement some kind of anti-analysis protection, both directly and indirectly. Direct approaches make use of methods such `ptrace` and `exit` to detach from a debugger. Indirect approaches make use of methods such as `time` to infer the performance overhead imposed by analysis solutions.

During dynamic analysis execution, the samples presented fewer network interactions than expected given the number of function identified on static analysis. We credit this effect to samples requiring resources unavailable in our system—such as old libraries—to run. This hypothesis is corroborated by the fact that this effect is greater on 32 bit—thus, older—samples. In newer, 64-bit ones, dynamic analysis produced more network interactions than identified during static analysis. This fact is expected as some calls are runtime-generated.

Regarding construction, we observe most samples are implemented in a modular way, launching child processes, through `fork` and `clone`, and relying on third-party binaries, through `execve`.

To better understand how the samples internally operate, we retrieved the accessed filesystem locations, as shown in Figure 13. We discovered the most prevalent samples action is to read and write information from the `/proc` directory. The `/proc` is a filesystem-mapping for configuration and environment variables, thus allowing malware to leak process information and even tamper with their execution. The second most prevalent action is to modify the `resolv.conf` file, responsible for storing DNS configuration. This is typical Proxy behavior and is also related to the high rate of network use. In addition, some samples also access the `shadow` and `passwd` files, responsible for storing login credentials. Such accesses are related to privilege elevation attempts.

We observe that most interactions are performed in the form of filesystem accesses, due to the `Linux` paradigm of "*everything is a file*". It reflects in the number of file reads and writes, as shown in the Figure 14. It also shows few user interactions, such as `stdio` reads and writes, indicating most samples operates autonomously in the background.

All presented data can be considered as a lower bound for malware behavior as the samples present a significant use of evasive methods, as presented in Figure 15.

Around 10% of samples rely on the `ptrace` syscall for analysis evasion. By acquiring the `ptrace` lock, samples block inspection mechanisms, such as debuggers, from attaching to them. Samples also avoid being analyzed by preventing monitoring solutions from injecting

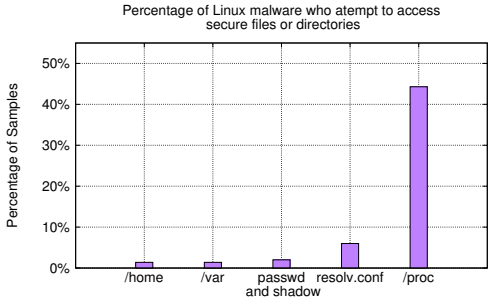

Figure 13. Accessed files and directories. Samples interfere with system configurations and steal credentials.

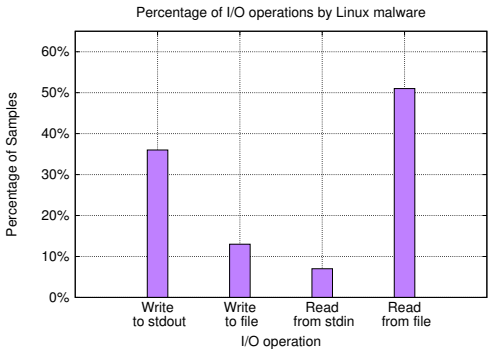

Figure 14. I/O operations. Most samples do not present direct user interaction

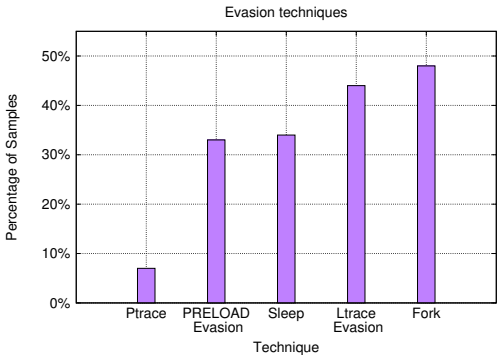

Figure 15. Evasion Techniques. Samples present diversified evasion methods.

instrumentation code within them. In this sense, 30% of samples block `LD_PRELOAD` injection attempts. Moreover, 30% of samples use a `sleep` call for analysis evasion. As sandboxes solutions often stop their execution after a timeout, a long enough delay may prevent the malicious payload from being inspected.

Some samples adopt indirect strategies to avoid analysis procedures. 40% of samples are statically-linked, thus preventing `ltrace` from dynamically tracing them. Other samples adopt modular constructions to obfuscate the execution flow. Given the creation of multiple (forked) malicious processes, analysts need correlated independent tasks to draw the general malicious scenario.

4.3. Network Traffic

From the firewall logs generated during dynamic execution was retrieved source and destination IP addresses. The source IP were all from the local machine, but the destination IP addresses were from attempted connections. Figure 16 shows the rate of samples which performed at least one network connection attempt.

Corroborating dynamic analysis results, we observe Intel x86-64 samples perform many more connections attempts than Intel 80386. When discarding network scanning samples, 50% of all contacted IPs, on average, were unique, indicating diversity. The `scanners` impact is noticeable as we have identified a sample which uniquely attempted to contact more than 75 thousand distinct IP addresses.

In addition to IP information, we performed reverse DNS queries to identify the associated domains. Given the scanners, most domains (≈60%) are associated to domestic internet providers.

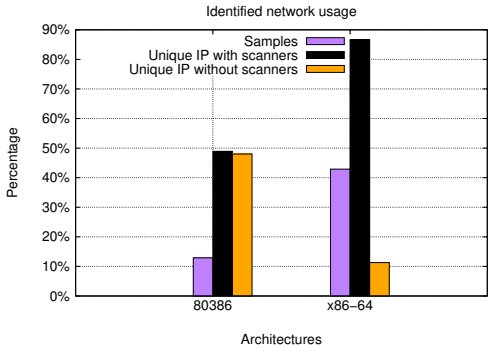

Figure 16. Identified network usage. Scanners dominate unique IP rate.

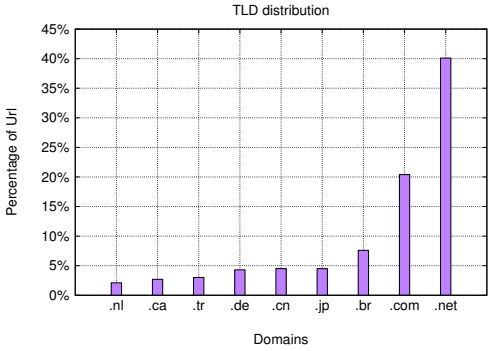

Figure 17. TLD distribution. Global domains (.net and .com) are prevalent. Local domains are present due to scanners enumeration.

This fact is also noticeable when we observe the most prevalent top level domains, presented in Figure 17. Whereas global domains (`.net` and `.com`) are prevalent, regionalized domains are well-distributed, as scanners aren't region-aware.

5. Discussion

In this section, we discuss our findings and compare the obtained results with other work to draw a landscape of `Linux` threats. Our first finding is that the `Linux` environment is very diverse, presenting samples of distinct architectures, endianesses and word sizes. Whereas this fact have already been identified by a previous study [Cozzi et al. 2018], we are the first to discuss samples implementation in details, presenting, for instance, a comprehensive analysis of linked libraries and network traffic.

Besides comparing `Linux` studies, we also identified differences when comparing `Linux` threats to `Windows` ones [Botacin et al. 2015], such as the use of packers. 50% of `Windows` malware samples are packed (24% of these are `UPX`) whereas our dataset presented a rate of at most 4% of packed samples. Such difference is explained by the high rate of exploit samples present in our dataset, as shown by the AV labels. In comparison, no exploit was identified in the `Windows` dataset.

In common, both environments present a similar rate of network traffic (≈50%), which indicates it is a general trend regarding malware. However, on each environment, the performed network action is distinct. The `Windows` dataset presents a major share of `downloaders` whereas the `Linux` one presents a significant amount of `backdoors`. Moreover, samples of both OS install connection proxies in the target machine. `Windows` samples redirect network traffic by using Proxy Auto Configuration (PAC) files whereas `Linux` ones modify the `resolv.conf` file.

Finally, we discovered that both `Linux` and `Windows` malware present comparable, significant potential to cause damage in their target machines. Nevertheless, due to environmental, internal reasons, their malicious actions are deployed by distinct methods.

6. Conclusion

In this paper, we have presented an overview of malicious `Linux` binaries. Through static and dynamic analysis, we discovered the most prevalent system calls (`fork` and `execve`) and their associated behaviors (`evasion` and `modularization`). We also performed network traffic analysis and discovered that ≈50% of samples rely on the Internet to achieve their malicious goals. We compared malware samples targeting `Linux` and `Windows` and discovered that they can cause the same damage extent and present similar characteristics, including the use of

anti-analysis tricks. Given OS particularities, some behaviors are more tied to OS internals, which should be understood to allow proper countermeasure development. An extended version of this paper is available at `https://github.com/marcusbotacin/Linux.Malware`.

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