A BENCHMARK API CALL DATASET FOR WINDOWS PE MALWARE CLASSIFICATION

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ABSTRACT

The use of operating system API calls is a promising task in the detection of PE-type malware in the Windows operating system. This task is officially defined as running malware in an isolated sandbox environment, recording the API calls made with the Windows operating system and sequentially analyzing these calls. Here, we have analyzed 7107 different malicious software belonging to various families such as virus, backdoor, trojan in an isolated sandbox environment and transformed these analysis results into a format where different classification algorithms and methods can be used. First, we'll explain how we got the malware, and then we'll explain how we've got these software bundled into families. Finally, we will describe how to perform malware classification tasks using different computational methods for the researchers who will use the data set we have created.

Keywords Malware analysis; cyber security; dataset; sandbox environment; malware classification

1 Introduction

Nowadays, the use of computers in daily life is becoming widespread and as a result, computer attackers are attacking computers using different methods, or they use these computers as weapons. Although computers become more secure with each new operating system version or update, attackers can bypass these security components using different methods. The most common scenario of security component bypass methods is that the malware changes its source code and behavior on each infected computer [1]. All of the methods used by analysts to detect malicious software is called malware analysis. Malware analysis is a very broad term and includes many stages. These stages include examining the contents of the suspicious software without running the software and then running the software in an isolated environment, examining the domain name system (DNS) resolution requests, recording the registry reads/writes, file accesses and the application programming interface (API) calls.

These malware act for a specific purpose. We know that they are used for many different purposes such as preventing a system from working, gaining unauthorized access to a system, obtaining personal data. For such purposes, many different platforms such as servers, personal computers, mobile phones, and cameras are targeted. Today, the number of platforms that have become a target is increasing. Consequently, malicious software developed for these platforms are also quite different. In particular, in the first 4 months of 2018, 40,000,000 is considered to be the face of the danger of new malware.

Nowadays, there is a considerable amount of time spent to protect from this software and significant budget expenditures. In order to protect against malicious software, many products are produced both commercially and academically. There is a serious struggle between attackers producing malware and the parties trying to identify these software. As a result of this situation, it increases the competencies and capabilities of both sides. Metamorphic malware are the result of this struggle.

Metamorphic malware are the most advanced members of the malware family. These malicious software, using different methods, can make their structures change continuously by making changes in their own source codes. In this way, they change the code signatures. In addition, these software may have the ability to recognize the environment and store their harmful actions by counter-analysis actions in the environments created for malware analysis [2]. Metamorphic malware are difficult to detect and classify as they have such capabilities.

Considering the development of malware, it is observed that they underwent a structurally perfect evolution. But there is one constant characteristics in each phase. These features are designed to benefit in an undesirable way. That is, they have a harmful behavior. All malware should perform some actions to achieve their goals. Assuming that a malware is on a computer running the Windows operating system, this malware needs to use some of the services offered by the operating system. The entire set of requests to get these services (Windows API calls) creates a malicious behavior. Malicious software detection and classification can be performed if such malicious behavior is well analyzed.

Detection of malicious software includes many design issues that need to be addressed, such as incorrect jump op codes in the assembly codes, hidden content in the .text block in portable executable (PE) file, and encrypted content. In this study, we have collected the current malware and their variants such as WannaCry and Zeus, especially on the Github website, we obtained the family classes from VirusTotal site by finding the hash values of each malware and finally, all the behaviors were recorded by running them in a Cuckoo sandbox environment. Our argument is that almost all malware change their behavior using a variety of methods, although they change their behavior, malicious software have a target and have a pattern of paths to achieve this goal. Furthermore, a malware makes unnecessary API calls during the behavior change, it can be detected by a model to be trained by analysts because the pattern is the same.

Malware analysis may be defined as the branch of cyber security which consists of two phases: (1) static analysis, (2) dynamic analysis of suspicious files. The static analysis can broadly be defined as examining the executable file without viewing the actual instructions by executing in an isolated environment. The well-known example of static analysis are MD5 checksums, recognition by antivirus detection tools, finding strings. Dynamic analysis refers to actual run malware to understand its functionality, observe its behavior, identify technical indicators. A most important part of the behavioral records is API call sequences. Most studies in the field of dynamic malware analysis have only focused on the classification algorithms. The key problem with those research are that there is no benchmark datasets to check the efficiency of the proposed models [3].

This study seeks to obtain data which will help to address these research gaps. The specific objective of this study is to build a benchmark dataset for Windows operating system API calls of various malware. This is the first study to undertake metamorphic malware to build sequential API calls. It is hoped that this research will contribute to a deeper understanding of how metamorphic malware change their behavior (i.e. API calls) by adding meaningless opcodes with their own dissembler/assembler parts.

We shared our data set over github site ¹. We believe that this dataset can be used by researchers who conduct studies on behavior-based malware analysis.

2 Methods

The dataset contains raw data regarding the cuckoo sandbox based known malware execution and VirusTotal based classification of files using their MD5 signatures.

2.1 Windows API Calls

The Windows API is an interface for developing applications on the Windows operating system. Application developers can communicate with your operating system using the Windows APIs. Therefore, the operating system offers many services as an API. A Windows application needs to use the APIs to use a function provided by the operating system. The use of these functions is defined as the API call. An application makes API calls many times during its execution. For example, when an application is requested to create a file, it must call the *CreateFileA* API [4]. API calls made by an application on the system can show the behavior of this application. For this reason, API calls are often used in dynamic malware analysis. The basic entries of the data set used in this study are API calls made by malware on the operating system.

https://github.com/ocatak/malware_api_class

2.2 Cuckoo Sandbox

You can check any suspicious file in a few minutes with Cuckoo. It provides a detailed report showing the behavior of the file is executed in an isolated and realistic environment. Nowadays, it is not enough to detect and remove the effects of malware: it is vital to understand the context, motivations and how they work to understand the purposes of a violation. Cuckoo Sandbox is a free software that automates the task of analyzing malicious files under Windows, OS X, Linux and Android. Cuckoo Sandbox is an advanced, highly modular and open source automated malware analysis system with endless application possibilities.

In computer security, the sandboxing is a security mechanism used to separate running programs. Usually sandboxing is used for unconfirmed applications from third parties, suppliers, untrusted users, and untrusted websites. The Cuckoo Sandbox system has two basic components. The first component is the management machine where the analysis of malware is started, the results are written to the database and the web service is provided for the users. The second component is the analysis machines to run malicious software. Analysis machines can be virtual or physical machines [5].

2.3 VirusTotal

Virus Total is a free service that allows you to analyze files or URL addresses online. Many antivirus application engines and website scanners are used for analysis. Files considered to be harmful are analyzed individually in antivirus application engines. Each antivirus application engine creates an analysis report for the suspicious file [6].

The same analysis case is valid for URLs to be analyzed. The VirusTotal service includes a very large set of analyzes. In this way, a new scan can be performed, as well as previous analysis information can be obtained. Virus Total offers a service interface (VirusTotal Public API v2.0) to provide results without using a browser, as well as through a web browser. With this interface, files / URL addresses can be analyzed automatically.

Virus Total Public API provides the results of the analysis as a JSON object. The results of each antivirus application engine and web browser analysis are obtained separately.

2.4 Dataset Creation

The data set as presented herein has a very simple structure. Our dataset is provided as comma-seperated values (csv) files to enhance the interoperability, and no specific software or library is required to read them. The data were collected with *git* command line utility from various github pages. Each row in this data set is an ordered sequence of Windows operating system API calls that belong to an analysis in the cuckoo sandbox environment.

The following steps were followed when creating the dataset.

- 1. Preparation of Cuckoo Sandbox Environment: The Ubuntu operating system was installed on the analysis machine. Then the Cuckoo Sandbox application has been installed. The analysis machine is run as a virtual server, where malware will be run and analyzed. Windows operating system is installed on this server. The firewall has been turned off and operating system updates have not been applied to prevent any obstacles during the operation of malicious software.
- 2. **Analysis of malware**: More than 20,000 malware were run in Cuckoo Sandbox one at a time. The application has written the analysis information of each malware into the MongoDB database. From this analysis information, the behavior data of the malware on the analysis machine were obtained. These data are all Windows API call requests made by the malware on the Windows 7 operating system.
- 3. **Processing of Windows API calls**: We have observed 342 kinds of API calls in our dataset. These API calls are indexed with numbers 0-341 to create a new dataset. We have used the results of the analysis of the malware that had at least 10 different API calls in this data set.
- 4. **Analysis of malware using Virus Total Public API**: In addition to our own analyzes, all malicious software contained in the data set were also analyzed by requesting the Virus Total service. In this way, each malware is analyzed by many different antivirus engines and their results are recorded.
- 5. **Processing of analysis results**: The Virus Total service uses approximately 66 different antivirus applications for file analysis. Using the results of each analysis we obtained with this service, we identified the families of each malware. As a result of our observations, we found that different antivirus applications for the same malicious software give different results. In addition, it was observed that not every antivirus application can detect some malicious software. For example; When the malware file with the hash value of 06e76cf96c7c7a3a138324516af9fce8 is analyzed in the Virus Total service, many applications indicate that

this file is a worm, while some applications such as *DrWeb* show that it is a trojan, and *Babable* application indicates that this executable is a clean file. Therefore, while detecting class of each malware; it is accepted that it belongs to the majority class of all analysis.

Figure 1 shows the general flow of the generation of the malware data set. As shown in the figure, we have obtained the MD5 hash values of the malware we collect from Github. We searched these hash values using the VirusTotal API, and we have obtained the families of these malicious software from the reports of 67 different antivirus software in VirusTotal. We have observed that the malicious software families found in the reports of these 67 different antivirus software in VirusTotal are different.

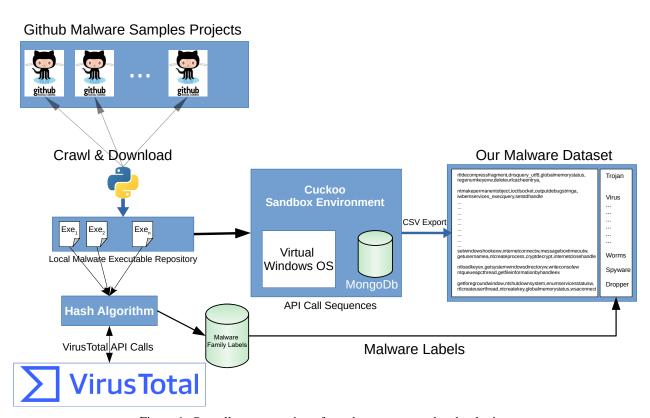
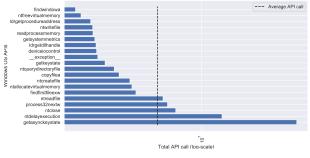


Figure 1: Overall representation of our data sources and technologies.

In our research, we have translated the families produced by each of the software into 8 main malware families: Trojan, Backdoor, Downloader, Worms, Spyware Adware, Dropper, Virus. Table 1 shows the number of malware belonging to malware families in our data set. As you can see in the table, the number of samples of other malware families except AdWare is quite close to each other. There is such a difference because we don't find too much of malware from the adware malware family.

Malware Family	Samples	Description
Spyware	832	enables a user to obtain covert information about another's computer activities by transmitting data covertly from their hard drive.
Downloader	1001	share the primary functionality of downloading content.
Trojan	1001	misleads users of its true intent.
Worms	1001	spreads copies of itself from computer to computer.
Adware	379	hides on your device and serves you advertisements.
Dropper	891	surreptitiously carries viruses, back doors and other malicious software so they can be executed on the compromised machine.
Virus	1001	designed to spread from host to host and has the ability to replicate itself.
Backdoor	1001	a technique in which a system security mechanism is bypassed undetectably to access a computer or its data.
Total	7107	

Table 1: Distribution of malicious software according to their families.



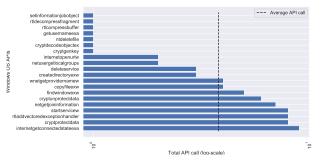


Figure 2: The first 20 APIs used in our analysis.

Figure 3: The last 20 APIs used in our analysis.

The operating system APIs used by malware families vary depending on their structure. These differences can be API or API calls. Malicious software can also make unnecessary API calls to hide themselves and have a different signature on each client. The main reason for creating different signatures is that anti-viruses detect malicious software according to their signatures.

Figure 4 shows the normalized values of Windows operating system API calls that belong to each family of malware.

Figure 5 shows the most correlated 30 API calls heatmap for each malware type. As can be seen from the figure, some APIs are called together for each family of malware. The malware follow the pre-defined API call sequence when performing their malicious activities. Although the order of these API calls is different for different malware, it may be quite similar in terms of malware families. For this reason, the figure shows 5-10 APIs, which are highly correlated especially for Dropper and Worms malware families.

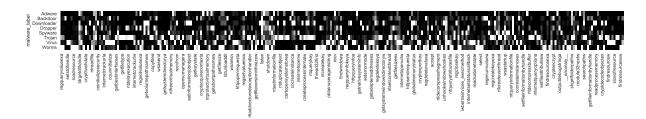


Figure 4

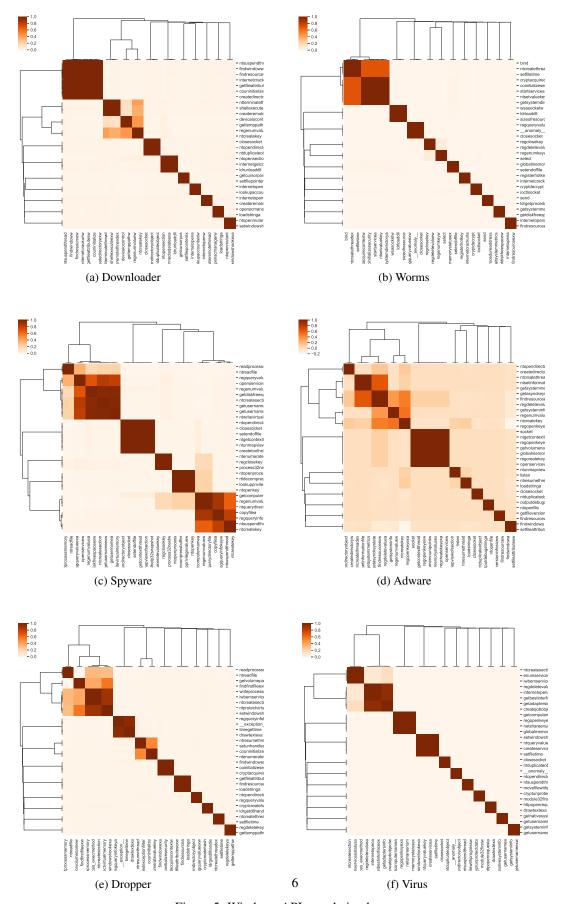


Figure 5: Windows API correlation heatmap.

Downloader Adware **Dropper API Pairs** Corr **API Pairs** Corr **API Pairs** Corr Corr **API Pairs** getfileversioninfosizew 1.0 regclosekey 1.0 ntopendirectoryobject 1.0 iwbemservices_execmethod 1.0 findresourcew process32nextw ntduplicateobject writeprocessmemory 1.0 1.0 1.0 1.0 ntduplicateobject regcreatekevexa openscmanagerw gettemppathw ldrgetprocedureaddress loadstringa openservicew regdeletekeya 1.0 1.0 1.0 1.0 findresourceexw internetopena getcursorpos ntcreatethreadex regdeletevaluea findresourceexw setfilepointerex setfiletime 1.0 1.0 1.0 ntcreatethreadex closesocket createremotethread ntprotectvirtualmemory 1.0 ntsetinformationfile ldrgetprocedureaddress setwindowshookexa internetopenw 1.0 getadaptersinfo 1.0 1.0 ntreadfile 1.0 regdeletevaluea ntcreatekey regenumvaluew getasynckeystate reggueryvalueexa readprocessmemory 1.0 1.0 1.0 1.0 deviceiocontrol iwbemservices_execmethod ntcreatekey ntcreatethreadex regopenkeyexa ntopenmutant gettemppathw ntcreatesection 1.0 0.99 1.0 1.0 getsystemmetrics ntopenfile closesocket ntcreatesection ntcreatethreadex unhookwindowshookex ntduplicateobject writeprocessmemory 1.0 0.99 1.0 createdirectoryw ntclose ntopendirectoryobject getvolumepathnamesforvol... 1.0 ntopendirectoryobject getbestinterfaceex findfirstfileexw closesocket 0.99 1.0 1.0 1.0 findresourceexw ntallocatevirtualmemory ntopenmutant ntopendirectoryobject getasynckeystate getusernameexw setwindowshookexa regqueryvalueexw 0.99 0.99 0.99 1.0 getsysteminfo getsystemwindowsdir... findresourcew coinitializesecurity regenumvaluew ntenumeratevaluekey findwindoww cryptacquirecontextw 0.99 0.99 0.99 closesocket 1.0 unhookwindowshookex getfileattributesw findresourcea ntduplicateobject gethostbyname findresourcew loadstringa

Table 2: The most correlated API calls.

Spyware		Trojan		Virus		Worms	
API Pairs	Corr	API Pairs	Corr	API Pairs	Corr	API Pairs	Corr
readprocessmemory ntreadfile	1.00	ntclose createdirectoryw	1.00	closesocket ntduplicateobject	1.00	internetopena findresourceexw	1.0
regqueryvalueexa openservicew	1.00	bind wsasocketw	1.00	enumservicesstatusa iwbemservices_execmetho	1.00	getsystemdirectorya coinitializesecurity	1.00
createtoolhelp32snapshot ntgetcontextthread	1.00	getbestinterfaceex regdeletevaluea	1.00	iwbemservices_execmet. ntcreatesection	1.00	startservicea getsystemdirectorya	1.00
ntcreatesection getusernameexw	1.00	ntcreatesection setsockopt	1.00	getbestinterfaceex regdeletevaluea	1.00	ntsetvaluekey getsystemdirectorya	1.00
createtoolhelp32snapshot setendoffile	1.00	ntduplicateobject ntcreatethreadex	1.00	getusernamea getnativesysteminfo	1.00	ntcreatethreadex setfiletime	1.00
ntopendirectoryobject closesocket	1.00	searchpathw createdirectoryw	0.99	internetopena regdeletevaluea	1.00	startservicea ntsetvaluekey	1.00
setendoffile ntgetcontextthread	1.00	writeprocessmemory createremotethread	0.99	enumservicesstatusa ntcreatesection	1.00	closesocket regqueryvalueexw	1.00
ntunmapviewofsection ntgetcontextthread	1.00	regdeletevaluea getusernameexw	0.99	setfiletime createservicea	1.00	getsystemdirectorya cryptacquirecontextw	1.00
createtoolhelp32snapshot ntunmapviewofsection	1.00	getbestinterfaceex getusernameexw	0.99	getadaptersinfo createjobobjectw	1.00	setfiletime bind	1.0
copyfilea regqueryinfokeyw	0.99	httpsendrequestw regqueryinfokeya	0.99	getadaptersinfo createjobobjectw	1.00	ntcreatethreadex bind	1.00

References

- [1] B. Athiwaratkun and J. W. Stokes. Malware classification with 1stm and gru language models and a characterlevel cnn. In 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 2482-2486, March 2017.
- [2] S. Maniath, A. Ashok, P. Poornachandran, V. G. Sujadevi, A. U. P. Sankar, and S. Jan. Deep learning 1stm based ransomware detection. In 2017 Recent Developments in Control, Automation Power Engineering (RDCAPE), pages 442-446, Oct 2017.
- [3] R. S. Pirscoveanu, S. S. Hansen, T. M. T. Larsen, M. Stevanovic, J. M. Pedersen, and A. Czech. Analysis of malware behavior: Type classification using machine learning. In 2015 International Conference on Cyber Situational Awareness, Data Analytics and Assessment (CyberSA), pages 1–7, June 2015.
- [4] and and. An information retrieval approach for malware classification based on windows api calls. In 2013 International Conference on Machine Learning and Cybernetics, volume 04, pages 1678–1683, July 2013.

- [5] S. L. S. Darshan, M. A. A. Kumara, and C. D. Jaidhar. Windows malware detection based on cuckoo sandbox generated report using machine learning algorithm. In 2016 11th International Conference on Industrial and Information Systems (ICIIS), pages 534–539, Dec 2016.
- [6] R. Masri and M. Aldwairi. Automated malicious advertisement detection using virustotal, urlvoid, and trendmicro. In 2017 8th International Conference on Information and Communication Systems (ICICS), pages 336–341, April 2017.