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Malsharp: Analiza aplicaţiilor de tip malware

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Malsharp: Malicious application analysis

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Abstract

Malware is currently a major security threat for computers and smartphones, with efforts being taken into improving malware detectors with behavior-based detection. In order to classify applications, malware detectors need some form of malicios behavior specification which are usually identified manually by researchers. We present a Linux implementation of the malspec-mining algorithm which automates this process. This algorithm recognizes such specifications by comparing known malicious and benign applications. The output consists of behavior patterns which are specific to the inputted malware and that do not occur in benign applications.

Keywords: behavior-based detection; malspec-mining algorithm; malicious behavior; kernel programming

În prezent, aplicaţiile de tip malware reprezintă o ameninţare majoră pentru securitatea calculatoarelor şi a smartphone-urilor, luându-se măsuri pentru îmbunătăţirea detectoarelor de malware bazate pe comportament. Pentru a putea clasifica aplicaţii, detectoarele de malware au nevoie de specificaţii ale comportamentului maliţios, care sunt de obicei identificate manual de către cercetători. Vom prezenta o implementare pe Linux a algoritmului de malspec-mining care automatizează acest proces. Acest algoritm identifică astfel de specificaţii prin compararea de aplicaţii cunoscute ca fiind maliţioase şi aplicaţii benigne. Rezultatul constă în tipare de comportament care sunt specifice malware-ului şi care nu apar în aplicaţiile benigne.

Cuvinte cheie: detecţie bazată pe comportament; algoritmul de malspec-mining; comportament maliţios; programare kernel

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Notations and Abbreviations

API   – Application Programming Interface
DDoS – Distributed Denial of Service
DOM   – Document Object Model
fd   – file descriptor
ICMP – Internet Control Message Protocol
malspec – malware specification
NAT   – Network Address Translation
NI   – Network Interceptor
pid   – process id
procfs – proc filesystem
SB   – signature database
SCID – System Call Interceptor Driver
symlink – symbolic link
syscall – system call
TCP   – Transmission Control Protocol
UDP   – User Datagram Protocol
VM   – Virtual Machine
XML   – Extensible Markup Language

Chapter 1

Introduction

From large corporations to the average user, computer and network environment security is an important requirement to which malware is a threat. Malicious software is a program that has been written by an attacker to fulfill a harmful intent. In order to achieve this, the program has to interact with the victim's operating system.

The number of users of a specific operating system is directly correlated to the degree of interest malware writers take in developing software to target that specific operating system. Due to Linux's increasing popularity, better security for operating systems that are based on the Linux kernel has become a necessity. This supports the need for developing tools for Linux malware analysis and improving malware detection methods.

Earlier detection methods focused on analyzing the contents of the executable file of the malware program, such as identifying instruction sequences which were characteristic for specific malware instances. These methods performed poorly when confrunted with unknown malware or new variants of existing ones. Also, in response, attackers started to write malware that modifies its own file while replicating itself, thus eluding these detection methods.

This resulted in a switch to developing behavior based detection systems that are independent from the exact contents of the executable file. Therefore, when analyzing malware samples, analysts started to search for program behavior patterns that suggest a malicious intent. In order for these patterns to work, programs need a higher-level common behavior specification.

The system call interface meets this requirement as malware needs to interact with the operating system to achieve its goals and it is common to all malware. A typical malware example would be an executable file that replicates itself by reading its own file and then copying it to system directories. This can be captured in a behavior pattern which, compiled into malware specifications, can then be used by malware detectors in order to classify programs based on their behavior.

The project presented in this thesis, named **Malsharp**, is a Linux tool for automatically searching for malicious program behavior patterns. This tool is a Linux implementation of the malware specification mining algorithm which identifies these behavior patterns by comparing known malware samples to known benign programs. These patterns are a collection of Linux system call parameter dependencies that capture the malicious behavior.

The malware specification mining algorithm takes the system call execution traces for the malicious and benign programs as input and creates a graph for each program. The nodes in the graphs represent system calls and the edges show parameter dependencies between the nodes. The malspec mining algorithm computes the minimal contrast subgraph patterns for

each pair of malicious and benign programs and then they are maximally unioned. The resulting set of graphs is the malware specification.

Malsharp is intended to be used by malware specialists to help them analyze new malware samples. It can also be used as part of an automatic detection mechanism which classifies programs based on their behavior by using the malicious behavior specifications.

Our implementation of the malspec mining algorithm successfully identified malware specifications for the tested malware samples. These malspecs captured behaviour found in the malware samples but not in benign programs.

This thesis organized as follows: in Chapter 2 we describe the main types of malware threats, current detection types, methods that malware uses to avoid detection and a short presentation of the malware specification mining algorithm.

In Chapter 3 we define several notions used in the algorithm, a detailed view of the malspec mining algorithm and we reveal our own architecture. Chapter 4 presents the implementation details for each element of architecture from the kernel modules the to userspace application.

Chapter 5 describes our test environment, explains a short test scenario and how the algorithm works and shows the results we obtained with our implementation on actual malware samples. Chapter 6 presents the conclusions and future work.

Chapter 2

State of the Art

Computer security mostly refers to the mechanisms that are used to protect computers and networks from different threats. Recent history is full of famous attacks on computers, networks and especially over the Internet. Although this field deals with many more security related issues, one of the major threats to computer security is malware.

2.1 Computer security and threats

The computer security field covers the mechanisms by which computers and computer related equipment are protected from different types of threats, such as: attacks from crackers and malicious software. This field also covers protection methods from physical damage.

Computer security is generally achieved by limiting resource access to users and programs such that each has only the privileges it needs to function properly.

Given the fact that the Internet was not initially designed with the intent of ensuring a secure channel of communication, most computer security issues are network related. Although security mechanisms have been implemented over the Internet, some are still vulerable to attacks.

In computer security, a threat refers to an action that has the potential to harm an information system by obtaining unauthorized access to the system, modifying data, revealing sensitive information or by performing a Denial-of-Service attack.

The basis of Information Security is the CIA triad: Confidentiality, Integrity and Availability.

Attacks are classified into active or passive attacks. An attack is considered *active* when it attempts to alter system resources or to affect their operation, therefore compromising the system's Integrity and Availability. A *passive* attack acquires information from the system but it does not affect its resources or operation, therefore compromising Confidentiality [12].

2.2 Malware types

Malware, or malicious software, is software programmed and used by attackers in order to gain access to private computers, to obtain sensitive information or to simply disrupt normal computer operation. Malware generally refers to a variety of program forms: viruses, worms, Trojan horses, Backdoors, rootkits, botnets, adware and spyware.

A virus is a program that attempts to replicate itself into other executable files by injecting or replacing code. When the infected programs are run, they can infect other ones in turn. They typically target executables and common programs which are found on most machines and copy themselves to key directories.

Worms are similar to viruses, only that they spread over the network to other hosts which have the same vulnerability as the initial host. This is done by performing network port scans, DNS queries and then trying to infect other machines. Also, this type of malware usually downloads a second program from a remote server.

Trojan horses, or Trojans, are non-self-replicating code that try to gain privileged access to an operating system and while they seem to be performing a legitimate action they deliver a malicious payload. The payload often contains a backdoor for the attacker that gives him access to the computer or a botnet to send spam or perform Denial-of-Service attacks.

Backdoors are an alternative method of authentification to a system which bypasses normal authentification and secures illegal remote acces. This type of malicious software is installed by attackers after they have compromised a system through an alternative method.

Rootkits are used by attackers to keep access to a compromised system and are designed to hide files and the existence of processes and network connections from detection methods. Rootkit instalation can be done automatically or an attacker can install it after he has gained root or administrator access to the system.

A botnet is a network of "zombie" computers that have been compromised and that are used to perform malicious actions like Distributed Denial-of-Service attacks (or DDoS). DDoS attacks are carried out in order to stop a machine or a network resource from functioning efficiently or from functioning at all.

Adware, or advertising-supported software, is a term that refers both legitimate advertising software and malware. When used to refer malware, adware refers to programs that present unwanted advertisments on infected computers.

Spyware is software created for gathering information without the user's consent. This kind of malware is usually installed without the knowledge of the user or by tricking the user into installing an application or add-ons to existing applications [14].
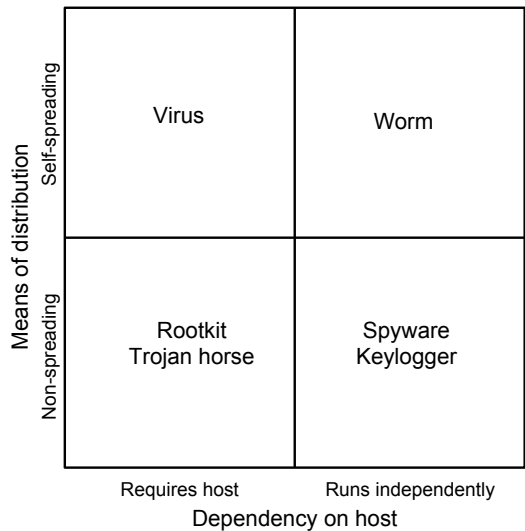

Figure 2.1: Malware Types

Figure 2.1 shows a classification of malware types based on means of distribution and their dependency on host programs to propagate themselves.
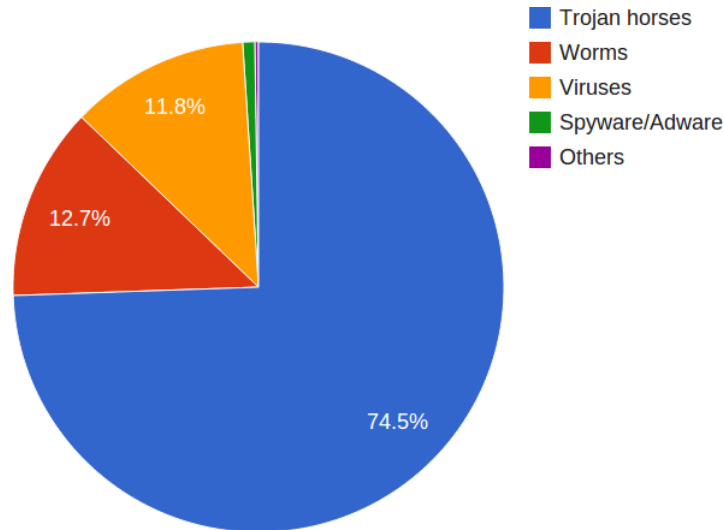

Figure 2.2: Malware distribution by type

In Figure 2.2 we can see malware distribution by type. These statistics were produced by **Panda Security** for the 1$^{\text{st}}$ quarter of 2013.

2.3   Avoiding detection

Malware and anti-malware software evolution is tightly coupled: when detection methods become more efficient, malware writters start using better hiding techniques. In response, anti-malware developers use better algorithms. In the course of time, the development of anti-malware software has led attackers to start using different obfuscation methods to avoid detection, such as: concealing API-calling behavior, polymorphic and metamorphic malware.

Malware writers obscure API-calling behavior by using indirect calls. In this respect, API calls can be achieved by using hard coded addresses but this method is incompatible with different versions of the operating system. Another method commonly employed is to define homonymy functions that first locate the API functions addresses and then use the stored address. Also, arrays can be used to store the API function name and the relocation address [9].

Polymorphic viruses use a polymorphic engine to change its executable while keeping the original function intact. A common technique to "morph" viruses is to encrypt the malicious payload and decrypt it at runtime. The encrypted code will then apear to be meaningless and it will be ignored. To obfuscate the decryption routine, the code is transformed by inserting **nop** instructions, permuting register allocation, reordering instructions and inserting jump instructions to maintain the semantics.

Metamorphic viruses also use an engine to change their code in a variety of ways, such as code transposition and substituting instruction sequences with equivalent ones. In addition to this, they interweave their code with the original program's code to trick heuristic detection methods. An important difference between a metamorphic engine and a polymorphic one is that the first can rewrite itself while the second cannot [7].

2.4   Malware detectors

Malware detectors are developed by performing analysis on samples gathered through various means: honeypots, web crawlers, spam traps and security analysts that collect them from infected computers. Bayer *et al.* [5] provided insight into common behavior by analyzing almost one million malware samples by monitoring their network activity and tracking data flows.

Bayer *et al.* created a platform, named Anubis [1], for the dynamic analysis of malware samples which targeted Windows operating systems. The behavior of malware samples was monitored for file system, registry, network and botnet activity, GUI windows and sandbox detection. Sandboxes are contained environments used to run and test malicious software. The statistics they presented offer insight into common malware behavior and give a hint to what the main goal of malware detectors should be.

Signature based malware detectors use a list of signatures (signature database or SB) to identify known viruses. The signatures are patterns of data withing executable code and they are generated after static and dynamic analysis by specialists. If a part of a program matches a signature entry from the list, then it is classified as malware. This detection method performes very poorly when confrunted with new samples because the signature is unknown. Also, malware writers can easily avoid detection from this type of detectors by using obfuscation techniques in their programs, like polymorphism or metamorphism [8].

Over time, the approach in detecting malware has evolved from analyzing the contents of infected executable files towards identifying malicious or potentially malicious behavior patterns. These patterns are extracted from the malware sample by static or dynamic analysis.

Static analysis of the executable involves scanning the file for particular instruction sequences or different API calls. In order to avoid detection from this type of analysis, attackers attempt to obscure their API-calling behavior or they use a polymorphic engine.

Another method for analysis is to monitor the behavior of the malicious program during runtime in a sandbox, otherwise known as dynamic analysis. This method monitors the malware's interraction with the operating system and the network traffic it produces in order to determine its behavior.

As pointed out in [4], where a taxonomy of malware detectors for smartphones is presented, the signatures used by signature based detectors can be a simple hash/byte signature or a behavior signature. Behavior signatures can be generated from static analysis, containing information such as code syntax and structure, and from dynamic analysis, which consist of malicious behavior patterns that appear on runtime.

Semantics-aware malware detectors can overcome the problems posed by obfuscation by using specifications of malicious behavior which are not affected by polymorphic malware. By using a higher-level specification, different versions or implementations of malware which perform the same behavior can be detected. Another advantage of this type of detector is that it can also successfully classify unknown malware [11].

2.5   Malspec Mining Algorithm

The problem with behavior-based detection is that the required specifications have to be manually identified by a malware specialist. The malspec mining algorithm developed by Christodorescu *et al.* in [8] provides a method for automating this otherwise time consuming task.

Their malspec mining algorithm starts by collecting execution traces from malware and benign programs, then it constructs the corresponding dependency graphs and then it computes the

specification of malicious behavior as difference of dependency graphs in the form of minimal contrast subgraph patterns [13].

The malspec mining algorithm was implemented and tested on a Windows operating system and, although it identified a large number of malware specifications, it also managed to capture most of the specifications that were indicated by specialists [8].

In this thesis we present an implementation of this algorithm for GNU/Linux based operating systems. In order to capture a program's behavior we developed a system call interceptor and a network traffic interceptor as Linux kernel modules.

Then, a user space program reads the traces from the kernel module and constructs a graph where each node represents a system call and the edges represent parameter dependencies. The edges are determined by interpreting the parameter type, direction and value of the recorded system calls. Finally, the malspec mining algorithm will generate the malicious behavior specifications.

Chapter 3

Malspec Mining Algorithm Malsharp Design

For a better grasp of the malspec mining algorithm and of the different graph algorithms it involves, we will now introduce the necessary definitions and theorems. Then, we will shortly describe the maximal common edge set algorithm which is used in the malspec mining algorithm. Finally we reveal the design aspects of Malsharp and the main components.

3.1 Mining Minimal Contrast Subgraph Patterns

The minimal contrast subgraph patterns used in the malspec mining algorithm were introduced by R. Ming Hieng Ting *et al.*. They defined the following notions in [13] and these will provide a better understanding of the malspec mining algorithm.

An **edge set** is a labelled graph, *i.e.* a graph with labels attached to its vertices and edges, that has no isolated vertices.

Given two graphs, G_p and G_n, C is a **common edge set** if and only if C is an edge set and it is a common subgraph. C is a **maximal common common edge set** if it is a common edge set of the two graphs and if and only if there does not exist a superset which is also a common edge set.

The notions of **maximal common edge set** and **minimal contrast edge sets** are connected and we can determine the second set by obtaining the complement of the first with respect to the original graph and then computing the minimal transversal.

Given G_p and $\{G_{n1}, G_{n2},...,G_{nk}\}$, let M_i be the set of maximal common edge sets between G_p and G_{ni}. Then the set of minimal transversals of $\bar{M_1} \cup \bar{M_2} \cup ... \cup \bar{M_k}$ will be the set of all **minimal contrast edge sets** between G_p and $\{G_{n1}, G_{n2},...,G_{nk}\}$, where $\bar{M_i}$ is the graph complement of M_i with respect to G_p.

For a graph, a **partition** is a set of disjoint and not empty subsets, named cells, of V, *i.e.* the set of all the vertices in the graph. All the vertices in the same cell have the same label and vertices from different cells are labelled differently. The union of all the cells in the partition is equal to V.

Given G_p and G_n that are associated with the partitions T_p and T_n, a **minimal contrast vertex set** is a subset of a cell from T_p such that its cardinality is larger by 1 in comparison with the cells from T_p.

The **minimal contrast subgraph** of a positive graph, G_p, with respect to a negative graph, G_{ni}, is the minimal union of the **minimal contrast edge sets** and the **minimal contrast vertex sets** of the two graphs. The minimal union works like normal union but it removes any graphs that are supergraphs of others in the set.

3.2   Maximal Common Edge Set

In determining the minimal contrast edge set, the most demanding computational task is finding the maximal common edge set. The problem of testing whether a subgraph relationship exists between two graphs is NP-complete.

The maximal common edge set is determined using the backtrack algorithm proposed by J. McGregor for computing the maximal common subgraph.

The algorithm takes as input two graphs, G_1 and G_2, with $|V_1| < |V_2|$, and for each node in G_1 it tries to find a correspondent node from G_2 while maximizing the number of matching edges. The result of the algorithm is a list of pairs of corresponding nodes [10].

In order to maximize the number of matching edges of the two graphs, a mapping matrix MARCS is used to indicate if an arc from G_1 can correspond to G_2. Initially, all the edges from the first graph can correspond to any edge from the second graph. When a node is paired with another, the edges connected to it can only correspond to edges that are connected to the other node. The edges that do not correspond are marked in MARCS with a zero value [10].

3.3   Malspec Mining Algorithm

The malspec mining algorithm collects the execution traces and uses them to create a dependency graph for each program.

Each node of the dependency graph represents one system call with its arguments, while the edges represent dependencies between arguments of different system calls. The dependency graphs are constructed after aggregating similar operations like multiple reads and writes using the same buffer and file descriptor, thus resulting in fewer nodes.

Edges are established between nodes which present def-use dependencies: if a previous (in execution order) system call parameter has an out (or inout) parameter with the same value as an in (or inout) argument of a later system call then an edge can be established from the first node to the second node.

Then, the minimal contrast subgraph miner operates in three stages. First, the maximal common edge set for the malware graph and all the benign graphs is determined using the algorithm designed by McGregor [10].

Next, the common edge sets are unioned together and the minimal traversals of their complements are computed, thus obtaining the minimal contrast edge sets for the malware graph.

Finally, the contrasts are minimally unioned with the minimal contrast vertex sets to give the complete set of minimal contrast subgraphs.

The resulting subgraphs for each comparison of the malware sample with a benign program are maximally unioned, *i.e.* removing graphs which are subgraphs of others, giving the desired malicious behavior specifications.

The following example shows how an execution trace is transformed into a dependency graph. Every system call from Listing 3.1 is represented by a node in the dependency graph as seen in Figure 3.1.

Then, each node is compared only with the nodes that succeed it in execution order. In this example, the three system calls are connected by two def-use dependency edges because they operate on the same file descriptor.

```
1  open("/bin/ls",O_RDWR) = 3;
2  read(3, 0x80000001, 255) = 127;
3  close(3) = 0;
```

Listing 3.1: System call trace
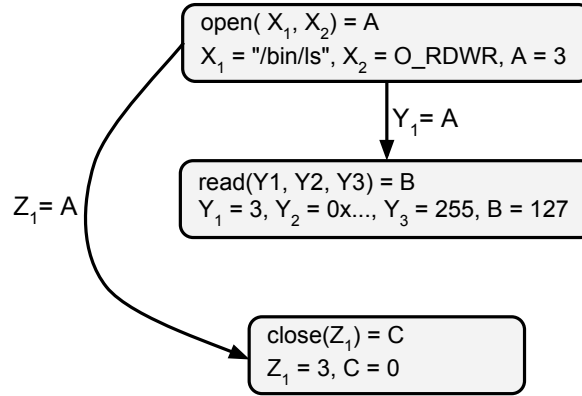
Figure 3.1: System call dependency graph

3.4   Malsharp Design

The architecture of Malsharp that was used in implementing the algorithm is presented in Figure 3.2. Also, in Figure 3.3 we present a workflow diagram.

The malware analysis module of Malsharp receives a malware sample and a set of benign programs to analyze. It then sends the pathfiles of the samples to the graph builder module and uses it to get the dependency graphs. In turn, the graph builder module uses the system call interceptor module to collect information about the execution trace.

The network module can be used for a better understanding of malware behavior. It can be configured to monitor network activity and the information it gathers can be read.

Malsharp takes as input three pathfiles to:

- an XML file which contains the system calls, with argument type and direction, that will be considered for the analysis,

- the malware sample that will be analyzed and

- a file which contains a set of benign programs, one per line.

Figure 3.2: Malsharp Architecture

3.4.1 System Call Interceptor

The system call interceptor is a module used for obtaining execution traces for specific processes. The module is configured by the graph builder and it collects information about the system calls that are used by a running process.
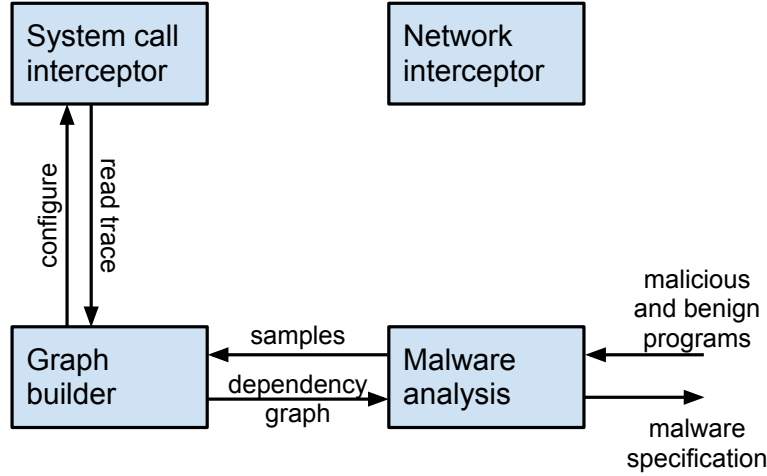
In order to control it, the graph builder module uses commands such as: setting the process identifier to be monitored and setting the system calls to be monitored. Also, each execution trace entry for a system call can be read and removed, the trace history can be cleared and the total number of entries can be read.

This module will be configured to monitor each malicious or benign program from the graph builder module. The resulting execution trace will then be read and used to generate the dependency graph.

3.4.2 Network Interceptor

The network interceptor is a module that was created for monitoring network traffic for specific protocols, such as: TCP, UDP and ICMP. It can controlled in a similar way to the system call interceptor module and it can be configured to monitor traffic by inspecting source or destination ports for TCP and UDP.

The information it gathers is currently not used in the malspec algorithm. Currently, it collects information such as the total number of packets sent or received and their total size.

3.4.3 Graph builder

The role of the graph builder module it to create dependency graphs based on a set of system calls. These system calls, along with information on how to decode them, are written in a configuration XML file. The graph builder communicates with the system call interceptor module: it configures it and then it reads the system call trace.

The graph builder will create a new process for each program that it will analyze. Before running the program it will configure the system call interceptor module to monitor the new process and then will wait for it to finish. Only system calls that have entries in the XML input file will be monitored.

After the child process ends it will start reading the execution trace from the system call interceptor driver. Using this trace, it will then construct the dependency graph.

3.4.4   Malware analysis

This module contains the implementation of the malware mining algorithm. It uses the graph builder module to generate the dependency graphs for the program samples. The graphs are then used to compute the malware specifications.

First, for each malware and benign program it sends their pathfiles to the graph builder in order to get the dependency graphs. Next, each pair of graphs is run through the different stages of the algorithm. The output consists of a set of malware specifications that are behavior patterns found in the malware sample that did not occur in any of the benign programs. These specifications can later be used for detecting malware.
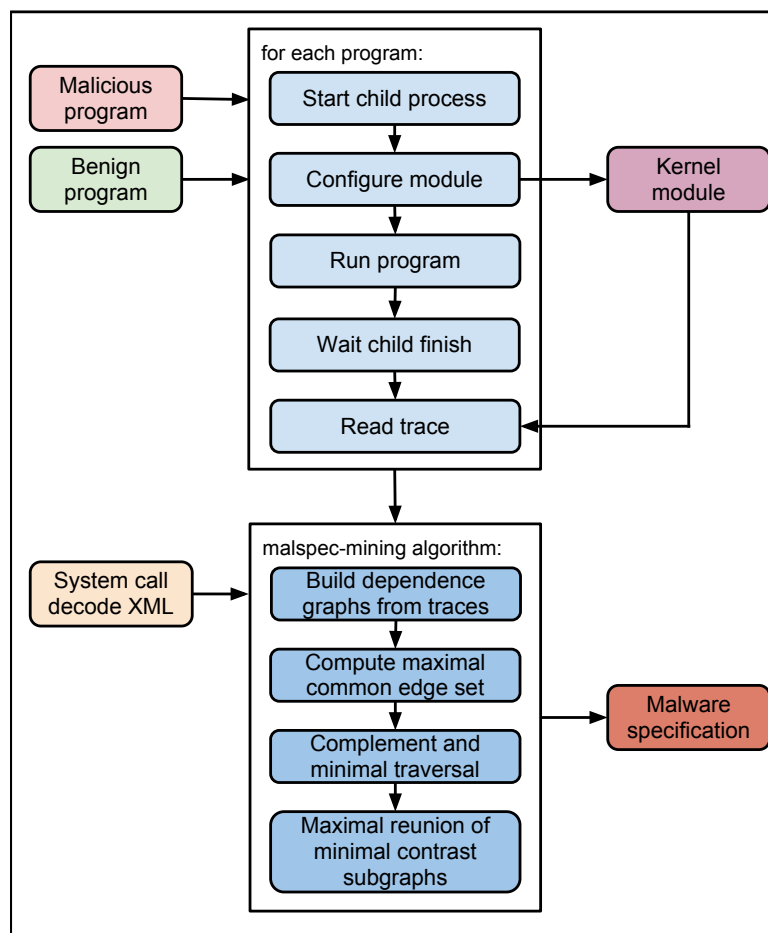

Figure 3.3: Workflow

Chapter 4

Implementation of Malsharp

Malsharp was implemented in C++, a natural choice considering we had to comunicate with the Linux kernel modules which are implemented in C. Both the kernel modules and the userspace application use the same header file that contains the common data structures required for configurating the modules and reading the execution traces.

4.1   System Call Interceptor Driver

The System Call Interceptor Driver (SCID) can be configured by giving the pid of the process as an argument at module insertion or by opening the device and calling `ioctl`. The system calls to be monitored can only be configured by `ioctl`.

The SCID registers itself as a character device named **scid** using the misc device interface provided by the Linux kernel. It also creates a symlink to procfs that is used by the userspace part of the application for opening the device.

This driver logs only the system call number and the arguments and return values. The system calls are intercepted by replacing the original entry value in the system call table with the address of an interceptor function which will run the system call and it will perform the necessary logging.

System call history is implemented with a queue, which contains the recorded system call values and the actual system call number. When an `ioctl` read call is received from userspace, it will remove and return the first entry in the queue. It is also possible to clear the entire log history if needed or to get the total number of entries from the queue.

The kernel module uses the `syscall_params` struct to retrieve the parameters from the stack when intercepting system calls. The data structure returned by the kernel is called `sctrace_t` and it contains the system call number, a `syscall_params` struct with the argument values and the return value. Listing 4.1 contains the definitions for the data structures used by the kernel module.

```
1  /* data struct for syscall intercepting */
2  struct syscall_params {
3          long ebx, ecx, edx, esi, edi, ebp, eax;
4  };
5
6  /* data struct for read syscall history */
7  typedef struct _sctrace_t {
```

```
 8          int sc_no;
 9          struct syscall_params sc_params;
10          long ret;
11 } sctrace_t;
```

Listing 4.1: SCID data structures

The SCID module `ioctl` commands are defined using the macros provided by the Linux kernel. For the necessary code value required in the kernel macros we chose `0xA1`, which is currently unused according to the documentation file in the kernel.

```
1 #define IOCTL_SET_PID          _IOW(0xA1, 1, int)
2 #define IOCTL_ADD_SYSCALL      _IOW(0xA1, 2, int)
3 #define IOCTL_DEL_SYSCALL      _IOW(0xA1, 3, int)
4 #define IOCTL_CLEAR_HISTORY    _IO(0xA1, 4)
5 #define IOCTL_COUNT_HISTORY    _IOR(0xA1, 5, int)
6 #define IOCTL_READ_HISTORY     _IOR(0xA1, 6, sctrace_t)
```

Listing 4.2: Command macros for ioctl

- `IOCTL_SET_PID` sets the pid of the process that will be monitored

- `IOCTL_ADD_SYSCALL` start monitoring a system call

- `IOCTL_DEL_SYSCALL` stop monitoring a system call

- `IOCTL_CLEAR_HISTORY` deletes all entries with trace information

- `IOCTL_COUNT_HISTORY` returns the number of trace entries

- `IOCTL_READ_HISTORY` get and remove the first trace entry

4.2   Network Interceptor

The Network Interceptor (NI) is also a kernel module that can be configured in a similar manner to the SCID. This module uses kernel netfilter hooks to intercept packets on the PRE_-ROUTING chain and it logs statistics such as total number of packets and total size transmitted.

The NI is controlled through `ioctl` calls which receive a `intercept_info_t` struct containing the protocol, source and destination ports it should monitor. A zero value destination or source port enables monitoring for all the traffic.

```
1 typedef struct _intercept_info_t {
2          /* IPPROTO_*, TCP, UDP, ICMP */
3          unsigned char xport_protocol;
4          /* used only in TCP and UDP */
5          unsigned short int source;
6          unsigned short int dest;
7 } intercept_info_t;
```

Listing 4.3: parameter data structures

Like SCID, the network interceptor also makes a symlink to procfs from which statistics can be read. The information that is collected includes the total number of packages transmitted and the total information size sent for each pair of source and destination ports.

The information gathered by the NI is not used in the determining the malware specifications at the moment, but integration is possible. Currently, the module can be used to verify if a sample malware program tried to use the network to spread itself or to send information.

4.3   Reading traces

The entries recorded by the SCID module do not contain any type and direction information about the system call. Therefore, in order to successfully identify def-use dependencies, the type and direction have to be properly set in a `syscall_t` struct, which is defined in Listing 4.4, before the graph is constructed.

```
1   /* param data structure to describe a syscall's parameters */
2   #define MAX_NUM_PARAM    8
3
4   typedef struct param {
5           unsigned char type; /* fd, int, unsigned int, char*, void*,
                   unsigned short, size_t */
6           unsigned char dir;   /* 1 in, 2 out, 3 inout */
7           long value;
8   } param_t;
9
10  typedef struct _syscall_t {
11          int syscall_no;                  /* the system call number */
12          param_t param[MAX_NUM_PARAM]; /* last element is the return
                   value */
13  } syscall_t;
```

Listing 4.4: Parameter data structures

The `syscall_t` struct contains an array of param structures with a maximum of 8 argument entries. The first 7 entries are used for the register values of the system call and the 8th entry holds the return value. Possible argument directions are in, out and inout, while data types considered are `int`, `unsigned int`, file descriptor, `char*`, `void*`, `unsigned short` and `size_t`.

Malsharp keeps the system call decoding information in an XML file which contains for each system call the type and direction information for each register. The file is parsed using the open source library named **pugixml** [3].

We chose this library because the XML configuration files do not contain many entries and **pugixml** uses DOM representation. Also, it supports XPath queries, which we used to query information about particular system calls when we added type and direction information to the execution trace.

Each program is run separately by creating a new process, making it yield the processor by waiting on a named semaphore and then replacing its image with `execve`. The new process has to be forced to yield the processor in order for the parent process to have sufficient time to set the child's process pid as the target for the interceptor module. Otherwise, a partial system call trace would be obtained instead and the results would be compromised.

After the parent process has configured the kernel module to monitor its child process, it increments the semaphore to enable it to continue execution. After that, the parent process waits for the child process to end and then it starts reading the execution trace.

4.4   Building dependency graphs

The execution trace inputted is used to create a graph for the sample program. Each node of the graph will contain a `syscall_t` struct. On creation, each graph object receives an array of these structs from which to create the graph's nodes.

After the nodes are created, each pair of nodes is verified for def-use dependencies and if such dependencies exist then a new edge is added in a vector as a pair of node pointers. To determine if a def-use dependency exists between two nodes, the two `param` arrays from the `syscall_t` structs are compared.

In addition to system call information, each node contains a unique identification number (or index) in order to uniquely identify nodes within the same graph, even if they have the same system call number and argument values.

Although file descriptors are returned as integer values in Linux, they are treated as different data types because integer values are a common argument type for system calls.

Treating file descriptors the same way as integers would result in false def-use dependencies. If an `open` system call would return file descriptor number 3 and a `read` call on a different file would try to read 3 characters, then a false def-use dependency edge would be generated between this pair of nodes because the fd and the integer have the same value.

Also, due to the fact that Linux reuses file descriptors, an additional check had to be implemented when generating the dependencies. Otherwise, false extra def-use edges would be generated that do not reflect actual argument dependencies.

As pointed out by Christodorescu *et al.* in [8], consecutive system calls of the same type which operate on the same resources can be aggregated into a single node. On a file descriptor, one read of N bytes is equivalent to N consecutive reads of 1 byte.

Aggregation is particulary important because it reduces the number of nodes that have to be paired in the backtracking algorithm designed by McGregor for determining the maximal common edge set. According to [8], two nodes, n_1 and n_2, should be aggregated if:

- n_1 and n_2 had the same system call

- n_1 and n_2 shared a common def-use predecessor, p

- there was no node between n_1 and n_2 that performed a different system call on the same resource.

In addition to these, we added an extra constraint:

- for each in-edge, or out-edge, that connects n_1 to another node n_3, a corresponding in-edge, or an out-edge, respectively, that connects n_2 to n_3 must exist.

Although the fourth constraint we added reduces the number of aggregated nodes, it ensures that information related to consecutive nodes that have other def-use dependencies to other resources is not lost.

4.5   Malspec algorithm

McGregor's backtrack algorithm was implemented using recursion, although the original proposed pseudocode was iterative.

The initial algorithm assumed that the graphs are not labelled, but in [13] labelling is presented as one of several powerful pruning methods. Apart from aggregation, label pruning was also

used in implementing the backtracking algorithm: only the nodes which shared the same label, the system call number, were tentatively paired.

After the complements of the maximal common edge sets are computed, the minimal transversal of their union must be computed. In our implementation all the edges represent def-use dependencies, so there is no "weight" attached to the edge labels. Therefore, the minimal transversal of the graph can be computed by doing a simple breadth first search and keeping a list of the edges that added a new node to the queue.

Testing for subgraph and supergraph relationships between two graphs was performed by finding the maximal common subgraph and then testing if every node of a graph was matched by another node from the second graph.

Chapter 5

Malsharp Evaluation

In this chapter we will present our evaluation for Malsharp. We begin by describing the test environment we used for analyzing malware in section 5.1. Then we describe a typical test scenario and we use a short example to illustrate how the malspec mining algorithm works on a small graph in section 5.2. Finally, we present our evaluation results for a set of malware samples in section 5.3.

5.1 Malware test environment

Malsharp was tested in a sandbox environment: a VMware virtual machine with a distribution of Ubuntu with the Linux 3.7.8 kernel which has been bridged to the local network for Internet access.

To ensure that all the malware samples were tested in the same environment, we used snapshots so that each file was tested on the same virtual machine state. In this way, different malware samples could not influence each other's execution.
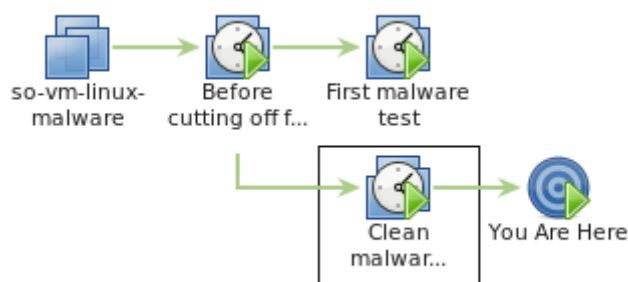

Figure 5.1: Virtual Machine test configuration

In Figure 5.1 the snapshot test configuration is shown. The "Clean malware state" is the malware test snapshot we mentioned earlier. "Before cutting off for malware test" is the VM state before changing the connection type from NAT to bridge and before removing all ssh keys from the machine.

5.2   Test scenario

In a typical test scenario, Malsharp receives an XML file which contains the system calls with parameter information that we want to monitor in our executables. We can test for malware specifications only on a subset of the total system calls a Linux operating system has.

For a better comprehension on how the malspec mining algorithm works, we will consider the following example. Let us assume that we want to search for malware specifications with `open`, `read`, `write` and `close` system calls. In this example, `program_test` will be the malware sample and `diff_test` will be the benign program.

The following table presents the system calls that each executable file makes and the relevant argument information for the dependency edges.

Table 5.1: System calls for program_test and diff_test

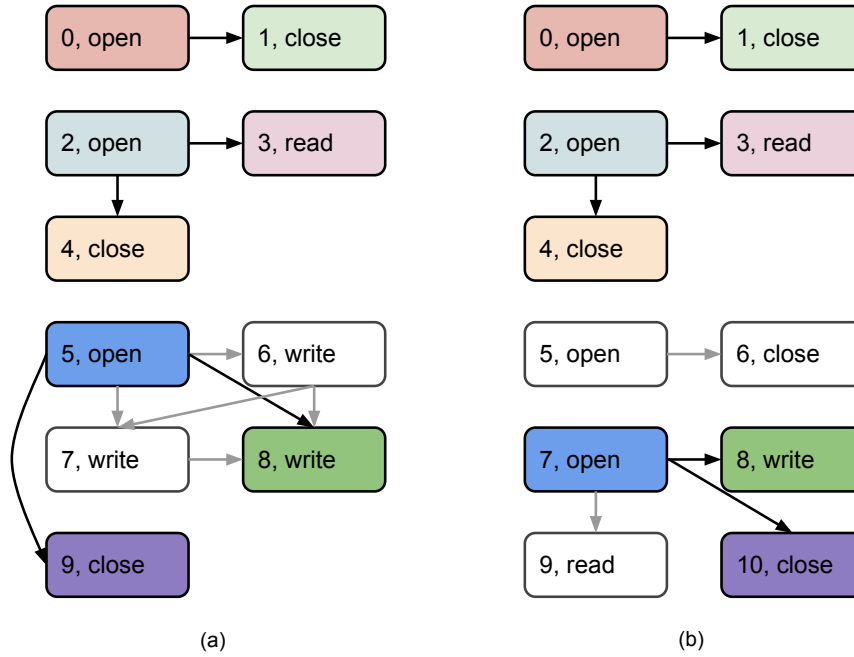|	program_test	diff_test
1	open(...) = fd1	open(...) = fd1
2	close(fd1)	close(fd1)
3	open(...) = fd2	open(...) = fd2
4	read(fd2, ...)	read(fd2, ...)
5	close(fd2)	close(fd2)
6	open(...) = fd3	open(...) = fd3
7	write(fd3, ...)	close(fd3)
8	write(fd3, ...)	open(...) = fd4
9	write(fd3, ...)	write(fd4, ...)
10	close(fd3)	read(fd4, ...)
11	–	close(fd4)

Figure 5.2: Maximal common edge set. (a) program_test; (b) diff_test.

In [Figure 5.2](#) the generated graphs for the two programs presented in [Table 5.1](#) are shown. For

each node we have written its index in the graph and its label.

Although there are three `write` calls in `program_test` that operate on the same file descriptor, these nodes are not aggregated because of the fourth restriction we added to node aggregation in Section 4.4. The three nodes cannot be aggregated because of the edges that exist between them.

The maximal common edge set that was determined using McGregor's algorithm is shown by drawing paired nodes with the same colors. The nodes that do not have a matching node in the other graph have no color. The edges connecting them are gray because they are not a part of the maximal common edge set.

After computing the maximal common edge set, its complement in the malware graph is computed. In this particular example, the complement is a single connected graph, so the minimal union step of the algorithm is not required.

Then, a breadth first search is used to find the minimal transversal of the complement. The result of these two steps of the algorithm can be seen in Figure 5.3. The malspec contains two nodes which are colored red and the black edge connecting them. Because we used a single benign program to find the malspec, this will be the final result of the algorithm.

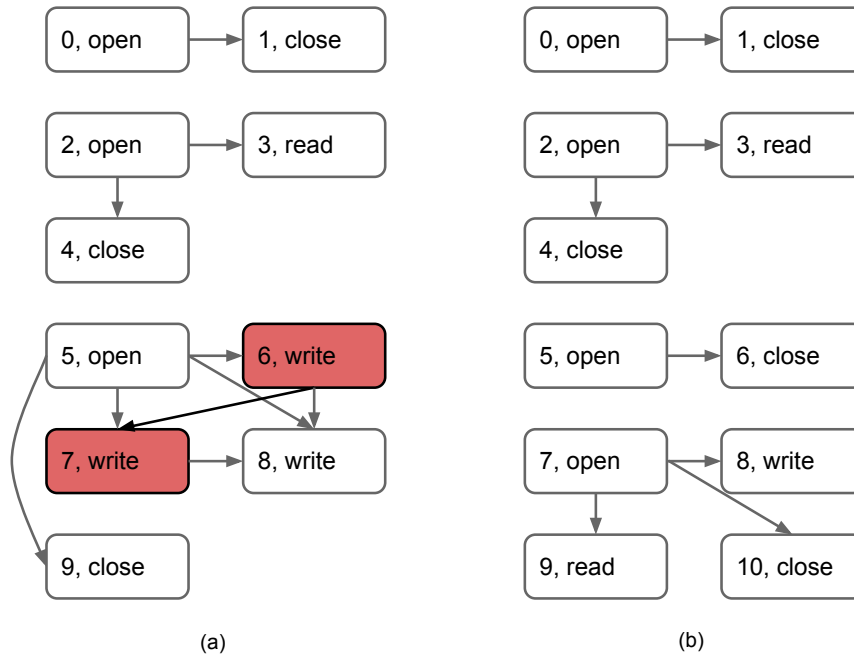Figure 5.3: Minimal transversal of complement graph. (a) program_test; (b) diff_test.

The complete output from Malsharp for `program_text` and `diff_test` can be seen in Appendix B.1.

5.3   Evaluation results

Malsharp was tested using the Linux malware samples provided by [2]. All the malware samples that were tested also had additional classification information provided by antivirus software.

As pointed out by Burguers *et al.* in [6], the increasing number of smartphones on the market with the Android platform, which has a Linux kernel, make malware analysis an important issue.

Therefore, we used two sets of system calls to monitor the malicious and benign programs: a smaller set which was indicated by Burguers *et al.* in their paper about behavior-based detection on Android [6] and a larger set which contained other system calls that might be used for malicious purposes.

The larger set is a superset of the other and has more system calls that use file descriptors and perform socket communication. Only a part of this XML file has been added to this paper as Appendix A.1 because the original file was two large.

The results for each set of system calls can be seen in the following two tables, one per set. The set of benign programs we considered for testing consisted of: `ls`, `lsmod`, `ping` and `cat`.

In Table 5.2 and Table 5.3, we used the following notation:

- N - number of nodes of the dependency graph

- N' - number of nodes left after node aggregation

- E - number of edges of the dependency graph

Table 5.2: Malware sample analysis for android.xml

Sample	N	N'	E	Malspecs	Time	Observed behavior
Backdoor.Linux.CGI.a	12	12	5	1	10.208s	`open, read, close`
Backdoor.Linux.Phobi.1	36	35	16	1	0.0641s	`open, read, close`
Trojan.Linux.Rootkit.n	12	11	5	1	0.558s	`open, read, close`
Virus.Linux.Osf.8759	692	442	285	0	-	-
Virus.Linux.Radix	14	13	4	1	0.786s	`open, read`
Virus.Linux.Rike.1627	47	47	21	1	0.674s	`open, read.  close`
Virus.Linux.Silvio.b	46	46	24	1	0.983s	`open, read, close`
Virus.Linux.Snoopy.c	128	93	39	1	1.271s	`open, read, close`
Virus.Linux.Svat.b	23	23	12	0	0.617s	-

In Table 5.2, we show the results for 9 malware samples. Although the initial collection of malware samples had 20 samples, some samples could not be tested because the operating system on our VM did not have all the shared libraries they required in order to run. Also, other samples were actually tools for flooding a range of ip addresses in a network.

`Virus.Linux.Osf.8759` could not be compared to the set of benign programs because it infected the benign programs. Due to the fact that this particular sample inserted itself into the benign programs before we extracted their trace, the analysis was not relevant because the programs already contained malicious behavior. Also, it had a specific feature from the other malware samples, it accessed the system call interceptor driver.

We compared the system calls that the `ls` command, which is part of the benign program set, made before and after the `Virus.Linux.Osf.8759` sample was run. Although, in appearance, the behavior of the command was the same, in fact it made additional calls to `fork`, `socket`, `listen`, `bind` and `pipe`. These system calls were not a part of the initial program trace before the sample was run.

`Virus.Linux.Osf.8759` generated the biggest graph and we can see that the node aggregation method reduced the total number of nodes considerably, from 692 to 442. Although analysis was not possible, the node aggregation method is done separately and the results are valid.

Most of the samples generated dependency graphs with a very small number of nodes. This is a consequence of the fact that android.xml contains a very small number of system calls used for monitoring: `read`, `open`, `close`, `chmod`, `lchown` and `access`.

Table 5.3: Malware sample analysis for all_syscalls.xml

Sample	N	N'	E	Malspecs	Time	Observed behavior
Backdoor.Linux.CGI.a	13	13	5	1	0.827s	`open, read, close`
Backdoor.Linux.Phobi.1	36	35	16	1	0.641s	`open, read, close`
Trojan.Linux.Rootkit.n	14	14	5	1	1.044s	`open, read, close`
Virus.Linux.Osf.8759	19	19	9	0	-	-
Virus.Linux.Radix	25	22	6	1	0.673s	`open, read, write;` `creat, write`
Virus.Linux.Svat.b	25	25	12	0	3.495s	replaces `stdio.h`

Analysis results for the larger set of system calls is shown in Table 5.3. The total analysis took longer due to the fact that the generated dependency graphs were larger, especially in the case of the benign programs.

Our implementation succeeded in obtaining malspecs for the analyzed malware samples. The most remarcable result was for the `Virus.Linux.Radix` sample, although it had a shorter analysis time in comparison to other samples. The malspec it returned consisted of two graphs.

The first graph contains the following nodes: `open`, `read`, `write`. The `open` node had descriptor dependencies with the other two calls. The second graph contained two nodes: a `creat` system call and a call to `write`.

`Virus.Linux.Radix` also presented another interesting behavior pattern, it inserted itself into the executable file for the `ls` command, `/bin/ls`, and `cp` command, `/bin/cp`. It also searched the current directory for executable files and it infected those as well.
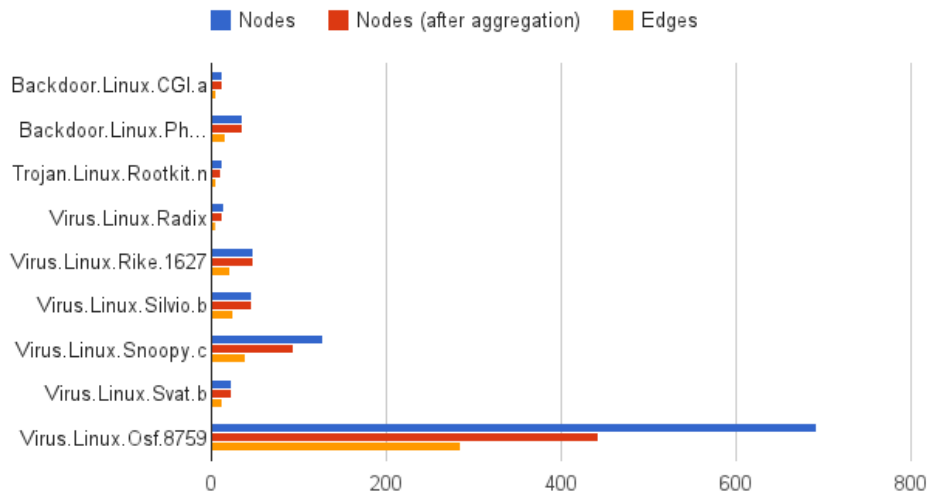
Figure 5.4: Node aggregation for android.xml

Node aggregation reduced the total number of nodes for the dependency graphs, especially in the case of large graphs. In Figure 5.4 we can see the total number of nodes was reduced by a significant factor for `Virus.Linux.Osf.8759` and `Virus.linux.Snoopy.c`.

In Figure 5.5 we present the analysis duration for the malware samples we considered for the android.xml test.
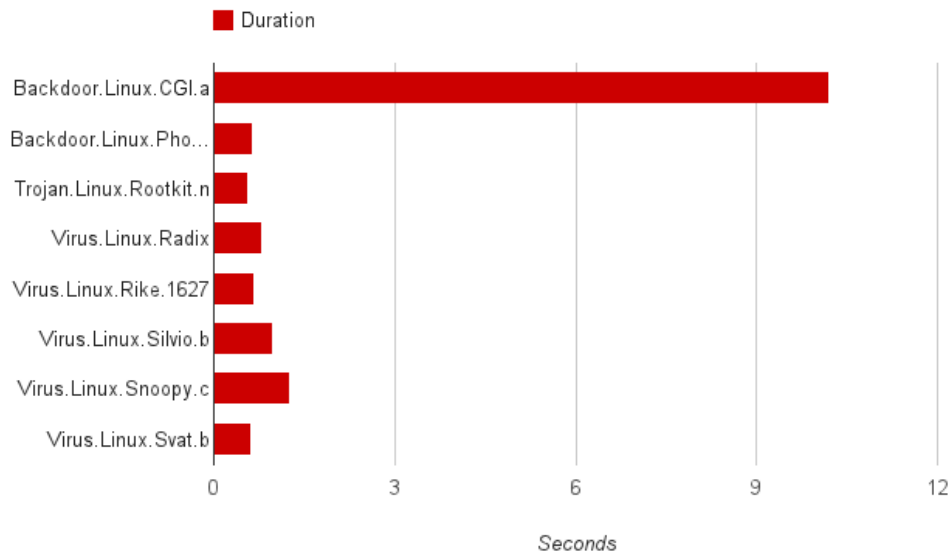
Figure 5.5: Analysis time for android.xml samples

Figure 5.6 shows the memory use of Malsharp for the android.xml test. Memory usage was measured by using **Valgrind** while also checking for potential memory leaks.

For each malware sample, the blue area, drawn according to the left vertical axis, shows how much memory was used by Malsharp while the red area, drawn according to the right vertical axis, represents the number of nodes in the dependency graph.

It can be observed that the memory usage is proportional to the number of nodes of each malware sample. This was the expected result considering that all the malware samples were tested against the same benign programs which had a constant number of system calls.

Figure 5.6: Malsharp memory use for android.xml test

Chapter 6

Conclusions and Future Work

Computer security is an important field and continuous advances ensure protection from threats such as disruption of normal computer and network operation, information leaks and attackers who benefit financially from compromised hosts.
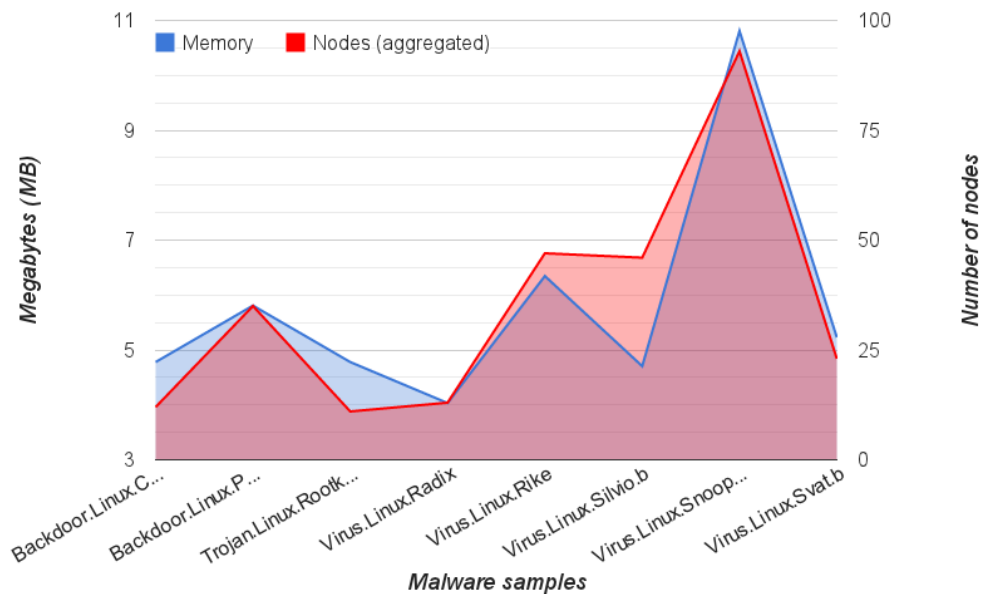
As Linux based operating systems are becoming evermore popular, malware security for these systems will continue to grow in importance. Also, use in embedded systems makes Linux an important target for malware writers.

In this thesis, we propose a solution for automating the dynamic analysis of malware samples, called **Malsharp**, which implements the malware specification mining algorithm. It compares malicious and benign programs and identifies behavior patterns specific to malware.

Our implementation of the malspec mining algorithm successfully collected the execution traces of all the malware samples. The dependency graphs that it generated were correct and the edges connected only nodes that had def-use dependencies.

As shown by our evaluation results, the node aggregation we implemented reduces the number of nodes in large graphs by a considerable factor which resulted in a shorter execution time.

The XML configuration file we used for decoding system call argument type and direction can be easily modified to include different sets of system calls from the ones we used. Also, by omitting registers from this file a selective decoding pattern can be implemented which uses only particular system call arguments for dependency graph generation.

The **Malsharp** tool represents a proof of concept for a Linux implementation of the malware specification mining algorithm. The malware specifications it identified demonstrate that this algorithm applies for Linux based operating systems and that further improvements will certainly improve the results that we obtained so far.

First, the traces are currently obtained by using the system call interceptor driver. In the future we plan to switch to using strace instead. Also, using iptables instead of the network interceptor module might be a possible improvement.

Secondly, another possible improvement includes adding other dependency edges apart from def-use, such as: comparing strings for common substrings or self-referential dependencies for when the malware sample opens its own file.

Finally, the backtracking algorithm for determining the maximal common subgraph can be further improved with other pruning methods like node ordering strategies and ancestor-leaf equivalence pruning.

Malsharp will be released under an Open Source license to permit others to contribute to this project. Work will be continued on this project and we believe it will become a powerful and reliable tool for Linux malware analysts.

Appendix A

Configuring Monitored System Calls

A.1   syscalls.xml

```xml
1  <?xml version="1.0" encoding="UTF-8"?>
2  <syscalls>
3          <syscall no="2" name="fork">
4                  <ebx type="int"    dir="in"/>
5          </syscall>
6          <syscall no="3" name="read">
7                  <ebx type="fd"     dir="in"/>
8                  <ecx type="pvoid"  dir="out"/>
9          </syscall>
10         <syscall no="4" name="write">
11                 <ebx type="fd"     dir="in"/>
12                 <ecx type="pvoid"  dir="in"/>
13         </syscall>
14         <syscall no="5" name="open">
15                 <ebx type="pchar"  dir="in"/>
16                 <ecx type="int"    dir="in"/>
17                 <edx type="ushort" dir="in"/>
18                 <ret type="fd"     dir="out"/>
19         </syscall>
20         <syscall no="6" name="close">
21                 <ebx type="fd"     dir="in"/>
22                 <ret type="void"   dir="none"/>
23         </syscall>
24         <syscall no="8"  name="creat">
25                 <ebx type="pchar"  dir="in"/>
26                 <ecx type="ushort" dir="in"/>
27                 <ret type="fd"     dir="out"/>
28         </syscall>
29         <syscall no="9" name="link">
30                 <ebx type="pchar"  dir="in"/>
31                 <ecx type="pchar"  dir="in"/>
32         </syscall>
```

```
33              <syscall no="10" name="unlink">
34                      <ebx type="pchar"  dir="in"/>
35              </syscall>
36              <syscall no="11" name="execve">
37                      <ebx type="pchar"  dir="in"/>
38                      <ecx type="pchar"  dir="in"/>
39                      <edx type="pchar"  dir="in"/>
40              </syscall>
41              <syscall no="12" name="chdir">
42                      <ebx type="pchar"  dir="in"/>
43              </syscall>
44              <syscall no="15" name="chmod">
45                      <ebx type="pchar"  dir="in"/>
46                      <ecx type="ushort" dir="in"/>
47              </syscall>
48              <syscall no="16" name="lchown">
49                      <ebx type="pchar"  dir="in"/>
50                      <ecx type="ushort" dir="in"/>
51                      <edx type="ushort" dir="in"/>
52              </syscall>
53              <syscall no="19" name="lseek">
54                      <ebx type="fd"      dir="in"/>
55                      <ecx type="int"     dir="in"/>
56                      <edx type="int"     dir="in"/>
57              </syscall>
58              <syscall no="20" name="getpid">
59                      <ret type="int"    dir="out"/>
60              </syscall>
61              <syscall no="23" name="setuid">
62                      <ebx type="uint"    dir="in"/>
63              </syscall>
64              <syscall no="24" name="getuid">
65                      <ret type="uint"   dir="out"/>
66              </syscall>
67              <syscall no="33" name="access">
68                      <ebx type="pchar"  dir="in"/>
69                      <ecx type="int"     dir="in"/>
70              </syscall>
71              <syscall no="37" name="kill">
72                      <ebx type="uint"    dir="in"/>
73                      <ecx type="int"     dir="in"/>
74              </syscall>
75              <syscall no="38" name="rename">
76                      <ebx type="pchar"  dir="in"/>
77                      <ecx type="pchar"  dir="in"/>
78              </syscall>
79              <syscall no="39" name="mkdir">
80                      <ebx type="pchar"  dir="in"/>
81                      <ebx type="ushort" dir="in"/>
82              </syscall>
83  </syscalls>
```

Listing A.1: System Calls Decode Information XML (syscalls.xml)

Appendix B

Malsharp output sample

B.1 program_test, diff_test

```
1  Monitored syscalls are:
2  3 4 5 6
3  Getting system call trace for ../test/program_test
4  driver contains 10 syscall entries
5  Malware graph:V[10]={ (0 sc=5), (1 sc=6), (2 sc=5), (3 sc=3), (4 sc
      =6), (5 sc=5), (6 sc=4), (7 sc=4), (8 sc=4), (9 sc=6), };
6  E[10]={ (0, 1), (2, 3), (2, 4), (5, 6), (5, 7), (5, 8), (5, 9), (6,
      7), (6, 8), (7, 8), };
7
8  Analyzing malware vs ../test/diff_test
9  Getting system call trace for ../test/diff_test
10 driver contains 11 syscall entries
11 Benign graph:V[11]={ (0 sc=5), (1 sc=6), (2 sc=5), (3 sc=3), (4 sc
      =6), (5 sc=5), (6 sc=6), (7 sc=5), (8 sc=4), (9 sc=3), (10 sc=6),
       };
12 E[7]={ (0, 1), (2, 3), (2, 4), (5, 6), (7, 8), (7, 9), (7, 10), };
13
14 -1 -1 -1 -1 -1 0 -1 -1 -1 1
15 -1 -1 -1 -1 -1 7 -1 -1 8 10
16 -1 -1 0 -1 1 7 -1 -1 8 10
17 -1 -1 2 3 4 7 -1 -1 8 10
18 0 1 2 3 4 7 -1 -1 8 10
19
20 Malspecs found:
21 Malspec 0
22 V[2]={ (0 sc=4), (1 sc=4), };
23 E[1]={ (0, 1), };
```

Listing B.1: Output for comparing program_test and diff_test

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