

# An approach to fast malware classification with machine learning technique

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## **Abstract of Bachelor Thesis**

### **An approach to fast malware classification based on malware's meta-data using machine learning technique**

With the rapid increase of malware, it is important for malware analysis to classify unknown malware files into malware families. From that, the behavior and characteristics of malware will be characterized accurately. In this paper, an approach was introduced for perform fast malware classification based on meta-data of malware's file. A machine learning technique, called decision tree algorithm, is used to classify malware rapidly and correctly. Experimental results of the malware samples show that the system successfully determined some semantic malware similarities, especially showed their inner similarities in behavior and static malware characteristic.

Keywords:

Malware, static analysis, decision tree.

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# Chapter 1

## Introduction

### 1.1 Background

Malware is a general word for all types of malicious software. Malware includes Virus, Trojan house, Back door, Worm, and other malicious software which are characterized by malicious code. Because of the widespread use of the Internet, computer users face many dangerous propagations of malware. The modern malware's purpose is usually to gain illegal profit. For example, a larger number of computers are infected by keylogger and 24.3 billion USD is leveraged by e-payment system losing [3]. In addition, According to 2010 Annual Security Report, on May 2010, tens of millions computer world wide was infected by email worm such as I LOVE YOU, LOVE LETTER, LOVEBUG[2]. As a result, preventing, detecting, and removing malware is very important for security networking.

### 1.2 Malware analysis problem

Instead of effective preventing, detecting, removing, and analyzing malware is analysed to find common areas that all viruses in a family share uniquely, and can thus create a set of signature in order to detect malwares.

Commonly, when new malware was detected, dynamic malware analysis and static malware analysis have used to analyze the malware. Dynamic malware analysis technique execute malware in the Virtual Machine and use ProcMon, RegShot, and other tools. Dynamic malware analysis tools are used to identify the general behavioral analysis techniques such as network traffic analysis; file system; and other Window feature: service, process, the registry.

However, these dynamic techniques are susceptible to a variety of anti-monitoring defenses, as

well as *time bombs* or *logic bombs* and can be slow and tedious to identify and disable code analysis techniques to unpack the code for examination [36]. Furthermore, it takes large amount of time to prepare environment to analyze malware such as virtual machine environment but some malware can not be executed in virtual machine environment.

With the static malware analysis technique, researcher perform reverse engineering using IDA Pro and Ollydbg tool to analyze malware by seeing the structure of malware, to discover its purpose and functionality but it takes a lot of time to see the malware structure.

Malware analysis is necessary to understand the behavior of malware. As a result, malware signature is created to effectively detect malware. Nevertheless, it wastes a lot of time to find out the behavior and characterization of malware. With a vast amount of sample increased day by day, anti-virus industry and virus researchers is harder to analyze malware without information of new malware. With the aim of reducing time of malware analysis, it is necessary to have an automatically malware classification system.

### 1.3 Approach

Two following issues are focused on:

- Automatically perform fast malware classification based on malware file's meta-data using a machine learning technique, called decision tree algorithm to classify unknown malwares or subspecies rapidly and correctly.
- Help researcher to understand which family malware belongs to and detect some semantic information about malware so they can make.

For that reason, in this paper, an approach is proposed to perform fast malware classification based on malware's meta-data using machine learning technique, known as decision tree.

### 1.4 Thesis outline

The rest of this thesis is structured as follows:

- Chapter 2 describes malware meta-data, and the method in static classification of malware. In sight is provided the purpose of method given in this research.
- Chapter 3 presents the other malware static classification approach.



- Chapter 4 approach, and the design and operation of malware classification system is described.
- Chapter 5 presents environment and implementation of static malware system.
- Chapter 6 describes the system evaluation method and results.
- Summary, the conclusion and future work is presented in chapter 7

## Chapter 2

# Back ground

This chapter presents the growth of malware. Afterwards, malware analysis technique is introduced. Afterwards, malware categories and the way to use Virus total service detect malware name that defined by anti-virus vendor is introduced. Finally, the problems of using malware name to detect semantic meaning of malware.

### 2.1 Growth of malware attack

Malware can self-replicate recursively. For example, Mota is a kind of worm that spread itself by sending spam email to address that harvested local machine [21]. In addition, Downadup is a malware that receive and execute file through a peer-to-peer systems by communication between computers[? ]. Malware infects system and spread to the other systems by communication tools. Recently, malware infects system and send the copy of itself to the others systems by Internet.

Since the rise of widespread broadband Internet access, the number of malware samples has rapidly increased. According to the report issued by Kaspersky's research team, 205 million pieces of malware were detected and neutralized [27]. In addition, in 2010 the number of malware samples increased by 20 millions [7].Figure 2.1 show the increasing of malware from 2003 to 2009 by Kaspersky Lab. As a result of the rapid growth malware, malware is still a huge problem in security internet and network connectivity.

At this time, malware is easy created by Malware Creation Tool, as know as a program that used by attacker to generate malware[4]. In addition, unlike early attack tools that implement one type of attack, such tools now can be changed quickly by upgrading or replacing their code. This causes rapidly evolving attacks and, at the extreme, results in polymorphic tools that self-evolve, changing with each active instance of the attack. Therefore, a large amount of malware has



**Figure 2.1:** Number of malicious program

[7]

challenged anti-virus vendor and researcher in effective analysis.

## 2.2 Malware avoidance technique

At the present time, malware is implemented with avoidance technique in order to invalidate static signature based method by anti-virus software and make analysis process more complicated. Avoidance technique can change malware signature and syntax without the changing the behaviors of malware. The avoidance technique consists of obfuscating code and packing technique. Therefore, a avoidance technique make malware analysis more complicated.

Obfuscating code change the form of instance malware to other form in order to invalidate signature based detection technique. Obfuscating code consists of polymorphism and metamorphism [15]. Polymorphic technique change the representation of malware. Virus, worm, and other self-propagating software if often used polymorphic technique such as encryption, data appending, and data pre-pending. Metamorphic malware automatically recode it self when it distributed or executed[15]. Simple metamorphic techniques include: adding varying lengths of NOP instructions, adding useless instruction, and loop the code segment. Advantage metamorphism techniques

include: function reordering, program flow modification, static structure modification.

Packing malware can compress the Win32 portable execution file by several tool such as UPX. According to a study carried out by Panda Research, 78% of new malware used some kind of file packing to evade detection. PE-packer is designed to reduce the size of malware through compression. The size of packed malware is small but it is bigger when it run in system[17]. When uncompressed in memory, packed malware is normally executed. UPX and some PE-packer compress malware binary files and make analysis malware more harder.

For the reason that modern malware is implemented with avoidance technique, detection method by the use of static signatures is criticized for being ineffective.

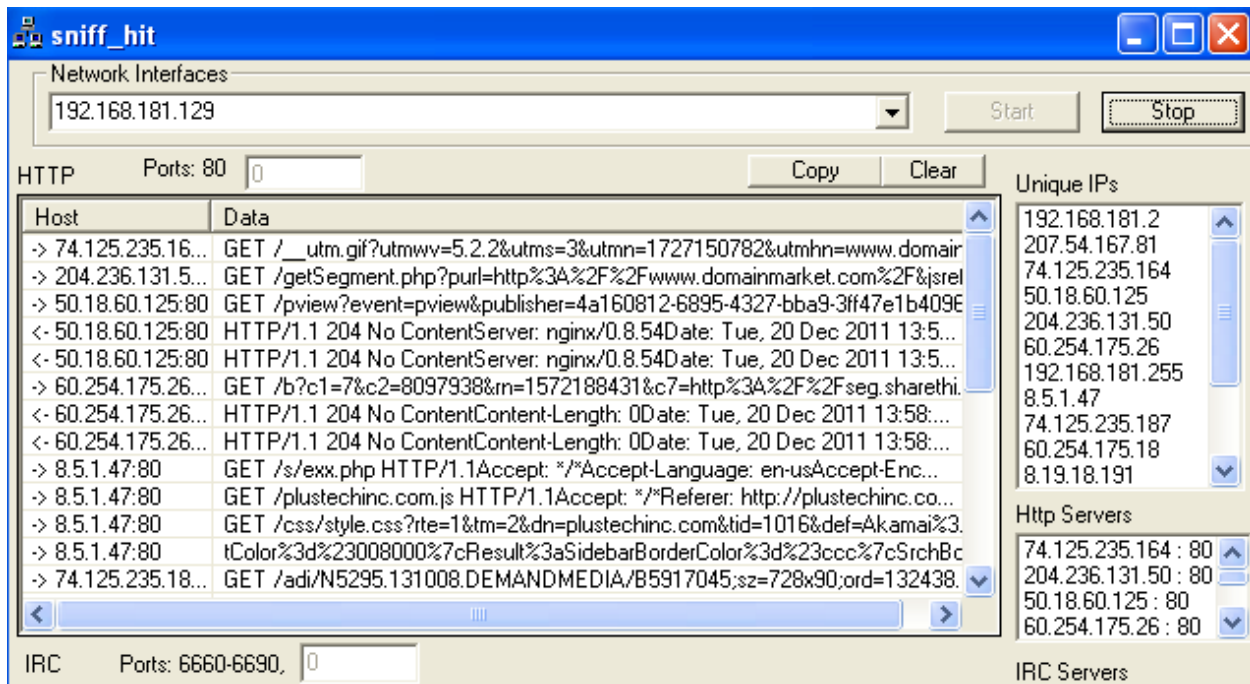
## 2.3 Malware analysis technique

This section describes two malware analysis technique includes: dynamic and static analysis. The detail of two techniques is described as follow:

### 2.3.1 Dynamic malware analysis

Dynamic malware analysis technique is technique to find out the purpose of malware by run it and make sure what happen in system. In general, malware is executed in the Virtual Machine. After that, malware researcher use SysAnalyzer, Process Explorer, ProcMon, RegShot, and other tools to identify the general behavioral analysis techniques. For example, SysAnalyser is useful analysis tool to monitors many aspects of system and process states such as running process, open ports, loaded drivers, injected libraries, key registry changes, APIs called by a target process, file Modifications, http, IRC, and DNS traffic. Figure 2.2 show the example of using SysAnalyser tool to analyse malware.

The advantage of Dynamic malware is easy to detect malware behavior. Therefore, researcher can remove malware effectively. However, these dynamic techniques are susceptible to a variety of anti-monitoring defenses, as well as *time bombs* or *logic bombs* and can be slow and tedious to identify and disable code analysis techniques to unpack the code for examination [36]. Furthermore, it takes large amount of time to prepare environment to analyze malware such as virtual machine environment but some malware cannot be executed in virtual machine environment.



**Figure 2.2:** SysAnalyser tool for dynamic analysis.

### 2.3.2 Static malware analysis

Static malware analysis is technique that identify malware program without executing it. With the static malware analysis technique, researcher performs reverse engineering using disassemble tools, decompile tools, source code analyzer tools such as IDA pro and Ollydbg in order to understand malware by seeing the structure of malware. Static malware analysis have an advantage that it can completely discover malware purpose and functionality. However, research takes many time to understand the malware functionality by analysing malware structure.

Figure 2.3 show the example of using OllyDbg tool in order to analyse malware.

## 2.4 Malware categories

In general, malware is classified into a few categories or types based on behaviors, method of infection, and the resulting propagation of malware. For example, this is some malware categories: virus, trojan, worm, spyware, and rookit. The categories detail specific types of malware threats:

- Virus :”Software which infects other application and use them as a spreading medium” [25].
- Trojan :”A malicious application which present itself as something else” [25].

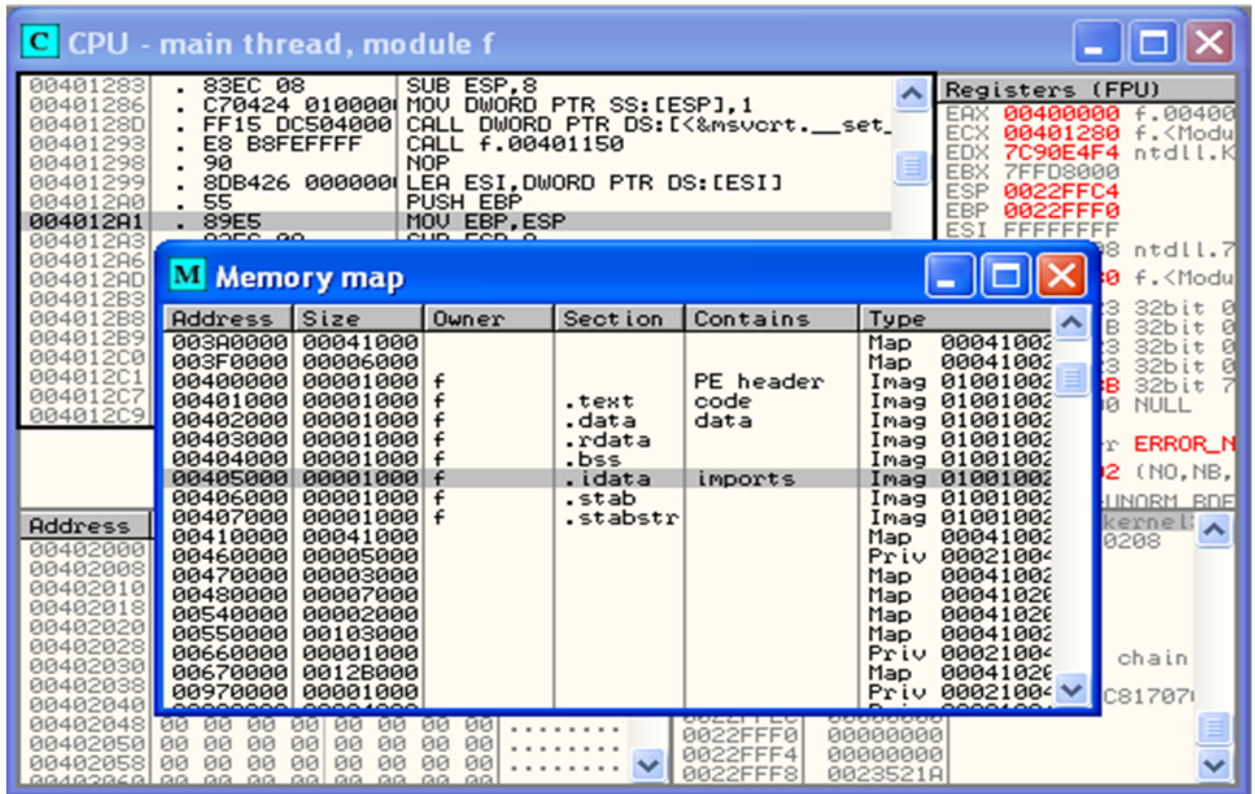


Figure 2.3: Ollydbg tool for static analysis.

- Worm : "Code with ability to spread from computer to computer by means of different network protocols" [25].
- Spyware : "Application aiming to havest personal information" [25].
- Rookit : "Hidden tools providing stealth services to its writer" [25].

However, As the different between the categories are a bit fuzzy, and the classes are obviously not exclusive. In addition, depend on purpose of virus industry a unique malware can belong to rookit, virus, or spyware. The detail of malware categories is presented on the next section.

#### 2.4.1 Use virus total to detect the name of categories.

In this thesis, MD5 hash is used to detect malware name which provided by many anti-virus vendor. An MD5 hash is generated by MD5 Message-Digest Algorithm, is a widely used cryptographic hash function that produces a 128-bit (16-byte) hash value. An MD5 hash is typically expressed as a 32-digit hexadecimal number, and MD5 is not collision resistant[24].

## 2.4.2 Using virus total to getting vendor name

In this paper, MD5 hash of malware is used to search the name of malware by virus total. Virustotal is a web service that analyzes malware files and facilitates quick detection of viruses, worms, trojans, and all kinds of malware detected by antivirus engines. Malware's name is provided by various anti-virus vendor, but there are many name for unique malware. The Figure 2.4 shows malware name detected by antivirus engines.

| Antivirus     | Version       | Last Update | Result                                    |
|---------------|---------------|-------------|---|
| AhnLab-V3     | 2011.08.13.00 | 2011.08.13  | Win-Trojan/Downloader.6144.QR             |
| AntiVir       | 7.11.13.37    | 2011.08.12  | TR/Crypt.XPACK.Gen                        |
| Antiy-AVL     | 2.0.3.7       | 2011.08.13  | Trojan/Win32.Agent.gen                    |
| Avast         | 4.8.1351.0    | 2011.08.14  | Win32:Trojan-gen                          |
| Avast5        | 5.0.677.0     | 2011.08.14  | Win32:Trojan-gen                          |
| AVG           | 10.0.0.1190   | 2011.08.14  | Win32/Heur                                |
| BitDefender   | 7.2           | 2011.08.14  | Trojan.Generic.304464                     |
| CAT-QuickHeal | 11.00         | 2011.08.13  | TrojanDownloader.Agent.pkw                |
| ClamAV        | 0.97.0.0      | 2011.08.13  | Trojan.Downloader-38041                   |
| CommTouch     | 5.3.2.6       | 2011.08.13  | W32/Downldr2.BXKD                         |
| Comodo        | 9739          | 2011.08.14  | TrojWare.Win32.TrojanDownloader.Small.OBW |
| DrWeb         | 5.0.2.03300   | 2011.08.14  | Trojan.DownLoader.61643                   |
| Emsisoft      | 5.1.0.8       | 2011.08.14  | Trojan-Dropper.Agent!IK                   |
| eSafe         | 7.0.17.0      | 2011.08.10  | Win32.Agent.pkw                           |
| eTrust-Vet    | 36.1.8499     | 2011.08.12  | -   |
| F-Prot        | 4.6.2.117     | 2011.08.13  | W32/Downldr2.BXKD                         |
| F-Secure      | 9.0.16440.0   | 2011.08.14  | Trojan.Generic.304464                     |
| Fortinet      | 4.2.257.0     | 2011.08.14  | W32/Agent.PKW!tr.dldr                     |
| GData         | 22            | 2011.08.14  | Trojan.Generic.304464                     |
| Ikarus        | T3.1.1.107.0  | 2011.08.14  | Trojan-Dropper.Agent                      |
| Jiangmin      | 13.0.900      | 2011.08.13  | TrojanDownloader.Agent.aavi               |
| K7AntiVirus   | 9.109.5010    | 2011.08.12  | Trojan-Downloader                         |
| Kaspersky     | 9.0.0.837     | 2011.08.14  | Trojan-Downloader.Win32.Agent.pkw         |

Figure 2.4: Malware name is detected by antivirus engines.

## 2.5 Problems of malware name

As the malware name detected by anti-virus engines show in Figure 2.4, unique malware is not classified into unique name. For each anti-virus vendor, the name of malware detected is different to

the other anti-virus vendor. The classification of each anti-virus engine is unlike others. Therefore, malware detected by anti-virus engines cannot provide meaningful characterization of malware for virus researcher. In order to overcome this problem, this paper proposed to classify the malware into families based on malware specific target and its operation behavior. As a result of malware name detected by anti-virus vendor was presented above, the new malware families is required for detect meaningful characterization of malware.

## **2.6 Malware families is used in this paper**

This paper use malware families which is reported by Information-technology Promotion Agency [8]. The table show malware families used in this paper such as Win32/Virut, Win32/Autorun, Win32/IRCbot, Win32/Gaobot, Win32/Waledac, Win32/Downadup, Win32/Sality, and W32.Mota.



| Malware families | Summary   |
|------------------|---|
| Win32/Virut      | "Win32/Virut is a family of file infecting viruses that target and infect .EXE and .SCR files accessed on infected systems. Win32/Virut also opens a backdoor by connecting to an IRC server, allowing a remote attacker to download and run files on the infected computer." [12]  |
| Win32/Autorun    | "Win32/Autorun is a family of worms that spreads by copying itself to the mapped drives of an infected computer. The mapped drives may include network or removable drives." [11]   |
| Win32/IRCbot     | "Win32/IRCbot is a large family of backdoor Trojans that targets computers running Microsoft Windows. The Trojan drops other malicious software and opens a backdoor on the infected computer to connect to IRC servers. The Trojan can maintain multiple IRC server connections simultaneously to receive commands from attackers." [10] |
| Win32/Gaobot     | "The Win32/Gaobot worm family spreads using different methods, depending on the variant. Some variants spread to machines with weak passwords. Others exploit vulnerabilities to infect machines. Once a machine is infected, the worm connects to an IRC server to receive commands." [9]  |
| Win32/Waledac    | "Win32/Waledac is a trojan that is used to send spam. It also has the ability to download and execute arbitrary files, harvest email addresses from the local machine, perform denial of service attacks, proxy network traffic and sniff passwords." [? ]  |
| Win32/Downadup   | "Win32/Downadup attempts to spread to network shares by brute-forcing commonly used network passwords and by copying itself to removable drives." [? ]  |
| Win32/Sality     | "Virus:Win32/Sality is a family of polymorphic file infectors that target Windows executable files with the extensions .SCR or .EXE. They may execute a damaging payload that deletes files with certain extensions and terminates security-related processes and services.   |
| W32.Mota         | W32.Mota is a worm that propagates by sending itself to email addresses gathered from the computer." [21]   |

**Table 2.11** Malware

## Chapter 3

# Related research

This chapter presents the recent approach for automatically classify malware into malware families. For the reason that the detection based static signature is no longer effective in chapter 2, at this time new malware classification method is required to detect malware writers used avoidance technique.

### 3.1 Flow graph

Another approach is using emulator to automatically unpack the packing malware, then from reverse code produce flowgraph, then flowgraph matching to perform classification[28]. The system created by the approach follows:

- First, System automatically unpack malware based on application level emulation, and then use entropy analysis to detect.
- Second, Produce control flowgraph by using graph invariant based signature in order to measure similarity between malware.
- Next, Generic string based control flow signature, in order to using string edit distance. Automatically unpack malware based on application level emulation.
- Finally, Malware classification use a set similarity function and a set similarity search algorithm to represent benign and malicious classes.

The disadvantage in flowgraph approach is high cost of runtime complexity. Firstly, runtime complexity of malware classification is  $O(N \log M)$  where M is the number of control flow

graphs in database, and  $N$  is the number of control flow graph input binary [28]. In addition, To identify two flowgraph is  $N^3$ , and  $N$  is the number of nodes in each graph. Further more, needs to unpack the sample if it was packed with an executable packer. There fore, this approach is ineffective in malware classification system with a large number of instances.

In addition, malware classification based flowgraph approach cannot accurately detect metamorphic malware. As presented at chapter 2, metamorphic malware can recode it self with program follow modification, function reordering. There fore, it is hard to classify malware based a set similarity between follow graph.

### 3.2 Optimizing decision tree in malware classification system by using Generic Algorithm

In this time, malware classification system can use machine learning classifier. The main idea of machine learning technique classifier is search algorithm that learn from externally supplied instances to produce a concise model of the distribution, which then make prediction about new instances. Current machine learning classifier in malware classification include: Naive Bayse, Suport Vector machine, Decision tree, K-nearest Neighbor [14]. This approach use combining Generic algorithms with Decision tree. The data set is separated in training data set and testing data set. The data set is include:

```
// Malware target, specific target for malware attack
vector<list<MalwareClass>> _slots;
// Malware classes for chromosome
hash_map<MalwareClass,int> _Dataclasses;
hash_map<MalwareClass,int> _Appsclasses;
hash_map<MalwareClass,int> _Sysclasses;
hash_map<MalwareClass,int> _Dosclasses;
```

Generic algorithm is methods that analogous to the process of natural evolution. Generic algorithm is used to optimize decision tree in order to accurately classify malware. Malware classification system, which implemented by the combining generic algorithm with decision tree algorithm approach, is for classify malware into two classes: benign program and malicious program, not for detect semantic characterization of malware by classifying malware into families. There fore, the combining generic algorithm with decision tree algorithm approach cannot use for detecting

semantic characterization of malware.

### **3.3 Conclusion**

To achieve fast malware classification, two approach is described before can not be used in this system. New approach for fast malware classification system will introduced in the next chapter.

## Chapter 4

# Classification based on malware's meta-data using decision tree approach

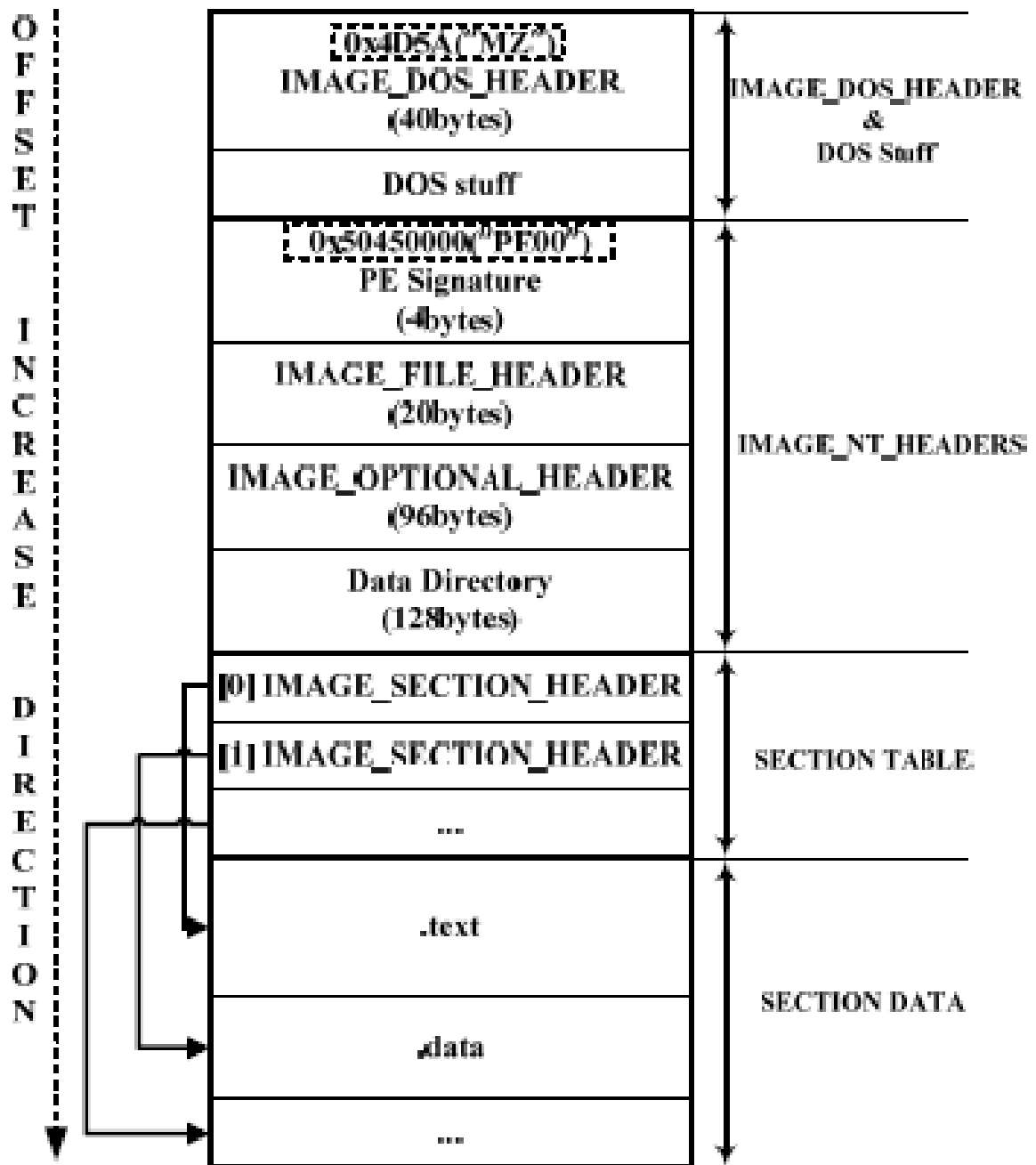
This chapter describes Win32 executive files structure, known as PE files structure, that used in classification system as malware meta-data. Afterwards, the machine learning technique, known as decision tree method, that used in classification malware system is described. Finally, this chapter presents classification based on malware's meta-data using decision tree approach.

### 4.1 PE file format

#### 4.1.1 PE file overview

The real content of the PE file is divided into blocks called sections. A section is nothing more than a block of data with common attributes such as code/data, read/write etc. You can think of a PE file as a logical disk. The PE header is the boot sector and the sections are files in the disk. The files can have different attributes such as read-only, system, hidden, archive and so on. When the PE loader maps the sections into memory, it examines the attributes of the sections and gives the memory block occupied by the sections the indicated attributes.

If the PE file format is viewed as a logical disk, the PE header as the boot sector and the sections as files. Each structure contains the information about each section in the PE file such as its attribute, the file offset, virtual offset. If there are 5 sections in the PE file, there will be exactly



**Figure 4.1:** PE file format.

5 members in this structure array. Each member of the array is equivalent to the each directory entry in the root directory.

That's all about the physical layout of the PE file format. The major steps in loading a PE file into memory is described as follow:

- When the PE file is running, the PE loader examines the DOS MZ header for the offset of

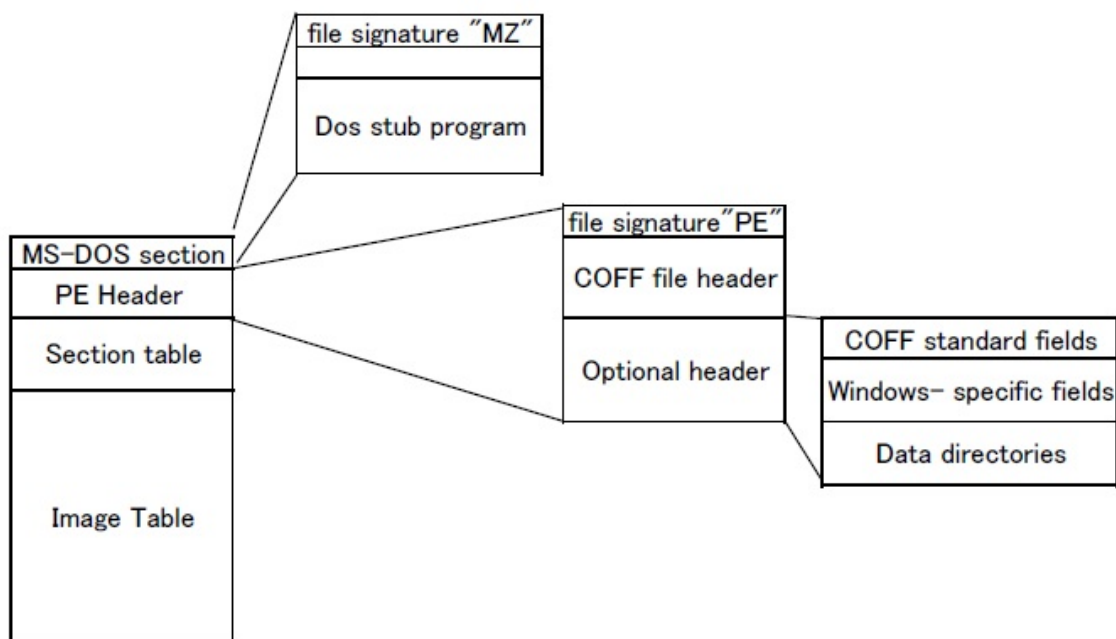
the PE header. If it is found, it would skip to the PE header.

- The PE loader checks if the PE header is valid. If so, it goes to the end of the PE header.
- Following the PE header is the section table. The PE header reads information about the sections and maps those sections into memory using file mapping. It also gives each section the attributes as specified in the section table.
- After the PE file is mapped into memory, the PE loader concerns itself with the logical parts of the PE file, such as the import table.

The above steps are oversimplification and are based on my own observation. There may be some inaccuracies but it should give you the clear picture of the process.

#### 4.1.2 PE header

PE header of second part of PE files structure. PE header includes important information of ma . As shown in Figure 4.2 PE header consists of four parts, a MS-DOS section, PE header, a section table, images pages.



**Figure 4.2:** Layout a file in PE header format.

The PE header starts with two characters "PE" as know as the PE header file signature.

The file header contains seven fields shown in Figure 4.3. The number of the members in section is determined by *NumberOfSection* file in file header.

| Member               | Offset   | Size  |
|----------------------|----------|-------|
| Machine              | 000000DC | Word  |
| NumberOfSections     | 000000DE | Word  |
| TimeStamp            | 000000E0 | Dword |
| PointerToSymbolTable | 000000E4 | Dword |
| NumberOfSymbols      | 000000E8 | Dword |
| SizeOfOptionalHeader | 000000EC | Word  |
| Characteristics      | 000000EE | Word  |

**Figure 4.3:** Layout of a file header

The following of the file header is the Optional header which consists of three parts. The first part is the COFF standard fields which contains the sizes of various parts of code and the *AddressOfEntryPoint* which indicates the location of the entry point of the application and, the location of the end of the Import Address Table(IAT).

In order to create a fast malware classification system, classification malware system based on PE header's meta-data.

## 4.2 Decision tree[5]

Decision tree is a algorithm generally used in machine learning technique. Decision tree is to create a model that predicts the value of a target variable based on several input variables. An example is shown on the right. Each interior node corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf.

In data mining, trees can be described also as the combination of mathematical and computational techniques to aid the description, categorization and generalization of a given set of data. Data comes in records of the form  $\mathbf{x}, Y = x_1, x_2, x_3, \dots, x_k, Y$  The dependent variable, Y, is the target variable is analysed to understand, classify or generalise. The vector x is composed of the input variables, x1, x2, x3, that are used for that task.



### 4.3 Classification based on malware's meta-data using decision tree approach

To make malware classification rapid and correct, decision tree algorithm is used in malware classification system.

As the previous section, Data comes in records of the form:  $\mathbf{x}, Y = x_1, x_2, x_3, \dots, x_k, Y$  In malware classification system,  $Y$  is malware families name,  $x_1, x_2, x_3, \dots, x_k, Y$  is meta-data. Malware name is provided by anti-virus engines that presented in chapter 2 cannot used in this system. The new malware families is required for detect meaningful characterization of malware. This classification system use famous malware families that reported in Information technology agency such as netsky, mydoom, autorun, mytob, and other famous malware families. Therefore, when new malware is classified into famous malware families, researcher detect some meaningful characterize of malware, and reduce time for malware analysis.

## Chapter 5

# Implementation

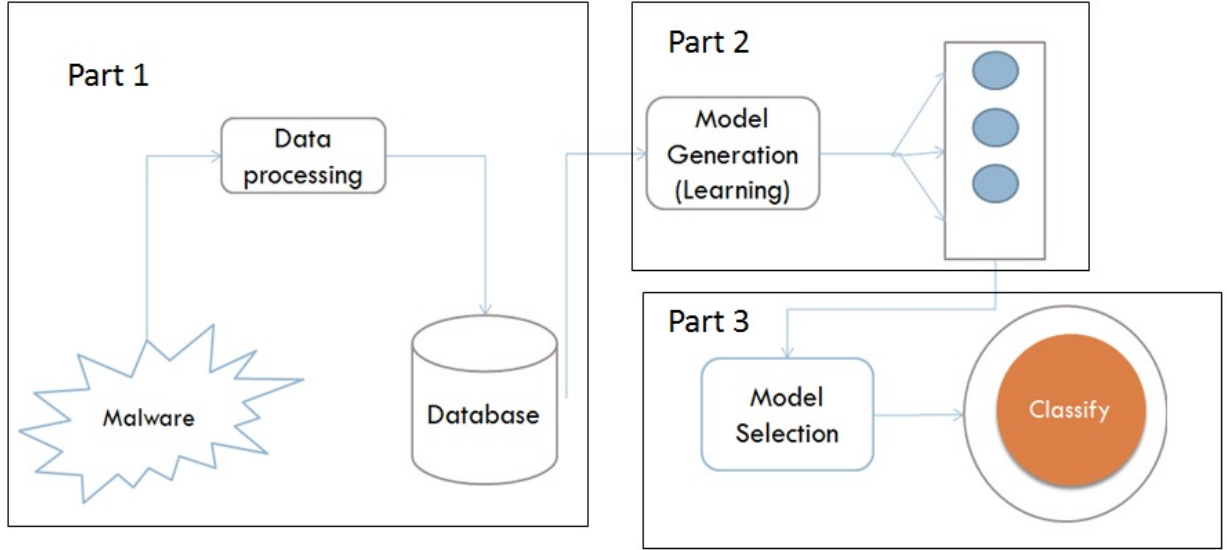
### 5.1 Environment

### 5.2 Overview

The system uses machine learning technique, known as decision tree algorithm for malware classification. The goal is classifying malware fast and decision tree algorithm is used to achieve that goal. Classification is a form of supervised learning, which requires training data, with known input/output, to form knowledge [33]. As shown in Figure 5.1, the system contains three following parts.

- First part: Read binary file to take meta data and input to database.
- Second part: Manually cluster malware which load from database.
- Third part: Use decision tree algorithm to classify malware.

A vast amount of malware need analyzing, and the system use database to store malware file's meta-data, to easily control a large number of data and to share them in the internet among web browsers. The flow of data is shown in the Figure 5.1. Firstly, binary file meta-data are read, and all of the meta-data are input into database. In the second part, the system exports meta-data in database as the training data to create the decision tree for classifying malware. Finally , the decision tree algorithm created in the second step is utilized to class unknown malware into the different malware families.



**Figure 5.1:** The system architecture.

## 5.3 Classification based on machine learning technique

### 5.3.1 Meta-data

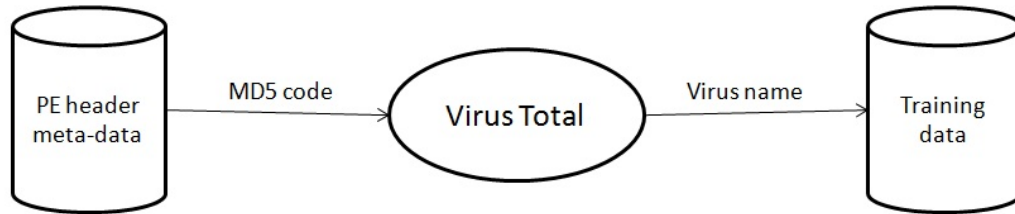
In order to create a fast malware classification system, the system only use PE header's meta-data to classify malware. PE header includes meta-data of MS-DOS section, COFF file header, Optional header, and Section header.

There is a problem that PE file's meta data value is too large to detect unknown malwares which have meta-data's differences from the training data of the system. The meta-data of PE header file are indexed to give semantic information for malware classification. For example, normally *ImageBase* field of PE header file has value of 400000h [37]. The value of *ImageBase* of malware file in the system is 0 if it has 40000, and it is 1 if it has other value, ; in this research, that value is named as semantic value. This approach use all of PE file's meta-data, specifically *HeaderFilesize*, *AddressOfEntryPoint*, *Sizeofsection*, *Imagebase*, *Numberofsection*, *StackCommit*, *SizeHeap Commit*, *SizeImage*, *Characteristics*. The semantic value of all malware file's meta-data is calculated.

### 5.3.2 Create training data

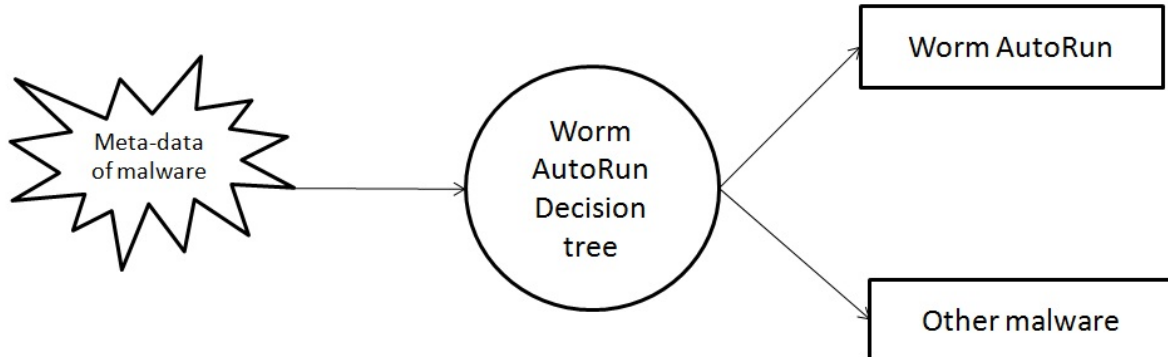
Virustotal is a service that analyzes malware and facilitates quick collection of viruses, worms, trojans, and all kinds of malware are detected by antivirus vendor such as Norton and Kaspersky [? ]. This research applies virustotal service to take the name of malware provided by Kaspersky and uses it to cluster malware into malware families with semantic information. Figure 5.2 indicates

http post technique to automatically get name from virus total service and cluster malware into malware families which given in Figure ??.



**Figure 5.2:** Clustering method.

### 5.3.3 Classification

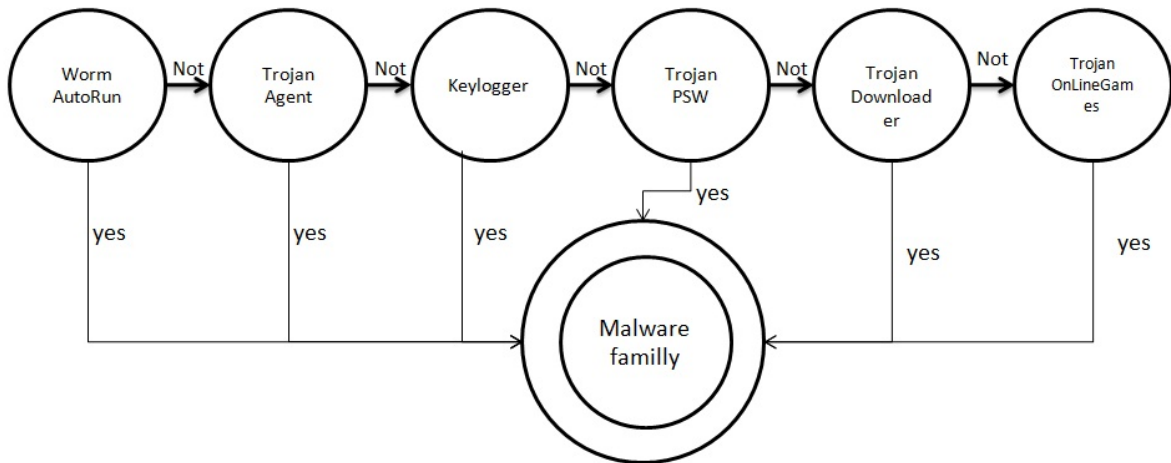


**Figure 5.3:** Worm autorun decision tree.

To make malware classification rapid and correct, decision tree algorithm is utilized. At that time, it is easy update a new malware family, the classification uses decision tree algorithm to determine each malware family. For example, based on training data from clustering part, six decision trees are created. In the worm autorun decision tree, shown is indicated in Figure 5.3.

Malware' meta-data are known as input data for each decision tree, and the the decision tree determines whether the malware belongs to worm autorun family or not. If the input malware belongs

to worm autorun, malware classification shall detect which the family that malware is, otherwise it moves to the next decision tree. Lists of malware PE header file's meta-data are Magic, MajorLinkerVersion, MinorLinkerVersion, SizeOfCode, SizeOfInitializedData, SizeOfUninitializedData, AddressOfEntryPoint, BaseOfCode, BaseOfData, ImageBase, SectionAlignment, FileAlignment, MajorOperatingSystemVersion, MinorOperatingSystemVersion, MajorImageVersion, MinorImageVersion, MajorSubsystemVersion, MinorSubsystemVersion, Reserved1, SizeOfImage, SizeOfHeaders, CheckSum, Subsystem, DllCharacteristics, SizeOfStackReserve, SizeOfStackCommit, SizeOfHeapReserve, SizeOfHeapCommit, LoaderFlags, NumberOfRvaAndSizes, Machine, NumberOfSections, TimeDateStamp, PointerToSymbolTable, NumberOfSymbols, SizeOfOptionalHeader, Characteristics. The value of each field in PE header has semantics for decision tree algorithm if it is appeared at 10% in malware training data. With this approach, the semantic value list of meta-data malware is made. For example, this is a list of meta-data created :1, 2, 6, 4, 0, 1, 1, 4, 0, 200, 4, 0, 0, 0, 4, 0, 0, 1.00E+00, 200, 0, 2, 0, 100000, 4000, 100000, 1000, 0, 10, 14c, 2, 1000, 8, 0, e0, 3, 818e. This is value before being computed :35328, 10b, 2, 0, 6200, 0, 200, b32e, b000, 9000, 400000, 1000, 200, 3, 0, 0, 0, 4, 0, 0, d000, 400, afe8, 2, 0, 1000, 1000, 10000, 0, 0, 10, 14c, 6, 0, 0, 0, e0, 10e. The malware classification part is shown in Figure 5.4. The training data from the malware clustering part is used to create the order of decision tree that makes malware classification system correct. The decision tree is given as in Figure 5.5. When PE header's meta-data of malware is inputted into the worm autorun decision tree in order for determining unknown malware. Then, it decides whether it belongs to worm auto run family or not.



**Figure 5.4:** Malware classification system.



## Chapter 6

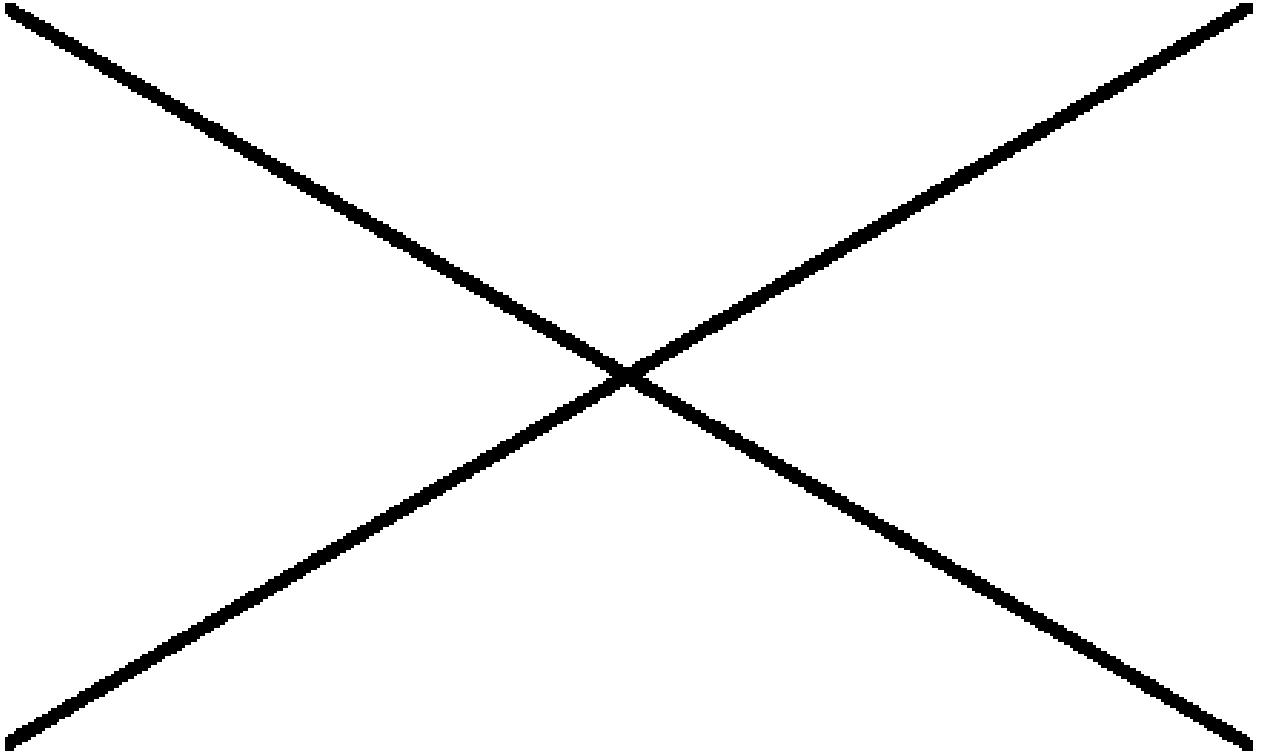
# Evaluation

### 6.1 Accuracy evaluation

In 935 malware PE files obtained, 635 of them are to make eight decision trees. 200 malware meta-data in training data is applied to, in order to sort 8 decision tree, and to make the best order of decision tree as shown in Figure 6.1, this order has the best experimental result with ? malware training data. Finally, Lasrly, 100 remaining malware meta-data are kept to test experimental result the system. Experiment results in the order of decision tree given in Figure 6.1.

In the decision tree order, 100 malware are taken to check the experimental result of system, and Table 6.2 reveals that result. Some of data in axis show these total number of malware in that family, and that number is separated into groups that these malware has been classified by the system. For example, there are four malwares in Win32/Virut family, and three of them are successfully sorted into Win32/Virut family and, while one malware is in other family. Therefore, the system recognizes the trojan agent family with 75 % of accuracy.

The system is useful to help virus researcher determine the malware family that unknown malware belongs to. The malware family contains Win32/Virut, Win32/Autorun, Win32/IRC'bot, Win32/Gaobot, Win32/Waledac, Win32/Downadup, Win32/Sality, W32.Mota, known as famous malware family. Virus researchers who know the family of malware can easily find out some semantic similarities between malwares and shows their inner similarity in behavior and static malware characteristics.



**Figure 6.1:** The best decision tree order.

| Malware  | Virut | Autorun | IRCbot | Gaobot | Waledac | Downadup | Sality | Mota | Accuracy |
|----------|-------|---------|--------|--------|---------|----------|--------|------|----------|
| Virut    | ?     | ?       | ?      | ?      | ?       | ?        | ?      | 75%  |          |
| Autorun  | 0     | 0       | 0      | ?      | ?       | ?        | ?      | 50%  |          |
| IRCbot   | 0     | 0       | 2      | 0      | 1       | 0        | 0      | 66%  |          |
| Gaobot   | 1     | 0       | 0      | 2      | 8       | 0        | 3      | 53%  |          |
| Waledac  | 0     | 0       | 0      | 0      | 0       | 0        | 0      | 0%   |          |
| Downadup | 0     | 0       | 0      | 0      | 0       | 1        | 1      | 50%  |          |
| Sality   | 0     | 0       | 0      | 0      | 0       | 1        | 1      | 50%  |          |
| Mota     | 4     | 4       | 2      | 3      | 15      | 2        | 41     | 57%  |          |

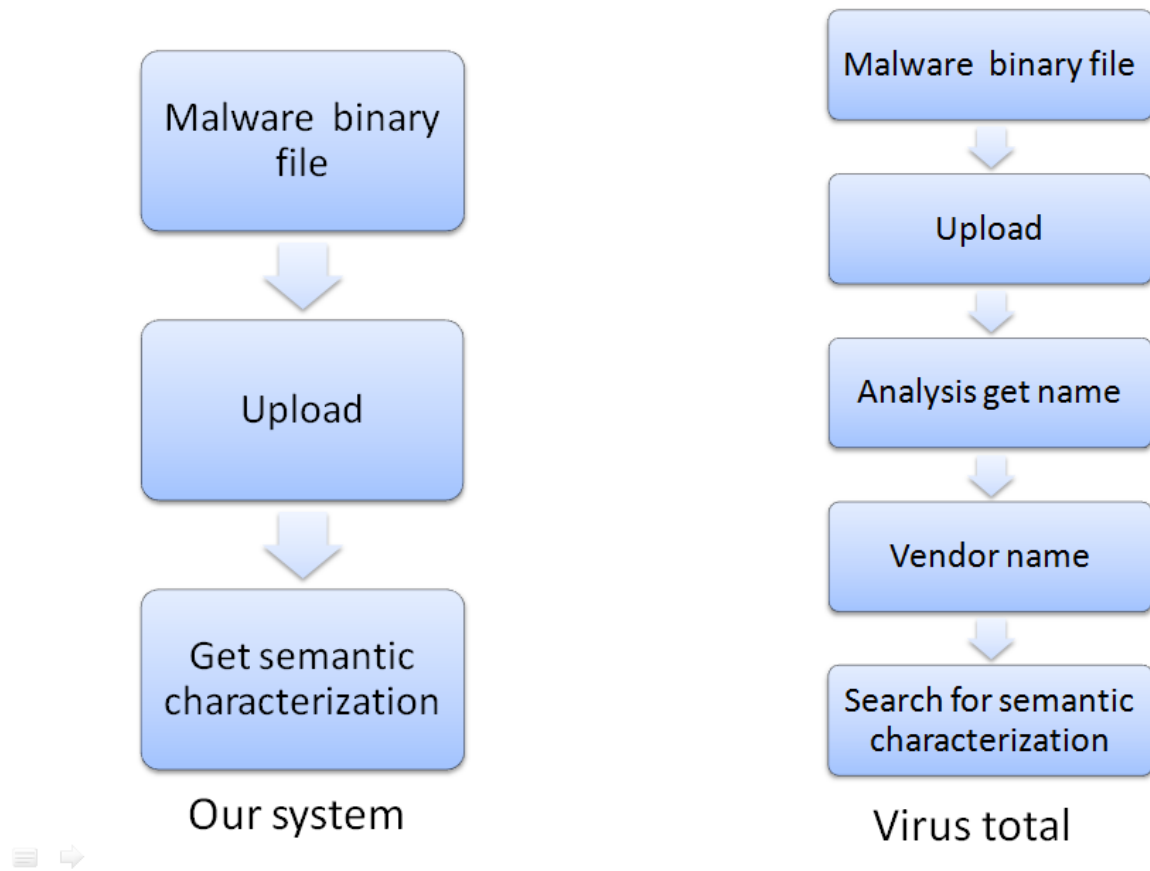
**Figure 6.2:** Experimental result

## 6.2 Efficiency of classifying

Figure show comparing the step to detect semantic malware characterization using Virus total with the system.

The figure 1 show classifying time in the system. The evaluation was performed on a 2.4 HZ

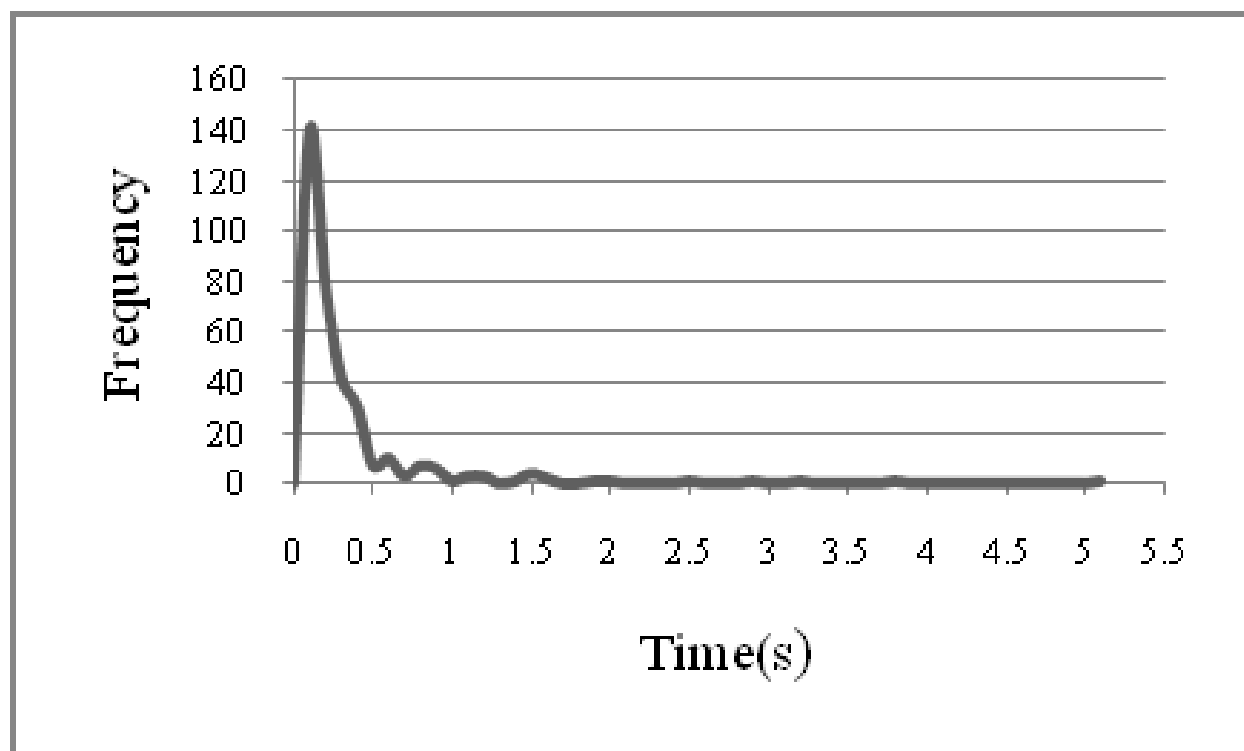




**Figure 6.3:** The best decision tree order.

core i3 laptop with 4G memory, running in ubuntu 11.4.

The result was shown in figure ?? . The median time to perform classification was 0.25 seconds. The slowest sample classified required 5.12 seconds. Only 6 samples required more than 2 seconds. Processing time of followgraph approach was shown in figure 6.4.



**Figure 6.4:** The best decision tree order.

## Chapter 7

# Conclusion

### 7.1 Conclusion

Analyzing a great number of new malware samples each day is a difficult problem. The malware fast malware classification system is successful to classify unknown malware into malware family which have semantic specifications. It is strongly believed that system is useful in malware analysis to determine malware behavior and semantic malware characteristics, and to more easily examine a large number of malwares. However, there is a problem that the system only uses malware meta-data and cannot detect the malware family which have same program structure.

Surprisingly, the system cannot be used to classify W32 malware which does not have the signature of PE file signature.

### 7.2 Future work

The anonymous malwares in the system are classified into malware family, and in the future work, Windows API shall be applied to determine this with similarity in program structure.

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