INDIAN INSTITUTE OF TECHNOLOGY BOMBAY

Project Report on

MALWARE DETECTION

SUBMITTED TOWARDS THE
PARTIAL FULFILLMENT OF THE REQUIREMENTS OF

CS725:Foundations of Machine Learning (Computer Science and Engineering)

BY

Anurag Chaudhary **Roll No:193050061**
Himanshu Aswal **Roll No:193059001**
Pranav Chaudhary **Roll No:193059004**
Sanyam Raj **Roll No:193050096**

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY BOMBAY

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Project Entitled

MALWARE DETECTION

Submitted by

Anurag Chaudhary	**Roll No:193050061**
Himanshu Aswal	**Roll No:193059001**
Pranav Chaudhary	**Roll No:193059004**
Sanyam Raj	**Roll No:193050096**

is a bonafide work carried out by students and it is submitted towards the partial fulfillment of the requirement of CS725:Foundations of Machine Learning (Computer Science and Engineering).

Prof. Sunita Sarawagi
Department of Computer Science, IIT Bombay

Abstract

In recent years, the malware industry has become a well organized market involving large amounts of money. Well funded, multi-player syndicates invest heavily in technologies and capabilities built to evade traditional protection, requiring anti-malware vendors to develop counter mechanisms for finding and deactivating them. In the meantime, they inflict real financial and emotional pain to users of computer systems.

One of the major challenges that anti-malware faces today is the vast amounts of data and files which need to be evaluated for potential malicious intent. For example, Microsoft's real-time detection anti-malware products are present on over 160M computers worldwide and inspect over 700M computers monthly. This generates tens of millions of daily data points to be analyzed as potential malware. One of the main reasons for these high volumes of different files is the fact that, in order to evade detection, malware authors introduce polymorphism to the malicious components. This means that malicious files belonging to the same malware "family", with the same forms of malicious behavior, are constantly modified and/or obfuscated using various tactics, such that they look like many different files.

In order to be effective in analyzing and classifying such large amounts of files, we need to be able to group them into groups and identify their respective families. In addition, such grouping criteria may be applied to new files encountered on computers in order to detect them as malicious and of a certain family.

Contents

1 Problem Statement

In the past few years, the malware industry has grown very rapidly that, the syndicates invest heavily in technologies to evade traditional protection, forcing the anti-malware groups/communities to build more robust softwares to detect and terminate these attacks. The major part of protecting a computer system from a malware attack is to identify whether a given piece of file/software is a malware.

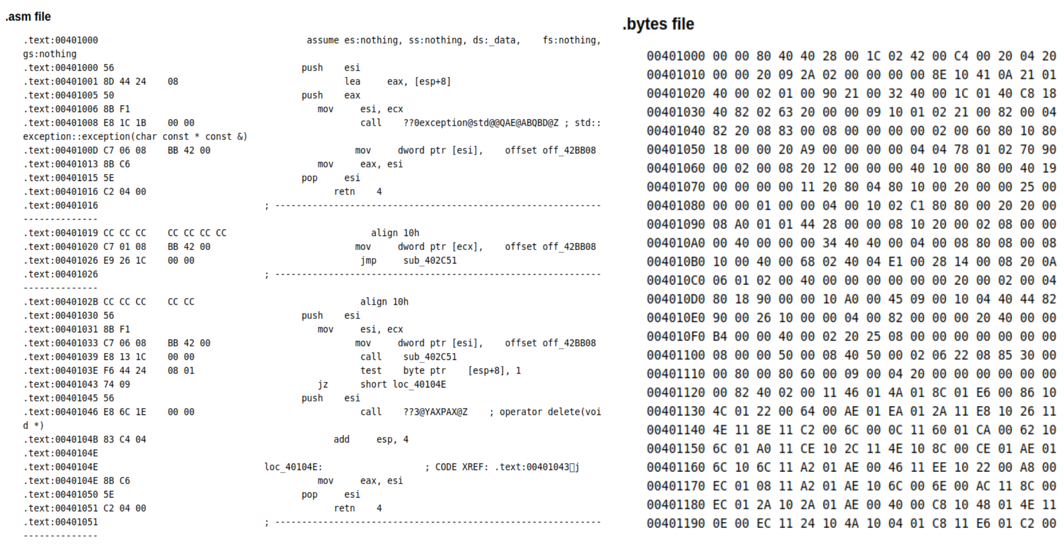
2 Goal and Objective

- Minimize multi-class error.
- Multi-class probability estimates.
- Malware detection should not take hours and block the user's computer. It should finish in a few seconds or a minute.

3 Data

Source : `https://www.kaggle.com/c/malware-classification/data`

For every malware, we have two files
.asm file
.bytes file (the raw data contains the hexadecimal representation of the file's binary content, without the PE header).



```
.text:00401000                          assume es:nothing, ss:nothing, ds:_data,    fs:nothing,
gs:nothing
.text:00401000 56                       push    esi
.text:00401001 8D 44 24    08                   lea     eax, [esp+8]
.text:00401005 50                       push    eax
.text:00401006 8B F1                       mov     esi, ecx
.text:00401008 E8 1C 1B    00 00                call    ??0exception@std@@QAE@ABQBD@Z ; std::
exception::exception(char const * const &)
.text:0040100D C7 06 08    BB 42 00            mov     dword ptr [esi],    offset off_42BB08
.text:00401013 8B C6                       mov     eax, esi
.text:00401015 5E                       pop     esi
.text:00401016 C2 04 00                      retn    4
.text:00401016                    ; ------------------------------------------------------------
-------------
.text:00401019 CC CC CC    CC CC CC CC            align 10h
.text:00401020 C7 01 08    BB 42 00            mov     dword ptr [ecx],    offset off_42BB08
.text:00401026 E9 26 1C    00 00                jmp     sub_402C51
.text:00401026                    ; ------------------------------------------------------------
-------------
.text:0040102B CC CC CC    CC CC                align 10h
.text:00401030 56                       push    esi
.text:00401031 8B F1                       mov     esi, ecx
.text:00401033 C7 06 08    BB 42 00            mov     dword ptr [esi],    offset off_42BB08
.text:00401039 E8 13 1C    00 00                call    sub_402C51
.text:0040103E F6 44 24    08 01                test    byte ptr    [esp+8], 1
.text:00401043 74 09                       jz      short loc_40104E
.text:00401045 56                       push    esi
.text:00401046 E8 6C 1E    00 00                call    ??3@YAXPAX@Z    ; operator delete(voi
d *)
.text:0040104B 83 C4 04                      add     esp, 4
.text:0040104E
.text:0040104E                    loc_40104E:                   ; CODE XREF: .text:00401043□j
.text:0040104E 8B C6                       mov     eax, esi
.text:00401050 5E                       pop     esi
.text:00401051 C2 04 00                      retn    4
.text:00401051                    ; ------------------------------------------------------------
-------------
```

```
00401000 00 00 80 40 40 28 00 1C 02 42 00 C4 00 20 04 20
00401010 00 00 20 09 2A 02 00 00 00 00 8E 10 41 0A 21 01
00401020 40 00 02 01 00 90 21 00 32 40 00 1C 01 40 C8 18
00401030 40 82 02 63 20 00 00 09 10 01 02 21 00 82 00 04
00401040 82 20 08 83 00 08 00 00 00 00 02 00 60 80 10 80
00401050 18 00 00 20 A9 00 00 00 00 04 04 78 01 02 70 90
00401060 00 02 00 08 20 12 00 00 00 40 10 00 80 00 40 19
00401070 00 00 00 00 11 20 80 04 80 10 00 20 00 00 25 00
00401080 00 00 01 00 00 04 00 10 02 C1 80 80 00 20 20 00
00401090 08 A0 01 01 44 28 00 00 08 10 20 00 02 08 00 00
004010A0 00 40 00 00 00 34 40 40 00 04 00 08 80 08 00 08
004010B0 10 00 40 00 68 02 40 04 E1 00 28 14 00 08 20 0A
004010C0 06 01 02 00 40 00 00 00 00 00 00 20 00 02 00 04
004010D0 80 18 90 00 00 10 A0 00 45 09 00 10 04 40 44 82
004010E0 90 00 26 10 00 00 04 00 82 00 00 00 20 40 00 00
004010F0 B4 00 00 40 00 02 20 25 08 00 00 00 00 00 00 00
00401100 08 00 00 50 00 08 40 50 00 02 06 22 08 85 30 00
00401110 00 80 00 80 60 00 09 00 04 20 00 00 00 00 00 00
00401120 00 82 40 02 00 11 46 01 4A 01 8C 01 E6 00 86 10
00401130 4C 01 22 00 64 00 AE 01 EA 01 2A 11 E8 10 26 11
00401140 4E 11 8E 11 C2 00 6C 00 0C 11 60 01 CA 00 62 10
00401150 6C 01 A0 11 CE 10 2C 11 4E 10 8C 00 CE 01 AE 01
00401160 6C 10 6C 11 A2 01 AE 00 46 11 EE 10 22 00 A8 00
00401170 EC 01 08 11 A2 01 AE 10 6C 00 6E 00 AC 11 8C 00
00401180 EC 01 2A 10 2A 01 AE 00 40 00 C8 10 48 01 4E 11
00401190 0E 00 EC 11 24 10 4A 10 04 01 C8 11 E6 01 C2 00
```

Total train dataset consist of 200GB data out of which 50Gb of data is .bytes files and 150GB of data is .asm files.
There are total 10,868 .bytes files and 10,868 asm files total 21,736 files
There are 9 types of malwares (9 classes) in our given data:

- Ramnit
- Lollipop
- Kelihos_ver3
- Vundo
- Simda
- Tracur
- Kelihos_ver1
- Obfuscator.ACY
- Gatak

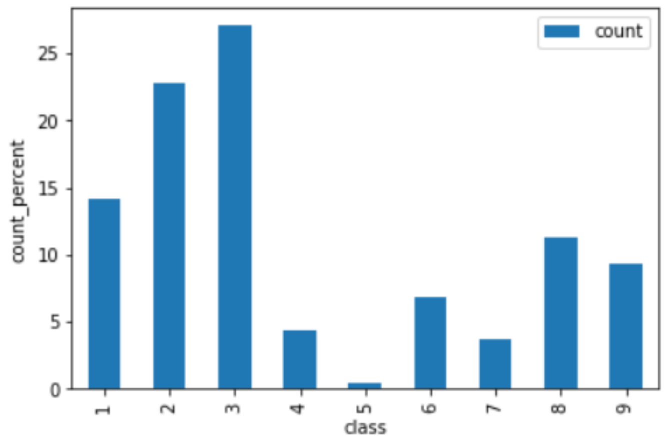


Figure 1: Data Distribution of various classes

4 Related Literature

- Microsoft Malware Winners' Interview: 1st place,"NO to overfitting!"
  http://blog.kaggle.com/2015/05/26/microsoft-malware-winners-interview-1st-place-no-to-overfitting/

- Novel Feature Extraction, Selection and Fusion for Effective Malware Family Classification
  https://arxiv.org/pdf/1511.04317.pdf

- First place approach in Microsoft Malware Classification Challenge (BIG 2015)
  https://www.youtube.com/watch?v=VLQTRlLGz5Y

- Malware Detection github
  https://github.com/dchad/malware-detection

5 Description of the set of approaches tried

- Logistic Regression- We first tried with the Logistic Regression Model and using this model, 0.0473 fraction of points are misclassified. This gave a lower accuracy.
- Random Forest- Using this model, 0.0473 fraction of points are getting misclassified.

6 Experiments

6.1 Code

The code is developed in Python with the help of libraries mainly matplotlib,numpy,pandas and sklearn.
The code started by first of all visualising the data distribution among various classes.
The code can be found on this link: `https://git.cse.iitb.ac.in/pranavchaudhary/CS725`

6.2 Experimental Platform

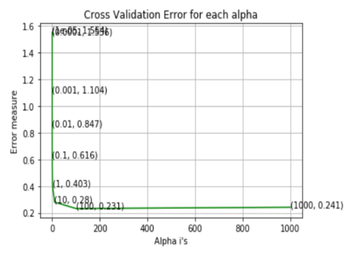
The code was developed and tested on Windows using Jupyter Notebook.
The code was run on a machine with configurations as:

- Processor: i7-9th Gen
- RAM: 16GB
- SSD: 256GB

The code ran on this machine for 60 hours(approx.)

6.3 Experimental Results

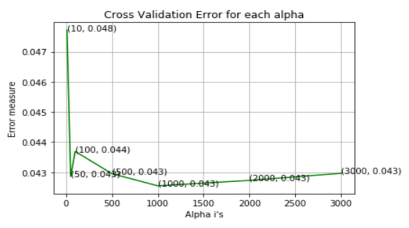
```
log_loss for c =  1 is 0.403417001251513
log_loss for c =  10 is 0.2800322738539702
log_loss for c =  100 is 0.23146665117482457
log_loss for c =  1000 is 0.24121827492307482
```



```
log loss for train data 0.21292385914963557
log loss for cv data 0.23146665117482457
log loss for test data 0.2249717022715482
```

Figure 2: Logistic Regression Classifier Alpha vs. Loss Graph

```
log_loss for c =  10 is 0.047716095315105386
log_loss for c =  50 is 0.042859630699671816
log_loss for c =  100 is 0.04369260598280953
log_loss for c =  500 is 0.04295321911674641
log_loss for c =  1000 is 0.04255114042507899
log_loss for c =  2000 is 0.04273066203790236
log_loss for c =  3000 is 0.04296630258270441
```



```
For values of best alpha =  1000 The train log loss is: 0.01644034189871256
For values of best alpha =  1000 The cross validation log loss is: 0.04255114042507899
For values of best alpha =  1000 The test log loss is: 0.03794906769143639
```

Figure 3: Random Forest Classifier Alpha vs. Loss Graph

7 Effort

The different parts of the project along with fraction of time taken by each part:

- Learning about Malwares and bytes and asm files-0.05
- Data Visualization-0.05
- Data Preprocessing-0.4
- Training-0.2
- Validation-0.2

- Testing-0.1

The most challenging and time taking part in this project was the pre-processing of dataset to a reasonable size without loss of information as the original dataset was large enough to train the model on our machines(around 184 GB). Fraction of work done by different team members:

- Anurag Chaudhary-0.25
- Himanshu Aswal-0.25
- Pranav Chaudhary-0.25
- Sanyam Raj-0.25

8 Conclusion

The dataset provided by Microsoft was of a very large size and had to be preprocessed using Feature Extraction to bring it to a size which could be run on our machines. The model was trained on bytes files as well as asm files using Logistic Regression Model and Random Forest Classifier Model. The results achieved by the Random Forest Model was much better as compared to the results achieved by the Logistic Regression Model.