

# ProDefense - A Binary Similarity Model for Malware Classification

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Research Deliverable

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# Agenda

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## Purpose

Enhancing our software's ability to **automatically detect** potential malware using **machine learning algorithms** is crucial to effectively combat the ever-evolving **threats** to our computers, networks, and data security, **reducing the workload** and **speeding up the detection process**.

According to IBM's 2022 Data Breach Report, 83% of organizations experiences more than one data branch during 2022

According to Verizon's 2022 Data Breach Investigations Report, the total number number of ransomware attacks surged by 13%

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## Binary Similarity Model

- A Binary Similarity Model is an analytical approach of examining and computing the similarity of some input (i.e. functions, files) against some standard of comparison.
  - This project is a perfect example insofar as some unknown program file can be examined and its similarity to **known** malware can be computed; if such similarity is high, then it is likely that such a file is malware and of that malware type.
- With a plethora of malware variants and benign programs, it is imperative to train a neural network that will compute the degree of similarity between some given input against malware inputs that the neural network was trained on to detect.

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## Requirements

- Fundamentally, the key necessities of the output of this project is a functional neural network(s), that can read in files consisting of program data, and compute a similarity score of the given file against some malware files of various types.
- This similarity score would fundamentally **place** the input file within different malware families, or not at all if it is not malware.
- The remaining core topics of this project, such as technology stacks and tools, are up to research and design decisions made by the team throughout this course.

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## Project Key Deliverables

- At its core, this project requires three fundamental phases:
- First – Malware Selection, Reverse Engineering, and Data Gathering
- Second – Feature Engineering, Data Formatting & Preparation for the Neural Network
- Third – Development, training, and testing of the Neural Network

## Malware Selection

- Goal – Finding the most popular and widespread type of malwares.
- Findings – Remote Access Trojans where one of the most popular forms of Malware types within all the different types but also within the Trojan Family.
- Researching for particular malwares, Smoke Loader and Zbot where found on many different lists from government websites, to hacker forums.



## Reverse Engineering

- Detect It Easy – Portable Executable (PE) packers detection tool, which allows us to analyze the malicious and suspicious content of malware binaries.
- IDA – Interactive disassembler allows us to reverse engineer and analyze executable files such as malware binaries, also offers control flow graph view, and scripting support.
- Sandbox Environment – Windows 10 machine for analyzing malware, in a safe environment.



# Additional Tools For Reversing/Research

- WinDbg: Kernel Debugger
- Process Hacker 2
- Various IDA Python Plugins to aid reversing
- ChatGPT, for translating asm to readable c++ code



Process Hacker [METALLICA-PC\Metallica] - (Administrator)

Hacker View Tools Users Help

Refresh Options Find handles or DLLs System information

Processes Services Network Disk

Name	PID	CPU	I/O total rate	Private bytes	User name	Description
System Idle Process	0	74.38		0	NT AUTHORITY\SYSTEM	NT Kernel & System
System	4	0.63	64 kB/s	148 kB	NT AUTHORITY\SYSTEM	Windows Task Manager
smss.exe	268			380 kB	NT AUTHORITY\SYSTEM	Windows Task Manager
Integrals				0		Interrupt Handler
curl.exe	340			1.97 MB	NT AUTHORITY\SYSTEM	Client Side SSL
wininit.exe	388			1.3 MB	NT AUTHORITY\SYSTEM	Windows Task Manager
services.exe	476			5.65 MB	NT AUTHORITY\SYSTEM	Services
svchost.exe	616			4.12 MB	NT AUTHORITY\SYSTEM	Host Process
VBoxService.exe	680		64 B/s	3.02 MB	NT AUTHORITY\SYSTEM	VirtualBox
svchost.exe	732			4.12 MB	NT AUTHORITY\SYSTEM	Host Process
svchost.exe	788			19.61 MB	NT AUTHORITY\SYSTEM	Host Process
audiogd.exe	6116	0.75		15.87 MB	NT AUTHORITY\SYSTEM	Windows Media Player
svchost.exe	908			112.68 MB	NT AUTHORITY\SYSTEM	Host Process
dvwm.exe	2264			1.38 MB	METALLICA-PC\Metallica	Desktop
svchost.exe	948			9.39 MB	NT AUTHORITY\SYSTEM	Host Process
svchost.exe	980	0.11		30.67 MB	NT AUTHORITY\SYSTEM	Host Process
svchost.exe	1092			29.7 MB	NT AUTHORITY\SYSTEM	Host Process
spoolsv.exe	1188			5.93 MB	NT AUTHORITY\SYSTEM	Spooler
svchost.exe	1224			12.37 MB	NT AUTHORITY\SYSTEM	Host Process
svchost.exe	1320			5.41 MB	NT AUTHORITY\SYSTEM	Host Process
svchost.exe	1360			6.51 MB	NT AUTHORITY\SYSTEM	Host Process

DebugView on \\MAKA (local)

File Edit Capture Options Computer Help

#	Time	Debug Print
0	0.00000000	[27812] Failed to initialize.
1	4.36322975	drv15: DriverEntry
2	4.36329508	Driver 'drv15' Successfully Loaded
3	4.36378193	drv15: DriverDispatchOpen

## Data Gathering

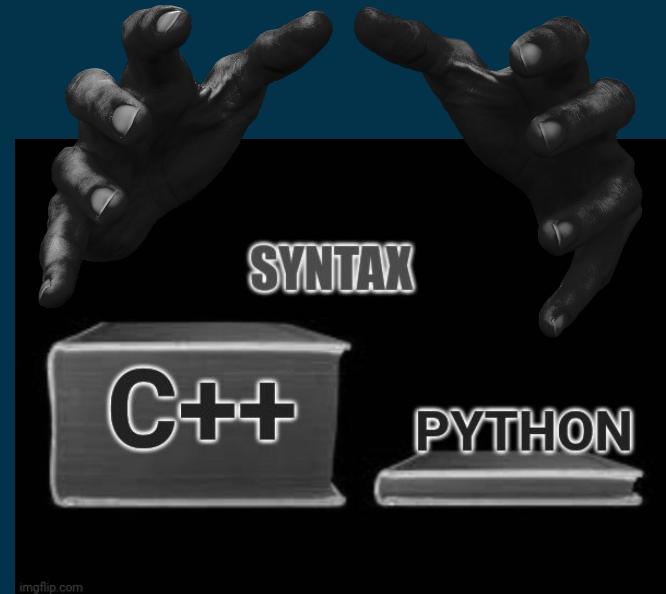
- Goal – Accrue as many samples/strain of each family of malware family for both Zbot and Smoke Loader.
- Findings – Acquired sample strains for malware analysis.
  - VirusTotal
  - Malware Bazar
  - VX Underground



# Programming Language

- C++:
  - Windows API, able to read/dump file memory
  - Most malware are written in C/C++
  - Robust, low level language. Best of memory reading/write/ exploiting.

Windows API can be used by anyone with line of code to read another programs memory.



# Smoke Loader: The first findings



# Smoke Loader: Analysis thus far

```
rdata:00429C18 db 2Ch          ; shellcode start
rdata:00429C19 db 0Ah
rdata:00429C1A db 31h
rdata:00429C1B db 33h ; 3
rdata:00429C1C db 8
rdata:00429C1D db 14h
rdata:00429C1E db 16h
rdata:00429C1F db 13h
rdata:00429C20 db 1Fh
rdata:00429C21 db 1Eh
rdata:00429C22 db 30h
rdata:00429C23 db 33h ; 3
rdata:00429C24 db 30h ; +
rdata:00429C25 db 0Fh
rdata:00429C26 db 2
rdata:00429C27 db 28h
rdata:00429C28 db 29h ; )
rdata:00429C29 db 21h
rdata:00429C2A db 28h ; +
rdata:00429C2B db 35h
```

```
push    eax          ; OLD_PROTECTION
push    [ebp+f1NewProtect] ; PAGE_EXECUTE_READWRITE
mov     dword_4615EA, 74636574h
push    dwSize        ; dwSize
mov     dword_4615E6, 6F72506Ch
push    dword_45CF08 ; SHELLCODE ADDRESS
mov     word_4615E0, 6956h
mov     byte_4615EE, bl
call    ds:VirtualProtect
```

**ntdll.dll**

- NtUnmapViewOfSection
- NtWriteVirtualMemory

**kernel32.dll**

- CloseHandle
- CreateFileA
- CreateProcessA
- ExitProcess
- GetCommandLineA

```
push    ebp
mov     ebp, esp
sub    esp, 8
push    ebx
push    esi
push    edi
push    0D5786h      ; LoadLibraryA
push    0D4E88h      ; kernel32.dll
call    find_function
mov     [ebp+var_8], eax
push    348BFAh      ; GetProcAddress
push    0D4E88h      ; kernel32.dll
call    find_function
mov     [ebp+var_4], eax
jmp    loc_1F742
sub_1F65B endp
```

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## Feature Engineering, Data Formatting, and Preparation

- Examining common and comparing features pertaining to non-malicious programs and those that are malicious.
  - Static analysis of two malware families to start with: **SmokeLoader** and **ZBot**.
- Choosing feature categories to develop a **feature model**.
  - Developed a simple, but wholesome set of features for initial extraction and experimentation.
- Developing **Python** scripts to automate development of neural network input files built using **Numpy** arrays and **Pandas** dataframes.

# Feature Engineering Process Diagram

Reverse Engineering and Data Extraction

```
1001010111010  
011MALWARE1  
0100101010100  
101 1010101010101  
0010101010101  
010101010101010  
0101010111110  
00001010
```

Feature Extraction and Formatting

```
def norm(df):  
    res = df.copy()  
    for f in df.columns:  
        max=df[f].max()  
        res=df[f] / max  
    return res  
  
python build_data.py
```

Feature Matrices = Neural Network Input

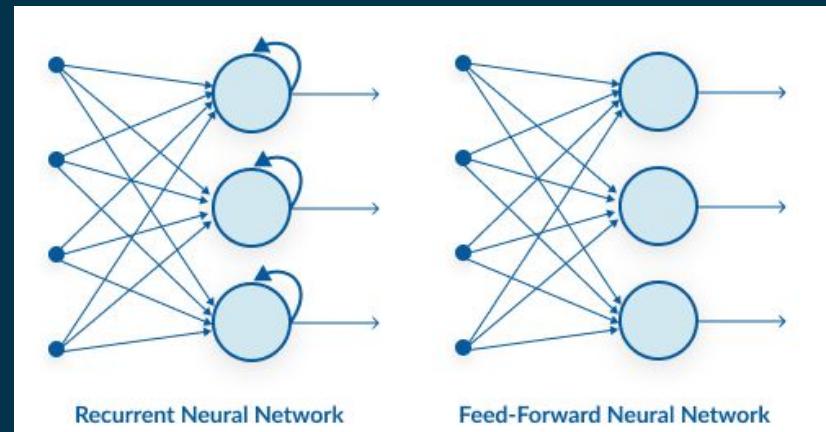
File Size	Memory	Hashes	Functions
15	1	139235	[1, 12, 7]
22	0	1312134	[0, 2, 3]
15	1	139235	[1, 12, 7]
22	0	1312134	[0, 2, 3]

# Development, Training, and Testing of the Neural Networks

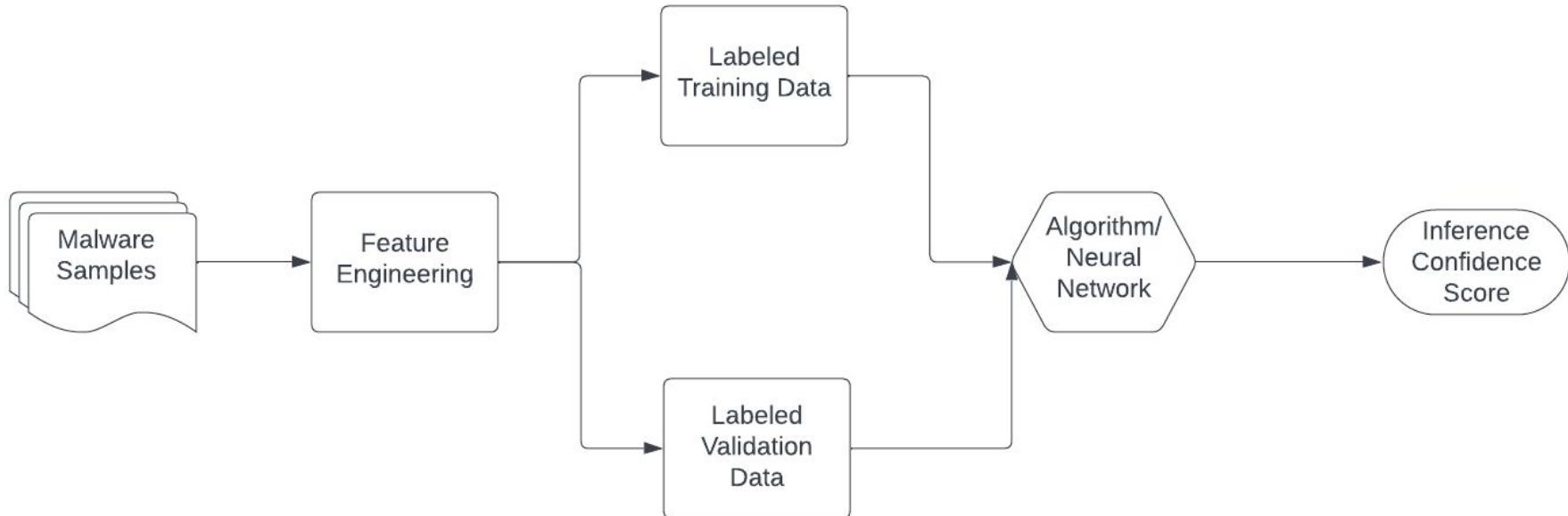
Looking into...

- Pytorch
- VulSeeker
- Gemini
- BinFinder
- Algorithms:
  - Random Forest
  - KNN
  - XgBoost

■ We will be comparing multiple algorithms against one another to determine which is most accurate



# Machine Learning Diagram



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## Value Created

- Automates the detection process of malware files, indicating whether a file is malware or not.
  - Enables the customer to be free from having to manually perform static analysis on program files.
- Categorizes the type of malware family that a given file may belong to in addition to indicating whether a file may be malicious or not.
  - Provides some level of insight into the type of malware provided, thus giving the customer a better understanding of the malware input at hand.

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## Lessons Learned

- The complexity of breaking down a project into requirements, organizing team functions, determining tasks per sprint.
- The heavy assortment and needed refinement of features that can be used to classify a binary as either malware, belonging to a specific malware family, and being non-malicious.
- Different types of neural networks, their purposes, strengths and weaknesses.
- Further Optimization of ML model requires considerable data.
- With number of neural network types that are available, choosing the one to fit the data problem proved to be challenging.

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## Future Plans for Next Semester

- To determine the robustness of the current prototype.
  - Begin experimenting with hyperparameters such as the depth of the neural network, activation function, and number of inputs.
- Coupled with researching other open source machine learning models that we can modify using our data inputs to train.
- Reconsideration, evaluation, and enhancements of the feature model.



## References

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<https://www.cisa.gov/news-events/cybersecurity-advisories/aa22-216a>

<https://www.crowdstrike.com/cybersecurity-101/malware/types-of-malware/>

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