Machine Learning for Malware Analysis

Andrew Davis Data Scientist



Introduction - What is Malware?

- Software intended to cause harm or inflict damage on computer systems
- Many different kinds:
 - Viruses

- Adware/Spyware

- Backdoors

- Trojans

- Ransomware

- Botnets

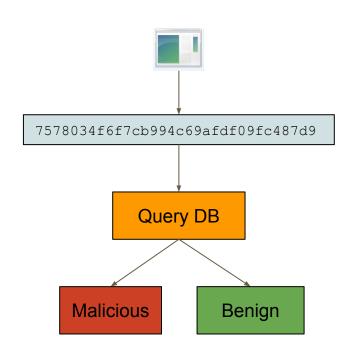
- Worms

- Rootkits

-

Malware Detection - Hashing

- Simplest method:
 - Compute a fingerprint of the sample (MD5, SHA1, SHA256, ...)
- Check for existance of hash in a database of known malicious hashes
- If the hash exists, the file is malicious
- Fast and simple
- Requires work to keep up the database



Malware Detection - Signatures

Look for specific strings, byte sequences, ... in the file.

If attributes match, the file is likely the piece of malware in question

Signature Example

```
rule Stuxnet Malware 3
          meta:
               description = "Stuxnet Sample - file ~WTR4141.tmp"
               author = "Florian Roth"
               reference = "Internal Research"
               date = "2016-07-09"
               hash1 = "6bcf88251c876ef00b2f32cf97456a3e306c2a263d487b0a50216c6e3cc07c6a"
               hash2 = "70f8789b03e38d07584f57581363afa848dd5c3a197f2483c6dfa4f3e7f78b9b"
104
          strings:
               $x1 = "SHELL32.DLL.ASLR." fullword wide
               $s1 = "~WTR4141.tmp" fullword wide
               $s2 = "~WTR4132.tmp" fullword wide
               $s3 = "totalcmd.exe" fullword wide
               $s4 = "wincmd.exe" fullword wide
               $s5 = "http://www.realtek.com0" fullword ascii
               $s6 = "{\%08x - \%08x - \%08x - \%08x}" fullword wide
          condition:
114
               (uint16(0) == 0x5a4d \text{ and filesize} < 150KB \text{ and } ($x1 \text{ or } 3 \text{ of } ($s*))) \text{ or } (5 \text{ of them })
```

Problems with Signatures

- Can be thought of as an overfit classifier
- No generalization capability to novel threats
- Requires reverse engineers to write new signatures
- Signature may be trivially bypassed by the malware author

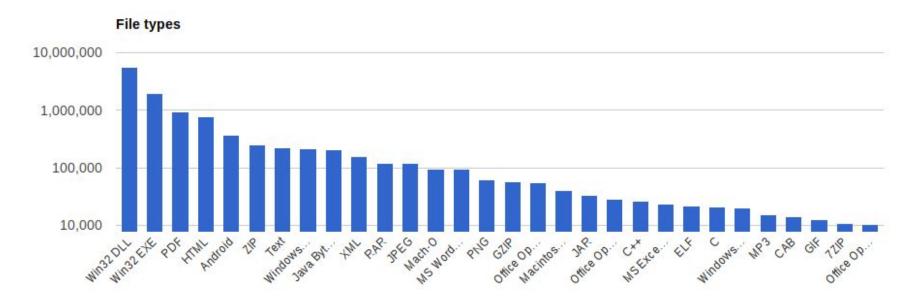
Malware Detection - Behavioral Methods

- Instead of scanning for signatures, examine what the program does when executed
- Very slow AV must run the program and extract information about what the sample does
- Malicious samples can "run out the clock" on behavior checks

Scaling Malware Detection

- Previously mentioned approaches have difficulty generalizing to new malware
- New kinds of malware require humans in the loop to reverse-engineer and create new signatures and heuristics for adequate detection
- Can we automate this process with machine learning?

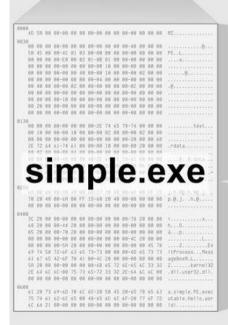
Focus: Windows DLL/EXEs (Portable Executable)

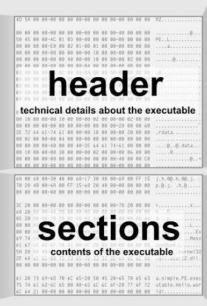


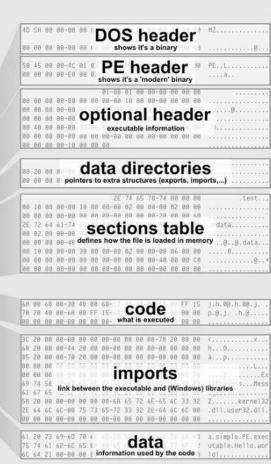
Number of samples submitted to VirusTotal, Jan 29 2017



Portable Executable (PE) Format







Feature Engineering - Static Analysis

- What kinds of features can we extract for PE files?
- Objective: extract features from the EXE without executing anything
- PE-Specific features
 - Information about the structure of the PE file
- Strings
 - Print off all human-readable strings from the binary
- Entropy features
 - Extract information about the predictability of byte sequences
 - Compressed/encrypted data is high entropy
- Disassembly features
 - Get an idea of what kind of code the sample will execute

☆ FileVersionInfo properties

Copyright © Microsoft Corporation. All rights reserved.

Product Microsoft® Windows® Operating System

Original name NOTEPAD.EXE

Internal name Notepad

File version 5.1.2600.0 (xpclient.010817-1148)

Description Notepad

≡ PE header basic information

Target machine Intel 386 or later processors and compatible processors

Compilation timestamp 2001-08-17 20:52:29

Entry Point 0x00006AE0

Number of sections 3

| A PE section | ns | | | | |
|----------------|-----------------|--------------|----------|---------|----------------------------------|
| Name | Virtual address | Virtual size | Raw size | Entropy | MD5 |
| .text | 4096 | 28018 | 28160 | 6.28 | ccf25baa681168e6396609387910d90a |
| .data | 32768 | 7080 | 1536 | 1.40 | cf692e5fbaebba02c2ad95f4ba0e60be |
| .rsrc | 40960 | 35144 | 35328 | 5.41 | c65b2250b8dd3870595004ca95f8f8b3 |
| ● PE impor | ts | | | | |
| (+) ADVAPI3 | 2.dll | | | | |
| [+] COMCTL3 | 2.dll | | | | |
| [+] GDI32.dll | | | | | |
| [+] KERNEL3 | 2.dll | | | | |
| [+] SHELL32. | dll | | | | |
| [+] USER32.d | 11 | | | | |
| (+) WINSPOO | DL.DRV | | | | |
| [+] comdlg32. | dll | | | | |
| [+] msvcrt.dll | | | | | |

| →) PE imports | |
|-----------------------|--|
| [+] ADVAPI32.dll | |
| RegCloseKey | |
| RegSetValueExW | |
| RegQueryValueExA | |
| RegCreateKeyW | |
| RegOpenKeyExA | |
| IsTextUnicode | |
| RegQueryValueExW | |
| [+] COMCTL32.dll | |
| [+] GDI32.dll | |
| [+] KERNEL32.dll | |
| [+] SHELL32.dll | |
| [+] USER32.dll | |
| [+] WINSPOOL.DRV | |
| [+] comdlg32.dll | |
| [+] msvcrt.dll | |

| [+] ADVAPI32.dll | |
|-----------------------|--|
| [+] COMCTL32.dll | |
| [+] GDI32.dll | |
| GetTextMetricsW | |
| SetMapMode | |
| TextOutW | |
| CreateFontIndirectW | |
| GetTextExtentPoint32W | |
| EnumFontsW | |
| LPtoDP | |
| GetDeviceCaps | |
| DeleteDC | |
| SetBkMode | |
| EndDoc | |
| StartPage | |
| DeleteObject | |
| GetObjectW | |
| Orașta DOM | |

Feature Engineering - String Features

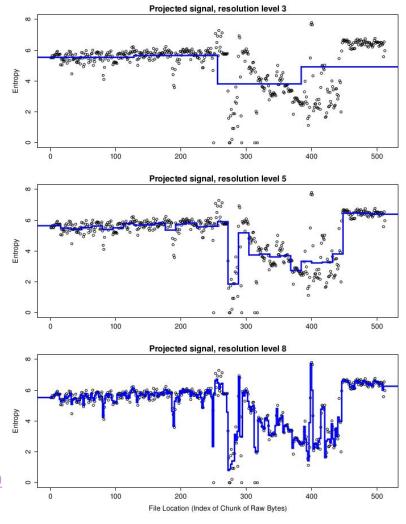
- Extract contiguous runs of ASCII-printable strings from the binary
- Can see strings used for dialog boxes, user queries, menu items, ...
- Samples trying to obfuscate themselves won't have many strings

```
notepad strings Notepad.exe | head -n 25
!This program cannot be run in DOS mode.
Rich
 data
rsrc
comdlg32.dll
SHELL 32 d11
WINSPOOL DRV
COMCTL 32 d11
msvcrt.dll
ADVAPI32 dll
KERNEL 32. dll
NTDLL.DLL
GDI32.dll
USER32.d11
WARAW
i=v?
RegisterPenApp
notepad.chm
hhetrl.ocx
LSID\{ADB880A6-D8FF-11CF-9377-00AA003B7A11}\InprocServer32
```

Entropy Features

- Interpret the stream of bytes as a time-series signal
- Compute a sliding-window entropy of the sample
- Information can determine if there are compressed, obfuscated, or encrypted parts of the sample

"Wavelet decomposition of software entropy reveals symptoms of malicious code". Wojnowicz, et. al. https://arxiv.org/abs/1607.04950



Disassembly Features

- Contains information about what will actually execute
- Disassembly is difficult:
 - Hard to get all of the compiled instructions from a sample
 - x86 instruction set is variable-length
 - Ambiguity about what is executed depending on where one starts interpreting the stream of x86 instructions

```
65 1b dd
                         gs sbb %ebp,%ebx
                                0x1000f9f
18 dd
                         fnsave -0x36(%edi)
                         fnsave 0x0(%edi)
00 00
00 0d 77 96 71 00
00 9a 86 c8 77 b7
                                %bl.-0x4888377a(%edx)
20 ca
88 c8
                                0x10010a9
6a c7
```

Difficulties for Static Analysis

- Polymorphic code
 - Code that can modify itself as it executes
- Packing
 - Samples that compress themselves prior to execution, and decompress themselves while executing
 - Can hide malicious behavior in a compressed blob of bytes
 - Can obscure benign code as well
 - Requires expensive implementation of many unpackers (UPX, ASPack, Mew, Mpress, ...)
- Disassembly
 - Malware authors can intentionally make the disassembly difficult to obtain

Modelling - Malicious versus Benign

- Boils down to a binary classification task
- N: hundreds of millions of samples
- P: millions of highly sparse features (s=0.9999)



Benign

Modelling - Training on ~600 million samples

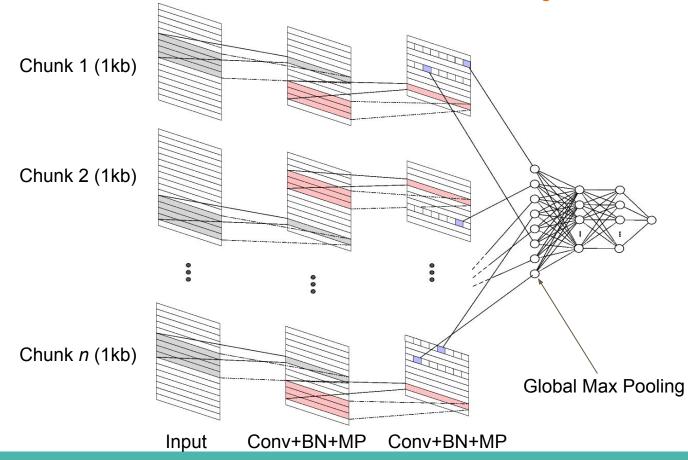
- Strong preference for minibatch methods and fast, compact models
- Logistic regression works very well
- Neural networks coupled with dimensionality reduction techniques are the workhorse
- Tend to combine lasso, dimensionality reduction, and neural networks

Convolutional Methods on Disassembly

```
%rbp
push
push
       %rbx
                                                           53
       %rdi,%rbp
mov
                                                           48 89 fd
       $0x718700, %edx
mov
                                                           ba 00 87 71 00
       $0x8,%rsp
sub
                                                           48 83 ec 08
       (%rdx),%ecx
mov
                                                            8b 0a
       $0x4,%rdx
add
                                                           48 83 c2 04
       -0x1010101(%rcx), %eax
lea
                                                           8d 81 ff fe fe fe
not.
       %ecx
                                                           f7 d1
       %ecx, %eax
and
                                                           21 c8
       $0x80808080, %eax
and
                                                           25 80 80 80 80
       41aa4e < sprintf chk@plt+0x18b3e>
jе
                                                           74 e9
```

```
push
       %rbp
       %rbx
       %rdi,%rbp
       $0x718700,%edx
       $0x8,%rsp
       (%rdx),%ecx
       $0x4,%rdx
       -0x1010101(%rcx),%eax
lea
       %ecx
not
       %ecx, %eax
       $0x80808080,%eax
jе
       41aa4e < sprintf chk@plt+0x18b3e>
```

Convolutional Methods on Disassembly



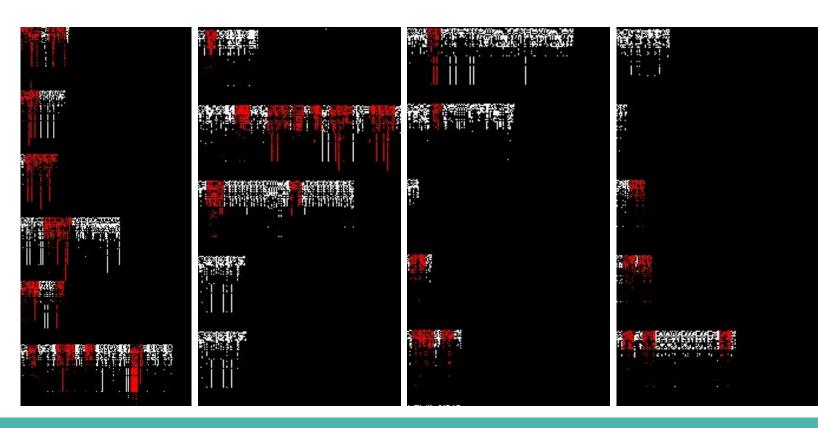
Spatial Structure in Instruction Visualizations







Global Max Pooling → Interpretability



MS Malware Kaggle Dataset

9 malware family classes:

```
Ramnit
        Lollipop
                 Kelihos ver3
                                 Vundo
                                        Simda
                                                Tracur
                                                        Kelihos ver1
                                                                      Obfuscator.ACY
                                                                                       Gatak
1541
           2478
                       2942
                                 475
                                          42
                                                 7.5.1
                                                             398
                                                                         1228
                                                                                       1013
```

- ~10k training, ~10k testing
- Provides Ida disassembly and raw bytes, minus the PE header

Methodology:

- Separate training data into 90% training, 10% validation
- Use 10k testing samples to generate "pseudo-labels" (semi-supervision)

Model Definition

| Layer (type) | Output | Shape | Param # | Connected to |
|----------------------------------|--------|----------------|---------|----------------------------|
| input_1 (InputLayer) | (None, | 8, None, 1024) | 0 | |
| convolution2d_1 (Convolution2D) | (None, | 32, None, 512) | 2080 | input_1[0][0] |
| batchnormalization_1 (BatchNorma | (None, | 32, None, 512) | 128 | convolution2d_1[0][0] |
| activation_1 (Activation) | (None, | 32, None, 512) | 0 | batchnormalization_1[0][0] |
| maxpooling2d_1 (MaxPooling2D) | (None, | 32, None, 256) | 0 | activation_1[0][0] |
| convolution2d_2 (Convolution2D) | (None, | 64, None, 128) | 16448 | maxpooling2d_1[0][0] |
| batchnormalization_2 (BatchNorma | (None, | 64, None, 128) | 256 | convolution2d_2[0][0] |
| activation_2 (Activation) | (None, | 64, None, 128) | 0 | batchnormalization_2[0][0] |
| maxpooling2d_2 (MaxPooling2D) | (None, | 64, None, 64) | 0 | activation_2[0][0] |
| convolution2d_3 (Convolution2D) | (None, | 96, None, 32) | 49248 | maxpooling2d_2[0][0] |
| batchnormalization_3 (BatchNorma | (None, | 96, None, 32) | 384 | convolution2d_3[0][0] |
| activation_3 (Activation) | (None, | 96, None, 32) | 0 | batchnormalization_3[0][0] |
| maxpooling2d_3 (MaxPooling2D) | (None, | 96, None, 16) | 0 | activation_3[0][0] |
| convolution2d_4 (Convolution2D) | (None, | 128, None, 8) | 98432 | maxpooling2d_3[0][0] |

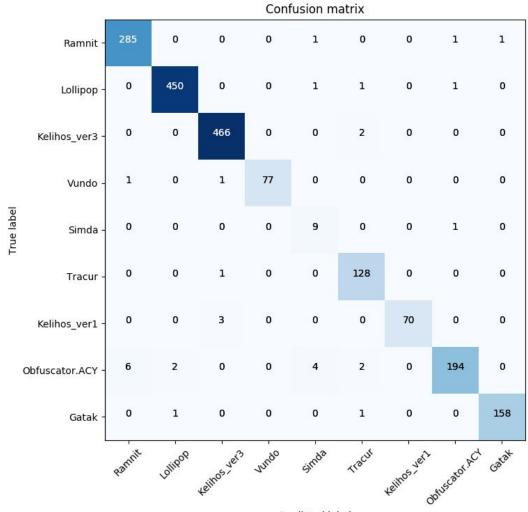
Model Definition

| batchnormalization_4 (BatchNorma | (None, | 128, None, 8) | 512 | convolution2d_4[0][0] |
|----------------------------------|--------|---------------|-------|----------------------------|
| activation_4 (Activation) | (None, | 128, None, 8) | 0 | batchnormalization_4[0][0] |
| maxpooling2d_4 (MaxPooling2D) | (None, | 128, None, 4) | 0 | activation_4[0][0] |
| permute_1 (Permute) | (None, | None, 128, 4) | 0 | maxpooling2d_4[0][0] |
| timedistributed_1 (TimeDistribut | (None, | None, 512) | 0 | permute_1[0][0] |
| globalmaxpooling1d_1 (GlobalMaxP | (None, | 512) | 0 | timedistributed_1[0][0] |
| dropout_1 (Dropout) | (None, | 512) | 0 | globalmaxpooling1d_1[0][0] |
| dense_1 (Dense) | (None, | 128) | 65664 | dropout_1[0][0] |
| batchnormalization_5 (BatchNorma | (None, | 128) | 512 | dense_1[0][0] |
| activation_5 (Activation) | (None, | 128) | 0 | batchnormalization_5[0][0] |
| dense_2 (Dense) | (None, | 128) | 16512 | activation_5[0][0] |
| batchnormalization_6 (BatchNorma | (None, | 128) | 512 | dense_2[0][0] |
| activation_6 (Activation) | (None, | 128) | 0 | batchnormalization_6[0][0] |
| dense_3 (Dense) | (None, | 9) | 1161 | activation_6[0][0] |

Model: Results

| Overall Acc | 98.30% |
|-------------|--------|
| Ramnit | 98.96% |
| Lollipop | 99.34% |
| Kelihos_v3 | 99.57% |
| Vundo | 97.47% |
| Simda | 90.00% |
| Tracur | 99.22% |
| Kelihos_v1 | 95.89% |
| Obfusc | 93.27% |
| Gatak | 98.75% |

#184 on Kaggle leaderboard



Predicted label

Thank You!

Questions?