Fileprints: Identifying File Types by n-gram Analysis

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Agenda

The Problem

- Efficiently Identifying file types from content
- Security related issues
- Related Work
- 1-gram models
 - Alternative modeling
- Experiments
- Performance Results

The Problem

- Can we categorize the type of an arbitrary file object effectively using (partial) binary content without extensive knowledge of syntax and deep parsing?
- Can we verify the type of file?
- Can we do so *efficiently* without specialized knowledge of every possible file type that exists now and will exist in the future?

Security Issues

Change the file extension to hide true type

- Malicious executable code can pretend to be a plain .txt
- Document.txt.exe
- By-pass security policy (users may not be allowed to email .doc files)
- Code obfuscation
 - A technique to protect source code
- Network environment
 - Files can be fragmented across packets

File Types

How to identify file types?

- Check the file extension
 - .doc, .pdf, .jpg etc
- Read the file header
 - Unix *file* command (some file types have "magic numbers")

Related Research

- N-gram analysis using machine learning [Matthew G. Schultz, Eleazar Eskin, and Salvatore J. Stolfo 2001, Jeremy Kolter and Marcus A. Maloof 2004]
 - Too expensive
- 1-gram analysis of network payload [Ke Wang, Salvatore J. Stolfo 2004]
 - Network packet content analysis
- Generate "fingerprints" of file types using byte-value distributions [Mason McDaniel and M. Hossain Heydari 2004]
 - Single model for each file type
 - Poor performance
 - Normalization issue

N-gram Analysis

- An n-gram is a subsequence of N consecutive tokens in a stream of tokens
- Compare the *distributions* of n-grams contained in a set of data to determine how consistent some new data may be with the set of data in question
- Each distribution is the average byte value frequency and their standard deviation

1-gram file binary content distribution



Observation:

Each File Type has a distinct Frequency Distribution

Modeling Methods, Truncation



Modeling Methods, Centroids





Comparing Distributions

 Simplified Mahalanobis Distance – comparing two distributions (mean and variance)

$$D(x, y) = \sum_{i=0}^{n-1} (|x_i - y_i| / (\sigma_i + \alpha))$$

- Compare unknown file distribution F to pre-trained model M_t , i.e. compute $D(F, M_t)$ for all models
- The smaller the distance, the more similar to the model
- Classify the file as the type that it has the smallest distance to, i.e.

Type(F) = t if M_t = argmin { $D(F, M_i)$ | i=1,...,n}

Experiment

Dataset:

- 800 files of 8 different file types
- .EXE, .DLL, .GIF, .JPG, .PDF, .PPT, .DOC, .XLS
- Files were randomly chosen from a Google search
- 80% used for training models, and the remaining 20% for testing

Modeling methods

- One centroid file type model
 - Use one single model for each file type
 - For each file type T, build a model M_t
 - Build *n* models *M*₁, *M*₂...., *M*_n, from *n* different file types
 - Compute the distance of the testing file F to each model, and then F is classified to the model with the smallest distance

Modeling methods

Multi-centroids file type model

- For each file type T, build k models $M_{t1}, M_{t2}...M_{tk}$ using k-means algorithm
- Compute the distance of F to each model, and then F is classified to the model with the smallest distance
- Exemplar files used as centroids
 - Each trained file is an individual model
 - □ The # of models is the same to the number of training files
 - Compute the distance of F to each model, and then F is classified to the model with the smallest distance

Performance

One-centroid file type classifying accuracy						
Truncation Size	EXE	GIF	JPG	PDF	DOC	AVG.
20	98.9%	100%	99%	100%	98.3%	98.9%
200	98.3%	91.1%	97%	82.8%	93.7%	93.6%
500	97%	97%	93.4%	80.4%	96.7%	94.3%
1000	97.3%	96.1%	93.5%	83.4%	82.6%	88.2%
All	88.3%	62.7%	84%	68.3%	88.3%	82%
Multi-centroids file type classifying accuracy						
Truncation Size	EXE	GIF	JPG	PDF	DOC	AVG.
20	99.9%	100%	98.9%	100%	98.8%	99.4%
200	97%	98.3%	96.6%	95%	97.2%	96.9%
500	97.2%	98.4%	94.8%	90%	96.9%	96%
1000	97%	95.1%	93.5%	90.7%	94.5%	94.6%
All	88.9%	76.8%	85.7%	92.3%	94.5%	89.5%
Classifying accuracy using exemplar files as centroids						
Truncation Size	EXE	GIF	JPG	PDF	DOC	AVG.
20	100%	100%	100%	100%	98.9%	99.6%
200	99.4%	91.6%	99.2%	100%	98.7%	98.2%
500	99%	93.6%	96.9%	99.9%	98.5%	98%
1000	98.9%	94.9%	96.1%	86.9%	98.6%	96.4%
All	94.1%	93.9%	77.1%	95.3%	98.9%	93.8%

Performance



The classification accuracy -- comparison of three different methods. X-axis: Size of truncation (in bytes). Y-axis: accuracy.



- 1-gram models are effective at identifying file types using purely binary content
- Prefix portion of files reveals their file type quite accurately
- It may be possible to detect ZERO-DAY (new) malcode within portions of files using this technique

Future and Ongoing Work

Goal: Detecting malware embedded in normal files

Demonstrate it is possible to detect malware using fileprints, not signatures

Preliminary experiment:

Inserted viral executables at the head of a random collection of pdf and doc files, tested whether pre-learned fileprints of known malware can be detected within the pdf file.

Findings

- Symantec AV missed several embedded viruses
- A few pdf files infected by a virus can still be successfully opened by Acrobat.
- □ For example, Slammer...







Conclusion

- Efficient 1-gram binary analysis to identify the type of a file from its binary byte-value distribution
 - Useful to detect security policy violations
 - Useful for identifying suspect files with possible malcious code
- The method introduces several nuances
 - the truncated modeling techniques and of multicentroids for increased accuracy