Security Analysis of HTML and JS Contents of Alexa top 1m Websites

Team 6

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Problem Statement

Content analysis of Alexa 1m domains to

 Detect security relevant modifications in the contents of web pages



Problem Statement

Content analysis of Alexa 1m domains to

 Detect security relevant modifications in the contents of web pages

and

 Classification of websites as malicious or benign on the basis of scores from the classifier

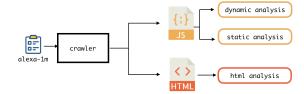


Strategy and Approach

- Crawler for data collection
 - Categorized Search
- Feature extraction
 - HTML Features
 - JS Features
- Designed and implemented a system to detect content modifications having security relevance
- Machine Learning Classifier
 - ▶ Off-line training mode
 - On-line testing mode



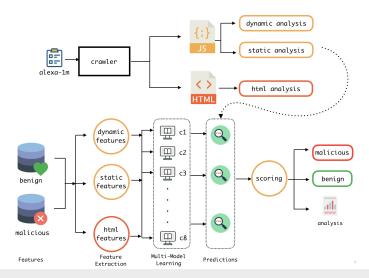
Architecture: The Big Picture





Strategy and Approach Web Crawling HTML Analysis JavaScript Analysis Training and Classification Results

Architecture: The Big Picture





Crawler - Golang

- We chose Go to write crawler
 - ▶ It is succinct, minimalistic and fast compared to others
 - Designed and optimized for scaling
 - Supports to write a multi-threaded programs
- On an average the crawler takes 1.2 days to crawl the alexa-1m websites (HTML & JS contents).



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HTML Analysis: Feature Extraction

- 1. Number of iframe tags
- 2. Number of hidden elements
- 3. Number of elements with small area
- 4. Number of script elements
- 5. Percentage of scripting content in a page
- 6. Percentage of whitespace in a page
- 7. Presence of meta refresh tags
- 8. Number of embed or object tag
- 9. Number of elements with src on external domain
- 10. Number of included urls
- 11. Number of characters in a page



trategy and Approach Web Crawling HTML Analysis JavaScript Analysis Training and Classification Results

Static JS Analysis

- 1. Ratio of keywords to non-keywords
- 2. Number of strings with lengths larger than 40
- 3. Number of suspicious tags
- 4. Number of iframe tags
- 5. Entropy of the total script
- Number of suspicious strings
- 7. Number of decodeURIcomponent
- 8. Number of functions clearAttributes, insertAdjacentElement, and replaceNode
- 9. Number of setTimeOut
- 10. Number of exec calls
- 11. Number of applets and scripts



Dynamic JS Analysis

- 1. Number of dynamic function calls
- 2. Number of Wscript saved files
- 3. Number of URLs
- 4. Number of Wscript objects
- 5. Number of setTimeout() calls
- 6. Number of eval() calls
- 7. Number of *unescape()* calls
- 8. Number of browser documents



Classification Overview

- Converting scripts to points in euclidean space
- Classifier operates on euclidean space
- Each classifier trained with subset of the benign and malicious samples
- Each classifier is tested with rest of the samples

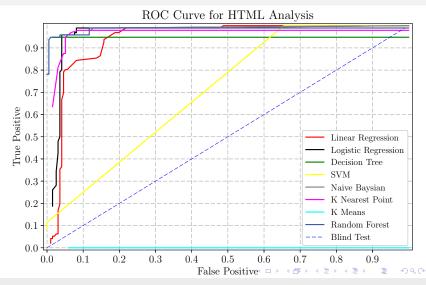


Multi-model Training and Classification

- Usage of seven supervised and one unsupervised classifier
- Classifier exhibiting best results chosen
 - HTML Analysis Random Forest
 - ► Static JS Analysis Random Forest
 - Dynamic JS Analysis Decision Tree

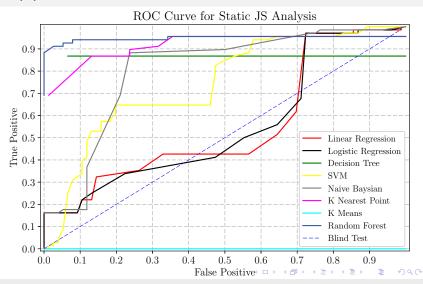


► Used 80 percent of our the known samples for training and 20 for testing our classifiers



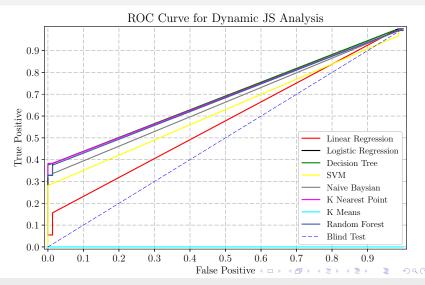
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| | Benign | Malicious |
|--------------------|--------|-----------|
| HTML analysis | 998 | 467 |
| Static JS analysis | 363 | 353 |
| Dynamic JS analy | 377 | 648 |

Figure: Number of Samples for Training

| | Precision |
|--------------------|-----------|
| HTML analysis | 0.013 |
| Static JS analysis | 0.019 |
| Dynamic JS analy | 0.016 |

Figure: Precision of Error Probabilities



Results

| Project | FP | FN | Static | Dynamic | Obfuscation resilient |
|----------|-------|-------|--------|---------|-----------------------|
| Our Work | 4.85% | 7.4% | ✓ | ✓ | ✓ |
| Zozzle | 4.56% | 4.51% | ✓ | Х | Х |

- Our static JS analyzer provides almost same false positive rate as Zozzle - a fast precise static JS analysis tool
- ▶ In addition, we facilitate dynamic analysis absent in Zozzle.



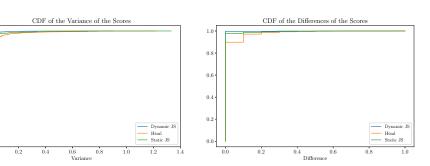


Figure: CDF's of Variance and Difference of Scores



Security Problems (1)

- Day 1 to Day 2 in webdade.com: Lot of scripts in day 1 vanished in day 2 and there were several calls in day 1 that point to www.smartsuppchat.com which is a black-listed website across multiple blacklists.
- ▶ Day 3 to Day 4 in webdade.com: The references are gone and the website is back to normal.
- ▶ Day 1 to Day 2 in Torrent-ultra.com: Day two contained hidden inputs that are script generated to change privacy settings of the user in privacy.html this may be to get access to restricted information about the user.



Security Problems (2)

- Day 3 to Day 4 in Torrent-ultra.com Malicious scripts gone and there is no hidden input or reference to any sort of privacy settings
- Across 6 days in shoowplay.tk This websites takes user cookies and references find better results.com a black listed website several times based on user interaction with the website to send cookie information divulging sensitive user data.

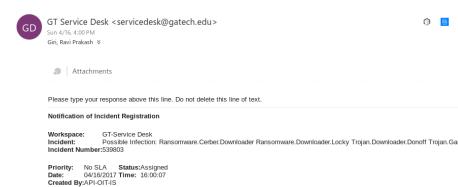


▶ Blocked internet access for performing dynamic JS analysis.



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Possible Infection: Ransomware.Cerber.Downloader Ransomware.Downloader.Locky Trojan.Dov ISSUF=539803 PROJ=5



- Blocked internet access for performing dynamic JS analysis.
- Got notification emails from OIT tracing the crawler activities.



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 During dynamic analysis of JS, encountered a script making 32 calls to eval() function.

Conclusion

- Content Modifications impact the classifier scores
- Fed our classifier with crawled data spanning across one month
- Find websites with the most security score changes
- Manually finding security issues



Future Work

- Seeding the classifier with larger set of data and verifying the consistency of results
- Utilizing the sandboxing environment to extract more features that can have security relevance



Acknowledgment

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