AdGraph: A Machine Learning Approach to Automatic and Effective Adblocking

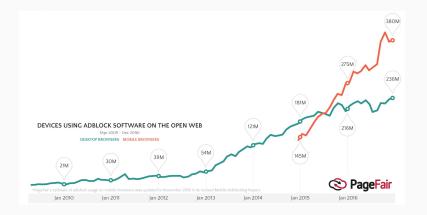
From Arxiv Security Reading Group - 11/28

Outline

- Background
- Motivation
- Approach
 - System overview
 - Graph representation
 - ML model
 - Challenges
- Evaluation
 - Accuracy
 - Against adversaries
- Conclusions

Background

- Adblockers are used on more than 600 million devices globally as of December 2016
- Adblockers use manually curated filter lists to block ads and trackers based on informally crowdsourced feedback from the adblocking community
- State-of-the-art: manually curated filter lists with RegExp-based rules

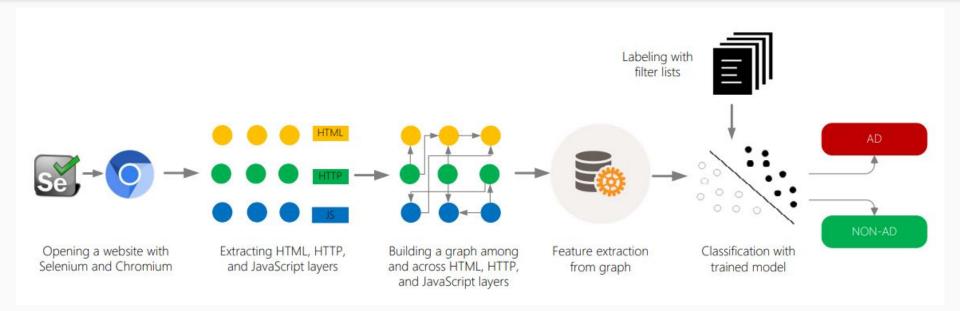


List	# Rules
EasyList	72,660
EasyPrivacy	15,507
Anti-Adblock Killer	1,964
Warning Removal List	378
Blockzilla	1,155
Fanboy Annoyances List	38,675
Peter Lowe's List	2,962
Squid Blacklist	4,485

Motivation

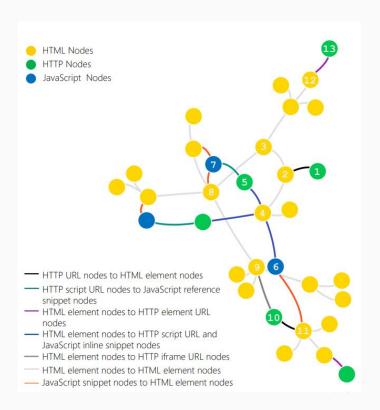
- Limitations of state-of-the-art (manual lists)
 - Manual nature is problematic
 - Bloat (FN, less than 3% HTTP rules in EasyList trigger)
 - Accuracy (FP, exception rules catering for other overly broad rules)
 - Evasion from publishers
 - Concealing signatures
 - Obfuscation (native ads etc.)
 - Domain Generation Algorithm
 - Anti-adblockers
 - Actively detects adblockers and issues warning messages
- Some ML attempts to automate filter list curation, which are mostly based on URL features only
- Root weaknesses:
 - manual process;
 - contextless/hardcoded rules

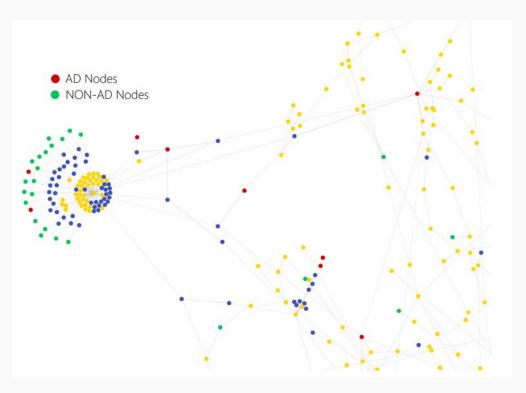
AdGraph - overview



- Automatic: ML classification based on existing filter lists
- Contextual/structural: combining HTML/HTTP/JS layers' information into a graph

AdGraph - graph representation





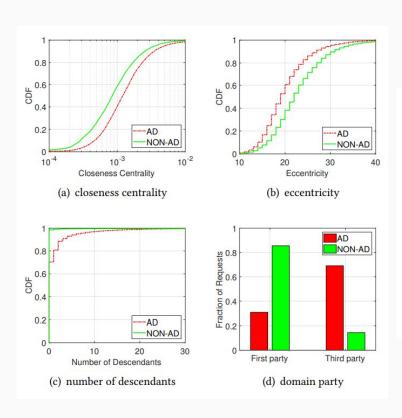
AdGraph - ML model

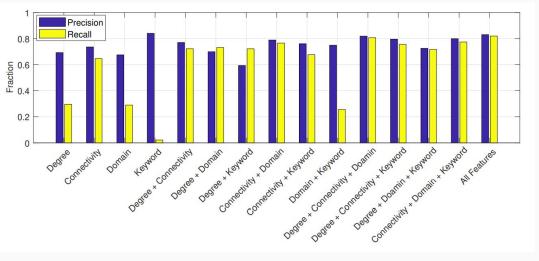
Random forest - an ensemble of 10 decision trees

Features:

- Degree Features
 - In-Degree/Out-Degree/Descendants/Addition of nodes/Modification of node attributes/Event listener attachment
- Connectivity Features
 - Katz centrality/Closeness centrality/Mean degree connectivity/Eccentricity
- Domain Features
 - Domain party/Sub-domain/Base domain in query string/Same base domain and request domain/Node category
- Keyword Features
 - Ad keywords/Query string parameters/Ad dimension information in query string

AdGraph - ML model



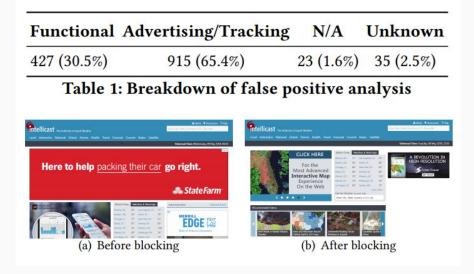


AdGraph - challenges

- Most of same- and cross-layer links in graph are straightforward to establish
- JS attribution is tricky how to track which JS created/modified this
 HTML element
 - Browser instrumentation required, no existing mechanism
 - We use JSgraph [1], a forensics tool originally designed for monitoring JS activities
 - It leverages the single-threaded nature of JS engine (i.e. at any given time point there can be only one JS being executed)
 - It instruments points when control is exchanged between Blink and V8 (i.e. createElement() etc.), and attributes the event to the executing script
 - We sync all nodes in the same page to construct the graph

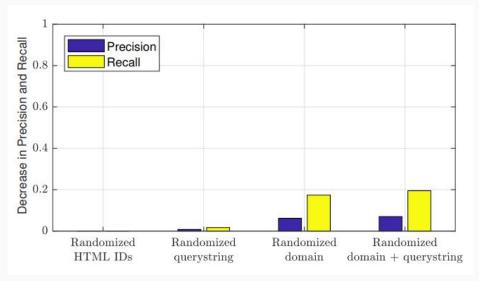
Evaluation - accuracy

- 10-fold cross-validation among Alexa Top 10K crawl: 97.7% accuracy, 83.0% precision, and 81.9% recall
- We have disagreements with filter lists, but are they really our mistakes, or the lists are wrong?
 - We did FP analysis to confirm a sample of these disagreements



Evaluation - adversary

- HTML Element Obfuscation
- HTTP URL Obfuscation
 - Query string randomization
 - Domain name randomization
 - Randomization of both query string and domain name



Conclusions

- Graph-based machine learning approach that automatically and effectively block ads and trackers on the web
- Replicates popular crowdsourced filter lists with an 97.7% accuracy
- Detects a significant number of ads and tracker which are missed by popular crowdsourced filter lists
- Applications
 - Offline use
 - Improving filter lists
 - Automatic ad blocking in less critical regions
 - Online use (WIP)
 - Live in-browser ad blocking

Q & A?

https://arxiv.org/abs/1805.09155