

Using Lexical Features for URL Classification- A Machine Learning Approach

Apoorva Joshi FireEye Levi Lloyd Lawrence Livermore National Lab Paul Westin FireEye Srini Seethapathy FireEye

OUTLINE

- Motivation
- Previous Work
- Deployment Specification
- Requirements and Goals
- Tasks and Tools
- Observations
- Conclusions
- Future Work

MOTIVATION

From: "Help Desk" < @marshall.edu> Date: November 20, 2017 at 11:12:45 AM EST To: @live.marshall.edu Subject: Termination Notice Reply-To: masonjohn459@gmail.com

1 Office 365

A notice from my IT Department

Our record indicates that you recently made a request to terminate your Office365 email. And this process has begun by our administrator.

If this request was made accidentally and you have no knowledge of it, you are advised to cancel the request now

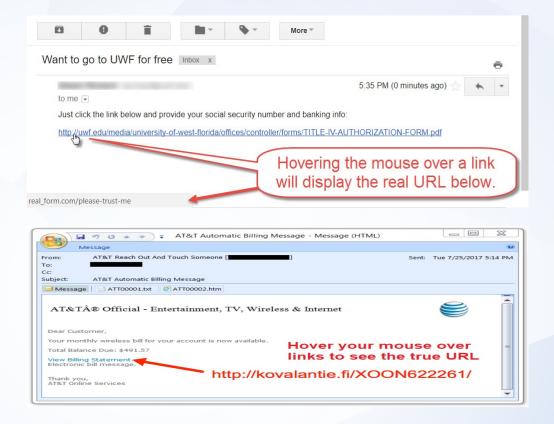
Please give us 24 hours to terminate your account OR.

Sign in here to cancel termination

Thanks

Failure to cancel termination w http://bit.do/dUcQw of your account

Hover mouse over URL; not a marshall.edu site



PREVIOUS WORK

Blacklists



Host information, network traffic etc.



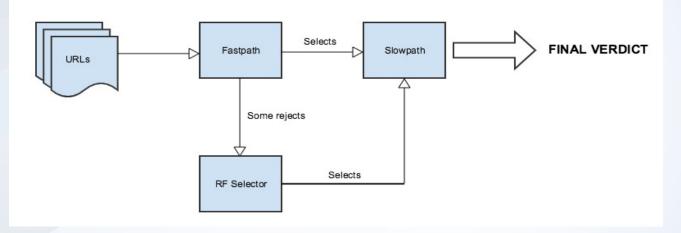
HTML and Javascript content



LEXICAL FEATURES ONLY???

DEPLOYMENT SPECIFICATION

- Model should run as plugin for FAUDE (FireEye Advanced URL Detection Engine)
- Should correct FNs from fastpath analysis
- URLs to be sent for slowpath analysis based on the model verdict



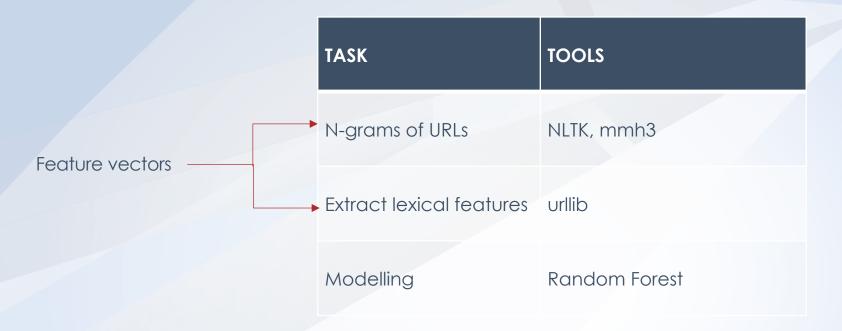
REQUIREMENTS AND GOALS

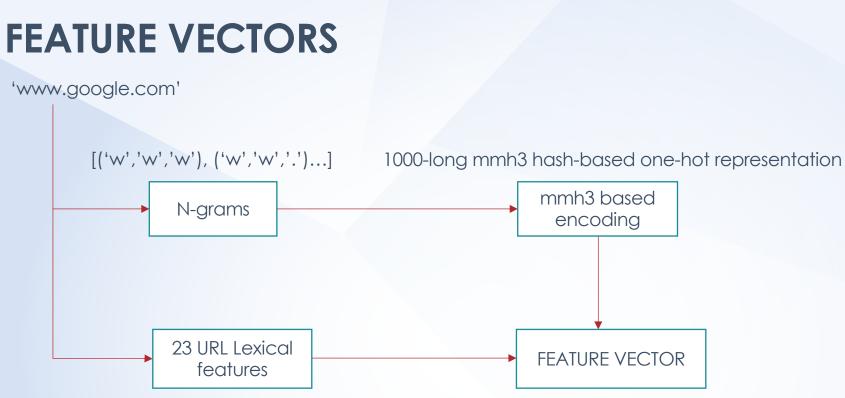
- Model should act as a means of down selection and/or detection
- False Negative Rate should be very low
- False Positive Rate such that the model results in at most 20% increase in current load
- Model latency should be in the order of 10⁻¹ ms

THE DATASET

- ~5.5 million labelled URLs
- 60% benign, 40% malicious URLs
- Collected from different sources Openphish, Alexa whitelists, FireEye products and honeypots

TASKS AND TOOLS



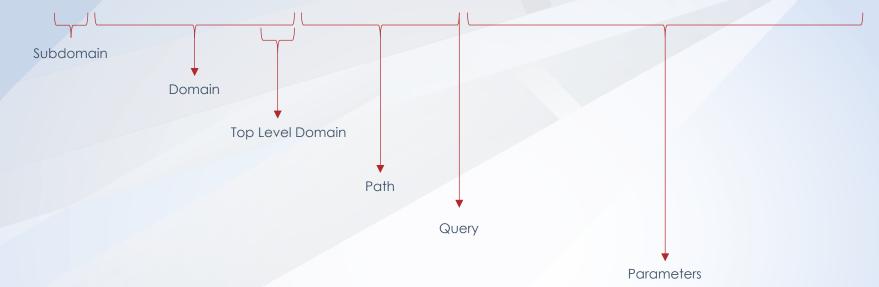


Length of domain, number of subdomains, special characters in URL path etc.

1023-long vector representation of the URL

FEATURE VECTORS

http://www.video.platinumindustrialcoatings.com/wp-content/plugins.php?to=calgaryps3&message=28dd33dc15e8c68934883418341967



Complete list of features: <u>https://arxiv.org/abs/1910.06277</u>

10 ©2019 FireEye

MODELLING

- Simple Classifiers-Logistic Regression, Naïve Bayes
- Bagging and Boosting Classifiers- Random Forest, Gradient Boost, Adaboost
- Metrics- Accuracy, AUC, FNR

ALGORITHM	ACCURACY (%)	AUC	FNR (%)
Logistic Regression	87	0.96	4.75
Naïve Bayes	70	0.74	10.38
Random Forest	<mark>92</mark>	<mark>0.99</mark>	<mark>0.38</mark>
Gradient Boost	90	0.92	9
Adaboost	90	0.9	10

Suspicious URL patterns:

- TLDs in shady list-.biz, .info, .ru, .cn
- Keywords, special characters in URL path
- IP address in primary domain
- High entropy hostnames
- Uppercase or single character directory

13 ©2019 FireEye

Number of trigrams	Number of lexical features	Accuracy (%)	FPR (%)	FNR (%)
1000	0	85	29.8	0.4
1000	23	<mark>92</mark>	16.8	<mark>0.38</mark>
300	23	93	12.5	0.93
100	23	94	11.5	1.09
0	23	95	8.15	1.11

The Random Forest feature importances also showed that it was focusing on both ngram and lexical features



Max depth	Accuracy (%)	FNR (%)
5	72	1.13
15	88	0.48
20	<mark>92</mark>	<mark>0.38</mark>
27	94	0.73
30	95	0.75

Tuning other parameters had no real effect on the evaluation metrics

CONCLUSIONS

- ~22% increase in detections for < 20% increase in load
- Reduction in FNs
- Purely lexical models can be used for fast verdicts on URLs
- Alternative to heuristic-based downselection which needs manual updates

FUTURE WORK

- Deep Learning approach
- Augment the model with new features as necessary
- Cache model verdicts

ACKNOWLEDGMENTS

Levi Lloyd

Paul Westin

Srini Seethapathy

FireEye



Thank You!

Email: apoorva.joshi@fireeye.com