

Detection of malicious domains through lexical analysis

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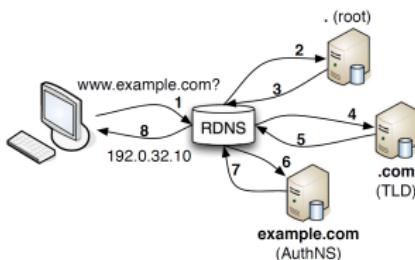
Domain Names and DNS

DNS: Domain Names System

- ▶ Used everywhere, by everybody on the Internet
- ▶ ... also criminals!
- ▶ Technology/service choke-point
- ▶ Only small fraction of Internet traffic

Example domains

- ▶ www.example.com
- ▶ goggle.com
- ▶ yf32d9ac7f0a9f463e8da4736b12d7044a.tk



Source: Antonakakis et al. 2011.

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Abuse and Malicious Domains



- ▶ Command and control
- ▶ Phishing
- ▶ Spamming
- ▶ Typo-squatting
- ▶ Blending in, tunnelling
- ▶ Fast-flux, Double-flux
- ▶ Domain-flux (DGA)



Source: Haymarket Media, Inc.¹

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Malicious domain: Any domain that is used for criminal, malicious or otherwise nefarious activities.

¹: <https://www.scmagazineuk.com/cyber-criminals-becoming-increasingly-professional/article/531709/>

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Assumption and Method

Assumption:

“Malicious domain names can be detected by lexical features.”

Method:



Machine Learning: Supervised, 10-fold cross validation, 10 repeats,
Random Forrest, Python, Scikit-learn.

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Table I: DATA SETS OF MALICIOUS DOMAIN NAMES.

Data sets		Number of domains	
		Non-DGA	DGA
abuse.ch	ZeuS Tracker	437	-
	Palevo Tracker	14	-
	Ransomware Tracker	1248	-
malware-\domains.com	Just domains	13073	-
	Zeus Gameover	-	190033
	Conficker	-	106101
	Pushdo	-	10951
	GOZ	-	7348
host-file.net	Microsoft Botnet	22036	-
	Adtracking servers (ATS)	47960	-
	Malware distribution (EMD)	137237	-
	Exploit sites (EXP)	17282	-
	Fraud sites (FSA)	134501	-
	Spamming sites (GRM)	674	-
	Spamming sites (HFS)	573	-
	Hijack sites (HJK)	74	-
	Misleading marketing (MMT)	5533	-
	Pharmacy activities (PHA)	23143	-
	Phishing sites (PSH)	133913	-
	Warez distribution (WRZ)	3231	-
	Cryptolocker	-	34319
	Goz	-	7347
	New Goz	-	10999
malware\domainlist.com	Malware-related domains	1253	-
malcode.com	Malware-related domains	208	-
malwarepatrol.net	Malicious URLs	35518	-
phishank.com	Phishing URLs	14807	-
AAU-STAR	Domains from malw.testing	27778	-
Total		620493	367098

Table II: DATA SETS OF BENIGN DOMAIN NAMES.

Data sets		Number of domains	
		Non-DGA	DGA
alexa.org	Most popular domains	971424	-
datadriven\security.info	Legitimate DGA domains	-	133927



Features

1. Basic Domain Features

- ▶ Count, Categorical
- ▶ TLD and FQDN

2. Simple Lexical Features

- ▶ Length, count, ratio
- ▶ 2LD, character classes

3. Advanced Lexical Features

- ▶ Approximating language, recognising words
- ▶ Entropy of letter distribution
- ▶ N-gram analysis ([alexa.org](#), English)

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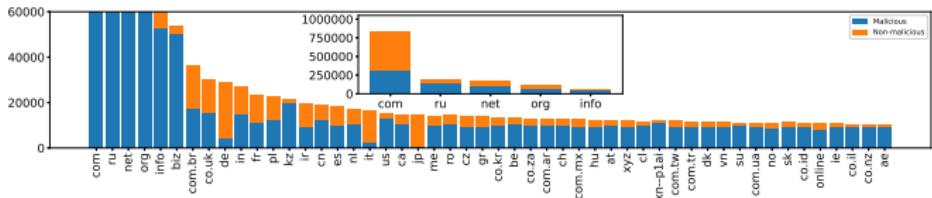
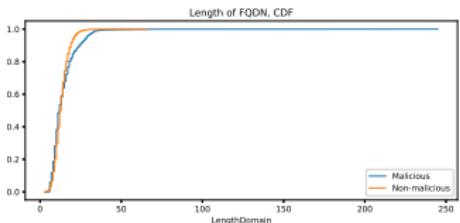
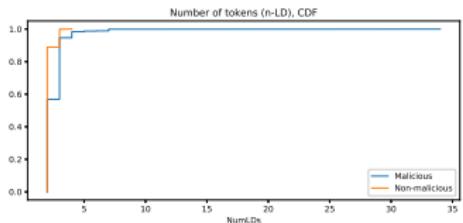
Conclusion

Top-Level Domain (TLD): **www.example.com**.
Second-Level Domain (2LD): **www.example.com**.
Fully Qualified Domain Name: **www.example.com**

Feature Analysis

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Basic Domain Features



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Detection: Scenario I - Full Data Set

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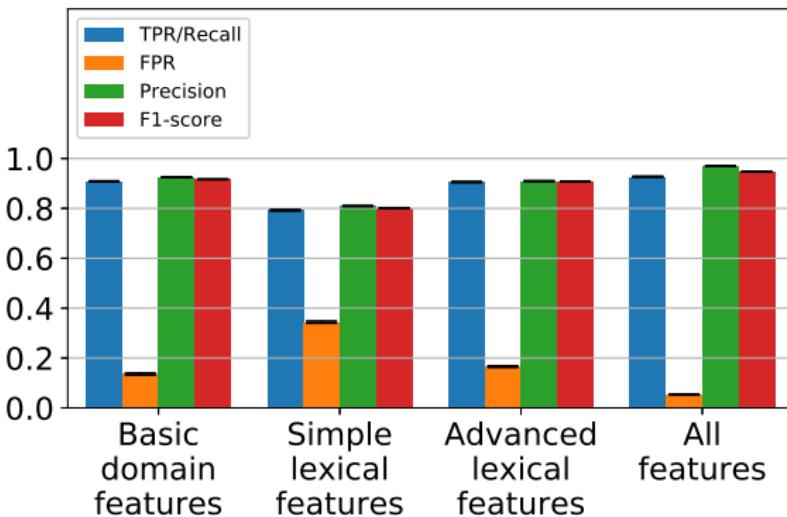
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Detection: Scenario II - Non-DGA

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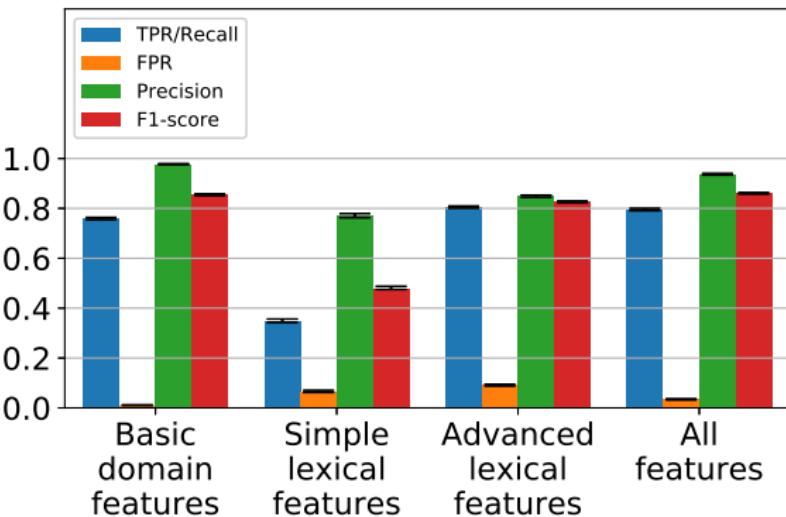
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Detection: Scenario III - DGA

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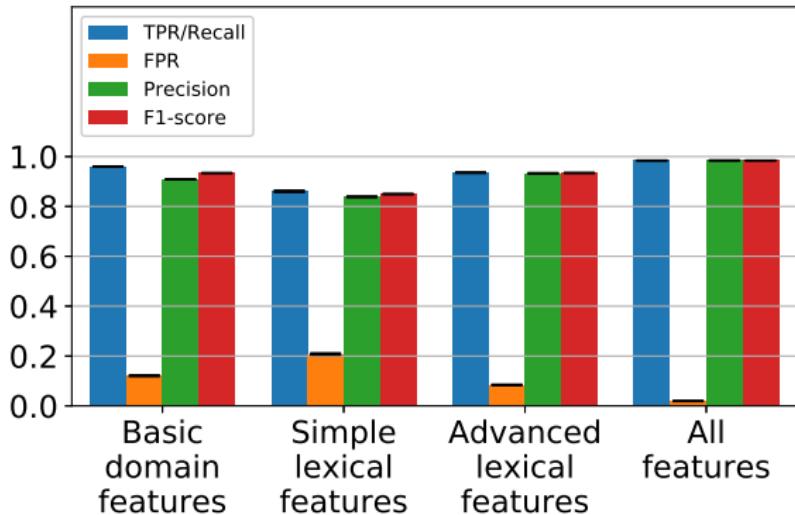
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Scenario III includes the benign non-DGA domains.

Conclusion

Results

**Malicious domains can be detected
by using lexical features only**

- ▶ Detection of DGA-domains is particular promising
 - ▶ Precision: 0.984. Recall: 0.984. F1-score: 0.948.
- ▶ Detection of Non-DGA-domains requires further work
 - ▶ Precision: 0.937. Recall: 0.795. F1-score: 0.860.
- ▶ Using all features outperforms the individual sets

General

- ▶ Vague distinction between DGA and Non-DGA
- ▶ Labelled data of high quality is hard to come by

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Future work

- ▶ Explore other lexical features
- ▶ Explore effect of combining with non-lexical features
- ▶ Improve performance for non-DGA domains
- ▶ More substantial data sets
- ▶ Evaluate in a practical, online setting
- ▶ Apply unsupervised machine learning

Backup slides



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Existing Solutions

Existing Solutions

- ▶ Reputation
- ▶ Traffic and activity (DNS, e-mail, ...)
- ▶ Resilience/anonymity techniques

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Basic Domain Features

1. Number of domain levels (n-LD).
2. Top level domain (TLD).
3. Length of Fully Qualified Domain Name (FQDN).

Simple Lexical Features

1. Length of 2nd Level Domain (2-LD).
2. Ratio of consonants in the 2-LD.
3. Number of vowels in 2-LD.
4. Number of numeric characters in 2-LD.
5. Number of special characters in 2-LD.
6. Ratio of special characters in 2-LD.

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Features

Advanced Lexical Features

1. Language indicator (`langid.py`)
2. Number of English words in 2-LD.
3. Entropy of 2-LD.
4. N-gram analysis of 2-LD (www.alexa.org) ¹.
5. N-gram analysis of 2-LD (English dictionary).

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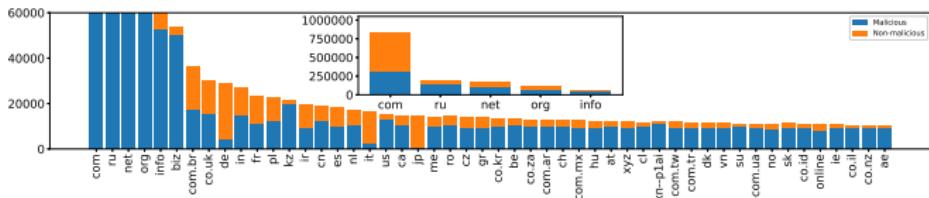
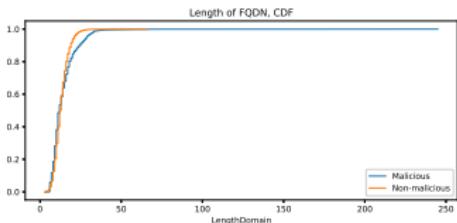
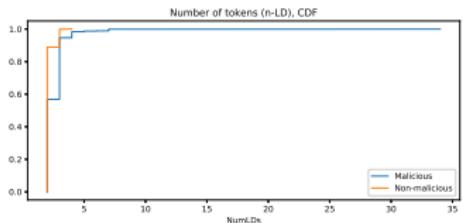
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¹{3,4,5}-grams,

Feature Analysis

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Basic Domain Features



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Feature Analysis

Simple Lexical Features

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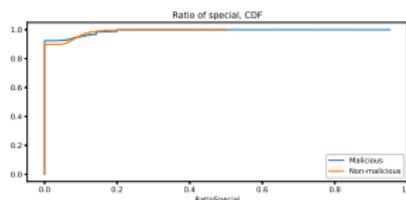
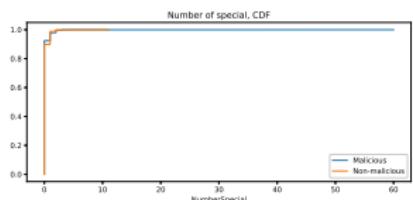
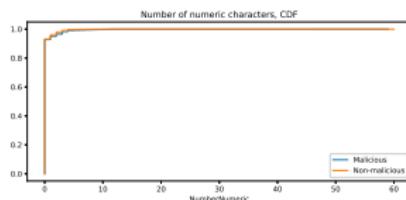
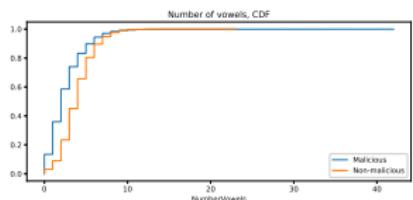
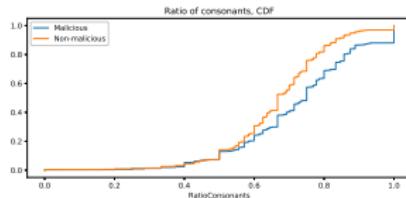
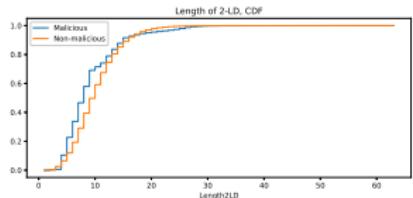
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Feature Analysis

Advanced Lexical Features

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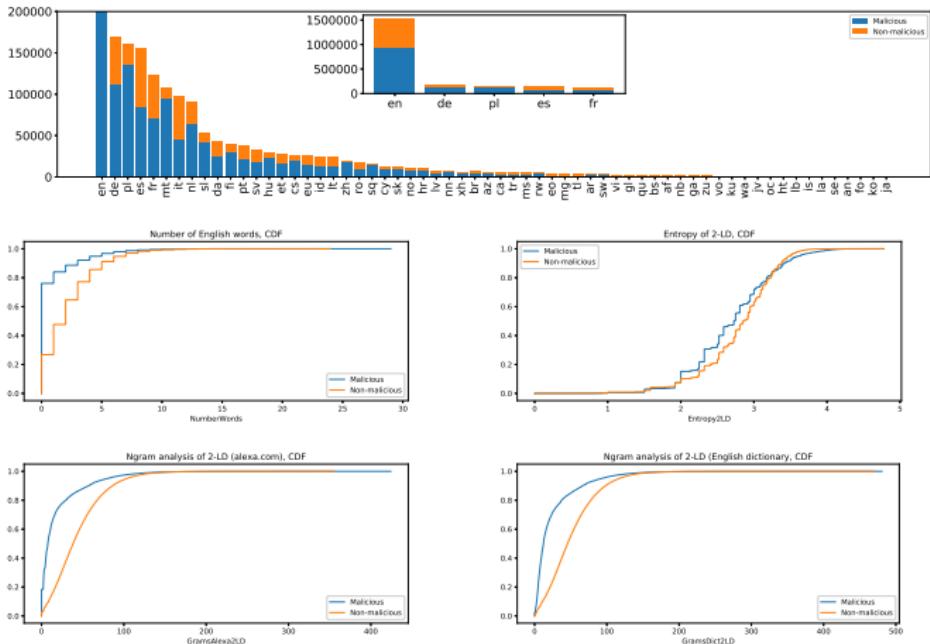
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Detection: Mean performance

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Scenario	Features	TPR/Recall	FPR	Precision	F1-score
I (Full)	1	9.09e-01	1.36e-01	9.25e-01	9.17e-01
	2	7.93e-01	3.44e-01	8.10e-01	8.01e-01
	3	9.06e-01	1.66e-01	9.10e-01	9.08e-01
	All	9.27e-01	5.35e-02	9.70e-01	9.48e-01
II (Non-DGA)	1	7.59e-01	1.10e-02	9.78e-01	8.55e-01
	2	3.50e-01	6.69e-02	7.69e-01	4.81e-01
	3	8.05e-01	9.16e-02	8.49e-01	8.26e-01
	All	7.95e-01	3.41e-02	9.37e-01	8.60e-01
III (DGA)	1	9.60e-01	1.21e-01	9.09e-01	9.34e-01
	2	8.61e-01	2.08e-01	8.38e-01	8.50e-01
	3	9.35e-01	8.40e-02	9.33e-01	9.34e-01
	All	9.84e-01	1.98e-02	9.84e-01	9.84e-01