Breaking Bad:
Detecting malicious domains using word segmentation

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Rethink Possible®

Who We Are

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Our main question

How well can we predict whether a website is malicious

using only information from its domain name?

Explore the solution with

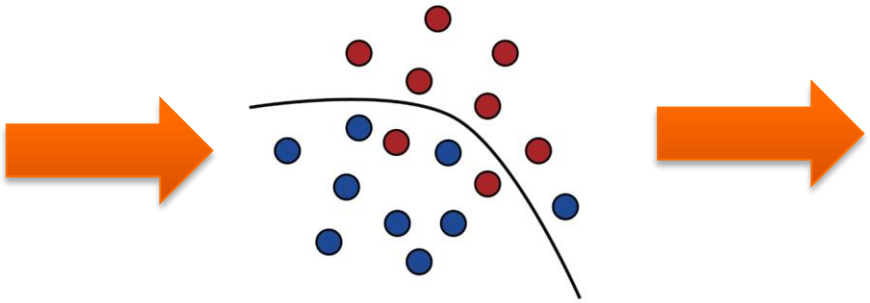
(1) word segmentation and

(2) machine learning

Toy example

Is it safe to visit the domain safestplaceintown.com?

"safest"
"place"
"in"
"town"
some other predictors



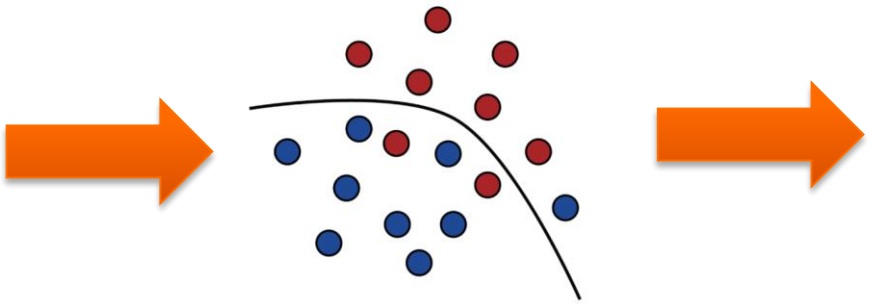
17.2% chance of being malicious

(1) word segmentation (2) machine learning (3) make prediction

Toy example

What about the domain freecashandnikejerseys.com?

"free"
"cash"
"and"
"nike"
"jerseys"
some other predictors



99.9% chance of being malicious

(1) word segmentation (2) machine learning (3) make prediction

Outline

Background

Data and Experimental Setup

- Data (Domains + Outcome Variable)
- Experiments
- Features

Results

Conclusions

Problem: Malicious Domains

What are malicious domains used for?

1. Malware binary download site
2. Phishing/scam site
3. Botnet command-and-control (C&C)
4. Data exfiltration site
5. Site for obfuscation to avoid detection

Previous Machine Learning Approaches (1)

Features based on the content of webpages

- Download the page and analyze/characterize its content

- Highly accurate, but potentially slow

Previous Machine Learning Approaches (2)

Features based on domain names, URLs, hosts:

1. Lexical characteristics
   - length of domain name, number of digits, etc.
   - keywords (i.e. manually curated list of brand names)
   - Markov models for character-to-character transitions

2. DNS and host-based features
   - # of distinct IP addresses and other DNS and WHOIS information

Ref: Garera '07, McGrath '08, He et al '10, Bilge et al '11

Previous Machine Learning Approaches (3)

Large-scale machine learning on full URLs [Ma et al 2009 (KDD and ICML), 2011] Most Relevant Work

- Combine lexical characteristics of full URL (including bag-of-words model on URL path) with host-based features (from DNS and WHOIS queries)

- High accuracy, but real-time implementation requires 3-4 seconds per URL

Our idea…

Q: Can we extract any more features without sacrificing speed?

A: *Word segmentation* of the domain name

Thousands of new features: word segmentation

Word segmentation = break a string into one or more substrings

- Recent applications to domain names, Twitter hashtags, etc.
- Methodological research with the goal of recovering a true, known segmentation of a domain name [Wang '11, Srinivasan '12]
- [Norvig '09] a book chapter that included an introduction to word segmentation using language models (and code!)

Our Approach: A combination of two methods

Word Segmentation on domain names (not full URLs)

+

Machine learning

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Review: Definition of a domain name

Full URL	http://www.more.example.com/path-to-url.html
Top level domain	http://www.more.example.com/path-to-url.html
Second-level domain	http://www.more.example.com/path-to-url.html

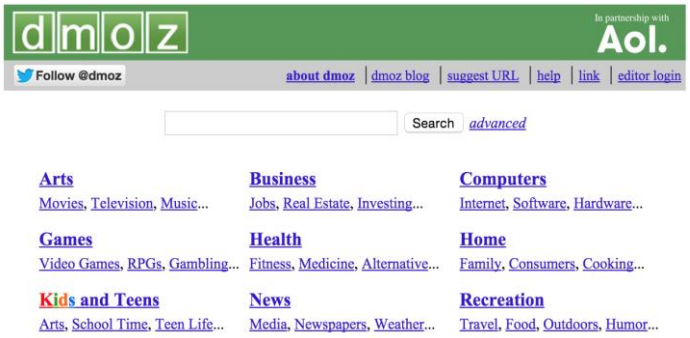
Domain name may only consist of:

- Alphanumeric characters
- Hyphens
- Top-level-domain (TLD)

Data – Two Sources

1. A sample of domains visited on a cellular network
   - ~1.3 million unique domain names from Sept. 2014

1. Domains from DMOZ, the Open Directory Project
   - 30,000 randomly sampled domain names from Nov. 2014



How to define “malicious”: Web of Trust

What: Web of Trust (WOT), at www.mywot.com

- crowd-sourced website reputation and review service
- The ratings are validated with trusted third party information

Each domain has:

rating	confidence score	category
[0,100]	[0,100]	“trustworthiness” ~~“child safety”~~

~261,000 out of 1,372,120 (20%) cellular domains had non-empty WOT scores

Three experiments

1. "Balanced Data"

- Why: to compare to Ma'09 and other studies that used DMOZ data.
- Malicious = 1 if rating < 60
- All DMOZ are benign.

	DMOZ	Cellular	Row total
Training	15,000 (benign)	15,000 (malicious)	30,000
Testing	15,000 (benign)	15,000 (malicious)	30,000

Three experiments

2. “Unfiltered Cellular”

- Use all cellular data
- Malicious = 1 if rating < 60
- Baseline rate ~ 14.6% malicious

	Cellular
Training	80%
Testing	20%
Column total	100% (~261,000)

Three experiments

3. "Filtered Cellular"

- Attempt to use only high-quality cellular data
- Remove those with rating in [40, 59] or confidence < 10
- Malicious = 1 if rating < 40
- Baseline rate ~ 24.5% malicious

	Cellular
Training	80%
Testing	20%
Column total	100% (~80,000)

Feature sets

1. “Basic” (22 features)

- number of characters; number of hyphens; number of digits; number of numbers

  (discretized to allow for non-linear relationships)

“4downs-10yards.com”

→ 14 characters, 3 digits, 1 hyphen, and 2 numbers

2. “Character indicators” (36 features)

- Indicator(a-z, 0-9)

Feature sets

3. "Character Markov model log-likelihood" (22 features)

- top 1/3 million unigrams from the Google Ngrams corpus to train a 1st order Markov model
- transition probability between characters (11 bins)

4. "Top level domains (TLDs)" (~400 features)

5. "Words" (~94,000 features) * this is our innovation

Word segmentation

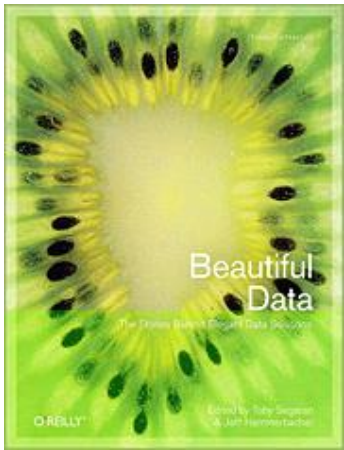
"duckduckgo.com" → {"duck", "duck", "go"} (3 tokens)
→ {"duck", "go"} (2 words)

Dynamic programming algorithm

[Norvig'09, *Beautiful Data*]

Find the most likely segmentation of a string of characters into a set of one or more tokens based on Google bigrams corpus

2.34 tokens/domain on average



The most frequent words

	Word	Freq		Word	Freq		Word	Freq
1	a	6772	11	on	1638	21	shop	1168
2	the	6186	12	my	1593	22	world	1157
3	i	3515	13	is	1426	23	music	1143
4	of	3183	14	club	1393	24	city	1078
5	s	2789	15	web	1380	25	it	1056
6	in	2630	16	art	1297	26	center	1047
7	online	2554	17	inc	1234	27	news	1034
8	and	2495	18	co	1187	28	st	1032
9	e	1847	19	for	1181	29	free	1017
10	to	1772	20	de	1171	30	group	1012

30 most frequent words: some stop words, some common "web" words

Total Vocabulary Size: 94,050 words

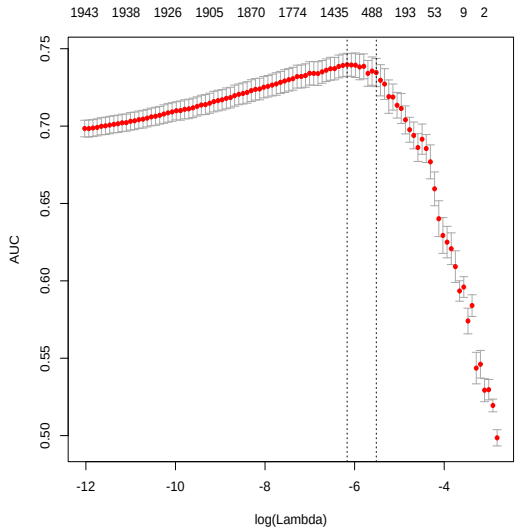
Model: lasso-regularized logistic regression

Model: logistic regression with lasso penalty (binary classification)

R package glmnet

[Ma'09 found that this was roughly as accurate as SVM and Naïve Bayes]

Training: 10-fold cross-validation



Sparse coefficients (many zeroes)

Features are of the same scale → the coefficients are interpretable

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Individual set

focus of this study!

	Feature Sets	MCR	AUC	# Features	# $\neq 0$
M1	Basics				
M2	Characters				
M3	TLD				
M4	Log-likelihood				
M5	Words				
M6	M1 + M2 + M3 + M4				
M7	M6 + Words				

MCR results are based on a naive threshold of 0.5

Summary of model fits to "Balanced Data" (Experiment 1)

	Feature Sets	MCR	AUC	# Features	# $\neq 0$
M1	Basics	0.435	0.595	22	6
M2	Characters	0.478	0.536	36	29
M3	TLD	0.288	0.763	489	101
M4	Log-likelihood	0.492	0.512	22	13
M5	Words	0.373	0.667	24772	4588
M6	M1 + M2 + M3 + M4	0.297	0.771	569	104
M7	M6 + Words	**0.277**	**0.813**	25341	2928

- M7 decreases the MCR of M6 by 2% and increases the AUC by about 4%
- M7 has slightly fewer than 3000 active (nonzero) features

Summary of model fits to "Unfiltered Cellular" data (Experiment 2)

	Features	MCR	AUC	# Features	# $\neq 0$
M1	Basics	0.146	0.563	22	13
M2	Characters	0.145	0.576	36	27
M3	TLD	0.140	0.657	479	99
M4	Log-likelihood	0.146	0.542	22	18
M5	Words	0.137	0.708	77866	12568
M6	M1 + M2 + M3 + M4	0.137	0.696	559	158
M7	M6 + Words	**0.125**	**0.779**	78425	9938

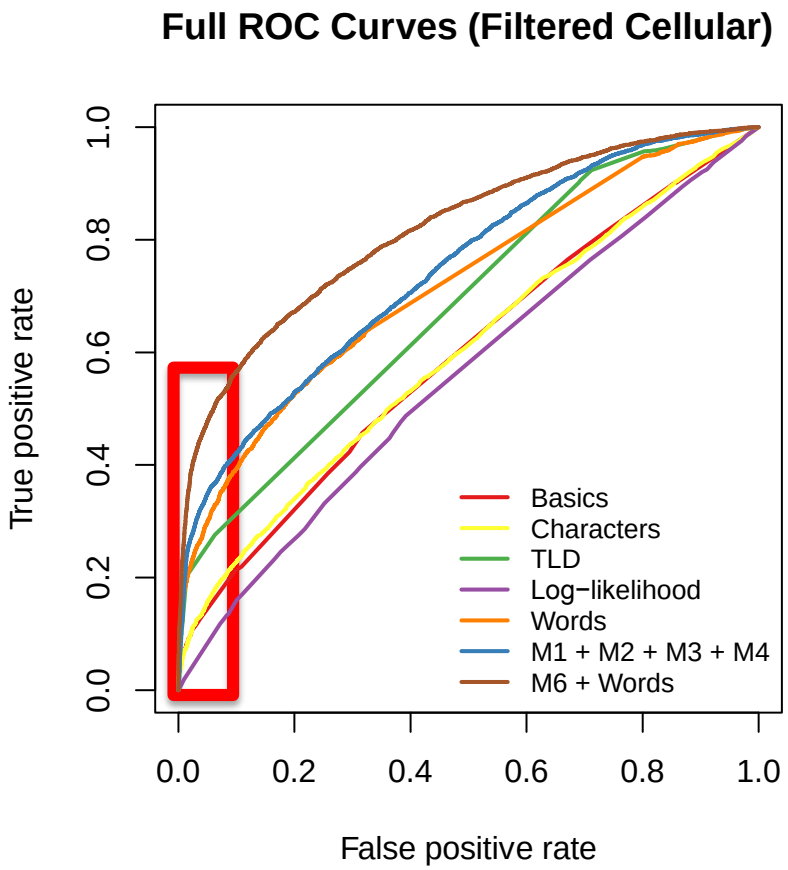
- Improvement in MCR is smaller than the "balanced"
- M7 is substantially better than M6 in AUC (about 8% higher)

Summary of model fits to "Filtered Cellular" data (Experiment 3)

	Features	MCR	AUC	# Features	# $\neq 0$
M1	Basics	0.240	0.593	22	11
M2	Characters	0.242	0.597	36	23
M3	TLD	0.211	0.681	323	33
M4	Log-likelihood	0.250	0.557	22	9
M5	Words	0.212	0.720	38025	8578
M6	M1 + M2 + M3 + M4	0.199	0.744	403	119
M7	M6 + Words	**0.167**	**0.817**	38428	5416

- Similar results to those in the "unfiltered cellular"
- MCR rates decrease faster, and the AUC is 4% higher than M7 in the "unfiltered cellular"

Results – ROC Curves



Words associated with malicious domains

1) Brand names: **rayban, oakley, nike, vuitton, hollister, timberland, tiffany, ugg**

2) Shopping: **dresses, outlet, sale, dress, offer, jackets, watches, deals**

3) Finance: **loan, fee, cash, payday, cheap**

4) Sportswear: **jerseys, kicks, cleats, shoes, sneaker**

5) Basketball Player Names (associated with shoes): **kobe, jordan, jordans, lebron**

6) Medical/Pharmacy: **medic, pills, meds, pill, pharmacy**

7) Adult: **webcams, cams, lover, sex, porno**

8) URL spoof: **com**

Words associated with benign domains

1) Locations: **european, texas, india, europe, vermont, zealand, washington, colorado**

2) Hospitality Industry: **inn, ranch, motel, country**

3) Common Benign Numbers: **2000, 411, 911, 2020, 365, 123, 360**

4) Realty: **realty, builders, homes, properties, estate**

5) Small Businesses: **rentals, outfitters, lumber, audio, funeral, flower, taxidermy, inc, golf, law, farm, chamber, farms, rider, photo**

6) Geographical Features: **creek, hills, lake, ridge, river, valley, springs, grove, mountain, sky, island**

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1. Word segmentation added substantial predictive power to a logistic regression model
2. Models are interpretable
3. Highly predictive words may change over time
4. Potential complementary method to more accurate, but expensive and time-consuming approaches

Future work

1. Use different source(s) for the outcome variable
2. Long term evaluation of the system
3. Online learning with streaming data

Q & A