DEFCON

Defending Networks with Incomplete Information: A Machine Learning Approach

Alexandre Pinto
alexcp@mlsecproject.org
@alexcpsec
@MLSecProject

** WARNING **

- This is a talk about DEFENDING not attacking
  - NO systems were harmed on the development of this talk.
  - We are actually trying to BUILD something here.

- This talk includes more MATH than the daily recommended intake by the FDA.

- You have been warned...

Who's this guy?

- 12 years in Information Security, done a little bit of everything.
- Past 7 or so years leading security consultancy and monitoring teams in Brazil, London and the US.
  - If there is any way a SIEM can hurt you, it did to me.
- Researching machine learning and data science in general for the past year or so. Participates in Kaggle machine learning competitions (for fun, not for profit).
- First presentation at DefCon! (where is my shot?)

Agenda

- Security Monitoring: We are doing it wrong
- Machine Learning and the Robot Uprising
- Data gathering for InfoSec
- Case study: Model to detect malicious activity from log data
- MLSec Project
- Attacks and Adversaries
- Future Direction

The Monitoring Problem

- Logs, logs everywhere

The Monitoring Problem

- Logs, logs everywhere

FSC
100%
From well-managed forests
Cert no. CU-COC-807873
www.fsc.org
© 1996 Forest Stewardship Council

Are these the right tools for the job?

Figure 3. First, Second and Third Most Challenging Aspects of Log Management and Integration

- SANS Eighth Annual 2012 Log and Event Management Survey Results (http://www.sans.org/reading_room/analysts_program/SortingThruNoise.pdf)

Are these the right tools for the job?

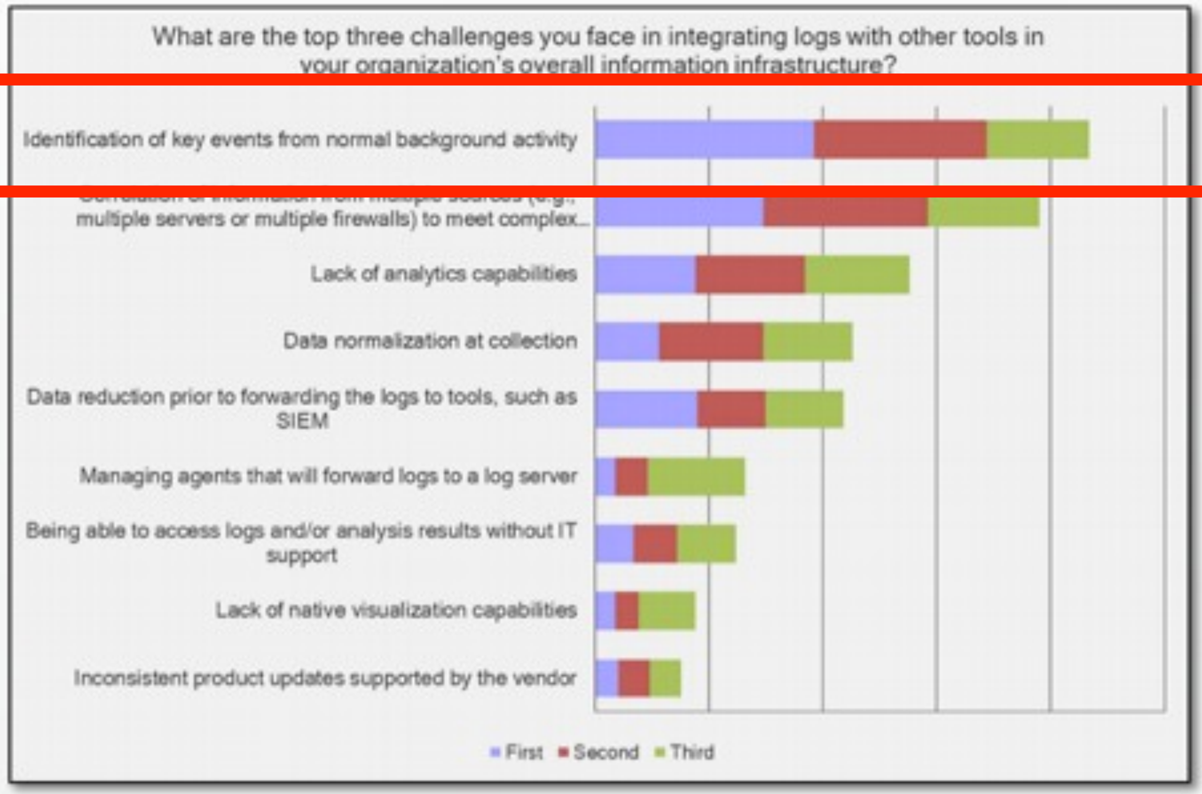


Figure 3. First, Second and Third Most Challenging Aspects of Log Management and Integration

- SANS Eighth Annual 2012 Log and Event Management Survey Results (http://www.sans.org/reading_room/analysts_program/SortingThruNoise.pdf)

Correlation Rules: a Primer

- Rules in a SIEM solution invariably are:
  - "Something" has happened "x" times;
  - "Something" has happened and other "something2" has happened, with some relationship (time, same fields, etc) between them.

- Configuring SIEM = iterate on combinations until:
  - Customer or management is ~~fooled~~ satisfied; or
  - Consulting money runs out

- Behavioral rules (anomaly detection) helps a bit with the "x"s, but still, very laborious and time consuming.

Not exclusively a tool problem

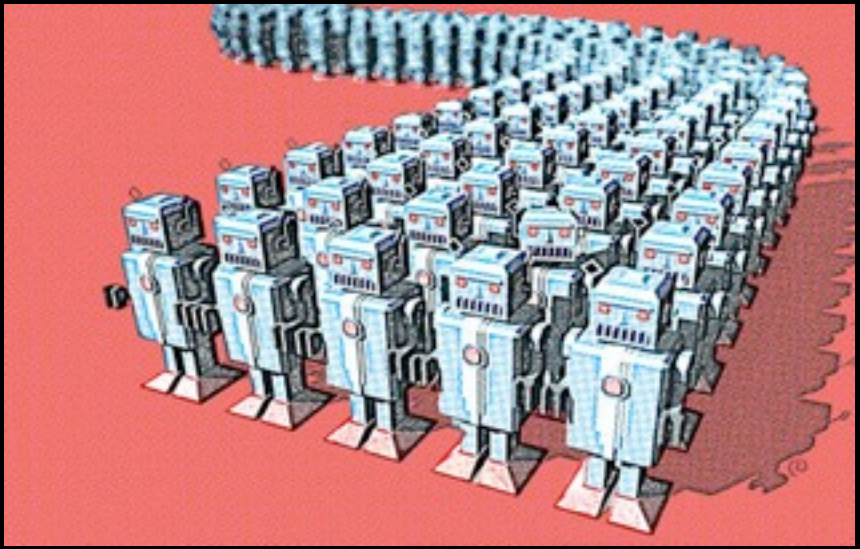
- However, there are individuals who will do a good job
- How many do you know?
- DAM hard (ouch!) to find these capable professionals

Next up: Big Data Technologies

- How many of these very qualified professionals will we need?

- How many know/ will learn statistics, data analysis, data science?

We need an Army! Of ROBOTS!



Enter Machine Learning

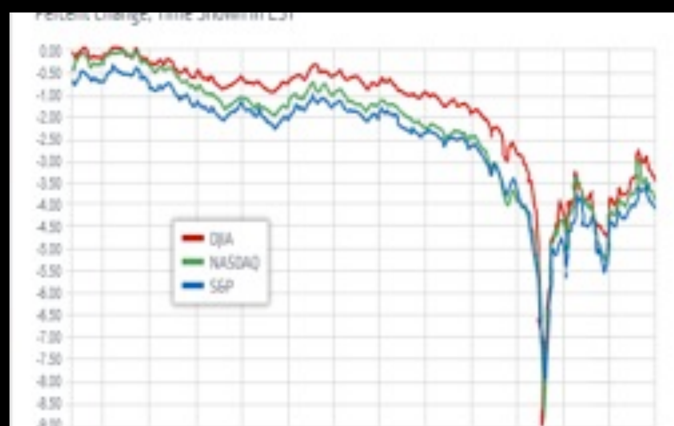
- "Machine learning systems automatically learn programs from data" (*)
- You don't really code the program, but it is inferred from data.
- Intuition of trying to mimic the way the brain learns: that's where terms like "artificial intelligence" come from.

(*) CACM 55(10) – A Few Useful Things to Know about Machine Learning

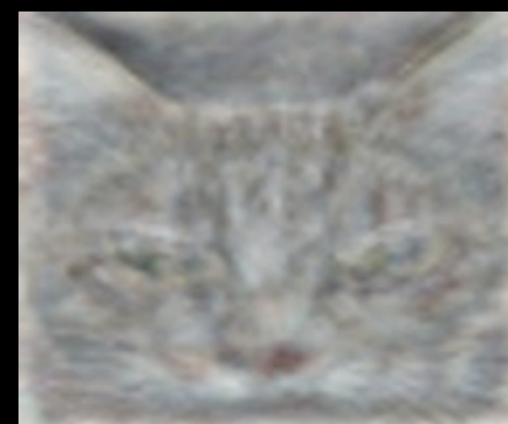
Applications of Machine Learning

- Sales

- Trading

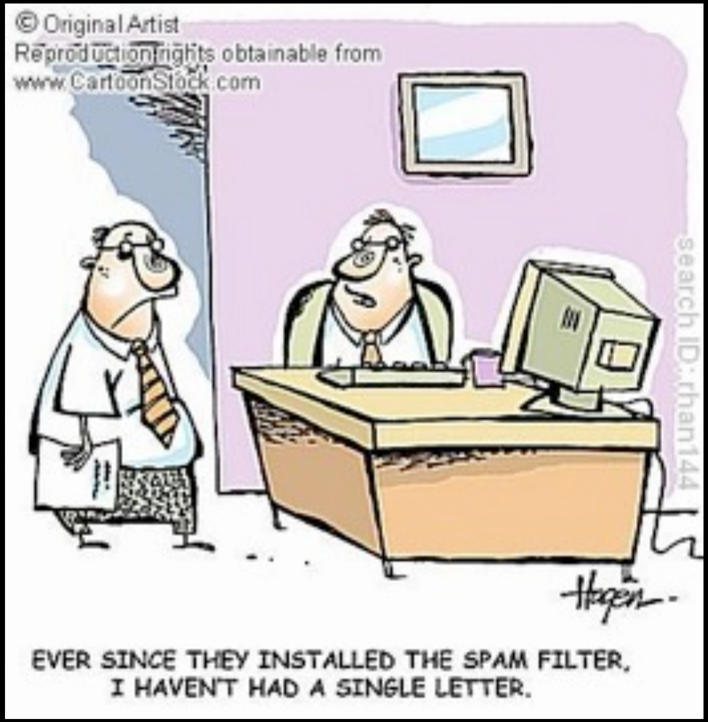


- Image and Voice Recognition



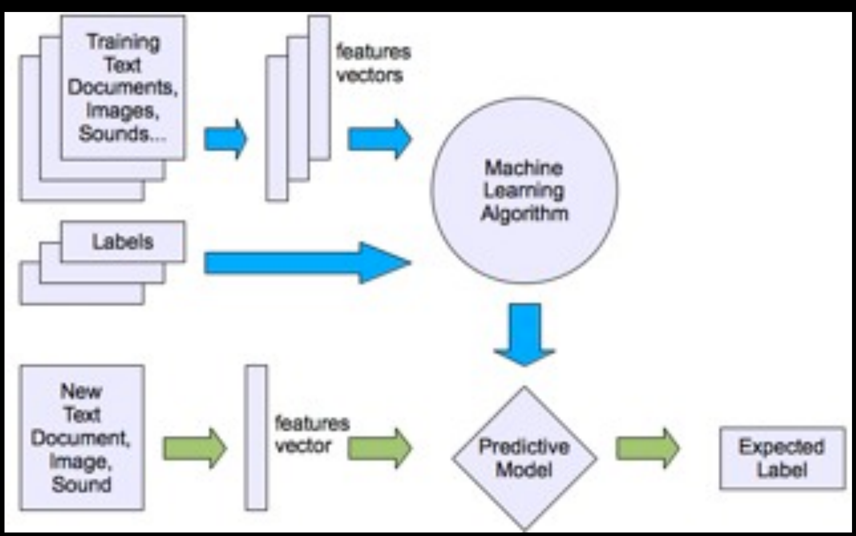
Security Applications of ML

- Fraud detection systems:
  - Is what he just did consistent with past behavior?
- Network anomaly detection (?):
  - NOPE!
  - More like statistical analysis, bad one at that
- SPAM filters
  - Remember the "Bayesian filters"? There you go.
  - How many talks have you been hearing about SPAM filtering lately? ;)

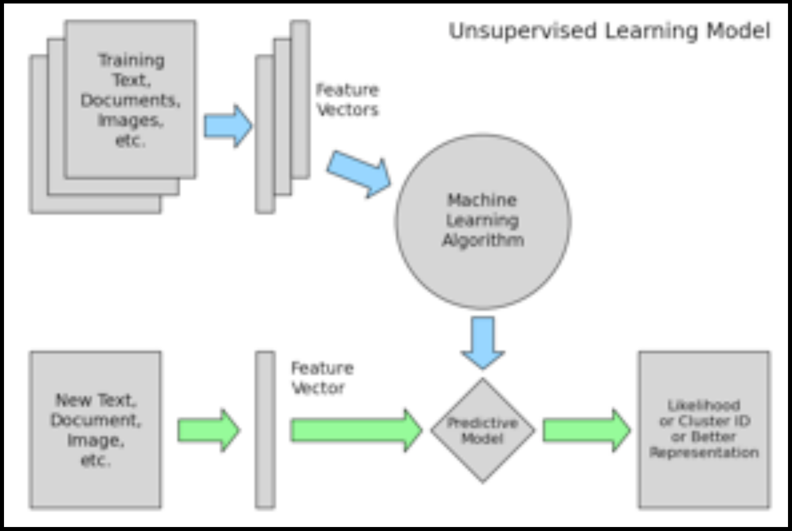


Kinds of Machine Learning

- Supervised Learning:
  - Classification (NN, SVM, Naïve Bayes)
  - Regression (linear, logistic)



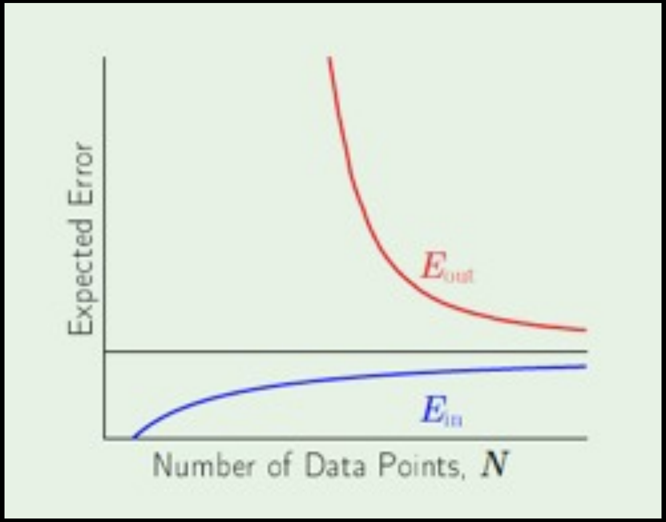
- Unsupervised Learning :
  - Clustering (k-means)
  - Decomposition (PCA, SVD)



Source – scikit-learn.github.io/scikit-learn-tutorial/

Considerations on Data Gathering

- "I've got 99 problems, but data ain't one"
- Models will (generally) get better with more data
  - We always have to consider bias and variance as we select our data points
  - Also adversaries – we may be force-fed "bad data", find signal in weird noise or design bad (or exploitable) features



Abu-Mostafa, Caltech, 2012

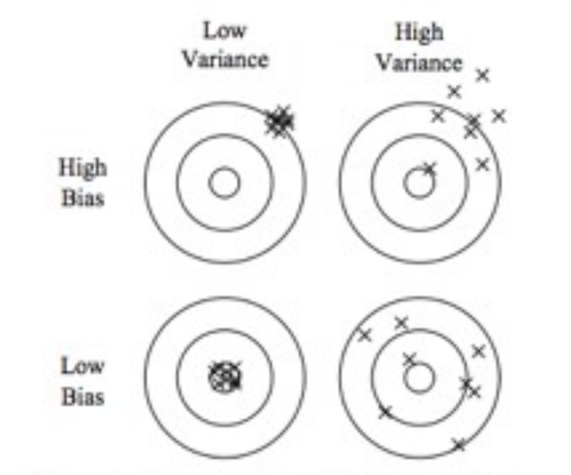


Figure 1: Bias and variance in dart-throwing.

Domingos, 2012

Considerations on Data Gathering

- Adversaries - Exploiting the learning process
- Understand the model, understand the machine, and you can circumvent it
- Something InfoSec community knows very well
- Any predictive model on InfoSec will be pushed to the limit
- Again, think back on the way SPAM engines evolved.

Designing a model to detect external agents with malicious behavior

- We’ve got all that log data anyway, let’s dig into it
- Most important (and time consuming) thing is the “feature engineering”
- We are going to go through one of the algorithms I have put together as part of my research

Model: Data Collection

- Firewall block data from SANS DShield (per day)
- Firewalls, really? Yes, but could be anything.
- We get summarized “malicious” data per port

```
> sans
              date              ip targetPort protocol reports targets firstSeen lastSeen
      1: 20130622  89.248.171.125         80      TCP   64853   64775  00:14:14 17:51:54
      2: 20130622   93.174.93.179         80      TCP   59580   58487  05:11:15 22:21:41
      3: 20130622   213.186.60.63         80      TCP   58429   58429  00:15:41 21:42:28
      4: 20130622 202.121.166.203         22      TCP  106621   53328  05:18:26 10:10:33
      5: 20130622 218.207.176.125         80      TCP   53241   53241  21:16:09 21:56:07
     ---
1107159: 20130622    65.55.37.104      16766      TCP       2       1  12:31:06 12:31:12
1107160: 20130622    65.55.37.104      16765      TCP       1       1  00:45:24 00:45:24
1107161: 20130622    65.55.37.104      16761      TCP       3       1  09:47:49 09:48:39
1107162: 20130622    65.55.37.104      16759      TCP       2       1  03:29:51 03:30:37
1107163: 20130622    65.55.37.104      16721      TCP       1       1  20:29:24 20:29:24
```

- Number of aggregated events (orange)
- Number of log entries before aggregation (purple)

Model Intuition: Proximity

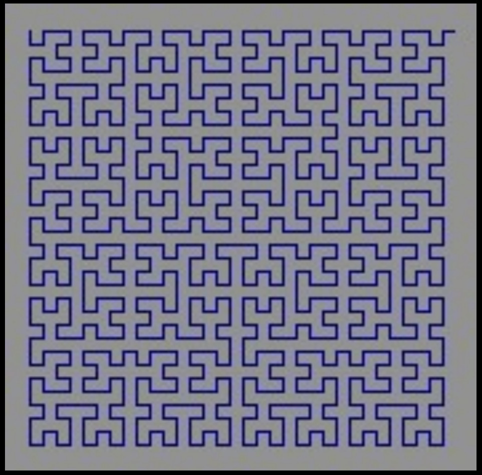
- Assumptions to aggregate the data
- Correlation / proximity / similarity BY BEHAVIOR
- "Bad Neighborhoods" concept:
  - Spamhaus x CyberBunker
  - Google Report (June 2013)
  - Moura 2013

- Group by Netblock (/16, /24)
- Group by ASN
  - (thanks, Team Cymru)

Map of the Internet

(Hilbert Curve)
Block port 22
2013-07-20

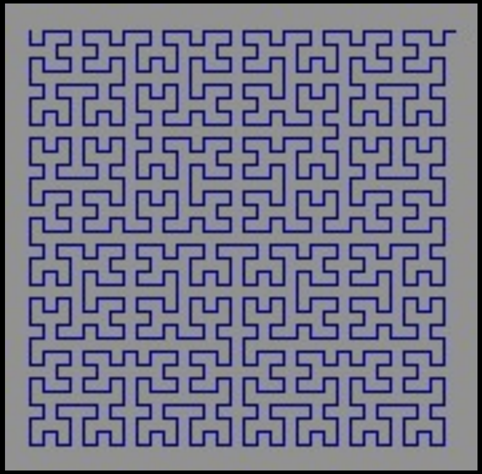
Notice the clustering behaviour?

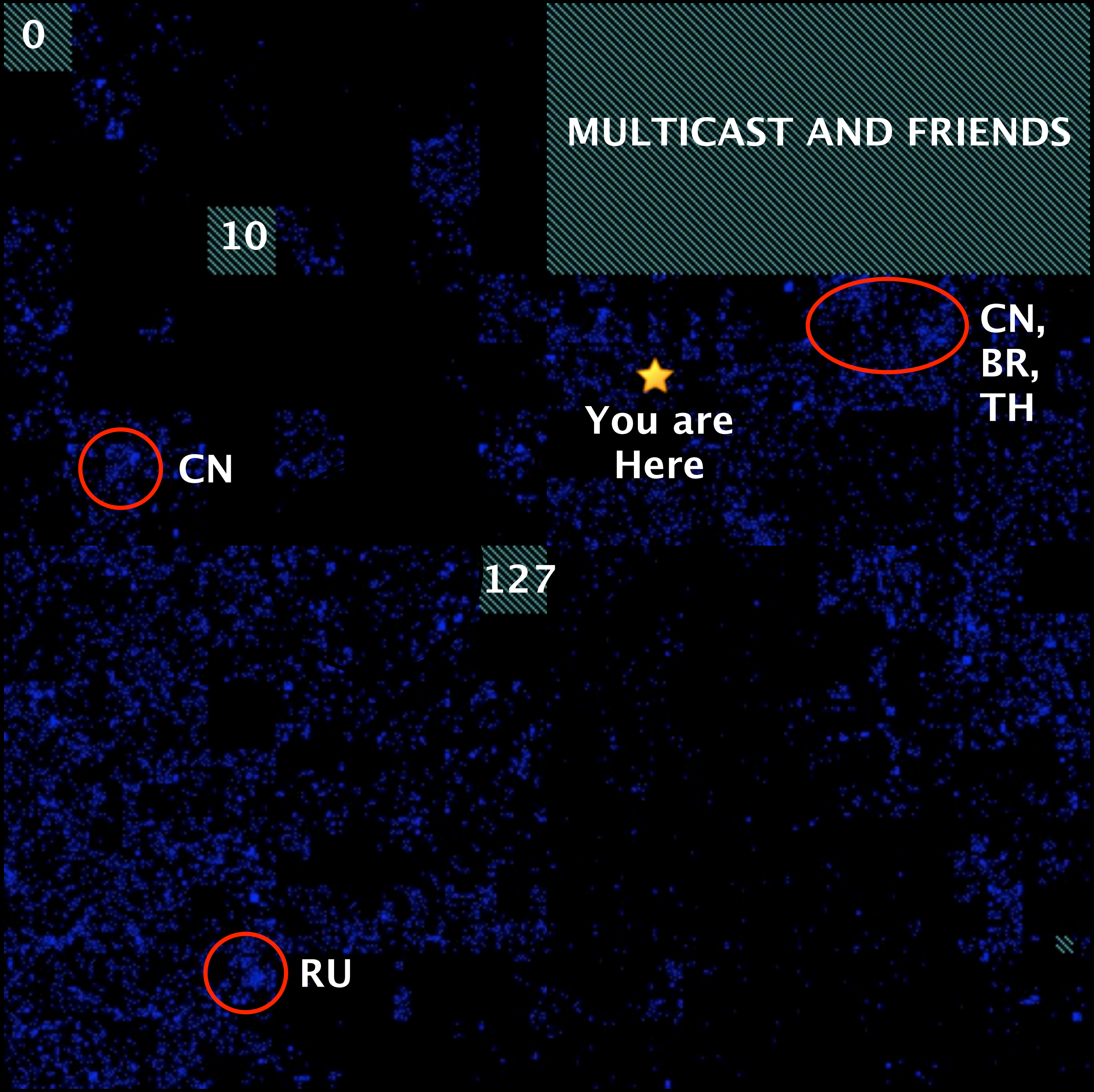


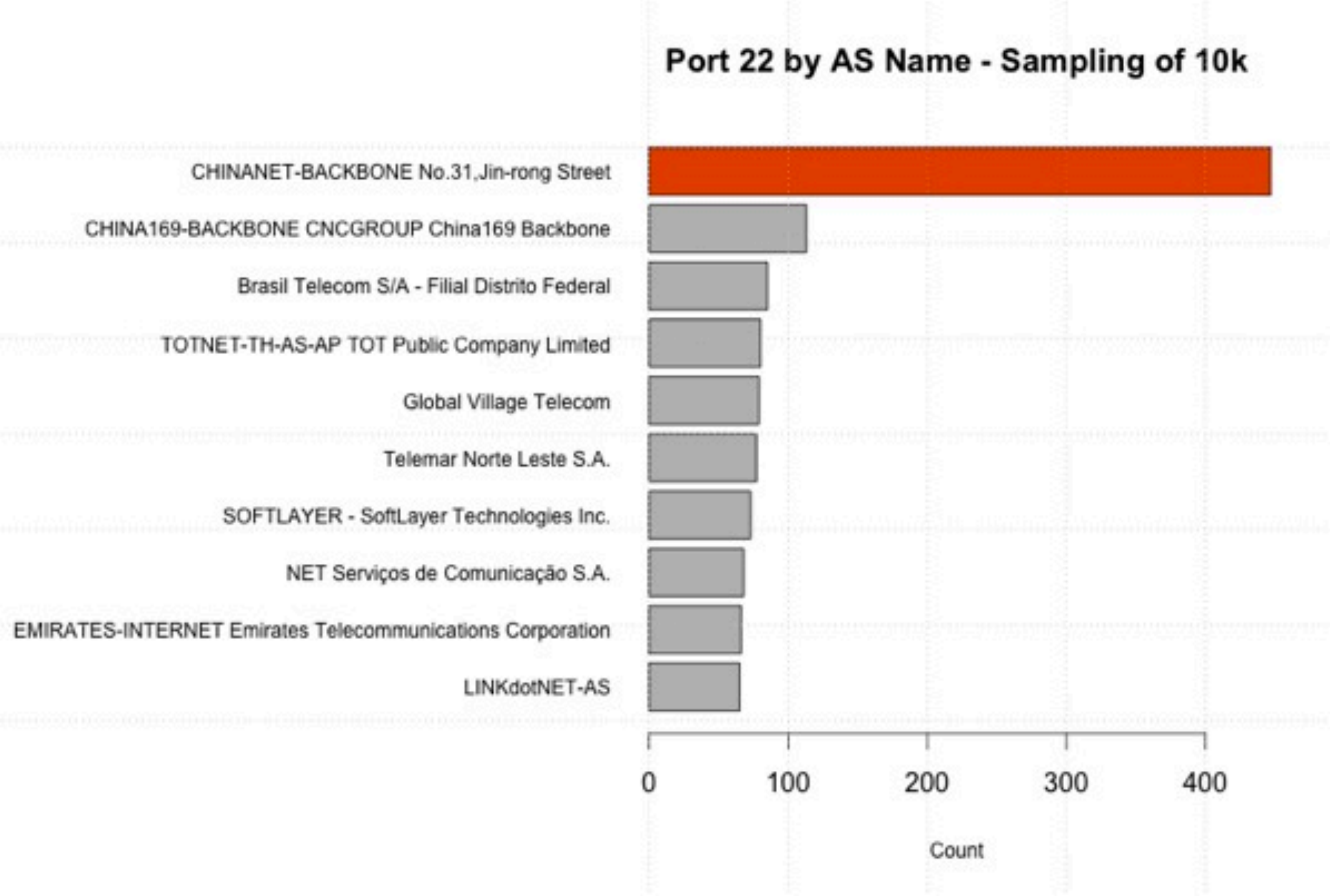
Map of the Internet

(Hilbert Curve)
Block port 22
2013-07-20

Notice the clustering behaviour?

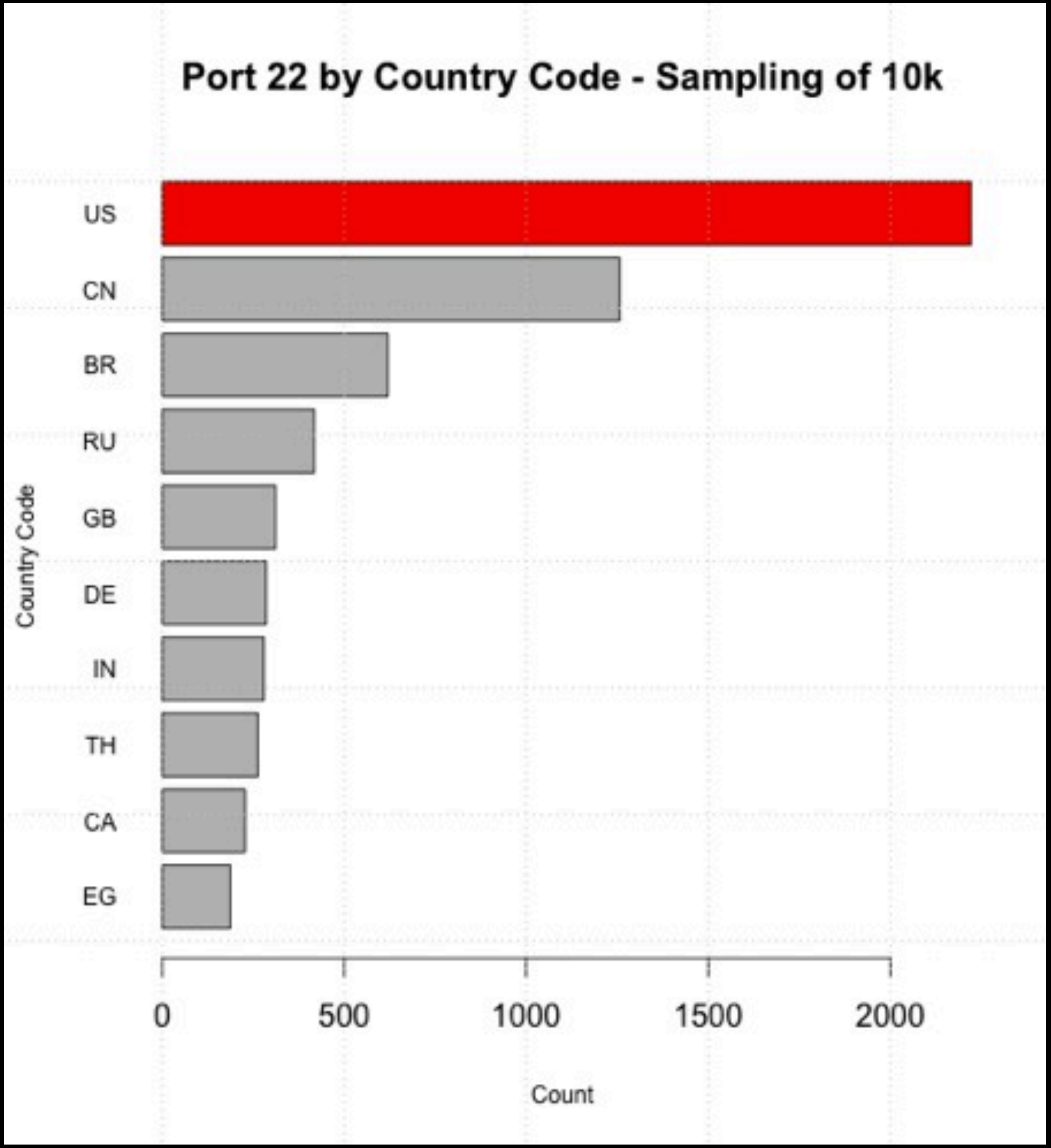





Port 22 by AS Name - Sampling of 10k
CHINANET-BACKBONE No.31,Jin-rong Street
CHINA169-BACKBONE CNCGROUP China169 Backbone
Brasil Telecom S/A - Filial Distrito Federal
TOTNET-TH-AS-AP TOT Public Company Limited
Global Village Telecom
Telemar Norte Leste S.A.
SOFTLAYER - SoftLayer Technologies Inc.
NET Serviços de Comunicação S.A.
EMIRATES-INTERNET Emirates Telecommunications Corporation
LINKdotNET-AS
0
100
200
300
400
Count

Be careful with confirmation bias

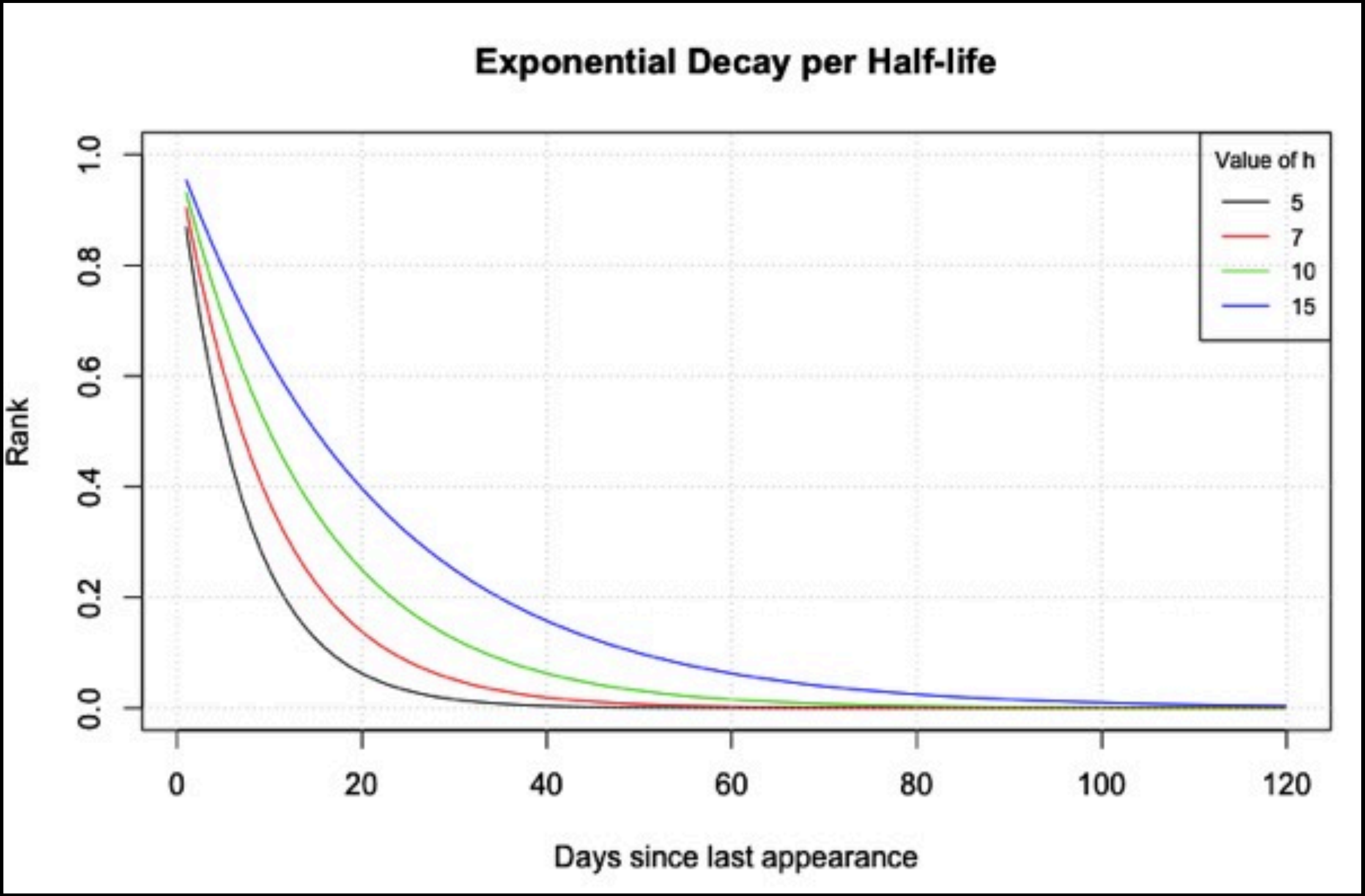
Country codes are not enough for any prediction power of consequence today



Model Intuition: Temporal Decay

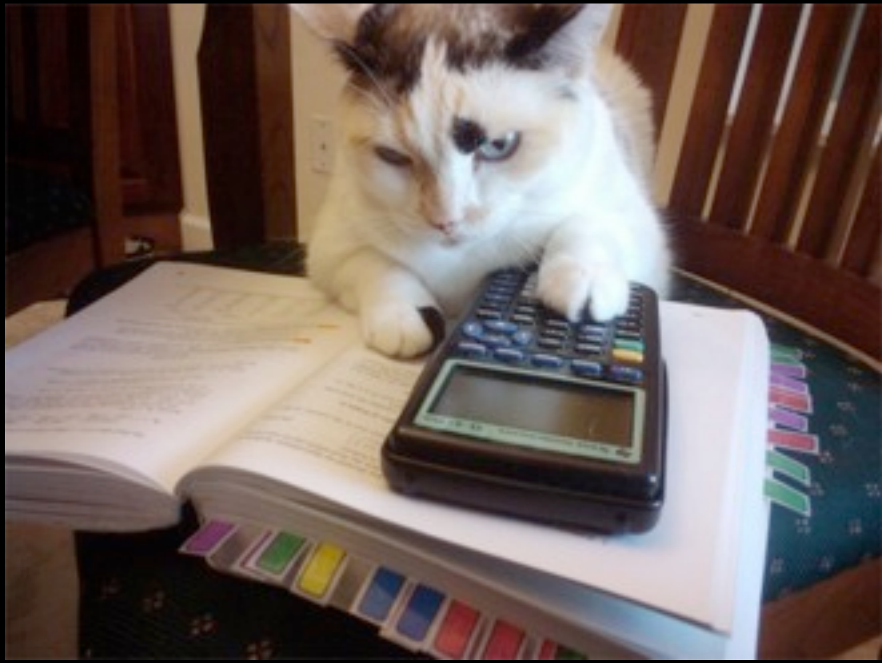
- Even bad neighborhoods renovate:
  - Atackers may change ISPs/proxies
  - Botnets may be shut down / relocate
  - A little paranoia is Ok, but not EVERYONE is out to get you (at least not all at once)
- As days pass, let's forget, bit by bit, who attacked
- A Half-Life decay function will do just fine

Model Intuition: Temporal Decay



Model: Calculate Features

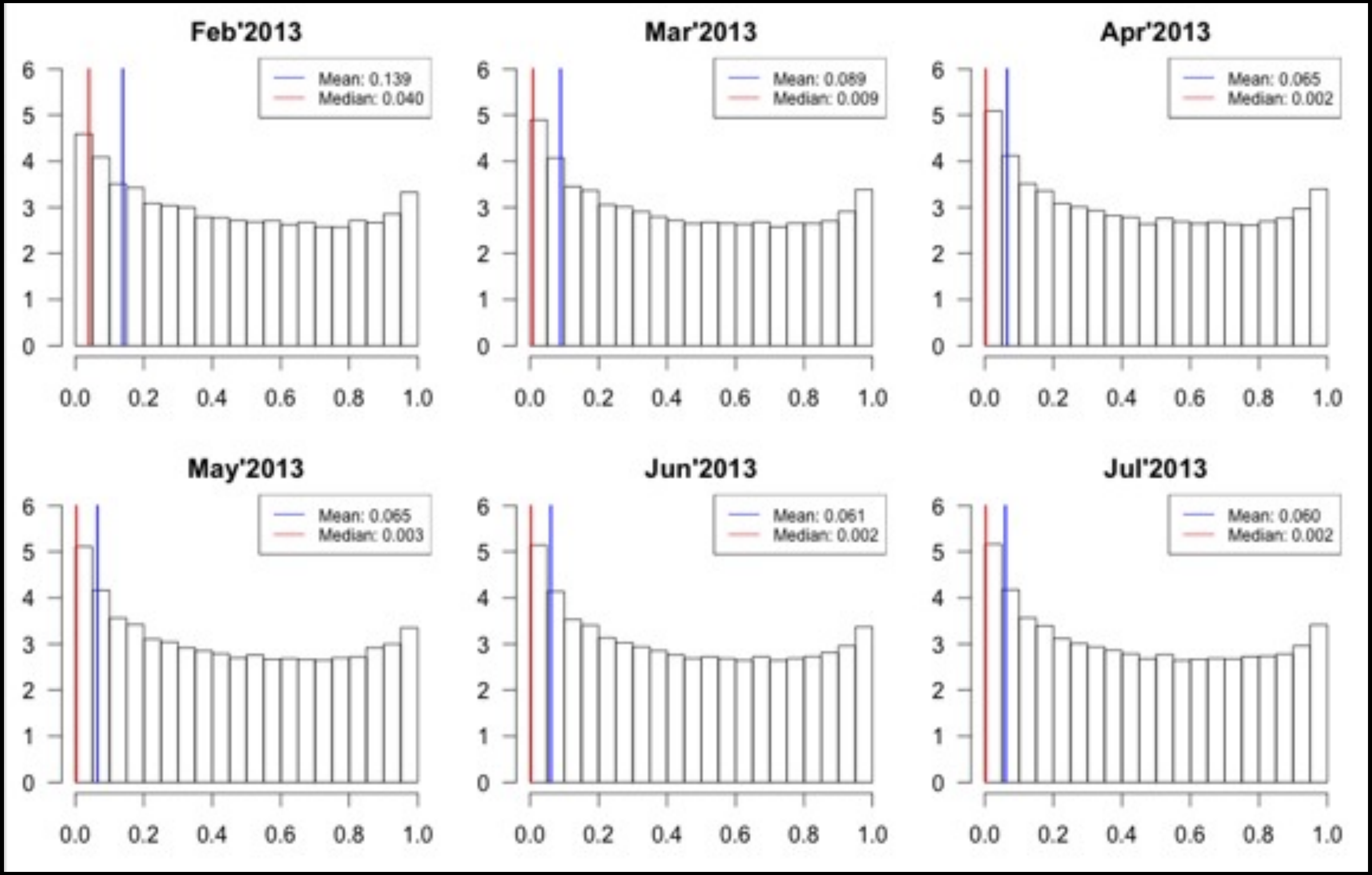
- Cluster your data: what behavior are you trying to predict?
- Create “Badness” Rank = lwRank (just because)
- Calculate normalized ranks by IP, Netblock (16, 24) and ASN
- Missing ASNs and Bogons (we still have those) handled separately, get higher ranks.



Model: Calculate Features

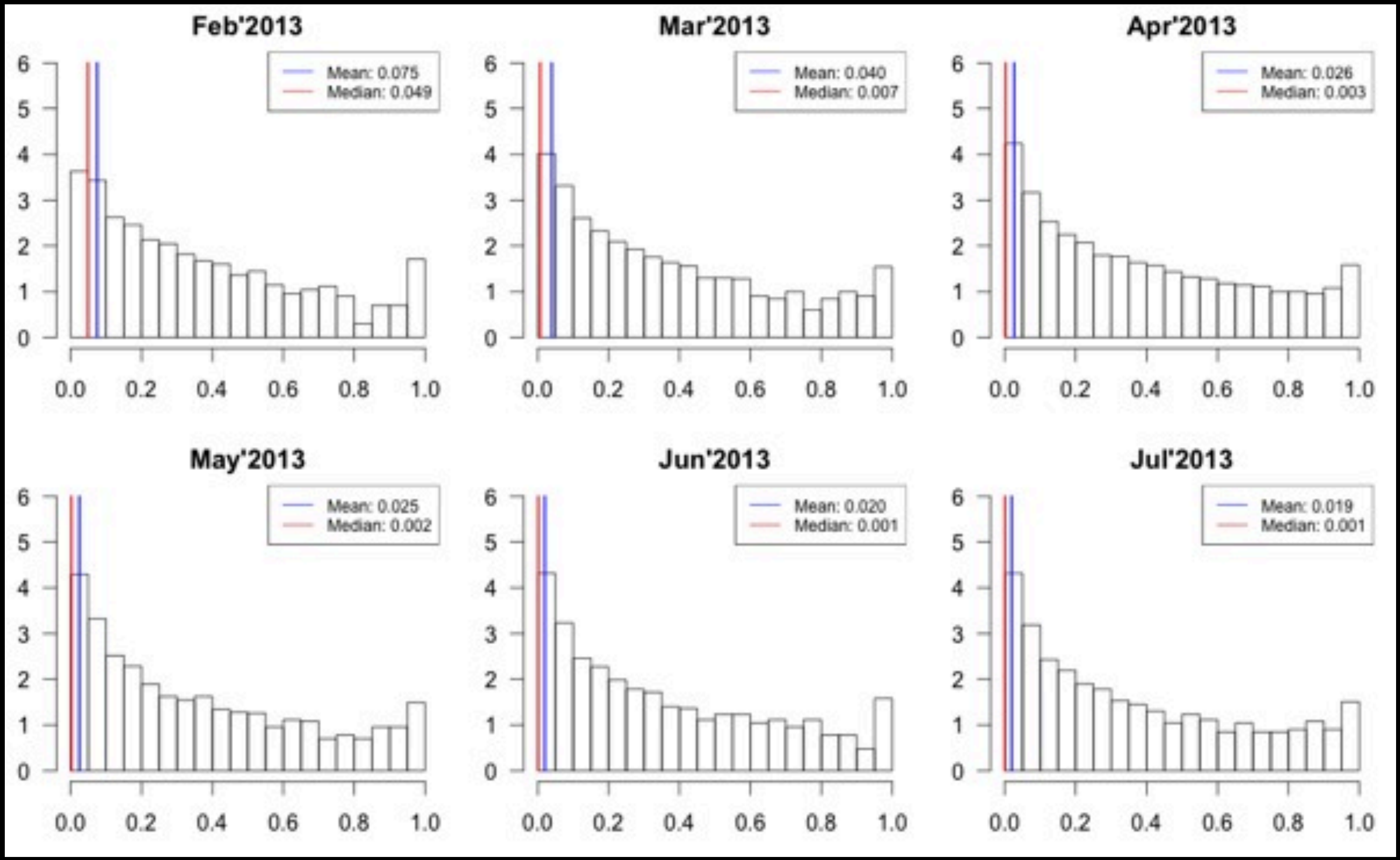
- We will have a rank calculation per day:
  - Each “day-rank” will accumulate all the knowledge we gathered on that IP, Netblock and ASN to that day
  - Decay previous “day-rank” and add today’s results
- Training data usually spans multiple days
- Each entry will have its date:
  - Use that “day-rank”
  - NO cheating ---------->
  - Survivorship bias issues!

Model: Example Feature (1)



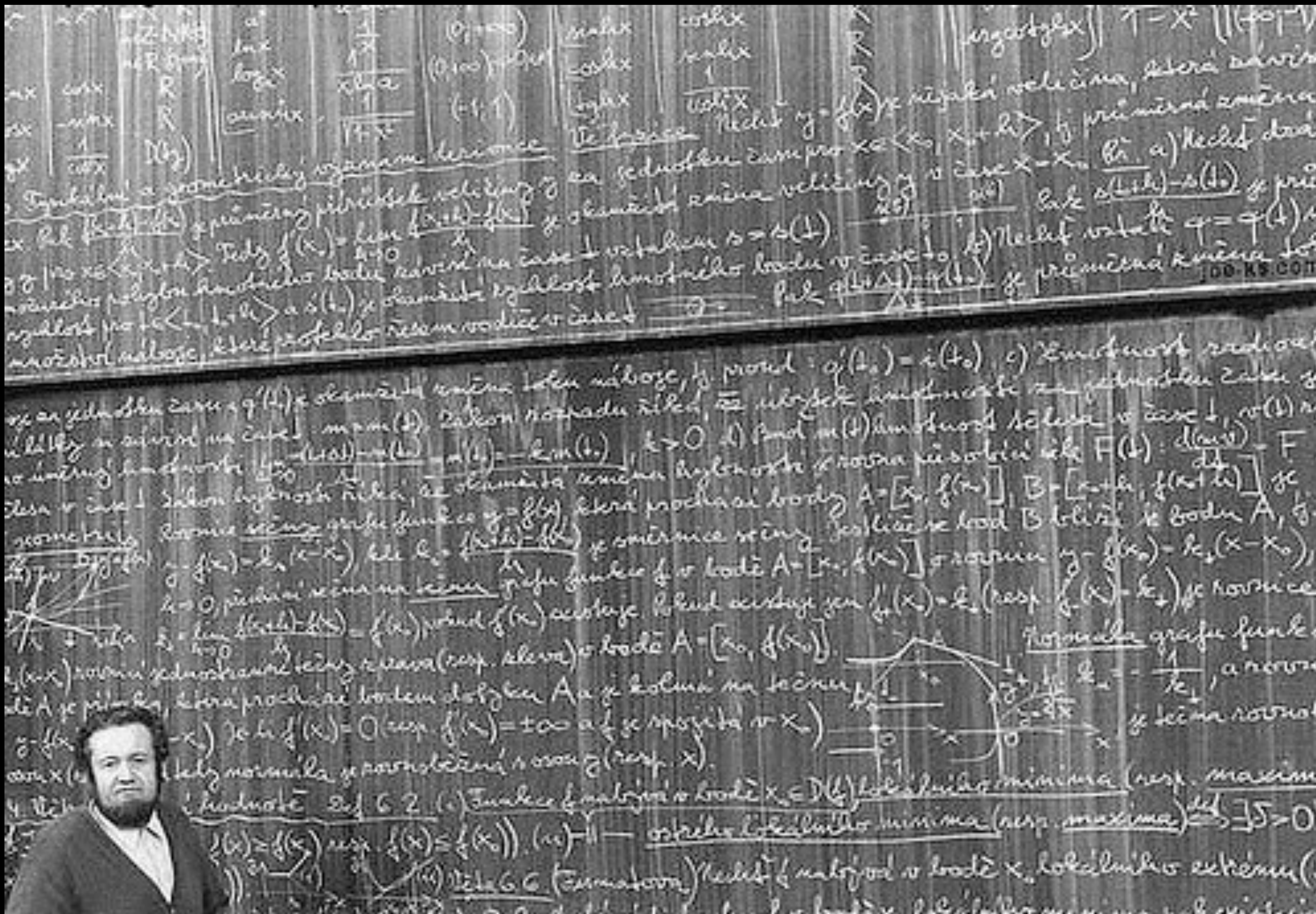
- Block on Port 3389 (IP address only)
  - Horizontal axis: lwRank from 0 (good/neutral) to 1 (very bad)
  - Vertical axis: log10(number of IPs in model)

Model: Example Feature (2)



- Block on Port 22 (IP address only)
  - Horizontal axis: lwRank from 0 (good/neutral) to 1 (very bad)
  - Vertical axis: log10(number of IPs in model)

How are we doing so far?



Training the Model

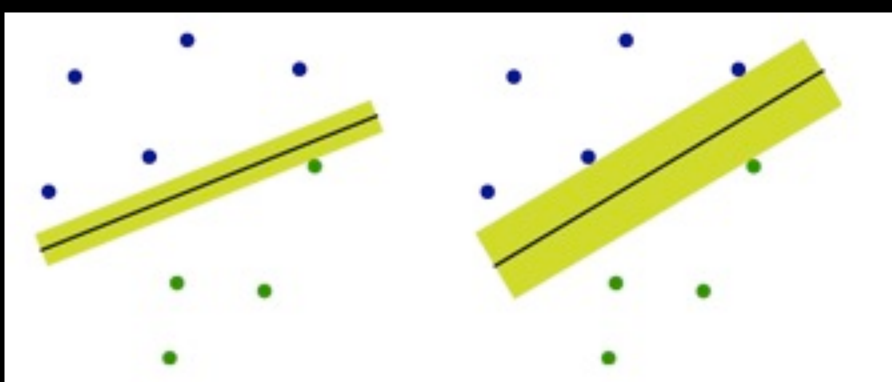
- YAY! We have a bunch of numbers per IP address!
- We get the latest blocked log files (SANS or not):
  - We have "badness" data on IP Addresses - <u>features</u>
  - If they were blocked, they are "malicious" - <u>label</u>
- Now, for each behavior to predict:
  - Create a dataset with "enough" observations:
  - Rule of Thumb: 70k - 120k is good because of empirical dimensionality.

Negative and Positive Observations

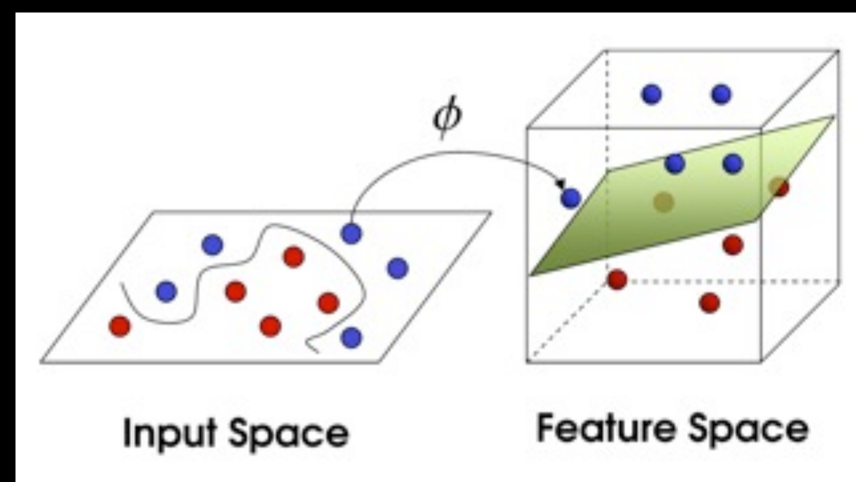
- We also require “non-malicious” IPs!
- If we just feed the algorithms with one label, they will get lazy.
- CHEAP TRICK: Everything is “malicious” - trivial solution
- Gather “non-malicious” IP addresses from Alexa and Chromium Top 1m Sites.

SVM FTW!

- Use your favorite algorithm! YMMV.
- I chose Support Vector Machines (SVM):
  - Good for classification problems with numeric features
  - Not a lot of features, so it helps control overfitting, built in regularization in the model, usually robust
  - Also <u>awesome</u>: hyperplane separation on an unknown infinite dimension.



Jesse Johnson – shapeofdata.wordpress.com



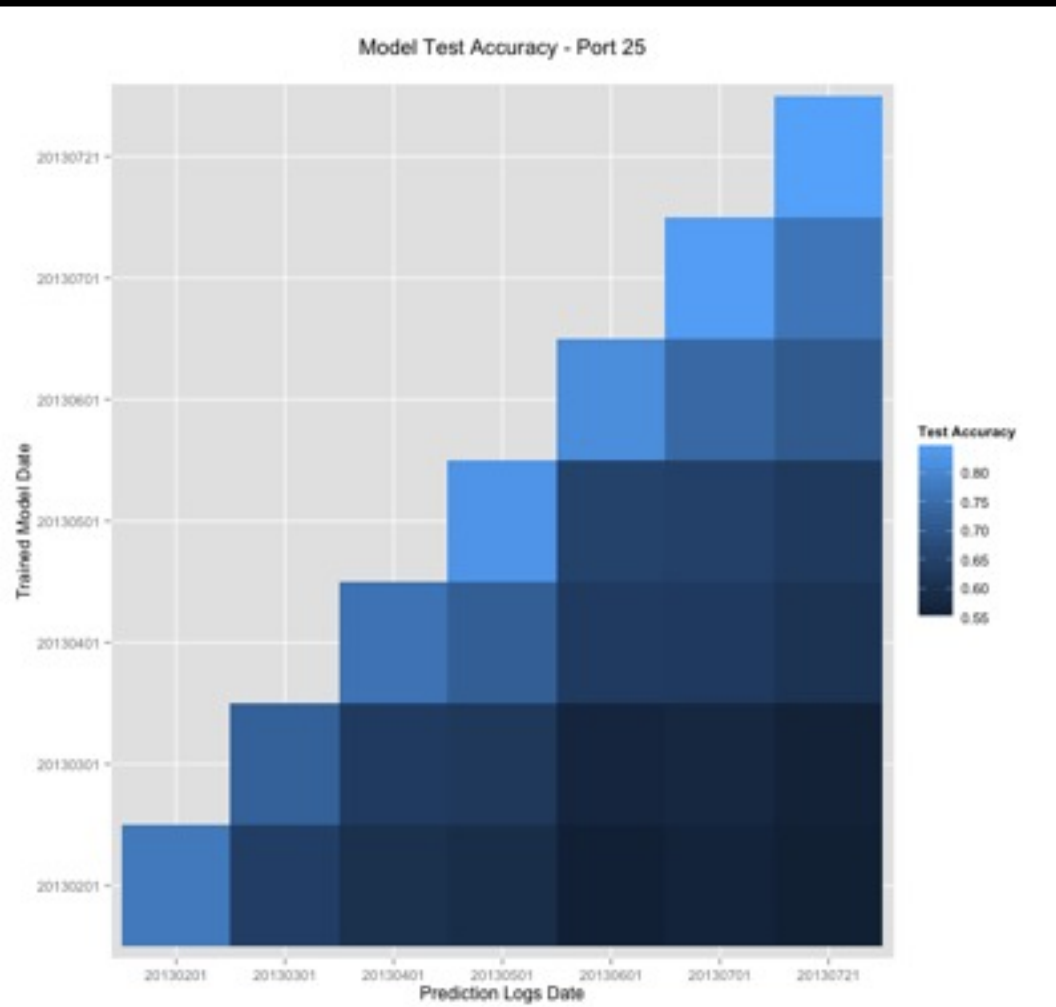
No idea… Everyone copies this one

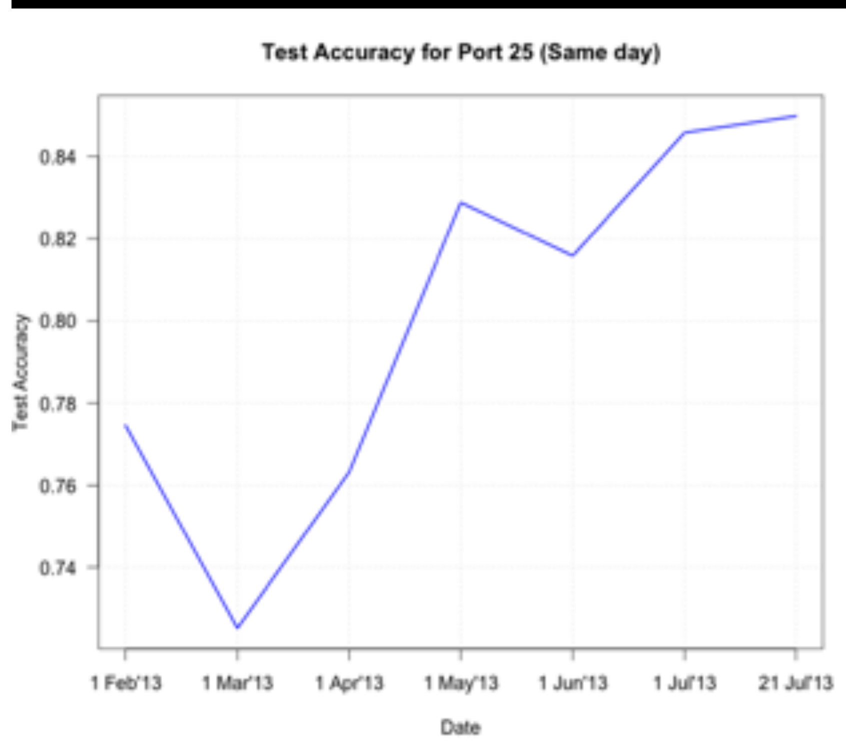
Results: Training/Test Data

- Model is trained on each behavior for each day
- Training accuracy* (cross-validation): 83 to 95%
- New data – test accuracy*:
  - Training model on day D, predicting behavior in day D+1
  - 79 to 95%, roughly increasing over time

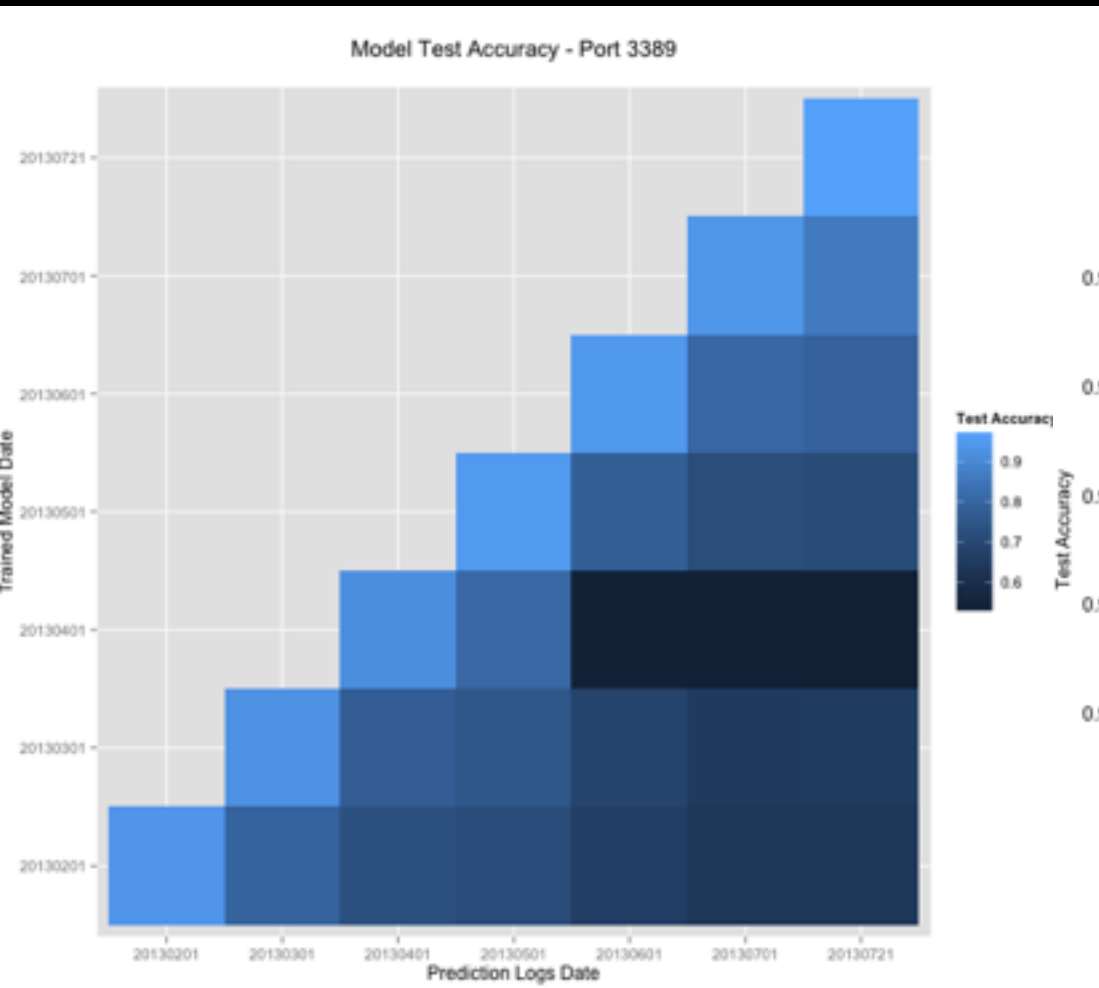
(*)Accuracy = (things we got right) / (everything we tried)

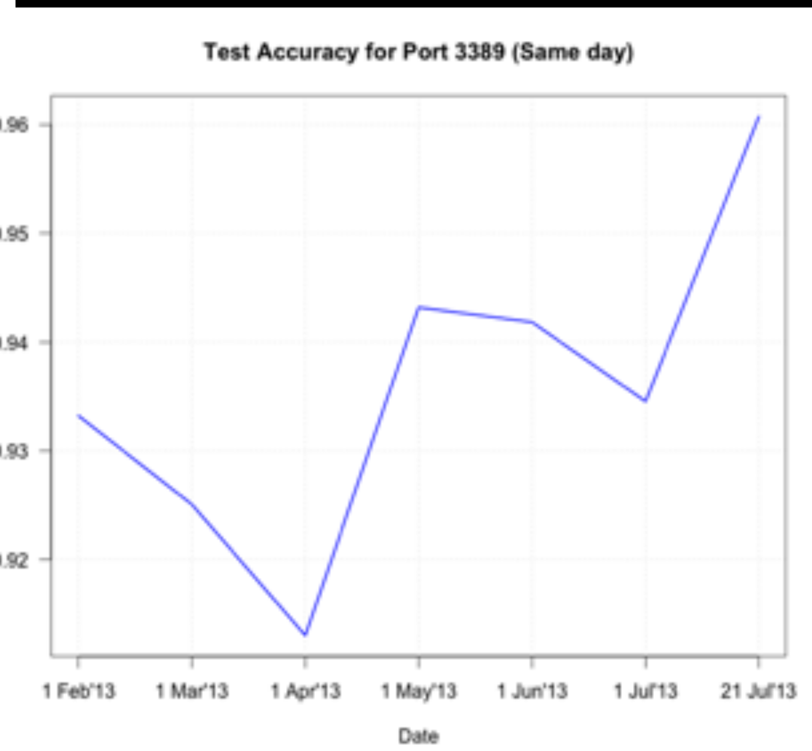
Results: Training/Test Data





Results: Training/Test Data





Results: New Data

$$LR+ = \frac{\Pr(T+|D+)}{\Pr(T+|D-)}$$

- How does that help?
- With new data we can verify the labels, we find:
  - 70 – 92% true positive rate (sensitivity/precision)
  - 95 – 99% true negative rate (specificity/recall)
- This means that (odds likelihood calculation):
  - If the model says something is “bad”, it is <u>13.6 to 18.5 times MORE LIKELY to be bad</u>.

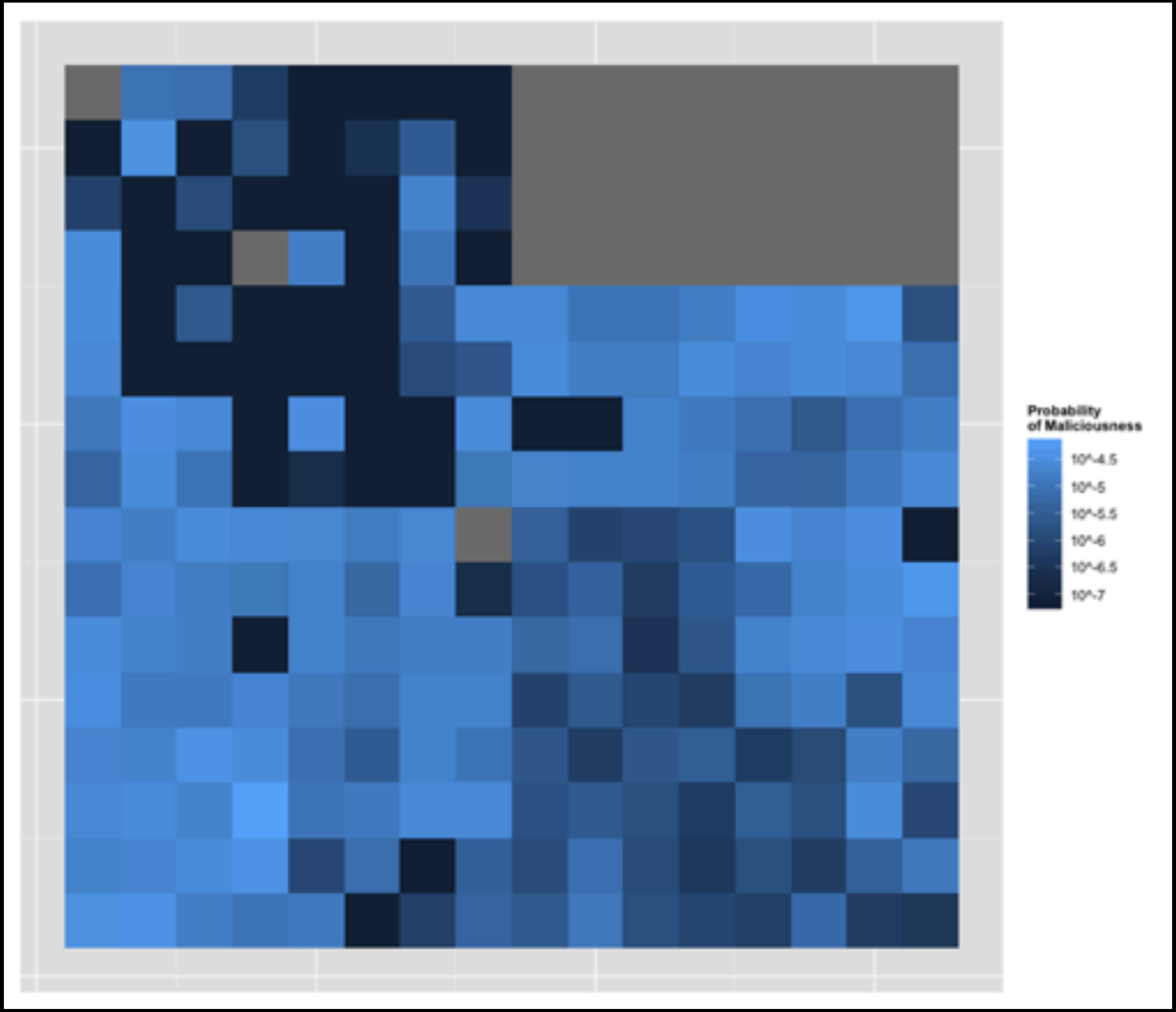
- Think about this.
- Wouldn’t you rather have your analysts look at these first?

Remember the Hilbert Curve?

<u>Behavior</u>: block on port 22

Trial inference on 100k IP addresses per Class A subnet

Logarithm scale: brightest tiles are 10 to 1000 times more likely to attack.

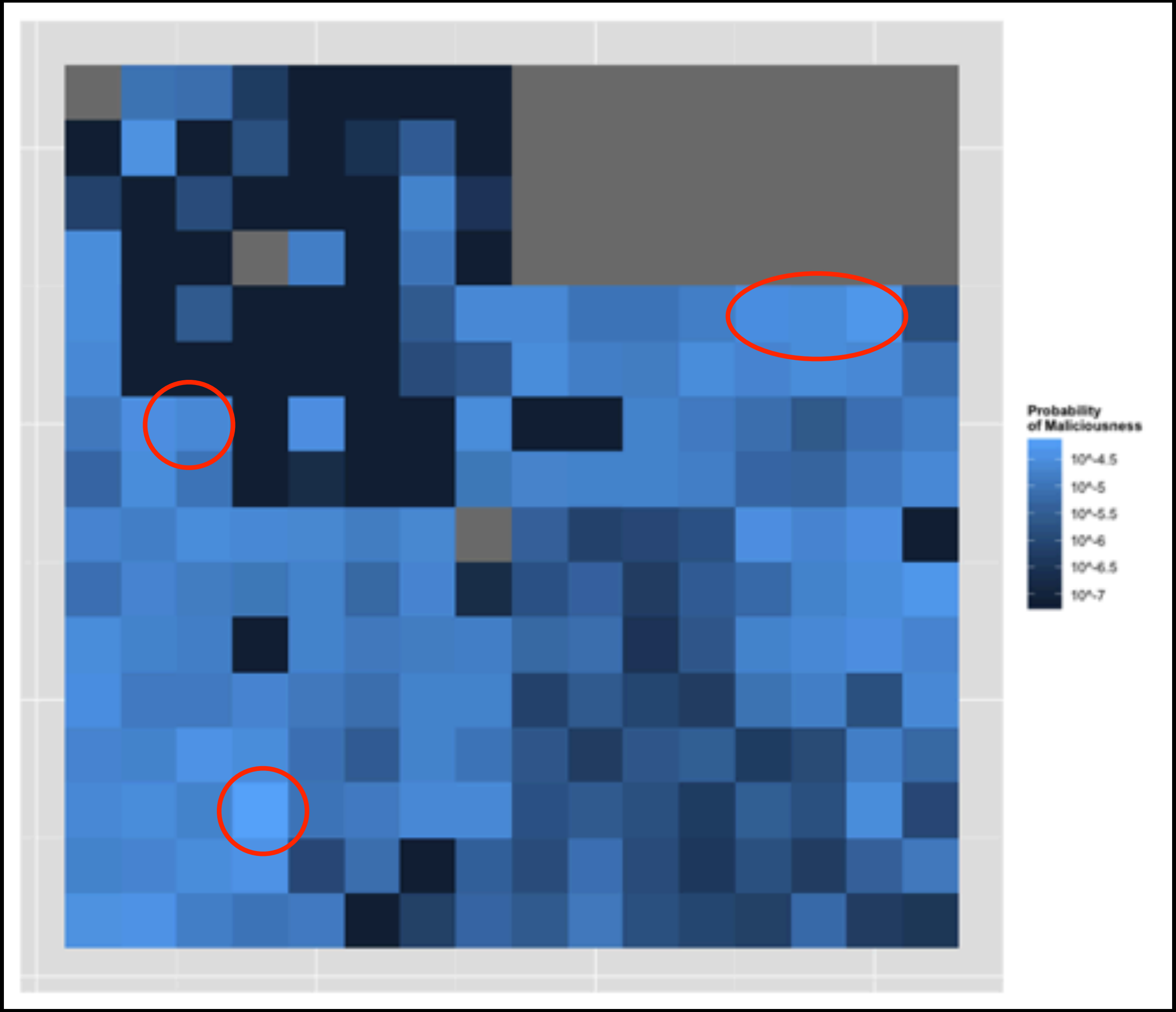


Remember the Hilbert Curve?

Behavior: block on port 22

Trial inference on 100k IP addresses per Class A subnet

Logarithm scale: brightest tiles are 10 to 1000 times more likely to attack.



Attacks and Adversaries

- IP addresses are not as reliable as they could be:
  - Forget about UDP
  - Lowest possible value for DFIR
- This is not attribution, this is defense
- Challenges:
  - Anonymous proxies (not really, same rules apply)
  - Tor (less clustering behavior on exit nodes)
  - Fast-flux Tor - 15~30 mins
- Process was designed with different actors in mind as well, given they can be clustered in some way.

Future Direction

- As is, the results from the predictions can help Security Analysts on tiers 1 and 2 of SOCs:
  - You can't "eyeball" all of the data.
  - Makes the deluge of logs produce something actionable
- The real kicker is when we compose algorithms (ensemble):
  - Web server -> go through firewall, then IPS, then WAF
  - Increased precision by composing different behaviors
- Given enough predictive power (increased likelihood):
  - Implement an SDN system that sends detected attackers through a "longer path" or to a Honeynet
  - Connection could be blocked immediately

Final Remarks

- Sign up, send logs, receive reports generated by machine learning models!
  - FREE! I need the data! Please help! ;)

- Looking for contributors, ideas, skeptics to support project as well.

- Please visit **https://www.mlsecproject.org** , message @MLSecProject or just e-mail me.

MLSec

MACHINE LEARNING SECURITY

Take Aways

- Machine learning can assist monitoring teams in data-intensive activities (like SIEM and security tool monitoring)

- The odds likelihood ratio (12x to 18x) is proportional do the gain in efficiency on the monitoring teams.

- This is just the beginning! Lots of potential!

- MLSec Project is cool, check it out and sign up

Thanks!

- Q&A?
- Don't forget to submit feedback!

Alexandre Pinto
alexcp@mlsecproject.org
@alexcpsec
@MLSecProject

"Prediction is very difficult, especially if it's about the future."

– Niels Bohr