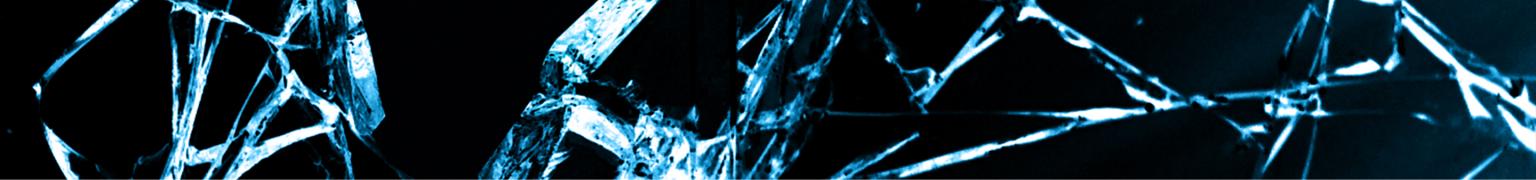


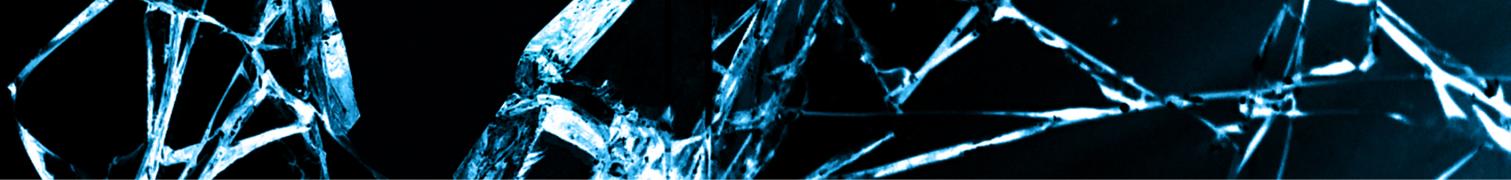


JULY 30 - AUGUST 4, 2016 / MANDALAY BAY / LAS VEGAS

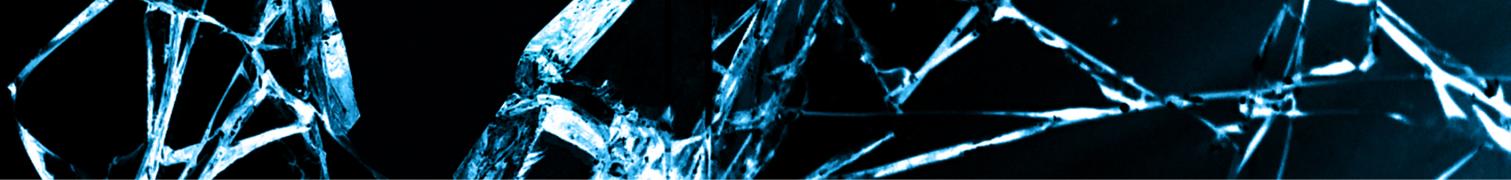


CALL ME: GATHERING THREAT INTELLIGENCE ON TELEPHONY SCAMS TO DETECT FRAUD

Aude Marzuoli, Ph.D.
Pindrop

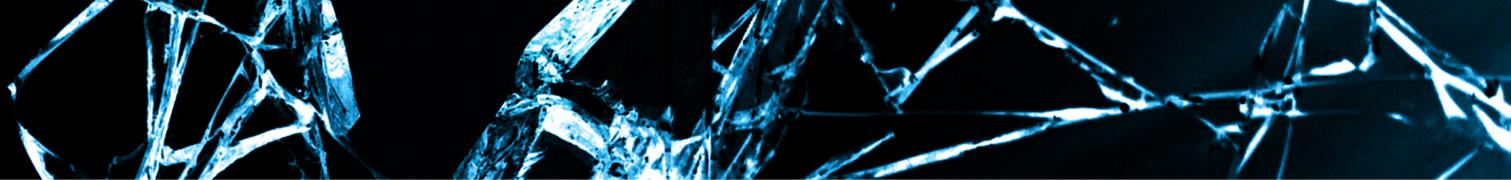


- Pioneer in voice fraud prevention and authentication helping companies eliminate phone fraud.
- Patented Phoneprinting™ technology can identify, locate and authenticate phone devices uniquely just from the call audio.
- Selected by the world's largest banks, insurers, brokerages and retailers, detecting over 80% of fraud, even for attackers never seen before.
- Pindrop was founded in 2011 and to date has raised \$122 million.



Outline

- Introduction to our Honeypot, a.k.a. Phoneypot
- Tracking spam/scam campaigns
- Gathering Intelligence on Telephony abuse
- Conclusion

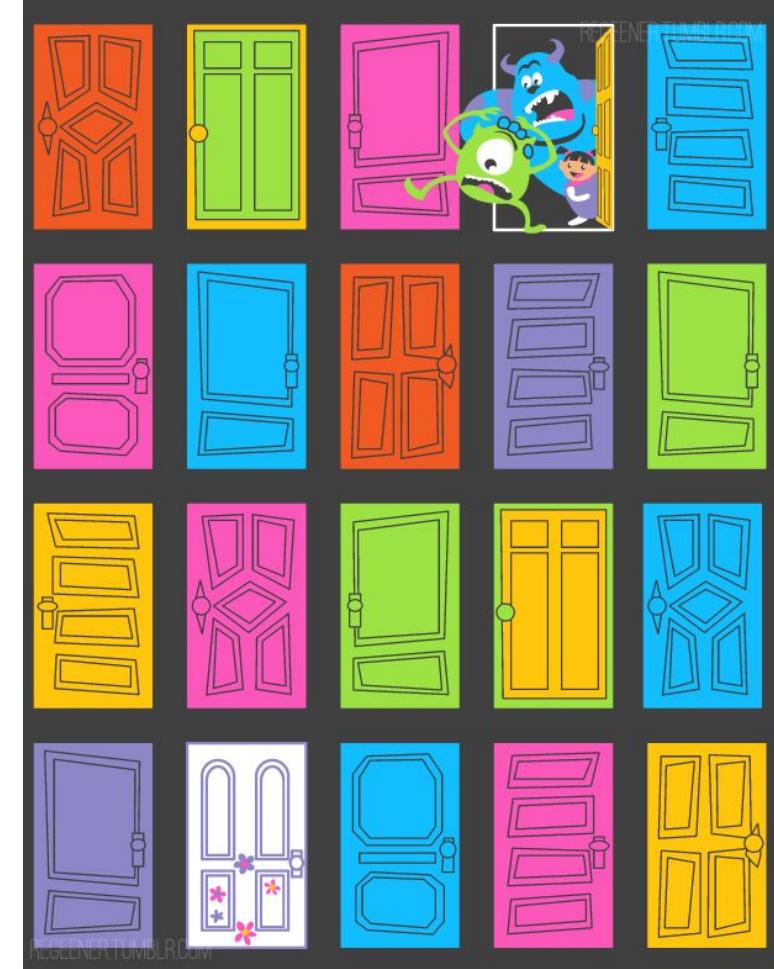


Introduction to Phoneypot

Who's REALLY calling you?



But now scammers are calling you direct





AT&T Says It Hates Robocalls Too; Still Not Giving Most Customers A Way To Block Them

 CNN Money

U.S. +

Business Markets Tech Media Personal Finance Sma

Google strikes back at robocalls

 ConsumersUnion®

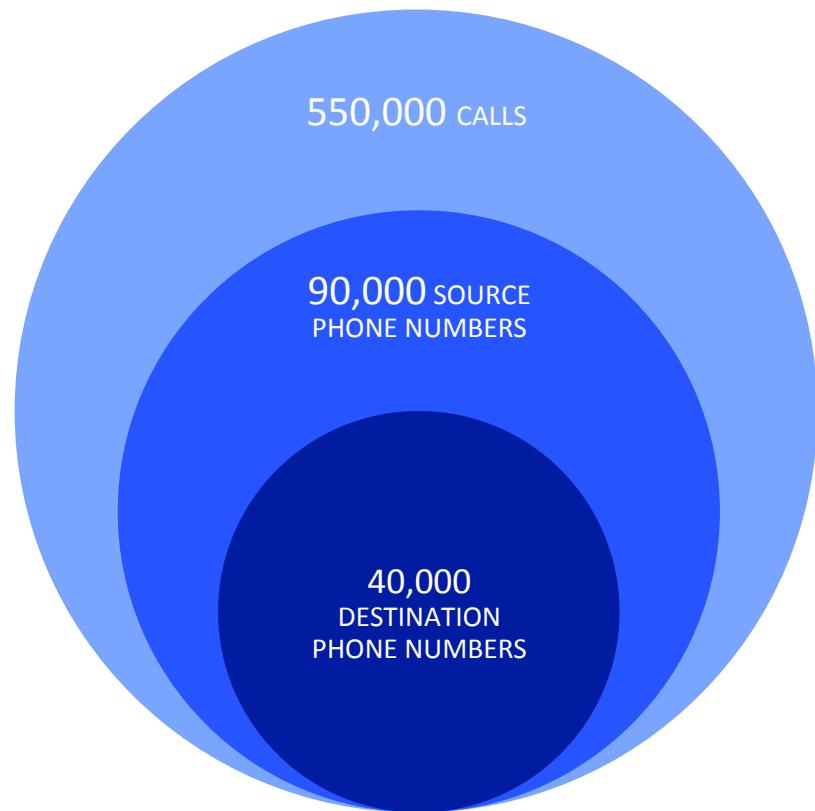
End Robocalls Activists File Over 15,000 Comments
with the FCC: No Robocalls to my Cell!

Why research telephony fraud?

- Understand the telephony fraud/scam ecosystem
- Gather threat intelligence through measurements and experiments
- Design defense strategies and deploy them

Honeypot

IN ONE MONTH



LIMITATIONS

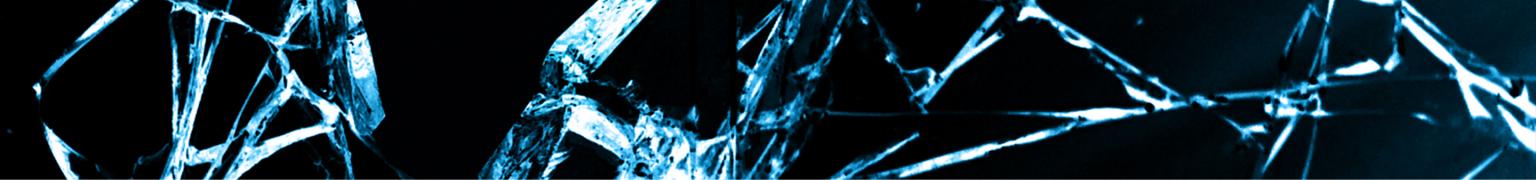
- Source phone numbers spoofing
- Most phone numbers call once or twice
- Labels Needed

During the first half of 2016, we recorded 100,000 calls to our Honeypot.

PHONEYPOT VS ONLINE COMMENTS

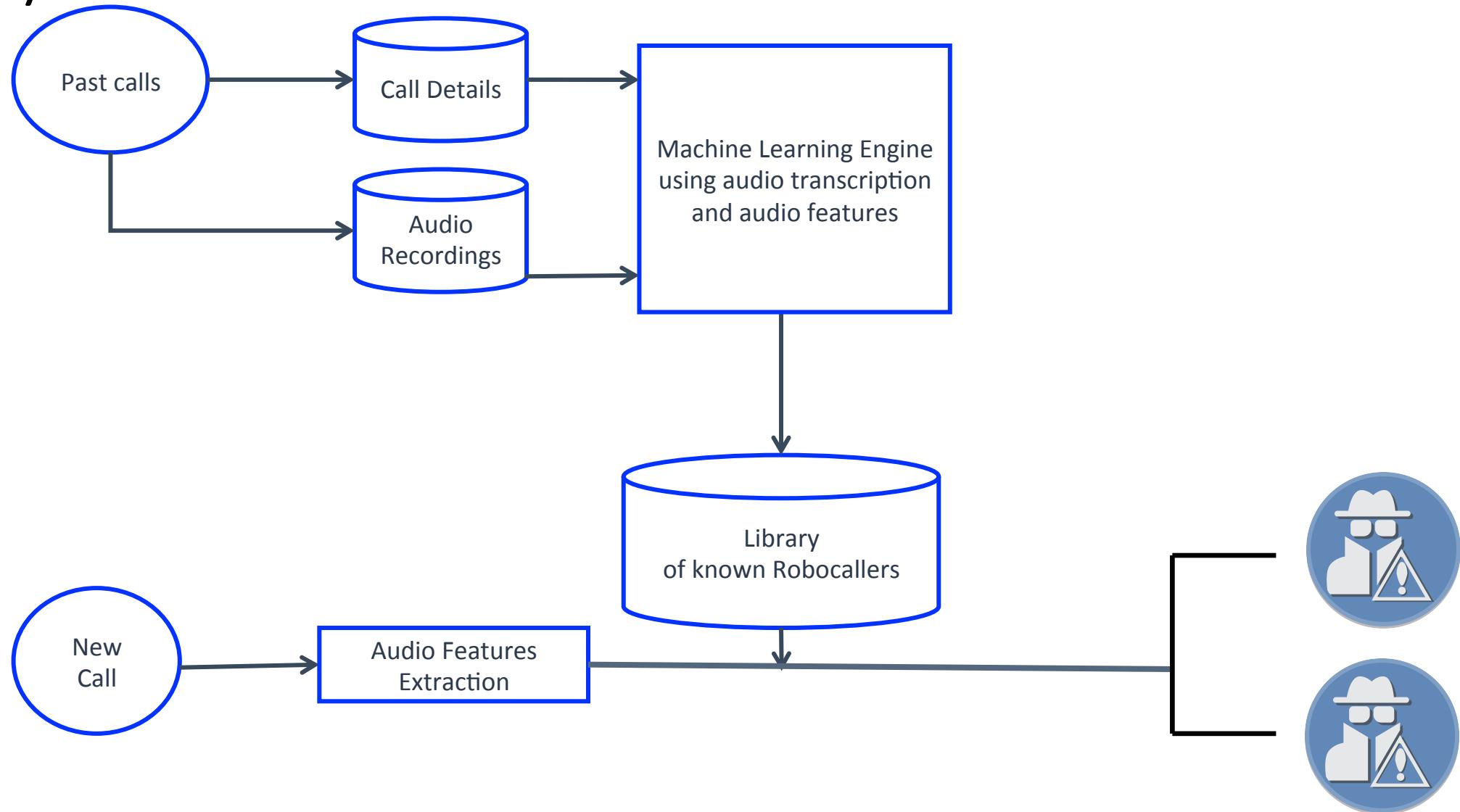
Data set	# of calls	# of source phone numbers	Max. # of calls or comments per source phone number
Phoneypot	8,000,000	880,000	21,329
Online Comments	660,000	74,000	2,156

- Data set collected for year 2015.
- 66% of online comments are complaining about only 2% of sources in the Phoneypot.



Tracking spam/scam campaigns

System Overview

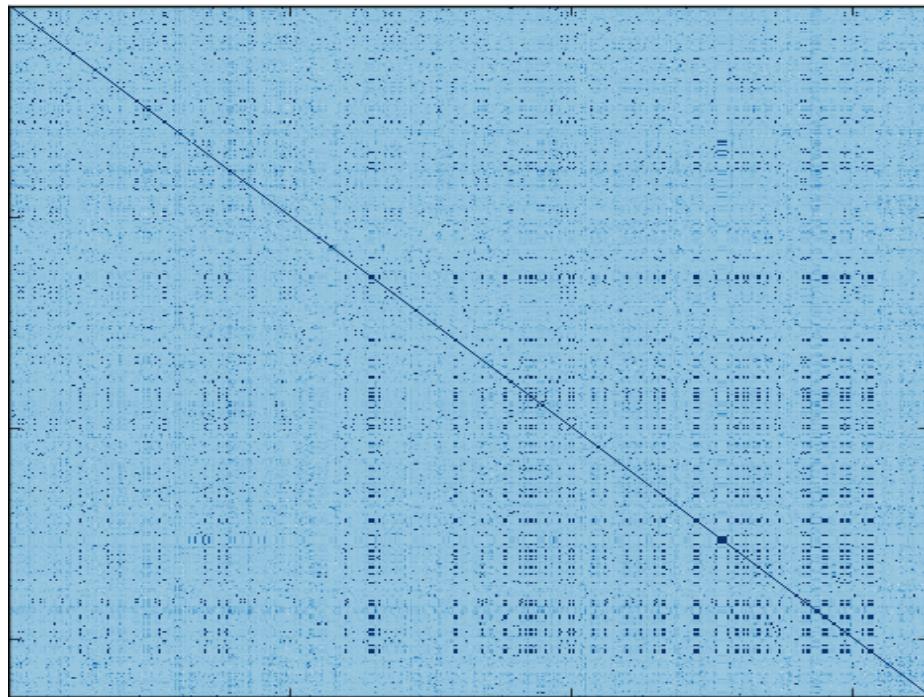


Keywords are too noisy

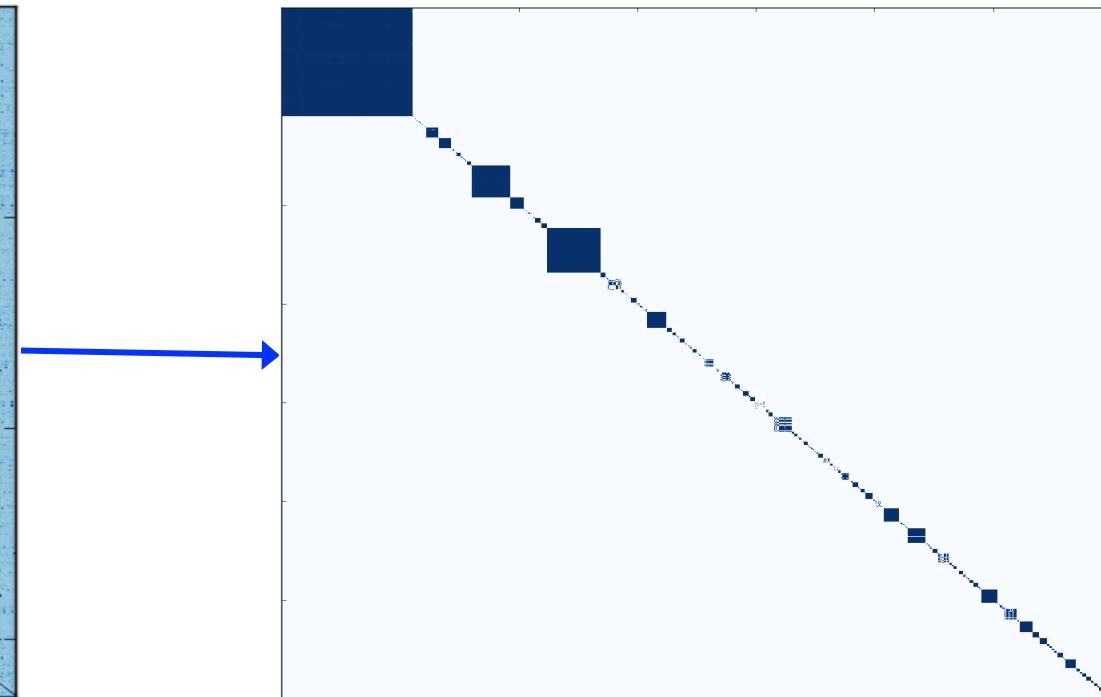
Transcript to compare:

- “press one to say **fifty per cent** on your **electric bill** with **no money out of pocket** using in **new jersey** sober company with **hundreds of satisfied customers** pressed to and **continue paying one of the highest electric utility rates**”
- **93%** similarity to:
 - “oh **press one** to say **fifty percent** on your **electric bill** with **no money out of pocket** to using a **new jersey's older company** with **hundreds of satisfied customers** pressed to in **continue paying one of the highest electric utility rates**”
- **63%** similarity to:
 - “hi we're just doing the quick survey where you where the **new jersey** residence or now entitled to the rebate on their **electric bills** twice a year and a twenty five dollar visa gift card press one”
- **39%** similarity to:
 - “do you have at least ten thousand dollars in credit card debt and medical **bills** would you like to hear about of program that can reduce your bounds or than effectively eliminate your interest”

Clustering of transcripts similarity matrix

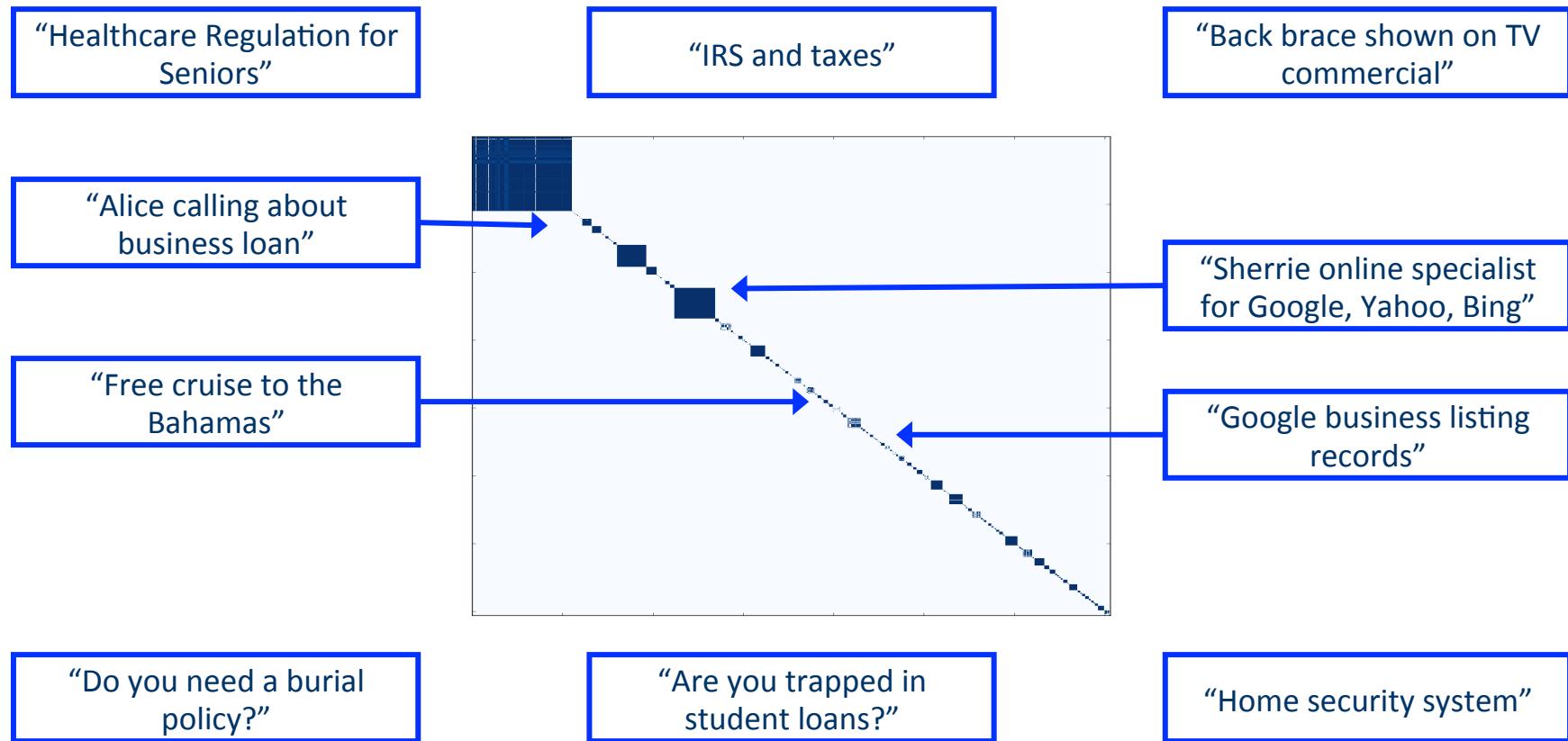


Raw similarity matrix between all pairs of transcripts
Dark dot if transcript i is similar to transcript j

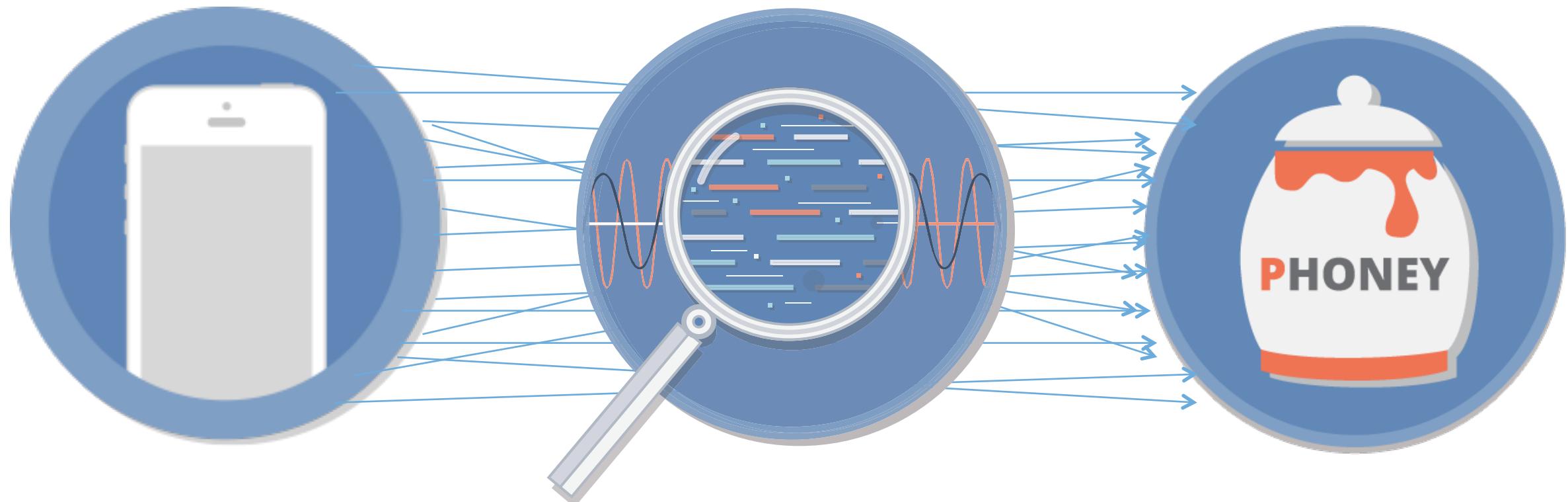


Spectral clustering Results

Cluster extraction



Cluster Phoneprinting



Source phone numbers
whose calls correspond to
identical audio recordings

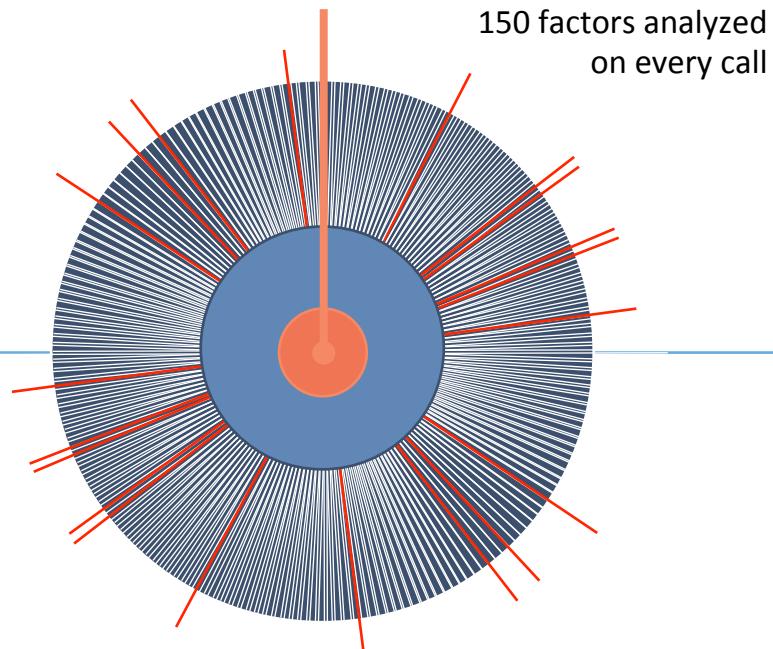
Extract **150** audio
features for all calls in
the same cluster

Phoneypot destination
phone numbers

Phoneprinting



Initial call



Call Type



Geo-Location



Unique Phone



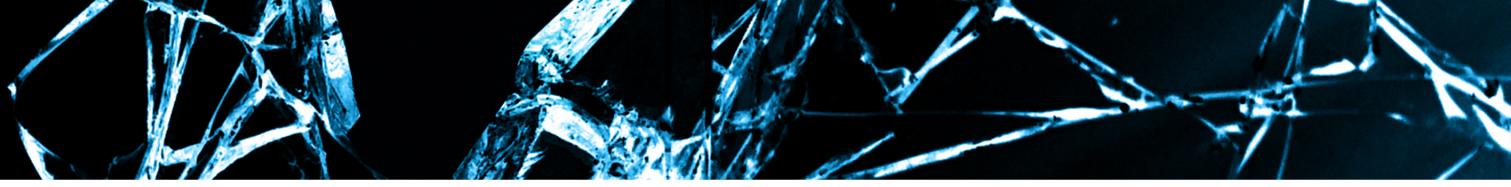
Spectrum
Quantization, Frequency
filters, Codec artifacts



Noise
Clarity, Correlation,
Signal-to-noise ratio

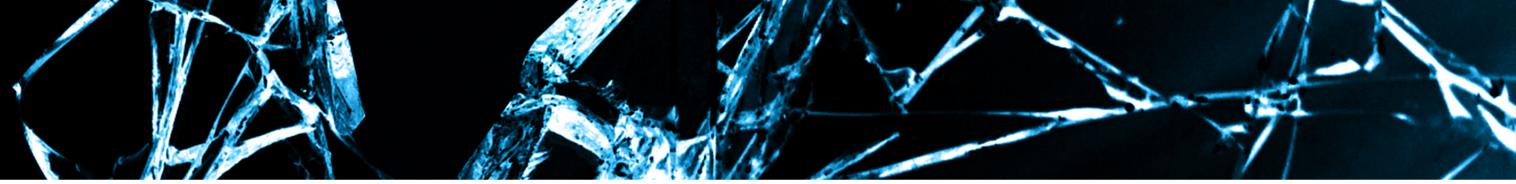


Loss
Packet loss, Robotization,
Dropped frames



Phoneprinting distinct bad actors

- Feed the classifier:
 - Positive class: audio features from all calls in the same cluster
 - Negative class: audio features from any other call
- Tested across more than 50 clusters:
 - Average performance: 85.5% True Positive Rate at 0.25% False Positive Rate
 - Good performance even with <2 calls for each source phone number.
- Good phoneprint performance on a cluster implies that all calls from this cluster come from the same physical telephony infrastructure.

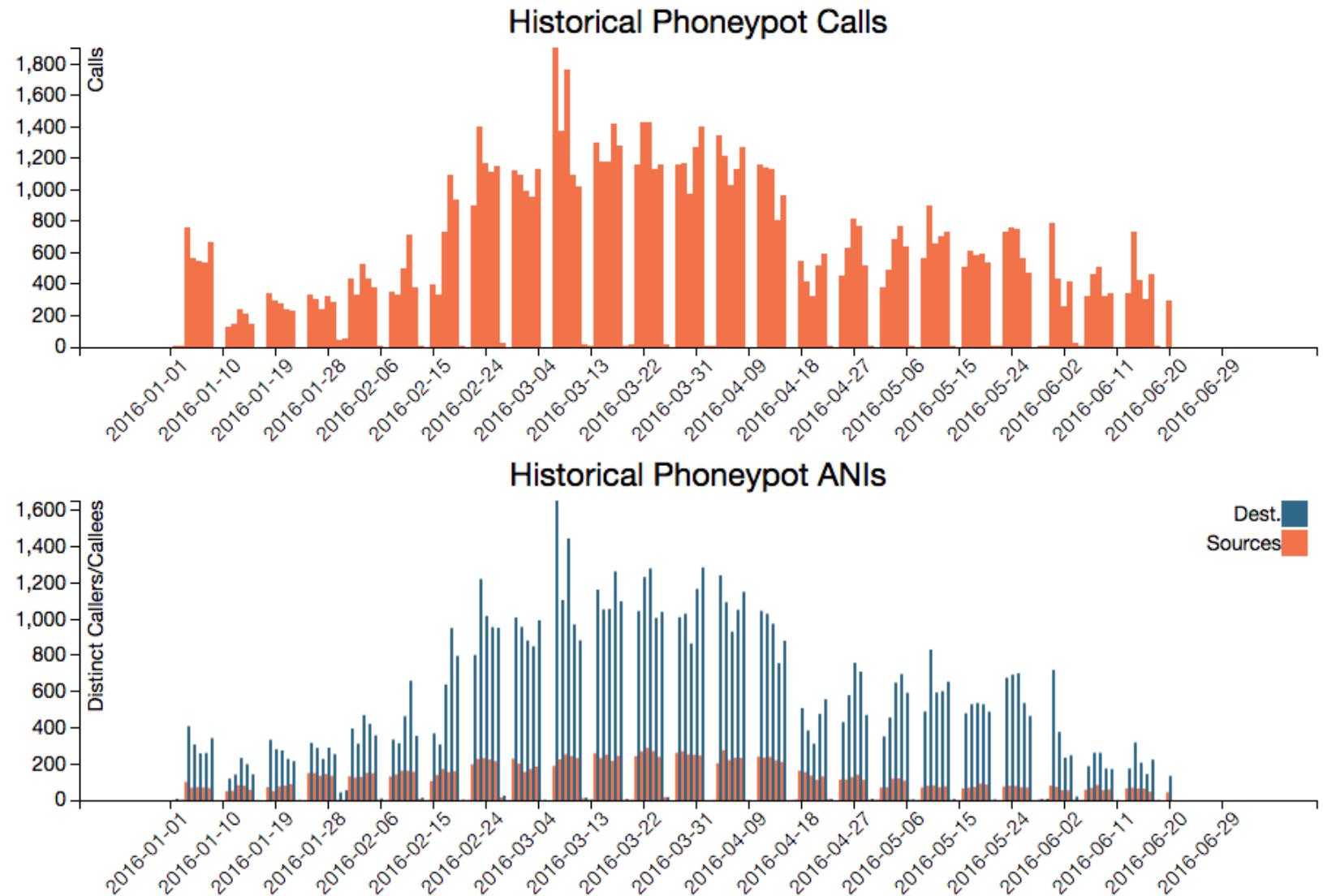


Gathering Intelligence on Telephony abuse

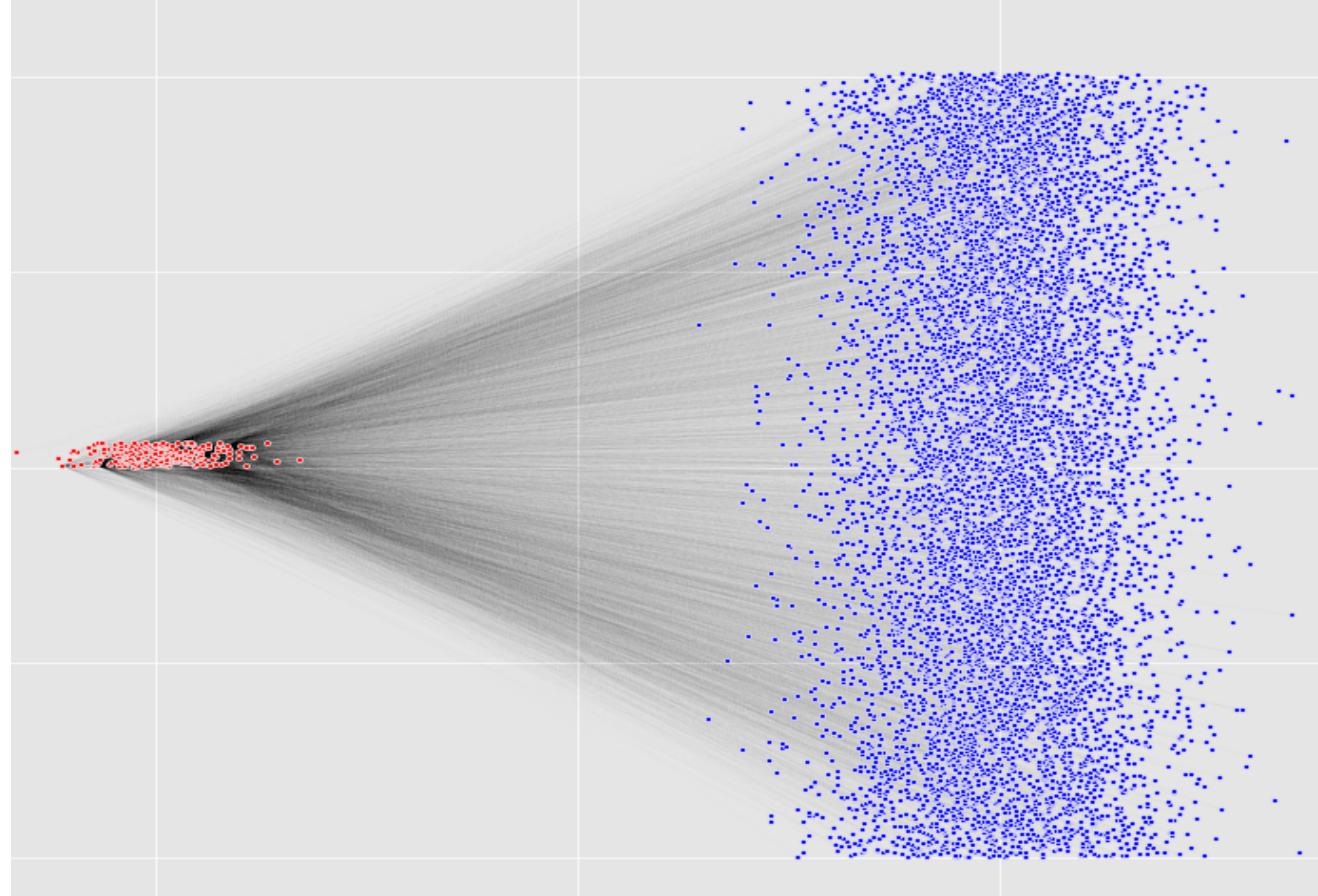
Google-related scams

- One of the most complex scams
- More than 10 different recordings targeting Google users, from Google maps to Google plus.
- Asking you to pay money for front page placement on Google search results.
- Asking you to “verify” personal information.

* two of our backers are Google capital and GV



Sharon, your Google specialist



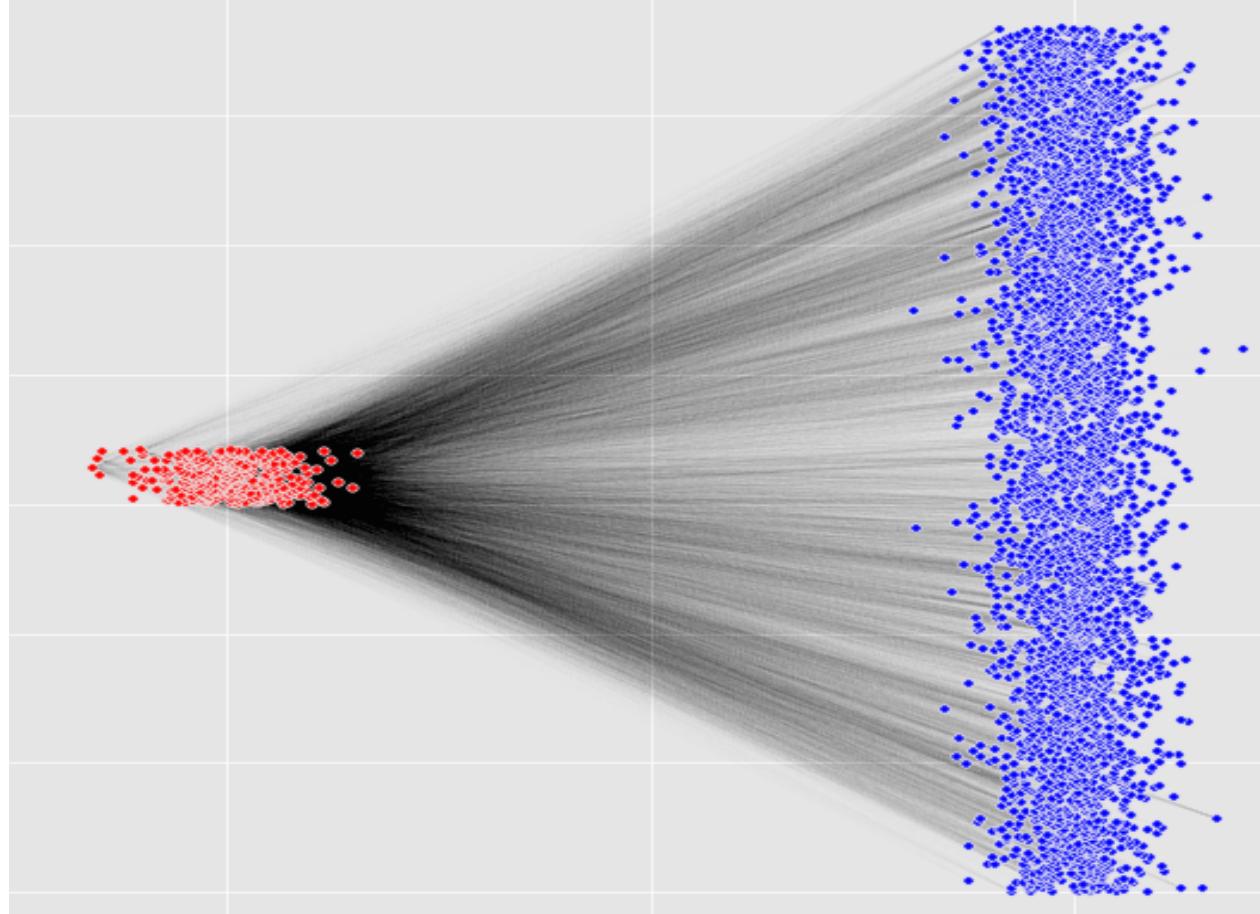
253 Source phone numbers

27,928 calls from January to July 2016

17,160 destination phone numbers from Phoneypot

- “Hi this is Sharon your local Google specialist. We have a front page position available for a business like yours and can guarantee front page placement with unlimited clicks 24 hours a day at a flat rate on Google. Press one key right now to see if you qualify and are interested in receiving calls from companies who are locally searching for your type of business. Please press one now or press the two key to be removed. Thank you.”
- Phoneprint performance: 93.4% TPR at 0.4% FPR

Google Business listing



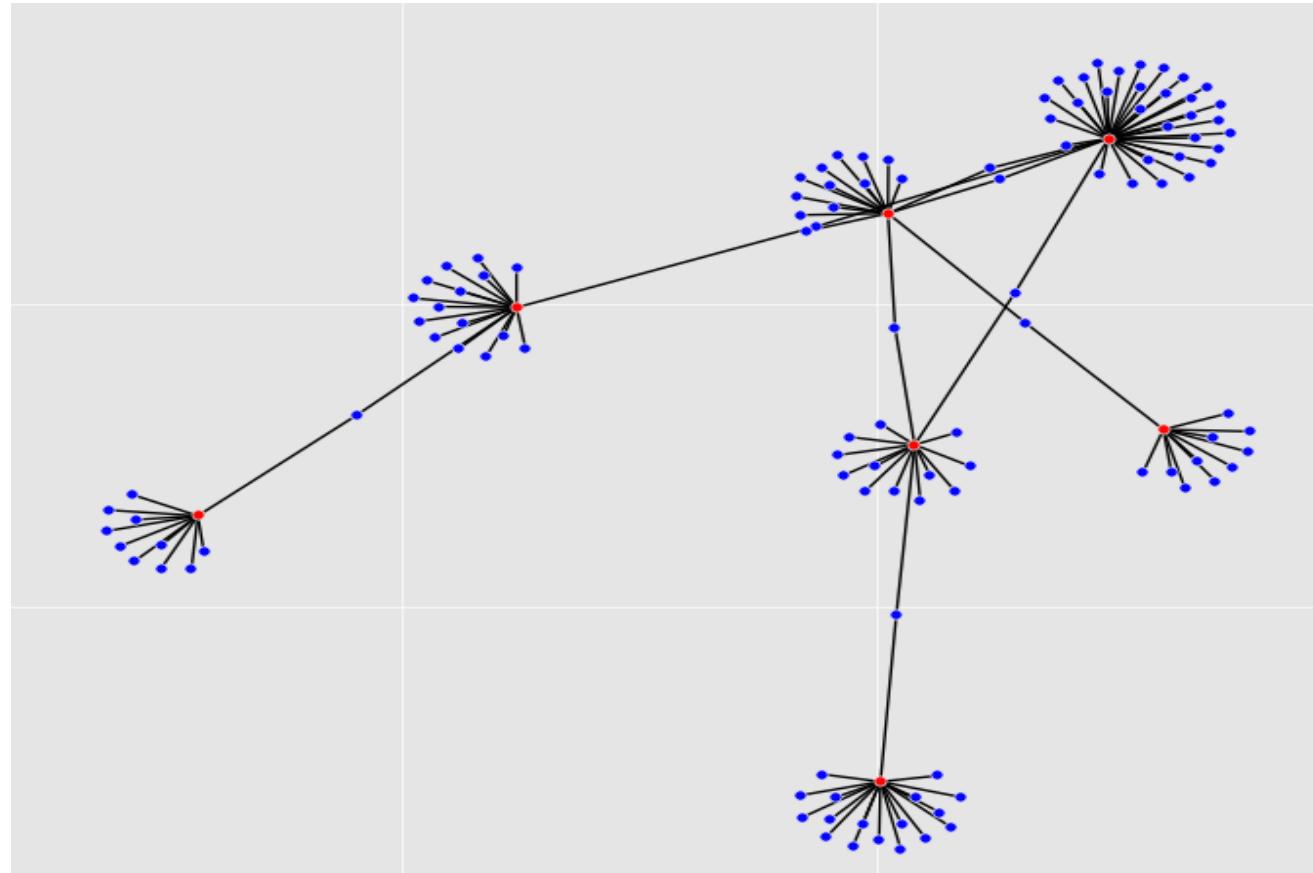
410 Source
phone numbers

34,048 calls
from January
to July 2016

26,841 destination phone
numbers from Phoneypot

- “This is an important call regarding your google business listing. We need to verify your contact information. Press one now to verify your google business listing. Press seven to remove yourself from the verification system. ”
- Phoneprint performance: 92.7% TPR at 0.2% FPR

Debt Collectors



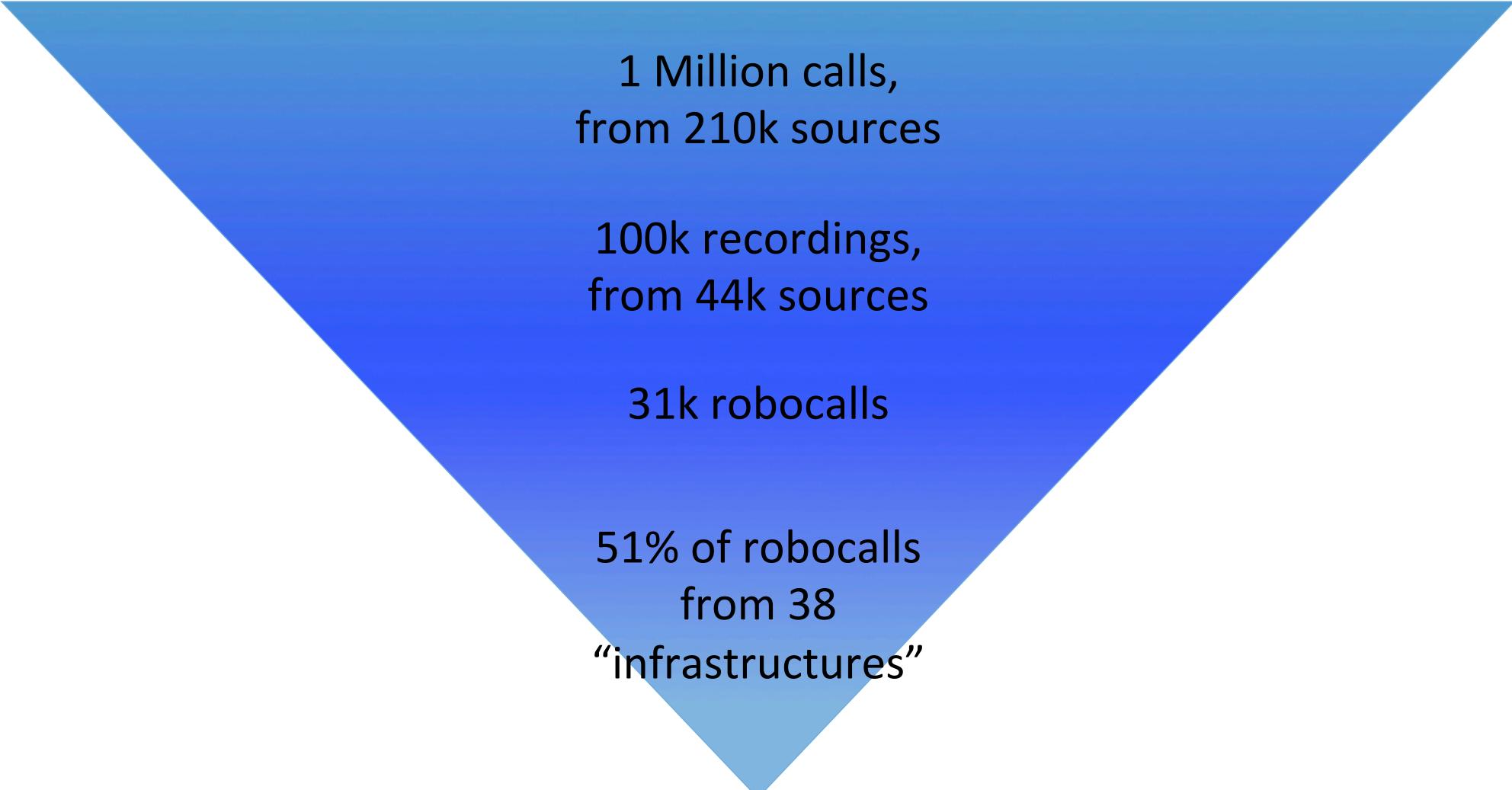
7 Source phone
numbers

1,301 calls
from January
to July 2016

92 destination phone
numbers from Phoneypot

- “This call is from XXXX outsourcing, a debt collector. Please return my call at 866-XXX-XXXX. ”
- Targeted harassment tactics

Experiment Overview

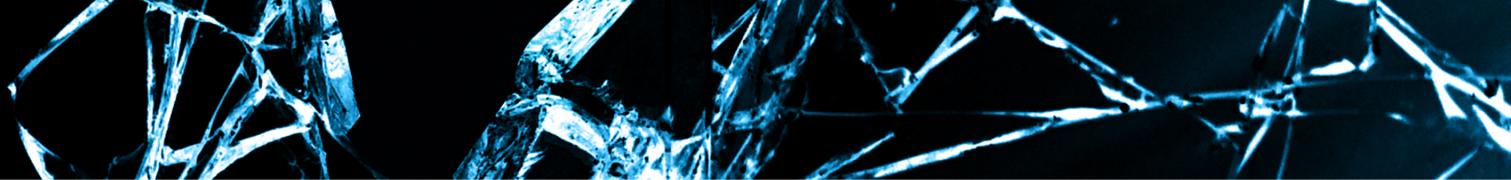


1 Million calls,
from 210k sources

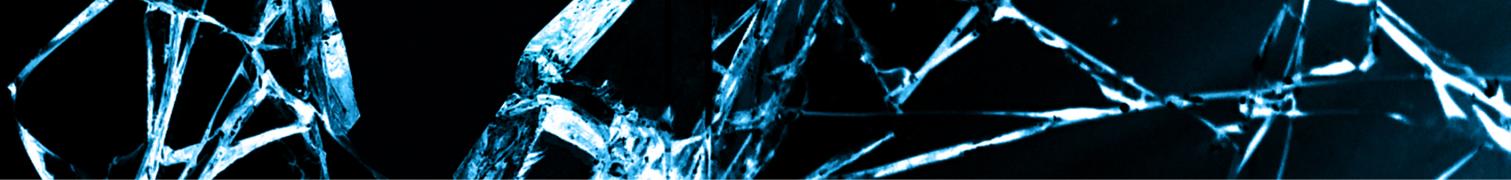
100k recordings,
from 44k sources

31k robocalls

51% of robocalls
from 38
“infrastructures”



CONCLUSION



Conclusion

- We recorded 100,000 calls over several months in 2016.
- Using machine learning on call patterns, semantics and audio features, we can uniquely identify one bad actor hiding behind several source phone numbers, whether these numbers are legitimate or spoofed.
- Our results show that 51% of the robocalls recorded are placed by 38 distinct telephony infrastructures which can be uniquely identified with more than 85% TPR on average.

Acknowledgements & Questions

Data Science team at Pindrop:

Hassan Kingravi, David Dewey, Aaron Dallas, Telvis Calhoun, Terry Nelms

