



**AUGUST 6-7, 2025**  
MANDALAY BAY / LAS VEGAS



# Exploiting DNS for Stealthy User Tracking

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IoT security, vulnerability  
research  
Scientist at heart



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Junior Security Researcher  
Applied ML techniques, IoT  
security



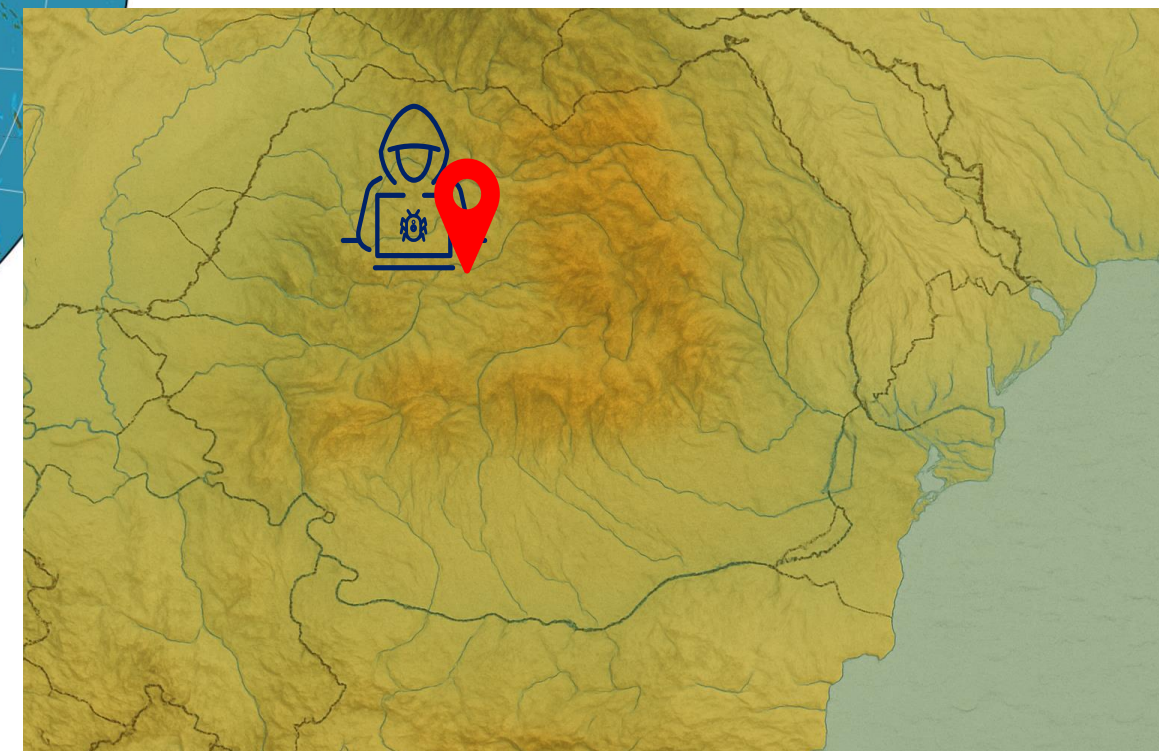
**Dan MACOVEI**

Director of Product  
Management  
Security Product Strategy

**Bitdefender.**



# The Transylvanian researchers



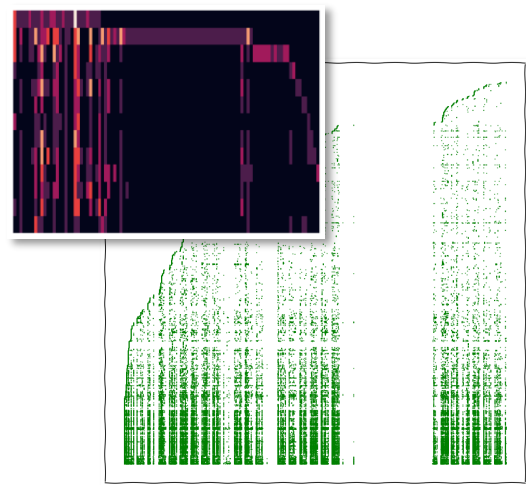


# Agenda

1  
Introduction  
& the why?



DNS request patterns & transformations



Conclusions & key  
takeaways

5

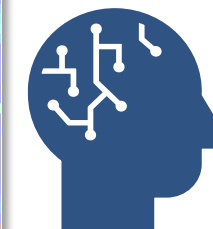
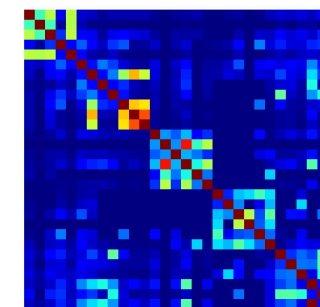


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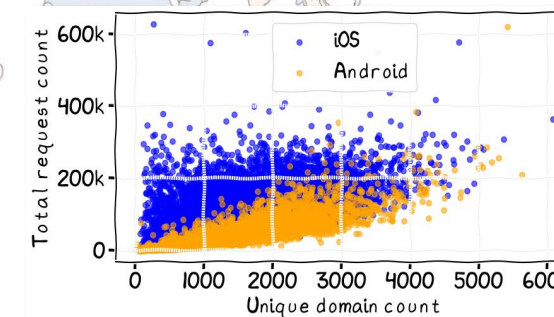
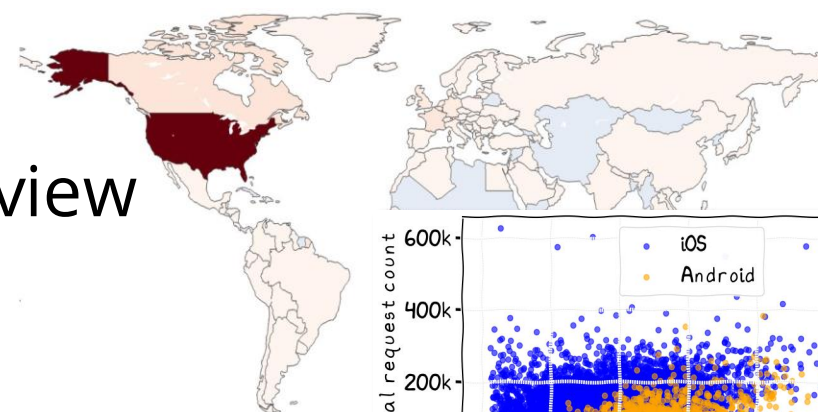
4

User tracking:  
approach and  
results



2

A bird's eye view





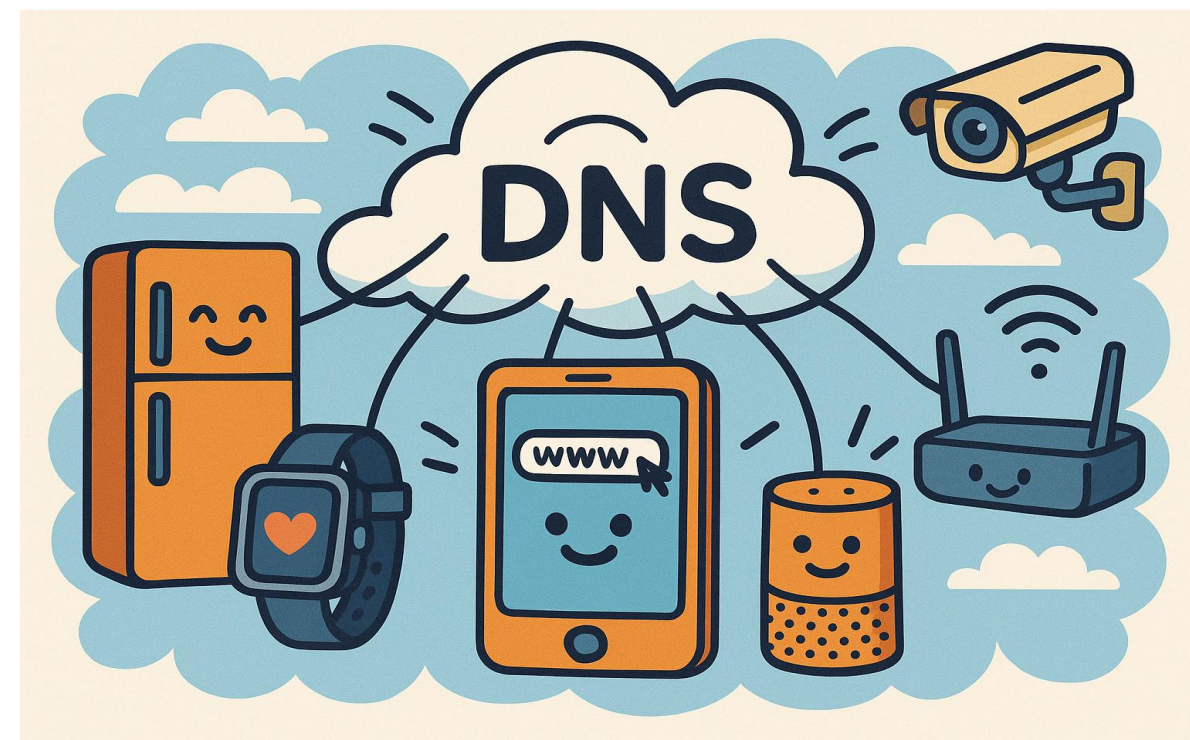
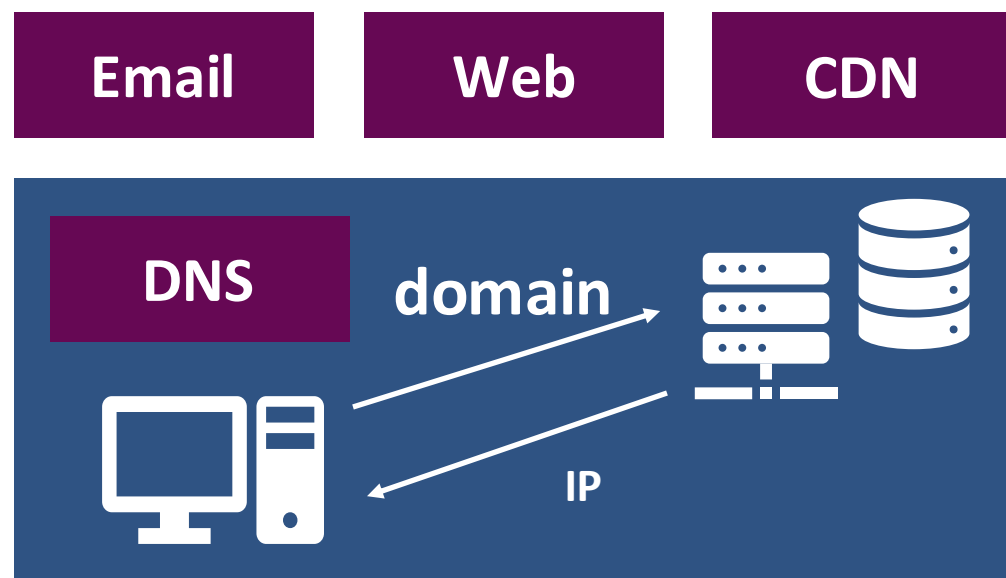
# Introduction & motivation





# The Domain Name System (DNS)

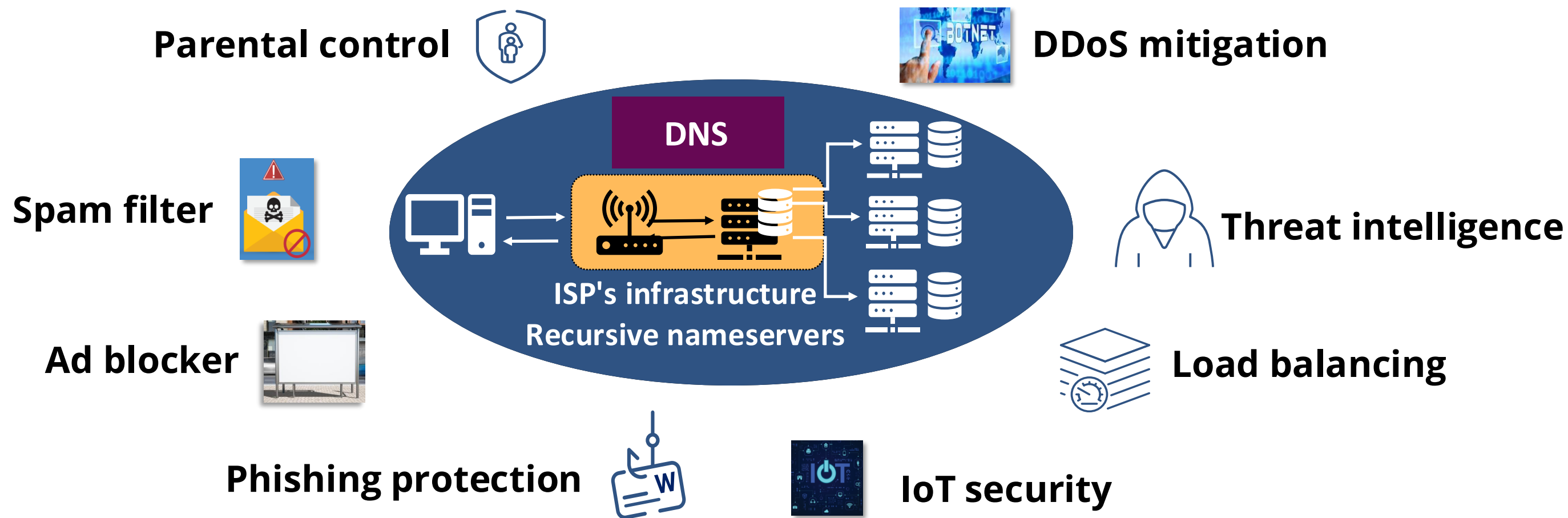
- The "phonebook of the internet"
- Translate human-readable domain names into IP addresses
- ALL devices use DNS



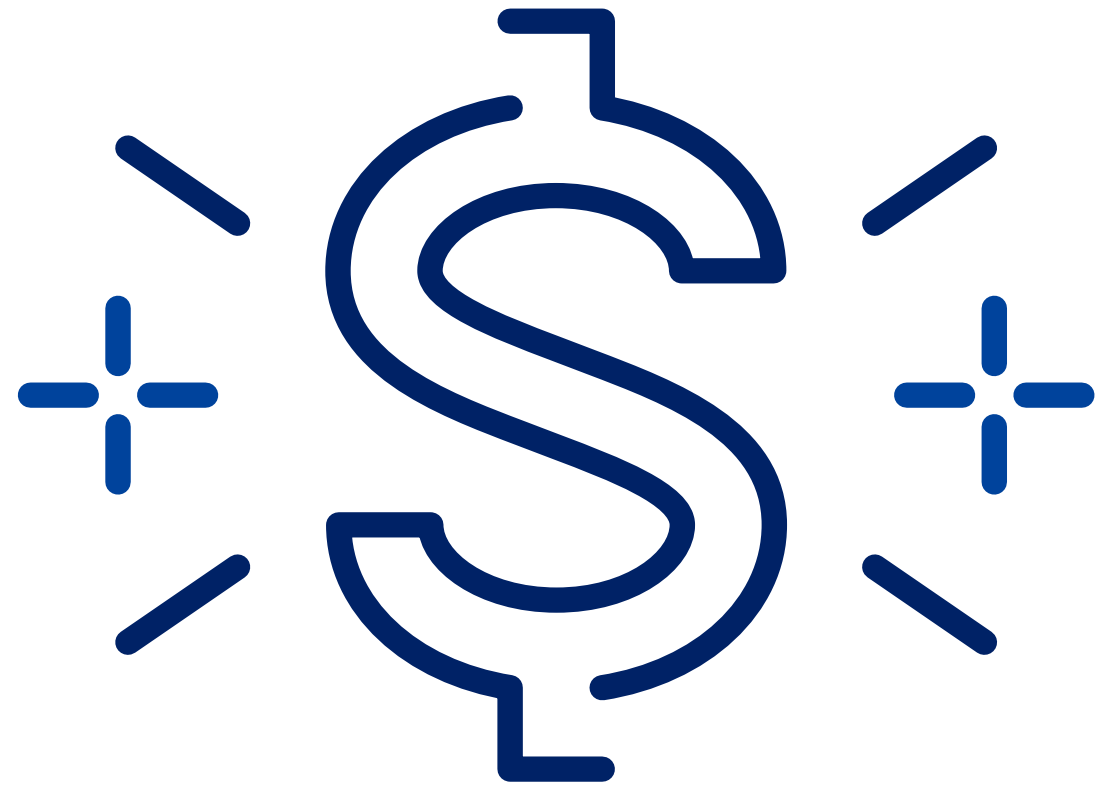


# DNS and security applications

- DNS has a critical role in security applications
- DNS fuels the applications aimed to protect networks and users



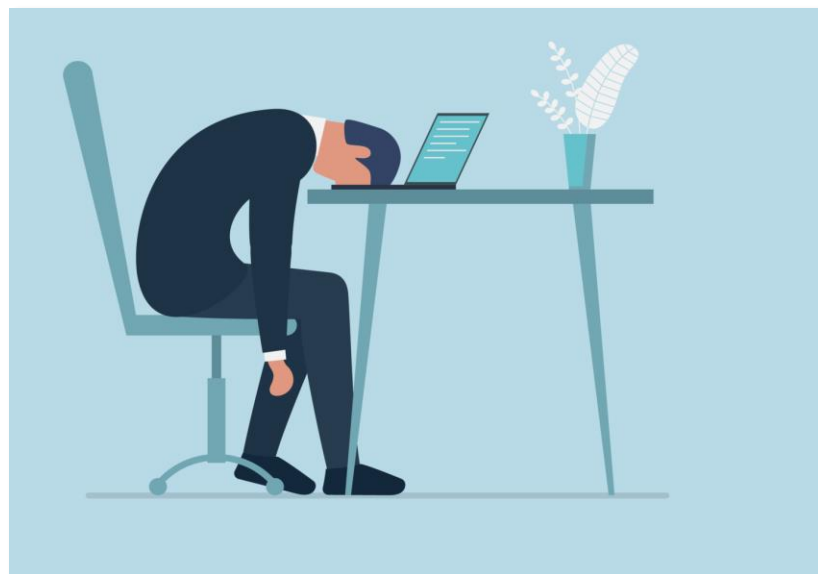




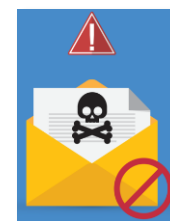


# Why this research on DNS?

Looking for ways to improve security solutions



**Parental  
control**



**Spam  
filter**



**Ad  
blocker**





# What we observed

Noticed **interesting** sequences for devices in our testbed @office

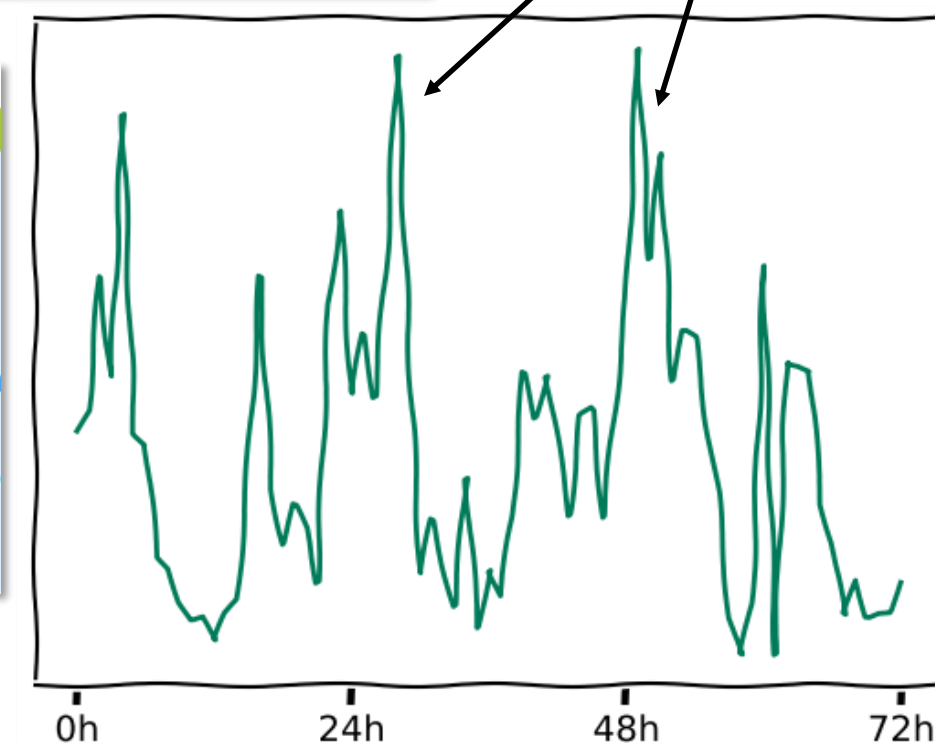
Protocol	Length	Info
DNS	163	Standard query response 0xc9b7 HTTPS mask.apple-dns.net SOA ns-1096.awsdns-09.org
DNS	147	Standard query response 0xf034 A comm-main.ess.apple.com CNAME comm-main.ess-apple.com.akadns.net
DNS	85	Standard query 0x8d80 A comm-cohort.ess.apple.com
DNS	151	Standard query response 0x8d80 A comm-cohort.ess.apple.com CNAME comm-cohort.ess-apple.com.akadns
DNS	69	Standard query 0x7269 HTTPS slack.com
DNS	69	Standard query 0xd4ed A slack.com
DNS	151	Standard query response 0x7269 HTTPS slack.com SOA ns-1493.awsdns-58.org
DNS	165	Standard query response 0xd4ed A slack.com A 52.29.238.212 A 3.68.124.95 A 18.159.197.225 A 3.68.1
DNS	77	Standard query 0x7d2f HTTPS captive.apple.com
DNS	77	Standard query 0xb55b A captive.apple.com

iOS

Repetitive  
behavior

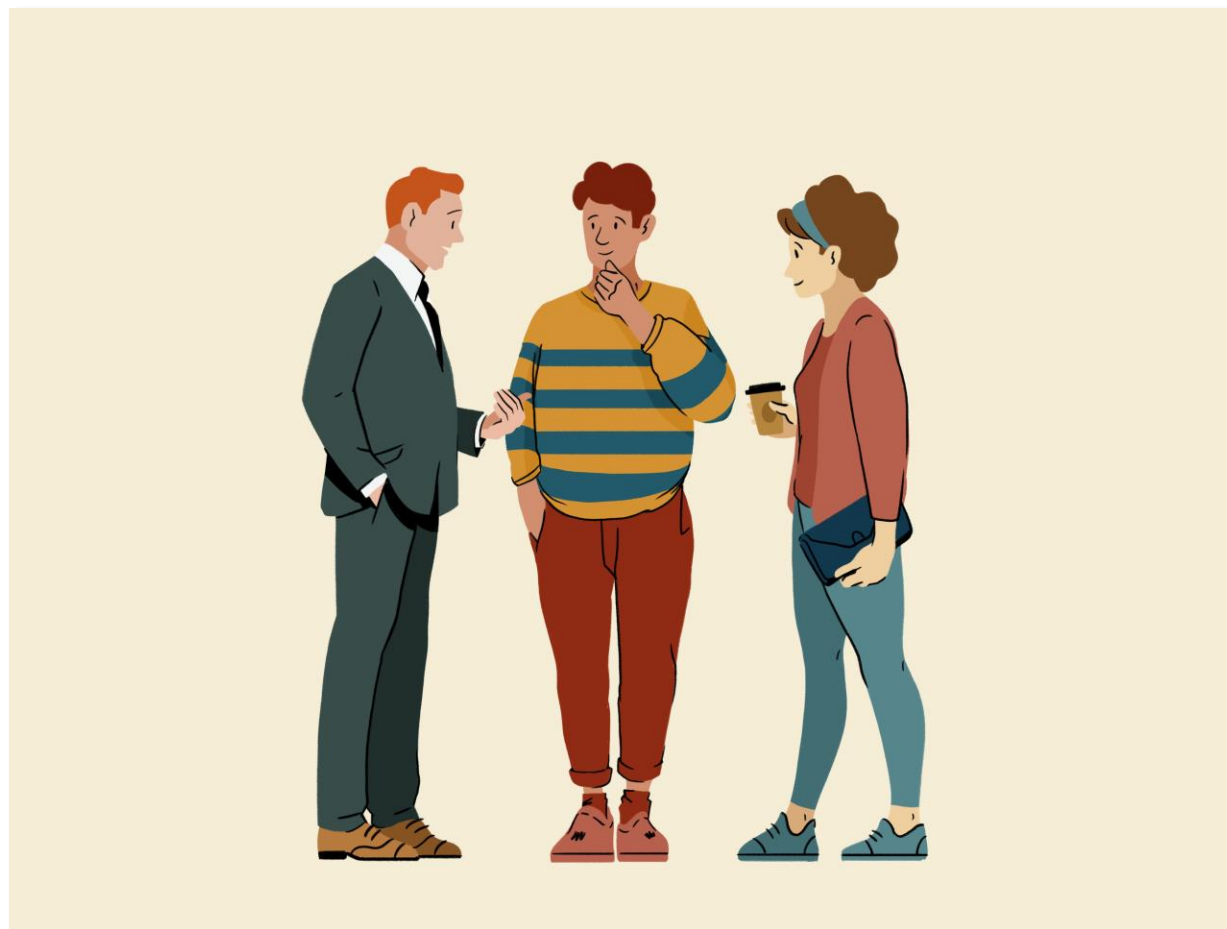


Protocol	Length	Info
DNS	74	Standard query 0x0043 A www.google.com
DNS	89	Standard query 0x13b0 A connectivitycheck.gstatic.com
DNS	90	Standard query response 0x0043 A www.google.com A 142.251.141.36
DNS	105	Standard query response 0x13b0 A connectivitycheck.gstatic.com A 216.58.206.67
DNS	76	Standard query 0x7b07 A mtalk.google.com
DNS	121	Standard query response 0x7b07 A mtalk.google.com CNAME mobile-gtalk.l.google.com
DNS	74	Standard query 0xb028 A g.whatsapp.net
DNS	113	Standard query response 0xb028 A g.whatsapp.net CNAME chat.cdn.whatsapp.net A 185
DNS	78	Standard query 0xf4d1 A graph.facebook.com
DNS	118	Standard query response 0xf4d1 A graph.facebook.com CNAME star.c10r.facebook.com





# The question



# DNS and smartphone activity

User activity from DNS request perspective can be (**IT IS!**) repetitive!



**Incentive for user tracking!**

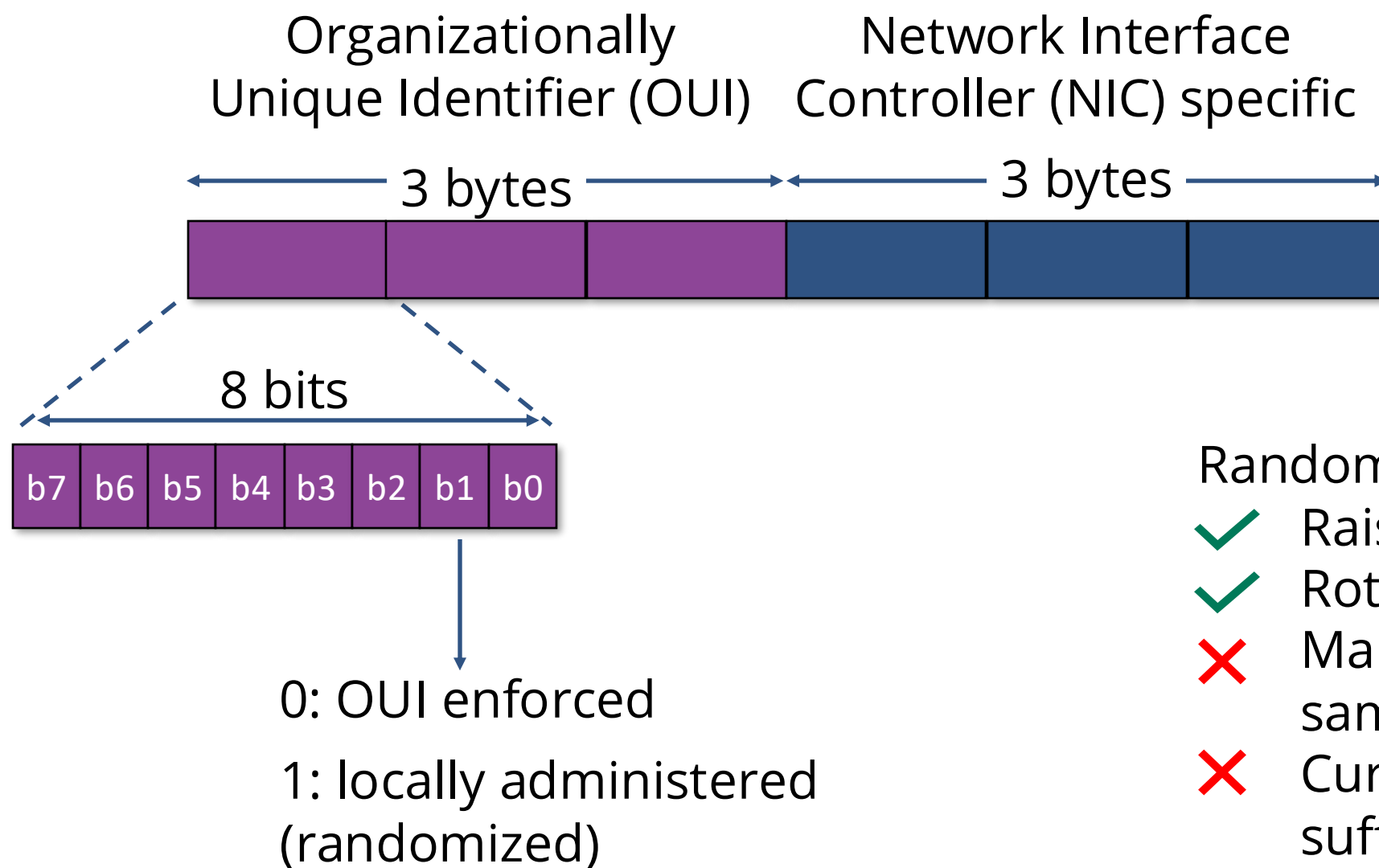


# Privacy-related policies

- Organisation for Economic Co-operation and Development (OECD) Privacy Guidelines
- European Union's General Data Protection Regulation (GDPR)
- Country-based (PIPEDA – Canada, HIPAA – US Healthcare, ...)
- ...



## 1 Random MAC address as **privacy feature** to **prevent tracking**



### Randomized MAC:

- ✓ Raises the bar for tracking
- ✓ Rotating MAC limits profiling window
- ✗ Many devices use the same MAC for the same network
- ✗ Current time window for rotating MAC is sufficient for tracking



2

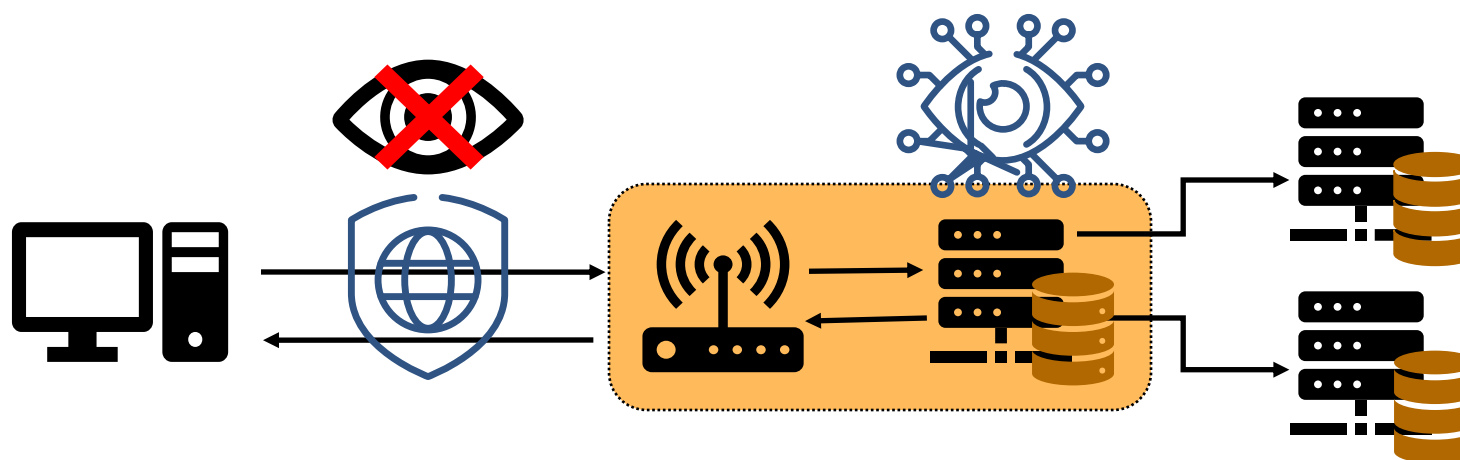
## Secure DNS (DNS / HTTPS, DNS / TLS):

- ✓ Eliminates **local** snooping
- ✗ Not as wide-spread (yet)
- ✗ Requests still need resolving – the case of the curious DNS resolver

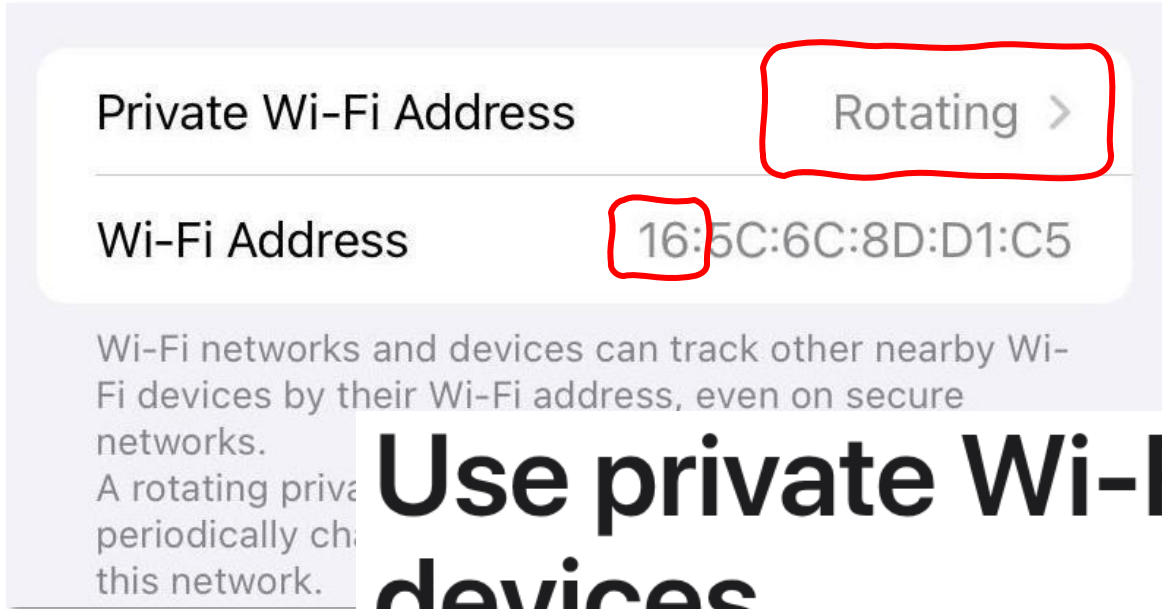


Two flavors:

DNS / **HTTPS** (DoH) ✓  
DNS / **TLS** (DoT)



iOS Wi-Fi settings:



## Use private Wi-Fi addresses on Apple devices

To improve privacy, your iPhone, iPad, iPod touch, Mac, Apple Watch, or Apple Vision Pro identifies itself to each network using a different Wi-Fi address, and might rotate (change) the address periodically.

- The Private Wi-Fi Address feature offers these settings, which you can change at any time:
  - *Rotating:* When set to Rotating, your device uses a private address that rotates to a different private address every 2 weeks. Your device chooses Rotating by default when joining a new network that uses weak security or no security.

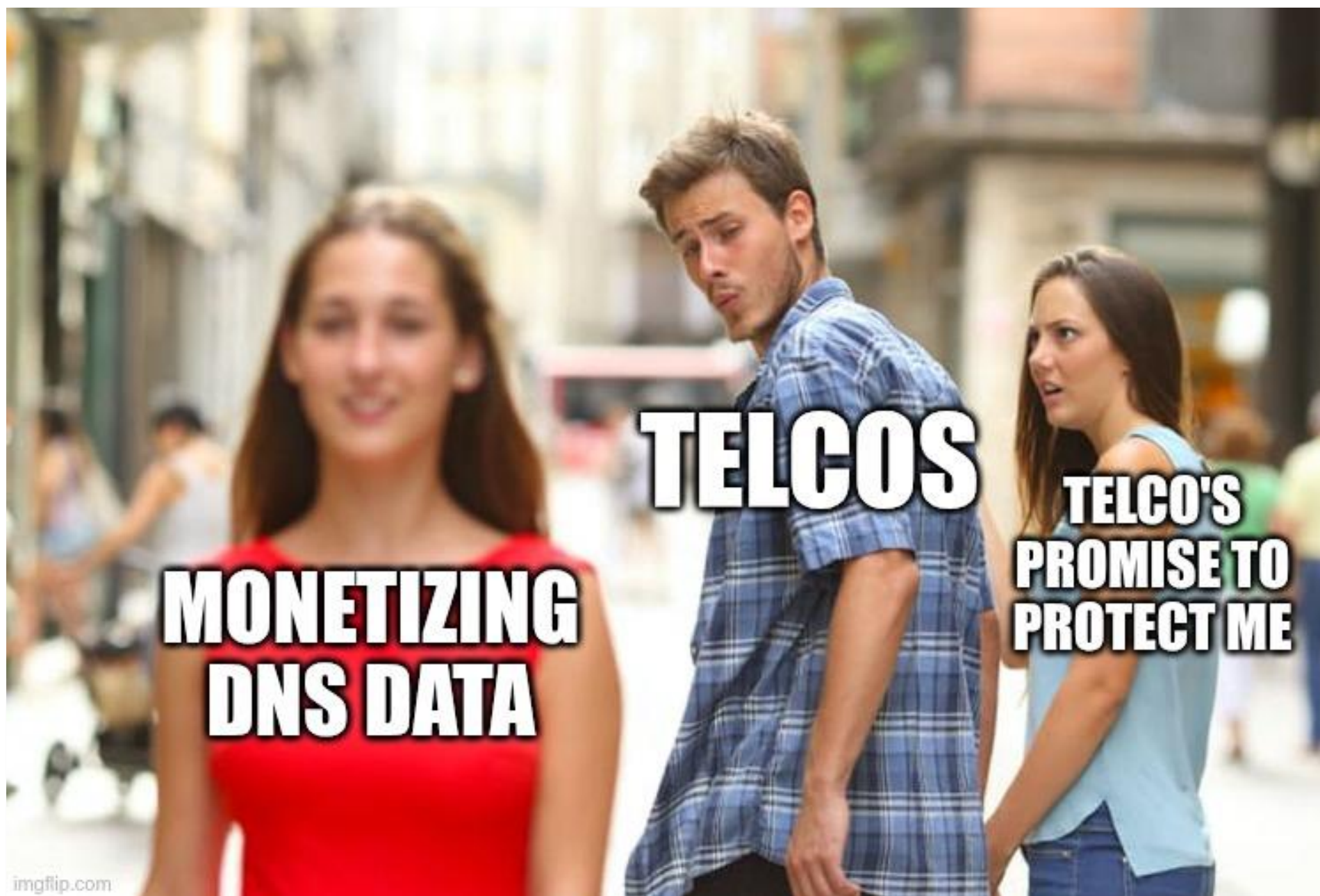


# Tracking deadline





# Can we trust telcos?





# Looking into the past

2006-2008



**secretly tested**  
Phorm's deep packet inspection technology on thousands of broadband users

2013-2014



published a report admitting some governments had **direct access to customer data and networks**

2018



**shared access to consumers' location data** without obtaining proper user consent

2020



fined for **unauthorized use of personal and location data** for advertising and profiling

2023



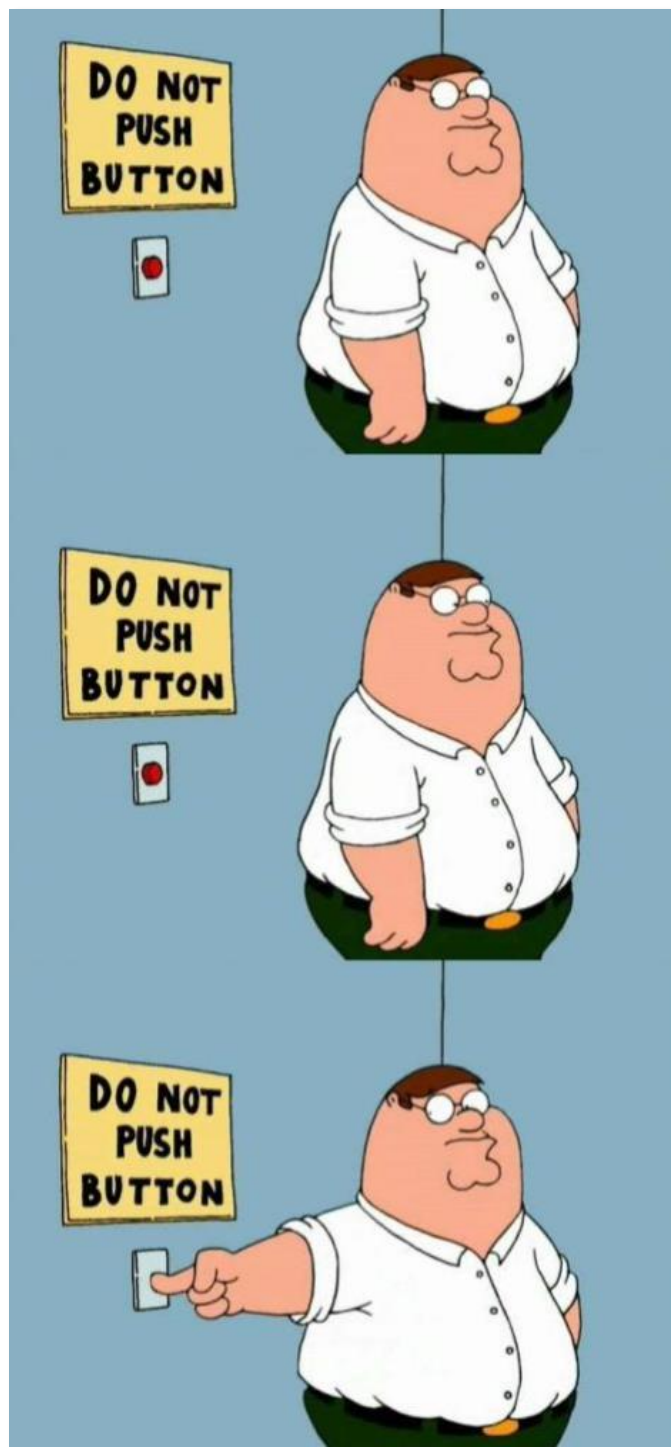
formed a joint venture to **develop a digital advertising platform** that leverages the telcos' extensive customer data for **targeted advertising**

2024



targeted advertisements based on users' inbox activity **without obtaining explicit consent**

# The temptation



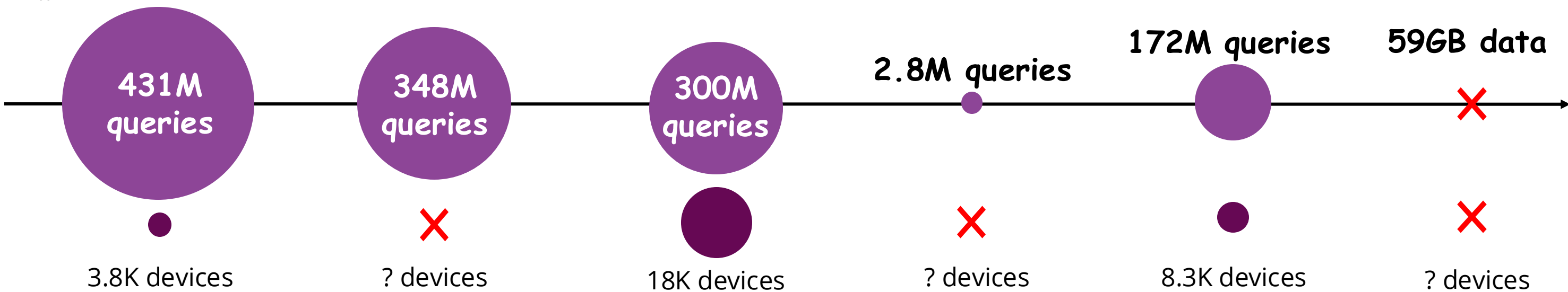


# How new is this research?

D. Herrmann, et al.: *Behavior-based tracking: Exploiting characteristic patterns in DNS traffic*, **2013**

K. Schomp, et al.: *Towards a Model of DNS Client Behavior*, **2016**

Jian Qu, et al.: *Who is DNS serving for? A human-software perspective of modeling DNS services*, **2023**



Qingnan Lai, et al.: *Visualizing and characterizing DNS lookup behaviors via log-mining*, **2015**

M. Panza, et al.: *Extracting human behavior patterns from DNS traffic*, **2022**

Zhiyang Sun, et al.: *DNS Request Log Analysis of Universities in Shanghai: A CDN Service Provider's Perspective*, **2024**

# Key distinctions

- 1 First study with exclusive focus on Smart Phones
- 2 Large pool of devices, 985M requests
- 3 Key insights specific to popular platforms: **iOS** and **Android**

## Work & productivity



## Shopping & payments



## Health & fitness



## Communication



## Entertainment & gaming



## Internet access



## Multimedia



## Navigation & travel



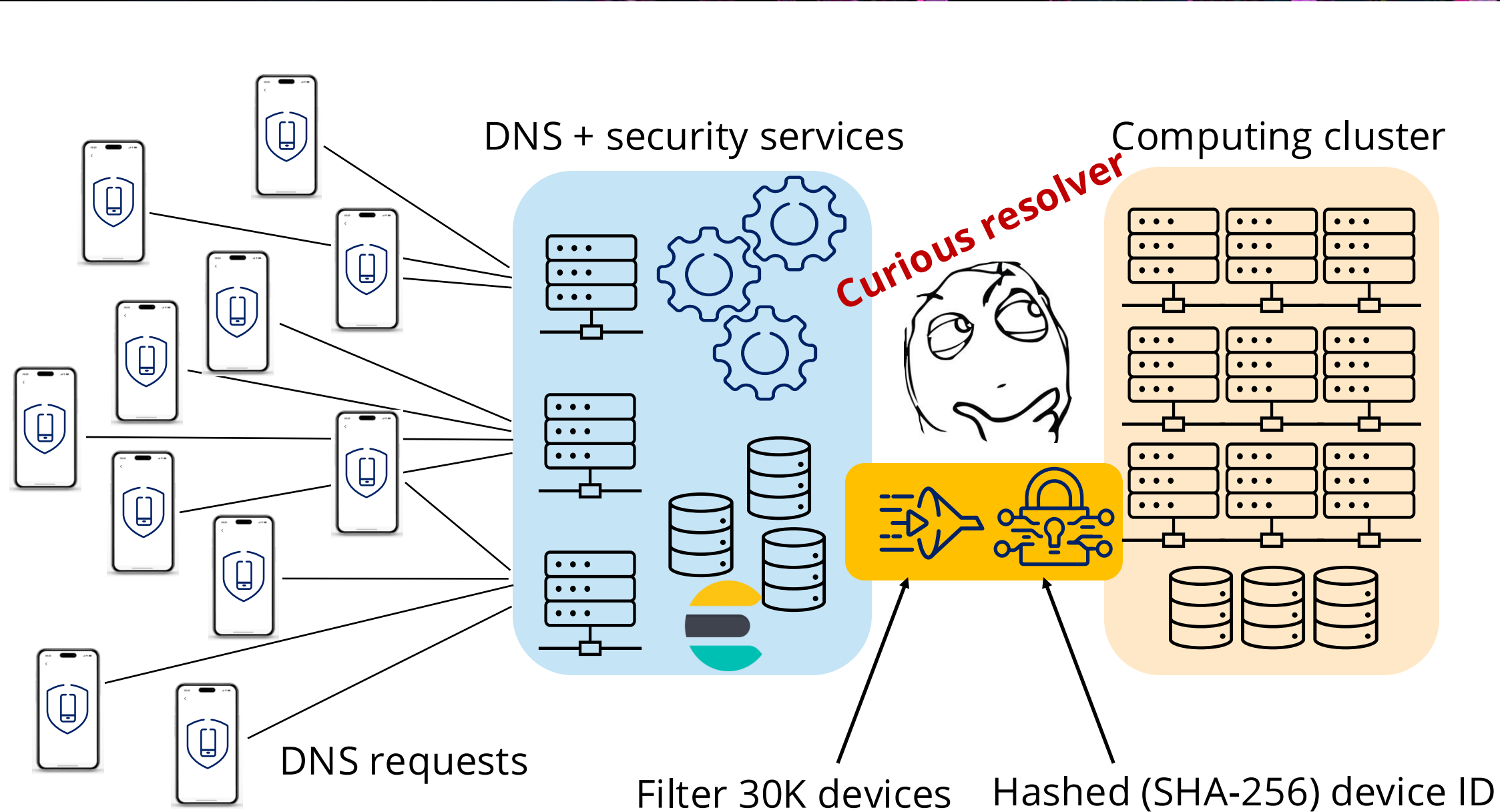


# Down to business: a bird's eye view





# The curious DNS resolver



**35 days** of DNS requests  
Request count (after pre-processing): **985M**



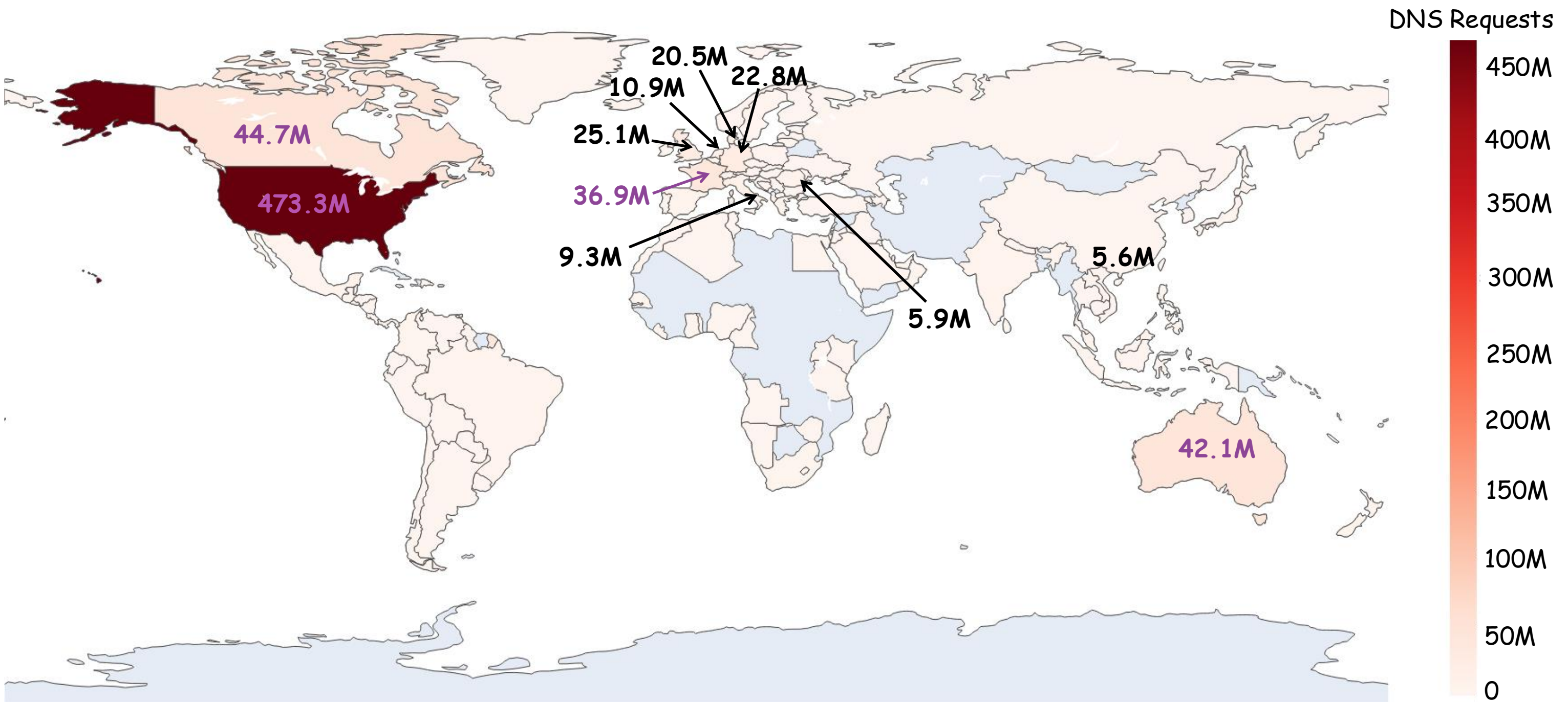
**4 computational clusters**  
Total RAM: **1.5 TB**  
Total vCPUs: **80**



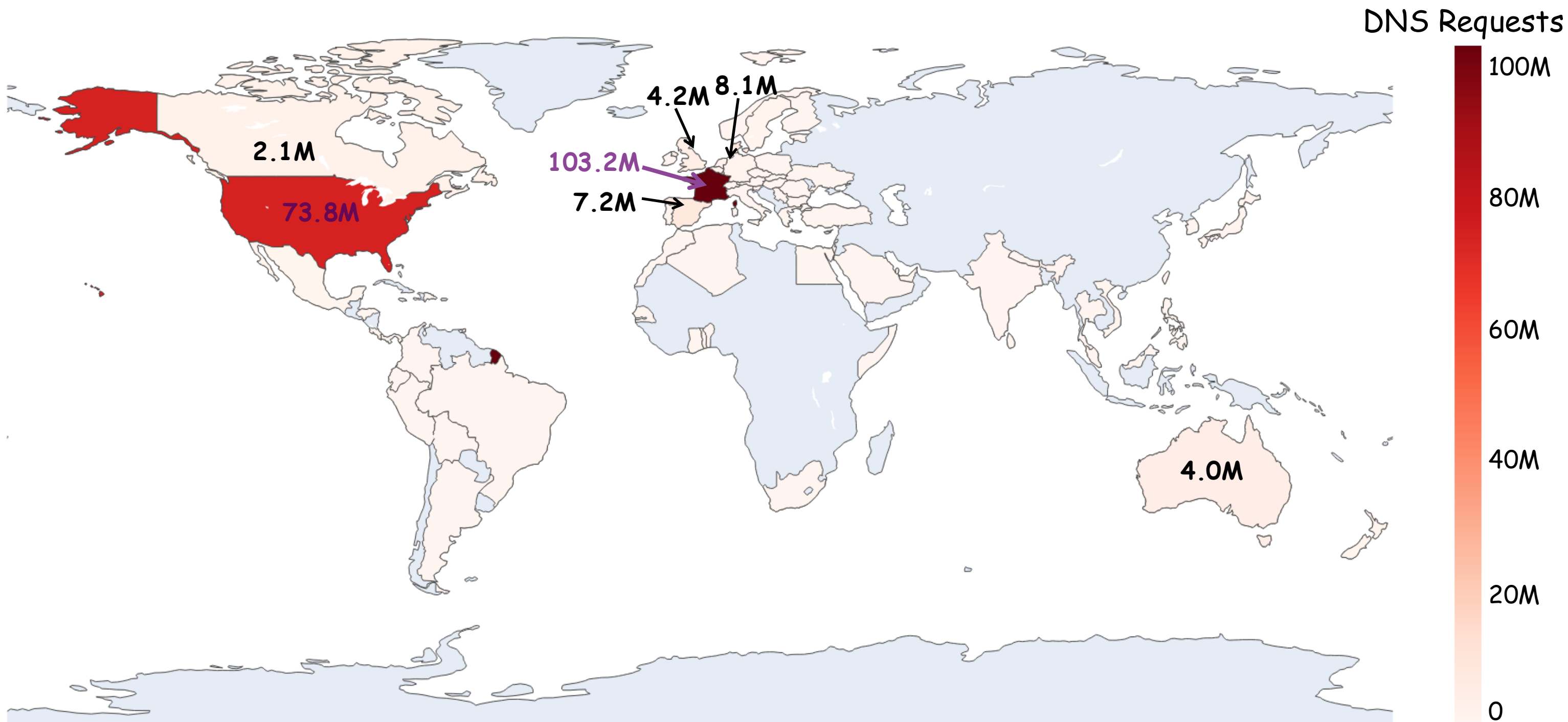
**~28K phones**  
(after pre-processing)



# DNS requests by country - iOS



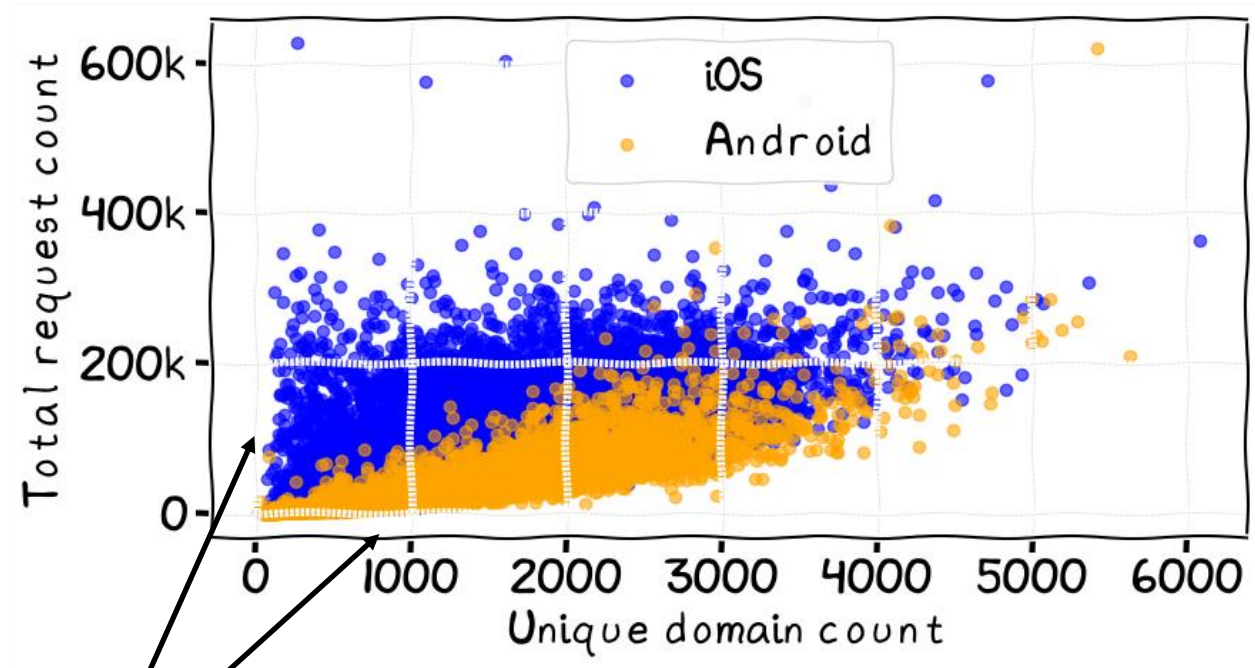
# DNS requests by country - Android





# Distribution of domain requests

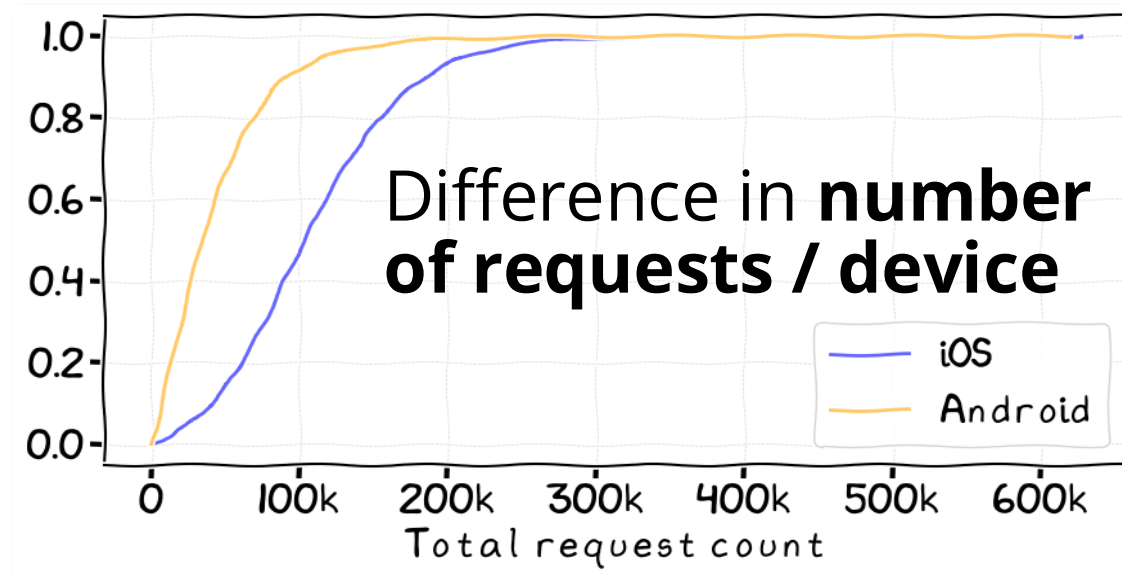
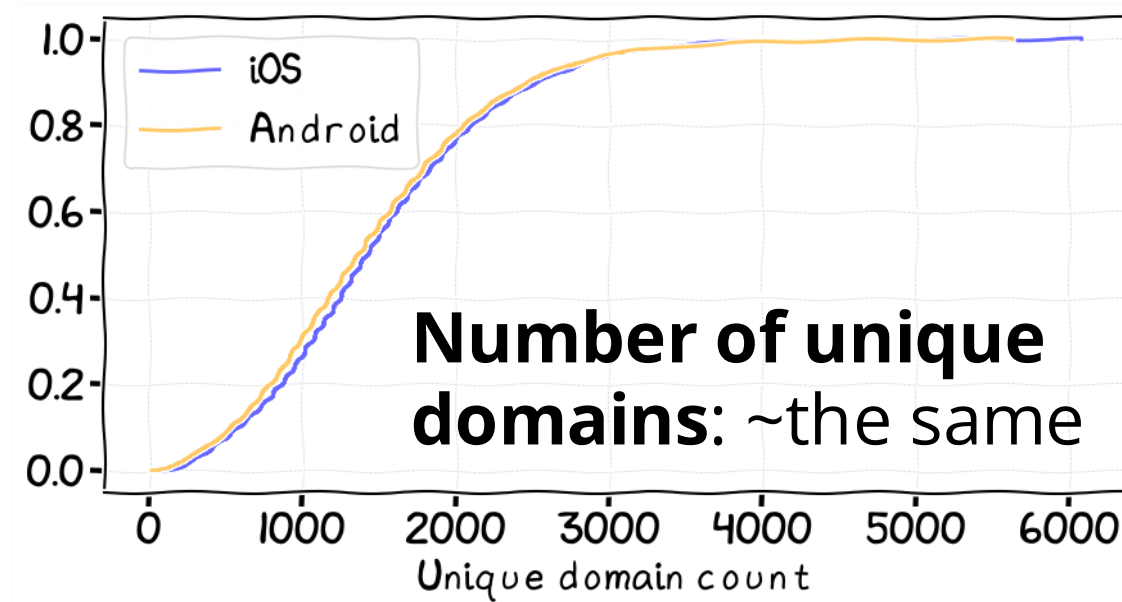
Unique vs total number of accessed domains



Visible distinction between **iOS** and **Android**



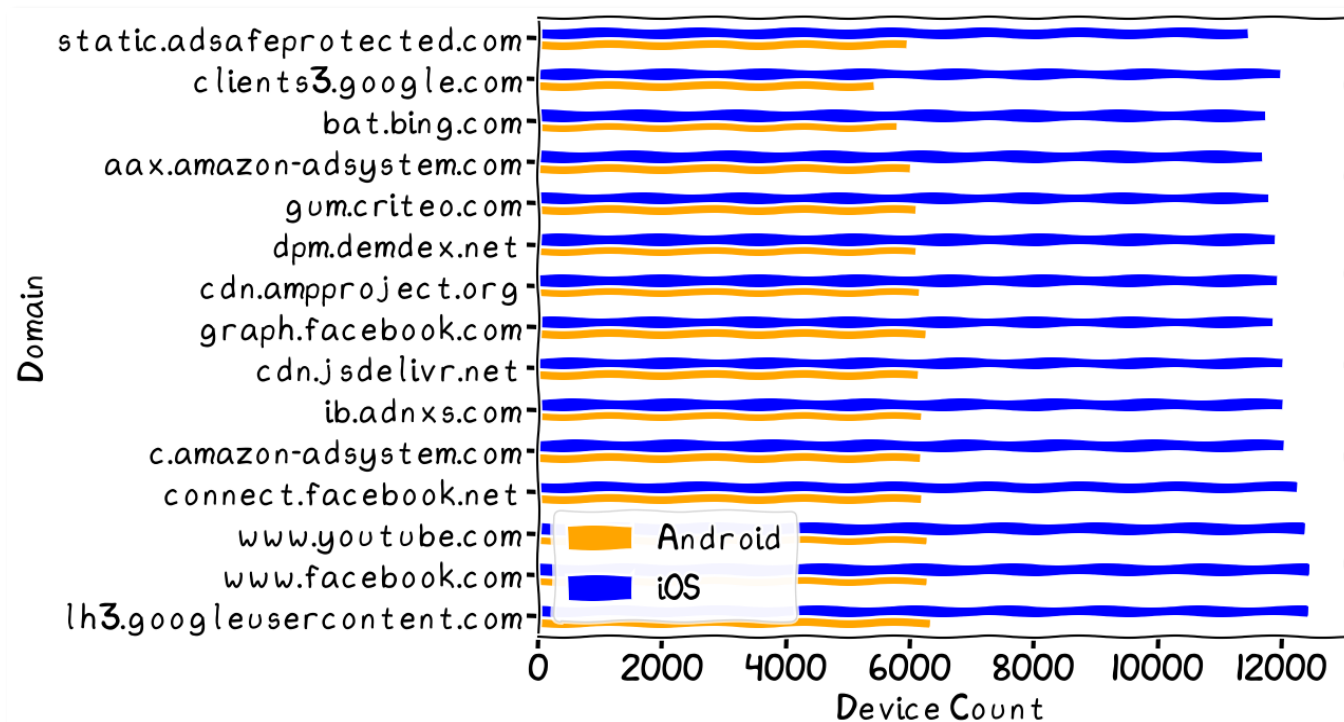
Cumulative Distribution Functions (CDF)



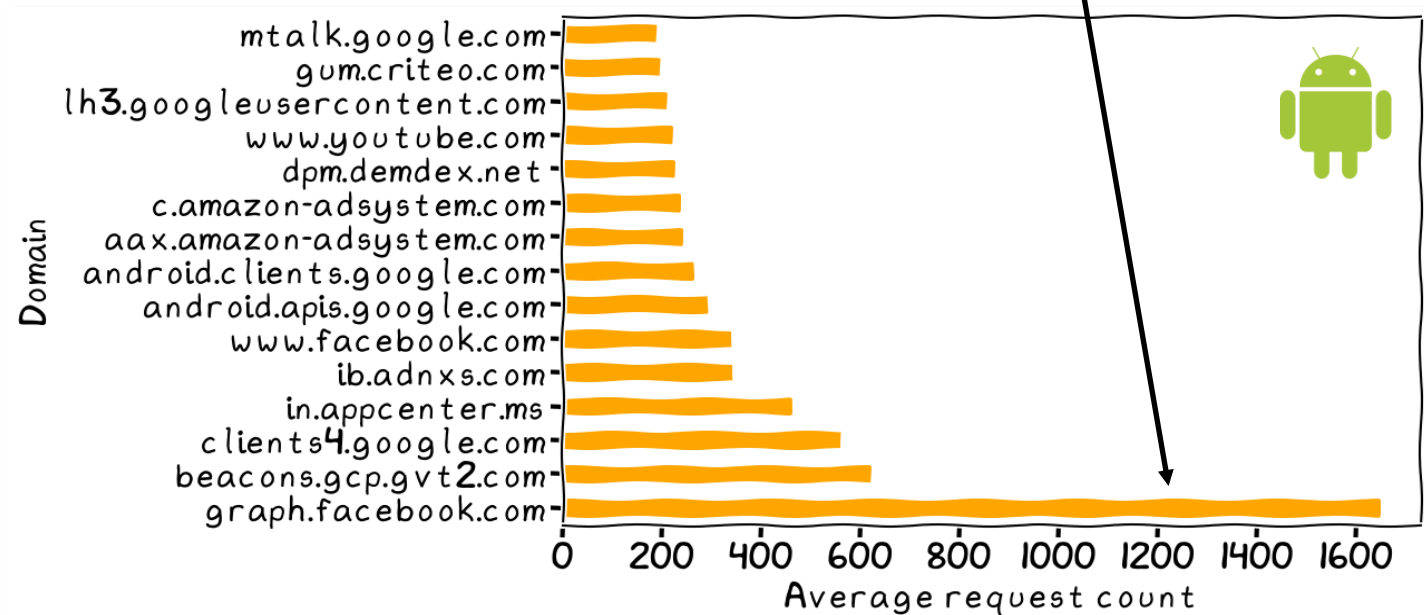
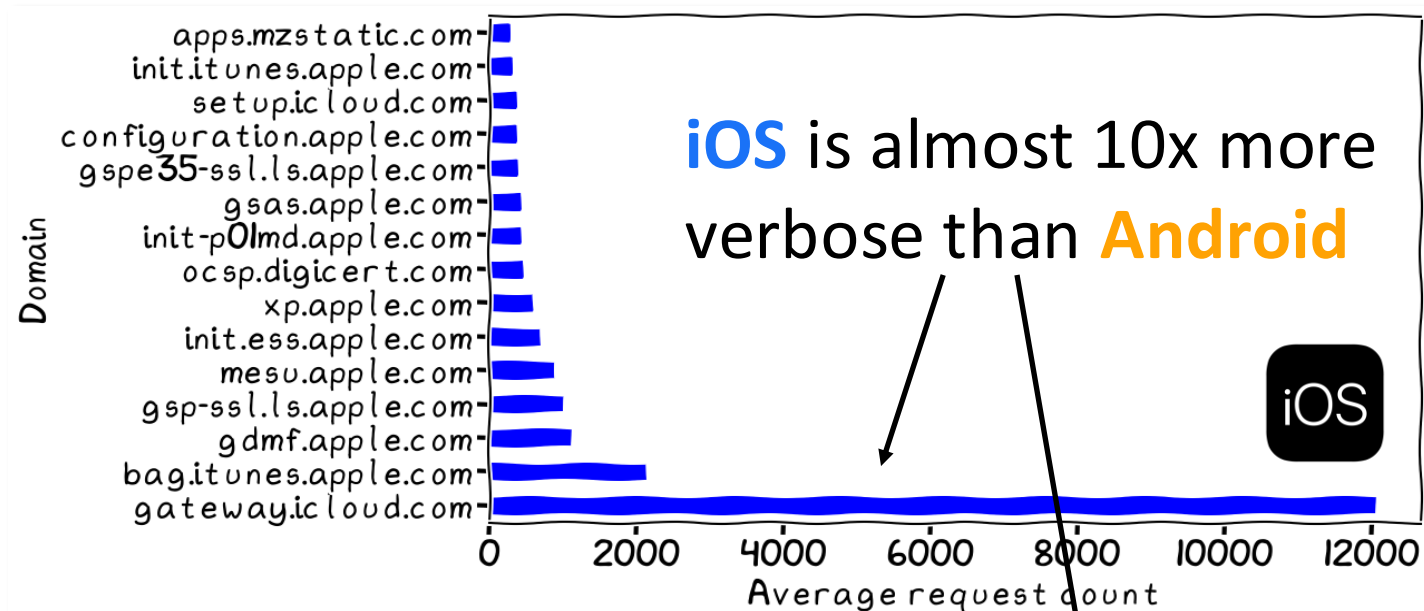
# Most frequently accessed domains

- Most common domains: from popular applications
- **iOS**: mostly Apple related
- **Android**: Google and popular platforms

Top 15 common domains



Top 15 domains / OS



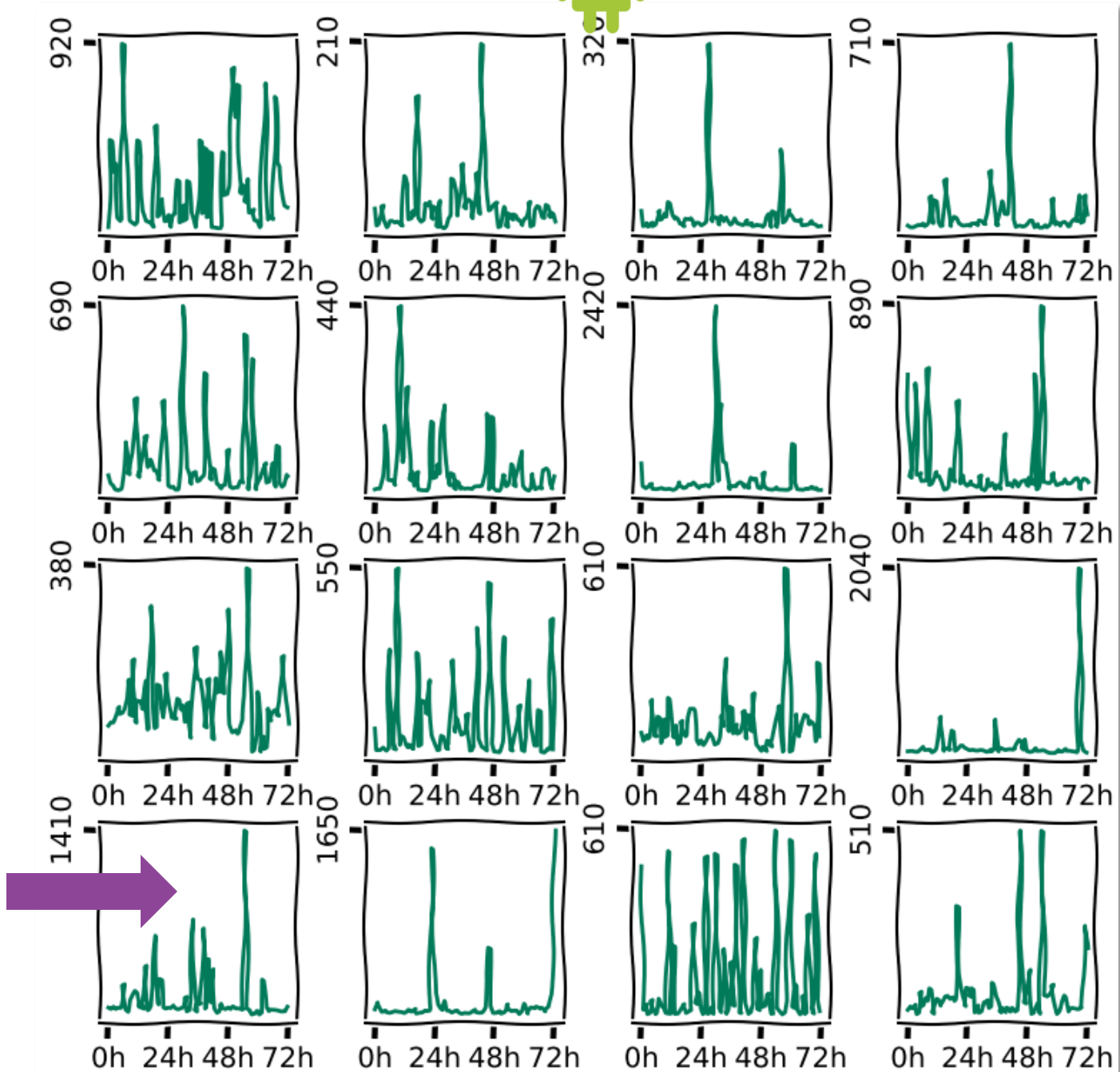


# DNS requests as patterns

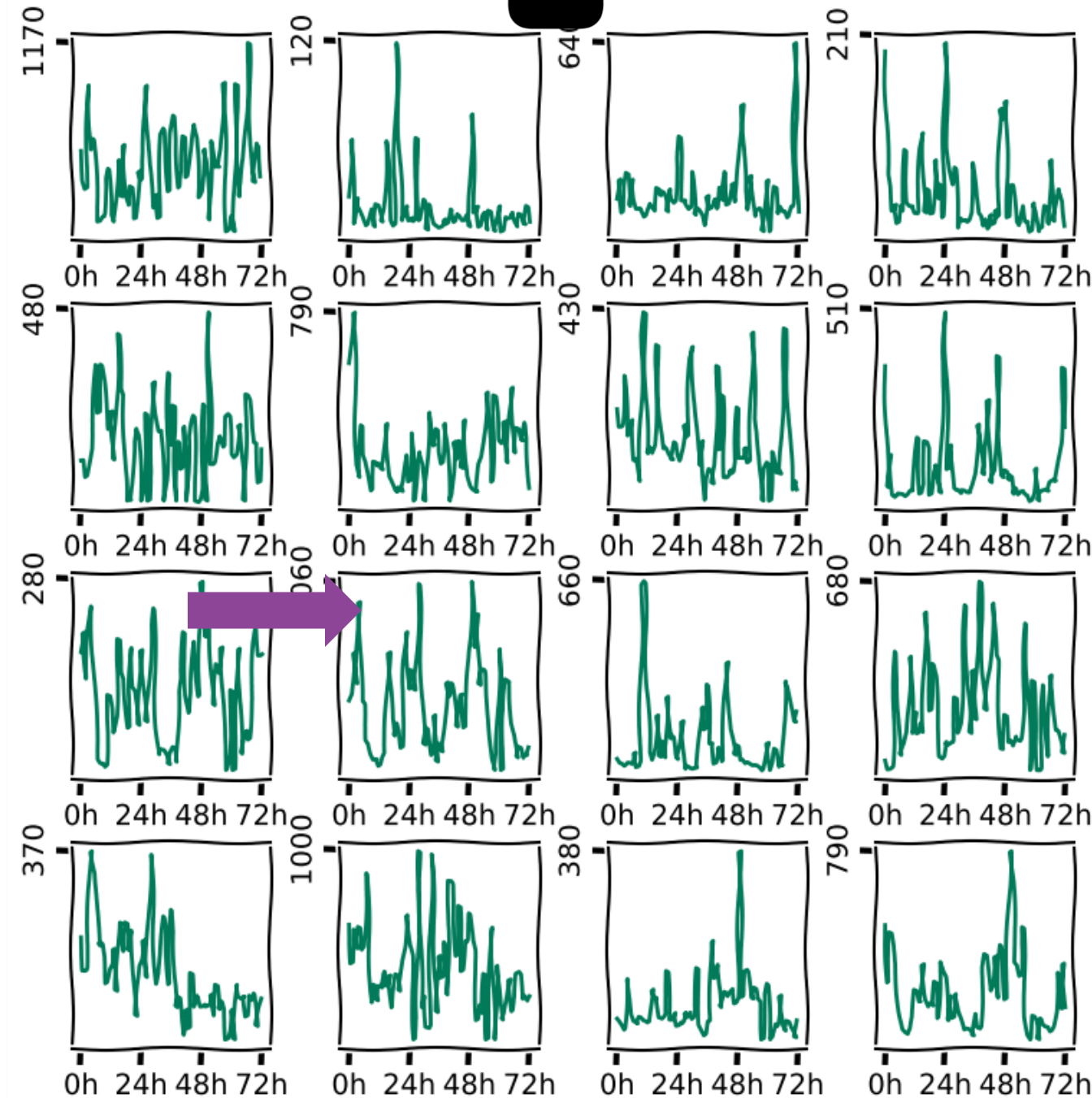




# Number of requests

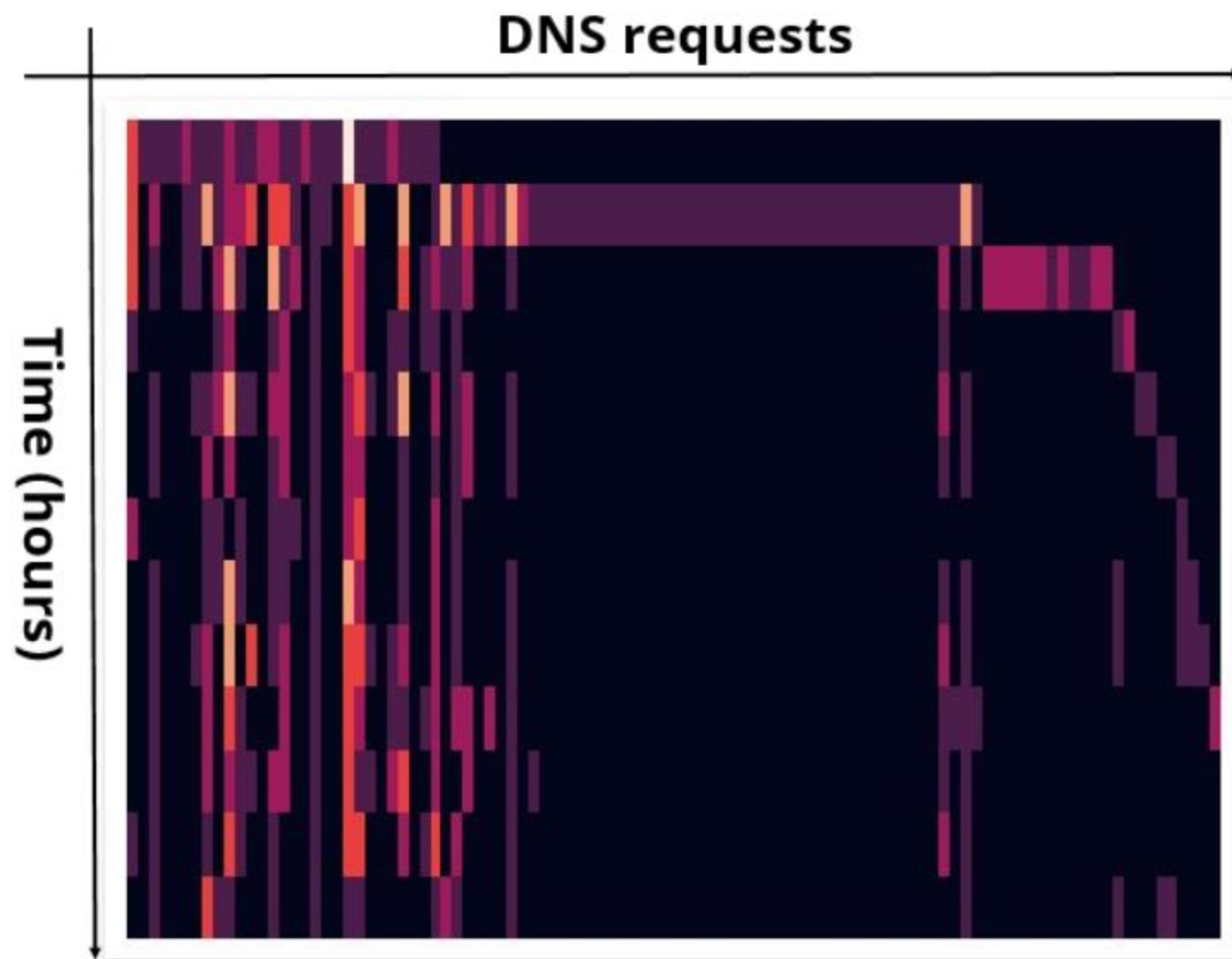


iOS

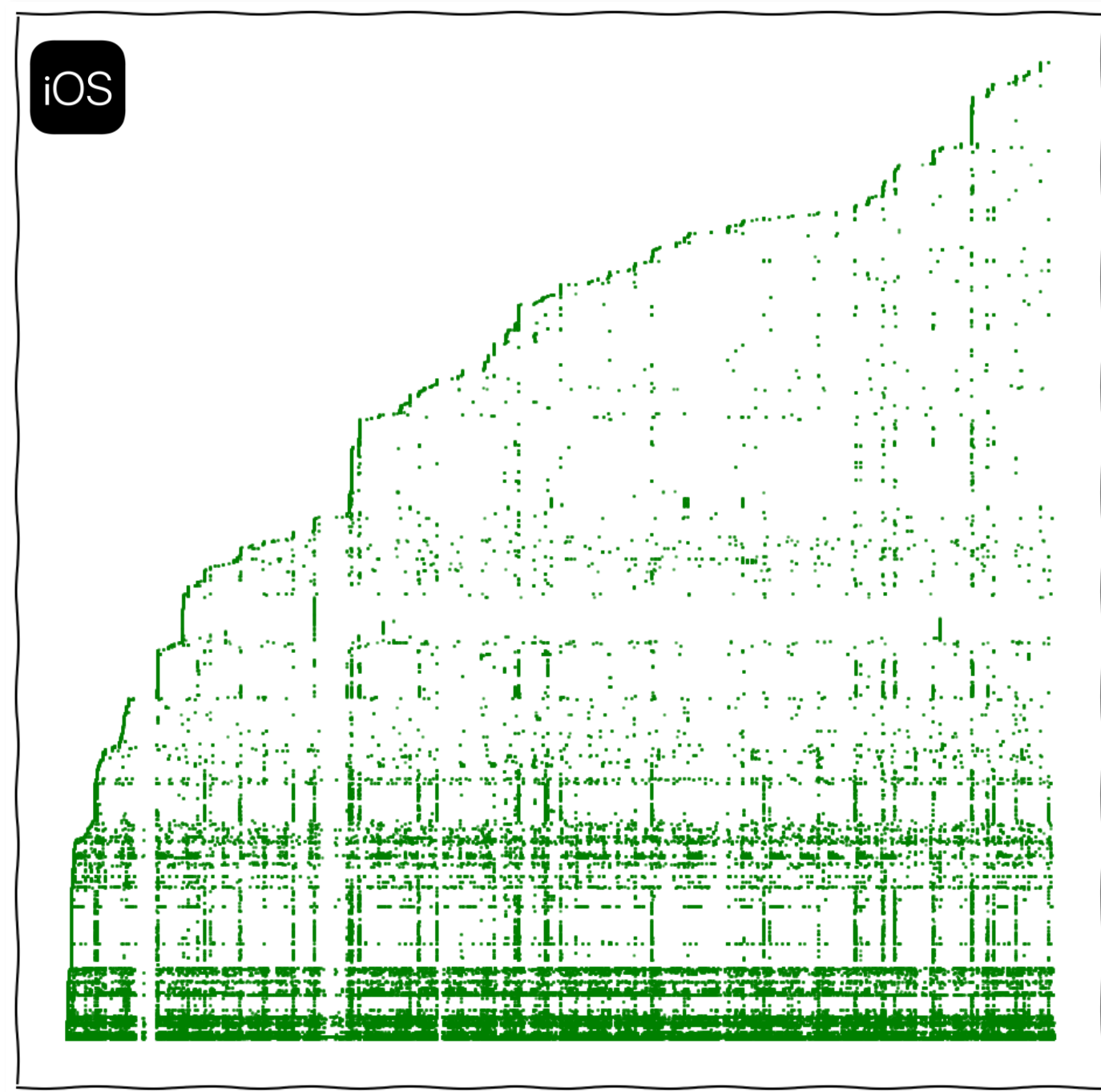
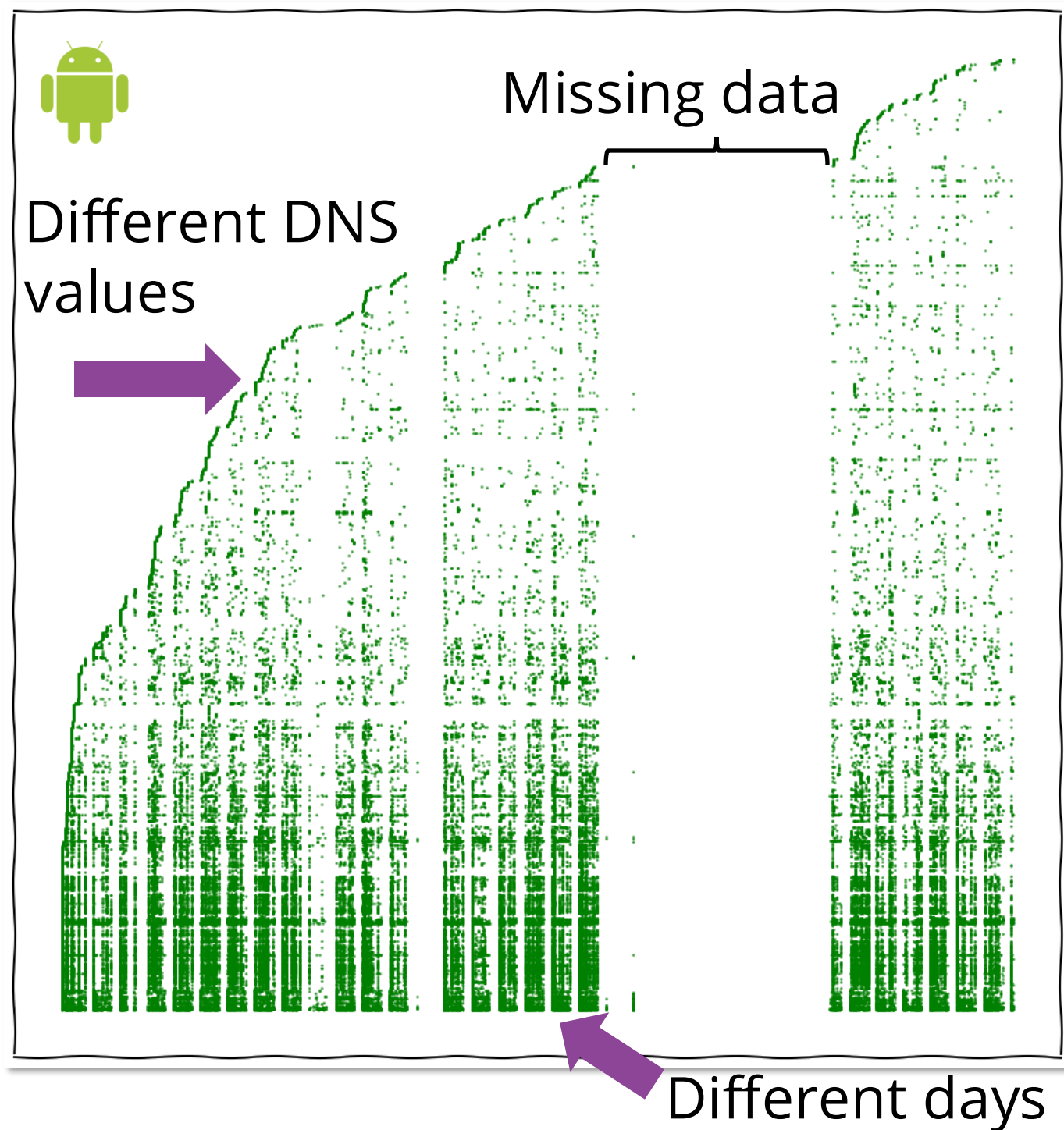




# Hourly requests

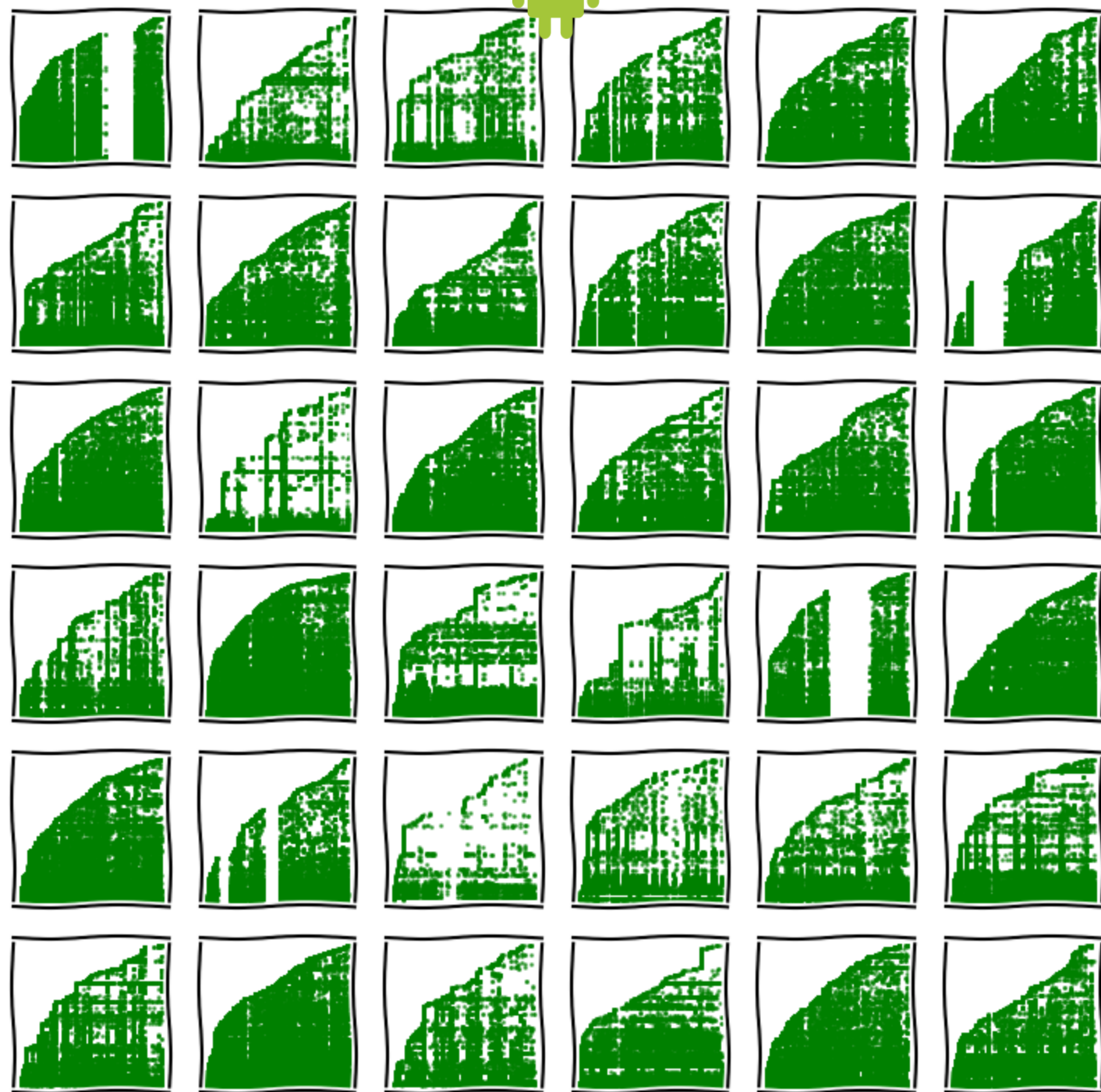


# Android vs iOS – requests/domain

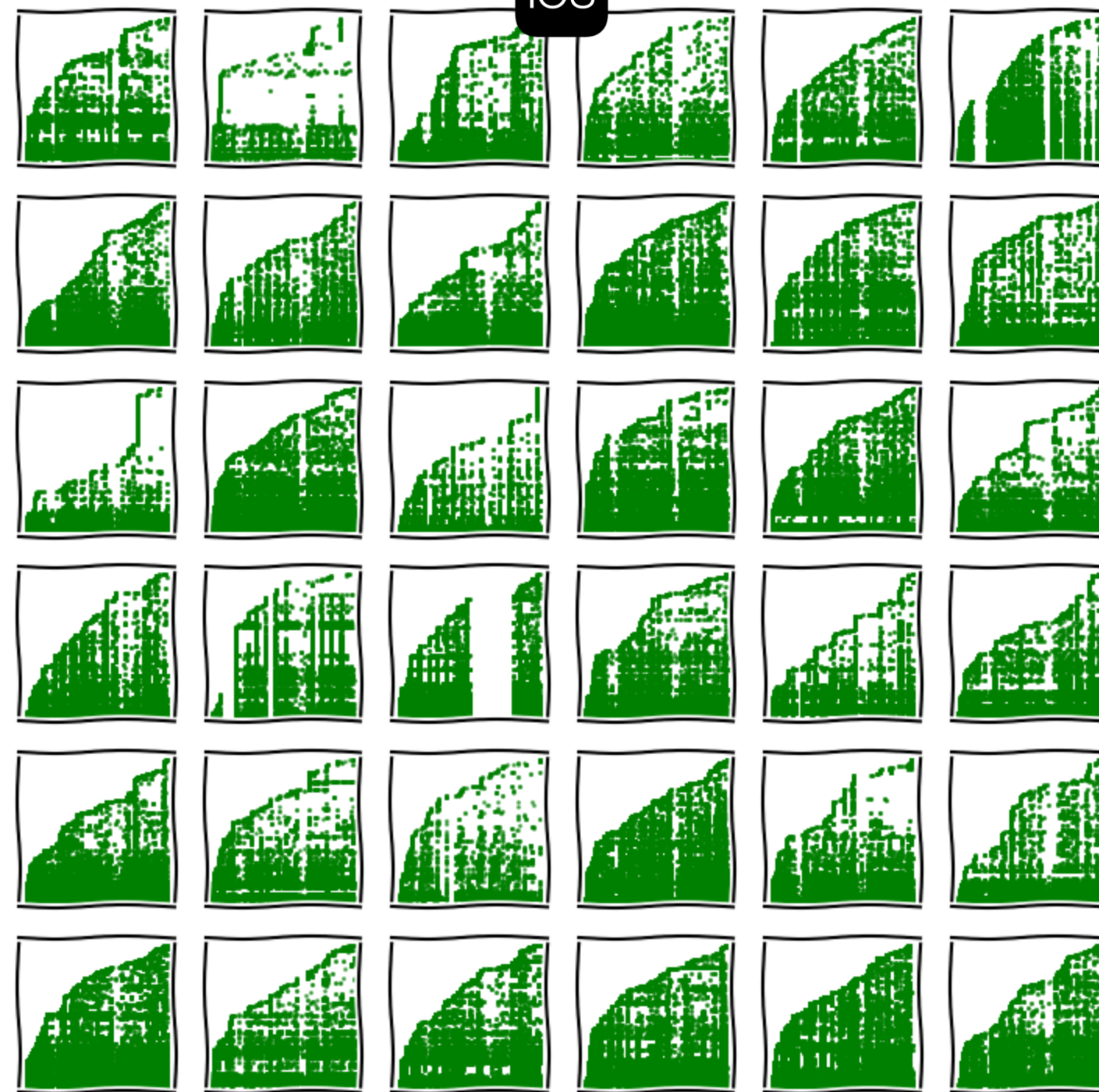




# Android vs iOS – requests/domains



iOS



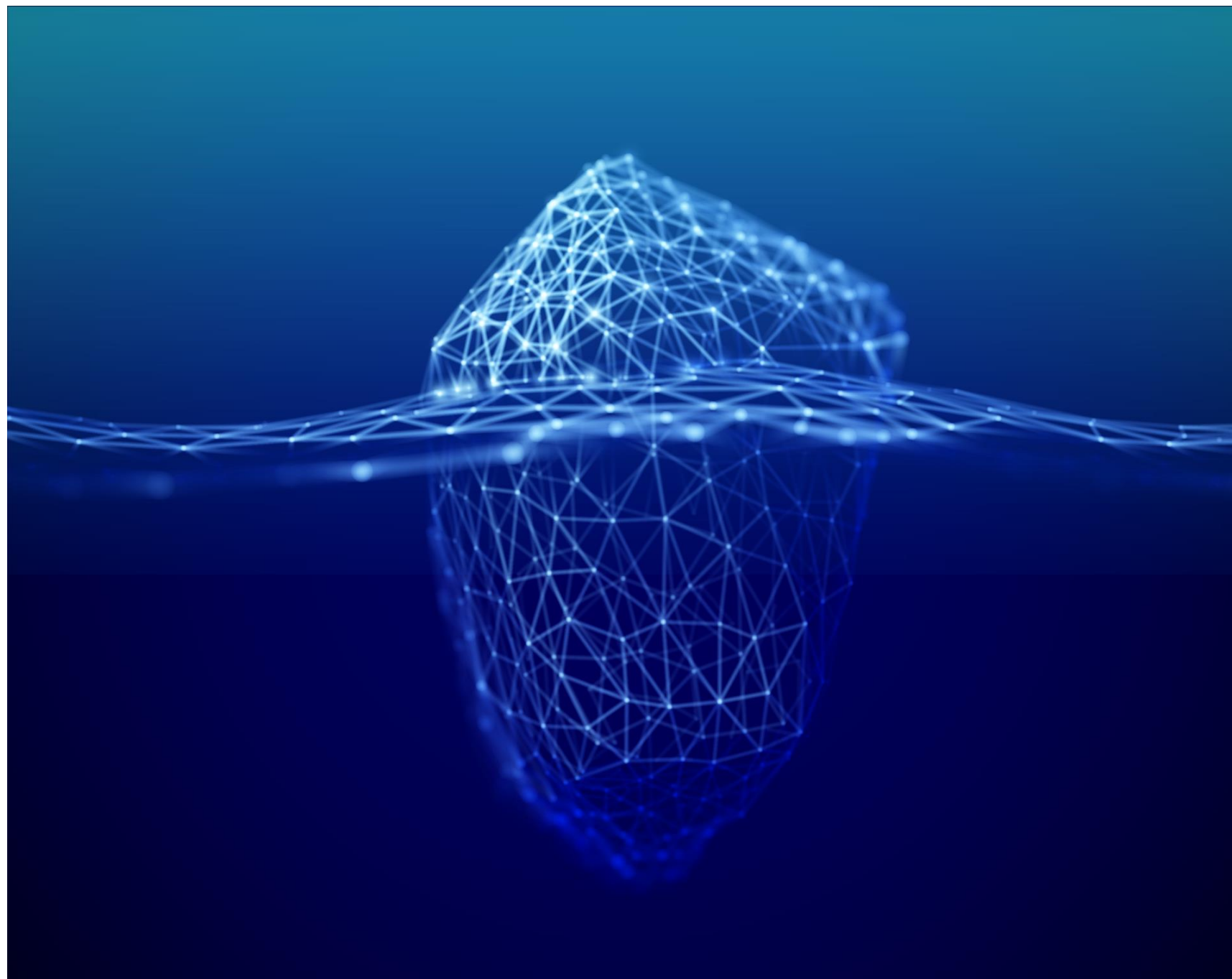
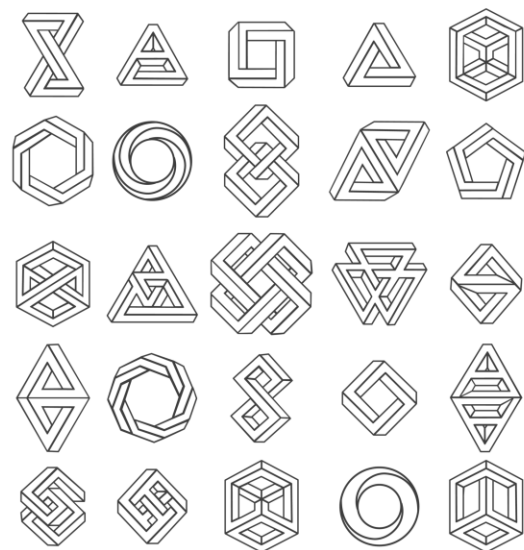
# DNS request data processing





1

Categorical  
values



2

Large number  
of requests



# Challenge 1: Encoding

- In general, algorithms are good with numbers, bad with strings
- We need to transform strings to numbers





## One-hot encoding ❌

play.googleapis.com	itunes.apple.com	captive.apple.com	youtube.com	facebook.com
1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

## Label encoding ❌

2	1	0	3	4
---	---	---	---	---

## Feature hashing ❌

288	12	98	45	187
-----	----	----	----	-----



- High dimensionality 😬
  - Sparsity
  - Lack of ordinal relationship
  - Scalability issues 😬
  - Potential overfitting
- 
- Imposes ordinal relationship 😬
  - Unsuitable for algorithms relying on distance (e.g., linear regression)
  - Risk of unintended bias 😬
- 
- Hash collision 😬
  - Irreversible mapping
  - Difficult to find optimal hash function 😬

# Eureka! Word encoding

- View DNS requests as word sequences in a *document/trace*
- Inspiration from the field of Natural Language Processing (NLP)
- Compute the *Term Frequency-Inverse Document Frequency*



**Term frequency (TF):** how often a term appears in a trace

**Inverse document frequency (IDF):** how rare the term is across traces

Android 

```
cl4.apple.com cl4.apple.com gspe19-
ssl.ls.apple.com gspe19-ssl.ls.apple.com
ocsp.digicert.com ocsp.digicert.com 36-
courier.push.apple.com web.facebook.com
web.facebook.com 11-courier.push.apple.com
gateway.facebook.com chat-e2ee.facebook.com
itunes.apple.com itunes.apple.com
mask.icloud.com mask.icloud.com
```

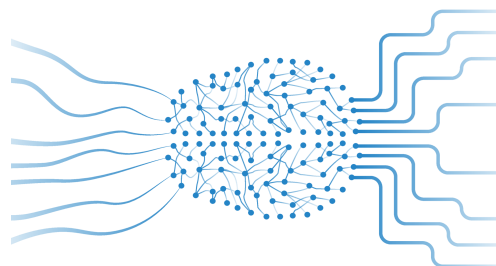
Repetitive requests

vs.

iOS 


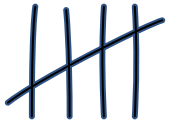



```
amazon.com kinapp-notifications-
na.amazon.com fls-na.amazon.com
unagi.amazon.com m.media-amazon.com
api.weather.com api.account.samsung.com
kinapp-notifications-na.amazon.com
amazon.com api.audible.com m.media-
amazon.com fls-na.amazon.com...
api.weather.com auth.simplisafe.com
cdn.contentful.com sdk.iad-06.braze.com
```

Repetitive requests





## *Term Frequency-Inverse Document Frequency: **TF-IDF***

- ✓ Suitable for string-based processing 
- ✓ Quantifies term (word) frequency 
- ✓ Highlights terms that are not common across all traces 
- ✓ Scales well 
- ✓ Low risk for bias 

0 TF-IDF value interpretation 1



- The term **is common** across documents or **is less frequent** in the document
- The term **is less useful** to distinguish this document from others

- The term **appears frequently** in a document, but is not that frequent in other documents
- The term **is important / unique** to that document



## Example traces

- ① The Black Hat conference always rocks with exciting talks
- ② My friend thinks Black Hat rocks
- ③ Black Hat rocks the tech world with new talks

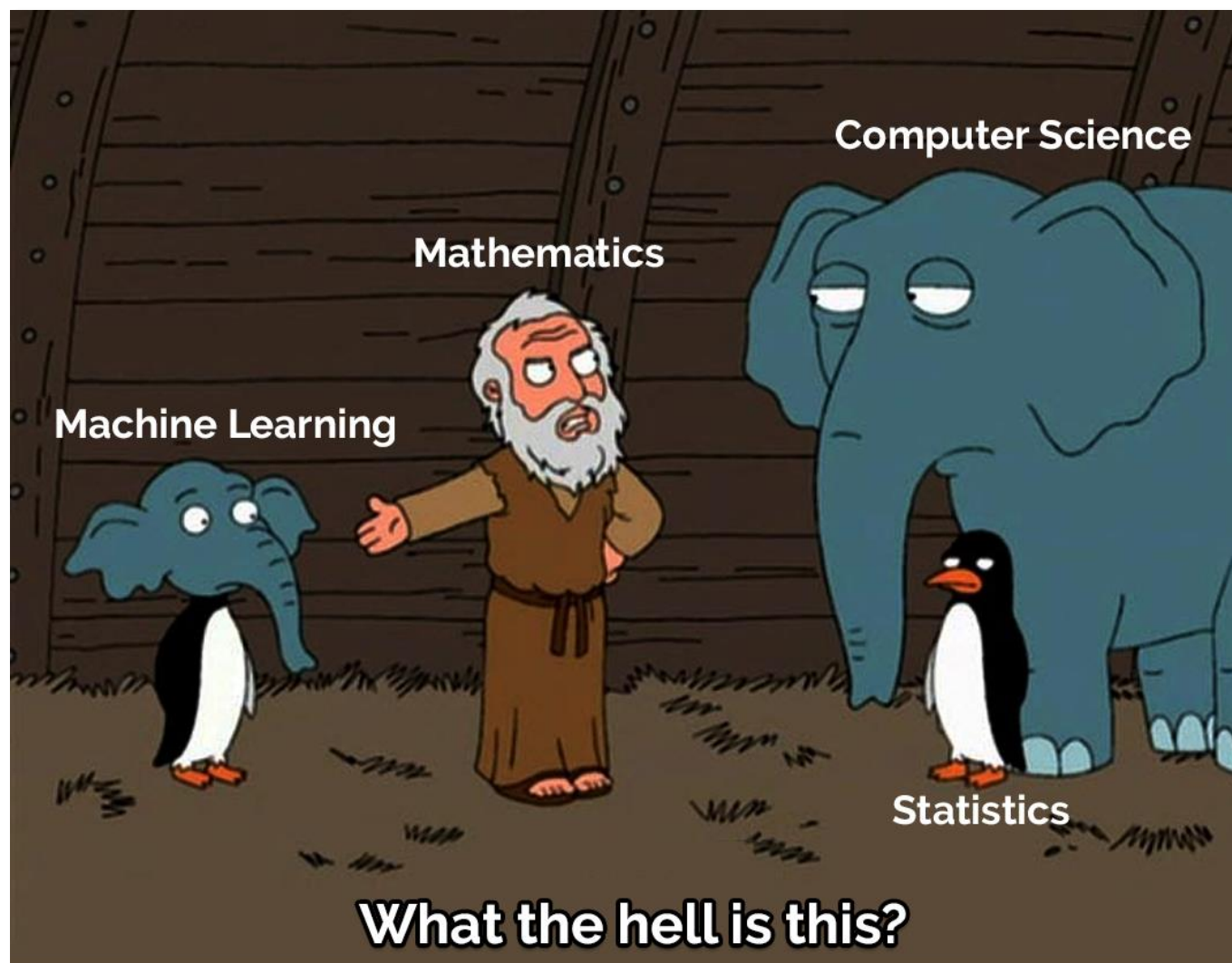
*Inverse document frequency: idf*

the	black	hat	conference	always	rocks	with	exciting	talks	my	friend	thinks	tech	world	new
1.0	0.7123	0.7123	1.4055	1.4055	0.7123	1.0	1.4055	1.0	1.4055	1.4055	1.4055	1.4055	1.4055	1.4055

*tf-idf*

	the	black	hat	conference	always	rocks	with	exciting	talks	my	friend	thinks	tech	world	new
①	0.1111	0.0791	0.0791	0.1562	0.1562	0.0791	0.1111	0.1562	0.1111	0	0	0	0	0	0
②	0	0.1187	0.1187	0	0	0.1187	0	0	0	0.2342	0.2342	0.2342	0	0	0
③	0.1111	0.0791	0.0791	0	0	0.0791	0.1111	0	0.1111	0	0	0	0.1562	0.1562	0.1562

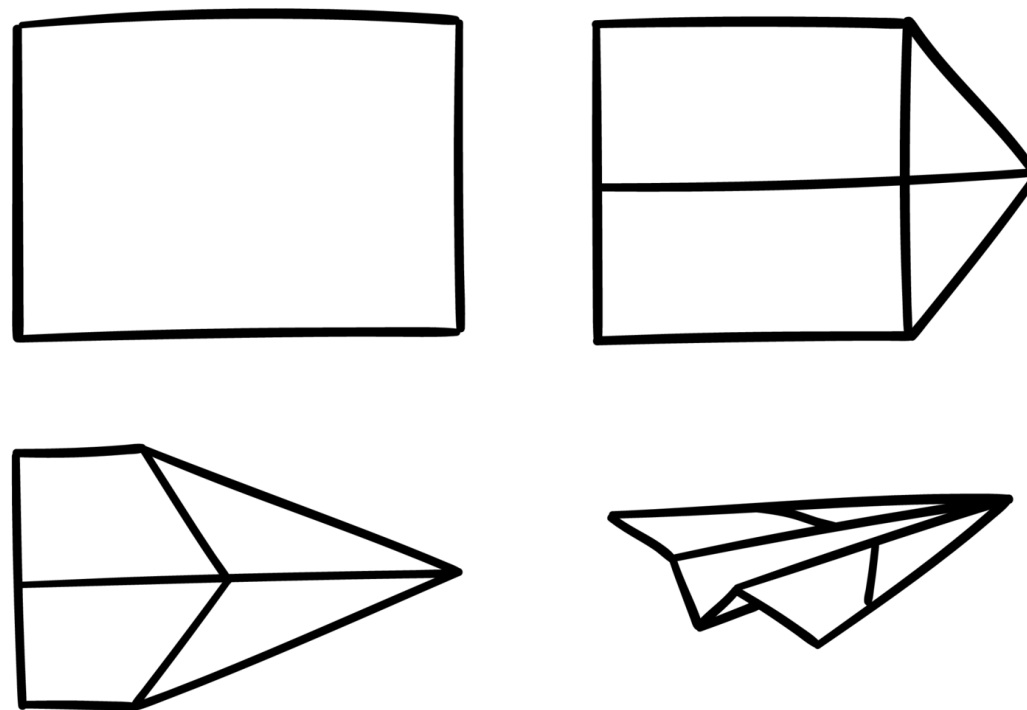
# To AI or not to AI?



weights-initialization  
hidden-layers  
adam  
nr-neurons  
sgd metrics  
activation-function  
learning-rate  
adamw randomness  
optimizers



# We kept it simple



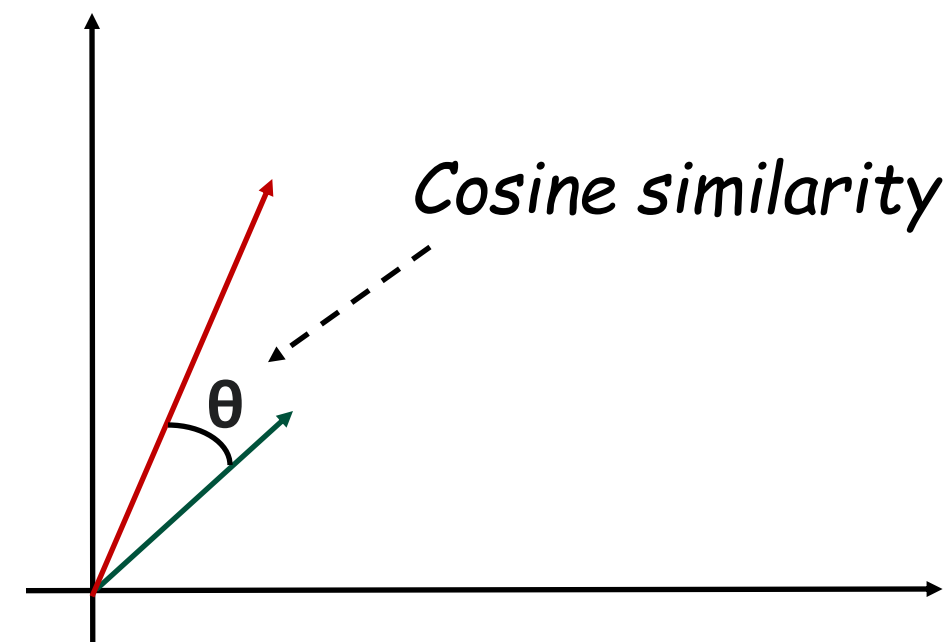
# Compare traces: Cosine similarity

- Preferred approach for measuring similarity between traces
- Handles well high-dimensional, sparse data
- Compares angles, instead of magnitude (i.e., vector length)

Cosine similarity: 
$$\frac{\vec{A} \cdot \vec{B}}{||\vec{A}|| \times ||\vec{B}||}$$

$\vec{A} \cdot \vec{B}$  Dot product: captures direction and magnitude

$||\vec{A}|| ||\vec{B}||$  Denominator: normalize computations



We end up with **direction**  
(compare ratio of values)



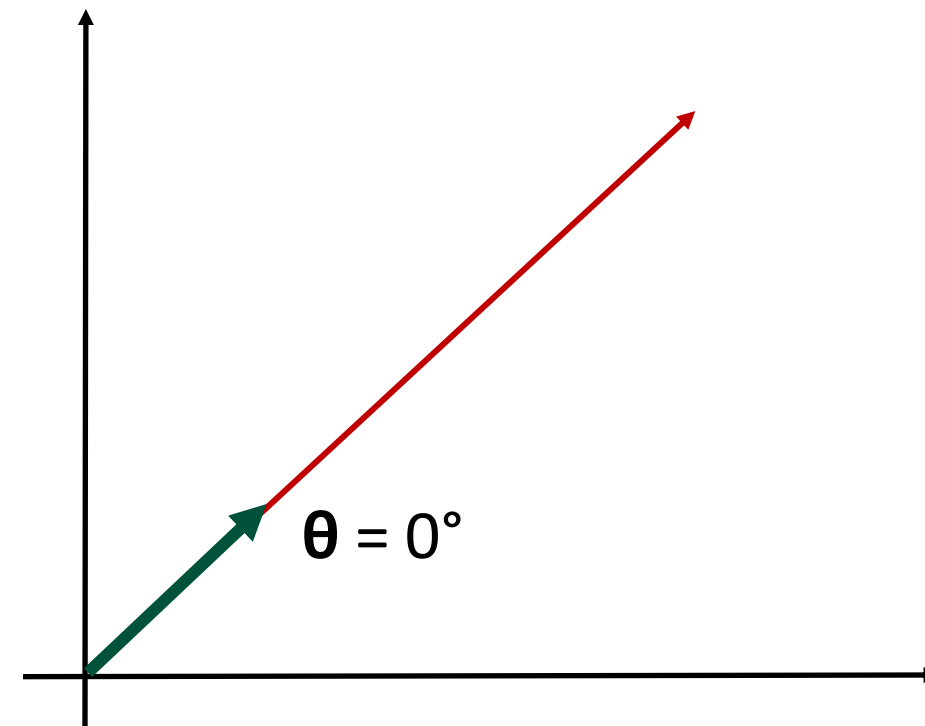
# Cosine similarity: Example

Trace ① *Black Hat*

Trace ② *Black Hat Black Hat Black Hat*

**Vector representation** (using raw term counts)

Term	Trace 1: Black Hat	Trace 2: Black Hat Black Hat Black Hat
Black	1	3
Hat	1	3






**Vectors: A: [1, 1] B: [3, 3]**

**Cosine similarity: 1.0** —————> Vectors point in the same direction  
Same words, just repeated – so **they're basically the same**

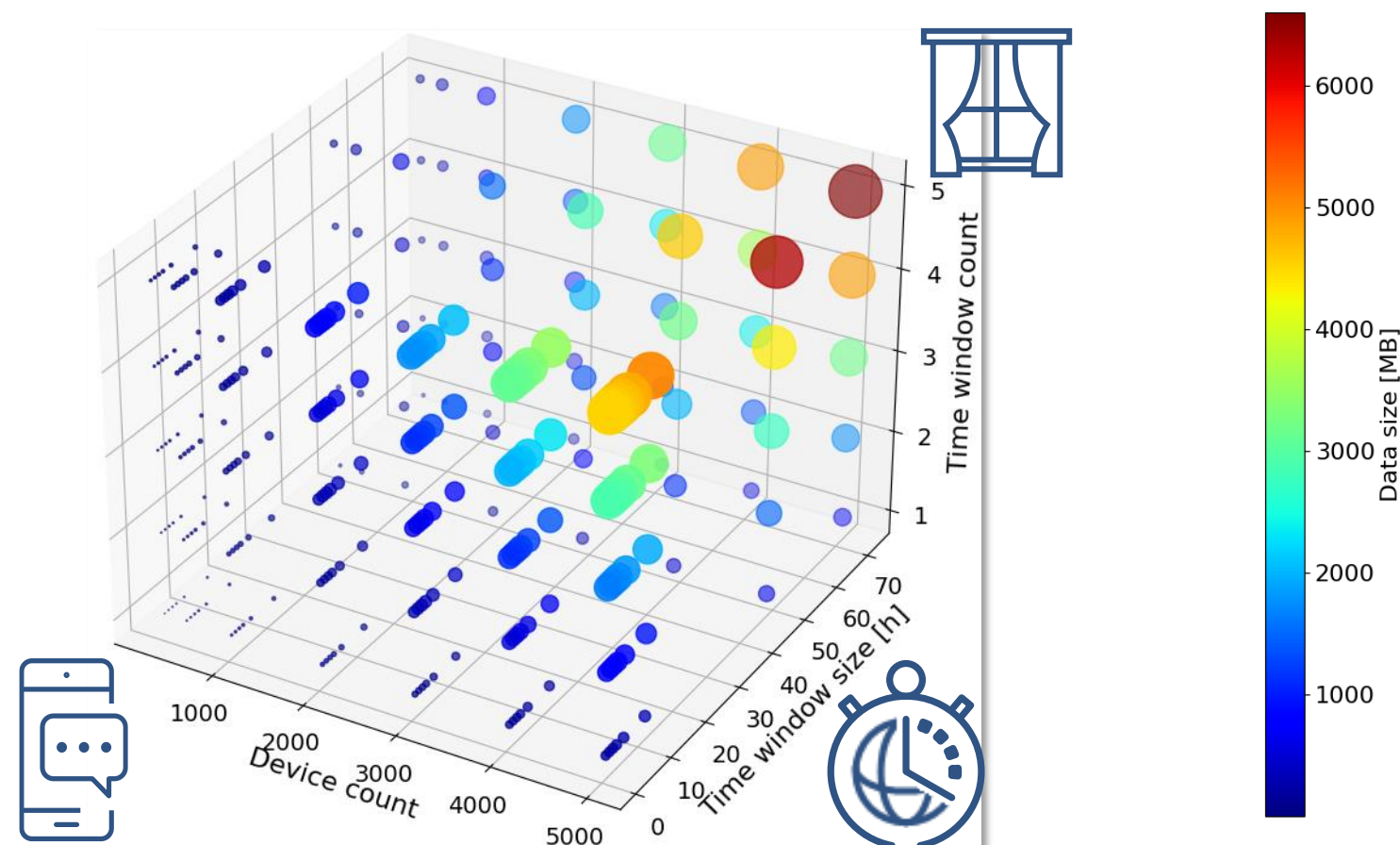
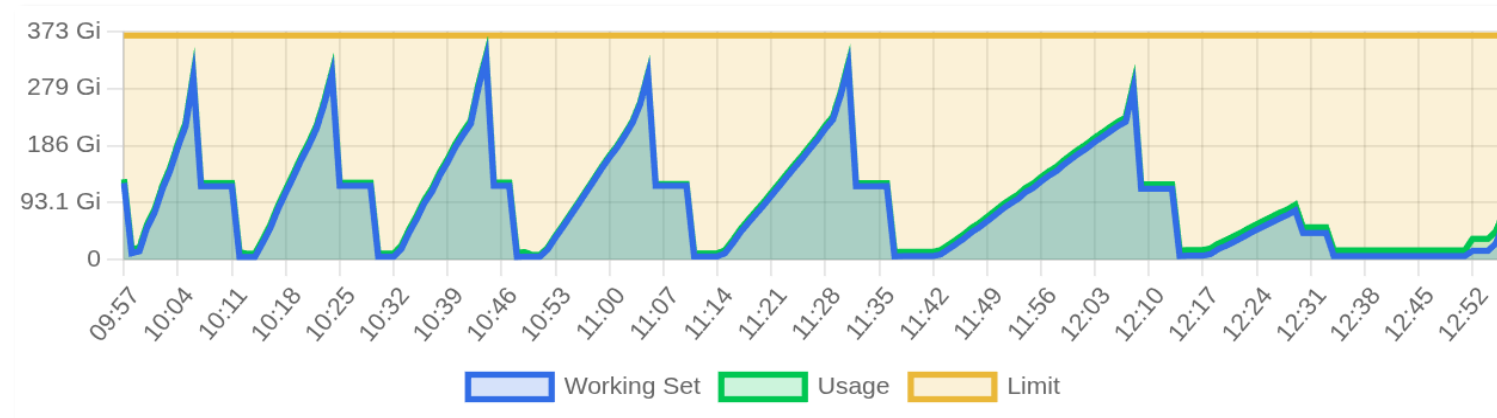
**Euclidean distance: 2.83** —————> The vectors are far apart in absolute space  
They're far apart numerically – so **they're different**

# Challenge 2: Data size

- Cannot fit all data in memory!
- Three key parameters:
  -  Number of devices
  -  Number of time windows
  -  The size of each time window
- Process **device batches (200 ... 5000)**



Memory usage: 5k devices x 24 time windows (1 hour each)





# User (device) tracking



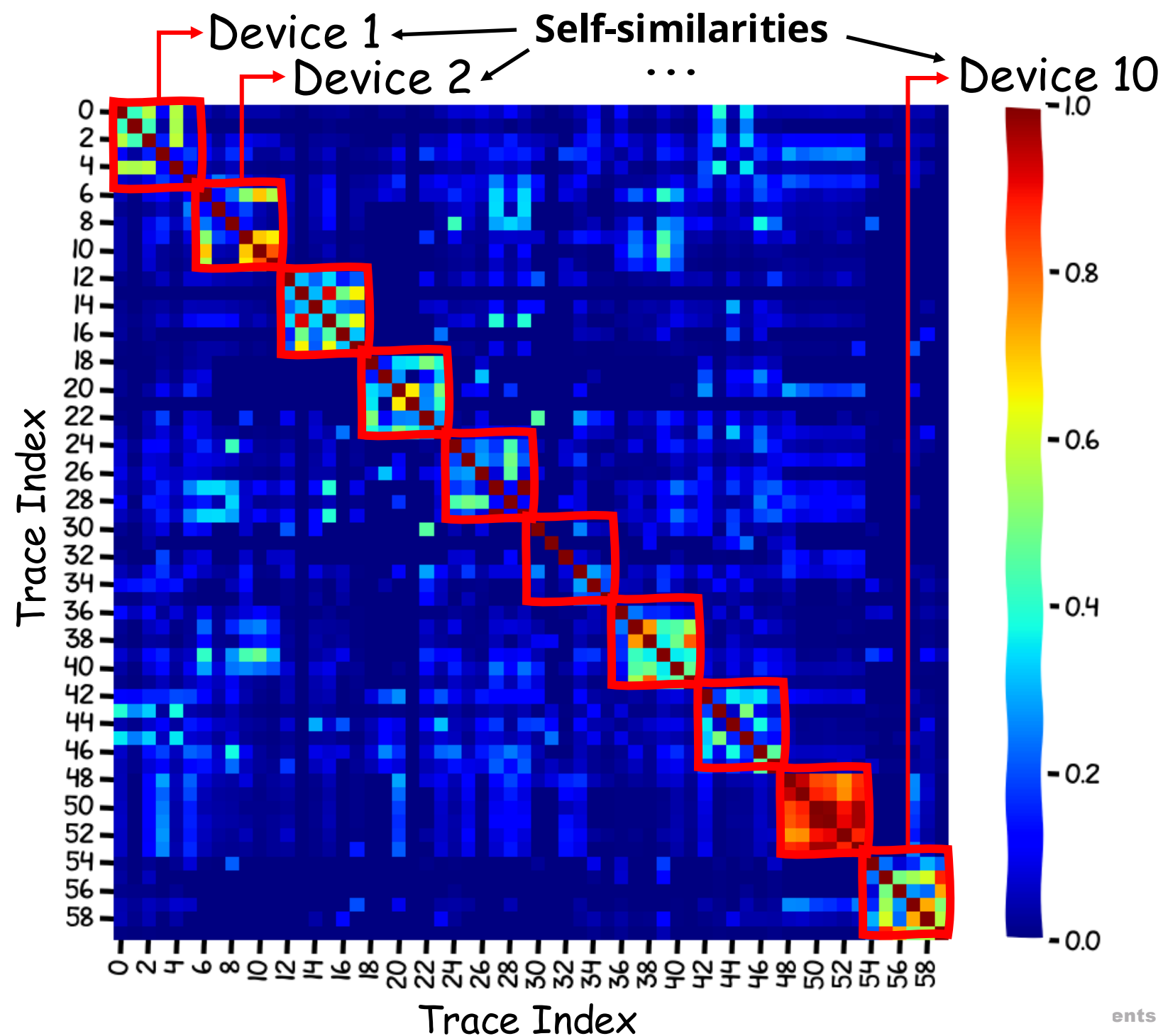
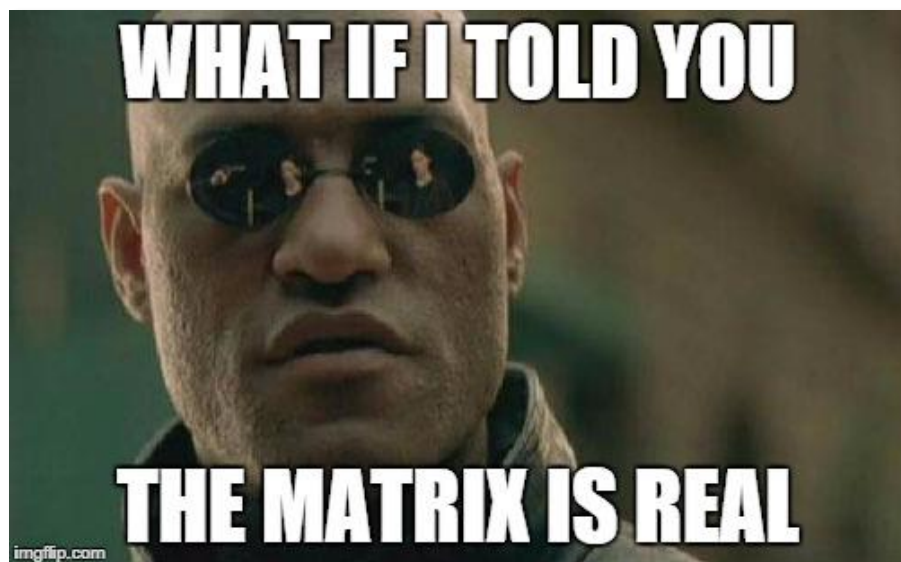
# Device tracking problem





# Analyze the (similarity) matrix

- ✓ Symmetric
- ✓ Each "dot" is a similarity between two traces (i.e., DNS request sequences)
- ✓ Self-similarity is on the diagonal



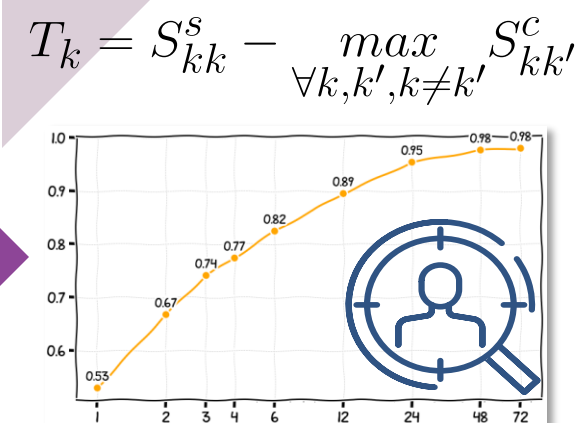
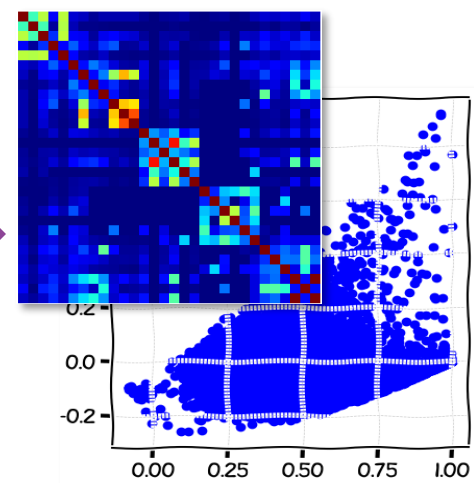
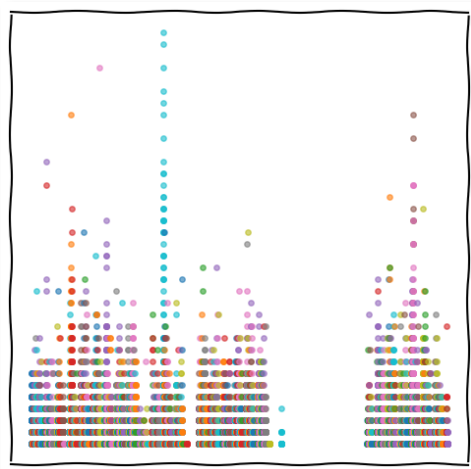
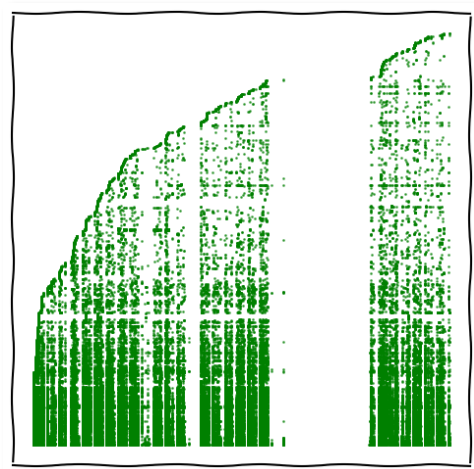
# The approach

DNS traces

Split in time  
windows

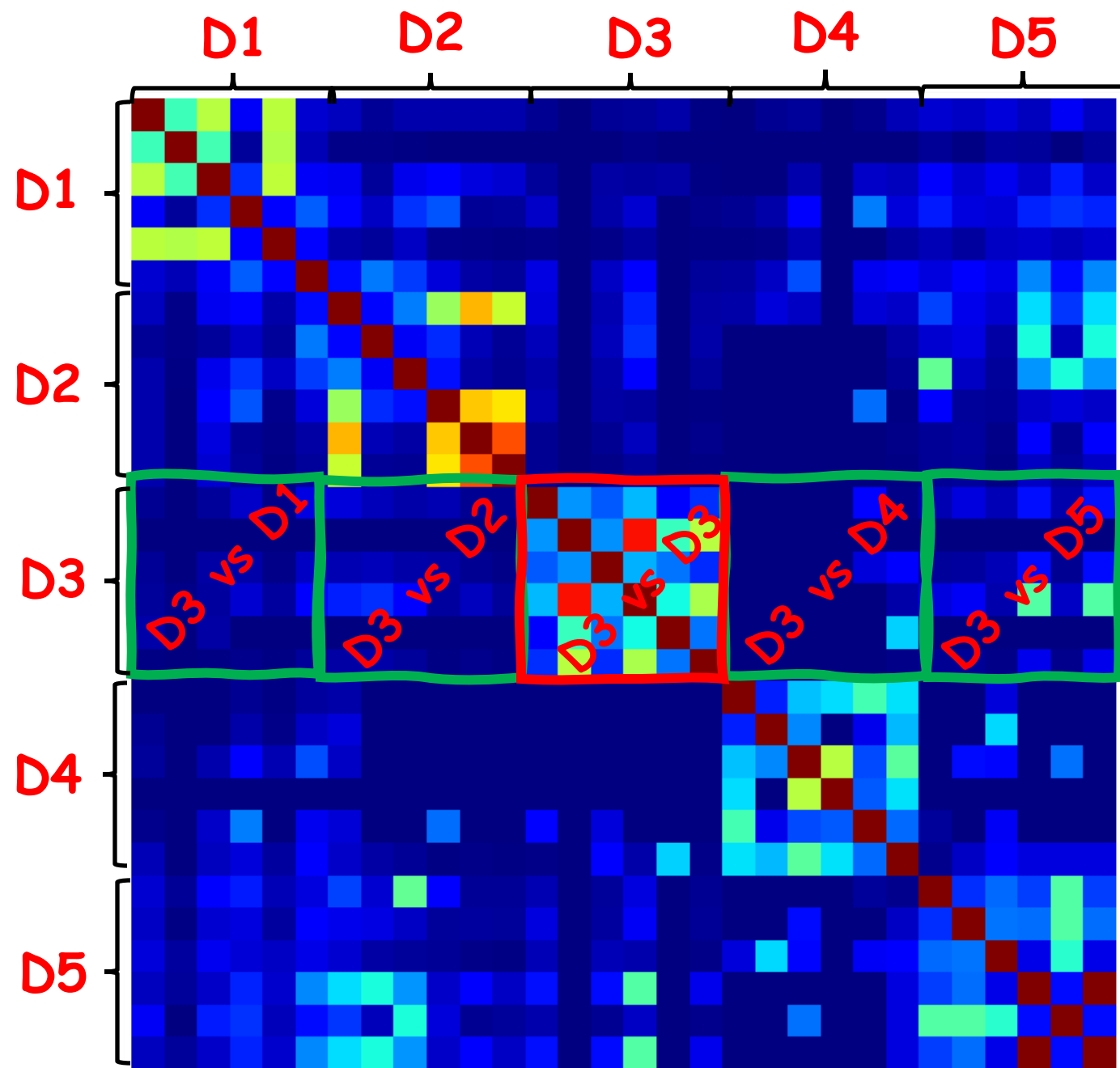
Compute tf-idf &  
cosine similarity

Apply tracking  
index

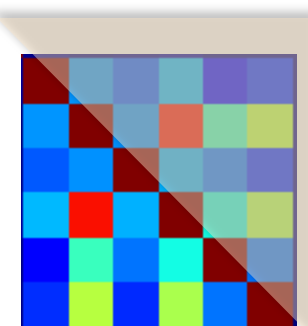




# Similarity index computation



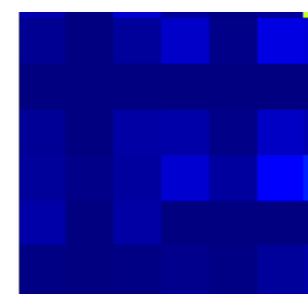
Average self-similarity ( $k = 3$ )



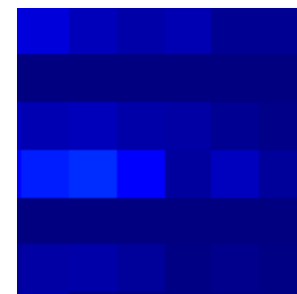
D3

$$S_{kk}^s = \frac{1}{n(n-1)/2} \sum_{i=0}^{n-1} \sum_{j=i+1}^{n-1} M_{i,j}^{kk}$$

Average cross-similarity ( $k = 3, k' = 1, 2, 4, 5$ )



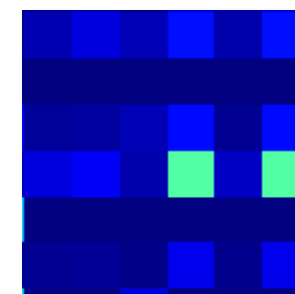
D1



D2



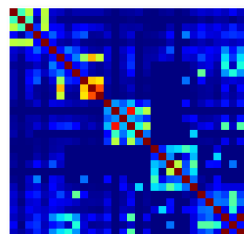
D4



D5

$$S_{kk'}^c = \frac{1}{n^2} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} M_{i,j}^{kk'}$$

# Index for tracking



Tracking index:

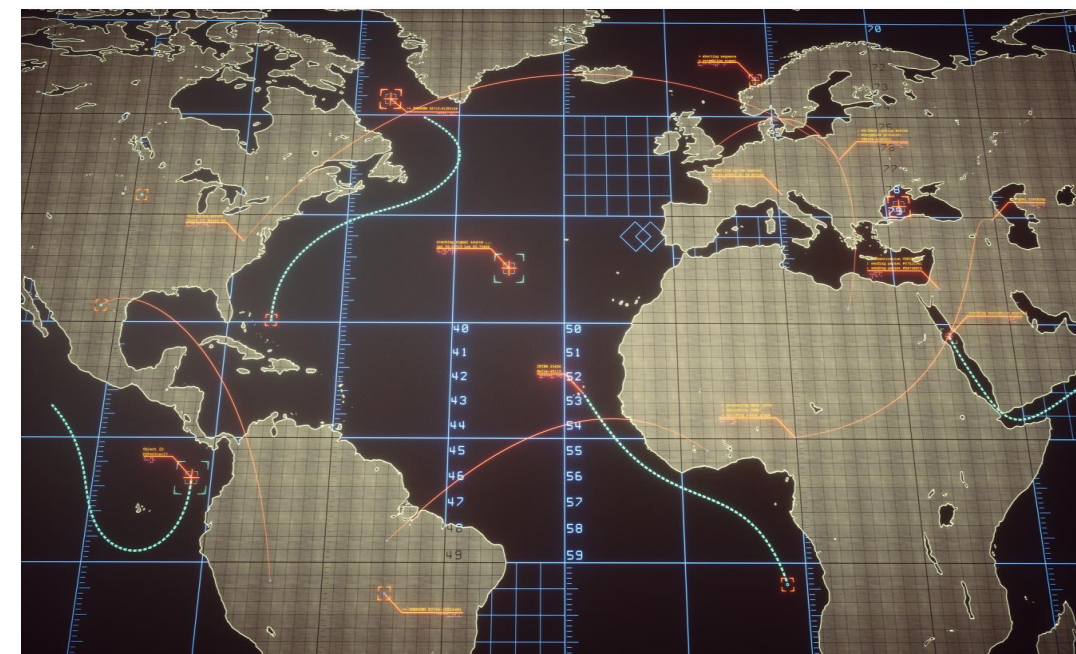
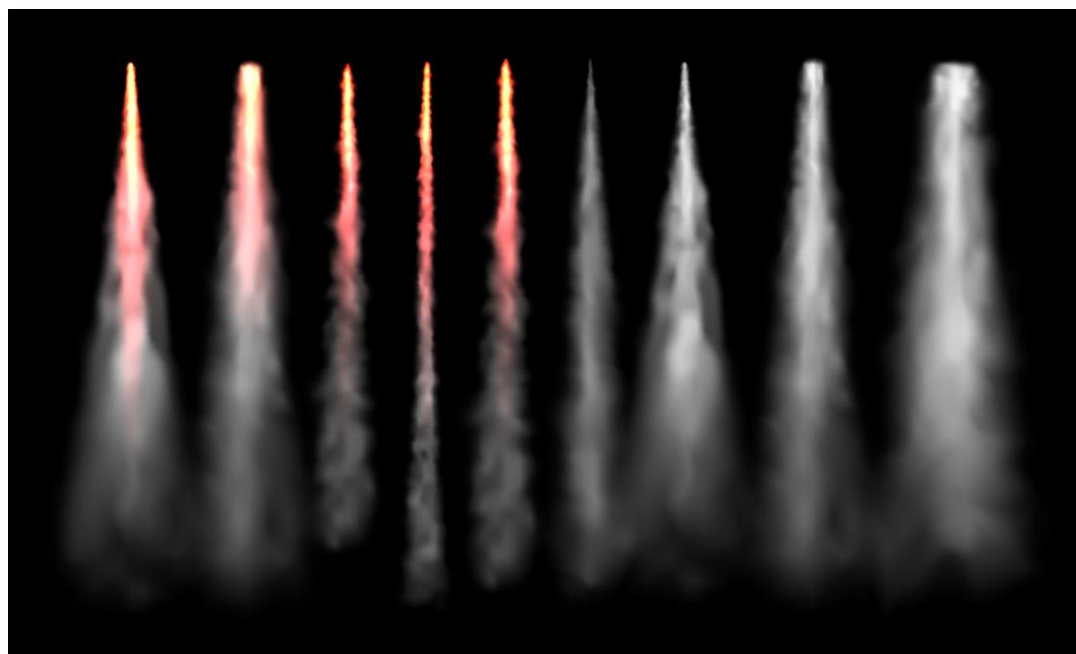
$$T_k = S_{kk}^s - \max_{\forall k, k', k \neq k'} S_{kk'}^c$$



If  $T_k > 0$



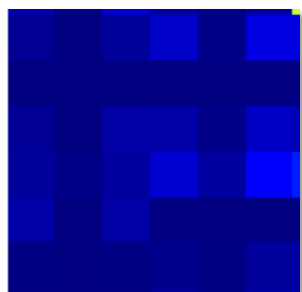
Device  $k$  is *trackable*



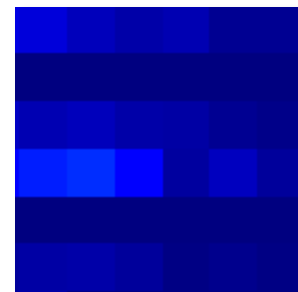


# Index for tracking: example

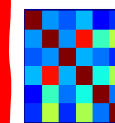
$$S_{31}^c = 0.0219$$



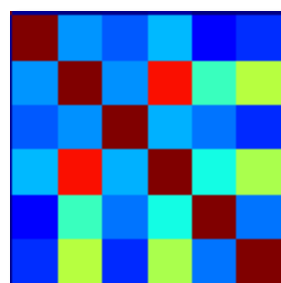
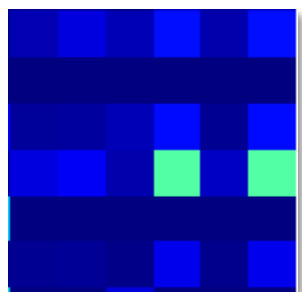
$$S_{32}^c = 0.0311$$



$$\begin{aligned} T_3 &= S_{33}^s - S_{35}^c \\ &= 0.3403 - 0.0647 \\ &= 0.2756 (> 0!) \end{aligned}$$

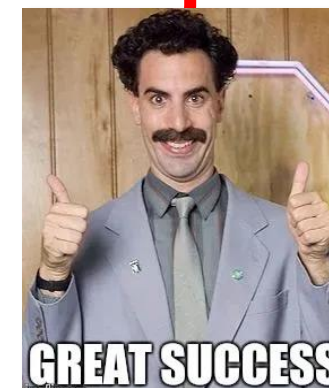


$$S_{35}^c = 0.0647$$

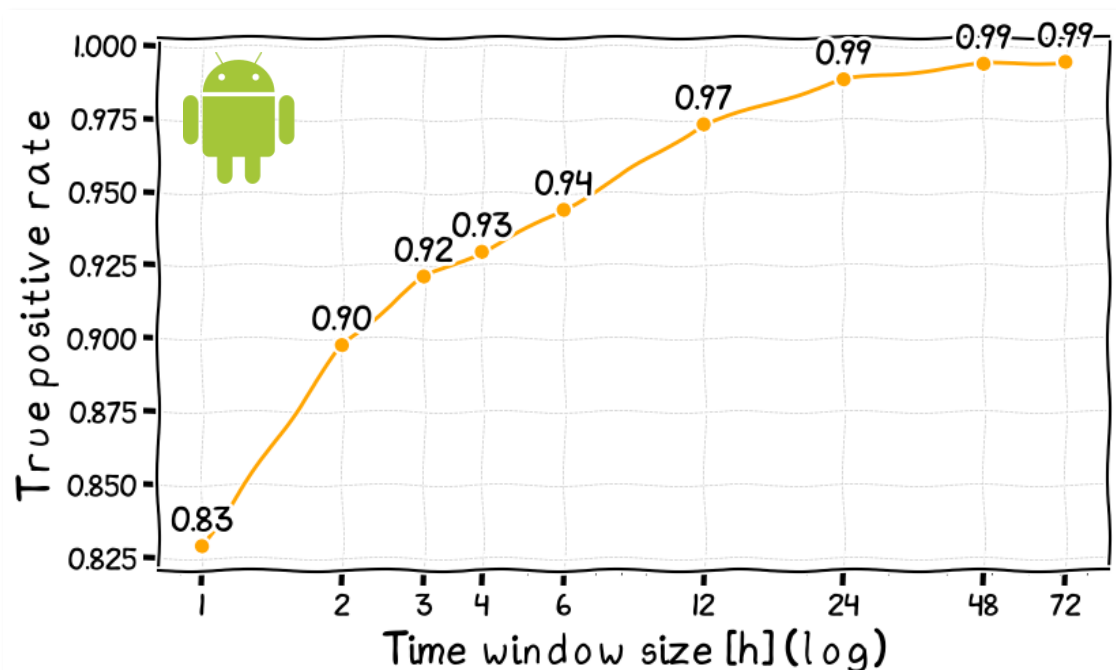
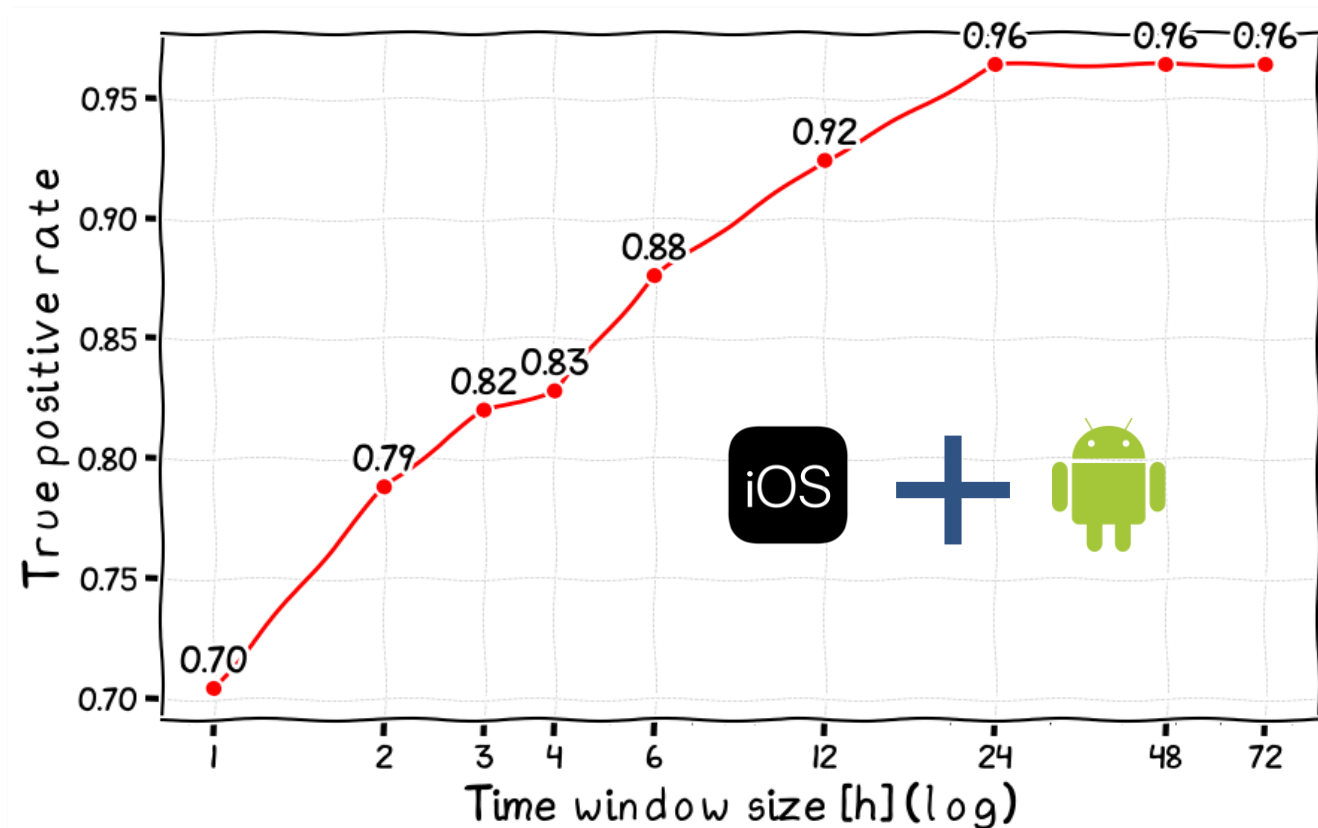
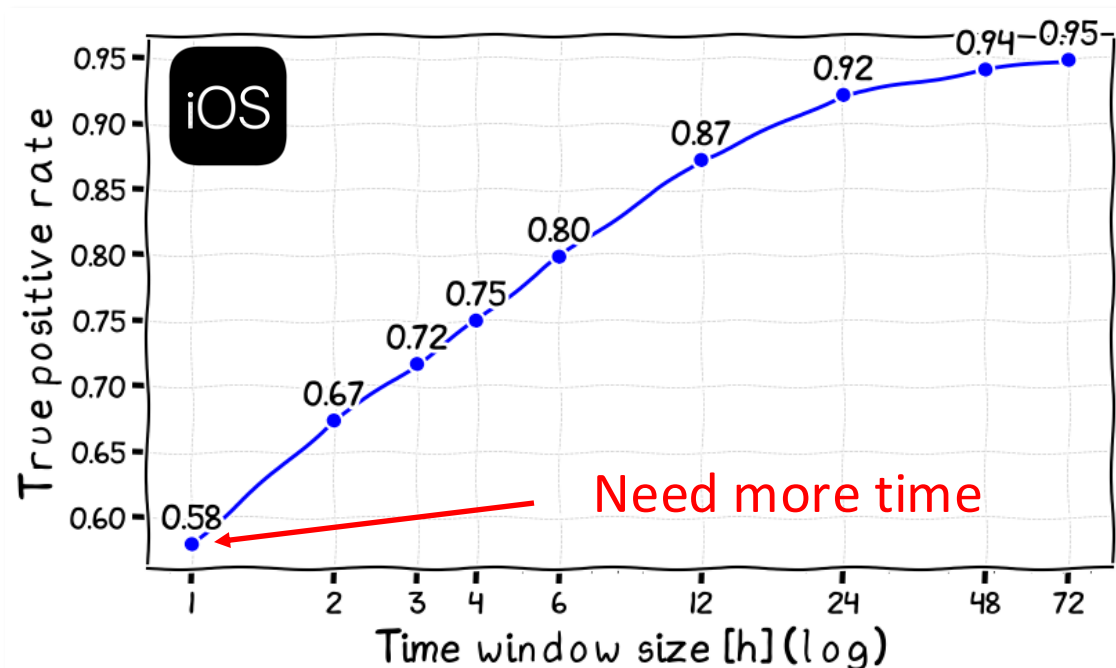


$$S_{33}^s = 0.3403$$

$$S_{34}^c = 0.0194$$



# Tracking accuracy: 250 devices



- Larger time windows yield better results
- After 2 hours, **accuracy > 80%**



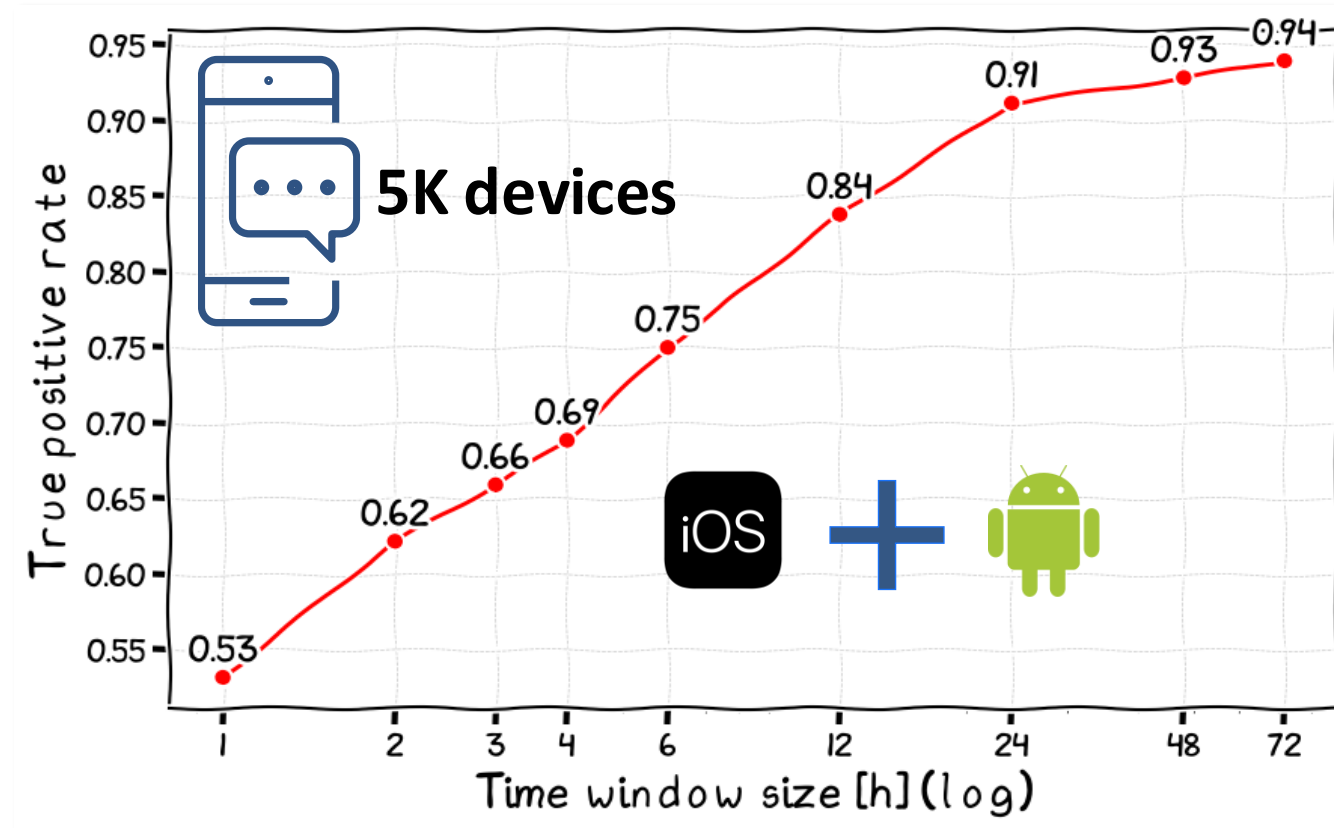
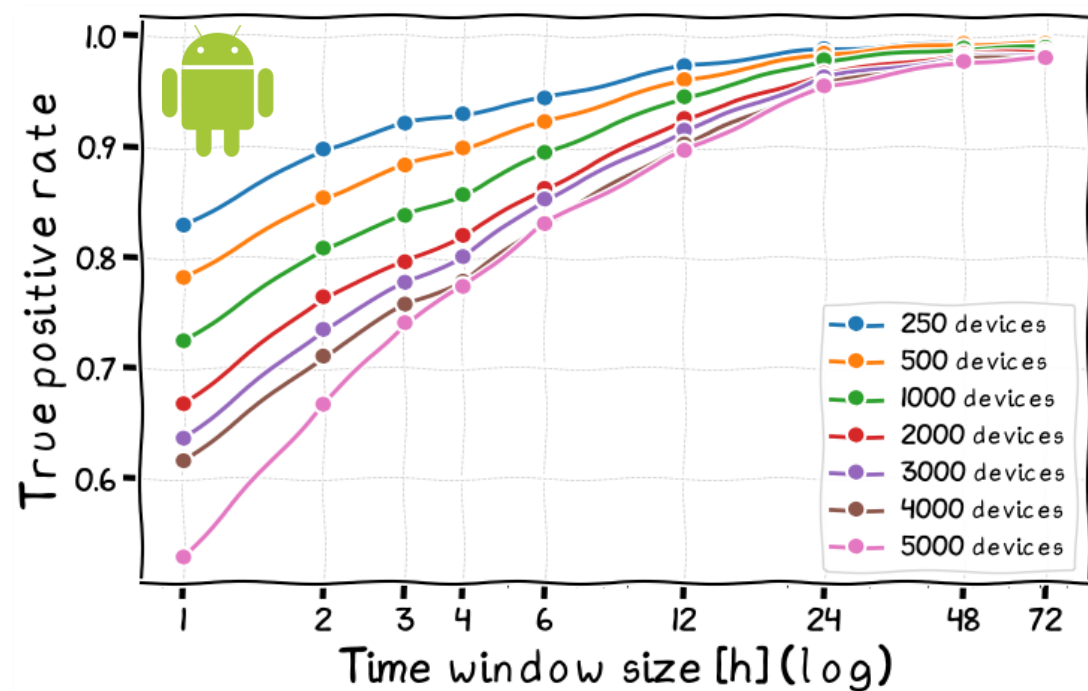
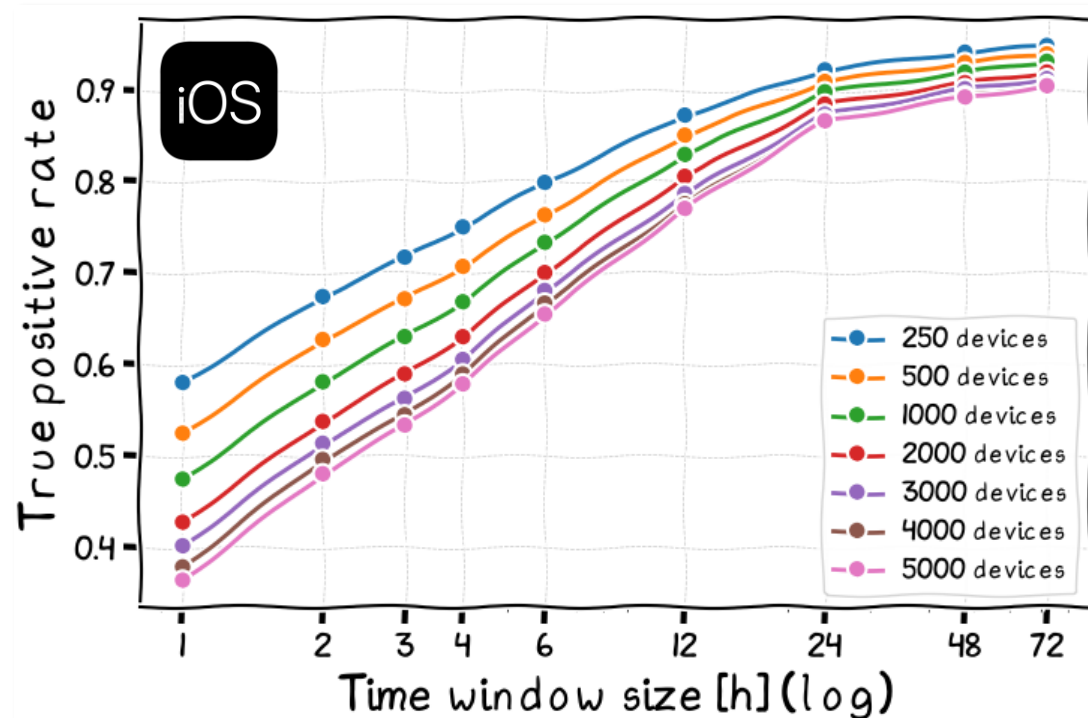
\* Used  $\leq 12$  time windows spread across two weeks



# Lesson 1: change device ID (MAC)



# Tracking results: in the crowd



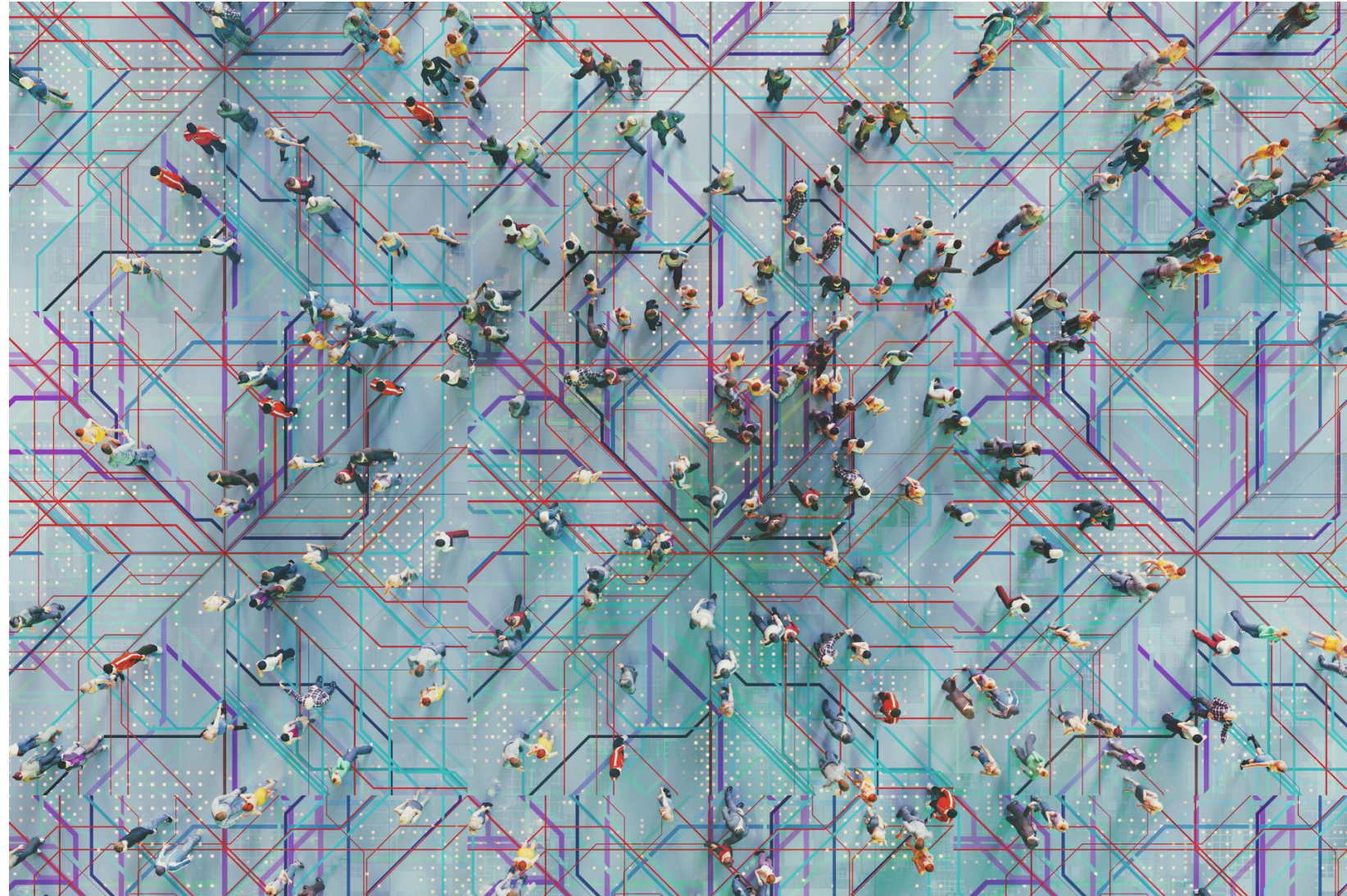
- A larger pool of devices reduce chances of tracking
- 2 hours **accuracy 62%**
- **More time: 90+%**





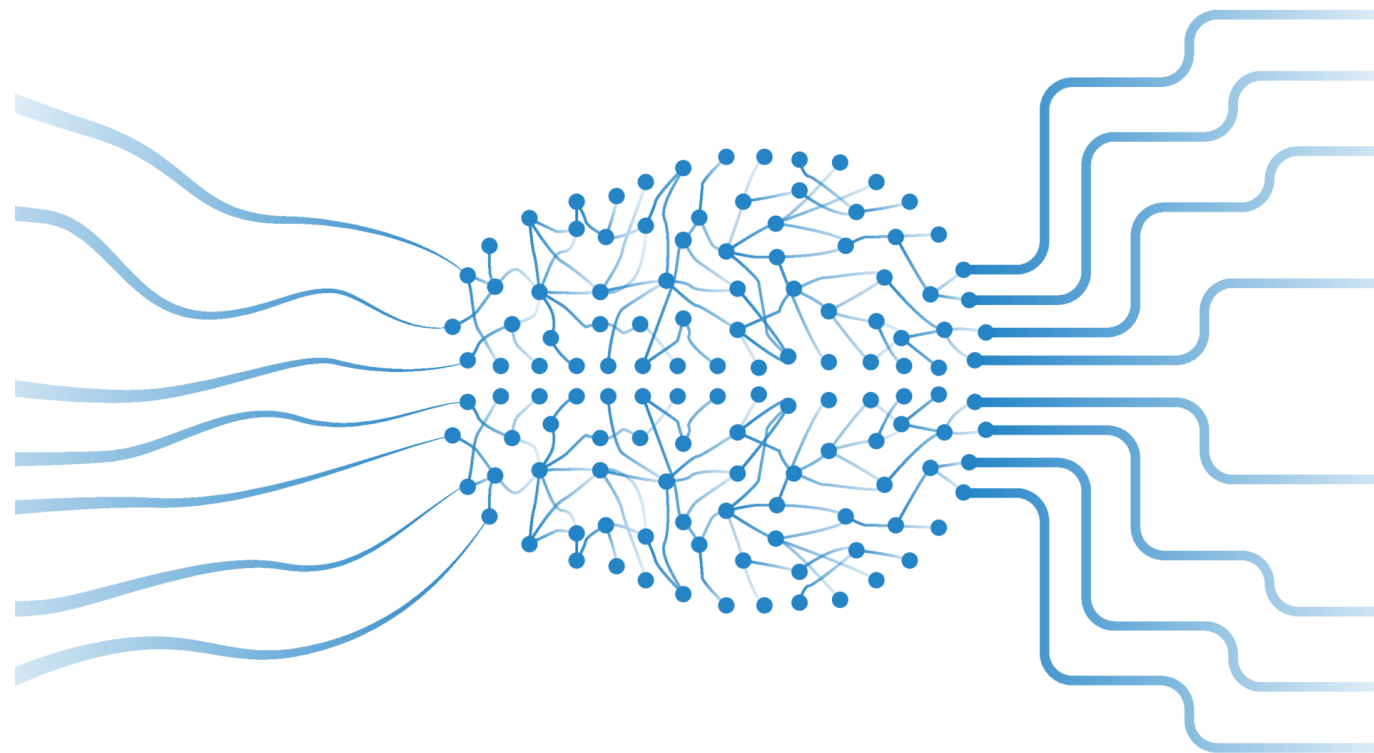
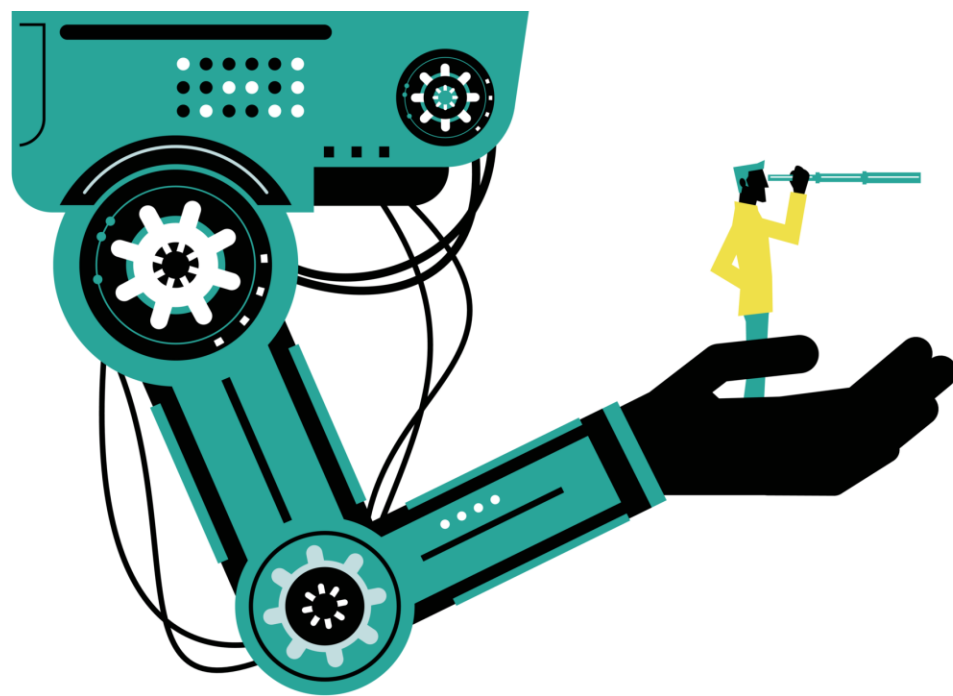
# Lesson 2: stay in the crowd

**The more crowded, the better (for loosing track)!**



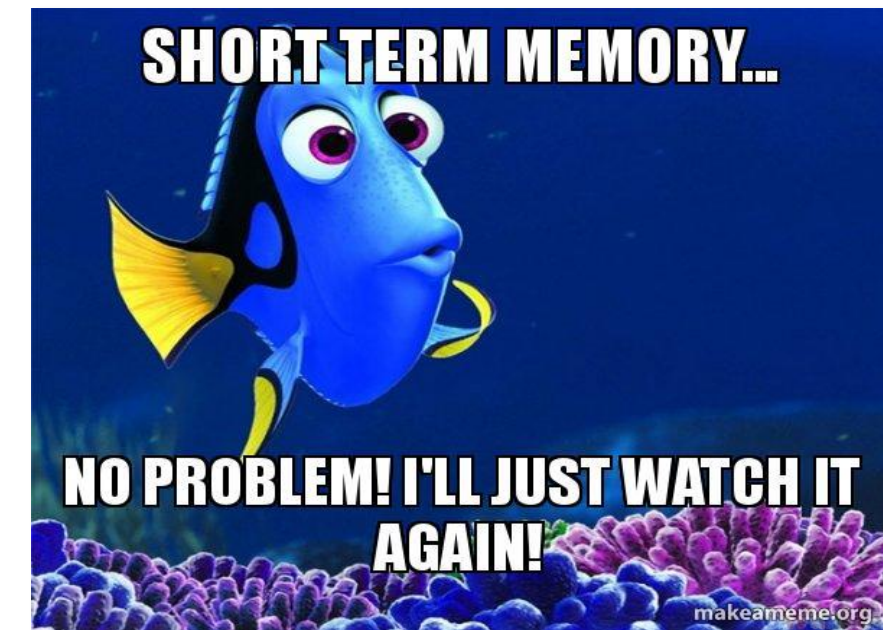
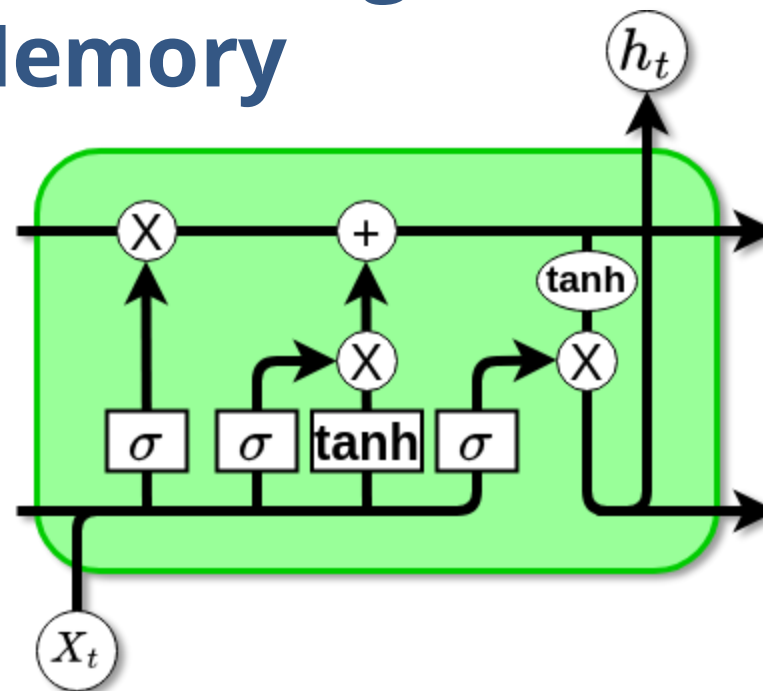
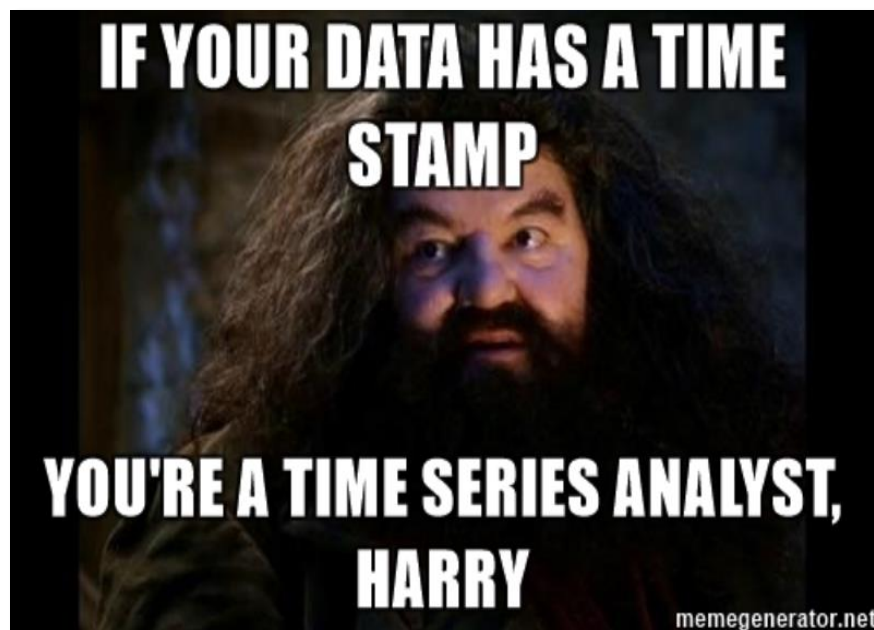


# Time for some machine learning





## LSTM: Long Short-Term Memory



Use cases:

- Speech recognition
- Time series
- Robot control
- ....





100



100



1h



3 weeks

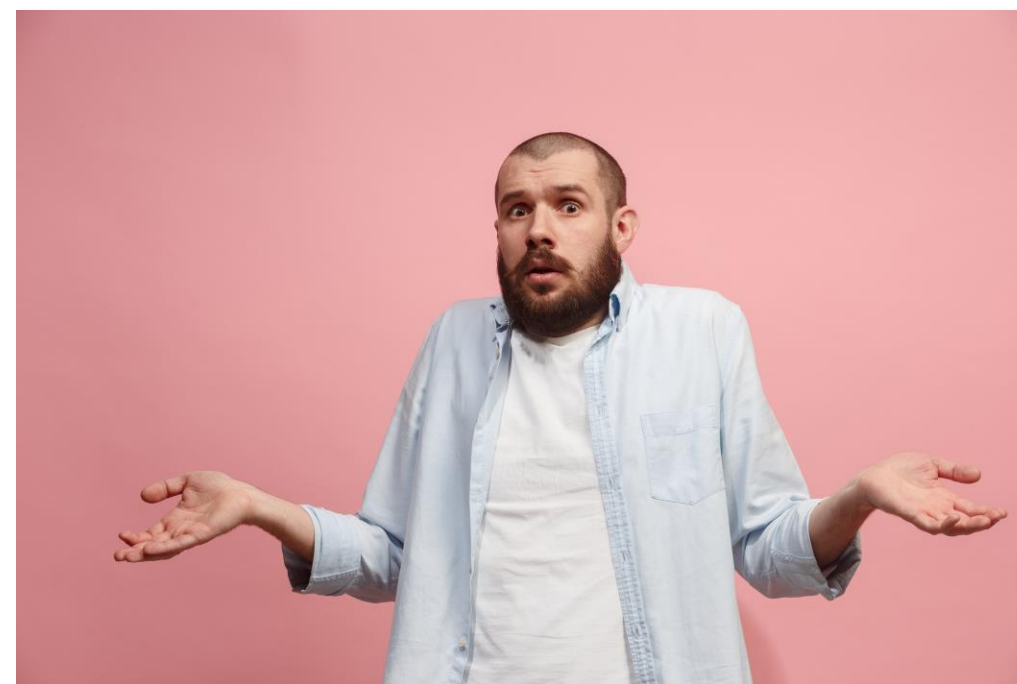
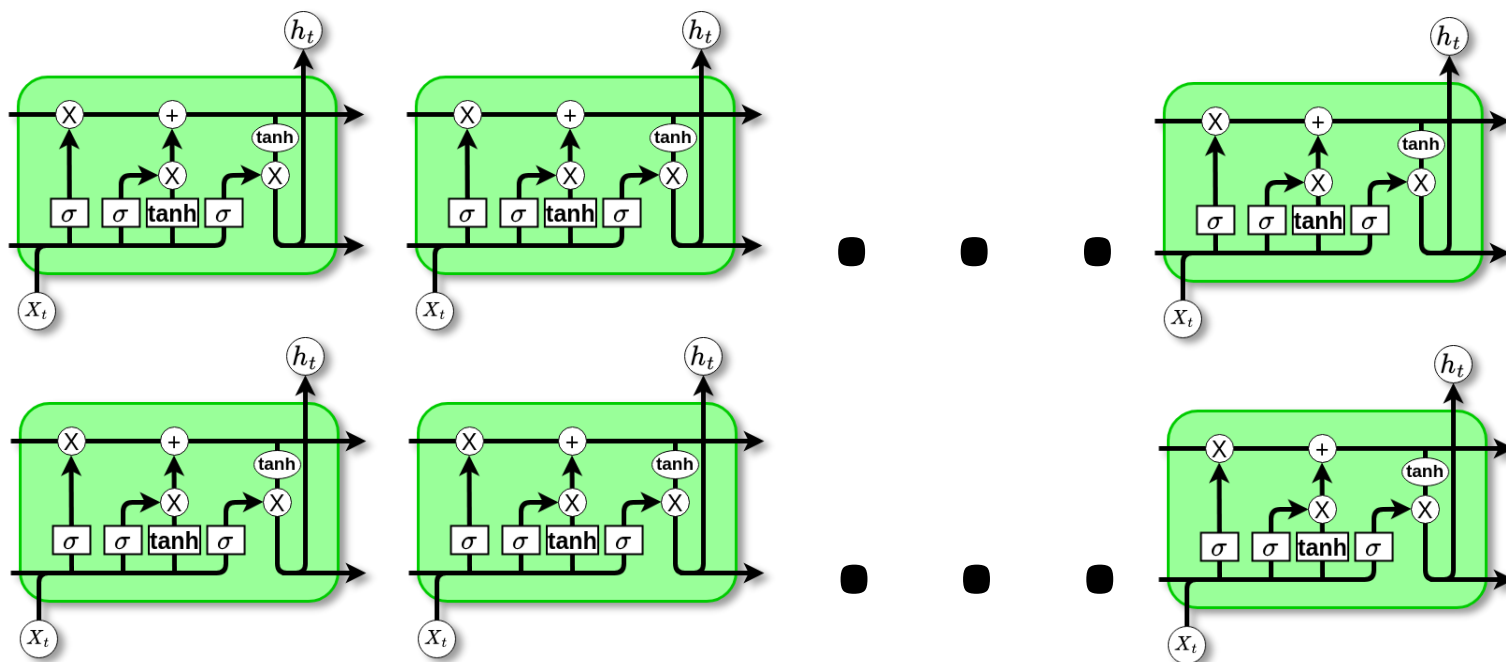
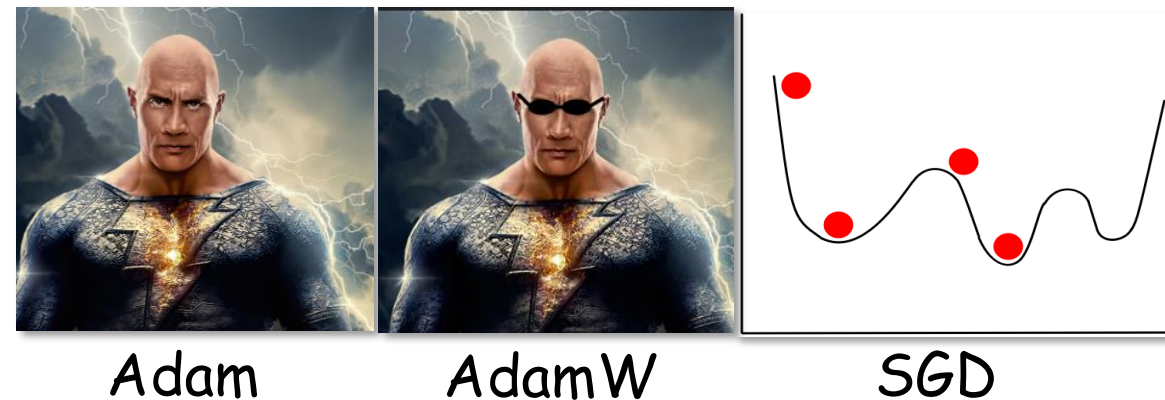
Model	Validation accuracy	Test Accuracy
LSTM - Model 1	83.14%	78.18%
LSTM - Model 2	76.43%	76.43%





# Choosing an appropriate model

weights-initialization  
hidden-layers  
nr-neurons  
activation-function  
adam  
sgd metrics  
learning-rate  
adamw randomness  
optimizers



# LSTM: hunger for resources

For Internal Use Only



5K phones

Time window →

3h

240k	352k
136k	352k
171k	352k

OOM

I'm too big!

6h

120k	348k
69k	348k
87k	348k

OOM

Me too...

12h

64k	342k
36k	342k
47k	342k

OOM

I was close!

24h

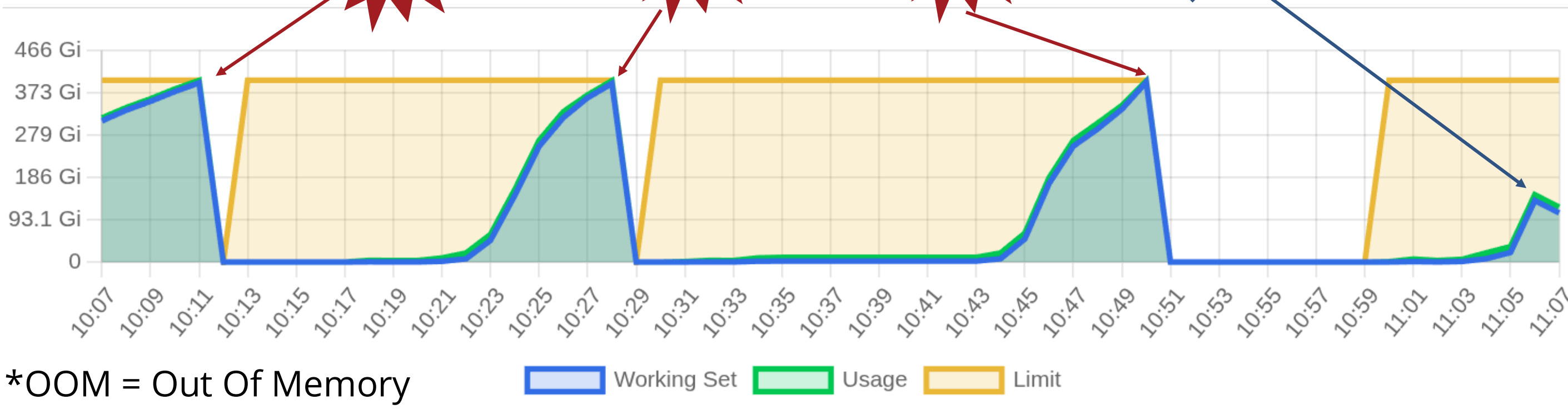
34k	340k
20k	340k
26k	340k

Success!

GREAT SUCCESS



!!HIGH FIVE!!





# LSTM architecture parameters



2500

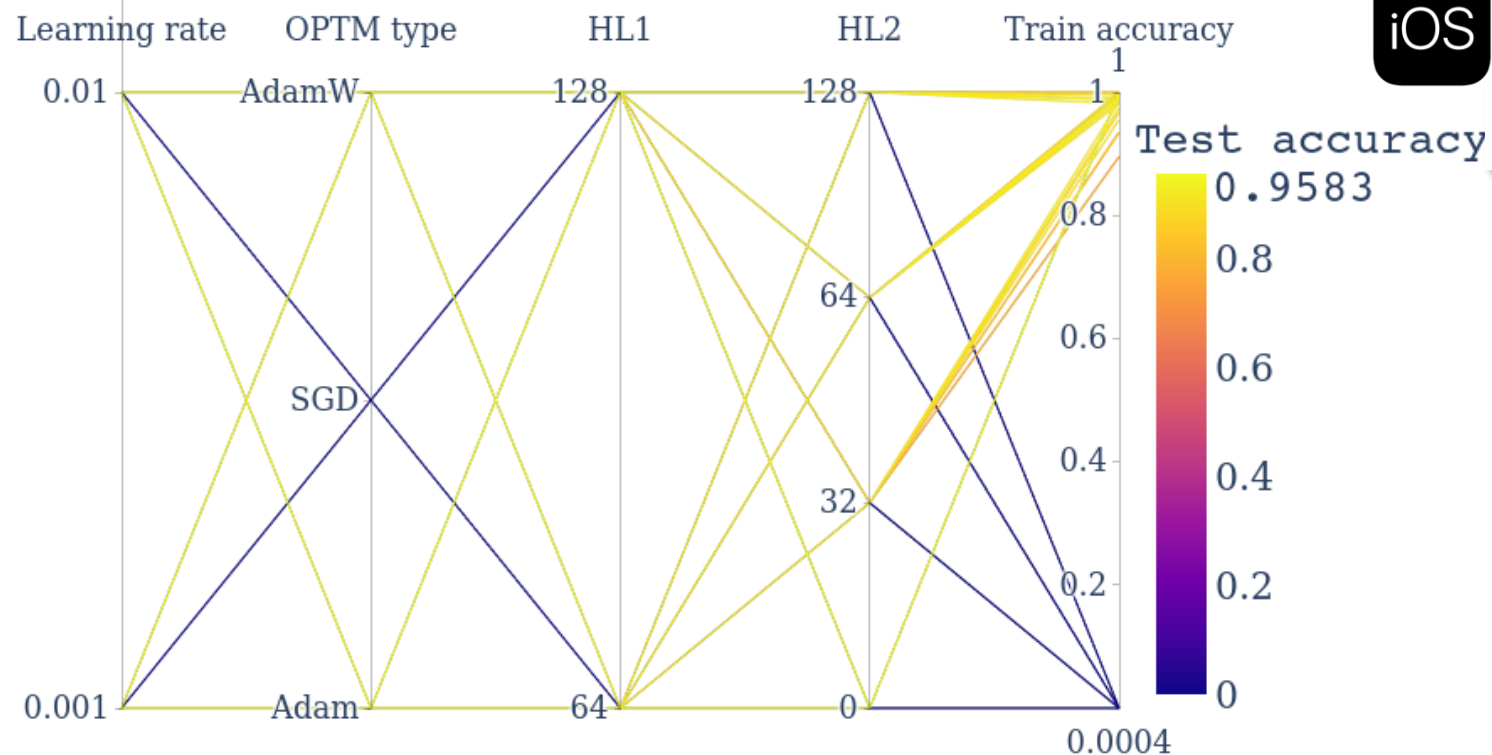


24h

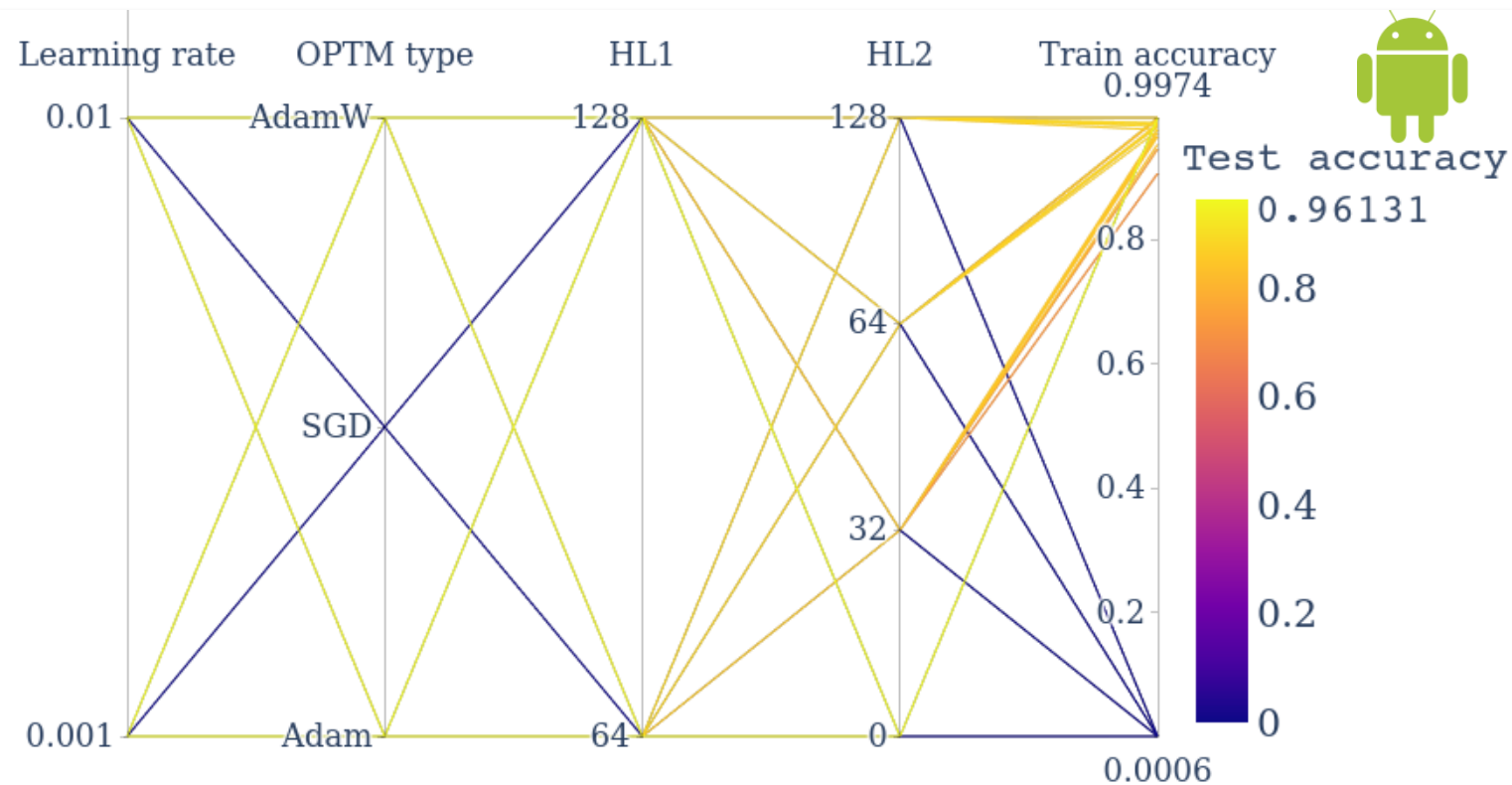


3 weeks

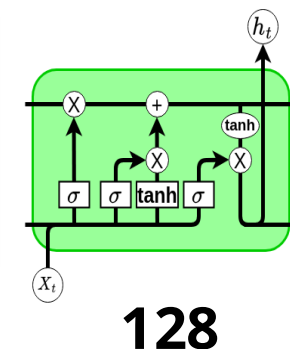
2500



iOS



1 LSTM  
layer

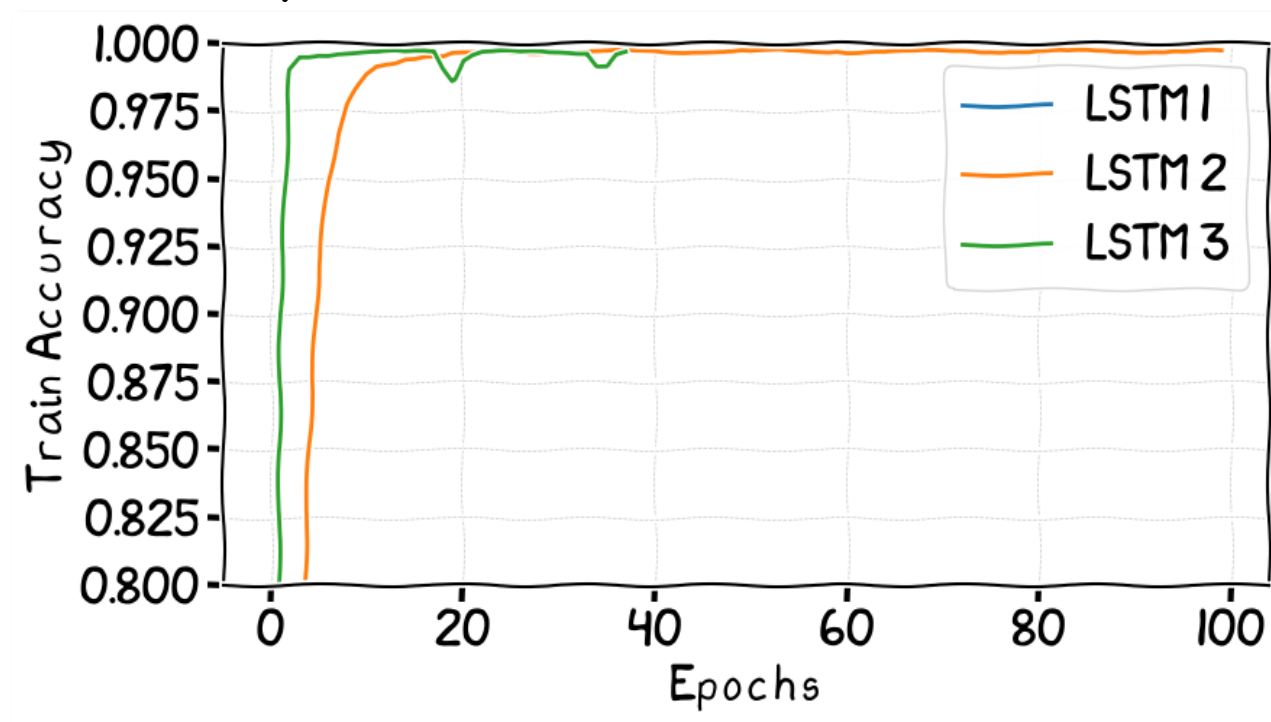


iOS

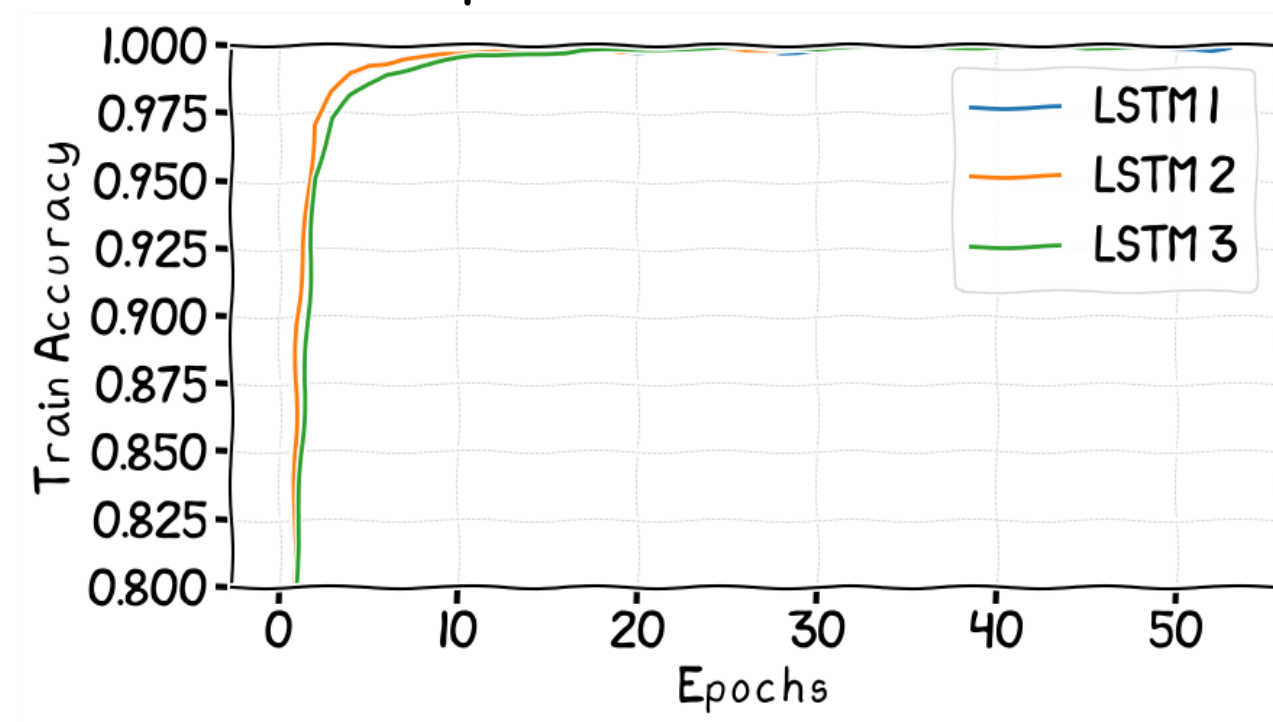


Model	Train accuracy	Test accuracy	Time
LSTM1	99.97%	95.83%	284 min
LSTM2	99.96%	95.68%	144 min
LSTM3	99.97%	95.25%	116 min

Top 3 Android LSTM models



Top 3 iOS LSTM models



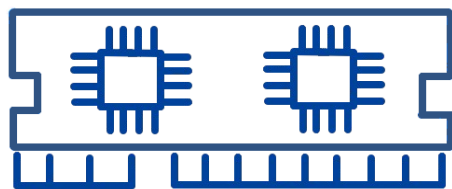
Model	Train accuracy	Test accuracy	Time
LSTM1	99.73%	96.31%	307 min
LSTM2	99.74%	96.28%	235 min
LSTM3	99.70%	95.70%	106 min



# LSTM's resource consumption

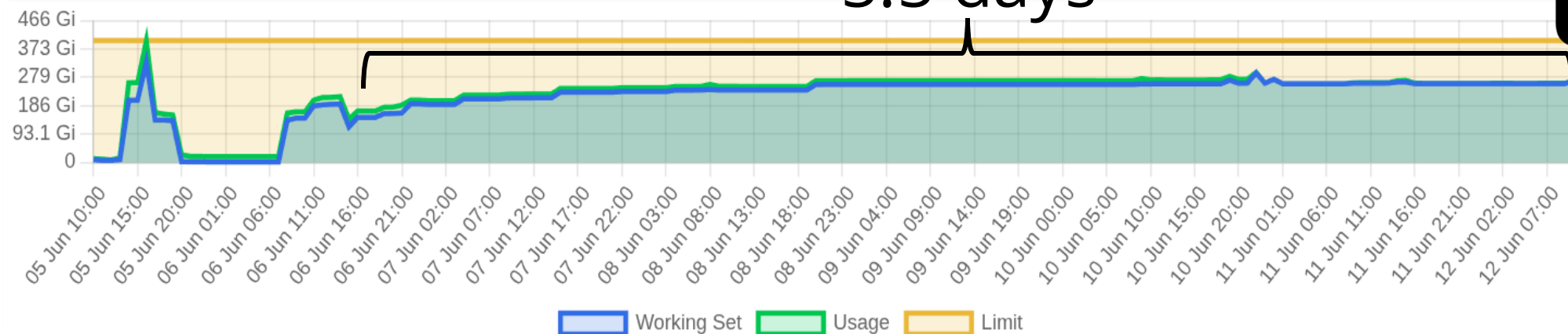
2500

~ 280 / 190 GB RAM 2 clusters (64 vCPUs) 48 models

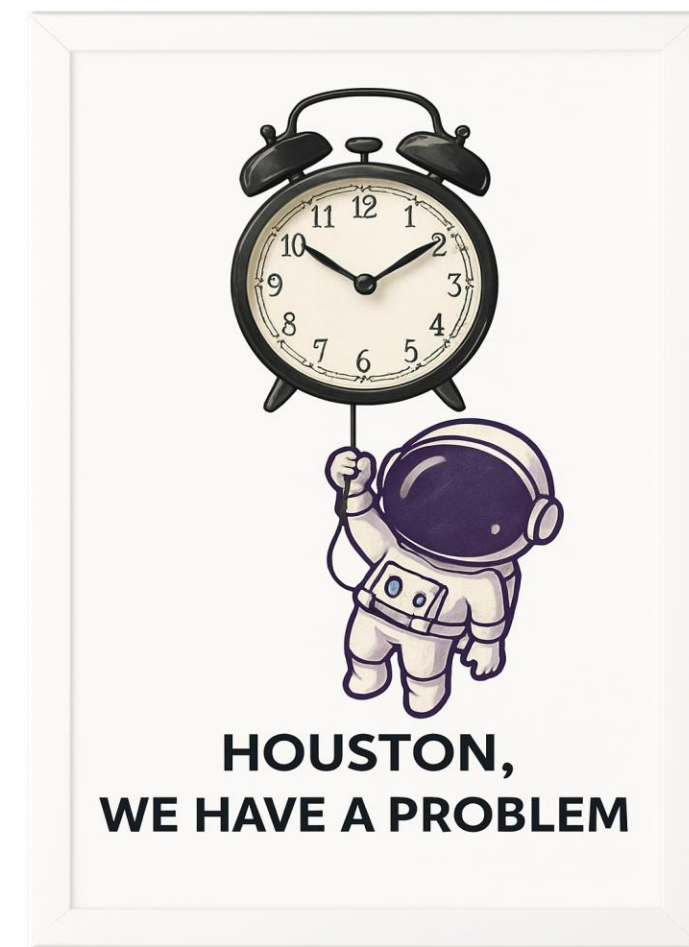
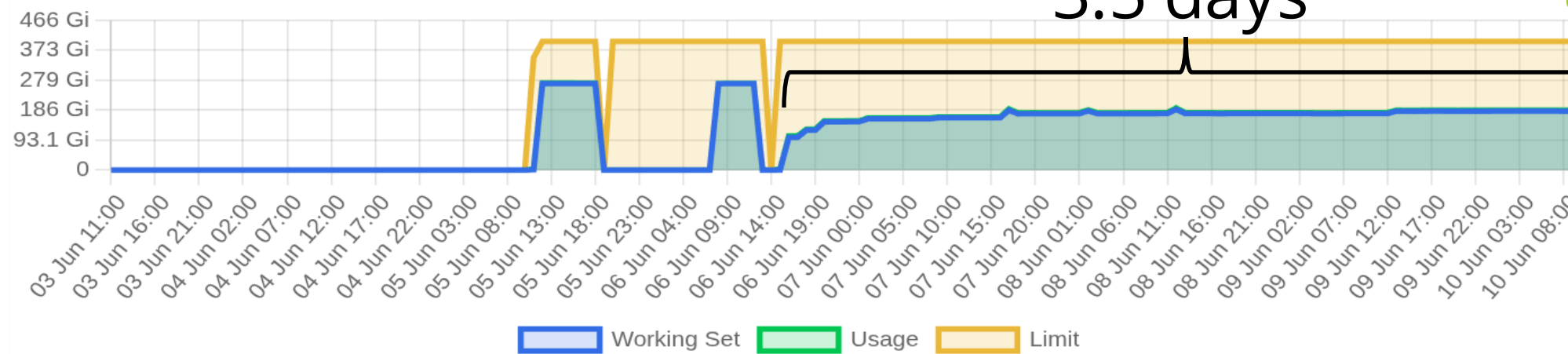


5.5 days

iOS



3.5 days





	LSTM	COS similarity
Accuracy score	HIGHER	HIGH
Memory usage	HIGHER	MEDIUM
Number of CPUs	HIGH	LOW
Time consumption	HIGH	LOW

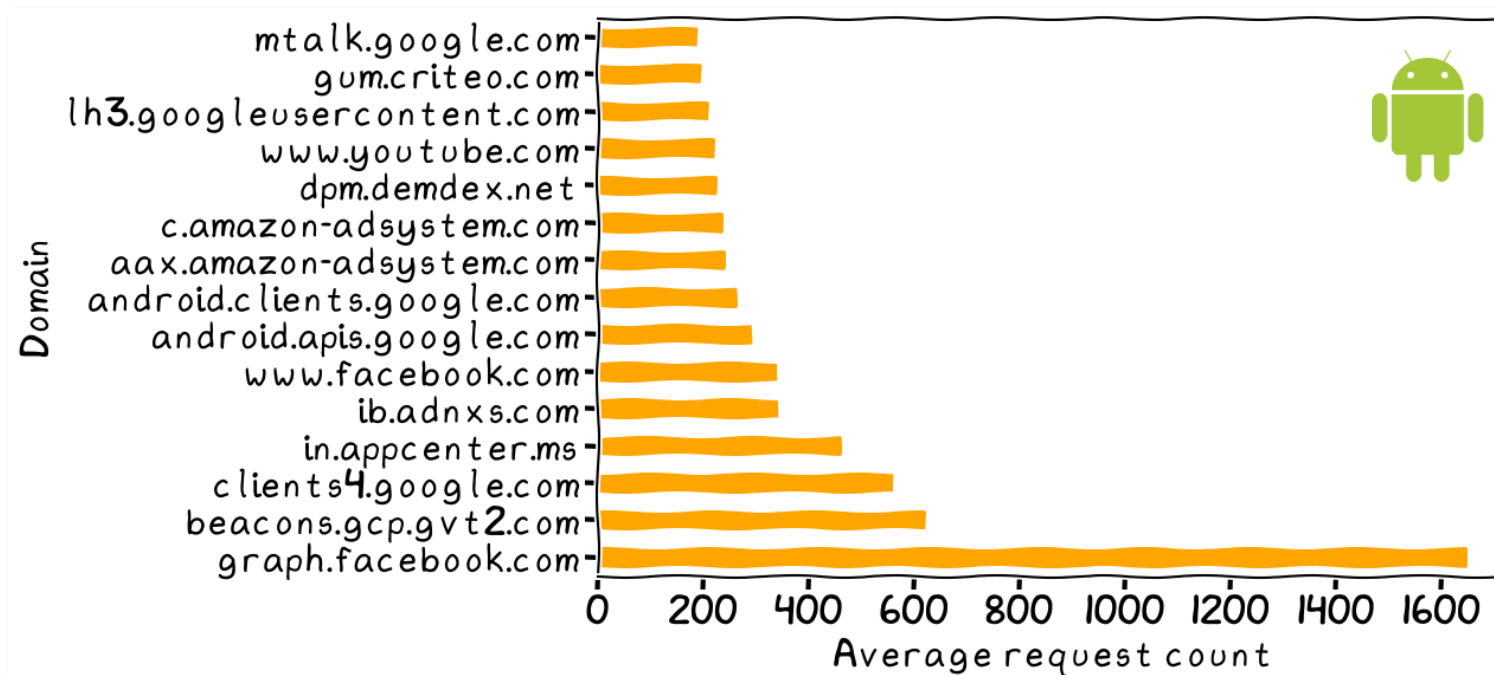
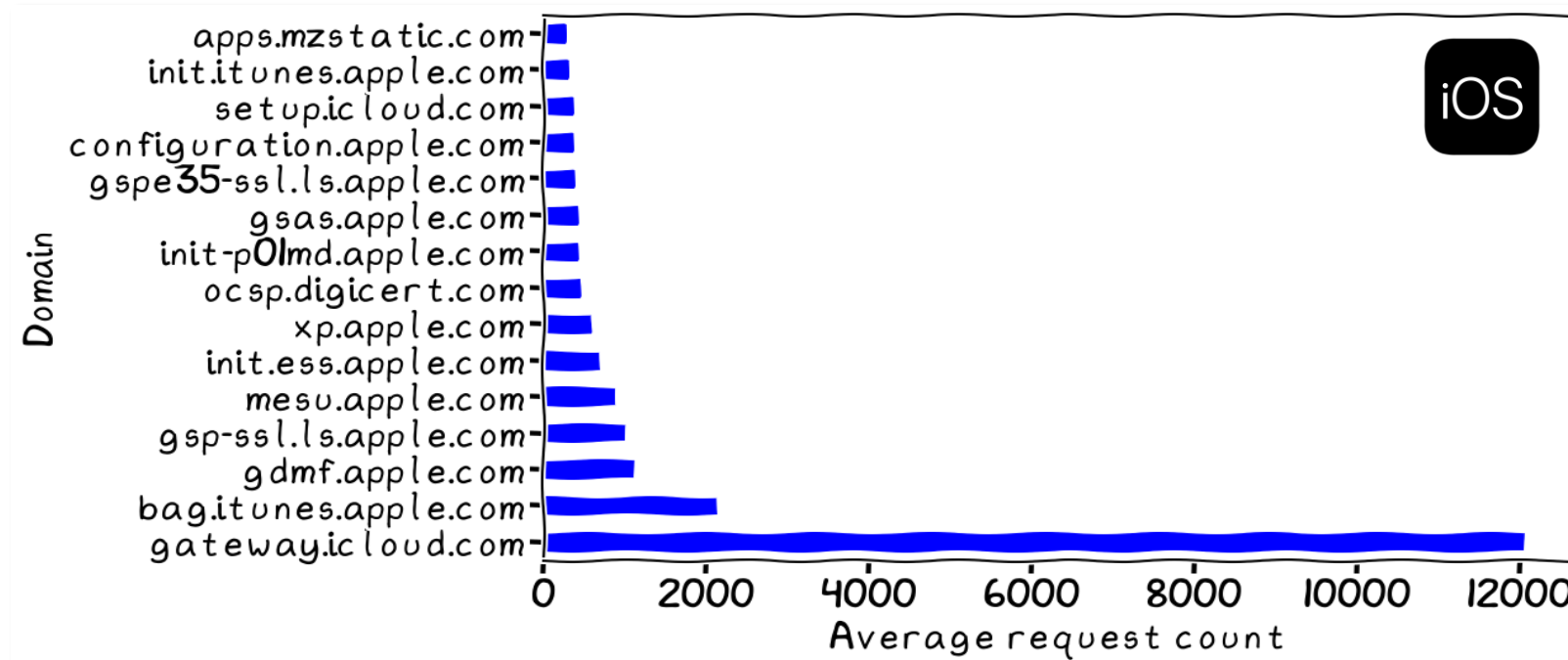
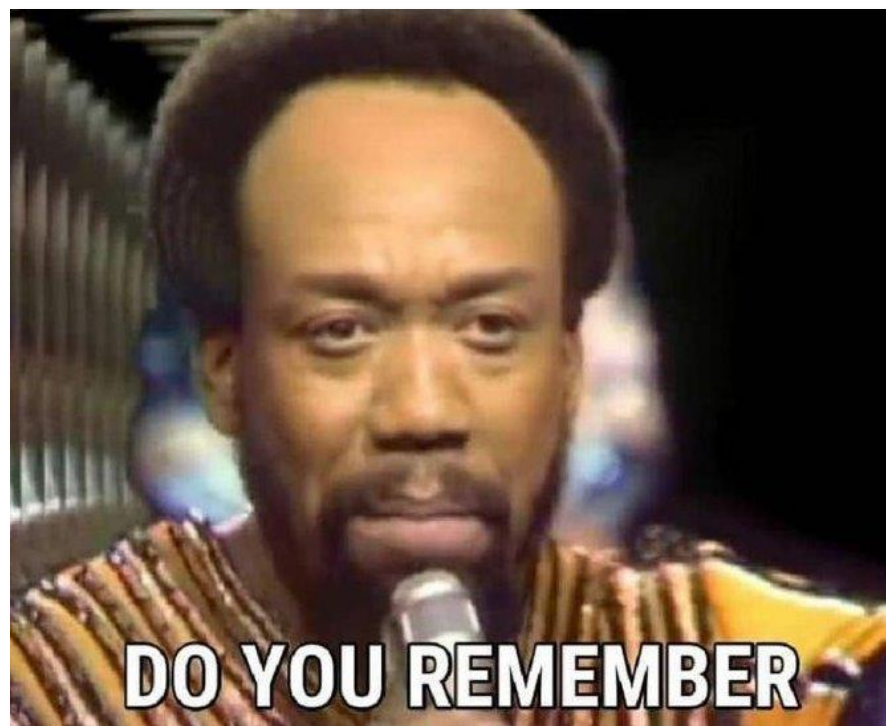


# How much does it cost?

Provider	Computation + RAM	Storage (2 TB SSD)	Total/day	Total/month
AWS	\$87.28/day	\$6.30/day	\$94/day	\$2,820
GCP	\$101/day	\$5.80/day	\$107/day	\$3,210
Azure	\$129/day	Included	\$129/day	\$3,870
Oracle	\$116/day	\$2.86/day	\$119/day	\$3,570
Alibaba	~\$96/day	\$5.12/day	\$101/day	\$3,030



# Wait ... there is more



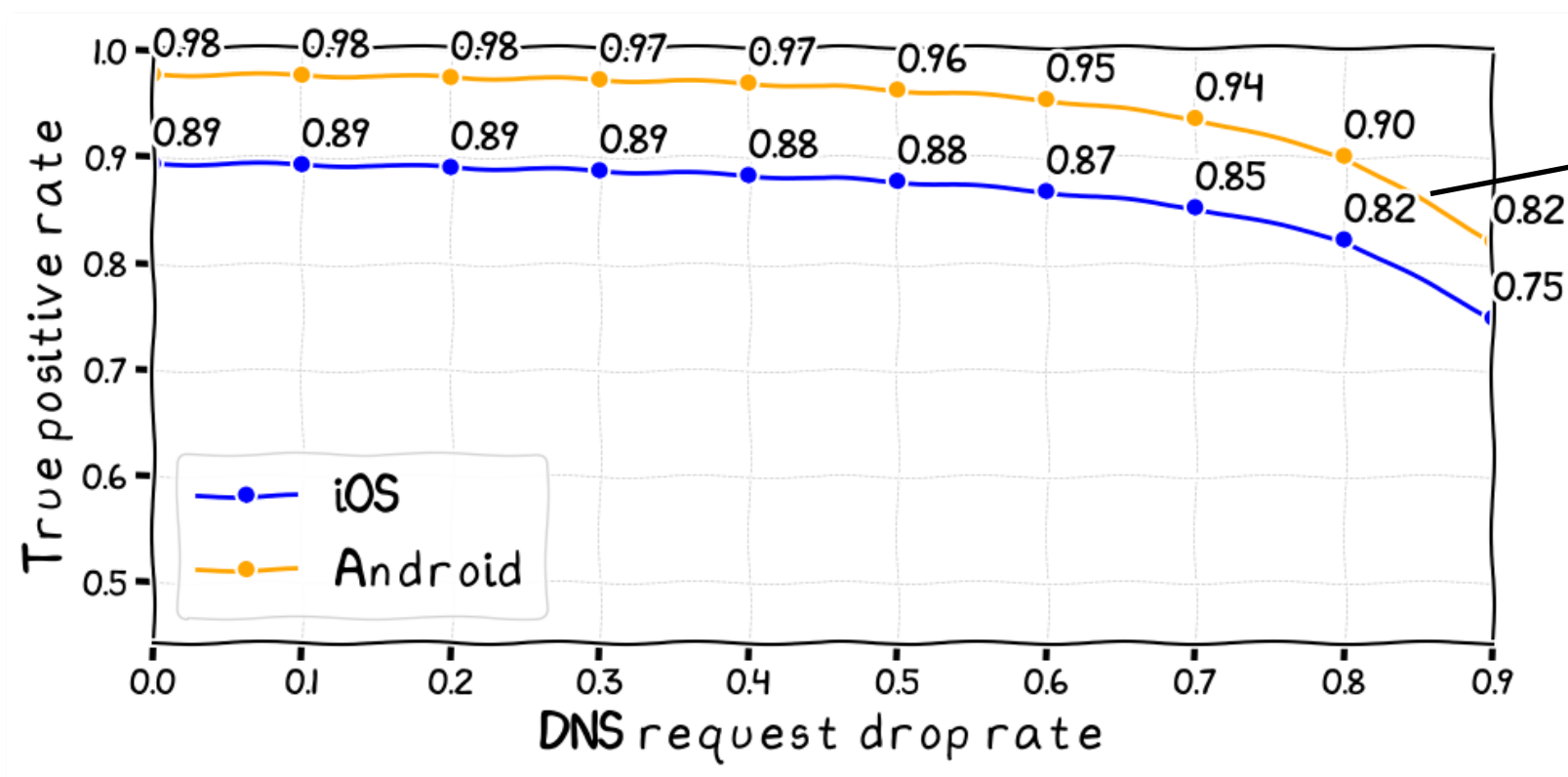


# We can do without all that traffic

- Randomly dropping DNS requests preserves statistical distribution
- We can achieve good accuracy with **only 20%**!



**1000 phones**  
(of each type)

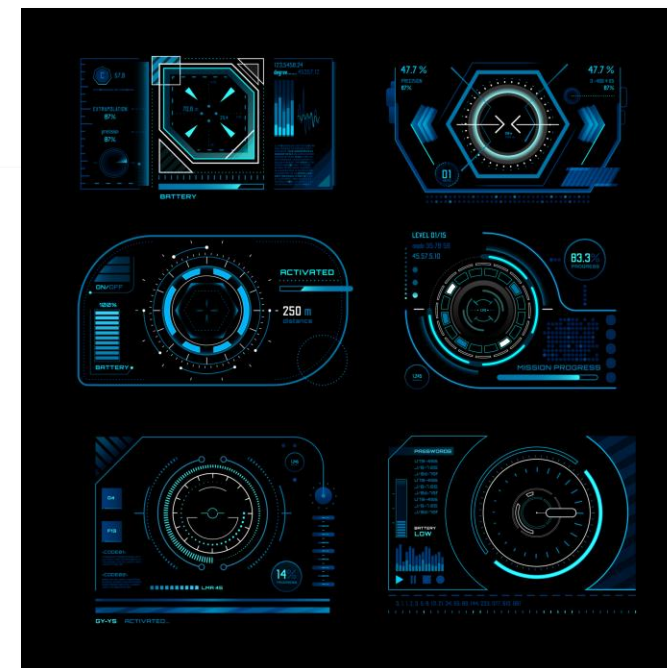


Beyond **0.8**, we start losing statistical significance



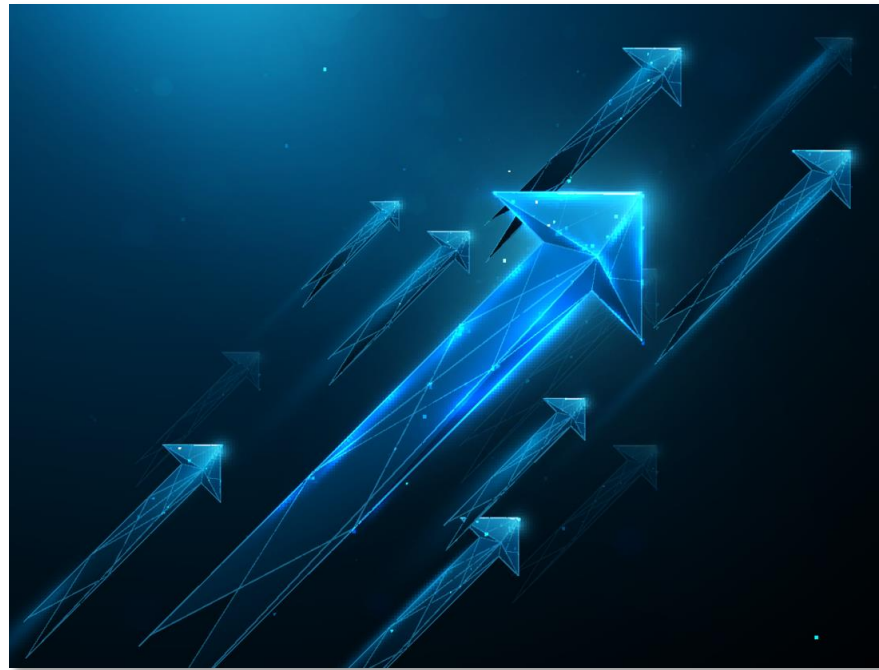








# Lessons learned & way forward






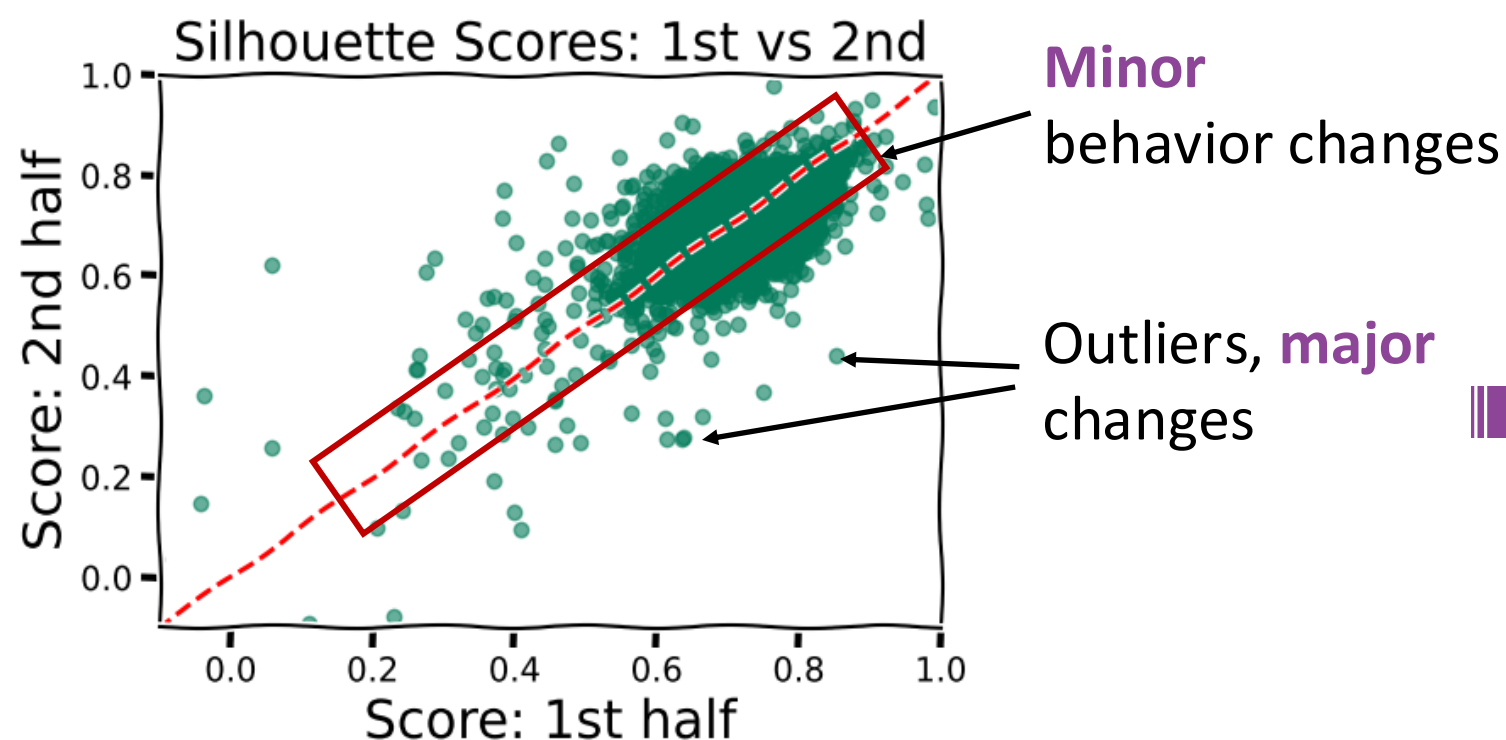
- **User Tracking is feasible** with **shocking accuracy** that may increase **above 95%** (subject to various parameters)
- Simple **statistics can handle larger amounts of data**, with good accuracy
- **AI-based algorithms require more resources** (time, memory, processing power), but can yield **slightly better accuracy** (subject to various parameters)
- **Accurate user-device profiles** expose users to other threats: targeted commercials, placement of products, behavioral analytics



# Other applications: user behavior

- Not our main objective, but **behavioral analytics is plausible**
- Analysis of one week vs another, applied clustering + Silhouette score
- **Silhouette**: evaluates clustering quality

THIS WEEK				NEXT WEEK		
MON	TUE	WED		FRI	SAT	SUN
		1		1		3
		2		6		6
		3		7		7
	1	6	7	8		7



Change in **apps**



Change in **browsing** preferences



Change of **location**



**Privacy** exposure

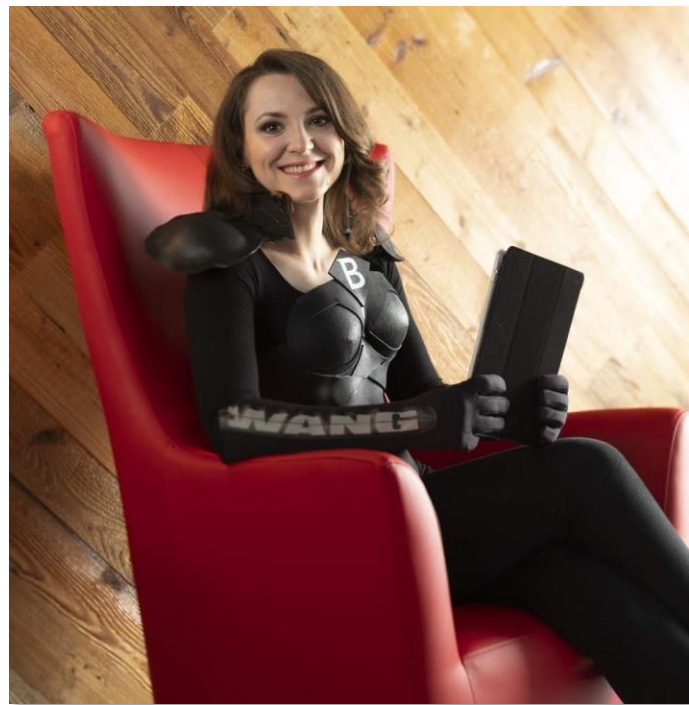




- 1 Enable **MAC randomization** (with rotating MAC, if option is available), **make it more aggressive** (e.g., change it for each network connection)
- 2 Use **encrypted DNS**, if available, **enable it by default**
- 3 Telcos should **inform the user** on the collection of DNS requests an **on their use**



Machine learning team @ **Bitdefender**.



**Elena BURCEANU**



**Dragoș Alexandru  
BOLDIȘOR**



**Cristian Daniel  
PĂDURARU**





**AUGUST 6-7, 2025**  
MANDALAY BAY / LAS VEGAS

# Thank you!

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## Bitdefender<sup>®</sup>