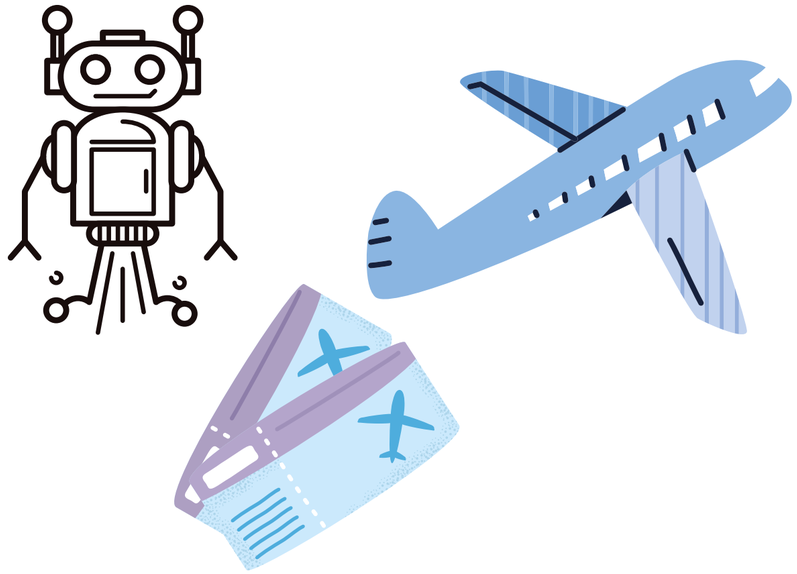
Using a honeypot to mitigate and study scrapers



Elisa Chiapponi
PhD student at EURECOM - GSO APP

EURECOM
Sophia Antipolis

aMaDEUS
Global Security Operations

Agenda

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1. Introduction
and motivations

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2. Honeypot

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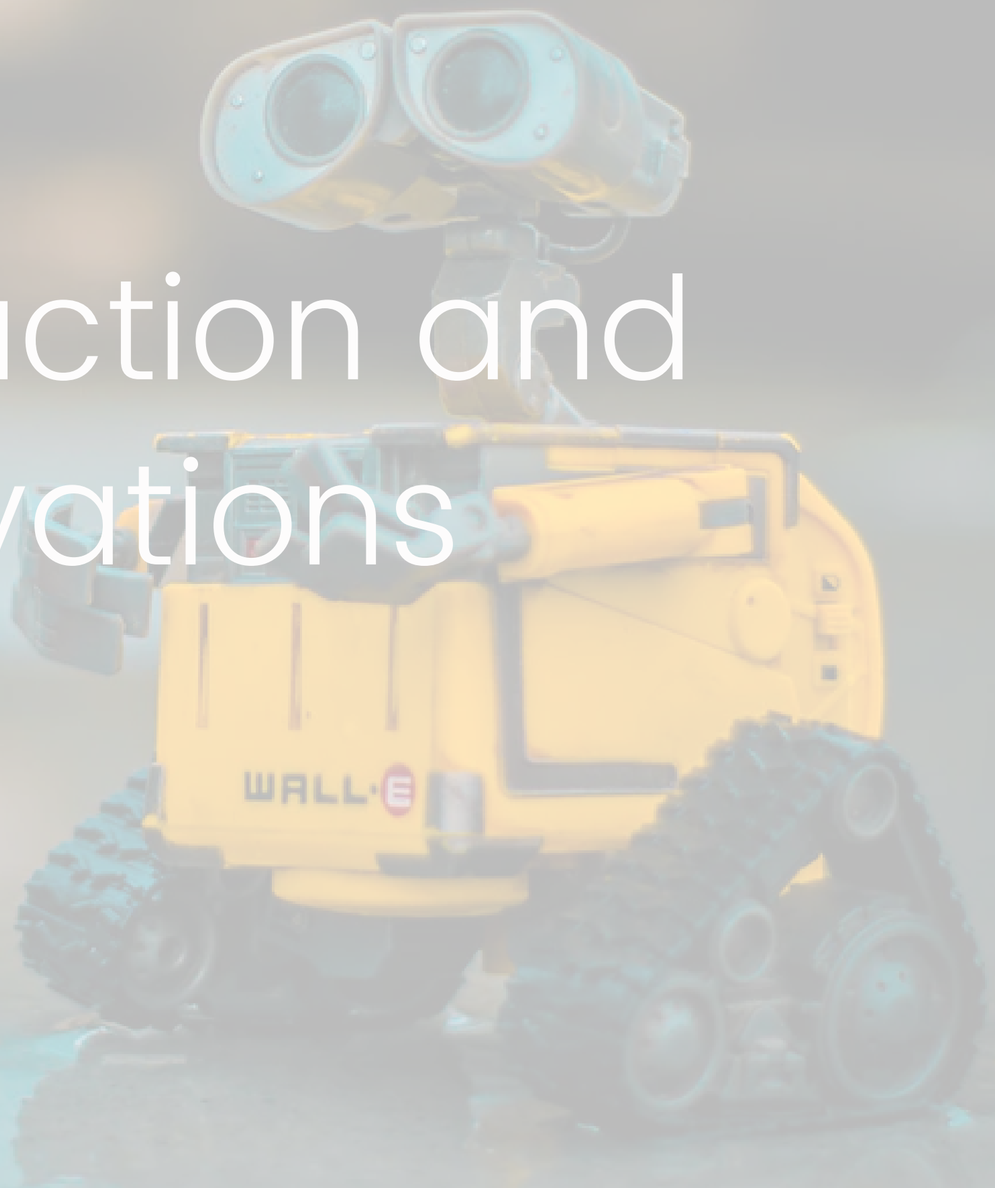
4. Conclusions and future work

1. Introduction and motivations



Who am I?

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Master thesis internship in Amadeus GSO -APP

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Phd student Amadeus GSO-APP and EURECOM

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Finding practical means to defeet scraping bots

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Phd student Amadeus GSO-APP and EURECOM

Finding practical means to defeet scraping bots

Understanding their ecosystem (actors, techniques, infrastructure)

Web scraping

Web scraping is the periodical or continuous retrieval of accessible data and/or processed output contained in web pages.

Scraping bots and airlines

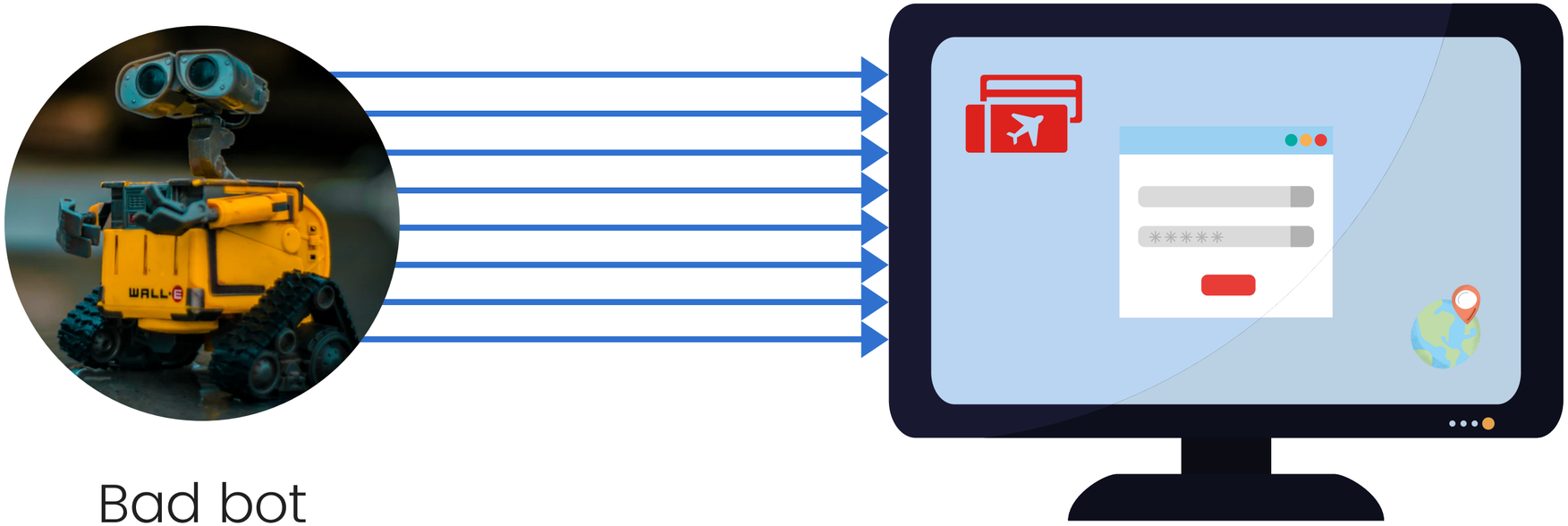
How bots affect airlines - Imperva 2019

Web scraping bad bots

Bad bot

Airline booking domain

Web scraping bad bots



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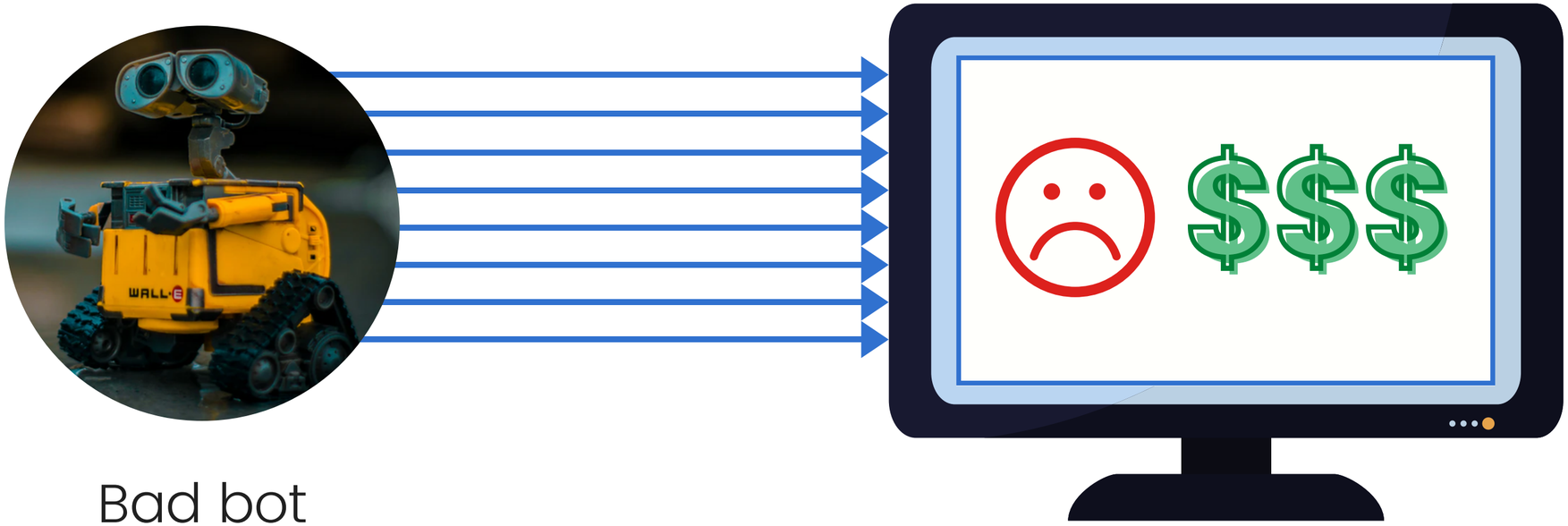

Bad bot

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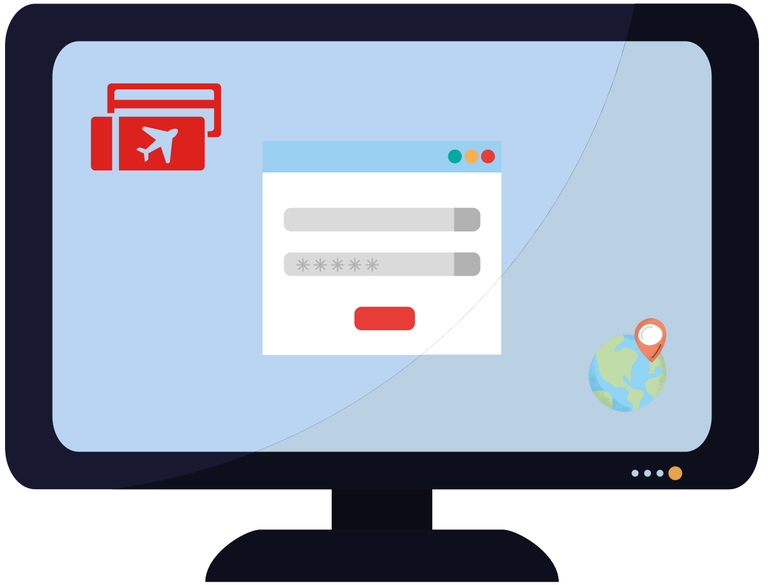
Anti-bot solutions

imperva

User

Bot

Browser fingerprinting



Booking domain of airline X

Anti-bot solutions

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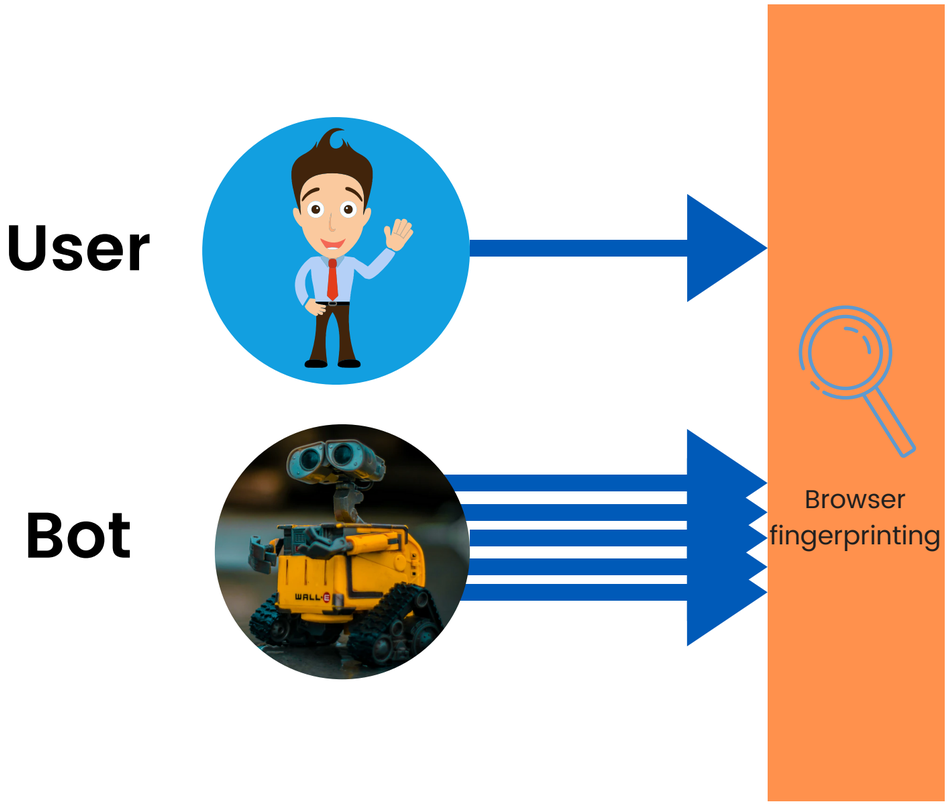

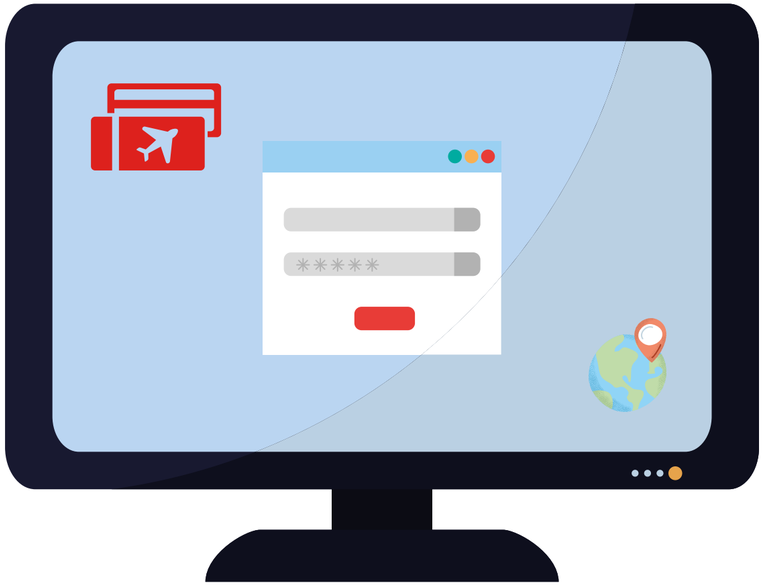

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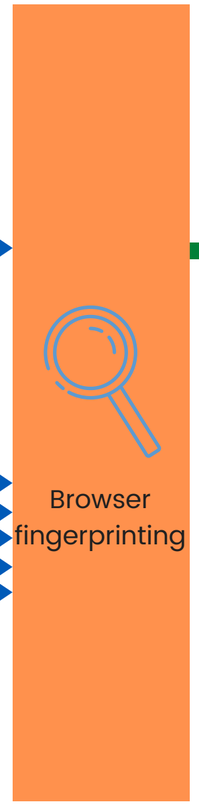
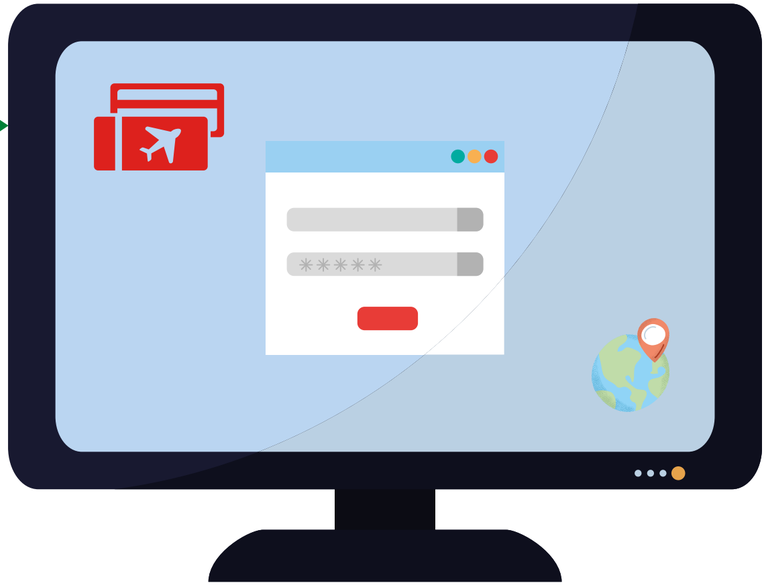


Detected user



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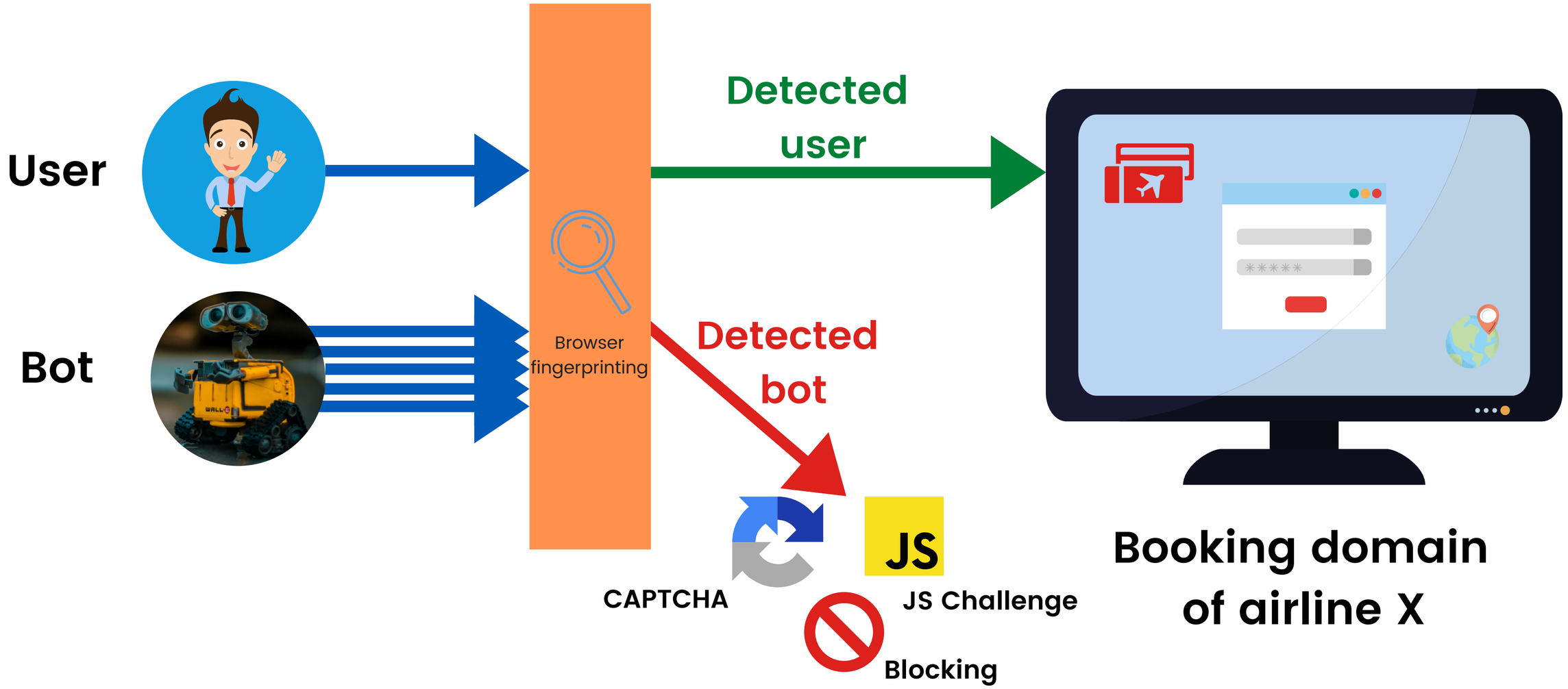

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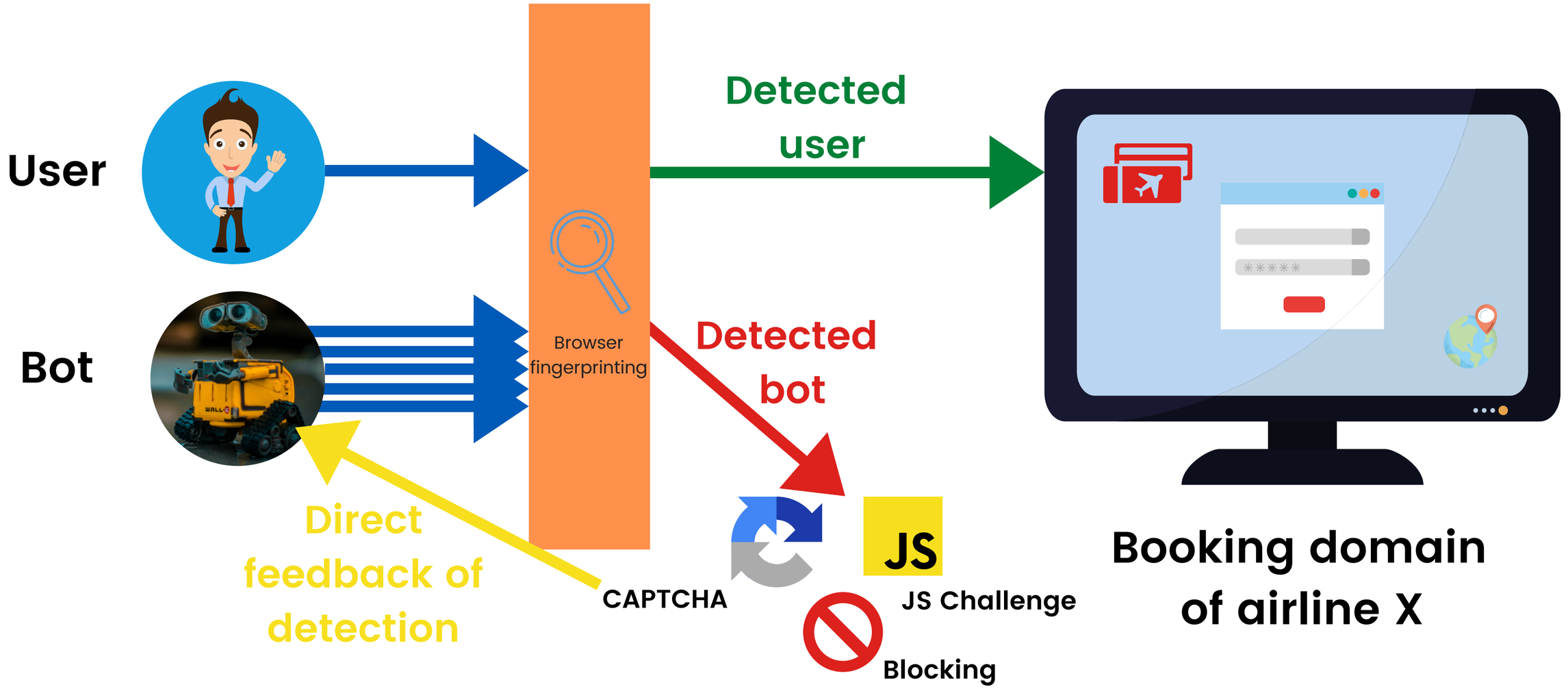

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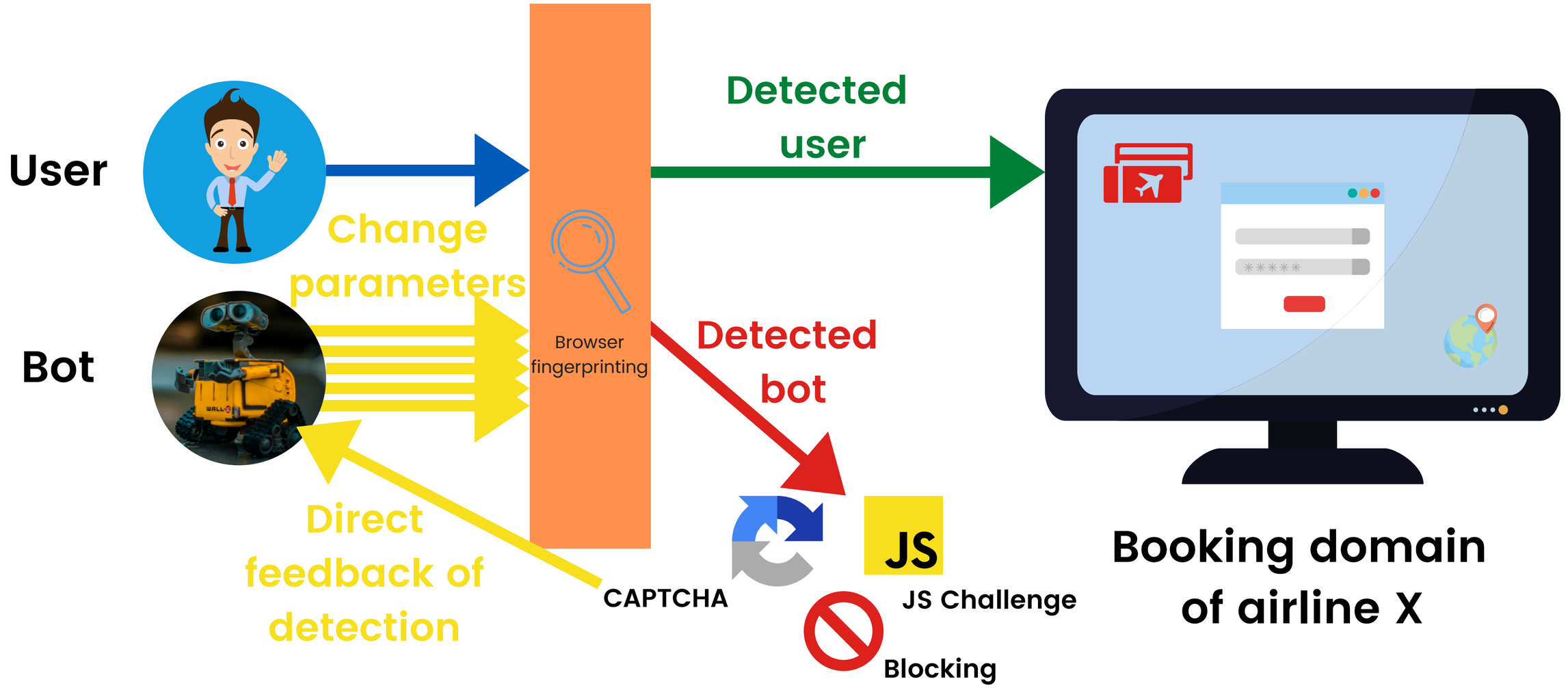

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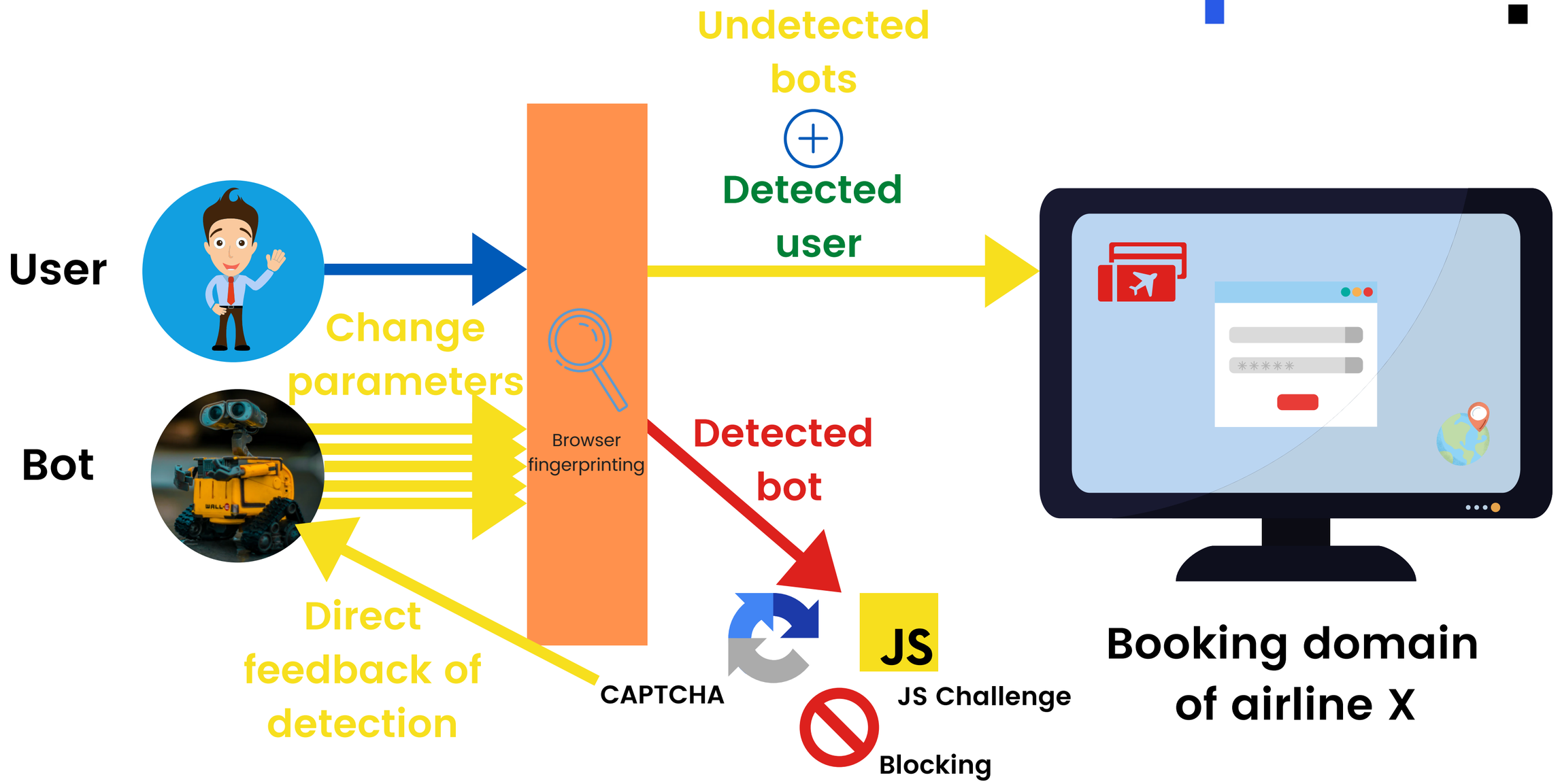

What 3rd parties works tell us

Blocked bots die

- Continuous verification of stealthiness and efficacy of the bots
- Rapid modification to avoid detection

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Harnessed information is verified

- Continuous verification of the correctness of the information
- Incorrect information is a direct feedback they have been detected

Initial idea

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Prevent bots to know they have been detected & save costs for the provider

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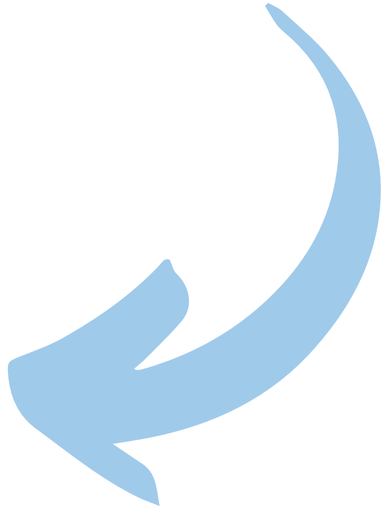

Provide bots incorrect but plausible answers

The idea

imperva

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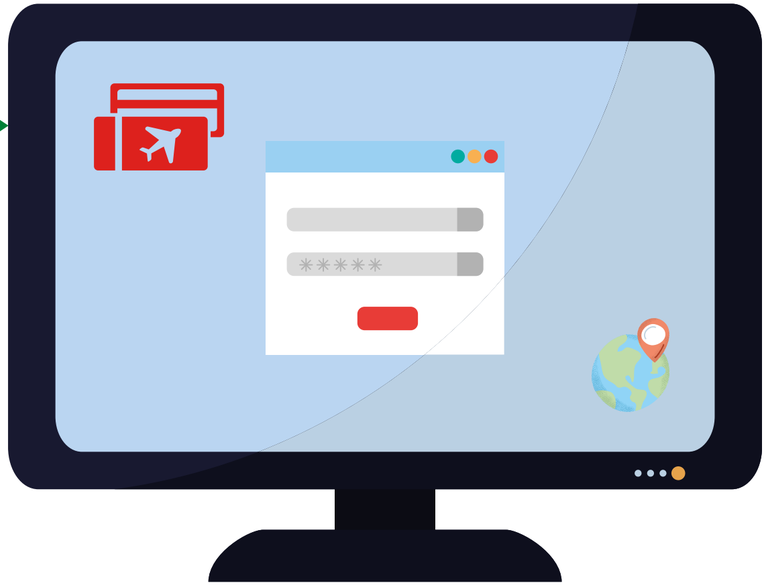
Detected user



Booking domain of airline X

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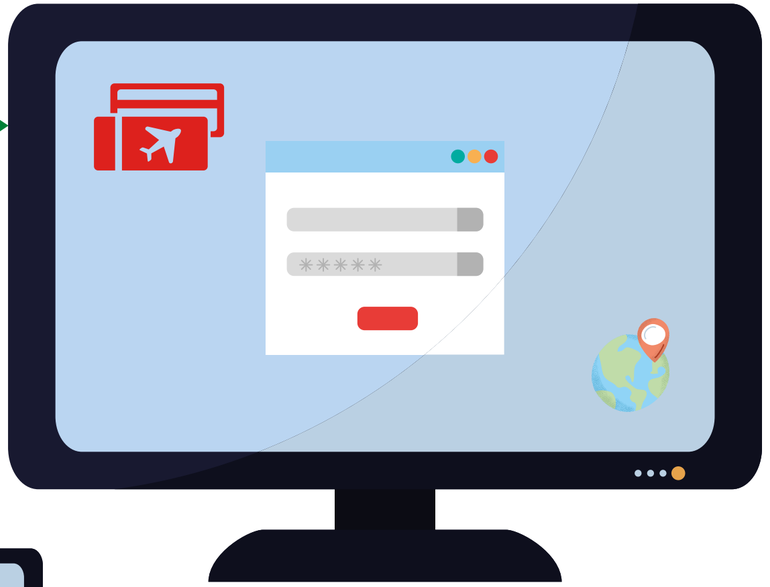
Honeypot



Booking domain of airline X

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- Modification of the fares

2. Honeypot

Pilot airline

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- 1 millions requests per day
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- Redirection of the traffic of specific bot signatures to the honeypot

Pricing strategy

After 3 days, modification of fares: increase 10% of the requests by 5%

Goal: understanding if the bot master was checking for anomalies in the price

Some questions…

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- Is it possible to recognise a bot campaign from the information included in the payloads?
- Are bots crafting payloads to detect the honeypot?
- Can we derive meaningful information studying the patterns of bot IPs?

Success criteria

Volume of traffic in the ranges before the case study, for at least 14 days after the fares modification

Master thesis

- Bot signature active all day long but with differences among days

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  - Behavioural patterns
    - Same actor behind

Second case-study

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- Running for 56 days (interruption linked with COVID-19 restrictions on flights)
- Reception of 22,991 HTTP requests at the Honeypot
- No change of behavior from before and during the case-study

Lessons learned modifying values

No ground truth to compared returned values

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Plausibility check not sophisticated enough for small changes

Behavioral analysis

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- Only 25 combination of departure and arrival airports, small fraction of the airline's offer

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- Segment=combination of one way/return flight, departure and arrival location
- Homogeneous distribution among different segments and request dates

Tuples statistics

- 4-tuples made of:
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  - Type of flight (one way/return)

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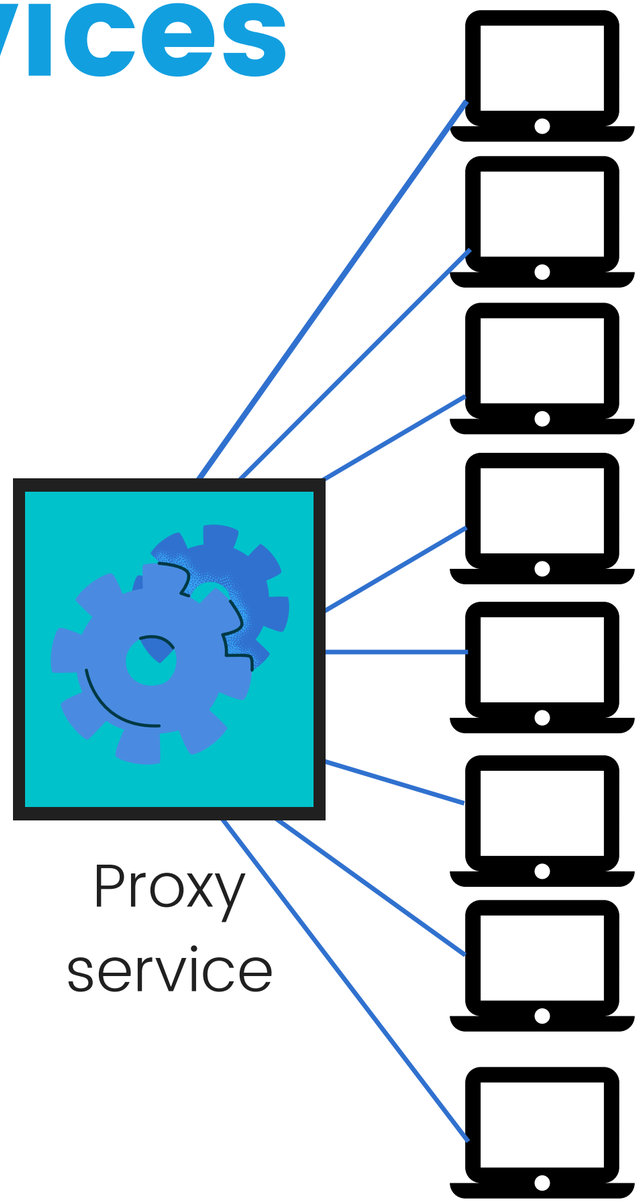
Check for consistency, but not sophisticated enough

3. Proxy services and IP addresses

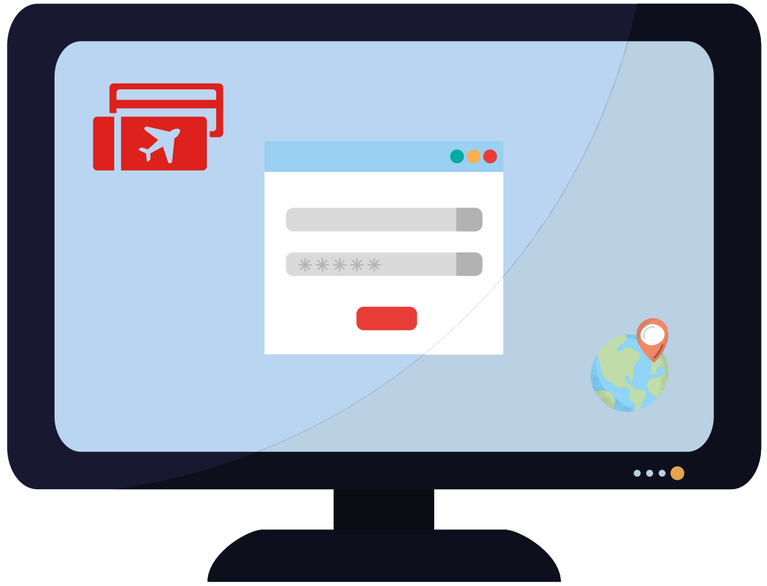
Proxy services

Bad bot



Proxy service

Proxy gateways



Airline booking domain

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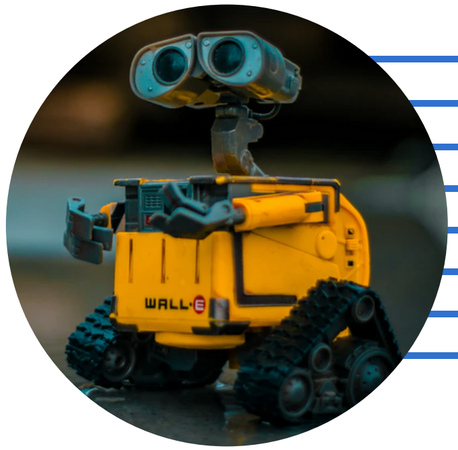

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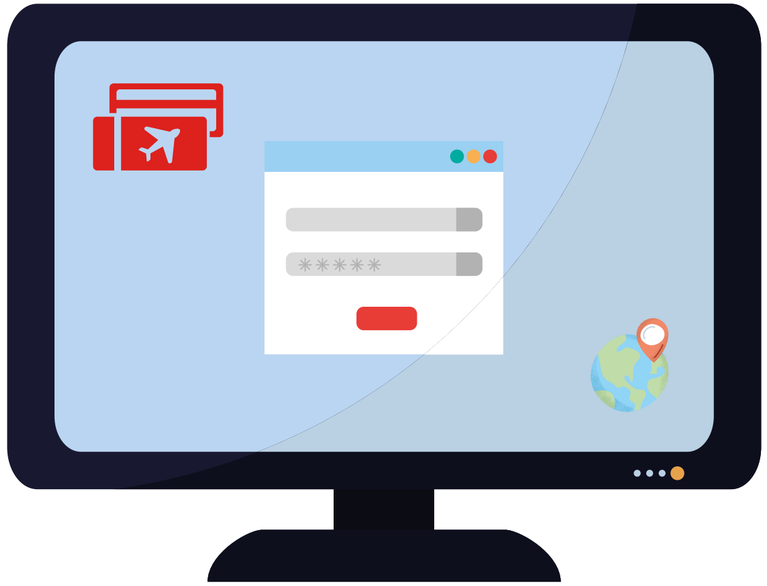

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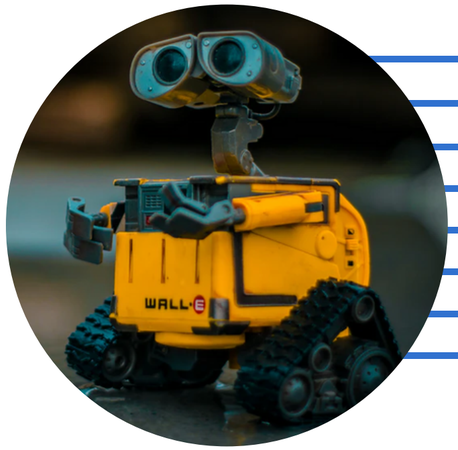

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Airline booking domain

Bots using proxy service

Impossible to link bot campaign to organization

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No need for private distributed infrastructure

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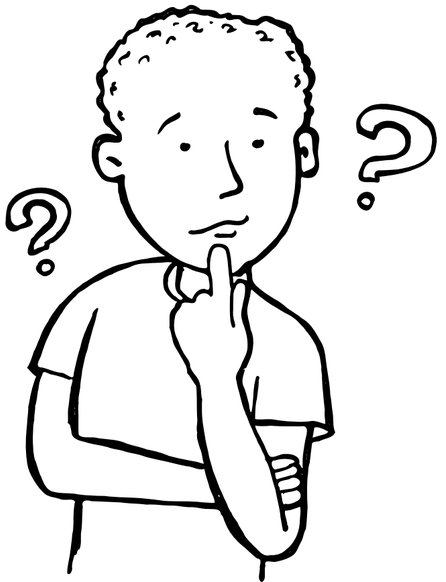
Impractical blocking IPs strategy

Question

Are our IP addresses coming from proxy services?



IPs analysis in other airlines

Analyses of the traffic of other 17 airlines

- Only 5 bookings during the running time of the case-study
- Dates different from the ones in which the IP was seen in the honeypot
- Requests not associated with the bot signature

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1. Some IPs are used by legit users
2. Risk of blocking legit users remains low

IPs reputation

IPQualityScore analysis

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They were not allocated for the botnet only

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Proxy services claims

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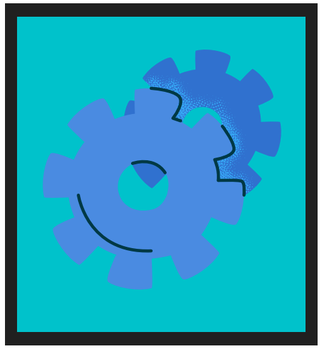
We have millions of IP addresses!



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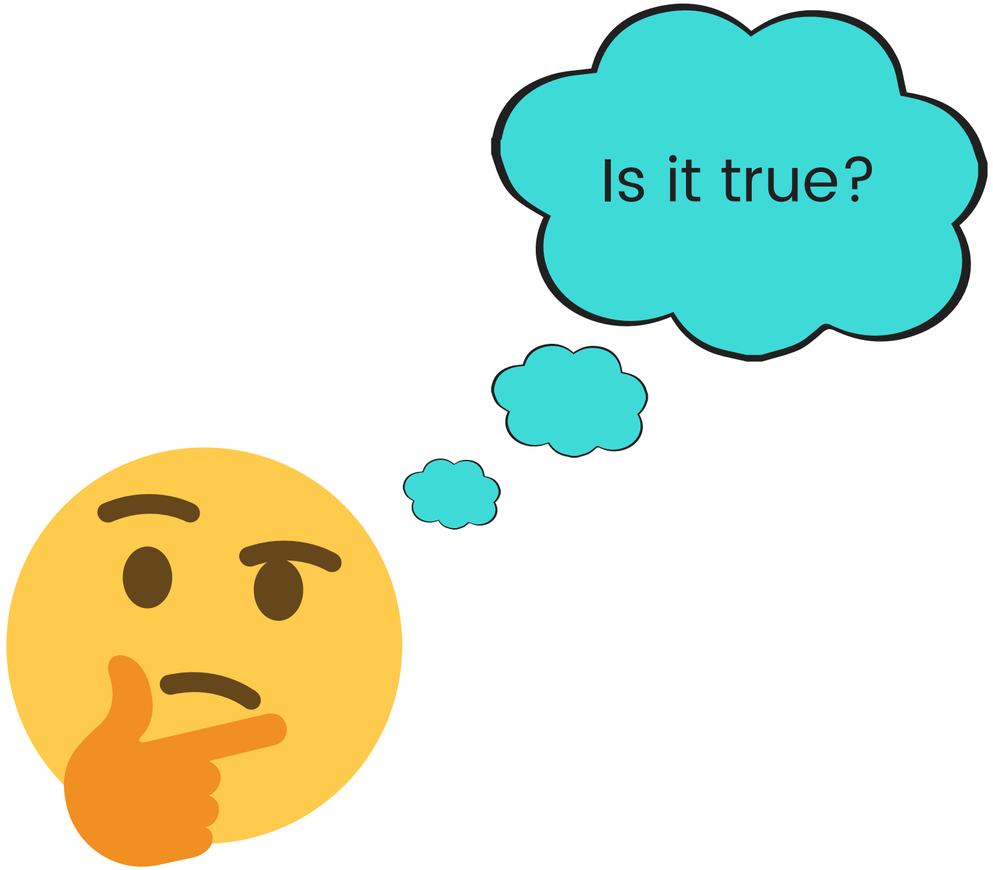

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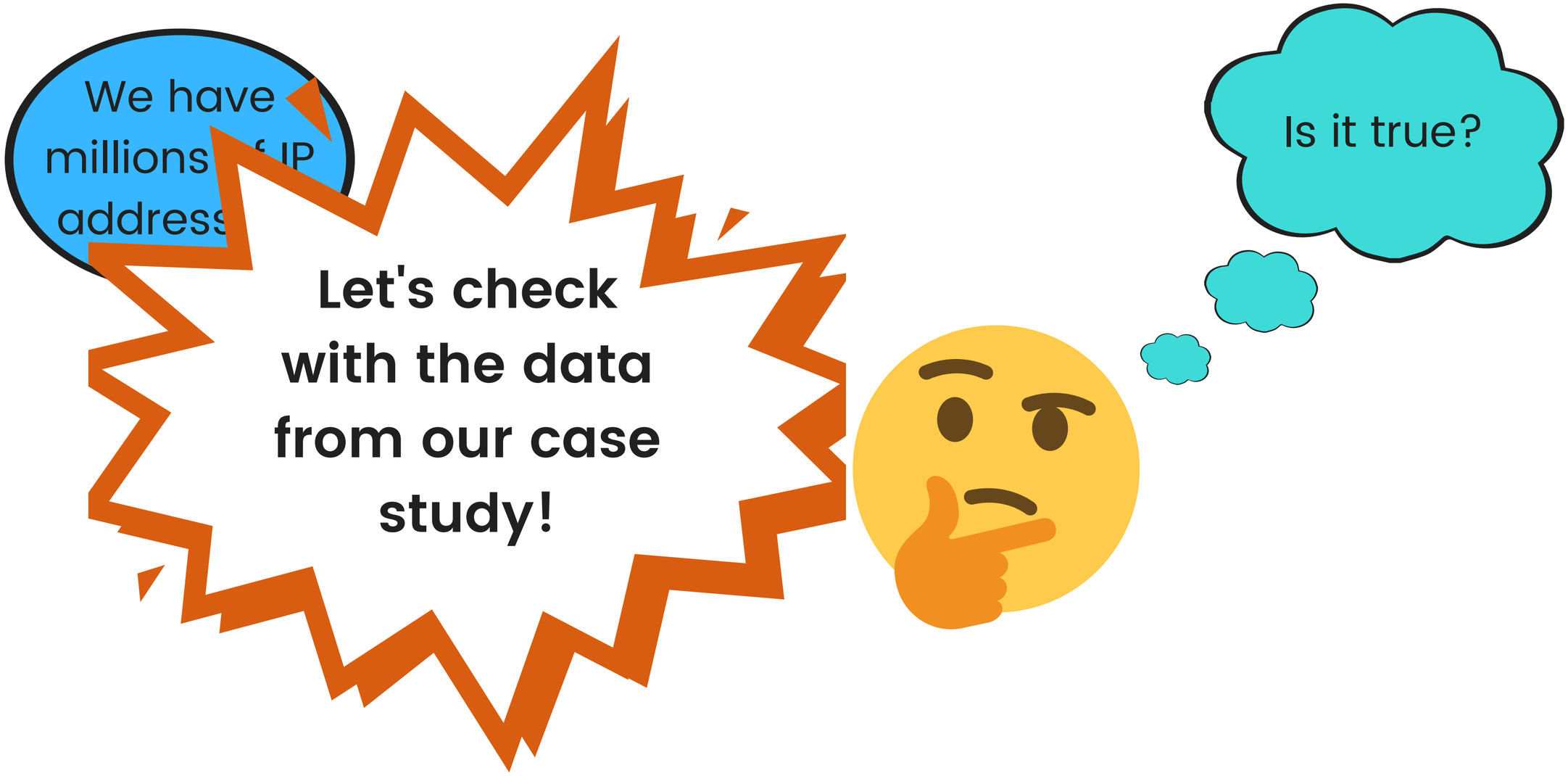

IP addresses study

13,897
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1,187 /16 blocks

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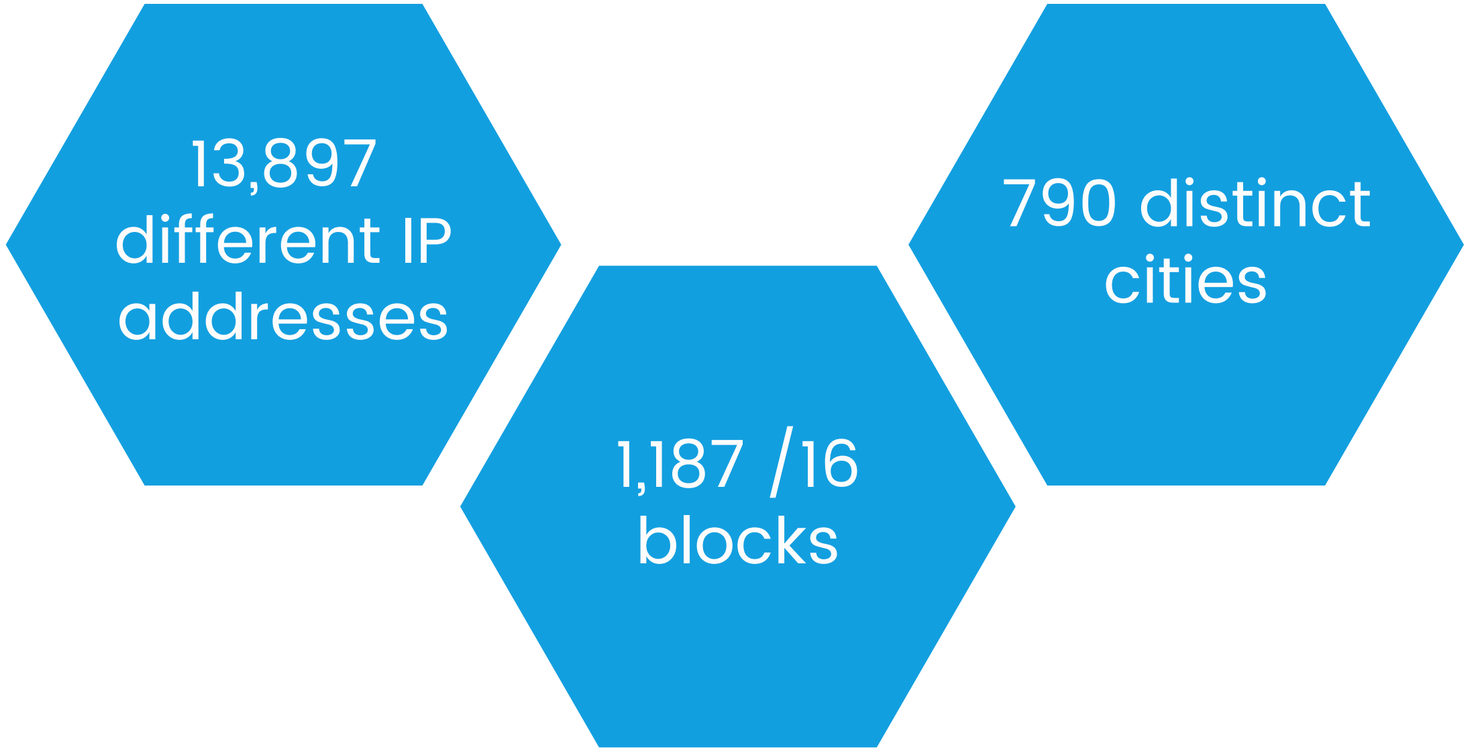

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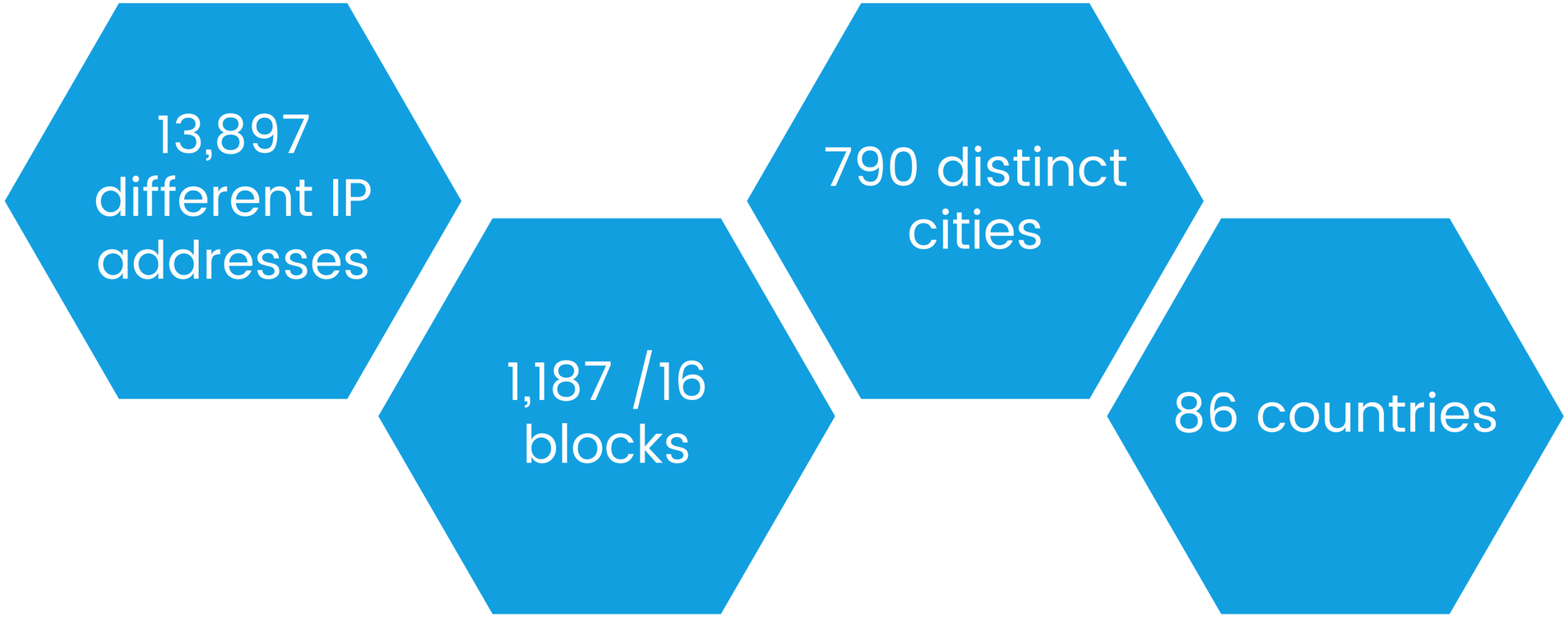
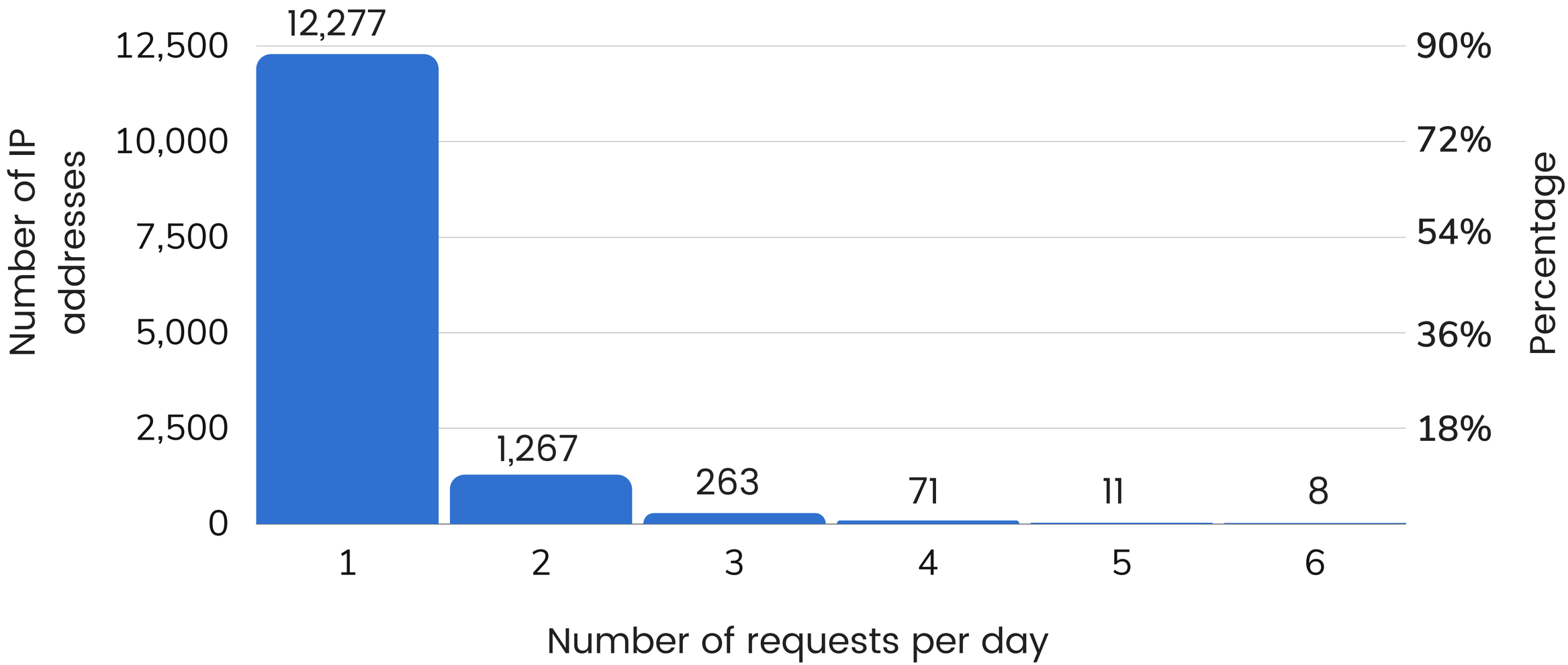


Daily number of requests per IP



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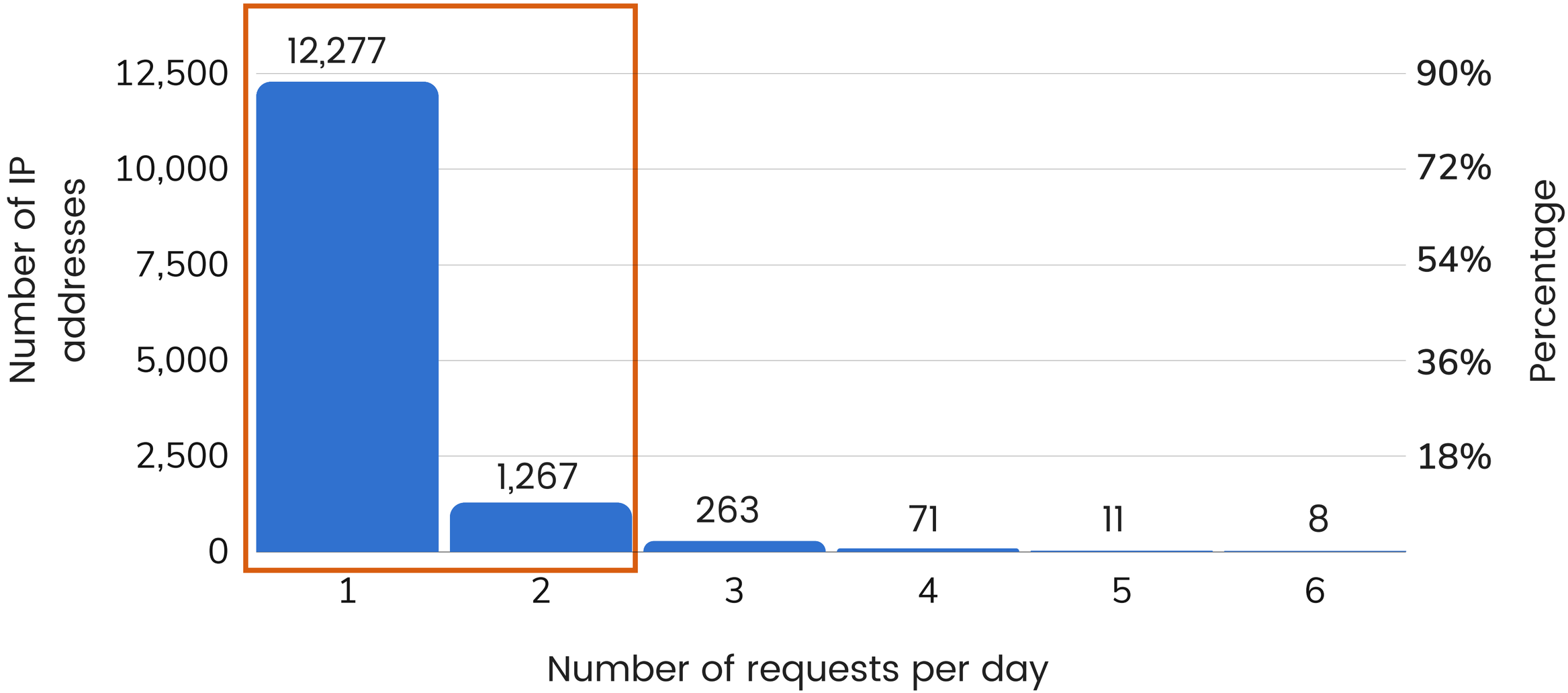

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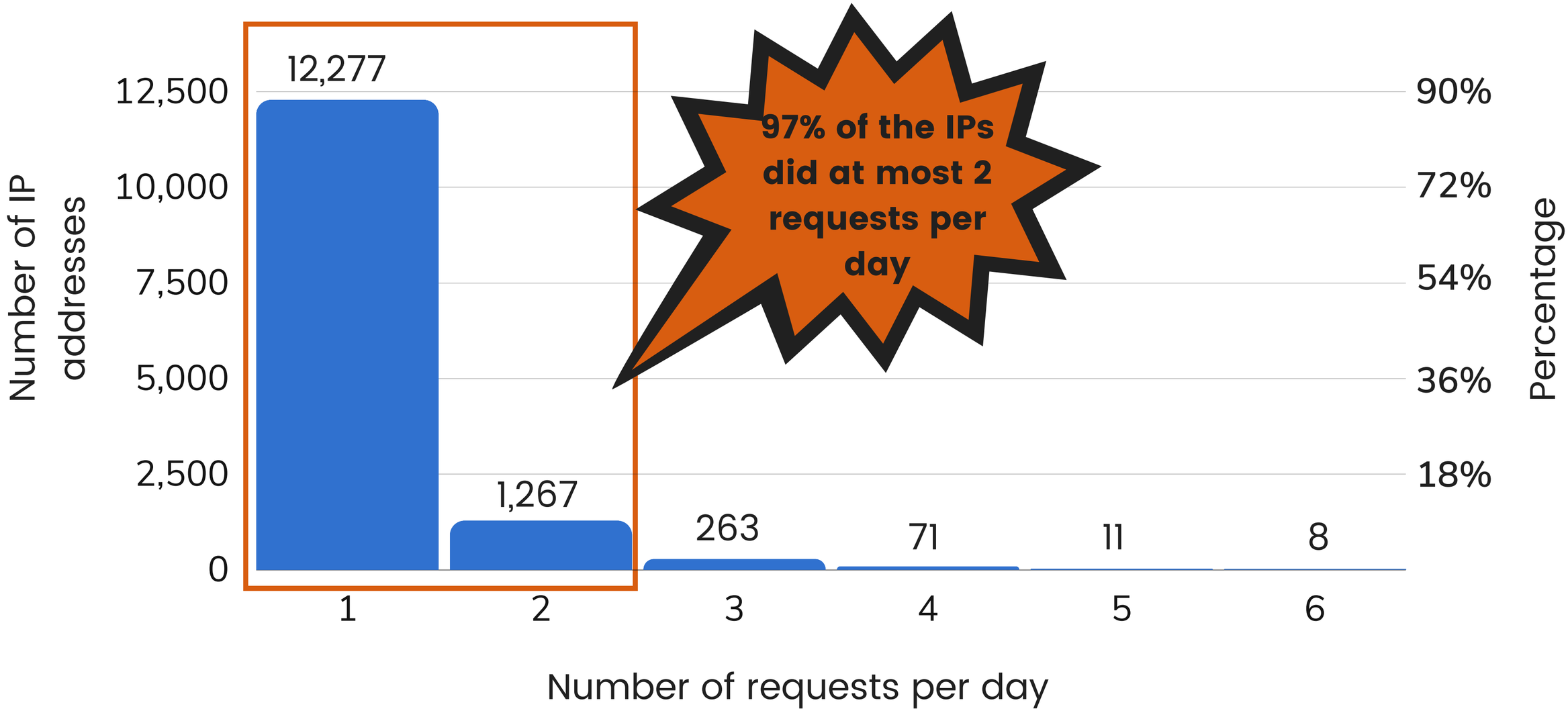

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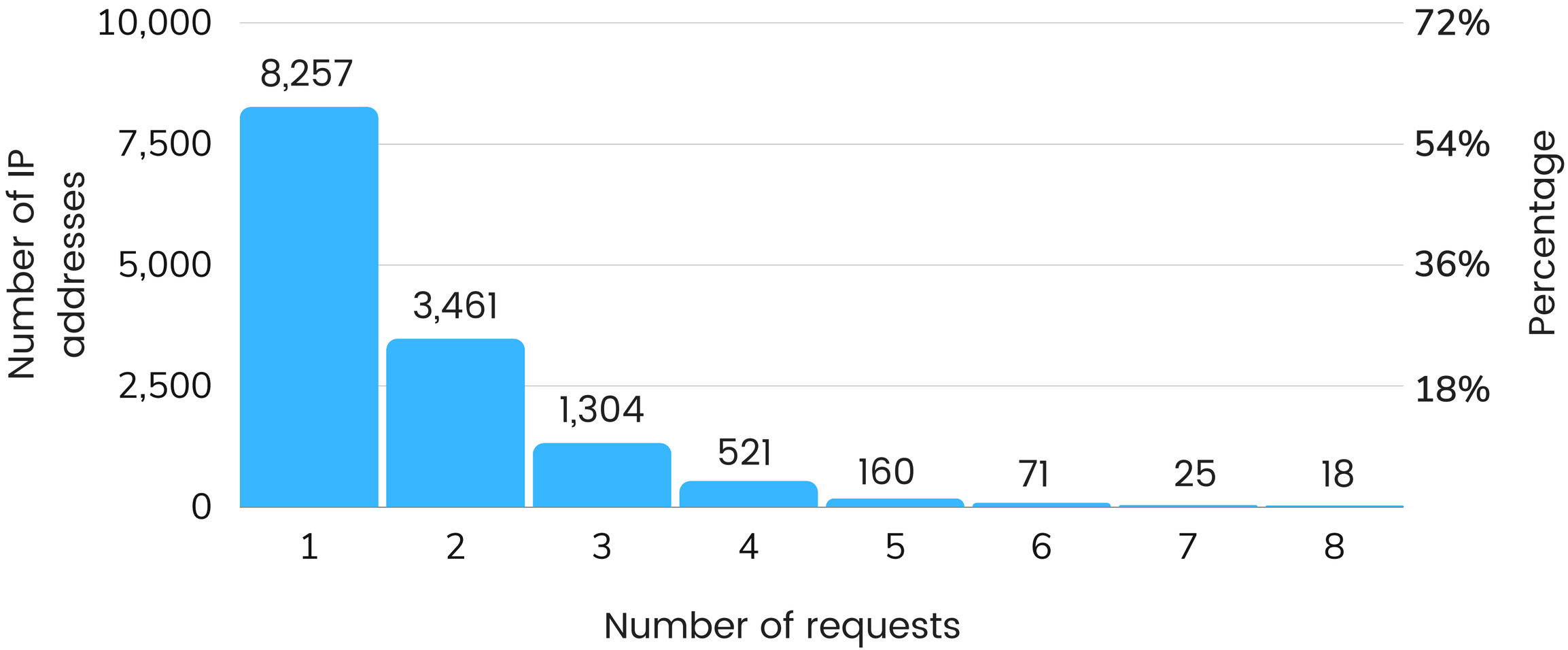

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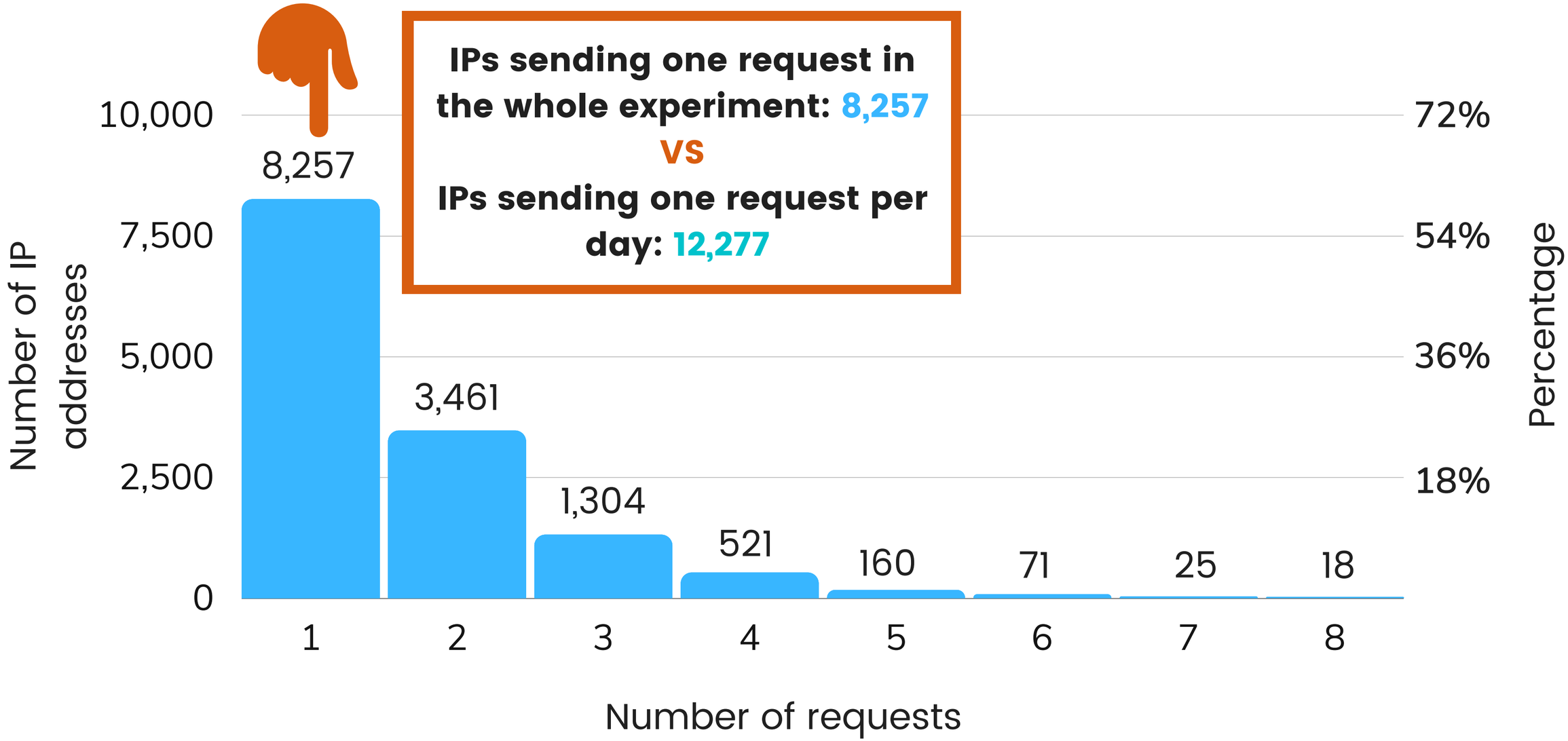
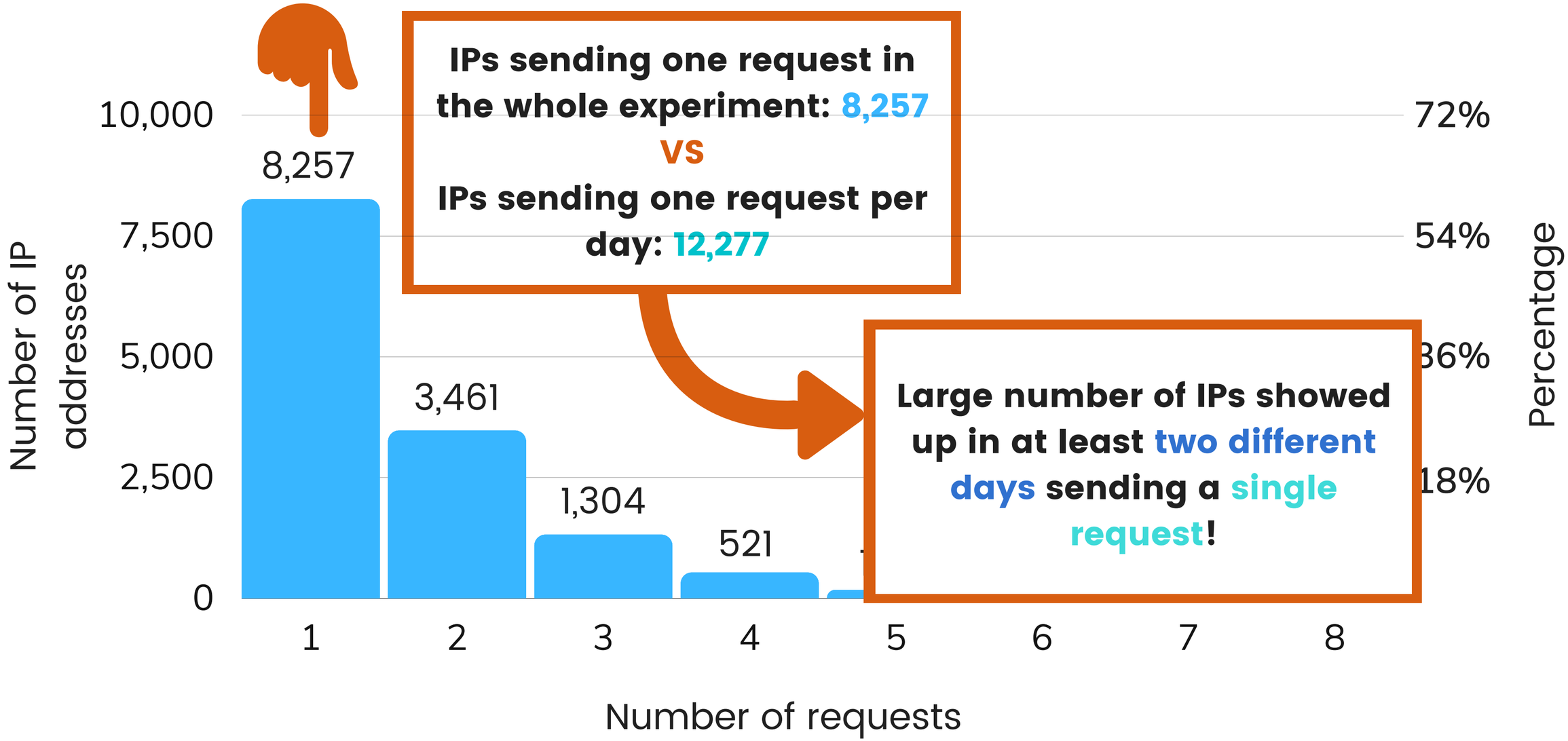
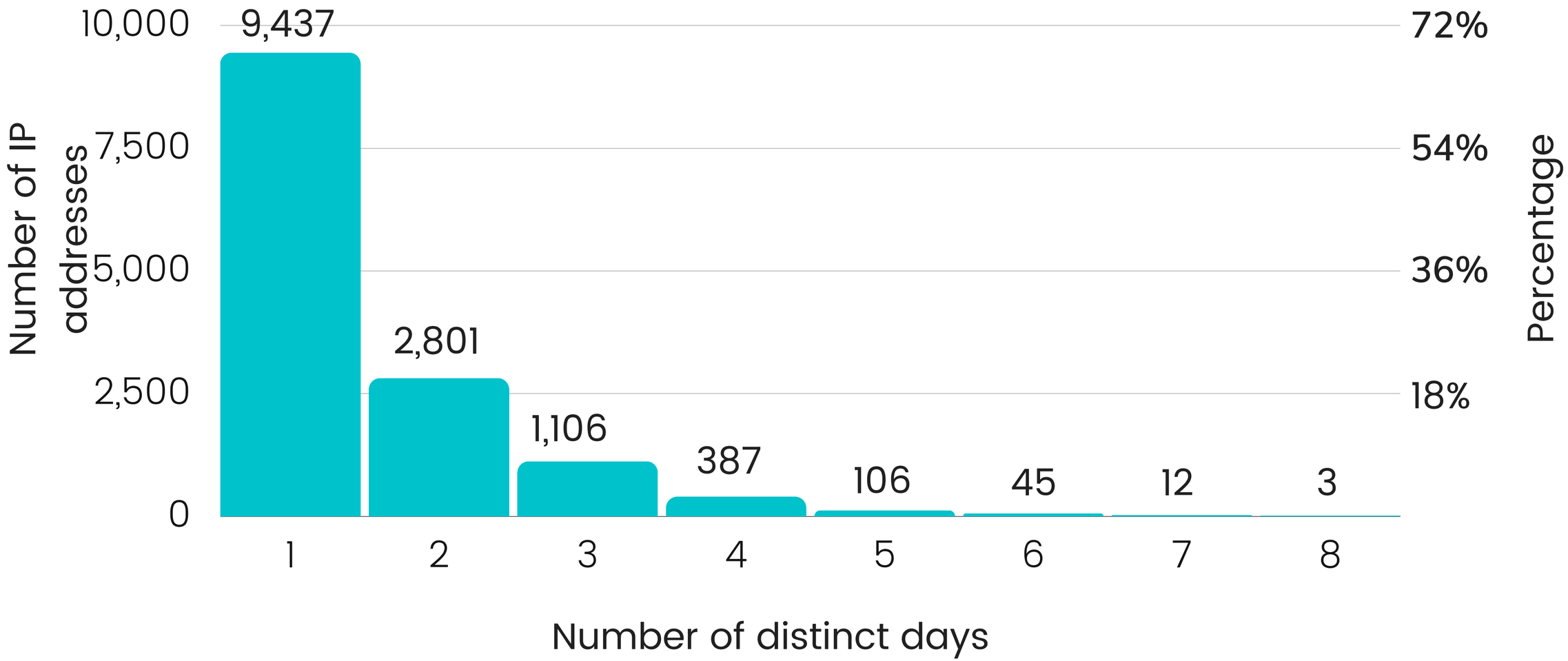


Maximum number of requests per IP



Number of IPs seen in distinct days



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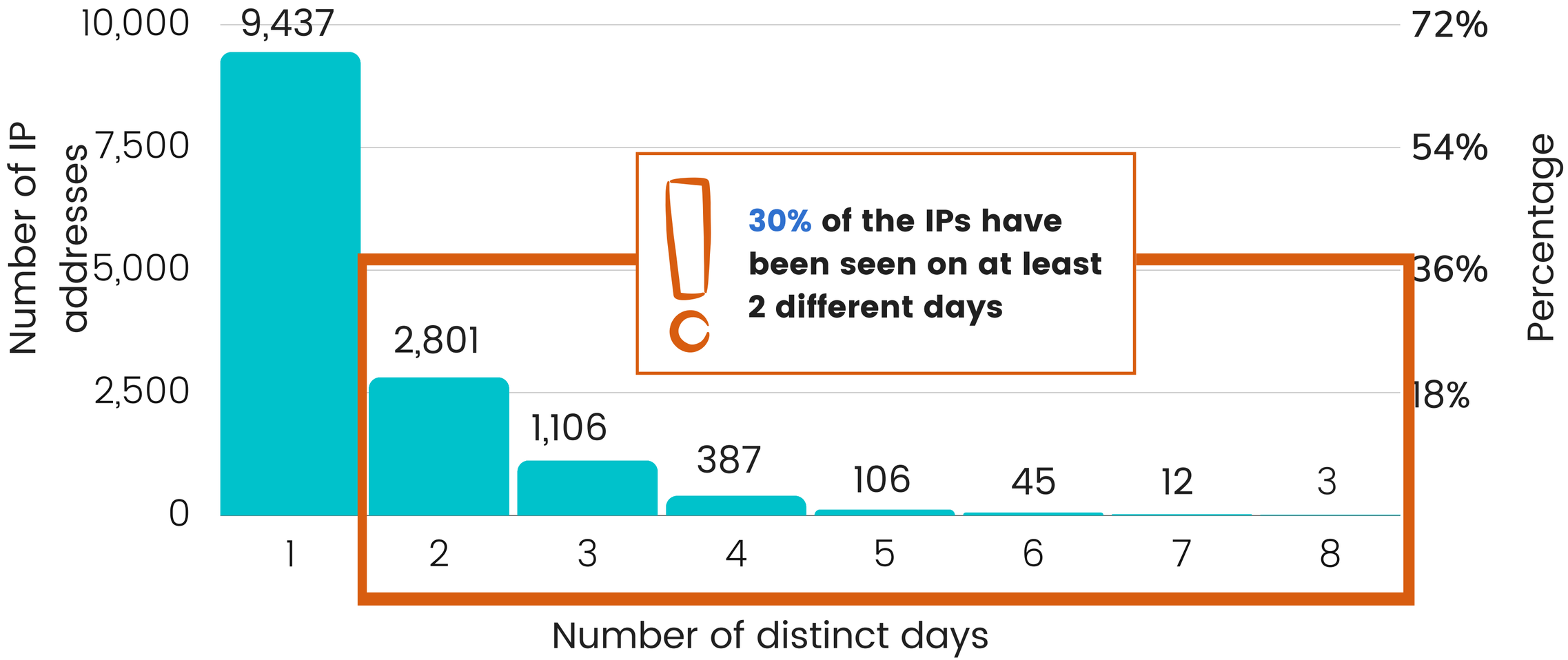

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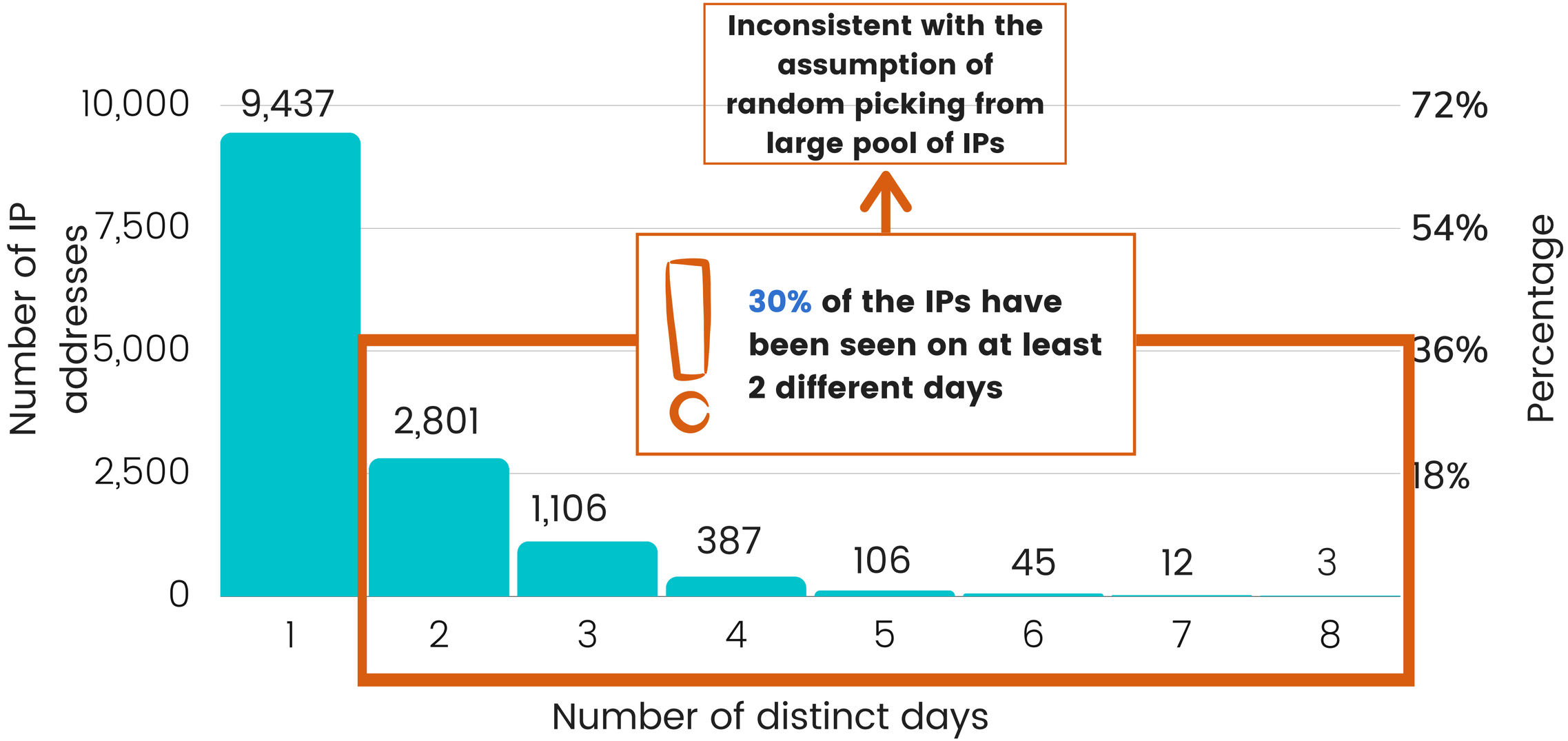

The Birthday Paradox

Given 56 random integers drawn from a discrete uniform distribution with range $[1,P]$, what is the probability $p(56; P)$ that at least two numbers are the same?

Is this likely to happen?

- Approximate result: $1-\left(\frac{P-1}{P}\right)^{\frac{56(55-1)}{2}}$

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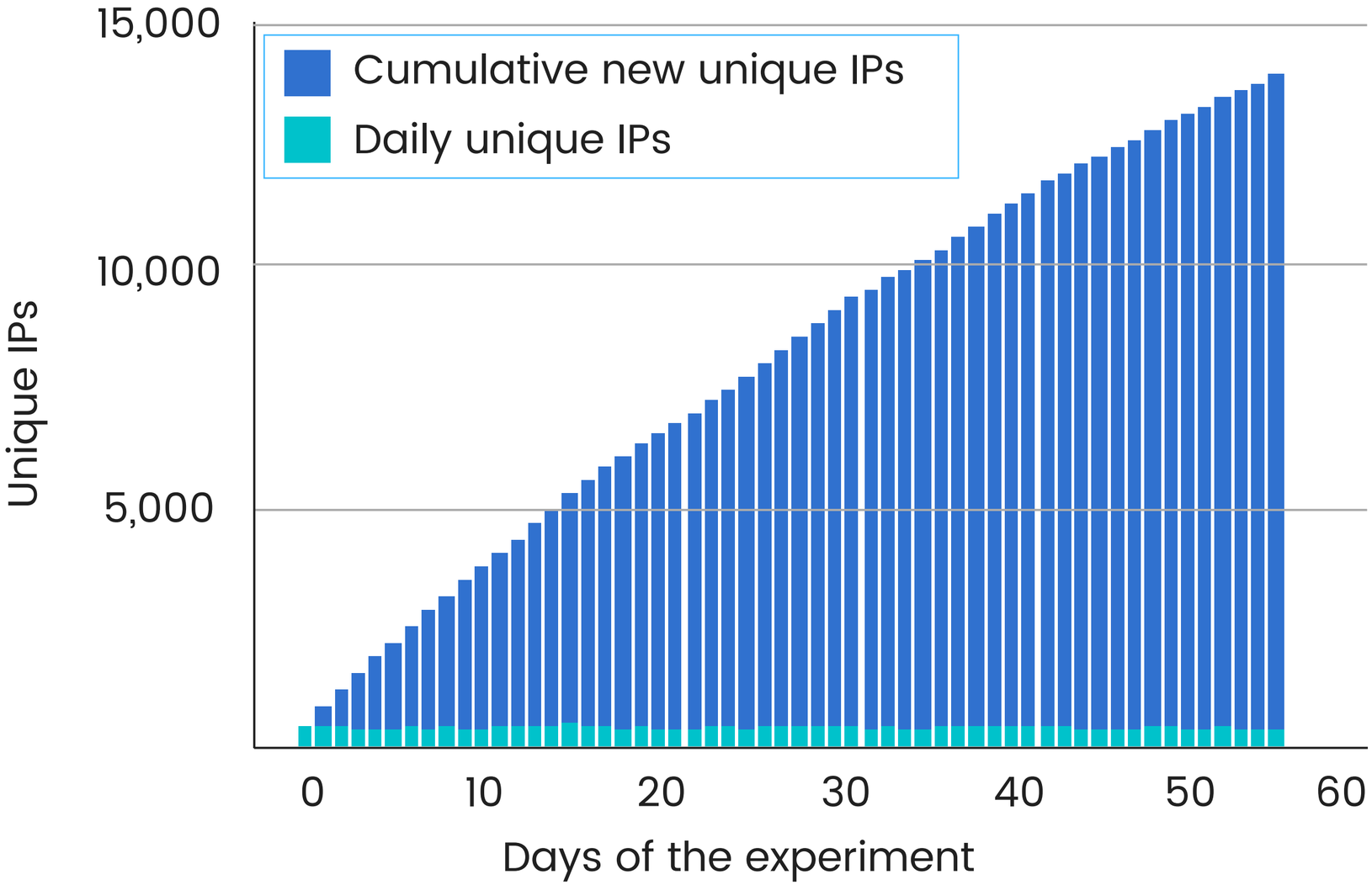
- P=100,000 → $p(56,100K)\approx0.015282$

P is significantly lower than the claimed numbers AND/OR the assignment is not randomly done

Cumulative curve of new unique IPs



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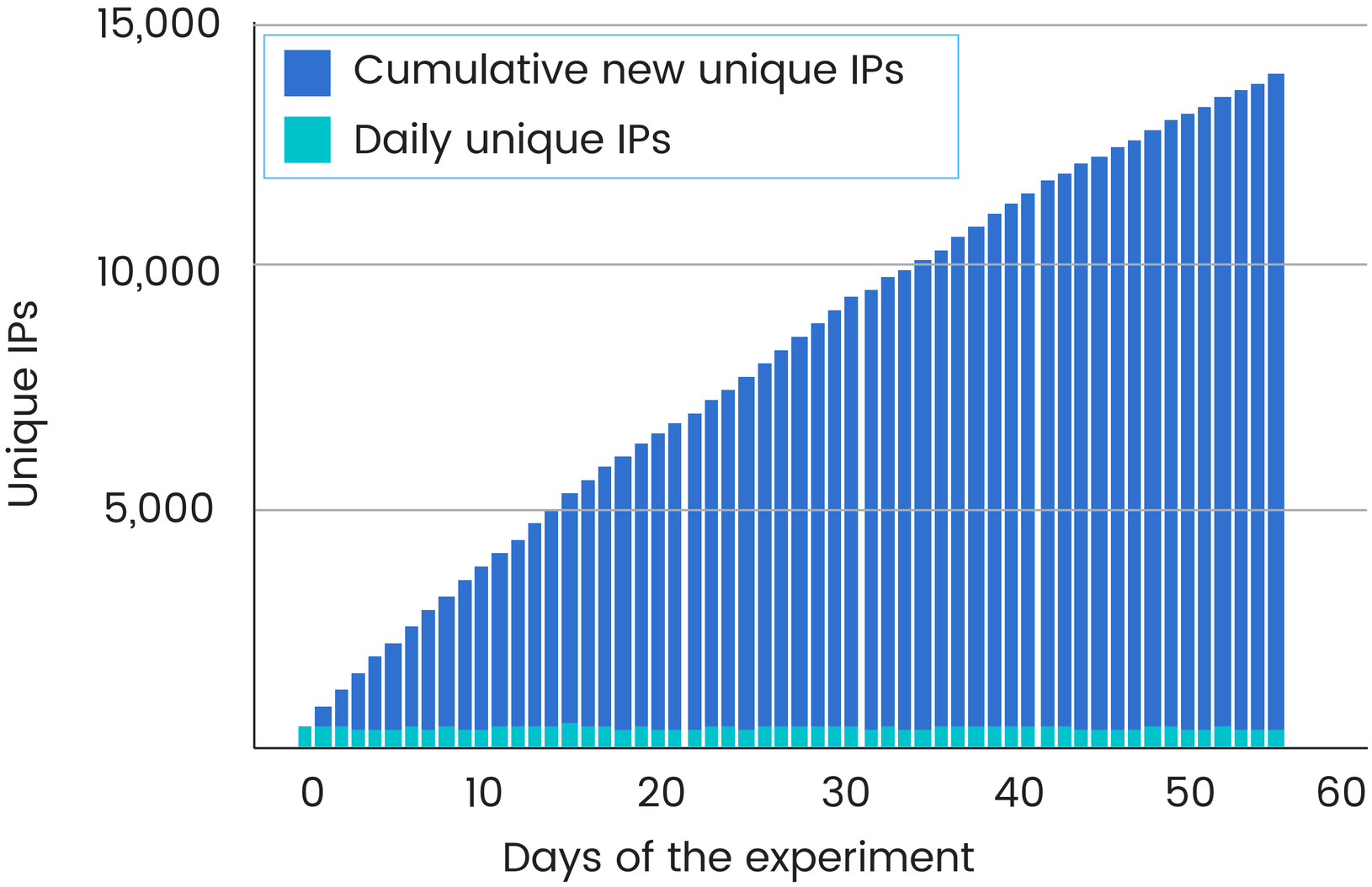
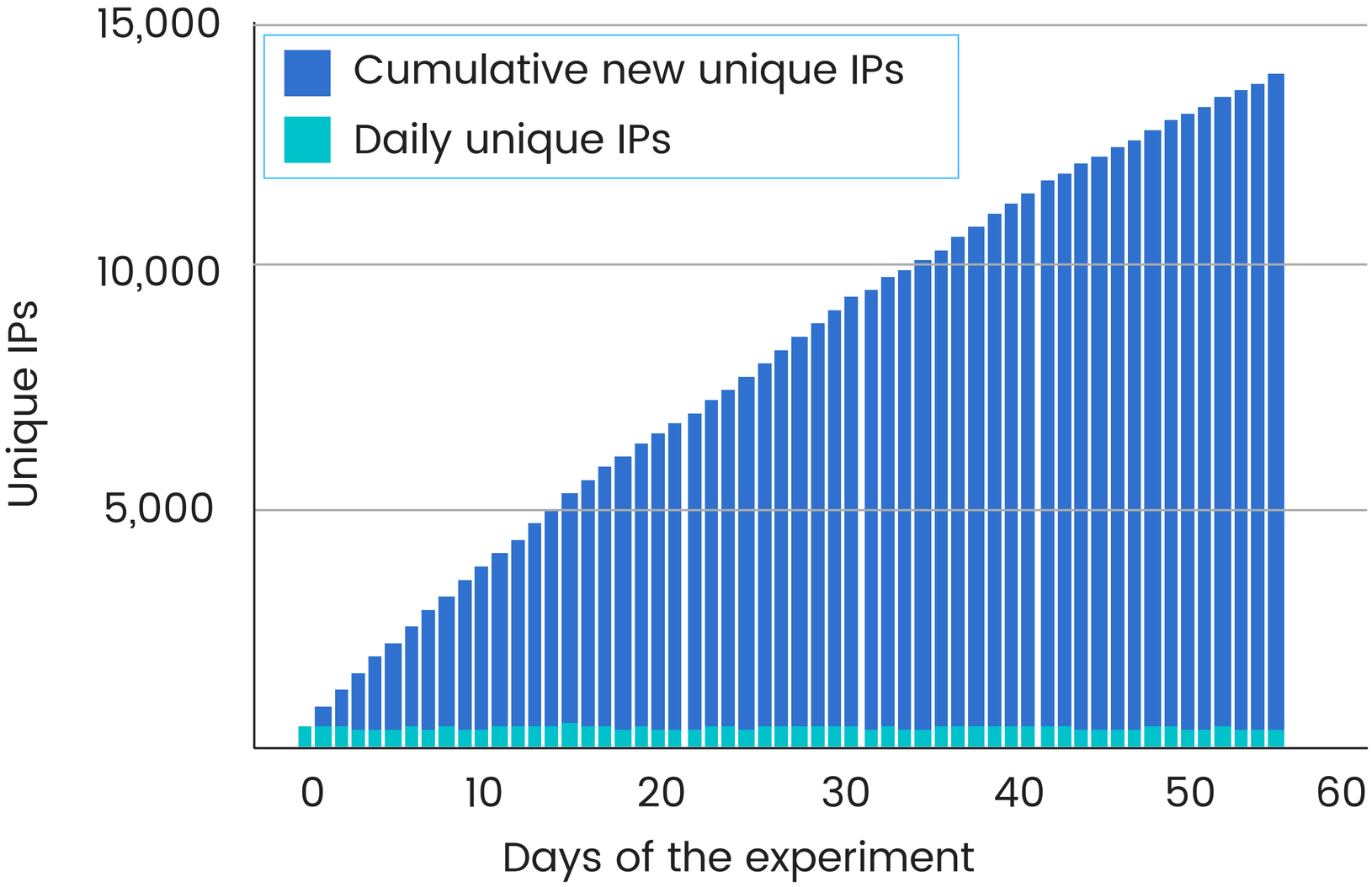


The daily increment decreases over time

Cumulative curve of new unique IPs



The daily increment decreases over time

Eventually it will reach a maximum!

Modeling

1

IP assignment as a drawing process
Modeling the drawing process of IPs, looking for a probability distribution for our results and deriving the value of P.

2

Fitting the cumulative curve of new unique IPs
Fitting the curve, extrapolating and finding what maximum value can be reached and when.

IP assignment as a drawing process

- Model the assignment process by a daily probabilistic drawing process without replacement

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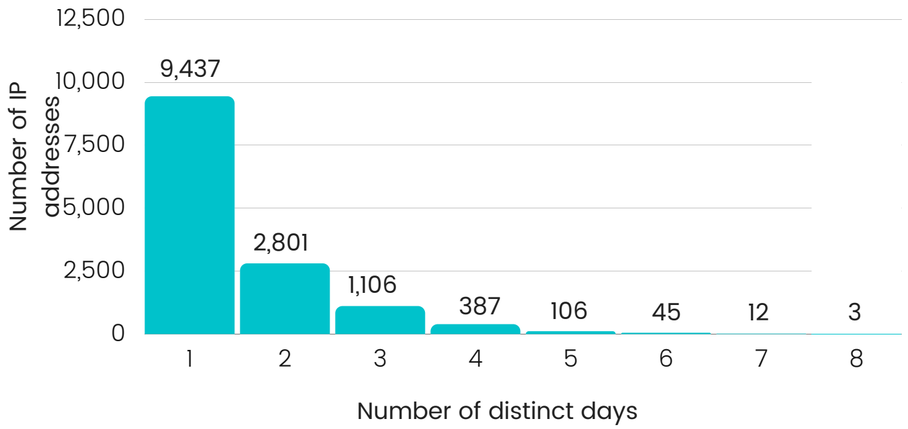
- Do it for all the days of the experiment and build a histogram with the number of IPs seen in distinct days

Histograms comparison



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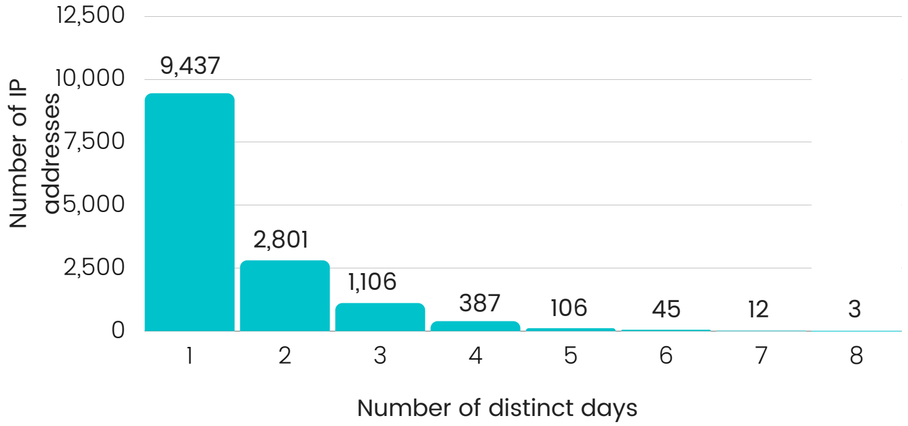

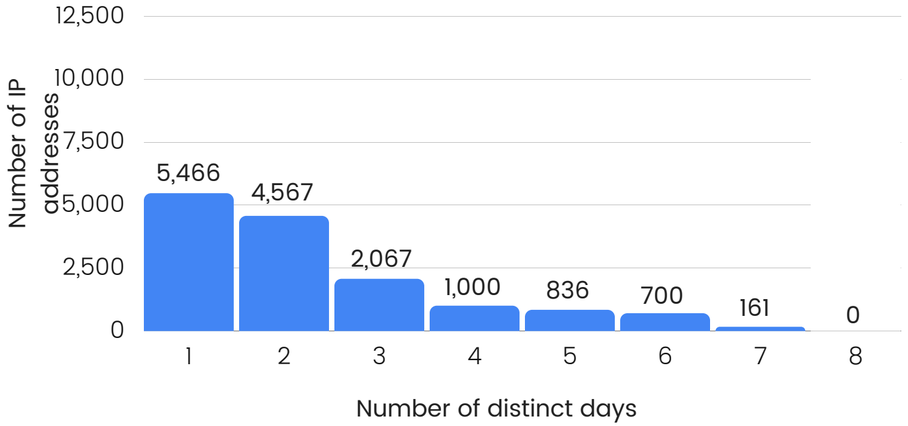

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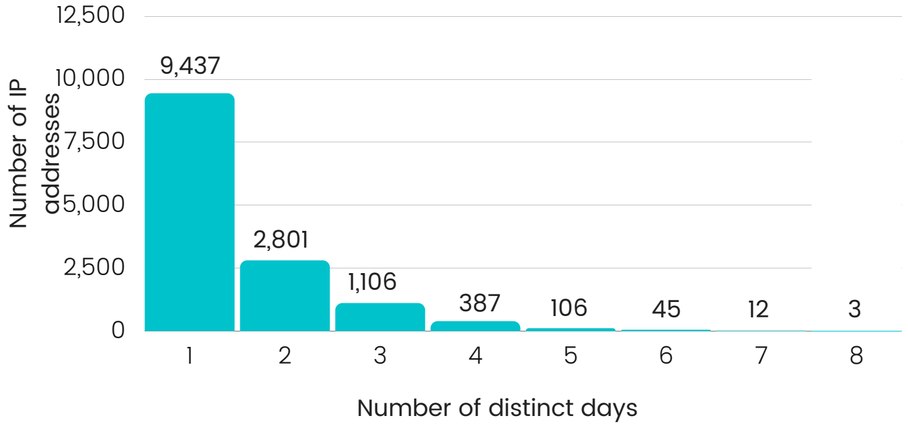

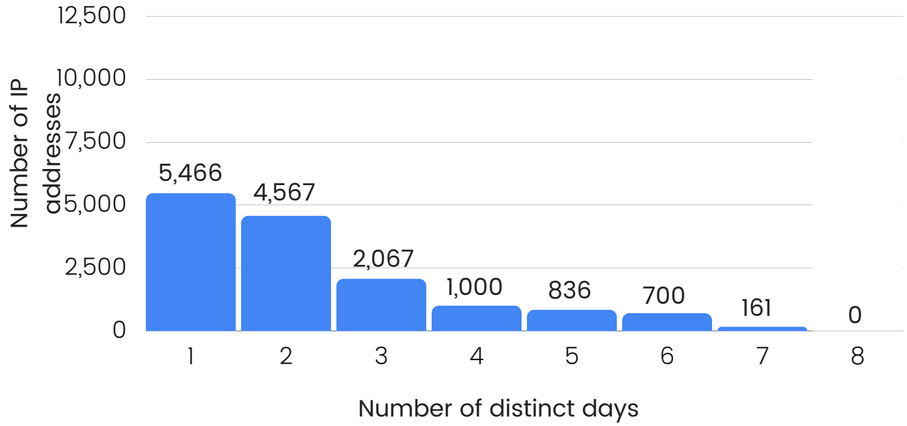

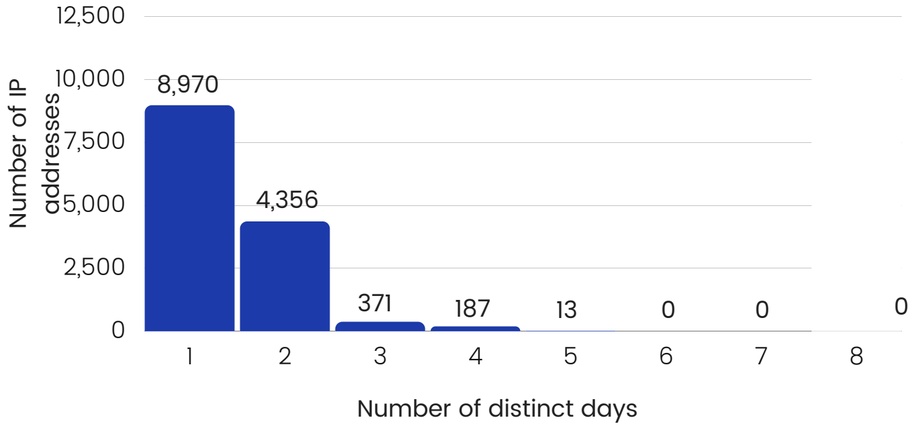

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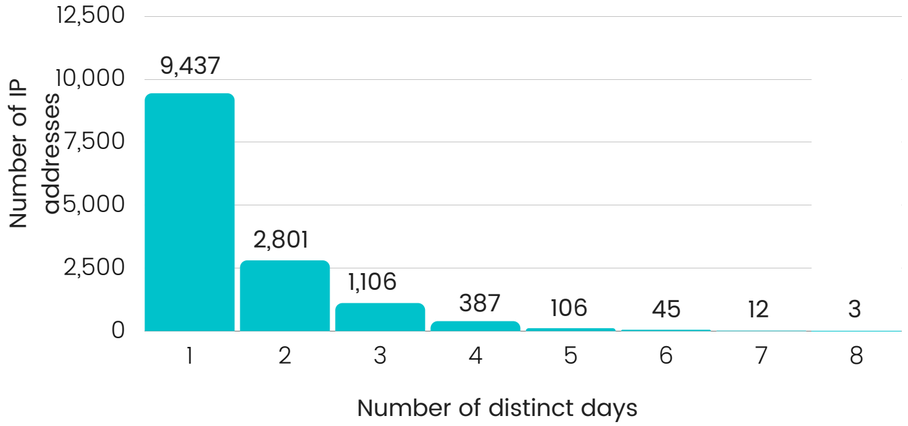

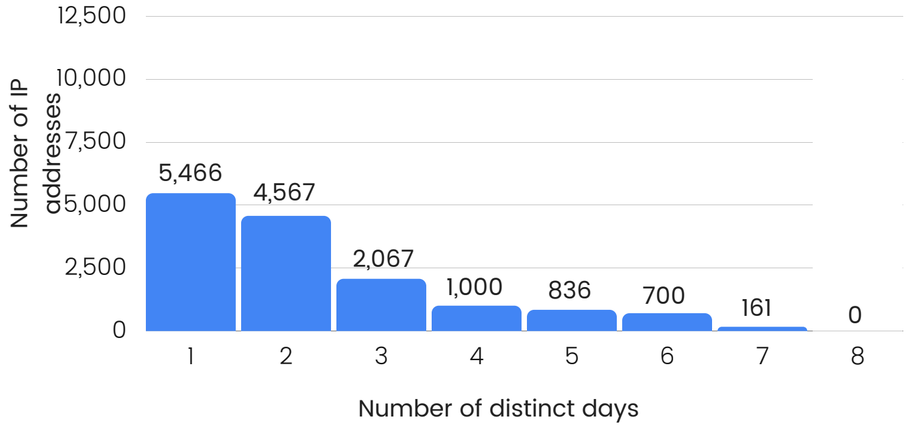

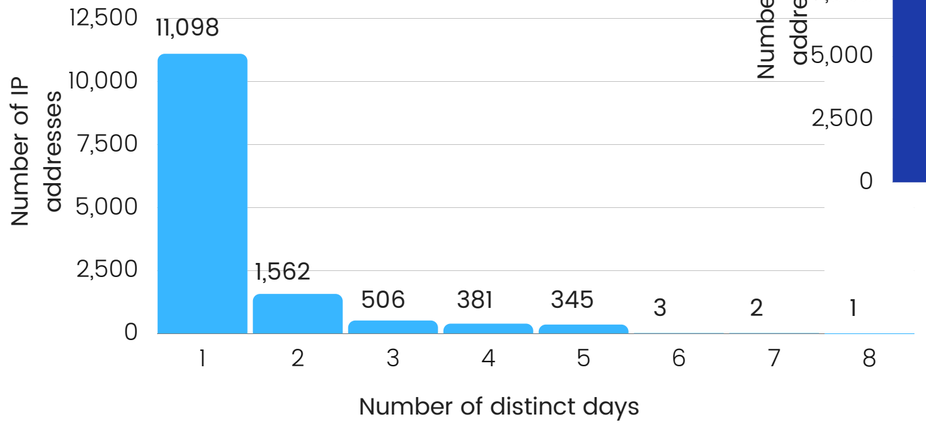

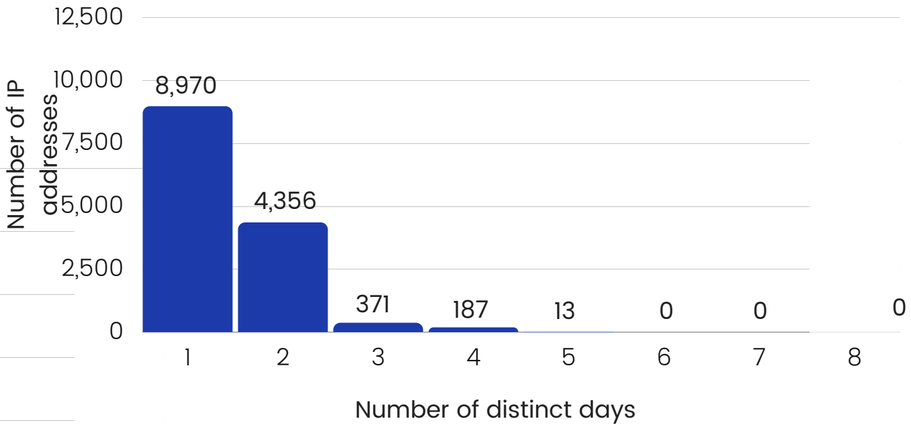

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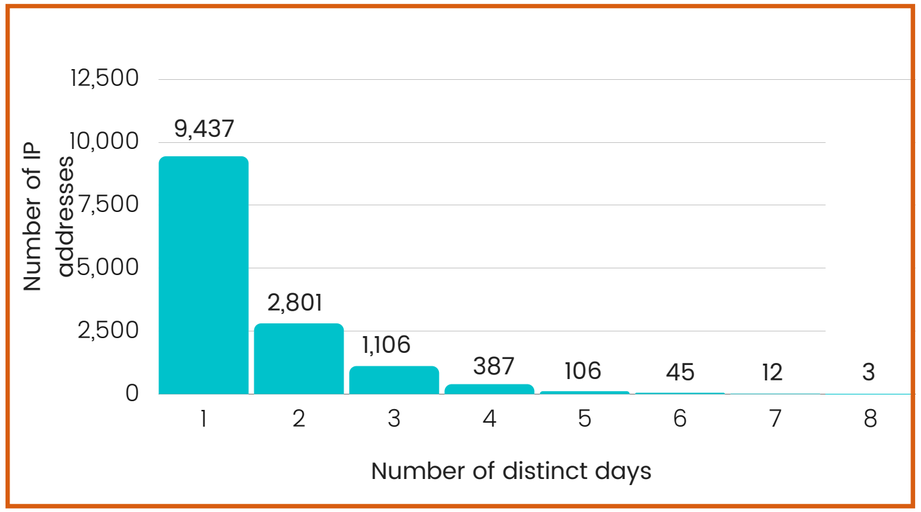

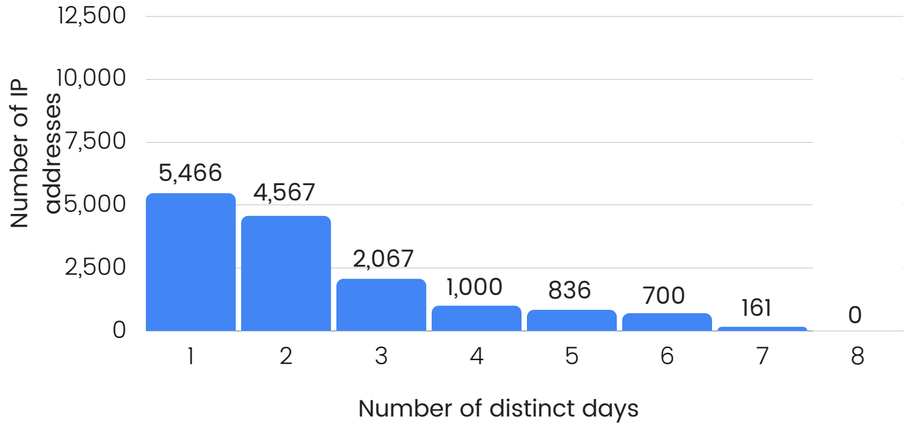

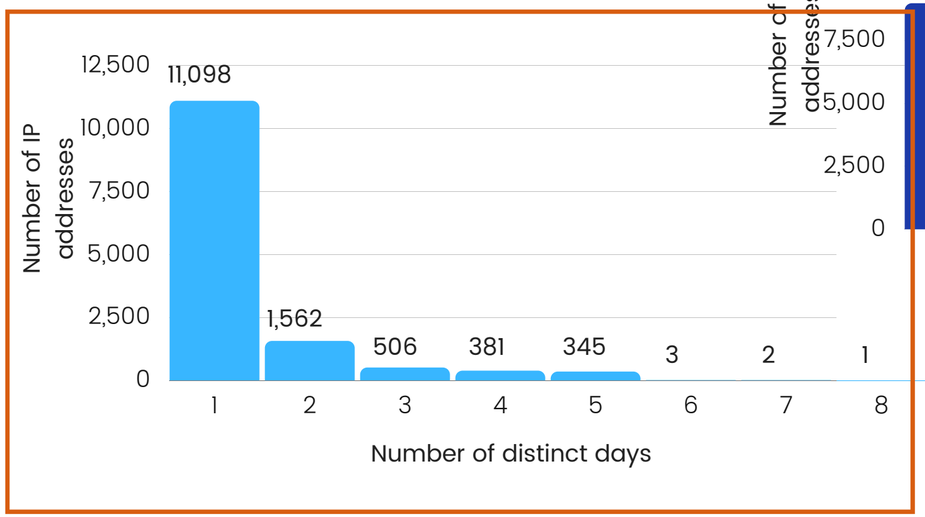

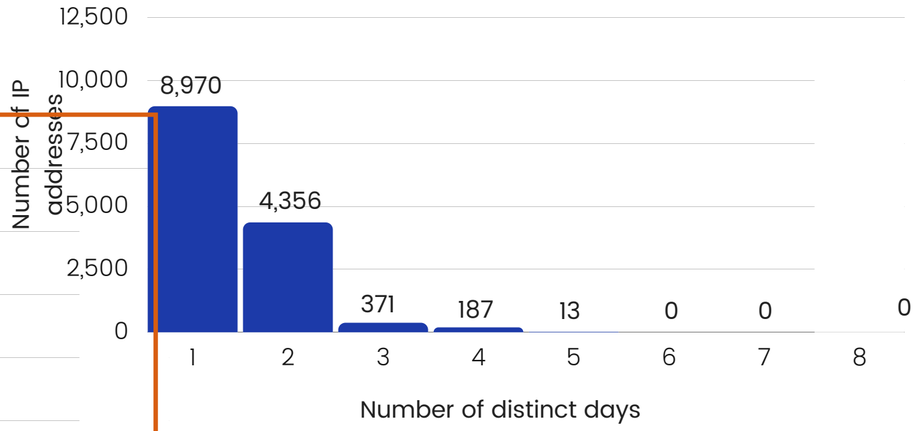

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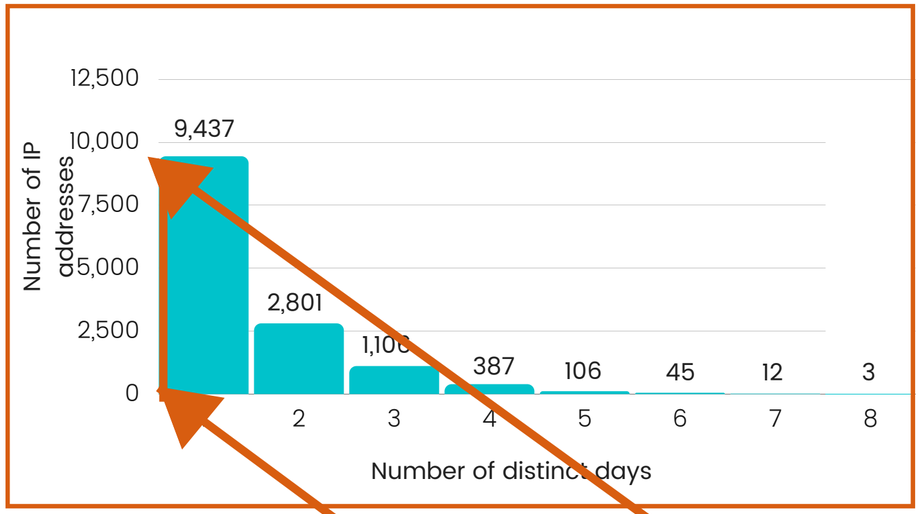

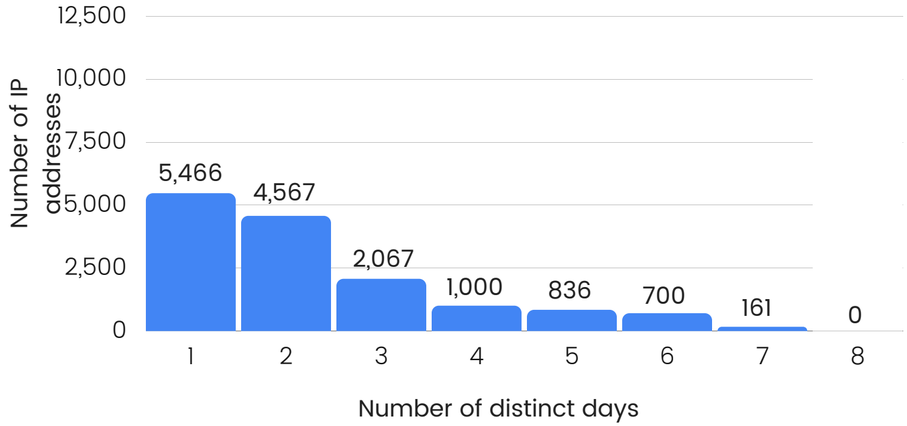

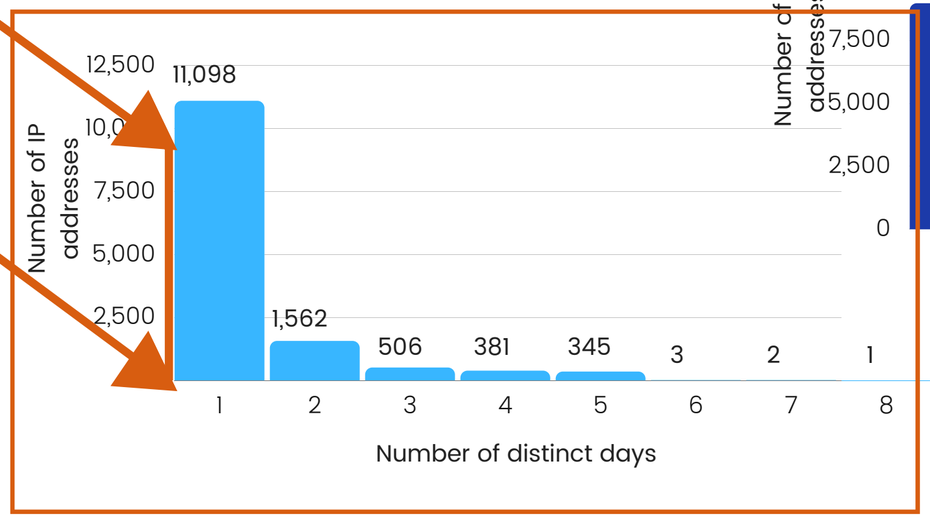

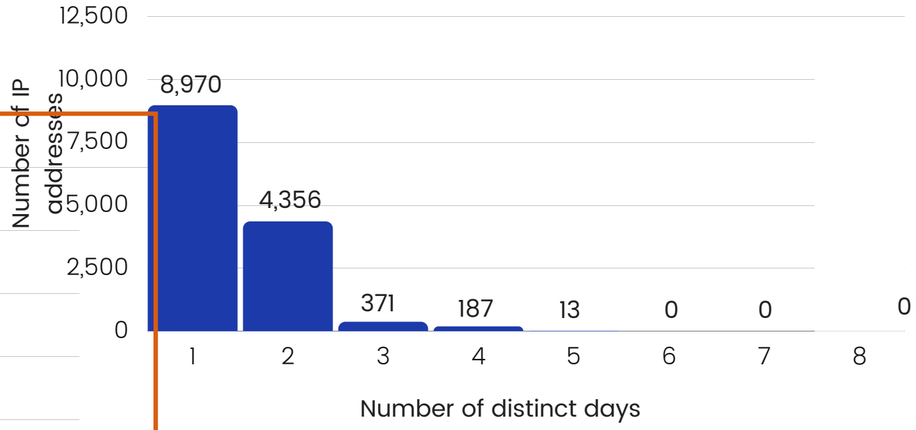

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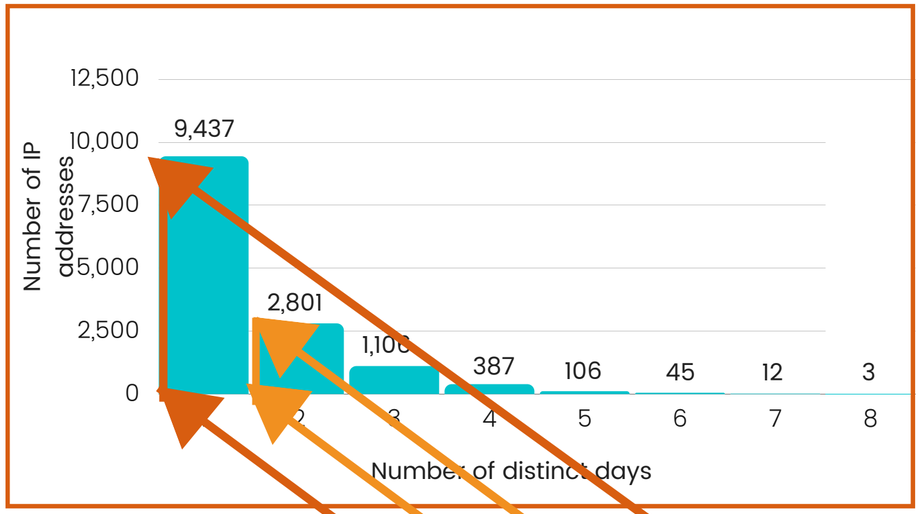

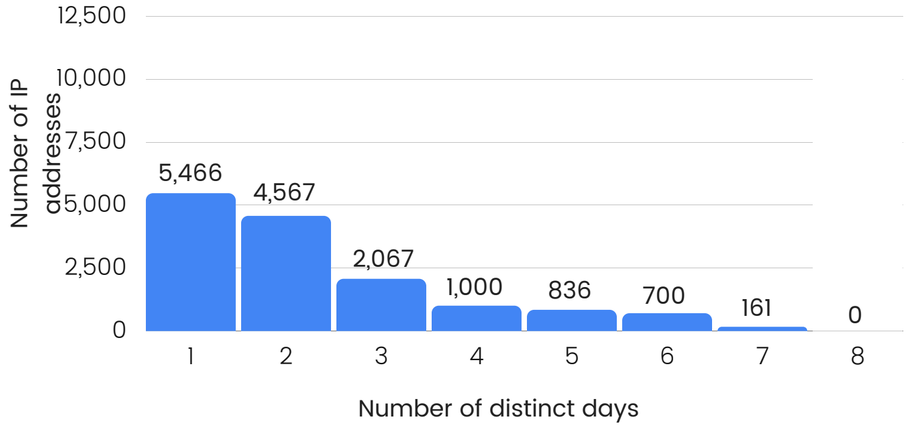

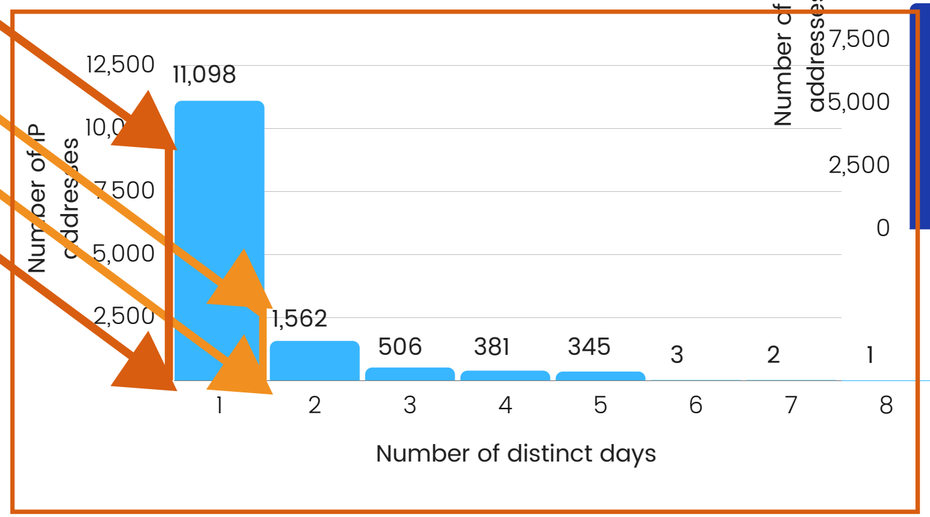

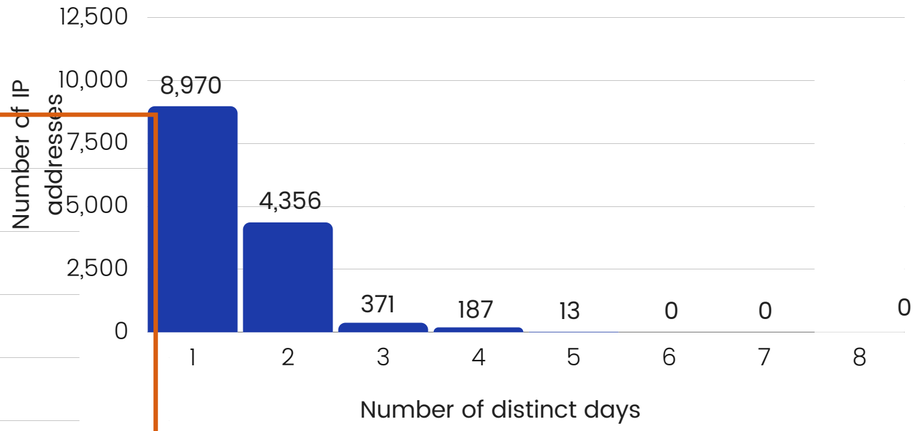

Wasserstein distance

“the minimum amount of "work" required to transform one histogram into another, where "work" is measured as the amount of distribution weight that must be moved, multiplied by the distance it has to be moved”

The value of which produces the histogram with the lowest distance from the empirical data corresponds to the size P which best represents the observed data.

What if the drawing is not daily based?

Repeat the process with window sizes from 2 to 10 days

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- Repeat the process with window sizes from 2 to 10 days
- Drawing with replacement

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- Drawing with replacement
- Additional constraint: a given value cannot be drawn more than times, i.e. once per day

Findings

- **Uniform distribution:** best population size equal to 20,000

Findings

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Uniform distribution means random picking

- All IPs available all the time
- Selection done without taking into account any condition, e.g. geo-localization

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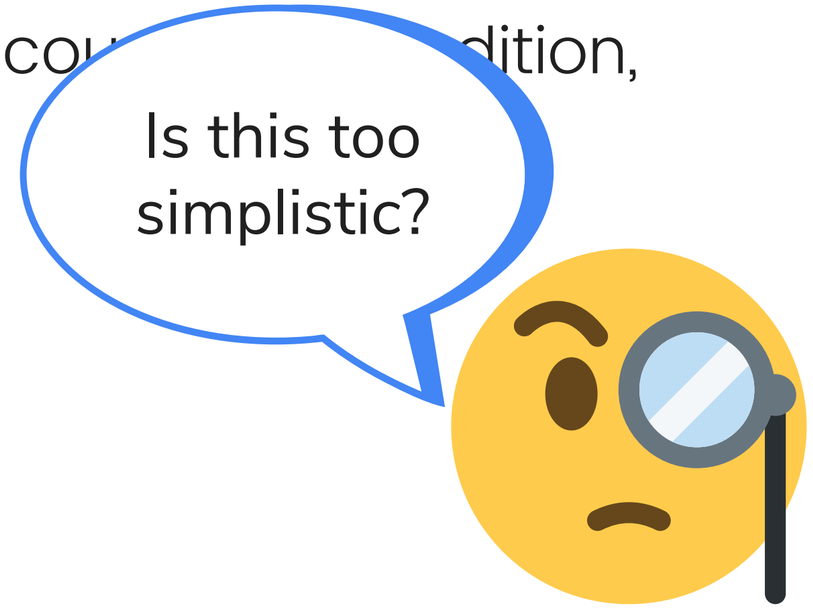

Let's try with other distributions

Model different probability to be picked by different IPs

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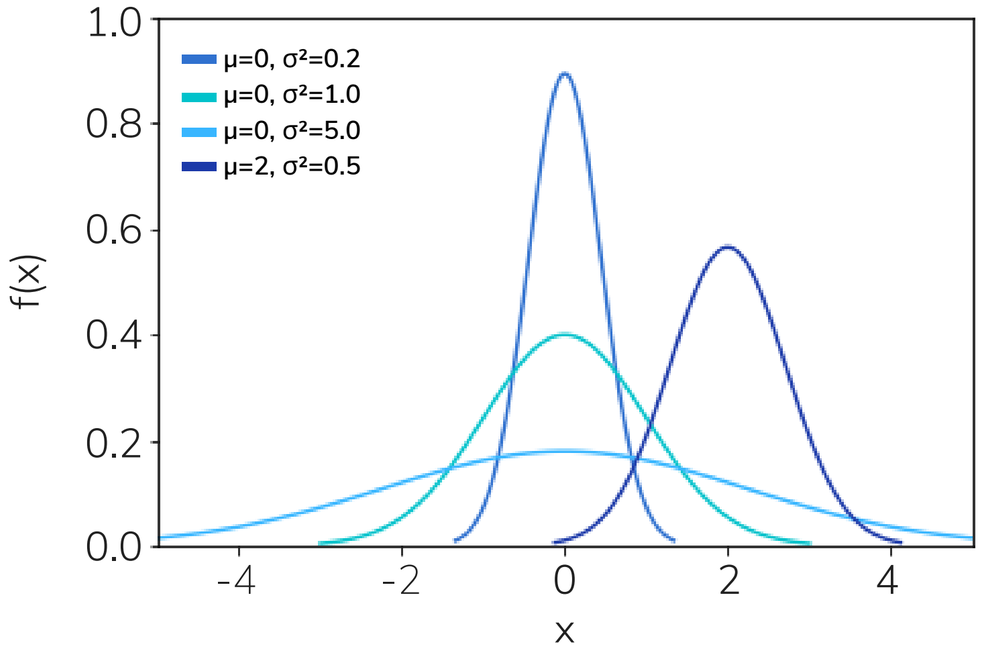
- **Gaussian**



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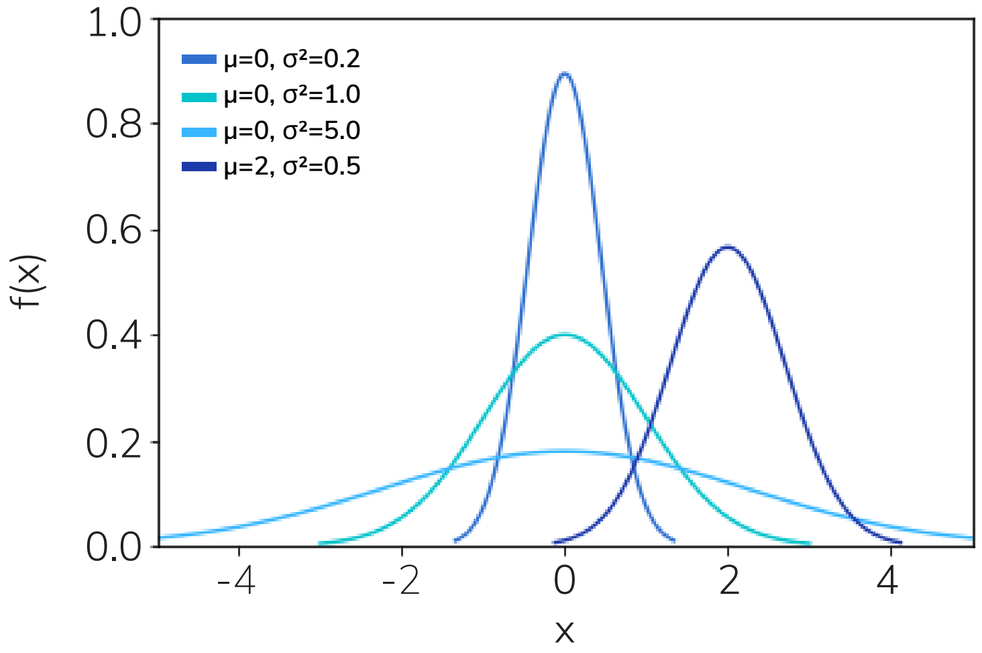
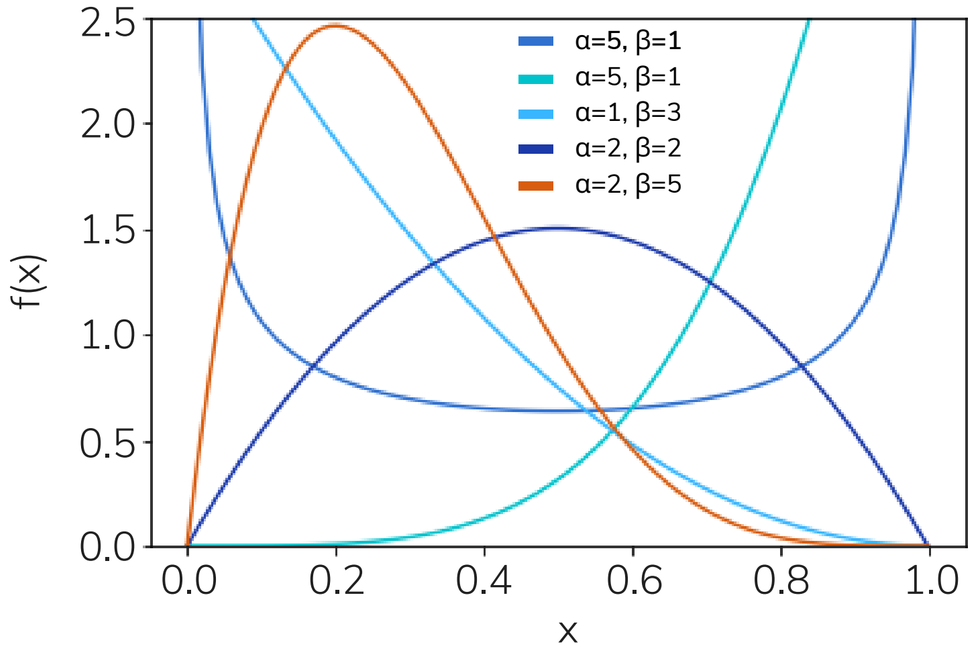


- **Beta**



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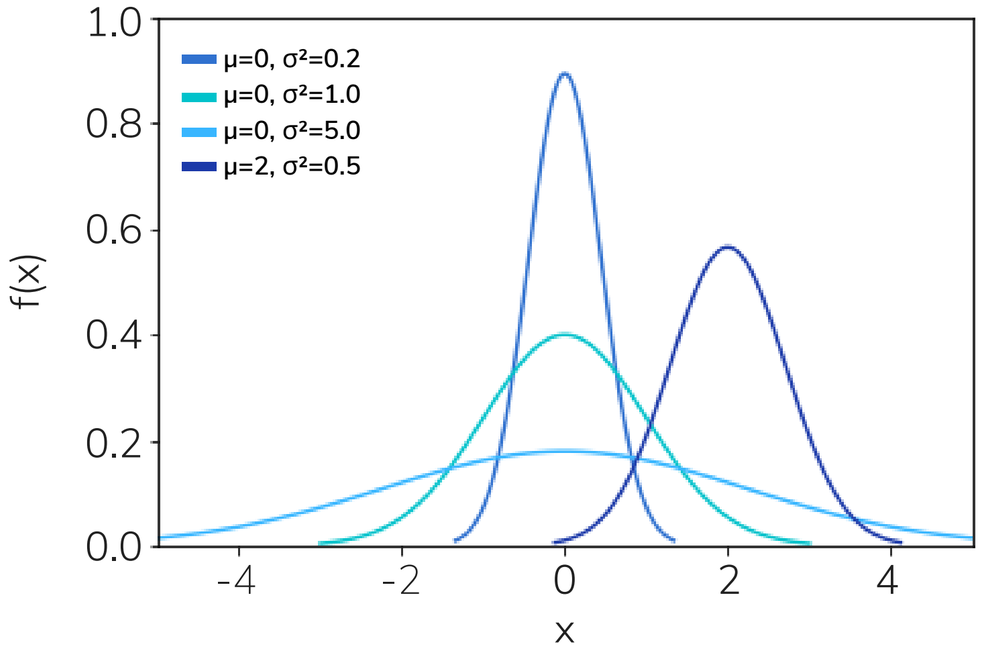

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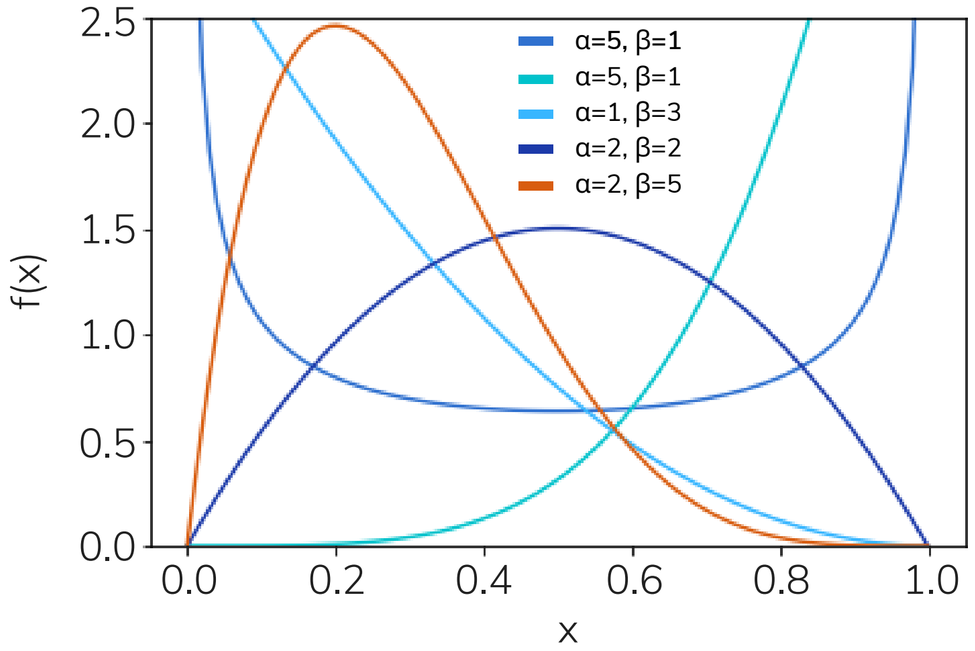

Take the combination of parameters giving us the lowest Wasseinsten distances

Bias results

- Gaussian distribution: best population size equal to 60,000
- Beta distribution: best population size equal to 60,000

What does it mean?

For all considered distributions, the found size of the pool is significantly smaller than proxies claim.

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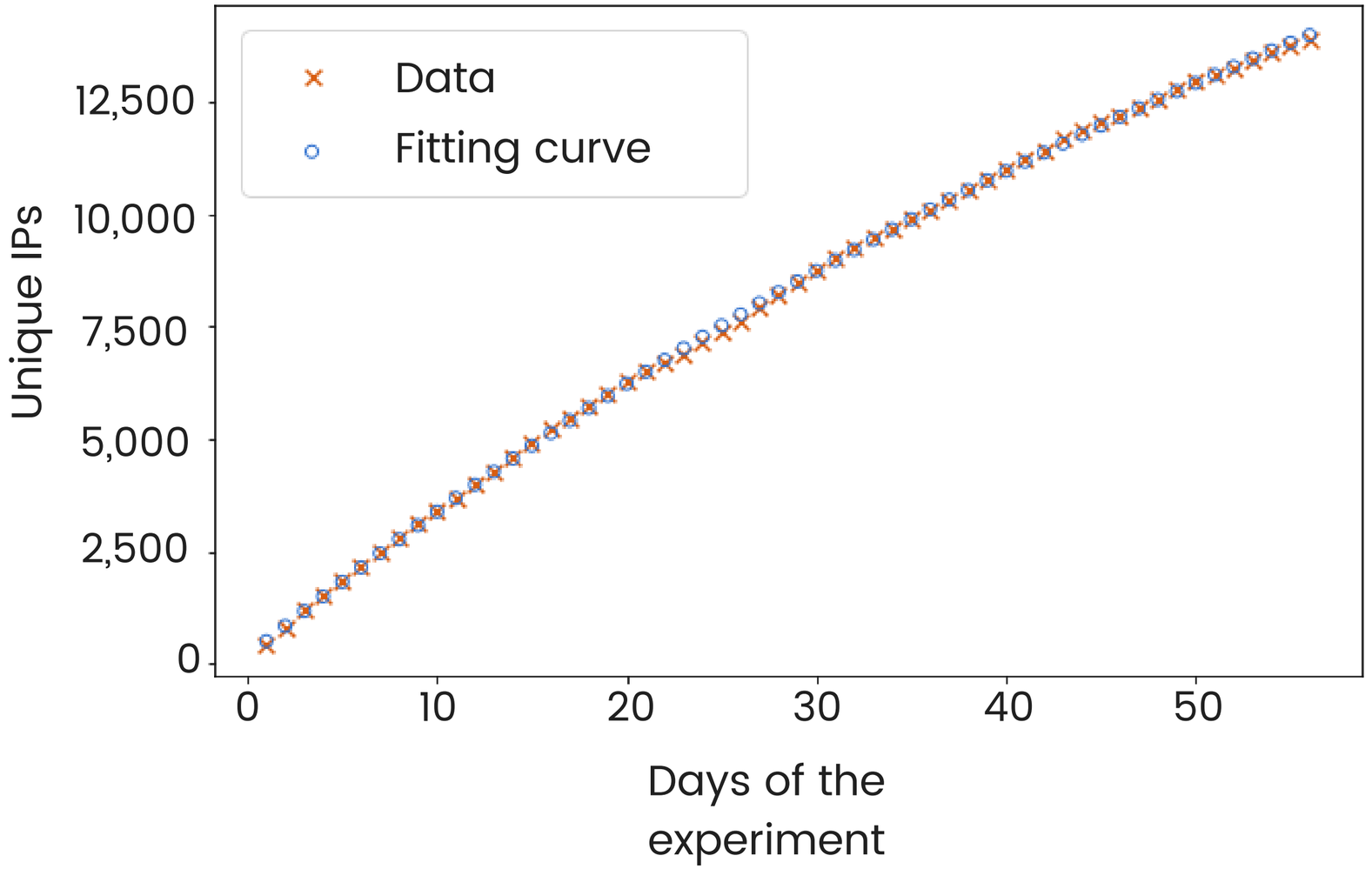
- BUT it suggests that there is a not a complete allocation of the IPs.

The number of IPs that we receive
it is not in the range of millions!

Fitting cumulative curve of new unique IPs



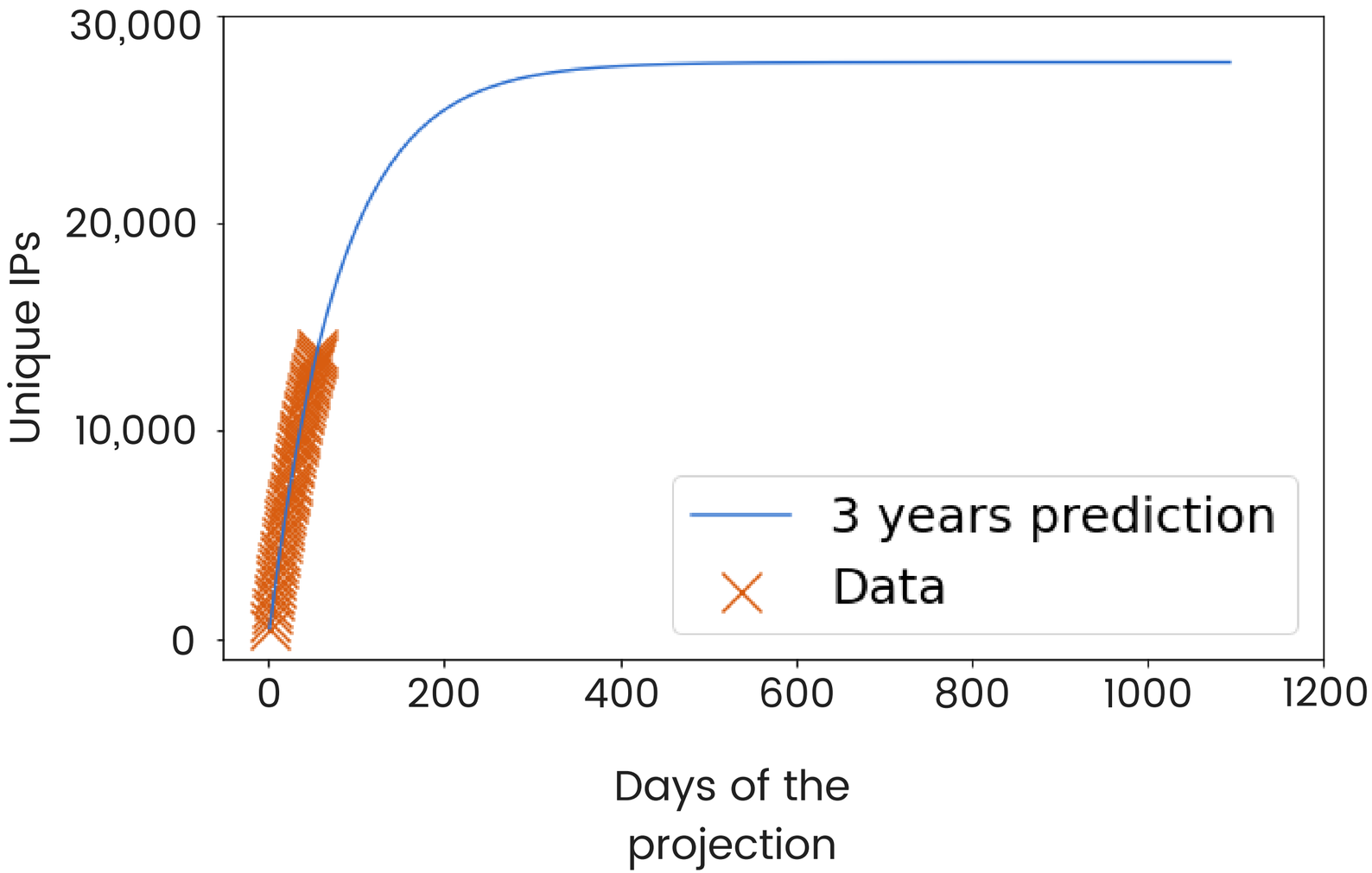
$$f = a^* \left(1 - e^{\frac{-(x-b)}{c}}\right)$$

a=2.77e+04

b=-4.78e-01

c=8.05e+01

Three years prediction



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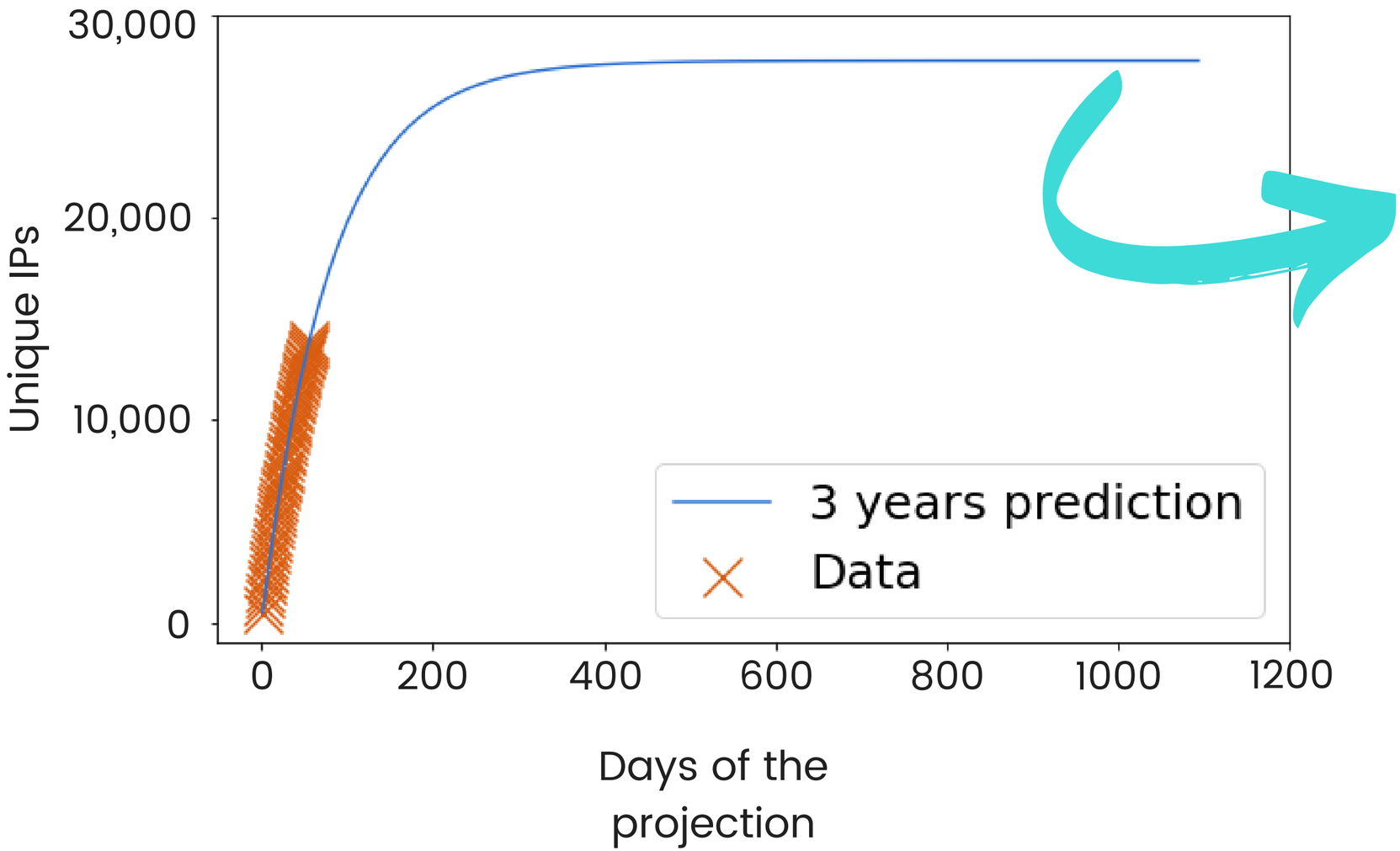
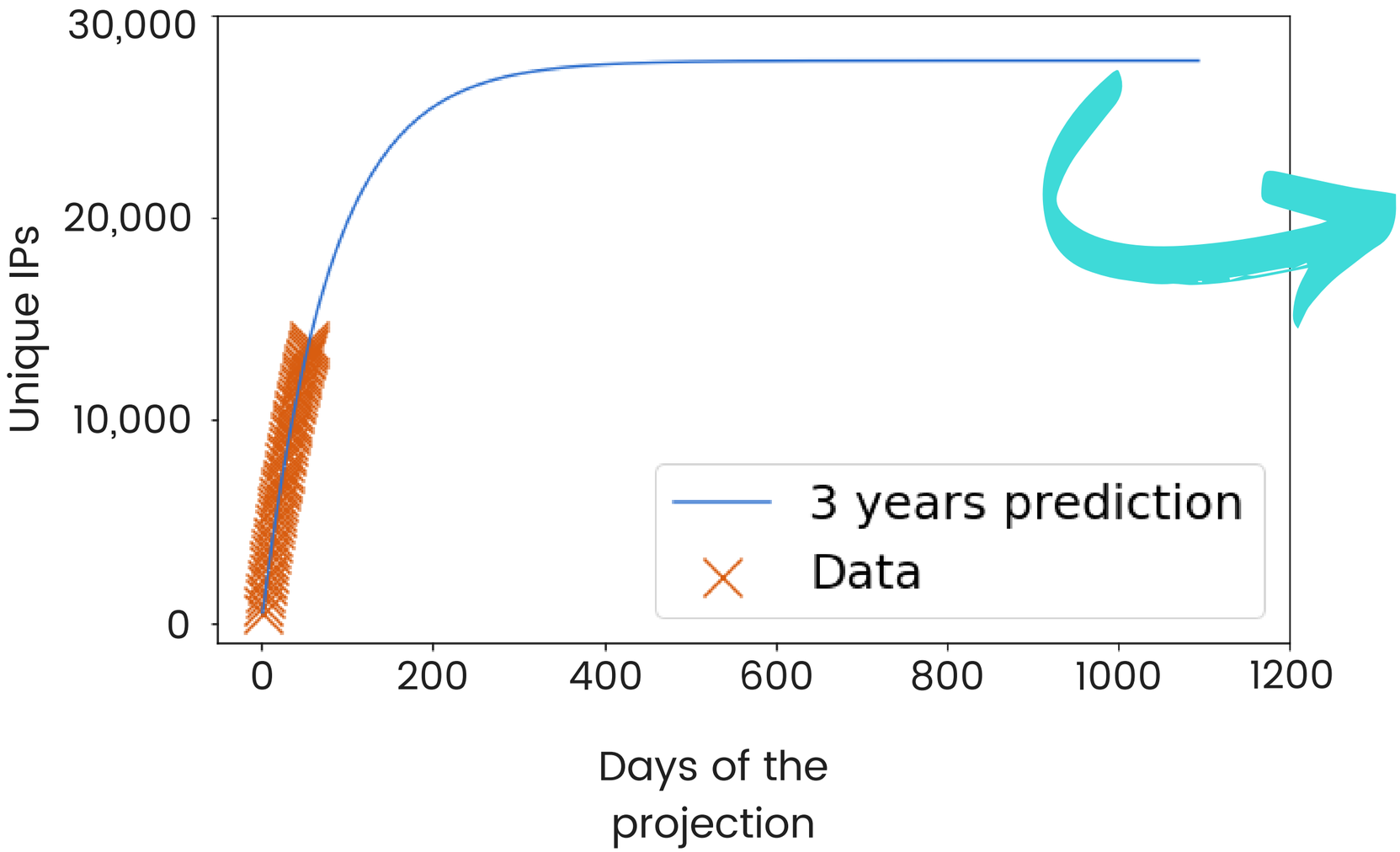


The plateau is less than 30,000 IPs

Three years prediction



The plateau is less than 30,000 IPs

Consistent with the previous approach

4. Conclusions and future work

What we have done so far

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Served modified prices without being detected for 56 days

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Served modified prices without being detected for 56 days

Found behavioral pattern that gives confidence they are all under the same bot master

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Two conference papers and a journal paper

And now? 🤔

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- Implementation of the honeypot inside the system and more experiments
  - Study of other bot signatures
  - Verification of behavioral patterns as second layer detection

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- Implementation of the honeypot inside the system and more experiments
  - Study of other bot signatures
  - Verification of behavioral patterns as second layer detection
- In-depth study of proxies ecosystems

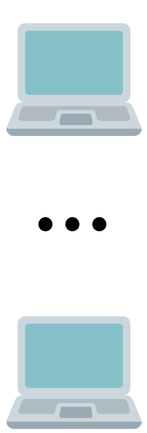
BAD PASS: Bots taking ADvantage of Proxy AS a Services

BAD PASS: Bots taking ADvantage of Proxy AS a Services

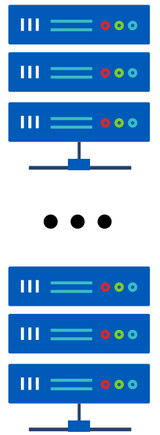
...

Clients

BAD PASS: Bots taking ADvantage of Proxy AS a Services

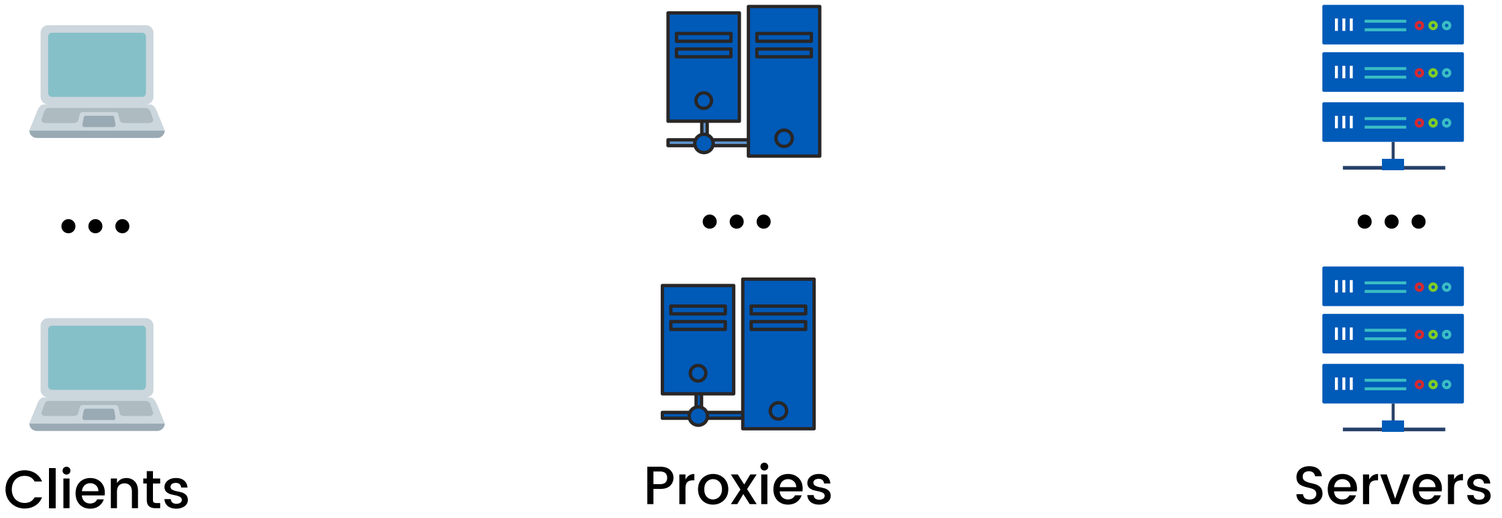


Clients



Servers

BAD PASS: Bots taking ADvantage of Proxy AS a Services



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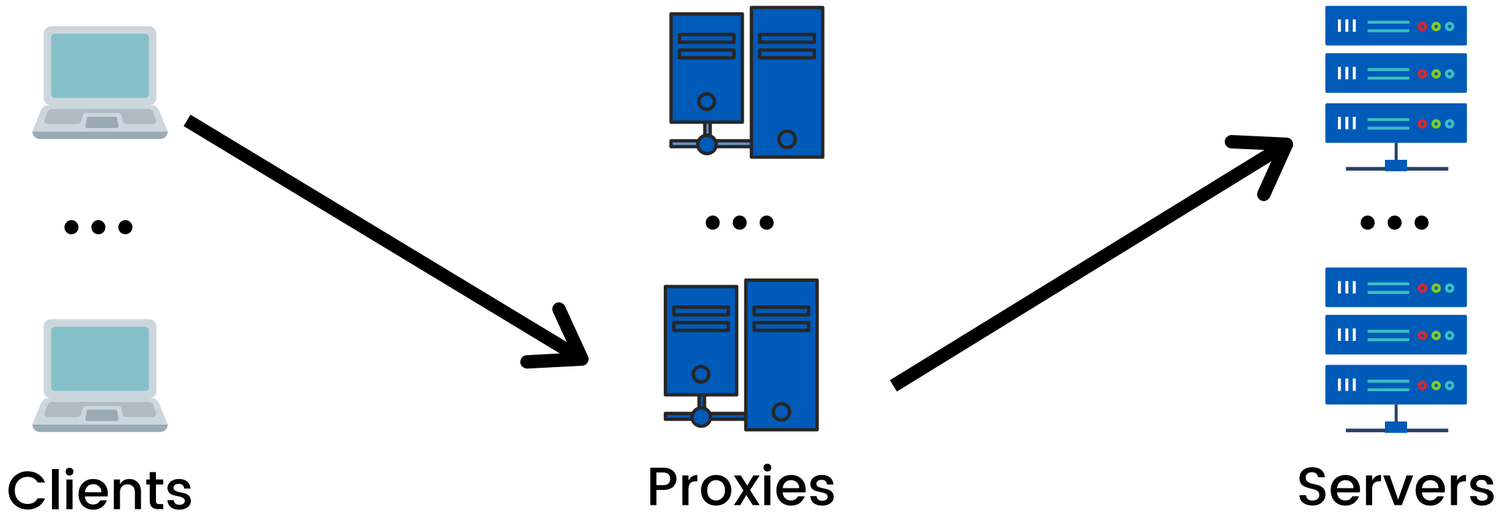

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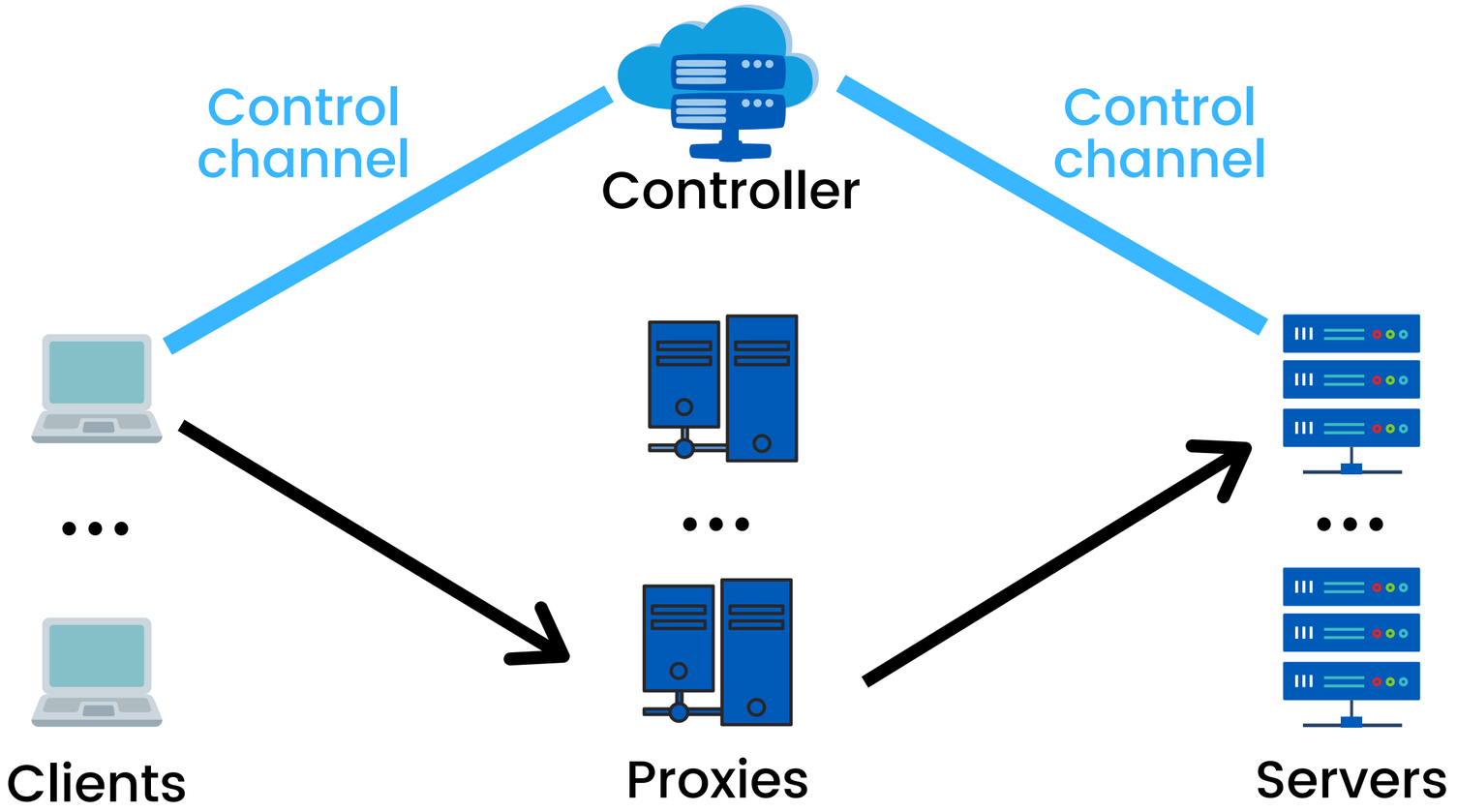

BAD PASS: Bots taking ADvantage of Proxy AS a Services

- Collection of proxy services exit points

BAD PASS: Bots taking ADvantage of Proxy AS a Services

- Collection of proxy services exit points
- Validation of IP blocking solution

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  - Geo-localization
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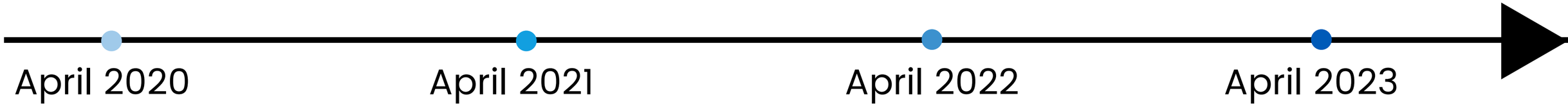
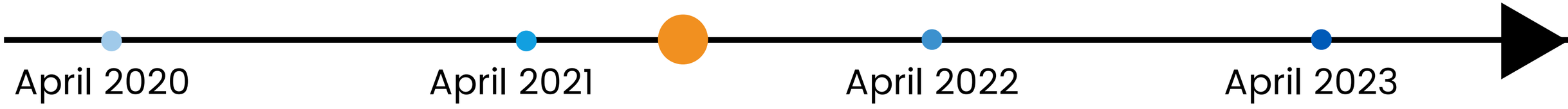
- Check if pool sharing between different proxies
- Proxies fingerprinting

Timeline

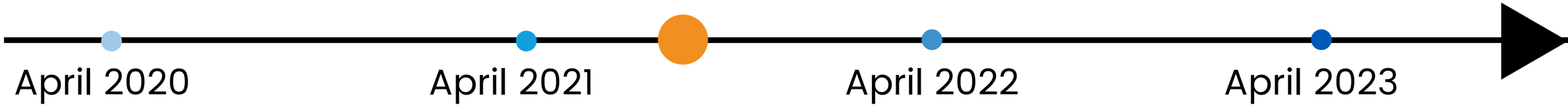


Timeline



Timeline

First year: botnet study through honeypot, identification of proxy services problem



Timeline

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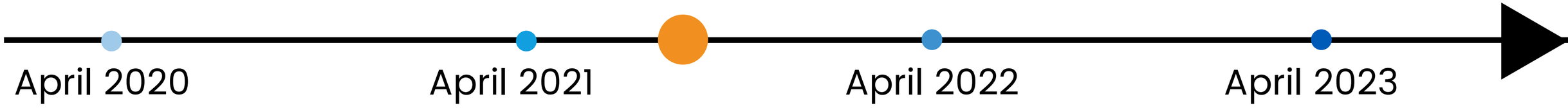
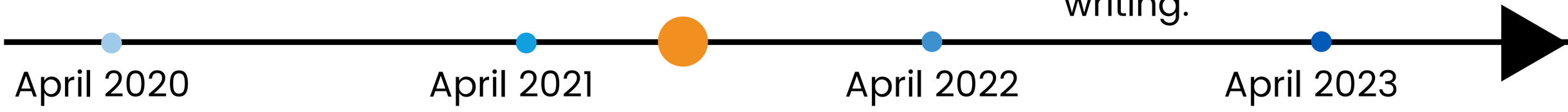


Second year: in-depth study of proxy services, experiments to know their structure. Further experiments with the honeypot.

Timeline

First year: botnet study through honeypot, identification of proxy services problem

Third-year: wider view on botnet ecosystems and experiments with various mitigation strategies. Thesis writing.



Second year: in-depth study of proxy services, experiments to know their structure. Further experiments with the honeypot.

Thank You

...Any question?

Our pubblications:

- Chiapponi, E., Dacier, M., Catakoglu, O., Thonnard, O., & Todisco, M. (2021). **Scraping Airlines Bots: Insights Obtained Studying Honeypot Data**. International Journal of Cyber Forensics and Advanced Threat Investigations, 2(1), 3-28. https://doi.org/10.46386/ijcfati.v2i1.23

- Chiapponi, E., Dacier, M., Todisco, M., Catakoglu, O., & Thonnard, O. (2021). **Botnet sizes: When maths meet myths**. Service-Oriented Computing–ICSOC 2020 Workshops (pagg. 596–611). Springer International Publishing. https://doi.org/10.1007/978-3-030-76352-7_52

- Chiapponi, E., Catakoglu, O., Thonnard, O., Dacier, M. (2020). **HoPLA: a Honeypot Platform to Lure Attackers**. Computer & Electronics Security Applications Rendez-vous (C&ESAR). https://www.eurecom.fr/publication/6366