# Lecture #8: IoT Device Behavior

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University of Twente | June 2, 2021

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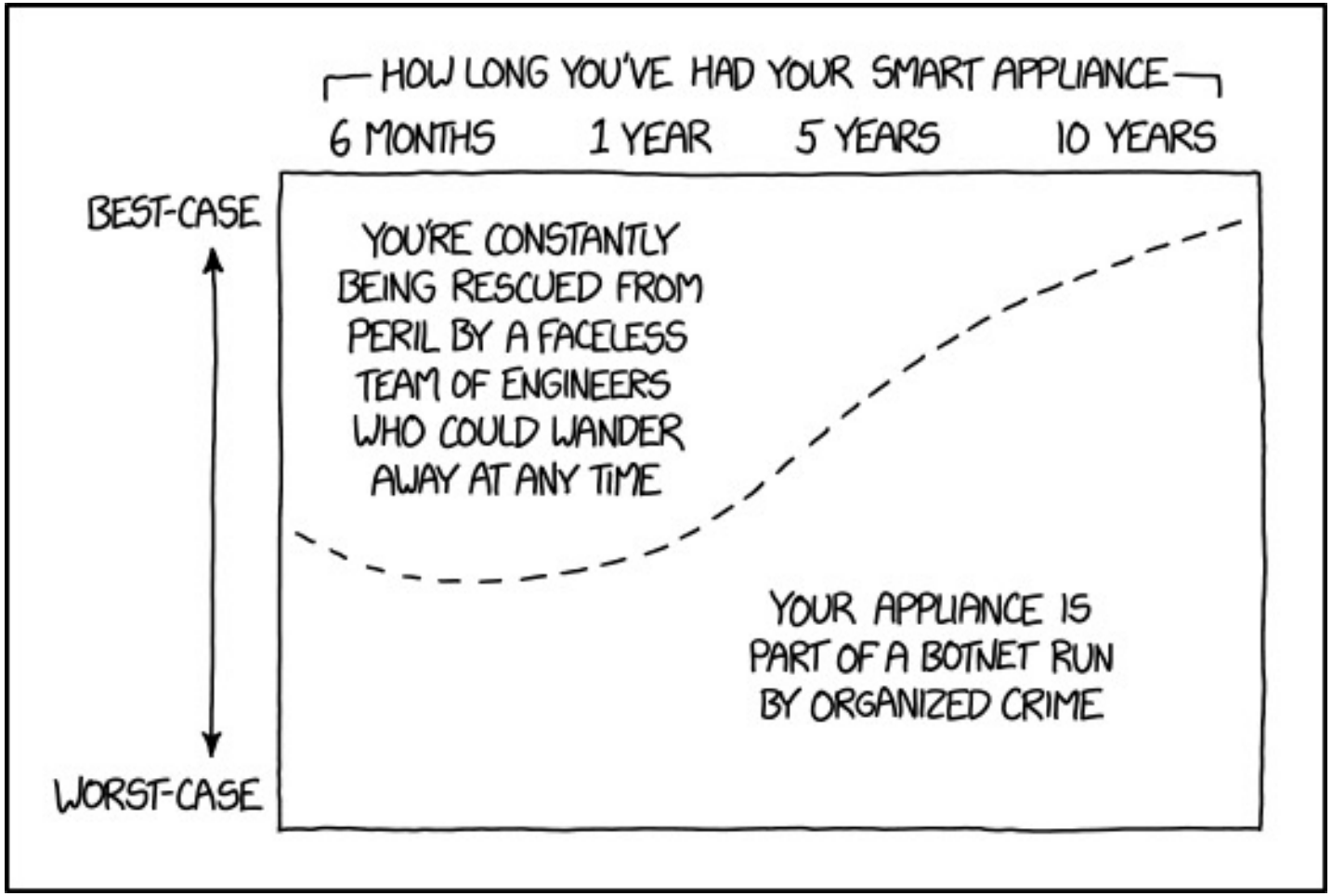
# Key concept: Monitoring Device Behavior



# Today's agenda

- Admin
- Introduction
- Paper #1: AuDI
- Paper #2: IMC
- Discussion

# Admin

# Oral exams

## Monday 28 June 2021

- Online through Canvas
- Signup through Canvas ‘Appointment’ (starting this afternoon)
- 45 minutes
- See: https://courses.sidnlabs.nl/ssi-2021/#oral-exam



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# Lab report progress

How far are you with the Lab report?

A. Developing methodology

B. Gathering network data from IoT devices

C. Analyzing  network data from IoT devices

D. Writing report

# Interactive lectures

- Overall objective: enable you to learn from each other and further increase your understanding of the papers, contributes to preparing yourself for the oral exam

- Interactive format
  - Teachers summarize two papers per lecture
  - Multiple-choice questions (not graded) and discussion
  - We ask at least one of you to share their thoughts on each paper (main lesson learned, etc.)
  - Enables you to learn from each other, so mandatory to participate

- A 7th “re-sit” lecture in case you miss a lecture (optional for everybody else), same format

# Where are we now?

| No. | Date | Contents |
|---|---|---|
| 1 | Apr 21 | Course introduction<br>Guest lecture #1: how the core of the internet is organized, Marco Davids (SIDN Labs) |
| 2 | Apr 28 | Guest lecture #2: the relationship between regulation & IoT security, Eelco Vriezekolk, Agentschap Telecom (Dutch telecoms regulator) |
| 3 | May 6* | Lecture: IoT Concepts and Applications |
| 4 | May 12 | Lecture: IoT Botnet Measurements |
| 5 | May 18 | Lecture: IoT Honeypots |
| 6 | May 25* | Guest lecture #3: The Life Of An IoT Device, Eliot Lear, Cisco Systems |
| 7 | May 26 | Lecture: IoT Edge Security Systems |
| **8** | **Jun 2** | **Lecture: IoT Device Behavior** |
| 9 | Jun 9 | Lecture: IoT in Non-Carpeted Areas |
| 10 | Jun 16 | Lecture: IoT Edge Security Systems (re-sit) |

* Different lecture times/days. Default slot: Wednesdays 11:00 - 12:45



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# Introduction

# Motivation for today: Understanding the problems

What's happening => Securing

Physical interaction

AV / controls



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# Discussion

Statement: I inspected the traffic of my IoT device(s) prior to this course.

A. Yes, of course!

B. No

C. I don’t have any IoT devices

D. I started inspecting when I got the SPIN device

# Today's papers

Are about measuring IoT device behavior

- [**AuDI**] Marchal, S., Miettinen, M., Nguyen, T. D., Sadeghi, A-R., & Asokan, N. (2019). AuDI: Towards Autonomous IoT Device-Type Identification using Periodic Communication. IEEE Journal on Selected Areas in Communications
- [**IMC**] J. Ren, D. J. Dubois, D. Choffnes, A. M. Mandalari, R. Kolcun, and H. Haddadi, "Information Exposure from Consumer IoT Devices: A Multidimensional, Network-Informed Measurement Approach", Internet Measurement Conference (IMC2019), Amsterdam, Netherlands, Oct 2019

# Today's learning objective

- After the lecture, you will be able to discuss why passive measurements on IoT devices are an important means to understand the problem of IoT Security.

- AuDI shows how to do device type classification through fingerprints based on an IoT device's network traffic.

- IMC shows a novel way to setup a completely automated testing facility and what kind of analyses are possible with such a lab.

- Contributes to SSI learning goal #1: "Understand IoT concepts and applications, security threats, technical solutions, and a few relevant standardization efforts in the IETF"

# “AUDI: Towards Autonomous IoT Device-Type Identification using Periodic Communication”

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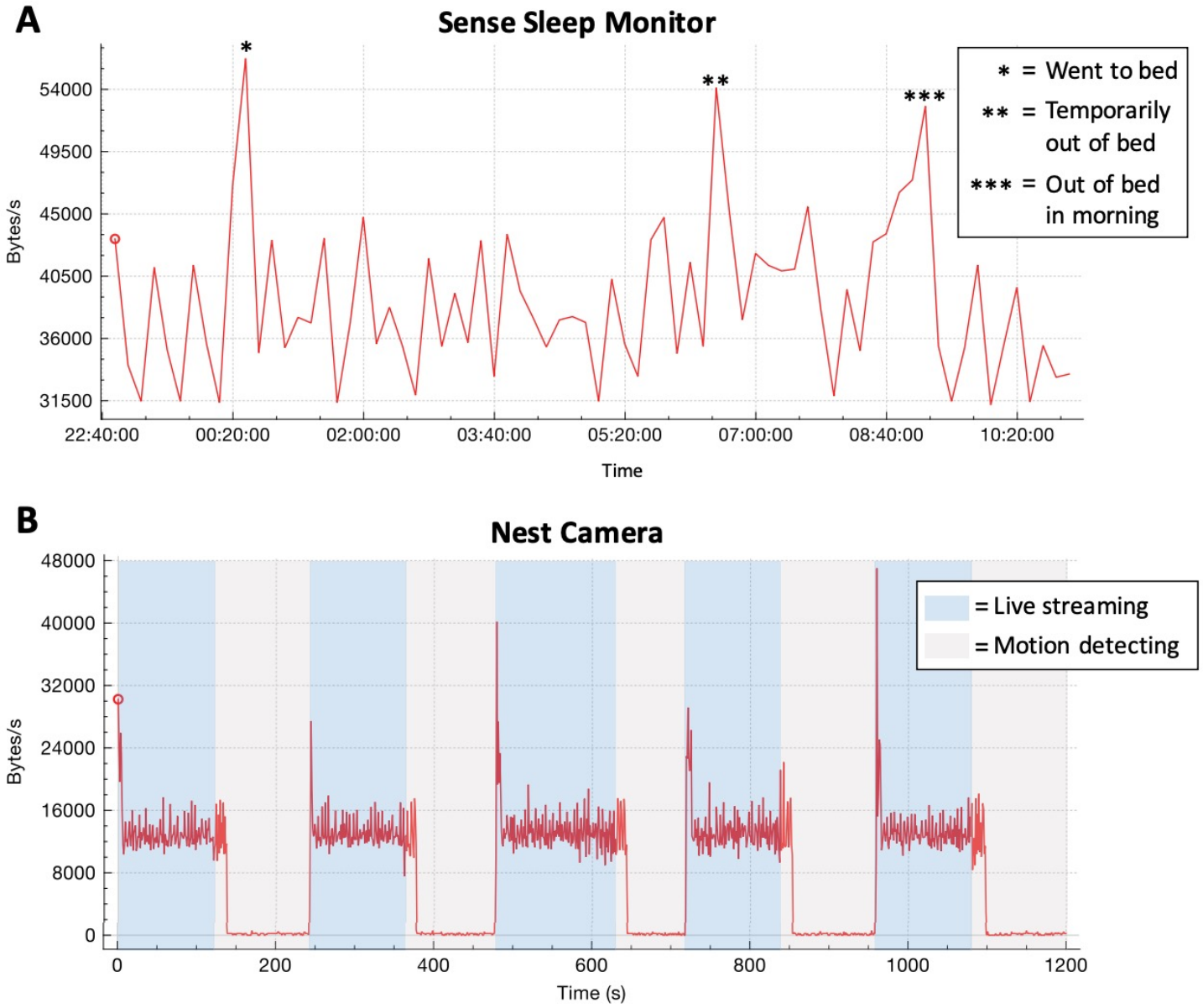
# Passive monitoring

Encryption-agnostic

See also:

Noah Apthorpe, Dillon Reisman, Nick Feamster, "**A Smart Home is No Castle: Privacy Vulnerabilities of Encrypted IoT Traffic**", Workshop on Data and Algorithmic Transparency (DAT '16), New York University Law School, November 2016

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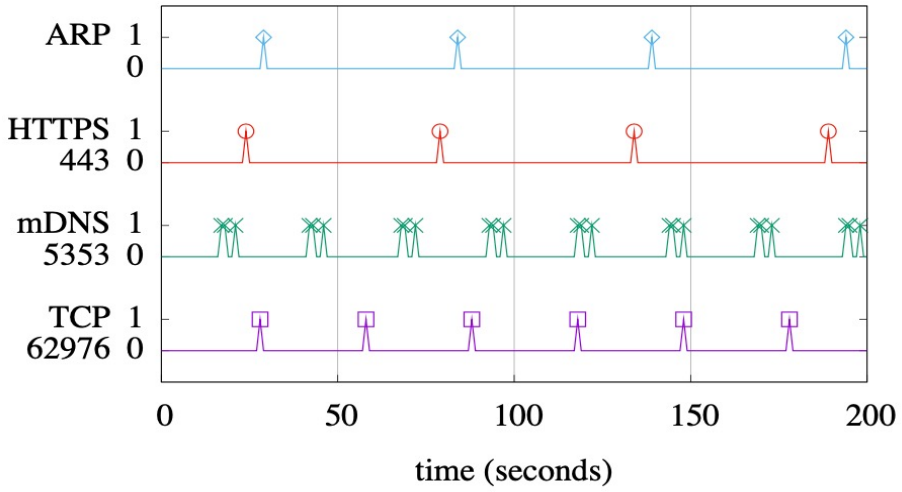
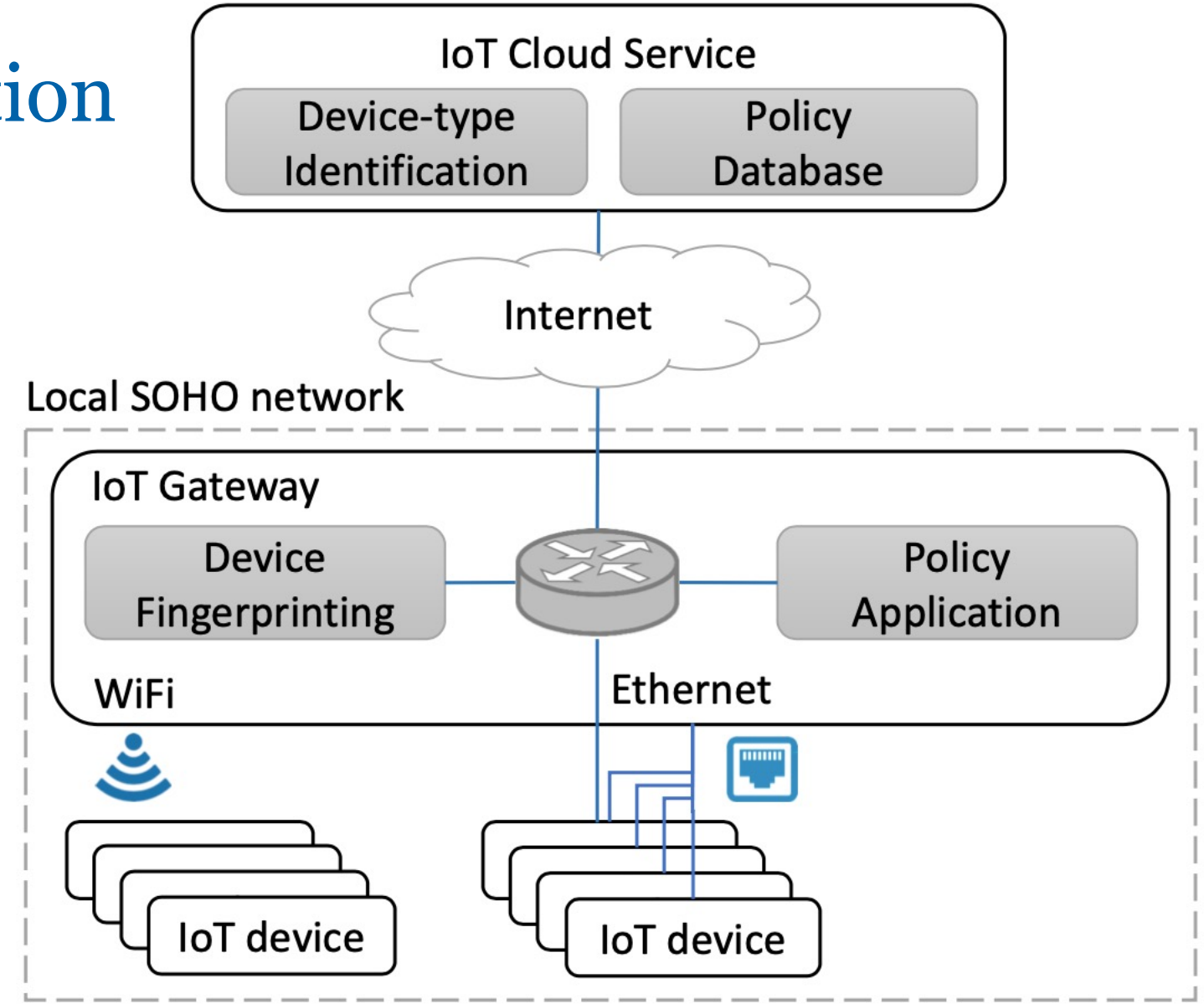
# Device Type identification

- Goal: “quickly, accurately and *autonomously* identifying the type of IoT devices”
- QoS or security policies
- Passive fingerprinting of periodic network traffic
- 98.2% accuracy in tests

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# How do they do it?

- Periodic background network traffic
- Analyse per flow
- Time series: traffic 1/0 every second
- Compute periods Fourier transform
- Autocorrelation to find periodicity
- Fingerprinting periods

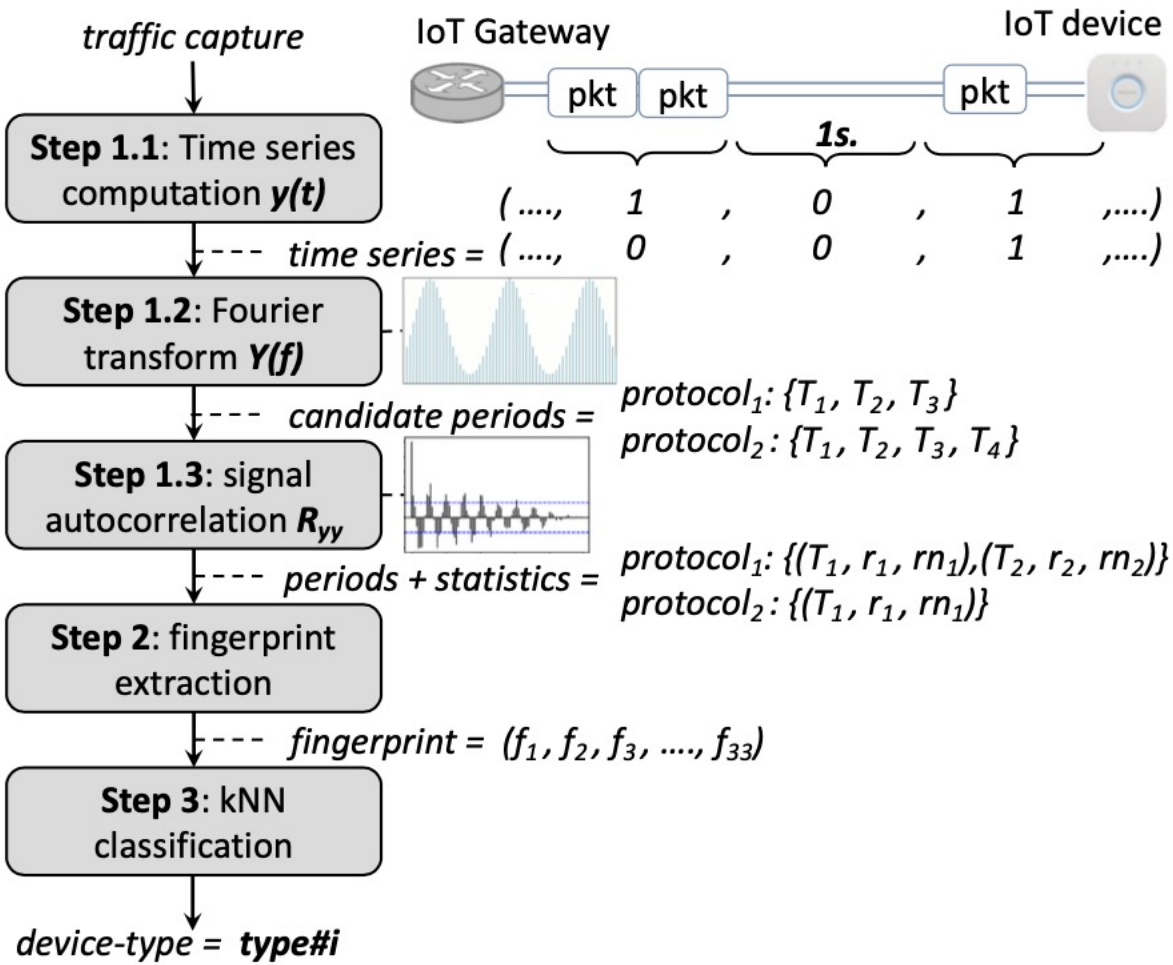


Fig. 2: Overview of device-type identification.

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# Quiz: countering detection

How can you avoid getting fingerprinted?

A. Generate a constant stream of traffic
B. Encrypt the network traffic
C. Open connections to random hosts
D. Disable the ICMP finger protocol
E. You can’t

# Fingerprints

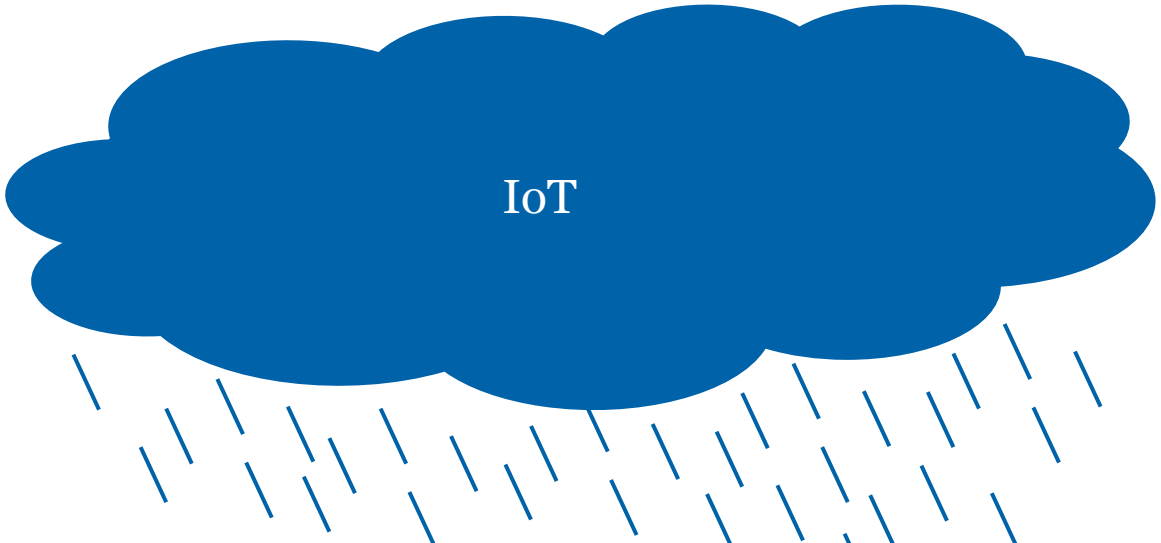
33 features in 4 categories

Manually designed

| Category | $f$ | Description | Importance |
|---|---|---|---|
| periodic flows | 1 | # periodic flows | 0.440 |
| | 2 | # periodic flows (protocol $\leq$ layer 4) | 0.465 |
| | 3 | Mean periods per flow | 0.068 |
| | 4 | SD periods per flow | 0.037 |
| | 5 | # flows having only one period | 0.429 |
| | 6 | # flows having multiple periods | 0.176 |
| | 7 | # flows with static source port | 0.533 |
| | 8 | Mean frequency source port change | 0.310 |
| | 9 | SD frequency source port change | 0.137 |
| period accuracy | 10 | # periods inferred in all sub-captures | 0.329 |
| | 11 | Mean period inference success | 0.037 |
| | 12 | SD period inference success | 0.022 |
| period duration | 13 | # periods $\in [5s.; 29s.]$ | 0.409 |
| | 14 | # periods $\in [30s.; 59s.]$ | 0.408 |
| | 15 | # periods $\in [60s.; 119s.]$ | 0.467 |
| | 16 | # periods $\in [120s.; 600s.]$ | 0.419 |
| period stability | 17 | # Mean$(r) \in [0.2; 0.7[$ | 0.386 |
| | 18 | # Mean$(r) \in [0.7; 1[$ | 0.436 |
| | 19 | # Mean$(r) \in [1; 2[$ | 0.239 |
| | 20 | # Mean$(r) \in [2; +\infty[$ | 0.124 |
| | 21 | # SD$(r) \in [0; 0.02[$ | 0.185 |
| | 22 | # SD$(r) \in [0.02; 0.1[$ | 0.151 |
| | 23 | # SD$(r) \in [0.1; +\infty[$ | 0.185 |
| | 24 | # Mean$(rn) \in [0.2; 0.7[$ | 0.288 |
| | 25 | # Mean$(rn) \in [0.7; 1[$ | 0.307 |
| | 26 | # Mean$(rn) \in [1; 2[$ | 0.313 |
| | 27 | # Mean$(rn) \in [2; +\infty[$ | 0.246 |
| | 28 | # SD$(rn) \in [0; 0.02[$ | 0.217 |
| | 29 | # SD$(rn) \in [0.02; 0.1[$ | 0.217 |
| | 30 | # SD$(rn) \in [0.1; +\infty[$ | 0.220 |
| | 31 | # Mean$(rn)-$ Mean$(r) \in [0; 0.02[$ | 0.408 |
| | 32 | # Mean$(rn)-$ Mean$(r) \in [0.02; 0.1[$ | 0.248 |
| | 33 | # Mean$(rn)-$ Mean$(r) \in [0.1; +\infty[$ | 0.482 |

# IoT Cloud service

- Fingerprints are sent to IoT Cloud service
- Cloud services uses fingerprints to learn (and find) device types (i.e., step 3)
- Fingerprints per 30 minutes.
- Unsupervised (?) clustering algorithm: autonomously group these fingerprints into clusters and create an abstract label for each cluster

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# Evaluation

33 devices

Background + activity

6224 fingerprints

ID in +- 30 minutes

| Device-type | Identifier | Device model | WiFi | Ethernet | Other | Background | Activity |
|---|---|---|---|---|---|---|---|
| *type#01* | ApexisCam | Apexis IP Camera APM-J011 | ● | ● | ○ | ● | ● |
| *type#02* | CamHi | Cooau Megapixel IP Camera | ● | ● | ○ | ● | ● |
| *type#03* | D-LinkCamDCH935L | D-Link HD IP Camera DCH-935L | ● | ○ | ○ | ● | ● |
| *type#04* | D-LinkCamDCS930L | D-Link WiFi Day Camera DCS-930L | ● | ● | ○ | ● | ○ |
| | D-LinkCamDCS932L | D-Link WiFi Camera DCS-932L | ● | ● | ○ | ● | ○ |
| *type#05* | D-LinkDoorSensor | D-Link Door & Window sensor | ○ | ○ | ● | ● | ● |
| | D-LinkSensor | D-Link WiFi Motion sensor DCH-S150 | ● | ○ | ○ | ● | ● |
| | D-LinkSiren | D-Link Siren DCH-S220 | ● | ○ | ○ | ● | ● |
| | D-LinkSwitch | D-Link Smart plug DSP-W215 | ● | ○ | ○ | ● | ● |
| | D-LinkWaterSensor | D-Link Water sensor DCH-S160 | ● | ○ | ○ | ● | ● |
| *type#06* | EdimaxCamIC3115 | Edimax IC-3115W Smart HD WiFi Network Camera | ● | ● | ○ | ● | ● |
| | EdimaxCamIC3115(2) | Edimax IC-3115W Smart HD WiFi Network Camera | ● | ● | ○ | ● | ● |
| *type#07* | EdimaxPlug1101W | Edimax SP-1101W Smart Plug Switch | ● | ○ | ○ | ● | ● |
| | EdimaxPlug2101W | Edimax SP-2101W Smart Plug Switch | ● | ○ | ○ | ● | ● |
| *type#08* | EdnetCam | Ednet Wireless indoor IP camera Cube | ● | ● | ○ | ● | ● |
| *type#09* | EdnetGateway | Ednet.living Starter kit power Gateway | ● | ○ | ● | ● | ● |
| *type#10* | HomeMaticPlug | Homematic pluggable switch HMIP-PS | ○ | ○ | ● | ● | ● |
| *type#11* | Lightify | Osram Lightify Gateway | ● | ○ | ● | ● | ● |
| *type#12* | SmcRouter | SMC router SMCWBR14S-N4 EU | ● | ● | ○ | ● | ● |
| *type#13* | TP-LinkPlugHS100 | TP-Link WiFi Smart plug HS100 | ● | ○ | ○ | ● | ● |
| | TP-LinkPlugHS110 | TP-Link WiFi Smart plug HS110 | ● | ○ | ○ | ● | ● |
| *type#14* | UbnTAirRouter | Ubnt airRouter HP | ● | ● | ○ | ● | ● |
| *type#15* | WansviewCam | Wansview 720p HD Wireless IP Camera K2 | ● | ○ | ○ | ● | ● |
| *type#16* | WeMoLink | WeMo Link Lighting Bridge model F7C031vf | ● | ○ | ● | ● | ● |
| *type#17* | WeMoInsightSwitch | WeMo Insight Switch model F7C029de | ● | ○ | ○ | ● | ● |
| | WeMoSwitch | WeMo Switch model F7C027de | ● | ○ | ○ | ● | ● |
| *type#18* | HueSwitch | Philips Hue Light Switch PTM 215Z | ○ | ○ | ● | ● | ● |
| *type#19* | AmazonEcho | Amazon Echo | ● | ○ | ○ | ○ | ● |
| *type#20* | AmazonEchoDot | Amazon Echo Dot | ● | ○ | ○ | ○ | ● |
| *type#21* | GoogleHome | Google Home | ● | ○ | ○ | ● | ○ |
| *type#22* | Netatmo | Netatmo weather station with wind gauge | ● | ○ | ● | ● | ○ |
| *type#23* | iKettle2 | Smarter iKettle 2.0 water kettle SMK20-EU | ● | ○ | ○ | ● | ● |
| | SmarterCoffee | Smarter SmarterCoffee coffee machine SMC10-EU | ● | ○ | ○ | ● | ● |

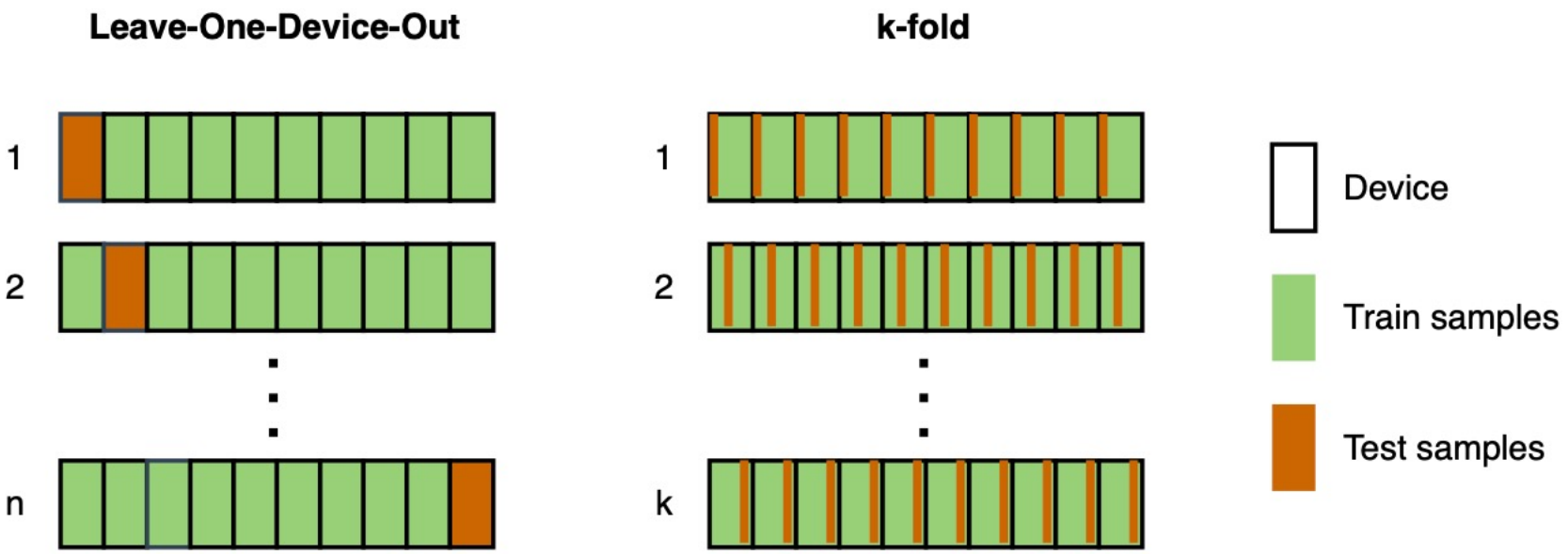
# Quiz: attack!

Devices can spoof their fingerprint. How do the authors counter this?

A. The gateway will detect this thanks to the ReliefF feature selection
B. They propose to add active scanning as future work
C. Add the device's MAC address as a feature
D. They assume that the device is not infected during the first 30 minutes

# Discussion (1)

- Unseen data vs unseen devices (lower accuracy):

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# Discussion (2)

- Announcing self (MUD) vs passive identification?
- Privacy implications?
- Sharing policies with central cloud service
- Fingerprinting attack traffic?

# Information Exposure From Consumer IoT Devices

## A Multidimensional, Network-Informed Measurement Approach

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# Motivation

IoT devices are the new normal (+7.000.000.000 devices around us)

- But don't just take my word for it, take Bosch's
    - https://www.youtube.com/watch?v=v2kV6pgJxuo

But time and time again we have seen that:

- IoT cameras might record you in unexpected scenarios
- IoT assistants might activate/record unexpectedly
- IoT TVs show you ads in your launcher/menu
    - https://www.thedrum.com/news/2019/09/10/the-first-thing-you-see-lg-smart-tv-now-ad

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# Expectations

- My IoT device only connects to the server of the manufacturer
- My IoT device only transmits its data in an encrypted fashion
- My IoT device only transmits relevant data to the manufacturer
- My IoT device only does its IoT task when I ask it to do so
- My IoT device purchased in my region, won't connect to any other jurisdiction

- Quick question: Do you have any additional expectations?

# Data Collection Methodology

- Well to see if our expectations hold true, lets put them to the test
- 81 different IoT devices in two different jurisdictions: UK and US
- All traffic is captured at a central server before egressing into the Internet

- But how do we test? As we've seen before, there is no standard IoT testbed.
- How do we test smart assistants?


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# Data Collection Methodology

34,586 experiments (92.6% automated)

- **Controlled interactions**
  - Manual (repeated 3 times)
  - Automated (repeated 30 times)
    - Text-to-speech to smart assistants (Alexa/Google/Cortana/Bixby)
    - Monkey instrumented control from Android companion apps

| Activity | Description |
|---|---|
| Power | power on/off the device |
| Voice | voice commands for speakers |
| Video | record/watch video |
| On/Off | turn on/off bulbs/plugs |
| Motion | move in front of device |
| Others | change volume, browse menu |

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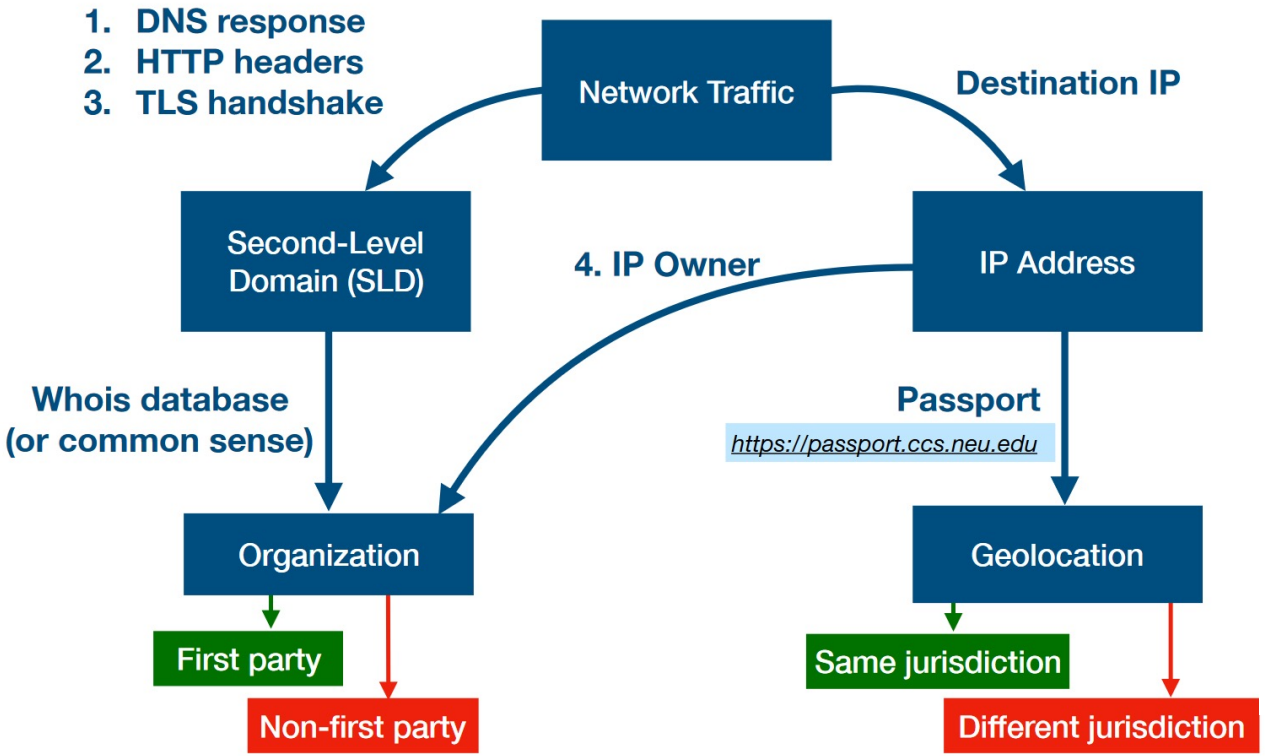
# Destination Analysis




- Number of devices contacting non-first party organizations

High reliance on cloud and CDN providers

Nearly all TVs contact Netflix w/o it being logged in or used

Chinese cloud providers

| Organization | US 46 | UK 35 | US Common 24 | UK Common 24 |
|---|---|---|---|---|
| Amazon | 31 | 24 | 16 | 17 |
| Google | 14 | 9 | 10 | 8 |
| Akamai | 10 | 6 | 6 | 5 |
| Microsoft | 6 | 4 | 1 | 1 |
| Netflix | 4 | 2 | 3 | 2 |
| Kingsoft | 3 | 3 | 1 | 1 |
| 21Vianet | 3 | 3 | 1 | 1 |
| Alibaba | 3 | 4 | 2 | 2 |
| Beijing Huaxiay | 3 | 3 | 1 | 1 |
| AT&T | 2 | 0 | 1 | 1 |

Regional differences

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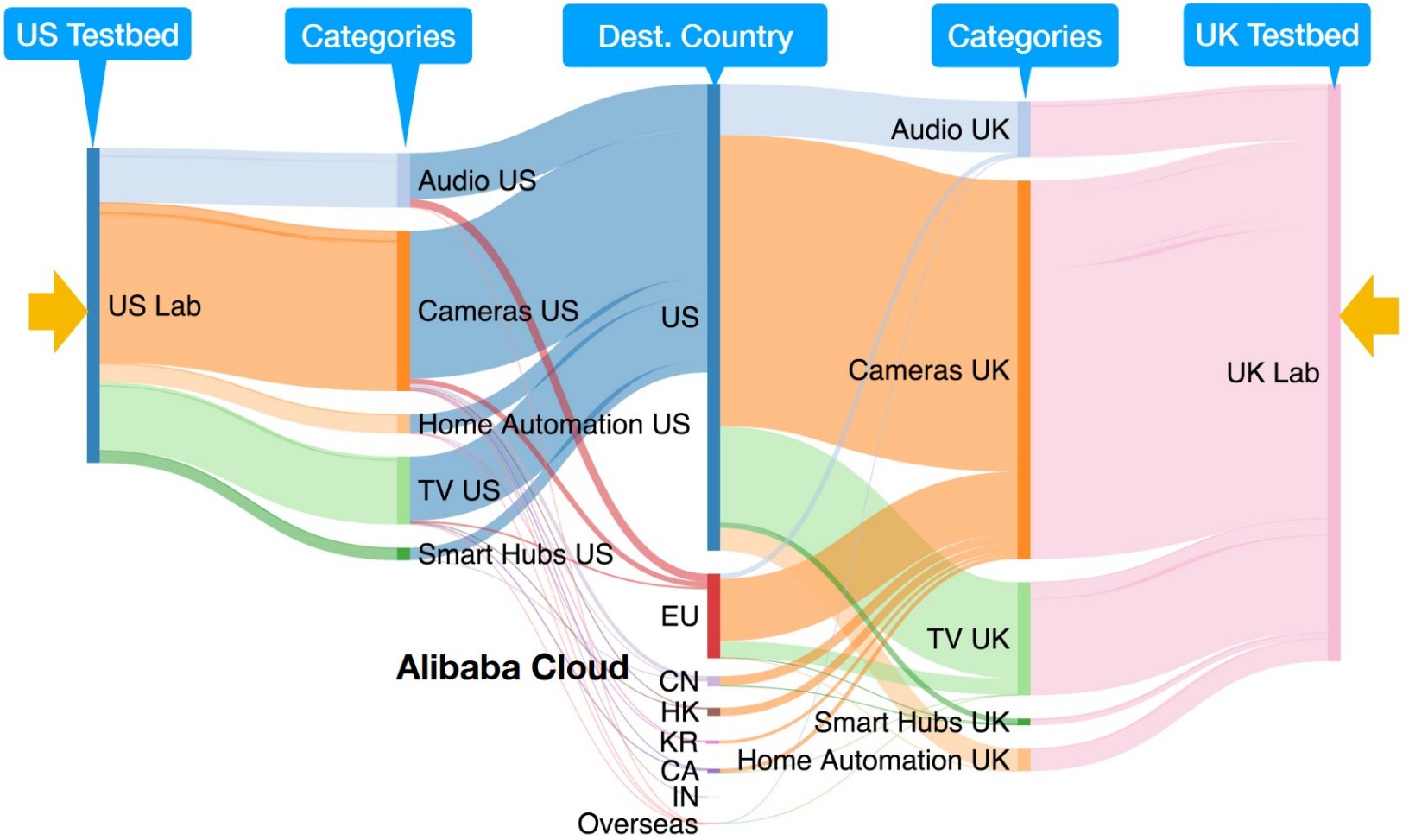
# Destination Analysis

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# Encryption Analysis

- Remove everything which is not detected by Wireshark as TLS or QUIC
- Get a baseline entropy for HTTP (0.25) and HTTPS (TLS) (0.85) traffic
- But depending on the content (IMC 2019 websites) you might get different results:
    - HTTP (0.55, max = 0.62) / fernet (0.73, min = 0
- Suddenly the picture isn't so clear anymore?
- Open discussion: What do you think the unidentified traffic might be?
- Open discussion: Shouldn't MITM analysis be deployed as well?

| Enc | Range | US | UK | US∩ | UK∩ | VPN US→UK | VPN UK→US | VPN US∩ | VPN UK∩ |
|---|---|---|---|---|---|---|---|---|---|
| ✗ | >75 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 50-75 | 1 | 1 | 0 | 0 | 2 | 0 | 1 | 0 |
| | 25-50 | 4 | 1 | 1 | 1 | 3 | 2 | 0 | 1 |
| | <25 | 41 | 31 | 24 | 24 | 41 | 31 | 24 | 24 |
| ✓ | >75 | 7 | 7 | 5 | 5 | 4 | 5 | 3 | 3 |
| | 50-75 | 5 | 7 | 4 | 6 | 7 | 8 | 5 | 7 |
| | 25-50 | 10 | 5 | 5 | 4 | 12 | 5 | 7 | 5 |
| | <25 | 24 | 14 | 11 | 10 | 23 | 15 | 10 | 10 |
| ? | >75 | 16 | 10 | 8 | 7 | 17 | 11 | 8 | 7 |
| | 50-75 | 11 | 6 | 5 | 5 | 11 | 5 | 5 | 4 |
| | 25-50 | 11 | 7 | 6 | 5 | 13 | 10 | 8 | 9 |
| | <25 | 8 | 10 | 6 | 8 | 5 | 7 | 4 | 5 |

**Table 5: Number of devices by encryption percentage in quartile groups across lab and network.**

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# Unexpected Behavior


**Popular doorbells**

Video recording on detected motion (cannot be disabled)


**Popular smart TVs**

Contact **Netflix**, **Google**, and **Facebook** unexpectedly


**Alexa-enabled devices**

Frequently falsely triggered (e.g. "I like Star Trek")

- Other notable cases of activities detected when idle
  - Cameras reporting **motion** in absence of movement
  - Devices spontaneously **restarting** or reconnecting

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# Conclusion

- **First step towards more large-scale IoT measurements:**
  - 81 devices, 2 countries, 34K experiments
- **Main results:**
  - 57% (50%) of destinations of the US (UK) devices are not first-party
  - 56% (84%) of the US (UK) devices have at least one destination abroad
  - 89% (86%) of the US (UK) devices are vulnerable to at least one activity inference
  - Activity inference can be used to identify *unexpected* activities
- **Impact:**
  - Press coverage FT FINANCIAL TIMES BBC WORLD NEWS CR Consumer Reports
  - Working with manufacturers to understand information exposure LG zmodo amazon
  - **Testbed/analysis framework and data are publicly available**

    https://moniotrlab.ccis.neu.edu/imc19/

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# Discussion (if time permits)

- We heard one opinion at the beginning, maybe some more?
- How would you improve this study?
- Can we say anything about the long-term feasibility of projects like these?

# Today's objective revisited

- After the lecture, you will be able to discuss why passive measurements on IoT devices are an important means to understand the problem of IoT Security.

- AuDI shows how to do device type classification through fingerprints based on an IoT device's network traffic.

- IMC shows a novel way to setup a completely automated testing facility and what kind of analyses are possible with such a lab.

- Contributes to SSI learning goal #1: "Understand IoT concepts and applications, security threats, technical solutions, and a few relevant standardization efforts in the IETF"

# Lecture feedback

1. To what extent do you think you'll be able to discuss the design, usefulness and pros/cons of AuDI? (A = 🟢, B = 🟠, C = 🔴)

2. To what extent do you think you'll be able to discuss the design, usefulness and pros/cons of IMC (A = 🟢, B = 🟠, C = 🔴)

*Volg ons*

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# Discussion & feedback

Next lecture: **Wed June 9, 11:00-12:00**
Topic: IoT Security in Non-Carpeted Areas

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