## Who Let the Smart Toaster Hack the House?

Exploring Security and Privacy Risks in Connected Devices

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What if we are exchanging privacy for gimmicks and minor convenience? What is IoT exposing when it comes to privacy in a <u>Smart Home</u>?

What might this mean for the future?

### Why were we interested in this?

information

They may listen to you (e.g., smart speakers)



Amazo A sec.

assistant res to spving

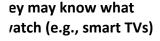
Technology

You Te

A global teal

• Lack of understanding on what information they expose, on when they expose it, and to whom

They can (by definition) access the Internet





rt TV Snooping Features



Lack of understanding of regional differences (e.g., GDPR)

and therefore may expose private

technology called ACR. Here's how to turn it off.

## **Course Overview**

- Benchmarking privacy in IoT devices
- IoT devices identification
- Benchmarking security in IoT devices
- Benchmarking security solutions for IoT devices
- Privacy solutions for IoT devices at the edge
- Security solutions for IoT devices at the edge
- IoT devices certification scheme



#### The Problem

- 21.5 billion IoT devices in the world
- They have access to user private information
- They are a threat for user privacy and security



What is IoT exposing when it comes to privacy in a <u>Smart Home?</u>

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#### **Goal of Research**

What is the destination of IoT network traffic?

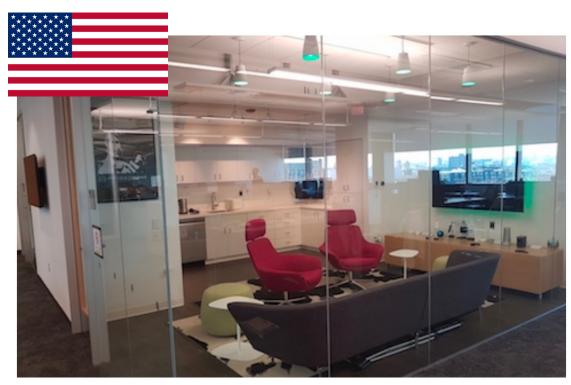
What information is sent?

Does a device expose information unexpectedly?

Google, Amazon, and Apple have decided to collaborate on a universal smart home ecosystem.



#### 210 devices in two different countries





# **Design of Experiments**

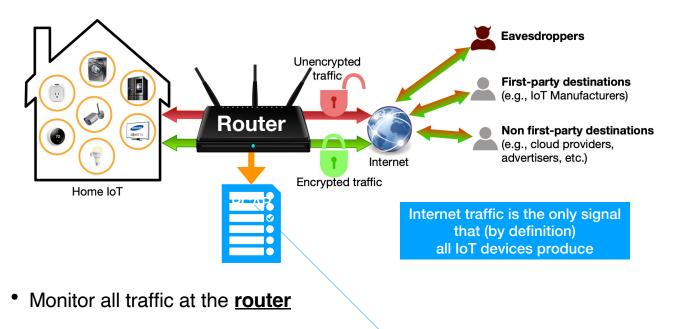
#### >200k Experiments

- Controlled interactions
  - Automated (repeated 30 times)
    - Text-to-speech to smart assistants (Alexa/Google/Cortana/Bixby)
    - Monkey instrumented control from Android companion apps
- Idle: background traffic

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	

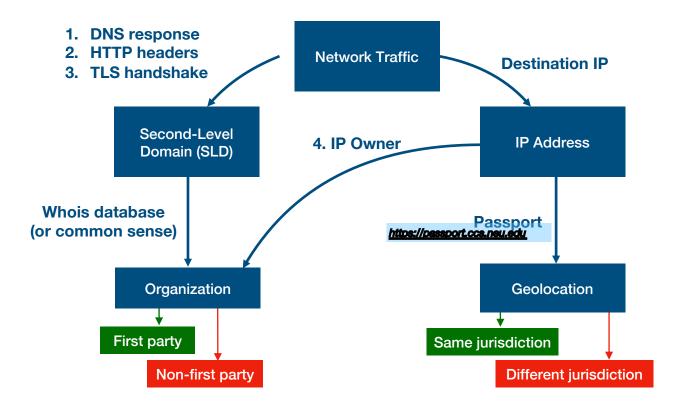


# **Data Collection Methodology**



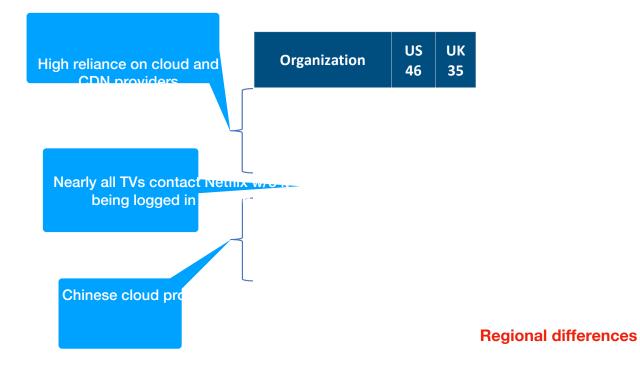
- per-device
- per-experiment

# What Is the Destination?

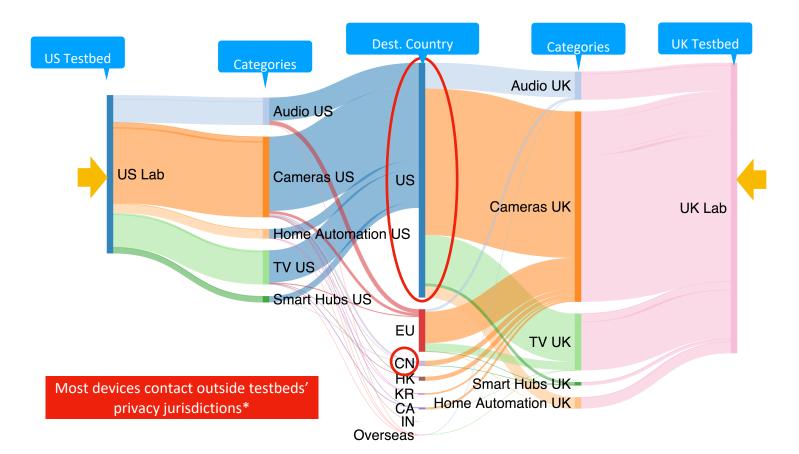


#### What Non-First Parties Are Contacted?

Number of devices contacting non-first party organizations



#### Most traffic goes beyond Europe



#### **Cases of Unexpected Behavior**



/// Other notable cases of activities detected when idle

// Cameras reporting motion in absence of movement

// Devices spontaneously restarting or reconnecting

## WHEN ALEXA FINDS OUT YOU'VE



#### **Are Smart Speakers Listening to Us?**



# What happens when the wake word is misunderstood?



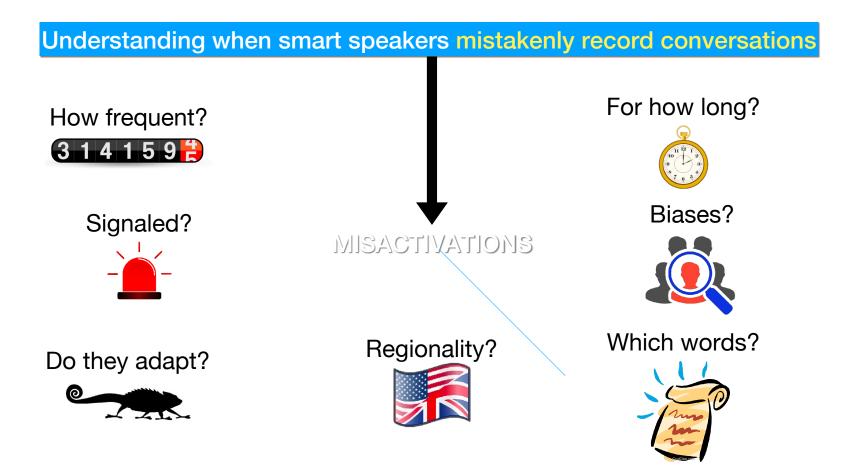
- Smart speakers signal activation (wake word detection) by lighting up
- They send the recording to the voice assistant cloud service
- The cloud service may store the recording and produce an answer



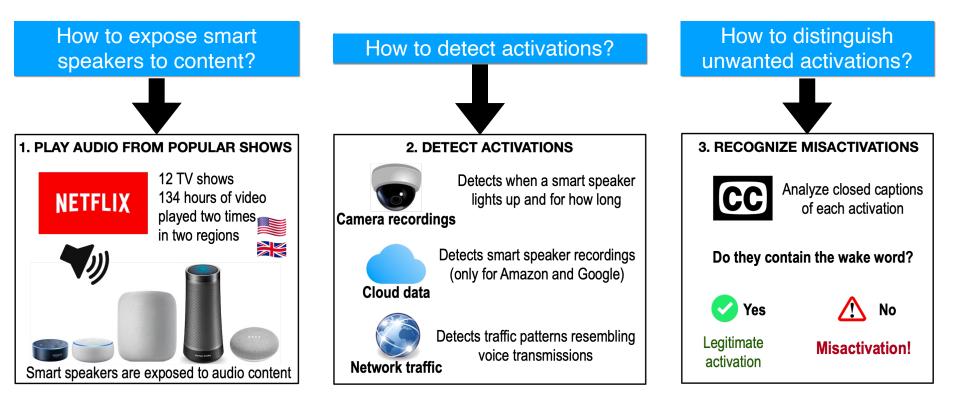


Electronics & Computers / Audio & Video / Smart Speakers / Smart Speakers That Listen When They Shouldn't Shouldn't

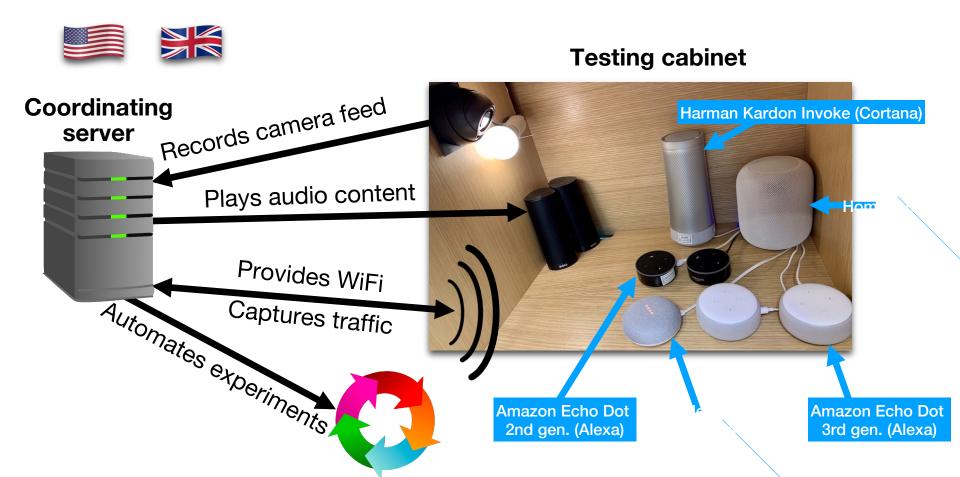
### Goals



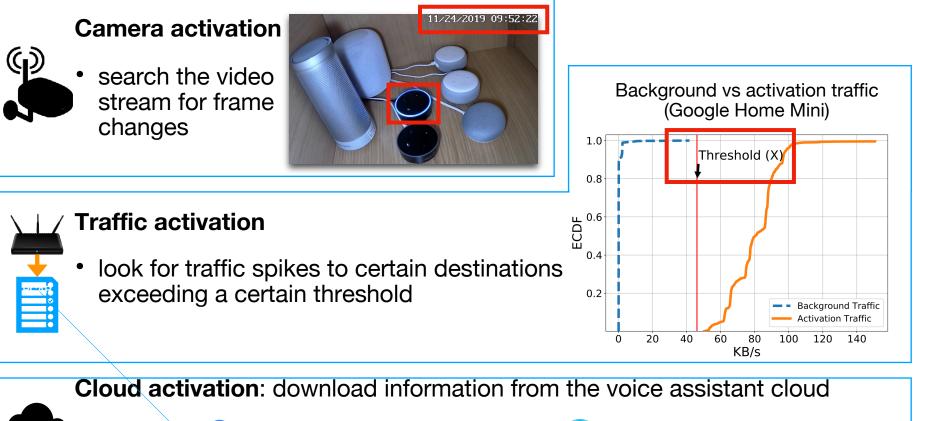
#### **Measurement challenges and solutions**



### **Test environments**



## **Activation detection methods**

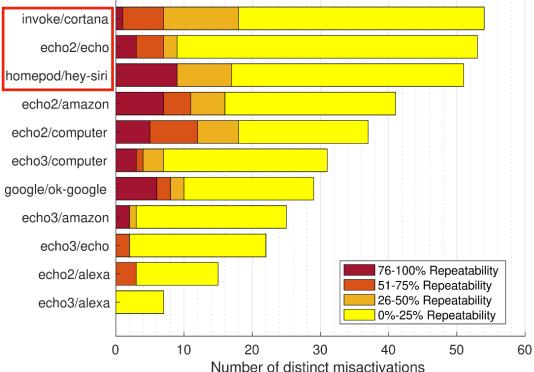


Google Assistant and O amazon alexa

Only for

# How frequently do smart speakers misactivate?

#### Most misactivating devices



#### Repeatability

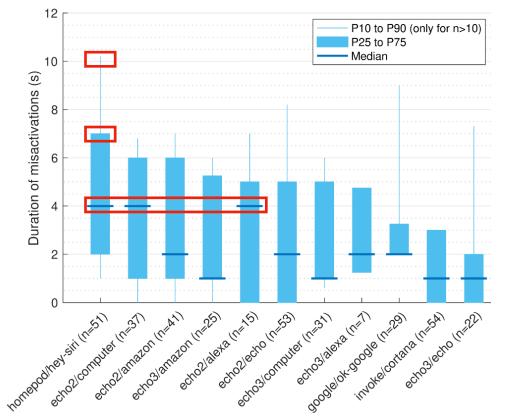
 Consistency of misactivations across experiments

#### Takeaways

- Devices with the most recordings (Invoke, Echo2, Homepod) expose user privacy more often
- Prevalence of low repeatability suggests low determinism

#### How long do smart speakers record?

Misactivation duration: amount of time the smart speaker is lit up after a misactivation



#### Most common case (median)

• up to 4s (Homepod, Echo Dot 2G)

Less common case (top 25%)

• up to 7s (Homepod)

Rare case (top 10%)

• up to 10s (Homepod)

Enough to grasp a conversation?

#### What words cause most misactivations?

Words	Some patterns	Some examples from the closed captions of highly repeatable misactivations
OK/Hey Google	Words rhyming with "hey"/"hi" followed by "ol"/"g"/"w"	"Okay, where were we?", "hey you told", "A-P girl"
Hey Siri	Words rhyming with "hey" or "hi" followed by voiceless "s", "f", "th" sound and "i"/"ee" vowel	"yeah. I was thinking", "Hi. Mrs. Kim", "they secretly"
Alexa		"I care about", "I messed up", "I got something"
Echo		"head coach", "I got", "that cool", "pickle"
Computer	Words starting with "comp" or that rhyme with "here"	"Comparisons", "come here", "nuclear accident"
Amazon		"it was a", "life goes on", "want some water?", "I was in"
Cortana	"k" sound closely followed by "r" or "t"	"lecture on", "quarter", "courtesy", "according to"

- Most are wake word variations, no evidence of secret wake words
- Potential for some patterns to be used by an attacker to forge commands



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Providers need to "identify" and "locate" loT devices in the network



#### Detecting IoT Devices at the Provider is Challenging

Traffic patterns across IoT devices are diverse

Deploying an agent inside at each ISP customers is not scalable

Active measurements do not work with devices behind NATs

Deep packet inspection raises privacy concerns

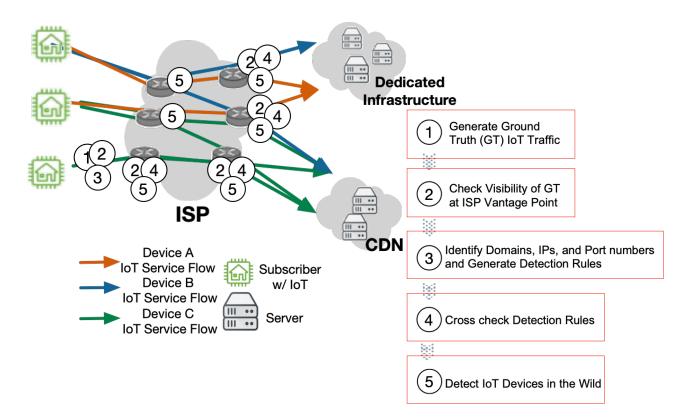
Our contribution: a methodology for *detecting* and monitoring IoT devices with *limited, passive,* and *sparsely sampled* flow data in the *wild.*(Detection rules available at <u>https://moniotrlab.ccis.neu.edu/imc20/</u>)

### **Key Insights**

• Devices have repeating patterns of communication that appear even in sparsely sampled data

- Detection rules can be generated using limited packet fields
- Detected devices from 77% of studied IoT manufacturers in an ISP and IXP within minutes to hours

#### Methodology



#### **Generate Ground Truth IoT traffic**



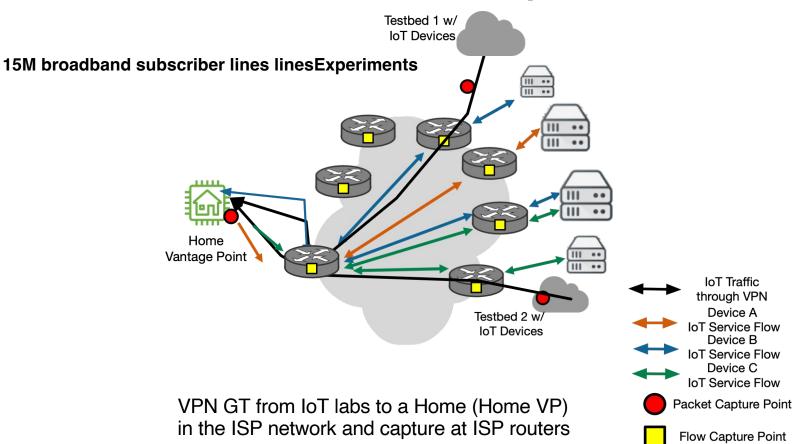


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- Idle Experiments
- Active Experiments

56 different IoT products

#### **ISP Setup**



#### **Generating Detection Rules**

Detection Levels:

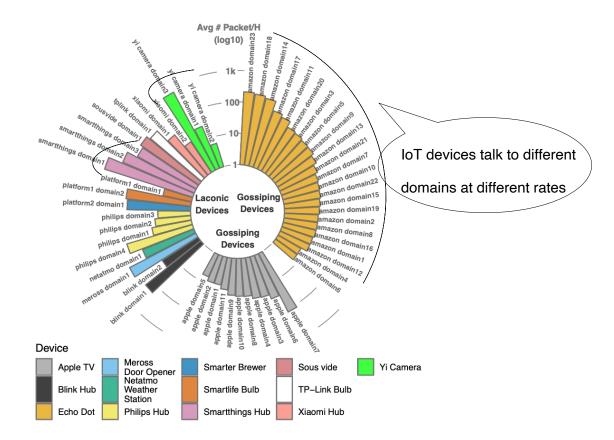
Product-level: Amazon Echo

Manufacturer-level: A Samsung Device

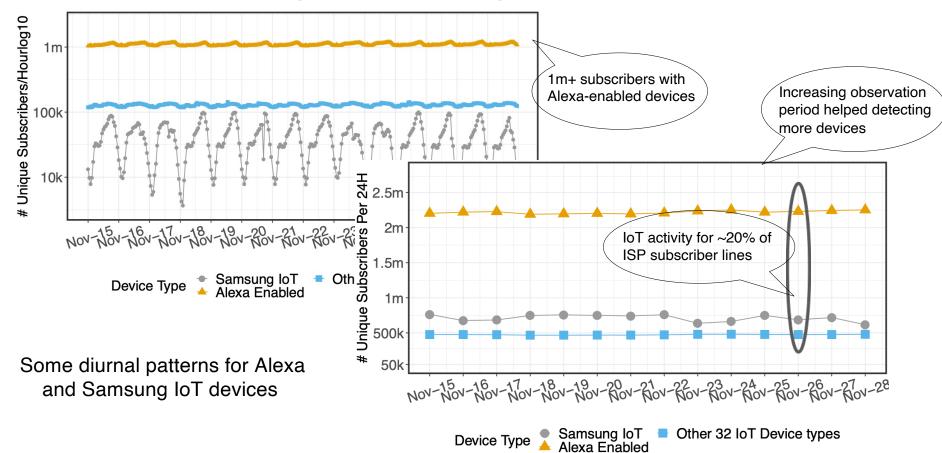
Platform-level: an IoT device

Detection Rules: 5 IoT Platforms 20 Manufacturers 11 Products 77% of the manufacturers in the testbeds

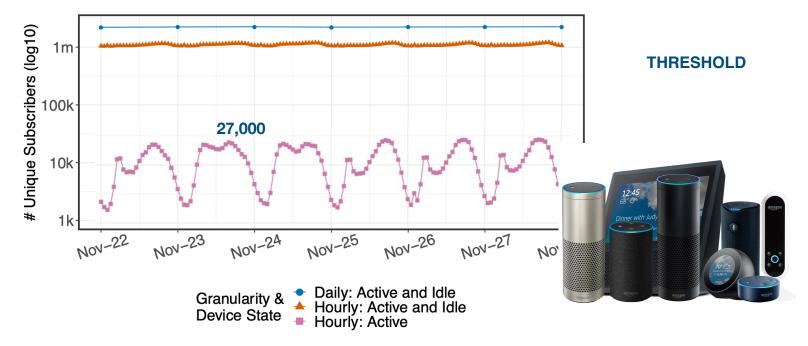
#### **Cross Check Detection Rules**



## Number of ISP Subscribers with IoT Devices (Per hour/24h)



## Detecting IoT Devices Activity in the Wild



For some devices we can infer activity

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## Contributions

- We develop an automated methodology for evaluating security vulnerabilities in common consumer IoT devices using large-scale, diverse experiments and sets of attacks
- We assess the security vulnerabilities of popular IoT devices against existing network and device attacks and identify privacy risks

## Assumptions

- Threat modelling
  - Adversary: Any party that can access the IoT device's network
  - Victim: The victim is anyone who enters the service area of the IoT device
  - *Threat*: We assume the presence of malicious or compromised IoT devices in a smart home. Adversaries may be incentivised to compromise other devices in the network to infer user activities or deny their usage of them.
- Goals
  - Are consumer IoT devices vulnerable to common security attacks?
  - Do IoT devices detect threats?
- Non-goals
  - We have no control over how an IoT device works internally.
  - We do not test all threats.
  - We only focus on consumer IoT devices.

## Testbed

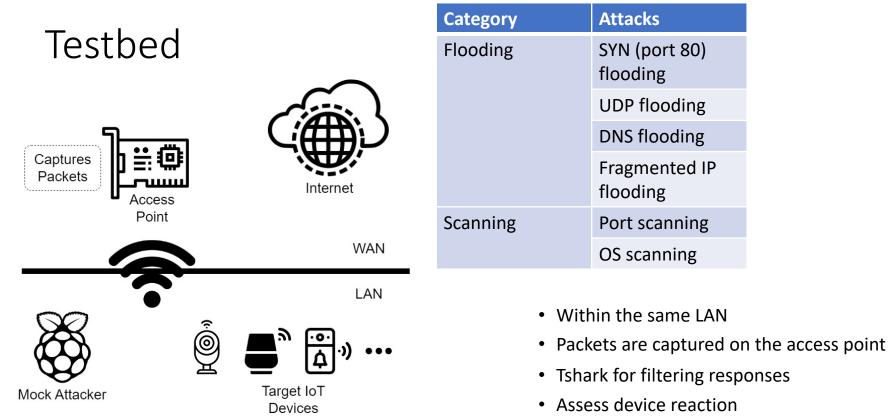






## Testbed

Category	Device		
Smart speaker	Bose Smart Speaker 500		
	Sonos One (Gen2)		
	Echo Dot 5		
Smart doorbell	Ring Chime Pro		
	Ring Video Doorbell (2 <sup>nd</sup> Gen)		
Smart camera	Google Nest Cam		
	SimpliSafe Security Camera Indoor		
	Furbo 360° Dog Camera		
Appliances	WeeKett Smart Wi-Fi Kettle		
	Govee Alexa LED Strip Lights		
	Sensibo Sky Smart AC		



- Counter-measures detected attack
   *unsuccessful*
- No counter-measures detected attack successful

## Software

- We write and use configurable and automated scripts for simulating attacks and analysing the replies
- We setup tcpdump to continuously capture network traffic on the network access point
- Dedicated network traffic capturing for active experiments
- Devices are activated with their companion applications remotely and automatically using ADB
- We verify the attacks using two RPis

## Software – testing usecase

- Activate the device with ADB
- Start running a simulated attack on the device's IP address
- Wait until the attack stops
- Download the captured traffic
- Analyse the traffic using tshark

## Results - flooding

Devices	SYN	UDP	DNS	Frag. IP
Bose Speaker	$\checkmark$	X	X	$\checkmark$
Sonos One (Gen2)	X	Х	X	$\checkmark$
Echo Dot 5	X	X	X	$\checkmark$
Ring Chime Pro	X	X	X	$\checkmark$
Ring Doorbell	X	X	$\checkmark$	$\checkmark$
Google Nest Cam	X	X	X	$\checkmark$
SimpliSafe Cam	Х	X	X	$\checkmark$
Furbo Camera	X	X	X	$\checkmark$
WeeKett Kettle	X	$\checkmark$	$\checkmark$	$\checkmark$
Govee Lights	X	X	$\checkmark$	X
Sensibo Sky	X	$\checkmark$	$\checkmark$	$\checkmark$

• Most of the devices are vulnerable to Frag. IP flooding, as opposed to SYN flooding, which is only successful on the Bose Speaker.

## Results – port scanning

• Open ports can be detected on 7 devices out of 11.

Devices	Identified Open Ports			
Bose Speaker	80/7000/8082/8083/8085/8091/8200/30030/40002/40031/40035			
Sonos One (Gen2)	1400/1410/1443/1843/7000			
Echo Dot 5	1080/4070/8888/55442/55443			
Ring Chime Pro	847/1003/1020/1393/3736/7240/8173/12302/15986/16891/17704/17944/17993/ 18682/20307/21257/23825/24669/25781/25958/25997/26757/27234/28363/29161/ 32466/33377/33544/33616/33862/35470/38657/44100/46108/46194/47199/50852/ 51212/52663/54739/55524/55530/56621/65488			
Ring Doorbell	Blocking ping probes & none found			
Google Nest Cam	8012/10101/11095			
SimpliSafe Cam	19531			
Furbo Camera	None found			
WeeKett Kettle	6668			
Govee Lights	None found			
Sensibo Sky	None found			

## Results – OS scanning

Devices	Operating System		
Bose Speaker	Linux 3.2 - 4.9		
Sonos One (Gen2)	Linux 3.2 - 4.9		
Echo Dot 5	No exact match, can be Linux		
Ring Chime Pro	Too many fingerprints match		
Ring Doorbell	2N Helios IP VoIP doorbell (95%)		
Google Nest Cam	Too many fingerprints match		
SimpliSafe Cam	Too many fingerprints match		
Furbo Camera	Too many fingerprints match		
WeeKett Kettle	No exact OS matches		
Govee Lights	Espressif esp8266 firmware (IwIP stack), NodeMCU firmware (IwIP stack)		
Sensibo Sky	Philips Hue Bridge (IwIP 1.4.1), Philips Hue Bridge (IwIP stack)		

• OS can be identified on 5 devices out of 11.

## Discussion

- Potentially consequential user implications can be identified (e.g. a successful DoS attack on the LED light)
- Open ports and identified OS could be exploited for obtaining private info (e.g. camera feed)
- Limitations
  - We consider devices as black-boxes
  - We only tested 11 devices
- Ethical considerations
  - We follow the ethical guidelines of our affiliated organisation
  - We conduct our experiments locally

## Install IoT security camera

camera has security flaw

strangers can watch the video feed

strangers can watch the video feed

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Benchmarking security in IoT devices

#### Benchmarking security solutions for IoT devices

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- Security solutions for IoT devices at the edge

□IoT devices certification scheme



## The Problem

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#### Problem: IoT Devices Expose Information Over the Internet



#### IOT PROTECTION SYSTEMS: SAFEGUARDS



## Why Were We Interested in This?



Control

Device detection

Intelligent profiles



Security

Vulnerability Assessment

**Brute Force Protection** 

Anomaly Detection



Privacy

Content filtering

Network Intrusion Prevention

These safeguards may currently be ineffective in preventing risks.
Their cloud interactions and data collection operations may introduce privacy risks.

#### **Research Questions**

- □ Goal 1: What are the privacy and security implications on how a safeguard works?
- Goal 2: Do the safeguards detect threats?
- Goal 3: What are the side effects of the safeguards?



### IoT Safeguards

### **Challenges for Measuring IoT Safeguards**

Difficult to automate the testing of commercial IoT safeguards

- Closed systems
- Blackbox approach

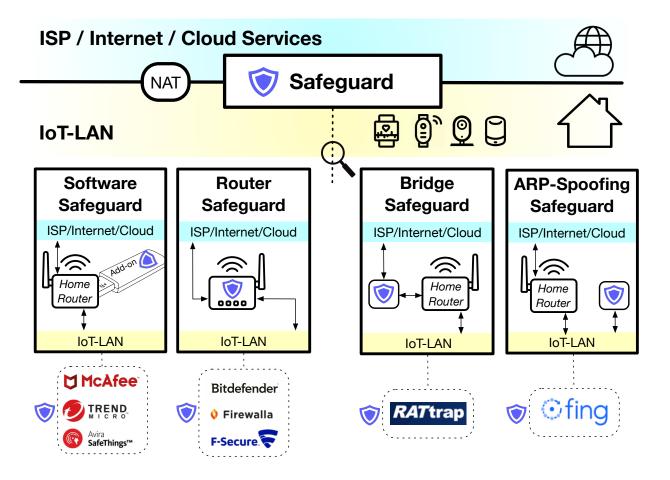
Difficult to perform <u>IoT</u> experiments and generalize

- Lack of automation and emulation tools
- Lack of standard testbed

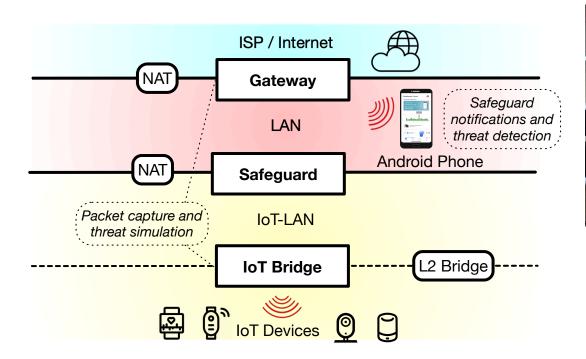
<u>Our contribution</u>: a large IoT testbed used to test IoT safeguards in real-world scenarios (software and data available online).



#### Selecting IoT Safeguards



#### Testbed







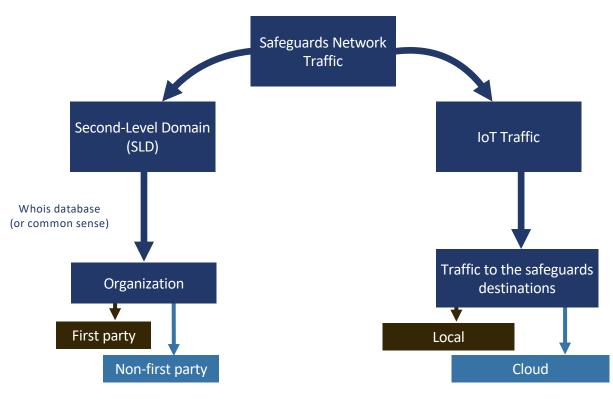
#### **Research Questions**

- □ Goal 1: What are the privacy and security implications on how a safeguard works?
  - Identify locality: cloud vs local operation
  - **Operation**: usage third-party services to operate



### IoT Safeguards

#### Processing Locality & Party Characterization



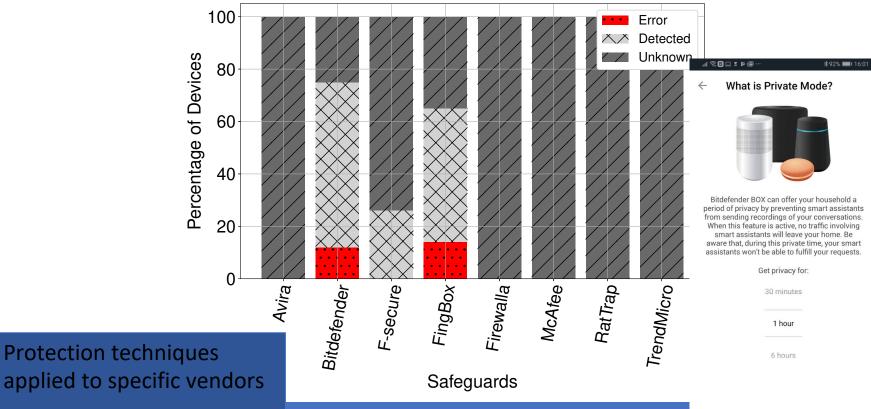
#### Processing Locality & Party Analysis

Safeguard	Destinations #	Cloud	# and list of Support/3rd Parties
Avira	10	Yes	(1) api.mixpanel.com
Bitdefender	5	Yes	-
F-secure	1	Yes	-
FingBox	5	Yes	(2) api.snapcraft.io, mlab-ns.appspot.com
Firewalla	4	No	(1) api.github.com
McAfee	22	Yes	(3) app-measurement.com, commscope.com, avast.com
RatTrap	1	Yes	-
TrendMicro	3	Yes	(1) policy.ccs.mcafee.com

<u>Take away</u>: - Usage of the cloud for performing analysis, potentially leaving the user vulnerable in the event of a data breach.

- Destinations contacted that are not first parties.

#### IoT Device Identification



percentage of IoT devices is correctly identified.

#### **Research Questions**

# Goal 2: Do the safeguards detect threats?

 Safeguards notify the user when detecting privacy or security threats



## IoT Safeguards

#### Testing Threat Detection Capability

#### Security

# Threats

Anomalous behavior Open Port

Weak Password

Device Quarantine

DoS attacks

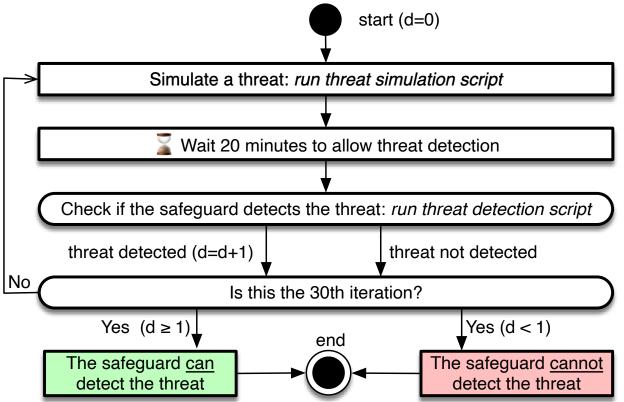
Port/OS Scanning MaliciousDestinations

#### • Privacy

#### Threats

PII Exposure Unencrypted Traffic DNS over HTTPS

#### Threat Detection Experiments



## Evaluation of Threat Detection Capability

	Threat	Avira	Bitdefender	F-Secure	Fingbox	Firewalla	McAfee	RaTtrap	TrendMicro
	Anomaly ON/OFF	-	Х	Х	-	Х	Х	Х	-
Security	Anomaly Traffic Pattern	-	X	X	Tim	e cons	sister	ncv	
	Abnormal Upload	-	X	X			JJJCI	icy	レン
	Open Port	Х	√(30s)	-	Х	√(30s)	Х	-	X
	Weak Password	Х	X	-	-	-	Х	-	X
	Device Quarantine	-	$\checkmark$	-	$\checkmark$	$\checkmark$	-	Х	-
	SYN Flooding	Х	√(30s)	Х	-	√(40s)	X	X	Х
	UDP Flooding	Х	X	X	-	X	Х	Х	X
	DNS Flooding	Х	X	X	-	X	Х	Х	Х
	HTTP Flooding	Х	√(3m)	X	-	√(2m)	Х	Х	Х
	IP Fragmented Flood	X	×	Х	-	Х	X	Х	X
	Port Scanning	√(45s)	X	Х	-	Х	-	Х	√(30s)
	OS Scanning	√(45s)	×	Х	-	Х	-	X	Х
	Malicious Destinations	$\checkmark$	$\checkmark$	Х	-	$\checkmark$	Х	Х	$\checkmark$
	PII Exposure	Х	X	-	-	X	-	-	-
Privacy	Unencrypted Traffic	Х	Х	-	-	X	-	-	-
	DNS over HTTPS	Х	$\checkmark$	-	-	$\checkmark$	-	-	-

<u>Take away</u>: - only 3 out of 14 threats are detected by the safeguards. 3 out of 8 safeguards do not detect any threats at all, despite they claiming to do so in their specifications - Some of safeguards take between 45 seconds and 3 minutes to detect a security threat.

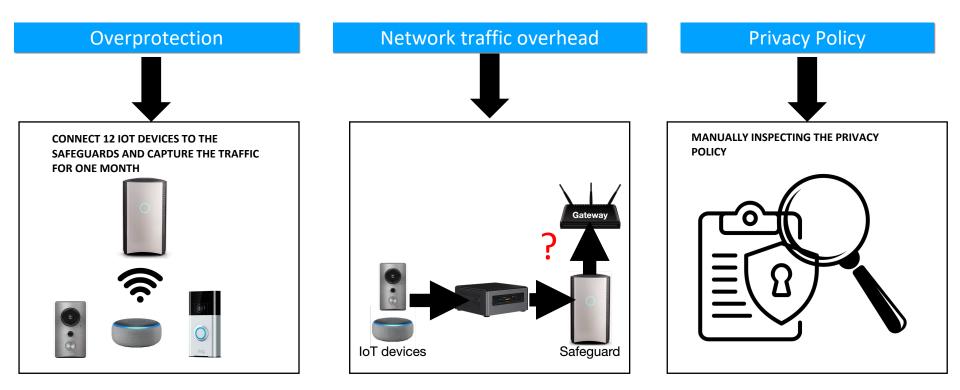
#### **Research Questions**

- Goal 3: What are the side effects of the safeguards?
  - Traffic overhead, overprotection, privacy implications



IoT Safeguards

#### Safeguard Side Effects



#### Overprotection

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<	

#### BOX has blocked a malware attempt via URL.

V The device is safe

#### 10 May 2022, 19:26

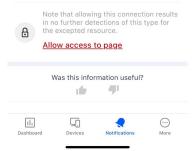
#### Description

Dangerous pages attempt to install software that can harm the device, gather personal information or operate without your consent.

Device name

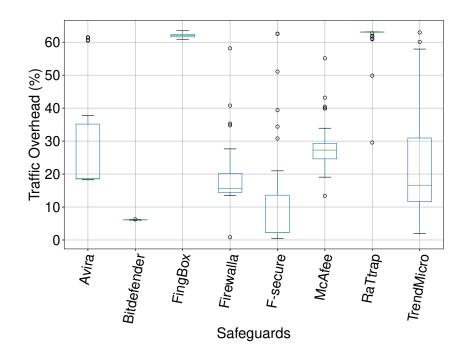
Century Xinyang computer

Blocked URL http://0735sh.com/



Take away: Most safeguards do not overprotect (i.e., they do not report threats that do not occur).

#### Traffic Overhead



<u>Take away</u>: Some of the safeguards introduce significant traffic overhead. In general the overhead is never less than 10% of the traffic of the IoT devices.

### **Privacy Policy**

Privacy Policy	Avira	Bitdefender	F-Secure	Fingbox	Firewalla	McAfee	RaTtrap	TrendMicro
Anonymization	$\checkmark$	√ [pseudonymize]	X [ceasing subscription]	$\checkmark$	Х	X	X	Х
Usage of Personal Data	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
Retention Period	In accordance with legal requirements	10 years	6 months	As long as necessary	Indefinitely	Subscription period	Subscription period	Ongoing legitimate business need
Third Party	SaaS vendor, Akamai. Mixpanel, Ivanti	Partners	Partners	Partners	X	Partners	Partners	Partners

<u>Take away</u>: Most user information is shared with third-party entities, sometimes without anonymization. Sharing data outside user's privacy jurisdiction.

# 57% (50%) of destinations of the US (UK) devices are not first-party

## Why is this a problem?







#### **User emotion**



## TODAY JECURITY ENGINEER JITUATION



### DEAR HACKERJ PLJ DON'T DO ANYTHING TODAY!



# What might this mean for the future?







Control



MUD profile



Certificate

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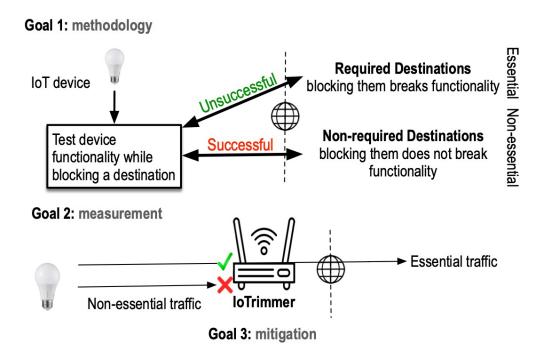
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# THE INDERNET OF THINGS

# WHAT COULD POSSIBLY GO WRONG?

memegenerator.net

### Solution at the Edge



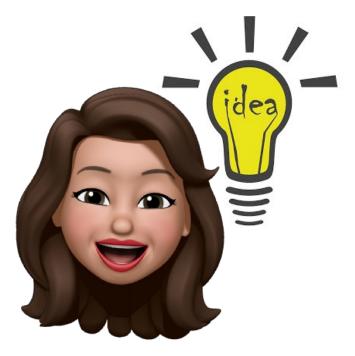
/ Generalizable

/ Self adaptive

/ Accurate IoT blocker

### Idea

- What we learn: some IoT traffic is essential and some of it is non-essential
- Can we (partially) "silence" IoT devices and still be able to enjoy them?



## Goals

- Measurement Methodology: How to automatically separate essential traffic from non-essential traffic?
- Identification: How prevalent is non-essential traffic in our testbed of 31 IoT devices?
- *Generalizations*: Are there any **common patterns** in non-essential traffic?
- Mitigation:

How to build a system for filtering non-essential traffic?

# Challenges

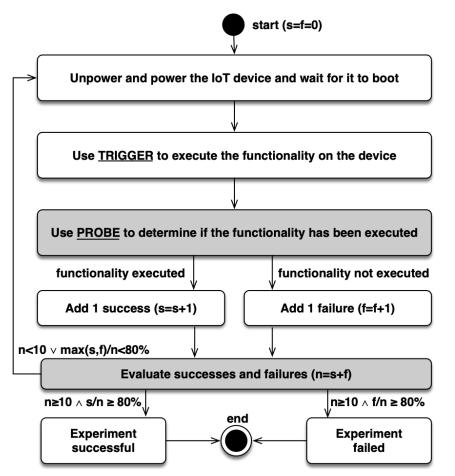
- IoT devices are hard to test automatically
  - They offer very different functionalities
  - They suffer (in our experience) from frequent service outages that must be detected
  - They typically require user interaction (i.e., they are not directly programmable)
  - Hard to verify if a functionality was actually executed or not
- Ideas:
  - use companion devices (phones and voice assistants)
  - use **network traffic patterns** to classify IoT devices responses

# **Measurement Methodology**

### Hardware and Software of our IoT testbed

- IoT devices
  - 31 in total: 6 cameras, 15 home automation, 5 smart hubs, 3 smart speakers, 2 video
- **Router** with IP filtering and DNS filtering capabilities
- **Power plugs** and scripts to power cycle the devices
- **Trigger scripts** to invoke IoT devices functionality
  - Companion app interaction and voice assistant interaction
- **Probe scripts** to detect success or failure in functionality execution
  - Compare companion app *screenshots* and identification of *traffic peaks*

# **Functionality Experiment**



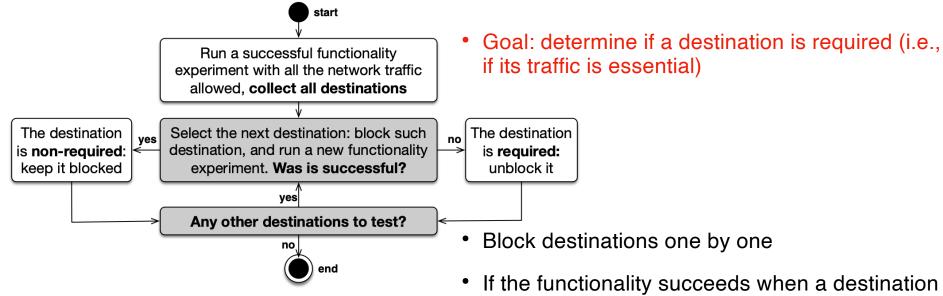
Goal: determine if a functionality works

- Test the functionality at least **10 times**
- Terminate if 80% consensus is reached

- When tested **30 times** against **ground truth**, probes have been **80% correct**
- If probes are 80% correct, the chance of an incorrect functionality experiment result is less than 0.01%

# **Identifying Non-essential Traffic**

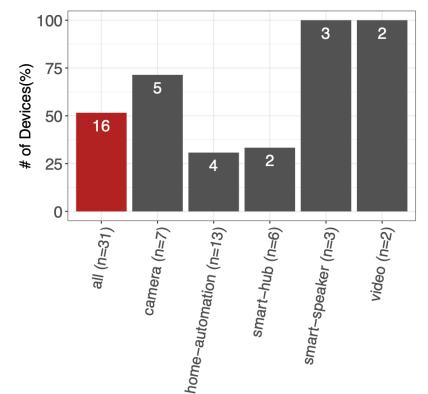
### **Distinguishing Required from Non-Required Destinations**



- is blocked, such destination is **non-required**
- Otherwise it is required

# **Overall Results**

#### Devices with at least one non-required destination



- 16/31 devices have non-essential traffic
- Mostly cameras, smart speakers, and video
- Possible explanations:
  - complexity (skills and apps)
  - uncommon vendors / rebranding (for cameras)

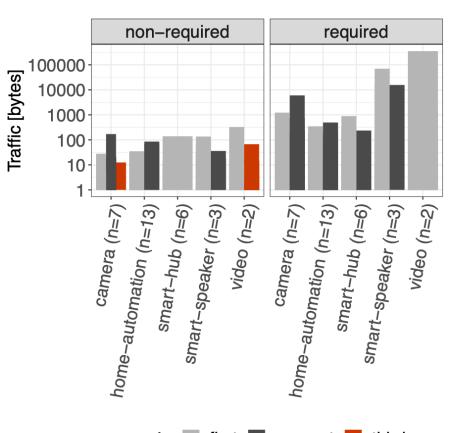
### **Required vs. Non-required Destinations**

Device	# of Destinations	Required	Non-Required
Camera			
Blink-camera	2	2 2	0
Bosiwo-camera	L	2	2
Icsee-doorbell	ť	j 2	4
Reolink-cam	2	2 1	1
Wansview-cam	ç	) 3	6
Yi-camera	5	53	2
Home-automation			
App-kettle	2	2 2	0
Honeywell-thermostat	2	2 2	0
Magichome-strip	1	l 1	0
Meross-dooropener	1	l 1	0
Nest-tstat	3	3 2	1
Netatmo-weather-station	1	1	0
Smarter-coffee-mach	1	l 1	0
Smartlife-bulb	1	1	0
Smartlife-remote	1	1	0
Sousvide	1	l 1	0
Switchbot	1	l 1	0
Tplink-bulb	4	1	3
Tplink-plug	4	1	3
Wemo Plug	2	2 2	0
Xiaomi-ricecooker	7	7 3	4

Device	# of Destinations	Req	uired	Non-Required
Smart-hub				
Insteon-hub		1	1	0
Lightify-hub		3	3	0
Philips-hub		4	2	2
Samsung Hub		3	2	1
Sengled-hub		2	2	0
Smart-Speaker				
Allure-speaker		3	1	2
Echodot		10	3	7
Google-home		9	4	5
Video				
FireTV		14	3	11
Roku TV		10	2	8
Total	i	119	57	62

- Non-required destinations are contacted the most by cameras, speakers, and video devices
- But it also happens on simpler devices such as the TP-Link smart plug and smart bulb

# Amount of Data Sent During One Experiment



- **Good news**: non-essential traffic is relatively small (less than 1KB/device)
- However, it is still possible to transmit:
  - Presence of the device
  - Its status
  - Basic data from the sensors (e.g., open/close, motion/still, alarm/no alarm)

# **Similarities with Existing Blocklists**

- We consider Pi-hole, Firebog, MoAB, StopAD lists
- No required destinations on such lists
- Up to 6 out of 62 non-required destinations present in existing blocklists

 Public blocklists are of limited help in blocking IoT non-essential traffic

Device	Non-req Dest.	Pi-hole	Firebog	MoAB	StopAd
Allure Speaker	2	0	0	0	0
Bosiwo Camera	2	0	0	0	0
Echo Dot	7	1	1	0	0
Fire TV	11	2	3	1	0
Google Home	5	0	0	0	0
Icsee Doorbell	4	0	0	0	0
Nest Thermostat	1	0	0	0	0
Philips Hub	2	0	0	0	0
Reolink Camera	1	0	0	0	0
Roku TV	8	1	2	1	0
Samsung Hub	1	0	0	0	0
TP-Link Bulb	3	0	0	0	0
TP-Link Plug	3	0	0	0	0
Wansview Camera	6	0	0	0	0
Xiaomi Ricecooker	4	0	0	0	0
YI Camera	2	0	0	0	0

Number of non-required destinations present in public blocklists

# **Mitigating Non-essential IoT Traffic**

- A blocking system: **IoTrim** 
  - Filtering router between the IoT devices and the Internet
  - Block/allow lists based on (non-)required destinations → crowdsourced
  - Software to declare device types and manage the lists / blocking rules
  - A proof-of-concept prototype is available for download

# **Course Overview**

- Benchmarking privacy in IoT devices
- IoT devices identification
- Benchmarking security in IoT devices
- Benchmarking security solutions for IoT devices
- Privacy solutions for IoT devices at the edge
- Security solutions for IoT devices at the edge
- IoT devices certification scheme



### The Problem

- 21.5 billion IoT devices in the world
- They have access to user private information
- They are a threat for user privacy and security

#### Motivation

- Inefficiency of existing IoT solutions
- Most of them are cloud-based: might share users' personal/sensitive data

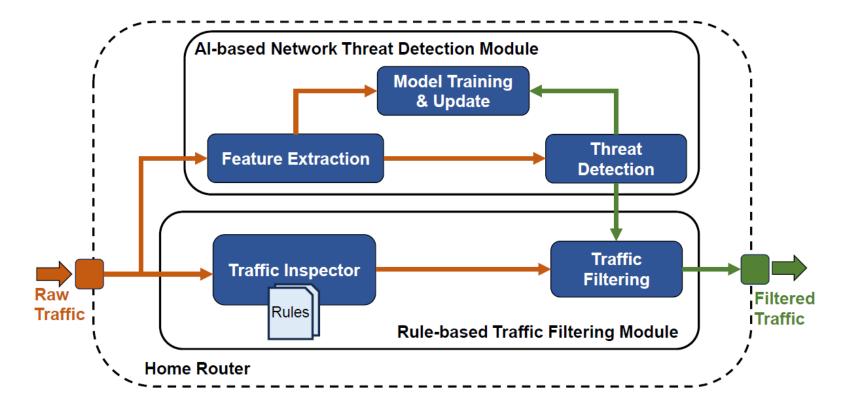
#### Research Questions

- Can we replace cloud-based IoT protection systems by a local IDS/IPS running on a home router?
- If so, what is the performance overhead?

#### Benefits

- Security improvement: cover wider spectrum of IoT threats in a home network
- Privacy improvement: All users' data processed locally and not shared with cloud

#### SunBlock Architecture



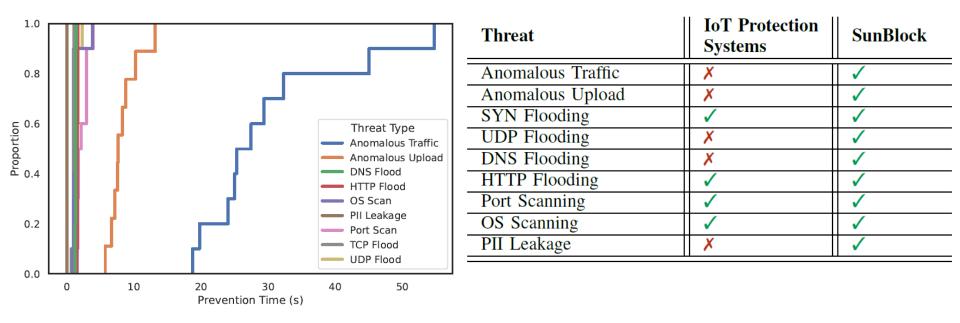
Implementation: home router with IoT protection

- LinkSys WRT3200ACM, OpenWRT Linux-based OS
- ~4GB flash, 512MB swap (for ML training only), 512 MB RAM
- Snort3 for rule-based filtering, netml with OCSVM for AI-based module

Testbed

- 10 most popular IoT device types (according to IoT Inspector paper)
- Smart speakers (Echo spot, Google Home), Video (FireTV), Camera (Yi, Blink), Home automation (Nest thermostat, TP-Link/Wemo plugs, Gosund/TP-Link bulbs)
- Devices were triggered daily using the methodology similar to the S&P paper

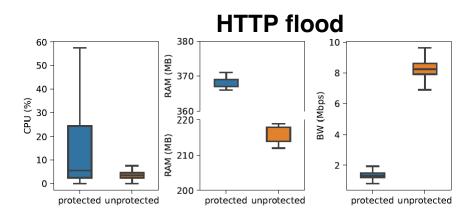
#### Evaluation: threat coverage and prevention time

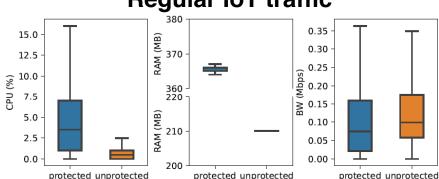


#### Evaluation: performance overhead

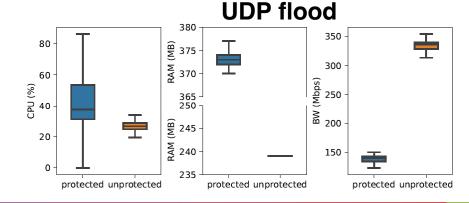
**Model training** 

Protection Level	CPU (%)	RAM (MB)	swap (MB)	Training Time (s)
Rule-based & AI-based	18 ±3	444 ±4	296 ±21	924 ±253
AI-based only	26 ±2	442 ±6	197 ±28	429 ±171
Rule-based only	32 ±4	423 ±9	132 ±20	180 ±22
Unprotected	39 ±2	410 ±3	55 ±1	113 ±10





#### **Regular IoT traffic**



#### Takeaways

• IoT threats can be rapidly detected on a home router with Rule&AI-based filtering algorithms

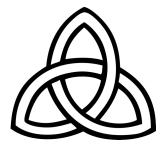
• No need in cloud-based solutions and in sharing your personal data

 Increase in CPU and RAM doesn't affect main router functions leaving plenty of free resources: >50% free CPU and ~30% free RAM

• Further plans: beta testing and precise performance benchmarking against existing IoT solutions

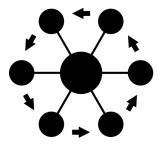


### **Strengthening the IoT Ecosystem**



#### Trust

- Endpoints' practices
- Trusted platform modules
- Domain-specific guidelines and frameworks
- Access networking system & machine learning



#### Interconnectivity

- Understand threats in real world scenario
- New secure IoT (wireless) networking protocols & systems
- Privacy preserving technologies at the edge



Awareness, Authentication & Management

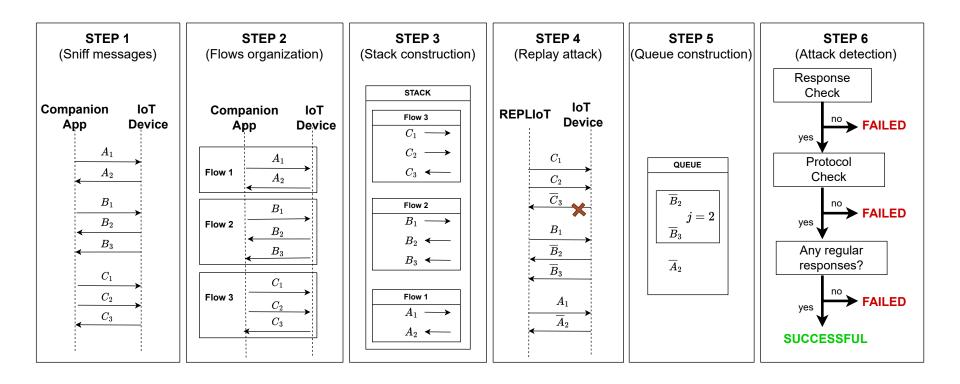
- Usable monitors for IoT
- Context-aware privacy
- Personalised privacy

### Is Your Kettle Smarter Than a Hacker?

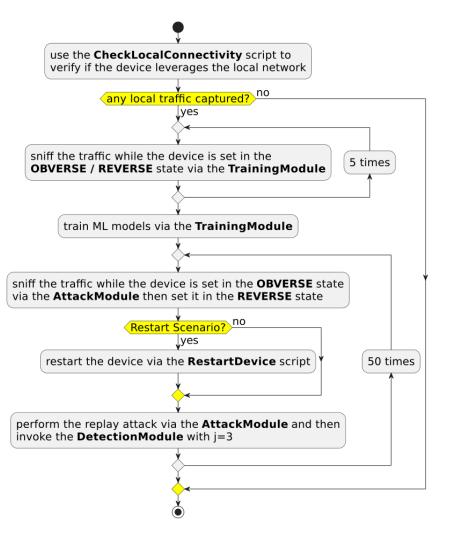
- Assessing Replay Attack Vulnerabilities on Consumer IoT Devices using AI
  - Automated methodology for large-scale testing replay attack vulnerabilities on IoT devices
  - Using AI for detecting the success of the attack



### Methodology



### Methodology



### Results

### REPLAY ATTACK RESULTS. $\checkmark$ INDICATES WHETHER THE REPLAY ATTACK IS SUCCESSFUL OR NOT (X).

Device (*Tested via APIs)	Non-Restart Scenario	Restart Scenario	
Yeeligth lightstrip	Stenario	Stellario	
	V	V	
Yeelight bulb	V	V	
Wiz ligthbulb	✓	✓	
Lifx bulb	$\checkmark$	$\checkmark$	
Lepro bulb	$\checkmark$	$\checkmark$	
Govee lightstrip *	$\checkmark$	$\checkmark$	
Nanoleaf triangle *	$\checkmark$	$\checkmark$	
Tapo smartplug	$\checkmark$	X	
Meross smartplug	✓	<ul> <li>✓</li> </ul>	
WeeKett Kettle	✓	✓	
Eufy robovac 30C	$\checkmark$	<b>V</b>	
OKP vacuum	$\checkmark$	$\checkmark$	
iRobot roomba i7	X	X	
Sonos Speaker *	$\checkmark$	$\checkmark$	
Bose Speaker *	$\checkmark$	<ul> <li>✓</li> </ul>	
Wyze cam pan	X	X	
Vtech baby monitor	X	X	
Boyfun Baby monitor	X	X	
Furbo camera	X	X	
Meross Garage Opener	$\checkmark$	$\checkmark$	

### **Responsible Disclosure**



[TP-Link Support]-[TKID231119229] Responsible disclosure

To: vincenzo.deangelis@dimes.unical.it, Cc: Mandalari, Anna Maria, Francesco Buccafurri & 2 more

Details

#### ▲ Caution: External sender

Many thanks for your valued reply.

After confirming with our security team, the vulnerability has been resolved in the latest firmware of P110.

Since this firmware is currently in gray release, we are not sure whether your P110 could receive the firmware right now, you could check it in Tapo App.

If there is no firmware update for your P110, please provide the MAC address with us, we will release the firmware for your P110 and hope you could help verify the remediation work in the latest firmware.

If you have additional concerns or information, please feel free to let us know. If you have any subsequent plan or processing of the vulnerability, we also hope that you can further synchronize to us.

Thank you for your cooperation and patience.

Ian.xu TP-Link Technical Support

Website: https://www.tp-link.com/support/

Feedback: Report a suggestion/complaint on this email service by clicking here

## Why Were We Interested in This?



Control

Device detection

Intelligent profiles



Security

Vulnerability Assessment

**Brute Force Protection** 

Anomaly Detection



Privacy

Content filtering Network Intrusion Prevention

These devices may introduce privacy and security risks.
Their cloud interactions and data collection operations may introduce privacy risks.

## Aim and Contribution

- □ Goal 1: Develop a system abled to inject realistic anomalies for healthcare IoT devices.
- □ Goal 2: Explore how the time window used for training affects the accuracy of the anomaly detection, for three different types of anomalies.
- □ Goal 3: Demonstrated that training the model at the edge of the network on a representative edge device (Raspberry Pi) is feasible.



PRISM

#### **Challenges for Measuring IoT Devices**

Difficult to automate the testing of commercial IoT safeguards

- Closed systems
- Blackbox approach

Difficult to perform IoT experiments and generalize

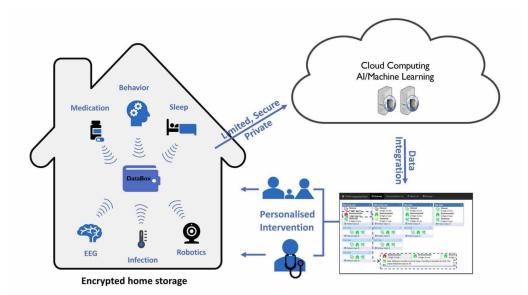
<u>Our contribution</u>: a system for injecting and detecting IoT anomalous behavior in real-world scenarios (software and anomaly data available online).

Lack of standard testbed



### Dataset

- Collected by the UK Dementia Research Institute and Technology Centre (UK DRI).
- In-home activity of people living with dementia (PLWD), from motion sensors, wearable devices and physiological measurements.
- **44 different households**, each fitted with **22 IoT devices**.



### Dataset

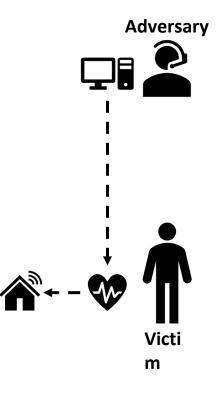
Function	Format	IoT Device	Continuous
Location	Binary	WC, bathroom, bedroom, corridor dining room, hallway - kitchen, living room, lounge office, study	-
Door	Binary	back door, conservatory fridge door, front door garage, main door secondary, utility	$\checkmark$
Appliances	Binary	iron use, kettle use, microwave use - socket use, toaster use	-
Temperature	Float	temperature, body temperature skin temperature	$\checkmark$
Health Related	Float	blood pressure, body mass index body muscle mass, body weight - heart rate, body fat body water, bone mass	-
Light	Integer	light level	$\checkmark$
Sleep Event	Binary Float Integer	sleep event, sleep mat snoring sleep mat heart rate √ sleep mat respiratory rate sleep mat state, agitation	√ -

## **Threat Model**

Victim: A person that uses a healthcare IoT device. Adversary: Any party with access to the IoT device Traffic.

#### Threat:

- Adversaries may be incentivized to share privacy-sensitive information of patients.
- Malicious attacks hijack the communication channel, modifying the data sent by the IoT device.



# ANOMALIES

ANOMALIESEVERYWHERE

WALT PUTT LIGHTYEAR

imgflip.com

# **Types of anomalies**

#### On-off:

- $\circ$  For Binary sensors (i.e switches, doors)
- Recreates a sensor which repeatedly switches on and off.

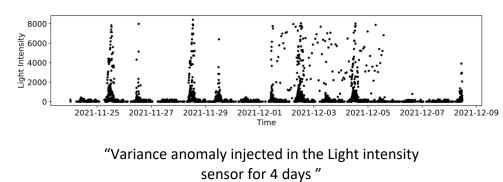
#### Variance:

- $\circ$  For sensors which record floats or integers
  - (i.e thermometer, blood pressure)
- ${\scriptstyle \circ}$  Recreates noise or randomized readings.

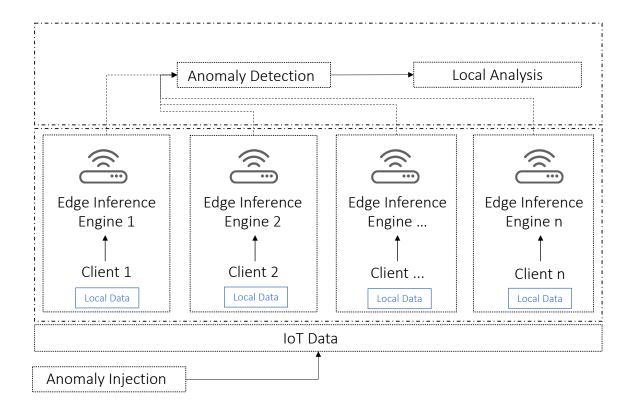
#### Spike:

- $\circ$  For sensors which record floats or integers
- $\circ$  Recreates a random abnormal spike in the readings

Anomaly	IoT device
On-Off	Room Location, Appliance Use, Sleep Event
Variance	Ambient Temp, Body Temp, Light
Spike	Sleep Respiratory, Hearth Rate, Sleep Hearth Rate



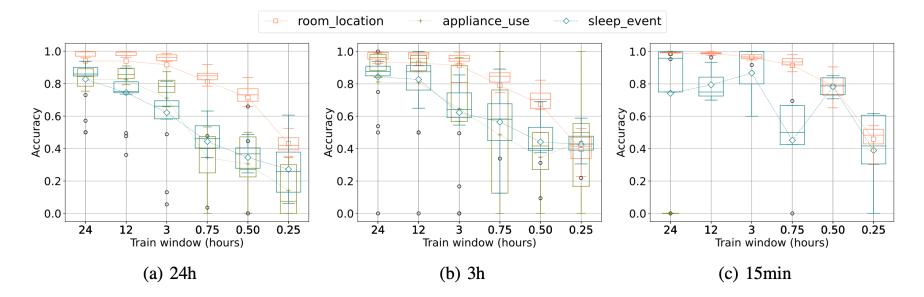
# **System Design**



## **Overview of Methodology**

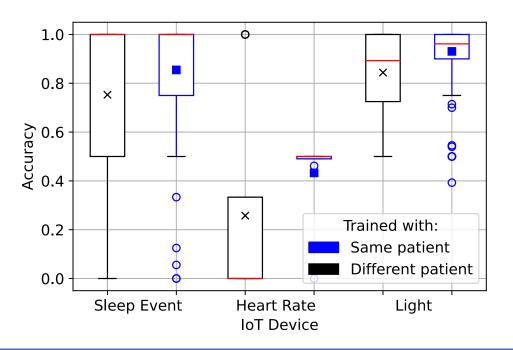
Data	Anomaly	Data Pre-	Model	Anomaly
Loader	Injection	Processing	Inference	Detection
<ul> <li>Options:</li> <li>Select specific patients.</li> <li>Select one or multiple patients.</li> </ul>	<ul> <li>Options:</li> <li>Type of anomaly.</li> <li>Number of anomalies.</li> <li>Time window length that anomalies will be injected in.</li> </ul>	<ul> <li>Sliding time window.</li> <li>Train, Valid. split based on time window.</li> <li>Features: Sensor readings, Time interval between readings (δt).</li> </ul>	<ul> <li>Architectures tested: DNN, CNN, KNN.</li> <li>Library used: PyTorch.</li> <li>Early stopping for training.</li> <li>Unsupervise d Learning.</li> </ul>	<ul> <li>The average training loss of the final epoch is calculated.</li> <li>Multiplied by a coefficient, it acts as the threshold to detect anomalies.</li> </ul>

### **Anomaly Detection Accuracy**



<u>Take away</u>: On-Off Anomaly. The anomaly detection accuracy changes with training window size and different validation window sizes.

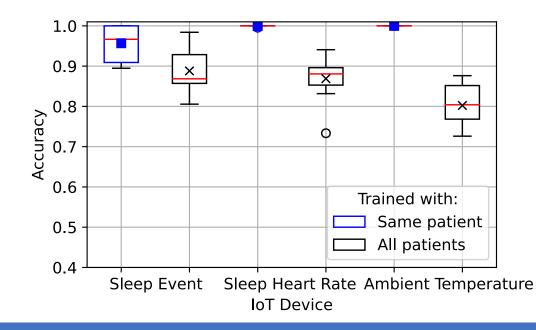
### **Personalized Models**



Average accuracy across all patients while training and validating with the same and different patients.

<u>Take away</u>: A model updated using data from one patient does not perform well on another patient and vice versa.

### **Personalized Models**



Average accuracy across all patients while training with all patients and validating with one patient, compared to training with all and validating with one patient.

<u>Take away</u>: The accuracy decreases when training the model with all patients. This shows that a model updated with data specific to each patient will achieve better performance.

### **Course Overview**

- Benchmarking privacy in IoT devices
- □ IoT devices identification
- Benchmarking security in IoT devices
- Benchmarking security solutions for IoT devices
- Privacy solutions for IoT devices at the edge
- Security solutions for IoT devices at the edge
- □IoT devices certification scheme



#### The Problem

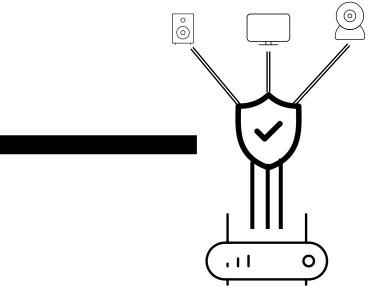
- 21.5 billion IoT devices in the world
- They have access to user private information
- They are a threat for user privacy and security

1 2

# Mitigation

- Regularly train the ML models at the edge to keep up with the changes in device usage trends
- Approaches that rely on local traffic analysis: edge-based solutions running on the home gateway





# WHEN YOU SEE HOW SOPHISTICATED CYBERTHREATS HAVE BECOME

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#### **COPSEC: Compliance-Oriented IoT Security** and Privacy Evaluation Framework

**Cybersecurity guidelines\*** such as ENISA, NIST, *IoT Regulation Policy (UAE)* have been released for improving IoT design practice

**Privacy regulations**\*\* such as GDPR (in EU) and CCPA (in California)

There is a lack of understanding whether IoT devices comply with them

\*NOT mandatory \*\*Mandatory

#### Motivation

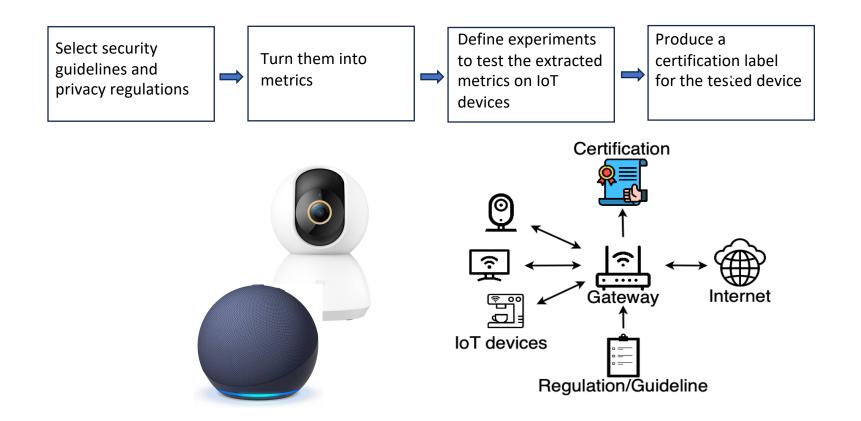
• In 2023 the Cyber Resilience Act (in EU) and the US Cyber Trust Mark (in US) make further step towards a certification program of smart devices

• For consumer IoT devices, the certification process is thought as a <u>self-assesment</u> performed by the vendors themselves

• Should we trust vendors?



### Methodology



#### Results

Device	# of Unused Open Ports	# of Unrecognized Protocols	Compliant with GDPR Art. 32 (a)
Bose Speaker	(11 ports)	(0 protocols)	$\checkmark$
Echo Dot 5	(5 ports)	X(3 protocols)	$\checkmark$
Furbo Dog Camera	(0 ports)	X(1 protocol)	
Google Nest Cam	(3 ports)	(1 protocol)	
Govee lights	(0 ports)	(0 protocols)	
Ring Video Doorbell	(0 ports)	(2 protocols)	
Sensibo Sky Sensor	(0 ports)	(0 protocols)	
SimpliSafe Cam	(1 ports)	(0 protocols)	×
Sonos One	(5 ports)	(1 protocol)	(mac in the clear)
WeeKett Kettle	(1 ports)	(2 protocols)	$\mathbf{v}$

IoTrim



# What's Next?



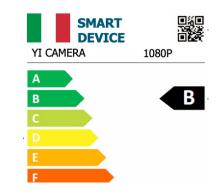
Privacy Preserving IoT Security Management

- Real industrial gateway
- Medical IoT Devices
- Real-world trial



#### Mitigation

- Real deployment and evaluation
- Third party certification



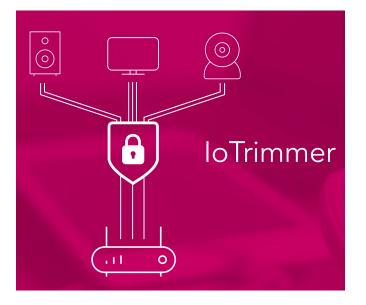
#### Privacy and Security Label/Certification

 Privacy and security by default

## GET INTO IOT THEY SAID

## IT WILL BE FUN THEY SAID

makeameme.org



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