BehavIoT: Measuring Smart Home IoT Behavior Using Network-Inferred Behavior Models

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Northeastern University
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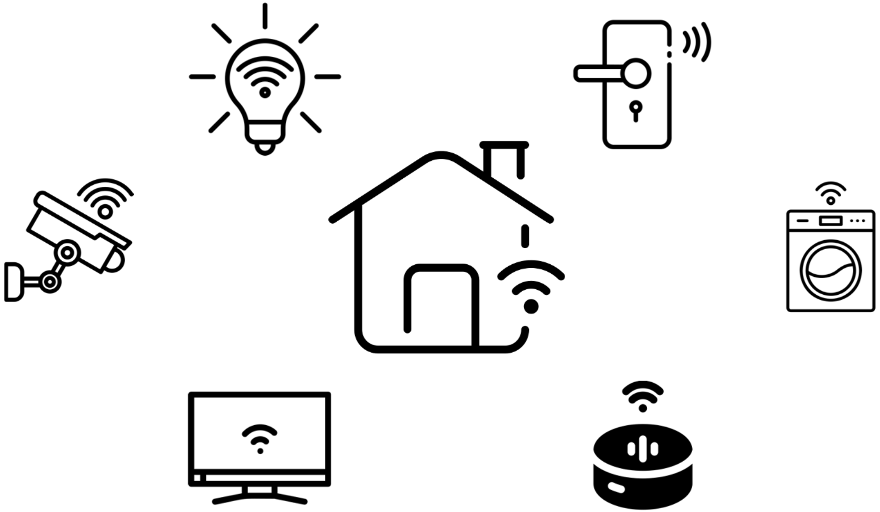
ProperData

Background

Internet-enabled smart home



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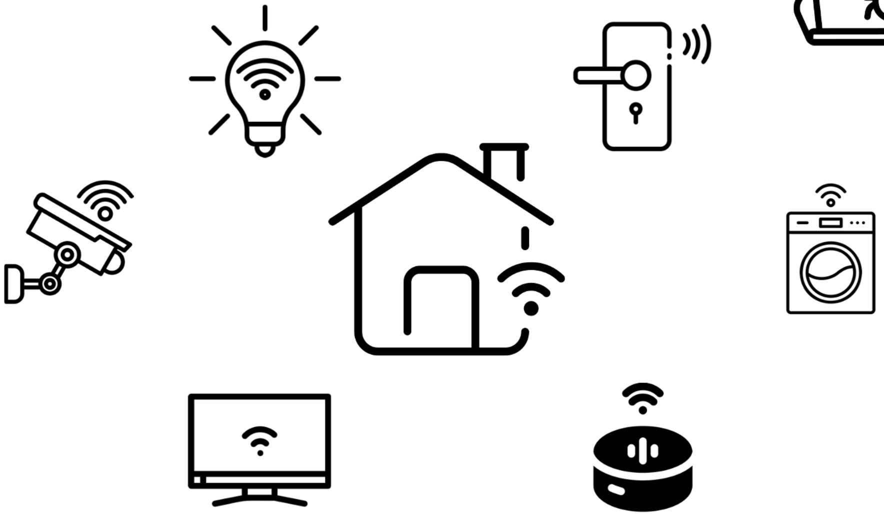

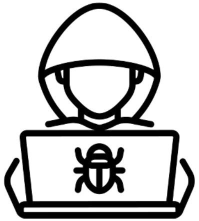

The Mirai botnet explained: How teen scammers and CCTV cameras almost brought down the internet

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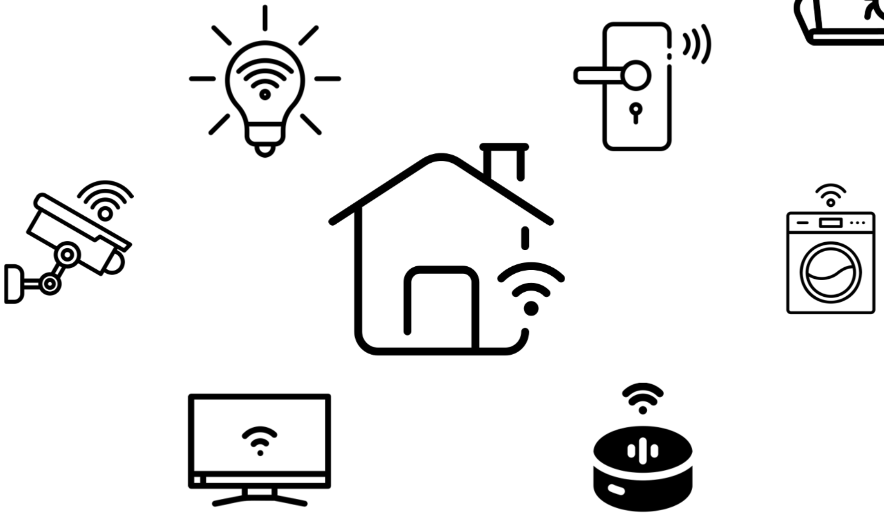

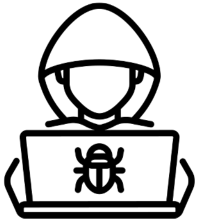

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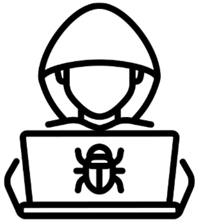

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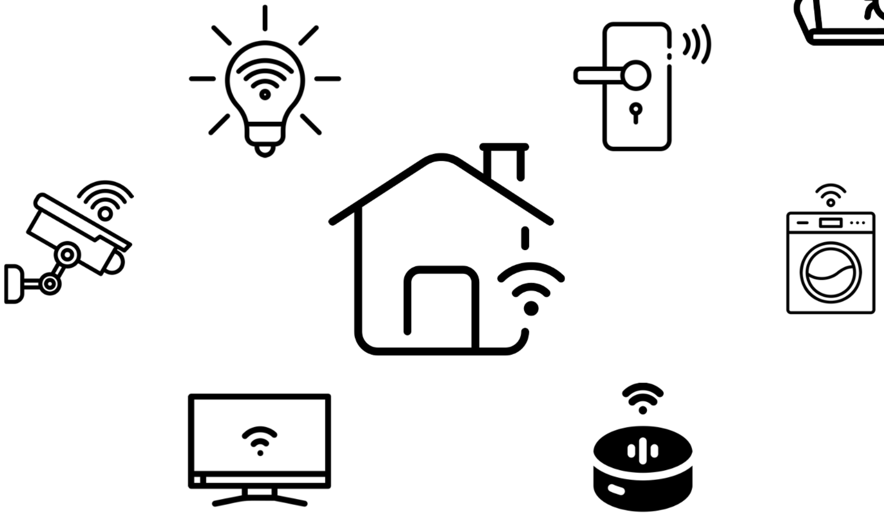

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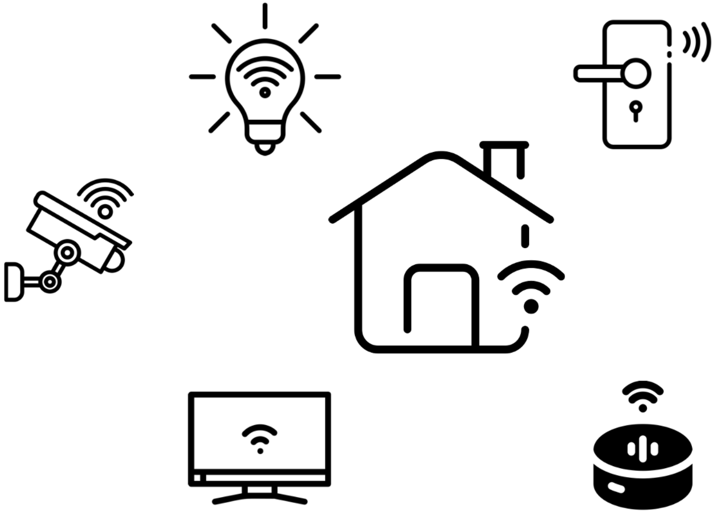

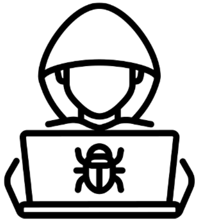

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- Diverse security, privacy, and safety issues
- Due to attacks, malfunctions, misconfigurations, etc.

Why is it hard to model IoT behavior?

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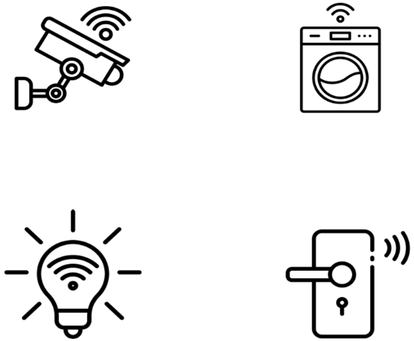
Diversity



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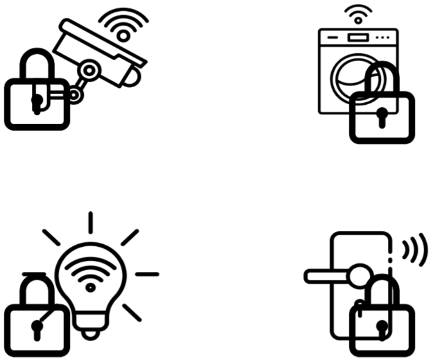
Diversity

Opaqueness



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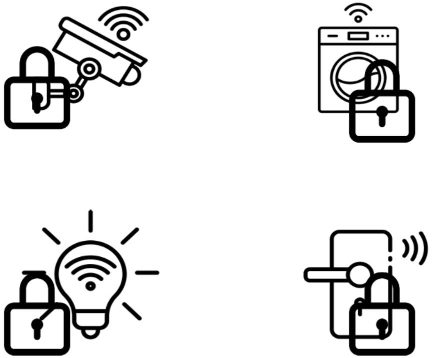
Hard to fully understand

- **what is normal device behavior**
- **how it changes over time**



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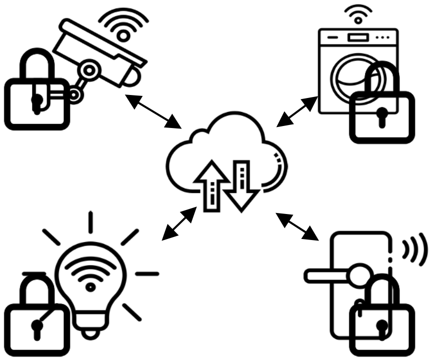

Key observation: IoT reveals behavior via **network traffic**

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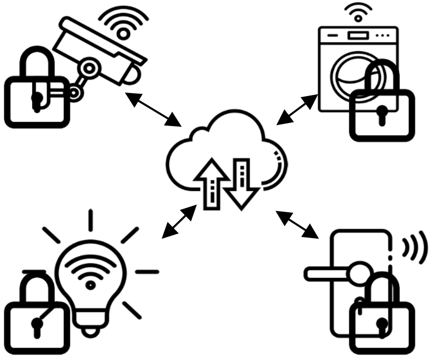
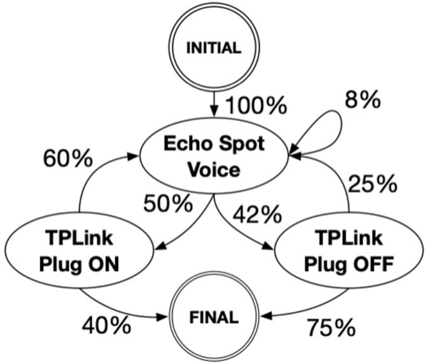
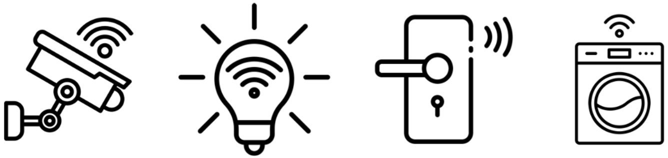




Key observation: IoT reveals behavior via **network traffic**

Open question: *Can we model IoT behavior based on this traffic?*

Motivation



- **Predictable** network traffic patterns

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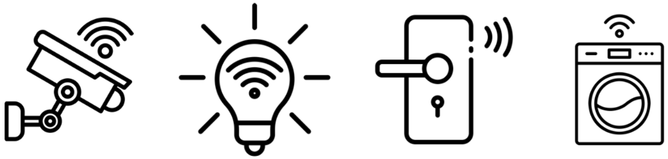

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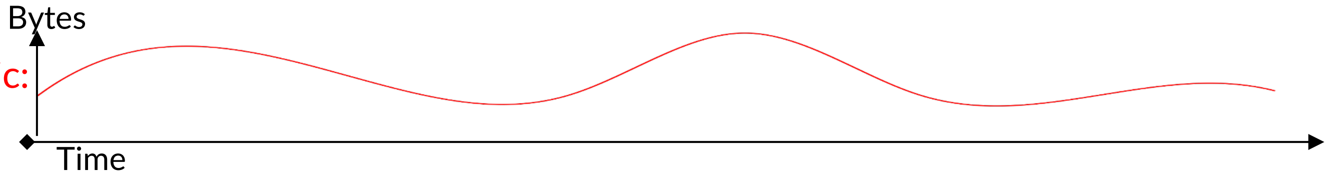
Network Traffic:



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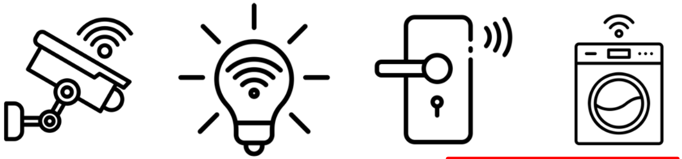
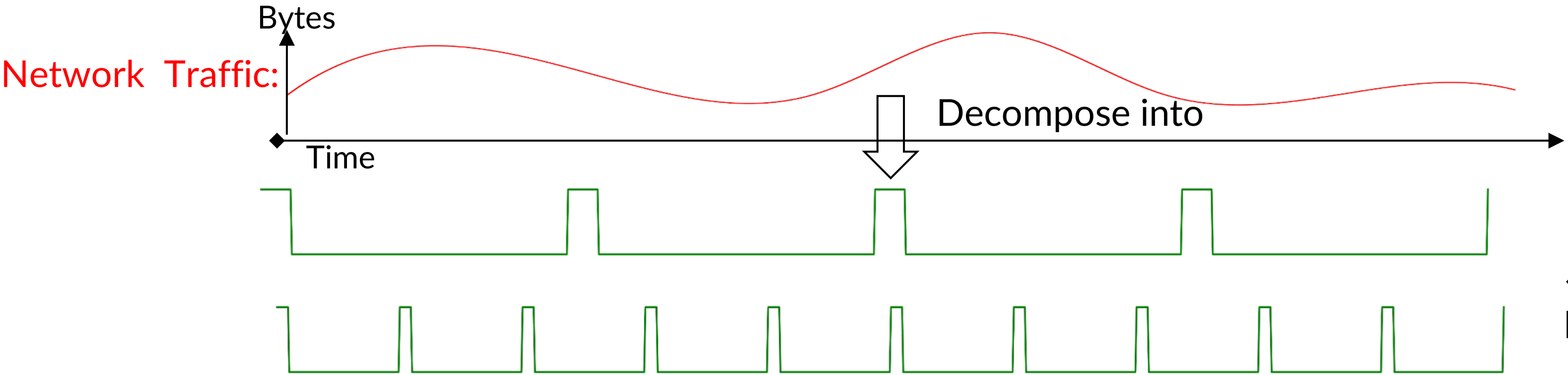
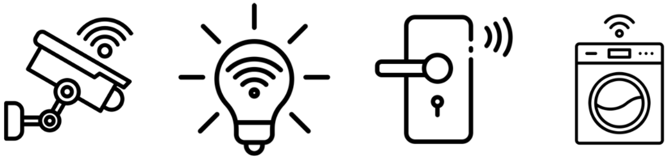


- **Predictable** network traffic patterns → **periodic**

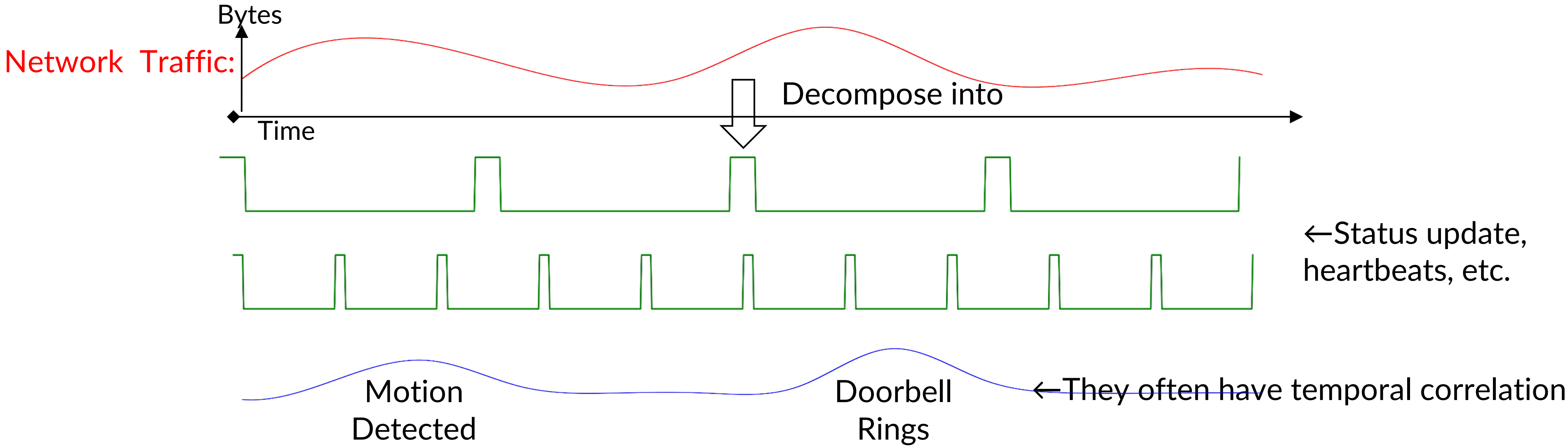


←Status update, heartbeats, etc.

Motivation



- **Predictable** network traffic patterns
  - → periodic
  - → **correlate with the actual functions**



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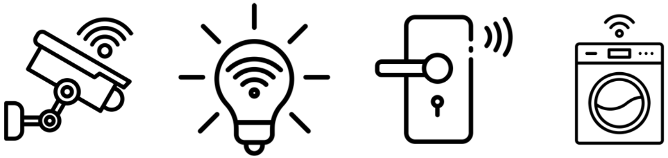

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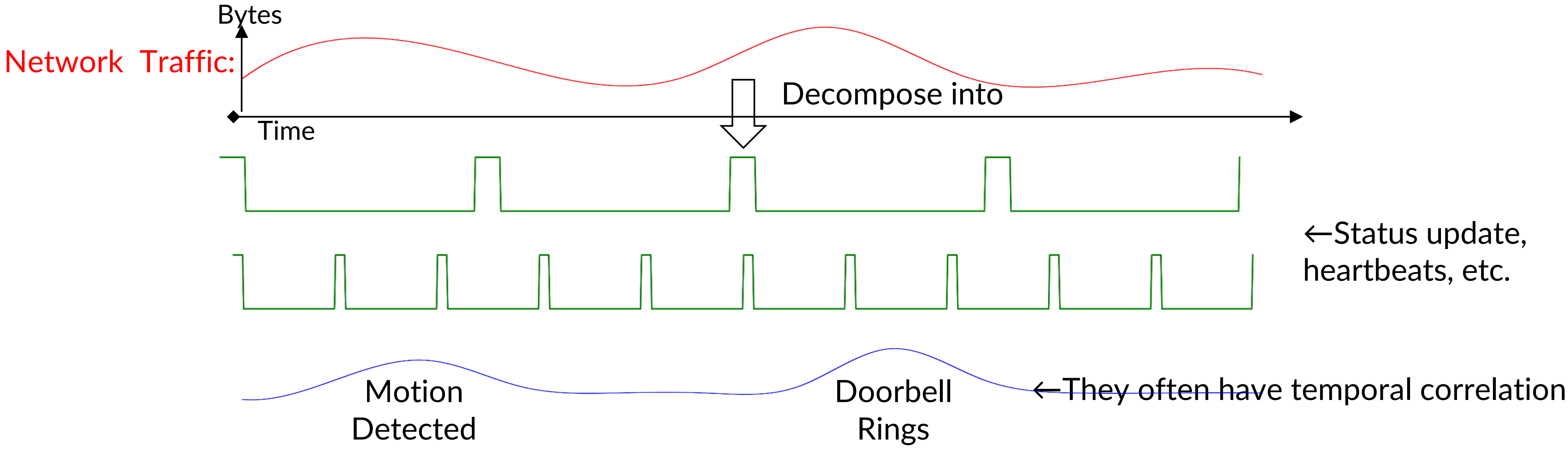

- **Relatively simple** — having **a limited set of functionalities and states.**

Research Questions

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RQ1: How do we measure and characterize the behaviors of smart home system from their (mostly encrypted) network traffic?

RQ2: How do we measure and characterize behavior deviations of a smart home system?

Our Approach - BehavIoT

Traffic Capture

1. **Capture** IoT devices' encrypted **network traffic**

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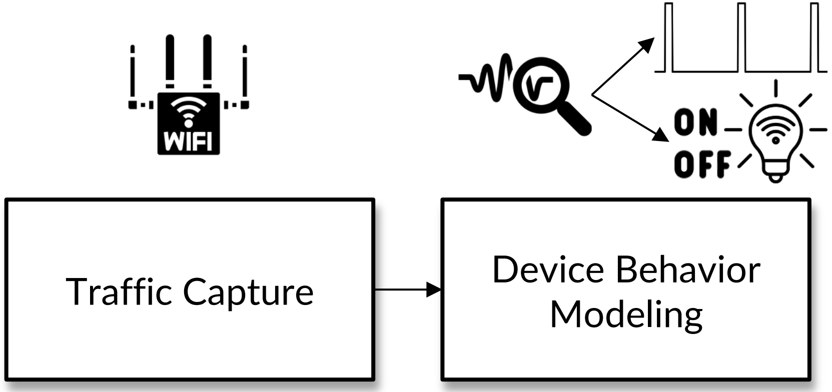

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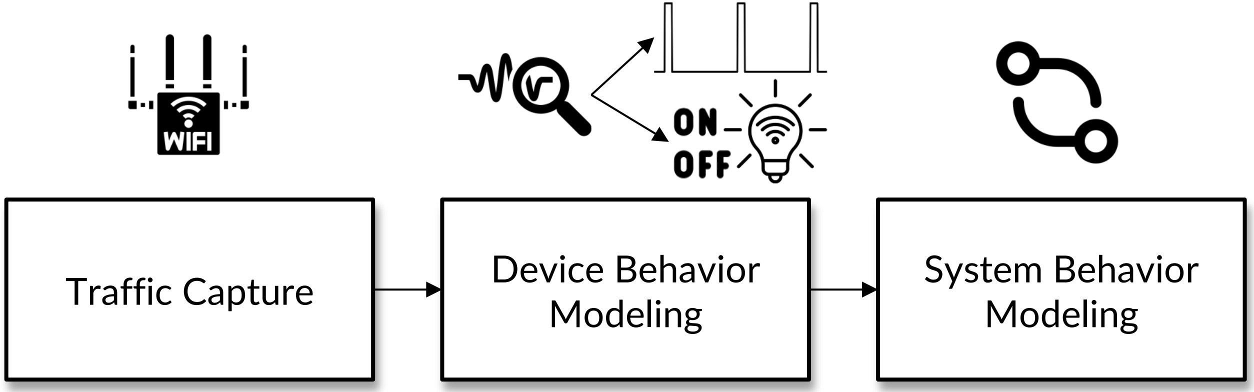

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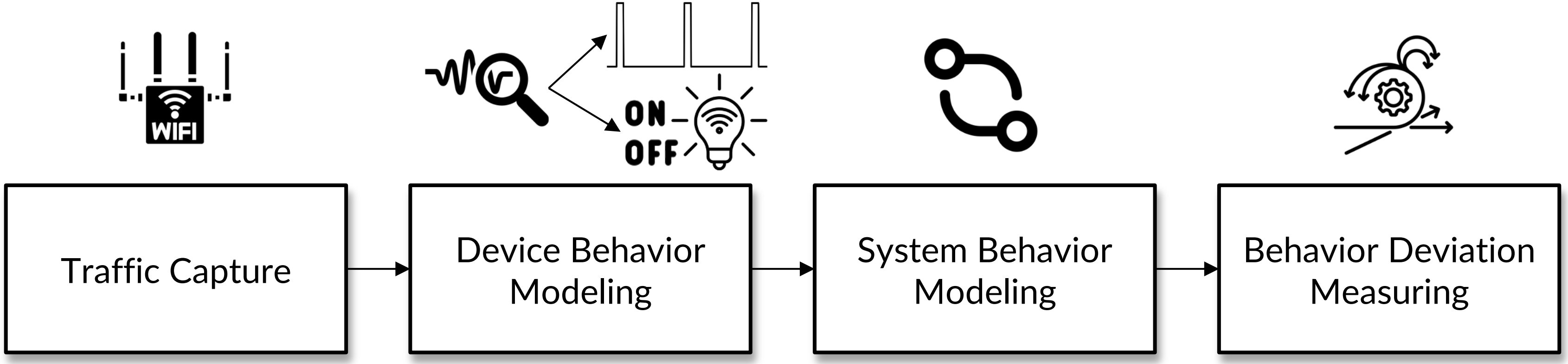

1. **Capture** IoT devices' encrypted **network traffic**
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3. **Characterize** smart home **system behavior**
4. **Measure and quantify behavior deviation**

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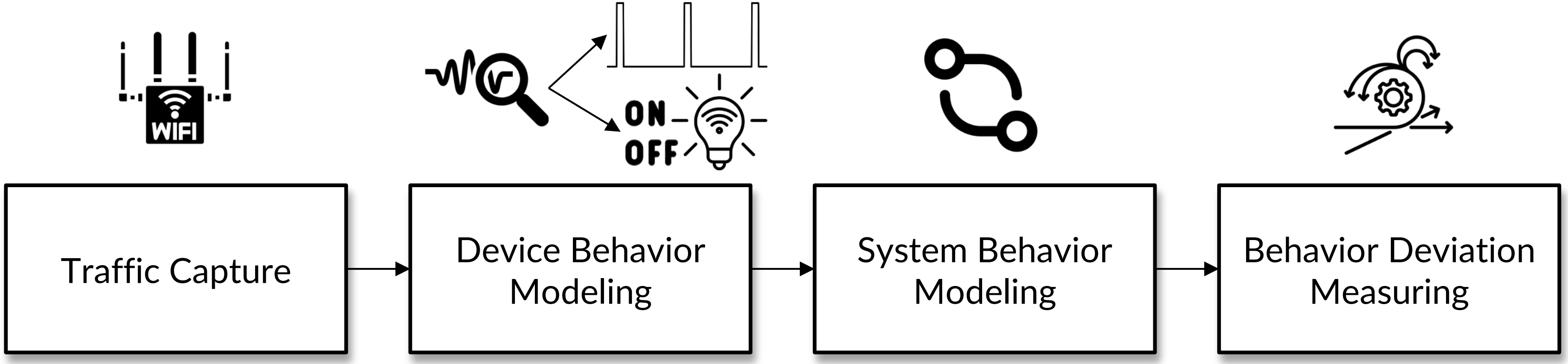

Key advantages of the approach

- works across **a wide range of IoT devices**.
- requires **no privileged access** to devices or APIs. Deployable on routers.
- models behaviors of both **individual devices and a smart home system**

Testbed & Datasets

Traffic Capture → Device Behavior Modeling → System Behavior Modeling → Behavior Deviation Measuring

49 devices from a wide range of categories

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- **Controlled interactions** (4,230 experiments):

  Capture device behaviors of actual functions.

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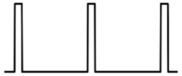
- **Idle experiments** (5 days):
  Capture device periodic background behaviors.



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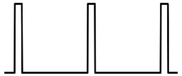

- **Routines** (16 routines, 24 hours):
  Capture smart home system behaviors.

IFTTT

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- **Routines** (16 routines, 24 hours):
  Capture smart home system behaviors.
- **Uncontrolled interactions** (3 months, 40 participants, IRB-approved):
  Measure behavior deviation over time.

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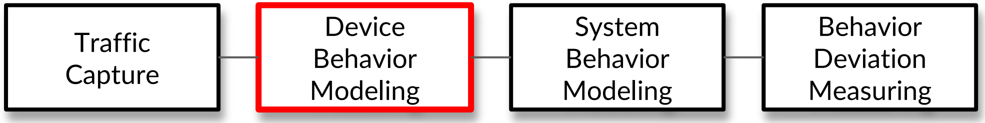
Methods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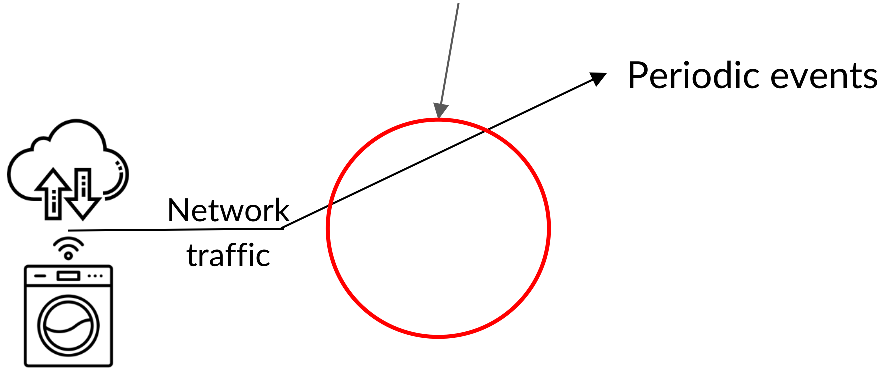
Methods

→ periodic

Event Inference:
Classify traffic → events



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Traffic Capture → **Device Behavior Modeling** → System Behavior Modeling → Behavior Deviation Measuring

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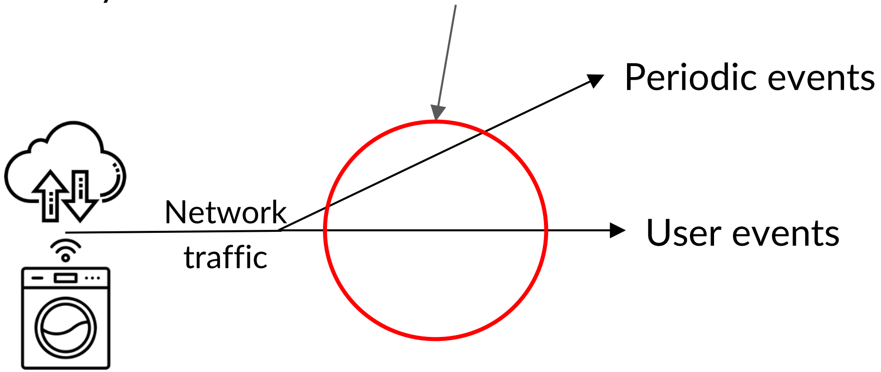

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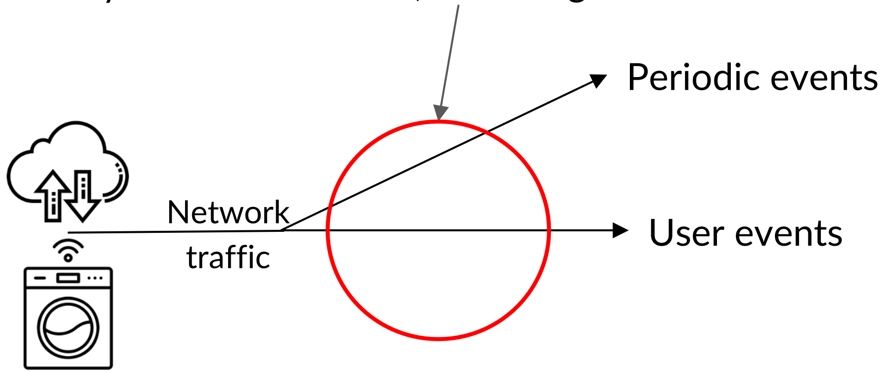

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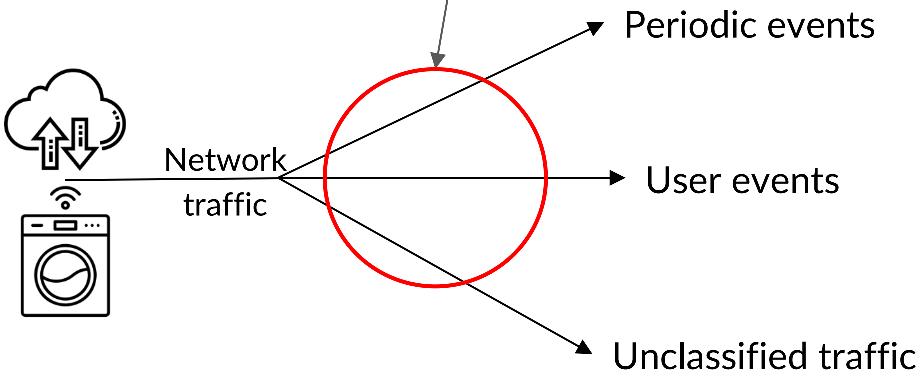

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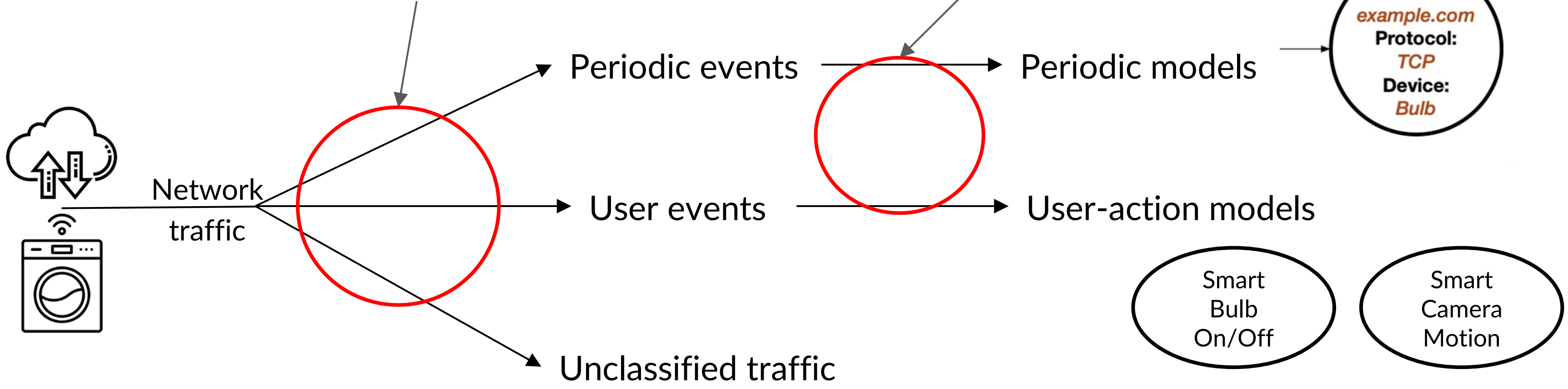
Model generation:
Annotate with labels



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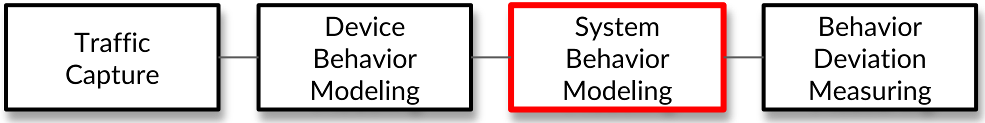
The vast majority of IoT (mostly encrypted) traffic (99.3%) **can be modeled**.

The vast majority of IoT traffic (97.8%) i**s periodic**.

A small portion of traffic (0.675%) cannot be modeled — most from devices running complex software.

Methods



Key insight: can be modeled as a finite state machine

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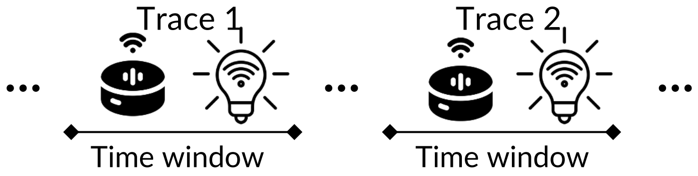

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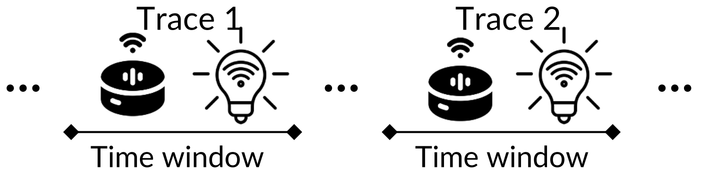

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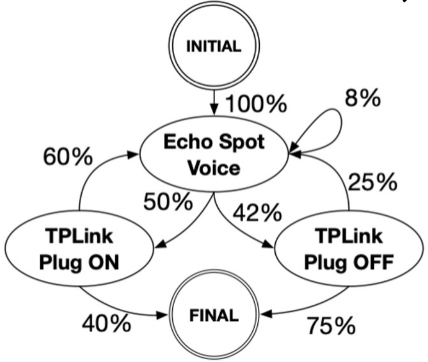
2. Generate a **probabilistic finite state machine (PFSM) model from traces** using Synoptic [1]



- State: user activity
- Transition: probability

[1] Beschastnikh, Ivan, et al. "Leveraging existing instrumentation to automatically infer invariant-constrained models." *Proceedings of the 19th ACM SIGSOFT symposium and the 13th European conference on Foundations of software engineering*. 2011.

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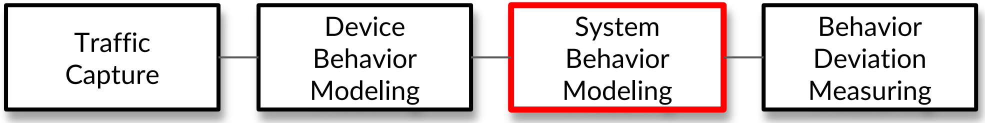

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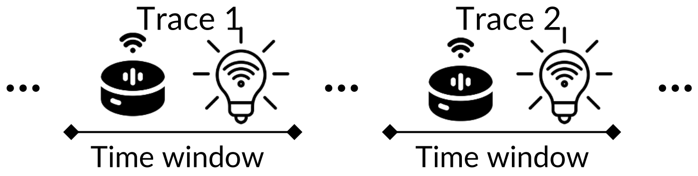

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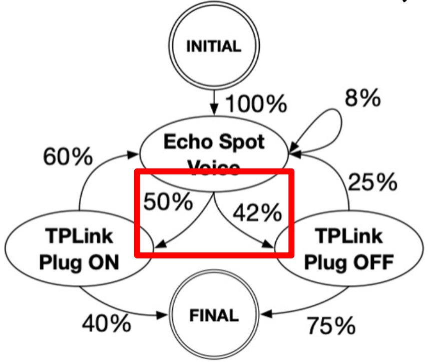

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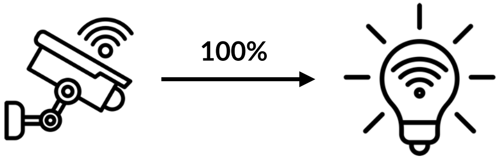

Automation: turn on light if motion is detected

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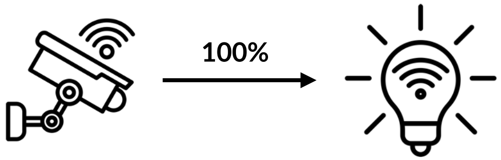
  - programmed behaviors introduced by automations
  - non-programmed behaviors introduced by human interactions



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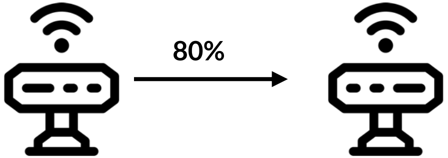

Co-located motion sensors

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Identify significant changes in behavior

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- **Deviation metrics** that quantify the amount of behavior change
- Thresholds to capture **statistically significant deviations**

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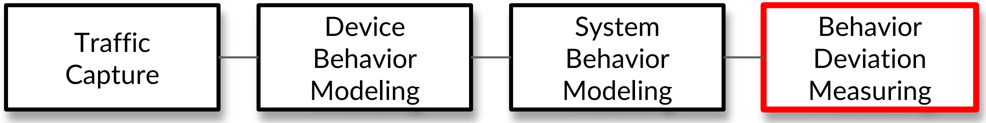

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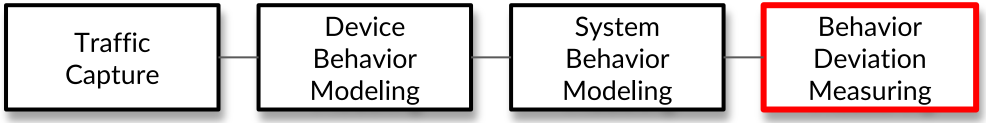

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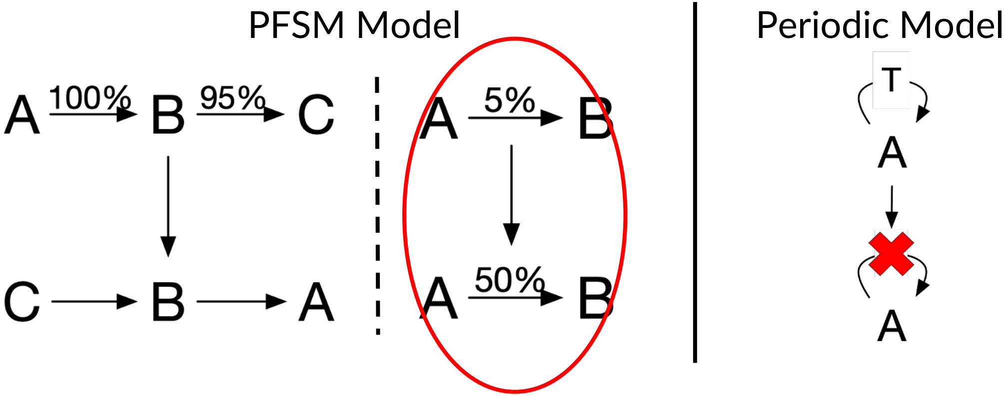
- Thresholds to capture **statistically significant deviations**



Key Takeaways

RQ2: How do we measure and characterize behavior deviations of a smart home system?

- Our metrics identify significant deviations from real-world examples

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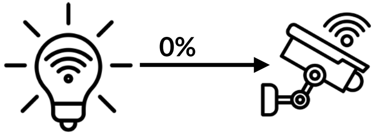

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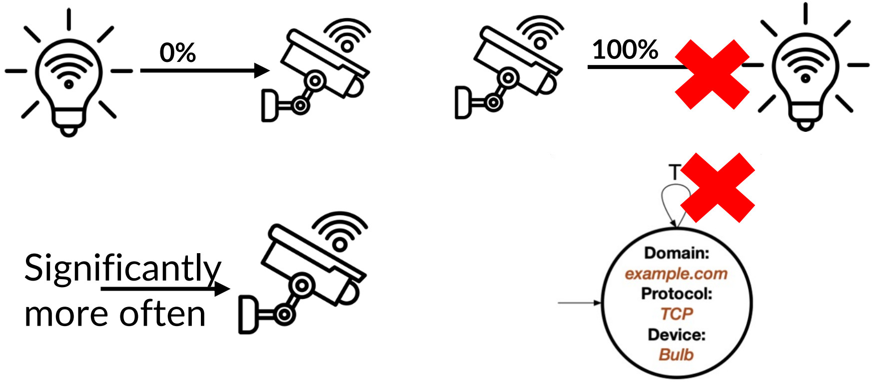

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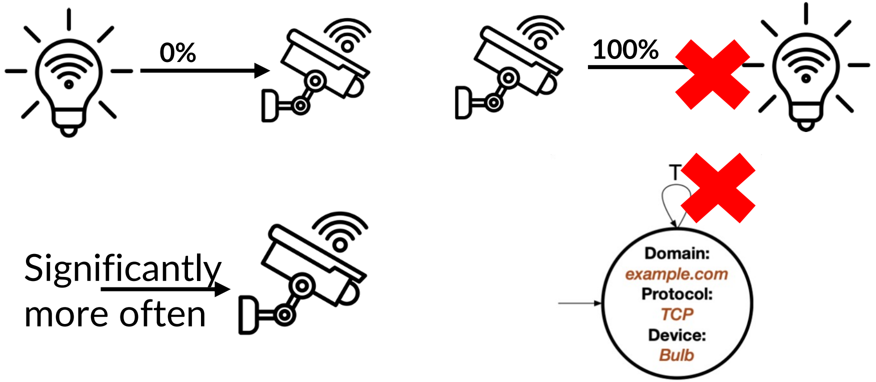
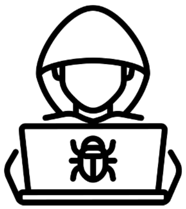


- We detect a total of 177 significant behavior deviations (2 per day on average) among three months
    - **Device malfunctions and misconfiguration**
    - **Misactivation**
    - **Network outages**
    - **Change of device positions**
    - **Change of user habits, etc.**

Behavior Model Applications

- **Create IoT profiles** (MUD RFC8520) and **verify compliance** to existing profiles.
- **Behavior triage to help with auditing** such as security, regulatory, and privacy.
- **Allocate attention to significant behavior deviation**



Conclusion

- **Characterize IoT device and system behaviors**:
  - Most smart home devices are **amenable to modeling** through network traffic.
  - 97% of traffic is periodic; 2.33% is due to user actions; 0.68% is unmodelable.
- **Measure behavior deviation over time:**
  - Detect and quantify a range of behavior deviations.
  - Behavior was relatively stable during a longitudinal study
- **BehavIoT benefits:** creating IoT profiles, triage behaviors and deviation

Thank you!

Datasets and code available here:

https://moniotrlab.khoury.northeastern.edu/behaviot/