TECHNISCHE UNIVERSITÄT DARMSTADT

ARGUS: Context-Based Detection of Stealthy IoT Infiltration Attacks

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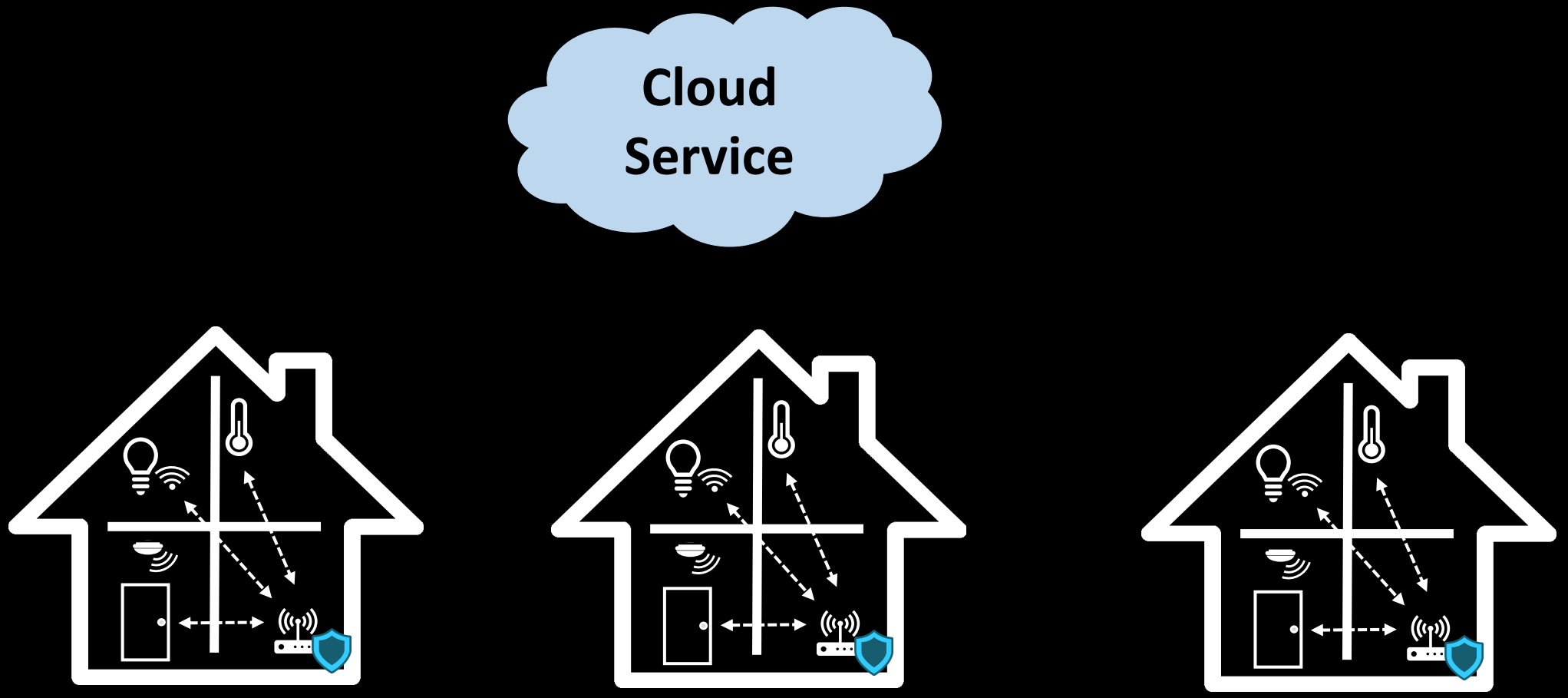
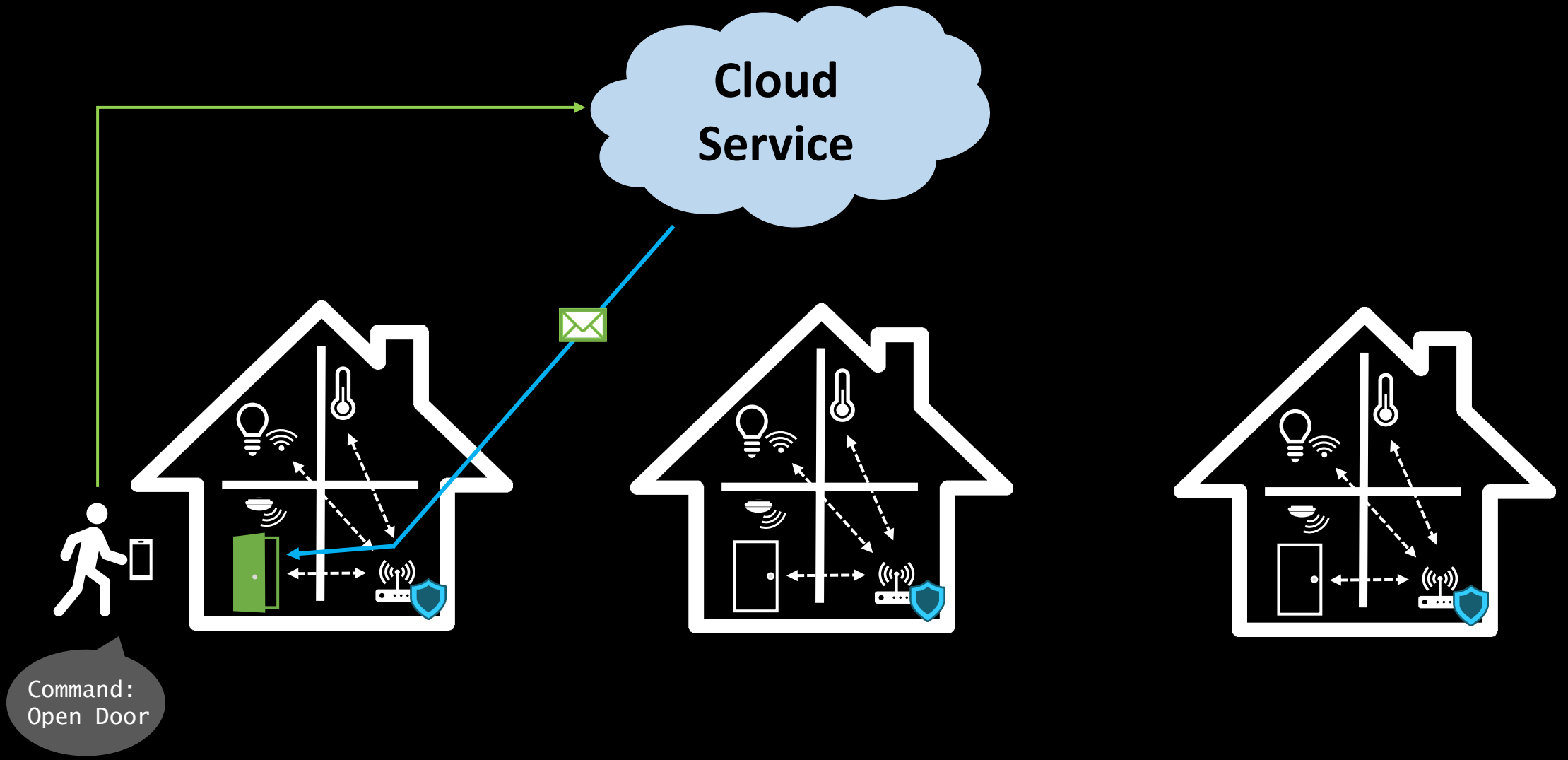
System Security Lab

Contextual Attacks



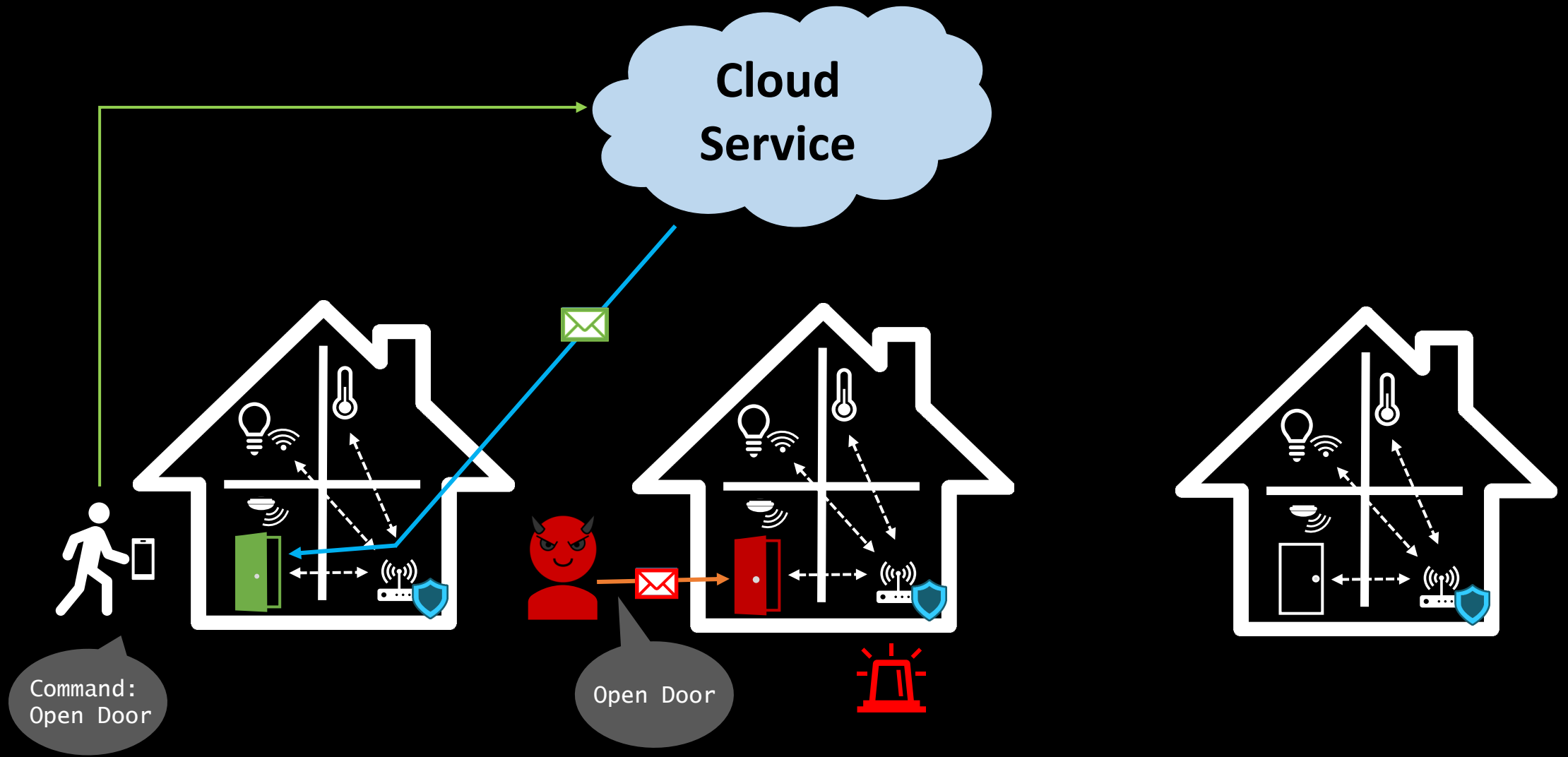
Benign Scenario

Contextual Attacks



Benign Scenario

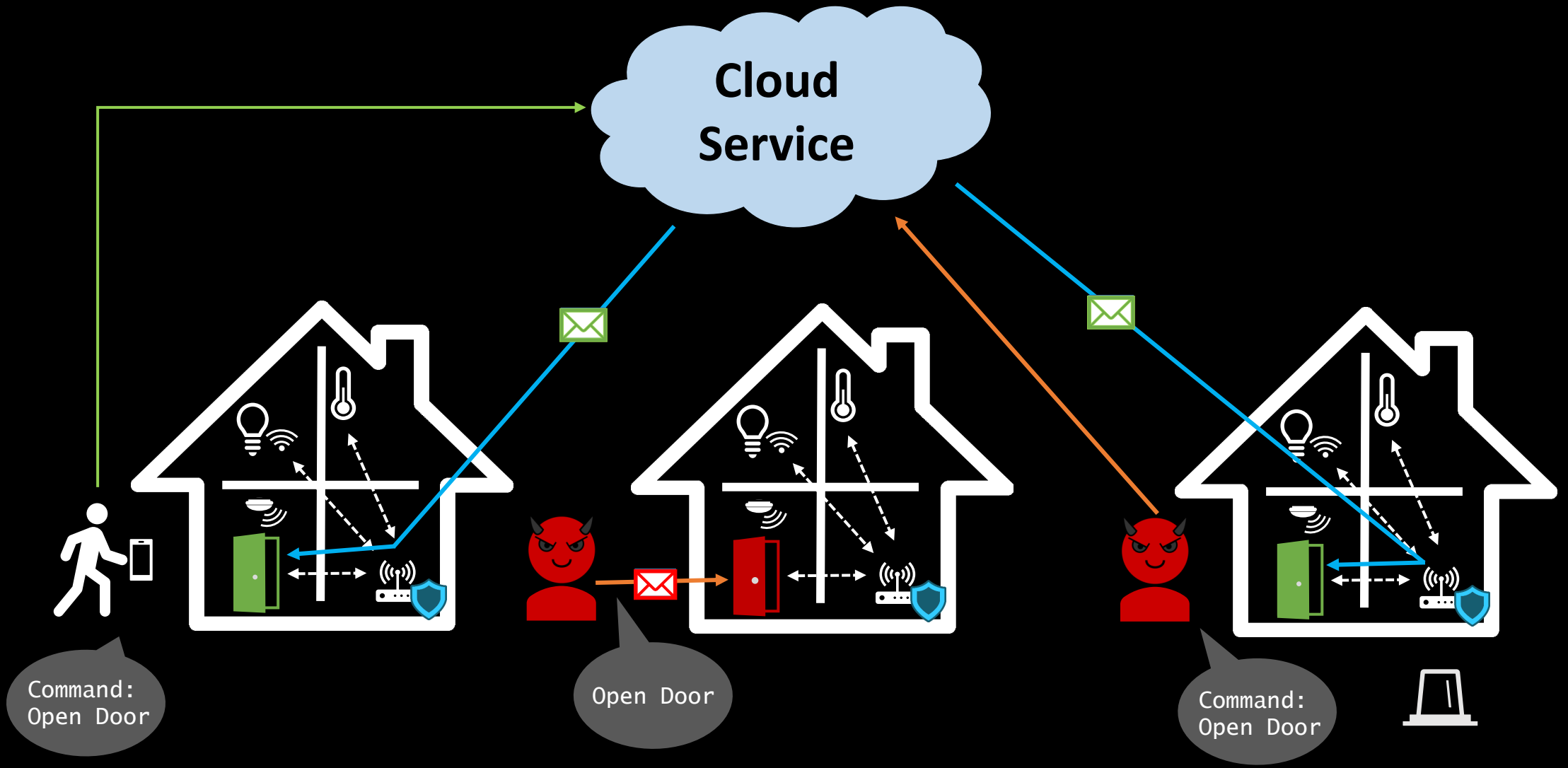
Contextual Attacks



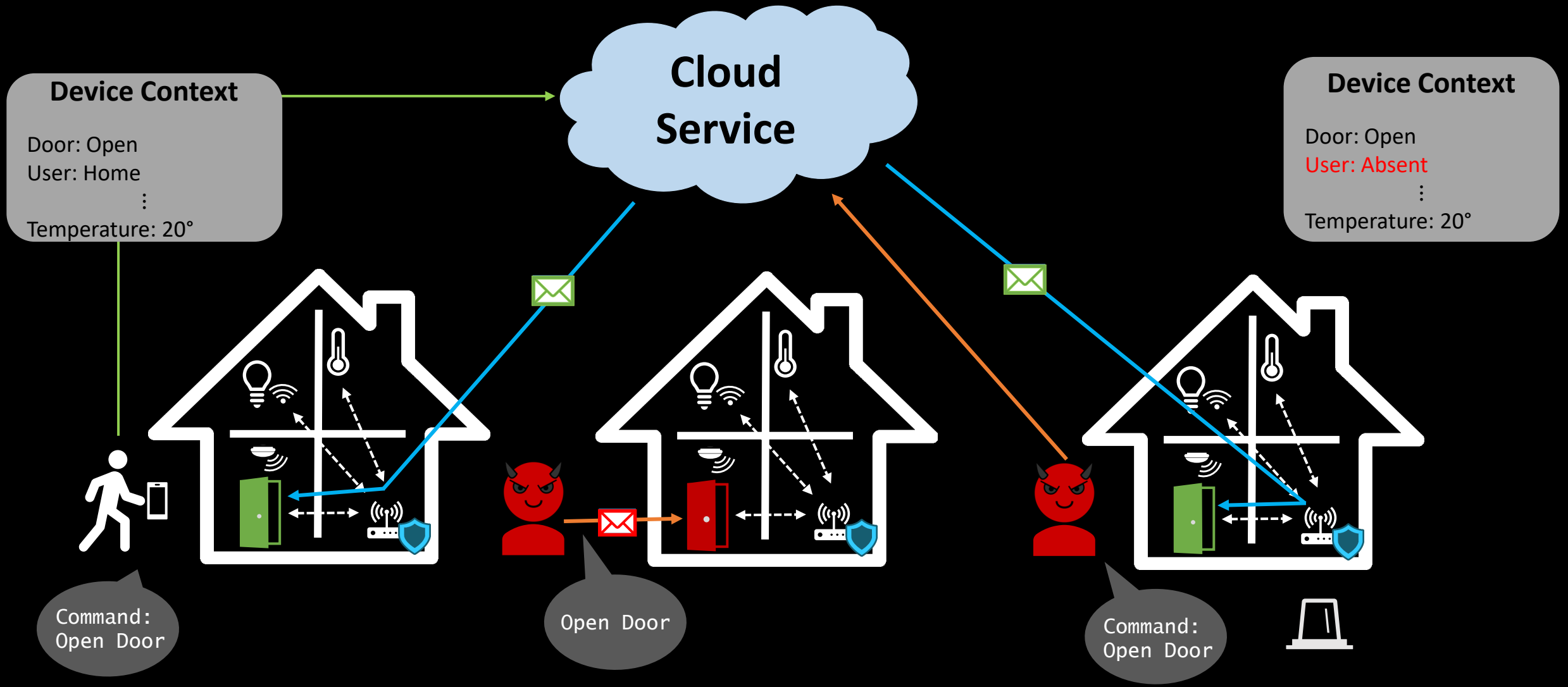
Benign Scenario

Compromised IoT Device

Contextual Attacks



Contextual Attacks



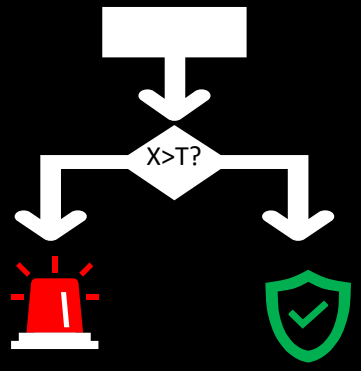
Existing Solutions

Network-Intrusion Detection

Cannot detect attacks exploiting control-infrastructure

[Nguyen et al., ICDCS 2019]
[Fan et al., BigDataSE 2020]
[Oconnor et al., WISEC 2019]

Policy-Based Detection

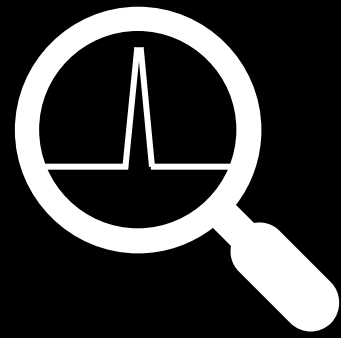


Requires tedious setup by users

Attacker might find gap in policies

[Yahyazadeh et al., SACMAT 2019]
[Celik et al., USENIX ATC 2018]

Contextual Anomaly Detection

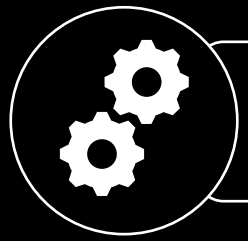


1. Require additional information about devices
2. Restricted to known attacks
3. Consider only commands

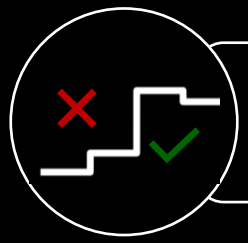
1. [Fu et al., USENIX Security 2021]
2. [Dai et al., IWCC 2022]
3. [Amraoui et al., CRISIS 2020]

Contributions

- Detects contextual attacks being invisible for network inspection-based systems



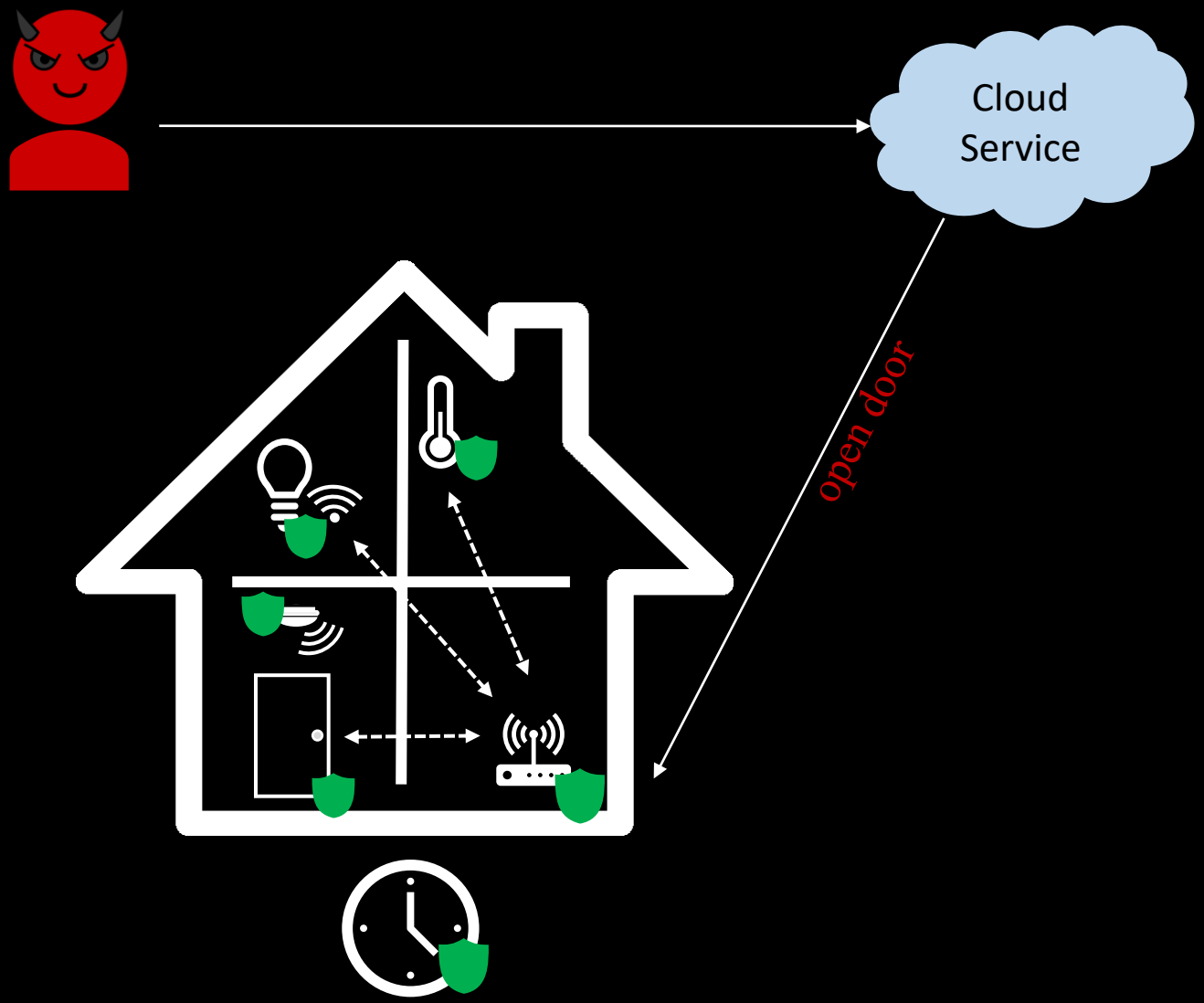
- Operates without manual configuration or knowledge of the devices



- Automatic tuning of detection boundary for classifying anomaly scores

- Evaluated on 5 real-world diverse smart-home setups
- Dataset published as benchmark for future work

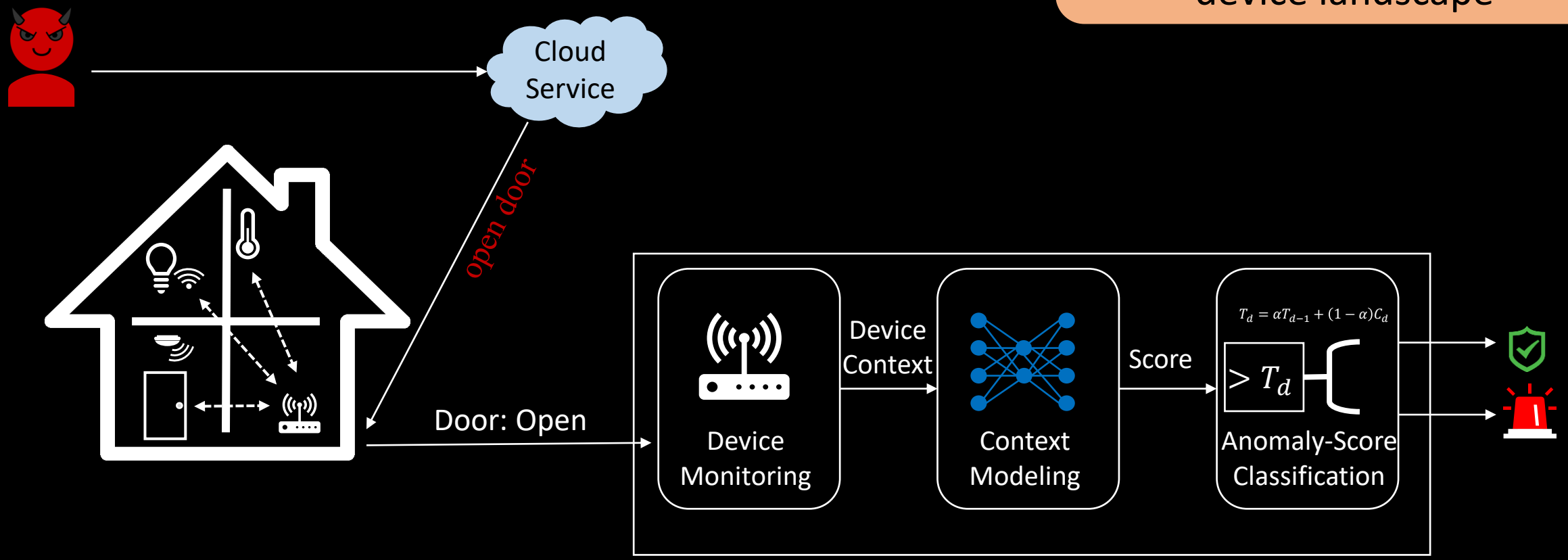
Argus – Assumptions



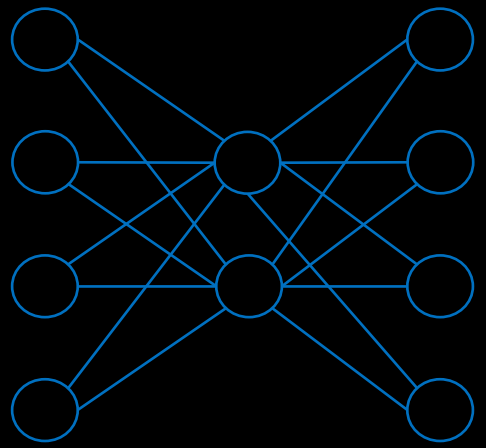
- Security device not compromised
- Benign Setup Phase
- IoT devices itself not compromised

Argus – High Level Overview

Technical Challenge: Obtain context for heterogenous device landscape



Argus – Context Modelling



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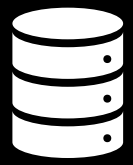
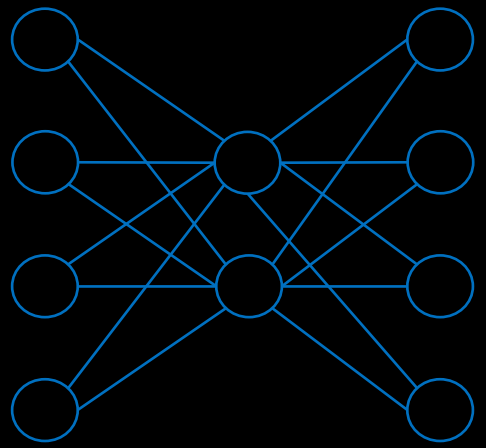
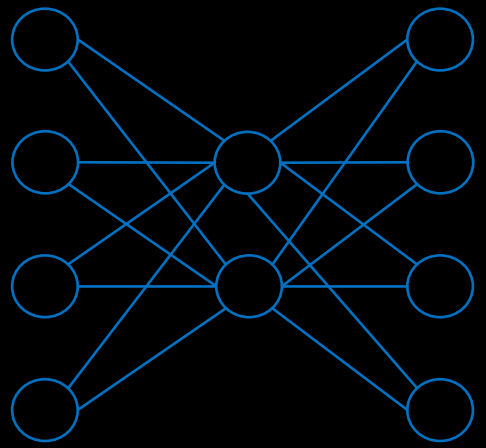


Captured
Normal Behavior



Argus – Context Modelling

Technical Challenge: Train system without attack samples



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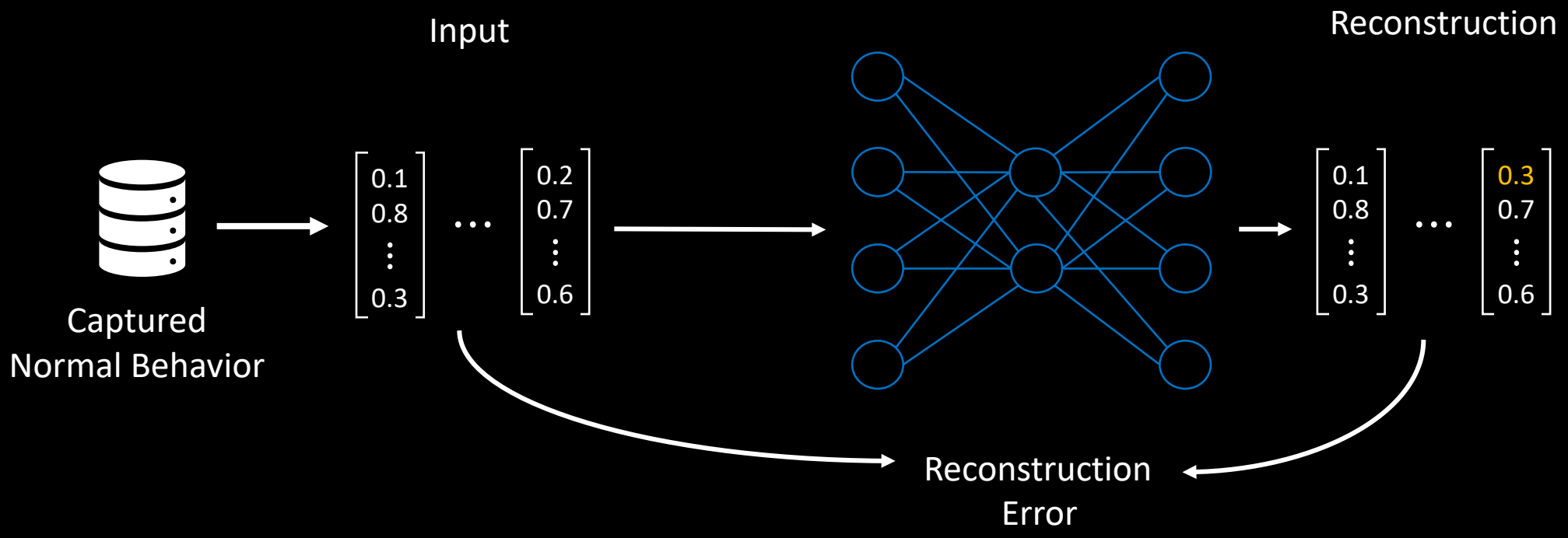

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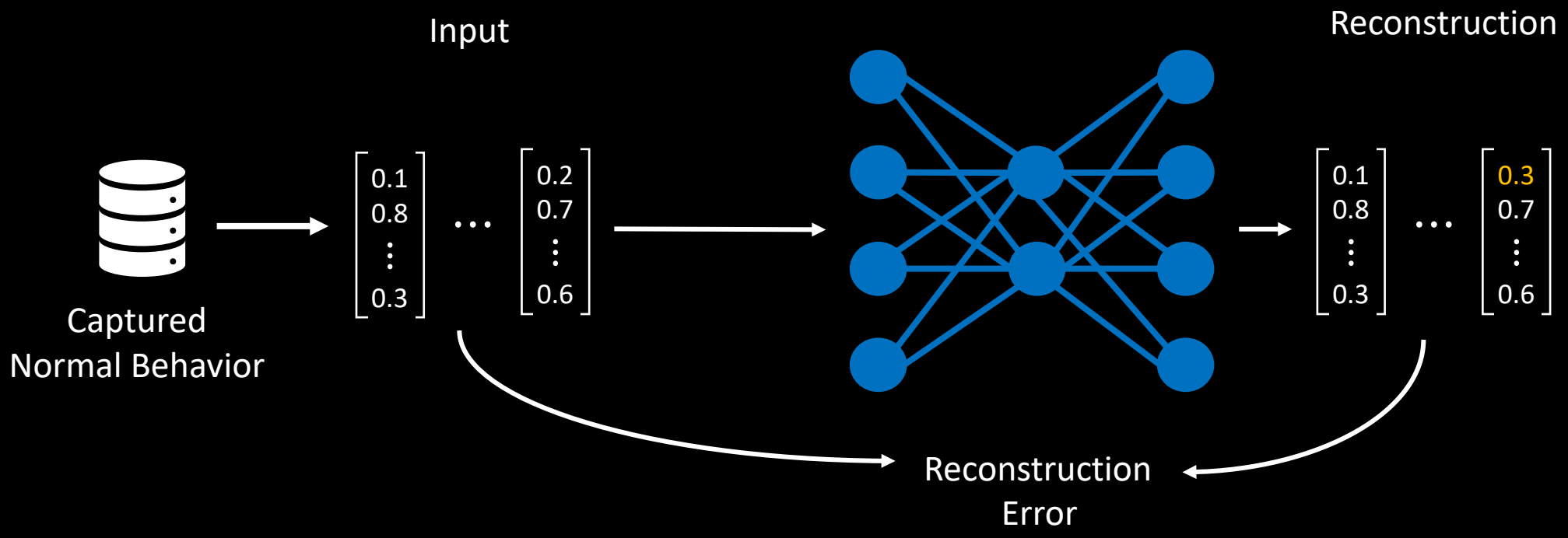

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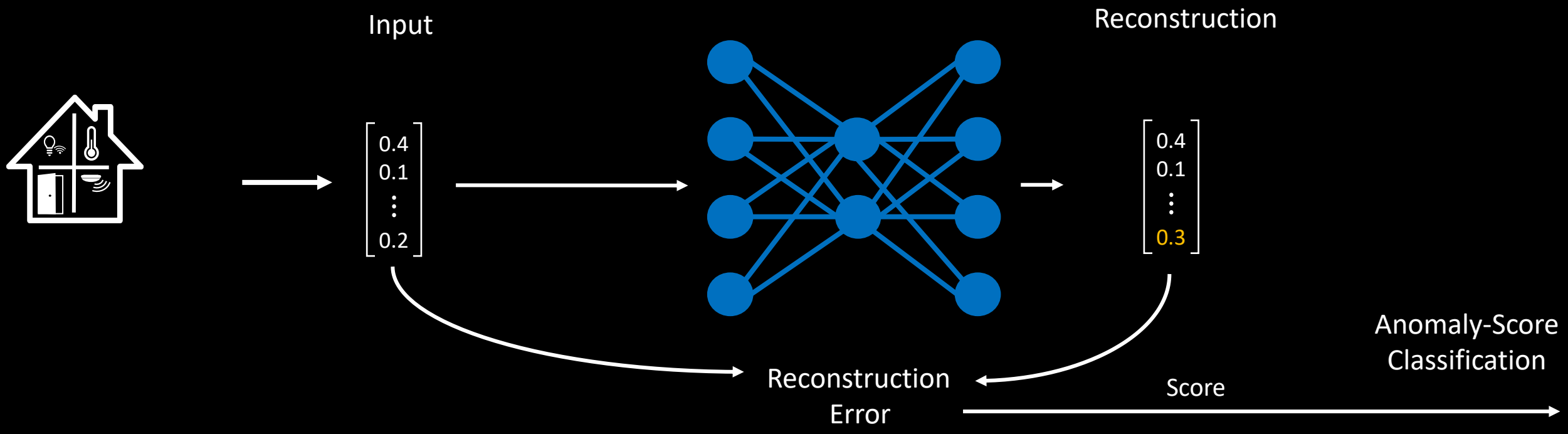
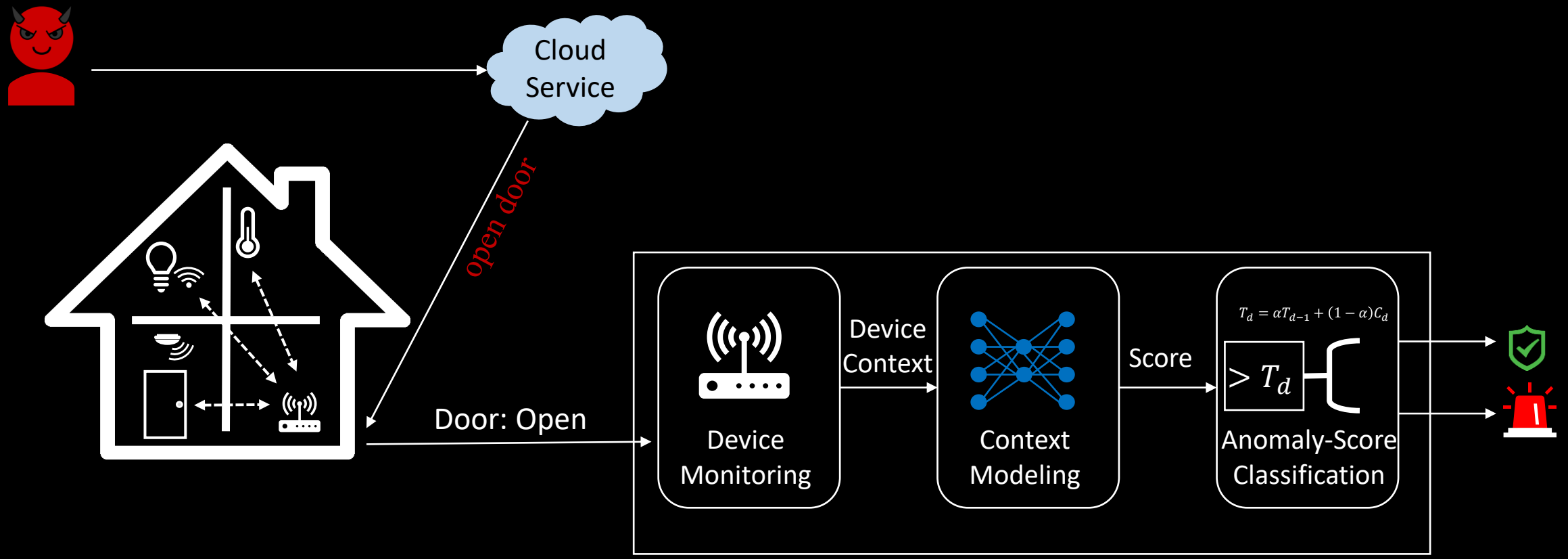


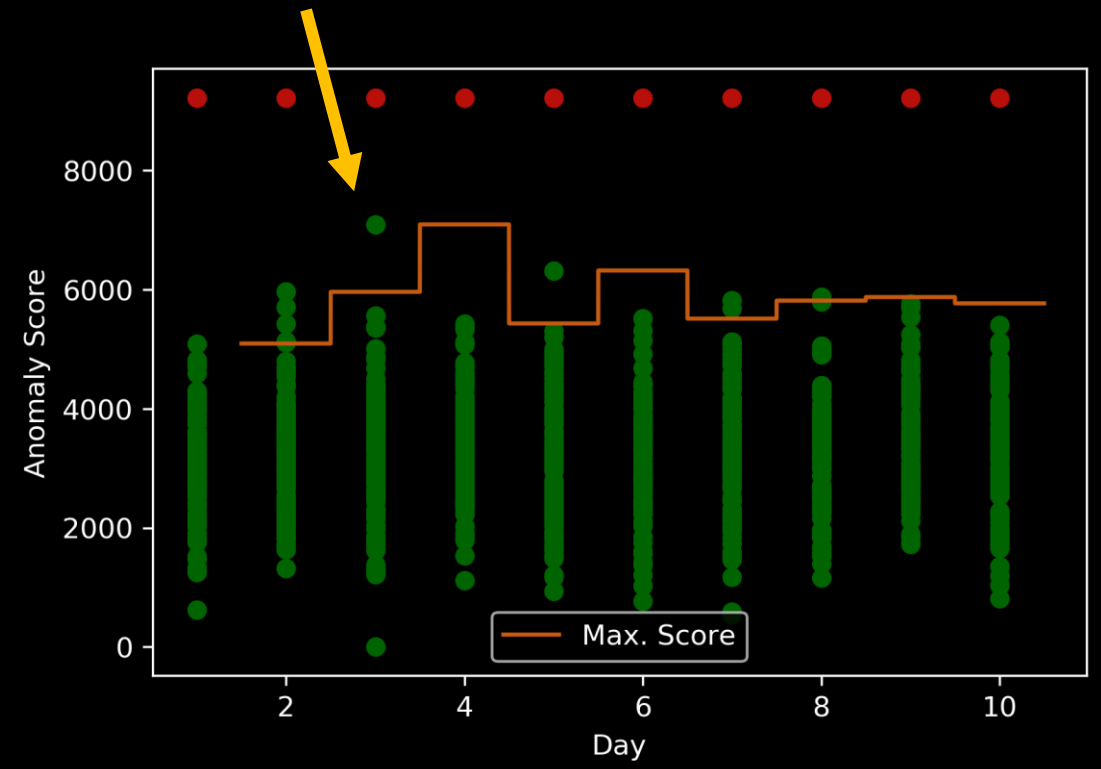
Argus – High Level Overview



Argus – Anomaly-Score Classification

1. Calculate max. score of previous day

$$Max_{d-1} = \max(Scores_{d-1})$$



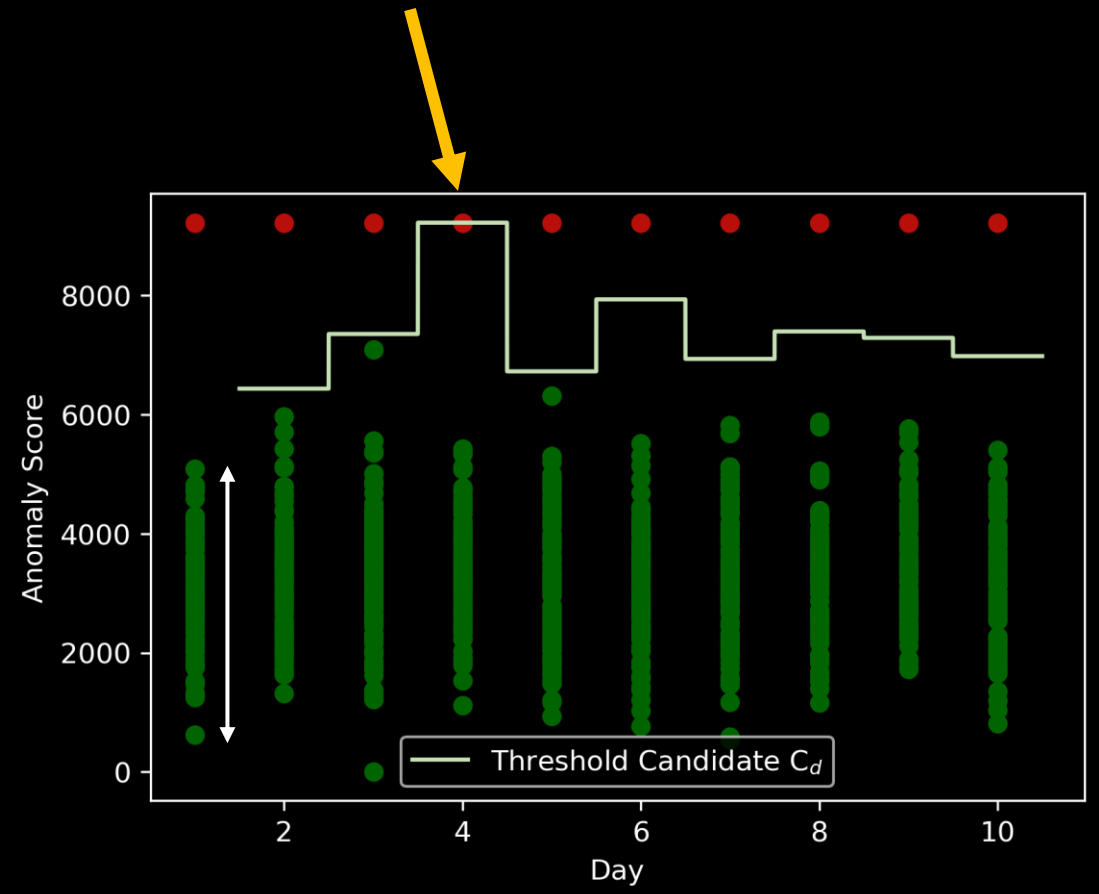
Argus – Anomaly-Score Classification

1. Calculate max. score of previous day

$$Max_{d-1} = \max(Scores_{d-1})$$

2. Add interval of values from previous day
   - Multiply interval with security level β
   - Threshold Candidate C_d:

$$C_d = Max_{d-1} + \beta \cdot (Max_{d-1} - Min_{d-1})$$



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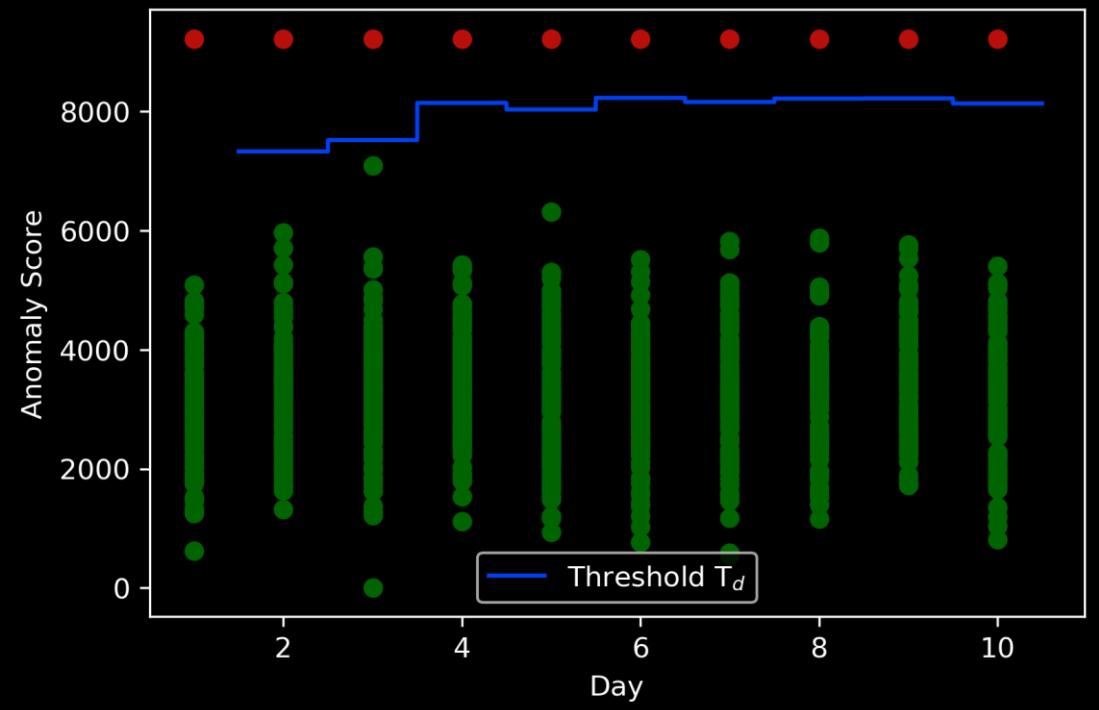
   - Threshold Candidate C_d:

$$C_d = Max_{d-1} + \beta \cdot (Max_{d-1} - Min_{d-1})$$

3. Consider history to avoid extreme changes
   - Multiply with aging factor α
   - Threshold T_d:

$$T_d = \alpha \cdot T_{d-1} + (1 - \alpha) \cdot C_d$$

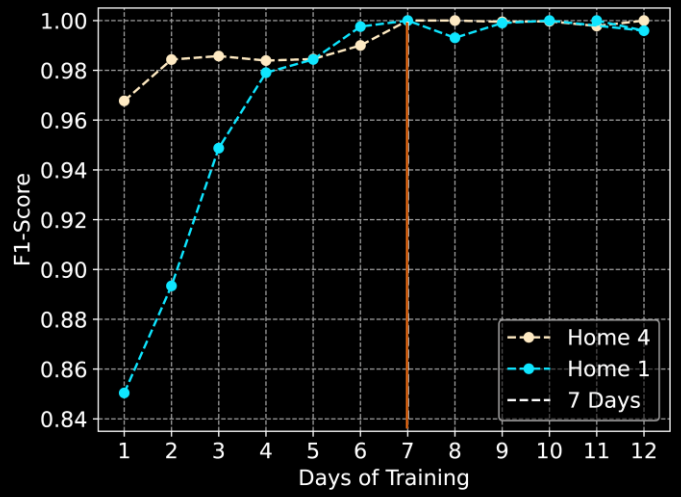


Evaluation Results

FPR: False Positive Rate
PRC: Precision
REC: Recall

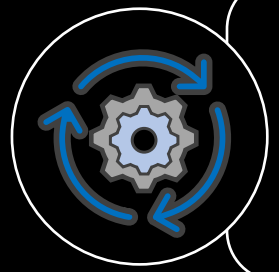
- Evaluation Setup
  - 5 Real World Homes
  - Child and Adult Inhabitants
  - Apartments, Single-Room Apartment, Room in shared Flat
- Evaluated Attacks Include:
  - Door Open during Absence
  - Lights-On during Absence
  - Movement during Absence
  - Lights-On During Night
- 7 Days of Training Data Sufficient

Dataset	FPR	PRC	REC	F1-Score
Home 1	0.03%	99.22%	100.00%	99.64%
Home 2	0.00%	100.00%	100.00%	100.00%
Home 3	0.00%	100.00%	100.00%	100.00%
Home 4	0.00%	100.00%	100.00%	100.00%
Home 5	0.00%	100.00%	100.00%	100.00%



Conclusion

- IoT Devices are vulnerable to attacks via insecure control devices
- Network-Based Detection mechanisms fail detecting such attacks as network traffic is indistinguishable
- Existing contextual defenses requires manual setup or information about devices



- ARGUS monitors IoT device context to detect attacks exploiting insecure control plane
- Models normal behavior using Deep Auto-Encoder to calculate anomaly score
- Calculates dynamic threshold to classify anomaly-score

- No knowledge on devices or attacks necessary
- Works without manual setup
- 7 days of training data achieved F1-Score $\geq$ 99.64% on 5 real-world homes