

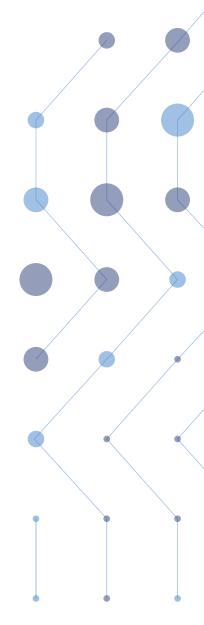
CP-IoT: A Cross-Platform Monitoring System for Smart Home

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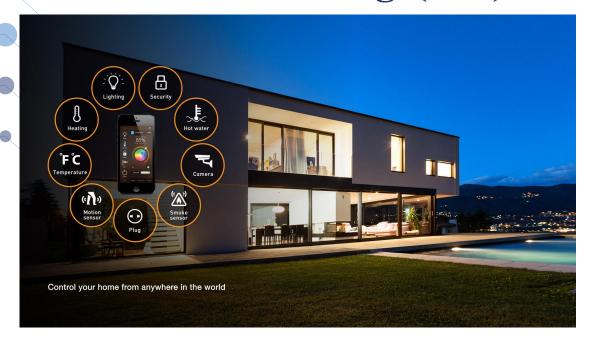








Internet of Things(IoT) is all around





Smart Homes

Smart Farms





Smart Healthcare

Smart Home facilitates our life

Smart Home Platforms







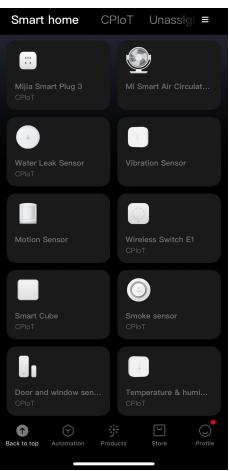


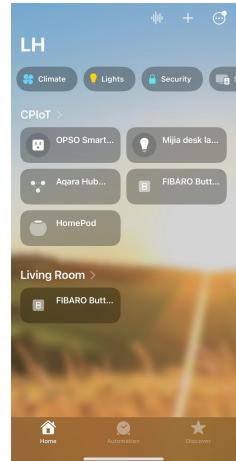




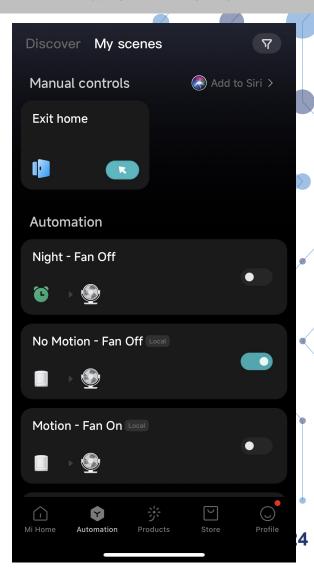


Smart Applications

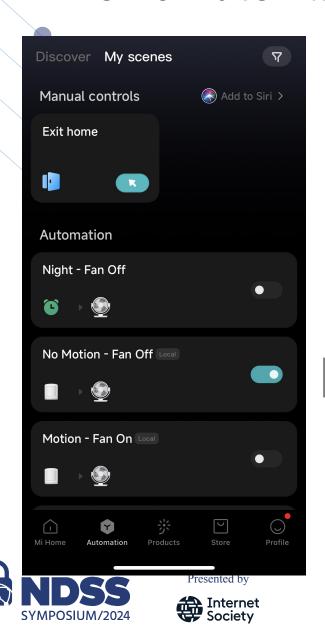




Automations



Home Automation Rule





IF Event occurs THEN send Command this that

Automation Rule: Night-Fan Off

E: Time at night(22 pm) C: Turn off the fan

 $E_{time.night}^{Time} \rightarrow C_{switch.off}^{Fan}$

Automation Rule: No Motion- Fan Off

E: No motion detected C: Turn off the fan

 $E_{motion.active}^{Sensor} \rightarrow C_{switch.off}^{Fan}$

Home automation faces various security problems

Automation is not trigging - Will run manually

■ Configuration automation



glen4cindy

I've got a sensor for my garage door that reports open/closed conditions.

I've tried to set up an automation that will send a message if the door has been left open.

I'm pretty sure there must be something going on with how I have the automation configured because if I run it manually it works and sends the alert. If I just let things ride the automation never fires off even if I open the door and leave it open beyond the 10 minute threshold.

All of these problems caused by attacks, device malfunctions or faulty applications

2d

Sometimes lights turn off randomly

■ SmartApps & Automations



Aug 2020

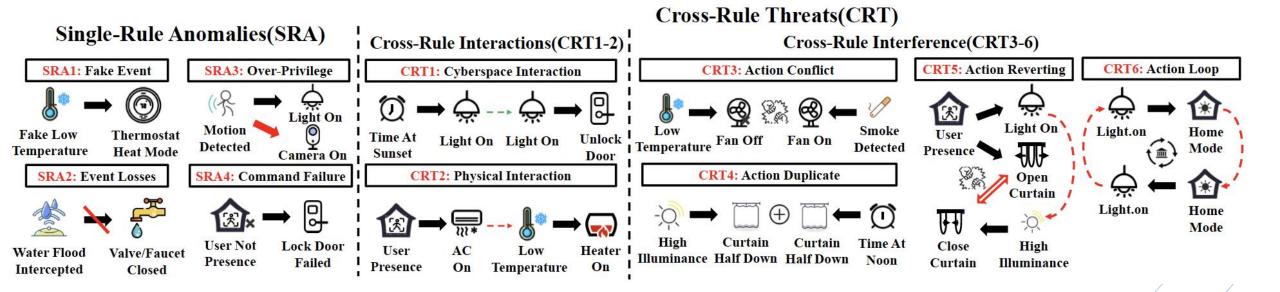
Hello all,

I have a couple GE smart switches that seem to turn off all by themselves at random times. All switches are 1-5 years old and I haven't mad any new routines lately, either. I do, however, have guite a few devices to control the switches (Action Tiles, Google Home, phones, tablets, etc.) Where do I start troubleshooting?





Various known threats types in home automation



Single-Rule Anomalies(SRA): Anomalies in automation rule execution

Cross-Rule Threats(CRT): Dangerous interactions and interferences across multiple rules. CRT also occur across multiple platforms.





How can we detect all these threats and support multiple smart home platforms?

Solution

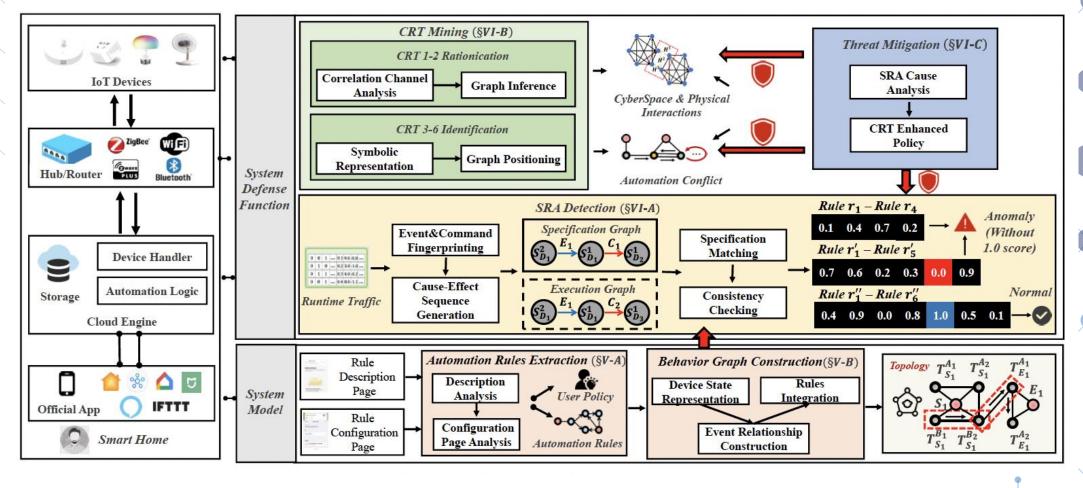
We need a monitoring system for smart home to ...

- **Extracting semantics** of automation rules from different platform apps
- ➤ **Modeling** devices and rules deployed on each platform
- ➤ **Identifying** the behavior of rule execution from the runtime environment and **detecting** anomalies
- ➤ Mining potential threats among various rules and proposing security policies to mitigate them





***CP-IoT**



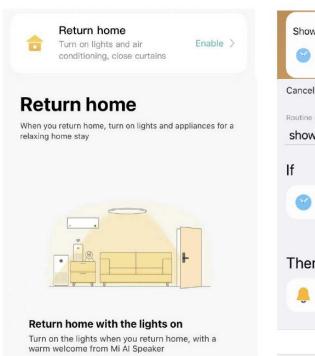
CP-IoT is a monitoring system for automation rule and device behaviors.

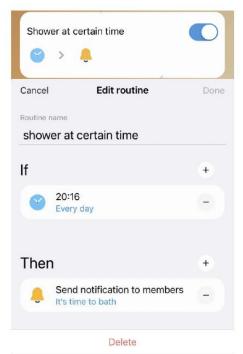
CP-IoT supports multiple smart home platforms.

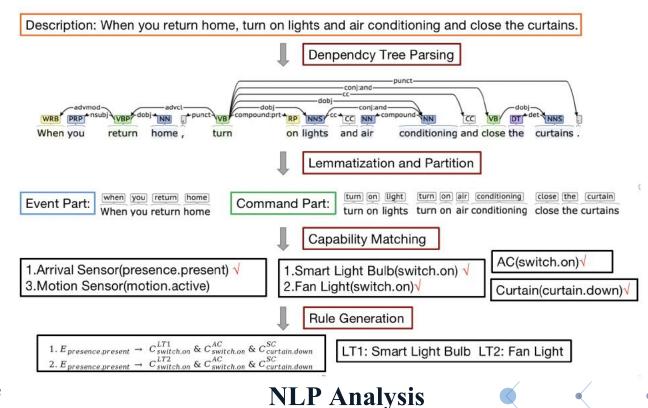


SYMPOSIUM/2024

Automation rules extraction



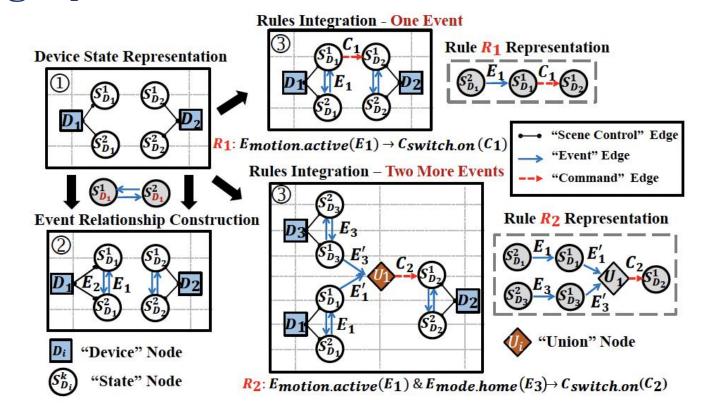




Rule description page Rule configuration page

- Two-stage analysis method on app pages
- > First Stage: Apply NLP analysis to collect semantics in rule description sentences.
- > Second Stage: Extract user-defined parameters from the rule configuration page and supplement first-stage rule semantics.

Behavior graph construction



- Building a centralized graph containing information from multiple platforms
- ➤ Model device information and device state as **nodes**
- > Model the event and command parts of a rule as edges between state nodes
- ➤ A state transfer chain represents the execution specification of a rule

Runtime Behavior Identification - Event&Command Fingerprinting

$$P = \{p_1, p_2, ..., p_N\}$$

The traffic generated by a rule execution(N packets)



$$P = \{P_1, P_2, ..., P_Q\}$$
 s.t. $\sum_{i=1}^{Q} |P_i| = N$

Split the traffic into flows of events/commands



$$m_{P_i} = \begin{cases} p_{1,s_1} & p_{1,s_2} & p_{1,s_3} \\ p_{2,s_1} & p_{2,s_2} & p_{2,s_3} \\ \vdots & \vdots & \vdots \\ p_{s,s_1} & p_{s,s_2} & p_{s,s_3} \end{cases}$$

Packet-Level Fingerprint



Internet Society

Presented by

Constructing fingerprint for each event/command P_i (has s packets)

$$f_{P_i}:(f_{i,1},\,f_{i,2})$$

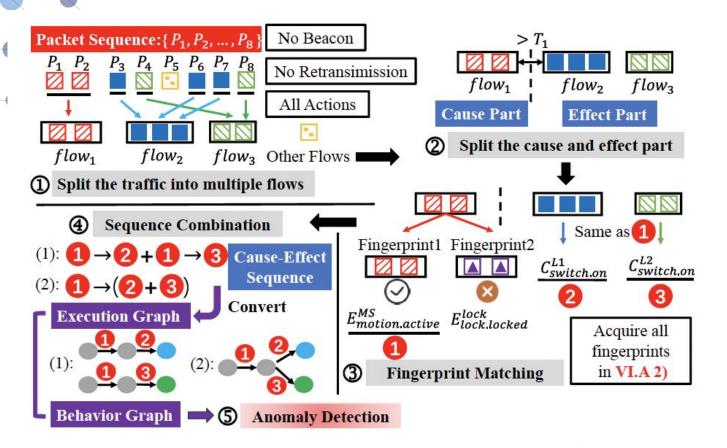


Execute the rule T times and perform KMeans clustering on the resulting T event fingerprints

Eliminate the effects of **network** latency and signal interference

Type	Statistic	Notation	Description		
	Size	s_1	Packet size will vary from event to event		
Packet	Protocol	s_2	WiFi(0), Z-Wave(1) Zigbee(2), Bluetooth(3)		
	Direction	s_3	$\begin{array}{c} 0: \ device \rightarrow router \\ 1: \ router \rightarrow device \end{array}$		
El	Interval	f_1	Average packet interval		
Flow	Length	f_2	The length of packet sequence		

Runtime Behavior Identification - Cause-Effect Sequence Generation

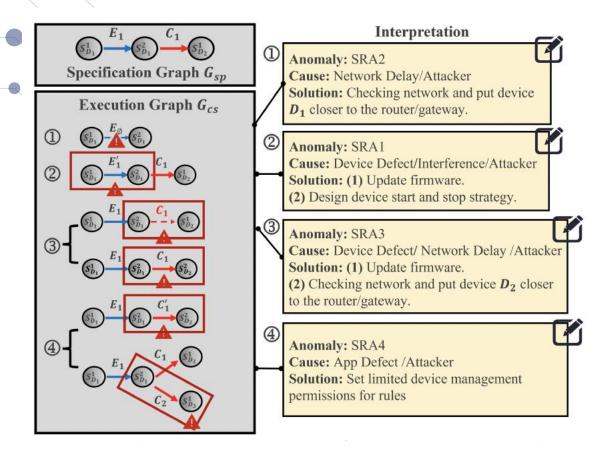


$$\underset{E_{i}/C_{i}}{\operatorname{argmin}} \left(\underbrace{\lambda \cdot D\left(F_{i}, \ f_{j}\right)}_{Flow \ d_{f}} + \underbrace{\delta \cdot D\left(M_{i}, m_{j}\right)}_{Packets \ d_{p}} \right) \quad s.t. \ d_{f} + d_{p} \leq d_{p}$$

Calculate the **Manhattan Distance** and select the event/command that has the minimum weighted distance

- \triangleright Match runtime flow features (f_j, m_j) with all fingerprints (F_i, M_i) to identify which event occurs
- > Combine multiple events and commands into cause-effect sequence based on dependencies
- Convert cause-effect sequence to the rule execution graph

Single-Rule Anomalies(SRA) detection



Specification Matching

Locate the most similar part in the centralized graph based on all the events and commands contained in the execution graph.

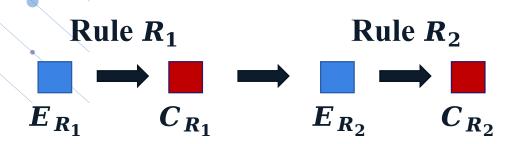
Consistency Checking

- Calculate the similarity between two graphs based on node attributes, edge attributes and topology
- Any inconsistency that occurs is an anomaly

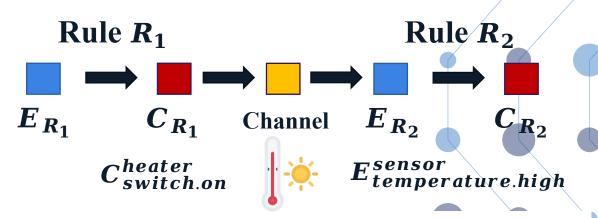




Cross-Rule Interactions Discovery



- Cyberspace Interactions
- ightharpoonup The result of the execution of Rule R_1 can directly trigger Rule R_2
- \triangleright Constraints: $C_{R_1} \supseteq E_{R_2}$



- Physical Interactions
- The result of the execution of Rule R_1 change the physical environment and indirectly trigger Rule R_2
- ➤ Physical Correlation Analysis: Applying the BERT model to calculate the correlation scores between the command actions of each rule and the 11 physical channels.
- ightharpoonup Constraints: $Corr(C_{R_1})\supseteq E_{R_2}$





Cross-Rule Interferences Identification

Туре	Representation			
Action Conflict CRT3	$\exists q_1 \in C_{r1}, q_2 \in C_{r2} S_1^s = q_1.suc, S_2^s = q_2.suc s.t. S_1^s.cp = S_2^s.cp, S_1^s.val \neq S_2^s.val$			
Action Duplicate CRT4	$\exists q_1 \in C_{r1}, q_2 \in C_{r2} $ $S_1^s = q_1.suc, S_2^s = q_2.suc$ $s.t. \ S_1^s.cp = S_2^s.cp, S_1^s.val = S_2^s.val$			
Action Reverting CRT5	$\exists q_1 \in C_{r1}, q_n \in C_{rn} \\ S_1^s = q_1.suc, S_n^s = q_n.suc \\ s.t. \ S_1^s.cp = S_2^s.cp, S_1^s.val \neq S_n^s.val, \\ \forall_{i=1}^{n-1}(r_i, r_{i+1}) \in S_{cyb}/S_{phy} $			
Action Loop CRT6	$s.t. E_{r1} \subseteq C_{rn}$ $\forall_{i=1}^{n-1}(r_i, r_{i+1}) \in S_{cyb}/S_{phy}$			

Symbolic Representation

Representation of various interference types as constraints on graphs based on their semantics.

Graph Positioning

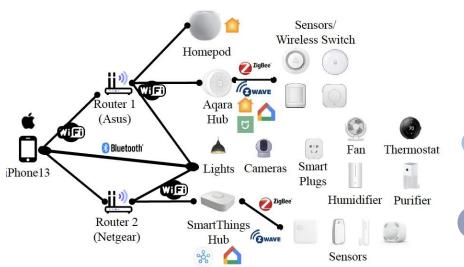
- For action conflict and action duplicate, find **two** rules on the graph that satisfy the constraints.
- For action reverting and action loop, find **two** more rules on the graph that satisfy the constraints.





Testbed





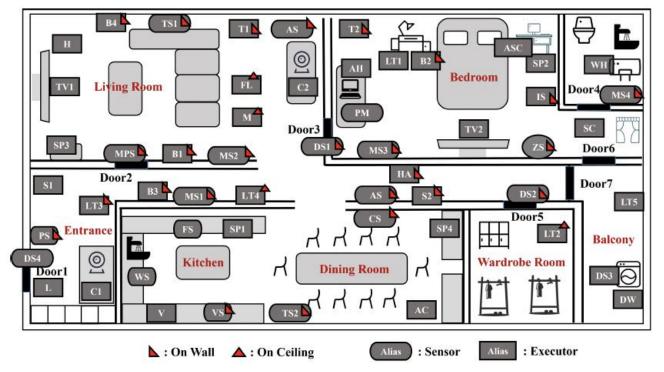
Real Testbed

- ➤ 32 IoT devices and 4 platforms: Homekit, SmartThings, Google Home, Xiaomi Home
- Automation rules: SmartThings(105), Homekit(128), Google Home(160), Xiaomi Home(192)
- Anomalies: Each rule injects four anomaly types





Testbed





- > 54 IoT devices
- **2491 automation rules**: Crawl 10796 applets from the IFTTT website and 82 SmartApp from the SmartThings Public GitHub Repository, and filter 2491 rules associated with these devices.





Rule Extraction Accuracy

Platform	Word2	Vec [47]	BERT [38]		
Flationii	DAnalysis	+CAnalysis	DAnalysis	+CAnalysis	
SmartThings(105)	89.52%	92.38%	91.43%	97.14%	
Apple Homekit(128)	89.06%	96.09%	92.97%	99.22%	
Google Home(160)	83.13%	95.63%	91.25%	98.13%	
Xiaomi Home(192)	85.94%	91.15%	88.02%	98.96%	

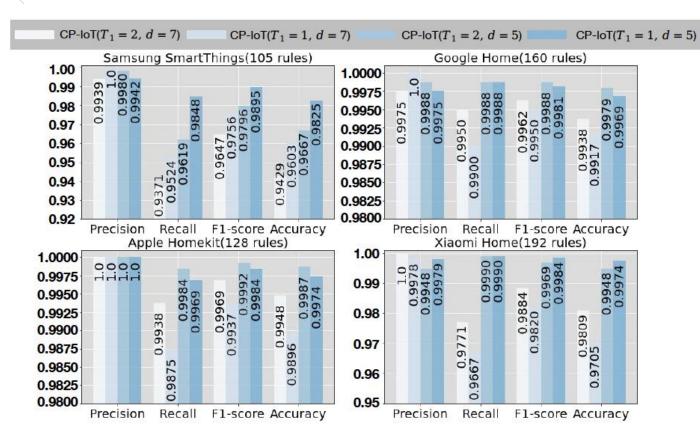
DAnalysis: Description Page Analysis **CAnalysis**: Configuration Page Analysis

- ➤ Using Word2vec or BERT for device capability matching and BERT outperform Word2vec.
- ➤ BERT average accuracy higher than **98.9%**
- A percentage of the description statements are ambiguous, and the accuracy of rule semantic extraction can be improved by configuration analysis





Anomaly Detection Performance



T₁, d: Predefined parameters
T₁: Time interval of dependencies
d: Allowable error range for fingerprint matching

- ➤ **Average precision:** higher than 99.0%
- > Average recall of CP-IoT with the best configuration: higher than 98.0%.
- False Negative Causes: (1) Small packet deviation (2) Fail to get the log information
- (3) SmartThings have high response latency and may be caused by proxy servers.

Cross-Rule Threats Discovery Performance

No.	Rule1	Rule2	Type	Testbed	Risk	No.	Rule1	Rule2	Type	Testbed	Risk
1	$E_{presence.present}^{sensor} \rightarrow C_{switch.on}^{fan}$	$E_{motion.active}^{sensor} \rightarrow C_{switch.on}^{light}$	P	R	Low	9	$E_{motion.active}^{sensor} \rightarrow C_{switch.on}^{light}$	$E_{illuminance.high}^{sensor} \rightarrow C_{windowShade.close}^{curtain}$	P	S	Low
2	$E_{vibration.active}^{sensor} o C_{switch.on}^{humidifier}$	$E_{water.wet}^{sensor} \rightarrow C_{color.blue}^{light}$	P	R	Low	10	$E^{sensor}_{CO.detected} \rightarrow C^{siren}_{alram.siren}$	$E_{sound.high}^{sensor} \rightarrow C_{volume.down}^{TV}$	P	S	Low
3	$E_{motion.active}^{sensor} \rightarrow C_{switch.on}^{humidifier}$	$E_{humidity.high}^{sensor} \rightarrow C_{switch.on}^{fan}$	P	R	Low	11	$E^{sensor}_{dustLevel.high} \rightarrow C^{robot}_{switch.on}$	$E_{motion.active}^{sensor} \rightarrow C_{switch.on}^{dishwasher}$	P	S	High
4	$E^{sensor}_{smoke.detected} \rightarrow C^{fan}_{switch.on}$	$E_{temperature.low}^{sensor} \rightarrow C_{mode.heat}^{thermostat}$	P	R	High	12	$E_{humidity.low}^{sensor} \rightarrow C_{switch.on}^{humidifer}$	$E_{energy.high}^{powerMeter} \rightarrow C_{switch.off}^{camera}$	P	S	High
5	$E_{button.pressed}^{button} \rightarrow C_{mode.heat}^{thermostat}$	$E_{temperature,high}^{sensor} \rightarrow C_{switch.on}^{fan}$	P	R	Low	13	$E_{contact.closed}^{sensor} \rightarrow C_{switch.off}^{TV}$	$E_{sound.low}^{sensor} \rightarrow C_{switch.on}^{camera}$	P	S	High
6	$E_{temperature.low}^{sensor} \rightarrow C_{switch.off}^{fan}$	$E_{motion.inactive}^{sensor} \rightarrow C_{switch.on}^{camera}$	P	R	High	14	$E_{dustLevel.high}^{sensor} \rightarrow C_{switch.on}^{robot}$	$E_{presence.present}^{sensor} \rightarrow C_{lock.unlocked}^{lock}$	P	S	High
7	$E_{contact.open}^{sensor} \rightarrow C_{switch.on}^{light}$	$E_{switch.on}^{light} o C_{color.blue}^{light}$	C	R	Low	15	$E^{sensor}_{illuminance.low} \rightarrow C^{light}_{switch.on}$	$E_{switch.on}^{light} \rightarrow C_{windowShade.open}^{curtain}$	C	S	Low
8	$E^{Time}_{time.night} \rightarrow C^{Mode}_{mode.night}$	$E^{Mode}_{mode.night} \rightarrow C^{camera}_{switch.on}$	C	R	High	16	$E_{motion.active}^{sensor} \rightarrow C_{mode.home}^{Mode}$	$E_{mode.home}^{Mode} ightarrow C_{window.open}^{window}$	C	S	High

Found some typical cross-rule interactions

Number Method	LaTCara	Dulan	CP-IoT
Kind	IoTGaze	iRuler	CP-101
Physical Interactions(CRT1)	827	N/A	1461
Cyberspace Interactions(CRT2)	344	N/A	1072
Action Conflict(CRT3)	N/A	4619	4723
Action Duplicate(CRT4)	N/A	6025	6108
Action Reverting(CRT5)	N/A	2704	2855
Action Loop(CRT6)	N/A	1856	2039

- Find more cross-rule interactions: CP-IoT considers more channels and rules combination
- Slightly more cross-rule interferences: both CP-IoT and iRuler perform a complete searching of the rule combination space, but CP-IoT considers more feasible rule chains triggered by multiple physical interactions.





Thanks for listening!



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