IOT Security With Parametric Signal Temporal Logic

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ABSTRACT

Being one of the most rapidly growing technologies today with its predicted count of 22 billion in 2025, IoT devices and the systems containing these devices are getting increasingly more diverse and complicated. Keeping these IoT systems secure is an important yet challenging problem due to the hidden interactions between devices that can potentially result in security rule conflicts and violations of user intentions. To detect these conflicts and violations due to hidden interactions, we first introduce a novel approach to characterizing time-based interaction rules using Parameterized Signal Temporal Logic (PSTL). Then, we then propose STLTree, an adaptation and expansion of a decision tree learning algorithm for PSTL, to learn these interaction rules from a device operational log. Next, we define a notion of security in an IoT environment as an environment free of conflicts between interactions and user-desired security rules. Building on this work, we then propose two complementary approaches to detecting rule conflicts: (1) STLMon, which dynamically monitors IoT device behavior for rule violations, and (2) STLCheck, statically checks for the conflicting behaviors between and within device state changes and the user-defined rules. Finally, we show that STLTree is able to automatically generate rules that capture relevant interactions in our testing environment. Also, we demonstrate the efficiency of STLMon in detecting rule violations at runtime, and the utility of STLCheck in static generation of possible rule violations.

Dedication

Thank you Professor Eunsuk Kang to being a great thesis mentor, thank you for your continuous encouragement, support and steering to me towards the right direction for moving the project forward.

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List of Abbreviations

G

GG Gini Gain. xxi

I

IG Information Gain. ii, xvi, xx, l

IoT Internet of Things. iii, viii

M

MCCP Multi-Class Classification Problem. i, xv

MCR Misclassification Rate. xv

P

PSTL Parametric Signal Temporal Logic. iii, viii, x, xii, xiii, xlvii, xlviii

S

SA Simulated Annealing. ii, xx, xxiv, l

SMT Satisfiability Modulo Theory. xiii

STL Signal Temporal Logic. xii, xiii, xlvii

1 Introduction

Internet of Things (IoT) is a blanket term for various gadgets that most people do not think as computers but still have the computing power and an internet connection, which makes them able to communicate with each other in their corresponding IoT environment. In the modern era of automation, IoT devices have a considerable impact on people's daily lives; even common household kitchenware and lights that people use everyday can be implemented as IoT. As these IoT devices are becoming increasingly more prevalent, especially in private households, it is crucial to ensure the security of these devices and the environment containing them. However, it is often difficult to keep these IoT environments secure as they can have complex behaviors from the hidden interactions between the IoT devices. This project is motivated by the complications in achieving IoT security from the hidden interactions and aims to solve the challenges caused by these interactions by characterizing, learning, and conflict checking them through Parametric Signal Temporal Logic (PSTL).

In subsection 1, we show an example of the hidden interactions in IoT environments and demonstrate its impact on security. Then, from the inspiration of our example, we define our notion of IoT environment safety in subsection 2. Finally, in subsection 3 and 4, we formalize our problem statement for the project and provide an overview of our proposed solution approach.

1.1 Motivating Example

To demonstrate the effect of hidden interactions in IoT environments, consider an apartment where the owner has installed an oven, a smoke alarm, and a door as IoT devices. In an apartment setting, these IoT devices are often implemented and installed by third parties with interaction rules that may not be known to the household owner. In our example case, suppose that the owner only knows about the safety claims made by the third parties, such as the door will be unlocked to let the owner out to safety when the smoke alarm sirens, without actually knowing how these devices are implemented.

Now, while the owner could be satisfied by this claim, interactions that are capable of controlling important devices such as the door raises red flags in the perspective of a security expert. While unlocking the apartment door is a necessary measure to protect the owner from fires, unlocking the door in situations such as when the owner is not at home during a false alarm could also lead to security risks. Although for some situations it is safe for the owner to assume that the IoT devices are not installed maliciously, due to the increasing complexity in IoT household environments, it is fairly easy for designers to overlook hidden interactions among devices during implementation that could result in unsafe behaviors.

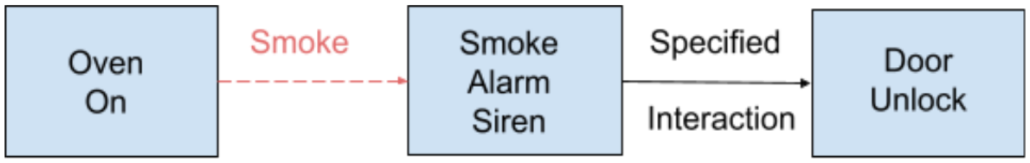


Figure 1: Example hidden interaction, turning on the oven sets of smoke that unlocks the door

For example, in a simple IoT environment shown in Figure 1, while there is no direct device interaction between the oven and the door, the oven has the hidden interaction with the smoke alarm in that it is able to set off smoke when turning on at high temperature for a long time. While the smoke alarm may be highly secure against attacks due to its key role in the security of the apartment with its ability to unlock the door, the oven may be implemented in a less secure way since it has no observable or physically implemented interaction with other devices. As a result, an attacker can compromise the security of the apartment when the owner is not at home by turning the oven on and wait for the door to open as the smoke alarm sirens even if the smoke alarm and the door are perfectly secure.

1.2 Defining Safety

As shown in our motivating example above, to ensure the safety of the apartment, it would be necessary for the owner to know the actual rules that the device interactions follow, including the hidden ones shown in the case above with oven and smoke. Furthermore, the owner would need a way to check for whether any of the interactions would violate the owner's desired safety behavior (For example, the behavior in Figure 1 would violate the safety desire for the door to stay locked if the owner is not home). In our project, we represent these device interactions and used desired behaviors by extracting rules from the IoT environment. Formally, these rules are defined in definition 1 below.

Definition 1: Rule: A rule r can be defined by an implication $precondition \implies state\ value\ specification$, where preconditions describe the necessary conditions that devices in the environment need to be in to trigger the rule, while specification represent the value of a specific device when the preconditions are met.

With device interactions and user desired behaviors being described as abstract rules, we then define an IoT environment to be safe in Definition 2 and 3 below.

Definition 2: Safety Given a set of device interaction rules $R = \{r_1, r_2, ..r_n\}$ in environment E and user desired behavior rules $U = \{u_1, ...u_n\}$, E is safe if and only if there are no conflicts in $R \cup U$.

Definition 3: Conflict: Given a set of rules S, a conflict occurs if there are multiple rules $s_1, ...s_n$ that specify the same devices to be in different state values $k_1, ...k_n$ that have rule preconditions that can be satisfied at the same time.

By definition 1, $rule\ violation$ is straightforwardly defined to be having devices in different states than what is specified in the rule when the preconditions are met. We defined environment safety in terms of lack of conflicts due to the intuition that it is impossible to have device, say a light switch, to be on and off at the same time. Such conflicts inevitably results in rule violations that are likely to result in safety failures.

1.3 Problem Statement

From our motivation, we define the problem this project is trying to solve in the following statement:

In an IoT environment, how do we detect hidden interactions among the devices that could result in safety failures?

By our definition of rule, safety, and conflicts above, our problem statement is broken down into the following subproblems:

1. Extracting rules from the environment that capture hidden interactions
2. Detecting conflicts among device interaction and user desired behavior rules

In our project, the second subproblem for conflict detection is further broken down into finding a runtime and a static time solution.

1.4 Proposed Approach

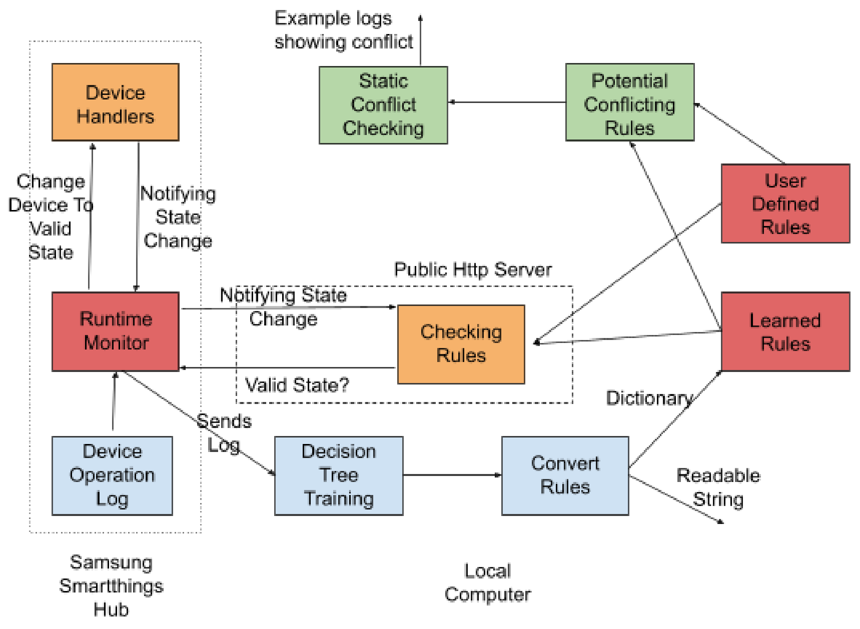


Figure 2: Proposed Approach Overview, Blocks regarding STLTree implementation are shown in blue, STL-Mon in orange, and STLCheck in green. Shared blocks are shown in red.

As demonstrated in Figure 2, we have first characterized the device interaction and user desired behavior through immediate rules specifying immediate device changes and PSTL rules defined in [ADMN12] specifying time related behavior. We then have constructed STLTree, a decision learning tree algorithm adapted from the tree model in [BVP^{+}16] and expanded with the capability of learning PSTL rules from device operation logs of each IoT environment, and TreeNoSTL, a decision tree learning algorithm for learning the immediate rules. Then, to solve the second subproblem regarding security concerns, we have implemented STLMon, a monitor that checks for device changes and detects rule violations within each environment at runtime, and STLCheck, a static time conflict checker for the rules. Currrently, our tools are implemented specifically for Samsung Smartthings IoT environments due to the platform's virtual simulation feature; however, the implementations can be trivially converted for environments on other platforms with minor adjustments in acquiring and preprocessing device operational logs.

For the remaining of the paper, Section 2 introduces the background for Samsung Smartthings Environment, PSTL rules, and mathmatical foundations that are needed for the implementation of the tools. Then, Section 3 elaborates on the implementation and evaluation of STLTree and TreeNoSTL, Section 4 on STLMon, and Section 5 on STLCheck respectively. Finally, we discuss the related work, conclusion, and future work in section 6 and 7.

2 Preliminaries

2.1 Samsung Smartthings IoT Environment

The IoT environments our models will be targeting and using for testing are constructed through the Samsung Smartthings platform [Smab]. A Samsung Smartthings environment can further be broken down into smartapps, device handlers, and rest of the hub for coordinating and storing log regarding device operations. An illustration of a Smartthings environment is shown in Figure 3, and we will elaborate on each part of the environment in the subsections below.

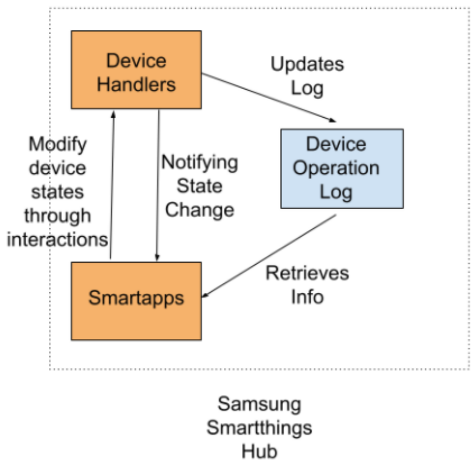


Figure 3: Smartthings Environment Overview

Each IoT device can be either controlled physically or through Smartapps, which can automatically change a device's behavior when conditions for the app to run are met. As a result, these smartapps contribute significantly to the device interactions of the environment. There would be noise while device interactions, as devices are able to change states by purely random choice of user's physical control. Due to this noise, our models would only operate on device interactions that they have a high confidence on, so that this noise would have a negligible impact.

2.1.1 Smartapps

Each Samsung Smartapp first specifies a list of devices it has access to their preference configuration block. When a device grants access to a Smartapp, it gives the app the ability to subscribe to its state changes, directly change its state, and access all of its past state changes. Each Smartapp also has the ability to communicate outside of Smartthings using OAuth, and is able to handle requests from local servers with the correct key and token for accessing data.

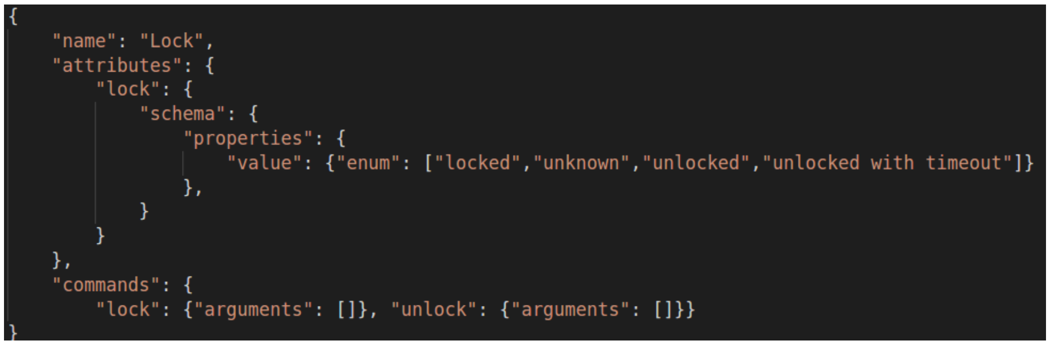
2.1.2 Device Handlers

Each Smartthings device is associated with a device handler, which is used to handle state change commands sent by the Smartapp. The device handlers have specific functions for each possible state change, which is described by the capabilities of their corresponding device. In order to change the device state, Smartapps can simply communicate with the device handlers by calling the function on their subscribed device.

For most capabilities, the corresponding state change function has the identical name as the state value the user wanted to change. For example, calling *switch.on()* turns a switch on. For others, it is fairly easy to infer the state change function for the corresponding value change as shown in Figure 4 below. A complete list of Samsung Smartthings device capabilities and their corresponding state change functions can be found in [Smaa].

2.1.3 Samsung Smartthings Hub

The Samsung Smartthings Hub is used to coordinate interactions between devices and Smartapps in each IoT environment. When a device state change occurs, the hub sends the event to all Smartapps that are subscribed to the handler event. When a Smartapp responds with a device change, the Smartthings Hub sends the device change to the device handler to execute. All the events and device state changes in a Smartthings environment are also stored in



```
{
    "name": "Lock",
    "attributes": {
        "lock": {
            "schema": {
                "properties": {
                    "value": {"enum": ["locked","unknown","unlocked","unlocked with timeout"]}
                },
            }
        }
    },
    "commands": {
        "lock": {"arguments": []}, "unlock": {"arguments": []}}
}
```

Figure 4: A part of the capability specification for the Lock device; 'lock' changes the device state to locked while 'unlock' changes it to unlocked. Other property values can only be reached through device failures

Samsung Smartthings Hub and can be retrieved through Smartapp communication. However, it is only possible to store 200 state and event changes for each device in the hub, and past changes will be replaced by newer ones.

2.2 PSTL Rules

In a typical IoT environment, most device interactions does not happen immediately; instead, time is always relevant factor for most device interactions. For example, in the oven and door example in the introduction, turning the oven on would not cause smoke to occur immediately; it would require the oven being on for a period of time for our hidden action of smoke to trigger. As a result, we used Parametric Signal Temporal Logic (PSTL) [ADMN12], an extension of Signal Temporal Logic (STL) [MN04] with setting parameters as learning objectives, as the underlying language for specifying the preconditions for device interaction and user defined behavior rules in the environment to encapsulate this time-sensitive characteristic. We chose PSTL over other approaches such as state machines in characterizing device interaction rules due to the language's simplicity and readability.

2.2.1 Syntax and Semantics of STL

A signal is defined to be a continuous-time, continuous-valued function s mapping from $\mathbb{R}^+$ to $\mathbb{R}^n$. We use $s(t)$ to denote the value of signal s at t, and $s[t]$ to denote the value of s shifted by t time units. Then, by our definition, $\forall \tau \in \mathbb{R}^+, s[t](\tau) = s(\tau + t)$. The Boolean clauses of a STL rule are corresponding to each individual component s_i of s, $i \in \{1, 2, ..., n\}$, which each component can be obtained through functions in set $G = \{g_i : \mathbb{R}^n \to \mathbb{R}, g_i(s) = s_i\}$. Now, the syntax of STL is defined as follows:

$$\phi ::= \top \mid p_{g(x)\leq\mu} \mid \neg\phi \mid \phi_1 \wedge \phi_2 \mid \phi_1 \vee \phi_2 \mid \phi_1 U_{[a,b)} \phi_2$$

where $\top$ is True, and $p_{g(x)\leq\mu}$ is a predicate clause over $\mathbb{R}^n$ defined by the function $g \in G, \mu \in \mathbb{R}$, and $p_{g(x)\leq\mu} \iff g(x) \leq \mu$. $\neg$, negates the predicate, $\vee, \wedge$ joins the predicates by boolean or and and relations, and $U_{[a,b]}$ is a special until operator to for time dependent predicates. With this, the semantics of STL is defined as:

$$\begin{aligned}
s[t] \models \top &\iff \top \\
s[t] \models p_{g(x)\leq\mu} &\iff g(s(t)) \leq \mu \\
s[t] \models \neg\phi &\iff \neg(s[t] \models \phi) \\
s[t] \models (\phi_1 \wedge \phi_2) &\iff (s[t] \models \phi_1) \wedge (s[t] \models \phi_2) \\
s[t] \models (\phi_1 \vee \phi_2) &\iff (s[t] \models \phi_1) \vee (s[t] \models \phi_2) \\
s[t] \models (\phi_1 U_{[a,b)} \phi_2) &\iff \exists t' \in [t+a, t+b] \; s.t \; (s[t'] \models \phi_2) \\
&\quad\;\; \wedge (\forall t_1 \in [t, t'], s[t_1] \models \phi_1)
\end{aligned}$$

A signal $s \in S$ is said to satisfy STL formula ϕ if and only if $s[0] \models \phi$. Due to their common appearance, $\top U_{[a,b]} \phi$ is defined to be the *eventually* operator, denoted $\mathbf{F}_{[a,b]}\phi$, and $\neg\mathbf{F}_{[a,b]}\neg\phi$ is defined to be the *globally* operator, denoted $\mathbf{G}_{[a,b]}\phi$. The name *eventually* and *globally* is due to the until operator's semantics, which gives us the following after plugging in the predicates:

$$\mathbf{F}_{[a,b]}(\phi) \iff \exists t' \in [t+a, t+b] \; s.t \; (s[t'] \models \phi)$$

and

$$\mathbf{G}_{[a,b]}(\phi) \iff \forall t' \in [t+a, t+b], \neg(s[t'] \models \neg\phi) \iff \forall t' \in [t+a, t+b], s[t'] \models \phi$$

Finally, $p_{g(x)>\mu}$ can be trivially extended to our syntax, defined as $\neg p_{g(x)\leq\mu}$.

2.2.2 Parametric Signal Temporal Logic

A PSTL formula is an extension to a STL formula where all the time bounds $[a, b]$ in temporal operators and associated constants μ are replaced by free parameters. The parameters for $[a, b]$ and μ are called time and space parameters respectively. Note that if ψ is a PSTL formula, then every parameter assignment θ induces a corresponding STL formula ϕ_θ, which is constructed by having all the space and time parameters of ψ fixed according to θ.This process is called a valuation of ψ. Finally, the parameter space for a PSTL formula ψ with no additional restrictions is infinite, as there are infinite possible tuples $[a, b]$ for time parameters where a, b is in domain $\mathbb{R}^+$.

2.2.3 PSTL Primitives in IoT Environments

To characterize the preconditions device interaction and user defined rules in an IoT environment, we utilize [BVP+16]'s construction of first and second level primitives from PSTL formulas; the primitives are defined below.

First-Level Primitives Let $S \subset \mathbb{R}^n$ be a set of signals with $n \geq 1$, the first level-primitives is defined as

$$P_1 = \{\mathbf{F}_{[a,b]}(x_i \sim \mu) \textit{ or } \mathbf{G}_{[a,b]}(x_i \sim \mu) | \; i \in \{1, ..., n\}, \sim \in \{\leq, >\}\}$$

where a, b, μ being the parameters. The space of parameters is defined to be
$\Theta_1 = \mathbb{R} \times \{(\tau_1, \tau_2) | \tau_1 < \tau_2, \tau_1, \tau_2 \in \mathbb{R}^+\}$. The meaning of first level primitives can be directly translated from the the definition of their respective temporal operators. With $\mathbf{F}_{[a,b]}(x_i \sim \mu)$ meaning $x_i \sim \mu$ happens at least once in $[a, b]$, and $\mathbf{G}_{[a,b]}(x_i \sim \mu)$ meaning $x_i \sim \mu$ happens for all times in $[a, b]$ from semantics in 2.2.1.

Second-Level Primitives Let $S \subset \mathbb{R}^n$ be a set of signals with $n \geq 1$, the second level-primitives is defined as

$$P_2 = \{\mathbf{F}_{[a,b]}\mathbf{G}_{[0,c]}(x_i \sim \mu) | \; i \in \{1, ..., n\}, \sim \in \{\leq, >\}\}$$

where a, b, c, μ being the parameters. The space of parameters is defined to be
$\Theta_1 = \mathbb{R} \times \{(\tau_1, \tau_2) | \tau_1 < \tau_2, \tau_1, \tau_2 \in \mathbb{R}^+\} \times \mathbb{R}^+$. The meaning of this primitive can be translated as $x_i \sim \mu$ of duration c must be performed within $[a, b]$ deriving from semantics in 2.2.1.

Note that the proposed PTSL primitives are not the only possible formations, it is possible to have other combinations of **F**, **G** for second-level primitives, and it is possible to create higher level primitives. For example, one possible second-level primitive we can construct is **GF**. Similarly to conversion with in First-Level primitives through manipulation of the semantics in 2.2.1, where we have $\mathbf{FG}(\phi) = \neg\mathbf{GF}(\neg\phi)$. And intuitively from the semantics in 2.2.1, $\mathbf{G}_{[a,b]}\mathbf{F}_{[0,c]}(\phi)$ would mean for every interval of size c with start time in $[a, b]$, ϕ is true for at least once.

However, the cases for such primitives may specify to more complicated relationships that are not as helpful in an IoT environment. We do note that while **GF** primitives are not directly used in describing our IoT relationships, it is used to check the validity for the negation of **FG** rules in our runtime monitor in section 4.

2.3 Boolean expressions and SMT Formulas

A boolean expression is a combination of boolean variables, operators AND ($\wedge$), OR($\vee$), NOT($\neg$) and parenthesis. For boolean clauses ϕ_1, ϕ_2, the boolean operators joins the boolean variables with the following semantics:

- $\phi_1 \wedge \phi_2$ is True if both ϕ_1, ϕ_2 are True, False otherwise
- $\phi_1 \vee \phi_2$ is False if both ϕ_1, ϕ_2 are False, True otherwise
- $\neg\phi_1$ is True if ϕ_1 is False, True otherwise.

Then, a Satisfiability Modulo Theory (SMT) formula can be seen as a expansion of boolean expression with the addition of first order logic constraints and constructs from domian-specific theories (i.e. Integers and Strings). This constraints come in the form of predicates, which are binary-valued function of non-binary variables from these constructs (ex. 3x > 4). A SMT solver, then, aims to solve the satisfiability problem over practical subsets of SMT formulas.

In the scope of our research project, we will transform learned device interaction rules in an IoT environment into SMT formulas with boolean expressions and predicates with integer variables. The transformed SMT formulas are then used to detect existence of conflicts within interaction rules through Microsoft's z3 solver [dMB08] in section 5.

2.4 Powerset and Cartesian Products

Given a set S, the powerset $P(S)$ of S is the subset of all subsets of S, including the empty set and S itself. For example, let $s = \{x, y, z\}$, $P(S) = \{\{\}, \{x\}, \{y\}, \{z\}, \{x, y\}, \{y, z\}, \{x, z\}, \{x, y, z\}\}$.

Given sets $S_1, S_2, ...S_n$, a cartesian product $S_1 \otimes S_2 ... \otimes S_n$ is a set of n-tuples defined as follows:

$$\{(x_1, ...x_n), x_1 \in S_1, x_2 \in S_2, ...x_n \in S_n\}$$

Both set theory ideas are used in deriving all possible rule combinations that can cause conflicts in STLCheck.

3 Learning Rules with Decision Tree

3.1 Multi-Class Classification Problem (MCCP)

In order to learn the device interaction rules, we first define the classes for decision tree's classification task. In an IoT environment context, for each device, the classes are defined correspondingly to the possible state values it can take. Thus, specifying the behavior of a device for a rule when the preconditions are satisfied can be formulated into a MCCP, formalized below.

MCCP Let $C = \{C_1, ...C_n\}$ be the set of classes, let s^i be an n dimensional signal and let $l^i \in C$ be its label. Find a formula ϕ for class $C_i, i \in \{1, ...n\}$ such that the Misclassification Rate (MCR) is minimized, where $|\cdot|$ represents set cardinality, N the total number of signal label pairs, and

$$MCR(\phi) := \frac{|\{s^i | (s^i \models \phi \wedge l^i \neq C_i) \vee (s^i \not\models \phi \wedge l^i = C_i)\}|}{N} \tag{1}$$

For continuous valued devices such as thermostats, there are potentially infinite number of classes which tremendously complicates the MCCP. However, knowing the exact value of these devices such as knowing the exact temperature is not particularly useful in most situations. As a result, we decide to not classify continuous valued devices in our decision tree models.

3.2 STLTree

As described in 2.2, since a significant portion of device interaction rules in an IoT environment is dependent on time, we plan to capture these interactions using PSTL primitives. Thus, we have constructed STLTree, a decision tree model that learns device interactions with PSTL rules using IoT environments' device operational logs. The main structure of STLTree is based on the approach for data classification described in [BVP$^+$16], and we have made modifications and expansion to the original structure to tailor towards IoT environments. Detailed descriptions of all the modifications made are listed in section 3.2.7.

3.2.1 Model Overview

The decision tree model is binary to accommodate for the binary nature of $\leq, >$ operators in defining the PTSL primitives. Without loss of generality, the left subtree is set to be the true branch and right subtree false branch for satisfying the primitive corresponding to the split. The implementation of STLTree is shown below.

```
//$\phi$: The path representing PTSL formula upto current split
//S: Label set to split on, h: Current depth
//Returns a subtree that splits S
buildTree($\phi$, S, h):
    if stopCondition($\phi$, S, h):
        return leaf($argmax_{c \in C}$ prob(S, c, $\phi$), 1-$max_{c \in C}$prob(S, c, $\phi$))
    $\phi^*$ = findBestPartition(S)
    t = Node($\phi^*$)
    newpath = $\phi^*$ if $\phi$ != null else $\phi \wedge \phi^*$
    $S_T^*, S_F^*$ = partition(S, newpath)
    t.left = buildTree(newpath, $S_T^*$, h+1)
    t.right = buildTree(newpath, $S_F^*$, h+1)
    return t
```

Since learning the optimal decision tree is a NP complete problem [HR76], the model restricts the total depth and least number of data traces to split on with **stopCondition** (details in 3.2.2), and performs a greedy growing algorithm with **findBestPartition** (details in 3.2.3) . If the stop condition is satisfied, a leaf node with the corresponding predicted class. Intuitively, it is set to be the class with the most labels in the current signal set S, defined below:

$$argmax_{c \in C}\, prob(S, c, \phi) = argmax_{c \in C} \frac{|\{(s^i, l^i) | l^i = c)\}|}{|S|} \tag{2}$$

Otherwise, we find the best PSTL primitive ϕ^* to split our dataset S with line 7, construct a node t representing ϕ^*, and join path $\phi \wedge \phi^*$, and recursively split the resulting subtrees until there are only leaves left. The details for splitting S through checking rule satisfaction is in 3.2.4. The special case where ϕ is null is added for constructing the tree from the root, since at the beginning there is no split path yet. The splited S_T^*, S_F^* represents data satisfying the true and false branch of splitting on ϕ^* correspondingly, specifically:

$$S_T^* = \{(s^i, l^i) \in S | S^i \models \phi^*\}, \quad S_F^* = \{(s^i, l^i) \in S | S^i \not\models \phi^*\} \tag{3}$$

A decision tree can be learned by executing $buildTree(null, S, 0)$, where S is the starting set of labeled signal traces. By our formulation of the MCCP problem, each device has different classes corresponding to their state values; therefore, we construct a separate tree for classifying each individual device in the environment to learn all the device interaction rules. Finally, from each learned tree, the device interactions rules can be extracted from by traversing through the tree from root to each leaf, with the leaves being the specified state values, and the path of traversal being the list of preconditions.

3.2.2 Stop Condition

Several stop criteria can be set for $buildTree$ in 3.2.1. While it is straightforward to split until each node only contains signals from a signal class, such stopping conditions results in large trees that takes a long time to train and are very prone to overfitting. In STLTree, we have chosen to stop training once a large proportion of signals belong to the same class or the number of signals for each node is less than a certain threshold. Furthermore, while IoT environments can be complex with vast amount of device interactions, we believe it is reasonable to assume each individual interaction to be fairly simple. That is, there should not be rules with long preconditions that associate tens of devices with each other. Thus, for training STLTree, we also limited the height of the tree to be at most 5 to avoid overfitting.

3.2.3 Finding the Best Partition

In order to find the PSTL rule that gives the "best" partition, STLTree first defines best according to the Information Gain (IG) measure, defined below: [Qui14]

$$IG(S, \{S_T, S_F\}) = H(S) - (\frac{|S_T|}{|S|}H(S_T) + \frac{|S_F|}{|S|}H(S_F)) \tag{4}$$

where H to be the entropy measure with $prob(S, c, \phi)$ defined as in 3.2.1:

$$H(S) = -\sum_{c \in C} prob(S, c, \phi) log(prob(S, c, \phi)) \tag{5}$$

As a result, each time STLTree finds the PSTL rule split that gives the greatest information gain or, in other words, minimizes the split entropy H.

Now, the **findBestPartition** algorithm is shown below. In the algorithm, line 7 bounds the search space for time and space parameters as described above and Line 8 constructs the PSTLprimitive by specifying the type of the primitive, what the relation is, and the time and space parameter restrictions. Note by our definition of PSTL, there are a total of 6 combinations to construct a primitive, and for each primitive, the parameters for PSTL rule ϕ are picked to give the least entropy defined in equation (5). Finally, as remarked in the beginning of this section, the PSTL rule ϕ with the least entropy parameter assignment upon split will give the greatest IG as defined in equation (4), which is used to split our set S through checking rule satisfaction methods for $buildTree$ in 3.2.1 (details in 3.2.4).

```
1   //S: Label set to split on
2   //Returns the PSTL primitive to split S on
3   findBestPartition(S):
4       minEntropy = math.Inf
5       $\phi^*$ = $\top$
6       for ptype in [F, G, FG]:
7           for sim in [$\leq$, $>$]:
8               timebound, spacebound = boundParams(S)
9               p = PSTLprimitive(ptype, sim, timebound, spacebound)
10              entropy, $\phi$ = FindParameters(S, p)
```

```
                if entropy < minEntropy:
                    minEntropy = entropy
                    $\phi^*$ = $\phi$
        return $\phi^*$
```

3.2.4 Checking Rule Satisfaction

In order to split our data traces to grow the decision tree and to evaluate using our learned model, we check whether a data trace satisfies for each type of PSTL primitive as follows:

1. $F_{[a,b]}(x \sim \mu)$. To check the **F** rule, $x \sim \mu$ needs to be true for at least 1 occurrence in $[a, b]$. Thus, if $\sim$ is $\leq$, the minimum value v for x in the interval $[a, b]$ is compared with μ. If $v \leq \mu$, F rule is satisfied. Similarly, if $\sim$ is $>$, maximum value m for x in $[a, b]$ is compared to see if $m > \mu$.
2. $G_{[a,b]}(x \sim \mu)$. To check the **G** rule, by 2.2.1, $G_{[a,b]}(x \leq \mu)$ is converted into $\neg F_{[a,b]}(x > \mu)$ and $G_{[a,b]}(x > \mu)$ into $\neg F_{[a,b]}(x \leq \mu)$ and the corresponding **F** rule is not satisfied instead.
3. $F_{[a,b]}G_{[0,c]}(x \sim \mu)$ To check the **FG** rule, $x \sim \mu$ need to be true for c continuous timestamps in $[a, b]$. The rule is checked by computing min max or max min filters with window size c. If $\sim$ is $\leq$, for each window i of length c starting within $[a, b]$, the maximum value m_i is computed for x, and we return $m = \min_i m_i$ for the minimum window. Whether rule is satisfied can then be checked by straightforwardly comparing $m \leq \mu$. Similarly if $\sim$ is $>$,a max min filter is used instead by finding minimum value v_i over all windows and computing $v = \max_i v_i$ to compare with $> \mu$.

3.2.5 Inference with Tree Model

Given a data trace for a device, classifying the device state with the learned rules can be done through a traversal on the device's learned tree. Starting from root, if the data trace satisfies the PSTL rule for the node, we traverse to the true branch of the tree corresponding to S_T^* in 3.2.1, and otherwise to false branch corresponding to S_F^*. We stop until a leaf node is reached and we output the class the leaf node predicts. A prediction mismatch occurs when the output prediction and the actual state for the device in data trace are not the same; however, such mismatches may not be errors within the learned model and further analysis of these mismatches are described in 3.2.7.

3.2.6 Visualizing Device Interaction Rules

Converting the decision tree into their corresponding learned PSTL rules can be done by simply traversing down the tree from root, joining each PSTL primitive each node along the path represents. The path of traversal is then directly mapped to the preconditions of the rules, while the final leaf destination corresponds to the specified device value. STLTree adapts to the algorithm to convert such rules by [BVP+16], with details shown below.

```
//root - root node
//Returns a dictionary mapping device class to associated rules
Tree2STL(root):
    ruledict = {}
    //t - subtree's root node
    //$\phi$ - PSTL rule respective to current path
    Recurse(t, $\phi$):
        if t is a leaf with class $C_i$:
            if t.error > THRESHOLD:
                return
            if i in ruledict's keys:
                ruledict[i] = ruledict[i] $\vee$ $\phi$
            else:
                ruledict[i] = $\phi$
            return
        $\phi^*$ = t.PSTLprimitive
        Recurse(t.left, $\phi \wedge \phi^*$)
        Recurse(t.right, $\phi \wedge \neg\phi^*$)
        **return**
    Recurse(root, $\top$)
    **return** ruledict
```

Note the check on line 9 makes sure that only the device interaction rules with high prediction accuracy in training will be reported. The inner recursive helper is first entered with start primitive $\top$ for the case where our entire tree is a leaf node and all of our data traces will be predicted to the class corresponding to the leaf. An example for the algorithm's translation is shown in Figure 5 below, with $C1, C2$ as classes and $p1, p2$ as PSTL primitives.

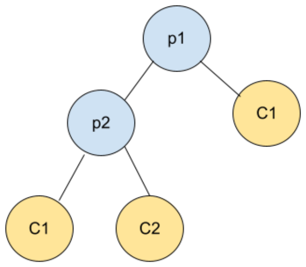


Figure 5: Example translation, the above tree translates to a dictionary mapping 1 **to** $(p1 \wedge p2) \vee (\neg p1)$ **and** 2 **to** $(p1 \wedge \neg p2)$

3.2.7 Modifications to the framework

The decision tree framework described in [BVP$^+$16] can not be directly used in the IoT environment settings due to the following limitations

- Not considering the noise from random physical device changes
- Unable to learn from discrete string state values and discrete timestamped data
- Unable to handle the potentially infinite search space for parameters
- Vulnerable to overfit

To accommodate for these limitations, we have modified [BVP$^+$16]'s decision tree framework by adding in an error threshold for learning the rules, preprocessing device operation log into a learnable format, restricting the parameter search space, and adding in tree pruning in addition to the stop condition restrictions described in 3.2.2. We have also added in miscellaneous modifications to the framework by removing unnecessary features and defining an schema for translating the learned PSTL rules. The details for each modification are described in each subsection below.

Handling rules learned due to random events As described in section 2.1, it is possible for STLTree to learn unwanted rules in the environment due to random event noises that are not caused by interactions such as the homeowner physically changing device states. To address for such issue, we include an error term for each leaf when training our tree, which is defined to be $1 - max_{c \in C}\ prob(S, c, \phi)$, with $prob(S, c, \phi)$ being the proportion of traces that class c satisfy in the dataset correspodning to the leaf as described in equation (2) of section 3.2.1. Then, we added an error threshold constant so that only rules with error less than the constant will be visualized as described in 3.2.6 and only prediction mismatches for rules with error less than the threshold will be reported when evaluating as described in 3.2.5. These rules represents the environment interaction STLTree is most confident about, and prediction mismatches with regards to these rules are the most likely the potentially dangerous behaviors that resulted from anomalies in the environment violating the device interactions. Similarly, only rules with error less than the threshold is reported and outputted to the user.

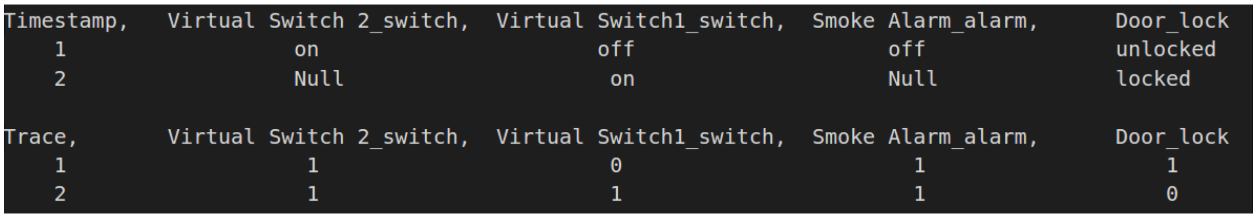
Preprocessing data In section 2.2.1, signals are defined to be continuous-time, continuous-valued functions, which [BVP$^+$16]'s framework is also targeting towards. However, in data traces for an IoT environment device states, data is obtained through device operational logs with discrete time stamps(described in 2.1.3 for Samsung Smartthings). The values for device state change themselves in some cases are discrete as well (Ex. A light switch can only be on or off).

To handle the discrete nature for timestamps in state change logs, given an IoT environment's device operational log, we first set the trace with smallest time stamp to timestamp 1, and increment other traces with timestamp relative to the smallest timestamp. For STLTree, we have chosen the difference to be in seconds since an IoT hub would typically need ~ 1 second to handle device events, making smaller time units unnecessary.

Each trace is defined to be a small fixed interval basing on timestamps and we generate such interval based on a gap g. That is, if data trace for interval i starts at timestamp t, the data trace for interval $i+1$ would start at timestamp $t+g$. For the timestamps on the device change log, we mark the device corresponding to the state with the value of the state change. Other devices that have not changed state at that time stamp would be set to Null. Now, to make sure we have enough timestamp to generate an interval for each logged device change, we would also fill in dummy traces (all device state value set to Null) for g seconds before each timestamp where device change occurs, if it is not already included. Finally, we backfill the traces by putting device states with value Null to be the last known state it has before this timestamp, since there are no state changes from the last timestamp for the device.

Now, for the devices with state values that are not real numbers such as light switches, we assume that there are only a finite number of states the device can be in. Then, we iterate through all data traces to give each device state value a class number and create a dictionary mapping the device state to its corresponding class number. We change these device states to the class number it corresponds to instead of its actual state name. An example of the data processing process is portrayed in Figure 6, 7 below.

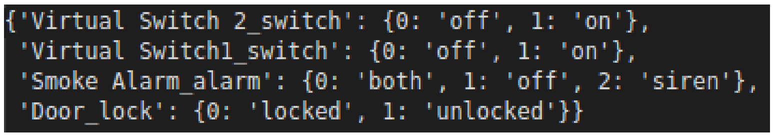
Finally, for some devices, it is significantly more likely for them to be in one state over others (For example, Smoke Alarm should be off most of the time). To avoid the complication of our decision tree model overlooking certain device interactions due to lack of data for a certain state value of the device, the data for each device with different state value labels that has appeared in the dataset is kept below a fixed ratio r. For our STLTree, r is set to be 10, so that there is at least a $1:10$ ratio among data for different values of the same device state that are present in the dataset.



```
Timestamp,   Virtual Switch 2_switch,  Virtual Switch1_switch,  Smoke Alarm_alarm,      Door_lock
    1                 on                       off                   off               unlocked
    2                 Null                      on                   Null              locked

Trace,       Virtual Switch 2_switch,  Virtual Switch1_switch,  Smoke Alarm_alarm,      Door_lock
    1                 1                        0                      1                     1
    2                 1                        1                      1                     0
```

Figure 6: Example data handling, Top: Before, Bottom: After



```
{'Virtual Switch 2_switch': {0: 'off', 1: 'on'},
 'Virtual Switch1_switch': {0: 'off', 1: 'on'},
 'Smoke Alarm_alarm': {0: 'both', 1: 'off', 2: 'siren'},
 'Door_lock': {0: 'locked', 1: 'unlocked'}}
```

Figure 7: Example dictionary mapping states to class number for Figure 6

Restricting search space for PSTL parameters As described in 2.2.2, the search space for first level and second level primitive parameters is infinite, as there are infinite possible time parameter tuples $[a, b]$. To handle this issue, we restrict our parameter search space as follows:

1. Bounding the time parameter. By our data preprocessing, we have separated the device operation log into fixed intervals of size g. As a result, we restrict picking the time parameter $[a, b]$ to be within the range $[0, g]$ where 0 represent the first timestamped data trace of the current interval and $b > a$. For second level primitives, we pick c within the range $(0, g - b]$
2. Bounding the space parameter. By our data preprocessing, we have converted the discrete valued devices states into integer valued class labels. Then, for each of these devices, we count the number of different class labels it has, and we would restrict our space parameter μ to not exceed the number. By a straightforward translation, $x_i \leq \mu$ means device x_i is in one of the first μ class labels, similarly translation applies for $x_i > \mu$. Trivially by our construction, such μ can be restricted to only integers. For real valued devices, μ is simply

restricted to integers bounded by the lowest and uppermost value the signal achieves in the data trace. We round real values to integers under the assumption that in a household environment, rounding conditions to the nearest whole number is precise enough for capturing the device interactions.

3. Simulated Annealing (SA). After bounding the time and space parameters, the search space for time and space parameters can still be large for the decision tree to explore all possible PSTL rules for split (There are already $O(|g|^2)$ ways to pick the space parameter $[a, b]$). To speed up our training process, STLTree utilizes a simulated annealing algorithm in picking the PSTL rule. The algorithm performs a random walk on selecting the PSTL parameters that will converge at a local maximum in IG [Ing96] (details in section 9.2). In STLTree, the model first computes an upper bound on the total possible parameter assignments for each PSTL formula, and utlizes SA if the total assignments exceeds an user defined threshold. Otherwise, STLTree iterates through all possible parameter assignments to find the best split.

Tree pruning As described in 3.2.2, by our assumption that device interaction rules in an IoT environment should be fairly simple, our learned decision tree is very susceptible to overfit. To reduce the overfitting behavior, we conduct an optional pruning on the learned tree model as follows:

1. Set a improve threshold, so that if for a split we have neither the left subtree error or the right subtree error gets reduced by more than the threshold comparing to the current node, the split is considered futile. For futile splits, we prune them by making the parent node a leaf and chopping out its children. We start from the parents of leaves and work upwards toward the root.

2. After pruning, we run a cross validation on the new tree model. Then, we continue to chop off leaves of the tree until we only have the root node. The chopping order of leaves is determined by the effective alpha of parent nodes, which we have the leaf with the least effective alpha to be chopped first (details in section 9.3). Each time we chop off a leaf, we store the current tree model in a dictionary and run validation on the same validation set. Finally, the tree model with the least validation error is returned.

Impurity Measures In the original model proposed by [BVP$^+$16], the measure that determines the best partition rule is based on an Information Gain (IG) on robustness measurement, which not only measures the degree of misclassification of the split, but also the extent of misclassification (Details in section 9.1). However, such measurement does not make sense in the context of discrete valued device states. As a result, we use the robustness measure only on the finding split rules for continuous valued states. For discrete valued state splits, we use normal IG as measurement instead, shown in equation (4). After obtaining the best parition rule for each device state, we then calculate the normal IG of the best split rules for continuous valued states from robustness measurement to compare each rule, and using the rule with the best IG to split our tree.

Translating PSTL rules to a readable format After converting the tree into a dictionary mapping device states to PSTL rules in 3.2.6, we translate each PSTL rule into a readable text format for user friendliness, with instruction shown below:

1. $F[a, b](x \sim \mu)$: Between seconds a to b, x becomes $\sim \mu$

2. $G[a, b](x \sim \mu)$: From seconds a to b, x is always $\sim \mu$

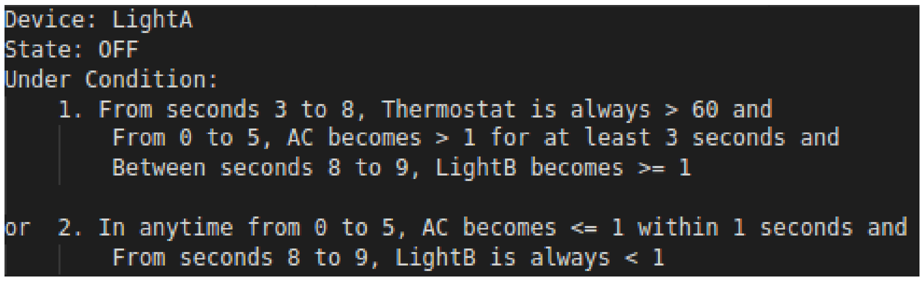
3. $F[a, b]G[0, c](x \sim \mu)$: From seconds a to b, x becomes $\sim \mu$ for at least c consecutive seconds

4. $\neg F[a, b]G[0, c](x \sim \mu)$: In anytime from a to b, x becomes $(\neg \sim)\mu$ within c seconds

where we define $(\neg \sim)$ to be the following: $(\neg \leq)$ being $>$, $(\neg >)$ being $\leq$. For the ¬ **F** and ¬ **G** rules, note that $G[a, b](x \sim \mu) = \neg F[a, b](x(\neg \sim)\mu)$, we translate $\neg F[a, b](x \sim \mu)$ to $G[a, b](x(\neg \sim)\mu)$ and $\neg G[a, b](x \sim \mu)$ to $F[a, b](x(\neg \sim)\mu)$. Finally, $\wedge$ and $\vee$ are translated directly to or and and respectively. An example translated rule output is shown in Figure 8 below.

3.3 TreeNoSTL

While a significant portion of device interactions in an IoT environment is dependent on time, there are also immediate interactions. To detect such interaction rules, we constructed TreeNoSTL, a decision tree that learns immediate device interaction rules to solve MCCP with the environment's device operational log.



```
Device: LightA
State: OFF
Under Condition:
    1. From seconds 3 to 8, Thermostat is always > 60 and
     |   From 0 to 5, AC becomes > 1 for at least 3 seconds and
     |   Between seconds 8 to 9, LightB becomes >= 1

or  2. In anytime from 0 to 5, AC becomes <= 1 within 1 seconds and
     |   From seconds 8 to 9, LightB is always < 1
```

Figure 8: Example rule output after text translation for STLTree

3.3.1 Model Overview

We have used Python's sklearn tree module [PVG+11] for implementing the TreeNoSTL model. Similarly to STLTree, TreeNoSTL learns a binary tree, restricts the maximum depth of the tree to avoid overfitting, and preprocesses device interaction log into discrete valued traces (details of preprocessing is described in 3.3.2). TreeNoSTL utilizes Gini Gain (GG) [Qui14] instead of IG as measure for evaluating the quality of a rule split, defined below:

$$GG(S, \{S_T, S_F\}) = Gini(S) - (\frac{|S_T|}{|S|}Gini(S_T) + \frac{|S_F|}{|S|}Gini(S_F)) \tag{6}$$

where S is the data traces for current split, S_T the data traces that satisfies our split rule, and S_F the data traces that do not. Also, we have

$$Gini(S) = \sum_{c \in C} prob(S, c, \phi)(1 - prob(S, c, \phi)) \tag{7}$$

where C is the set of possible classes for a device that is obtained from the device's possible states (details in 3.3.2). ϕ is the split rule, and $prob(S, c, \phi)$ is defined the same as in STLTree described in 3.2.1 equation (2). Similar to how we have trained for STLTree, we learn a decision tree for each discrete valued devices.

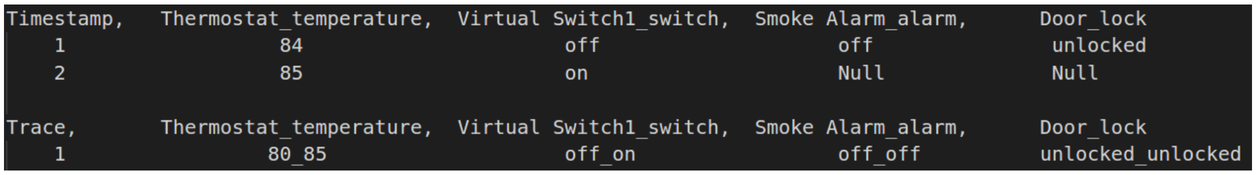
3.3.2 Preprocessing Data

Similarly to data processing for STLTree, we first generate the dataset from environment device operational log through using relative timestamps and backfilling unknown Null states. For the immediate device changes within the environment, at any time stamp i, we are only interested in the interaction between timestamp i and $i + 1$. As a result, we form a data trace by combining adjacent rows on the processed data, if their corresponding timestamps are also adjacent. Then, we generate dummy rows for singleton rows and backfill the device states to what they are last known. For a device with non-real value in the data, we simply combine the rows by modifying each entry of the data into the format $statebefore\_stateafter$. Similarly to the preprocessing done in STLTree to avoid overlooking device interactions due to lack of data for certain state changes, the states between different $statebefore\_stateafter$ tuples that are present in the dataset is kept under the threshold $r = 10$.

For a real numbered device, due to the difficulty for decision trees in handling continuous valued data, we separate the device state into fixed value intervals and classify the state values based on the lowest possible value their interval can achieve. The fixed interval for each continued valued data is provided from the user as a dictionary. The lowest starting point of the fixed value interval is determined by the largest integer lower than the lowest value the device achieves, and we stop adding intervals once the interval corresponding to the largest values includes the largest value the device achieves in the log. For example, for a thermostat with lowest value 0 and fixed intervals of 5, a temperature of 84 will be classified in interval 80, and a temperature of 85 will be classified in interval 85.

While such processing loses information regarding the real valued devices, the model's accuracy can be improved by reducing the interval size. We assume that the number of intervals never grows too large, as there is often limitations in the values a device can achieve (For example, a thermostat could probably only reach -20 to 120 degrees F.). An example of our data after processing is shown in Figure 9 below.

As a result of this data processing, the set of possible classes C is obtained through all possible combinations of $statebefore\_stateafter$ appearant in the dataset. TreeNoSTL splits on conditions of whether a device has a specific $statebefore\_stateafter$ value. Finally, since sklearn's tree model only supports integer valued data traces and classes, we have used sklearn's OneHotEncoder [PVG+11] to convert all state values and classes within the dataset to integers. After the decision tree is learned, the state values and classes are converted back to our original string combination formulation above (details in 9.4).



```
Timestamp,   Thermostat_temperature,  Virtual Switch1_switch,  Smoke Alarm_alarm,      Door_lock
    1                84                       off                    off               unlocked
    2                85                       on                     Null              Null

Trace,       Thermostat_temperature,  Virtual Switch1_switch,  Smoke Alarm_alarm,      Door_lock
    1               80_85                     off_on                 off_off           unlocked_unlocked
```

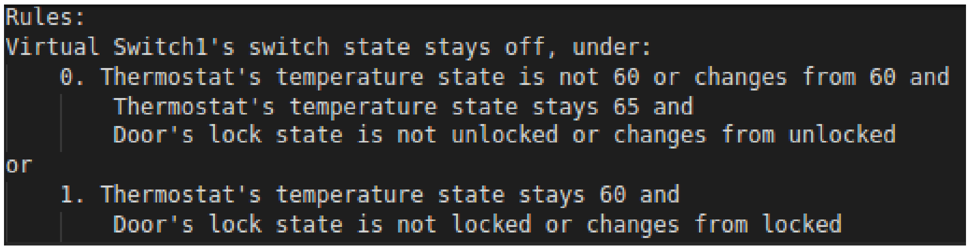
Figure 9: Example data handling, Top: Before, Bottom: After

3.3.3 Evaluation with Tree Model

Evaluating the learned tree models can simply be done using sklearn tree model's $predict\_proba$ function, which returns the probabilities for each class the device is in. The class with the highest probability is outputted; however, similar to what is done in STLTree, only prediction mismatches within rules of error less than a defined threshold constant will be considered.

3.3.4 Visualizing Device Interaction Rules

Visualizing the device interaction rules for TreeNoSTL can be done in a similar fashion as STLTree, using the rule splits learned for our model instead of the PSTL primitives. We traverse down the tree from root and joins each rule along the path. We also return a dictionary that maps each class to the device interaction rules specified by learned decision trees with training prediction error below our defined threshold.



```
Rules:
Virtual Switch1's switch state stays off, under:
    0. Thermostat's temperature state is not 60 or changes from 60 and
    |   Thermostat's temperature state stays 65 and
    |   Door's lock state is not unlocked or changes from unlocked
or
    1. Thermostat's temperature state stays 60 and
    |   Door's lock state is not locked or changes from locked
```

Figure 10: Example rule output after text translation for TreeNoSTL

To convert the $statebefore\_stateafter$ into a readable text format, they are translated by the schema below:

1. $valA\_valA$: Device's state stays $valA$
2. $\neg\ valA\_valA$: Device's state is not $valA$ or changes from $valA$
3. $valA\_valB$: Device's state changes from $valA$ to $valB$
4. $\neg\ valA\_valB$: Device's state does not change from $valA$ to $valB$

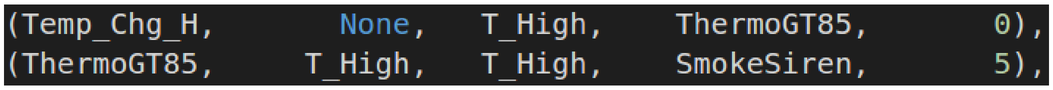
Finally, the rule splits are joined along the same path with *and*, and different paths with *or* for the same class. An example for rule translation result is shown in Figure 10 above.

3.4 Evaluations

To evaluate the performance of STLTree and TreeNoSTL, we have created 5 household IoT environments with fixed rules that for the tree models to learn. For the first 2 household IoT environments, the device operation logs for training are generated through a state machine that follows our fixed rules. The last 3 environments are directly created on Samsung Smartthings through Smartapps and virtual devices, and their device operation logs are generated through automated testing on Smartthings' virtual simulation using Selenium [Smac] [Aut].

3.4.1 Environments Using State Machine

To generate an IoT environment using state machines, we first set a dictionary of transition rules with a 5-tuple of $(InEvent, InState, OutState, OutEvent, TimeDelay)$. Each 5-tuple can then be directly translated to that an occurrence of *InEvent* at *InState* will results in *OutState* and trigger the *OutEvent* after *TimeDelay* timestamps. The states in these 5-tuples are used to represent device conditions in the environment. An example transition rule is shown in figure 11 below. In the figure, an *InState* of None means the event can be triggered from any state, and T_High represents the state where thermostat has a high temperature reading.



```
(Temp_Chg_H,        None,    T_High,     ThermoGT85,        0),
(ThermoGT85,      T_High,    T_High,     SmokeSiren,        5),
```

Figure 11: Example rule. A high temperature of greater than 85 degrees triggers the smoke alarm siren

Some events can also occur randomly at each timestamp to reflect for users' random behavior in physical control of devices as described in 2.1. We generate the environment device operation log through a timer object, which is used as a counter of the timestamps to perform the random triggering of events and store the events that need to be triggered after a time delay. At each timestamp, device objects in the state machine perform the state changes as specified by the events generated from the timer, and their final states for the timestamp are recorded as a part of the operation log.

3.4.2 Environments Using Smartthings Simulation

To generate an IoT environment on the Samsung Smartthings hub, we defined our device interaction rules through Smartapps. After installing the app on the Smart devices, we are able to virtually simulate the interactions on the Smartthings hub through a sidebar of buttons as shown in figure 12 below. We can change a device state through clicking the tiles representing the devices, and we can physically trigger an app run through the *trigger now* button.

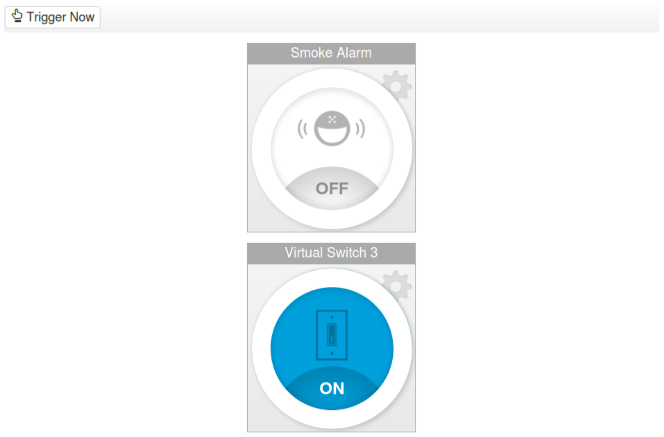


Figure 12: Samsung Smarttthings simulation

For each virtual environment, we generate the device operation logs through selenium automation. At each timestamp, the automation can trigger events randomly by clicking on the device tiles to change the device states. To obtain the device operation log, we created a monitor Smartapp to communicate with the Smartthings Hub and request these device state change information. The log is then processed as described in 3.2.7 and 3.3.2 for the two models.

In real Smartthings household environments, the operation log would be derived in a similar manner by directly requesting state change information from the hub. We finally note, from section 2.1.3, due to Samsung hub can only store a maximum of 200 state changes for each device, the training data in real life would need to be obtained in a quite frequent manner.

3.4.3 Results

For each state machine environment, we have trained our model on 10000 data traces, and for each Samsung Smartthings environment, we have trained our model on 3000 data traces (less due to limitations on Samsung Hub in storing states changes, as described in 3.2.3). For STLTree, we have processed our data into 10 second intervals to look for device interactions, and for both models, we have restricted the maximum depth to be 4 and a stop condition for accuracy at 0.90. As a result, we also only record the learned rules with an error less than 0.10. For STLTree, the training time for state machine environment is about 2 hours and for Smartthings environment is about 1 hour. For TreeNoSTL, the model is able to terminate within minutes.

Out of 7 time dependent rules and 5 immediate rules for the state machine environments, our STLTree is able to learn 5 out of 7 of the rules and TreeNoSTL is able to learn 5 out of 5 rules. Out of 10 time dependent rules and 3 regular rules for Samsung Smartthings environment, our STLTree is able to learn 8 out of the 10 rules and TreeNoSTL is able to learn 3 out of 3 rules.

Successfully Learned Rules For the context of evaluation, *successfully* learning a rule is defined to be learning a rule that closely resembles of our defined device interactions. That is, if the preconditions of the learned rules are true, the rule's respective defined device interaction will occur. Two example of successfully learned rule are shown in 13 and 14 below.

To visualize this definition of close resemblance, as shown in line 2 for the rule learned in figure 13 (1 means on and 0 means off for switches), while we have not directly learned that switch 2 turns on after 3 seconds when switch 1 turns on, if switch 1 is on at 3 seconds before at second 7, the rule on the line will be satisfied. The discrepancy between the learned rules and designed device interactions mostly comes from the time parameters for time dependent rules. And, as shown in both Figure 13 and 14, for both time dependent and immediate rules, another discrepancy comes from having additional rule restrictions for device interactions that we have not designed our environment to have.

We believe these discrepancies comes from the limitations in training data size and side effects from other interactions. For example, in figure 13, the additional restrictions regarding the smoke alarm resulted from the interaction rule that switch 1 on leads to smoke alarm siren. Despite these discrepancies, the successfully learned rules, while may be more restrictive in their preconditions, are able to capture our designed device interactions for IoT environments as desired.

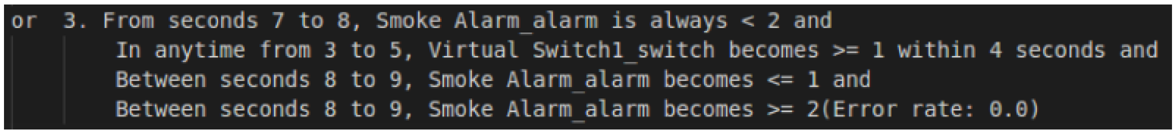

```
or  3. From seconds 7 to 8, Smoke Alarm_alarm is always < 2 and
        In anytime from 3 to 5, Virtual Switch1_switch becomes >= 1 within 4 seconds and
        Between seconds 8 to 9, Smoke Alarm_alarm becomes <= 1 and
        Between seconds 8 to 9, Smoke Alarm_alarm becomes >= 2(Error rate: 0.0)
```

Figure 13: Successfully learned time dependent rule: Switch 1 on leads to Switch 2 on after 3 seconds

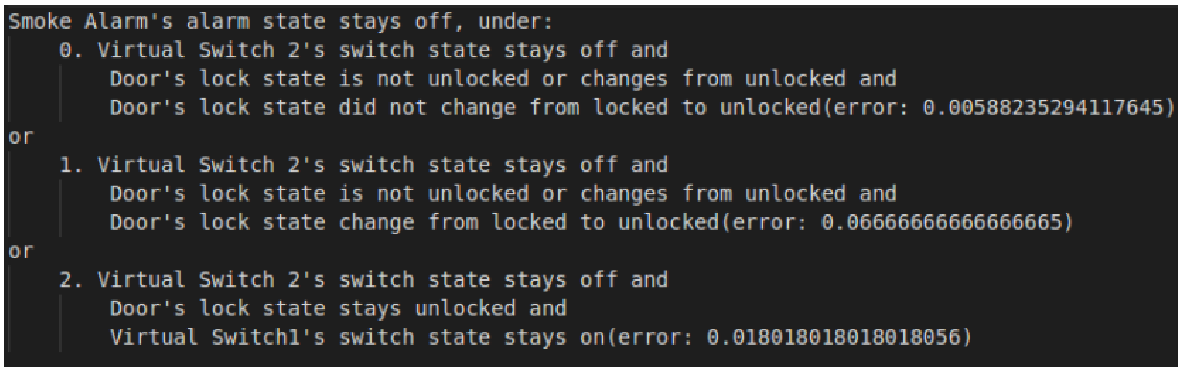

```
Smoke Alarm's alarm state stays off, under:
    0. Virtual Switch 2's switch state stays off and
        Door's lock state is not unlocked or changes from unlocked and
        Door's lock state did not change from locked to unlocked(error: 0.00588235294117645)
or
    1. Virtual Switch 2's switch state stays off and
        Door's lock state is not unlocked or changes from unlocked and
        Door's lock state change from locked to unlocked(error: 0.06666666666666665)
or
    2. Virtual Switch 2's switch state stays off and
        Door's lock state stays unlocked and
        Virtual Switch1's switch state stays on(error: 0.018018018018018056)
```

Figure 14: Successfully learned immediate rule: Switch 2 off leads to Smoke Alarm off

Unsuccessfully Learned Rules In our evaluation, we have only encountered failure in learning time dependent rules. This is due to time dependent rules being inherently more difficult to learn, especially with the vast search space in PSTL parameters and the limitation in our approximation algorithm with Simulated Annealing (SA). For 3 out of 4 failures, STLTree failed to learn the rule completely, which we believe they are mainly resulted by the noise in random device state changes as described in 2.1. Such failures can be reduced by training our model on a greater dataset size.

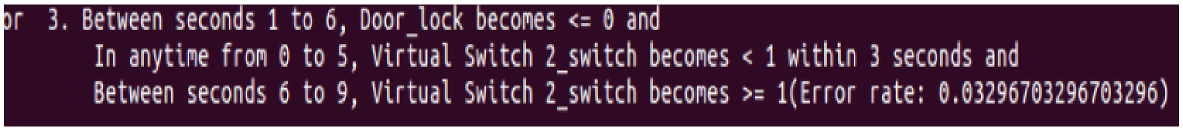

```
or  3. Between seconds 1 to 6, Door_lock becomes <= 0 and
        In anytime from 0 to 5, Virtual Switch 2_switch becomes < 1 within 3 seconds and
        Between seconds 6 to 9, Virtual Switch 2_switch becomes >= 1(Error rate: 0.03296703296703296)
```

Figure 15: Failure in capturing interaction in entirety

The last failure showed our model's limitation in capturing interactions in its entirety. In our environment, we have set the rules to be

1. Switch 2 off for 1 second —> Switch 1 on

2. Switch 2 on —-> Switch 2 off after 1 second

which we have Switch 2 turns on leads to Switch 2 turns off directly. As shown in figure 15 below, our model only learned Switch 2 on leads to Switch 1 on after 2 seconds while ignoring the abnormal circular interaction defined by rule 2. This failure could be a result of our splitting algorithm when learning the tree, since our learned rule is correct and can be directly inferred by the two rules above. One other possibility of this failure is due to our modifications to avoid overfitting, so we will choose to learn simple rules rather than rules with many precondition requirements. We will leave resolving such complications in rule learning for our future work.

Learning Unintended Rules Despite our effort in recording rules with a high confidence only, we have learned a total of 31 rules out of the 25 rules defined in our data environments. The learning of these unintended rules, as described in 2.1, is also significantly due to the noise in random device state changes and can be reduced in training our model under a greater dataset size.

4 STLMon: Runtime Monitoring of Smartthings Environments

After learning the device interaction rules with STLTree and TreeNoSTL introduced, we created STLMon, a runtime monitor on Smartthings environments to check for rule violations in real time. For the safety of IoT environments, STLMon not only checks for violations among the learned device interaction rules, but also for violations of user inputted safety behavior rules. To build STLMon, we have first created a parser that converts the learned rules from our decision tree models and additional rules defined by the user for the monitor to a dictionary. Then, we have built the monitor structure with an http server that communicates with the Samsung Smartthings Hub to both access device change information in the environment and issue commands to the environment upon detection of rule violations. Finally, we have designed checking algorithms for these potential rule violations and evaluated STLMon using Smartthings Environment simulations. The details for each part of the implementation is described in the sections below.

4.1 Parsing Device Interaction Rules

Since both data preprocessing and learned rules are done differently between STLTree and TreeNoSTL, the rules learned from the two models are also parsed differently into two types of dictionaries. Recall by our decision tree model design, only learned rules with accuracy exceeding a set threshold will be considered for our monitor. For user inputted rules, we have limited each rule to be specified under a fixed language, which we are able to parse them directly into PSTL rules.

4.1.1 Parsing PSTL Rules

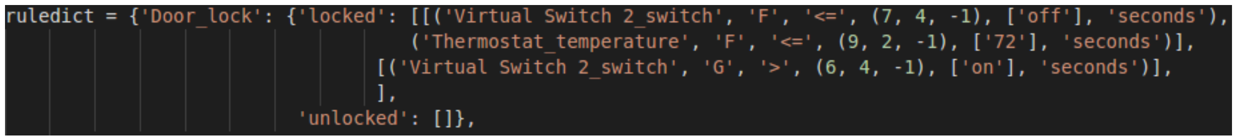
We parse our PSTL rules learned from STLTree, in a similar way as translating these rules to a readable format in 3.2.6, by traversing and joining PSTL primitives. Instead of simply printing our rules as conjunctions of the PSTL primitives, we first process each primitive into a 6 tuple format in the order as follows:

1. The $deviceName\_deviceState$ tuple associated with the primitive.
2. The primitive type $(F/G/FG/GF^*)$.
3. The inequality associated with primitive.
4. The time interval associated with primitive. A triple of (From last x timestamps from current time, To last y timestamps from current time, duration of event). The value of x, y is obtained through the size of interval i we used for learning the rule, which, intuitively, for a time parameter of $[a, b]$, $x = i - a, y = i - b$. The duration of event is only useful for second-level primitives, and it is assigned to the duration parameter learned.
5. The list of state values l that satisfies the primitive. This is obtained using the classdict generated in data processing described in 3.2.7. For the space parameter μ learned in the primitive for discrete variables, we simply include all the possible state values for the device in the classdict that satisfies the primitive's inequality with respect to μ. (or does not satisfy if we are currently on the False branch). If the primitive is corresponding to a continuous valued device, l would be a singleton list $[\mu]$ and we would check the validity through the inequality specified.
6. The timestamp unit associated with learning the primitive (Ex. Seconds/Minutes). Since every primitive and rule is learned with the same timestamp unit by our data processing, the timestamp unit for each rule would always be the same for each primitive.

For the primitives on the False branch of the decision tree, we utilize the the STL rule property described in 2.2.1 that $\neg F(\neg\phi) = G(\phi)$ and $\neg FG(\neg\phi) = GF(\phi)$. As a result, we can check $\neg F(\phi)$ by creating a new primitive specifying $G(\neg\phi)$, $\neg G(\phi)$ with $F(\neg\phi)$, and $\neg FG(\phi)$ by $GF(\neg\phi)$. While GF rules are not directly learned in STLTree, they are present in the converted PSTL rule primitives for representing the false branch of FG rules.

Finally, we note that by the process defined in 3.2.6, each primitive is a node of the tree, and each rule is formed by joining primitives along the traversal path. We thus represent each rule as a list of the 6-tuples, and joining primitives by elongating the list. After processing the rules, we generate two dictionaries corresponding to the "DONT" and "DO" rules of the environment, the names of which are adapted from [IoT]. The details for the two dictionaries are listed below.

DONT Rule Dictionary We define "DONT" rules to be rules that if their preconditions are satisfied, the rules' corresponding device states should not change to a state value differing from the rule specifications. The dictionary for DONT rules is straightforwardly generated through mapping each device state tuple to a dictionary mapping each possible value for the device to a list of the rules with device specification at that state value, converted into the 6-tuple format. An example for the DONT rule dictionary is shown in figure 16. Recall that STLTree learns rules for discrete valued devices only, there would only be DONT rules for them.



```
ruledict = {'Door_lock': {'locked': [[('Virtual Switch 2_switch', 'F', '<=', (7, 4, -1), ['off'], 'seconds'),
                                      ('Thermostat_temperature', 'F', '<=', (9, 2, -1), ['72'], 'seconds')],
                                     [('Virtual Switch 2_switch', 'G', '>', (6, 4, -1), ['on'], 'seconds')],
                                    ],
                          'unlocked': []},
```

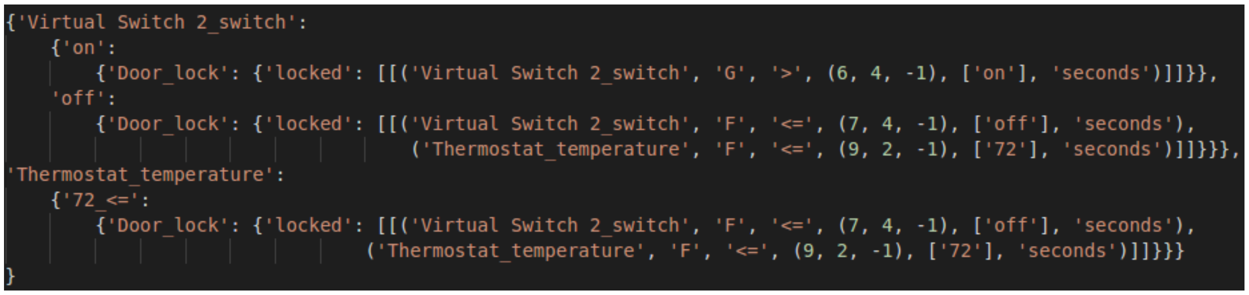
Figure 16: Example DONT rule dictionary, there are two rules for the "Door_lock" to be locked

DO Rule Dictionary We define the "DO" rules to be rules that if their preconditions are satisfied, the devices corresponding to them should change to the state value according to the rule specification in the near future. These DO rules are formed due to current device change will result in satisfying the preconditions of some interaction or user input rules in the future, which we then need to check for rule violation when the preconditions become true.

To visualize the inituition behind the DO rules, consider an example learned interaction where we have the converted precondition to be $(Switch\ 1, G, <, (2, 1, -1), [on], seconds)$ and specification to be $Switch\ 2\ off$. Then, after receiving the device change that $Switch\ 1$ is turned on, the precondition for the rule will be satisfied after 2 seconds, which we need to check whether $Switch\ 2$ is off at that time.

The DO rule dictionary can be directly formed from iterating through each primitive precondition in all rules contained in the DONT dictionary, since the satisfaction of each primitive can trigger a DO rule being satisfied by our definition. For each PSTL primitive, we update our entries in the DO rule dictionary in the following manner. For primitive p in rule ϕ that specifies $deviceA\_stateA$ to be v, say p is specified for $deviceB\_stateB$ with satisfying list l, we map $deviceB\_stateB$ to a dictionary mapping each μ in l to rule dictionary $Dict_r$. In $Dict_r$, we map $deviceA\_stateA$ to a dictionary mapping v to a list containing ϕ (Append to the list if there are already rules being mapped, create a singleton list if first time).

For continuous variables, we construct μ by appending the inequality after the singleton value specified for the primitive. As an example, the converted DO dictionary for DONT dictionary in figure 16 is shown below.



```
{'Virtual Switch 2_switch':
    {'on':
        {'Door_lock': {'locked': [[('Virtual Switch 2_switch', 'G', '>', (6, 4, -1), ['on'], 'seconds')]]}},
    'off':
        {'Door_lock': {'locked': [[('Virtual Switch 2_switch', 'F', '<=', (7, 4, -1), ['off'], 'seconds'),
                                   ('Thermostat_temperature', 'F', '<=', (9, 2, -1), ['72'], 'seconds')]]}}},
'Thermostat_temperature':
    {'72_<=':
        {'Door_lock': {'locked': [[('Virtual Switch 2_switch', 'F', '<=', (7, 4, -1), ['off'], 'seconds'),
                                  ('Thermostat_temperature', 'F', '<=', (9, 2, -1), ['72'], 'seconds')]]}}}
}
```

Figure 17: Conversion of DO dict from figure 16

It is possible for temporal rules to have multiple primitives within each rule specifying the same $deviceA\_stateA$ with value v in the satisfying list with different STL operators and time intervals. To avoid duplication of rules in our dictionary, only the first occurrence of primitive specifying each $(deviceA\_stateA, v)$ in each rule is added according to the method above.

4.1.2 Parsing TreeNoSTL Rules

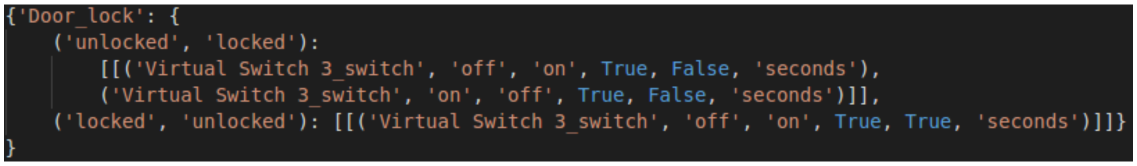
Similarly to parsing STLTree rules, the rules for TreeNoSTL is also parsed into "DO" and "DONT" rule dictionaries. First, we processed the learned immediate rules through the tree traversal method in 3.3.4 into a list of 6-tuples (converting each node precondition in the tree to a 6-tuple in the process). However, since the immediate rules have an emphasis on transition of state values rather than on rule's time dependency as in PSTL rules, the 6-tuple is processed differently in the order as follows:

1. The $deviceName\_deviceState$ tuple associated with the node.

2. The start state corresponding to the node.
3. The end state corresponding to the node.
4. Boolean value on whether the node is corresponding to a state change, found through checking whether start and end state are the same.
5. Boolean value on whether we are on the false branch.
6. The timestamp unit for the rule. Since every primitive and rule is learned with the same timestamp unit by our data processing, the timestamp unit for each rule would always be the same for each primitive.

As described in 3.3.2, the class labels for immediate rules is in the format of $statebefore\_stateafter$. Thus, the second and third item in the tuple can be obtained by simply pattern matching. For continuous variables, TreeNoSTL has processed them into fixed value discrete intervals by our construction. These intervals can be processed in the exact same way as the discrete valued device states with our saved dictionary for each continuous variable interval in 3.3.2. Now, we generate our DO and DONT rule dictionaries in a similar way as in STLTree, described below.

DONT Rule Dictionary In the context of immediate rules, a DONT rule is defined as the device should not perform a state transition that does not match the transition specified (or transition at all if the rule does not specify a state change) when the preconditions for the rule are satisfied. The DONT dictionary is generated in a similar way as in PSTL rules with a simpler structure, where we map each device_state tuple to a dictionary, where we map each state change key tuple $(statebefore, stateafter)$ to a list of rules associated with the state change, converted in the 6-tuple format. An example DONT rule dictionary is shown in figure 18 below. TreeNoSTL also learns rules for discrete valued devices only; thus, there would only be DONT rules for discrete valued devices.

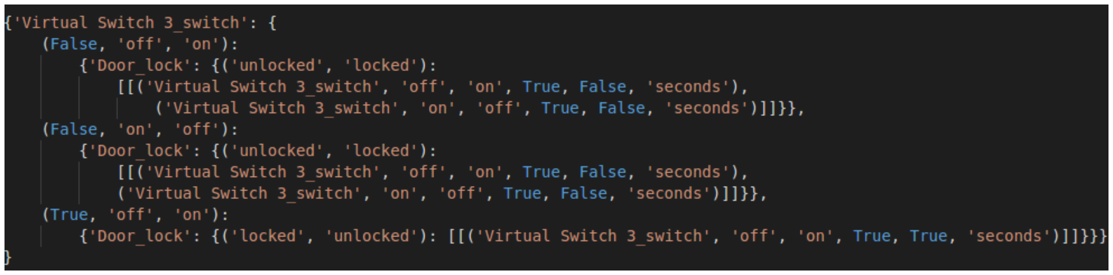


```
{'Door_lock': {
    ('unlocked', 'locked'):
        [[('Virtual Switch 3_switch', 'off', 'on', True, False, 'seconds'),
        ('Virtual Switch 3_switch', 'on', 'off', True, False, 'seconds')]],
    ('locked', 'unlocked'): [[('Virtual Switch 3_switch', 'off', 'on', True, True, 'seconds')]]}
}
```

Figure 18: Example DONT rule, there are two rules for the "Door_lock" basing on thermostat temperature

DO Rule Dictionary Similarly, the immediate DO rules are rules specifying their corresponding state change should happen in the near future when the current device state change results in all of the rule's preconditions being satisfied. Intuitively, DO rules are only triggered through state changes, thus we only consider precondition nodes that correspond to a state change, or on the False branch for a non state change node to be relevant when constructing the DO rules from the preconditions of each learned interaction rule.

We construct the immediate DO rule dictionary from the immediate DONT rule dictionary, similarly to in STLrules. For each relevant precondition node p in rule ϕ specifying $deviceA\_stateA$ to have a transition from v to v' and p being a condition speciftubg $deviceB\_stateB$ to have a transition from μ to μ', we map $deviceB\_stateB$ to a dictionary mapping key triple $(falsebranch?, \mu, \mu')$ to a rule dictionary $Dict_r$. In $Dict_r$, we map $deviceA\_stateA$ to a dictionary mapping (v, v') to a list of rules containing ϕ (Append or create a singleton list if needed). As an example, the converted DO dictionary for DONT dictionary in figure 18 is shown below.



```
{'Virtual Switch 3_switch': {
    (False, 'off', 'on'):
        {'Door_lock': {('unlocked', 'locked'):
            [[('Virtual Switch 3_switch', 'off', 'on', True, False, 'seconds'),
                ('Virtual Switch 3_switch', 'on', 'off', True, False, 'seconds')]]}},
    (False, 'on', 'off'):
        {'Door_lock': {('unlocked', 'locked'):
            [[('Virtual Switch 3_switch', 'off', 'on', True, False, 'seconds'),
            ('Virtual Switch 3_switch', 'on', 'off', True, False, 'seconds')]]}},
    (True, 'off', 'on'):
        {'Door_lock': {('locked', 'unlocked'): [[('Virtual Switch 3_switch', 'off', 'on', True, True, 'seconds')]]}}}
}
```

Figure 19: Conversion of DO dict from figure 18

4.1.3 Parsing User Rules

Aside from monitoring the environment under rules learned from STLTree and TreeNoSTL, we have also provided a language for users to additionally input their desired safety rules within IoT environments. The rule language is constructed from a combination of keywords which are parsed into PSTL rules. The grammar for the rule language is described below.

- $\{Specification\}$ WHEN $\{Precondition\}$ AND/OR $\{Precondition\}$ ...

In $Specification$, the device and state value corresponding to the rule is specified in the format

- THE $\{device\_state\ tuple\}$ IS $\{value\}$ (AFTER $\{time\}$ SECONDS/MINUTES)

where the parenthesis part speciftying time is optional. If no time is specified, the state change is assumed to happen within the next timestamp unit. Since both STLTree and TreeNoSTL learn rules for discrete valued device states only, we also only allow discrete valued rules in the $Specification$.

Each rule can have multiple preconditions separated by AND/OR relation. When parsing our language, AND has a higher precedence than OR. For each $Precondition$, the primitive for the rule to be satisfied is described in the format

- $\{state\}$ OF $\{device\}$ $\{Restriction\}$

where in $Restriction$ we specify the rule primitive corresponding to their temporal logic, listed below:

- IS $\{value\}$ FOR $\{time\}$ SECONDS/MINUTES – G rule
- BECOME $\{value\}$ (IN LAST $\{time\}$ SECONDS/MINUTES) – F rule
- BECOME $\{value\}$ IN LAST $\{time\}$ SECONDS/MINUTES FOR $\{time\}$ SECONDS/MINUTES – FG rule

For discrete valued devices, $\{value\}$ is simply the value of the device state, while for continuous states, $\{value\}$ can be specified through

- GREATER / LESS / GREATER EQUAL / LESS EQUAL THAN $\{v\}$

which corresponds to $<, >, \geq, \leq$ in temporal logic inequalities. For discrete variables, the $value$ can only be of one single value rather than a list of possible values. If the rule works under specifications of multiple values of the state, we currently need to specify an additional condition in the rule joined by OR.

The user inputted rules will then be parsed in the same way as the PSTL rules in the corresponding DO and DONT dictionaries, with each primitive precondition being parsed into the 6-tuple format as follows:

- The $deviceName\_deviceState$ tuple: obtained through combining $\{state\}$ and $\{device\}$ in the $\{Conditions\}$ section of rule.
- Primitive type: obtained through pattern matching the $\{Restriction\}$ section.
- Inequality with primitive: For discrete valued states, the field is irrelevant. For continuous valued states, obtained through pattern matching the $\{value\}$ field for restriction as specified above.
- Time interval associated: By our construction, this is a triple of (From last x timestamps from now, To last y timestamps from now, duration of event). The duration of event is simply obtained by the time value after "FOR" in the FG rule restriction (irrelevant for other cases). We then determine y, which is default to be 0 unless specified in the $\{Specification\}$ behind the keyword AFTER. Then, x is defined to be $y + t$, where t is the time specified in the restriction after keyword FOR in G rule and after IN LAST for F rule. For user rules, we default timestamp unit to be seconds, so that rule containing other time unit specification (Ex. Minutes) will be converted to seconds for this term.
- State values satisfying the primitive: Specified by the $\{value\}$ in the $\{Restriction\}$ field
- Timestamp unit: Determined from the $\{Precondition\}$ field.

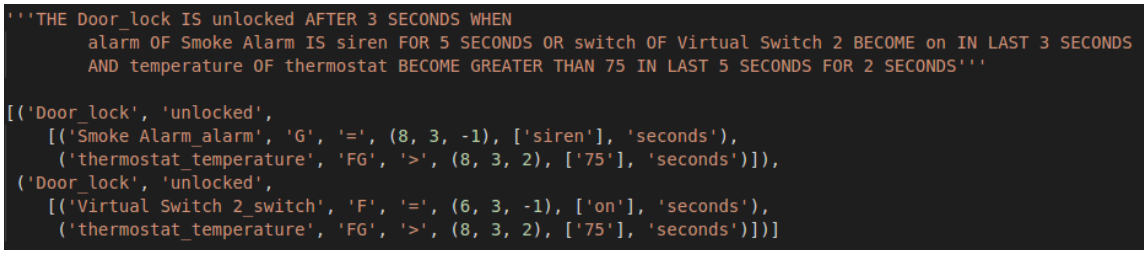
Since conditions are joined by AND/OR keywords for each rule and AND has a higher parse precedence, each rule is then parsed into a list l of the converted 6-tuple lists. Each list of converted 6-tuple lists appear in AND relation and each individual 6-tuples within the same list appears in OR relation. In other words, for a rule condition to be satisfied, at least one 6-tuple of each list in l needs to be satisfied. Thus, we can form a list of rules for the described $Specification$ with our provided conditions from each individual user provided rule by taking a Cartesian product of each 6-tuple list within the list l, since satisfying any element of the Cartesian product implies our rule is satisfied by this OR relation. An example of this rule conversion is shown in figure 20 below.

The time restraint for F rule preconditions can be optional, and it will default to becoming the specified state in last second. Allowing such syntax would make us able to specify immediate rules without setting up a separate rule for parsing, since immediate transitions essentially means it will transition within the last second by how we trained our TreeNoSTL. We specify a transition of device2's state2 to value2 implies device1's state1 transition to value1 through the following:

- THE $\{device1\_state1\ tuple\}$ IS $\{value1\}$ WHEN $\{state2\}$ OF $\{device2\}$ BECOME $\{value2\}$

Rules specified in this way will be translated to the 6-tuple in the exact manner as above, with rule to be F and the time interval tuple being $(1, 0, -1)$ (From last 1 second).

With this process, we form a DONT rule dictionary that has the same structure as described in 4.1.1 for user defined rules, which maps $device\_state$ tuples to a dictionary mapping $values$ to a list of rules converted from the Cartesian product method. Since the dictionary has the same structure as in 4.1.1, the DO dictionary is converted in the same manner.



```
'''THE Door_lock IS unlocked AFTER 3 SECONDS WHEN
        alarm OF Smoke Alarm IS siren FOR 5 SECONDS OR switch OF Virtual Switch 2 BECOME on IN LAST 3 SECONDS
        AND temperature OF thermostat BECOME GREATER THAN 75 IN LAST 5 SECONDS FOR 2 SECONDS'''

[('Door_lock', 'unlocked',
    [('Smoke Alarm_alarm', 'G', '=', (8, 3, -1), ['siren'], 'seconds'),
     ('thermostat_temperature', 'FG', '>', (8, 3, 2), ['75'], 'seconds')]),
 ('Door_lock', 'unlocked',
    [('Virtual Switch 2_switch', 'F', '=', (6, 3, -1), ['on'], 'seconds'),
     ('thermostat_temperature', 'FG', '>', (8, 3, 2), ['75'], 'seconds')])]
```

Figure 20: Conversion of user defined rule. Above: rule, Below: converted list used to construct the DONT dict after Cartesian product method

4.2 Monitor Structure

As described in 2.1.3, in order to access the state change events from and issue commands to devices, STLMon needs to directly communicate with the Samsung Smartthings Hub. To achieve this communication, STLMon consists of a public http server that connects to the Smartthings Hub through Oauth. When a state change event is received by the server, STLMon stores the change and checks for rule violations through its backend. An illustration of the overall monitor struture is shown in Figure 21 below.

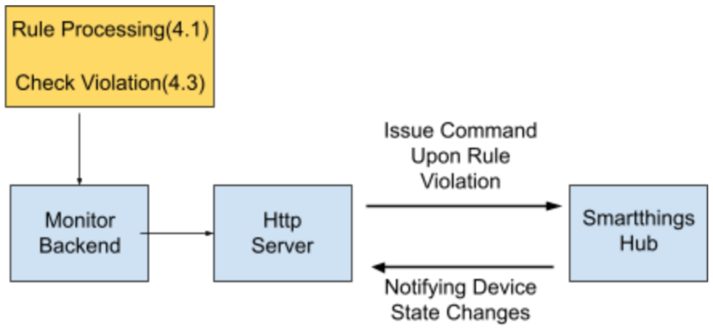


Figure 21: Runtime Monitor Structure

4.2.1 Monitor Backend

In order to check for rule violations, STLMon stores both the DO and DONT dictionaries for both PSTL and immediate rules described in section 4.1 and an internal record of device state changes of the environment. Due to space limitations, STLMon uses a fixed size list to store the state changes, and when the maximum number for the list is reached, STLMon pops out the earliest state change in the record. Each state changes is stored as a tuple of a tuple $(time\ of\ change, value\ of\ change)$ in the list.

The details for using the rule dictionaries and state change lists to detect rule violations is described in section 4.3. Finally, to handle continuous variables for immediate rules, our monitor would also need to access the continuous variable dictionary we created in 3.3.2.

4.2.2 Communicating with Smartthings Hub

As described in 2.1.1, Smartapps are able to issue state changes and access past logs for all the devices they have access to. Thus, STLMon communicates with the Smartthings Hub through Oauth with the same monitor Smartapp the decision tree models used to access the device operation log in section 3, after granting the Smartapp access to all the devices in the environment. When a device change has occurred, the monitor Smartapp sends a request to STLMon regarding the state change with parameters in the order as follows:

1. Time of the state change.
2. Device name for the change.
3. Device state for the change.
4. State value for the change.

To receive these requests from Samsung Smartthings Hub, STLMon simply needs the monitor Smartapp's APIKey and APIEndpoint to issue commands to the Smartapp through Oauth.

4.2.3 Issuing Command to Devices

Upon receiving device state change events from the monitor Smartapp, STLMon first registers the event to the backend record and checks for immediate and temporal DONT rules violations. If a violation is detected, STLMon sends to the monitor Smartapp the state value specified by the rule, which the Smartapp executes the state change through calling devicehandler functions as described in 2.1.2. This state change will be registered on the backend but not analyzed further for rule violations.

If none of the DONT rules is violated by the state change, STLMon then checks for DO rule violations. For each DO rule r with preconditions being satisfied, we would know the time t for the amount of time we need to wait for the device to change state according to the DO rule (Details in 4.3.2) We note that for immediate rules, $t = 0$. STLMon then sends the device, rule specified state value, and t to its scheduler to schedule checking for rule violation after $t + 1$ timestamps. We add an additional time buffer on t since the DO rule is only violated if the desired state change did not happen after t, and we allow 1 timestamp unit duration for the change to happen. The timestamp unit is determined by the 6-tuple for the rule primitives as described in 4.1.

After time $t + 1$ timestamp unit has passed, the scheduler conduct a final check of the state change regarding rule r to check for additional state changes that invalidate the rule's preconditions and whether the $r's$ specified state change has already happened. If none of the checks are true, the DO rule is violated and the scheduler issues the state change command to the Smartapp similar to DONT rule violations. In our monitor, the scheduler for DO rule checks is implemented through Python's apscheduler package [Gr1].

It is possible to have race conditions in the scheduler due to direct conflicts within DO rules, where we have commands that change the same device to different states at the same time due to the wait time difference for rules. To avoid such race conditions, all the device change commands for the same device at the same timestamp unit is handled altogether sequentially with the final check method above, with only the first scheduled device change being sent to the Smartthings Hub.

Finally, to issue the state change commands to the devices, STLMon included a dictionary mapping common household device capabilities (ex. Switch and Lock) to their corresponding value change functions. The dictionary is obtained manually through Samsung Smartthing's capability reference site [Smaa], and additional capabilities that is not included can be found on the same reference site and manually added to the monitor. We plan to include the complete list of capabilities on the reference site to our monitor for future work.

4.3 Checking Rule Violations

From our construction, for each relevant state change event passed from the Hub under the 4-tuple $(currtime, device, state, value)$, STLMon checks whether the state change violate any DONT rules and whether the change would trigger any DO rule to have its precondition being satisfied for both temporal and immediate rules. The details of checking DONT and DO rule violations for PSTL and immediate rules are described in the subsections below.

Since it is not possible to specify a device to be in different state values at the same time, we handle rule conflicts by prioritizing the immediate rule violations over PSTL rule violations. If the two rules are of the same type, the monitor picks the state change according to the the last rule violated with all conditions satisfied. Finally, as mentioned in 4.2.3, STLMon only checks for DO rules for state changes that does not violate any DONT rules.

4.3.1 Checking PSTL DONT Rules

Consider a device state change where $deviceA\_stateA$ is changed to value v. To check for DONT rule violations, STLMon iterates through its DONT dictionary $Dict$ to check for whether any rule in set R has its preconditions being satisfied, with R defined by

$$R = \{rules \in Dict[deviceA\_stateA][key],\ \ key \neq v\}$$

Then, if any rule $r \in R$ is satisfied, we know that r is violated in the state change, since the device should have state value specified by r's key in the DONT dictionary.

To check for whether a rule is satisfied, we iterate through all the preconditions specified in the 6-tuple format (detailed in 4.1.1) for the rule to check whether they are all satisfied. For each of the four precondition rule types F, G, FG and GF in the 6-tuple representation that specifies device D with state S in interval $[hi, lo, dur]$ with available states l (Or for continuous variables, l representing values satisfying the inequality), we check if the precondition is satisfied through the following:

F rule For F rules, we iterate through the record for all the past state changes of D with state S to find all the state change values that is in l. Then, out of all the satisfying device changes, we note by 4.2.1 they are stored in tuple $(t_{chg}, value)$, which we can use to compute the relative time of the each previous change to the current time of our current device state change with $diff = currtime - t_{chg}$ and convert it to the timestamp unit associated with the rule. Finally, by the time interval construction in the 6-tuple format, we need to check whether $lo \leq diff \leq hi$, and the existence of any state change satisfying this inequality would mean the condition is satisfied.

If the condition is not satisfied after the previous check and the first state change within the interval is not exactly at hi seconds away from current time, we also need to consider the case that the device is already in a valid state upon entering the interval. To do so, we check whether the last state before the first state change within the interval exists in our record, and whether it is in a valid state if it exists. The rule is satisfied if the check returns True, and not satisfied otherwise.

G rule Checking G rule is very similar to F rules, we instead need to make sure the device stays in a valid state value for the entirety of the interval. To find if the rule is satisfied, we verify whether the device change passes the following checks:

1. Find all state changes that has relative time difference $diff$ to the current state change being in interval $lo \leq diff < hi$, if any of the state change has a value not in l, the condition is not satisfied since the valid state does not last the entirety of interval.

2. Find the last state change for D with state S that happened before or at exactly hi timestamps from $currtime$, if it is not a valid state in l, the condition is not satisfied since the device would be at an invalid state immediately after hi in the interval. If we can not find such state change, which may be a result of insufficient capacity of our record in holding device changes or lack of information, we also assume the rule is not satisfied.

FG rule To check FG rules, we additionally need to take account of the duration dur. First, we obtain all the state changes from its record for D with state S that has a relative time difference $diff$ within $lo \leq diff \leq hi$. Then, for each device state change chg, we first check if chg is a satisfying state change in l. If it is, we then check whether there is any invalid change (state changes with value outside of l) within the next dur seconds relative to the state change time of chg return satisfied if none is found. We also store $first\_invalid\_date$ that represents the first state change within the relative time difference interval that is not in a valid state, if any, for our next check step.

If the above check failed, we check the last state change before the first state change within the interval to see if it exists in the record. If the state change exists, we then verify whether $first\_invalid\_date$ happens at least dur time stamps away from hi or does not exist at all. This check will let us know that the device is in a valid state for at least dur at the beginning of the interval and we return satisfied. Otherwise, the rule is not satisfied.

GF rule Checking GF rules is more complicated as we need to make sure the device is in a valid state for all of the intervals of size dur within the range $[lo, hi]$. We check whether the condition is satisfied through simultaneously iterating the interval lists and device change state list in our record in the algorithm below.

```
 1 intervals: The intervals of size dur to check, stored in the order
 2            where first interval is farthest away from current time.
 3 changes: The state changes in our record
 4          (relative time diff, value) pairs
 5 CheckGF:
 6     last_valid, last_not = $\infty, \infty$
 7     intval_idx, chg_idx = 0, 0
 8     while intval_idx < len(intervals) and chg_idx < len(changes):
 9         diff, value = changes[chg_idx]
10         curlo, curhi = intervals[intval_idx]
11         if diff < curlo:
12             if last_not $\geq$ curhi and last_not < last_valid:
13                 return False
14             else:
15                 intval_idx += 1
16         else:
17             if value is valid and last_valid >= last_not:
18                 last_satisfied = diff
19             elif value is not valid and last_not >= last_valid:
20                 last_not = diff
21             chg_idx += 1
22     while intval_idx < len(intervals):
23         curlo, curhi = intervals[intval_idx]
24         if not(last_not $\geq$ curlo and last_not $\leq$ curhi):
25             return last_valid < last_not
26         intval_idx += 1
27     else:
28         return True
```

The $last\_valid$ and $last\_not$ defined on line 6 represents the last occurrence of a state change from a not valid value to valid and valid to not valid respectively, in terms of relative timestamp difference from current time. We iterate through the two provided lists simultaneously based on different conditions. If condition on line 11 is True, we know that the current analyzed state change occurs after our current interval since it is less time stamps away. If that is the case, line 12 checks whether the entire interval is in a not valid value, and return not satisfied if it is True. Otherwise, we know this interval is satisfied, we go check the next interval.

If condition on line 12 is False, we continue to update state changes, since the state changes are still within the interval. Line 18 and Line 20 updates the $last\_valid$ and $last\_not$ accordingly. Finally, line 22 checks whether all the intervals have been checked, and if not, we continue to check the intervals to see if they still contain the last invalid state change. If check on line 24 passes, we know the last invalid state change is no longer within the interval before all intervals have been checked. Then, we finally check if our device is currently in a valid state on line 25 and return True if the check passes. Otherwise, we know all the intervals have been checked and satisfied, and we return satisfied accordingly.

4.3.2 Checking PSTL DO Rules

Consider a device state change where $deviceA\_stateA$ is changed value v. To check for DO rule violations, we first iterate through our DO rule dictionary Do to find the rule dictionary $Rule$ containing the rules that will have their preconditions being satisfied in the near future by the current device state change. Recall that we have

$$Rule = Do[deviceA\_stateA][v]$$

And by our construction in 4.1.1, $Rule$ has the exact same structure as the DONT dictionary, which maps each device to a dictionary mapping the device's possible values to its corresponding rules. However, it is possible to have multiple rule dictionaries $Rule$ where all of the contained rules have their preconditions being satisfied by current change in the case of continuous valued devices. For example, a value specified to be > 80 would imply values specified by > 70 to also be satisfied by the current change, so rules in both rule dictionaries representing $Do[deviceA\_stateA][> 80]$ and $Do[deviceA\_stateA][> 70]$ will have their preconditions being satisfied by the current change in the near future. Then, for each rule dict $Rule$ corresponding to the current change, the set of rules R for the monitor to check for condition satisfaction can be defined by

$$R = \{rules \in Rule[devB\_stateB][key],\ devB\_stateB \in Rule.keys, key \in Rule[devB\_stateB].keys\}$$

For DO rules, one additional factor to consider is that they are most likely not specifying immediate behaviors. When a device change that corresponding to a condition happens, the condition may not be immediately satisfied. For example, for a F rule condition of $switch$ being on with time interval $[hi, lo, dur]$, we need to wait at least lo timestamp unit for a state change of turning on a switch to be in the valid time interval to satisfy the condition.

As a result, for each candidate DO rule in R corresponding to our state change, the monitor instead searches for a time t such that after waiting t timestamp units, all the preconditions will be satisfied for the rule due to the current change. This t is used to schedule sending commands upon DO rule violation through the monitor server's scheduler described in 4.2.3 above. If it is not possible to find such t, we know that the conditions will not be satisfied, and no possible violations will exist for the rule.

To find the wait time t or to verify such t does not exist for a rule in R, the monitor checks in two steps. First, similarly to how the DONT rules are checked, the monitor would iterate through each precondition i for the rule to find a list of wait time intervals l_i for i, so that $\forall t \in [t^i_{lo}, t^i_{hi}], [t^i_{lo}, t^i_{hi}] \in l_i$, i is satisfied in the interval.

Before iterating through all the preconditions, we first check whether the wait time interval for the precondition corresponding to the current change to be satisfied. The monitor first assumes the rule is not satisfied before our current change, since otherwise the rule would already be processed by the previous valid change. Now, If the current change condition is corresponding to a F rule with specified time interval $[currhi, currlo, currdur]$, the wait time must be in the $range = [currlo, \infty]$, since waiting less than $currlo$ timestamps would put our current state change outside of the condition specified by interval. FG rule similarly restricts the wait time to be in $range = [currlo + currdur, \infty]$ to account for the duration requirement. For G rules, however, we would have to wait at least $currhi$ times since we would need the condition to be satisfied for the entire interval, and we can wait for as long as possible since the device would always stay in this valid state with our current information (we ignore possible change of states in the future for now), giving us $range = [currhi, \infty]$. Finally, GF rules behaves similar to G rules, but we just need the first satisfying state change to be within dur timestamps from hi, giving $range = [currhi - currdur, \infty]$

As described in 4.1.1, there could be multiple primitives within the same rule that corresponds to the same $deviceA\_stateA$ with value v in its satisfying value list, but for different operators and respective time intervals. We note that since we assume there is no state change after the current change, waiting longer would not invalidated any primitives that is already satisfied. Thus, we determine $range$ based on the primitive that would require us wait the longest (having the largest lower bound in range) if multiple primitives for the same device state value occur.

With this information, the wait time intervals $[t^i_{lo}, t^i_{hi}] \in l_i$ for other preconditions can be first restricted within the interval specified by $range$. Then, the wait time intervals for other F, G and FG conditions is found in the method described below:

G rule For a G rule with time interval $[hi, lo, dur]$ and $range = [rangelo, rangehi]$, the relevant time frame would be $[max(0, lo - rangehi), max(0, hi - rangelo)]$ to check for wait time intervals. We determine the list of valid time intervals in the following steps:

1. Find the last state change s_{last} before or at exactly $max(0, hi - rangelo)$ relative timestamps away from current time, check if it is of a valid state. If it is a valid state, add in interval $[rangelo, hi - t_1 - 1]$ to the list. t_1 is determined by the relative timestamps from the next invalid state change after s_{last} within the relevant time frame. If such t_1 can not be found, the monitor can wait for as long as possible and we add in interval $[rangelo, rangehi]$ instead. If we can not find s_{last}, we skip this step since we have no information.

2. For all the state changes starting from the next state change from s_{last} that is in the relevant time frame, we start a new interval when there is a valid state change and there is no existing interval that has already been started, and we end the interval upon the next invalid state change encountered. If there is an open interval in the end of the process, we set its endpoint to be $rangehi$ and append it to the satisfying interval list. The algorithm for this process is shown in $findIntervalsG$ below.

3. For all the intervals in the satisfying interval list constructed from above, we only keep intervals with range longer than $hi - lo$, since the device need to be in the state value for the entirety of $[lo, hi]$ interval after waiting. For the intervals with range longer than $hi - lo$, we keep the portion of $(startpt, endpt - (hi - lo))$ to satisfy this requirement. The process is done in the call to function $removeInvalid$ in $findIntervalsG$

We note by our method, the intervals in the list will not have any overlaps as overlapping valid state changes will be contained in the same interval by step 2.

```
1  relevantStates: state change in record within the relevant time frame
2      (described in step 2 above)
3  findIntervalsG:
4      intervals = [] or [(rangelo, hi-$t_1$)] from step 1
5      startpt = -1
6      for (date, value) in relevantStates:
7          if startpt < 0 and value is valid:
8              startpt = hi - relative(date)
9          elif startpt $\geq$ 0 and value is not valid:
10             endpt = hi - relative(date) - 1 #inclusiveness
11             intervals.append((startpt, endpt))
12             startpt = -1
13     if startpt $\geq$ 0:
14         intervals.append((startpt, rangehi))
15     return removeInvalid(intervals)
```

F rule For a F rule with time interval $[hi, lo, dur]$ and $range = [rangelo, rangehi]$, the monitor checks for validity of the condition, similarly to the method in checking G rule above within the relevant time frame $[max(0, lo - rangehi), max(0, hi - rangelo)]$ in the following 2 steps.

1. We find the last state change s_{last} before or exactly at $max(0, hi - rangelo)$ from current time and add in $[rangelo, hi - t_1]$ if it is a valid state. This time, t_1 is determined by the next state change after s_{last}, not necessarily need to be invalid. This may result in overlaps in intervals, which we will handle later. If such t_1 can not be found, the monitor can wait for as long as possible and we add in interval $[rangelo, rangehi]$ instead. If we can not find s_{last}, we skip this step since we have no information.

2. Step 2 behaves identical to the G rule step 2, but this time the interval $startpt$ on line 8 is calculated through $lo - relative(date)$, since the F rule becomes valid upon the state change enters the $[lo, hi]$ interval after waiting rather than need to last an entirety. The endpoint stays the same as $hi - relative(date) - 1$ for a similar reason since we can have the state change to be at any point of the interval.

We do not need to restrict the wait time interval size for F rules since the device state does not need to be valid for the entire $[lo, hi]$ interval after waiting. We note that this method will likely result in overlapping intervals since it is possible to have multiple valid state changes in the interval $[lo, hi]$ after waiting a found valid waittime, and we use a $removeOverlap$ method to combine overlapping intervals in the satisfying waititme list to return. To remove the overlaps, we take advantage of the fact that device change tuples in the monitor's record are stored in the order of time for their occurrence. Since in our algorithm we processed the device changes in the same order, the found interval list would already be sorted in terms of their $startpt$. Then, $removeOverlap$ simply iterates through each stored interval in the list, and combine them if possible, in the process shown below:

```
1  removeOverlap(intervals):
2      result = []
```

```
3     currstartpt, currendpt = -1, -1
4     for startpt, endpt in intervals:
5         if startpt < currendpt:
6             if endpt > currendpt:
7                 currendpt = endpt
8         else:
9             result.append((currstartpt, currendpt))
10            currstartpt, currendpt = startpt, endpt
11    result.append((currstartpt, currendpt))
12    return result[1:]
```

In the algorithm, the $[currstartpt, currendpt]$ represents the previous combined interval that our current interval represented by $[startpt, endpt]$ can overlap with, and if $endpt$ is farther than $currendpt$, we extend the interval to be $[currstartpt, endpt]$. Otherwise we know the intervals are disjoint, and for the other unchecked intervals, they would also be disjoint due to the sorted nature. As a result, we append $[currstartpt, currendpt]$ to the result list and start a new interval to be checked for overlaps with the rest. Line 11 accounts for the last interval we formed, and Line 12 removes the dummy value $[-1, -1]$ we set in the beginning.

FG rule Checking a FG rule is essentially checking a F rule with taking account of the duration. With time interval $[hi, lo, dur]$, $range = [rangelo, rangehi]$, and relevant time frame $[max(0, lo - rangehi), max(0, hi - rangelo)]$, finding valid intervals for FG rule is identical to the algorithm defined for F, with a different definition for a valid state change. For FG rule, in order for a state change to be valid, it would additionally need to stay in a valid state from the time of the change for dur. This check is identical to what the monitor used to check a FG rule condition is satisfied in DONT rules, and $startpt$ would be $lo - relative(date) + gap$ instead to take account of dur. Similarly, the $endpt$ being calculated would be $hi - relative(date) - gap - 1$ upon encountering an invalid value.

GF rule Checking GF rule is different comparing to the other 3 rules above. For a GF rule with time interval $[hi, lo, dur]$ and $range = [rangelo, rangehi]$, we check the validity of the condition with the following 2 steps:

1. We first iterate through the record of device state changes, and create a list of intervals representing the range of relative timestamps away from current time in which the device is in a valid state. This is done simply in an identical way as in the method in $findIntervalsG$, with starting $interval$ to be [], $startpt$ and $endpt$ defined on line 8 and 10 to be $relative(date)$. We note again that the valid intervals found in this list would appear in the order where the first interval is farthest away from current time.

2. Then, we find the valid waittime intervals by iterating through all possible waittimes t within $range = [rangelo, rangehi]$ to see if any satisfies our condition. Similarly to checking DONT rules, the monitor checks whether each waittime satisfies the condition through simultaneously iterating the list of valid intervals found in step 1 and the list of size dur intervals. The algorithm is shown below:

```
validlist = list of valid intervals found in step 1
findIntervalsGF:
    reslist = [], startpt = -1
    for t in [rangelo, rangehi]:
        intervals = Intervals of size dur,within range [hi - t, lo - t]
                    order where first interval farthest from curTime.
        intervalidx, valididx = 0, 0
        while intervalidx < len(intervals) and valididx < len(validlist) - 1:
            satisfied = True
            intlo, inthi = intervals[intervalidx]
            vallo, valhi = validlist[valididx]
            if inthi < vallo:
                valididx += 1
```

```
14          else if validhi < intlo:
15              if startpt >= 0:
16                  reslist.append((startpt, t))
17                  startpt = -1
18              satisfied = False
19              break
20          else:
21              intervaidx += 1
22      if satisfied:
23          if intervalidx < len(intervals):
24              checkLastValidInterval()
25          else:
26              startpt = t if startpt < 0 else startpt
27  return reslist
```

The algorithm checks for whether there is an intersection between each interval in the list of size dur intervals with a valid interval found in Step1. If there is, we know there is a valid state in the interval for at least 1 time stamp and we can continue to check the next size dur interval specified on line 21. Line 12 and Line 14 checks for the two other cases, with Line 12 checking for our size dur interval appears after our current checked valid interval, which we then increment the interval index to check the next valid interval. Line 14 checks whether current valid interval appears after the size dur interval, since both $validlist$ and $intervals$ are sorted based on farthest from current time, we know that this size dur interval is not satisfied since otherwise previous valid intervals would already check this interval with line 21. We terminate the current satisfying interval, if exists, by setting this waittime as an endpoint.

We note by line 8 that we set the last valid interval item as a special case, which we handle by $checkLastValidInterval()$. We check the case similarly to before, with the addition that if there is no overlap between the last valid interval and current checking intervals, the condition is not satisfied for the current waittime. Furthermore, if the last valid interval appears before the current checking interval, since there are no change of states after, any future waittimes will not satisfy our condition either. As a result, we can terminate our entire loop. Similarly, if there is an overlap, we check whether we are still at the first interval and whether the last valid interval has validlo = 0 (In other words, the device is currently in a valid state). If that is the case, there is no need to check future waittimes, since they will always be satisfied. We return with our result interval list with the addition of $(startpt, offsethi)$.

Otherwise, if all the checks have been passed, we start a new satisfying interval if there is not one already on line 26. Also, due to our special case in $checkLastValidInterval()$, the loop will guarantee to terminate before waittime t exceeds hi, since there would be not any new information in $[lo, hi]$ interval. This makes sure our loop termination while $rangehi$ may be initially set to ∞.

Finding Waittime for Entire Rule After finding the list of satisfying waittime intervals for each condition of the rule, STLMon would know that the rule preconditions will not be satisfied if any of the wait time interval list is empty. Otherwise, the monitor would then need to determine whether there exist a waittime that satisfies all conditions. While there may be multiple waittimes satisfying all conditions, the rule will be satisfied immediately when all conditions are met and the monitor would simply need to check for the earliest possible waittime to return for issuing commands described in 4.2.3. This is equivalent to finding the earliest value t that is in range of some interval $[t^i_{lo}, t^i_{hi}]$ for each one of the condition interval list l_i. The algorithm for $findWaittime$ is shown below:

```
n: Number of conditions
$l^i$: interval list for condition $i$
findWaittime:
    endptlist = []
    for i in range(n):
        for $t^i_{lo}, t^i_{hi}$ in $l^i$:
            endptlist.append(($t^i_{lo}$, L))
            endptlist.append(($t^i_{hi}$, R))
```

```
9          sortedlist = sorted(endptlist, compare_fn)
10         count = 0
11         for time, id in sortedlist:
12             if id == L:
13                 count += 1
14             else if id == R:
15                 count -= 1
16             if count == n:
17                 return time
18         return -1
19
20     compare_fn((t0, id1), (t0, id2)): if id1 == L then > else <
21     compare_fn((t0, id1), (t1, id2)): if t0 < t1 then < else >
```

The algorithm takes advantage of the fact that each interval list l^i has no overlaps, so that if we have found an overlap of n after combining all intervals for all the condition interval lists, all the wait times t within the interval can satisfy all of the n conditions. The number of overlap can be found through first sorting the list that we formed through combing all intervals' start and end points for all rules. We sort our list based on time in $compare\_fn$ and prioritizing start points over end points with the same time due to our rule's inclusive nature. We then obtain the number of intervals that is overlapped up to the time specified by $time$ on line 11 by counting the number of start points we have encountered in our sorted list subtracting the number of endpoints we have encountered.

Since we are interested in the earliest time this is achieved, we return the start point t for the last interval that makes the overlap happen the first time. Our monitor would then send the rule and t to our monitor's scheduler to send commands in 4.2.3. If we can not find such wait time t, the rule is not satisfied by our current device change.

4.3.3 Checking Immediate Rules

For immediate rules, checking DO and DONT rules are done in identical ways since finding waittime would no longer be an issue. Similar to checking temporal rules, the immediate rules are checked by breaking each individual rule into a list of preconditions and check if all of them have been satisfied. For a device state change where we have $deviceA\_stateA$ to change to value v, the set of rules R to be checked for DO and DONT immediate rules are defined identically to their temporal counterparts in 4.3.1 and 4.3.2. However, recall that the conditions specifying for each rule is in a different 6-tuple, defined in 4.1.2 to be

$$(device\_state,\ startState,\ endState,\ statechange,\ falsebranch,\ timestamp\_unit)$$

Checking if each condition is met is done under the following algorithm, described below:

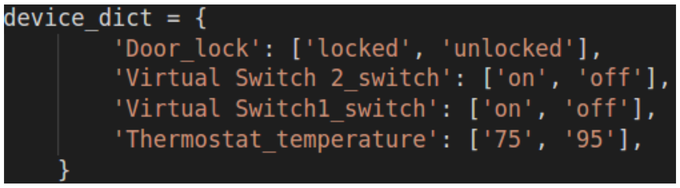
```
record: The monitor's record of the state changes for condition's device
checkCondition:
    lastChangeTime, lastChangeValue = record[-1]
    satisfied = False
    if lastChangeValue == endState:
        if not statechange:
            satisfied = relative(lastChangeTime, currTime) > 1
        else:
            beforeChangeTime, beforeChangeValue = record[-2]
            satisfied = relative(lastChangeTime, currTime) ≤ 1 and
                        beforeChangeValue == startState
    if falsebranch:
        return !satisfied
    return satisfied
```

In the algorithm, the $relative$ function computes the relative timestamp unit difference between the two parameters, which we would need to be within 1 timestamp unit by our definition of immediate. If a condition is corresponding to a state change, then it must have been transitioned to $endState$ from $startState$ within the last time stamp unit, which is checked in line 10 and 11. Otherwise, the device stays in the $endState/startState$, which can be checked in line 7 to show it stayed in the state value for more than a timestamp unit. Finally, we return the negation of satisfied if we are on the false branch.

The algorithm above ignores the event where we are unable to find $lastChange$ or $beforeChange$ on line $3, 9$ due to the lack of information in our monitor's record. As a result, we can not infer anything about the condition, and we return False for either true or false branch the condition corresponds to. If all conditions for a rule are satisfied, the rule is then passed to our monitor server to check for violation and issue commands.

4.4 Evaluation

To evaluate the performance of STLMon, we have incorporated a fuzztesting framework to randomly generate device operational log input for the monitor to detect rule violations. To begin our log generation, we first manually input a dictionary $input$ mapping each $device\_state$ tuple in the environment to a list of possible values the device may take. For continuous variables such as temperature, the possible values would instead be a list of 2 items, the first being the value's lower bound while the second being upper bound. An example input is shown in Figure 22 below.



```
device_dict = {
        'Door_lock': ['locked', 'unlocked'],
        'Virtual Switch 2_switch': ['on', 'off'],
        'Virtual Switch1_switch': ['on', 'off'],
        'Thermostat_temperature': ['75', '95'],
    }
```

Figure 22: Input dictionary for fuzz testing

Then, the generation process takes 2 steps. First, we generate a random set of rules for the environment; then, we use the rules to generate device operation logs that are likely to reflect rule behavior and cause violations. The details for each process is described in the sections below, and the evaluation result would be discussed in the final section.

4.4.1 Generating Rules

From the rule parsing technique described in 4.1, it is sufficient for our testing framework to only generate the DONT rules for both temporal and immediate behavior, since the DO rules can be directly converted from them.

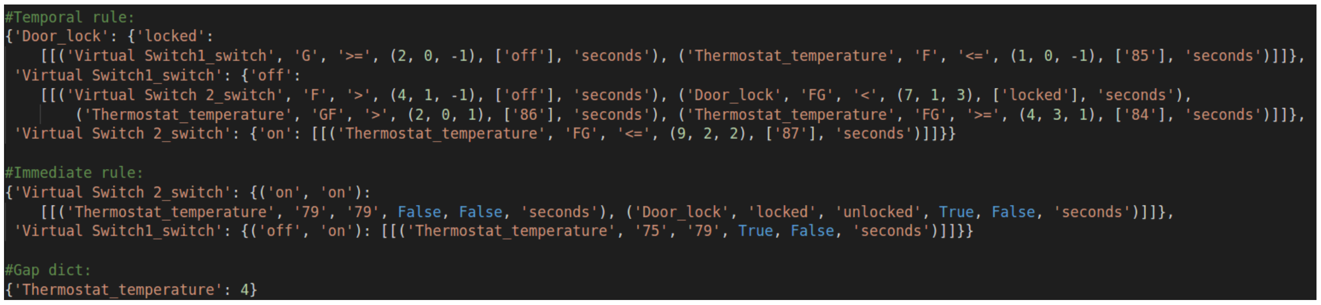
Our rule generation first takes in a $maxdepth$ and $timebound$ parameter for the environment, where the $maxdepth$ specifies the maximum number of preconditions per rule in our environment (recall in 4.1 that each rule is a list of preconditions either specifying PSTL primitives or immediate behavior) and $timebound$ specifies the maximum value for hi can be in each PSTL rule condition time intervals.

Then, for temporal rules, we generate each member of the 6-tuple for each condition randomly by picking random associated primitive type, a random satisfying time parameter $[hi, lo, dur]$, a random inequality, and a random integer we use to find satisfying state values with the inequality we picked. For discrete valued devices, the random integer is picked between 0 and the length of the possible value list in our input dictionary $input$ and all the values of indices satisfying the inequality to the integer we picked is kept as valid state. For continuous valued devices, the valid value is picked between the middle 50% of the value range described by the corresponding lower and upper bounds in $input$.

For immediate rules, the start and end state values are picked in a similar way for discrete valued devices through a random index in possible value list. For continuous variables, we categorize the possible values into 5 equally gapped discrete states and we store the gap for the state in a $gapdict$ for generating state change logs.

For each rule we want to generate for the environment, we first randomly select whether the rule would be a PSTL rule or an immediate rule. Since we expect that a household environment to have more temporal rules than immediate rules in real life, the number of temporal rules to immediate rules is kept at approximately a $7:3$ ratio. An example generated rule dictionary for input in Figure 22 is shown below.

Finally, we note that it is possible for us to generate rules specifying impossible behavior due to randomness, such as a device being on and off at the same time interval. In practice, however, such the probability of such rules being generated is negligible and will not have a impact on the accuracy of our evaluation.



```
#Temporal rule:
{'Door_lock': {'locked':
    [[('Virtual Switch1_switch', 'G', '>=', (2, 0, -1), ['off'], 'seconds'), ('Thermostat_temperature', 'F', '<=', (1, 0, -1), ['85'], 'seconds')]]},
 'Virtual Switch1_switch': {'off':
    [[('Virtual Switch 2_switch', 'F', '>', (4, 1, -1), ['off'], 'seconds'), ('Door_lock', 'FG', '<', (7, 1, 3), ['locked'], 'seconds'),
        ('Thermostat_temperature', 'GF', '>', (2, 0, 1), ['86'], 'seconds'), ('Thermostat_temperature', 'FG', '>=', (4, 3, 1), ['84'], 'seconds')]]},
 'Virtual Switch 2_switch': {'on': [[('Thermostat_temperature', 'FG', '<=', (9, 2, 2), ['87'], 'seconds')]]}}

#Immediate rule:
{'Virtual Switch 2_switch': {('on', 'on'):
    [[('Thermostat_temperature', '79', '79', False, False, 'seconds'), ('Door_lock', 'locked', 'unlocked', True, False, 'seconds')]]},
 'Virtual Switch1_switch': {('off', 'on'): [[('Thermostat_temperature', '75', '79', True, False, 'seconds')]]}}

#Gap dict:
{'Thermostat_temperature': 4}
```

Figure 23: Generated rule output

4.4.2 Device Change Log Generation

In order for our monitor to check for rule violations for each device change, we need both information about the current change to be checked and a log of past device state changes to store in the monitor's record. To generate the log of past state changes, we first note that it is difficult to generate device changes that satisfy the conditions of our generate rules from pure randomness. Thus, in order to have a high chance to satisfy conditions for our device interaction rules generated above, we form our device state change logs basing on each individual rule in two steps. First, we pick a random rule and generate a event log based on the preconditions of the rule, so that if no other state changes is added to the log, all the preconditions of the rule would be satisfied. Then, we add in random device state changes in the log for the randomness in input. As a result, a significant portion of the generated logs would remain not impacted by the added random changes to make sure we have both satisfying and not satisfying test cases for the monitor.

For the current change, we first need to generate the current time $curTime$ to be a random time within 24 hours of the time when testing is ran. We recall from Figure 23 and section 4.1 that both DO and DONT PSTL dictionaries have a structure mapping $deviceA\_stateA$ to a dictionary mapping each $valueA$ of the state to either the list of rules (for DONT case) or dictionary of rules (for the DO case) corresponding to when $deviceA\_stateA$ changed value to $valueA$. For immediate rule dictionaries, the structure is similar, mapping $deviceA\_stateA$ to $(ValueBefore, ValueAfter)$ value pairs specifying a state or nonstate change. As a result, for PSTL rules, the $deviceA\_stateA$ and $valueA$ for the current change is determined by what the rule we have picked to generate change logs corresponds to. For immediate rules, the current change behaves the same with $valueA$ determined by $ValueAfter$. To start our device change generation, we first need our input device dictionary $input$, $timebound$, and $gapdict$ in addition to the generated rule dictionaries from our rule generation above. The details for generating past device change log and current change for each type of rule is described in the sections below.

Generate Device Change Log for temporal DONT Rules To generate the current device change from a temporal DONT rule, we first randomly determine whether the generated current change would cause a rule violation, if all preconditions are satisfied by the past device change log. If rule violation is determined to not occur, we simply return a current change at $curTime$ of $deviceA\_stateA$ to $valueA$. Otherwise, we return a change for our device state to change to $valueB \neq valueA$, a randomly selected value that $deviceA\_stateA$ can be.

Now, for generating an environment satisfying the conditions of the rule, we iterate through all the conditions of the rule to generate an device change event to satisfy each condition. For PSTL DONT rules, each condition is a primitive specifying a $device\_state$, for each of the primitive, we construct a state change event satisfying the condition as follows (Recall each primitive is in the 6-tuple structure defined in 4.1.1):

1. Determining the time of the state change. For a primitive defined with time interval $[hi, lo, dur]$, we first determine the $lowerbound$ for the state change. If we have F or FG rules, the state change must happen at least lo timestamps before the current time ($lo + dur$ for FG rules). Similarly, for G and GF rules, the state change must happen at least hi timestamps before the current time ($hi - dur$ for GF rules). We set $lowerbound$ accordingly.

   The upper bound for state change can be determined by $timebound$, since we have no rules regarding state changes more than $timebound$ away. Thus, the time of the state change will be randomly picked within the interval $[lowerbound, timebound]$ away before $curTime$.

2. Determining the value of the state change. This is done by randomly picking from index of the possible states specified in the primitive for discrete states. For continuous valued devices, the value is randomly picked

within the lowerbound and upperbound specified by the manually inputed dictionary $input$ that satisfies the inequality in the primitive.

Finally, we add in random state changes to the log generated by the step above. For each timestamp from $timebound$ away to $curTime$, we determine the number of state changes happening through a random generator. For each state change, we simply randomly pick a $device\_state$ in the environment and change its value to a possible value specified in $input$ at the corresponding timestamp.

Generate Device Change Log for temporal DO Rules To generate device changes for temporal DO rules, we need to additionally consider the waittime needed for the condition to be satisfied. Thus, we first randomly generate the wait time t that is upperbounded by $timebound$ for the rule to be satisfied. For the lowerbound of t, we note that as described in checking DO rule method in 4.3.2, the $(deviceA\_stateA, valueA)$ pair we picked in current change should corresponds to a primitive condition p with time interval $[hi, lo, dur]$ in our picked rule. And similarly to determining the range in 4.3.2, we need to wait at least lo for F rules, $lo + dur$ for FG rules, hi for G rules, and $hi - dur$ for GF rules for p to be satisfied. We set this to be the lowerbound in picking t.

After picking t, we adjust the time interval $[hi', lo', dur']$ for each condition in the rule to be $[hi' - t, lo' - t, dur]$ that does not correspond to $(deviceA\_stateA, valueA)$ pair, so that after waiting t time stamps, the condition will be satisfied with respect to time interval $[hi', lo', dur']$. The rest of the data log and current change would follow identically as the temporal DONT rule case on the newly modified condition intervals.

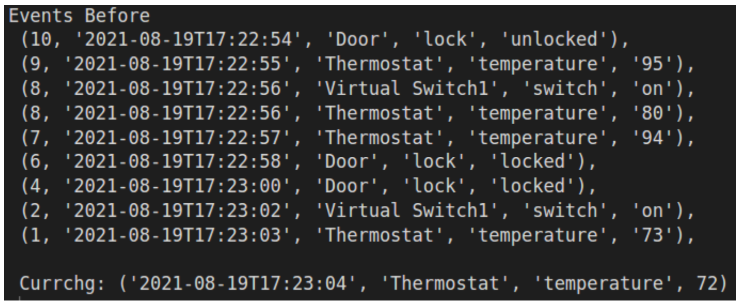
Generate Device Change Log for immediate Rules Generating immediate rule device change is different than temporal rules in that we also need to consider both the before state and after state and whether the precondition is on the negate branch. As a result, for each precondition in the rule, we generate an environment satisfying the rule in our first step of generating device state change log for each of the 4 cases as follows: (Recall each primitive is in the 6-tuple structure defined in 4.1.2)

1. StateChange: True, Negate Branch: False. In this case, we generate two events for the condition, one to make sure the device is changed to the before state before the last timestamp, and one to make sure the device is changed to the after state within the last timestamp. For the before change event, the device can change to this state at any timestamp before the last timestamp, which we pick the time to be a random value within the interval $[1, timebound]$ away before the $curTime$ (we set $timebound$ as the upperbound for similar reason as temporal rule case). For the after state change, the event would need to happen within 0 or 1 timestamp before $curTime$.
2. StateChange: False, Negate Branch: False. In this case, we simply need one event to make sure the device is changed to the before state before the last timestamp, and we pick the time to be within interval $[1, timebound]$ away before $curTime$.
3. StateChange: True, Negate Branch: True. In this case, we first randomly determine whether the device changes state or not. If the device changes state, we randomly pick the before state and after state from the available states provided by our $Input$ that does not match the states specified by the condition. Then, the event changes corresponding to the before state and after state we picked can be generated identically as in case 1. If the device does not change state, we randomly pick an available state provided by $Input$ and generate event change respective to the picked state identically as in case 2.
4. StateChange: False, Negate Branch: True. Similar to the case above, we randomly determine whether device changes state or not. If the device changes state, we randomly pick a before state and after state pair and generate event changes as in case 1. If the device does not change state, we randomly pick a state that is different from the specified state in the condition and generate event change as in case 2.

After the environment satisfying the conditions have been generated, we add in the random state changes at each timestamps identically to what we do for generating temporal DONT and DO rules. However, before the random state changes are added, we also need to make sure the $deviceA\_stateA$ that our picked rule for log generation corresponds to has value $valueBefore$ before the current change for $valueAfter$ happens. As a result, we add in an event changing state value to $valueBefore$ to our generated log from step above, with event time to be randomly picked within interval $[1, timebound]$ away before $curTime$. The log is then added with random state change events and paired with the current change to $valueAfter$ to send to our monitor to be checked in an identical fashion as for temporal DONT rules and DO rules.

We finally note that for the steps above, we also need to consider the difference between the immediate rules and temporal rules is in the handling of continuous valued devices. For a continuous value device x specified by an immediate rule condition, we can obtain the gap g used for generating the value from our generated $gapdict$ in 4.4.1. From this, we can randomly pick a valid value within the state x in the interval $[x, x + g - 1]$ by our construction.

Example Output An example for generated (Device Change Log, current Change) pair is shown in Figure 24 below. Each device change in the log is specified by a 5-tuple of (timestamps away from $curTime$, change Time, device, state, value), and current change is specified by ($curTime$, device, state, value). We note due to the insertion of random state changes, it is possible for a device to change to the same state value as its current value as shown by the Door's lock state in the figure. Such behavior would not impact our monitor in any aspect.



```
Events Before
 (10, '2021-08-19T17:22:54', 'Door', 'lock', 'unlocked'),
 (9, '2021-08-19T17:22:55', 'Thermostat', 'temperature', '95'),
 (8, '2021-08-19T17:22:56', 'Virtual Switch1', 'switch', 'on'),
 (8, '2021-08-19T17:22:56', 'Thermostat', 'temperature', '80'),
 (7, '2021-08-19T17:22:57', 'Thermostat', 'temperature', '94'),
 (6, '2021-08-19T17:22:58', 'Door', 'lock', 'locked'),
 (4, '2021-08-19T17:23:00', 'Door', 'lock', 'locked'),
 (2, '2021-08-19T17:23:02', 'Virtual Switch1', 'switch', 'on'),
 (1, '2021-08-19T17:23:03', 'Thermostat', 'temperature', '73'),

 Currchg: ('2021-08-19T17:23:04', 'Thermostat', 'temperature', 72)
```

Figure 24: Generated log output

4.4.3 Evaluation Results

We ran our fuzz testing on STLMon with a simple environment with 4 devices, 3 being discrete stated and 1 being continuous shown in Figure 22. From the environment, we randomly generated 10 device interaction DONT rules with $maxdepth$ set to 4 and $timebound$ set to 10(a combination of temporal and immediate rules as described in 4.4.1). From the DONT rules, we then constructed the DO rules in the environment. For each rule we generated, we then generate 2 (device change log, current change) pairs as described in 4.4.2 corresponding to the rule for the monitor to be checked.

The process above is done 5 times to ensure the robustness of the monitor and we reached 100% accuracy and violation detection. Each evaluation of STLMon is also timed to ensure the efficiency. In testing, each evaluation on a (Device change log, current change) pair takes less than $0.4ms$, showing STLMon's efficiency is compatible for real time detection. To test for the accuracy of the monitor, each generated log pairs is first manually analyzed with the randomly generated rules to compare with monitor's output. Then, the pairs where our monitor detects a rule violation are then virtually simulated on the Samsung Smartthings platform through issuing commands with the monitor Smartapp (details in section 9.5). Out of the 268 generated test cases for both temporal and immediate DO and DONT rules, our monitor has accurately detected all the rule violations, showing robustness.

5 STLCheck: Checking Conflicts within Interaction Rules

While STLMon is able to efficiently and accurately detect rule violations within IoT systems at runtime, it has several limitations. Particularly, STLMon can only detect rule violations once they have already happened, which at that time the safety of the environment can be already compromised. STLMon is also unable to guarantee our notion of safety in definition 2 since it can only detect rule violations that are potentially caused by conflicts rather than detect all the conflicts within the environment. As a result, we have created STLCheck, a static checker for these conflicts in device interaction and user input safety rules. To exhibit the conflicts found, STLCheck generates an example device change log that will reflect the behavior. The implementation details for STLCheck is described in the sections below. Finally, we note that through the parsing algorithm in section 4.1.3, each user defined security rule is conveniently converted to an PSTL rule, ridding us the need of creating separate conflict checkers for learned and user defined rules.

5.1 Checking Rule Satisfaction

If a conflict exists, it is necessary and sufficient for our generated device conflict log to satisfy all the precondition of the associated rules at the time of current change. In order to generate this log, we have utilized the $z3$ SMT solver to derive an environment satisfying all the conditions for each of the rules in near linear time [dMB08] (Details about SMT formulas can be found in section 2.3).

Before it starts checking for rule conflicts, STLCheck first needs information on the devices and the rules that we would like to find conflicts on. Specifically, STLCheck requires an input dictionary $input$ mapping each $device\_state$ tuple in the environment to a list of the possible values the state may take for discrete valued devices and a two-item list of lowerbound and upperbound for continues valued devices similarly to the case for fuzz testing described in 4.4. STLCheck also needs the $timebound$ parameter representing the upper bound for hi in PSTL rules for each device to restrict the number of timestamps to consider in conflict checking, since the device state information before $timebound$ will not impact our rule conditions.

In order to derive a state change log that satisfies all the conditions for all of the rules if a conflict exists, we need to know the exact values each $device\_state$ tuple in the environment at all the relevant timestamps. As a result, we created a timestamp integer variable d_i to represent the value of $device\_state$ tuple d at timestamp i away from current time, i ranges from 0 to $timebound$ from our restriction above. For discrete valued d, each d_i is mapped to an index in the list of available values specified in $input$, and for continuous valued d, each d_i is mapped to a value within the range of $[lowerbound_d, upperbound_d]$ from $input$. This also gives us the initial SMT constraints below:

1. $\forall d \in Discrete, 0 \leq d_i \leq len(input[d])$
2. $\forall d \in Continuous, lowerbound_d \leq d_i \leq upperbound_d$

Now, we treat each preconditions of the rules as constraints that needs to be satisfied by our d_i's for each $device\_state$ d and derive a SMT formula for each precondition in the methods below.

PSTL Rules For PSTL rules, we recall from 4.1 that each primitive precondition is represented by a 6-tuple $(device\_name, type, inequality, timeInterval, satisfyingStates, timestamp\ unit)$. For each type of primitive with $device\_state$ d, $timeInterval$ $[hi, lo, dur]$, and satisfyingStates l, its respective formula is derived as follows:

1. For F rules, we need the device state to be in one of the values in l for at least 1 timestamp in the range. This can be expressed through the or operator. That is, $Or_{i\in[lo,hi]}\ (d_i \in l)$, where we define $Or_{\phi_1,\phi_2,...\phi_n} = \phi_1\ \vee\ \phi_2\ ...\ \vee\ \phi_n$ for SMT formulas $\phi_i' s$. Finally, we note that $d_i \in l$ can be expressed through the SMT formula $Or_{v_i \in l}\ (d_i = v_i)$ for any specific i for discrete variables, and can simply be converted into $d_i\ (inequality)\ (l[0])$ for continuous variables by our 6-tuple construction.

2. For G rules, we need the device to be in one of the values in l for all of the respective timestamps in the range, which can be expressed through the and operator with $And_{i\in[lo,hi]}\ (d_i \in l)$. ($And_{\phi_1,\phi_2,...\phi_n} = \phi_1\ \wedge\ \phi_2\ ...\ \wedge\ \phi_n$ similarly to the Or case).

3. For FG rules, we need the device to be in one of the values in l for at least dur timestamps within the $[lo, hi]$ range, which can be expressed through $Or_{i\in[lo,hi-dur]}\ And_{j\in[i,i+dur]}(d_j \in l)$.

4. For GF rules, we need the device to be in one for the values in l for at least 1 timestamp in all of the size dur intervals within the $[lo, hi]$ range. This can be expressed through $And_{i\in[lo,hi-dur]}\ Or_{j\in[i,i+dur]}(d_j \in l)$.

Immediate Rules As described in 4.1, each immediate rule precondition is also represented by a 6-tuple $(device\_State, startState, endState, stateChange, Negate, timestamp\ unit)$. We handle the SMT formula generation for the immediate rule preconditions by separating into two cases based on the $Negate$ flag as follows:

1. If the $Negate$ flag is set to $False$, we know that the $device\_state$ d has immediately changed from $startState$ to $endState$ before current time. This can be expressed as $d_1 = startState \wedge d_0 = endState$. We note the $stateChange$ flag does not affect this, since if $startState = endState$, we need the device to be in the $startState$ for at least 1 second, which is exactly expressed by our formula above.
2. If the $Negate$ flag is set to $True$, we know that transitions at the last second that correspond to all $(start, end)$ pairs different from $(startState, endState)$ satisfies our condition. Thus, the condition can be expressed as $Or_{(start,end)\in l'}$ $(d_1 = start \wedge d_0 = end)$ where l' is defined as the list of $(start, end)$ pairs defined above.

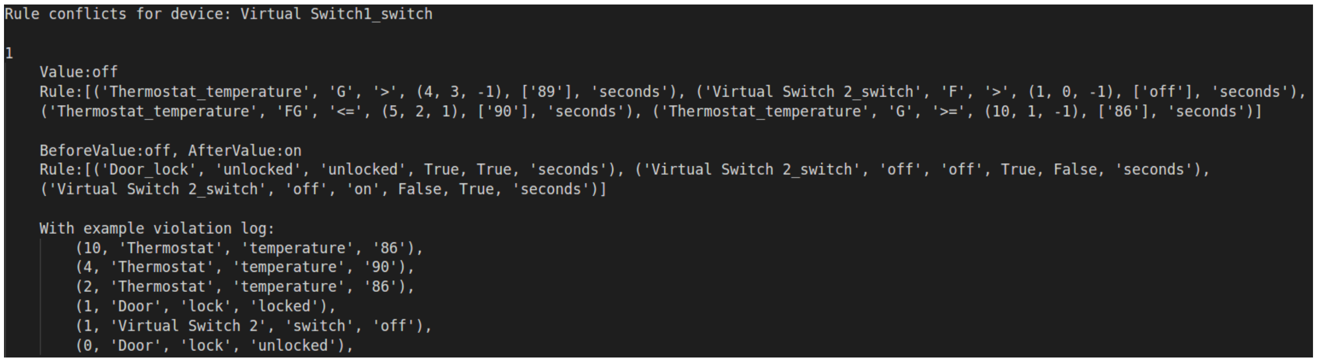
Since it is necessary and sufficient for all of the preconditions of all of the rules to be satisfied at current time for a conflict to occur, our derived environment would need to satisfy both the initial constraints and all of the SMT formulas corresponding to each of the preconditions generated from our method above. Formally, define ϕ_{init} to be the set of our initial SMT constraints from our $input$ dictionary, and ϕ_{cond} be the set of SMT constraints from the preconditions of our rules, a satisfying environment that will result in rule conflict can be represented by the solution to the SMT formula

$$\Phi = (And_{\phi\in\phi_{init}}\phi) \wedge (And_{\phi'\in\phi_{cond}}\phi')$$

If $z3$ determines our Φ as unsat, we know that there are no conflicts within the set of rules, since they can never be satisfied at the same time. Otherwise, $z3$ will return a solution to a satisfying assignment for Φ with a dictionary mapping d_i's for each corresponding $device\_state$ tuple d to their corresponding assignment value (or index of the value list for discrete variables). By our construction, each d_i can be interpreted as the state value d at i seconds away from current time. As a result, we generate a log from our solution set as follows:

1. For each device d, starting from $i = timebound$ to $i = 0$, every time the device is not of the same state as its previous timestamp ($d_i \neq d_{i+1}$), the device has changed state. STLCheck then generates a state change to be added to the log at the corresponding timestamp away from current time.
2. For other variable d_i's, there is no state changes needed, and no entries would need to be added to the log.

We note that the $z3$ solver only guarantees the existence of a satisfying formula; that is, if a conflict is detected, our generated device state change log may not be the only possible way for the conflict to occur. Finally, for clarity, the event log generated from step above is sorted in the order of timestamps away from current time. An example log output for when a rule conflict is detected is shown in Figure 25 below.



```
Rule conflicts for device: Virtual Switch1_switch

1
    Value:off
    Rule:[('Thermostat_temperature', 'G', '>', (4, 3, -1), ['89'], 'seconds'), ('Virtual Switch 2_switch', 'F', '>', (1, 0, -1), ['off'], 'seconds'),
    ('Thermostat_temperature', 'FG', '<=', (5, 2, 1), ['90'], 'seconds'), ('Thermostat_temperature', 'G', '>=', (10, 1, -1), ['86'], 'seconds')]

    BeforeValue:off, AfterValue:on
    Rule:[('Door_lock', 'unlocked', 'unlocked', True, True, 'seconds'), ('Virtual Switch 2_switch', 'off', 'off', True, False, 'seconds'),
    ('Virtual Switch 2_switch', 'off', 'on', False, True, 'seconds')]

    With example violation log:
        (10, 'Thermostat', 'temperature', '86'),
        (4, 'Thermostat', 'temperature', '90'),
        (2, 'Thermostat', 'temperature', '86'),
        (1, 'Door', 'lock', 'locked'),
        (1, 'Virtual Switch 2', 'switch', 'off'),
        (0, 'Door', 'lock', 'unlocked'),
```

Figure 25: Generated log output for conflict between the two rules. Each entry in log is in 4-tuple of (timestamp from current time, device, state, value)

5.2 Checking Conflicts within Environment

With our method in checking rule satisfaction above, we are able to analyze conflicts in an IoT environment through both of its learned and user defined rules. Such check is straightforward and can be done through trying to generate a conflict log specified in 5.1 for all possible rule combinations. Since only rules specifying for the same $device\_state$ with different values can be in conflict, we only need to select at most 1 rule for each value in each combination for a fixed $device\_state$. We also note that only discrete valued devices are associated with the rules by our decision tree and user input constructions described in section 3 and 4; that is, continuous valued devices are only allowed in the preconditions, but are not specified by rules themselves. Now, for a $device\_state$ d, we find all the possible combinations of temporal and immediate rules for it in the environment that can be in conflict with the following steps:

1. First, we find the list of all possible values l_d that d can take through the same input dictionary $input$ as described in 5.1. For each value $v_i \in l_d$, we then consider all the possible combinations for PSTL rules by creating a set of rules S_i containing all the temporal PSTL rules regarding changing d to v_i. We then add in an empty rule for each set, so that for all of the values $v_i \in l$, there is a corresponding set S_i that has at least 1 element $Empty$.

2. Now, since only rules corresponding to different values can be in conflict, a list of all possible combinations of the temporal rules can be obtained through taking a Cartesian product of all the S_i's (Details of Cartesian product is described in 2.4). Define $S_\otimes$ to be the Cartesian product. Then, by our construction, each element $e \in S_\otimes$ is of a $len(l_d)$-tuple, with the i^{th} entry corresponds to the i^{th} possible value of l_d. We treat $Empty$ entries in each element e as no rules being selected for the corresponding value and any element.

3. Then, we add in the possible combinations with immediate rules. For each element e in $S_\otimes$, we check for any entries assigned with $Empty$ and form a list l_{empty} containing the values in l_d corresponding to these entries. To form a new combination e', we then add at least 1 and at most $len(l_{empty})$ (1 for each $Empty$ entry) immediate rules to e. Then, for an element $e \in S_\otimes$, we can then form set S_e containing all possible e' we can form from e in step 4 below.

4. To form S_e, we first select all the possible entries that we can add an immediate rule to by finding the powerset $P(l_{empty})$ of l_{empty} (Details of powerset is described in 2.4). Then, for each element $p \in P(l_{empty})$, we find a set S'_v for each value v in p containing the set of immediate rules specifying a change of state to value v and we can form a Cartesian product of all of S'_v, denote $S'_{\otimes,p}$. If any of the S'_v is empty, we simply set $S'_{\otimes,p}$ to be empty and skip the element p since there is no immediate rule that we can add for the value. Otherwise, for each element $s' \in S'_{\otimes,p}$, we form a valid new combination through $e' = s' \oplus e$ (adding rules in s' to the corresponding $Empty$ entries in e). S_e, then, can be found through $\{p \in P(l_{empty}), s' \in S_{\otimes,p}, s' \oplus e\}$.

5. Finally, our set of all possible rule combination S can be obtained through $S = S_\otimes \cup (\bigcup_{e \in S_\otimes} S_e)$. Since we need at least 2 rules to check for conflict, any element in S with at least 2 non-Empty entries is then a valid combination to run our SMT solver described in 5.1.

5.3 Evaluation

To evaluate the correctness and the efficiency of our conflict checking tool, we have utilized our fuzz testing framework described in 4.4. We used the same devices as described in Figure 22, and have generated random environments with 10 device interaction rule specifications. Then, we run STLCheck to detect whether there are any conflicts in the generated temporal and immediate rules. The process is done 5 times to ensure the robustness of our tool. For each iteration of the process, we manually check for each detected conflict that the output log is valid. Then, we also virtually simulated them on Samsung Smartthings by our monitor Smartapp (details in 9.5) to verify that the generated conflict logs can actually happen in real life.

One concern we had in our conflict checking tool before evaluation was the runtime of our SMT solver due to solving satisfiability for SMT formulas is a NP complete problem [FFWP17]. To access the scalability of STLCheck, we first note that the runtime of our z3 SMT checker is impacted by the number of rule sets to check, number of SMT formulas, and number of SMT variables translated from each IoT environment. These factors, from our translation schema of the rules described in section 5.1, are directly influenced by the number of devices, number of total rules, and the maximum timebound $timebound$ defined in the environment. Consequently, we run our STLCheck on increasingly complex environments through incrementing these parameters. For each of the parameter combinations, STLCheck is ran on 10 randomly generated environment under these parameters with our fuzz testing framework, and the average runtime for each combination is recorded in Table 1.

The $numDevices$ and $Rules/Device$ parameters for the environment are picked through the reasoning that while IoT systems are becoming increasingly prevalent, it is still fairly unlikely for a typical household to have a very large set of devices and rules per device. We have not selected greater $timebound$ parameters since a greater timebound in learning rules can be interchanged with a greater granularity in timestamp unit, which does not impact our runtime efficiency much.

numDevices	Rules/Device	Timebound	runtime(s)
4	4	10	0.336
4	8	10	0.614
4	8	30	0.971
8	8	10	1.33
8	8	30	1.94
16	8	30	4.58
16	16	30	17.8

Table 1: Average runtime of STLCheck for environments with different parameter combinations

For small $numDevices$ and $Rules/Device$ combinations, STLCheck's runtime grows fairly linearly as expected with z3's near linear algorithm. The impact for increasing the $timebound$ parameter does not impact the runtime as much in these small combinations as we expected for linear growth. One possible explanation is that while increasing $timebound$ increases the number of parameters for SMT formulas, not all parameters are relevant since we do not have enough rules to have PSTL intervals that cover the entire time period specified by $timebound$.

Overall, for each of the generated environment, STLCheck is able to detect for conflicts within all possible combinations of the rules, even with the overestimate of rules and devices for a typical household IoT environment in our last combination, in under half a minute. This evaluation results shows STLCheck significantly exceeds our efficiency expectations.

6 Related Works

Current research on IoT environment safety mostly rely on static checking for developing safety rules and analyzing device interactions. Our work is initially inspired by the work done by [IoT], which defined seven classes of multi-app interaction threats and implemented formal models for IoT systems to automatically detect such threats. As our work's static analysis counterpart, [TAC+20] created IoTCheck, a device interaction learning and conflict detection tool through statically analyzing pairs of Smarthings apps and their execution traces. Similarly, [DH18] implemented IoTMon, a static checking framework that discovers and assess the security risks of hidden interaction chains among Samsung Smartapps by statically checking each Smartapp's source code. Interestingly, [DH18] has also utilized machine learning models of natural language processing in discovering the device interactions; however, it is still restricted to using the model in statically analyzing the description of Smartapps. Currently, no known research has been found in learning IoT device interactions through environment's runtime operation log and in learning time-dependent rules through PSTL, making our work novel. Furthermore, all of the related work described above are limited in that only learning interactions and detect conflicts between pairs of Smartapps, which is able to capture significantly less safety properties than our work does with our ability to explore the hidden interaction with multiple Smartapps that is dependent on the depth set for STLTree and TreeNoSTL and detect conflicts within any subset of the interaction and user defined rules using STLCheck.

There is currently no known work for incorporating STL or PSTL rules to IoT environments. However, PSTL rules is a powerful tool with prevalent uses in other fields of cyberphysical systems. In the original decision tree framework that STLTree is adapted from, [BVP+16] utilizes PSTL in distinguishing abnormal naval trajectories' and vehicle fuel sensors' signal data to issue warnings. Similar work on learning rules about vehicles brakes through STL is explored in [JKB14]. We are also fascinated by Signal Temporal Logic's expressive power, and are also excited to expand and experiment with STL and PSTL into other cyberphysical systems in the future.

7 Conclusion and Future Work

In our work, we have developed a novel way in representing device interactions and user desired environment security properties through Parametric Signal Temporal Logic (PSTL). Then, in order to learn these interaction rules and capture hidden behaviors, we have adapted and expanded the decision tree learning algorithm on PSTL rules proposed in [BVP$^+$16] with our model STLTree. To capture all the interactions in an environment holistically, we have also implemented a decision learning algorithm TreeNoSTL to learn all the immediate rules of the environment.

From our learned rules with STLTree and TreeNoSTL, we have implemented a runtime monitor STLMon and a static conflict checker STLCheck to evaluate the safety properties of an IoT environment.To express individual user's desired safety behaviors, we implemented a language for user defined rules that can be parsed into PSTL formulas. After receiving user's desired safety rules of the environment, STLMon checks for violations of both interaction rule and user defined safety rules of the environment at runtime and physically revoke the state change actions causing the violations. Finally, STLCheck statically checks for conflicts between and within both learned device interaction rules and user defined safety rules to ensure the safety property of an IoT environment defined in Definition 2.

Since introducing PSTL logic is new to IoT environment safety, there are plenty of opportunities to expand on our current work in the future. First, we plan to consider adding static analysis to our learned rules to see if we are able to construct longer interaction chains and more complicated rules than our decision tree algorithms are able to learn. For example, in our motivation example in section 1.1, it is possible that our decision tree algorithms to learn the separate pieces that oven is able to trigger smoke alarm with smoke, and smoke alarm is able to unlock the door than simply than entirety of behavior of oven unlocking the door, since the interaction with oven and the door is significantly less likely to happen than smoke alarm and the door. Being able to form a control flow graph between learned fragments of the rules to forge longer rules will make us able to capture more interactions in the environment.

Also, for our evaluation of STLTree, we have set the interval for data processing to be 10 timestamps, which is simply a number for convenience of testing. This interval size may not be the best measure for reflecting the interaction rules between devices, and additional analysis on determining the best time intervals for preprocessing the device state changes for various situations and environments could lead to our decision tree model learning more accurate rules.

Furthermore, our implemented STLMon and STLCheck are only able to detect potential safety conflicts and remedy the safety violations by revoking state changes. This is often not enough in preventing actual attacks, and we plan to implement other mechanisms to IoT environments such as fail safe measures at time of attacks on the vulnerabilities of conflicts (For example, making the door to always stay locked unless there is sufficient evidence for not doing so) to further strengthen the safety of IoT systems.

Finally, one key measure of our safety analysis in STLMon and STLCheck is the user desired security properties that is parsed through our defined rule language into STL rules. In the future, we plan to expand upon this language to capture more behaviors, and implementing a more user friendly interface than the current requirement of physically writing down the rules.

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9 Appendix

9.1 Information Gain (IG) with robustness

For continuous valued device states, there can be multiple valid splits with the same information gain. For example, in a temperature measurement of a household, learning a rule that the temperature should always be less than 110 degrees would be more useful than learning a rule of temperature should always be less than 1000 degrees, while both may give the same one sided splits that has the same information gain with equation (4).

In order to distinguish such rules and pick the better one for the context, [BVP$^+$16] proposed a robustness measurement that not only calculates information gain based on misclassification, but also on the degree of misclassification. In this measurement, robustness $r(s_i)$ for a signal s_i under rule with space parameter μ is defined in a similar way as how we checked for validity of PSTL rules in 3.2.4, as follows

1. $F_{[a,b]}(x \leq \mu) = \mu - \min_{[a,b]} v$, where v is the value for the dimension at a timestamp in the interval $[a, b]$ for signal s_i. Similarly, $F_{[a,b]}(x > \mu) = \max_{[a,b]} v - \mu$
2. $G_{[a,b]}(x \leq \mu) = -F_{[a,b]}(x > \mu)$ and $G_{[a,b]}(x > \mu) = -F_{[a,b]}(x \leq \mu)$ by 2.2.1.
3. $F_{[a,b]}G_{[0,c]}(x \leq \mu) = \mu - \max_{i\in[a,b-c]} \min_{[i,i+c]} v$ with the max min window filter of length c method described in 3.2.4. In this case, v is the value for the dimension at a timestamp in the interval window $[i, i + c]$ for signal s_i. Similarly, $F_{[a,b]}G_{[0,c]}(x > \mu) = \min_{i\in[a,b-c]} \max_{[i,i+c]} v - \mu$

With the robustness measure, the information gain is calculated by adjusting equation (4) through changing $prob(S, c, \phi)$ when calculating entropy as follows:

$$prob(S, c, \phi) = \frac{\sum_{(s^i,l^i)\in S, l^i=c} r(s_i)}{\sum_{(s,l)\in S} r(s)} \tag{8}$$

Intuitively, instead of only factoring the count of misclassification, the extent of misclassification is included through the robustness measure.

9.2 Simulated Annealing (SA) in STLTree

In order to efficiently find the PSTL rule to split our data and growing the tree over a potentially large search space of parameters, we utilize the Simulated Annealing algorithm when training STLTree.[Ing96] In simulated annealing, the algorithm performs a random walk over the parameter search space in a function of temperature and energy. At each iteration of the random walk, the algorithm computes the energy corresponding to the walk's state. If the algorithm has walked to a state with lower energy, the algorithm decides whether to change the current state to the lower energy state randomly depending on the walks temperature value. The higher the temperature value is, the more likely it is for the algorithm to change to the lower energy state. To speed up convergence for the algorithm, temperature is set initially to be a high number and continues to decrease as iteration increases.

In STLTree, we utilize Python's simanneal package by [Per19]. When running the algorithm, we set the energy to be our objective function, which is the entropy for rule split as described in equation (5) in 3.2.4. We set the state to be the parameters for the PSTL primitive, and a random walk to be a random selection of the time and space parameters within the restricted bounds as described in 3.2.4. After running the algorithm for enough iterations, SA would converge at a local minimum, which means we have found the parameters that gives the least entropy split (which also means the greatest Information Gain (IG)) for the current PSTL primitive type [Ing96].

9.3 Treepruning with Effective Alpha

As described in 3.2.2, the decision tree models learned from our IoT environment device logs are very prone to overfit. As a result, we have used Python sklearn library's Cost Complexity Pruning to post prune our learned STLTrees [sci]. In the process, a tree T's cost complexity measure is given by

$$R_\alpha(T) = R(T) + \alpha|T| \tag{9}$$

where $R(T)$ is the total training error of leaf nodes, $|T|$ is the number of leaf nodes, and α being a complexity parameter. The Cost Complexity Pruning process aims to find the subtree T' of T that minimizes $R_\alpha(T')$.

We note for a single node t, $R_\alpha(t) = R(t) + \alpha$, and in general, for a tree T_t rooted at t, $R(T_t) < R(t)$ since splitting a tree should reduce the total prediction error. In our case described in 3.2.7, $R(T_t)$ should reduce by at least the improve threshold on one branch when comparing to $R(t)$. However, by how we have defined α, we can have $R_\alpha(T_t) = R_\alpha(t)$ since $|T_t| \geq 1$. Thus, we define the effective alpha of a node t to be the value that equality happens, that is

$$\alpha_{eff}(t) = \frac{R(t) - R(T_t)}{|T| - 1} \tag{10}$$

We note a small α_{eff} would mean $R(t)$ and $R(T_t)$ are fairly close, which means the split is less helpful in improving tree model's classification. In our tree pruning method described in 3.2.7, leaves will be pruned based on the order of their parents' effective order, with the smallest effective alpha to be pruned first. The process continues until we reached a minimum in validation error.

9.4 OneHotEncoder

Sklearn's tree module only accepts data traces that are solely formed by integers. In order for us to learn a tree with non-real value device states (Ex. A switch's state can be on_off based on our preprocessing in 3.3.2), we utilize Sklearn's OneHotEncoder module [PVG+11]. In the encoder, the transformer encodes our non-real values into a numeric array using a one-hot encoding scheme for each unique value in our data trace. After learning our tree, we can simply get back our original class value for each device by calling the $encoder.decode()$ function.

9.5 Samsung Smartthings Conflict Simulation

Since both STLMon and STLCheck are first evaluated under a fuzztesting framework, we are interested in finding out the actual behavior of the conflict in a real life situation. To do so, we have constructed a simulation tool that simulates the device operation log generated from either fuzztesting for STLMon or log output from STLCheck using Samsung Smartthings Hub's virtual devices. The simulation is achieved through 2 steps: processing the generated conflict log example locally, and sending the processed log to Samsung Smartthings Hub's to perform the simulation. The details of each step is described below.

Conflict Log Processing Given a device operation log, we note each entry of the log can be described by the elements in the $4-tuple$: $(timestamp\ from\ current\ time,\ device,\ state,\ value)$ from our construction in section 4.4.2 and 5.1. This is not as useful in our simulation, since we can not start from current time and change device states from the past, and we are more interested in the actual commands to change the $device\_state$ to the specified $value$. As a result, we process our log in the following two steps.

1. Shifting the timeline: Since time parameters are learned in a fashion relative to fixed size intervals in all of our PSTL rules, we can shift the timeline from the log so that the first described event that is t_0 away from current time in the log is happening at current time + 1 timestamp. Then, for each future event t_i away from current time, they can then be shifted to $t_i - t_0 + 1$ timestamp away from current time. Then, from our shifting schema, the conflict would then happen at $t_n + (t_n - t_0 + 1)$ seconds away from current time, where t_n corresponds to the time for last event in the log before our timeline shift.

2. Retrieving state change commands: Obtaining the state change command for each state is identical to what is done in the monitor in section 4.2.3. We reuse the dictionary mapping capabilities to their corresponding value change functions to retrieve the device change function. One additional factor to consider, however, is that we need to change continuous variables states in our device log, instead of only the discrete variables in our monitor, that does not have such value change functions. Instead, these continuous variable changes are done through the function $set\{StateName\}(value)$ instead [Smaa].

As a result, our final processed conflict log would be in a list of 3-tuple, of $(shifted\ timestamp, device, command)$.

Simulating Conflict through Samsung Hub After processing our conflict log, we then send the processed log to Samsung Smartthings Hub through adding a simulation feature to our monitor Smartapp used in 4.2.2 through Oauth (details 2.1.1). Upon receiving the processed log, the monitor Smartapp then is able to schedule the events corresponding to the log with the following two steps.

1. Finding devices: Before the monitor schedules to trigger the events, it would first need to find the corresponding device in the environment as specified from $device$ in each $3-tuple$ of the processed log. This is simply done through iterating all devices the monitor subscribed to in the environment to find a match.

2. Scheduling Events: We utilized the $runIn$ feature on Samsung SmartHub Apps to schedule the events with their corresponding shifted timestamps in the future from current time. As described in 2.1.2, the device

change events can simply be done through calling $device.command$ provided from our processed conflict log. There are limitations in the SmartHub scheduling feature on large quantities of events as it is only able to provide limited memory, however, this should not be an issue as we expect the environment rules to be simple and thus the generated log to be small.

Unfortunately, it is not possible for us to know locally when the scheduled events on Samsung Smartthings Hub gets finished, as a result, we have set a safety time buffer to wait between each simulation. A natural number that we determined is the $timebound$ parameter we have used for fuzztesting and generating the conflict log in our conflict checking tool, since no device change events is generated before $timebound$ by our log construction. This guarantees the previous operation log simulation's termination before evaluating for the next log simulation.