

Scalable Tree-based Register Automata Learning

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Abstract. Existing active automata learning (AAL) algorithms have demonstrated their potential in capturing the behavior of complex systems (e.g., in analyzing network protocol implementations). The most widely used AAL algorithms generate finite state machine models, such as Mealy machines. For many analysis tasks, however, it is crucial to generate richer classes of models that also show how relations between data parameters affect system behavior. Such models have shown potential to uncover critical bugs, but their learning algorithms do not scale beyond small and well curated experiments. In this paper, we present SL^λ , an effective and scalable register automata (RA) learning algorithm that significantly reduces the number of tests required for inferring models. It achieves this by combining a tree-based cost-efficient data structure with mechanisms for computing short and constrained tests. We have implemented SL^λ in a publicly available tool. We evaluate its performance by comparing it against SL^* , the state-of-the-art RA learning algorithm, in a series of experiments, and show superior performance and substantial asymptotic improvements in bigger systems.

1 Introduction

Model Learning (aka *Active Automata Learning* (AAL) [7,40,50]) infers automata models that represent the dynamic behavior of a software or hardware component from tests. Models obtained through (active) learning have proven useful for many purposes, such as analyzing security protocols [18,19,25,41,44], mining APIs [6], supporting model-based testing [26,46,52] and conformance testing [5]. The AAL algorithms employed in these works are efficient and supported by various domain-specific optimizations (e.g., [31]), but they all generate finite state machine (FSM) models, such as Mealy machines.

For many analysis tasks, however, it is crucial for models to also be able to describe *data flow*, i.e., constraints on data parameters that are passed when the component interacts with its environment, as well as the mutual influence between dynamic behavior and data flow. For instance, models of protocol components must describe how different parameter values in sequence numbers, identifiers, etc. influence the behavior, and vice versa. Existing techniques for extending AAL to *Extended FSM* (EFSM) models [1,9,11] take several different approaches. Some reduce the problem to inferring FSMs by using manually supplied abstractions on the data domain [1], which requires insight into the control/data dependencies of a system under learning (SUL). Others extend AAL for finite state models by allowing transitions to contain predicates over rich data domains, but cannot generate state variables to model data dependencies

between consecutive interactions [13, 36]. Finally, there exist extensions of AAL to EFSM models with guards and state variables, such as *register automata* [2, 3, 11]. While their potential has been shown by being able to uncover critical bugs in e.g., TCP implementations [15, 16], their learning algorithms do not scale beyond small and well curated experiments.

We follow the third line of works and address the scalability of register automata (RA) learning algorithms in our work. The main challenge when scaling AAL algorithms is reducing the number of tests that learners perform on a SUL. Generally, these tests are sequences of actions that take the form $u \cdot v$, where u is the prefix and v the suffix of the sequence. Tests $u \cdot v$ and $u' \cdot v$ are then used to determine if prefixes u and u' can be distinguished based on the SUL's output triggered by v . When inferring RA models, prefixes are sequences of actions with data values, e.g., `push(1) push(2)`, and suffixes are sequences of actions with symbolic parameters, e.g., `pop(p_1) pop(p_2)`, that, when instantiated, can incur a number of tests that is exponential in the length of the suffix for identifying dependencies between prefix values and suffix parameters, e.g., different test outcomes for $(p_1 = 2 \wedge p_2 = 1)$ and $(p_1 = 2 \wedge p_2 = 3)$, and for distinguishing prefixes based on suffixes. To make register automata learning scalable, it is crucial to reduce the use of suffixes in tests along three dimensions: (i) First, it is important to use only *few tests*. (ii) Second, when using suffixes in tests, *shorter suffixes* should be preferred over longer ones. (iii) Third, it is essential to *restrict tests to relevant dependencies* between prefix values and suffix parameters instead of bluntly testing all possible dependencies.

In this paper, we present the SL^λ algorithm for learning register automata which achieves scalability by optimizing the use of tests and suffixes in tests in the three stated dimensions. SL^λ uses a *classification tree* as a data structure, constructs a minimal prefix-closed set of prefixes and a suffix-closed set of *short* and *constrained* suffixes for identifying and distinguishing locations, transitions, and registers. Technically, we adopt the idea of using a classification tree from learners for FSMs [32, 34] where it proved very successful for reducing tests. We also adopt the technique of computing short suffixes incrementally in order to keep them short [7, 32]. This has not been studied for RAs before and leads to an improved worst case complexity compared to state-of-the-art approaches (Theorem 1). Finally, we show how suffixes can be constrained to relevant data dependencies, which is essential for achieving scalability (Section 4).

We have implemented the SL^λ algorithm in a publicly available tool and, for comparison, also the SL^{CT} algorithm that uses a classification tree but relies on suffixes from counterexamples instead of computing short suffixes from inconsistencies. We evaluate the SL^λ algorithm by comparing its performance against the SL^* [11] and SL^{CT} algorithms in a series of experiments, confirming that: (i) classification trees scale much better than observation tables for register automata, (ii) using constraining suffixes leads to a dramatic reduction of tests for all compared learning algorithms, and (iii) computing short suffixes from inconsistencies outperforms using suffixes from counterexamples.

Related Work. For a broad overview of AAL refer to the survey paper of de la Higuera [27] from 2005 and to a more recent paper by Howar and Steffen [28].

Learning beyond DFAs has been investigated for many models aside from register automata. For example, algorithms have been presented for workflow Petri nets [14], data automata [24], generic nondeterministic transition systems [51], symbolic automata [13], one-timer automata [48], and systems of procedural automata [22]. Learning of register automata has been performed by combining a FSM learner with the Tomte front-end [2, 3]. A different approach using bespoke RA learning algorithms [30, 38] has been implemented in RALib [10].

Applications of AAL are diverse. Active learning enables the generation of behavioral models for software [42, 45], e.g. for network protocol implementations [41, 53], enabling security analyses and model checking [4, 20, 21]. It can be used in testing [37, 43] and to enable formal analyses [47]. Finally, it can be combined with passive learning approaches to support life-long learning [8, 23]. More theoretical advances include the use of Galois connections to model SUL-oracle mappers [35] and the introduction of apartness [49], to formalize state distinction.

Outline. We present the key ideas in tree-based learning of RA informally in the next section, before providing formal definitions of basic concepts in Section 3. Sections 4 to 6 present the SL^λ algorithm, its properties, and the experimental evaluation of its performance. The paper ends with few concluding remarks.

2 Main Ideas

In this section, we introduce the main ideas behind the SL^λ algorithm. As illustrating example, we will use a stack of capacity two, which stores a sequence of natural numbers. The stack supports the operations **push** and **pop**, both of which take one natural number as a parameter. The operation **push**(*d*) succeeds if the stack is not full, i.e., contains at most one element; the operation **pop**(*d*) succeeds if the last pushed and not yet popped element is *d*. Let a *symbol* denote an operation with data value, such as **push**(1), and let \mathcal{L}_{Stack} denote the prefix-closed language consisting of the words of symbols representing sequences of successful operations. Figure 1 shows an acceptor for \mathcal{L}_{Stack} . The initial location l_0 corresponds to an empty stack, location l_1 corresponds to a stack with one element, and l_2 to a location where the stack is full. There is also an implicit sink location for each word that is not accepted by \mathcal{L}_{Stack} , e.g. pushing a third element, or popping a non-top element. In each location, registers contain the elements in the stack: for $i = 0, 1, 2$, location l_i has i registers, where the register with the highest index contains the topmost stack element.

The task of the SL^λ algorithm is to learn the acceptor in Fig. 1 in a black-box scenario, i.e., knowing only the operations (**push** and **pop**) and the relations that may be used in guards (here tests for equality), by asking two kinds of queries. A *membership query* asks whether a word w is in \mathcal{L} ; it can be realized by a simple test. An *equivalence query* asks whether a hypothesis RA accepts \mathcal{L} ; if so, the query is answered by *yes*, otherwise by a *counterexample*, which is a word on which the hypothesis and \mathcal{L} disagree; in a black box setting it is typically approximated

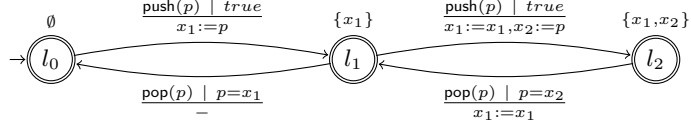
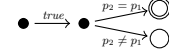


Fig. 1: Register automaton accepting language of stack with capacity two.

by a conformance testing algorithm. Like other AAL algorithms, SL^λ iterates a cycle in which membership queries are used to construct a hypothesis, which is then subject to validation by an equivalence query. If a counterexample is found, hypothesis construction is resumed, etc., until a hypothesis agrees with \mathcal{L} .

Classical AAL algorithms that learn DFAs maintain an expanding set of words, S_p , called *short prefixes*, and an expanding set of words, called *suffixes*, which induce an equivalence relation \equiv on prefixes, defined by $u \equiv u'$ iff $uv \in \mathcal{L} \Leftrightarrow u'v \in \mathcal{L}$ for all suffixes v ; this allows equivalence classes of prefixes to represent states in a DFA. The SL^λ algorithm maintains a set U of data words called *prefixes*, which is the union of S_p and one-symbol extensions of elements in S_p . Instead of suffixes, SL^λ maintains a set \mathcal{V} of *symbolic suffixes*, each of which is a *parameterized* word, i.e., a word where data values are replaced by parameters p_1, \dots, p_m . For each prefix u , say $\text{push}(0)$, and symbolic suffix v , say $\text{push}(p_1)\text{pop}(p_2)$, membership in \mathcal{L} of words of form uv depends on the relation between the data values of u and the parameters p_1, p_2 of v , which in SL^λ is represented by a function $\mathcal{L}[u, v]$ with parameters x_1 (representing the data value of u), p_1 , and p_2 . In this case $\mathcal{L}[u, v](x_1, p_1, p_2)$ is $+$ iff $p_2 = p_1$ and $-$ otherwise. In SL^λ , such functions are represented as decision trees of a specific form. To the right is the decision tree for the just described function $\mathcal{L}[u, v](x_1, p_1, p_2)$. Note that it checks constraints for parameters one at a time: first the constraint on only p_1 (which is *true*), and thereafter the constraint on p_2 (a comparison with p_1). Two prefixes u, u' are then equivalent w.r.t. \mathcal{V} if $\mathcal{L}[u, v]$ and $\mathcal{L}[u', v]$ are “isomorphic modulo renaming” for all $v \in \mathcal{V}$ (details in Section 4).



Functions of form $\mathcal{L}[u, v]$ are generated by so-called *tree queries*, which perform membership queries for relevant combinations of relations between data values in u and parameters in v , and summarize the results in a canonical way. The tree query above requires five membership queries. SL^λ employs techniques for reducing this number by constraining the symbolic suffix; see end of this section.

Initially, S_p and \mathcal{V} contain only the empty sequence ϵ . Since ϵ is a short prefix, one-symbol extensions, $\text{push}(0)$ and $\text{pop}(0)$, are entered into U . Tree queries are performed for the prefixes in U and the empty suffix, revealing that $\text{push}(0)$ is accepted and $\text{pop}(0)$ is rejected. Thus, $\text{push}(0)$ cannot be distinguished from ϵ , but $\text{pop}(0)$ can, so it must lead to a new location, hereafter referred to as the *sink*, which is therefore added to S_p . One-symbol extensions of $\text{pop}(0)$, in this case $\text{pop}(0)\text{push}(1)$ and $\text{pop}(0)\text{pop}(1)$, are added to U and tree queries for them and the empty suffix are performed, revealing that they cannot be separated from the sink. At this point, we can formulate hypothesis \mathcal{H}_0 in Fig. 2(left) from S_p , U , and the computed decision trees.

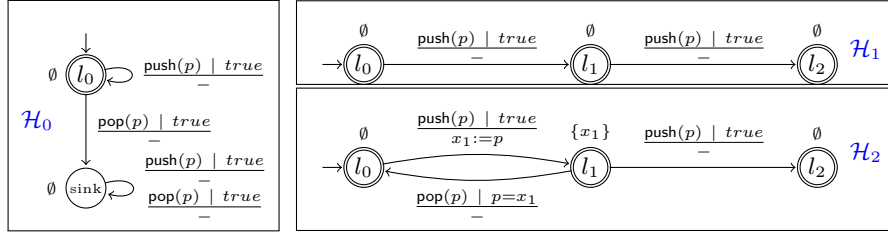


Fig. 2: Three hypotheses constructed by SL^λ : \mathcal{H}_0 (left), \mathcal{H}_1 and \mathcal{H}_2 (right).

This hypothesis is then subject to validation. Assume that it finds the counterexample $\text{push}(0)\text{push}(1)\text{push}(2)$, which is accepted by \mathcal{H}_0 but rejected by \mathcal{L}_{Stack} . Analysis of the counterexample reveals that ϵ and $\text{push}(0)$ are inequivalent, since they are separated by the suffix $\text{push}(p_1)\text{push}(p_2)$ (since the concatenation of ϵ and $\text{push}(p_1)\text{push}(p_2)$ is accepted for all p_1, p_2 but $\text{push}(0) \cdot \text{push}(p_1)\text{push}(p_2)$ is always rejected for all p_1, p_2). It could seem natural to add $\text{push}(p_1)\text{push}(p_2)$ to \mathcal{V} , but SL^λ will not do that, since it follows the principle (from L^λ [29]) that a new prefix in S_p must extend an existing prefix by one symbol, and that a new suffix in \mathcal{V} must prepend one symbol to an existing one. This principle keeps S_p prefix-closed and \mathcal{V} suffix-closed, and aims to avoid inclusion of unnecessarily long sequences. Therefore, instead of adding $\text{push}(p_1)\text{push}(p_2)$ as a suffix, SL^λ enters the prefix $\text{push}(0)$ into S_p , and adds one-symbol extensions of $\text{push}(0)$, in this case $\text{push}(0)\text{push}(1)$ and $\text{push}(0)\text{pop}(1)$, to U . It notes that $\text{push}(0)\text{push}(1)$ is inequivalent to both ϵ and $\text{push}(0)$, separated by the suffix $\text{push}(p_1)$. Again, $\text{push}(0)\text{push}(1)$ is therefore promoted to a short prefix, and its one-symbol extensions, $\text{push}(0)\text{push}(1)\text{push}(2)$ and $\text{push}(0)\text{push}(1)\text{pop}(2)$, are entered into U . Now, SL^λ is able to add suffixes to \mathcal{V} that separate all prefixes in S_p , by two operations that achieve consistency.

1. The push -extensions of ϵ and $\text{push}(0)\text{push}(1)$, (i.e., $\text{push}(0)$ and $\text{push}(0)\text{push}(1)\text{push}(2)$) are separated by the empty suffix, hence these two prefixes are separated by the suffix $\text{push}(p_1)$, which is added to \mathcal{V} .
2. The push -extensions of ϵ and $\text{push}(0)$ (i.e., $\text{push}(0)$ and $\text{push}(0)\text{push}(1)$) are separated by the suffix $\text{push}(p_1)$, hence ϵ and $\text{push}(0)$ are separated by $\text{push}(p_1)\text{push}(p_2)$, formed by prepending a symbol to the just added suffix $\text{push}(p_1)$, which is added to \mathcal{V} .

After adding the suffixes, the closedness and consistency criteria are met, producing hypothesis \mathcal{H}_1 in Fig. 2(right, top). Assume that the validation of \mathcal{H}_1 finds counterexample $\text{push}(0)\text{pop}(0)$, which is in \mathcal{L}_{Stack} , but rejected by \mathcal{H}_1 . This counterexample reveals that after $\text{push}(0)$, the two continuations $\text{pop}(0)$ and $\text{pop}(1)$ lead to inequivalent locations (separated by suffix ϵ), suggesting to refine the $\text{pop}(p)$ -transition after $\text{push}(0)$. To this end, \mathcal{V} is extended by a suffix formed by prepending $\text{pop}(p)$ to the empty suffix, and a tree query is invoked for $\mathcal{L}[\text{push}(0), \text{pop}(p_1)]$, which is $+$ iff $p_1 = x_1$ and $-$ otherwise. Since $\mathcal{L}[\text{push}(0), \text{pop}(p_1)]$ makes a test for x_1 , which represents the data value of $\text{push}(0)$, we infer that the data parameter of the $\text{push}(0)$ -prefix must be remembered in

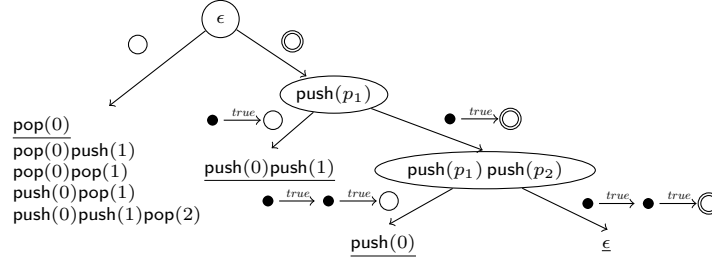


Fig. 3: Classification tree for hypothesis \mathcal{H}_1 in Fig. 2. Short prefixes are underlined.

a register, and that the $\text{pop}(p)$ -transition must be split into two with guards ($x_1 \neq p$) and ($x_1 = p$). The resulting hypothesis, \mathcal{H}_2 , is shown in Fig. 2(right, bottom), which is subject to another round of validation; the subsequent hypothesis construction reveals the pop -transitions from l_2 in Fig. 1.

In SL^λ , the sets U and \mathcal{V} are maintained in a *classification tree* CT , a data structure that is specially designed to represent how the suffixes in \mathcal{V} partition U into equivalence classes corresponding to locations. This permits an optimization that can elide superfluous membership queries. A classification tree is a decision tree. Each leaf is labeled by a subset of U . Each inner node is labeled by a symbolic suffix v and induces a subtree for each equivalence class w.r.t. v , whose leaves contain prefixes in this equivalence class. For example, in Fig. 3, which shows a CT corresponding to hypothesis \mathcal{H}_1 , the nodes are labeled by the suffixes ϵ , $\text{push}(p_1)$ and $\text{push}(p_1)\text{push}(p_2)$, which separate the leaves into four equivalence classes corresponding to the four locations in Fig. 1. Each edge is labeled by the results of the tree queries for a prefix in its equivalence class and the symbolic suffix of the source node.

Each tree query requires a number of membership queries which may grow exponentially with the length of the suffix. SL^λ reduces this number by *constraining* the involved symbolic suffix to induce fewer membership queries, as long as the tree query can still make the separation between prefixes or transitions for which it was invoked. To illustrate, recall that the analysis of the counterexample $\text{push}(0)\text{push}(1)\text{push}(2)$ for \mathcal{H}_0 shows that ϵ and $\text{push}(0)$ are inequivalent. To separate these, we need not naively use the symbolic suffix $\text{push}(p_1)\text{push}(p_2)$; but we can constrain it by considering only values of p_1 and p_2 that are *fresh*, i.e., different from all other preceding parameters in the prefix and suffix. With this constraint, the suffix can still separate ϵ and $\text{push}(0)$, and the tree query for prefix $\text{push}(0)$ requires only one membership query instead of five.

3 Data Languages and Register Automata

In this section, we review background concepts on data languages and register automata. Our definitions are parameterized on a *theory*, which is a pair $\langle \mathcal{D}, \mathcal{R} \rangle$ where \mathcal{D} is a (typically infinite) domain of *data values*, and \mathcal{R} is a set of *relations* (of arbitrary arity) on \mathcal{D} . Examples theories include: (i) $\langle \mathbb{N}, \{=\} \rangle$, the theory of

natural numbers with equality, and (ii) $\langle \mathbb{R}, \{<\} \rangle$, the theory of real numbers with inequality; this theory also allows to express equality between elements. Theories can be extended with constants (allowing, e.g., theories of sums with constants).

Data Languages. We assume a set Σ of *actions*, each with an arity that determines how many parameters it takes from the domain \mathcal{D} . For simplicity, we assume that all actions have arity 1; our techniques can be extended to handle actions with arbitrary arities. A *data symbol* is a term of form $\alpha(\mathbf{d})$, where α is an action and $\mathbf{d} \in \mathcal{D}$ is a data value. A *data word* (or simply *word*) is a finite sequence of data symbols. The concatenation of two words u and v is denoted uv , often we then refer to u as a *prefix* and v as a *suffix*. Two words $w = \alpha_1(\mathbf{d}_1) \dots \alpha_n(\mathbf{d}_n)$ and $w' = \alpha_1(\mathbf{d}'_1) \dots \alpha_n(\mathbf{d}'_n)$ with the same sequences of actions are \mathcal{R} -*indistinguishable*, denoted $w \approx_{\mathcal{R}} w'$, if $R(\mathbf{d}_{i_1}, \dots, \mathbf{d}_{i_j}) \Leftrightarrow R(\mathbf{d}'_{i_1}, \dots, \mathbf{d}'_{i_j})$ whenever R is a j -ary relation in \mathcal{R} and i_1, \dots, i_j are indices among $1 \dots n$. A *data language* \mathcal{L} is a set of data words that respects \mathcal{R} in the sense that $w \approx_{\mathcal{R}} w'$ implies $w \in \mathcal{L} \Leftrightarrow w' \in \mathcal{L}$. We often represent data languages as mappings from the set of words to $\{+, -\}$, where $+$ stands for *accept* and $-$ for *reject*.

Register Automata. We assume a set of *registers* x_1, x_2, \dots , and a set of *formal parameters* p, p_1, p_2, \dots . A *parameterized symbol* is a term of form $\alpha(p)$, where α is an action and p a *formal parameter*. A *constraint* is a conjunction of negated and unnegated relations (from \mathcal{R}) over registers and parameters. An *assignment* is a parallel update of registers with values from registers or the formal parameter p . We represent it as a mapping π from $\{x_{i_1}, \dots, x_{i_m}\}$ to $\{x_{j_1}, \dots, x_{j_n}\} \cup \{p\}$, meaning that the value $\pi(x_{i_k})$ is assigned to x_{i_k} , for $k = 1, \dots, m$. In multiple-assignment notation, this would be written $x_{i_1}, \dots, x_{i_m} := \pi(x_{i_1}), \dots, \pi(x_{i_m})$.

Definition 1. A register automaton (RA) is a tuple $\mathcal{A} = (L, l_0, \mathcal{X}, \Gamma, \lambda)$, where

- L is a finite set of locations, with $l_0 \in L$ as the initial location,
- \mathcal{X} maps each location $l \in L$ to a finite set $\mathcal{X}(l)$ of registers,
- Γ is a finite set of transitions, each of form $\langle l, \alpha(p), g, \pi, l' \rangle$, where
 - $l \in L$ is a source location and $l' \in L$ is a target location,
 - $\alpha(p)$ is a parameterized symbol,
 - g , the guard, is a constraint over p and $\mathcal{X}(l)$, and
 - π (the assignment) is a mapping from $\mathcal{X}(l')$ to $\mathcal{X}(l) \cup \{p\}$, and
- λ maps each $l \in L$ to $\{+, -\}$, where $+$ denotes accept and $-$ reject. \square

A *state* of a RA $\mathcal{A} = (L, l_0, \mathcal{X}, \Gamma, \lambda)$ is a pair $\langle l, \mu \rangle$ where $l \in L$ and μ is a valuation over $\mathcal{X}(l)$, i.e., a mapping from $\mathcal{X}(l)$ to \mathcal{D} . A *step* of \mathcal{A} , denoted $\langle l, \mu \rangle \xrightarrow{\alpha(\mathbf{d})} \langle l', \mu' \rangle$, transfers the state of \mathcal{A} from $\langle l, \mu \rangle$ to $\langle l', \mu' \rangle$ on input of the data symbol $\alpha(\mathbf{d})$ if there is a transition $\langle l, \alpha(p), g, \pi, l' \rangle \in \Gamma$ such that (i) $\mu \models g[\mathbf{d}/p]$, i.e., \mathbf{d} satisfies the guard g under the valuation μ , and (ii) μ' is defined by $\mu'(x_i) = \mu(x_j)$ if $\pi(x_i) = x_j$, otherwise $\mu'(x_i) = \mathbf{d}$ if $\pi(x_i) = p$. A *run* of \mathcal{A} over a data word $w = \alpha(\mathbf{d}_1) \dots \alpha(\mathbf{d}_n)$ is a sequence of steps of \mathcal{A}

$$\langle l_0, \mu_0 \rangle \xrightarrow{\alpha_1(\mathbf{d}_1)} \langle l_1, \mu_1 \rangle \quad \dots \quad \langle l_{n-1}, \mu_{n-1} \rangle \xrightarrow{\alpha_n(\mathbf{d}_n)} \langle l_n, \mu_n \rangle$$

for some initial valuation μ_0 . The run is *accepting* if $\lambda(l_n) = +$ and *rejecting* if $\lambda(l_n) = -$. The word w is *accepted (rejected)* by \mathcal{A} under μ_0 if \mathcal{A} has an accepting (rejecting) run over w from $\langle l_0, \mu_0 \rangle$. Define the language $\mathcal{L}(\mathcal{A})$ of \mathcal{A} as the set of words accepted by \mathcal{A} . A language is *regular* if it is the language of some RA.

We require a RA to be *determinate*, meaning that there is no data word over which it has both accepting and rejecting runs. A determinate RA can be easily transformed into a deterministic one by strengthening its guards, and a deterministic RA is by definition also determinate. Our construction of RAs in Section 4 will generate determinate RAs which are not necessarily deterministic. RAs have been extended to Register Mealy Machines (RMM) in several works and it has been established how RA learning algorithms can be used to infer models of systems with inputs and outputs [10], which we do, too.

4 The SL^λ Learning Algorithm

In this section, we present main building blocks of SL^λ before an overview of the main algorithm, followed techniques for reducing the cost of tree queries (page 12) and for analyzing counterexamples (page 13).

Symbolic Decision Trees. The functions, of form $\mathcal{L}[u, \mathbf{v}]$, that result from tree queries, should represent how the language \mathcal{L} to be learned processes instantiations of \mathbf{v} after the prefix u . Since SL^λ is intended to construct canonical RAs, it is natural to let these functions have the form of a tree-shaped “mini-RA”, which we formalize as *symbolic decision trees* of a certain form.

Assume a word $u = \alpha_1(\mathbf{d}_1) \dots \alpha_k(\mathbf{d}_k)$ and a symbolic suffix $\alpha'_1(p_1) \dots \alpha'_m(p_m)$. A (u, \mathbf{v}) -path τ is a sequence g_1, \dots, g_m , where each g_i is a constraint over x_1, \dots, x_k and p_1, \dots, p_i . Define the condition represented by τ , denoted \mathcal{G}_τ , as $g_1 \wedge \dots \wedge g_m$. A (u, \mathbf{v}) -tree T is a mapping from a set $Dom(T)$ of u -paths to $\{+, -\}$. Write $\bar{\mathbf{d}}$ for $\mathbf{d}_1, \dots, \mathbf{d}_k$, \bar{x} for x_1, \dots, x_k and \bar{p} for p_1, \dots, p_m . A (u, \mathbf{v}) -tree T can be seen a function with parameters \bar{x}, \bar{p} to $\{+, -\}$, defined by $T(\bar{x}, \bar{p}) = T(\tau)$ whenever $\tau \in Dom(T)$ and $\mathcal{G}_\tau(\bar{x}, \bar{p})$ holds. If \mathcal{L} is data language, then $\mathcal{L}[u, \mathbf{v}]$ is a (u, \mathbf{v}) -tree representing membership in \mathcal{L} in the sense that for any values of p_1, \dots, p_m we have $\mathcal{L}[u, \mathbf{v}](\bar{\mathbf{d}}, \bar{p}) = +$ iff $u\alpha'_1(p_1) \dots \alpha'_m(p_m) \in \mathcal{L}$, and $\mathcal{L}[u, \mathbf{v}](\bar{\mathbf{d}}, \bar{p}) = -$ iff $u\alpha'_1(p_1) \dots \alpha'_m(p_m) \notin \mathcal{L}$.

SL^λ generates (u, \mathbf{v}) -trees $\mathcal{L}[u, \mathbf{v}]$ representing the language \mathcal{L} to be learned through so-called *tree queries*, which perform membership queries for values of the data parameters p_1, \dots, p_m that cover relevant equivalence classes of $\approx_{\mathcal{R}}$. This number can grow exponentially with the length of \mathbf{v} .

From the results of tree queries, we can extract registers and guards in the location reached by a prefix u . Intuitively, the registers must remember the data values of u that occur in some guard in some $\mathcal{L}[u, \mathbf{v}]$, and the outgoing guards from u can be derived from the initial guards in the trees $\mathcal{L}[u, \mathbf{v}]$, since the initial guards represent the constraints that are used when processing the first symbol of \mathbf{v} . Let $mem_{\mathbf{v}}(u)$, the set of *memorable parameters*, denote the set of registers among $\{x_1, \dots, x_k\}$ that occur on some (u, \mathbf{v}) -path in $Dom(\mathcal{L}[u, \mathbf{v}])$. Intuitively, if x_i is a memorable parameter, then the i^{th} data value in u will be remembered

in the register x_i in the location reached by u . Define $mem_{\mathcal{V}}(u)$ as $\cup_{\mathbf{v} \in \mathcal{V}} mem_{\mathbf{v}}(u)$. For a prefix u and symbolic suffix \mathbf{v} whose first action is α , let $\mathcal{G}_{\{\mathbf{v}\}}(u, \alpha)$ denote the initial guards in the (u, \mathbf{v}) -tree $\mathcal{L}[u, \mathbf{v}]$, with p_1 replaced by p . For a set \mathcal{V} , let $\mathcal{G}_{\mathcal{V}}(u, \alpha)$ denote the set of satisfiable conjunctions of guards in $\mathcal{G}_{\{\mathbf{v}\}}(u, \alpha)$ for $\mathbf{v} \in \mathcal{V}$ with first action α .

Two (u, \mathbf{v}) -trees, T and T' , are *equivalent* denoted $T \equiv T'$, if $Dom(T) = Dom(T')$ and $T(\tau) = T'(\tau)$ for each $\tau \in Dom(T)$. For a mapping γ on registers, we define its extension to (u, \mathbf{v}) -paths in the natural way. For a (u, \mathbf{v}) -tree T , we define $\gamma(T)$ by $Dom(\gamma(T)) = \{\gamma(\tau) : \tau \in Dom(T)\}$ and $\gamma(T)(\gamma(\tau)) = T(\tau)$.

Let $u \equiv_{\mathcal{V}} u'$ denote that $\mathcal{L}[u, \mathbf{v}] \equiv \mathcal{L}[u', \mathbf{v}]$, for all symbolic suffixes $\mathbf{v} \in \mathcal{V}$. Let $u \simeq_{\mathcal{V}}^{\gamma} u'$ denote that γ is a bijection from $mem_{\mathcal{V}}(u)$ to $mem_{\mathcal{V}}(u')$ such that for all $\mathbf{v} \in \mathcal{V}$ we have $\gamma(\mathcal{L}[u, \mathbf{v}]) \equiv \mathcal{L}[u', \mathbf{v}]$. Let $u \simeq_{\mathcal{V}} u'$ denote that $u \simeq_{\mathcal{V}}^{\gamma} u'$ for some bijection γ . Intuitively, two words u and u' are equivalent if there is a bijection γ which for each $\mathbf{v} \in \mathcal{V}$ transforms $\mathcal{L}[u, \mathbf{v}]$ to $\mathcal{L}[u', \mathbf{v}]$. Note that in general, when $u \simeq_{\mathcal{V}} u'$, there can be several such bijections.

Data Structures. During the construction of a hypothesis, the SL^{λ} algorithm maintains: (i) a prefix-closed set S_p of *short prefixes*, representing locations, (ii) and a set of one-symbol extensions of the prefixes in S_p , representing transitions; we use U to represent the union of S_p and this set, and (iii) a suffix-closed set \mathcal{V} of symbolic suffixes. Each one-symbol extension of form $u\alpha(\mathbf{d})$ is formed to let \mathbf{d} satisfy a specific guard g ; we then always choose \mathbf{d} as a *representative data value*, denoted \mathbf{d}_u^g , satisfying g after u .

The sets U and \mathcal{V} are maintained in a *classification tree* CT , which is designed to represent how the suffixes in \mathcal{V} partition the set U into equivalence classes corresponding to locations. A classification tree is a rooted tree, consisting of nodes connected by edges. Each inner node is labeled by a symbolic suffix, and each leaf is labeled by a subset of U . To each node N is assigned a representative prefix $rp(N)$ in U . For a node N , let $\mathcal{V}(N)$ denote the set of symbolic suffixes of N and all its ancestors in the tree. Each outgoing edge from N corresponds to an equivalence class of $\simeq_{\mathcal{V}(N)}$ from which a representative member is chosen as the representative prefix of its target node. Each leaf node N is labeled by a set of data words, which are all in the same equivalence class of $\simeq_{\mathcal{V}(N)}$. Thus, nodes in different leaves are guaranteed to be inequivalent, since they are separated by the symbolic suffixes in $\mathcal{V}(lca(N, N'))$, where $lca(N, N')$ is the lowest common ancestor node of N and N' . We let \mathcal{U} denote the mapping, which maps each prefix $u \in U$ to the classification tree leaf where it is contained. We also let $\mathcal{V}(u)$ denote $\mathcal{V}(\mathcal{U}(u))$, the suffixes of all ancestors of $\mathcal{U}(u)$. The representative prefix, $rp(N)$, of each leaf node N will induce a location in the RA to be constructed.

The insertion of a new prefix u into the classification tree CT is performed by function *Sift* (cf. Algorithm 1). It traverses the CT from the root downwards. At each internal node N , it checks whether $u \simeq_{\mathcal{V}(N)} rp(N')$ for any child N' of N . If so, it continues the traversal at N' , otherwise a new child of N is created as a leaf N with $rp(N) = u$. When reaching a leaf N , the mapping \mathcal{U} is updated to reflect that u has been sifted to N .

Algorithm 1: Operations on the Classification Tree.

Function $Sift(u, N)$ **is**

- if** N is a leaf **then** $\mathcal{U} \leftarrow \mathcal{U}[u \mapsto N]$
- else**
 - Compute $\mathcal{L}(u, suff(N))$
 - if** N has u_{rap} -child N' with $u \simeq_{\mathcal{V}(N)} rp(N')$ **then** $Sift(u, N')$
 - else**
 - Create new leaf N' as child of N with $rp(N') = u$
 - $Sift(u, N')$

Function $Expand(u)$ **is**

- $S_p \leftarrow S_p \cup \{u\}$
- for** $\alpha \in \Sigma$ **do** $Sift(u\alpha(d_u^g), root(CT))$ for each $g \in \mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$

Function $Refine(N, v)$ **is**

- Replace N by an inner node N' with $suff(N') = v$
- for** $u \in \mathcal{U}^{-1}(N)$ **do** $Sift(u, N')$

The SL^λ Algorithm. The core of the SL^λ algorithm, shown in Algorithm 2, initializes the classification tree to consist of one (root) inner node, for the empty suffix (which classifies words as accepted or rejected); U and S_p are empty. It then sifts the empty prefix ϵ , thereby entering it into U . Thereafter, Algorithm 2 repeats a main loop in which CT is checked for a number of closedness and consistency properties. Whenever such a property is not satisfied, a corrective update is made by adding information to CT . These corrective updates fall into two categories, carried out by the following functions:

- *Expand* takes a prefix $u \in U$ and makes it into a short prefix. Since each short prefix must have a set of one-symbol extensions in U , the function forms one-symbol extensions of form $u\alpha(d_u^g)$, which are entered into the classification tree by sifting.
- *Refine* takes a leaf node N and a symbolic suffix v ; it sifts the prefixes u in N , thereby obtaining $\mathcal{L}[u, v]$ from a tree query. This can either split N into several equivalence classes, refine the initial guards or extend the set of registers in the location represented by N .

Let us now describe the respective corrective updates in Algorithm 2.

Location Closedness is satisfied if each leaf contains a short prefix in S_p . Whenever a leaf N does not contain a short prefix in S_p , one of its prefixes u is chosen for inclusion in S_p by calling $Expand(u)$, which adds one-symbol extensions to U .

Transition Closedness is satisfied if for each short prefix u , action α , and initial guard in $\mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$, the extension $u\alpha(d_u^g)$ is in U . If this is not satisfied, the missing $u\alpha(d_u^g)$ is added to U by sifting into CT .

Register Closedness is satisfied if for each pair of prefixes u and $u\alpha(d)$ in U , the memorable parameters found for u contain the memorable parameters revealed by the suffixes for $u\alpha(d)$, except for $x_{|u|+1}$. Register closedness guarantees that in a hypothesis \mathcal{H} , values of registers in the location of $u\alpha(d)$ can all be obtained

Algorithm 2: The SL^λ Learning Algorithm.

Initialize CT as inner node $root(CT)$ with suffix ϵ and $U \leftarrow \emptyset$, $S_p \leftarrow \emptyset$
 $Sift(\epsilon, root(CT))$
HYP: repeat
 \triangleright Check closedness
 if exists leaf N for which $\mathcal{U}^{-1}(N) \cap S_p = \emptyset$ **then** // location
 | $Expand(u)$ for some $u \in \mathcal{U}^{-1}(N)$
 if $u \in S_p$ and $g \in \mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$ but $u\alpha(\mathbf{d}_u^g) \notin U$ **then** // transition
 | $Sift(u\alpha(\mathbf{d}_u^g), root(CT))$
 if $u\alpha(\mathbf{d}) \in U$ s.t. $mem_{\mathcal{V}(u\alpha(\mathbf{d}))}(u\alpha(\mathbf{d})) \not\subseteq mem_{\mathcal{V}(u)}(u) \cup \{x_{|u|+1}\}$ **then** // register
 | Let $\mathbf{v} \in \mathcal{V}(u\alpha(\mathbf{d}))$ with $mem_{\mathbf{v}}(u\alpha(\mathbf{d})) \not\subseteq (mem_{\mathcal{V}(u)}(u) \cup \{x_{|u|+1}\})$
 | $Refine(\mathcal{U}(u), \alpha\mathbf{v})$
 \triangleright Check consistency
 if $u, u' \in \mathcal{U}^{-1}(L) \cap S_p$ with $u \simeq_{\mathcal{V}(N)}^\gamma u'$ for leaf N with
 $u\alpha(\mathbf{d}_u^g), u'\alpha(\mathbf{d}_{u'}^{g'}) \in U$ but $\mathcal{U}(u\alpha(\mathbf{d}_u^g)) \neq \mathcal{U}(u'\alpha(\mathbf{d}_{u'}^{g'}))$ **then** // location
 | $Refine(\mathcal{U}(u), \alpha\mathbf{v})$ with $\mathbf{v} = suff(lca(u\alpha(\mathbf{d}_u^g), u'\alpha(\mathbf{d}_{u'}^{g'})))$
 if $g \in \mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$ and $u\alpha(\mathbf{d}_u^g), u\alpha(\mathbf{d}) \in U$ with $(u, \mathbf{d}) \models g$ but
 $\mathcal{U}(u\alpha(\mathbf{d}_u^g)) \neq \mathcal{U}(u\alpha(\mathbf{d}))$ **then** // transition(a)
 | $Refine(\mathcal{U}(u), \alpha\mathbf{v})$ with $\mathbf{v} = suff(lca(u\alpha(\mathbf{d}_u^g), u\alpha(\mathbf{d})))$
 if $u\alpha(\mathbf{d}_u^g), u\alpha(\mathbf{d}) \in U$ with $u\alpha(\mathbf{d}_u^g) \not\preceq_{\mathcal{V}(u\alpha(\mathbf{d}))}^{\mathbf{d}} u\alpha(\mathbf{d})$ **then** // transition(b)
 | $Refine(\mathcal{U}(u), \alpha\mathbf{v})$ with \mathbf{v} s.t. $u\alpha(\mathbf{d}_u^g) \not\preceq_{\{\mathbf{v}\}}^{\mathbf{d}} u\alpha(\mathbf{d})$
 if $u, u\alpha \in U$ with $u \simeq_{\mathcal{V}(u)}^\gamma u\alpha$ and no extension γ' of γ with
 $u\alpha(\mathbf{d}) \simeq_{\mathcal{V}(u\alpha(\mathbf{d}))}^{\gamma'} u\alpha(\mathbf{d})$ **then** // register
 | $Refine(\mathcal{U}(u), \alpha\mathbf{v})$ with \mathbf{v} s.t. $u\alpha(\mathbf{d}) \not\preceq_{\{\mathbf{v}\}}^{\gamma'} u\alpha(\mathbf{d})$ for any γ'
until closed and consistent
 $\mathcal{H} \leftarrow Conjecture(CT)$
if $\exists w \in \Sigma^+$ s.t. $\mathcal{H}(w) \neq \mathcal{L}(w)$ **then** $Analyze(w)$ and **goto** HYP **else return** \mathcal{H}

by assignment from the registers in location u and the just received parameter. If it is not satisfied, a suffix \mathbf{v} of $u\alpha(\mathbf{d})$ which reveals a missing register is prepended by $\alpha(p_1)$ and added to the suffixes for u , whereafter $Refine(\mathcal{U}(u), \alpha\mathbf{v})$ will reveal the missing parameter. Here, and in the following, we use α to denote $\alpha(p_1)$, and $\alpha\mathbf{v}$ to denote the result $\alpha(p_1)\alpha'_2(p_2) \dots \alpha'_{m+1}(p_{m+1})$ of prepending α to $\mathbf{v} = \alpha'_1(p_1) \dots \alpha'_m(p_m)$. If possible, we try to choose a shortest \mathbf{v} , and also constrain the parameters of $\alpha\mathbf{v}$ to reduce the cost of the tree query for $\mathcal{L}[u, \alpha\mathbf{v}]$.

Location Consistency. Analogously to consistency in the classic L^* algorithm, we split a leaf containing two short prefixes u, u' , in case their corresponding extensions are not equivalent, i.e., there is a $g \in \mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$ such that $\mathcal{U}(u\alpha(\mathbf{d}_u^g)) \neq \mathcal{U}(u'\alpha(\mathbf{d}_{u'}^{g'}))$. The splitting is done by calling $Refine(\mathcal{U}(u), \alpha\mathbf{v})$, where \mathbf{v} is the symbolic suffix labeling the common ancestor of the leaves of $u\alpha(\mathbf{d}_u^g)$ and $u'\alpha(\mathbf{d}_{u'}^{g'})$.

Transition Consistency is satisfied if for all one-symbol extensions $u\alpha(\mathbf{d})$ that satisfy some guard g in $\mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$, are sifted to the same leaf as the extension $u\alpha(\mathbf{d}_u^g)$ with the representative data value \mathbf{d}_u^g . $u\alpha(\mathbf{d}')$ of $u \in S_p$. If not, the guard g should be split by calling $\text{Refine}(\mathcal{U}(u), \alpha\mathbf{v})$, where \mathbf{v} is the symbolic suffix labeling the common ancestor of the leaves of $u\alpha(\mathbf{d}_u^g)$ and $u\alpha(\mathbf{d})$. A similar case (*Transition Consistency(b)*) occurs when $u\alpha(\mathbf{d}_u^g)$ and $u\alpha(\mathbf{d})$ are sifted to the same leaf, but are not equivalent under the identity mapping between registers. Also here, the guard g should be split by calling $\text{Refine}(\mathcal{U}(u), \alpha\mathbf{v})$, where \mathbf{v} is a shortest suffix under which $u\alpha(\mathbf{d}_u^g) \not\equiv_{\{\mathbf{v}\}}^{\text{id}} u\alpha(\mathbf{d})$.

Register Consistency. For some short prefix u with memorable values $\text{mem}_{\mathcal{V}(u)}(u)$, there may be symmetries in $\mathcal{L}[u, \mathbf{v}]$ for some $\mathbf{v} \in \mathcal{V}(u)$, i.e., for some permutation γ on $\text{mem}_{\mathcal{V}(u)}(u)$ we have $u \simeq_{\mathcal{V}(u)}^\gamma u$. It may be that this symmetry does not exist in the SUL, but we did not yet add a suffix that disproves it (cf. example in Appendix A). Register consistency checks for the existence of such suffixes by comparing symmetries in u and its continuations $u\alpha(\mathbf{d})$. If a symmetry between data values of u does not exist in $u\alpha$ while one or more of the data values are memorable in $u\alpha$, we can construct a suffix that breaks the symmetry also for u .

Constrained Symbolic Suffixes. To reduce the number of membership queries for tree queries of form $\mathcal{L}[u, \mathbf{v}]$, we impose, when possible additional constraints to the parameters of \mathbf{v} , meaning that $\mathcal{L}[u, \mathbf{v}]$ represents acceptance/rejection of $u\mathbf{v}$ *only for the suffix parameters that satisfy the imposed constraints*. An illustration was given at the end of Section 2. A more detailed description is in Appendix B. Since a constrained symbolic suffix \mathbf{v}' represents fewer actual suffixes than an unconstrained one \mathbf{v} , it has less separating power, so suffixes should only be constrained if their separating power is sufficient. The principles for adding constraints are specific to the theory; we have implemented them for the theory $\langle \mathbb{N}, \{=\} \rangle$ with equality. There, we consider two forms of constraints on suffix parameters p_i : (i) *fresh*(p_i), meaning that p_i is different from all other preceding parameters in the prefix and suffix, (ii) $p_i = p_j$, where $j < i$, i.e., p_j is an earlier parameter in the constrained suffix. Let us consider how constrained suffixes arise when prepending an action α to an existing suffix \mathbf{v} , in a call of form $\text{Refine}(\mathcal{U}(u), \alpha\mathbf{v})$, in the case that u , α , and \mathbf{v} are chosen such that $\text{mem}_{\mathbf{v}}(u\alpha(\mathbf{d}))$ contains a particular memorable parameter. Let us denote the parameters of $\alpha\mathbf{v}$ by $p_1, \dots, p_{|\mathbf{v}|+1}$. The constraint for suffix $\alpha\mathbf{v}$ is then obtained by

1. letting the parameter of α be fresh if \mathbf{d} is not equal to a previous data value in u , and
2. constraining each parameter p_i with $i > 1$ in $\alpha\mathbf{v}$ to be (i) fresh whenever p_{i-1} is fresh in \mathbf{v} or the branch taken in $\mathcal{L}[u\alpha(\mathbf{d}), \mathbf{v}]$ for fresh p_{i-1} reveals the sought register, and (ii) equal to a previous value p_j in $\alpha\mathbf{v}$ if the branch taken in $\mathcal{L}[u\alpha(\mathbf{d}), \mathbf{v}]$ for p_{i-1} equal to the corresponding value reveals the sought register.

Hypothesis Construction. We can construct a hypothesis from a closed and consistent classification tree. Location closedness ensures that every transition

Algorithm 3: Analyze Counterexample.

Function $Analyze(w)$ **is**

```

  for  $|w| \geq i > 0$  do
    for  $u \in As(w_{1:i-1})$  do
      Let  $u\alpha(\mathbf{d}_u^g) \in U$  represent the last transition of  $w_{1:i}$  in  $\mathcal{H}$ 
      Let  $\mathbf{v} = Acts(w_{i+1:|w|})$  (or  $\epsilon$  for  $i = |w|$ )
      if  $u\alpha(\mathbf{d}_u^g) \not\approx_{\{\mathbf{v}\}} u'$  for all  $u' \in As(w_{1:i})$  then // location
        |  $Expand(u\alpha(\mathbf{d}_u^g))$  and stop analysis of  $w$ 
      if initial guard  $g$  in  $\mathcal{L}(u, \alpha\mathbf{v})$  but no  $u\alpha(\mathbf{d}_u^g) \in U$  then // transition
        |  $Sift(u\alpha(\mathbf{d}_u^g), root(CT))$  and stop analysis of  $w$ 

```

has a defined source and target location, transition closedness ensures that every transition that is observed by the tree queries we have performed so far, is represented by a prefix, and register closedness ensures that registers exist for all memorable data values in corresponding locations. Location consistency, transition consistency, and register consistency ensure that we can construct a unique (up to naming of locations and registers) determinate register automaton.

We construct the register automaton $\mathcal{A} = (L, l_0, \mathcal{X}, \Gamma, \lambda)$, where

- L is the set of leaves of CT , and l_0 is the leaf containing the empty prefix ϵ ,
- \mathcal{X} maps each location $l \in L$ to $mem_{CT}(u)$, where u is the short prefix of the leaf corresponding to l , and
- $\lambda(l) = +$ if the leaf l is in the accepting subtree of the root, else $\lambda(l) = -$.
- for every location l with short prefix u , action α , and guard g in $\mathcal{G}_{\mathcal{V}(u)}(u, \alpha)$, there is a transition $\langle l, \alpha(p), g, \pi, l' \rangle$, where
 - $l' = \mathcal{U}(u\alpha(\mathbf{d}_u^g))$ is the target location, and
 - π (the *assignment*) is defined by γ for which $u\alpha(\mathbf{d}_u^g) \simeq_{\mathcal{V}(u\alpha(\mathbf{d}_u^g))}^\gamma rp(u\alpha(\mathbf{d}_u^g))$

Analysis of Counterexamples. When an equivalence query returns a counterexample w , we process the counterexample as is shown in Algorithm 3. From right to left, we split the counterexample at every index into a location prefix $w_{1:i-1}$, a transition prefix $w_{1:i}$, and a suffix $w_{i+1:|w|}$. We use the location and transition prefixes to find corresponding short prefixes u and prefixes $u\alpha(\mathbf{d}_u^g)$ by tracing $w_{1:i-1}$ and $w_{1:i}$ on the conjecture. We write $As(w_{1:i})$ for the short prefix corresponding to the location reached by $w_{1:i}$ in a conjecture and $Vals(w)$ for the sequence of actions of w . We can then distinguish two cases: (1) The word $u\alpha(\mathbf{d}_u^g)$ is inequivalent to all corresponding short prefixes for the suffix of the counterexample. In this case, we make $u\alpha(\mathbf{d}_u^g)$ a short prefix. (2) The tree query $\mathcal{L}(u, \alpha\mathbf{v})$ shows a new initial guard. In this case, we add the corresponding (new) prefix $u\alpha(\mathbf{d}_u^g)$ to the set of prefixes. If neither case applies, we continue with the next index. Since w is a counterexample, one of the cases will apply for some index (cf. Lemma 1).

5 Correctness and Complexity

Let us now briefly discuss the correctness and query complexity of SL^λ . The correctness arguments are analogous to the arguments presented for other active

learning algorithms. One notable difference to SL^* is that SL^λ establishes register consistency instead of relying on counterexamples for distinguishing symmetric registers. Proofs and a more detailed discussion can be found in Appendix C.

Lemma 1. *A counterexample leads to a new short prefix or to a new prefix.*

This is a direct consequence of Algorithm 3. Using a standard construction that leverages properties of counterexamples (cf. [11, 40]), it can be shown that one of the two cases in the algorithm will trigger for some index of the counterexample. As long as expanding (or sifting) new prefixes does not trigger a refinement, the current counterexample can be analyzed again, until a refinement occurs.

Lemma 1 establishes progress towards a finite RA for a language \mathcal{L} . Let m be the length of the longest counterexample, t the number of transitions, r the maximal number of registers at any location, and n the number of locations in the final model. (t dominates both n and r .)

Theorem 1. *SL^λ infers a RA for regular data language \mathcal{L} with $O(t)$ equivalence queries and $O(t^2 n^r + tmn m^m)$ membership queries for sifting words and analyzing counterexamples.*

$O(t)$ is an improvement over the worst case estimate of $O(tr)$ equivalence queries for SL^* [11]. SL^λ also improves the worst case estimate for membership queries for sifting to $O(t^2 n^r + tmn m^m)$ from $O(t^2 r n^r)$ for filling the table in SL^* . For analyzing counterexamples, SL^λ replaces $O(trm m^m)$ with $O(tmn m^m)$.

6 Evaluation

We have implemented the SL^λ algorithm in RALib [10], an extension of LearnLib [33] to AAL algorithms for register automata. RALib already implemented the SL^* algorithm [11] that uses an observation table as its data structure. In order to evaluate the effect of analyzing counterexamples as described in Section 4, we have also implemented the SL^{CT} classification tree learning algorithm that uses the same counterexample analysis technique as the SL^* algorithm, i.e., adding suffixes from counterexamples to the classification tree directly. We compare the performance of the SL^λ algorithm against that of SL^* and SL^{CT} . Our experimental setup and all benchmarks are already publicly available on a GitHub repository, and will also be submitted as an artifact for evaluation.

Experimental Setup. We use two series of experiments: (1) A black-box learning setup with random walks for finding counterexamples on small models from the Automata Wiki [39] to establish a baseline comparison with other results and to evaluate the impact of using non-minimal counterexamples. In these experiments, we verify with a model checker that the inferred model is equivalent to the SUL and we stop as soon as the correct model is produced by a learning algorithm. (2) A white-box setup with a model checker for finding short counterexamples to analyze the scalability of algorithms on (2a) 24 consecutive hypotheses of the

Table 1: Results on AutomataWiki Systems.

SUL					Tests Learner			Tests L. + T.			CounterExs			WCT Learn [ms]			WCT Test [ms]		
	$ Q $	$ I $	$ X $	$ C $	SL^*	SL^λ	SL^{CT}	SL^*	SL^λ	SL^{CT}	SL^*	SL^λ	SL^{CT}	SL^*	SL^λ	SL^{CT}	SL^*	SL^λ	SL^{CT}
channel-frame	5	8	3	2	11	11	15	24	28	32	1	2	2	49	43	36	295	289	294
abp-receiver3	6	10	3	2	489	88	466	614	249	610	4	4	4	147	74	245	256	282	264
palindrome	6	15	4	0	479	358	476	508	384	504	5	5	5	73	52	51	406	403	402
login	12	19	4	0	436	244	433	509	300	512	3	2	3	86	54	67	301	303	310
abp-output	30	50	1	2	363	208	311	590	4552	6151	5	11	11	142	151	696	260	175	154
sip	30	72	2	0	487	233	345	934	3633	2772	9	15	16	370	347	353	194	149	160
fifo3	12	16	4	0	29	24	23	212	202	209	5	5	5	114	106	108	547	636	563
fifo5	18	24	6	0	66	55	60	435	434	468	6	7	7	1303	1144	1451	575	600	584
fifo7	24	32	8	0	118	96	123	738	839	989	7	8	9	317435	279888	346897	589	591	583

Mbed TLS 2.26.0 server,¹ as well as (2b) sets of randomly generated automata.² All results were obtained on a MacBook Pro with an Apple M1 Pro CPU and 32 GB of memory, running macOS version 12.5.1 and OpenJDK version 17.0.8.1.

Results. Table 1 summarizes the results of the experiments in a black-box learning setup. For every SUL, we report its complexity (in number of locations $|Q|$, transitions $|I|$, registers $|X|$, and constants $|C|$) and, for each learning algorithm, the number of tests (i.e., resets) during the learning phase, total tests (incl. counterexample search), the number of counterexamples found, and wall clock times (WCT) for learning and testing. In Table 1, all numbers are averages from 20 experiments. It can be seen that the SL^λ algorithm consistently outperforms the other two algorithms w.r.t. the number of tests during learning. As can be expected, the SL^* algorithm requires the fewest counterexamples. Execution times do not show a consistent pattern for these small systems or a clear ‘winner’ between these three RA learning algorithms, but there is a strong correlation between the number of learner tests and the time that learning requires. Due to this, in most cases, SL^λ is fastest overall.

The SULs of the previous set of experiments were all quite small ($|I| \leq 72$), and did not show any scalability differences between the three algorithms. Also, with the exception of fifo, the benchmarks were not parametric. In the following experiments, we scale the SULs which are learned.

Figure 4 shows the results of our experiments with DTLS models. For each algorithm, the graphs show the relationship between the number of transitions in each hypothesis model and the number of resets with constrained and unconstrained suffixes (in the first two graphs), the number of counterexamples (3rd graph), and execution times (4th graph). It is evident that, with increasing model complexity, the number of counterexamples grows linearly for all algorithms at roughly the same rate, yet the number of resets grows much more rapidly for SL^* than it does for SL^{CT} and SL^λ . In terms of time performance, the trend is even more pronounced. For SULs with more than 100 transitions, learning times

¹ We obtained these hypotheses by extending the machinery of DTLS-Fuzzer [17], a publicly available tool for learning state machine models of DTLS implementations.

² We used the algorithm of Champarnaud and Paranthoën [12] to enumerate semantically distinct DFAs with a specific alphabet and number of locations. We then replaced the alphabet symbols with RA actions of arity one, and finally replaced a fraction of the transitions with simple gadgets that store and compare data values.

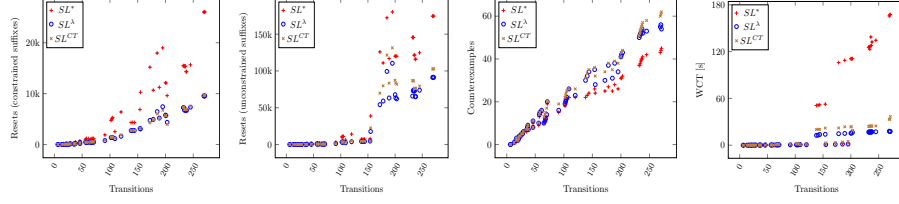


Fig. 4: Number of resets (two leftmost graphs), counterexamples (3rd graph), and wall clock times (4th graph) for inferring models of the Mbed TLS 2.26.0 server.

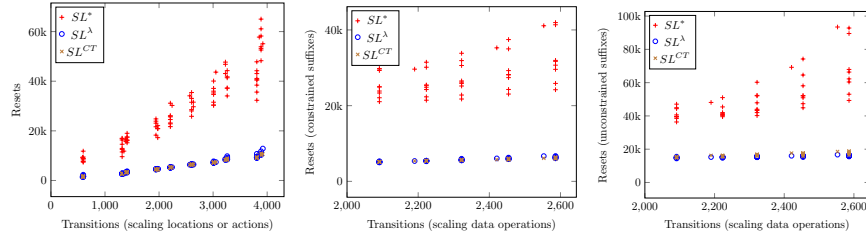


Fig. 5: Resets for inferring models of generated SULs, scaling the number of transitions through locations and actions as well as by increasing the percentage of transitions with data operations using constrained and unconstrained suffixes.

grow significantly worse for SL^* than the other two algorithms, and SL^λ clearly also beats SL^{CT} on even bigger systems.

Finally, Fig. 5 shows the results of the experiments with randomly generated automata. The graphs show how the number of resets scales with the number of locations and actions (left) and the number of registers when using both constrained (center) and unconstrained suffixes (right). The number of resets grows much more rapidly for SL^* than for the other algorithms. Not constraining suffixes leads to a 2–4x increase in resets; notice the different scales on the y-axis.

Overall, the experiments show a clear advantage of SL^λ over table-based RA learning algorithms in terms of the number of resets and execution times for bigger systems. These results confirm the theoretical properties of the algorithms and are consistent with the behavior of AAL algorithms for FSMs.

7 Conclusion

We have presented SL^λ , a scalable tree-based algorithm for register automata learning. The algorithm reduces the membership queries needed for inferring RA models by constructing short constrained suffixes incrementally. This enables active learning in scenarios not feasible with previous algorithms. We prove a reduction in the worst-case number of tests and, via a practical evaluation, show performance improvements on both real-world (i.e., on a complex network protocol) and synthetic models compared the state-of-the-art RA learning algorithm.

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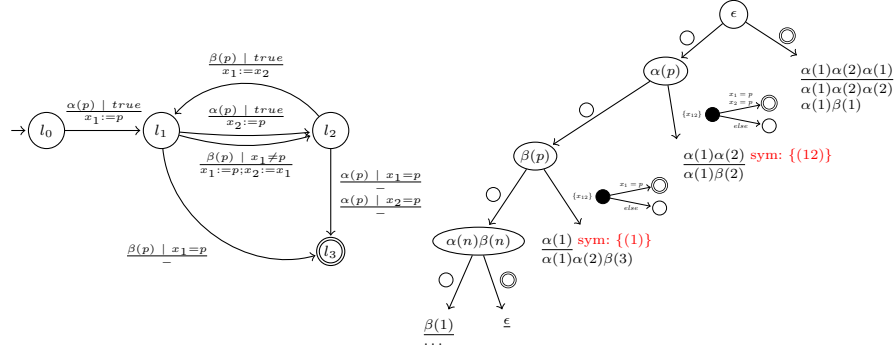


Fig. 6: SUL (left) and Classification Tree (right) illustrating symmetry.

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A Example: Symmetries in an SDT

The classification tree in Fig. 6 (right) represents all locations and transitions of the RA (left). For the words in leaf $\alpha(1)\alpha(2)$ there are symmetries that could lead to an incorrect remapping. The symmetry is not in the RA. A check for register consistency finds information to break it: in word $\alpha(1)\alpha(2)\beta(3)$ only 2 is memorable. This is a *register inconsistency* and can be resolved by refining the leaf of $\alpha(1)\alpha(2)$ by constrained suffix $\beta(n)\beta(p)$.

B Imposing Constraints on Symbolic Suffixes

As described in Section 2, a tree query for a prefix u and symbolic suffix v can be realized by a bounded number of membership queries for selected values of the data parameters of v . The number of these values can grow exponentially in the length of v . In order to reduce this number, we impose additional constraints on the parameters of symbolic suffixes. We consider two forms of constraints on suffix parameters p_i : (i) *fresh*(p_i), meaning that p_i is different from all other preceding parameters in the prefix and suffix, (ii) $p_i = p_j$, where $j < i$, i.e., p_j is an earlier parameter in the suffix. How these constraints are added to a symbolic suffix v differs depending on the context. During analysis of counterexamples, symbolic suffixes are formed from concrete prefixes and suffixes, so a direct comparison can be made between parameters in the prefix and suffix. When adding a symbolic suffix αv to the classification tree, e.g., in a call to *Refine*($\mathcal{U}(u), \alpha v$), the parameters of v are symbolic, so comparisons between parameters in the prefix and suffix must instead be done using tree queries. Let us explain how constraints are added for these two different contexts.

Constraining Suffixes During Counterexample Analysis. During analysis of a counterexample $w = \alpha_1(d_1) \dots \alpha_n(d_n)$, we split w into a prefix $\alpha_1(d_1) \dots \alpha_k(d_k)$ and a suffix $v = \alpha_{k+1}(d_{k+1}) \dots \alpha_n(d_n)$. When forming a symbolic suffix \mathbf{v} from v , constraints on the parameters p_i of \mathbf{v} are obtained by

- letting p_i be fresh if $d_{k+i} \neq d_j$ for any $j < i$.
- letting p_i equal a preceding parameter p_j if $d_{k+i} = d_{k+j}$, and p_j is fresh.

For example, suppose that we find a counterexample `push(0)push(1)pop(1)pop(0)` for hypothesis \mathcal{H}_0 of Fig. 2, and we split it into prefix $u = \text{push}(0)$ and suffix `push(1)pop(1)pop(0)`. When forming the symbolic suffix $\mathbf{v} = \text{push}(p_1)\text{pop}(p_2)\text{pop}(p_3)$, we observe that p_1 can be fresh since the data value of `push(1)` does not equal any preceding data value. Parameter p_2 can be constrained as equal to p_1 since the data value of `pop(1)` is equal to that of `push(1)`, and p_1 is fresh. The last parameter p_3 cannot be constrained since the data value of `pop(0)` is equal to a data value in the prefix, namely the data value of `push(0)`. With the constraints $\langle \text{fresh}(p_1), p_2 = p_1 \rangle$ on \mathbf{v} , only three membership queries must be made when performing the tree query $\mathcal{L}(u, \mathbf{v})$, as opposed to a total of fifteen membership queries required if \mathbf{v} were unconstrained.

Constraining Suffixes Added to the Classification Tree. Whenever a symbolic suffix is added to the *CT*, this suffix is formed by prepending a symbol α to a symbolic suffix $\mathbf{v} \in \mathcal{V}$. In this case, since the parameters of \mathbf{v} are symbolic, we cannot compare them directly, so instead we compare guards from tree queries.

In the cases of register closedness or register consistency, the symbol α is formed from a concrete symbol $\alpha(d)$ in a prefix $u\alpha(d)$. In these cases, u , α and \mathbf{v} are chosen such that $\text{mem}_{\mathbf{v}}(u\alpha(d))$ contains particular memorable parameters. The parameters of $\alpha\mathbf{v}$ can be constrained by examining the guards of $\mathcal{L}(u\alpha(d), \mathbf{v})$. Let us denote the parameter of α as p_1 and the parameters of \mathbf{v} as $p_2, \dots, p_{|\mathbf{v}|+1}$. The constraint for suffix $\alpha\mathbf{v}$ is then obtained by:

1. letting the parameter of α be fresh if d is not equal to any previous data value in u , and
2. constraining each parameter p_i with $i > 1$ in $\alpha\mathbf{v}$ to be (i) fresh whenever p_{i-1} is fresh in \mathbf{v} or the branch taken in $\mathcal{L}[u\alpha(d), \mathbf{v}]$ for fresh p_{i-1} reveals a sought register, and (ii) equal to a previous value p_j in $\alpha\mathbf{v}$ if the branch taken in $\mathcal{L}[u\alpha(d), \mathbf{v}]$ for p_{i-1} which is equal to the corresponding value reveals a sought register.

As an example, assume that we have a prefix $\alpha(0)\alpha(1)$ and symbolic suffix $\mathbf{v} = \alpha(p_2)\alpha(p_3)$. We want to form an extended symbolic suffix $\alpha\mathbf{v} = \alpha(p_1)\alpha(p_2)\alpha(p_3)$, given the tree query $\mathcal{L}(\alpha(0)\alpha(1), \mathbf{v})$ shown in Fig. 7(left). The registers x_1 and x_2 are mapped to the data values 0 and 1, respectively, in the prefix. In this example, the symbolic suffix $\alpha\mathbf{v}$ is needed to reveal the memorable data value x_1 . First, we constrain p_1 as fresh, since the data value of $\alpha(1)$ does not equal any preceding parameter. Second, we constrain p_2 to be equal to p_1 , as the tree query has guard $p_2 = x_2$, and x_2 corresponds to the fresh parameter p_1 . Finally, we note that p_3

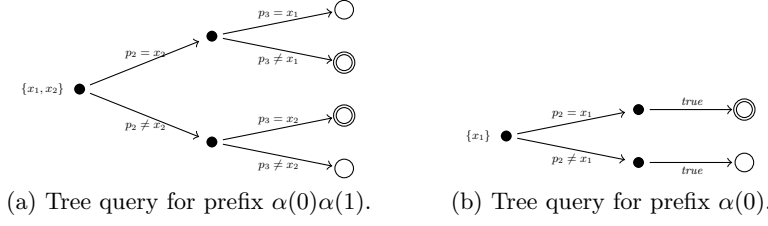


Fig. 7: Tree queries for two prefixes with symbolic suffix $\alpha(p_2)\alpha(p_3)$.

cannot be constrained, as there is a guard $p_3 = x_1$ and x_1 maps to a data value in u .

The case of transition consistency (b), where two prefixes $u\alpha(\mathbf{d})$ and $u\alpha(\mathbf{d}')$ lead to the same location but are not equivalent under the identity mapping between registers, is handled similarly to register consistency. Since $u\alpha(\mathbf{d}) \not\sim_v^{\text{id}} u\alpha(\mathbf{d}')$, we need only consider one of $\mathcal{L}(u\alpha(\mathbf{d}), \mathbf{v})$ and $\mathcal{L}(u\alpha(\mathbf{d}'), \mathbf{v})$ when imposing constraints on $\alpha\mathbf{v}$, with the caveat that one of \mathbf{d} and \mathbf{d}' will be equal to a parameter in u so the parameter of α cannot be constrained.

In the case of location consistency, we want to find a symbolic suffix $\alpha\mathbf{v}$ that separates two prefixes u and u' . As such, when we constrain $\alpha\mathbf{v}$, we must do so in a way such that $\alpha\mathbf{v}$ retains its ability to separate u and u' . Assume that we have found two continuations $u\alpha(\mathbf{d})$ and $u'\alpha(\mathbf{d}')$ which lead to different locations. Let us denote the parameter of α as p_1 and the parameters of \mathbf{v} as $p_2, \dots, p_{|\mathbf{v}|+1}$. Now, let (τ, τ') be a pair of (u, \mathbf{v}) -paths $\tau \in \text{Dom}(\mathcal{L}(u\alpha(\mathbf{d}), \mathbf{v}))$ and $\tau' \in \text{Dom}(\mathcal{L}(u'\alpha(\mathbf{d}'), \mathbf{v}))$ such that (i) the conjunction of the guard expressions of τ and τ' is satisfied, and (ii) $\mathcal{L}(u\alpha(\mathbf{d}), \mathbf{v})(\tau) \neq \mathcal{L}(u'\alpha(\mathbf{d}'), \mathbf{v})(\tau')$. For each such pair of (u, \mathbf{v}) -paths, a constrained symbolic suffix $\alpha\mathbf{v}_{(\tau, \tau')}$ is obtained by

1. letting p_1 be fresh if \mathbf{d} does not equal any data value in u and \mathbf{d}' does not equal any data value of u' ,
2. letting each parameter p_i with $i > 1$ be fresh if, in both τ and τ' , the guard for p_i is either $true$ or a disequality guard, and
3. constraining each parameter p_i with $i > 1$ as equal to a preceding parameter p_j if (i) the only guard on p_i in τ is $p_i = p_j$, (ii) the only guard on p_i in τ' is $p_i = p_j$, $p_i \neq p_j$ or $true$, and (iii) p_j is fresh.

We choose as our constrained suffix $\alpha\mathbf{v}$ the $\alpha\mathbf{v}_{(\tau, \tau')}$ with the smallest number of unconstrained parameters. The case of transition consistency (a) is handled similarly, with the only difference being that, in this case, $u = u'$.

As an example, assume we have two prefixes $u\alpha(\mathbf{d}) = \alpha(0)\alpha(1)$ and $u'\alpha(\mathbf{d}') = \alpha(0)$, which lead to different locations with lowest common ancestor in CT being $\mathbf{v} = \alpha(p_2)\alpha(p_3)$. The tree queries for $\mathcal{L}(\alpha(0)\alpha(1), \mathbf{v})$ and $\mathcal{L}(\alpha(0), \mathbf{v})$ are shown in Fig. 7. Note that in both tree queries x_1 is mapped to the parameter of $\alpha(0)$ and x_2 is mapped to the parameter of $\alpha(1)$. There are two pairs of (u, \mathbf{v}) -paths (τ, τ') to choose from which satisfy both conditions (i) and (ii), namely (1) $\tau = (p_2 = x_2, p_3 = x_1)$ and $\tau' = (p_2 = x_2, p_3 : true)$, or (2) $\tau = (p_2 \neq x_2, p_3 = x_2)$ and $\tau' = (p_2 \neq x_2, p_3 : true)$. We can constrain p_1 as fresh, since \mathbf{d} does not

equal any parameter in u and \mathbf{d}' does not equal any parameter in u' . For (1), we can constrain $p_2 = p_1$ as it is equal to the parameter corresponding to p_1 in both (u, \mathbf{v}) -paths (the parameter of $\alpha(1)$ for τ and of $\alpha(0)$ for τ'), and p_1 is fresh. However, we cannot place any constraint on p_3 , since, in τ , p_3 is equal to a data value in u (namely, x_1). For (2), we can constrain p_2 as fresh, since the guard is a disequality guard for both τ and τ' , and we can constrain p_3 as equal to p_1 since p_3 is equal to x_2 (i.e., equal to p_1) in τ and p_3 has a *true* guard in τ' . Since we have one unconstrained parameter in $\alpha\mathbf{v}$ for (1), but none for (2), we choose the set of constraints of (2). Thus, we constrain $\alpha\mathbf{v}$ by $\langle \text{fresh}(p_1), \text{fresh}(p_2), p_3 = p_1 \rangle$.

C Correctness and Complexity

In this appendix, we establish the correctness and complexity properties of SL^λ .

Lemma 1. *A counterexample always leads to a new short prefix (Case 1 of Algorithm 3) or new prefix (Case 2 of Algorithm 3).*

Proof. We know that at every index i , for $u \in As(w_{1:i-1})$, it holds that

1. $\mathcal{H}(u\alpha(\mathbf{d}_u^g), \mathbf{v}) \equiv \mathcal{H}(u', \mathbf{v})$ and that
2. $\mathcal{H}(u, \alpha\mathbf{v})$ has a g -guarded subtree $\mathcal{H}(u\alpha(\mathbf{d}_u^g), \mathbf{v})$.

We also know that $\mathcal{L}(u_m, \epsilon) \equiv \mathcal{H}(u_m, \epsilon)$ for $u_m \in As(w_{1:m})$ because ϵ is the symbolic suffix of the root in the classification tree and determines if the location of u_m is accepting or rejecting. On the other hand, $\mathcal{L}(\epsilon, \mathbf{v}) \not\equiv \mathcal{H}(\epsilon, \mathbf{v})$ for $\mathbf{v} = w_{1:m}$ since w is a counterexample.

As a consequence, at some index i it must either be the case that $\mathcal{L}(u\alpha(\mathbf{d}_u^g), \mathbf{v}) \not\equiv \mathcal{L}(u', \mathbf{v})$ or that $\mathcal{L}(u, \alpha\mathbf{v})$ has a g' -guarded subtree that is not present in $\mathcal{H}(u, \alpha\mathbf{v})$. When analyzing a counterexample, we make $u\alpha(\mathbf{d}_u^g)$ a short prefix (a prefix, respectively). Either a refinement occurs immediately, or next time we arrive at the same check $u\alpha(\mathbf{d}_u^g)$ will be a short prefix (prefix, respectively) and the condition will not be satisfied. The algorithm will continue with the next case or index of the counterexample and the arguments given above apply. \square

Let m be the length of the longest counterexample, t the number of transitions, r the maximal number of registers at any location, and n the number of locations in the final model.

Theorem 1. *SL^λ infers a RA for regular data language \mathcal{L} with $O(t)$ equivalence queries and $O(t^2 n^r + tmn m^m)$ membership queries for sifting words and analyzing counterexamples.*

Proof. Every counterexample will lead to progress: the counterexample will produce a new transition or a new short prefix and a corresponding refinement is guaranteed to occur before the next equivalence query. The canonic acceptor has a finite number of locations and transitions. By construction, the final model will accept \mathcal{L} .

The classification tree will have at most $n + 2r + 2t = O(t)$ inner nodes (since $t \geq n > r$) created through refinement operations in Algorithm 2 on any path to

a leaf. Suffixes at these nodes tree have at most r unconstrained parameters. The size of U is limited by $t + 1$, resulting in at most $O(t^2)$ tree queries. A tree query in the classification tree results in at most $O(n^r)$ membership queries as prefixes are of length n or shorter. The number of counterexamples is limited by t . For the longest counterexample of length m , it can be necessary to compute mn tree queries that each can require $O(m^m)$ membership queries in the worst case. \square

This is an improvement over the worst case estimate of $O(tr)$ equivalence queries for SL^* [11]. SL^λ also improves the worst case for membership queries for sifting to $O(t^2 n^r + tmn m^m)$ from $O(t^2 r n^r)$ for filling the table in SL^* .

For analyzing counterexamples, SL^λ replaces SL^* 's $O(trm m^m)$ worst case estimate with $O(tmn m^m)$, where t dominates n and r .