Learning Asynchronous Typestates for Android Classes

Arjun Radhakrishna\textsuperscript{1}, Nicholas Lewchenko\textsuperscript{2}, Shawn Meier\textsuperscript{2}, Sergio Mover\textsuperscript{2}, Krishna Chaitanya Sripada\textsuperscript{2}, Damien Zufferey\textsuperscript{3}, Bor-Yuh Evan Chang\textsuperscript{2}, and Pavol Černý\textsuperscript{2}

\textsuperscript{1}University of Pennsylvania
\textsuperscript{2}University of Colorado Boulder
\textsuperscript{3}Max Planck Institute for Software Systems

Abstract. In event-driven programming frameworks, such as Android, the client and the framework interact using callins (framework methods that the client invokes) and callbacks (client methods that the framework invokes). The protocols for interacting with these frameworks can often be described by finite-state machines we dub \textit{asynchronous typestates}. Asynchronous typestates are akin to classical typestates, with the key difference that their outputs (callbacks) are produced asynchronously.

We present an algorithm to infer asynchronous typestates for Android framework classes. It is based on the \textsc{L*} algorithm that uses membership and equivalence queries. We show how to implement these queries for Android classes. Membership queries are implemented using testing. Under realistic assumptions, equivalence queries can be implemented using membership queries. We provide an improved algorithm for equivalence queries that is better suited for our application than the algorithms from literature. Instead of using a bound on the size of the typestate to be learned, our algorithm uses a \textit{distinguisher bound}. The distinguisher bound quantifies how two states in the typestate are locally different.

We implement our approach and evaluate it empirically. We use our tool, \textsc{Starling}, to learn asynchronous typestates for Android classes both for cases where one is already provided by the documentation, and for cases where the documentation is unclear. The results show that \textsc{Starling} learns asynchronous typestates accurately and efficiently. Additionally, in several cases, the synthesized asynchronous typestates uncovered surprising and undocumented behaviors.

1 Introduction

Event-driven programming frameworks interact with client code using callins and callbacks. Callins are framework methods that the client invokes and callbacks are client methods that the framework invokes. The client-framework interaction is often governed by a protocol that can be described by a finite-state machine.

For example, consider a typical interaction between a client application and the framework when the client wants to use a particular service. The client asks for the service to be started by invoking a \texttt{startService()} callin. After the framework receives the callin, it asynchronously starts initializing the
service. When the service is started and ready to be used, the framework notifies the client by invoking a `onServiceStarted()` callback. The client can then use the service. After the client finishes using the service, it invokes a `shutdownService()` call in to ask the framework to stop the service.

The protocol for the interaction in the example can be described by a finite-state machine we call **asynchronous typestate**. Typestates [32] were introduced to describe synchronous interfaces that specify order of method calls. As they are synchronous, typestates involve only callins (which can return output values). In contrast, asynchronous typestates have both inputs (corresponding to callins) and outputs (corresponding to callbacks). In automata theory, asynchronous typestates can be seen as interface automata. Interface automata [12] are a well-studied model of automata that can receive outputs asynchronously w.r.t. inputs.

We choose to use the name asynchronous typestates to emphasize that they are a generalization of typestates as used in the programming languages literature.

**Problem.** We consider the problem of inferring asynchronous typestates from framework code, in particular in the Android framework. Asynchronous typestates are useful in a number of ways. First, asynchronous typestates are a form of documentation. They tell client application programmers in what order to invoke callins and which callback to expect. Some Android framework documentation already uses pictures very similar to asynchronous typestates (Figure 1). Second, asynchronous typestates are also useful in verification of client code. They enable checking that a client uses the framework correctly. Third, even though we infer the asynchronous typestates from framework code, they can be used for certain forms of framework verification. For instance, one can infer typestates for different versions of the framework, and check if the interface has changed.

**Method.** We present a method for inferring typestates for Android classes. However, our method is equally applicable in other contexts. The core algorithm is based on Angluin’s L* algorithm [5] adapted to Mealy machines [28]. A learner tries to learn a finite-state machine — in our case an asynchronous typestate — by asking a teacher membership and equivalence queries. We note that the teacher does not need to know the solution, but only how to answer the queries.

**Membership and equivalence oracles.** The key question we answer is how to implement oracles for the membership and equivalence queries. The membership query asks whether a given sequence of callins is legal, i.e., it does not raise an exception when invoked on the class C, and, if so, what sequence of callbacks C generates in response. We implement the membership oracle by testing. The equivalence query asks whether the current hypothesis H is a typestate for C. If not, the teacher provides a counterexample: a sequence of callins and callbacks allowed by H which does not arise when a client interacts with C, or vice versa. Answering the equivalence query requires checking language inclusion for two programs (C and H). This is an undecidable problem in general.

However, under realistic assumptions, the equivalence oracle can be implemented on top of the membership oracle. This follows from an automata-theoretic result on the length of the longest minimal counterexample for equivalence of two automata. The equivalence oracle uses the following boundedness
assumption: if $C$ has an asynchronous typestate, then its number of states is less than a constant $k$. Unfortunately, the equivalence check implemented in this way (as is done in previous algorithms [10,14] for conformance testing) is exponential in $k$. Therefore, we introduce the notion of a *distinguisher bound*. A distinguisher bound limits the size of a witness word that differentiates two states. Intuitively, a distinguisher bound quantifies how states are *locally different*. The distinguisher bound is always smaller than the state bound; for Android classes, we found empirically that the distinguisher bound is significantly smaller than the state bound. The largest asynchronous typestates of an Android class we found have at most 10 states and a distinguisher bound of 2.

**Implementing membership oracle on Android.** We implement the membership oracle using testing. Concretely, we run the sequence of callins, and log exceptions, errors, and callbacks that occur. Since testing might not expose all the framework’s behaviors, the oracle can return incorrect results. We explain in detail the assumptions under which we learn the correct typestate in Section 3.2 and how our implementation deals with them in Section 5.

**Empirical evaluation.** We implemented our approach in a tool called Starling. We use Starling to synthesize asynchronous typestates for Android framework classes. The results show that Starling learns asynchronous typestates accurately and efficiently. This is confirmed by documentation, code inspection, and manual comparison to simple Android applications. The small bound hypothesis is also confirmed. Furthermore, by inspecting our typestates, we uncovered corner cases with surprising behavior that are undocumented and might even be considered as bugs. Section 6 presents our results in more detail.

**Contributions.** The contributions of this paper are: (a) We introduce the notion of asynchronous typestates and develop an approach, based on the L∗ algorithm, to infer them. (b) We show how to implement efficiently membership and equivalence oracles required by the L∗ algorithm. (c) We evaluate our approach on examples from the Android framework, and show its accuracy and effectiveness.

## 2 Illustrative Example

Let us consider the asynchronous typestate in Figure 1, taken from the documentation for the Android class called MediaPlayer. Callins are represented by single arrows and callbacks by double arrows. Let us look at one part of the protocol that governs the client-framework interaction. The client first invokes the callin `setDataSource()`, and the protocol transitions to the *Initialized* state. In this state, the client can invoke the callin `prepareAsync()`, and the protocol transitions to the *Preparing* state. In the *Preparing* state, the client cannot invoke any callins, but the framework can invoke the `onPrepared()` callback, and then the protocol transitions to the *Prepared* state. Only at this point, the client can invoke the `start()` callin, and the media starts playing.

Our approach follows the structure of the L∗ algorithm. A learner asks membership queries, until she can form a hypothesis automaton and ask an equivalence query. If a counterexample is returned, the algorithm learns from it. This process repeats until the hypothesis is correct. For the MediaPlayer, the first set
of membership queries each invoke a different callin. Of these, only the query containing `setDataSource()` succeeds. The testing-based membership oracle raises an exception on all the other callins. The learner continues with longer membership queries while building the hypothesis automaton. For instance, it learns that `prepareAsync()` and `prepare()` cannot lead to the same state: it is possible to invoke the `start()` after `prepare()`, but not after `prepareAsync()`. Once the client receives the callback `onPrepared()`, `start()` may be called. The learner thus hypothesizes a transition from the `Preparing` to the `Prepared` on `onPrepared()`. Once the hypothesis is complete, the learner asks the equivalence query. In this example, the solution is found after 5 equivalence queries.

Assuming small typestates it becomes possible to implement the equivalence check using testing. However, equivalence queries are still expensive and to make them practical we present an new optimization based on a distinguisher bound. We can observe in Figure 1 that for any pair of states there is a transition in one state which leads to an error in the other. This corresponds to a distinguisher bound of 1. This property arises because typestates are not random automata but part of an API designed for ease of use and robustness. Such APIs are coded defensively and are fail-fast [31], i.e., errors are not buffered but reported immediately. Each state in the typestate has a specific function and an associated set of callins and callbacks. In automata terms, the alphabet is roughly the same size as the number of states and the states have only a few transitions. Therefore, two states are easy to distinguish. In Section 4.3, we explain how we use the distinguisher bound to implement equivalence queries and discuss why distinguisher bounds are small in practice.

3 The Asynchronous Typestate Learning Problem

We introduce models of interfaces, define the asynchronous typestate learning problem, and present an impossibility result about learning typestates.

3.1 Definitions and Problem Statement

Asynchronous interfaces. Let $\Sigma_i$ and $\Sigma_o$ be the set of callins and callbacks of an asynchronous interface. We abstract away parameter and return values of callins and callbacks, and model a behavior of the interface as a trace $\tau_i =$
Interface automata. We use interface automata [12] to represent asynchronous interfaces. An interface automaton $A$ is given by $\langle Q, q_\text{ι}, \Sigma_i, \Sigma_o, \Delta_A \rangle$ where: (a) $Q$ is a finite set of states, (b) $q_\text{ι} \in Q$ is the initial state, (c) $\Sigma_i$ and $\Sigma_o$ are finite sets of input and output symbols, and (d) $\Delta_A \subseteq Q \times (\Sigma_i \cup \Sigma_o) \times Q$ are a set of transitions. A trace $\tau_a$ of $A$ is given by $\sigma_0 \ldots \sigma_n$ if $\exists q_0 \ldots q_{n+1}: q_0 = q_\text{ι} \land \forall i. (q_i, \sigma_i, q_{i+1}) \in \Delta_A$.

Problem statement. Given an interface $I = \langle \Sigma_i, \Sigma_o, \Pi_i \rangle$, the asynchronous typestate learning problem is to learn an interface automaton $A$ such that $\Pi_i = \text{Traces}(A)$. We allow the learner to ask a membership oracle $\text{MOracle}[I]$ membership queries. For a membership query, the learner picks $m_{\text{Query}} = i_0i_1 \ldots i_n \in \Sigma_i^*$ and the membership oracle $\text{MOracle}[I]$ returns either: (a) a trace $\tau_a \in \Pi_i$ whose sequence of calls is exactly $m_{\text{Query}}$, or (b) $\perp$ if no such trace exists.

3.2 The Theory and Practice of Learning Typestates

In general, it is impossible to learn asynchronous typestates using only membership queries; no finite set of membership queries fixes a unique interface automaton (see Appendix B for a formal statement). However, asynchronous typestates can be effectively learned given extra assumptions. Below, we analyze the causes behind the impossibility and highlight the assumption necessary to overcome it.

Unbounded asynchrony. Membership queries alone do not tell us if the interface will emit more outputs (callbacks) at any point in time. Hence, we assume:

Assumption 1: Quiescence is observable.

This assumption is commonly used in ioco-testing frameworks [33]. In our setting, we add an input wait and an output quiet, where quiet is returned after a wait only if there are no other pending callbacks. In practice, quiet can be implemented using timeouts, i.e., pending callbacks are assumed to arrive within a fixed amount of time. If no callbacks are seen within the timeout, quiet is output.

Example 1. Using wait and quiet, in the MediaPlayer example, we have that setDataSource() · prepareAsync() · onPrepared() · wait · quiet is a valid trace, but setDataSource() · prepareAsync() · wait · quiet is not.

Behavior unboundedness. For any set of membership queries, let $k$ be the length of the longest query. It is not possible to find out if the interface exhibits significantly different behavior for input sequences much longer than $k$. While this is a theoretical limitation, it is not a problem in practice as most asynchronous typestates are rather small ($\leq 10$ states).

Assumption 2: An upper bound on the size of the typestate being learned is known.

Non-determinism. We need to be able to observe the systems’ behaviors to learn them and non-determinism can prevent that. Therefore, we assume:

Assumption 3: The interface is deterministic.

We assume that for every trace $\tau_a$ of the interface, there is at most one output $o \in \ldots \sigma_n \in (\Sigma_i \cup \Sigma_o)^*$. The interface $I$ is given by $\langle \Sigma_i, \Sigma_o, \Pi_i \rangle$ where $\Pi_i \subseteq (\Sigma_i \cup \Sigma_o)^*$ is the prefix-closed set of all feasible traces of the interface.
such that $\tau_a \cdot o \in \Pi_i$. In practice, the non-determinism problem is somewhat alleviated due to the nature of asynchronous typestates (see Section 5). See [1] for a detailed theoretical discussion of how non-determinism affects learnability.

**Example 2.** Consider an interface with traces given by $(\text{input} \cdot (\text{out1} \mid \text{out2}))^*$. All membership queries are a sequence of input's; however, it is possible that the membership oracle never returns any trace containing $\text{out2}$. In that case, no learner will be able to learn the interface exactly.

### 4 Learning Asynchronous Typestates using $L^*$

Given Assumption 1 and Assumption 3, we first build a “synchronous closure” of an asynchronous interface (Section 4.1). Then, we show how to learn the synchronous closure effectively given Assumption 2 (Section 4.2 and 4.3).

#### 4.1 From Asynchronous to Synchronous Interfaces

Using Assumption 1 and 3, we build a synchronous version of an interface in which inputs and outputs strictly alternate following [1]. For synchronous interfaces, we can draw learning techniques from existing work [5,1,22,28].

Define $\Sigma_i = \Sigma \cup \{\text{wait}\}$ and $\tilde{\Sigma}_o = \Sigma_o \cup \{\text{quiet, } \epsilon, \text{ err}\}$. The purpose of the additional inputs and outputs is discussed below. For any $\tau_s \in (\tilde{\Sigma}_i \cdot \tilde{\Sigma}_o)^*$, we define $\text{async}(\tau_s) = \tau_s \in (\Sigma_i \cup \Sigma_o)^*$ where $\tau_s$ is obtained from $\tau_a$ by erasing all occurrences of wait, quiet, $\epsilon$, and err.

**Synchronous closures.** The synchronous closure $I_s$ of an asynchronous interface $I = (\Sigma, \Sigma_o, \Pi_i)$ is given by $(\tilde{\Sigma}_i, \tilde{\Sigma}_o, \Pi_s)$ where $\tilde{\Sigma}_i$ and $\tilde{\Sigma}_o$ are as above, and $\Pi_s \subseteq (\tilde{\Sigma}_i \cdot \tilde{\Sigma}_o)^*$ is defined as the smallest set satisfying the following:

$$(\epsilon \in \Pi_s) \land \bigwedge \tau_s \in \Pi_s \begin{cases} \text{async}(\tau_s) \cdot i \in \Pi_i \implies \tau_s \cdot i \cdot \epsilon \in \Pi_s \\ \text{async}(\tau_s) \cdot o \in \Pi_i \implies \tau_s \cdot \text{wait} \cdot o \in \Pi_s \\ \text{async}(\tau_s) \cdot i \notin \Pi_i \implies \tau_s \cdot i \cdot \text{err} \in \Pi_s \\ \forall o \in \Sigma_o: \text{async}(\tau_s) \cdot o \notin \Pi_i \implies \tau_s \cdot \text{wait} \cdot \text{quiet} \in \Pi_i \\ \tau_s \text{ ends in } \text{err} \implies \tau_s \cdot i \cdot \text{err} \in \Pi_s \end{cases}$$

Informally, in $I_s$: (a) Each input is immediately followed by a dummy output $\epsilon$; (b) Each output is immediately preceded by a wait input wait; (c) Any call to an input disabled in $I$ is immediately followed by an err. Further, all outputs after an err are err’s. (d) Any call to wait in a quiescent state is followed by quiet.

Given MOracle[I] and Assumption 1, it is easy to construct the membership MOracle[Iₕ]. Note that due to Assumption 3, there is exactly one possible reply MOracle[Iₕ](mQuery) for each query mQuery. Further, by the construction of the synchronous closure, the inputs and outputs in MOracle[Iₕ](mQuery) alternate.

**Mealy machines.** We model synchronous interfaces using the simpler formalism of Mealy machines rather than interface automata. A Mealy machine $M$ is a tuple $(Q, q_i, \Sigma_i, \Sigma_o, \delta, \text{Out})$ where: (a) $Q, q_i, \Sigma_i,$ and $\Sigma_o$ are states, initial state, inputs and outputs, respectively, (b) $\delta : Q \times \Sigma_i \rightarrow Q$ is a transition function, and (c) $\text{Out} : Q \times \Sigma_i \rightarrow \Sigma_o$ is an output function. We abuse notation and write $\text{Out}(q, i_0 \ldots i_n) = o_1 \ldots o_n$ and $\delta(q, i_0 \ldots i_n) = q'$ if $\exists q_0, \ldots, q_{n+1} : q_0 = q \land q_{n+1} = q' \land \forall 0 \leq i \leq n : \delta(q_i, i_i) = q_{i+1} \land \text{Out}(q_i, i_i) = o_i$. A sequence
Algorithm 1 returns \( M \) check with a number of membership queries using the following theorem.

For the sake of completeness, we describe the classical L* learning algorithm by Angluin [5] as adapted to Mealy machines in [28]. A reader familiar with the literature on inference of finite-state machines may safely skip this subsection.

Fix an asynchronous interfaces \( I \) and its synchronous closure \( I_\ast \). In the L* algorithm, in addition to a membership oracle \( MOracle[I_\ast] \), the learner has access to an equivalence oracle \( EOracle[I_\ast] \). For an equivalence query, the learner passes a Mealy machine \( M \) to \( EOracle[I_\ast] \), and is in turn returned: (a) A counterexample input \( cex = i_0 \ldots i_n \) such that \( M(cex) = o_0 \ldots o_n \) and \( MOracle[I_\ast](cex) \neq i_0 o_0 \ldots i_n o_n \), or (b) Correct if no such \( cex \) exists.

The full L* algorithm is in Algorithm 1. In Algorithm 1, the learner maintains: (a) a set \( S_Q \subseteq \Sigma_i \ast \) of state-representatives (initially set to \( \{e\} \)), (b) a set \( E \subseteq \Sigma_i \ast \) of experiments (initially set to \( \Sigma_i \)), and (c) an observation table \( T : (S_Q \cup S_Q \cdot \Sigma_i) \rightarrow (E \rightarrow \Sigma_\ast) \). The observation table maps each prefix \( w_i \) and suffix \( e \) to \( T(w_i)(e) \), where \( T(w_i)(e) \) is the suffix of the output sequence of \( MOracle(w_i \cdot e) \) of length \(|e|\). The entries are computed by the sub-procedure \( \text{FillTable} \).

Intuitively, \( S_Q \) represent Myhill-Nerode equivalence classes of the Mealy machine the learner is constructing, and \( E \) distinguish between the different classes. For \( S_Q \) to form valid set of Myhill-Nerode classes, each state representative extended with an input, should be equivalent to some state representative. Hence, the algorithm checks if each \( w_i \cdot i \in S_Q \cdot \Sigma_i \) is equivalent to some \( w_i' \in S_Q \) (line 3) under \( E \), and if not, adds \( w_i \cdot i \) to \( S_Q \). If no such \( w_i \cdot i \) exists, the learner constructs a Mealy machine \( M \) using the Myhill-Nerode equivalence classes, and queries the equivalence oracle (line 5). If the equivalence oracle returns a counterexample, the learner adds a suffix of the counterexample to \( E \); otherwise, it returns \( M \). For the full description of the choice of suffix, see [26,28].

**Theorem 1 ([28]).** Let there exist a Mealy machine \( M \) with \( n \) states such that \( \text{Traces}(M) \) is the set of traces of \( I_\ast \). Then, given \( MOracle[I_\ast] \) and \( EOracle[I_\ast] \), Algorithm 1 returns \( M \) making at most \( |\Sigma_i|^2 n + |\Sigma_i|^n n^2 m \) membership and \( n \) equivalence queries, where \( m \) is the maximum length of counterexamples returned by \( EOracle[I_\ast] \). If \( EOracle[I_\ast] \) returns minimal counterexamples, \( m \leq O(n) \).

### 4.3 An Equivalence Oracle using Membership Queries

Given a black-box interface in practice, it is not feasible to directly implement the equivalence oracle required for the L* algorithm. Here, we demonstrate a method of implementing an equivalence oracle using the membership oracle using the boundedness assumption (Assumption 2). As before fix an asynchronous interface \( I \) and its synchronous closure \( I_\ast \). Further, fix a target Mealy machine \( M^* \) such that \( \text{Traces}(M^*) \) is the set of traces of \( I_\ast \).

**State bounds.** A state bound of \( B_{\text{State}} \) implies that the target Mealy machine \( M^* \) has at most \( B_{\text{State}} \) states. Given a state bound, we can replace an equivalence check with a number of membership queries using the following theorem.
Theorem 2. Let $M$ and $M'$ be Mealy machines having $k$ and $k'$ states, respectively, such that $\exists w_i \in \tilde{\Sigma}_i : M(w_i) \neq M'(w'_i)$. Then, there exists an input word $w_i$ of length at most $k + k' - 1$ such that $M(w_i) \neq M'(w'_i)$.

The proof is similar to the proof of the bound $k + k' - 2$ for finite automata (see [29, Theorem 3.10.5]). We can check equivalence of $M^*$ and any given $M$ by testing that they have equal outputs on all inputs of length at most $k_M + B_{\text{State}} - 1$, i.e., using $O(|\tilde{\Sigma}_1|^{B_{\text{State}} + k - 1})$ membership queries. While this simple algorithm is easy to implement, it is inefficient and the number of required membership queries make it infeasible to implement in practice. Other algorithms based on state bounds have a similar problems with efficiency (see Remark 2). Further, the algorithm does not take advantage of the structure of $M$. The following discussion and algorithm rectifies these shortcomings.

**Distinguisher bounds.** A **distinguisher bound** of $B_{\text{Dist}} \in \mathbb{N}$ implies that for each pair of states $q^*_1, q^*_2$ in the target Mealy machine $M^*$ can be distinguished by an input word $w_i$ of length at most $B_{\text{Dist}}$, i.e., $\text{Out}^*(q^*_1, w_i) \neq \text{Out}^*(q^*_2, w_i)$. Intuitively, a small distinguisher bound implies that each state is “locally” different, i.e., can be distinguished from others using small inputs. The following theorem shows that a state bound implies a comparable distinguisher bound.

**Theorem 3.** A state bound of $k$ implies a distinguisher bound of $k - 1$.

**Small distinguisher bound.** In practice, distinguishers are much smaller than the bound implied by the state bound. For the media-player, the number of
states is 10, but only distinguishers of length 1 are required. This pattern tends
to hold in general due to the following principles of good interface design:

- **Clear separation of the interface functions.** Each state in the interface has
  a specific function and a specific set of callins and callbacks. There is little
  reuse of names across state. The typestate’s alphabet is roughly the same
  size as the number of states.
- **Fail-fast.** Incorrect usage of the interface is not silently ignored but reported
  as soon as possible. This makes it easier to distinguish states as unexpected
  callins directly leads to errors.
- **No buffering.** More than just fail-fast, a good interface is interactive and
  the effect of callins must be immediately visible rather than hidden. A good
  interface is not a combination lock that requires a long sequence on input that
  get stored and only at the end of the sequence the result is communicated.

**Equivalence algorithm.** Algorithm 2 is an equivalence oracle for Mealy ma-
chines using the membership oracle, given a distinguisher bound. First, it com-
putes state representatives \( R : Q \rightarrow \tilde{\Sigma}^*_i \): for each \( q \in Q \), \( \delta(q_i, R(q)) = q \) (line 1). Then,
for each transition in \( M \), the algorithm first checks whether the output
symbol is correct (line 4). Then, the algorithm checks the “fidelity” of the trans-
ition up to the distinguisher bound, i.e., whether the representative of the pre-
vious state followed by the transition input, and the representative of the next
state can be distinguished using a suffix of length at most \( B_{\text{Dist}} \). If so, the al-
gorithm returns a counterexample. If no transition shows a different result, the
algorithm returns \text{Correct}.

Two optimizations further reduce the number of membership queries: (a) \text{Qui-
escence transitions.} Transitions with input \text{wait} and output \text{quiet} need not be
checked at line 6; it is a no-op at the interface level. (b) \text{Error transitions.} Simi-
larly, transition with the output \text{err} need not be checked as any extension of an
error trace can only have error outputs.

Remark 1. Note that if Algorithm 2 is being called from Algorithm 1, the state
representatives from \( L^* \) can be used instead of recomputing \( R \) in line 1. Similarly,
the counterexample analysis stage can be skipped in the \( L^* \) algorithm, and the
relevant suffix can be directly returned (suffix in lines 9 and 10; and \( i \) in line 4).

**Theorem 4.** Assuming the distinguisher bound of \( B_{\text{Dist}} \) for the target Mealy
machine \( M^* \), either (a) Algorithm 2 returns \text{Correct} and \( \forall w_i : M(w_i) = M^*(w_i) \), or (b) Algorithm 2 returns a counterexample \( cex \) and \( M(cex) \neq M^*(cex) \).
Further, it performs at most \( |Q| \cdot |\tilde{\Sigma}_i|^{B_{\text{Dist}} + 1} \) membership queries.

Remark 2 (Relation to conformance testing algorithms). Note that the problem
being addressed here, i.e., testing the equivalence of a given finite-state machine
and a system whose behavior can be observed, is equivalent to the conformance
testing problem from the model-based testing literature. However, several points
make the existing conformance testing algorithms unsuitable in our setting.

Popular conformance testing algorithms, like the W-method [10] and the \( W_{P^r} \-
method [14], are based on state bounds and have an unavoidable \( O(|\tilde{\Sigma}_i|^{B_{\text{Dist}}}) \).
Proof sketch. Starting with an asynchronous interface $I$ and a membership oracle $MOracle[I]$, using Assumption 1 and Assumption 3 we can construct

\begin{algorithm}
\caption{Equivalence oracle with distinguisher bound}
\textbf{Input:} Mealy machine $M = (Q, q_0, \bar{\Sigma}, \hat{\Sigma}, \delta, \text{Out})$, Distinguisher bound $B_{\text{Dist}}$, and Membership oracle $MOracle$
\textbf{Output:} Correct if $M = M^*$, and $\text{cex} \in \bar{\Sigma}_{i}^{*}$ such that $M(\text{cex}) \neq M^*(\text{cex})$ otherwise
1: \textbf{for all} $q \in Q$ \textbf{do} $R(q) \leftarrow w_i \mid \delta(q, w_i) = q$ such that length of $w_i$ is minimal 
2: \textbf{for all} $q, i \in \bar{\Sigma}_i$ \textbf{do} 
3: \textbf{if} $\text{Out}(q, i) \neq \text{last output symbol of } MOracle(w_i \cdot i)$ \textbf{then return} $R(q) \cdot i$
4: $q' \leftarrow \delta(q, i); w'_i \leftarrow R(q')$
5: \textbf{suffix} $\leftarrow$ \text{check}(w_i, w'_i)$
6: \textbf{if} suffix $\neq \text{Correct}$ \textbf{then}
7: \textbf{if} $M(R(q) \cdot i \cdot \text{suffix}) \neq \text{output symbols of } MOracle(R(q) \cdot i \cdot \text{suffix})$ \textbf{then return} 
8: $R(q) \cdot i \cdot \text{suffix}$
9: \textbf{else return} $R(q') \cdot \text{suffix}$
10: \textbf{return} $\text{Correct}$
11: \textbf{function} \text{check}(w_i, w'_i)$
12: \textbf{for all} suffix $\in \bar{\Sigma}_i^{\leq B_{\text{Dist}}}$ \textbf{do} 
13: $w_o \leftarrow \text{output symbols of } MOracle(w_i \cdot \text{suffix})$
14: $w'_o \leftarrow \text{output symbols of } MOracle(w'_i \cdot \text{suffix})$
15: \textbf{if} the last |suffix| symbols of $w_o$ and $w'_o$ differ \textbf{then return} suffix
16: \textbf{return} $\text{Correct}$
\end{algorithm}

factor in the complexity. In our experiments, the largest typestate had 10 states and 7 inputs. The $O(|\Sigma|^{B_{\text{Dist}}})$ factor leads to an infeasible (i.e., $> 10^8$) number of membership queries. However, since distinguisher bounds are often much smaller than state bounds, $O(|\Sigma|^{B_{\text{Dist}}})$ membership queries are feasible (i.e., $10^4$). The $W$- and $W_p$-methods cannot be directly adapted to use distinguisher bounds.

The other common algorithm, the D-method [19,17], does not apply in our setting either. The D-method is based on building a distinguishing sequence, i.e., an input sequence which produces a different sequence of outputs from every single state in the machine. However, for asynchronous typestates, such single distinguishing sequences do not exist in practice. For similar reasons, conformance testing algorithms such as the UIO-method [27] do not apply either.

In this light, we believe that Algorithm 2 is a novel conformance testing algorithm useful in specific settings where resets are inexpensive and implementations are designed to have small distinguisher bounds.

4.4 Putting it all together

We now present the full solution to the asynchronous typestate learning problem.

**Theorem 5.** Given a deterministic interface $I$ with observable quiescence and the membership oracle $MOracle[I]$. Assume there exists an interface automaton $A$ with $n$ states with distinguisher bound $B_{\text{Dist}}$ modeling the typestate of $I$. Interface automaton $A$ can be learned with $O(|\Sigma| \cdot n^3 + n \cdot |\Sigma|^{B_{\text{Dist}}})$ membership queries.
the membership oracle $M_{\text{Oracle}}[I_s]$ for the synchronous closure $I_s$ of $I$. Given the
distinguisher bound (or a state bound using **Assumption 2** and **Theorem 3**),
we can construct an equivalence oracle $E_{\text{Oracle}}[I_s]$ using Algorithm 2. Oracles
$M_{\text{Oracle}}[I_s]$ and $E_{\text{Oracle}}[I_s]$ can then be used to learn a Mealy machine $M$
with the same set of traces as $I_s$. This Mealy machine can be converted into the
interface automata representing the asynchronous typestate of $I$ by: (a) Deleting
all transitions with output $\text{err}$ and all self-loop transitions with output $\text{quiet}$, and
(b) Replacing all transitions with input $\text{wait}$ with the output of the transition.

5 Applying Active Learning to Android

We implemented our method in a tool called STARLING. In this section we de-
scribe how it works, the practical challenges we faced when working with An-
droid, and our solutions to overcome them. STARLING is implemented as an
Android application and learns asynchronous typestates from within Android.

5.1 Designing an Experiment

To learn a typestate, a STARLING user creates an *experiment*. An experiment is a
small code harness that covers the usual inputs of an active learning algorithm,
as well as the inputs specific to learning on Android. The main components are:

Class of Study. STARLING learns the typestate of Java classes. The user spec-
fies this *class of study* and provides a *constructor* and optionally a *destructor*
which are used to reset the environment and isolate membership queries.

Distinguisher Bound. If known, the distinguisher bound can be provided di-
rectly. Otherwise, it can be obtained from **Assumption 2** by **Theorem 3**.

Instrumented Alphabet. The instrumented alphabet specifies an abstract al-
phabet for the learning algorithm and translation between the abstract al-
phabet and concrete callins/callbacks of the *class of study*.

Query Filter. The user can restrict the sequence of symbols in the alphabet
with a filter for sequences already known to be illegal or uninteresting. The
*Query Filter* and the *Instrumented Alphabet* together comprise a *Learning
Purpose* [1], i.e., a predefined automata that constrains the behavior to learn.

Platform Specific Parameters. Several more options are available for ad-
justing the learning. The most important is the *quiescence timeout* which
specifies the duration before a state is considered as quiescent. The choice
of this timeout corresponds to **Assumption 1**.

5.2 Observing Asynchronous Callbacks

In our approach we assume *bounded asynchrony* (**Assumption 1**) and, therefore,
we can observe when the interface does not produce any new output (quiescence).
We enforce this assumption on a real system with timeouts: the membership
query algorithm waits for a new output for a fixed amount of time $t_{\text{max}}$, assuming
that quiescence is reached when this time is elapsed. However, Android does not
provide any worst case execution time for the asynchronous operations and we
rely on the user to choose a large enough $t_{\text{max}}$. The membership query also
assumes the existence of a minimum time $t_{\text{min}}$ before a callback occurs. This
ensures that we can issue a membership query with two consecutive callins (so,
without a wait input in between), i.e., we have the time to execute the second callin before the output of the first callin.

Consider the MediaPlayer example from Section 2. The membership query `setDataSource(URL) · wait · prepareAsync() · wait` may not return the `onPrepared()` if `t_{max}` is violated, i.e., if the callback does not arrive before the timeout. On the other hand, while testing, it is possible that the `prepareAsync()` · `start()` might not return an error as expected if the lower bound `t_{min}` is violated. To avoid such issues we try to reliably control the execution environment and parameters to ensure that callbacks occurred between `t_{min}` and `t_{max}`. For the MediaPlayer case, we need to pick the right media source file.

### 5.3 Checking and Enforcing our Assumptions

The simplest experiment to learn a class’s asynchronous typestate ties a single input symbol to each of its callins and a single output symbol to each of its callbacks. However, many Android classes have behaviors which cause this simple experiment to fail and require more detailed experiments to succeed.

The main challenges when designing an experiment are (a) **Non-deterministic behaviors**, i.e., the state of the device and external events may influence an application. These elements are inherently non-deterministic; however, non-determinism violates **Assumption 3**. (b) The **parameter space** required to drive concrete test cases to witness a membership query is potentially infinite. Though we have ignored callin parameters till now, they are a crucial issue for testing. (c) The implementation of the protocol we are learning may not be a regular language. Note that this is a violation of **Assumption 2**.

**Non-Deterministic Behavior.** Non-deterministic behavior is disallowed by our **Assumption 3**. However, to make this assumption reasonable we must make non-determinism straightforward to eliminate when it arises. We explain two primary classes of non-deterministic behaviors and strategies to eliminate these behaviors. The first class is related to the state of the environment before a callin and the second is environment changes during an asynchronous computation.

Because the learning algorithm cannot learn from non-deterministic systems, **STARLING** will terminate if a non-deterministic behavior is detected. In such case, **STARLING** reports the causing input sequence and disagreeing output sequences. It detects this behavior by caching all membership queries as input/output sequence pairs. When a new trace is explored, **STARLING** checks that the trace prefixes are compatible with the previously seen traces.

In the first case, the state of the environment prior to a callin influences the output. We resolve this non-determinism by manually modeling how the environment may affect the callbacks and create a finer input alphabet that explicates the previously hidden state of the environment. For example, in the class **SQLiteOpenHelper**, the `getReadableDatabase()` may either trigger a `onCreate()` callback or not, depending on the parameter value to a previous callin (constructor) was the name of an existing database file. Hence, the behavior of the callin is non-deterministic, depending on the status of the database on disk. In the **SQLiteOpenHelper** example, we split the constructor callin into `constructor/fileExists` and `constructor/noFileExists` and pass the right
parameter values in each case. With this extra modeling we can learn the interface automaton, since the execution `getReadableDatabase()` ends in two different states of the automaton (see Figure 2).

Fig. 2: Eliminating non-determinism in SQLiteOpenHelper

The second class is the effect of the environment on asynchronous computations. Such effects, by definition, cannot be controlled or made explicit prior to the call. We choose to ignore this non-determinism by merging different outputs, considering them to be the same. This is the dual of the previous solution.

An example is the `SpeechRecognizer`, for which calling `startListening()` produces different callbacks depending on the environment. As the environment cannot be reasonably controlled, we merge outputs to go to the same state. If outputs are erroneously merged, the non-determinism will propagate and continue to manifest. Therefore, there is no risk when merging outputs.

Handling Callin Parameters. While parameter-less callins such as `start()` and `stop()` are common in Android classes, many parameterized callins exist. Because input symbols need to be listed in the experiment definition, the full range of parameter values cannot be explored. In practice, we found that parameters often have little effect on the typestate automaton. In cases where they do affect the automaton, multiple input symbols can be defined to represent the same method called with several different parameters. This solution is similar to splitting on environmental effects when dealing with non-determinism.

Learning from Non-Regular Languages. An intrinsic limitation of `L^*` is that it learns only regular languages. However, some classes expose non-regular protocols. Common cases include situations where a `request` callin may be called an unbounded number of times, and a `response` callback is called exactly the same number of times. For example, in the SpellCheckerSession class, callin `getSuggestion()` and callback `onGetSuggestions()` follow this pattern.

However, even in such cases, it can be useful to build a regular approximation of the typestate. For example, restricting the typestate to behaviors where there is at most one pending request (a regular subset) provides all the information a programmer would need. Hence, in such cases, we use the technique of learning purposes [1] to learn a regular approximations of the infinite typestate.

6 Empirical Evaluation

Implementation. We implemented the typestate learning algorithm, along with the membership oracle for the Android framework, in a tool called STARLING. STARLING is implemented in Java and can be run on both emulators and physical devices. We run the experiments on a LG Nexus 5 running the Android framework version 23. The major challenge during the development of STAR-
LING was not in the implementation of the learning algorithm, but instead in interfacing the algorithm, specifically the membership oracle, with Android.

**Goals.** Our experiments were designed to empirically evaluate the following:

Question 1. Does our technique learn typestates efficiently?

Does they support the small distinguisher bound hypothesis?

Question 2. What is the size of distinguisher bounds that occur in practice?

Question 3. Do the asynchronous typestates learned reveal interesting or unintended behavior in the interfaces?

**Methodology.** We sampled 10 classes from the Android framework and ran STARLING on it. For each class, the relevant callins and callbacks were identified manually, and a test harness was written to connect inputs and outputs symbols to the corresponding callins and callbacks of the class. Each test harness consisted of 100 – 200 lines of, mostly boiler-plate, Java code. In addition, for some classes, we provided a query filter to restrict the learning purpose (see Section 5).

To evaluate efficiency, we measure the overall time taken for learning, as well as the number of membership (MQ) and equivalence queries (EQ). The number of queries is likely a better measure of performance than running time: the running time depends on external factors. For example, in the media player the running time depends on play-length of the media file chosen during testing.

We validate the accuracy of learned asynchronous typestates using two approaches. First, for classes whose documentation contains a picture or a description of what effectively is an asynchronous typestate, we compare our result to the documentation. Second, for all the other classes we perform manual code inspection and run test apps to evaluate correctness of the produced typestates.

We used a distinguisher bound of 2 for our experiments; further, we manually examined the learned typestate and recorded the actual distinguisher bound. For our third question, i.e., does the learned asynchronous typestate reveal interesting behaviors, we manually examined the learned typestate, compared it against the official Android documentation, and recorded discrepancies.

**Results.** We discuss the results (in Table 1) with respect to our three questions.

**Question 1: Efficiency.** The table shows that the learning algorithm runs reasonably fast: most typestates learned within a few minutes. The longest one takes 71 minutes, still applicable to nightly testing. The numbers for membership queries

| Class name          | states | Time (s) | MQ | EQ | MQ per EQ | $B_{dist}$ (needed) |
|---------------------|--------|----------|----|----|-----------|---------------------|
| AsyncTask           | 5      | 49       | 372 (94) | 1  | 356 (0)   | 2 (1)               |
| CountDownTimer      | 3      | 134      | 232 (61) | 1  | 224 (0)   | 2 (1)               |
| FileObserver        | 6      | 104      | 743 (189) | 2  | 351 (8)   | 2 (1)               |
| MediaCodec          | 8      | 371      | 1354 (871) | 1  | 973 (482) | 2 (1)               |
| MediaPlayer         | 10     | 4262     | 13553 (2372) | 5 | 2545 (384) | 2 (1)               |
| MediaRecorder       | 8      | 248      | 1512 (721) | 1  | 1280 (545) | 2 (1)               |
| MediaScannerConnection | 4   | 200      | 403 (161) | 2  | 163 (57)  | 2 (1)               |
| SpeechRecognizer    | 7      | 3460     | 1968 (293) | 3  | 646 (35)  | 2 (1)               |
| SpellCheckerSession | 6      | 133      | 798 (213) | 4  | 374 (8)   | 2 (1)               |
| SQLiteOpenHelper     | 8      | 43       | 1364 (228) | 2  | 665 (6)   | 2 (2)               |

Table 1: STARLING experimental results.
are reported as \( X(Y) \)—\( X \) is the number of membership queries asked by the algorithm, while \( Y \) is the number actually executed by the membership oracle. This number is lower as the same query may be asked multiple times, but is executed only once and the result is cached. For each benchmark, the accuracy validation showed that the produced typestate matched the actual behavior.

**Question 2: Distinguisher Bounds.** As mentioned before, we used a distinguisher bound of 2 for all experiments. However, a manual examination of the learned asynchronous typestates showed that a distinguisher bound of 1 would be sufficient in all cases except the `SQLiteOpenHelper` where a bound of 2 is necessary. This supports our conjecture that, in practice, interfaces are designed with each state having a unique functionality (see Section 4.3).

**Question 3: Interesting Learned Behavior.** Of the three questions, our experiments to examine the learned asynchronous typestate for interesting behavior turned out to be the most fruitful, uncovering several discrepancies, including corner cases, unintended behavior and likely bugs, in the Android framework. These results reaffirm the utility of our main goal of automatically learning asynchronous typestate, and suggest that learning typestate can serve valuable roles in documentation and validation of asynchronous interfaces.

In 2 cases, the learned typestate and documented behavior differed in certain corner cases. We carefully examined the differences, by framework source examination and manually writing test applications, and found that the learned typestate was correct and the documentation was faulty. In 3 other cases, we believe the implemented behavior is not the intended behavior, i.e., these are likely bugs in the Android implementation. Further, in 1 additional case, we found that the typestate learned on different versions of the Android framework were different. These discrepancies mostly fall into two separate categories:

- **Incorrect documentation.** In such cases, it turned out that the discrepancy is minor and unlikely to cause erroneous behavior in client programs.

- **Race conditions.** Several likely bugs were due to a specific category of race conditions. These interfaces have (a) a callin to start an action and a corresponding callback which is invoked when the action is successfully completed; (b) a callin to cancel an already started action and a corresponding callback which is invoked if the action is successfully cancelled. When the start action and cancel action callins are called in sequence, the expectation is that exactly one of the two callbacks are called. However, when the time between the two callins is small, we were able to observe unexpected behaviors, including neither or both callbacks being invoked, and even the interface showing arbitrary further behavior.

The second category indicates a common implementation issue, and suggests potential avenues for introducing system or language features to avoid this issue.

**Case studies.** Of 10 benchmarks, we pick 3 and briefly explain them here. Full details of all benchmarks are in the appendix.

- **MediaPlayer.** This is the class from the example in Section 2. The learned typestate differs from the existing documentation. The learned typestate: (a) has the `pause` callin enabled in the “playback completed” state, and (b) shows that
onPrepared() is invoked even after the synchronous call in prepare(). Though undocumented, these behaviors are unlikely to cause any issues.

SpellCheckerSession. This class provides an interface to request spelling suggestions on text fragments. A client requests suggestions via getSentenceSuggestions() and the suggestions are delivered via onGetSentenceSuggestions() unless cancel() or close() is called. The full interface is non-regular; the number of callbacks is equal to the number of calls. We used a query filter to restrict learning to the fragment with at most one call to getSentenceSuggestions(). For this fragment, the resulting typestate shows that calling cancel() does not prevent receiving callbacks with results, potentially leading to errors in applications that rely on this guarantee.

MediaRecorder. The MediaRecorder class provides a single interface to recording audio and video various sources such as the microphone, camera, and voice calls. The learned typestate differs from the documentation in one aspect and reveals a problematic behavior: calling start() followed immediately by stop() in the “prepared” state throws an exception. However, calling start(), waiting for a short time (wait), followed by stop() is not an error. Note that the interface does not perform any callback after start() (i.e., we get quiet on wait). This behavior is not documented, and also, is completely unexpected, as the client program has no indication of whether it is safe to call stop(). Apart from this behavior, the typestate is equivalent to the one shown in the documentation. The unexpected behavior could be fixed either by: (a) adding a callback onStart() to inform the client that it is safe to call stop(), or (b) modifying the implementation of start() to only return after the task is truly completed.

7 Related Work

Works which automatically synthesize specifications of the valid sequences of method calls (e.g. [3,30,4,16]) typically ignore the asynchronous callbacks.

Static analysis has been successfully used to infer typestates specifications (importantly, without callbacks) [3,20,30]. The work in [3] infers interfaces for Java classes using L*. In contrast, our approach is based on testing. Therefore, we avoid the practical problem of abstracting the framework code. On the other hand, the use of testing makes our L* oracles sound only under assumptions.

Inferring the interface using execution traces of client programs using framework is another common approach [4,36,2,11,15,34,37,25]. In contrast to dynamic mining, we do not rely on the availability of client applications or a set of execution traces. The L* algorithm drives the testing.

The analysis of event-driven programming framework has recently gained a lot of attention (e.g. [6,8,9,23]). However, none of the existing works provide an automatic approach to synthesize interface specifications. Analyses of Android applications mostly focus on either statically proving program correctness or security properties [6,8,18,35,13] or dynamically detecting race conditions [24,21,7]. These approaches manually hard-code the behavior of the framework to increase the precision of the analysis. The asynchronous typestate specifications that we synthesize can be used here, avoiding the manual specification process.
Our work builds on the seminal paper of Angluin [5] and the subsequent extensions and optimizations. In particular, we build on $L^*$ for I/O automata [1,28]. The optimizations we use include the counterexample suffix analysis from [26] and the optimizations for prefix-closed languages from [22]. The relation to conformance testing methods [10,14,19,17,27] has been discussed in Remark 2.

References

1. F. Aarts and F. Vaandrager. Learning I/O automata. In CONCUR 2010, pages 71–85, 2010.
2. M. Acharya, T. Xie, and J. Xu. Mining interface specifications for generating checkable robustness properties. In Software Reliability Engineering, 2006. ISSRE '06. 17th International Symposium on, pages 311–320, Nov 2006.
3. R. Alur, P. Černý, P. Madhusudan, and W. Nam. Synthesis of interface specifications for Java classes. In POPL, pages 98–109, 2005.
4. Glenn Ammons, Rastislav Bodík, and James R. Larus. Mining specifications. In POPL '02, pages 4–16, New York, NY, USA, 2002. ACM.
5. Dana Angluin. Learning regular sets from queries and counterexamples. Inf. Comput., 75(2):87–106, 1987.
6. Steven Arzt, Siegfried Rasthofer, Christian Fritz, Eric Bodden, Alexandre Bartel, Jacques Klein, Yves Le Traon, Damien Octeau, and Patrick McDaniel. FlowDroid: Precise context, flow, field, object-sensitive and lifecycle-aware taint analysis for Android apps. page 29, 2014.
7. Pavol Bielik, Veselin Raychev, and Martin T. Vechev. Scalable race detection for android applications. In OOPSLA, pages 332–348, 2015.
8. Sam Blackshear, Bor-Yuh Evan Chang, and Manu Sridharan. Selective control-flow abstraction via jumping. pages 163–182, 2015.
9. Yinzhi Cao, Yanick Fratantonio, Antonio Bianchi, Manuel Egele, Christopher Kruegel, Giovanni Vigna, and Yan Chen. Edgeminer: Automatically detecting implicit control flow transitions through the android framework. In NDSS, 2015.
10. T. S. Chow. Testing software design modeled by finite-state machines. IEEE Transactions on Software Engineering, SE-4(3):178–187, May 1978.
11. Valentin Dallmeier, Christian Lindig, Andrzej Wasylkowski, and Andreas Zeller. Mining object behavior with adabu. In Proceedings of the 2006 International Workshop on Dynamic Systems Analysis, WODA '06, pages 17–24, New York, NY, USA, 2006. ACM.
12. L. de Alfaro and T. Henzinger. Interface automata. In FSE, pages 109–120, 2001.
13. Yu Feng, Saswat Anand, Isil Dillig, and Alex Aiken. Apposcopy: Semantics-based detection of Android malware through static analysis. pages 576–587, 2014.
14. S. Fujiwara, G. v. Bochmann, F. Khendek, M. Amalou, and A. Ghedamsi. Test selection based on finite state models. IEEE Transactions on Software Engineering, 17(6):591–603, Jun 1991.
15. Mark Gabel and Zhendong Su. Javert: Fully automatic mining of general temporal properties from dynamic traces. In Proceedings of the 16th ACM SIGSOFT International Symposium on Foundations of Software Engineering, SIGSOFT '08/FSE-16, pages 339–349, New York, NY, USA, 2008. ACM.
16. Mark Gabel and Zhendong Su. Online inference and enforcement of temporal properties. In ICSE, ICSE ’10, pages 15–24, New York, NY, USA, 2010. ACM.
17. Guney Gonenc. A method for the design of fault detection experiments. IEEE Trans. Computers, 19(6):551–558, 1970.
18. Michael I. Gordon, Deokhwan Kim, Jeff Perkins, Limei Gilham, Nguyen Nguyen, and Martin Rinard. Information-flow analysis of Android applications in DroidSafe. 2015.

19. F. C. Hennie. Fault detecting experiments for sequential circuits. In 5th Annual Symposium on Switching Circuit Theory and Logical Design, Princeton, New Jersey, USA, November 11-13, 1964, pages 95–110, 1964.

20. Thomas A. Henzinger, Ranjit Jhala, and Rupak Majumdar. Permissive interfaces. In Proceedings of the 10th European Software Engineering Conference Held Jointly with 13th ACM SIGSOFT International Symposium on Foundations of Software Engineering, ESEC/FSE-13, pages 31–40, New York, NY, USA, 2005. ACM.

21. Chun-Hung Hsiao, Jie Yu, Satish Narayanasamy, Ziyun Kong, Cristiano L. Pereira, Gilles A. Pokam, Peter M. Chen, and Jason Flinn. Race detection for event-driven mobile applications. In PLDI, PLDI ’14, pages 326–336, New York, NY, USA, 2014. ACM.

22. H. Hungar, O. Niese, and B. Steffen. Domain-specific optimization in automata learning. In CAV, pages 315–327, 2003.

23. Magnus Madsen, Frank Tip, and Ondřej Lhoták. Static analysis of event-driven node.js javascript applications. In OOPSLA, OOPSLA 2015, pages 505–519, New York, NY, USA, 2015. ACM.

24. Pallavi Maiya, Aditya Kanade, and Rupak Majumdar. Race detection for android applications. In PLDI 2014, page 34, 2014.

25. Michael Pradel and Thomas R. Gross. Automatic generation of object usage specifications from large method traces. In ASE, pages 371–382, 2009.

26. Ronald L. Rivest and Robert E. Schapire. Inference of finite automata using homing sequences. Inf. Comput., 103(2):299–347, 1993.

27. Krishan K. Sabnani and Anton T. Dahbura. A new technique for generating protocol test. In SIGCOMM ’85, Proceedings of the Ninth Symposium on Data Communications, British Columbia, Canada, September 10-12, 1985, pages 36–43, 1985.

28. Muzammil Shahbaz and Roland Groz. Inferring mealy machines. In FM 2009: Formal Methods, Second World Congress, Eindhoven, The Netherlands, November 2-6, 2009. Proceedings, pages 207–222, 2009.

29. J. Shallit. A Second Course in Formal Languages and Automata Theory. Cambridge University Press, 2008.

30. Sharon Shoham, Eran Yahav, Stephen Fink, and Marco Pistoia. Static specification mining using automata-based abstractions. In ISSTA, ISSTA ’07, pages 174–184, New York, NY, USA, 2007. ACM.

31. J. Shore. Fail fast [software debugging]. IEEE Software, 21(5):21–25, Sept 2004.

32. R. Strom and S. Yemini. Typestate: A programming language concept for enhancing software reliability. IEEE Trans. Software Eng., 12(1):157–171, 1986.

33. Frits W. Vaandrager. On the relationship between process algebra and input/output automata. In Proceedings of the Sixth Annual Symposium on Logic in Computer Science (LICS ’91), Amsterdam, The Netherlands, July 15-18, 1991, pages 387–398, 1991.

34. N. Walkinshaw and K. Bogdanov. Inferring finite-state models with temporal constraints. In Proceedings of the 2008 23rd IEEE/ACM International Conference on Automated Software Engineering, ASE ’08, pages 248–257, Washington, DC, USA, 2008. IEEE Computer Society.

35. Fengguo Wei, Sankardas Roy, Xinning Ou, and Robby. Amandroid: A precise and general inter-component data flow analysis framework for security vetting of android apps. In SIGSAC, pages 1329–1341, 2014.
36. John Whaley, Michael C. Martin, and Monica S. Lam. Automatic extraction of object-oriented component interfaces. In *Proceedings of the 2002 ACM SIGSOFT International Symposium on Software Testing and Analysis*, ISSTA ’02, pages 218–228, New York, NY, USA, 2002. ACM.

37. Jinlin Yang, David Evans, Deepali Bhardwaj, Thirumalesh Bhat, and Manuvir Das. Perracotta: Mining temporal api rules from imperfect traces. In *Proceedings of the 28th International Conference on Software Engineering*, ICSE ’06, pages 282–291, New York, NY, USA, 2006. ACM.
A Detailed Descriptions of the Results

AsyncTask. The AsyncTask class turns arbitrary computations into asynchronous operations with progress tracking and results are delivered via callbacks. For our experiment, the computation is a simple timer. A constructed AsyncTask object performs its task when it receives the execute() call, and then either returns the results when they are available with the onPostExecute() callback, or returns an onCancelled() if cancel() is called first. The object is single-use; after it has returned a callback it will accept no further execute() commands.

In order to test this class, the get() input had to be dismissed (i.e., we did not include get() in our learning purpose, see Section 5) because its results were non-deterministic when called directly after the onPostExecute() callback. Our experiment revealed an unexpected edge-case: if execute() is after cancel() but before the onCancelled() callback is received, it will not throw an exception but will never cause the asynchronous task to be run.

Fig. 3: Learned typestate of the AsyncTask class

SpeechRecognizer. The SpeechRecognizer is a simple interface to the speech-to-text services provided in the Android framework, and is necessarily asynchronous due to the time spent waiting for speech and communicating with remote speech-to-text services over the network. An application constructs a SpeechRecognizer with a listener for various errors and result callbacks. The process is set off with a call to startListening(). The SpeechRecognizer calls onReadyForSpeech() and then either returns the recognized speech results with onResults() or one of several error cases with onError().

Like the SQLiteOpenHelper, this class provides another case of environmental non-determinism. The particular callback that signals the end of the speech session—either an onResults() or an onError()—is determined by the environment (in particular, the sound around the phone during the test). In this case, to reduce the system to a deterministic one we can learn, we supposed that the state after an onResults() or onError() is the same and merged the two
callbacks into a single `onFinished()` symbol. The determinism observed in the resulting typestate confirmed this assumption.

Our results revealed two interesting corner cases for the ordering of inputs. First, if an app calls `cancel()` between calling `startListening()` and receiving the `onReadyForSpeech()` callback (represented by our “starting” output symbol), calling `startListening()` again will have no effect until after a certain amount of time, as shown by the `wait` transition from state “Cancelling” to “Finished”. Delays in readiness like this can be generally considered bugs; if a system will not be ready immediately for inputs it should provide a callback to announce when the preparations are complete, so as not to invite race conditions.

Our second corner case is where the app calls `stopListening()` as the very first input on a fresh SpeechRecognizer. This will not throw an exception, but calling `startListening()` at any point after will fail, making the object effectively dead.

---

**Fig. 4: Learned typestate of the SpeechRecognizer class. The behavior inside the dotted line is “normal” behavior, while everything outside is unusual or “exceptional” behavior.**

While we performed all other tests on an Android 5.1.1 system, the SpeechRecognizer’s callback behavior was so buggy—callbacks would repeat themselves several times, sometimes interleaving with later callbacks—that we could not learn a consistent automaton. We therefore performed this experiment on an Android 6.0.1 system, where this behavior is fixed.

**CountDownTimer.** The CountDownTimer is an asynchronous timer that is initialized with a period of time and then invokes the `onFinish()` callback when the time is up, unless a `cancel()` method is called in the meantime.

This class is not a regular language; calling `start()` multiple times will result in that same number of `onFinish()` callbacks. In order to learn a regular language subset, we used the learning purpose approach to limit the number of `start()` inputs in a valid query to one.

**FileObserver.** The FileObserver is a listener class that tracks changes to a file or directory, making callbacks as they occur. The class itself has only two input
methods—startWatching() and stopWatching()—so for our experiment we considered the environmental actions of modifying (and possibly creating) and deleting the watched file as additional inputs. An onEvent() callback returns with various event types; the ones we track are MODIFY and DELETE_SELF. One interesting bit of behavior we correctly observe (which is in the documentation for the class) is that if the file is deleted while being watched, no further callbacks will be made even if it is recreated.

MediaPlayer. This is the class from the introductory example in Section 2. There are two interesting aspects about the run of STARLING on MediaPlayer and the learned typestate:

- The learned typestate has the pause() call in is enabled in the “paused” state. Though undocumented, we do not believe this behavior is a bug.
- The class returns the onPrepared() callback even after the synchronous prepare() call—in this callback is unnecessary as it is not necessary to wait for it after calling prepare. However, this unnecessary callback leads to STARLING generating many more states than necessary; every state after prepare() is called has an “equivalent” duplicate there: one where the unnecessary onPrepared() is pending, and one where it is not. In the table, the number of states reported in brackets is the number including the duplicate states. We believe that these states can be eliminated automatically; however, this is not implemented currently.

MediaCodec. The MediaCodec class provides an interface for decoding encoded media files (audio and video) in a continuous manner, i.e., audio and video data is continuously passed into the interface, and the interface passes the results back as soon as they are ready. The interaction with this interface is done fully asynchronously: the interface calls the onInputBufferAvailable() callback whenever it is ready to accept input, and onOutputBufferAvailable() callback when results are ready. The interaction is started and stopped using the start() and stop() calls; and further, the flush() call invalidates all available buffers. The typestate of MediaCodec is described with a high-level diagram in the documentation: https://developer.android.com/reference/android/media/MediaCodec.html. STARLING is able to learn the typestate of the interface exactly in this case, and the learned typestate matches the description in the documentation.

MediaRecorder. The MediaRecorder class provides a single interface to recording audio and video various sources such as the microphone, camera, and voice calls. The typestate for this class is present in the documentation at https://developer.android.com/reference/android/media/MediaRecorder.html. Of our benchmarks, the MediaRecorder is particularly unique, as the interface has no callbacks related to starting or stopping, i.e., at looks like a standard (not event-driven asynchronous) interface. The callbacks which do exist are for receiving updates or exceptions during recording. However, internally, the implementation of the class is asynchronous. This can be seen as follows: calling start() followed immediately by stop() in the “prepared” state throws an exception. However, calling start(), waiting for a short time (wait),
followed by \texttt{stop()} is not an error. Note that the interface does not perform any callback on \texttt{wait} (i.e., we get \texttt{quiet}). This behavior is not documented, and also, completely unexpected from the client programmer point of view. Other than this behavior, the typestate is equivalent to the one shown in the documentation.

The unexpected behavior can be fixed in one of two ways:

(a) Expose the asynchronous nature of the class, i.e., add a callback \texttt{onStart()}, and make calling \texttt{stop()} legal only after \texttt{onStart()} is called back.

(b) Modify the implementation of the \texttt{start()} call in to wait and only return after the task is truly completed, i.e., do not let the asynchronous nature of the implementation leak to the client.

\begin{center}
\begin{tikzpicture}
\node (idle) {Idle};
\node (prepared) [below right of=idle] {Prepared};
\node (starting) [below right of=prepared] {Starting};
\node (started) [above right of=starting] {Started};
\draw [->] (idle) -- node {\texttt{stop()}} (prepared);
\draw [->] (prepared) -- node {\texttt{start()}} (starting);
\draw [->] (starting) -- node {\texttt{wait()}} (started);
\draw [->] (started) -- node {\texttt{stop()}} (idle);
\end{tikzpicture}
\end{center}

Part of the typestate for the MediaRecorder. If the class was truly synchronous, the states “Starting” and “Started” would be the same, i.e., \texttt{stop()} would be enabled immediately after \texttt{start()}. Starling was able to discover this inconsistency automatically.

\textbf{MediaScannerConnection.} The MediaScannerConnection class implements an interface that applications may use to inform the standard android media services about new media files that the application has created. For example, an application may download an image, and then scan it using MediaScannerConnection: after the scan, the new image will be available through the standard image handling services (for example, the media gallery).

The MediaScannerConnection interface itself is simple with 3 relevant callins: \texttt{connect()}, \texttt{disconnect()}, and \texttt{scanFile()}. Further, it has 1 callback important to the typestate: \texttt{onMediaScannerConnected()}. The protocol for using the interface is as follows: (a) \texttt{connect()} is called to establish connection with the media scanner service; (b) the \texttt{onMediaScannerConnected()} callback is called by the interface to inform the client that the connection has been established; (c) the client may scan any number of files through the \texttt{scanFile()} call in; and (d) the client finally calls \texttt{disconnect()} to disconnect from the media scanner service. Starling was able to learn this typestate exactly. The only point of note is that the \texttt{onMediaScannerConnected()} callback will be called even if \texttt{disconnect()} is called immediately after \texttt{connect()} before the callback; however, the interface is in the disconnected state.

\textbf{SpellCheckerSession.} This class provides a high-level interface for apps to request spelling suggestions on text fragments. An app can request suggestions for
a particular sentence (via `getSentenceSuggestions()` ) which will be delivered via callback (`onGetSentenceSuggestions()` ) unless a `cancel()` or `close()` is called. The interface is asynchronous due to the computational intensity of the text-processing involved.

The full interface is non-regular; the number of callbacks with results is equal to the number of request calls. We therefore used the learning purpose approach to restrict learning to the fragment with at most one call to `getSentenceSuggestions()`. For this fragment, the resulting asynchronous typestate showed that calling `cancel()` will not prevent receiving callback with results. This might hurt applications that rely on a guarantee that the callback does not arrive after `cancel()`.

SQLiteOpenHelper. This class provides a more structured interface for apps to open and set up SQLite databases. It has callbacks for different stages of database initialization, allowing apps to perform setup operations only as they are needed. When a database is opened with `getWritableDatabase()` , a `configure()` is called, followed by an `onCreate()` if the database didn’t exist yet or an `onUpgrade()` if the database had a lower version number than was passed to the SQLiteOpenHelper constructor, all followed finally by an `open()` when the database is ready for reading. The database can then be closed with a `close()`.

Our experiment observed the callbacks received when opening databases in different states (normal, non-existent, and out of date) and performing the `close()` operation at different points in the sequence. We found that once the `getWritableDatabase()` method is called, calling `close()` will not prevent the callbacks from being run.

B Impossibility result for the asynchronous typestate learning problem from Section 3.2

We say that an interface automaton A is compatible with a membership query mQuery and its result MOracle[[mQuery]] if: (a) MOracle[[mQuery]] is a trace of A, or (b) MOracle[[mQuery]] = ⊥ and there is no trace of A whose sequence of inputs is to mQuery. The following impossibility theorem shows that membership queries are not sufficient to effectively learn typestates.

**Theorem 6.** There exists an interface I and an MOracle[[I]] such that:
- There exists an interface automaton A that models the typestate of I, and
- For every finite set of pairs (mQuery,MOracle[[mQuery]]) of membership queries and corresponding results, there exist interface automata A’ and A”, with different sets of traces, compatible with each pair.

C Proofs for theorems in Section 4

A run segment π of M is given by \( q_0 \rightarrow^{i_0}_{o_0} \ldots \rightarrow^{i_n}_{o_n} q_{n+1} \) where \( \forall 0 \leq i \leq n : \delta_M(q_i, i_i) = q_{i+1} \land \text{Out}(q_i, i_i) = o_i \). We use the following shorthands:
(a) \( \delta(q_0, i_0 \ldots i_n) \) for \( q_{n+1} \), and (b) \( \text{Out}(q_0, i_0 \ldots i_n) \) for \( o_0 \ldots o_n \). If \( q_0 = q_s \), then we say that \( i_0o_0 \ldots i_no_n \) is a trace of M. Further, if \( q_0 = q_s \), we write
\[ M(i_0 \ldots i_n) = o_0 \ldots o_n. \] A Mealy machine \( M \) is the \textit{asynchronous typestate} of \( I \), if every trace of \( M \) is a trace of \( I \), and vice versa.

\textbf{Proof of Theorem 2.} Let \( M = \langle Q, q_0, \Sigma_i, \Sigma_o, \delta, \text{Out} \rangle \) and \( M' = \langle Q', q_0', \Sigma_i, \Sigma_o, \delta', \text{Out}' \rangle \). Let \( \text{Out} : Q \cup Q' \times \Sigma_i \rightarrow \Sigma_o \) (resp. \( \delta : Q \cup Q' \times \Sigma_i \rightarrow Q \cup Q' \)) be a unified output (resp. transition) function that applies either \( \text{Out} \) or \( \text{Out}' \) (resp. \( \delta \) or \( \delta' \)) depending on if the first input is in \( Q \) or \( Q' \).

We first define a sequence of equivalence relations \( \equiv_m \) on \( Q \cup Q' \) for each \( m > 0 \). For each \( m \), we say \( q_1 \equiv_m q_2 \) if for all input words \( w_i \) of length at most \( m \), we have that \( \text{Out}(q_1, w_i) = \text{Out}(q_2, w_i) \). Note that each \( \equiv_{m+1} \) is a refinement of \( \equiv_m \). As we have that \( M(w_i) \neq M'(w_i) \), we get \( q_i \neq m q_i' \) for some \( m \). Further, we have that \( \equiv_1 \) is not universal, i.e., \( \exists q_1, q_2 : q_1 \neq q_2 \); otherwise, we will have \( \text{Out}(q_1, w_i) = \text{Out}(q_2, w_i) \) for every \( w_i \), \( q_1 \), and \( q_2 \), contradicting the premise of the theorem statement.

Below, we show that \( q_1 \neq m+1 q_2 \) if and only if \( q_1 \neq m q_2 \) or \( \exists i \in \Sigma_i : \overline{\delta}(q_1, i) \neq m \overline{\delta}(q_2, i) \). Hence, each \( \equiv_{m+1} \) is uniquely determined by \( \equiv_m \) and \( \overline{\delta} \) giving us that \( \equiv_m = \equiv_{m+1} \implies \equiv_{m+1} = \equiv_{m+2} \). Further, since all \( \equiv_m \) are successive refinements defined on a finite set, we can only have \( \equiv_{m+1} \neq \equiv_m \) for a finite number of \( m \). Let \( m^* \) be the least such that \( \equiv_{m^*+1} \neq \equiv_{m^*} \). By the two statements above, we get that

\[ \equiv_1 \neq \equiv_2 \neq \ldots \neq \equiv_{m^*} = \equiv_{m^*+1} = \equiv_{m^*+2} = \ldots \]

Hence, for every pair of states \( q_1 \) and \( q_2 \), if \( \exists w_i : \overline{\text{Out}}(q_1, w_i) \neq \overline{\text{Out}}(q_2, w_i) \), then there exists a word \( w_i' \) of length at most \( m^* \) such that \( \overline{\text{Out}}(q_1, w_i') \neq \overline{\text{Out}}(q_2, w_i') \).

Now, by the non-universality of \( \equiv_1 \) and the fact that each \( \equiv_m \) is a strict refinement of the previous for \( m \leq m^* \), we have that \( m^* \) can at most be \( |Q| + |Q'| - 1 \). This gives us the required result.

Now, to show that \( q_1 \neq m+1 q_2 \) if and only if \( q_1 \neq m q_2 \) or \( \exists i \in \Sigma_i : \overline{\delta}(q_1, i) \neq m \overline{\delta}(q_2, i) \).

Assume \( q_1 \neq m q_2 \) or \( \exists i \in \Sigma_i : \overline{\delta}(q_1, i) \neq m \overline{\delta}(q_2, i) \). If \( q_1 \neq m q_2 \), we have that \( q_1 \neq m+1 q_2 \) as each \( \equiv_{m+1} \) is a refinement of \( \equiv_m \). Otherwise, assume \( \exists i \in \Sigma_i : \overline{\delta}(q_1, i) \neq m \overline{\delta}(q_2, i) \). Now, there exists a \( w_i \) such that \( \overline{\text{Out}}(q_1, i, w_i) \neq \overline{\text{Out}}(q_2, i, w_i) \). It is easy to show that \( \overline{\text{Out}}(q_1, i, w_i) \) and \( \overline{\text{Out}}(q_2, i, w_i) \). Further, \( |i \cdot w_i| \) is at most \( m + 1 \) giving us \( q_1 \neq m+1 q_2 \).

Assume \( q_1 \neq m+1 q_2 \). There exists a word \( w_i \) of length at most \( m+1 \) such that \( \overline{\text{Out}}(q_1, w_i) \neq \overline{\text{Out}}(q_2, w_i) \). If \( |w_i| \leq m \), we get that \( q_1 \neq m q_2 \). Otherwise, let \( w_i = i \cdot w_i' \). If \( \overline{\text{Out}}(q_1, i, w_i') \neq \overline{\text{Out}}(q_2, i, w_i') \), we have that \( q_1 \neq q_2 \), and hence, \( q_1 \neq m q_2 \).

In the remaining case, we have that \( \overline{\text{Out}}(q_1, i) = \overline{\text{Out}}(q_2, i) \) and \( \overline{\text{Out}}(q_1, i, w_i') \neq \overline{\text{Out}}(q_2, i, w_i') \). From these, it is easy to show that \( \overline{\delta}(q_1, i, w_i') \neq \overline{\delta}(q_2, i, w_i') \). This gives us that \( \overline{\delta}(q_1, i) \neq m \overline{\delta}(q_2, i) \).

This completes the proof.

\textbf{Proof of Theorem 3.} Let \( M^* \) have \( |Q^*| \leq B \) states. Define a series of equivalence functions \( \equiv_m \) on \( Q \) such that \( q_1 \equiv_m q_2 \) if and only if \( q_1 \) can be distinguished from \( q_2 \) by words of length \( m \). The remainder of the proof is exactly similar
to the proof of Theorem 2. Again, the final bound obtained on the length of distinguishers is one less than the size of the domain of the equivalence relations. Here, the bound is $|Q^*| - 1 \leq k - 1$, giving us the theorem.

**Proof of Theorem 4.** The complexity bound is easy to show.

For part (a), assume towards a contradiction that Algorithm 2 returns Correct, but there exists an input word $cex = i_0 i_1 \ldots i_n$ such that $M(cex) \neq M^*(cex)$. Let $pre(k)$ and $suf(k)$ be the prefix of length $k$ and suffix of length $n + 1 - k$ of $cex$.

Let $q_0 \xrightarrow{s_k} q_1 \ldots q_n \xrightarrow{i_n} q_{n+1}$ be the run of $M$ on $cex$. Define the function $P(k)$ for $0 \leq k \leq n + 1$ as follows: $P(k) = o_1 \ldots o_{k-1} \cdot \text{Out}(\delta^*(q_k^*, R(q_k)), \text{suf}(k))$. The value of $P(k)$ is given by the first $k$ symbols of $o_1 \ldots o_n$ and concatenated with the last $n + 1 - k$ symbols of $M^*(R(q_k) \cdot \text{suf}(k))$. Informally, we run $pre(k)$ on $M$ and $suf(k)$ of $M^*$, with $R(q_k)$ acting as the link between the two machines.

As $R(q_k) = \varepsilon$, we can derive that $P(0) = M^*(cex)$ and $P(n+1) = M(cex)$. Since, by assumption, $P(0) \neq P(n+1)$, we have $\exists k : P(k) \neq P(k+1)$. Now, denoting $\delta^*(q_k^*, R(q_k))$ as $q_k^*$ and $\delta^*(q_k^*, R(q_{k+1}))$ as $q_{k+1}$, we have

$$o_1 \ldots o_{k-1} \cdot \text{Out}^*(q_k^*, \text{suf}(k)) \neq o_1 \ldots o_{k-1} o_k \cdot \text{Out}^*(q_{k+1}, \text{suf}(k+1))$$

$$\text{Out}^*(q_k^*, \text{suf}(k)) \neq o_k \cdot \text{Out}^*(q_{k+1}, \text{suf}(k+1))$$

$$\text{Out}^*(q_k^*, i_k \cdot \text{suf}(k+1)) \neq \text{Out}(q_k, i_k) \cdot \text{Out}^*(q_{k+1}, \text{suf}(k+1))$$

The first symbol on the left is $\text{Out}^*(\delta^*(q_k^*, R(q_k)), i_k)$ and on the right is $\text{Out}(q_k, i_k)$. If these were not equal, on line 4, the algorithm would have returned a counterexample—giving us a contradiction. On the other hand, if they were equal, removing the first symbol on both sides leaves us with:

$$\text{Out}^*(\delta^*(q_k^*, i_k), \text{suf}(k+1)) \neq \text{Out}^*(q_{k+1}, \text{suf}(k+1))$$

Hence, $\delta^*(q_k^*, i_k)$ and $q_{k+1}$ are distinguishable in $M^*$. Therefore, there exists a suffix of length at most $B_{\text{Dat}}$ such that $\text{Out}^*(\delta^*(q_k^*, i_k), \text{suf}) \neq \text{Out}^*(q_{k+1}, \text{suf})$. However, by definition of $q_k^*$ and $q_{k+1}$, the left and right hand sides are equal to the output symbols of $M_{\text{Oracle}}(R(q_k) \cdot \text{suf})$ and $M_{\text{Oracle}}(R(\delta(q_k, i_k)) \cdot \text{suf})$, respectively. Hence, when check was called at line 6 with the state $q_k$ and input $i_k$, a counterexample would have been returned—this leads to a contradiction again.

For part (b), assume that Algorithm 2 return a counterexample. If the counterexample is returned at line 4, then it is easy to see that the last output symbol of $M(R(q) \cdot i)$ and $M^*(R(q) \cdot i)$ differ. On the other hand, if the counterexample is returned at lines 9 and 10, we have that $M^*(R(q) \cdot i \cdot \text{suf})$ and $M^*(R(q') \cdot \text{suf})$ differ in the last $|\text{suf}|$ positions. However, $M(R(q) \cdot i \cdot \text{suf})$ and $M(R(q') \cdot \text{suf})$ are equal in the last $|\text{suf}|$ positions. Hence, we cannot have both $M(R(q) \cdot i \cdot \text{suf}) = M^*(R(q) \cdot i \cdot \text{suf})$ and $M(R(q') \cdot \text{suf}) = M^*(R(q') \cdot \text{suf})$. This implies at least one of $R(q) \cdot i \cdot \text{suf}$ and $R(q') \cdot \text{suf}$ is a counterexample, which is returned.