Abstracting Event-Driven Systems with Lifestate Rules

Shawn Meier  Aleksandar Chakarov  Maxwell Russek
Sergio Mover  Bor-Yuh Evan Chang
University of Colorado Boulder
{shawn.meier, aleksandar.chakarov, maxwell.russek, sergio.mover, evan.chang}@colorado.edu

Abstract

We present lifestate rules—an approach for abstracting event-driven object protocols. Developing applications against event-driven software frameworks is notoriously difficult. One reason why is that to create functioning applications, developers must know about and understand the complex protocols that abstract the internal behavior of the framework. Such protocols intertwine the proper registering of callbacks to receive control from the framework with appropriate application programming interface (API) calls to delegate back to it. Lifestate rules unify lifecycle and typestate constraints in one common specification language. Our primary contribution is a model of event-driven systems \( \lambda_{\text{life}} \) from which lifestate rules can be derived. We then apply specification mining techniques to learn lifestate specifications for Android framework types. In the end, our implementation is able to find several rules that characterize actual behavior of the Android framework.

1. Introduction

We consider the problem of specifying and mining the object protocols used by event-driven software frameworks. Programming against event-driven frameworks is hard. In such frameworks, programmers develop client applications (apps) against the framework by implementing callback interfaces that enable the application to be notified when an event managed by the framework occurs (e.g., a user-interface (UI) button is pressed). The app may then delegate back to the framework through method calls to the application programming interface (API) (e.g., to direct a change in the UI display). To develop working apps, the application programmer must understand the complex object protocols implemented by the event-driven framework. For example, the framework may guarantee particular ordering constraints on callback invocations (known as lifecycle constraints), and the application programmer may have to respect particular orderings of API calls (i.e., typestate constraints).

Unfortunately, such protocol specifications are complex to describe and maintain—and almost always incomplete. Because lifecycle constraints are so central to implementing apps, they are typically discussed in the framework documentation, but they are incomplete enough that developers spend considerable manual effort to derive more complete specifications [30].

To get a sense for the complexity of event-driven object protocols, consider the automaton-based specifications shown in Figure 1. The meaning of such a specification is that execution traces (projected on to the actions of interest) must be words accepted by the automaton. In Figure 1a, we describe a portion of a lifecycle specification for a protocol between a button object \( b \) and its click-listener \( l \). This automaton states that \( b.\text{onDraw}() \) callback notification happens before any \( l.\text{onClick}(b) \) callback invocations. This specification is a multi-object lifecycle constraint because it orders callbacks on objects \( b \) and \( l \).

In Figure 1b, we show another important property of buttons and their click-listeners: a button can be enabled or disabled via API calls \( b.\text{enable}() \) and \( b.\text{disable}() \), respectively. When button \( b \) is enabled (the upper state),
the click-listener \( l \) may receive the \( l.on\text{Click}(b) \) callback notification. Through an API call to \( b\).\text{disable}(), button \( b \) becomes disabled. When button \( b \) is disabled (the lower state), the click-listener \( l \) can no longer receive \( l.on\text{Click}(b) \) notifications. This specification mixes a lifecycle (or callback-ordering) constraint with a types-state (or API call-ordering) constraint.

We call API calls into the framework, \textit{callins}, to clearly contrast them with \textit{callbacks} that are calls back from the framework. The specification in Figure 1b mixes two kinds of invocations: (1) events labeled by the callbacks they invoke to notify the app (written \textit{slanted}) and (2) callins that the app invokes to change the state of the framework (written \textit{upright}).

From just the examples in Figure 1, we see that the specification space is rich and complex with multiple interacting objects over callbacks and callins. Worse, the composition of the \textit{onDraw}-before-\textit{onClick} specification from (a) and the \textit{enable}-\textit{disable}-\textit{onClick} specification from (b) is the product automaton shown in (c). In this product automaton, the left states are where button \( b \) is enabled versus the right states where \( b \) is disabled, and the upper states are where button \( b \) has yet to be drawn versus the lower states are where \( b \) has been drawn. While automata are descriptive and natural, the key observation of this paper is that automata are more precise than necessary or desired.

Thus, we take a departure from traditional automaton specifications and define a more abstract specification language consisting of \textit{lifestate rules} that captures the critical lifecycle and typestate constraints without representing them as automata. We shall see that this specification language is more compact than automata and exposes lifecycle and typestate constraints as duals. At a high level, lifestate rules focus on changes in the internal, hidden state of the event-driven framework. For example, the \textit{enable}-\textit{disable}-\textit{onClick} specification from Figure 1b can be summarized as the following rules:

\begin{align*}
  b.\text{enable}() & \text{ enables } l.on\text{Click}(b) \text{ for some } l \\
  b.\text{disable}() & \text{ disables } l.on\text{Click}(b) \text{ for some } l
\end{align*}

The first rule says that whenever the invocation \( b.\text{enable}() \) fires, the state of the framework changes to enable the event that invokes the \( l.on\text{Click}(b) \) callback, and the second rule says when \( b.\text{disable}() \) fires, the state changes to disable the event that invokes \( l.on\text{Click}(b) \). These rules do not enumerate the explicit invocation orders as in the automaton from Figure 1b.

Having defined lifestate rules for event-driven object protocols, we investigate specification mining techniques from dynamic traces of apps using a framework. To address the technical challenges to this end, we make the following contributions:

\begin{itemize}
  \item We formalize a concrete semantics for event-driven systems using an abstract machine model \( \lambda_{\text{life}} \) that captures an appropriate model of the internal, hidden state of the framework (section 3). We introduce the notion “allowedness” for API callins, which we shall see is parallel to “enabledness” for events.
  \item We define a language for \textit{lifestate rules}, which incorporates mixed lifecycle-typestate constraints (section 4).
  \item We introduce \textit{callback-driven trace slicing}, a form of trace slicing [14] adapted to events and callins (section 5). The \( \lambda_{\text{life}} \) model and this trace slicing algorithm is the basis for our dynamic analysis tool, DroidLife, that records events, callbacks, and callins in running Android applications.
  \item We apply specification mining techniques to derive lifestate specifications (section 6). In particular, we apply unsupervised automata-based learning techniques based on probabilistic finite state automata and hidden Markov models. We also develop a direct lifestate mining technique based on propositional model counting (\#SAT). The most significant challenge with lifestate mining is that the enables, disables, allows, and disallows that explain callback and callin invocations are not observable in concrete executions.
  \item We empirically evaluate our mining algorithms on 133 traces from a corpus of 1,909 Android apps (section 7). Our results show that we can in fact learn several rules corresponding to actual Android behavior and one of which was not in the Android documentation.
\end{itemize}

2. Overview

In this section, we motivate the challenges in specifying and mining event-driven object protocols and then exhibit how our approach models event-driven systems to mine lifestate rules about the Android framework.

We will show with our running example in Figure 2 that reasoning about the correctness of apps requires a comprehensive understanding of the lifestate rules of various Android framework components. In particular, the call marked with \( \Delta \) can throw an \textit{IllegalStateException}. This code is correct, but understanding why requires a specification of subtle relationships between the various callins and the events that trigger the callbacks. We will also see that a slight change of this code makes it buggy.

\textbf{Lifestate Specification.} Android is a prominent example of an event-driven framework that dispatches a multitude of events (e.g., from user interaction or sensors). An app gets notified about events by implementing callback interfaces that may then delegate back to the framework through the framework’s callin interface. We consider an event-driven object protocol to be the rules governing the use of an interface consisting of
callbacks and callins. Unfortunately, the protocol rules are determined by the complex, internal behavior of the framework, which becomes a major source of confusion for app developers and thus of defects in apps.

To see this complexity, consider the code shown in Figure 2. The app performs a time consuming operation (removing feeds) when the user clicks the button b. The operation is performed asynchronously using AsyncTask to not block the UI thread. Figure 2b shows an execution trace of the app. Execution time flows downwards. A box surrounds the callback and callin invocations that happen as the result of processing of a particular event. First event CREATE invokes the callback (a:Activity).onCreate() for the object a. In this case, object a has dynamic type MainActivity; for reasons we will discuss below, we label the object with its most precise supertype that is a framework type. In the onCreate callback, the code then invokes a callin for the AsyncTask constructor (i.e., (t1:AsyncTask).<init>()), and then the callin for setOnClickListener following the app code at line 5. Then, the trace shows the execution of other two events, CLICK, with the callback onClick, and POSTEXECUTE, with the callback onPostExecute.

Figure 2b also depicts the back and forth flow of control between framework and app code. The boxes along the lines show the lifetime of activations. In particular, we see that we can define a callback invocation as the invocation that transfers control from framework code to app code (arrows to the right), while a callin is the reverse (i.e., an invocation that transfers control from app code to framework). The difficulty in reasoning about the code in Figure 2a is that framework behavior that governs the possible control flow shown in Figure 2b is obfuscated in the code.

Our running example is inspired by an actual issue in AntennaPod [1] a podcast manager for Android with 100,000–500,000 installs from the Google Play Store (a similar issue appears in the Facebook SDK for Android [2]). The potential bug is that the callin AsyncTask.execute, called via remover.execute() (line 7), can throw an IllegalStateException.

In the example the execute call happens whenever the user clicks button b, which in turn triggers the event that dispatches to the OnClickListener.onClick callback on the click-listener (set on line 5). This code is indeed safe (i.e., does not throw the exception) because the developer enforces that the execute method on FeedRemover is only called once. This property is enforced by the disabling and enabling of button b in onClick and in onPostExecute, respectively. Buttons in Android are disabled and enabled via calls to setEnabled(false) and setEnabled(true), respectively (corresponding to disable and enable in section 1).

class FeedRemover extends AsyncTask {
    MainActivity a; Button b;
    void doInBackground() { ... remove feed ... }
    void onPostExecute() {
       a.remover = new FeedRemover(a, b);
       b.setEnabled(true);
    }
}

class MainActivity extends Activity {
    FeedRemover remover;
    void onCreate() {
       Button b = ...;
       remover = new FeedRemover(this, b);
       b.setOnClickListener(new OnClickListener() {
          void onClick(View v) {
             b.setEnabled(false);
             remover.execute();    //
          }
       });
    }
}

(a) The call remover.execute() on line 7 (marked with ▲) can throw an IllegalStateException if the remover task is already running. This execute call happens whenever the user clicks button b. This code is indeed safe because the developer enforces that only one instance of FeedRemover is ever executing through the disabling and enabling of the button on lines 6 and 2, respectively (shown with dashed underline).

(b) A DroidLife trace recorded dynamically. Each box is the processing of an event. Callbacks are depicted as arrows to the right from framework to app code; callins are arrows to the left, which are labeled with the corresponding program location from Figure 2a.

Figure 2. An example Android app whose safety depends on understanding the lifestate rules of two Android framework components AsyncTask and Button.
(t:AsyncTask).execute() \rightarrow \text{ci} t.\text{execute()}
(b:Button).setEnabled(false)
\rightarrow \text{evt CLICK} \gg (1:OnClickListener).onClick(b)
(t:AsyncTask).execute()
\rightarrow \text{evt POSTEXECUTE} \gg t.\text{onPostExecute()}
(b:Button).setEnabled(true)
\rightarrow \text{evt CLICK} \gg (1:OnClickListener).onClick(b)
(t:AsyncTask).\text{<init>()} \rightarrow \text{ci t.}\text{execute()}

**Figure 3.** Some lifestate rules for **AsyncTask** and **Button**.

The first rule specifies a typestate property, while the others are required to reason about the safety of the call to remover.\text{execute()} in Figure 2a.

To see why this button disabling and enabling enforces the single-executing-instance property, the developer needs to know the interactions between **AsyncTask**, **Buttons**, and **OnClickListener**s in the Android framework. Only with an understanding of the framework do we see that the call to b.\text{setEnabled}(false) (line 6) disables the event that could trigger the \text{onClickListener} (callback) which calls the potentially problematic remover.\text{execute()}. Button b (and thus the click event) can be enabled inside the callback \text{onPostExecute} (line 2), but again with an understanding of the framework, we see that \text{onPostExecute} is triggered by a post-execute event, which is in turn enabled by the call to remover.\text{execute()} (line 7). When this happens, remover is set to a newly-allocated instance of FeedRemover (line 1), which allows for the \text{execute} callin to be executed safely.

Without the calls to \text{setEnabled} that disables and enables button b, (on lines 6 and 2, respectively), the app is buggy because the user can click the button a second time, causing a second call to remover.\text{execute()} on the same instance of FeedRemover.

The “understanding” of the Android framework that is necessary to reason about the code in Figure 2a is precisely what we seek to capture with lifestate specifications. In Figure 3, we sketch the lifestate rules needed to reason about our running example. The first rule, (t:AsyncTask).\text{execute()} \rightarrow \text{ci t.}\text{execute()} says that when (t:AsyncTask).\text{execute()} is invoked for an object t of type AsyncTask, the \text{execute} callin on t is disallowed. We use the terms allowed and disallowed to refer to the state of callins; these terms are parallel to enabled and disabled for the state of events. Overall, this rule specifies that it is erroneous to call \text{execute} twice (without something else re-allows it).

The subsequent three rules specify disabling (written \rightarrow \text{evt}) and enabling (written \rightarrow \text{evt}) events (e.g. \text{setEnabled} enables the \text{onClick} callback). To make clear that the enabled-disabled state refers to events, we give names to events, such as \text{CLICK} (written in **SMALL CAPS**) and associate events with the callback(s) they trigger (written \text{EVENT} \gg \text{onCall}()). Finally, the last rule states that the asynchronous task constructor (t:AsyncTask).\text{<init>()} allows the t.\text{execute()} callin. We define and discuss the formal semantics of lifestate specifications in section 4.

We argue that specifications describing the enabling-disabling of events and the allowing-disallowing of callins are central to event-driven object protocols. The specifications capture the relations that informally say, “When a particular method invocation happens, the state of the framework changes to enable or disable an event or to allow or disallow a callin.” We unify the notions of events and callins by introducing the term \text{message}. To reason about lifestate specifications, we formalize an abstraction of event-driven frameworks, called \lambda\text{life}, that captures the internal state consisting of enabled and allowed messages in section 3.

**Callback-Driven Trace Slicing and Lifestate Mining.** We cannot actually observe the abstraction of the internal framework state of a running Android app. Instead, we can only observe the sequence of method invocations. We use the operational semantics of \lambda\text{life} to derive an instrumented semantics that captures the behavior that we can observe: messages classified into event, callback, callin, or internal invocations. This instrumented semantics specifies the recording needed to produce traces like the one shown in Figure 2b and is implemented in a tool called DroidLife.

We are interested in rules about the interactions between events and callins on framework objects. To collect traces across multiple executions, we apply the standard type abstraction to concrete objects, resulting in an abstract, signature message like AsyncTask.\text{execute()}.

To obtain relevant lifestate rules and improve the feasibility of mining, we slice recorded traces into sub-traces that group together related method calls. Our approach is roughly to slice a recorded trace into sub-traces that collect method invocations whose arguments share a particular concrete object, similar to Pradel et al. [32]. However, we face the additional difficulty that an event message is not directly a method invocation and the relevant framework object of the event is typically hidden in the internal state of the message. Our insight for identifying relevant event messages is that an event should eventually trigger a callback where the relevant framework object is also argument to the callback. Thus, our \text{callback-driven trace slicing} approach determines the relevance of an event message \text{m} based on the arguments to the callback(s) that \text{m} eventually triggers. For example, in our trace slice for the concrete object t1 of type AsyncTask, the slice includes the \text{POSTEXECUTE} event because it eventually triggers the callback t1.\text{onPostExecute()} and so the type-
We present our mining approach in section 6 and we λ express the syntax of v expressions is a λ-calculus in a let-normal form. The first line of this semantics serves as the concrete semantics for event-driven programs using an abstract machine model (λlife) that unifies enabledness for event lifecycles and allowedness for callin typestates. Crucially, this semantics motivates lifestate specifications, as the concrete states of this semantics serve as the concrete domain from which lifestate specifications abstract (section 4). This semantics also serves as a basis for describing our dynamic analysis for recording traces of events, callbacks, and callins (section 5).

3.1 Thunks, Handles, and Messages

The syntax of λlife is shown at the top of Figure 4, which is a λ-calculus in a let-normal form. The first line of expressions e are standard, including variables and values v, control flow, and whatever base values and operations of interest (e.g., integers, tuples) but excluding function application. We also assume that there are some heap operations of interest for manipulating a global store ρ. Events occur non-deterministically and return to the main event loop, so events must communicate through the shared, global heap.

The subsequent two lines split the standard call-by-value function application into multiple steps. The bind v1 v2 expression creates a thunk κ by binding a function value λ with an argument value v. A thunk may be forced by direct invocation or indirect event dispatch. Before a thunk may be forced, the allow v expression allocates a handle h for a given thunk κ, which may be viewed as a permission to force the message hκ. A message m is simply a handle-thunk pair (h, κ).

As an example, let λx be the execute method code and let aλ be an address for an AsyncTask. The standard function application (λx aλ) would simply translate to

\[ \text{let } k = \text{bind } \lambda x \ a_\lambda \ \text{in } h = \text{allow } k \ \text{in } \text{invoke } h \ k \]

The reason to split function application into these steps is that thunks and handles are now first-class values and can be used in event dispatch.

The direct invocation expressions are mirrored with expressions for event dispatch. An enable v expression allocates a handle h for a given thunk κ and enables it for the external event-processing system (i.e., gives the event-processing system permission to force the message (h, κ)), while the disable v expression disables the message named by a handle h. There is no expression directly parallel to invoke v1 v2. Instead, when an expression reduces to a value, control returns to the event-processing loop to (non-deterministically) select another enabled event. The force m expression is simply an intermediate in evaluation that represents a message that is forceable (i.e., has been permitted for forcing via allow or enable).

The remainder of the syntax is mostly standard, except that functions λ: fun x in e are tagged with a package g, which we discuss subsequently in subsection 3.3 regarding our instrumented semantics for recording traces. The let expression is variable binding with the usual semantics. Values v of this expression language are variables x, a variable used to bind the active event handle me, whatever base values of interest · · · , closures λ, store addresses a (which are the values of heap-allocated objects), thunks κ, handles h, and unit (). Messages m do not need to be first class, as they are referred to programmatically via their handles.

3.2 Semantics: Enabling Is Not Enqueuing

In contrast to the Android implementation, the state of a λlife program does not have a queue. Rather, the external
environment (e.g., user interactions) is modeled by the non-deterministic selection of an enabled event. When an event is processed, it begins execution in the current state, so the effects of external events can be modeled by effects on the global heap. This model eliminates the complexity of a queue that is an implementation detail for the purposes of lifestate specification.

We consider an abstract machine model with a store and a continuation, and we enrich it with an enabled events store $\mu$, which is a finite map from handles to thunks, and an allowed calls store $\nu$, which is also a map from handles to thunks. These stores can also be seen as the set of enabled and allowed messages, respectively. And thus a machine state $\sigma : \langle e, \rho, \mu, \nu, k \rangle$ consists of an expression $e$, a store $\rho$, enabled events $\mu$, allowed calls $\nu$, and a continuation $k$ (shown at the bottom of Figure 4). The store $\rho$ is a standard, finite map from addresses $a$ to values $v$. We explain the special state initial while discussing the trace semantics in subsection 3.3. A continuation $k$ can be the top-level continuation $\bullet$ or a continuation for returning to the body of a let expression let $x := k$ in $e$, which are standard. Continuations are also used to record the active messages via $m$ and $m \gg k$ corresponding to the run-time stack of activation records.

We define an operational semantics in terms of the judgement form $\sigma \rightarrow \sigma'$ for a small-step transition relation. In Figure 5, we show the inference rules defining the reduction steps related to creating, enabling-disabling, allowing-disallowing, and finally forcing messages. The Bind, Disable, Disallow, Enable, and Allow rules follow closely the informal semantics discussed previously in subsection 3.1. Observe that Enable and Allow are parallel in that they both allocate a fresh handle $h$, and Disable and Disallow look up a message via its handle. The only difference between Enable and Disable versus Allow and Disallow is that the former pair manipulate the enabled events $\mu$, while the latter touches the allowed calls $\nu$. We write $\mu[(h, \kappa)]$ for the map that extends $\mu$ with a mapping $(h, \kappa)$ (i.e., is the same as $\mu$ except at $h$) and similarly for other maps.

The Invoke and Event rules have similar parallels. The Event rule says that when the expression is a value $v$ and the continuation is the top-level continuation $\bullet$, then a message is a non-deterministically chosen from the enabled events $\mu$ to force. For instrumentation purposes (see subsection 3.3), we overload continuations to record the event message $(h, \kappa)$ in the continuation. The Invoke rule checks that the given handle-thunk pair is an allowed message in $\nu$ before forcing.

The Force rule implements the “actual application” that reduces to the function body $e'$ with the argument $v'$ substituted for the formal $x'$. So that the forced message has ready access to its handle $h$, the $h$ is substituted for the $\text{me}$ parameter. Observe that an enabled event remains enabled after an Event reduction. A “dequeueing” event-processing semantics can be implemented by an event disabling itself (via disable $\text{me}$) on execution. To adequately model Android, it is important to be able to model both events that are self-disabling (e.g., the event that invokes onCreate) and those that do not self-disable (e.g., the event that invokes onClick). Again for instrumentation purposes, we push the invocation message $m$ on the continuation (via $m \gg k$). The InvokeDisallowed rule states that a disallowed message invocation terminates the running program by dropping the continuation. The Return and Finish rules simply state that the recorded message $m$ frames are popped on return from a Force and Event, respectively. We elide these rules and the remaining reduction rules, as they are as expected.

### 3.3 Defining Callbacks and Observable Traces

We wish to record traces of “interesting” transitions from which we mine lifestate specifications. Lifestate specifications abstract Enable, Disable, Allow, and Disallow transitions, which are unfortunately unobservable or hidden. That is, they are transitions in $\lambda_{lfs}$ that are not observable in an implementation like Android. Our challenge is to infer lifestate specifications from observable transitions like, “An event message $m$ was initiated.”

In Figure 6, we define the judgment form $\sigma \xrightarrow{r} \sigma'$, which instruments our small-step transition relation.

| Bind | Disable | Disallow |
|------|---------|----------|
| $$(\text{bind } \lambda v, \rho, \mu, \nu, k) \rightarrow (\lambda[v], \rho, \mu, \nu, k)$$ | $$(\text{disable } h, \rho, \mu[(h, \kappa)], \nu, k) \rightarrow (\lambda[\nu], \rho, \mu, \nu, k)$$ | $$(\text{disallow } h, \rho, \nu[(h, \kappa)], k) \rightarrow (\lambda[\nu], \rho, \mu, \nu, k)$$ |

| Enable | Allow | Invoke |
|--------|-------|--------|
| $$(\text{enable } \kappa, \rho, \mu, v, k) \rightarrow (h, \rho, \mu[(h, \kappa)], \nu, k)$$ | $$(\text{allow } \kappa, \rho, \mu, v, k) \rightarrow (h, \rho, \nu[(h, \kappa)], k)$$ | $$(\text{invoke } h, \kappa, \rho, \mu, v, k) \rightarrow (\text{force } (h, \kappa), \rho, \mu, v, k)$$ |

| Force | Invokedisallowed | Event |
|-------|------------------|-------|
| $$(\text{force } m, \rho, \mu, v, k) \rightarrow (v[v'/x'][h/\text{me}], \rho, \mu, v, m \gg k)$$ | $$(\text{invokedisallowed } h, \kappa, \rho, \mu, v, k) \rightarrow (\lambda[\nu], \rho, \mu, v, \bullet)$$ | $$(\nu, \rho, \mu, v, \bullet) \rightarrow (\text{force } (h, \kappa), \rho, \mu, v, (h, \kappa))$$ |

**Figure 5.** Semantics. Create thunks and allocate handles to disable, disallow, enable, and allow messages.
transitions \( \tau \in T \subseteq \text{Trans} \) ::= oknd \( m \ | \ \varepsilon \ | \ \text{init} \)

observable kinds \( \text{oknd} \) ::= \text{evt} | \text{dis} | \text{cb} | \text{ci} | \text{ret} \)

traces \( \varpi \in \text{Trans}^* \) ::= \( \cdot | \tau \varpi \)

**ForceCallback**

\[
(\text{force } m, \rho, \mu, \nu, e) \xrightarrow{\text{h,fgang } x' \in e'} [h/m]\xrightarrow{\rho} [h/\text{ne}, \rho, \mu, \nu, m] \xrightarrow{\kappa} (\text{app } = \text{pkg}(k))
\]

**ForceCallin**

\[
(\text{msg } \text{let } x = k \text{ in } e) \xrightarrow{\text{let } x = k \text{ in } e} \text{msg}(k)
\]

\[
\text{msg}(m) \xrightarrow{\text{msg}(m) \xrightarrow{\kappa} m} \xrightarrow{\text{pkg}(k) \equiv g \text{ if } (h, (\text{fun } x \in e)[x]) = \text{msg}(k)}
\]

**Figure 6.** Callbacks and callins are transitions between framework and app code.

from the previous subsection with transition labels \( \tau \). Interesting observable transitions correspond primarily to introduction and elimination operations on messages. We instrument the Event rule to record that event message \( m \) was initiated (via observable \( \text{evt } m \)). Similarly, we instrument the InvokeDisallowed rule to record that an invocation of a message was disallowed (via \( \text{dis } (h, \kappa) \)). We use \( \varepsilon \) to instrument an uninteresting, “don’t care” transition or an unobservable, “don’t know” transition. The allowed invocation of a message with the Invoke rule is an uninteresting transition, so it is simply labeled with \( \varepsilon \). These cases are simply adding a transition label to the rules from Figure 5, so they are not shown here.

Recall from section 2 that we define a callback as an invocation that transitions from framework to app code and a callin as an invocation from app to framework code. In \( \lambda_{\text{life}} \), this definition is captured crisply by the context in which a message is forced. In particular, we say that a message is a callback if the underlying callee function is an app function (package \( \text{app} \)) and it is called from a framework function (package \( \text{fwk} \)) as shown in ForceCallback. The \( \text{pkg}(\cdot) \) function gets the package of the running message. Analogously, a message is a callin if the callee function is in the \( \text{fwk} \) package, and the caller message is in the \( \text{app} \) package (rule ForceCallin). There is a remaining rule not shown here, Force (ForceInternal), where there is no switch in packages (i.e., \( g' = \text{pkg}(k) \) where \( g' \) is the package of the callee message). It is not an interesting transition, so it is labeled with \( \varepsilon \).

These three cases for \text{force} replace the \text{Force} rule from Figure 5. We also instrument the Return rule to record returning via \text{ret } m \) to retain a call tree structure in the sequence of transitions. Finally, to simplify subsequent definitions, we introduce a “dummy” initial state and a “dummy” init transition with an \text{Init} rule. Any remaining rules defining the original transition relation \( \sigma \rightarrow \sigma' \) not discussed here are simply labeled with the “don’t care” transition label \( \varepsilon \).

We write \( [\epsilon] \) for the path semantics of \( \lambda_{\text{life}} \) expressions \( \epsilon \) that collects the finite (but unbounded) sequences of alternating state-transition-state \( \sigma \rightarrow \sigma' \) triples according to the instrumented transition relation \( \sigma \rightarrow \tau \sigma' \). From paths, we derive traces \( \varpi \) in an expected manner by keeping transitions but dropping intermediate states.

The design of the trace recording in DroidLife follows this instrumented semantics \( \sigma \rightarrow \tau \sigma' \) to obtain traces like the one shown in Figure 2b. In particular, it maintains a message stack corresponding to the continuation \( k \) to emit callback \text{cb} and callin \text{ci} transitions.

4. Lifestate Specification: Abstracting Enabledness and Allowedness

In this section, we define formally the meaning of lifestate rules building on the \( \lambda_{\text{life}} \) concrete model of event-driven programs from section 3.

We consider the abstraction of messages to be a parameter of our approach. We call the message abstraction of interest a message signature \( \hat{\mu} \in \text{Msg} \) and assume it comes equipped with a standard concretization function \( \gamma: \text{Msg} \rightarrow \gamma(\text{Msg}) \) to give signatures meaning and an element-wise abstraction function \( \beta: \text{Msg} \rightarrow \text{Msg} \) to lift a message to its signature satisfying the soundness and best-abstraction relationship. In the case of an Android method call like \( (\text{t: AsyncTask}.\text{execute}()) \) (which corresponds to a message \( m: (h, \lambda_{\text{t}}[a_{\text{t}}]) \) for some handle \( h_{\text{t}}, \) function \( \lambda_{\text{t}}, \) and object address \( a_{\text{t}} \),) the message signature can be the Java method signature \( \text{AsyncTask}.\text{execute}() \). In DroidLife, we make a further refinement on Java method signatures to split on values of primitive type, so \( \text{Button}.\text{setEnabled}(\text{false}) \) and \( \text{Button}.\text{setEnabled}(\text{true}) \) are considered distinct message signatures. For the implementation, the element-wise abstraction function \( \beta \) is applied to recorded messages to produce message signatures for lifestate mining.

A lifestate specification \( \mathcal{R} \) is a set of rules where a rule \( \hat{\tau} \) is an enable \( \rightarrow_{\text{evt}}, \) disable \( \rightarrow_{\text{dis}}, \) allow \( \rightarrow_{\text{ci}}, \) or disallow \( \rightarrow_{\text{ci}} \) constraint. We define the meaning of lifestate specifications by defining an abstraction of the concrete transition relation \( \sigma \rightarrow \sigma' \) for \( \lambda_{\text{life}} \).

To do so, we consider signature transitions \( \hat{\tau} \) and a signature traces \( \hat{\varpi} \). A signature transition \( \hat{\tau} \) are simply analogous to concrete transitions \( \tau \), except over signatures \( \hat{\mu} \) instead of concrete messages \( m \). As input to specification mining, we are only concerned with the event \( \text{evt}, \) callin \( \text{ci}, \) and disallowed \( \text{dis} \) transition kinds, so we drop the callback \text{cb} and return \text{ret} kinds. A signature trace \( \hat{\varpi} \) is simply a sequence of signature transitions. To define the meaning of signature transitions and traces, we
lifestyle specs \( \hat{R} \in \text{LifeSpec} ::= \cdot | \hat{R}, \hat{\tau} \)

rules \( \hat{\tau} ::= \hat{\tau} \rightarrow \hat{m} | \text{init} \)

forcings \( \hat{m} ::= \hat{m} | \text{init} \)

signature transitions \( \hat{\tau} \in \text{Trans} ::= \text{oknd} \hat{m} | \text{init} \)

signature stores \( \tilde{\tau} ::= \tilde{\tau} \rightarrow \tilde{\mu} \)

signature states \( \tilde{\tau} \in \text{State} ::= (\tilde{\tau}, \tilde{\mu}, \tilde{\nu}) \)

\( \hat{m} \in \hat{\mu} \quad \hat{\nu} = \hat{\mu} \cup \text{ext}(\hat{m}) \quad (\text{evt } \hat{m}, \tilde{\mu}, \tilde{\nu}) \rightarrow (\tilde{\tau}, \hat{\mu}, \hat{\nu} \cup \text{ext}(\hat{m})) \)

\( \hat{m} \in \hat{\nu} \quad \hat{\nu} = \hat{\mu} \cup \text{ext}(\hat{m}) \quad (\text{dis } \hat{m}, \tilde{\mu}, \tilde{\nu}) \rightarrow (\tilde{\tau}, \hat{\mu}, \hat{\nu} \cup \text{ext}(\hat{m})) \)

\( \hat{m} \in \hat{\nu} \quad \hat{\nu} = \hat{\mu} \cup \text{ext}(\hat{m}) \quad (\text{init } \hat{m}, \tilde{\mu}, \tilde{\nu}) \rightarrow (\tilde{\tau}, \hat{\mu}, \hat{\nu} \cup \text{ext}(\hat{m})) \)

\( \longrightarrow \hat{m} = \text{setEnabled}(\hat{m}) \quad \hat{\nu} = \text{disable}(\hat{m}) \)

\( \hat{m} \rightarrow \hat{c} \mathrm{m} \in \hat{R} \quad \hat{m} \rightarrow \text{ext } \hat{m} \in \hat{R} \quad \hat{m} \rightarrow \text{init } \hat{m} \in \hat{R} \)

### Figure 7

Meaning of lifestyle specifications. A lifestyle rule \( \hat{\tau} \) is an abstraction of enabling \( \text{enable } v \), disabling \( \text{disable } v \), allowing \( \text{allow } v \), or disallowing \( \text{disallow } v \) transitions.

lift the concretization on message signatures to signature transitions \( \tilde{\tau} \) and traces \( \tilde{\sigma} \) in the expected way.

We can then define a signature store \( \tilde{\mu}, \tilde{\nu} \) as a set of message signatures, which is an abstract analogue of a message store. In a signature state \( \tilde{\sigma} = (\tilde{\sigma}, \tilde{\mu}, \tilde{\nu}) \), the signature store \( \tilde{\mu} \) is a set of enabled message signatures (i.e., abstract messages) and \( \tilde{\nu} \) is a set of allowed message signatures. For convenience, we refer to the union \( \tilde{\mu} \cup \tilde{\nu} \) of enabled and allowed message signatures in a state as the set of \textit{permitted} signatures and all other message signatures that are disabled or disallowed as the \textit{prohibited} signatures.

A signature state \( \tilde{\sigma} = (\tilde{\sigma}, \tilde{\mu}, \tilde{\nu}) \) also includes a signature trace \( \tilde{\sigma} \) that controls the execution of a corresponding abstract machine defined by the transition relation \( \tilde{\sigma} \rightarrow \tilde{\sigma}^* \) that is parametrized by a set of rules \( \hat{R} \) and defined in Figure 7. This transition relation is relatively straightforward: it considers the signature transition \( \tilde{\tau} \) at the beginning of the \( \tilde{\sigma} \) and determines whether \( \tilde{\tau} \) is permitted according to the set of permitted signatures. If it is permitted, it updates the signature stores \( \tilde{\mu} \) and \( \tilde{\nu} \) according to the lifestyle rules \( \hat{R} \). For example, the \textit{Enabled} rule checks if the current transition \( \text{evt } \hat{m} \) can happen by checking if \( \hat{m} \) is in the enabled set \( \tilde{\mu} \). If so, it updates the permitted state according to the rules \( \hat{R} \).

The helper function \( \rightarrow \text{evt}(\hat{\tau}) \) gathers the set of messages that is enabled by \( \hat{\tau} \) and similarly for disable, allow, and disallow rules. For presentation cleanliness, we leave the rules \( \hat{R} \) implicit in the inference rules since it is constant.

Finally, the meaning of a lifestyle specification \( \llbracket \hat{R} \rrbracket \) is the set of signature traces that do not get stuck during reduction (where \( \rightarrow^* \) is the reflexive-transitive closure of the single step relation). And this definition gives rise to a natural description for when a trace is described by or sound with respect to a specification:

**Definition 1** (Trace Soundness). A signature trace \( \tilde{\sigma} \) is \textit{sound} with respect to a lifestyle specification \( \hat{R} \) if \( \tilde{\sigma} \) is described by \( \hat{R} \) (i.e., \( \tilde{\sigma} \in \llbracket \hat{R} \rrbracket \)). Or in other words, the signature trace \( \tilde{\sigma} \) can be reduced without getting stuck (i.e., \( (\tilde{\sigma}, \cdot, \cdot) \rightarrow^* (\cdot, \hat{\mu}, \hat{\nu}) \) for some \( \hat{\mu}, \hat{\nu} \)).

A specification is then sound with respect to a \( \lambda_{\text{life}} \) program if its signature traces abstract the set of concrete traces of the program:

**Definition 2** (Specification Soundness). A lifestyle specification \( \hat{R} \) is \textit{sound} with respect to an expression \( e \) iff for every trace \( \tilde{\sigma} \) of \( e \), it is in the concretization of a signature trace \( \tilde{\sigma} \) of \( \hat{R} \) (i.e., formally, \( \llbracket e \rrbracket \subseteq \gamma(\llbracket \hat{R} \rrbracket) \)).

### 5. Trace Slicing for Multi-Object Event-Driven Protocols

As the specification mining problem is severely under-constrained, we wish to constrain the search space of specifications as much as possible before applying the learning algorithms. As a first step, we wish to slice a trace into sub-traces that group together related messages or method invocations that (likely) correspond to different protocols. A well-known issue is that related method invocations may involve multiple objects. This issue is exacerbated in event-driven protocols where event messages correspond to some internal data structures of the framework rather than method calls per se. For instance, in our running example, a call to the callin \( \langle \text{b:Button} \rangle . \text{setEnabled}(\ldots) \) that enables or disables a button \( \text{b} \) should be associated with a \textit{click} event for \( \text{b} \).

One reasonable and common assumption is that two related messages should use some common values that are readily accessible, such as arguments for method invocations. This heuristic is similar to the one employed by Pradel and Gross [31] for mining multi-object API protocols. Following the argument-sharing strategy, we can slice observations so that they
contain only observable transitions that share a common argument (this strategy is essentially described as trace slicing [14]).

However, one issue in trace slicing for event-driven object protocols is that the messages of interest are the event messages (in event \( m \)) and the callin messages (in callin \( m' \)). As noted above, the “argument” of interest for the \( \text{Click} \) event message is the button \( b \) buried inside internal implementation-specific data structures.

From the \( (b:\text{Button}).setEnabled(...) \) callin and \( \text{Click} \) event example, we also see that regardless of how \( b \) may be stored in the \( \text{Click} \) event message, the \( \text{Click} \) event eventually invokes the callback \( \text{l.onClick}(b) \) on some listener \( l \) where button \( b \) becomes an argument (retrieving \( b \) in some implementation-specific manner).

Thus we extend the argument-sharing strategy to event messages by defining the arguments of an event message \( m \) as the arguments of any callbacks that it invokes (instead of \( m \)'s own arguments). Once the traces have been sliced for each object, we apply the message abstraction function \( \beta \) and partition the traces based on the abstraction of the sliced object.

While our particular argument-sharing strategy focuses on associating callbacks with their initiating events, this strategy is quite flexible in that other appropriate context information (e.g., values reached through the heap) could be incorporated into the trace slice.

6. Mining Lifestate Specifications

In the previous sections, we formalized a model for event-driven systems like Android centered around enabled events and allowed callins. From this model, we derive the notion of lifestate specifications. In this section, we discuss an application of specification mining techniques to learn lifestate specifications. For a set of signature traces \( \Pi \), let \( \Sigma \) be the set containing all the abstract messages contained in the traces \( \Pi \) and init. We learn specifications where the messages in the rules are elements of \( \Sigma \), hence restricting our learning algorithms to an abstraction of messages that we observed concretely. We denote with \( \text{RuleSet} \) the set of all the possible rules that can be learned from \( \Sigma \).

The goal of the mining algorithms is to find a specification \( R \in \wp(\text{RuleSet}) \) and to this end we consider 3 different approaches. Two of these are applications of an off-the-shelf machine learning tool Treba [23] learning probabilistic models of the interaction between the app and the Android framework, and a symbolic sampling one based on model counting of propositional Boolean formulas [20], implemented with pySMT [19] and the solver sharpSAT [35].

**Probabilistic Models.** Hidden Markov Models (HMM) and Probabilistic Finite State Automata (PFSA) are common statistical models famed for their simplicity and accuracy in modeling complex, often partially observable processes. The challenge of learning a probabilistic model of the interaction between the Android framework and an app over the alphabet of signature messages is that in general neither model has a direct interpretation.

For a state \( x_i \) of an a HMM or PFSA \( A \), we define the set of permitted message signatures to be the labels of all enabled outgoing transitions and the set of prohibited message signatures as its complement.

For a state \( x_i \) and an enabled outgoing transition labeled \( m_i \), we learn the lifestate enable (or resp. allow) rules that \( m_i \) permits all message signatures prohibited in \( x_i \) but permitted in the target set of this transition. Similarly, for the state \( x_i \) and an enabled outgoing transition labeled \( m_i \), we learn disable (or disallow) rules that \( m_i \) prohibits all messages permitted in \( x_i \) that become prohibited along the transition.

The final lifestate specification \( R \) is the union of permit and prohibit rules of all states of the automaton. To identify high probability rules, we associate with each rule \( m_i \rightarrow m_j \in R \) a weight that is the sum of the probabilities of all transition that define the rule normalized by the number of permitted sets \( m_i \) is in.

**Symbolic Sampling via \( \delta \text{SAT} \).** In contrast to the two-phase probabilistic automata approaches, we propose an algorithm that directly learns a lifestate specification from the set of signature traces \( \Pi \) that is potentially easier to interpret.

The learning algorithm proceeds by computing a weight for each possible rule in \( \text{RuleSet} \) using the traces in \( \Pi \) and then obtains a lifestate specification by selecting the rules that meet a weight threshold. The weight assigned to a rule is an average, among all the traces in \( \Pi \), of the fraction of the total executions that are sound for that rule.

Intuitively, the ideal settings to compute the weight is to observe the sequence of signature states and transitions (a signature path). The main difficulty we face is that the internal state of the permitted messages (i.e., the signature state \( \langle \hat{\sigma}, \hat{\mu}, \hat{\nu} \rangle \)) is not observable. To address the problem, we propose an abstraction of the signature paths, which we use in our learning algorithm.

We assume no prior knowledge on the internal behavior of the framework and define the most conservative abstraction via the non-deterministic transition relation \( \hat{\sigma} \rightarrow_{n} \hat{\sigma}' \) that, upon invoking a permitted enable or allow signature transition \( \hat{\tau} \), can non-deterministically change the internal state of the system (i.e., permits or prohibits any other message) but keeps the semantics of disallow and disables as in Figure 7. This choice of abstraction may produce a large number of spurious behaviors that could affect the quality of rules we learn, but we make the following observations: (i) the imprecision introduced by the spurious transition may be reduced by observing
Learn Specifications by Counting Paths. Given a signature trace \( \hat{\tau} : \hat{\tau}_1 \ldots \hat{\tau}_n \), let \( \text{Paths}(\hat{\tau}) \) denotes the set of all the sequences of states and transitions (paths) under the non-deterministic semantics. For each rule kind \( \hat{\tau} \rightarrow \text{evt} \hat{m} \) (resp. \( \rightarrow \text{evt}, \rightarrow \text{ci}, \rightarrow \text{ci} \)), we say that the rule is “matched” in a state of the path if, in that state, the message \( \hat{m} \) is enabled (resp. disabled, allowed, disallowed) and the abstract transition executes the message \( \hat{\tau} \).

We want to count all the paths of a trace such that the ratio of the number of states of the path that match the rule over the total number of times we seen \( \hat{\tau} \) in the trace is greater than a weight \( w \). For a signature trace \( \hat{\tau} \), we call \( \text{RulePaths}(\hat{\tau}, \hat{\tau}) \) such set of paths.

Given a signature trace \( \hat{\tau} \) and a rule \( \hat{\tau} \), the frequency of \( \hat{\tau} \) in \( \hat{\tau} \) with weight \( w \), is given by:

\[
\text{Freq}(w, \hat{\tau}, \hat{\tau}) \overset{\text{def}}{=} \frac{|\text{RulePaths}(\hat{\tau}, \hat{\tau})|}{|\text{Paths}(\hat{\tau})|}.
\]

The notion can naturally be lifted to a set of signature traces \( \Pi \) by taking the geometric mean of the fractions of the observed traces.

Let \( \delta \) be a real constant. The final specification is \( R \overset{\text{def}}{=} \{ \hat{\tau} \mid \text{Freq}(w, \hat{\tau}, \Pi) \geq \delta \} \). The threshold \( \delta \) is needed to select only the rules that, according to the frequency value, more likely capture the framework behavior.

The number of paths in the sets \( \text{Paths}(\hat{\tau}) \) and \( \text{RulePaths}(\hat{\tau}, \hat{\tau}) \) is exponential in the total number of messages. Thus, it is not feasible to explicitly enumerate them. Our solution is to encode all the paths in \( \text{Paths}(\hat{\tau}) \) as a propositional logic formula. The intuition is that each (complete) model of this formula represents a path in \( \text{Paths}(\hat{\tau}) \). Hence, we cast the problem of counting the cardinality of \( \text{Paths}(\hat{\tau}) \) to the problem of counting the number of models of the Boolean formula, for which several efficient tools exist (e.g. [35]). The encoding is an adaptation of Bounded Model Checking [10], a technique that encodes all the paths of length \( k \) of a transition system.

7. Empirical Evaluation: Mining

Here, we evaluate empirically whether our process finds meaningful lifestate specifications, as well as compare the quality of the specifications obtained from different mining algorithms.

Research Questions. Given a candidate specification (i.e., a set of lifestate rules) obtained from a learning method, we consider the following research questions.

- **RQ1 (Sufficiency):** Is a mined specification sound with respect to previously unseen traces? We say that a specification is sufficient for explaining a set of traces if each trace is sound with respect to the specification (according to Definition 1 in section 4). Foremost, we seek specifications that are, in the limit, sufficient to explain all actual Android behavior.

- **RQ2 (Veracity):** For each rule in a mined specification, does the rule correspond to actual Android behavior? We say that a specification is veracious if it captures when a message should be enabled or allowed during the execution of an app and when it should not. In the end, we want to find rules that in fact describe the true enabling, disabling, allowing, and disallowing behavior of Android.

Experimental Methodology. We consider the mining algorithms from section 6 based on probabilistic models (HMM and PFSA) and symbolic sampling (\( \text{zSAT} \)). For the symbolic sampling approach, we use two weight thresholds 0.6 and 0.8, corresponding intuitively to keeping only the rules that explain slightly more than half the paths and those that explain most paths, respectively. This selection of parameters gives us four learning methods to evaluate that we abbreviate as \( \text{zSAT-0.6, zSAT-0.8, HMM, and PFSA} \).

Traces recorded by DroidLife are sliced for each object, abstracted into message signatures, and grouped by the framework type of the slicing object. Thus, we have a corpus of sliced and abstracted traces for each framework type of interest. To evaluate a learning method, we divide a trace corpus into a training set and a testing set using 5-fold cross validation.

Corpus: Generating Sliced and Abstracted Traces

We begin with 133 traces of running Android applications recorded by DroidLife. These traces were generated from a corpus of 1909 apps retrieved from Github.

We used two different methods for generating traces: manual exercising of the app and automatic by means of the UI Exerciser Monkey. We chose to generate some traces using manual exercising because apps require user logins, API keys, and other inputs that present problems for automatic exploration tools (e.g., [5, 8, 27]). The manual method resulted in 65 traces and the automatic in 68. The process for manual trace generation was to exercise the app in a normal manner for 10 minutes under instrumentation. For the automatic Monkey, a script loaded the application on an Android emulator, waited 3 minutes for any application initialization, and then pulsed the UI exercising 40 times. Each time inputting 50 random events and delaying 30 seconds in between.
Table 1. The data set is partitioned by framework type (f-type) on the sliced object. For each trace set, we give the number of traces, the average length of the traces (len), the total number of distinct event message signatures (evts), callin signatures (cis), and the size of the specification space (|LifeSpec|).

| f-type       | traces (num) | len (mean) | evts (num) | cis (num) | |LifeSpec| (num) |
|--------------|--------------|------------|------------|-----------|----------------|--------|
| Fragment     | 52           | 9.7        | 6          | 19        | 1275           |        |
| FragmentV4   | 124          | 9.0        | 10         | 34        | 3916           |        |
| Button       | 654          | 4.6        | 4          | 28        | 2080           |        |
| asyncTask    | 63           | 3.8        | 1          | 4         | 55             |        |
| summary      | 893          | 6.8        | 21         | 85        | 7326           |        |

From the corpus of 133 recorded traces, we apply callback-driven trace slicing from section 5 to get 6134 sliced traces over 184 framework types. Each framework type corresponds to a partition of the 6134 sliced traces. We selected four of these framework types, which had trace sets of sufficient length and diversity of events and callins, for evaluating our learning methods. In Table 1, we list some statistics about the data set. The specification space (|LifeSpec|) is the number of possible lifestate rules as determined by the number of observed events (evts) and callins (cis). The summary line is the total number of traces, the mean of mean length of traces, the total number of event and callin signatures, the total specification space.

Candidate Specifications. In Table 2, we show the number of each rule kind learned using each method on the first training set. Our first observation is that the probabilistic model-based methods generate many more candidate rules than the symbolic sampling-based method. This observation is not unexpected, as the symbolic sampling-based method takes a more conservative approach for generating rules: it generates rules based on the frequency of explainable signature traces. Our second observation is that event-disables are the least frequently derived rules. This observation is also not unexpected, as event-disables are the least constrained rule kind. The total line is the total number of rules of each kind. The magnitude is not meaningful, but it shows the relative frequency of the rule kinds.

RQ1: Measuring Sufficiency. Given a testing set and a candidate specification, we measure sufficiency as the ratio of traces that are sound with respect to the specification to the number of traces in the testing set.

Figure 8 shows the sufficiency measure for each learned specification, grouped by method. No one method dominates the others by this measure. For example, the PFSA method is the only one that generates rules that have soundness fraction over 0.5 for Fragment but is worse than all other methods for asyncTask. The sufficiency measure for SAT-0.8 is generally high, but recall from Table 2 that SAT-0.8 learns far fewer rules than the other methods. It is quite conservative in the rules it learns, but for the rules that it does learn,
Table 3. Veracity is a measure of precision in finding actual rules by manually triaging the rules found by each learning method. The actual column shows the number of learned rules that correspond understood Android behavior. The direct shows the number of actual rules that also correspond to the root enable, disable, allow, or disallow in Android.

| f-type      | method    | rules | actual | direct |
|-------------|-----------|-------|--------|--------|
|             | f-type    | num   | num    | num (frac) |
| Fragment    | $\chi$SAT-0.6 | 20    | 10     | 7 (0.7) |
| Fragment    | PFSA      | 20    | 14     | 11 (0.8) |
| Fragment    | HMM       | 20    | 5      | 4 (0.8) |
| Fragment    | total unique | 42    | 22     | 18 (0.8) |
| FragmentV4  | $\chi$SAT-0.6 | 20    | 8      | 7 (0.9) |
| FragmentV4  | PFSA      | 20    | 12     | 10 (0.8) |
| FragmentV4  | HMM       | 19    | 11     | 9 (0.8) |
| FragmentV4  | total unique | 58    | 24     | 19 (0.8) |
| Button      | $\chi$SAT-0.6 | 20    | 6      | 3 (0.5) |
| Button      | PFSA      | 20    | 7      | 7 (1) |
| Button      | HMM       | 20    | 3      | 3 (1) |
| Button      | total unique | 49    | 14     | 11 (0.8) |
| AsyncTask   | $\chi$SAT-0.6 | 3     | 3      | 3 (1) |
| AsyncTask   | PFSA      | 13    | 10     | 4 (0.4) |
| AsyncTask   | HMM       | 19    | 12     | 6 (0.5) |
| AsyncTask   | total unique | 22    | 15     | 7 (0.8) |
| all objects | total unique | 171   | 75     | 55 (0.7) |

they tend to generalize well. The $\chi$SAT-0.6 and PFSA methods appear to balance producing more candidate rules and ones that generalize reasonably well. We thus consider manual triage of the rules produced by these two methods for evaluating veracity.

RQ2: Evaluating Veracity. To evaluate veracity, we take a candidate lifestate specification and manually triage the rules and categorize them with respect to the correctness in capturing the true behavior of the Android framework. We consider the following categories of correctness: (actual) the rule abstracts understood Android behavior from reading Android documentation or the framework code; (direct) the rule is actual and corresponds to the root cause in Android (e.g., a learned enable rule corresponds to direct enabling in Android); (false or unknown) the rule appears to contradict understood Android rules. If we cannot be sure that a learned rule corresponds to a actual rule, then we conservatively classify it as false.

In Table 3, we show veracity results for the $\chi$SAT-0.6, PFSA, and HMM methods for each framework type. We manually triaged the twenty rules with highest weight (using the parsimony assumption that the number of rules for each framework type should be small). We then add a row for the total number of unique rules in each column. Since no single method dominated most of the time, this row shows that the combination of methods can learn a more complete specification than any single method alone. In total we learned 75 unique rules which model the behavior of the framework. Of these, 55 directly correspond to the cause and effect that a developer would attribute to the system.

The highest level point is that a number of actual rules are learned for each framework type by both learning methods (the actual column) out of the thousands of possible rules shown in Table 1 (7326) by only examining the top 20 rated rules from each learning method. And furthermore, most actual rules that are learned correspond to the real root cause in the Android framework (the direct column). This observation provides supporting evidence for lifestate rules capturing event-driven object protocols at an appropriate level of abstraction.

The only exception to the high fraction of actual rules is the AsyncTask which can be fully specified by 7 rules as we describe further below. This biases the fraction to be low since we took the top 20 rated rules, and there were only 7 rules to learn. And every specification needed for AsyncTask was learned. Furthermore, most of the direct rules are found even in the top 10.

One remaining question is how many rules are required to specify the protocol. Is it the case that the number of rules for each framework type should be small compared to the number of possible rules. To address this question, we manually specified the full set of rules for AsyncTask for the observed events and callins (since this class is comparatively small with only 55 possible rules compared to the thousands possible for the other framework types, see Table 1).

Manual specification of AsyncTask resulted in 7 direct rules. The result is that we are learning 3 out of the 7 direct rules with the $\chi$SAT-0.6 method, 4 out of 7 with the PFSA method, and 6 out of 7 with the HMM method. There were no rules in the manually created set which were not learned by one of our algorithms.

Threats to Validity. The rules that can be learned are limited by the observations available in the traces. For example, there was no opportunity to learn anything about the AsyncTask.cancel() callin since our traces did not include any observations of such an invocation. In the end, we are limited by the extent by which framework behavior can be explored through dynamic execution. To try to mitigate this affect, we made traces with as many applications as possible minimizing duplicate traces. This exposes us to more possible ways developers may use a given framework object. There is a potential for bias in selecting the framework types on which to mine specifications. To minimize this effect, we selected by looking just at the number and length of traces and diversity of events and callins (from Table 1).
5

Mined Specifications. From the veracity summary, the SAT-0.6, PFSA, and HMM methods appear comparable, so we look more closely into the rules that are learned. From our running example in section 2, the most important rule that we would expect is that \( (\text{t:AsyncTask}).\text{execute}() \) call can only be called once. It is indeed learned by all three methods. Another important rule is that the \( \text{POSTEXECUTE} \) event is enabled by the \( (\text{t:x AsyncTask}).\text{execute}() \) callin. In this case, the SAT-0.6 and HMM methods learned this rule but the PFSA method did not.

The biggest source of false rules learned that we observed are rules that appear to come from common patterns in how developers use the framework. For example, one rule learned by PFSA is that \( (\text{b:Button}).\text{getWidth}() \) disallows itself, which perhaps corresponds to few traces with repeated calls to \( \text{getWidth}() \).

A source of actual but not direct rules relates to callbacks and \text{super} calls. We found that a common pattern in Android is to require a call to the \text{super} method. For example to implement \text{onActivityCreated}, \text{super.onActivityCreated} would need to be called. Thus in functioning applications, this \text{super} call is seen as a callin that always happens with the event the triggers the \text{onActivityCreated} callback. Thus, the left-hand–side of a actual but not necessarily direct rule is where the left-hand–side is either the event or the \text{super} callin. One could reasonably consider removing required \text{super} calls from our definition of callins.

In the end, we found a rule that captures an undocumented behavior of Android in the official Android documentation. The rule states that the \( (\text{f:Fragment}).\text{getResources}() \) is allowed when the event \text{ACTIVITYCREATED} that triggers the \text{onActivityCreated} callback. The \text{getResources} callin will throw an exception if called before this \text{ACTIVITYCREATED} event.

8. Related Work

Specification Mining. Our technique is broadly similar to mining typestate specifications for API interfaces from traces (e.g., [3, 6, 15, 17, 31, 36, 39, 40]). Our contribution can be seen as an extension that, in addition to inferring typestate properties, also infers the ordering constraints of lifecycle events that interleave and interact with typestate properties. Ammons et al. [6] presents one of the earliest attempts to infer temporal specifications of programs by mining observed traces. Notably, Yang et al. [40] extend the technique to scale to larger data-sets with imperfect traces, and Pradel and Gross [31] improve the technique to mining specifications for collaborations involving multiple, interacting objects. There is also work on combining automata mining with value-based invariant mining [24, 26]. However, we are unaware of any previous work that mines specifications for lifecycle events in addition to their interaction with typestate APIs for frameworks.

Other work also simplifies automata specifications by considering simpler rule-based approaches (e.g., [18, 38]). Subsequently, Lo et al. [25] extend this kind of specification to QBEC (quantified binary temporal rules with equality constraints) specifications. However, these rule-based approaches differ from lifestate rules in that they express necessary causation (e.g for every \text{lock} there must be a subsequent \text{unlock}). In contrast, lifestate rules do not express such conditions, and these conditions are actually undesirable, as most events in event-driven systems enable other events but do not cause them to occur.

Concerning static mining techniques, Alur et al. [4] propose a technique to infer a typestate interface for a given Java class. This technique could conceivably be used to statically infer typestate specifications for event-driven frameworks such as Android. However, their technique does not account for the unique relationship between typestate and lifecycle events in event-based systems. Additionally, Shoham et al. [34] develop a technique for inferring the typestate of a certain API by analyzing presumably correct client programs. The order of method invocations, determined statically, can produce a multi-object typestate specification. Ramanathan et al. [33] propose a similar technique, but one that can also derive invariant-based preconditions. However, to our knowledge these techniques also cannot be successfully extended to event-based systems, where typestate and lifecycle properties may interact.

Analysis of Event-Driven Systems. Recently, more and more program analyses have focused on event-driven systems. Both dynamic analyses, such as for race detection [22, 29], and static analyses for information flow [7] and safety properties [11] expect some specification of framework behavior with respect to callbacks. There has also been a number of recent static analyses targeting information flow concerns (e.g., [16, 21, 37]) where a significant concern is synthesizing models for taint flow through the framework [9].

There are also some tools concerned with exposing the implicit control flow from the framework to callbacks by linking callback registration methods with their callbacks [13, 28], modeling GUI components [41], and explicating reflection [12]. This information is useful for creating an over-approximation of the possible callbacks but does not capture precise events that may enable or disable a given event that then invokes the callback.

9. Conclusion

We have presented \text{lifestate rules}, a language for specifying event-driven object protocols. The key idea underlying lifestate rules is a model of event-driven programs
in terms of enabled events and allowed calls unified as suspended messages. As a result, lifestate rules are able to capture mixed lifecycle and typestate constraints at a higher level abstraction than automata. We then instantiated this model in a dynamic analysis tool called DroidLife that prepares Android traces for specification mining using a notion of trace slicing adapted to events and callbacks. Finally, we applied specification mining techniques to infer lifestate specifications based on unsupervised automata-based learning techniques that have been previously applied to typestate mining, as well as a direct lifestate mining technique based on propositional model counting. In the end, we were able to learn several actual lifestate rules that accurately capture the behavior of Android in a compact way.

References

[1] AntennaPod - FeedRemover bug report. https://github.com/AntennaPod/AntennaPod/issues/1304. Accessed: 2016-03-13.

[2] Facebook SDK for Android - AsyncTask bug report. https://github.com/facebook/facebook-android-sdk/pull/315. Accessed: 2016-03-13.

[3] M. Acharya, T. Xie, and J. Xu. Mining interface specifications for generating checkable robustness properties. In Software Reliability Engineering (ISSRE), 2006.

[4] R. Alur, P. Černý, P. Madhusudan, and W. Nam. Synthesis of interface specifications for Java classes. In Principles of Programming Languages (POPL), 2005.

[5] D. Amalfitano, A. R. Fasolino, P. Trambonata, S. D. Carmine, and A. M. Memon. Using GUI ripping for automated testing of Android applications. In Automated Software Engineering (ASE), 2012.

[6] G. Ammons, R. Bodik, and J. R. Larus. Mining specifications. In Principles of Programming Languages (POPL), 2002.

[7] S. Arzt, S. Rasthofer, C. Fritz, E. Bodden, A. Bartel, J. Klein, Y. L. Traon, D. Octeau, and P. McDaniel. FlowDroid: Precise context, flow, field, object-sensitive and lifecycle-aware taint analysis for Android apps. In Programming Language Design and Implementation (PLDI), 2014.

[8] T. Azim and I. Neamtiu. Targeted and depth-first exploration for systematic testing of Android apps. In Object-Oriented Programming Systems, Languages, and Applications (OOPSLA), 2013.

[9] O. Bastani, S. Anand, and A. Aiken. Specification inference using context-free language reachability. In Principles of Programming Languages (POPL), 2015.

[10] A. Biere, A. Cimatti, E. M. Clarke, and Y. Zhu. Symbolic model checking without bdds. In Tools and Algorithms for the Construction and Analysis of Systems (TACAS), 1999.

[11] S. Blackshear, B. E. Chang, and M. Sridharan. Selective control-flow abstraction via jumping. In Object-Oriented Programming Systems, Languages, and Applications (OOPSLA), 2015.

[12] S. Blackshear, A. Gendreau, and B. E. Chang. Droidel: A general approach to Android framework modeling. In State of the Art in Program Analysis (SOAP), 2015.

[13] Y. Cao, Y. Fratantonio, A. Bianchi, M. Egele, C. Kruegel, G. Vigna, and Y. Chen. Edgeminer: Automatically detecting implicit control flow transitions through the android framework. In Network and Distributed System Security (NDSS), 2015.

[14] F. Chen and G. Rosu. Parametric trace slicing and monitoring. In Tools and Algorithms for the Construction and Analysis of Systems (TACAS), 2009.

[15] V. Dallmeier, C. Lindig, A. Wasylkowski, and A. Zeller. Mining object behavior with ADABU. In Dynamic Systems Analysis (WODA), 2006.

[16] Y. Feng, S. Anand, I. Dillig, and A. Aiken. Apposcopy: Semantics-based detection of Android malware through static analysis. In Foundations of Software Engineering (FSE), 2014.

[17] M. Gabel and Z. Su. Javert: Fully automatic mining of general temporal properties from dynamic traces. In Foundations of Software Engineering (FSE), 2008.

[18] M. Gabel and Z. Su. Online inference and enforcement of temporal properties. In International Conference on Software Engineering (ICSE), 2010.

[19] M. Gario and A. Micheli. pySMT: a solver-agnostic library for fast prototyping of smt-based algorithms. In Workshop on Satisfiability Modulo Theories (SMT), 2015.

[20] C. P. Gomes, A. Sabharwal, and B. Selman. Model counting. In Handbook of Satisfiability. 2009.

[21] M. I. Gordon, D. Kim, J. Perkins, L. Gilham, N. Nguyen, and M. Rinard. Information-flow analysis of Android applications in DroidSafe. In Network and Distributed System Security (NDSS), 2015.

[22] C.-H. Hsiao, J. Yu, S. Narayanasamy, Z. Kong, C. L. Pereira, G. A. Pokam, P. M. Chen, and J. Flinn. Race detection for event-driven mobile applications. In Programming Language Design and Implementation (PLDI), 2014.

[23] M. Hulden. Treba: Efficient numerically stable EM for PFA. In Grammatical Inference (ICGI), 2012.

[24] D. Lo and S. Maoz. Scenario-based and value-based specification mining: Better together. In Automated Software Engineering (ASE), 2010.

[25] D. Lo, G. Ramalingam, V.-P. Ranganath, and K. Vaswani. Mining quantified temporal rules: Formalism, algorithms, and evaluation. Sci. Comput. Program., 77(6), 2012.

[26] D. Lorenzoli, L. Mariani, and M. PezzÃ . Automatic generation of software behavioral models. In International Conference on Software Engineering (ICSE), 2008.
[27] A. Machiry, R. Tahiliani, and M. Naik. Dynodroid: an input generation system for Android apps. In European Software Engineering Conference and Foundations of Software Engineering (ESEC/FSE), 2013.

[28] M. Madsen, F. Tip, and O. Lhoták. Static analysis of event-driven node.js javascript applications. In Object-Oriented Programming Systems, Languages, and Applications (OOPSLA), 2015.

[29] P. Maiya, A. Kanade, and R. Majumdar. Race detection for Android applications. In Programming Language Design and Implementation (PLDI), 2014.

[30] S. Pomeroy. Complete Android Fragment and Activity lifecycle. https://github.com/xxv/android-lifecycle. Accessed: 2016-03-13.

[31] M. Pradel and T. R. Gross. Automatic generation of object usage specifications from large method traces. In Automated Software Engineering (ASE), 2009.

[32] M. Pradel, C. Jaspan, J. Aldrich, and T. R. Gross. Statically checking API protocol conformance with mined multi-object specifications. In International Conference on Software Engineering (ICSE), 2012.

[33] M. K. Ramanathan, A. Grama, and S. Jagannathan. Static specification inference using predicate mining. In Programming Language Design and Implementation (PLDI), 2007.

[34] S. Shoham, E. Yahav, S. Fink, and M. Pistoia. Static specification mining using automata-based abstractions. In Software Testing and Analysis (ISSTA), 2007.

[35] M. Thurley. sharpSAT - counting models with advanced component caching and implicit BCP. In Theory and Applications of Satisfiability Testing (SAT), 2006.

[36] N. Walkinshaw and K. Bogdanov. Inferring finite-state models with temporal constraints. In Automated Software Engineering (ASE), 2008.

[37] F. Wei, S. Roy, X. Ou, and Robby. Amandroid: A precise and general inter-component data flow analysis framework for security vetting of Android apps. In Computer and Communications Security (CCS), 2014.

[38] W. Weimer and G. C. Necula. Mining temporal specifications for error detection. In Tools and Algorithms for the Construction and Analysis of Systems (TACAS), 2005.

[39] J. Whaley, M. C. Martin, and M. S. Lam. Automatic extraction of object-oriented component interfaces. In Software Testing and Analysis (ISSTA), 2002.

[40] J. Yang, D. Evans, D. Bhardwaj, T. Bhat, and M. Das. Perracotta: Mining temporal API rules from imperfect traces. In International Conference on Software Engineering (ICSE), 2006.

[41] S. Yang, D. Yan, H. Wu, Y. Wang, and A. Rountev. Static control-flow analysis of user-driven callbacks in Android applications. In International Conference on Software Engineering (ICSE), 2015.