Automated Concolic Testing of Smartphone Apps

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ABSTRACT

We present an algorithm and a system for generating input events to exercise smartphone apps. Our approach is based on concolic testing and generates sequences of events automatically and systematically. It alleviates the path-explosion problem by checking a condition on program executions that identifies subsumption between different event sequences. We also describe our implementation of the approach for Android, the most popular smartphone app platform, and the results of an evaluation that demonstrates its effectiveness on five Android apps.

Categories and Subject Descriptors

D.2.5 [**Software Engineering**]: Testing and Debugging—*Symbolic execution, Testing tools*

Keywords

GUI testing, testing event-driven programs, Android

1. INTRODUCTION

Mobile devices with advanced computing ability and connectivity, such as smartphones and tablets, are becoming increasingly prevalent. At the same time there has been a surge in the development and adoption of specialized programs, called *apps*, that run on such devices. Apps pervade virtually all activities ranging from leisurely to mission-critical. Thus, there is a growing need for software-quality tools in all stages of an app's life-cycle, including development, testing, auditing, and deployment.

Apps have many features that make static analysis challenging: a vast software development kit (SDK), asynchrony, inter-process communication, databases, and graphical user interfaces (GUIs). Thus, many approaches for analyzing apps are based on dynamic analysis (e.g., [7, 9, 10]).

A question central to the effectiveness of any dynamic analysis is how to obtain relevant program inputs. The most indivisible and routine kind of inputs to an app are *events*. A tap on the device's touch screen, a key press on the device's keyboard, and an SMS message are all instances of events. This paper presents an algorithm and a system for generating input events to exercise apps. Apps can have inputs besides events, such as files on disk and secure web content. Our work is orthogonal and complementary to approaches that provide such inputs.

Apps are instances of a class of programs we call *event-driven programs*: programs embodying computation that is architected to react to a possibly unbounded sequence of events. Event-driven programs are ubiquitous and, besides apps, include stream-processing programs, web servers, GUIs, and embedded systems. Formally, we address the following problem in the setting of event-driven programs in general, and apps in particular.

> **Branch-coverage Problem:** Given a constant bound $k \geq 1$, efficiently compute a set of event sequences that execute each branch of an event-driven program that can be executed by some event sequence of length up to k.

The above problem poses two separate challenges: (1) how to generate single events and (2) how to extend them to sequences of events. We next look at each of these in turn.

Generating Single Events. Existing approaches for generating all events of a particular kind use either *capture-replay* techniques to automatically infer a model of the app's GUI [22, 31] or *model-based* techniques that require users to provide the model [34, 36]. These approaches have limitations. Capture-replay approaches are tailored to a particular platform's event-dispatching mechanism but many apps use a combination of the platform's logic and their own custom logic for event dispatching. For example, where the platform sees a single physical widget, an app might interpret events dispatched to different logical parts of that widget differently. In contrast, model-based approaches are general-purpose, but they can require considerable manual effort.

In this paper, we present a new approach, which is both general and automatic, to address this problem. The approach builds on a systematic test-input generation technique called concolic testing [6, 15, 30] (also known as dynamic symbolic execution) which has made significant strides in recent years. Our approach symbolically tracks events from the point where they originate to the point where they are ultimately handled. The approach is thus oblivious to where and how events are dispatched.

Generating Event Sequences. Our concolic-testing approach for generating single events can be extended naturally to iteratively compute sets of increasingly longer sequences of events. An algorithm, hereafter called AllSeqs, can generate all event sequences of length up to k such that each event sequence executes a unique program path. However, AllSeqs does not scale as the value of k is increased because typical programs have a large number of program paths. For instance, for a simple music player app written for the Android mobile app platform, AllSeqs generates 11 one-event sequences, 128 two-event sequences, 1,590 three-event sequences, and 21K four-event sequences. This problem is known as the *path-explosion problem* [12], and, in practice, AllSeqs may fail to solve the aforementioned branch-coverage problem within a time budget for a high value of k.

Although several techniques have been developed in recent years to address the path-explosion problem (e.g., [1, 4, 12–14, 17, 19, 20, 29]), the problem is still intractable for real-world software. In this paper, we present a new technique, ACTEve (stands for Automated Concolic Testing of Event-driven programs), to alleviate the path-explosion problem. ACTEve is tailored to event-driven programs such as smartphone apps. The key insight underlying ACTEve is a notion of subsumption between two event sequences. If an event sequence π is *subsumed* by another event sequence π', then ACTEve avoids generating sequences that are extensions of π, and instead generates extensions of π' only. Such pruning of π results in compounded savings as longer event sequences are generated. We show that ACTEve is relatively complete with respect to AllSeqs. Specifically, ACTEve covers the same set of branches as AllSeqs for a given upper bound on the length of event sequences.[1]

ACTEve computes subsumption between event sequences by checking for simple data- and control-flow facts of each program execution in isolation. Compared to existing techniques for the path-explosion problem, ACTEve has at least four distinctive characteristics that greatly improves its applicability to real-world software such as Android apps. First, it does not impose any unrealistic assumption (e.g., methods are free of side effects) about the program. Second, it does not store and match program traces or program states, which can dramatically increase memory overhead. Third, it does not require powerful (e.g., support for quantifiers) or specialized constraint solvers to reason about path constraints of multiple program paths simultaneously. Fourth, it does not require static analysis of real-world code that often contain parts that are beyond the scope of static analysis. Despite its above-mentioned simplicity, in our empirical study, ACTEve produced significant savings because subsumption between event sequences exists frequently in real apps. For example, for the previously-mentioned music player app, using $k = 4$, our algorithm explores only 16% of the inputs (3,445 out of 21,117) that AllSeqs explores.

We have implemented ACTEve in a system for Android apps. Our system instruments and exercises apps in a mobile device emulator that runs an instrumented Android SDK. This enables our system to be portable across mobile devices, leverage Android's extensive tools (e.g., to automatically run the app on generated inputs), and exploit stock hardware; in particular, our system uses any available parallelism, and can run multiple emulators on a machine or a cluster of machines. Our system also builds upon recent advances in concolic testing such as function summarization [12], generational search [16], and Satisfiability Modulo Theories (SMT) solving [8]. We show the effectiveness of our system on five Android apps.

The primary contributions of this work are as follows.

1. A novel approach to systematically generate events to exercise apps. Our approach, based on concolic testing, is fully automatic and general, in contrast to existing capture-replay-based or model-based approaches.
2. An efficient algorithm, ACTEve, to solve the branch-coverage problem. Our key insight is a subsumption condition between event sequences. Checking the condition enables ACTEve to prune redundant event sequences, and thereby alleviate path explosion, while being complete with respect to AllSeqs.
3. An implementation and evaluation of ACTEve in a system for Android apps. Our system is portable, exploits available parallelism, and leverages recent advances in concolic testing.

2. OVERVIEW OF OUR APPROACH

In this section, we illustrate our approach using an example music player app from the Android distribution. We first describe the app by discussing its source code shown in Figure 1 (Section 2.1). We then describe how we generate events to exercise this app (Section 2.2) and how we extend them to sequences of events (Section 2.3).

2.1 The Music Player App

Android apps are incomplete programs: they implement parts of the Android SDK's API and lack a main method. When the music player app is started, the SDK creates an instance of the app's main activity `MainActivity`, and calls its `onCreate()` method. This method displays the main screen, depicted in Figure 2(a), which contains six buttons: *rewind*, *play*, *pause*, *skip*, *stop*, and *eject*. The method also sets the main activity as the handler of clicks to each of these buttons. The app waits for events once `onCreate()` finishes.

When any of the six buttons is clicked, the SDK calls the main activity's `onClick()` method, because the main activity was set to handle these clicks. If the *eject* button is clicked, this method displays a dialog, depicted in Figure 2(b), that prompts for a music file URL. If any of the other buttons is clicked, the `onClick()` method starts a service `MusicService` with an argument that identifies the button. The service processes clicks to each of the five buttons. For brevity, we show only how clicks to the *rewind* button are processed, in the `processRewind()` method. The service maintains the current state of the music player in `mState`. On start-up, the service searches for music files stored in the device, and hence the state is initialized to `Retrieving`. Clicks to each button have effect only in certain states; for instance, clicking the *rewind* button has no effect unless the state is `Playing` or `Paused`, in which case `processRewind()` rewinds the player to the start of the current music file.

2.2 Generating Single Events

Our first goal is to systematically generate single input events to a given app in a given state. For concreteness, we focus on tap events, which are taps on the device's touch screen, but our observations also hold for other kinds of events (e.g., key presses on the device's keyboard).

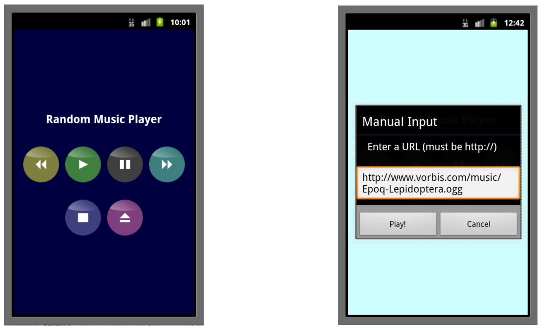
[1]ACTEve can also be used for bounded verification of safety properties, by converting a given `assert(e)` statement to `if (!e) assert(false)` and checking reachability of the `assert(false)` statement.

```
public class MainActivity extends Activity {
    Button mRewindButton, mPlayButton, mEjectButton, ...;
    public void onCreate(...) {
        setContentView(R.layout.main);
        mPlayButton = findViewById(R.id.playbutton);
        mPlayButton.setOnClickListener(this);
        ... // similar for other buttons
    }
    public void onClick(View target) {
        if (target == mRewindButton)
            startService(new Intent(ACTION_REWIND));
        else if (target == mPlayButton)
            startService(new Intent(ACTION_PLAY));
        ... // similar for other buttons
        else if (target == mEjectButton)
            showUrlDialog();
    }
}
public class MusicService extends Service {
    MediaPlayer mPlayer;
    enum State { Retrieving, Playing, Paused, Stopped, ... };
    State mState = State.Retrieving;
    public void onStartCommand(Intent i, ...) {
        String a = i.getAction();
        if (a.equals(ACTION_REWIND)) processRewind();
        else if (a.equals(ACTION_PLAY)) processPlay();
        ... // similar for other buttons
    }
    void processRewind() {
        if (mState == State.Playing || mState == State.Paused)
            mPlayer.seekTo(0);
    }
}
```

Figure 1: Source code snippet of music player app.

Our goal is to generate tap events such that each widget on the displayed screen of the app is clicked once. In Android, the widgets on any screen of an app are organized in a tree called the *view hierarchy*, where each node denotes the rectangular bounding box of a different widget, and the node's parent denotes its containing widget. Figure 3 shows the view hierarchy for the main screen of the music player app depicted in Figure 2(a). Given this hierarchy, we can achieve our goal of clicking each widget once, by generating Cartesian coordinates inside each rectangle in the hierarchy and outside its sub-rectangles.

As we discussed in the Introduction, existing approaches either infer the hierarchy automatically (via capture-replay [22, 31]) or require users to provide it (model-based techniques [34, 36]); both have limitations. We present a new approach that is general and fully automatic. Our approach is based on concolic testing, and symbolically tracks events from the point where they originate to the point where they are handled. For this purpose, our approach instruments the Android SDK and the app under test. In the case of tap events, whenever a concrete tap event is input, this instrumentation creates a fresh symbolic tap event and propagates it alongside the concrete event. As the concrete event flows through the SDK and the app, the instrumentation tracks a constraint on the corresponding symbolic event which effectively identifies all concrete events that are handled in the same manner. This not only lets our approach avoid generating spurious events but also enables it to exhaustively generate orthogonal events. For the main screen of our music player app, for instance, our approach generates exactly 11 tap events, one in each of the rectangles (and outside sub-rectangles) in the screen's view hierarchy depicted in Figure 3. Section 3 describes how our approach generates these events in further detail.



Enter a URL (must be http://)

http://www.vorbis.com/music/Epoq-Lepidoptera.ogg

(a) Main screen. **(b) Eject dialog.**

Figure 2: Screen shots of music player app.

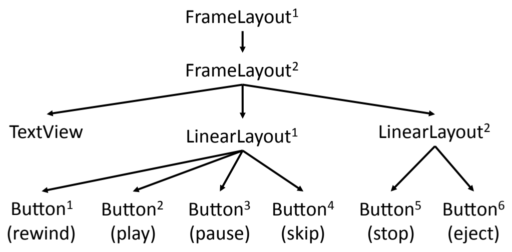


Figure 3: View hierarchy of main screen.

2.3 Generating Event Sequences

Our concolic testing approach for generating single events can be extended naturally to iteratively compute sets of increasingly longer sequences of events. However, as we discussed in the Introduction, the AllSeqs concolic testing approach [15, 30] causes the computed sets to grow rapidly—for the above music player app, AllSeqs produces 11 one-event sequences, 128 two-event sequences, 1,590 three-event sequences, and 21K four-event sequences.

We studied the event sequences produced by AllSeqs for several Android apps and found a significant source of redundancy, namely, that a large fraction of events do not have any effect on the program state. We call such events *read-only* because we identify them by checking that no memory location is written when they are dispatched and handled. Upon closer inspection, we found diverse reasons for the prevalence of read-only events, which we describe below.

First, many widgets on any given screen of any app *never* react to any clicks. As shown in the view hierarchy of the main screen of the music player app (Figure 3), these include boilerplate widgets (e.g., `FrameLayout` and `LinearLayout`), which merely serve to layout other actionable widgets (e.g., `Button`), and informational widgets that display non-editable texts (e.g., `TextView`). Thus, only 6 of 11 widgets on the main screen of the music player app (namely, the six buttons) are actionable, and clicks to the remaining 5 widgets constitute read-only events.

Second, many widgets that are actionable might be disabled in certain states of the app. This situation often occurs when apps wish to guide users to provide events in a certain order or when they wish to prevent users from providing undefined combinations of events.

Third, GUI-based programs are conservative in updating state. In particular, they avoid unnecessary updates, to suppress needlessly re-drawing widgets and notifying listeners. For instance, if an event wishes to set a widget to a state

γ, then the event handler for that widget reads the current state of the widget, and does nothing if the current state is already γ, effectively treating the event as read-only.

Based on the above observations, we developed ACTEve that does not extend event sequences that end in a read-only event. Pruning such sequences in a particular iteration of our approach prevents extensions of those sequences from being considered in future iterations, thereby providing compounded savings, while still ensuring completeness with respect to AllSeqs. We show that the read-only pattern is an instance of a more general notion of *subsumption* between event sequences. An event sequence that ends in a read-only event is subsumed by the same event sequence without that final event.

For our example music player app, using read-only subsumption, our approach explores 3,445 four-event sequences, compared to 21,117 by the AllSeqs approach, which does not check for subsumption but is identical in all other respects. Besides clicks to many passive widgets in this app (e.g., `LinearLayout`) being read-only, another key reason for the savings is that even clicks to actionable widgets (e.g., `Button`) are read-only in many states of the app. For instance, consider the two-event sequence [*stop*, *rewind*]. The first event (*stop*) writes to many memory locations (e.g., fields `mPlayer` and `mState` in class `MusicService` shown in Figure 1). However, the second event (*rewind*) does not write to any location, because the `processRewind()` method of class `MusicService` that handles this event only writes if the state of the music player is `Playing` or `Paused`, whereas after the first *stop* event, its state is `Stopped`. Thus, our approach identifies the *rewind* event in sequence [*stop*, *rewind*] as read-only, and prunes all sequences explored by AllSeqs that have this sequence as a proper prefix.

Section 4 presents a formal description of subsumption, the read-only instantiation of subsumption, and the formal guarantees it provides.

3. GENERATING SINGLE EVENTS

In this section, we describe how our approach systematically generates single events. We use tap events in Android as a proof-of-concept. Tap events are challenging to generate because they are continuous and have more variability than discrete events such as incoming phone calls, SMS messages, battery charging events, etc. Moreover, tap events are often the primary drivers of an app's functionality, and thus control significantly more code of the app than other kinds of events. The principles underlying our approach, however, are not specific to tap events or to Android.

We begin by describing how Android handles tap events. Figure 4 shows the simplified code of the `dispatchEvent()` method of SDK class `android.view.ViewGroup`. When a tap event is input, this method is called recursively on widgets in the current screen's view hierarchy, to find the innermost widget to which to dispatch the event, starting with the root widget. If the event's coordinates lie within a widget's rectangle, as determined by the `contains()` method of SDK class `android.graphics.Rect`, then `dispatchEvent()` is called on children of that widget, from right to left, to determine whether the current widget is indeed the innermost one containing the event or if it has a descendant containing the event. For instance, any tap event that clicks on the *pause* button on the main screen of our example music player app results in testing for the event's containment in

```
public class android.view.ViewGroup {
    public boolean dispatchEvent(Event e) {
        float x = e.getX(), y = e.getY();
        for (int i = children.length - 1; i >= 0; i--) {
            View child = children[i];
            if (child.contains(x, y))
                if (child.dispatchEvent(e))
                    return true;
        }
        return false;
    }
}
public class android.graphics.Rect {
    public boolean contains(float x, float y) {
        return x >= this.left && x < this.right &&
               y >= this.top && y < this.bottom;
    }
}
```

Figure 4: Source code snippet of Android SDK.

the following widgets in order, as the event is dispatched in the view hierarchy depicted in Figure 3. We also indicate whether or not each test passes: `FrameLayout`^{1} (yes) $\rightarrow$ `FrameLayout`^{2} (yes) $\rightarrow$ `LinearLayout`^{2} (no) $\rightarrow$ `LinearLayout`^{1} (yes) $\rightarrow$ `Button`^{4} (no) $\rightarrow$ `Button`^{3} (yes).

Our approach uses concolic testing to generate a separate tap event to each widget. This requires symbolically tracking events from the point where they originate to the point where they are handled. Let $(\$x, \$y)$ denote variables that our approach uses to symbolically track a concrete tap event (x, y). Then, for each call to `contains`(x, y) on a rectangle in the view hierarchy specified by constants $(x_{left},\ x_{right},\ y_{top},\ y_{bottom})$, our approach generates the following constraint or its negation, depending upon whether or not the tap event is contained in the rectangle:

$$(x_{left} \leq \$x < x_{right}) \ \wedge \ (y_{top} \leq \$y < y_{bottom})$$

Our approach starts by sending a random tap event to the current screen of the given app. For our example app, suppose this event clicks the *pause* button. Then, our approach generates the following *path constraint*:

$$\begin{array}{lll}
 & (0 \leq \$x < 480) \ \wedge \ (0 \leq \$y < 800) & // \ c_1 \\
\wedge & (0 \leq \$x < 480) \ \wedge \ (38 \leq \$y < 800) & // \ c_2 \\
\wedge & \$x' = \$x \ \wedge \ \$y' = (\$y - 38) & // \ p_1 \\
\wedge & \neg((128 \leq \$x' < 352) \ \wedge \ (447 \leq \$y' < 559)) & // \ c_3 \\
\wedge & (16 \leq \$x' < 464) \ \wedge \ (305 \leq \$y' < 417) & // \ c_4 \\
\wedge & \$x'' = (\$x' - 16) \ \wedge \ \$y'' = (\$y' - 305) & // \ p_2 \\
\wedge & \neg((344 \leq \$x'' < 440) \ \wedge \ (8 \leq \$y'' < 104)) & // \ c_5 \\
\wedge & (232 \leq \$x'' < 328) \ \wedge \ (8 \leq \$y'' < 104) & // \ c_6
\end{array}$$

Constraints c_1 and c_2 capture the fact that the event is tested for containment in `FrameLayout`^{1} and `FrameLayout`^{2}, respectively, and the test passes in both cases. The event is then tested against `LinearLayout`^{2} but the test fails (notice the negation in c_3). Constraints c_4 through c_6 arise from testing the event's containment in `LinearLayout`^{1}, `Button`^{4} (the *skip* button), and `Button`^{3} (the *pause* button). We explain constraints p_1 and p_2 below.

Our approach next uses this path constraint to generate concrete tap events to other widgets. Specifically, for each c_i, it uses an off-the-shelf constraint solver to solve the constraint $(\bigwedge_{j=1}^{i-1} c_j) \wedge \neg c_i$ for $\$x$ and $\$y$. If this constraint is satisfiable, any solution the solver provides is a new concrete tap event guaranteed to take the path dictated by this constraint in the view hierarchy. That path in turn generates a new path constraint and our approach repeats the above process until all widgets in the hierarchy are covered.

$$\begin{array}{rl}
\text{(condition label) } l & \in \ \mathsf{Label} \\
\text{(input variable) } a & \\
\text{(global variable) } g & \in \ \mathsf{GVar} = \{g_1, \ldots, g_m\} \\
\text{(expression) } e & ::= a \ | \ g \ | \ aop(\bar{e}) \\
\text{(boolean expression) } b & ::= bop(\bar{e}) \ | \ \mathsf{True} \ | \ \mathsf{False} \ | \\
& \quad \neg b \ | \ b \wedge b \ | \ b \vee b \\
\text{(program) } s & ::= \mathsf{skip} \ | \ g = e \ | \ s_1; s_2 \ | \\
& \quad \mathsf{if}\ b^l\ s_1\ \mathsf{else}\ s_2 \ | \ \mathsf{while}\ b^l\ s
\end{array}$$

Figure 5: Syntax of programs.

We now explain the role of constraints p_1 and p_2 in the path constraint depicted above. These constraints introduce new symbolic variables $\$x'$, $\$y'$, $\$x''$, and $\$y''$. They arise because, as a tap event is dispatched in the Android SDK, various offsets are added to its concrete x and y coordinates, to account for margins, convert from relative to absolute positions, etc. The already-simplified path constraint depicted above highlights the complexity for concolic execution that a real platform like Android demands: we instrument not only the SDK code shown in Figure 4 but *all* SDK code, as well as the code of each app under test. Dropping any of the above constraints due to missed instrumentation can result in the *path divergence* problem [16] in concolic testing, where the concrete and symbolic values diverge and impair the ability to cover all widgets.

4. GENERATING EVENT SEQUENCES

In this section, we describe how our approach generates sequences of events. To specify our approach fully and to express and prove the formal guarantee of the approach, we use a simple imperative language, which includes the essential features of Android apps. We begin with the explanation of our language and the associated key semantic concepts (Sections 4.1 and 4.2). We then describe our algorithm, proceeding from the top-level routine (Section 4.3) to the main optimization operator (Sections 4.4 and 4.5). Finally, we discuss the formal completeness guarantee of our algorithm (Section 4.6). Appendix B in [2] presents the proofs of all lemmas and the theorem discussed in this section.

4.1 Core Language

Our programming language is a standard WHILE language with one fixed input variable a and multiple global variables $g_1,\ldots,g_m$ for some fixed m. A program s models an Android app, and it is meant to run repeatedly in response to a sequence of input events provided by an external environment, such as a user of the app. The global variables are threaded in the repetition, so that the final values of these variables in the i-th iteration become the initial values of the variables in the following $(i+1)$-th iteration. In contrast, the input variable a is not threaded, and its value in the i-th iteration comes from the i-th input event. Other than this initialization in each iteration, no statements in the program s can modify the input variable a.

The syntax of the language appears in Figure 5. For simplicity, the language assumes that all the input events are integers and stored in the input variable a. It allows such an event in a to participate in constructing complex expressions e, together with global variable g and the application of an arithmetic operator $aop(\bar{e})$, such as $a + g$. Boolean expressions b combine the expressions using standard comparison operators, such as $=$ and $\leq$, and build conditions on program states. Our language allows five types of programming

$$\begin{array}{rcl}
\text{(integer) } n & \in & \mathsf{Integers} \\
\text{(global state) } \gamma & ::= & [g_1 : n_1, \ldots, g_m : n_m] \\
\text{(symbolic global state) } \Gamma & ::= & [g_1 : e_1, \ldots, g_m : e_m] \\
\text{(branching decision) } d & ::= & \langle l, \mathit{true} \rangle \ | \ \langle l, \mathit{false} \rangle \\
\text{(instrumented constraint) } c & ::= & b^d \\
\text{(path constraint) } C & ::= & c_1 c_2 \ldots c_k \\
\text{(concolic state) } \omega & ::= & \langle \gamma, \Gamma, C \rangle \\
\text{(input event sequence) } \pi & ::= & n_1 n_2 \ldots n_k \\
\text{(set of globals) } W & \subseteq & \{g_1, \ldots, g_m\} \\
\text{(trace) } \tau & ::= & \langle C_1, W_1 \rangle \ldots \langle C_k, W_k \rangle
\end{array}$$

Figure 6: Semantic domains.

constructs with the usual semantics: skip for doing nothing; assignments to global variables $g = e$; sequential compositions $(s_1; s_2)$; conditional statements (if b^l s_1 else s_2) with an l-labeled boolean b; and loops (while b^l s). Note that although the input variable a can appear on the RHS of an assignment, it is forbidden to occur on the LHS. Thus, once initialized, the value of a never changes during the execution of a program. Note also that all boolean conditions are annotated with labels l. We require the uniqueness of these labels. The labels will be used later to track branches taken during the execution of a program.

Example 1. The following program is a simplified version of the music player app in our language:

```
if (g==Stopped)^{l_0} {
    if (a==Play)^{l_1} {g = Playing}
    else if (a==Skip)^{l_2} {g = Skipping} else {skip}
} else {
    if (a==Stop)^{l_3} {g = Stopped} else {skip}
}
```

To improve the readability, we use macros here: Stopped = Stop = 0, Playing = Play = 1, and Skipping = Skip = 2. Initially, the player is in the Stopped state (which is the value stored in g), but it can change to the Playing or Skipping state in response to an input event. When the player gets the Stop input event, the player's state goes back to Stopped.

We write Globals(e) and Globals(s) to denote the set of free global variables appearing in e and s, respectively.

Throughout the rest of the paper, we fix the input program and the initial global state given to our algorithm, and denote them by s_{in} and γ_{in}.

4.2 Semantic Domains

We interpret programs using a slightly non-standard operational semantics, which describes the concolic execution of a program, that is, the simultaneous concrete and symbolic execution of the program. Figure 6 summarizes the major semantic domains. The most important are those for concolic states ω, input sequences π, and traces τ.

A ***concolic state*** ω specifies the status of global variables concretely as well as symbolically. The state consists of the three components, denoted by $\omega.\gamma$, $\omega.\Gamma$, and $\omega.C$, respectively. The γ component keeps the concrete values of all the global variables, while the Γ component stores the symbolic values of them, specified in terms of expressions. We require that global variables do not occur in these symbolic values; only the input variable a is allowed to appear there. The C component is a sequence of instrumented constraints $c_1 c_2 \ldots c_k$, where each c_i is a boolean expression b annotated with a label and a boolean value. As for symbolic values, we prohibit global variables from occurring in b. The annotation indicates the branch that generates this boolean value as well as the branching decision observed during the execution of a program.

An ***input event sequence*** π is just a finite sequence of integers, where each integer represents an input event from the environment.

A ***trace*** τ is also a finite sequence, but its element consists of a path constraint C and a subset W of global variables. The element $\langle C, W\rangle$ of τ expresses what happened during the concolic execution of a program with a *single* input event (as opposed to an event sequence). Hence, if τ is of length k, it keeps the information about event sequences of length k. The C part describes the symbolic path constraint collected during the concolic execution for a single event, and the W part stores variables written during the execution. As in the case of concolic state, we adopt the record selection notation, and write $(\tau_i).C$ and $(\tau_i).W$ for the C and W components of the i-th element of τ. Also, we write $\tau\langle C, W\rangle$ to mean the concatenation of τ with a singleton trace $\langle C, W\rangle$.

Our operational semantics defines two evaluation relations: (1) $\langle s, n, \omega\rangle \downarrow \omega' \triangleright W$ and (2) $\langle s, \pi, \gamma\rangle \Downarrow \gamma' \triangleright \tau$. The first relation models the run of s with a single input event n from a concolic initial state ω. It says that the outcome of this execution is ω', and that during the execution, variables in W are written. Note that the path constraint $\omega'.C$ records all the branches taken during the execution of a program. If the execution encounters a boolean condition b^l that evaluates to True, it still adds $\mathsf{True}^{\langle l,true\rangle}$ to the C part of the current concolic state, and remembers that the true branch is taken. The case that b^l evaluates to False is handled similarly.

The second relation describes the execution of s with an input event sequence. It says that if a program s is run repeatedly for an input sequence π starting from a global state γ, this execution produces a final state γ', and generates a trace τ, which records path constraints and written variables during the execution. Note that while the first relation uses concolic states to trace various symbolic information about execution, the second uses traces for the same purpose.

The rules for the evaluation relations mostly follow from our intended reading of all the parts in the relations. They are described in detail in Appendix A in [2].

Recall that we fixed the input program and the initial global state and decided to denote them by s_{in} and γ_{in}. We say that a trace τ is ***feasible*** if τ can be generated by running s_{in} from γ_{in} with some event sequences, that is, $\exists\pi, \gamma'.\ \langle s_{in}, \pi, \gamma_{in}\rangle \Downarrow \gamma' \triangleright \tau$. Our algorithm works on feasible traces, as we explain next.

4.3 Algorithm

ACTEve takes a program, an initial global state, and an upper bound k on the length of event sequences to explore. By our convention, s_{in} and γ_{in} denote these program and global state. Then, ACTEve generates a set Σ of traces of length up to k, which represents event sequences of length up to k that achieve the desired code coverage. Formally, Σ satisfies two correctness conditions.

1. First, all traces in Σ are feasible. Every $\tau \in \Sigma$ can be generated by running s_{in} with some event sequence π of length up to k.
2. Second, Σ achieves the full coverage in the sense that if a branch of s_{in} is covered by an event sequence π of length up to k, we can find a trace τ in Σ such that every event sequence π' satisfying τ (i.e., $\pi' \models \tau$) also covers the branch.

Algorithm 1 Algorithm ACTEve

```
**INPUTS:** Program $s_{in}$, global state $\gamma_{in}$, bound $k \geq 1$.
**OUTPUTS:** Set of traces of length up to $k$.
$\Pi_0 = \Delta_0 = \{\epsilon\}$
**for** $i = 1$ *to* $k$ **do**
  $\Delta_i = \mathsf{symex}(s_{in}, \gamma_{in}, \Pi_{i-1})$
  $\Pi_i = \mathsf{prune}(\Delta_i)$
**end for**
**return** $\bigcup_{i=0}^{k} \Delta_i$
```

The top-level routine of ACTEve is given in Algorithm 1. The routine repeatedly applies operations symex and prune in alternation on sets Π_i and Δ_i of traces of length i, starting with the set containing only the empty sequence ϵ. Figure 7 illustrates this iteration process pictorially. The iteration continues until a given bound k is reached, at which point $\bigcup_{i=0}^{k} \Delta_i$ is returned as the result of the routine.

The main work of ACTEve is done mostly by the operations symex and prune. It invokes $\mathsf{symex}(s_{in}, \gamma_{in}, \Pi_{i-1})$ to generate all the feasible one-step extensions of traces in Π_{i-1}. Hence,

$$\mathsf{symex}(s_{in}, \gamma_{in}, \Pi_{i-1}) = \\ \{\tau\langle C, W\rangle \mid \tau \in \Pi_{i-1} \text{ and } \tau\langle C, W\rangle \text{ is feasible}\},$$

where $\tau\langle C, W\rangle$ means the concatenation of τ with a single-step trace $\langle C, W\rangle$. The symex operation can be easily implemented following a standard algorithm for concolic execution (modulo the well-known issue with loops), as we did in our implementation for Android.[2] In fact, if we skip the pruning step in ACTEve and set Π_i to Δ_i there (equivalently, $\mathsf{prune}(\Delta)$ returns simply Δ), we get the standard concolic execution algorithm, AllSeqs for exploring all branches that are reachable by event sequences of length k or less.

The goal of the other operation prune is to identify traces that can be thrown away without making the algorithm cover less branches, and to filter out such traces. This filtering is the main optimization employed in our algorithm. It is based on our novel idea of subsumption between traces, which we discuss in detail in the next subsection.

Example 2. We illustrate our algorithm with the music player app in Example 1 and the bound $k = 2$. Initially, the algorithm sets $\Pi_0 = \Delta_0 = \{\epsilon\}$. Then, it extends this empty sequence by calling symex, and obtains Δ_1 that contains the following three traces of length 1:

$$\begin{aligned}\tau &= \langle \mathsf{True}^{\langle l_0,true\rangle}(a{=}{=}\mathsf{Play})^{\langle l_1,true\rangle},\ \{g\}\rangle,\\ \tau' &= \langle \mathsf{True}^{\langle l_0,true\rangle}(a{=}{=}\mathsf{Play})^{\langle l_1,false\rangle}(a{=}{=}\mathsf{Skip})^{\langle l_2,true\rangle},\ \{g\}\rangle,\\ \tau'' &= \langle \mathsf{True}^{\langle l_0,true\rangle}(a{=}{=}\mathsf{Play})^{\langle l_1,false\rangle}(a{=}{=}\mathsf{Skip})^{\langle l_2,false\rangle},\ \emptyset\rangle.\end{aligned}$$

Trace τ describes the execution that takes the true branches of l_0 and l_1. It also records that variable g is updated in this execution. Traces τ' and τ'' similarly correspond to executions that take different paths through the program.

[2] When s_{in} contains loops, the standard concolic execution can fail to terminate. However, symex is well-defined for such programs, because it is not an algorithm but a declarative specification.

$$\{\epsilon\} = \Pi_0 \xrightarrow{\mathsf{symex}} \Delta_1 \underset{\supseteq}{\xrightarrow{\mathsf{prune}}} \Pi_1 \xrightarrow{\mathsf{symex}} \Delta_2 \underset{\supseteq}{\xrightarrow{\mathsf{prune}}} \Pi_2 \xrightarrow{\mathsf{symex}} \ldots$$

Figure 7: Simulation of our ACTEve algorithm.

Next, the algorithm prunes redundant traces from Δ_1. It decides that τ'' is such a trace, filters τ'', and sets $\Pi_1 = \{\tau, \tau'\}$. This filtering decision is based on the fact that the last step of τ'' does not modify any global variables. For now, we advise the reader not to worry about the justification of this filtering; it will be discussed in the following subsections.

Once Δ_1 and Π_1 are computed, the algorithm goes to the next iteration, and computes Δ_2 and Π_2 similarly. The trace set Δ_2 is obtained by calling symex, which extends traces in Π_1 with one further step:

$$\begin{aligned}\Delta_2 = \{\ & \tau\langle \mathsf{True}^{\langle l_0, false\rangle}(a{=}{=}\mathsf{Stop})^{\langle l_3, true\rangle}, \{g\}\rangle,\\ & \tau\langle \mathsf{True}^{\langle l_0, false\rangle}(a{=}{=}\mathsf{Stop})^{\langle l_3, false\rangle}, \emptyset\rangle,\\ & \tau'\langle \mathsf{True}^{\langle l_0, false\rangle}(a{=}{=}\mathsf{Stop})^{\langle l_3, true\rangle}, \{g\}\rangle,\\ & \tau'\langle \mathsf{True}^{\langle l_0, false\rangle}(a{=}{=}\mathsf{Stop})^{\langle l_3, false\rangle}, \emptyset\rangle\ \}\end{aligned}$$

Among these traces, only the first and the third have the last step with the nonempty write set, so they survive pruning and form the set Π_2.

After these two iterations, our algorithm returns $\bigcup_{i=0}^{2} \Delta_i$.

4.4 Subsumption

For a feasible trace τ, we define

$$\mathsf{final}(\tau) = \{\gamma' \mid \exists\pi.\, \langle s_{in}, \pi, \gamma_{in}\rangle \Downarrow \gamma' \triangleright \tau\},$$

which consists of the final states of the executions of s_{in} that generate the trace τ.

Let τ and τ' be feasible traces. The trace τ ***is subsumed by*** τ', denoted $\tau \sqsubseteq \tau'$, if and only if $\mathsf{final}(\tau) \subseteq \mathsf{final}(\tau')$. Note that the subsumption compares two traces purely based on their final states, ignoring other information like length or accessed global variables. Hence, the subsumption is appropriate for comparing traces when the traces are used to represent sets of global states, as in our algorithm ACTEve. We lift subsumption on sets T, T' of feasible traces in a standard way: $T \sqsubseteq T' \iff \forall\tau \in T.\, \exists\tau' \in T'.\, \tau \sqsubseteq \tau'$. Both the original and the lifted subsumption relations are preorder, i.e., they are reflexive and transitive.

A typical use of subsumption is to replace a trace set T_{new} by a subset T_{opt} such that $T_{new} \sqsubseteq T_{opt} \cup T_{old}$ for some T_{old}. In this usage scenario, T_{new} represents a set of traces that a concolic testing algorithm originally intends to extend, and T_{old} that of traces that the algorithm has already extended. Reducing T_{new} to T_{opt} entails that fewer traces will be explored, so it boosts the performance of the algorithm.

Why is it ok to reduce T_{new} to T_{opt}? An answer to this question lies in two important properties of the subsumption relation. First, the symex operation preserves the subsumption relationship.

Lemma 1. *For sets T, T' of feasible traces,*

$$T \sqsubseteq T' \implies \mathsf{symex}(s_{in}, \gamma_{in}, T) \sqsubseteq \mathsf{symex}(s_{in}, \gamma_{in}, T').$$

Second, if T is subsumed by T', running symex with T' will cover as many branches as what doing the same thing with T covers. Let

$$\mathsf{branch}(C) = \{d \mid b^d = C_i \text{ for some } i \in \{1, \ldots, |C|\}\}.$$

Algorithm 2 The rprune operation

```
INPUTS: Set $\Delta$ of traces.
OUTPUTS: Set $\Pi = \{\tau \in \Delta \mid |\tau| \geq 1 \Rightarrow (\tau_{|\tau|}).W \neq \emptyset\}$
```

The formal statement of this second property appears in the following lemma:

Lemma 2. *For all sets T, T' of feasible traces, if $T \sqsubseteq T'$.*

$$\begin{aligned}&\bigcup\{\mathsf{branch}((\tau_{|\tau|}).C) \mid \tau \in \mathsf{symex}(s_{in}, \gamma_{in}, T)\}\\ &\quad\subseteq \bigcup\{\mathsf{branch}((\tau_{|\tau|}).C) \mid \tau \in \mathsf{symex}(s_{in}, \gamma_{in}, T')\}.\end{aligned}$$

In the lemma, $\tau_{|\tau|}$ means the last element in the trace τ and $(\tau_{|\tau|}).C$ chooses the C component of this element. So, the condition compares the branches covered by the last elements of traces.

Using these two lemmas, we can now answer our original question about the subsumption-based optimization. Suppose that T_{opt} is a subset of T_{new} but $T_{new} \sqsubseteq T_{opt} \cup T_{old}$ for some T_{old}. The lemmas imply that every new branch covered by extending T_{new} for the further $k \geq 1$ steps is also covered by doing the same thing for $T_{opt} \cup T_{old}$. More concretely, according to Lemma 1, the extension of T_{new} for the further $k-1$ or smaller steps will continue to be $\sqsubseteq$-related to that of $T_{opt} \cup T_{old}$. Hence, running symex with such extended T_{new} will cover only those branches that can also be covered by doing the same thing for the similarly extended $T_{opt} \cup T_{old}$ (Lemma 2). Since we assume that the k or smaller extensions of T_{old} are already explored, this consequence of the lemmas means that as long as we care about only newly covered branches, we can safely replace T_{new} by T_{opt}, even when T_{opt} is a subset of T_{new}.

4.5 Pruning

The goal of the pruning operator is to reduce a set Δ of feasible traces to a subset $\Pi \subseteq \Delta$, such that Δ is subsumed by Π and all strict prefixes of Δ:[3]

$$\Delta \sqsubseteq \Pi \cup \mathsf{sprefix}(\Delta), \tag{1}$$

where $\mathsf{sprefix}(\Delta) = \{\tau \mid \exists\tau'.\, |\tau'| \geq 1 \wedge \tau\tau' \in \Delta\}$. The reduction brings the gain in performance, while the subsumption relationship (together with an invariant maintained by ACTEve) ensures that no branches would be missed by this optimization.

Our implementation of pruning adopts a simple strategy for achieving the goal. From a given set Δ, the operator filters out all traces whose last step does not involve any writes, and returns the set Π of remaining traces. The implementation appears in Figure 2, and accomplishes our goal, as stated in the following lemma:

Lemma 3. *For all sets Δ of feasible traces,* rprune(Δ) *is a subset of Δ and satisfies the condition in* (1).

Note that the pruning operator can be implemented differently from rprune. As long as the pruned set Π satisfies the subsumption condition in (1), our entire algorithm ACTEve remains relatively complete, meaning that the optimization with pruning will not introduce new uncovered branches. Appendix C in [2] shows another implementation of pruning that uses the notion of independence.

[3] This condition typechecks because all prefixes of feasible traces are again feasible traces so that the RHS of $\sqsubseteq$ contains only feasible traces.

4.6 Relative Completeness

For $i \geq 0$, let $\mathsf{symex}^i(s_{in}, \gamma_{in}, T)$ be the i-repeated application of $\mathsf{symex}(s_{in}, \gamma_{in}, -)$ to a set T of feasible traces, where the 0-repeated application $\mathsf{symex}^0(s_{in}, \gamma_{in}, T)$ is defined to be T. Also, lift the branch operation to a trace set:

$$\mathsf{branch}(T) = \bigcup\{\mathsf{branch}((\tau_i).C) \mid \tau \in T \wedge i \in \{1, \ldots, |\tau|\}\}$$

Theorem 4 (Completeness)**.** *For every $k \geq 1$,*

$$\mathsf{branch}(\text{ACTEve}(s_{in}, \gamma_{in}, k)) = \mathsf{branch}(\textstyle\bigcup_{i=0}^{k} \mathsf{symex}^i(s_{in}, \gamma_{in}, \{\epsilon\})).$$

The RHS of the equation in the theorem represents branches covered by running the standard concolic execution without pruning. The theorem says that our algorithm covers the same set of branches, hence same program statements, as the standard concolic execution.

5. EMPIRICAL EVALUATION

In this section, we present the empirical evaluation of our technique. First, we describe the implementation of ACTEve (Section 5.1). Next, we present the studies, including the subjects used, the empirical setup, and the study results (Sections 5.2–5.4). Finally, we discuss threats to the validity of the studies (Section 5.5).

5.1 Implementation

The implementation of our system uses the Soot framework [32], and consists of 11,000 lines of Java code. Figure 8 shows a dataflow diagram of our system. Our system inputs Java bytecodes of classes in *Android SDK* and *App under test*. Java bytecodes of a class are obtained by either compiling its source code (as done in our empirical evaluation) or converting Android's Dalvik bytecode into Java bytecodes [25]. Our system outputs a set of tests, *Test inputs*, each of which denotes an event sequence. The script shown in the inset box is an example of a test that our system can generate. Each line in the script corresponds to an event. `Tap` generates a tap event on the screen at the specified `X` and `Y` coordinates. Tests similar to the one in this script can be automatically executed using Monkey—a tool in the Android SDK.

```
Tap(248.0,351.0)
Tap(279.0,493.0)
```

Our system has four components: Instrumenter, Runner, Concolic testing engine, and Subsumption analyzer. We explain each in turn.

Instrumenter inputs *Android SDK*, and the Java class files of the *App under test*, and outputs *Instrumented (SDK+App)*. This component instruments the Java bytecodes of each class of the *App under test* and any third-party libraries that the *App* uses. It also instruments classes in the Android framework (e.g., `android.*`) but this step is performed only once because the way in which a class is instrumented does not depend on any other class.

Instrumenter operates on a three-address form of Java bytecode produced by Soot, called Jimple. Instrumenter performs three types of instrumentations. First, it instruments *App* for concolic execution, which involves two main steps: (1) adds a meta variable (field) that stores the symbolic value corresponding to each variable (field); (2) inserts a new assignment before every assignment such that the new assignment copies the content of meta variable (field) corresponding to the r-value of the original assignment to the meta variable (field) corresponding to l-value of the original assignment. Second, Instrumenter instruments *App* to record fields of Java classes that are written only *during* the handling of the last event in the sequence of events corresponding to a test. Third, Instrumenter ensures that in *Instrumented (SDK+App)*, user-specified method summaries are symbolically executed instead of the original methods.

Runner inputs *Instrumented (SDK+App)*. The first time the component is called, it generates a test randomly; thereafter, it inputs tests from either the Concolic testing engine or the Subsumption analyzer. Runner outputs *Test inputs* that includes the randomly-generated test and tests that it inputs. For each of those tests in *Test inputs*, it also outputs a *Path constraint* and a *Write set*, which are used internally by the other two components.

Runner executes *Instrumented (App)* with the test on an emulator that uses *Instrumented (SDK)*. Besides these Android framework classes, no other components of the framework, such as Dalvik virtual machine of the Android execution environment, are modified. This feature of our system makes it easily portable to different versions of Android.

Execution of a test generates the path constraint of the path that the *App* takes and *Write set*, which is a set of fields of Java classes that are written during the last event in the input event sequence. Writes to array elements are recorded as writes to one distinguished field. Runner uses a set of (typically 16) emulators each of which can execute a different test at any time. Such parallelism enables our system to perform systematic testing of realistic apps. Execution of an app in a realistic environment, such as an emulator or an actual device, takes orders of magnitude more time than execution of similar desktop applications.

Concolic testing engine inputs *Path constraint* of a path, and outputs *New tests for current iteration*. The component first computes a set of new path constraints by systematically negating each atomic constraint (i.e., conjunct) of the input path constraint, as in standard concolic testing. Then, it checks satisfiability of each of those new path constraints, and generates and outputs new tests corresponding to satisfiable path constraints using the Z3 SMT solver [8].

Subsumption analyzer inputs *Write set*, a set of fields of Java classes that are written when *App* responds to the last event in the event sequence corresponding to a specific test. It may output one *Seed test for next iteration*.

Subsumption analyzer implements the rprune operator in Algorithm 2. It outputs the test that corresponds to its input *Write set* if *Write set* is non-empty. The output test is called the seed test because new tests are generated in the next iteration by extending this test with new events. If *Write set* is empty, Subsumption analyzer outputs no test.

One important feature of Subsumption analyzer is that it can be configured to ignore writes to a given set of fields. This feature is useful because, in Android, many events lead to writes to some memory locations, which fall into two classes: (1) locations that are written to and read from during the same event of an event sequence (i.e., never written and read across events); (2) locations that result from Android's low-level operations, such as optimizing performance and memory allocation, and correspond to fields of Android classes that are irrelevant to an app's behavior. Subsumption analyzer ignores writes to these two classes of writes

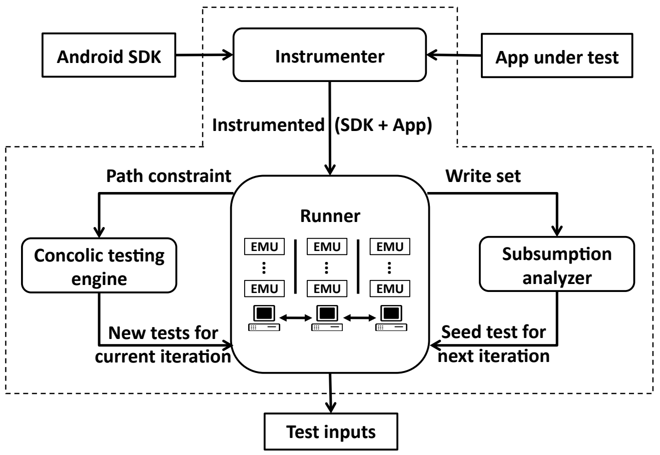


Figure 8: Dataflow diagram of our system.

because they are irrelevant to an app's behavior in subsequent events of an event sequence.

5.2 Subject Apps

We used five open-source Android apps for our studies. Random Music Player (RMP) is the app that is used as the example in Section 2. Sprite is an app for comparing the relative speeds of various 2D drawing methods on Android. Translate is an app for translating text from one language to another using Google's Translation service on the Web. Timer is an app for providing a countdown timer that plays an alarm when it reaches zero. Ringdroid is an app for recording and editing ring tones.

5.3 Study 1

The goal of this study is to measure the improvement in efficiency of ACTEve over AllSeqs. First, we performed concolic execution for each subject using ACTEve and AllSeqs. We used k=4 for RMP, Translate, and Sprite. However, because AllSeqs did not terminate for the other two apps when k=4 in our 12-hour time limit, we used k=3 for Timer and k=2 for Ringdroid. Note that ACTEve terminated for all five apps even for k=4. In this step, we used 16 concurrently running emulators to execute tests and compute path constraints for corresponding program paths. Second, for each algorithm, we computed three metrics:

1. The running time of the algorithm.
2. The number of feasible paths that the algorithm finds.
3. The number of satisfiability checks of path constraints that the algorithm makes.

We measure the running time of the algorithms (metric (1)) because comparing them lets us determine the efficiency of ACTEve over AllSeqs. However, by considering only running time, it may be difficult to determine whether the efficiency of our algorithm will generalize to other application domains and experimental setups. Furthermore, we need to verify that the savings in running time is due to the reduction provided by our algorithm. Thus, we also compute the other two metrics (metrics (2) and (3)).

Figure 9 shows the results of the study for our subjects. In the figure, the horizontal axis represents the three metrics, where each cluster of bars corresponds to one metric. Within each cluster, the five bars represent the corresponding metric

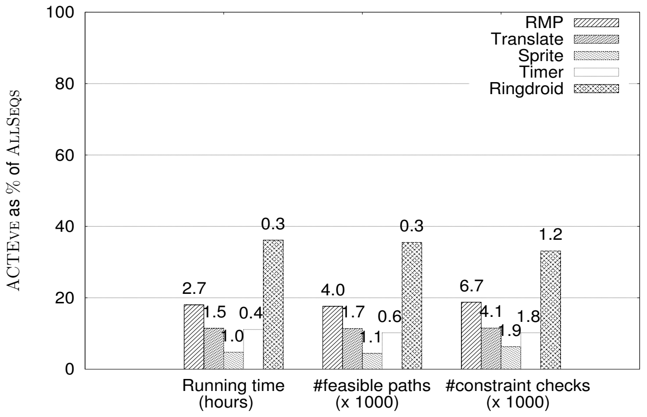


Figure 9: Results of Study 1: Running time, number of feasible paths explored, and number of constraint checks made by ACTEve normalized with respect to those metrics for AllSeqs.

for the five subjects. In the first cluster, the height of each bar represents the normalized ratio (expressed as a percentage) of the running time of ACTEve to that of AllSeqs. The number at the top of each bar in this cluster is the running time of ACTEve measured in hours. Similarly, in the second and third clusters, the height of each bar represents the normalized ratio of the number of feasible paths explored and the number of constraint checks made, respectively, by ACTEve to the corresponding entities for AllSeqs. The number at the top of each bar in the second and third clusters is the number of feasible paths explored and the number of constraint checks made, respectively, by ACTEve. For brevity, these numbers are rounded, and shown as multiples of a thousand. For example, the first cluster shows the ratio of the running time of ACTEve to that of AllSeqs: RMP is 18%; Translate is 15%; Sprite is 5%; Timer is 11%; Ringdroid is 36%. This cluster also shows that the running time of ACTEve is 2.7 hours for RMP, 1.5 hours for Translate, 1 hour for Sprite, 0.4 hours for Timer, and 0.3 hours for Ringdroid.

The results of the study show that ACTEve is significantly more efficient than AllSeqs. ACTEve requires only a small fraction (5%–36%) of the running time of AllSeqs to achieve the same completeness guarantee. Thus, using ACTEve provides significant savings in running time over AllSeqs (64%–95%). The results also illustrate why the running time for ACTEve is significantly less than for AllSeqs: ACTEve explores only 4.4%–35.5% of all feasible paths that AllSeqs explores; ACTEve checks significantly fewer constraints (6.2%–33.1%) than AllSeqs.

5.4 Study 2

The goal of this study is to record the number of paths pruned by ACTEve because this reduction in the number of paths explored highlights why ACTEve is more efficient than AllSeqs. To do this, we performed concolic execution of each app for k=4, and we recorded the following information for each iteration of ACTEve and AllSeqs:

1. The number of feasible paths that `symex` explores; recall that `symex` explores new feasible paths.
2. The number of feasible paths that remain after `prune`.

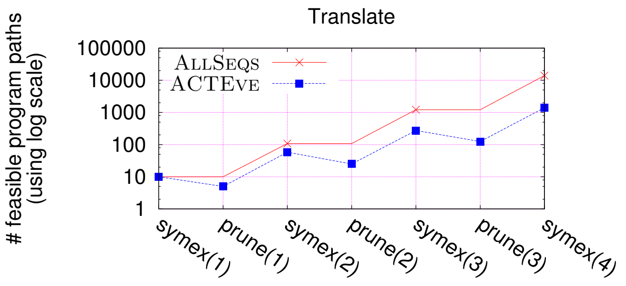


Figure 10: Results of Study 2 for *translate* app: The number of paths (using a logarithmic scale) after symex and prune operations in each iteration.

Figure 10 shows the results of the study for one subject app; the results for the remaining apps are similar, and are shown in Appendix D in [2]. In each graph, the horizontal axis represents the symex and prune operations performed in each iteration. The vertical axis shows the number of paths using a log scale. For example, the graph for Translate in Figure 10 shows that ACTEve explores 274 paths in iteration 3. The subsequent pruning step filters out 149 paths. Thus, only the remaining 125 paths are extended in iteration 4. In contrast, AllSeqs explores 1,216 paths in iteration 3, all of which are extended in iteration 4.

The results clearly show the improvement achieved by the pruning that ACTEve performs. First, the graphs show that ACTEve explores many fewer paths than AllSeqs, and the rate of improvement increases as the number of iterations increases. For example, in the fourth iteration of symex, ACTEve explores 1,402 paths and AllSeqs has explored 13,976 paths. Second, the graphs also show that, at each iteration of prune, the number of paths that will then be extended decreases: the descending line in the graphs represents the savings that prune produces. In contrast, the horizontal line for the same interval corresponding to AllSeqs shows that no pruning is being performed.

5.5 Threats to Validity

There are several threats to the validity of our studies. The main threat to internal validity arises because our system is configured to ignore writes to certain fields that do not affect an app's behavior (see Section 5.1 under "Subsumption analyzer"). We mitigate this threat in two ways. First, our implementation ignores only fields of Android's internal classes that are clearly irrelevant to an app's behavior; it never ignores fields of app classes, third-party libraries, or fields of Android classes (e.g., widgets) that store values that can be read by an app. Second, we ran our system using the AllSeqs algorithm (that performs no pruning), and checked if any ignored field is written in one event and read in a later event of an event sequence. Most of the fields that our system is configured to ignore are never read and written across events. For the few that were, we manually confirmed that it is safe to ignore them.

Threats to external validity arise when the results of the experiment cannot be generalized. We evaluated our technique with only five apps. Thus, the efficiency of our technique may vary for other apps. However, our apps are representative of typical Android apps considering the problem that our technique addresses.

6. RELATED WORK

Memon [21] presented the first framework for generating, running, and evaluating GUI tests. Several papers (e.g., [5, 23, 24, 35]) present components and extensions of this framework. Most existing GUI testing approaches either use capture-replay to infer the GUI model automatically [22, 31] or require users to provide the GUI model [34, 36]. An exception is the work of Ganov et al. [11], which uses symbolic execution to infer data inputs to GUI components. Our work also uses symbolic execution but focuses on event inputs. Our techniques for efficiently generating sequences of events are complementary to the above approaches.

Significant advances have been made in recent years to alleviate path explosion in concolic testing. These include compositional testing (e.g., [1, 12]), using program dependence information to avoid analyzing redundant paths (e.g., [4, 20, 27, 28]), using input grammars (e.g., [14]), using models of library classes (e.g., [18]) or constraint solvers that support higher-level program abstractions (e.g, [3, 33]), and using path-exploration heuristics that cover deep internal parts of a program (e.g., [19, 26]). Our input subsumption idea is complementary to the above ideas for taming path explosion. Our system indeed leverages some of the above ideas. It uses (1) method summaries and models for certain Android framework classes, (2) a grammar to specify input events, and (3) state-of-the-art constraint solving provided by the Z3 SMT solver.

7. CONCLUSION AND FUTURE WORK

In this paper, we presented a technique, ACTEve to automatically and systematically generate input events to exercise smartphone apps. We described our system that implements ACTEve for Android, and presented the results of our empirical evaluation of the system on five real apps. The results showed that for our subjects, ACTEve is significantly more efficient than the naive concolic execution technique, referred to as AllSeqs.

We have at least three important directions for future work. First, ACTEve only alleviates path explosion. The improved efficiency of ACTEve over AllSeqs may not be sufficient to handle apps that have significantly more paths than our subjects. An example of such an app is one that has many widgets (e.g., a virtual keyboard). We plan to study other subsumption patterns besides the read-only pattern that we currently exploit to tame path explosion. The independence pattern described in Appendix C in [2] is an example. Second, our system currently handles only one type of events (i.e., tap events). There are many other types of events such as incoming phone calls and gestures. Extending our system to handle other types of events will widen its applicability to more apps. Third, we intend to conduct a more exhaustive empirical evaluation with more subjects to further confirm ACTEve's improvement over AllSeqs.

Acknowledgments

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