ConsiDroid: A Concolic-based Tool for Detecting SQL Injection Vulnerability in Android Apps

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Abstract

Android is a famous OS among users. Existing vulnerabilities in Android apps cause severe harms to the security and privacy of users. Among different methods for detecting vulnerabilities, concolic execution is a dynamic method leading to high code coverage as opposed to random input generation testing. To the best of our knowledge, there is not any tool for detecting vulnerabilities in Android apps with concolic execution. In addition, there is not any Android concolic execution engine. By extending the code applications without any effect on their original source codes with mocking technique, they can be treated as Java application to be concolicly executed by SPF. Android apps are event-driven and inseparable from Google SDK. Our extending codes artificially generate events and make the codes independent from SDK libraries, generated automatically by static analysis. In addition, we take advantage of static analysis to adjust SPF to only inspect those suspicious paths to SQL injection vulnerability. A path is suspicious if it contains a vulnerable function leading to leakage. We conduct SPF such that it makes all application inputs and return values of vulnerable functions tainted. To taint such values, we present the idea of symbolic mock for input and vulnerable functions. An SQL injection vulnerability is detected when a vulnerable function receives a tainted value. Our extended SPF is equipped with taint analysis to detect SQL injection vulnerability. To illus-

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trate the applicability of ConsiDroid, we have inspected 140 apps from F-Droid repository selected randomly. From these apps, we found three apps vulnerable to SQL injection. To validate their vulnerability, we analyzed them manually based on ConsiDroid report.

**Keywords:** Concolic execution, Targeted Concolic Execution, Vulnerability Discovery, SQL Injection Vulnerability, Android apps

### 1. Introduction

At the end of 2017, 2.7 million devices used Android operating system. It makes 88 percent of total mobile devices [1]. In addition, there were 3.3 million apps available on Google Play in March 2018 [2]. These numbers shows that Android is the most popular OS among users and developers. Therefore, it is an important target for attackers in order to exploit security vulnerabilities on Android apps to affect a large number of victims. For preventing such attacks, various approaches are presented. There are a set of approaches like [3, 4, 5, 6, 7] based on static analysis to detect security vulnerabilities. These approaches have inherited the natural flaws of static analysis: high false alarm rates and the inability of analyzing dynamic codes loaded at runtime.

To overcome these flaws, an app is analyzed when it is running by dynamic approaches. To run apps, the input data and events that trigger their various parts should be generated artificially. Based on the taxonomy of [8], there are two main techniques used by dynamic approaches for input generation: fuzzing and concolic input generation. Fuzzing generates inputs randomly, for instance used by Android Monkey [9], but this technique suffers from low code coverage. Concolic input generation technique supports high code coverage and hence, more states of the program are inspected during the analysis (see Section 2.1). This technique improves symbolic analysis technique by which variables are represented symbolically and their values are chosen by a constraint solver to cover more execution paths of a program. By this technique, a program is executed by symbolic and concrete values simultaneously to resolve cases when
the constraint solver cannot generate new inputs for symbolic values. In this paper, we choose concolic executions to analysis more lines of codes. It is worth to mention that there is not any concolic and even symbolic engine for testing Android apps. Therefore, we are going to use and extend SPF \cite{10} (a symbolic extension of Java Pathfinder) in order to test and detect vulnerabilities in Android apps by using concolic testing technique. In this paper, we present ConsiDroid, a Concolic-based SQL Injection vulnerability detection tool in Android Apps.

For concolically executing an Android app by SPF, we extend apps under the test to make them behave like Java programs. Android apps have not main function as their entry point. They have different ways for starting to run like tapping a URL or receiving an incoming call. Without changing the source code, we extend the testing app by adding new classes, called DummyMain classes, which indicate how to start running the app. They are produced through static analysis of the app such that only events leading to call a vulnerable function are considered to overcome the path explosion problem of concolic execution. Google provides an SDK\footnote{Software Development Kit} to ease the development of Android apps. These apps are built by extending the SDK, which is an inseparable part of them. In addition, they are event-driven. Concolic execution of Android apps in SPF is impossible without the existence of SDK classes, which we trust in. Including SDK classes during concolic executions leads to path divergence problem. Therefore, we use the mock class idea \cite{11} for emulating SDK functionality. Mock classes are the same as real ones except that the bodies of their class functions have been omitted while their return values have been replaced with default ones.

We modify and extend the concolic engine in SPF to optimally detect SQL injection vulnerabilities. The quality of an app code is ranked in OWASP mobile top ten \cite{12}. We focus on SQL injection vulnerability as it is directly related to the quality of code. This attack happens when inputs fed into SQL related
functions are not properly controlled. For detecting this scenario, we use taint analysis, which tracks values from sources to sinks. We make it dynamic through concolic execution and the symbolic mock classes idea. In addition, we take advantage of static analysis for enhancing the performance of ConsiDroid. To this aim, we automatically extract vulnerable paths through static analysis and give them precedence during concolic execution. With this idea, the time analysis reduces very well.

The remainder of the paper is organized as follows. Section 2 covers some background about concolic execution, Android OS, challenges of concolic execution in Android apps, taint analysis, and SQL injection vulnerability. Section 3 gives an overview of ConsiDroid. Section 4 describes how to produce Dummy-Main classes and vulnerable paths. Section 5 gives information about mock and symbolic mock classes. Section 6 presents the ideas that are used in extended concolic execution for detecting SQL injection vulnerability. To validate the results of ConsiDroid, we explore manually the derived vulnerable paths by our tool with the help of Robolectric tool in Section 7. To illustrate the applicability of ConsiDroid on real world apps, we apply it on several application in Section 8. Section 9 is about related work and the paper is concluded in Section 10.

2. Background

In this part, we introduce concolic execution and its pros and cons briefly. In addition, we explain some essential topics in Android. We discuss challenges when dealing with concolic testing of Android apps. We explain taint analysis as we use it to track flow of values to detect SQL injection. Finally, we present the conditions that an attacker needs to exploit for SQL injection.

2.1. Concolic Execution

Concolic execution means simultaneously executing program symbolically and concretely. In symbolic execution, we consider some values as symbolic. For instance, the simple code in Listing 1 is executed with the symbolic variables $X_0$ for $x$ in line 9 and $Y_0$ for $y$ in line 10. In this approach, conditions are
important points. Each path condition is made of the logical conjunction of conditions, which are collected during the execution of a specific path. For example, in testMe function, one path condition can be \((Y_0 > 5 \land X_0 \times X_0 \times X_0 \leq 10)\). A path condition indicates which branches of the code have been executed recently. The execution tree of a program is the mixture of all path conditions (Fig. 1): the intermediate nodes contain constraints while the leaf nodes contain the concrete values satisfying the constraints over the path, generated by the constraint solver. In symbolic execution, we want to cover all possible paths in the execution tree. Therefore, we execute the code and construct a path condition during the execution. For each conditional statement, symbolic execution is forked to cover both then and else branches. At the end, the execution tree of the program is built. For producing a test input for a specific path in the execution tree, we use a constraint solver like SMT, which solves logical expressions and produces the suitable values. Constraint solvers have some weakness in solving some complex expressions like non-linear expressions, e.g., \((X_0 \times X_0 \times X_0 \leq 10)\). In pure symbolic execution, testing of the code is stopped at this point and we are not able to have test inputs to execute some lines of code like line 4.

For alleviating the problem, concolic execution is used which executes the code with concrete values in addition to symbolic ones. First, the concrete values are generated randomly. Assume that \(x = 0\) and \(y = -1\). These values produce the condition \((PC_1 = Y_0 \leq 5)\). New concrete values are generated by negating the last constraint in the path condition \((\neg(Y_0 \leq 5) = (Y_0 > 5))\). A constraint solver can solve the condition \((Y_0 > 5)\), resulting in \(x = 0\) and \(y = 6\) as the new values. These new values build the path condition \((PC_2 = Y_0 > 5 \land X_0 \times X_0 \times X_0 \leq 10)\). Whenever a constraint solver can not solve an expression, concrete values are randomly generated \((y = 6\) and \(x = 11\)). With this trick, we may reach codes that cannot be explored during symbolic execution (line 4). So, the concolic execution has better code coverage than pure symbolic execution.
With concolic execution, the problems of static analysis, i.e., the existence of false alarms [13] and the ignorance of codes loaded at runtime [8], are handled as the codes are executed. However, concolic execution has some issues:

- **Path explosion**: when we analyze real-world programs, we face too many lines of codes, hence, their execution trees contain a large number of paths. Testing in this situation is time and memory consuming. We tackle this problem by presenting our hybrid concolic execution for testing Android apps. In this approach, we take advantage of static analysis to make concolic execution targeted.

- **Frameworks and environment modeling**: a lot of programs are developed with frameworks. It means that a developer uses third-party libraries and software kits. In our testing approach, we trust this kind of codes and we just want to test developers program. Also in different systems, we face a different kind of environmental issues. For example in the Android system, apps have event-driven nature and we should model these events. In this work, we use the idea of mock classes [11]. Also, we present symbolic
mock classes as our own idea in order to overcome these issues.

Furthermore, we use SPF\textsuperscript{10} as a concolic engine and we extend it in order to detect SQL injection vulnerability in Android apps. SPF is built on JPF\textsuperscript{14}, a Java bytecode model checking tool. In SPF, bytecodes are converted to 3-address intermediate instructions. These instructions execute on a modified JVM. SPF supports different kind of constraint solvers including solvers which support strings. Also in SPF, we can indicate that which variables or methods should be symbolic.

2.2. Challenges on Concolic Execution in Android Apps

An Android app consists of some activities. An activity manages pages that can be seen on the device screen by users. According to the Android developer documentation, the activity lifecycle is specified by different states that its instances move between them. Each activity class provides a number of callback functions by which the activity instance is informed that its state has changed for example the system is creating, stopping, or resuming an activity, or destroying the process in which the activity resides \textsuperscript{15}. In Fig. 2 an activity lifecycle is shown. Each activity includes some visual components, which are implemented by the widget package like Button, EditText, and TextView. We call them widgets in this paper. Each widget has a unique ID, which is collected in the R class of an app. With this ID, developers could access supporting widget class methods.

Figure 2: A simplified illustration of activity lifecycle \textsuperscript{15}. 
Android offers a mechanism for inter process communication (IPC) using remote procedure calls, by which a method is called by an activity or other application components, but executed remotely (in another process), while its result is returned back to the caller \[10\]. With the content provider, it hides the details of how the interprocess communication is managed.

As we mentioned before, Google SDK is an inseparable part of Android apps, which has an event-driven nature. Therefore, in the concolic execution of Android apps, one problem is modeling events. Usually, Android apps are written in Java but there are fundamental differences between Android and Java programs. In addition, we utilize SPF as the concolic execution engine since there is no concolic and even symbolic engine for Android apps. Challenges of testing Android apps with concolic execution are:

- Android codes are run within DVM\(^2\). It means that codes are compiled to Dalvik bytecode. However, Java codes are run within JVM\(^3\) and compiled to Java bytecodes. In addition, unlike Java programs, which start from the main function, there is no such function in Android apps. These apps are event-driven, so they can start by tapping an icon or by receiving an SMS and tapping a URL within a text. To use Java engine, Android codes should be changed in order to be run within JVM. For this goal, we produce DummyMain classes by static analysis from which the Android programs starts. This class simulate the events as the consequence of the user involvement or operating system interaction by calling related functions.

- Android apps are too dependent on SDK. Therefore, it causes path divergence\[^{17}\] in testing. In symbolic execution, path divergence means the execution of a path leads to call a framework or a library function with symbolic values, making the execution diverge from the developed code. This causes two

\(^2\)Dalvik Virtual Machine
\(^3\)Java Virtual Machine
main problems:

– It is possible that during testing these libraries or frameworks, functions do not exist. For example, they exist in the device but not in the testing environment.

– If we assume that these methods are present, some constraints are added to the path condition due to the conditional statements in their body. Therefore, instead of focusing on developer codes, we stuck with testing of the framework or third-party libraries codes, which we trust in.

As a common example, accessing and modifying data communicated between apps are possible by IPC mechanisms. For example data stored in SQLite database of an app can be accessed by other apps with this mechanism. To this aim, the first app sends its query to SDK. Then, SDK sends it to the second app. For testing SQL injection vulnerability through IPC, path divergence problem is important. To overcome this issue, we present the idea of mock classes.

2.3. Taint Analysis

The purpose of taint analysis is to track information flow between sources and sinks [13]. Tainted values are derived from sources and other values are treated as untainted. For each taint analysis, a policy is defined and enforced. The policy determines which values are tainted, how they propagate through the program, and how they should be analyzed.

In this work, we are going to use dynamic taint analysis in order to detect SQL injection vulnerability in Android apps. In our analysis, sources are the inputs of an app and sinks are the vulnerable functions. As the source and sink functions belong to SDK classes, so they are used within mock classes. We make the input and output values of these functions symbolic, to denote tainted values, and hence, the resulting classes are called symbolic mock classes. Our
taint propagation and SQL injection vulnerability detection policy are explained in sections 6.2 and 6.3 respectively.

2.4. SQL Injection in App or through IPC

Android apps use SQLite database for storing data. SDK provides some libraries to manage using SQLite. There are secure and insecure methods for implementing database queries in this library. For implementing securely, the developer should use parametric functions in SDK. In parametric functions, a developer uses “?” character instead of user inputs. In the database, when a parametric function is used, first the parse tree of the query is built and then the user data substitute for “?” in the tree. This method prevents injecting commands in queries. In Fig. 2 lines 2 and 3 are an example of the insecure and secure method of building queries, respectively.

Android provides a mechanism for accessing and modifying other app data like SQLite databases if the second app permits. This feature is possible through IPC. If the developer of the second app does not use parametric functions, then SQL injection is possible between the two apps.

List of all functions in SDK through which SQL injection is possible is {query, queryWithFactory, rawQuery, rawQueryWithFactory, update, updateWithOnConflict, delete, execSQL}.

For detecting an SQL injection vulnerability, the following conditions should be present in apps: 1) existence of a path from an app input to a vulnerable function, 2) use of parametric functions, and finally 3) the result of query propagates to leakage functions by which an attacker can access the result of a database query. For example, printing the result on screen by TextView is considered as a leakage function.
String st = editText.getText().toString();
Cursor c = db.rawQuery("SELECT * FROM student WHERE stdno = '"+st+"'", null);
// insecure way
Cursor c = db.rawQuery("SELECT * FROM student WHERE stdno=?'", new String[]{st});
// secure way
textView.setText(buffer);

Listing 2: Secure and insecure way of building query in Android

3. Overview of ConsiDroid

An overview of ConsiDroid is given in Fig. 3. ConsiDroid has five main parts:

1. **Static Analysis**: By static analysis, we have two main goals. First is producing the main function in order to compile and run the app in JVM. We produce the main function in a class, which we call it DummyMain, and extend each app’s code with a set of DummyMain classes. Second is optimizing our dynamic analysis. To overcome the path explosion problem of concolic execution, we make our analysis hybrid and targeted. In other words, by means of static analysis, we limit the execution of an app to the desired paths, called *vulnerable paths*, during our concolic execution.

2. **Mock and Symbolic Mock Classes**: As we mentioned before, we use SPF. Therefore, for running Android apps on JVM, SDK libraries and its functions should be modeled. We use mock classes for modeling the SDK. In addition, for our taint analysis, we need to track the propagation of tainted variables from source to sink functions. We present symbolic mock classes idea for some specific SDK libraries to complete our taint analysis.

3. **Extended Concolic Execution Engine**: Our concolic execution engine is SPF, which is a Java testing tool. With extending Android app codes by DummyMain, mock and symbolic mock classes without changing the original source codes, we can test them on SPF. We extend SPF in two
aspects. First, we develop a component for SQL injection vulnerability detection. Second, we manage concolic execution to examine the vulnerable paths extracted by our static analysis at first.

4. **Vulnerability Detection Report**: Our analysis results help developers to patch their apps and fix SQL injection vulnerabilities. In the report, we present ID and the name of the source and sink functions and the stack trace of the program from the source to each vulnerable function. In addition, if parametric functions were not utilized to secure the code, we highlight them in our report.

5. **Robolectric**: For validating our result, we use Robolectric [19], which is a unit testing tool for Android apps. For testing an app with Robolectric, we should specify the testing path. We use DummyMain class and vulnerability detection report to build Robolectric test inputs.

4. **Static Analysis**

In our approach, we take advantage of static analysis to produce Dummy-Main classes. Our smart generation method causes the execution tree of the app to be pruned. Furthermore, we prioritize the paths of the resulting execution tree by static analysis to make dynamic analysis examine its vulnerable paths at first. We use Soot[20] framework to statically analyze apps. Soot extracts the essential graphs that our static analysis relies on. In this part, we discuss
our algorithms.

4.1. Generation of DummyMain classes

As we mentioned before, unlike Java programs there is no “main” function in Android apps. Therefore, for testing apps on SPF and running them on JVM, we need to extend its code. Our extending class is called DummyMain, which is produced by using static analysis without any changes in the original source code. For static analysis, we take advantage of the call graph (CG) of the program, which is built by the Soot framework. This graph is based on Android features and produced by connecting all possible sequences of calling functions to its root node. If we traverse the CG by a DFS algorithm, we can generate all possible DummyMain classes. For optimizing our analysis, we focus on testing extended apps with DummyMain classes which lead to call one of vulnerable functions during their execution. For generating such DummyMain classes, we traverse the CG backward from each vulnerable function to the root node, and a DummyMain class is generated from each possible backward path. It is worth to mention that if there is not any vulnerable function in an app, we do not continue its analysis. During the backward traversal of CGs, we collect information about called functions. There are three different types of functions. First type is Normal, which is built by developer in an app. Second is Listener, that the name of its class contains the special character “$”. This type of functions is called when an event is produced. In addition, for calling this functions, first we should call their corresponding parent class that its name is obtained by omitting $ suffix. Third is Android framework functions, for example functions which are called in the life cycle of an activity. These kind of functions are called in DummyMain class when we want to call a class extending the Activity class.

As an example in Fig. [4] the CG of a simple app is shown. This app consists of two activities, namely MainActivity and SecondActivity. In addition, there are Button, EditText and TextView in MainActivity. When Button is clicked, the string of EditText is used to generate an SQLite query and the result of
Figure 4: The call graph of a simple app.

Listing 3: A sample of DummyMain class.

```java
public class DummyMain {
    public static void main(String[] args) {
        MainActivity ma = new MainActivity();
        ma.onCreate(null);
        Button b = (Button) ma.findViewById(R.id.button);
        b.performClick();
    }
}
```

the query is shown in TextView. Only one DummyMain class is generated for analyzing this app as shown in Listing 3. For producing this DummyMain class, we start from the node 5, which contains a vulnerable function. By backward traversal, we visit the node 3, which is a listener function and then the root node. For building the code, we start from the last node except the root in our backward traversal, which is the node 3. The vulnerable function SQLiteDatabase.query() is called by MainActivity$1.onClick(). Therefore, we should produce codes that cause executing the onClick function. The parent class of the listener function onClick is MainActivity, which extends Activity. As we mentioned before, for listener functions, their parent classes should be called first, resulting in the code at line 3 in Listing 3. In addition, line 4 is added because MainActivity extends Activity and functions, which are related to Android framework should be called in order to follow up the Activity life cycle as illustrated in Fig. 2. For brevity the other functions of the life cycle have been omitted here. The listener onClick is performed when an event is produced by the interaction of users with the app. In DummyMain, we simulate this event by the codes at lines 5 and 6. By static analysis of the MainActivity code, we
find ID (R.id.button) and type (Button) of the relating component with the onClick listener function. Line 6 is actually the code which simulates the tap event on the button.

4.2. Prioritize execution paths

We optimize our dynamic analysis by limiting it to test the execution paths of an extended app with DummyMain classes leading to call vulnerable functions. We improve these tests by forcing SPF to execute our desired paths at first. By this idea, first we visit nodes in the execution tree of the extended app that are on vulnerable paths. By static analysis, Soot extracts inter-control flow graph (ICFG) of the app, which contains function calls in addition to the control flow graph of each functions. We find vulnerable paths from ICFG by backward traversing from a vulnerable function call to the root node. During the traversal, we collect information about each conditional statements. For each conditional branch, we also push the precedence of then branch over else or vice versa in a stack. We use stack because in concolic execution unlike our static analysis, we traverse the execution tree in a forward fashion. Therefore, the top entry in the stack is referred as the first conditional statement in the concolic execution.

In Fig. 5 a simple ICFG is shown. Without our static analysis, SPF executes it by a DFS algorithm in which then branches have precedence over else in conditional statements. Our static analysis extracts the vulnerable path passing through 1,2,3,6 and 8 nodes. In the stack we push the precedence of then for the node 3 and after that the else branch for the node 2. Therefore, after visiting
the nodes 1 and 2, we force SPF to execute the node 3 and then force it to run the node 6. By this idea, we execute the vulnerable path concolicly at first.

5. Mock and Symbolic Mock Classes

Mock classes are the same as their corresponding real ones except that the bodies of their functions have been removed while their return values have been changed to default ones. For example in Listing 4 (left), a part of EditText’s mock class is shown. In this class, return value of getText function is set to null at line 7. Symbolic mock classes are the same as mock ones except that symbolic values are returned instead of the default value. In Listing 4 (right) line 7, the return value of getText has been made symbolic by makeSymbolicString, which is a SPF engine function.

```java
1 public class EditText extends View
2 {
3     private String content;
4     public EditText(String text) {
5         this.content = text;
6     }
7     public String getText() {
8         return null;
9     }
10 }
```

Listing 4: The mock (left) and symbolic mock (right) classes generated for EditText

For running extended Android apps on JVM and preventing path divergence problem, we need to mock SDK classes. Mocking SDK classes needs more effort in order to simulate the Android environment. To this aim, we produce them manually. The idea of mocked classes come from the function summary method [21]. To prevent multiple execution of specific functions over different runs, the function summary method was introduced. By this method, the body of each function is tested at most once. During the execution of a body, constraints
from conditional statements are collected. In the next function calls, instead of executing the function again, these constraints are conjuncted with the path condition leading to this call. We take advantage of this idea within the mock class idea. In mocking, the default constraints of functions are always “true”. Therefore, they have not any effect on the path conditions of the app.

In addition to mock classes, we also produce symbolic mock for some specific SDK classes, which contain an input or vulnerable functions. As we mentioned in Section 2.3, we perform our taint analysis in parallel with concolic execution by making tainted values symbolic. Symbolic mock classes help us in this context. Actually, we make the input values of an app and also the result of vulnerable functions tainted.

6. Extended Concolic Execution Engine

For detecting SQL injection vulnerability, we use dynamic taint analysis. For detecting vulnerability, we should define our security policy of the detection [18]. We define our security policy in Sections 6.2 and 6.3 after discussing our optimization approach in Section 6.1.

6.1. Targeted Concolic Execution

In addition to limiting our analysis to extended apps with DummyMain classes which lead to calling vulnerable functions, for optimizing concolic execution, we use the vulnerable paths, which are found by our static analysis (see Section 4). SPF concolicly analyzes the program and traverses the execution tree forward. For each conditional statement in the code, SPF has two choices e.g., then and else branches. By default, SPF chooses the then branch. Therefore, SPF traverses the tree with a DFS algorithm. We prioritize branches, collected in the stack through the static analysis explained in Section 4.2. So, SPF first analyzes the vulnerable paths. By this idea, we improve the time and memory of analysis.
6.2. Dynamic Taint Analysis

As you know, injection attacks occur by manipulating the input data of a program and make them malicious. The input of an Android app could be at various points, e.g., user interface, network, file, system notifications, IPC, etc. From these points, data enter the app and propagate. If there is a path from input channels to vulnerable functions, there could be a chance for injection vulnerability. In addition, a successful injection attack happens when the result of vulnerable functions propagates to leakage functions to be observed by an attacker. Leakage functions are widgets in the user interface, network, file, IPC, etc.

To reduce the number of false alarms, we use dynamic taint analysis for detecting injection vulnerability. For this goal, we use concolic execution in combination with taint analysis by making tainted values symbolic. SPF has the ability to make specific variables symbolic. With SPF and symbolic mocked classes, we perform dynamic taint analysis for Android apps.

6.3. SQL Injection Detection

Apps connect to their own SQLite database or may connect to other app database with IPC mechanisms. In both scenarios, there is a possibility of SQL injection vulnerability. We design an algorithm and develop it as an SPF component for detecting SQL injection based on dynamic taint analysis and concolic execution.

In our analysis, we should produce symbolic mock of some classes for tracking propagation of symbolic values in the program as tainted values. These symbolic mock classes are inputs of the app like EditText or classes containing vulnerable functions like SQLiteDatabase. For supporting SQL injection detection through IPC (see Sections 2.2 and 2.4), it is enough to produce a mock class for ContentProvider of SDK by removing all statements except SQLiteDatabase function call statements in the body of its functions. ContentProvider is name of implemented SDK class for content provider concept.
We run the concolic execution until a vulnerable function is called. Next we check its input argument. If the input contains a symbolic variable (e.g. it is tainted value), then we check if its function development is parametric or not (see section 2.4). If it is not parametric, there could be a chance of injection vulnerability. Otherwise it is secure. For completing the chain of a vulnerability occurrence, we continue concolic execution until a leakage function is called. If the input argument of the leakage function is symbolic, which is coming from the result of the vulnerable function, we found a path from an input to a vulnerable function proceeded by a leakage function.

7. Exploitability Testing by Robolectric

By dynamic taint analysis, we find all the paths in a program, which conforms with our detection security policy. For ensuring the result of ConsiDroid, we use Robolectric, which is a testing tool for Android apps and independent of Android environment for its tests. Robolectric needs a target path for testing. In our work, we use DummyMain class (see Listing 3) and vulnerability detection report as its inputs to generate the Robolectric test input.

```
public void SqlInjection_Exploitability() throws Exception {
    Activity ma = Robolectric.setupActivity(MainActivity.class);
    Button b = (Button) ma.findViewById(R.id.button);
    EditText et = (EditText) ma.findViewById(R.id.editText);
    TextView tv = (TextView) ma.findViewById(R.id.textview);
    et.setText("a' or '1'='1");
    b.performClick();
    Logger.error((String) tv.getText(),null);
}
```

Listing 5: A sample input code of Robolectric for exploiting the app.

In Listing 5 an input of Robolectric is shown. As you can see, there are many similarities between this code and the code of Listing 3. Lines 4, 5, 6 and
8 are new in this code. The new codes containing IDs of the input (line 4) and leakage (line 5) widgets, which have been collected in the report. For testing SQL injection, we use malicious inputs like a’ or ‘1’=‘1 (line 6). For various type of SQL injection vulnerability, we should use different input strings, which we could guess them by the vulnerable reported query. The output of Robolectric execution, which is the result of a malicious query leaked by tv object, can prove the existence of vulnerability (line 8).

8. Evaluation

To evaluate ConsiDroid, we formulate three research questions:

1. Is ConsiDroid capable of generating test cases for real-world Android apps?
2. How scalable is the approach in detecting SQL injection vulnerabilities for real-world apps?
3. How well does ConsiDroid perform? Can ConsiDroid detect SQL injection vulnerabilities in a reasonable time? How much code coverage is needed to detect a vulnerability?

In our experiments, we use Ubuntu linux 16.04 installed on a virtual machine with 12 gigabytes RAM, configured with one processor. This VM is running on a machine with Intel(R) Core(TM) i7-6700 3.4GHz processor.

| Apps  | Total Methods | Max Number of Activities | Suspected Apps |
|-------|---------------|--------------------------|----------------|
| Type-0| 22            | < 5000                   | 9              | 1              |
| Type-1| 10            | 5000 - 10000             | 18             | 3              |
| Type-2| 28            | 10000 - 15000            | 9              | 1              |
| Type-3| 31            | 15000 - 20000            | 20             | 6              |
| Type-4| 29            | 20000 - 25000            | 21             | 1              |
| Type-5| 16            | 25000 - 30000            | 16             | 1              |
| Type-6| 4             | > 30000                  | 7              | 1              |

For investigating the question 1, we apply ConsiDroid to 140 real-world apps from F-Droid [22] that is an open source Android apps repository. We choose
the apps randomly without any limitation. We have categorized these apps into seven types according to their total number of methods as shown in Table 1, as this number has a direct effect at finding vulnerable methods in each app. To characterize each type category, we have also measured the maximum number of activities of its apps. As a result, ConsiDroid generated DummyMain classes only for 14 apps (due to the existence of at least one path from a vulnerable function to the root of their CGs) by its static analysis. It means that there is not any vulnerable functions or suspected paths in other apps. We checked the correctness of our generation by reviewing the apps manually before applying our dynamic analysis. From these apps, five cases were generated correctly and nine were generated wrongly due to their code obfuscation. As we know static analysis approaches cannot handle obfuscated codes. All the five apps were reported by our dynamic analyzer vulnerable to SQL injection except two that were protected by parametric functions. We evaluated the reports by using Robolectric as explained in Section 7 and they were truly vulnerable to SQL injection. From these five vulnerable apps, one of them was vulnerable through IPC mechanism.

For addressing the question 2, as you can see in Table 1, ConsiDroid can find SQL injection vulnerability in apps with different types. To show the complexity of these apps, Table 2 characterizes the 14 suspected apps in terms of two additional features, namely the number of exploited SDK classes, and the maximum method call sequence depth. The number of SDK classes specifies the hardness of producing mock classes while the maximum method call sequence depth determines the difficulty of producing DummyMain classes. We also added three vulnerable apps at the end of the table, one known and two

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4We extracted the total number of methods, SDK methods and activities for each app with the help of apkanalyzer tool. This tool works on the bytecodes of a class or method in smali format.

5We extracted the maximum method call sequence depth with the help of Soot. It is worth to mention that Soot analyzes Android apps in Jimple format, which is a simplified version of Java source code that has a maximum of three components per statement.
manually generated. The apps that dynamic analysis was not applied to them (due to the false positive result by the static analysis) have been specified by N/A (Not Applied) flag in the “Result” column. The apps that were reported vulnerable to SQL injection but protected by parametric have been identified by N flag. The apps with Y flag were reported as vulnerable.

Table 2: Specification of 17 apps, which is analyzed as suspected in static phase.

| Name            | Type  | Total Methods | SDK Methods | Activity | Max Method | Call Sequence | Result |
|-----------------|-------|---------------|-------------|----------|------------|---------------|--------|
| clock           | Type-0| 1306          | 532         | 3        | 17         | N/A           |        |
| mandarin        | Type-1| 6930          | 2240        | 18       | 21         | N/A           |        |
| ktodo           | Type-1| 8716          | 2725        | 4        | 13         | N/A           |        |
| siletric        | Type-1| 8984          | 2488        | 5        | 6          | N/A           |        |
| musicplayer     | Type-2| 13112         | 3564        | 4        | 10         | Y             |        |
| simpleaccounting| Type-3| 15086         | 4290        | 6        | 13         | N/A           |        |
| freetrackgps    | Type-3| 16385         | 3677        | 9        | 16         | Y             |        |
| iseeu           | Type-3| 16670         | 4052        | 2        | 15         | Y             |        |
| tinykeepass     | Type-3| 16975         | 4393        | 4        | 18         | N/A           |        |
| Tweetin         | Type-3| 18962         | 3768        | 7        | 12         | N/A           |        |
| smsdroid        | Type-3| 19067         | 4667        | 12       | 15         | N*            |        |
| reminder        | Type-4| 20287         | 4626        | 3        | 7          | N             |        |
| blackberrymanager| Type-5| 28635         | 5759        | 8        | 33         | N/A           |        |
| WifiLocationLogger| Type-6| 37017         | 6375        | 1        | 15         | N/A           |        |
| sieve**         | Type-0| 4006          | 1210        | 8        | 10         | Y             |        |
| testak-1***     | Type-4| 21533         | 4991        | 1        | 5          | Y             |        |
| testak-2***     | Type-4| 21537         | 4996        | 2        | 5          | Y             |        |

* This app is used by ContentProvider.
** This app is used by OWASP.
*** These apps are developed by author.

To show the impact of these four metrics namely, total number of methods (No. M), the number of exploited SDK classes (No. SDK), the maximum number of activities (No. Act), and the maximum method call sequence depth (Max MCS), on the scalability of our approach, we measure the complexity of the eight apps to which our dynamic analysis was applied to examine how their
complexity affects the execution time of the dynamic analysis. To this aim, we computed the percentile rank of their metrics as shown in Table 3. Following the approach of [11], the complexity class of each app can be computed in terms the percentile rank of their metrics. An application belongs to the 10th overall complexity class if it belongs to the 10th percentile in the four dimensions. In other words, an app belonging to a lower class is less complex with respect to all four dimensions compared to an app from a higher class. As it is illustrated in this table, “smsdroid” is the most complex app among them, and the increase in the app complexity results in a small increase in our dynamic analysis execution time due to our targeted analysis. We can conclude that cosiDroid is capable of scaling to even the most complex Android apps.

Table 3: Characterization of apps in terms of the percentile rank of their complexity metrics. The number of produced DummyMain classes, the amount of time and code coverage needed to detect SQL injection vulnerability are present.

| Name   | No. M | No. SDK | No. Act | Max MC | Time(ms) | Code Coverage | Produced DummyMains |
|--------|--------|---------|---------|--------|-----------|---------------|---------------------|
| musicplayer | 34%    | 34%     | 58%     | 34%    | 49        | 52%           | 3                   |
| freetrackgps | 45%    | 37%     | 90%     | 66%    | 22        | 33%           | 8                   |
| iseeu   | 49%    | 45%     | 21%     | 60%    | 13        | 24%           | 2                   |
| smsdroid| 61%    | 64%     | 95%     | 59%    | 23        | 36%           | 2                   |
| reminder| 66%    | 62%     | 40%     | 19%    | 17        | 26%           | 3                   |
| sieve   | 12%    | 12%     | 86%     | 33%    | 24        | 31%           | 4                   |
| testak-1| 72%    | 71%     | 2%      | 4%     | 41        | 46%           | 2                   |
| testak-2| 73%    | 72%     | 22%     | 6%     | 37        | 44%           | 3                   |

For answering the question 3, we present the time and the amount of the code coverage of analyzing each app with ConsiDroid for detection of SQL injection vulnerability in table 3. In addition, we have shown the number of produced DummyMain classes for each app. With ConsiDroid, we could find the vulnerability almost with less than 50% of the code coverage as a result of our targeted analysis in a reasonable time which is less than the time of running all the paths of each app. As we mentioned before, we present the first tool in this community...
for finding vulnerability in Android apps with concolic execution technique. So, there is not any similar tool for comparison with ConsiDroid.

9. Related Work

DART [13] is the first work that presented concolic execution method for testing programs. KLEE [24] is another tool for concolic execution. In this work unlike DART, in conditional statements, both branches are executed in parallel for enhancing the time of testing. DART and KLEE are just for C programs. In addition, there are some other tool like SAGE [25], AEG [26] and Mayhem [27] for detecting software vulnerabilities. In addition to detecting vulnerabilities, AEG and Mayhem produce exploit codes automatically. These works support Windows or UNIX based operating systems.

ACTEVE [28] is the first paper on testing Android apps with concolic execution. This tool only supports tap event sequences less and equal than four. Condroid [29], an extension of ACTEVE, detects logic bomb Android malware. AppIntent [30] is a tool for detecting privacy violation in Android apps with concolic execution. AppIntent uses static taint analysis in order to enhance concolic execution and make a targeted concolic analysis. Malton [31] is a tool for detecting Android malware apps by using binary analysis with the assistance of Valgrind [32]. Malton analyzes the app inside the device, so there is no need for producing mock classes. Sig-Droid [11] is a tool for testing Android apps with symbolic execution. We were inspired by this tool for producing mock classes of SDK and using SPF. In paper [33] a tool is introduced for detecting Android framework vulnerabilities with symbolic execution. The target of this tool is the Android framework and not Android apps. To the best of our knowledge, our research is the first one for detecting SQL injection vulnerability in Android apps.

In table 4 there is a comparison between ConsiDroid and other Android testing tools with different dynamic approaches. As it is shown, this comparison is based on searching methods, supporting event types, if they exploit static
analysis to enhance their dynamic approach, and the path explosion problem existence in the tools, which is not applicable to Monkey.

Table 4: Comparison of ConsiDroid with other dynamic testing Android tools.

| Tool       | Search method | Events                  | Static + Dynamic Analysis | Path explosion problem |
|------------|----------------|-------------------------|---------------------------|------------------------|
| Monkey     | Random         | Text, System, GUI       | No                        | -                      |
| ACTEVE     | Concolic       | GUI(Tap Event)          | No                        | Yes                    |
| Sig-Droid  | Symbolic       | Text, GUI               | No                        | Yes                    |
| ConsiDroid | Concolic       | Text, System, GUI       | Yes                       | No                     |

Furthermore, we have compared ConsiDroid with concolic or symbolic execution-based tools in table 5. Our comparison is based on features which are supporting event-driven nature of Android apps, the path explosion problem existence in the tools, utilizing static analysis in concolic or symbolic execution, and security related issues such as logic bomb, SQL injection vulnerability and privacy violation detection.

Table 5: Comparison of ConsiDroid with similar security concolic- or symbolic-based tools.

| Tool       | Event-Driven | Path explosion | Static + Dynamic Analysis | Logic Bomb Detection | SQL Inj. Vulnerability Detection | Privacy Violation Detection |
|------------|--------------|----------------|----------------------------|---------------------|----------------------------------|----------------------------|
| AppIntent  | Yes          | No             | Yes                        | No                  | No                               | Yes                        |
| Condroid   | Yes          | Yes            | No                         | Yes                 | No                               | No                         |
| Sig-Droid  | Yes          | Yes            | No                         | Yes                 | No                               | No                         |
| ConsiDroid | Yes          | No             | Yes                        | No                  | Yes                              | No                         |

10. Conclusion and Discussion

We presented a tool for detecting SQL injection vulnerability in Android apps. Our main contributions are (1) producing DummyMain classes by backward traversal of app’s call graph, (2) optimizing the analysis by giving prece-
dence to the vulnerable paths, (3) combining concolic execution with dynamic taint analysis by symbolic mock classes, (4) Detecting SQL injection vulnerability in Android apps by extending SPF and providing useful information for patching them in the report.

Although ConsiDroid is the first Android apps vulnerability detection tool, there are several points for future work and improvements. Currently we detect SQL injection vulnerability. For detecting other kinds of injections like OS shell injection, it is enough to study vulnerable functions and produce appropriate symbolic mock classes. In addition, vulnerability detection policy should be modified and SPF component adjusted accordingly. As we mentioned before, we produce mock classes manually, which is a time-consuming procedure. We are going to automate it by extending the codes of Robolectric. Furthermore, we can enhance our analysis by modeling SDK and Android environment following the same approach of [34] and [35]. Another idea could be presenting an Android concolic engine, which works on Dalvik bytecodes or ARM binaries on emulators. With this idea, we do not need mock classes anymore. Currently we only support Java apps and extending our approach for native codes is another direction of this research. Finally, our static analysis for producing DummyMain classes can be improved by mapping the nodes of CG to ICFG to compute vulnerable paths more accurately.

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