Locating Framework-specific Crashing Faults with Compact and Explainable Candidate Set

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***Abstract*—Nowadays, many applications do not exist independently but rely on various frameworks or libraries. The frequent evolution and the complex implementation of framework APIs induce lots of unexpected post-release crashes. Starting from the crash stack traces, existing approaches either perform application-level call graph (CG) tracing or construct datasets with similar crash-fixing records to locate buggy methods. However, these approaches are limited by the completeness of CG or dependent on historical fixing records, and some of them only focus on specific manually modeled exception types.**

To achieve effective debugging on complex framework-specific crashes, we propose a code-separation-based locating approach that weakly relies on CG tracing and does not require any prior knowledge. Our key insight is that one crash trace with the description message can be mapped to a definite exception-thrown point in the framework, the semantics analysis of which can help to figure out the root causes of the crash-triggering procedure. Thus, we can pre-construct reusable summaries for all the framework-specific exceptions to support fault localization in application code. Based on that idea, we design the *exception-thrown summary (ETS)* that describes both the key variables and key APIs related to the exception triggering. Then, we perform static analysis to automatically compute such summaries and make a data-tracking of key variables and APIs in the application code to get the ranked buggy candidates. In the scenario of locating Android framework-specific crashing faults, our tool CrashTracker exhibited an overall MRR value of 0.91 and outperforms the state-of-the-art tool Anchor with higher precision. It only provides a compact candidate set and gives user-friendly reports with explainable reasons for each candidate.

***Index Terms*—Fault Localization, Framework-specific Exception, Crash Stack Trace, Android Application**

I. Introduction

With the increasing size and rapid updating requirement of software, it is hard to eliminate all the bugs before the code release. To deal with these post-release bugs, developers need to analyze massive crash reports to find out the real buggy methods. Usually, one crash report is composed of three key elements, the *type* of exception, the *crash description message*, and the *crash stack trace*, in which the stack trace presents parts of the executed methods before the crash is triggered and is helpful for the developer's code debugging process [34]. However, for precise fault localization, only using trace information is not enough. The real buggy method may not be the last executed one in the stack trace, or even not appear in the stack [25], i.e., the buggy method may not lead to the crash-triggering directly. Instead, after the buggy method is executed, its execution results affect the subsequent code execution and finally lead to an exception being thrown.

To quickly fix bugs with execution results, several fault localization approaches have been proposed. The **spectrum-based methods** [28]–[31], [38], [41] rank suspicious statements by computing the ratio of failed and passed test cases that execute the statements. These techniques impose high requirements on test cases, which are not suited for post-released crashes. For these crashes, both the test cases and the runtime coverage are usually unknown. Recent years, **learning-based approaches** [25], [37], [42] are widely adopted to solve this problem, for which higher precision relies on spending more effort on dataset labeling. Despite working well when similar crash-fixing records are collected, they are not good at handling unfamiliar new crash reports. Considering the generalizability, users can choose the **analysis-based approaches** [22], [24], [27], [35] to recover the real execution trace of the target application by backward tracking on the CG. Some of them [24], [35] improve the precision by manually modeling specific exceptions, and Kong et al. [27] retrieve similar crashes from the collected dataset before static analysis to precisely locate the out-of-stack buggy methods.

Nowadays, many apps are developed based on specific frameworks or libraries, e.g., the Android framework [1], google-map SDK [8], zxing library [16], etc. These framework- and library-specific exceptions account for the majority of app crashes [22]. However, developers have difficulty debugging and fixing them, especially in the understanding of method call ordering between application code and framework code [20]. To locate and understand the non-application crash faults, there are three obstacles when adopting the existing analysis-based approaches. **First is the high modeling cost**. As there are thousands of or even more rapidly evolving exceptions in one framework, e.g., Android, it is not cost-effective to manually model all the framework-level exceptions. **Second is the deep call depth**. The buggy point may be far away from the stack trace, but the number of candidates increases quickly when tracing deeper along the CG, e.g., developers may need to examine hundreds of candidates to find a newly discovered buggy point [25]. And if the analysis starts from the exception-triggering point in the framework or library-level code, the candidate size will suffer more from long call traces and turn out to be extremely large. **Finally, the unlinked call edges**. Even though many candidates can be traced by CG analysis, the statically constructed CG is incomplete for reasons like UI callbacks, asynchronous methods, etc. So, the buggy method may be missed even with numerous candidates.

To cope with these problems, we propose a code-separation-based framework-specific fault localization approach that weakly relies on the CG edges and does not require extra prior knowledge. First, we separate the whole program code into two parts, the *application-level* and the *framework-level*. The application-level code contains a set of buggy methods to be located and fixed, which may misuse the APIs provided by the bottom-level code. The framework-level code provides APIs and throws exceptions when APIs are misused. By investigating the public framework-specific crash reports on GitHub [4], we note that one crash report with crash stack, exception type, and crash message can be mapped to a definite exception-thrown point in the framework. Thus, we can perform semantics analysis to pre-construct reusable summaries for framework-specific exceptions. To achieve that, the main challenges are **which key information should be extracted from frameworks** to understand the exception-triggering procedure, and **how to use the exception-related information** to precisely locate application-level buggy methods.

In this paper, we propose a specification technique, called *exception-thrown summary* (ETS), for framework-level methods, which describes the fault-inducing elements that lead to exception-triggering from the framework users' point of view. We first perform static analysis to automatically compute ETSs for all the framework methods and apply the matched ETS on the given crash stack trace. The target ETS points out the parameters (*keyVars*) that may be wrongly input to the framework code, or the framework APIs (*keyAPIs*) whose invocation may influence the status-checking of the corresponding exception. With that information, we can perform more targeted application-level code analysis for buggy localization and generate a compact candidate set. Also, it helps users quickly figure out the complete path from the buggy methods to deep exception-thrown points for better explainability.

Android apps are typical framework-based applications, whose frameworks are much more complex than their upper-level apps. It has over ten million lines of code [23] and millions of call edges. With rapid evolution, the number of exceptions increases eight times more (1,643 to 13,717) from API 8 to 32. The high complexity of Android frameworks brings difficulties in bug debugging. In this paper, we take the Android crash fault localization as a typical scenario and implement our approach into a tool *CrashTracker*. In the evaluation, we collect 580 instances (569 Android apps and 11 third-party SDKs) and ten versions of Android framework SDKs. The results show that CrashTracker exhibited an overall mean reciprocal rank (MRR) metric value of 0.91. It also outperforms the state-of-the-art tool Anchor [27] with 7.4%, 11.5%, and 12.6% improvement on finding real buggy in the top 1, 5, and 10 sorted candidates. On average, only 6.35 explainable candidates are reported for one crash.

Contributions. The contributions of this work are threefold:

- We propose a code-separation-based analysis approach and apply it to Android framework-specific fault localization.
- We propose a novel specification, ETS, and construct it for 76,247 exceptions thrown in multiple Android frameworks.
- We implement our crash fault localization approach in tool CrashTracker [17], which can precisely locate buggy methods within a compact and explainable candidate set.

II. Preliminary

A. Application-level and Framework-level Code

Among all the Android crashes, over 50% are framework-specific or library-specific ones [22], which indicates that the understanding of bottom-level code will influence code quality on the upper level. To avoid repetitive analysis of the large-scale and complex bottom-level code, we take the methods that may be debugged or fixed by developers as the *application-level* methods, and the methods that provide APIs to application-level methods as the *framework-level* ones. If we take all the methods in the whole program as M_{whole}, both the application- and framework-level methods are its subsets ($M_{whole} = M_{app} \cup M_{frame}$). There is no fixed division between two parts, i.e., the separation line could be totally customized by users under different scenarios. In this paper, to debug the Android framework-specific crashes, we add all the application and library code contained in the Android Packages (APKs) and the third-party Android software development kits (SDKs) into M_{app}, while adding the official Android framework methods in M_{frame}.

B. From Crash Report to Buggy Method

On the bug-tracking systems (e.g., GitHub [7], StackOverflow [13]), the crash reports provided by users mainly contain three elements, an *exception type*, a *crash message*, and a *stack trace* snapshot that reflects the *callee-caller* method chain when the exception is triggered. In the stack trace, the application- and framework-level methods may show up alternately. Table I displays one crash issue [3] of the Android app *cgeo*, which has 1.2k stars. In this example, an *IllegalStateException* is thrown out with a crash message *"attempt to re-open $\cdots$"*. We label *signaler*, *crashAPI*, *crashMethod*, and *entry* tags beside methods in the trace, and give the fixed buggy method in the last row, which is out of the stack.

Actually, when a crash is triggered, the buggy method must be located in the execution trace, i.e., it should be a

TABLE I: A Crash Report and Its Real Buggy Method

Type	java.lang.IllegalStateException
Msg	"attempt to re-open an already-closed object: SQLiteProgram: SELECT count(_id) FROM cg_caches WHERE reason >= 1"
Crash Stack Trace	android.database.sqlite.SQLiteClosable.acquireReference, [signaler] android.database.sqlite.SQLiteStatements.simpleQuery, [crashAPI] cgeo.geocaching.DataStore$PreparedStmt.simpleQuery, [crashMethod] cgeo.geocaching.DataStore.getAllCachesCount, cgeo.geocaching.MainActivity$CountBubbleUpdateThread.run [entry]
Buggy	cgeo.geocaching.DataStore$PreparedStmts.clearPreparedStmts

method that has been executed already. The execution trace of application app can be denoted as

$$T_{execute} = \langle f_0, ..., f_i, f_{i+1}, ..., f_n \rangle$$

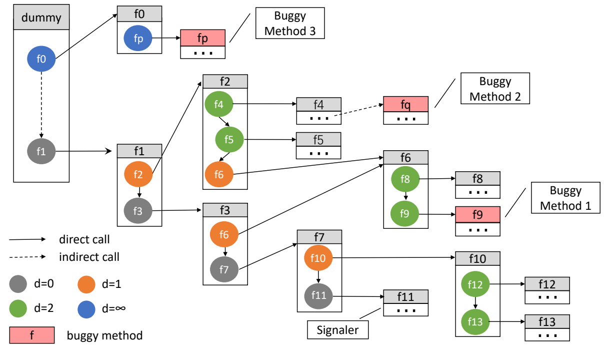
in which f_i is a method. For Java programs that have a single entry method $entry$, we have $entry$ = f_0. And the pair (f_i, f_{i+1}) is a call edge in the CG, i.e., f_i invokes f_{i+1}. For event-driven Android programs that have multiple callback entries, like component lifecycle and user/system callbacks, we have $f_0 \in S_{entry}$. In this case, the method f_{i+1} may be a callee of f_i, or be a callback method $f_{i+1} \in S_{entry}$. As $T_{execute}$ is a crash-triggering execution trace, its last method f_n is the *signaler* method that directly throws the exception out. The method f_i in $T_{execute}$ could be either an application-level or a framework-level method. As the Android framework-specific exceptions denote the exceptions thrown in the Android framework [22], here we focus on the crashes whose *signaler* $\in M_{frame}$. The target of the fault localization is to find out the real *buggyMethod* to be fixed, which must be one of the executed methods. That is to say, we can find an integer b so that f_b in $T_{execute}$ and *buggyMethod* = f_b.

During execution, methods in $T_{execute}$ will be pushed into a stack st in order and be popped out when finished. The crash trace T_{crash} records the unpopped methods in the stack st when the crash is triggered, whose set of elements is a subset of the complete execution trace, i.e., $Set(T_{crash}) \subseteq Set(T_{execute})$. We can denote T_{crash} as a sequence

$$T_{crash} = \langle f_n, ..., f_j, f_{j-p}, ..., f_e \rangle, (0 < p < j, 0 \leq e < j - p),$$

where each method in it also exists in $T_{execute}$. The *signaler* method f_n is the top element in stack st, and $entry$ is the bottom one. Sometimes, the app developers do not invoke the *signaler* directly, instead, they invoke the *crashAPI* f_{ca} to indirectly invoke the *signaler*, where for all $j, ca \leq j \leq n$, $f_j \in M_{frame}$. We call the last method that directly invokes *crashAPI* as the *crashMethod*. For a *crashAPI* f_{ca}, the *crashMethod* f_{cm} is its previous element in T_{crash}, where $f_{cm} \in M_{app}$ and $f_{ca} \in M_{frame}$. Trace T_{crash} is a slice of $T_{execute}$. However, it is not determined whether the *buggyMethod* is in the trace T_{crash} or not, which makes the fault localization challenging. **Starting from T_{crash}, the main task is to find a compact ranked candidate set that contains the most possible buggy methods that exist in $T_{execute}$.**

Fig. 1 introduces a simplified CG, in which each block denotes a method and each node in the block is a method call statement labeled with the callee. Here, f_0 and f_1 are both entry methods. We take $dummy$ as a dummy entry point of the program that invokes f_0 and f_1. Among methods, solid and dotted lines are used to represent the direct and indirect call edges. Suppose there is a crash-triggering execution that starts from the entry method f_0 and ends with the *signaler* method f_{11}. When the app crashed, only four methods $\langle f_1, f_3, f_7, f_{11} \rangle$ are stored in the method stack st, while others have finished their execution. As the *buggyMethod* may not be in st, existing approaches make an expansion of stack trace based on the call edges in CG. Their candidate size entirely depends on the call



d=0: {f_1, f_3, f_7, f_{11}}	d=2: {f_4, f_5, f_8, f_9, f_{12}, f_{13}}
Trace = T_{crash} = {f_1, f_3, f_7, f_{11}}	Trace = {f_1, f_2, f_3, f_4, f_5, f_6, f_7, f_8, f_9, f_{10}, f_{11}, f_{12}, f_{13}}
d=1: {f_2, f_6, f_{10}}	d=x, x∈[3,∞): {f_0, f_p, f_q}
Trace = {f_1, f_2, f_3, f_6, f_7, f_{10}, f_{11}}	Trace = $T_{execute}$ = {f_0, f_p, f_1, ..., f_q, ..., f_{13}}

Fig. 1: Execution Trace and Crash Trace

depth setting. The *call depth* of the function f_i with respect to a given crash trace T_{crash} is the least number of function call steps from any functions in T_{crash} to f_i [40]. In Fig. 1, the nodes with the same color have the same call depth. With a given call depth threshold d_t, methods that have a call depth no larger than d_t will be collected. And a larger depth means a higher possibility to find out the *buggyMethod*. When d = 0, we only have T_{crash}. Then we increase the depth until finding the buggy method. Suppose that f_9 is the *buggyMethod*, when d = 1, we can get seven ineffective candidates. And when d = 2, twice as many candidates will be collected, which includes f_9. **According to that, there are two challenging cases.** First, the *buggyMethod* may be far away from the mainstream, e.g., *buggyMethod* = f_q. To find it out, a larger depth brings more candidates to be reviewed and increases the difficulties in fault analysis, especially when $f_n \in M_{frame}$. Second, the CG may be incomplete due to the existence of callbacks, native methods, or asynchronous calls, and the buggy method can be called by these unlinked methods, e.g., *buggyMethod* = f_p. That means, tracing along the CG requires heavy effort, but the *buggyMethod* still could be lost. Thus, based on the basic CG relationship, we also pay attention to the information hidden in the framework-level thrown exceptions.

III. Motivating Example

We use the real crash report displayed in Table I as our motivating example. All the code snippets corresponding to this crash are shown in Fig. 2. First, the application-level method `getAllCachesCount()` invokes the *crashMethod* `simpleQuery()`. This *crashMethod* then invokes a framework-level *crashAPI* in line 8, which invokes the *signaler* method in line 24 and triggers an exception in lines 33-34. For this crash, the really buggy points (lines 11-12) are in `clearPreparedStmts()`, which is not shown in the stack trace T_{crash}. The buggy reason is that the instance of `PreparedStmt` is closed without a clear operation so that it will not be reinitialized but reused directly the next time, which finally leads to a crash. As the entry method `run()`

```
// In Android Application
public class DataStore {
    public static int getAllCachesCount(){// caller of the crashMethod
        return (int)PreparedStmt.COUNT_ALL.simpleQuery();
    }
    private static class PreparedStmt{
        public long simpleQuery(){ // the crashMethod
            return getStatement().simpleQuery();}
    }
    private static void clearPreparedStmts(){//buggyMethod
     - for (final SQLiteStatement statement : statements) {
     -       statement.close(); } //Invoke KeyAPI_2
     + for (final PreparedStmt preparedStmt: statements){
     +       preparedStmt.statement.close();
     +       preparedStmt.statement = null; }
        statements.clear();
    }
}
```

```
// In Android Framework
public final class SQLiteStatement extends SQLiteProgram{
    public long simpleQuery() { //crashAPI
        acquireReference();
    }
}
public abstract class SQLiteClosable implements Closeable{
    private int mRefCount = 1;
    public void acquireReference() { // signaler method, case1
    //public void acquireReference(int id, int count) { //case 2
        //mRefCount += count
        if (mRefCount <= 0){
            throw new IllegalStateException ("attempt to
            re-open an already-closed object: " + this);
        }
    }
    public void releaseReference(){ //keyAPI
        boolean refCountIsZero = false;
        refCountIsZero = --mRefCount == 0;
    }
    public void close(){ //keyAPI
        releaseReference();
    }
}
```

Fig. 2: Motivating Example of Framework-specific Exception

in T_{crash} is asynchronous, its caller is not stored in the stack, i.e., the real callback that invokes the *buggyMethod* is missed. Thus, the methods that are called by the real entry are also lost. However, even if the real entry method is included in the stack, the *buggyMethod* is still hard to be retrieved, as it is far away from the crash trace and is hidden in the large candidate set. Therefore, before making actual fault localization, we should first figure out how and why exceptions are thrown in M_{frame} and get their characteristics.

IV. Framework-specific Fault localization

In this paper, we propose an exception-oriented summary specification that points out the fault-including elements from the view of framework users. It can be the parameters (*keyVars*) that are wrongly input to the framework code, or the framework APIs (*keyAPIs*), whose invocation can influence the status-checking results of the exception-related key conditions (*keyConds*). Based on this specification, we perform a one-time static analysis to automatically compute summaries for framework code. For a crash report to be debugged, we match and apply the computed summary to the crash trace, which helps to retrieve the complete call trace between the application code and framework code. In the application-level analysis, according to the type of the fault-inducing elements, we can focus on the fault-inducing variable in the *crashAPI* invocation statement and make data tracking on it. Also, we can target the fault-inducing APIs that be invoked in the application code and track its callers. Using this approach, the methods that can be traced on the expanded CG but are not data-related will be excluded, while the methods that are data-related but cannot be traced by CG are included. Fig. 3 introduces the overview of our approach CrashTracker, which takes an APK file and a crash report as input and generates ordered candidate methods with inferred fault-inducing reasons. It has two modules. The **exception semantics analysis module** works on the framework-level code, which takes multiple Android framework files as input and outputs the summaries for exceptions in M_{frame}. The summaries will be passed to the **fault localization module**, which then uses the received information to locate buggy methods in M_{app}.

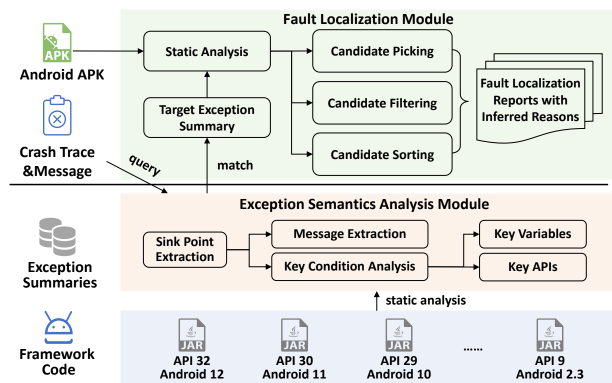


Fig. 3: Overview of CrashTracker

V. Exception Semantics Analysis on M_{frame}

On M_{frame}, the *Exception-thrown summary* (ETS) is designed for each exception-thrown point to present its fault-inducing elements. It can be formally defined as a 5-tuple $\mathcal{ETS}(e) = \langle id, S_{cond}, S_{condVar}, S_{keyVar}, S_{keyAPI}\rangle$, where

- id is the identifier of exception e, which is a four-tuple $\langle sink, signaler, type, msg\rangle$, in which $sink$ is a statement that throws the exception e; $signaler$ is the method that contains $sink$; $type$ is the type of the exception e; and msg is the description message when e is triggered, which is composed of constant and dynamically-assigned values. To match the context-related messages in all the forms, we represent msg by regular expressions;
- S_{cond} is a set of key conditions ($keyCond \in S_{cond}$) located in $signaler$, whose results can decide whether e is triggered. If e is triggered only when $keyCond$ is satisfied, $keyCond$ is a *basic check*. If the `throw(e)` statement can not be executed as the satisfaction of $keyCond$ leads to method return, $keyCond$ is a *not-return check*;
- $S_{condVar}$ is a set of condition variables ($condVar \in S_{condVar}$) whose values are directly checked in S_{cond};
- S_{keyVar} denotes a set of key variables, which can influence the value of $condVar$ and can be modified by framework users. Each $keyVar \in S_{keyVar}$ is a triple

$\langle mtd, loc, condVar\rangle$, in which mtd is a framework-level public method; loc is a parameter location in method mtd; the loc^{th} parameter in mtd can influence the value of $condVar \in S_{condVar}$ by inter-procedural parameter passing, i.e., its value can influence the checking results of the key conditions. For simplicity, we will use *keyVar* to denote the parameter variable in $keyVar.mtd$ with location loc.

- S_{keyAPI} denotes a set of key APIs, which can influence the value of $condVar$ and can be invoked by framework users. Each $keyAPI \in S_{keyAPI}$ is a 4-tuple $\langle mtd, field, condVar, dpt\rangle$, in which mtd is a framework-level public method; $field$ is a class-filed variable that is modified by mtd or its callees, whose value is data-related with the condition variable $condVar$ in $S_{condVar}$; dpt records the least number of function call steps from mtd to the method that directly modifies $field$, which is used in candidate sorting. We will use *keyAPI* to denote the method $keyAPI.mtd$ in the following.

Here, we use the running example in Fig. 2 to exemplify the defined elements in ETS. For the exception thrown in lines 33-34, its *keyCond* is *mRefCount*$\leq$*0* and *mRefCount* is a *condVar*. Also, *mRefCount* is a filed variable of class *SQLiteClosable* that can be modified out of the *signaler* method. As public methods *releaseReference()* and *close()* both modify its value, $\langle$*releaseReference()*, *mRefCount*, *mRefCount*, 1$\rangle$ and $\langle$*close()*, *mRefCount*, *mRefCount*, 2$\rangle$ are added into S_{keyAPI}. In this example, as no parameter variable is related to the *condVar*, S_{keyVar}=$\emptyset$. But if line 29 is replaced by lines 30-31 (case 2), we will get a parameter-related variable `count`, which can be modified outside and influence the value of *condVar*. As *signaler* is public, we will first add $\langle$*acquireReference()*, 2, *mRefCount*$\rangle$ into S_{keyVar} and then trace the caller of method *acquireReference()* to find more *keyVars*.

Sink Point Extraction. The ETS construction process is shown in Algorithm 1. The first step is to identify the sink points (line 1). First, all the `throw(e)` [14] invocation points are sink points. Besides, developers may also customize exception-thrown information and use the logged information to debug. To recognize them, we detect all the `Throwable` instances and trace their data flows. For the exceptions that are not thrown directly, we take the methods that receive these instances as exception-handling methods and take the invocation statements of them as sink points. `Throw(e)` statement is the most frequently used sink point type with many instances. Besides it, we get another 33 types of sink points, of which 12 store exception trace into logs or files.

Message Representation. Starting from the sink points, one challenge is how to extract the description message of the target exception (line 4). For the same exception, the runtime crash message may be different, as the values of some variables are dynamically assigned. To make a precise matching, we transform the exception message into a regular expression [11] pattern, so that it can match multiple runtime crash messages. The method *regexStringAnalysis()* in line 4 tracks the definition statement of the target exception, which may be a newly created one, e.g., *e = new RuntimeException()*, or the alias of another exception, e.g., *e = getFileException(*$\cdots$*)*. For the former, we perform backward value tracing of the message-related parameter in the exception's constructor method. For the latter one, we make inter-procedure tracing to get the real instantiate point and analyze it as the former. During the value tracing, we model a set of String-related APIs to stitch multiple parts together, in which we use `[\s\S]*` to represent a symbolic value and use `\Qstr\E` to represent the constant value of `str`. In lines 33-34 of Fig. 2, the target exception message is "\Qattempt to re-open an already-closed object: \E[\s\S]*", which can matche the crash message in Table I.

Key Condition and Condition Variable. Each exception is influenced by a set of conditions (*keyConds*), whose checking results decide whether the exception can be triggered. In line 6, we invoke method *getKeyCondsAndVars()* to trace all the predecessor statements of the sink point in the control flow graph, record the involved condition checks into S_{cond},

Algorithm 1 Exception-thrown Summary Extraction

Input: method $signaler$ in M_{frame}
Output: the exception summary set S_{ets} on method $signaler$
1: **for** sink in signaler.getSinkPoints() **do**
2: ets = createETS($signaler$, $sink$)
3: ets.type = exceptionTypeAnalysis()
4: ets.message = regexStringAnalysis()
5: cfg = $signaler$.getCFG()
6: getKeyCondsAndVars(ets, cfg, $sink$)
7: **if** ets.keyConds.size()=0 **then**
8: **for** return stmt $retStmt$ predsOf $sink$ in cfg **do**
9: getKeyCondsAndVars(ets, cfg, $retStmt$)
10: **end for**
11: **end if**
12: $worklist$ = ets.keyCondVars.copy()
13: **while** $worklist$.size()>0 **do**
14: **if** $worklist$.get(0) is parameter or field related **then**
15: add $worklist$.getAndPop(0) as *outsideVars*
16: **else**
17: $defStmt$ = getDefStmt($worklist$.getAndPop(0))
18: $worklist$.add($defStmt$.getRightOp().getVars())
19: **end if**
20: **end while**
21: **for** var_p in ets.parameterOutsideVars **do**
22: add var_p to ets.keyVars if $signaler$ is public
23: track var_p in $signaler$'s caller to update ets.keyVars
24: **end for**
25: **for** var_f in ets.fieldOutsideVars **do**
26: add public methods that modify var_f into ets.keyAPIs
27: update public caller of keyAPIs into ets.keyAPIs
28: **end for**
29: S_{ets}.add(ets)
30: **end for**
31: **return** S_{ets}

Algorithm 2 getKeyCondsAndVars

Input: ETS ets, control flow graph cfg, statement s
Output: updated ETS ets
for condition check stmt $condStmt$ predsOf s in cfg **do**
ets.keyConds.add($condStmt$.getCond())
ets.keyCondVars.add($condStmt$.getCond().getVars())
end for

and collect all the condition-related variables into $S_{condVar}$, as displayed in Algorithm 2. After that, we can collect all the *basic checks*. For example, `s==t` is a *basic check* for {`if(s==t)`{`throw(e)`}}. In another case, developers may take the method-return operation as expected behavior and throw exceptions if the method didn't jump out in time. The conditions related to these return statements are also key conditions. For example, `s==t` is a *not-return check* for {`if(s==t)`{`return`} `throw(e)`}. In lines 7-11, if there is no *basic check*, we extract the *not-return checks* by analyzing the basic checks of all the return statements prior to the sink point in the control flow graph. Besides, as the conditions far away from the exception-thrown point may have a weak relationship with the exception, we count the average condition length as a threshold size of S_{cond}.

Key Variable and Key API. To find out *keyVars* and *keyAPIs*, we first use a worklist algorithm to locate the method parameters and class-field variables that influence the value of *condVars* by performing backward data tracing along the use-def-chains [15] (lines 12-20). Note that, in line 17, method *getDefStm()* returns the Jimple [9] IR level definition statements, which reflect the variables that can influence that target one. As these variables can be modified outside *signaler*, they are called outside variables *outsideVars*. In lines 21-24, for each parameter-related *outsideVar* var_p, we record its method, the location in the parameter list, and the influenced *condVar*. If the *signaler* is a public method, var_p itself is a *keyVar* (line 22), e.g., we have ⟨*acquireReference()*, 2, *mRefCount*⟩ for case 2 in Fig. 2. Similarly, we perform backward inter-procedural parameter call-chain analysis (line 23) to trace more key variables passed through other framework APIs, which invoke the *signaler*. That is, for a formal parameter, we find the actual parameter variable in its caller and judge whether the passed variable is influenced by the caller's parameter-related *outsideVars*. If it is, these newly detected *outsideVars* in the public callers will be added into S_{keyVar}, e.g., for method `f(int count)`{`acquireReference(1,count)`}, we further have $\langle f(), 1, mRefCount\rangle$. In lines 25-28, for each field-related *outsideVars* var_f, its value can be changed by other framework APIs that influence the checking results of *keyConds*. In line 26, we record the methods that change the value of var_f, the field var_f, the influenced *condVar*, and the call depth from method to *signaler*. For Fig. 2, we first get the *keyAPI* ⟨*releaseReference()*, *mRefCount*, *mRefCount*, 1⟩. Then in line 27, we trace callers of the collected *keyAPIs* and get ⟨*close()*, *mRefCount*, *mRefCount*, 2⟩. Finally, in line 29, we add ETS for each exception into the ETS set S_{ets}.

VI. Crash Fault Localization on M_{app}

Based on the exception semantics analysis module, we further match the given crash report to its corresponding ETS and use the extracted *keyVars* and *keyAPIs* to guide the application-level buggy method analysis.

ETS Mapping. Algorithm 3 displays the process of crash fault localization on M_{app}. In line 1, we match the given crash message with the regular expression format message of each ETS. When the version of the framework is given, the target ETS is unique and can be used directly. If the version is undetermined, multiple ETSs may be matched as the exception with the same type and the description message can exist in many versions. In the latter case, the target ETS should be picked by a proper version-choosing strategy. Here, we first classify the matched ETSs by their characteristics into five ETS-related types, which are listed in Table II. Then we get a list of matched versions for the most classified type. To keep the randomness, the ETS in the middle of the list is picked.

TABLE II: ETS-related Types & Fault Localization Strategies

ETS-related Types	Fault Localization Strategy
T_1: No CondVar	S_1: Override analysis in subclasses
T_2: No OutsideVar	S_2: Data tracing from variables in crashAPI$_{inv}$
T_3: Only have keyVar	S_3: Data tracing of variables *keyVars*
T_4: Only have keyAPI	S_4: Call tracing of methods invoking *keyAPIs*
T_5: Have keyVar, keyAPI	S_3: Data tracing of variables *keyVars* + S_4: Call tracing of methods invoking *keyAPIs*

Candidate Picking. In lines 2-14, according to the information provided by the target ETS, we use different candidate-picking strategies. Table II also displays the four strategies that can be used for each ETS-related type. For the ETS who has **no condition variable**, i.e., no *condVar* and *keyCond*, we use strategy S_1. In this case, the *signaler* method should not be invoked directly, framework users should override that method and invoke the newly implemented method by the polymorphic mechanism. For this type, the number of candidates is limited by the number of subclasses of the declared class of *signaler*. For target ETS who has *condVar* but has **no outside variable**, we use strategy S_2. The exceptions caught from try-catch blocks and the exceptions whose *condition variables* are related to methods with unknown implementations (e.g., native method) are both in this type. Without extra information about how the fault could be induced, we just make data tracing starting from the invocation statement of *crashAPI* in the

Algorithm 3 Crash Fault Localization

Input: Android app app, crash stack trace st and message msg, framework version ver, exception summary set S_{ets} on M_{frame}
Output: fault localization reports $reports$

1: ets = getBestMatchETS(st, msg, S_{ets}, ver)
2: $condType$ = getConditionTypeOfETS(ets)
3: $strategies$ = getStrategiesByType($condType$)
4: **for** $strategy$ in $strategies$ **do**
5:     **if** $strategy$ = S_1 **then**
6:         locate methods that should override $ets.signaler$
7:     **else if** $strategy$ = S_2 **then**
8:         locate methods that are data-related with the crashAPI-invoking statement
9:     **else if** $strategy$ = S_3 **then**
10:         locate methods that are data-related with $keyVars$
11:     **else if** $strategy$ = S_4 **then**
12:         locate methods that are callers of $keyAPIs$
13:     **end if**
14: **end for**
15: $candis$ = filterAndSortCandidates()
16: getCodeandNonCodeFaultReasonReports($candis$, $reports$)
17: **return** $reports$

crashMethod. The strategy S_3 is for ETSs that **only have keyVars**. The difference with strategy S_2 is that, first, we can confirm this crash is caused by the wrong parameter value. And we may get the location of the fault-inducing parameters, even if the *crashAPI* is not the *signaler* method. So that, we can focus on where these target parameters are created or assigned. In this way, we can locate the methods that can influence the value of the *keyVars* but cannot be traced by CG extension. Similarly, the strategy S_4 targets ETSs that **only have keyAPIs**. These crashes have no relation to the passed parameter but are influenced by the previously invoked APIs, which change the value of field variables in the framework code and further influence the exception's condition-checking results. To cope with them, we focus on the methods that invoke the *keyAPIs* and further track their callers. In the motivating example, even if method `clearPreparedStmts()` cannot be traced along the CG, we still can find it as it invokes the *keyAPI* `close()`. Finally, one ETS can **have both keyVars and keyAPIs**. In this case, we collect all the methods tracked by either strategies S_3 or S_4 as possible candidates.

Candidate Filtering and Sorting. The candidates are mainly collected by data tracing from a set of variables or call tracing from specific APIs. In line 15, for the candidate f_i collected by the data-tracing of variables, we measure its distance to the *crashMethod* by the formula $dis(f_i) = min(callDepth(f_i, f_j) + callDepth(f_j, f_{cm}))$, where f_j is a method located in T_{crash} and f_{cm} is the *crashMethod*. For each candidate, we have an initial score $init$. The longer distance, the larger the score penalty. Their scores are computed by $score(f_i)$ = $init$ - $dis(f_i)$. And for the candidates collected by the call-tracing from specific APIs, if method f_k invokes the *keyAPI* api, its score can be computed by $score(f_k)$ = $init$ - $api.dpt$, in which dpt is the least distance from *keyAPI* to the field manipulating method. If f_t is a caller of f_k, its score can be computed by $score(f_t)$ = $init$ - $callDepth(f_t, f_k)$ - $api.dpt$. For all the candidates, we perform universal filtering and adjustment. First, we extract the *package* and *class* characteristics of candidates. At the package level, we filter the candidates that have different package prefixes (e.g., first two elements) with all the methods in T_{crash}. We suppose these methods are too far away from the *crashMethod* to be the right buggy method, even if they may invoke the *keyAPIs*. As library methods can also be traced through control- and data-flow tracing, we make a penalty on the methods that are not in the app-declared package. This penalty helps to decrease their priority. Users can customize it if the specific packages should be considered with high priority in the fault localization. Specifically, we observed that many methods work as utility functions and have many callers. One heuristic strategy is to filter the methods whose number of callers exceeds the user-defined upper limit. In our implementation, when tracing the application-level callers of *keyAPIs*, we filter the ones with more than ten callers according to our programming experiments. Finally, as a supplement, the methods in T_{crash} are added with a conservative score.

Candidate Reasoning. To make the localization results explainable, the reports should contain both the summary information of the corresponding exception, and the code-/non-code-level relationship between each buggy candidate and the triggered exception. By previous ETS matching, we can get the corresponding ETS summary of each crash and provide that to users. In line 16, based on the analysis results of the M_{frame} and M_{app} code, we report candidates with code-related buggy reasons, which discover the relationship between each candidate and the triggered exception. If one candidate is traced by multiple strategies, only the highest score is reserved, but all the possible reasons are recorded. More detailed fault localization reports and instructions can be found in our online tool documentation [17]. Overall, our approach gives six types of code-related reasons, including 1) *KeyAPI_Related*, invokes method *keyAPI* with trace *t*; 2) *KeyVar_Related_1*, influences the value of *keyVar* by modifying the value of the passed parameter *p*; 3) *KeyVar_Related_2*, influences the value of *keyVar* by modifying the value of related field *f*; 4) *Executed_1*, doesn't influence the *keyVar* but is in the crash trace; 5) *Executed_2*, not in the crash stack but has been executed; 6) *Not_Override*, forgets to override the *signaler*.

For the motivating example in Fig. 2, the simplified report is like this: **Candidate:** clearPreparedStmts(); **Rank:** 1; **Type:** *KeyAPI_Related*; **Trace:** {clearPreparedStmts() → call *keyAPI* close() → call releaseReference() → modify the *outsideVar* mRefCount → call acquireReference() with the *condVar* mRefCount → trigger exception.}.

In some cases, the crash-triggering not only relates to the misuse of APIs but also relates to the non-code reasons, e.g., Kong et al. [27] points out five non-code tags, including *Manifest*, *Asset*, *Hardware*, *OS Version* and *Resource*. To get this extra information, we scan the statements that are data-related with the *condition variables* to judge whether non-code-related keywords in Table III are hit or not. For instance, for tag *Manifest*, the usage of field *mActivityInfo* and all the permission strings are detected. For tag *OS Version*, we trace whether the filed *targetSdkVersion* is read. If these tags are matched, they will be displayed as non-code buggy reasons.

TABLE III: Non-Code Tags and Keywords

Tag	Keywords in Code Slices
Manifest	ActivityInfo mActivityInfo, android.permission
OS Version	ApplicationInfo: int targetSdkVersion
Hardware	MediaPlayer, BluetoothAdapter, Camera, etc.
Asset	android.content.res.AssetManager
Resource	android.content.res.Resources

VII. Evaluation

We implemented the framework-specific fault localization approach as a prototype CrashTracker [17], which consists of 11,554 lines of Java code. It is extensively based on the static analysis framework Soot [12] and uses Flowdroid [6] to construct call graphs. The evaluation of CrashTracker aims to answer the following research questions.

- **RQ1 (ETS Construction):** How many ETSs can we extract from multiple-version Android frameworks?

- **RQ2 (Fault Localization):** How beneficial are our strategies in fault localization? Can CrashTracker help to locate buggy methods effectively compared to the existing tool?
- **RQ3 (Precision Analysis):** What are the key reasons that lead to false positives and false negatives?

A. Experimental Setup

To answer RQ1, we collect multiple version framework files. As the `android.jar` files in the Android SDK only contain stub methods but not real code implementation, we load the published Android images and pull the complete jar files from the system. Overall, we collect ten versions of framework files, which correspond to Android 2.3 to 12.0 [2], in which Android 3 is excluded as it is unavailable.

To answer RQ2-RQ3, the Android framework-specific crash dataset is required. There are two off-the-shelf benchmarks that relate to Android crash datasets. For example, Fan et al. [21] extract 194 crashes from GitHub [7] to form a crash dataset. And in the recent benchmark ReCBench [26], more than 1,000 crashed apps are collected, in which nearly half of the crashes are framework-related. To focus on the framework-specific crashes only, Kong et al. [27] filters these two datasets with the following criteria. First, the stack trace must contain the application-level method. Second, the *signaler* must locate in M_{frame}. After filtering, it extracts 500 crashes (D500) on ReCBench [26] and 69 crashes (D69) in existing work [21], which are divided into three buckets according to the location of the *buggyMethod*. Category A: *buggyMethod* in T_{crash}; Category B: *buggyMethod* in $T_{execute}$ but not in T_{crash}; Category C: crash arises from non-code reasons. We reuse and update these 569 crashes as our evaluation dataset by adding oracle information about both the *condVars* and *outsideVars*. For type C, the *buggyMethods* are labeled with non-code characteristics only in the original dataset, e.g., lack of resources. These labels indicate the external cause of the crash triggering, while in fact, these non-code characteristics also have their corresponding code snippet, e.g., resource loading statements. As our approach can both provide code-level and non-code-level localization, we point out the code-level *buggyMethods* for crashes in category C and record their original labels as extra non-code characteristics. As CrashTracker is a general technique, it can also be applied to other scenarios. Besides the collected Android APKs, we also take the Android third-party SDKs as the application-level code. We search the SDK library projects on GitHub that have large star numbers, active commit behavior, and normalized issue submission specification. By manually reviewing, we pick two popular projects, facebook-android-sdk [5] and google-map [8]. Then, we filter issues with the keyword *is:issue is:closed "AndroidRuntime" OR "Crash"*. For the 84 + 53 issues matched, we manually check whether the crash is Android framework-specific and whether a fixing commit is given. Overall, 11 framework-specific crash reports with fixing revision (D11) are collected. They form a large dataset with 580 crash reports (D580).

For effectiveness evaluation, as the analysis-based Java fault localization tool CrashLocator [40] is not available, we implement a similar strategy (b1-ExtendCG) in our tool and perform self-comparison. Besides, *Anchor* [27] is a novel Android framework-specific fault localization tool, which first applies machine learning algorithms to categorize each new crash into a specific category (A/B/C), and then combines the application-level static analysis and similar crash query to achieve the final buggy ranking. We also compare with it the 569 test cases provided by them. All of our analyses are performed on a Linux server that has two Intel® Xeon® E5-2680 v4 CPUs and 256 GB of memory. Our approach has two phases, in which the framework-exception extraction is one-time work. We analyze ten versions of frameworks with 67 min, i.e., around 6.7 minutes for one version. In the app code analysis, we use around 95 minutes for 580 apps with 8 threads, i.e., 10 seconds per app.

B. RQ1: ETS Construction

The Android framework updates rapidly, so the exceptions may also change with time. Fig. 4 shows the number of ETS in different versions of the Android framework, in which each ETS denotes one unique exception. **With the evolution of the framework, the number of exceptions, exception types, and exception-thrown methods all increase.** For example, in Android 10.0, 10,385 exception-thrown methods throw 7,415 exceptions with 176 types. Among them, 6,917 ETSs have not-empty messages description, of which 29.0% of them contain non-constant values in the generated regular expression.

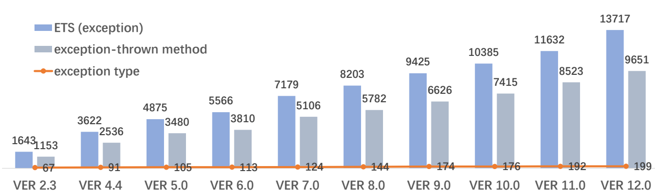


Fig. 4: ETS in Multiple Android Frameworks

For each exception, we trace its *keyConds*, *condVars* and the *outsideVars*. When tracing all the key conditions related to an exception, the average condition length is 2.78. So we set the threshold in *keyCond* collection as 3. Among all the conditions, most are basic ones. The *not-return* conditions account for 0.7%, which influences the precision of 462 framework exception triggering. Table V shows the distribution of the ETSs with different condition types. We give the statistical results on the oldest version (Android 2.3), the latest version (Android 12.0), and the average value for all ten versions. According to the results, most ETSs only have *keyVars* (42%) or *keyAPIs* (22%). Around 18% ETSs have both *keyVars* and *keyAPIs* and 4% ETSs do not have *keyCond*. About 15% ETSs could not link with any *outsideVar*, most of which are from the caught and re-thrown exceptions or the inter-procedural-call-related conditions. On average, we can get 7,625 ETSs from the Android framework code. Among them, there are 1,859 ETSs that contain 10,227 *keyVar* records, and 2,877 ETSs with 308,852 *keyAPIs*. For the *keyAPIs*, 81,872 are declared in the same class of *signaler*, and 226,980 are located in different classes.

TABLE IV: Effectiveness of CrashTracker with Multiple Strategies

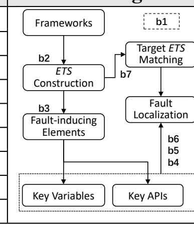
Strategy	Statistic			All (580)				CategoryB (56)				Relationship of Strategies
	#Find	RankSum	CandiAvg	#R@1	#R@5	#R@10	MRR	#R@1	#R@5	#R@10	MRR	
CrashTracker	568	954	6.35	500	562	567	0.91	14	38	43	0.44	
b1-ExtendCG	**-8**	**+564**	**+20.63**	-5	-11	-13	-0.02	-8	-7	-11	**-0.16**	
b2-AllConditon	-0	-0	+0.42	-0	-0	-0	-0.00	-0	-0	-0	0.00	
b3-NoCondType	**-15**	**+409**	-0.21	-4	-12	-15	-0.02	-8	-11	-14	**-0.19**	
b4-NoKeyVar	-3	+66	-0.15	-0	-3	-2	-0.01	-0	-3	-2	-0.06	
b5-NoKeyAPI	**-11**	**+182**	-1.18	-4	-8	-11	-0.01	-4	-7	-10	**0.10**	
b6-NoCallFilter	-0	-0	+0.84	-0	-0	-0	-0.00	-0	-0	-0	-0.00	
b7-Version2.3	**-7**	**+219**	-2.57	-3	-5	-8	-0.01	-3	-5	-8	**-0.10**	
b7-Version8.0	-0	+4	-0.01	-2	-0	-0	-0.001	-0	-0	-0	-0.00	

TABLE V: Statistic of Each ETS Type

Version	#ETS	key-Var	key-API	keyVar &keyAPI	No condVar	No out-sideVar
Ver 2.3	1,643	668	299	217	37	122
Ver 12.0	13,717	5,129	2,527	1,022	326	619
Agv 2-12	7,625	2,946	1,245	705	170	356

Moreover, we analyze the relationship between the ETS-related types and the crash categories in D580. As shown in Fig. 5, most crashes in category A only have *keyVars*, which is consistent with the *in-stack* behavior of crashes in category A. And for category B, whose buggy methods are *out-of-stack*, there are more crashes that have *keyAPIs* than in other categories. **This reflects the *keyVar* and *keyAPI* analysis work well on both the in-stack and out-of-stack crashes.**

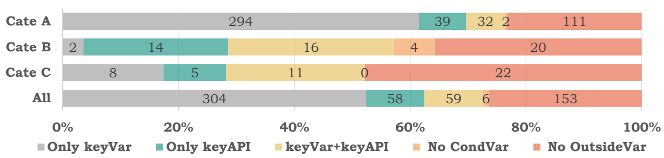


Fig. 5: ETS-related Types on Each Category

To check the correctness of the analyzed ETS-related type, we review the exception-triggering code snippets related to the collected 580 crash reports. Two experienced Java developers read the crash trace information and retrieve the corresponding exception in the source code of the Android framework. By manual analysis, they record the key conditions, the condition variables and the outside variables for all the exceptions triggered in D580. By comparison, we find that CrashTracker can correctly identify the ETS-related types (refer to Table II) for 95.5% crashes. There are 26 ones that are misidentified, of which 12 are exceptions in the Android support libraries, which are not collected as framework code; three crash reports provide empty message information, which makes the message matching fail. Three involve inter-procedural tracing. The others are condition related, including one lack of conditions due to the length limit, three getting unrelated *not-return* conditions, two re-throwing a catch condition with unknown *outsideVar*, and two wrongly taking synchronized variable or the final constant field as *outsideVars*, which actually will not influence the exception-triggering.

C. RQ2: Effectiveness of Fault localization

To evaluate the effectiveness of CrashTracker, we first made a group of self-comparisons. The results are displayed in Table IV. The second column displays how many *buggyMethod* can be located by the tool in its candidate list. The following *RankSum* gives the cumulative sum of the ranking of *buggyMethod* in the candidate list. If the *buggyMethod* is not found, we use $max(candiSize + 1, n)$ as its ranking value, in which we suppose users have to look up at least n candidates to find the target method ($n = 20$ by default). The column *CandiAvg* gives the number of provided candidates on average. The following eight columns give the precision evaluation results on D580, especially on the crashes with category B. Two metrics *Recall* and *Mean Reciprocal Rank (MRR)* [10] are used, in which #R@N counts the number of reports that rank *buggyMethod* in its first N candidates and MRR denotes the mean of the multiplicative inverse of the rank of the first correct location. It can be calculated by the formula $MRR = \frac{1}{E}\sum_{n=1}^{E}\frac{1}{Rank_i}$.

The first line gives the default results of CrashTracker, which can find correct *buggyMethod* for 568/580 crashes. For CrashTracker, its *RankSum* is 954. CrashTracker can provide a compact list with only 6.35 candidates. For all the 580 crashes, CrashTracker has high precision at R@1, R@5, and R@10. For crashes in category B, it can still find out most of the *buggyMethod* with a few candidates, e.g., 68% for 5 candidates and 77% for 10 candidates. Besides the code-level localization, we also label the non-code reasons as buggy tags for 45 crashes located in category C. Comparing the given labels, our non-code reason analyzer can correctly infer 27/45 already labeled tags, and we can observe another 40 tags that are not labeled in the original dataset.

Then, we compare CrashTracker with a set of variants. In strategy $b1$, we implement a CG-expansion-based approach [40] to trace invoked methods along the call edges with a call depth of 5. However, this approach generates too many candidates, which increases by 20.6 candidates for a crash on average. And it only can locate 57% *buggyMethod* in category B with 10 candidates. The strategy $b2$ is used to evaluate whether tracking conditions with length three influence the results. In this strategy, all the conditions will be collected. However, it did not bring higher precision but reported a bit more candidates. In $b3$, we suppose the ETS information is not available, i.e., only strategy S_2 is adopted, which decreases the overall precision, especially for cases in category B. Moreover, in Table VI, we present the precision of CrashTracker on these ETS-related types, including the number of cases under test (count), the ratio of reports that rank *buggyMethod* in the first N candidates ($R@N(\%) = \frac{\#R@N}{count}$), as well as the MRR. From the results, the crashes only relating to *keyVars* are easier to be located, as most of them exist in the stack. For type *No CondVar*, we can quickly locate the method which needs to be overridden. And the *keyAPI*-related crashes and those with unknown *outsideVar* are difficult to be located with one chance. Overall, the precision improves much on R@1(%) to R@5(%) which indicates the effectiveness of CrashTracker with a compact candidate set. Strategies $b4$ and $b5$ are designed to validate the effectiveness of *keyVar* and *keyAPI* identification, respectively. All of them decrease the overall precision and increase the sum of the ranking value. In b_6, we do not filter the candidate methods that have too many callers. The results show that the filtering will not influence the precision of fault localization. Finally, b_7 does not match target ETS from multiple versions and only considers a fixed version. For example, when using the fixed versions 2.3 and 8.0, parts of crashes cannot match their target exception. According to the results, **both the ETS construction and the multiple strategies contribute a lot to the precise fault localization.**

TABLE VI: Precision on Different ETS-related Types

Source Type	Count	R@1(%)	R@5(%)	R@10(%)	MRR
No CondVar	6	0.83	1.00	1.00	0.92
No OutsideVar	153	0.77	0.92	0.94	0.83
Only have keyVar	304	0.97	1.00	1.00	0.98
Only have keyAPI	58	0.74	0.91	0.96	0.82
Have keyVar, keyAPI	59	0.68	0.98	0.98	0.80

After the self-comparison, we compare the effectiveness of CrashTracker with the state-of-the-art tool *Anchor*. Table VII gives the R@N(%) and MRR results of Anchor and CrashTracker on the datasets D500 and D69. Overall, **CrashTracker achieves a big improvement in precision on both datasets**, i.e., achieves 7.4%, 11.5%, and 12.6% improvement than Anchor on R@1, R@5, and R@10 metrics, and improves MRR from 0.84 to 0.91. One special case is the result of R@1 in category B, which also influences the MRR. For these out-of-traces crashes, CrashTracker fails to find out the *buggyMethod* in the first place compared to Anchor. But if we review the first five candidates, our tool can actually locate more *buggyMethods*. The reason is that the crashes in category B are usually triggered due to the invocations of *keyAPIs* relate to the *signaler* method. The most common usages are pairwise API operations, e.g., `register()` and `unregister()`. It is difficult to know whether the `register()` is redundant or the `unregister()` is missed without understanding the developers' intention. Though it brings parts of FPs when only

TABLE VII: Comparison with Existing Fault localization Tool

Dataset	Anchor R@1 (%)	Anchor R@5 (%)	Anchor R@10 (%)	Anchor MRR	CrashTracker R@1 (%)	CrashTracker R@5 (%)	CrashTracker R@10 (%)	CrashTracker MRR
D500-A	0.90	0.91	0.91	0.90	0.96	1.00	1.00	0.97
D500-B	0.37	0.59	0.61	0.46	**0.22**	0.67	0.78	**0.42**
D500-C	0.72	0.75	0.75	0.73	0.95	1.00	1.00	0.98
D69-A	0.72	0.93	0.93	0.81	0.78	1.00	1.00	0.87
D69-B	0.43	0.43	0.43	0.43	0.43	0.71	0.71	0.55
D69-C	0.25	1.00	1.00	0.40	0.75	1.00	1.00	0.83
D569	0.81	0.87	0.87	0.84	0.87	0.97	0.98	0.91

the top one candidate is checked, we provide the complete call paths from each candidate to the *signaler* in the bug report to help make quick confirmation among multiple candidates.

Finally, we evaluate whether our explainable reports are understandable to testers. As the most difficult part of fault-localization is to identify the out-of-trace buggy method, we manually inspected all the buggy reports in D580 with category B. Two experienced Java developers read both the reports and the apps' code. The feedback is that among the 56 cases in category B, 12 failed in fault-localization, and the other 44 were reported with reasons. The manual evaluation shows that the reasons for 41 candidates are well understandable for debugging and 3 contain invalid information. Among the 44 reports, reasons with type *KeyAPI_Related*, *KeyVar_Related_2* and *Not_Override* are the most common, which match 29, 16, and 9 crashes, respectively. There are 18 candidates having multiple types of reasons, which give many-sided explanations about the crash. More details can be found in our artifact [17].

D. RQ3: Precision Analysis

False positive (FP) candidates denote the *non-buggyMethods* that are reported in the candidate list. For the 580 crashes, we totally get 3,684 candidates, i.e., 3,104 are FPs. There are two key reasons that can lead to FPs. First, our approach uses static analysis to compute the *keyConds*, based on which we further get the *keyVars* and *keyAPIs*. The imprecision in the static analysis, e.g., the FPs in CG construction, will lead to misidentified information in ETS and finally influence the fault localization results. Besides, even though conditions are collected, we did not combine the constraint-solving techniques to reduce the ineffective results, which will be explored in further work. Second, considering there may be misidentified ETS or ETS whose triggering information is unknown, we add the application-level methods in the crash stack as the default candidates conservatively, which also brings some FPs.

False Negative (FN) denotes the *buggyMethods* that are not in the candidate list. One reason is also the imprecision in the static analysis. Meanwhile, the exceptions with incomplete ETS information, e.g., caught from try-catch blocks or from native methods, may bring FNs. Also, we collect at most three conditions for an exception and filter the candidates whose callee has too many callers. These settings make a balance between efficiency and effectiveness but may cause unexpected FNs. For the 580 cases in D580, we can find 568 *buggyMethods* and miss 12 ones. Among them, 8 are related to native signaler methods, one suffers from unknown crash message information, and two are missed for lacking implicit data flow relationship, e.g., when the signaler *android.widget.Spinner.setAdapter* is invoked, another method must be overridden as its default value will lead to a crash.

VIII. Threats to Validity

The threats to external validity related to the generalizability of the experimental results. Although we reuse the two datasets proposed in recent works [21], [27] and add extra crashes relate to the third-party-SDKs, the data scale is limited and the crashes are not evenly distributed. That is because the *keyVar*-related misuses are more common, but the *keyAPI*-related issues are not many, which may be more difficult to find and fix. As our approach is analysis-based, it does not rely on the size of the dataset and achieves a high precision when locating these far-away *buggyMethods*. We will continuously explore the scalability of CrashTracker on more crash reports when more datasets are publicly available. Threats to internal validity are about the control over extraneous variables. In our collected datasets, the crash-triggering environment is unknown. To keep the randomness, we use the middle version of the matched frameworks, which may bring bias compared with other random strategies. There are several heuristically designed values in candidate ranking that are set according to our experience. Users can adjust them according to their requirements, which does not influence the effectiveness of the tool. Besides, to construct a practical and compact candidate set, we set threshold values during condition collection and caller filtering, which have a weak effect on the results, as evaluated in Table IV (b2 and b6).

IX. Related Work

Crash Trace Based Fault Localization. The crash stack trace is the key element in the crash report, based on which, Chen et al. [19] perform reverse symbolic execution and generate unit test cases. More works [25], [27], [36], [39], [40], [43] use crash stack information to narrow down or locate the *buggyMethod*. The key challenge is that the stack only contains partially executed methods and may not include the buggy one. So Gu et al. [25] provide an automatic approach to predict whether a crashing-fault resides in a stack trace or not, which denotes the existence of the out-of-stack *buggyMethods*. To locate them, CrashLocator [40] tries to recover the complete execution trace by CG extension on Java projects. However, without code separation and summary construction, CrashLocator may suffer from a large candidate set or low precision when handling framework-specific crashes. Compared with it, CrashTracker weakly relies on the CG but relies more on the extraction of *keyVars* and *keyAPIs*. To perform stack-trace-based fault-localization on Java programs, both Sinha et al. [35] and Ginelli et al. [24] focus on the semantic of exceptions. However, they do not analyze the real exception-thrown points in the frameworks and require manual modeling of specific exceptions, which limits the scalability. For this work, we first perform an automatic semantic analysis for all kinds of framework-level exceptions without any manual modeling. The extracted summaries can help the application-level analysis be more targeted.

To address the problem of Android framework-specific fault localization, researchers combine the learning-based approach with the stack-based analysis. By learning from similar faults, ExLocator [22] first classifies a crash trace within given exception types, and then generates the root causes by static analysis on target applications. This tool is not publicly available and only focuses on the given 5 exception types. To support more types, Anchor [27] collects a general dataset with 500 crashing reports for model training and testing. For a crash trace, it first predicts whether the *buggyMethod* exists on the crash stack, then sorts candidates according to the previous classification result. However, it relies on the labeling of a large-scale dataset, which can not completely cover the numerous and quickly evolving Android framework exceptions. Compared to it, our tool does not need any prior knowledge of crash fixing and works well for newly detected exceptions.

Analysis upon Pre-computed Summaries. Considering the large size of the framework code, a set of works focuses on how to make an analysis based on the pre-computed summaries. Some works [18], [32] noticed that the large-scale framework hinders the inner call relations and hinders the program understanding and debugging. Among them, Cao et al. [18] detect the implicit control flow transitions through the Android framework. Besides, Perez et al. [32] generate *predicate callback summaries* for the Android framework and sequence the callbacks. And recently, Samhi et al. [33] try to find out all the atypical methods around ICC in the Android framework. To achieve this goal, they retrieve the framework code with a lightweight static analysis. Though these works are framework-summary-related, none of them focus on exceptions of the Android framework and their summary could not be used as an effective specification to represent the exception-triggering information.

X. Conclusion

The post-release crashes are inevitable for application developers, which require a heavy effort of debugging and fixing. In this paper, we adopt a code-separation-based analysis approach to solve the Android framework-specific fault localization problem. We design a novel specification, ETS, for framework exceptions, and propose an effective crash-localization approach. By applying ETS on real crash stack traces, CrashTracker outperforms the state-of-the-art tool with higher precision and fewer candidates. Moreover, our approach is explainable in that it gives reasons for each recommended candidate method.

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