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Advanced Security Analysis for Emergent Software Platforms

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ADVANCED SECURITY ANALYSIS FOR EMERGENT SOFTWARE PLATFORMS

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ADVANCED SECURITY ANALYSIS FOR EMERGENT SOFTWARE PLATFORMS

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Emergent software ecosystems, boomed by the advent of smartphones and the Internet of Things (IoT) platforms, are perpetually sophisticated, deployed into highly dynamic environments, and facilitating interactions across heterogeneous domains. Accordingly, assessing the security thereof is a pressing need, yet requires high levels of scalability and reliability to handle the dynamism involved in such volatile ecosystems.

This dissertation seeks to enhance conventional security detection methods to cope with the emergent features of contemporary software ecosystems. In particular, it analyzes the security of Android and IoT ecosystems by developing rigorous vulnerability detection methods. A critical aspect of this work is the focus on detecting vulnerable and unsafe interactions between applications that share common components and devices. Contributions of this work include novel insights and methods for: (1) detecting vulnerable interactions between Android applications that leverage dynamic loading features for concealing the interactions; (2) identifying unsafe interactions between smart home applications by considering physical and cyber channels; (3) detecting malicious IoT applications that are developed to target numerous IoT devices; (4) detecting insecure patterns of emergent security APIs that are reused from open-source software. In all of the four research thrusts, we present thorough security analysis and extensive evaluations based on real-world applications. Our results demonstrate that the

proposed detection mechanisms can efficiently and effectively detect vulnerabilities in contemporary software platforms.

DEDICATION

To my parents Jamal Alhanahnah and Salha Alnajdawi,

my in-laws Raid and Evelyn Elhamawi,

and my beloved wife Zeineh Elhamawi.

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1 Introduction

Emergent software platforms have a tremendous impact on different aspects of modern society, including economic growth, human relationships, entertainment, scientific development, and education. These contemporary applications run at a high level of dynamism and often interact over complex infrastructures. This era of emergent software is driven by the increasing market and the rapid usage of mobile and smart devices. This chapter discusses the unique characteristics of contemporary software platforms, describes the consequent security challenges, and presents our methods to address the challenges by summarizing the contributions of this dissertation.

1.1 Emergent Software Platforms

Conventional software leverages stringent development chains, in which individuals/companies develop software and in many cases distributed it themselves. On the other hand, emergent software ecosystems involve a chain of actors who is responsible for the distribution of software, which is more loosely coupled in contrast to conventional development chains. Moreover, software development is becoming increasingly complex these days [1, 2], because applications, in the emergent platforms, are moving beyond inexpensive recreational applications to more business-centric usage [1]. Indeed, over the last decade, the emergent software

imposes intrinsic changes in the way software is produced and consumed and how users interact with mobile and smart devices [3]. Subsequently, contemporary software introduces emergent characteristics in comparison with conventional software.

Emergent software platforms are built from reusable units of software behaviour [4], unlike conventional apps that are self-contained. This trend encourages emergent software platforms to share features through inter-component communication (ICC) in Android platform [5] and IoT apps interactions manifested through the coordination between sensors and actuators in smart home [6]. This practice of sharing functionalities represents the first characteristic of emergent software, we formalize this attribute as *feature interaction*.

Emergent software platforms are deployed into highly dynamic environments and often interact over highly heterogeneous platforms [7, 8, 3]. This imposes the demand for cross-architecture implementation that allows delivering the functionality of an application over various hardware platforms (i.e. MIPS and ARM) and software platforms (i.e. Android and iOS) [9, 10]. This direction introduces *cross-architecture implementation*, the second attribute of emergent software.

Emergent software ecosystems provide programming frameworks for third-party developers to build apps to manage a single or even several smart devices at the same time to realize more advanced and automated control [11]. This motivates emergent software community to support open-source software that involves code reuse to achieve multi-vendor integration [12]. To this end, *code reuse* is considered as the third characteristic of emergent software.

The attributes of emergent software applications lead to unique security challenges, as illustrated in Figure 1.1. The first layer includes the three attributes of emergent software that have been mentioned in this section. The second layer

introduces the security challenges corresponding to each attribute, these challenges are discussed in detail in the Section 1.2. Finally, the third layer represents the emergent platform wherein we address the security challenges and lists the chapter that presents the solution.

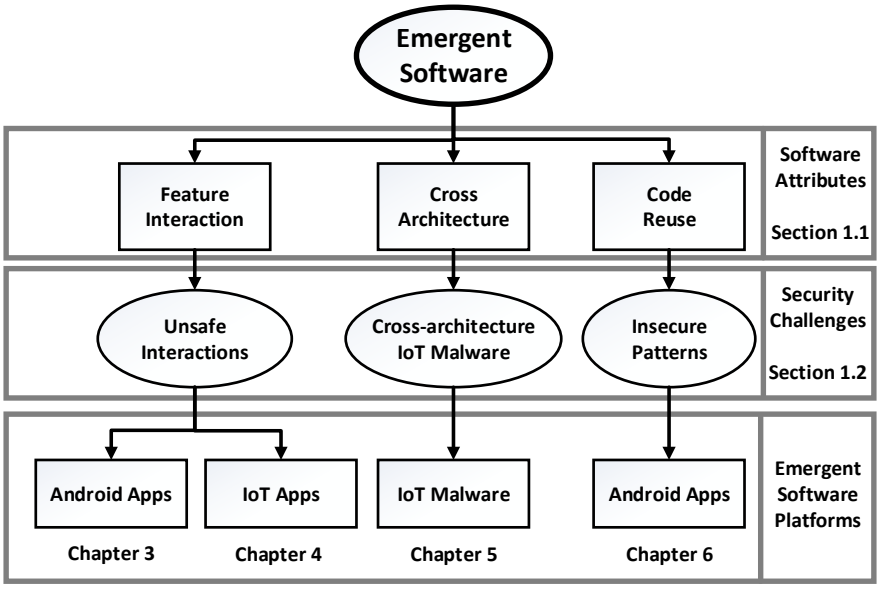


Figure 1.1: Dissertation Road-map

1.2 Security Challenges in Emergent Platforms

After introducing emergent software and its attributes in the previous section, this section discusses the security challenges related to these attributes and highlights the requirements to handle the challenges.

1.2.1 Feature Interaction (FI)

The interoperability in the emergent software era implies the ability of applications to interact and exchange information. This interaction can be perceived in the

Android platform through inter-app communication [13] and interactions between sensors and actuators in the trigger/action ecosystem [14]. The interaction between different components of the ecosystem is known as *Feature Interaction*, where the behavior of one feature is influenced by the presence of another feature (or a set of other features) [15, 16, 17, 18]. As a result, the feature interaction concept provides value-added services and thus contributes to rich the user's experience. For example, an IoT app can provide energy-saving service by integrating an air-conditioner, a ventilator, and thermometers [19]. Furthermore, applying the concept of feature-interaction also reduces the developers' burden and promotes functionality reuse. For instance, in the context of the Android platform, the ability to share pictures from one app with another [20], and a restaurant review application can ask other applications to display the restaurantâĂŹs website, provide a map with the restaurantâĂŹs location, and call the restaurant[21]. Nevertheless, feature interaction is challenging traditional security analysis frameworks. First, the number of interactions can be potentially exponential based on the number of features [22]. Second, interactions cannot be deduced easily from the behaviors of individual features. Third, the interaction introduces a new set of vulnerabilities and safety issues such as resource contention, where features compete for resources and loops in the communication among features [23]. Therefore, scalability aspect should be handled efficiently in the proposed methods. The following subsection discusses the feature interaction concept in the context of the Android and smart home platforms.

1.2.1.1 Feature Interaction in the Android platform

The Android platform provides intent APIs to facilitate the interaction between components within the app, which is known as Inter-Component Communica-

tion (ICC) or across-apps, known as Inter-app communication (IAC). Although IAC improving users' experience and reducing programming burden, it can be exploited to perform collusive attacks [24]. To conceal this exploit, dynamic java programming features such as Reflection and Dynamic Class Loading (DCL), can be employed. The usage of dynamic programming features is justifiable because its usage is expected to be growing in the appified era [2]. Java reflection mechanism is extensively used in Android apps for maintaining backward compatibility, accessing hidden/internal application program interface (API), providing external library support, and reinforcing app security [25, 26]. But the use of the reflection mechanism renders the security analysis approaches designed to analyze and detect malicious apps ineffective [27]. As the malicious code is not part of the apps' bytecode, rather is loaded at runtime using the dynamic class loading (DCL).

The current state-of-the-art security mechanisms, both static and dynamic analysis approaches, are insufficient for detecting the increasingly sophisticated security attacks.

Static analysis approaches [28, 29, 30, 31] can be easily bypassed by apps that covertly invoke malicious IAC using reflection or DCL. On the other hand, dynamic analysis approaches, such as TamiFlex [32], StaDyna [26], and DyDroid [33], suffer from false negatives largely due to the reachability challenges, where vulnerabilities are missed because of inputs that fail to reach the vulnerable code; they thus do not detect malicious IACs concealed behind reflective and DCL calls. In Chapter 3, we present a hybrid analysis approach for detecting such sophisticated behavior.

1.2.1.2 Feature Interaction in Smart Home Platform

In a smart home environment, the same set of sensors and actuators can be controlled from different IoT platforms (i.e. SmartThings Groovy and SmartThings

IFTTT). This can lead to the race to configure, control, and monitor these devices [34]. These platforms allow users to install third-party software *apps* that automate the devices in their homes. Through their control of physical devices in a system, software apps installed by the user can interact in both physical as well as cyberspaces, allowing complex and varied automation. While enhancing the user's experience by delivering many options for automating their home, such diversity at the same time escalates the attack surface for safety and security threats. Interaction between smart home apps and devices can go beyond affecting cyberspace to influencing the physical space, which might lead to severe safety and security violations. Hence, identifying risky interactions is a pressing need. This entails performing precise analysis that can assess the severity of interactions. For instance, a door control app can be triggered to unlock the door when the user arrives home, which is the desired behavior, but if the door unlocked while the user is not present, this constitutes a serious hazard. This undesired behavior can occur accidentally, or through unforeseen coordination between apps.

In this context, several techniques have been proposed in recent research to identify possible safety and security violations in the IoT domain. However, existing techniques provide an incomplete picture of the overall landscape of IoT app interactions. In particular, the state-of-the-art techniques target only certain types of inter-app attacks [34, 35, 11], do not take into account *physical channels* through which apps can interact (such as temperature or moisture levels) [36], which can underpin risky interactions, lack *cross-platform analysis capability* [34, 35], which is necessary to analyze diverse systems that can interoperate in the same IoT environment (e.g., Samsung SmartThings [37] and IFTTT [38]), and require manual specification of the initial system configuration, which may lead to missing potential unsafe behavior if it appears from different configurations [34]. Moreover,

these analyses have been shown to experience scalability problems when applied on large numbers of IoT apps [34, 11, 35]. In Chapter 4, we present a compositional analysis approach that can detect unsafe interaction threats in a given bundle of cyber and physical components co-located in an IoT environment.

1.2.2 Cross-Architecture Malware

Interoperability in emergent software era is underpinned by developing cross-architecture applications and firmwares [7, 8], which support various CPU architectures of IoT devices. This involves the ability to program across-architecture IoT devices with a single compiler [9] and thus facilitating heterogeneous firmware update instead of using monolithic binary updates. Moreover, promoting cross-architecture implies the code base will be compiled with different compilers using various configurations (e.g., different optimization levels). Cross-compile execution will impose significant changes in the representation of the generated binaries [39].

In the IoT malware domain, Mirai malware was developed to infect different architectures of IoT devices, as security researchers found binaries for the common architecturesâĂŤMIPS 32-bit, ARM 32-bit, and x86 32-bit belong to this malware [40]. Mirai caused a major Internet service breakdown for a few hours due to this cross-architecture capability, which supported the Mirai's actor to infect a large-scale of IoT devices [41]. Therefore, IoT devices have become enticing targets for cyber-attackers. Since IoT devices are fully integrated into our daily life, compromised devices can cause unprecedented damages. Even worse, IoT devices are usually resource-constrained with low-profile processors, which prevents the deployment of sophisticated host-based defenses as we commonly use on personal computers (PCs). Consequently, the attackers endeavor to recruit vulnerable IoT

devices to build a *large-scale* bot army to launch the attack, and the number of IoT malware has more than doubled in 2017 [42]. Therefore, in Chapter 5, we design a lightweight *cross-architecture* signature generation scheme for detecting/classifying IoT malware.

1.2.3 Code Reuse

Open-source application is a key aspect to facilitate the integration between the heterogeneous systems in which emergent software platforms are deployed [43, 2, 44, 45]. Therefore, the software communities open-source the software development [46], because open-source implementations support achieving multi-vendor interoperability [12, 44, 45]. So that 91% of IoT developers adopt open-source software at least one part of their development stack [2, 47].

However, this usage of others' implementations can lead to the propagation of security vulnerabilities [48, 44] because of weak programming practices [49]. The code reuse is observed between open source software and online programming discussion platforms (e.g., Stack Overflow) [50, 51, 52]. Several works showed that insecure code patterns propagated in production software [53, 54, 55]. To mitigate this issue, developers should be supported through a detection mechanism that can identify insecure implementations at the early stage of a software implementation, which consequently will promote the development of secure code. In Chapter 6 we identify insecure patterns of Secure Socket Layer/Transport Layer Security (SSL/TLS) in the context of Android and develop detection rules that can be used within the IDE.

This section discussed the security challenges that are considered in this dissertation, which shows the complexity and the demand for reliable methods.

Therefore, conducting rigorous security analysis for addressing the implications of these attributes requires: (1) performing a holistic analysis, (2) resolving scalability aspects, and (3) modeling different elements of the applications that will impact applications' behavior. All these requirements represent a severe demand for high levels of reliability and scalability in the proposed solutions. Section 1.3 summarizes our solutions to address these security challenges.

1.3 Research Contributions

In this dissertation, we propose **four security analysis frameworks** for addressing the challenges discussed in the previous sections and illustrated in Figure 1.1. Each project considers a specific challenge in the context of one of the emergent software ecosystems. We make the following contributions in this dissertation:

1. **FI in Android Platform:** We analyze feature interactions in the context of Android that manifested through inter-app communication (IAC). In this work, we expose a new attack that leverages reflection and dynamic class loading features in conjunction with inter-app communication to conceal malicious attacks to bypass existing security mechanisms. we also show the interaction between apps can lead to privacy leakage and spoofing attacks resulted from the interactions of Android applications. To identify such vulnerabilities, we design, develop and implement Dynamic INter-App Communication Tool (DINA), a novel hybrid analysis approach for identifying malicious IAC behaviors concealed within dynamically loaded code through reflective/DCL calls. DINA appends reflection and DCL invocations to control-flow graphs and continuously performs incremental dynamic analysis to detect the misuse of reflection and DCL that obfuscates Intent communications to hide

malicious IAC activities. DINA utilizes string analysis and inter-procedural analysis to resolve hidden IAC and achieves superior detection performance. This component of the dissertation is published in [56].

2. **FI in smart home platform:** we design and implement IOTCOM, a formal method tool to identify safety and security violations that can occur in the interactions between IoT apps in smart home environments. IOTCOM is a compositional approach that empowers end-users to safeguard a given bundle of cyber and physical components co-located in an IoT environment. It automatically discovers such complicated interaction threats. IOTCOM combines static analysis with lightweight formal methods to automatically infer relevant specifications of IoT apps in an analyzable formal specification language, taking into consideration the mapping between cyber and physical channels. IOTCOM then checks the extracted specifications as a whole for interaction threats.

3. **Detecting Cross-architecture IoT Malware:** we propose a data-driven signature generation method for detecting IoT malware, which generates distinguishable signatures based on high-level structural, statistical and string feature vectors, as high-level features are more robust against code variations across different architectures. The generated signatures for each malware family can be used for developing lightweight malware detection tools to secure IoT devices. The signature generation scheme extracts a reliable and easily extractable string and statistical features. The string feature is extracted using N-gram text analysis, while the statistical feature contains the code-level statistics. This work is published in [57]

4. **Insecure implementation of SSL/TLS:** this work aims to support developers in detecting insecure SSL/TLS implementation in their codes in the context of Android, whether this implementation is imported from other projects or other platforms such Stack Overflow. Our approach utilizes a *low-cost cross-language* static analysis tool called PMD. In the end, two insecure implementations of SSL/TLS have been identified, and subsequently, a new PMD ruleset is created. This ruleset consists of three rules for addressing *hostname validation vulnerability* and *certificate validation vulnerability*. This work is published in [58].

1.4 Organization

The rest of this dissertation is organized as follows: Chapter 2 presents the related work of this work and puts it in the context of describing the limitations of prior work. Chapter 3 presents our security analysis framework (namely DINA) for detecting vulnerable Android Inter-App Communication in dynamically loaded code. In Chapter 4, we introduce our formal method approach for detecting unsafe interactions in the context of a smart home. In Chapter 5, we discuss our approach for analyzing IoT malware and describe the data-driven framework for cross-architecture signature generation. Chapter 6 describes our approach for detecting code reuse in the context of StackOverflow. Finally, Chapter 7 concludes this dissertation and provides an outlook on future research directions.

2 Related Work

In this chapter, we discuss research related to the work presented in this dissertation and describes the limitation in prior work.

2.1 Android Inter-app Communication

This section discusses research efforts in the area of Android Inter-App Communication (IAC) and Inter-Component Communication (ICC). It then highlights the limitations of the related solutions. Numerous techniques have been proposed to analyze inter-component communication vulnerabilities [59, 60, 61, 62, 63, 64, 31, 65]. Among others, IccTA [60] and its successor [62] leverage an Intent resolution scheme to identify inter-component privacy leaks. However, their approach relies on a preprocessing step connecting Android components through code instrumentation, which can lead to scalability issues [31, 28]. SEPAR [29] and SEALANT [31] perform compositional security analysis at a higher level of abstraction. While these research efforts are concerned with security analysis of component interactions between Android apps, DINA's analysis enables reflection and DCL-aware assessment of the overall security posture of a system, greatly increasing the scope of potential ICC-based misbehavior analysis.

With respect to reflection and DCL, there have been several research efforts that attempt to improve the soundness of static analysis in the presence of dynamically

loaded code through Java reflection. Livshits et al. [66] propose a static analysis algorithm that can approximate reflection targets using points-to information. Felt et al. [67] discuss the challenges of handling reflection in Android applications and then attempt to address them using Stowaway, a static analysis tool that is capable of identifying reflective calls and tracking reflection targets by performing flow-sensitive analysis. More recent static analysis approaches aim to improve precision. These approaches include DroidRA [25] and Sparta [68]. DroidRA adapts TamiFlex [32] to statically analyze Android apps for dynamically loaded code. Unlike TamiFlex, DroidRA does not execute apps; instead, it uses a constraint solver to resolve reflection targets. It also uses its own version of *Booster* to manipulate Jimple, an immediate representation used by Soot directly. TamiFlex, on the other hand, manipulates Java bytecode. Sparta implements annotations in the Checker framework to track information flow and a type inference system to trace reflective calls. Sparta also operates at the source code level and not the bytecode or dexcode level. However, these static analysis approaches can work only in cases in which reflection targets can be identified from the source code. For the most up-to-date and comprehensive review of static analysis approaches for handling reflection, see Landman et al. [27]. Our approach however detects reflection targets and captures dynamically loaded code using dynamic analysis.

There have also been several research efforts to perform dynamic analysis to detect reflection/DCL targets. Davis et al. [69] provide an app rewriting framework named RetroSkeleton that is capable of intercepting reflections at runtime; however, this approach does not work with custom classloaders. Sawin et al. [70] propose an approach that combines static string analysis with dynamic information to resolve dynamic class loading via Java reflection. This approach operates only on the standard Java library. Execute This! [71] is a dynamic analysis approach that

relies on an Android VM modification to detect reflection calls. It first logs runtime events and then performs static analysis off-line. StaDynA [26] also performs dynamic analysis in two phases. Our approach, on the other hand, performs analysis continuously.

2.2 Smart home safety and security

This section discusses the stateof-the-art works that address the safety and securtiy of smart home. IoT safety and security has been broadly studied recently [72, 11, 73, 74, 75, 76, 77, 35, 34, 36, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97]. Many of these studies focus on data security issues such as permission overprivilege [72, 98], or sensitive information leakage [74, 11, 73, 99]. ContextIoT [11] and SmartAuth [73] both detect and enforce authorization policies at runtime to prevent such attacks. ProvThings [75] examines data security by determining data provenance in IoT systems, and can log interactions between IoT apps. However, these approaches primarily aim to protect sensitive data, and do not detect safety and security violations arising from interactions of apps in the physical world.

Soteria [35] reports violations either within a single app or between pairs of apps, indicating a possible cap on its scalability. IoTSAN [34] detects violations in bundles of more than two apps. However, the initial configuration of those apps and their connected devices must be provided manually for each analysis. Also, it must first translate the Groovy code of the SmartThings apps to Java, limiting its analysis to just less than half (27 of 65) of the devices supported by SmartThings [100]. In contrast, IotCom directly analyzes Groovy code, supports large app bundles and all SmartThings device types, and is completely automated.

To the best of our knowledge, none of these approaches can detect violations mediated by physical channels—a key feature of IotCom.

IoTMON [36] is a pure static analysis technique that analyzes rules based solely on triggers, neglecting the conditions for specific actions. In contrast, IotCom validates the safety of app interactions with more precision by effectively capturing logical conditions influencing the execution of app rules through a precise control flow analysis. Moreover, IoTMON does no analysis to detect potential safety and security issues, which is conducted in a formally rigorous manner in IotCom.

Other researchers have evaluated the security of IFTTT applets [98, 76, 101, 102]. Fernandes et al. [98] studied OAuth security in IFTTT, while Bastys et al. [76] used information flow analysis to highlight possible privacy, integrity, and availability threats. However, none of the studies examined the aforementioned IoT safety and security properties. In contrast, IotCom performs large scale safety and security analysis, examining interactions between tens of IFTTT smart home applets. IotCom also analyses bundles comprising both SmartThings Classic apps and IFTTT applets, demonstrating its unique cross-platform analytical capability.

2.3 IoT Malware Detection

In this section, we focus on reviewing malware analysis approaches that aim at classifying malware families and generating signatures for effective detection.

Malware Classification: Recently, Alazab [103] proposes a Windows malware (in PE format) classification method based on features extracted dynamically and statically from the malware files, including windows API sequences and their frequencies of appearance. But the API calls are different across different architectures, and can be easily forged or modified by attackers to disguise their

malicious activities. Santos et al.[104] present a malware classification method based on the frequency of opcode sequences, but opcode sequences can also be easily disrupted by simple code variations resulted from different compilation options. Zynamics Bindiff [105] and BinSlayer [106] measure binary similarities based on graph isomorphism between CFGs. BinSlayer further improves the binary comparison accuracy of BinDiff by incorporating graph edit distances, but also brings considerable overhead. Both Shabtai et al. and Hu et al. [107, 108] use static analysis to examine the effectiveness of malware detection using OpCode N-gram analysis. Kong et al. [109] map malware instances to their corresponding malware family using structural features of function call graph and statistical features including lists of API calls and opcodes with their respective frequencies.

Malware Signature Generation: High level string features and statistical features extracted from file size and file content have been used to classify firmware images of embedded devices [110]. Besides our different goals (known firmware classification versus unknown malware classification), they use a simple intersection method on string features to identify firmware images, while our N-gram string features can extract more representative features for each malware family. We also consider statistical features by counting instructions and functions at the assembly code level, which have finer granularity. Perdisc et al. [111] propose a multi-stage clustering approach for generating malware signatures using the network traffic generated by malware samples. FIRMA [112] also utilizes network traffic to generate behavioral signatures for malware detection. Unlike [111], FIRMA generates network signatures for each network behavior regardless of traffic types, the format of which follow popular signature-matching IDS. While the previous work deals with generic PC malware, we focus on the newly emerging IoT malware.

2.4 Insecure SSL/TLS implementation Detection

In this section, we review related work that consider the insecure implementation of cryptograpy. FixDroid plug-in for Android studio has been developed in [113], which addresses several limitations in Android Lint tool. It is used for helping App developers in improving the quality of their code including insecure implementations. FixDroid attempts to address the insecure implementations of SSL/TLS. However, FixDroid only considers a single pattern, which is Improper HostNameVerifier, while in our solution we consider three most commonly observed patterns.

Another plug-in called CogniCrypt is developed for assisting developers in generating secure implementation of crypto APIs [114]. This plug-in automatically generates secure implementation instead of detecting insecure patterns using static analysis technique. Although SSL API implementation is covered by the plug-in, it does not show details about the type of SSL implementations that have been covered.

HVLearn is a blackbox testing tool for verifying hostname ins SSL/TLS implementations based on automata learning algorithms [115]. However, developers do not actually need blackbox testing techniques for detecting insecure implementation, as the source code is available. Also, HVLearn focuses only on detecting one aspect of insecure SSL/TLS patterns.

Other solutions have been developed to detected insecure implementation of SSL/TLS [116, 117]. However, these solutions intended to analyze released applications and not to assist developers in detecting insecure patterns while implementing SSL/TLS APIs.

3 Dina: Detecting Hidden Android Inter-App Communication in Dynamic Loaded Code

Java reflection and dynamic class loading (DCL) are effective features for enhancing the functionalities of Android apps. However, these features can be abused by sophisticated malware to bypass detection schemes. Advanced malware can utilize reflection and DCL in conjunction with Android Inter-App Communication (IAC) to launch collusion attacks using two or more apps. Such dynamically revealed malicious behaviors enable a new type of stealthy, collusive attacks, bypassing all existing detection mechanisms. In this chapter, we present DINA, a novel hybrid analysis approach for identifying malicious IAC behaviors concealed within dynamically loaded code through reflective/DCL calls. DINA continuously appends reflection and DCL invocations to control-flow graphs; it then performs incremental dynamic analysis on such augmented graphs to detect the misuse of reflection and DCL that may lead to malicious, yet concealed, IAC activities. Our extensive evaluation on 3,000 real-world Android apps and 14,000 malicious apps corroborates the prevalent usage of reflection and DCL, and reveals previously unknown and potentially harmful, hidden IAC behaviors in real-world apps.

3.1 Background and Challenges

Android Apps: comprise different types of components, namely *activities*, *services*, *broadcast receivers*, and *content providers*[1]. These components communicate through a specific type of event messages called *Intent*, which can be either explicit, when its recipient component is specified, or implicit, when no specific recipient component is declared.

Inter-App Communication (IAC): Android apps typically use Inter-Component Communication (ICC), a message passing mechanism (i.e. intent), to exchange data. Components within or between apps use ICC to communicate with each other via explicit or implicit Intents, depending on whether the target component name is specified. The Android Intent is resolved at runtime based on the fields of `IntentFilter` declared in the apps' manifest files and the attributes of implicit Intents, including *action*, *category*, and *data*. Intents can be sent through three types of components (i.e., activities, services, receivers). Table 3.1 lists relevant Intent sending and receiving APIs, categorized based on their corresponding component types.

Components	Intent-sending APIs	Intent-receiving APIs
Receivers	sendBroadcast() sendOrderedBroadcast() sendStickyBroadcast() sendStickyOrderedBroadcast()	onReceive()
Activities	startActivity() startActivityForResult()	onCreate()
Services	startService() bindService()	onStartCommand()

Table 3.1: A non-exhaustive list of Intent APIs.

Reflection and Dynamic code loading (DCL): DCL allows Android apps to load and execute code that is not part of their initial code bases at runtime. DCL is used to overcome some restrictions (i.e. 64K maximum method references in a

[1]https://developer.android.com/guide/components/fundamentals.html

dex file) and extend the app's functionality [26]. Java reflection is a language feature that provides developers with the ability to inspect and determine program characteristics, such as classes, methods and attributes, at runtime. Reflection is used for maintaining backward compatibility, accessing hidden/internal application program interface (API), providing external library support, and reinforcing app security [25, 26]. Therefore, reflection and DCL have been used to enhance functionalities of Android applications for legitimate purposes. But reflection and DCL can also be used to hinder static analysis tools because they are resolved at runtime. Fig. 3.1 illustrates a reflective call where the actual reflection targets (i.e., *Classes B, C* and *D*) cannot be resolved by static analysis tools as the malicious code is not part of the apps' bytescode, rather is loaded at runtime using the dynamic class loading (DCL).

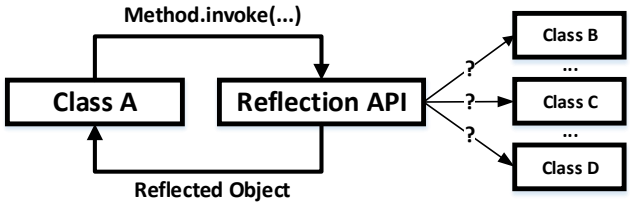


Figure 3.1: A typical reflective call used to defeat static analyzers.

Challenges: Analyzing the interactions among apps is a challenging task. The obfuscation techniques such as reflection and DCL impose additional challenges. We lay out the specific challenges in details below.

- The collaborative nature of Android apps indicates that the analyst needs to be able to analyze a large collection of apps that can potentially interact, and observe their collective runtime behaviors. Most existing program analysis approaches cannot support such needs, because they tend to operate in a close-world fashion (i.e., any change to the program under analysis requires

the entire analysis process to be rerun [118, 119]), require off-line processing to generate analysis results, and can only analyze one app at a time.

- Reflection implies missing nodes and edges in the call graph, and thus the control-flow and data-flow graphs regarding these missed nodes will not be generated. Therefore, it is critical for the analyzers to have the capability of resolving reflection and dynamically updating call graphs.

- DCL involves new codes that will be downloaded and executed at runtime. The analyzers need to capture the newly downloaded code and then update the call graph, control-flow and data-flow graphs at runtime.

3.2 Motivating Example

In this section, we present motivating examples to show how Intent can be used as an attack vector to launch information leakage through hidden (dynamically loaded) code, and to conceal method invocations through reflection.

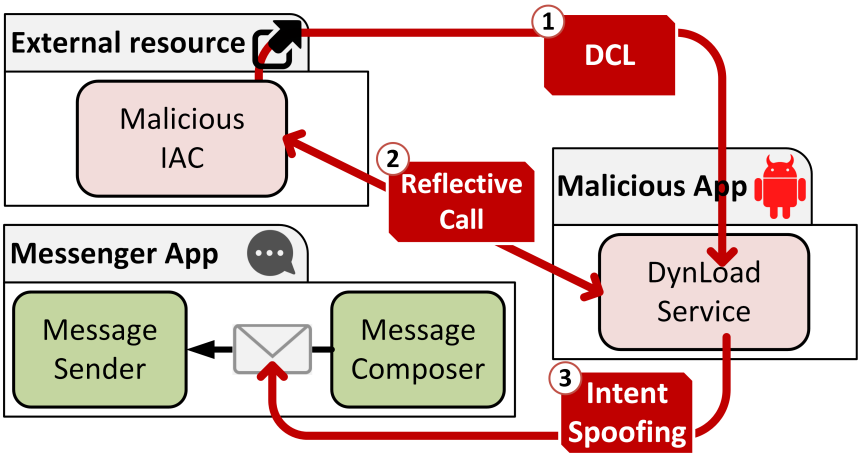


Figure 3.2: Malicious app downloads code at runtime, and then uses it for leaking sensitive information.

```
1  public class DynLoadService extends Service {
2   public int onStartCommand(Intent intent){ [...]
3    loadCode();
4   }
5   public void loadCode(){
6    // Read a jar file that contains classes.dex file
7    String jarPath=Environment.getExternalStorageDirectory().getAbsolutePath()
         ↪ +"/dynamicCode.jar";
8    // Load the code
9    DexClassLoader mDexClassLoader = new DexClassLoader(jarPath, getDir("dex",
         ↪  MODE_PRIVATE).getAbsolutePath());
10   // Use reflection to load a class and call its method
11   Class<?> loadedClass = mDexClassLoader.loadClass("MalIAC");
12   Method methodGetIntent = loadedClass.getMethod("getIntent", android.
         ↪ content.Context.class);
13   Object object = loadedClass.newInstance();
14   Intent intent = (Intent) methodGetIntent.invoke(object, DynamicService.
         ↪ this);
15   startService(intent); } }
```

Listing 3.1: *DynLoadService* component resides in the malicious app and performs DCL and reflection to hide its malicious behavior.

Fig. 3.2 presents a bundle of two apps, where a malicious IAC is initiated within a dynamically loaded component from an external source to leak sensitive information through the *Messenger* app. The *DynLoadService* component dynamically loads a malicious class from an external JAR file placed at the location specified on line 7 of Listing 3.1. It then instantiates a *DexClassLoader* object, and uses it to load the DEX (Dalvik Executable) file contained in the JAR file. Using Java reflection at line 12, the *mDexClassLoader* object loads a class called *MalIAC* and invokes its *getIntent* method at line 14. This method returns an implicit Intent, which *DynLoadService* uses to communicate with the *Messenger Sender* (line 15). Note that MYSTIQUE-S [120] uses the same invocations in lines 9, 11-13 of Listing 3.1 for constructing the attack template that loads the malicious payload on the fly.

Listing 3.2 depicts the hidden malicious class aiming at stealing users' sensitive information. On lines 3-4, *getIntent* obtains the sensitive banking information, and then creates an *implicit Intent* with a phone number and the banking information as the extra payload of the Intent (lines 5-8). This code is pre-compiled into

DEX format and archived to a JAR file. The JAR file could be downloaded by the malicious app after installation. The *Messenger* app, as shown in Listing 3.3, receives the Intent and sends a text message using the Intent payload, effectively leaking sensitive data.

```
1 public class MalIAC {
2  public Intent getIntent(Context context){
3   String account = getBankAccount("Bank_Account");
4   String balance = getBankBalance("Balance_USD");
5   Intent i = new Intent("SEND_SMS");
6   i.putExtra("PHONE_NUM", phoneNumber);
7   i.putExtra("Bank_Account", account);
8   i.putExtra("Balance_USD", balance);
9   return i; } }
```

Listing 3.2: Malicious IAC component is concealed as external code and loaded at runtime after app installation.

```
1 public class MessageSender extends Service {
2  public void onStartCommand(Intent intent) {
3   String number=intent.getStringExtra("PHONE_NUM");
4   String message=intent.getStringExtra("TEXT_MSG");
5   sendTextMessage(number, message);
6  }
7  void sendTextMessage (String num, String msg) {
8   SmsManager mngr = SmsManager.getDefault();
9   mngr.sendTextMessage(num,null,msg,null,null); } }
```

Listing 3.3: MessageSender resides in a benign app to receive Intents and send text messages.

Listing 3.4 presents an abbreviated code snippet from a real-world app (i.e., *com.example.qianbitou*) that uses reflection to conceal IAC behavior. The method *instantiate* in the class *Fragment* (line 2) calls the reflection method *newInstance()* (line 4). This reflective call will initialize the constructor of the class *_03_UserFragment* (line 6), and execute the method *onClick()* that invokes *toCall()*, which defines an implicit Intent for making a phone call to a hard-coded number between 8am and 10pm. The suspicious method *toCall()* is a private method concealed behind reflective calls, which is difficult to capture in the analysis.

```
1  public class Fragment {
2   public static Fragment instantiate(){
3    // Reflection call site
4    paramContext = (Fragment)localClass1.newInstance();}
5  }
6  public class _03_UserFragment extends Fragment {
7   public onClick(){
8    toCall();
9   }
10  // The method invoked through the reflective call at line 4
11  private void toCall(){
12      int i = Calendar.getInstance().get();
13      if ((i <= 22) || (i >= 8)) {
14        startActivity(new Intent("android.intent.action.DIAL", Uri.parse("tel
              ↪ :4000-888-620"))); } } }
```

Listing 3.4: Reflection is used to conceal IAC behavior in a real-world app

In order to detect the suspicious behaviors in the motivating examples, a systematic approach is needed to resolve reflection/DCL and update the method graphs dynamically. specifically, the proposed approach should 1) load the class *MalIAC* in the DCL (Listing 3.2), 2) append the method `getIntent` (Listing 3.2) to the method graph after resolving reflection, and 3) analyze the control-flow graphs of `loadCode` (Listing 3.1) and `getIntent` to perform IAC analysis for detecting suspicious IACs.

DINA is designed to load and resolve the reflective calls in Listings 3.1 and 3.4 at runtime. DINA's dynamic analyzer automatically and incrementally augments both the control-flow and data-flow graphs with the newly loaded code and resolved reflective calls. In tandem with the graph augmentation, DINA's vulnerability analyzer identifies potential malicious IAC activities on the fly. As a result, DINA has the capability to precisely and efficiently detect the malicious IAC behavior in the motivating examples although it is concealed by reflection.

3.3 Threat Model

This section describes the categories of suspicious inter-app communication behaviors that are considered in this work. The goal of the attacker considered in this work is to launch stealthy inter-app attacks without being detected. Such stealthy behavior can be manifested by different types of *collusive attacks* [121], where an attacker uses the DCL and reflection mechanisms to obfuscate IAC behaviors of the sender app and launch malicious behaviors, e.g., leaking sensitive information, via another receiver app.

Our security analysis is centered around identifying the *vulnerable IAC activities* that result in three types of serious threats: *Information leakage*, *Intent spoofing*, and *Android component activation*, described as follows:

1. *Information leakage* happens when a receiver app exfiltrates the sensitive data obtained through IAC communications from other apps and transmits it to an external destination.

2. *Intent spoofing* is a security attack where the sender app forges Intents to mislead receiver apps [21].

3. *Android component activation* happens when a malicious app intercepts an implicit Intent by declaring an Intent filter matching the Intent, since the Intent is not properly protected by permission restrictions [21].

We consider both explicit and implicit Intent. A *malicious component* refers to a component that uses Intent sending/receiving APIs to help transfer malicious Intents that contain sensitive information for data leakage, are forged for Intent spoofing, or are received in an unauthorized manner. The data leaks are initiated by a malicious component. Intent spoofing involves a path between two components

when the sender component is *malicious*, while unauthorized Intent receipt involves a path between two components when the receiver component is *malicious*. DINA is designed to detect all three types of security threats. Moreover, we consider the IAC communication that involves more than two apps, i.e., DINA will be able to capture collusive attacks concealed in a *transitive ICC path* through multiple apps.

3.4 DINA System Design

This section presents DINA, a hybrid analysis tool for identifying sensitive IAC paths that concealed through DCL and reflection. Fig. 3.3 illustrates DINA's architecture. DINA is a *graph-centered hybrid analysis* system that consists of three main modules: 1) the *collective static analysis* module that simultaneously analyzes multiple apps to automatically elicit DCL and reflection call sites within the apps. The identified DCL and reflection call sites become the execution targets for dynamic analysis; 2) the *incremental dynamic analysis* module that systematically capturing new nodes and edges that are loaded at runtime by DCL and reflection; 3) the *path construction* module that generates the dynamic IAC graph that includes all potential paths among the apps in the bundle. Specifically, it first generates the static IAC graph, and then augments the static IAC graphs after receiving the incremental updates; 4) the *IAC vulnerability analysis* module utilizes real-time IAC graphs to identify potentially vulnerable paths.

3.4.1 Collective Static Analysis

The collective static analysis of DINA aims to statically identify the reflection, DCL and IAC capabilities of each app in the app bundle, by analyzing multiple apps at the same time. We generate two different types of graphs for each app, the

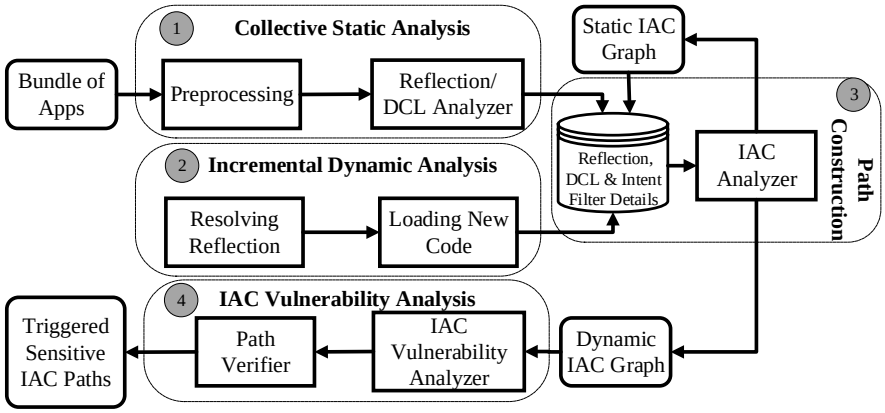


Figure 3.3: Architecture of DINA

method call graph (MCG) and *instruction graph* (IG). The MCG maintains the call relationships among the methods defined within the analyzed apps in the bundle, while the IG includes detailed control-flow and data-flow information for a certain method. DINA works on the bytecode level of the target application, and the analysis focuses on the app's Dalvik bytecode.

Algorithm 1 outlines the collective static analysis process, which consists of two major steps:

Preprocessing. We first decompile APKs in the collective app bundle to generate the bytecode of each app and extract its manifest file. Intent filter information for each app is then extracted from the manifest file. This step also involves the generation of MCG for each app and the IG for each method in the MCG. All extracted information and the generated graphs are stored in a database for fast access.

Reflection/DCL analyzer. We then identify DCL and reflective calls using the MCG of each app by detecting DCL and reflection APIs, such as `invoke()`, `newInstance()`, and `getMethod()`. The list of reflection and DCL APIs (i.e., *Ref_DCL_API_List* in Algorithm 1) is similar to the API list in StaDyna [26],

which mainly includes APIs of dynamic class loading. We extend that list to include additional reflection APIs involving method invocations [25]. As a result, this step identifies the apps that need to be executed in the incremental dynamic analysis module. We further extract the class and method names (call sites) implementing these APIs.

Finally, all the extracted information that is stored in the database will be leveraged for generating a *Static IAC Graph*, which contains all the potentially sensitive paths that have been constructed through the *Path Construction* component (see Section 3.4.3).

Algorithm 1 Collective Static Analysis

INPUT: Bundle of Apps: B, $Ref\_DCL\_API\_List$
OUTPUT: $static\_IAC$, $Intent\_Filter\_App_i$, $Ref\_Details$

// Preprocessing
$static\_IAC \leftarrow$ CreateNodes($|B|$)
$Intent\_Filter\_App_i \leftarrow \{\}$ **// initialize Intent filter list**
for each $App_i \in B$ **do**
  Decompile(App_i)
  parse_manifest(App_i)
  update($Intent\_Filter\_App_i$) $\leftarrow$ {(App_i, class-name, intent-action-string)}
end for
for each $App_i \in B$ **do**
  Generate $MCG(App_i)$
// Reflection analyzer
  for each $method \in MCG(App_i)$ **do**
    if $method_j \in Ref\_DCL\_API\_List$ **then**
      $update(Ref\_Details) \leftarrow$ {(App_i, class-name, method-name)}
    end if
    Generate $IG(method_j)$
// Generating Static IAC Graph
    $static\_IAC \leftarrow$ IAC_Analyzer($IG(method_j), App_i$)
  end for
end for

3.4.2 Incremental Dynamic Analysis

DINA performs incremental dynamic analysis for each app that contains reflective or DCL calls. The dynamic analysis is capable of capturing and loading code in various formats (i.e. APK, ZIP, JAR, DEX), resolving reflection, and performing

IAC analysis incrementally with progressive augmentation of graphs. We modified Android framework for resolving reflective calls and capturing newly loaded codes at runtime. The incremental dynamic analysis consists of two major steps as described below (see Algorithm 2).

Resolving reflection and loading new codes. Every app implementing reflection and DCL will be executed on a real Android device or an emulator. This step aims to capture the dynamic behaviors of the app. To reach the components that implement reflection, we use the reflection details extracted and stored in the database, which includes the component name and the corresponding method name that implement reflection and DCL in each app. These methods/components of an app, regarded as *method of interest (MoI)*, will be exercised in the dynamic analysis for resolving reflection and DCL call sites, which will augment the control-flow and data-flow graphs dynamically.

We utilize a fuzzing approach to trigger the components that contain reflection and DCL call sites. In the end, the static IAC graph will be refined by the IAC analyzer to include all the IAC detected inside the dynamically loaded codes after resolving reflection. New edges pertaining to the identified IAC are added to the graph at runtime.

3.4.3 Path Construction

This component is used to generate the *Static IAC Graph* after performing the *collective static analysis*, and it is also used to generate the *Dynamic IAC Graph* by augmenting the *Static IAC Graph* after adding dynamic information that is extracted through the *Incremental Dynamic Analysis*. Specifically, the IAC analyzer

Algorithm 2 Incremental Dynamic Analysis

INPUT: $static\_IAC$, $Ref\_Details$, $Intent\_Filter\_App_i$
OUTPUT: $dynamic\_IAC$

1: $dynamic\_IAC \leftarrow static\_IAC$
   // Resolving Reflection and Loading new code
2: **for each** App_i **do**
3: Install(App_i)
4: Launch(App_i)
5: Pull newly loaded code
6: **for each** Component $\in$ $Ref\_Details(App_i)$ **do**
7: Find method of interest (MoI)
8: **for each** $Method \in$ MoI(App_i) **do**
9: Execute the component using Monkey (if failed, execute the whole app using Monkey), and incrementally generate $IG(method_j)$
   // Generating Dynamic IAC Graph
10: $dynamic\_IAC \leftarrow$ IAC_Analyzer($IG(method_j), App_i$)
11: **end for**
12: **end for**
13: uninstall(App_i)
14: **end for**

updates the *Static IAC Graph* by attaching new nodes and edges that are loaded at runtime by DCL and reflection.

Algorithm 3 describes the operations performed by the *IAC analyzer* for constructing the potential paths among the apps in the bundle. The IAC analyzer first identifies explicit Intent APIs (i.e. *setClassName*, *setComponent*) by iterating over the nodes in the IG. The IAC analyzer then extracts the name of the receiver component, finds the details of the receiver component in the Intent filter list, and finally creates an edge between the sender and receiver components in the IAC graph. Otherwise, if the node contains *setAction*, it indicates IAC uses an implicit Intent. Therefore, the IAC analyzer extracts the Intent action string and then finds potential recipient components in the Intent filter list.

The component name (Algorithm 3, line 3) and Intent action string (Algorithm 3, line 8) are extracted using data-flow analysis based on the IGs. Note that the generated IGs maintain both control-flow and data-flow information.

Algorithm 3 Path Construction

INPUT: $IG(method_j)$, App_i, $Intent\_Filter$, Explicit_APIs
OUTPUT: IAC_Graph

```
    // Identify Intent Type
 1: for each node ∈ IG(method_j) do
      // Explicit Intent
 2:   if methodName ∈ Explicit_APIs then
 3:     componentName = extractCompName(node)
 4:     if componentName == Intent_Filter_App_r.component then
 5:       IAC_graph ← addEdge(App_i, App_r)
 6:     end if
      // Implicit Intent
 7:   else if methodName == setAction then
 8:     stringAction == extractStrAction(node)
 9:     if stringAction ∈ Intent_Filter_App_r.intent-action-string then
10:       IAC_graph ← addEdge(App_i, App_r)
11:     end if
12:   end if
13: end for
```

3.4.4 IAC Vulnerability Analysis

Algorithm 4 depicts the process of IAC vulnerability analysis, which consists of two components including: 1) IAC vulnerability analyzer that marks sensitive paths in the dynamic IAC graph, and 2) path verifier that automates the path triggering process by installing the apps involved in the identified sensitive paths and then triggering the corresponding APIs.

IAC vulnerability analyzer identifies whether the nodes in the dynamic IAC graph constitute a vulnerable path that reveals sensitive information. IAC vulnerability analyzer performs its analysis over all identified IAC paths in the dynamic IAC graph. Then for each path, every node is analyzed, by identifying whether it is a sender or receiver node, and then *depth-first search (DFS)* is conducted to find if this node can reach a sensitive source method in case of sender node, or can reach a sensitive sink in case the node is receiver. We leverage a sensitive API list that simplifies the widely used SuSi list [122] to identify these sensitive APIs. An inverted DFS searches from the recorded MoI (identified in Algorithm 2) to seek sensitive sources, while another DFS searches from Intent-receiving method

at the receiver (line 12 in Algorithm 4) to look for sensitive sinks. Finally, it marks the complete sensitive paths from the sensitive source to the sensitive sink across multiple apps. Fig. 3.4 represents a typical sensitive path that links sensitive source API to a sensitive sink through IAC after resolving the reflection/DCL calls. Note that these paths are stealthy and difficult to find, as they only appear after loading dynamic codes and resolving reflection calls, but they can be captured by DINA efficiently.

Path verifier tries to automatically trigger the sensitive paths in the dynamic IAC graph. A sensitive path contains a sensitive source and a sensitive sink node (cf. Fig. 3.4, Algorithm 4, line 28). After identifying the sensitive path, the pather verifier checks the type of reflection/DCL call site class. If the type is an activity, the sender and receiver apps will be installed on our tablet device. We use *adb utility* to execute the activity component and record the generated log using *logcat utility*. Finally, the path will be considered as a triggered path if the log contains the exercised activity, the Intent string action, and the name of the receiver app.

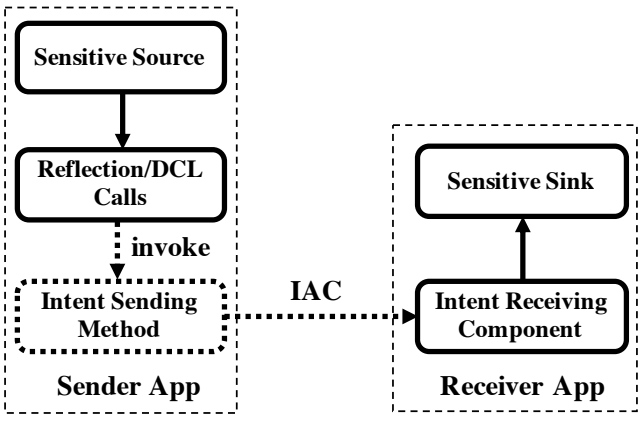


Figure 3.4: A simplified sensitive path example: the dashed method and paths can be captured during DINA's dynamic analysis phase.

Algorithm 4 IAC Vulnerability Analysis

INPUT: *dynamic_IAC*, *Sensitive_API_List*
OUTPUT: $node_i$.*sensitive*, triggeredSensitiveIAC_list

// 1) IAC vulnerability Analyzer
for each node of $App_m \in dynamic\_IAC$ **do**
  // 1.1) Identify sensitive methods in the sender node
  if $node_i$ is sender **then**
    for each *method* $\in$ DFS($node_i$.method-name) **do**
      if $method_j \in Sensitive\_API\_List$ **then**
        $node_i.sensitive$ = True
      else
        $node_i.sensitive$ = False
      end if
    end for
  // 1.2) Identify sensitive methods in the receiver node
  else if $node_i$ is receiver **then**
    for each method $\in$ MG(App_m) **do**
      if $method_j \in$ {`onCreate`, `onReceive`, `onStartCommand`} && (class-name of $method_j$ == class-name of $node_i$) **then**
        for each *method* $\in$ DFS($method_j$) **do**
          if $method_j \in Sensitive\_API\_List$ **then**
            $node_i.sensitive$ = True
          else
            $node_i.sensitive$ = False
          end if
        end for
      end if
    end for
  end if
end for
// 2) Path Verifier
for each path $\in dynamic\_IAC$ **do**
  if $path_i(sndNode)$.sensitive == True && $path_i(recNode)$.sensitive == True && $path_i(sndNode)$.callSite.type == activity **then**
    install $path_i(sndNode)$.app
    install $path_i(recNode)$.app
    adb start $path_i(sndNode)$.callSite
    if check(AdbLogcat) **then**
      triggeredSensitiveIAC_list $\leftarrow$ path_i
    end if
  end if
end for

3.5 DINA Implementation

This section explains the implementation details of DINA. We highlight major implementation aspects that are key to the DINA's functionality: specifically the IAC analyzer and the dynamic analyzer.

3.5.1 Class Loading Implementation

DINA is a class loader-based analysis system written in C++ that builds on top of Jitana [28]. Compared with compiler-based approach such as the popular Soot [119], DINA can investigate multiple apps simultaneously, while Soot requires to load the entire code of one app to perform analysis. DINA uses a *class loader virtual machine (CLVM)* implemented in the Android framework to load classes in both the static and dynamic analyses, which allows the loading of multiple apps simultaneously to generate graphs for analysis. The ability of analyzing multiple apps concurrently helps resolve the scalability challenge mentioned in Section 3.1.

DINA leverages BOOST Graph Library (BGL) [123] as a graph processing engine, which facilitates the graph analysis and makes graph processing more extensible. BGL is widely used, presents high performance, and supports multiple graph analysis libraries (i.e. depth first search).

3.5.2 IAC Analyzer Implementation

The IAC analyzer aims to identify all potential IAC paths. This implies the IAC analyzer should have program analysis capabilities. To concretize our idea of DINA's IAC analyzer, consider the code snippets obtained from two apps in DroidBench[2], shown in Listing 3.5. The code snippet from Echoer app contains two different Intent messages that will be constructed after extracting the two Intent actions (lines 4 and 7), which reflects the capability of Echor app to receive two different Intent actions and act accordingly. The runtime analysis can only reveal one of the activated paths, but will not be able to capture both the potential

[2]https://github.com/secure-software-engineering/DroidBench

Intent receiving behaviors. On the contrary, DINA will be able to effectively uncover both Intent actions from two different IAC paths (ACTION_SEND and ACTION_VIEW), even if only one of them is executed at runtime.

We extended IAC analyzer performs data-flow analysis to extract the receiver component name (for explicit intent) and the Intent action string (for implicit intent). To illustrate the analysis process, Figure 3.5 depicts the generated Instruction Graph (IG) for the method *onCreate* defined in code snippet extracted from BroadcastReceiverLifecycle2 app (Lines 12-15 in Listing 3.5), where blue edges represent control-flow and red edges represent data-flow. This method uses implicit Intent (i.e. setAction, line 14). Once the IAC analyzer identifies this API (thick border rectangle box in Figure 3.5) while iterating the IG, it will extract the Intent action string by performing data-flow analysis. The red edge *v1* contains the string value that is passed to the *setAction*.

```
1  //Echoer app
2  Intent i = getIntent();
3  String action = i.getAction();
4  if (action.equals(Intent.ACTION_SEND)) {
5   Bundle extras = i.getExtras();
6   Log.i("TAG", "Data received in Echoer: " + extras.getString("secret")); }
7  else if (action.equals(Intent.ACTION_VIEW)){
8   Uri uri = i.getData();
9   Log.i("TAG", "URI received in Echoer:" + uri.toString()); }
10
11 //BroadcastReceiverLifecycle2 app
12 protected void onCreate(Bundle savedInstanceState) {
13  Intent intent = new Intent();
14  intent.setAction("intent.string.action");
15 }
```

Listing 3.5: Excerpts from DroidBench's apps.

3.5.3 Dynamic Analyzer Implementation

The DINA's current dynamic analysis prototype is implemented for Android 4.3. We find Android 4.3 is sufficient for our study, since we observe no differences in

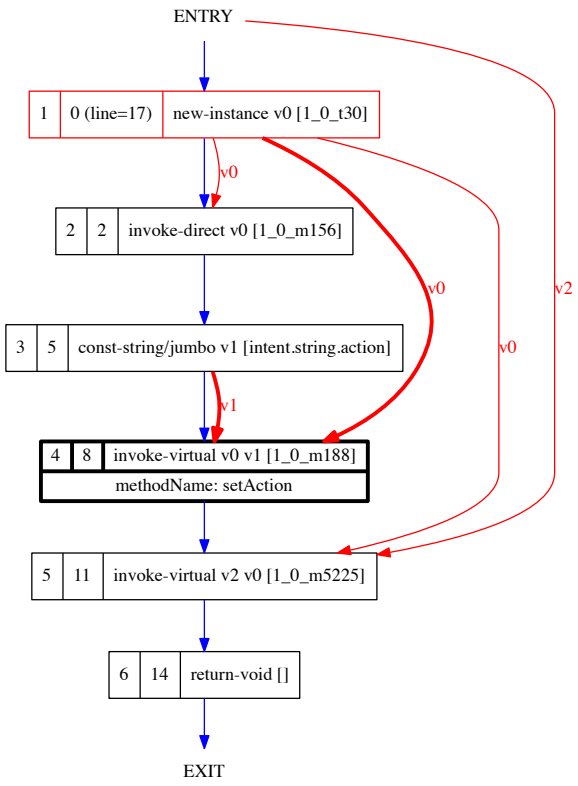


Figure 3.5: Instruction Graph for the method *onCreate* (Listing 3.5) that includes both control-flow and data-flow.

DCL-related APIs between Android 4.3 and Android 7.1. This observation is also confirmed by Qu et al. [33]. Currently, we have begun porting DINA to support ART, the latest Android run-time system. The modified version of Android 4.3 is adopted to keep incrementally capture newly downloaded codes, which includes JAR, DEX and APK. We utilize Java Debug Wire Protocol (JDWP) over Android Debug Bridge(ADB) [124] to pull the newly downloaded codes from the real device (Nexus 7 tablet) that we used for running our experiments.

In the dynamic analysis, we utilize Monkey to generate a series of random user inputs to reach the components that contain reflection/DCL APIs. Specifically, the

class names extracted in the static analysis phase that contain reflective calls are used for constructing component names that will be exercised by Monkey. Then, each component is executed at three times with different seeds in each execution to better cover the component. In the end, more reflective calls can be reached and executed at runtime. For instance, if the identified component is an activity with a button-click handler that triggers a reflective call that leads to IAC operations, Monkey will click that button to activate the hidden IAC operation.

3.6 Evaluation

This section presents our experimental evaluation of DINA. We conduct our evaluation to answer the following four research questions:

- **Question 1:** How *accurate* is DINA in identifying vulnerable IAC/ICC activities compared to the state-of-the-art static and dynamic analyses?
- **Question 2:** How *robust* is DINA in analyzing the capabilities/behaviors of reflection and DCL implementations in real-world apps?
- **Question 3:** How *effective* is DINA in detecting vulnerabilities in real-world apps?
- **Question 4:** How *efficient* is DINA in performing hybrid analysis?

3.6.1 How accurate is Dina?

Evaluating the accuracy of DINA requires performing the analysis on a ground truth dataset, where the attacks are known in advance. This constitutes a major challenge due to the lack of existing colluding apps [125], specifically benchmark

apps that are using reflection and DCL for performing malicious IAC. We found 12 suitable Benchmark apps (listed in Table 3.2) from DroidBench and other resources to validate DINA's detection effectiveness and efficiency, all of which perform ICC or IAC through reflection or DCL.

Comparing with static analysis tools. Next, we consider three state-of-the-art static analysis systems: IccTA [126], SEALANT [31], and DroidRA [25] designed to identify suspicious IAC and reflection activities. DroidRA focuses on detecting reflective calls using composite constant propagation. IccTA is a static analysis tool that can detect vulnerable ICC paths using inter-component taint analysis based on FlowDroid. SEALANT combines data-flow analysis and compositional ICC pattern matching to detect vulnerable ICC paths.

To construct a baseline system that shares the same capability as DINA, we attempted to integrate these two types of techniques: DroidRA was used to resolve reflective calls, while IccTA and SEALANT were used to detect vulnerable IACs in targets captured by DroidRA. Here, we compare DINA's reflection resolution and IAC detection performance with other baseline approaches.

Comparing reflection resolution performance: we compare reflection/DCL resolution capabilities of DINA and DroidRA over benchmark and real-world apps. We found that DroidRA was able to resolve reflective calls in 8 out of 12 benchmark apps in Table 3.2. DroidRA did not detect any reflective calls in *OnlyTelephony_Reverse.apk* and *OnlyTelephony_Substring.apk*, and it crashed during the inter-component analysis of *DCL.apk*. The only app that DroidRA can successfully analyze and annotate with reflection targets is *reflection11.apk*. On the other hand, DINA has resolved all reflection and DCL calls in the benchmark apps. For real-world apps, our results show that DINA can detect more reflective calls than

DroidRA. For instance, for a malware sample[3] that contains 14 reflective calls and 4 DCL calls. DroidRA detects 11 of them, while DINA captures all reflective/DCL calls. This is because DroidRA fails to detect the reflective calls within the dynamically loaded code.

Comparing IAC detection performance: we perform ICC/IAC analysis using SEALANT and IccTA over the instrumented benchmark apps by DroidRA. Although DroidRA successfully resolved the reflective calls of 8 benchmark apps, it was not able to correctly instrument the apps with those reflection targets required for IAC analysis. Our results indicate that many of these targets reside within the Android framework, and thus are not considered in the analysis conducted by DroidRA. We also found that while the annotated APK is structurally correct, it can no longer be executed. Moreover, we observed that SEALANT yields invalid results after analyzing the instrumented APKs by DroidRA, which may be caused by the incompatibility of the generated APK format with SEALANT's input. Therefore, we did not use the instrumented APKs, instead we used DroidRA's reported reflection resolution results, and then use these results in conjunction with SEALENT and IccTA's results to identify vulnerable IAC paths within benchmark apps.

Table 3.2 shows IAC detection comparison results in terms of precision, recall and F-measure scores. Note that we did not report the results of IccTA because it can only produce results for 5 out of 12 apps (*ActivityCommunication2, OnlyIntent, OnlySMS, reflection11, and SharedPreferences1*), but fails to detect any vulnerabilities. SEALANT performs better in a number of benchmarks, yet produces several false positives that affects its precision.

[3]MD5: 00db7fff8dfbd5c7666674f350617827

Table 3.2: IAC detection performance comparison between DroidRA+SEALANT and DINA. True Positive (TP), False Positive (FP), and False Negative (FN) are denoted by symbols ☑, ☒, □, respectively. (*X*#) represents the number # of detected instances for the corresponding symbol *X*. Also note that IccTA did not detect any vulnerable paths.

Test Cases	DroidRA+SEALANT	DINA
ActivityCommunication2	☑(☒3)	☑
AllReflection	☑(☒3)	☑
OnlyIntent	□	☑
OnlyIntentReceive	☑(☒2)	☑
OnlySMS	☑(☒3)	☑
OnlyTelephony	☑(☒3)	☑
OnlyTelephony_Dynamic	☑(☒3)	☑
OnlyTelephony_Reverse	□	☑
OnlyTelephony_Substring	□	☑
SharedPreferences1	□	□
Reflection_Reflection11	☑	☑
Dynamic class loading	□	☑
Precision	29.2%	**100%**
Recall	58.3%	**91.6%**
F-measure	38.9%	**95.62%**

The experimental results show that DINA can handle reflective and DCL calls to de-obfuscate ICC, and reaches 100% precision and 91.6% recall in detecting vulnerable ICC. As for the app *SharedPreferences1*, DINA detects the reflective calls, but misses its ICC path, because the shared preference mechanism used in the app is not considered by DINA.

Comparing with dynamic analysis tools. As for the dynamic analysis approach, the most closely-related technique is HARVESTER [127], which uses program slicing to deobfuscate reflective calls for dynamic execution, yet we were informed by the authors that neither the source code nor the binary version of HARVESTER is available. Moreover, HARVESTER's precision was not evaluated over benchmark

apps, which makes it hard to compare against. IntentDroid [128] is a dynamic analysis tool for detecting vulnerable IAC, but it cannot deal with reflection/DCL.

3.6.2 How robust is Dina?

In this section, we evaluate DINA's capabilities to reveal the behavior of reflection/DCL classes in complex, real-world apps. We used three datasets with 49,000 real-world apps, including: 1) 31,894 apps from AndroZoo project[4], 2) 3,000 most popular apps from Google Play store, and 3) 14,294 uncategorized malware samples from VirusShare[5].

Reflection/DCL Usage Landscape. We first performed the collective static analysis of DINA using the three previously-mentioned sets of apps to identify reflection and DCL call sites. The experimental results show that 92.0% (i.e., 26,361/ 31,894) of AndroZoo apps implement reflection calls, and 51.1% (i.e., 16,313/31,894) of them implement DCL calls. This shows the wide adoption of DCL and reflection mechanisms in Android apps. More remarkably, 99.4% of 3,000 popular apps implement reflection calls, and 90.1% of them implement DCL calls. Therefore, reflection and DCL mechanisms are even more widely adopted in popular apps. For the malware apps, 85.0% implement reflection mechanism, while only 24.3% of them adopt DCL mechanism. Solely based on our evaluation, it seems that fewer malware apps use the DCL mechanism. Note that DINA counts the number of APIs by traversing the whole method graph, which produces an accurate representation of the apps under analysis.

We then run the dynamic analysis on the popular apps and randomly-picked malicious apps. Table 3.3 presents the results, from which we can see that the

[4]androzoo.uni.lu
[5]virusshare.com

number of activated classes in the benign apps significantly exceeds that of the malicious apps.

We also perform further analysis to identify the entity, either the app itself or a third-party library, behind the activated reflection and DCL classes. Note that we ignore the Android framework classes.

We can see most of the activated reflection/DCL classes are included in third-party APIs in both malicious and benign apps, as has been confirmed by prior research [33].

Table 3.3: Dynamic analysis of real-world apps.

Dataset	# of installed Apps	# of apps contain reflection/DCL	# of activated reflection/DCL	% of 3rd party classes	% of app-owned classes
Benign	1,957	1,271	17,170	85.6%	7.66%
Malicious	2,378	1,033	7,336	54.6%	5.18%

Intent sending/receiving capabilities of DCL/reflection classes. Next, we evaluate DINA's incremental dynamic analysis to detect Intents in dynamically loaded code. We analyze the activated reflection/DCL classes of popular and malicious apps to identify the Intent sending and receiving APIs presided within the reflection/DCL classes. Table 3.4 presents the number of Intent sending APIs and receiving APIs. We use DFS as a reachability test to find whether MoI can reach the Intent sending APIs as shown in Table 3.4.

Table 3.4: Intent sending and receiving capabilities of activated ref/DCL classes.

Dataset	# of Intent sending APIs (reachable)	# of Intent receiving APIs
Benign	1022 (936)	146
Malicious	600 (390)	79

Sensitive sources within DCL/reflection classes. Table 3.5 presents the top 10 sensitive sources in the activated reflection and DCL classes in both benign and malicious apps. These sensitive sources can reach Intent-sending APIs concealed by reflection/DCL to leak sensitive information, including device ID, subscriber ID, etc.

Table 3.5: Top sensitive sources in the activated reflection and DCL classes.

Benign		Malicious	
Sensitive APIs	Freq.	Sensitive APIs	Freq.
getInstalledApplications()	113	getSubscriberId()	35
getMacAddress()	100	getSSID()	29
getCountry()	42	getMacAddress()	7
getActiveNetworkInfo()	33	getDeviceId()	6
getInstalledPackages()	21	getCountry()	6
openConnection()	20	getInstalledPackages()	6
getDeviceId()	7	openConnection()	4
getSubscriberId()	1	getSimSerialNumber()	2

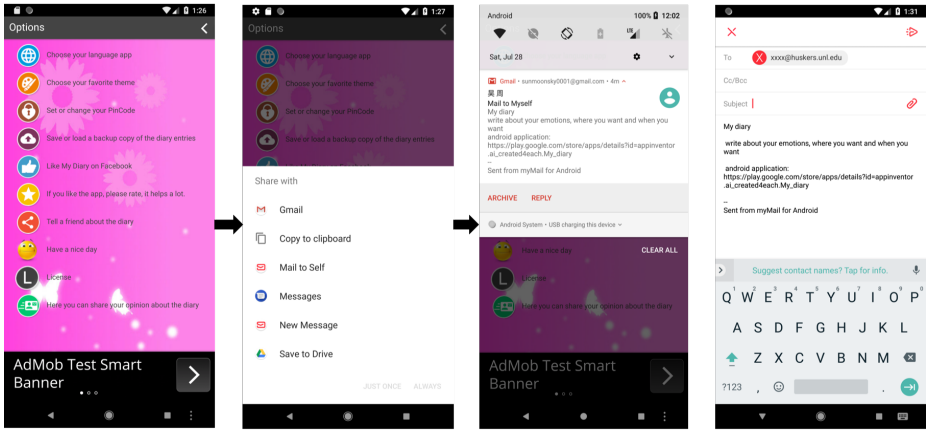
Our analysis reveals that apps can indeed conceal their IAC communication capabilities inside dynamically loaded classes. The experimental results show that the total number of matched Intent action strings is 18, with the top-7 matched strings depicted in Table 3.6. *android.net.conn.CONNECTIVITY_CHANGE* is the most matched Intent action string appearing after the reflective calls. Among all these dynamically executed apps, 38 apps are found to contain matched Intent strings, which means these apps can potentially perform stealthy IAC activities through reflection and DCL calls.

3.6.3 How effective is Dina?

In our experiment, we found some concealed IAC vulnerabilities that have been effectively detected by Dina, as presented in Table 3.7. We have manually triggered

Table 3.6: Number of matched cases of the top-7 matched Intent action strings.

Intent Action String	# Matched Cases
android.net.conn.CONNECTIVITY_CHANGE	135,771
android.intent.action.MAIN	135,276
com.android.vending.INSTALL_REFERRER	7,118
android.intent.action.PACKAGE_ADDED	6,954
android.intent.action.PACKAGE_REMOVED	3,703
android.intent.action.BATTERY_CHANGED	660
android.intent.action.DOWNLOAD_COMPLETE	573



(a) Activity 1 (b) Activity 2 (c) Activity 3 (d) Exploit

Figure 3.6: (a). Activity 1 of sender app; (b). Activity 2 of sender app initiated through reflection; (c). Activity 3 represents the activity of receiver app invoked by IAC; (d). Inject malicious email address in the sender app to launch attack via IAC.

these vulnerable IAC paths to verify that they can be activated at runtime, as described below.

Intent spoofing vulnerability is observed between *appinventor.ai_created4each.My_Diary* and *com.my.mail*. The receiver app manages the users' emails, which contains two components that can receive the implicit Intent *android.intent.action.SEND*. The sender app contains the method *ShareMessage()* that can be triggered through reflection, which initializes the Intent sending activity to configure the email setting for the receiver app. We modified this method to inject a specific email address,

Table 3.7: Risky vulnerabilities have been uncovered by DINA in real-world apps.

Sender app	# of Installs	Concealed method by reflection/DCL	Receiver app	Sensitive sink	Triggered component	Consequences
appinventor.ai_created 4 each.My _Diary	5,000,000	ShareMessage()	com.my.mail	android.util.log	Activity	Intent Spoofing
com.example.qianbitou	N/A	toCall()	com.axis.mobile	java.lang.ProcessBuilder	Activity	Android Component Activation
com.hbg.coloring.fish	5,000	shareImageOnTwitter()	cn.jingling.motu.photowonder	android.util.log	Activity	Information Leakage
com.sogou.novel	100,000	ui.activity.Main Novel Shelf.a()	com.gtp.nextlauncher.trial	android.util.log	Broadcast Receiver	Information Leakage

which can be used for phishing attacks. The complete attack process is shown in Fig. 3.6. The stealthy IAC initialized by the sender app cannot be detected by existing static and dynamic analyses. Moreover, the class of *ShareMessage()* requests to access the external storage, leading to serious privacy leakage. We scan the sender app (downloaded from official Google Play store) on VirusTotal, and is only detected by 2 engines out of 63.

Android component activation is observed between *com.example.qianbitou* and *com.axis.mobile*. The sender is an app providing services for used cars, including financial services. The app also implements reflection for invoking a method that activates an implicit Intent *android.intent.action.DIAL* to make a phone call to a hard-coded phone number. Therefore, any installed app (i.e. the receiver app) with components that have the matched Intent filter will be activated. The receiver app is a mobile banking app, whose component (*com.gtp.framework.UninstallShortcutReceiver*) will be activated to make random phone calls.

Information leakage: we report several examples of potential information leakage vulnerabilities:

- vulnerability is observed between *com.hbg.coloring.fish* and *cn.jingling.motu.photowonder*. The sender is a gaming app, and the receiver app is an image editing app. The sender app contains a reflective call that instantiates an implicit Intent for sending pictures from the mobile storage. We also observed this concealed method invokes a sensitive API (*queryIntentActivities*) to obtain the running activities on the mobile device. The implicit Intent can be received by any app that contains *android.intent.action.SEND*. This vulnerable IAC path may lead to the leakage of sensitive images, and it can be very harmful when both apps are managed by one party.

- this case is observed between *com.sogou.novel* and *com.gtp.nextlauncher.trial*. The sender app is a reader app, while the receiver app is used for 3D image processing. The reflection implemented in this app executes an implicit Intent *android.intent.action.SEND* for activating a broadcast receiver component of the receiver app. The implicit Intent sends information about a book, which can be easily replaced by sensitive information (e.g., bank accounts, location). This vulnerability can also be exploited to perform denial of service attack on the receiver app, by repeatedly invoking the implicit intent to send the broadcast messages.

- the vulnerability constituted between *com.slideme.sam.manager* and *com.google.android.googlequicksearchbox*. The sender is a mobile apps store, and the receiver app is a google search service. The sender app contains a reflective call that instantiates an implicit Intent (*android.speech.action.RECOGNIZE_SPEECH*) for sending voice records. The complete attack process is shown in Fig. 3.7, and the captured log confirms the activated IAC activity. This vulnerable IAC path may be used to spy on the user and leak voice records. This vulnerability

can be exploited to instruct *Google Now* to send messages to third parties. Such vulnerability has been demonstrated by AVG team [129], which can cause harmful consequences in which voice recognition techniques are used to perform voice impersonation attacks.

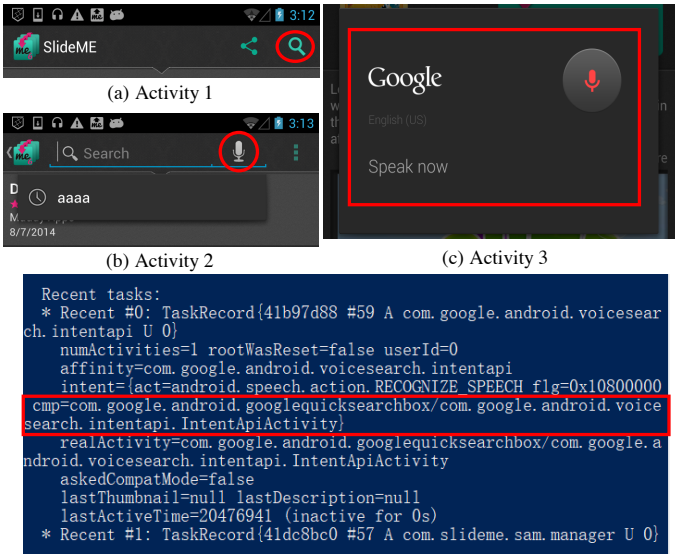


Figure 3.7: (a). Activity 1 of sender app; (b). Activity 2 of sender app initiated through reflection; (c). Activity 3 represents the activity of receiver app invoked by IAC; (d). Captured log confirms the IAC.

3.6.4 How efficient is Dina?

App stores including Google Play receive thousands of new apps every day, all of which require comprehensive security analysis. Therefore, we need efficient tools that can scale to the size of a large app market. We next report the running time of Dina's app analysis. We report the analysis time for both static analysis phase and dynamic analysis phase. The performance reported in this section was run on a Nexus 7 tablet connecting to a MacBook Pro laptop with Intel Core 2 Duo

2.4 GHz CPU and 8 GB memory. The static analysis was conducted on the laptop, while the dynamic analysis was performed on the tablet.

Fig. 3.8 shows the static analysis time with respect to the app bundle size in megabytes (MBs). With the growing app bundle sizes, the analysis time appears to be stable. For most of the bundles, DINA can finish the static analysis within 1 minute, demonstrating the efficiency of DINA's static analyzer. Fig. 3.9 presents the running time of dynamic analysis for 1,000 real-world popular apps. The result shows that over 90% of apps can finish the dynamic analysis within 5 minutes. The majority of the dynamic analysis time is spent on running the apps to boost the coverage, and this time cost is inevitable for dynamic analysis tools. For complex apps with an average app size of 42 MBs, DINA can accomplish the dynamic analysis within 2.5 minutes/app on average as similar to the analysis time of HARVESTER, showing that DINA can be used for large-scale security analysis.

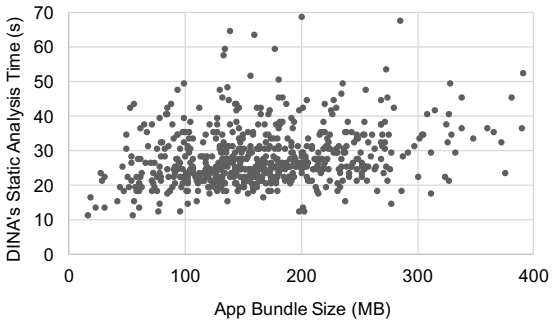


Figure 3.8: Static analysis time.

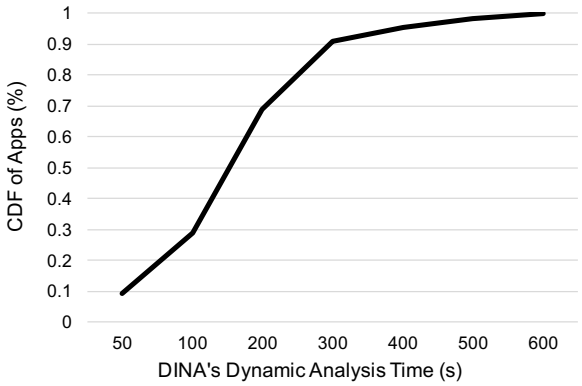


Figure 3.9: Dynamic analysis time.

We further compared DINA's runtime performance with the state-of-the-art IAC analysis tools, i.e., SEALANT and DroidRA, using the set of benchmark apps (cf. Section 3.6.1). Fig. 3.10 shows the results of performance comparison. DINA achieves the best performance for the majority of the apps (8 out of 12), with an average analysis time of 1 minute/app.

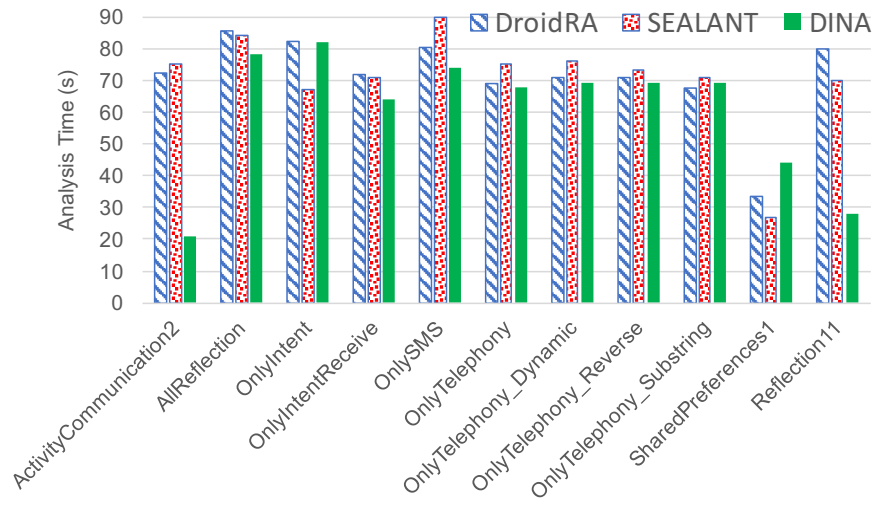


Figure 3.10: Runtime performance comparison.

3.7 Discussion

Dynamic analysis coverage. Improving coverage has been a major challenge for dynamic analysis approaches [130]. In DINA, we currently utilize Monkey for input generation to exercise the targeted components. Although we achieve excellent IAC detection performance, we may still suffer from potential false negatives. We inherit some of the input generation limitations of Monkey. However, this fuzzing approach is still widely used by recent approaches that target DCL (e.g., DyDroid [33]), which relies on the observation that third-party libraries launch their DCL events when starting the app, which is sufficient for our analysis. Furthermore, the empirical study performed in [131] shows Monkey has achieved the best coverage among all analyzed input generation tools including DynoDroid [132] and PUMA [133].

IntelliDroid [134] is a recently-proposed input generation tool using event-chain detection and input injection with constraint solver. We integrate Intellidroid with DINA to replace Monkey. However, it fails to trigger most of the reflective/DCL

calls. We found that most of the statically-identified paths related to reflective calls cannot be successfully triggered by Intellidroid, mainly due to the limited input type support, the limitations in the constrain solver, and its lack of support in dealing with environmental contexts/variables.

Furthermore, a malicious app may perform emulator detection to halt its malicious activities during the analysis. DINA addresses this issue by performing the analysis on real devices.

IAC detection accuracy. Compared with static and dynamic tainting analysis based approaches, DINA does not perform precise data flow tracking analysis, which may lead to the imprecision of our detection results. Thus, the static analysis results may contain false positives. However, we use dynamic analysis to narrow down the scope of analysis on the methods that are dynamically executed. Therefore, we can effectively alleviate the imprecision brought by the lack of tainting analysis. One major benefit of our approach, however, is the improvement on runtime performance as shown in Section 3.6.4 compared to other approaches.Furthermore, existing static IAC analysis cannot handle an Intent that has been obfuscated in a manifest file. In such scenario, static analysis cannot identify app pairs by simply matching the Intents.

3.8 Summary

In this chapter, we present DINA, a hybrid analysis approach for detecting malicious IAC activities in dynamically loaded code. DINA utilizes a systematic approach based on control-flow, data-flow, and method call graphs to identify malicious IAC activities across multiple apps. We have shown DINA can effectively resolve reflective and DCL calls at runtime for real-world apps. We demonstrate that

multi-app, colluding attacks concealed by reflection and DCL can be launched to perform stealthy attacks, and evading existing detection approaches. In particular, we discover several popular real-world apps, which can trigger vulnerable IAC activities through reflection and DCL, leading to surreptitious privacy leakage. We have compared DINA with existing IAC vulnerability and reflection analysis tools. DINA analyzes most of apps in less than five minutes, and can identify malicious IAC behaviors concealed by reflective calls that no previous approach was able to detect. We believe further effort is required to better regulate the usage of reflection and DCL calls to close the attack avenues without undermining their utilities.

4 IotCom: Compositional Safety and Security Analysis of IoT Systems

The ubiquity of Internet of Things (IoT) and our growing reliance on IoT apps are leaving us more vulnerable to safety and security threats than ever before. Many of these threats are manifested at the interaction level, where undesired or malicious coordinations between apps and physical devices can lead to intricate safety and security issues. This chapter presents IotCom, an approach and accompanying tool suite, to automatically discover such hidden and unsafe interaction threats in a compositional, yet scalable, fashion. It is backed with automated program analysis and formally rigorous violation detection engines. IotCom relies on program analysis to automatically infer the relevant app's behavior. Using a novel strategy to trim the extracted app's behavior prior to translating them to an analyzable formal specification, IotCom mitigates the state explosion associated with formal analysis. Our experiments with numerous bundles of real-world IoT apps have corroborated IotCom's ability to effectively detect a broad spectrum of interaction threats triggered through cyber and physical channels, many of which were previously unknown, and to significantly outperform the existing techniques in terms of scalability.

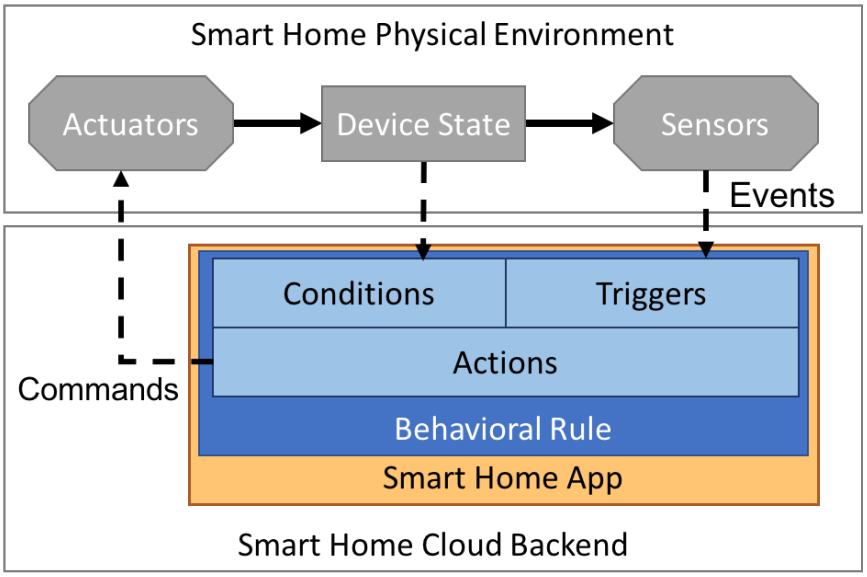


Figure 4.1: Smart Home Automation Model.

4.1 Background

Smart Home IoT Platforms

Smart home platforms allow users to configure, control, and monitor IoT devices installed in their smart home. These cyber-physical systems combine a virtual software-based backend, usually resident in the cloud, with physical devices—both *sensors* that monitor the physical environment and *actuators* that act upon it.

Users can install third-party software *apps* in the virtual backend to automate tasks performed by physical devices. Figure 4.1 summarizes the general model for smart home automation. Apps consist of one or more *rules* defined using an event-condition-action paradigm. *Events* sensed by the sensors are forwarded to the backend via software proxies, which invoke *triggers* defined in the rules. If the current state of the cyber-physical environment satisfies the *conditions* in a given rule, the rule executes one or more *actions*, which are forwarded to actuators as *commands*.

Apps come from either vendor-specific marketplaces, such as Samsung's SmartThings [37] and Google Home [135], or from cross-platform services like IFTTT [38]. Each framework defines and distributes apps differently. In IFTTT, for example, each app is a single trigger-action *rule* that responds to and actuates via RESTful web services. Other vendors allow for more complicated rules. Among others, Samsung SmartThings Classic apps [37] are defined as Groovy programs, and Alexa skills can be defined in any language supported by AWS Lambda [136].

Smart Home IoT Safety and Security

The convenience provided by the proliferation of automations and app marketplaces also presents challenges for smart home safety and security. The smart home app environment is collaborative, in that all installed apps or automations interact with each other, via both cyber *and* physical channels. Bugs, misconfiguration, or even malicious intent by app developers all present a threat of undesired behavior. End users may have to set complex configuration options without clear documentation, and some marketplaces allow third-party apps to be published by any developer with little to no oversight [76, 137]. Indeed, the concealed risks inherent in the complex coordination of third-party smart home apps can be very serious, ranging from data access issues such as permission misuse and data leakage to compromising the home's physical safety [138, 139].

The wide variety of app marketplaces and the diversity of APIs and specifications complicate any holistic safety analysis; analyzing the apps installed in even one smart home would involve multiple platforms, programming languages, and channels of coordination. While various recent approaches [34, 11, 74, 102, 78, 140, 141, 142] have attempted to chip away at the challenges underlying such analysis,

most focus on a single aspect of the problem [143, 72, 98, 74, 11, 73, 144] or on a single app platform [36, 35, 11, 75, 78, 73, 72, 76].

In the following sections, we present an approach that can holistically analyze safety properties of coordinating app bundles spanning multiple automation platforms as well as both cyber and physical channels.

4.2 Illustrative Example

This section illustrates an unsafe interaction between IoT apps using a simple example, shown in Figure 4.2. The example comprises three IoT apps—one malicious (MaliciousApp) and two benign. HomeModeApp changes the heating status of the oven based on the "mode" of the smart home system. The mode is a general, customizable setting used for automation that generally tracks whether the user is home or away or if it is day or night. FireAlarmApp opens the door when smoke is detected. MaliciousApp represents a third-party app that pretends to perform a benign activity but instead modifies the smart home's mode, unbeknownst to the home owner.

The detrimental interaction occurs when MaliciousApp switches the smart home mode to *Home*. This triggers HomeModeApp, which turns on the heating element in the oven. The oven may in turn activate the smoke detector, triggering FireAlarmApp to open the door. Together, the interaction of the apps compromises the safety of the home by opening the door when no one is at home. Such unsafe interactions occur in real-world, as demonstrated in prior research [36].

Identifying such perilous interactions is challenging due to both the variety of ways apps may communicate and the multiplicity of apps involved in each interaction. The challenge is exacerbated by considering the concealed interactions, such

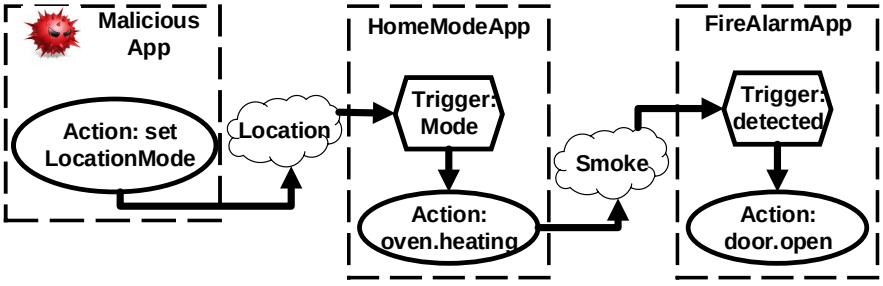


Figure 4.2: An example of malicious IoT apps interaction.

as the interaction between HomeModeApp and FireAlarmApp. In this case, HomeModeApp activates the oven, which does not concern FireAlarmApp; nonetheless, the two apps interact via the oven's heating element and the smoke detector. An analysis must be able to elucidate those hidden channels as well as holistically analyze all interactions in the system. For example, the individual interactions between MaliciousApp and HomeModeApp and between HomeModeApp and FireAlarmApp each could be benign. It is only when put together that the three apps compromise the IoT environment's safety.

4.3 Safety Goals for IoT App Interactions

This work focuses on identifying security and safety violations resulting from interactions among IoT apps installed in the same smart home environment. At a high level, these apps are intended to make the home owner's life more convenient and should only act on devices when intended and in a predictable, safe manner. Apps that are safe individually may begin to exhibit unintended, unpredictable, or unsafe behavior when multiple apps interact. We have identified three high-level goals that safe operation of IoT apps should satisfy:

(G1) No unintended behavior: IoT apps should not send unnecessary or repeated commands, which may lead to behavior not intended by the user. Such commands provide a pathway for possible misconfiguration, errors, or threats in the *cyber* components of the system to influence the physical world, which could lead to unneeded wear on some devices or waste electricity, among other things.

(G2) No unpredictable behavior: We also seek to warn the user if apps lead the cyber and physical components of the system to *interact* in a way that non-deterministically interferes with the actions of other parts of the system. For instance, if two apps each send a conflicting command to a same device, it may cause an objectionable situation that whichever app happens to act last will undo the action of the other, seemingly randomly.

(G3) No unsafe behavior: Lastly, IoT apps should never put the system in *physical* states that are unsafe, such as unlocking or opening the door at night (as described in our example from Section 4.2). Different from all the other approaches that require manual specification of the initial configuration, which in turn may miss some possible unsafe behavior if it appears from some different configurations, IotCom provides system-wide reasoning by exhaustively checking *all* possible system configurations, without requiring any manual specification of the initial configuration.

In Section 4.7, we evaluate our approach against a set of *safety and security properties* corresponding to each goal.

4.4 Approach Overview

This section introduces IotCom, a technique that automatically determines whether the interactions within an IoT environment could compromise the safety and security thereof. Figure 4.3 illustrates the architecture of IotCom and its two major components:

(1) Behavioral Rule Extractor (Section 4.5): The *Behavioral Rule Extractor* component automatically infers models of the apps behavior using a novel graph abstraction technique. The component first performs static analysis on each app to generate an inter-procedural control flow graph (ICFG). It then creates a *behavioral rule graph* containing only the flows pertinent to the events and commands forwarded to/from the physical devices in the smart home, along with any conditions required for those actions. Each flow is then automatically transformed into a formal model of the app.

(2) Formal Analyzer (Section 4.6): The *Formal Analyzer* component analyzes these models through bounded model checking. IotCom relies on three formal specifications: (1) a *base model of smart home IoT systems* that defines a set of rules to lay the foundation of cyber and physical channels, IoT apps, how they behave, and how they interact with each other, (2) assertions for *safety and security properties*, and (3) the *IoT app behavioral rule model* that Rule Extractor generates automatically for each IoT app. The set of specifications are then checked as a whole for violations of relevant safety properties.

Finally, a report is returned to the user describing the list of detected interaction vulnerabilities. Upon reviewing the report, end-users and third-party reviewers may choose to protect their system in a variety of ways, e.g., by disallowing

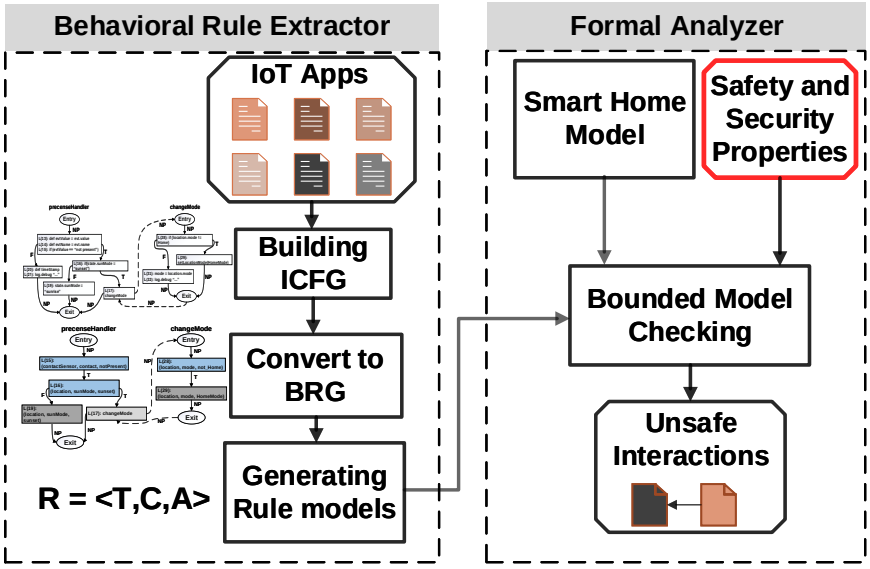


Figure 4.3: IoTCom System Overview.

the installation of certain combination of apps, or dynamically restricting certain inter-app communications.

In the following two sections, we describe the details of static analysis used to capture essential app information and formal analysis for automated detection of property violations.

4.5 Behavioral Rule Extractor

As shown in Figure 4.3, the Behavioral Rule Extractor uses static analysis to automatically infer the behavior of individual IoT apps. It executes three general steps: 1. build an *inter-procedural control flow graph (ICFG)*; 2. convert the ICFG to a *behavioral rule graph (BRG)* ; and 3. generate formal models for the behavioral rules.

4.5.1 Building ICFG

The Behavioral Rule Extractor first generates an inter-procedural control flow graph for each app. It analyzes the abstract syntax tree of the given app to build a *call graph* of local and API-provided methods as well as a *control flow graph* for each local method. Each graph is generated using a path-sensitive analysis [145] to preserve the logical conditions along each control flow. This improves the precision of our approach compared to the state-of-the-art techniques, which do not account for the conditions when identifying interactions between apps. It then combines each control flow graph with the call graph to construct an ICFG starting at each *entry method* in the graph. Entry methods are framework-specific methods invoked in response to events in the smart home backend software; for example, SmartThings defines a `subscribe` API that allows developers to specify custom event handlers.

4.5.1.1 ICFG Example: IFTTT

The details of generating the ICFG depend on how apps are defined for each platform. For example, IFTTT applets are reactive rules that interact with REST services exposed by smart home vendors or other service providers [146]. Each applet consists of a single trigger-action pair, without any conditions. IotCom treats each applet as a standalone IoT app defining exactly one rule. The Behavioral Rule Extractor performs string analysis [147] to extract an ICFG comprising a single entry node for the trigger and a single "method call" invoking a device API for the action. For instance, IFTTT applet "If I arrive at my house then open my garage door" [148] would result in an ICFG containing an entry node for "arrive at my house" and a method call node for "open my garage door".

Listing 1 Malicious IoT App activates Home Mode

```
1  preferences {
2    section("Select Mode:") { input "HomeMode","mode"}}
3    section("Presence sensor") { input "presence", "capability.presenceSensor"} }
4  def initialize() {
5    subscribe(presence, "presence", presenceHandler)}
6  def presenceHandler(evt) {
7    def evtValue = evt.value
8    if (evtValue == "not present"){
9      if (state.sunMode == "sunset") changeMode()
10     else state.sunMode = "sunrise"
11   } else {
12     def timeStamp = new Date()
13     log.debug "$timeStamp: status is $evtValue"} }
14 def changeMode() {
15   if (location.mode != HomeMode) {
16     setLocationMode(HomeMode)
17   } else {
18     mode = location.mode
19     log.debug "Current mode is: $mode" } }
```

4.5.1.2 ICFG Example: SmartThings Classic

Samsung SmartThings Classic apps are more complicated than IFTTT applets; they are written as small Groovy programs, allowing for multiple rules and more extensive logic. For example, Listing 1 shows the Groovy code defining the malicious app described in Section 4.2. Algorithm 5 describes the steps performed by the *Behavioral Rule Extractor*, detailed below, to derive models of a SmartThings app's behavior, starting with building the ICFG (lines 5-16).

To generate an ICFG, the Behavioral Rule Extractor first performs *Entity Extraction* to extract the information required to infer the rules in the app (Lines 6-10). Next, it creates a control flow graph for each trigger's entry method (Lines 11-15). The call graph will be updated while processing the entry method. An edge will be created between the caller (i.e. entry method) and the callee (i.e. local method). These graphs are combined to generate an inter-procedural control flow graph for the IoT app.

Algorithm 5 Behavioral Rule Extractor

INPUT: IoT App
OUTPUT: App: set of behavioral rules

```
1: App ← < {} >
2: ICFG ← {}, CFGs ← {}, CG ← {}, BRG ← {}
3: DevicesCap ← {}, Triggers ← {}
4: UserInput ← {}, GlobalVar ← {}
5: // Step 1 : Generating ICFG
6: // Step 1.1: Entity Extraction
7: DevicesCap ← extractDevicesCap(app)
8: UserInput ← extractUserInput(app)
9: GlobalVar ← extractGlobalVar(app)
10: Triggers ← extractTriggers(app)
11: // Step 1.2: Generating ICFG
12: for each trigger ∈ Triggers do
13:    CFGs ← constructCFG(trigger.entryMethod)
14:    CG ← updateCG()
15: end for
16: ICFG ← constructICFG(CG, CFGs)
17: // Step 2: Converting ICFG to BRG
18: BRG ← constructBRG (ICFG, Triggers, DevicesCap,
19: UserInput, GlobalVar)
20: // Step 3: Generating Behavioral Rules
21: for each trigger ∈ Triggers do
22:    App.R ← constructRules(BRG)
23: end for
```

Entity Extraction: The first subcomponent determines the entities on which the app operates, including: (1) the smart home devices and attributes altered/queried by this app; (2) any configuration values specified by the user, such as a desired setting for some device attributes; (3) any global variables used in the app; and (4) any events that trigger actions from the app, signified by use of certain APIs, and the methods invoked by those triggers.

The extraction algorithm traverses all statements in the AST, extracting the attached devices and user input from the `preferences` block (Listing 1, lines 1-10). Global variables are extracted based on the official SmartThings documentation [37].

Certain pre-defined values are assumed to be global, such as the `state` variable used on line 21 of Listing 1. We identify all the uses of these global variables.

IoT apps are event-driven, so each subscription or scheduled call defines a distinct entry point. Triggers and entry methods are thus extracted by traversing the AST for calls to the `subscribe`, `schedule`, `runIn`, or `runOnce` API methods. For instance, a contact sensor device—identified in SmartThings by the ***contactSensor*** capability [100]—has a ***contact*** attribute representing the state of the sensor. The attribute can take two values, either ***open*** or ***closed***. Depending on the value, such a device can be formalized as $\langle \textbf{\textit{contactSensor, contact, closed}} \rangle$, or $\langle \textbf{\textit{contactSensor, contact, open}} \rangle$. The extracted tuples are stored for later use in building the behavioral rule graph.

Generating ICFG: In conjunction with Entity Extraction, the Behavioral Rule Extractor also generates a *call graph* and *control flow graph* for each user-defined method using a path-sensitive analysis. To construct an ICFG, each control flow graph is incorporated with the call graph at each trigger's entry point. Figure 4.4a shows the ICFG corresponding to the malicious app code shown in Listing 1. The ICFG mode includes the CFG of the entry method `presenceHandler` (Figure 4.4a left side), and the CFG of the local method `changeMode` (Figure 4.4a right side). Note that existing state-of-the-art analysis techniques lack support for direct program analysis of Groovy code. By performing the analysis directly on the Groovy code, IotCom avoids the pitfalls (and cost) of translating the code into some intermediate representation.

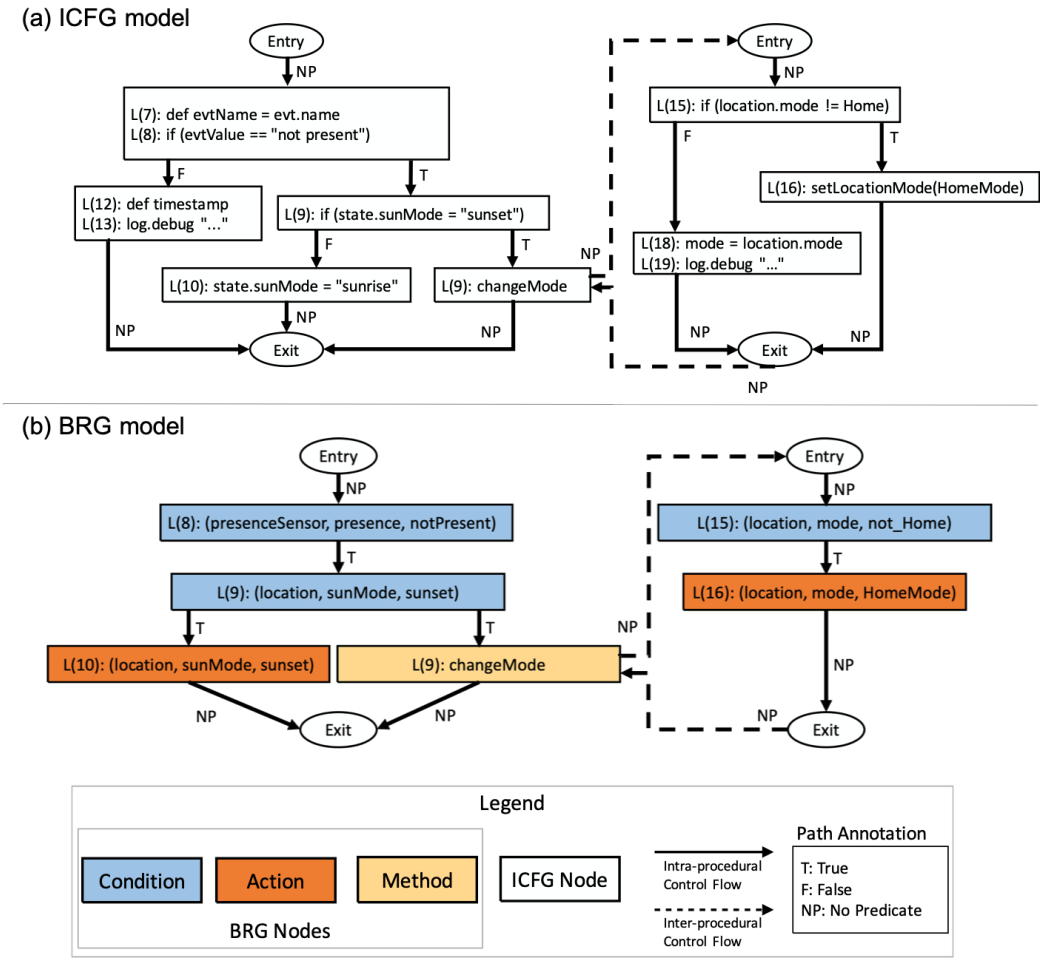


Figure 4.4: Extracted models for *MaliciousApp*, described in Listing 1, at different steps of analysis.

4.5.2 Generating Behavioral Rule Graph

The Behavioral Rule Extractor next tailors the ICFG into a succinct, annotated graph representing the relevant behavior of the IoT app—a *behavioral rule graph (BRG)*. By eliding all edges and nodes from the ICFG that do not impact the app's behavior with respect to physical devices, the BRG makes it easier to infer the behavior defined in the app, optimizing the performance of our analysis. To construct the BRG from the ICFG, the nodes in the ICFG are traversed starting from each entry method, generating nodes in the BRG as follows:

- **Trigger:** Entry method nodes from the ICFG are propagated to the BRG as trigger nodes.
- **Condition:** Control statements such as `if` blocks generate condition nodes in the BRG.
- **Action:** Any node that invokes a device API method creates an action node in the BRG.
- **Method Call:** Method calls to other local methods produce method call nodes in the BRG, as the called method may include relevant app behavior.

Each condition node has two edges, annotated with a **T** and **F** for the paths where the conditional statement is true or false, respectively. Trigger, action, and method call nodes each have exactly one outgoing edge, annotated as **NP** to signify there is no predicate associated with traversing the edge.

Example BRG: Continuing the example (Listing 1) from Section 4.5.1, lines 17-18 of Algorithm 5 convert the ICFG for the malicious app into a BRG, starting with the entry point `presenceHandler` shown in Figure 4.4a. The first node after the entry point contains two statements, L(7)-L(8), of which only L(8) will carry over to the BRG, shown in Figure 4.4b. L(12) and L(13) are assignment statements, which do not influence the behavior of the app. Therefore, that branch is trimmed from the BRG. L(9)—an `if` statement—will generate a condition node in the BRG. Following the false branch of the condition leads to the node containing L(10). This node is considered as action node because it influences the location mode. Following the true branch, L(9) invokes the local method changeMode, thus this node is considered as method node.

After creating the BRG, the statements corresponding to each node are converted to $\langle device, attribute, value \rangle$ tuples. If a value in any of the nodes does not correspond directly to a member of one of those sets, we perform backward inter-procedural data flow analysis [149] to resolve the dependency. Recall that the BRG captures all actions that affect sensors and actuators deployed in the smart home environment. All other details within the scope of the method are discarded. Furthermore, the edges maintain the control flow that reflects predicates required to activate a certain action.

4.5.3 Generating Rule Models

The final component of the Behavioral Rule Extractor generates formal models of each app's rules based on the BRG. As described in Section 4.1, the behavior of an IoT app consists of a set of rules $\boldsymbol{R}$, where each rule is a tuple of triggers, conditions, and actions, $\boldsymbol{R} = \langle \boldsymbol{T}, \boldsymbol{C}, \boldsymbol{A} \rangle$. This behavioral model follows the automation model in Fig. 4.1, where:

- $\boldsymbol{T}$ is a set of events that trigger specific rules. These events can be timed events, sensor/actuator notifications, or events directly triggered by the user.
- $\boldsymbol{C}$ is a set of conditions for executing specific rules, based on information about the state of the cyber and physical components of the system. This state information may originate from many sources—user configuration or input, the physical state of devices in the system, environmental values such as sunrise time—and are general represented as variables in the rule's programmatic control flow path or as global user configuration values.

- $\boldsymbol{A}$ is a set of actions that can be performed upon execution of a rule. The allowed actions are assumed to be exposed by the actuator proxies in the smart home framework software, such as the *capabilities* exposed by SmartThings to represent the behavior of their supported devices [100].

- Each rule $r \in \boldsymbol{R}$ has a set of Triggers$(r) \subseteq \boldsymbol{T}$, a set of Conditions$(r) \subseteq \boldsymbol{C}$, and a set of Actions$(r) \subseteq \boldsymbol{A}$ that define its behavior.

In order to tie the behavior of these rules back to the physical devices in the smart home, the elements of $\boldsymbol{T}$, $\boldsymbol{C}$, and $\boldsymbol{A}$ are each formalized as sets of tuples of $\langle \boldsymbol{device, attribute, value} \rangle$. Each type of device is assumed to have its own set of device-specific attributes, and each attribute constrains its own allowed values according to the device manufacturer's specifications. For example, a smart lock ***device*** may have a "locked" ***attribute*** to indicate the state of the lock, which accepts ***values*** of "locked" or "unlocked". An action to unlock a specific lock (***TheLock***) would contain a tuple composed of those elements, e.g., $\langle \boldsymbol{TheLock, locked, unlocked} \rangle$.

To generate the models from the BRG, IotCom starts from each trigger node (which is used as the Trigger for the rule) and traverses the graph to find the action nodes; every rule must have at least one Action. From each action node, it performs a reverse depth-first search back to the trigger, collecting the tuples for each condition node encountered along the path as the Conditions of the rule.

Since the BRG provides an abstraction of the app's behavior independent of the underlying framework, the process would be the same for both IFTTT and SmartThings Classic.

4.6 Formal Analyzer

This section describes the *Formal Analyzer* component of IotCom, which takes as input the behavioral rule models generated by the *Behavioral Rule Extractor*. These formal models are verified against various safety and security properties using a bounded model checker, i.e., the Alloy analyzer [150], to exhaustively explore every interaction within a defined scope. This allows IotCom to automatically analyze each bundle of apps without manual specification of the initial system configuration, which is required for comparable state-of-the-art techniques [34, 35]. We use Alloy to demonstrate our approach because it combines a concise, simple specification language with a fully-automated analyzer capable of exhaustively checking our models for safety and security violations. In particular, Alloy includes support for checking transitive closure, which is important to analyze more complex, chained interactions.

The bounded model checking uses three sets of formal specifications, as shown in Figure 4.3: (1) a base *smart home model* describing the general entities composing a smart home environment; (2) the app-specific *behavioral rule models* generated by the *Behavioral Rule Extractor*; and (3) formal assertions for our *safety and security properties*. Complete Alloy models are available online at our project site [151].

4.6.1 Smart Home Model

The overall smart home system is modeled as a set of Devices and a set of IoTApps, as shown in Listing 2. Each IoTApp contains its own set of Rules. Each Device has some associated state Attributes, each of which can assume one of a disjoint set of Values. Recall from Section 4.4, each rule contains its own set of Triggers, Conditions, and Actions. Each individual trigger, condition, and action is modeled as a tuple of

one or more Devices, the relevant Attribute for that type of device, and one or more Values that are of interest to the trigger, condition, or action. Defined in Alloy, each of the listed entities is an abstract signature which is extended to a concrete model signature for each specific type of device, attribute, value, IoT app, behavioral rule, etc.

Listing 2 Excerpt of base smart home Alloy model.

```
1  abstract sig Device    { attributes : set Attribute }
2  abstract sig Attribute { values : set Value }
3  abstract sig Value     { }
4  abstract sig IoTApp { rules : set Rule }
5  abstract sig Rule {
6    triggers   : set Trigger,
7    conditions : set Condition,
8    actions    : some Action }
9  // Trigger, Condition, and Action contain
10 // similar tuples
11 abstract sig Trigger {
12   devices    : some Device,
13   attribute  : one  Attribute,
14   values     : set  Value }
15 abstract sig Condition { ... }
16 abstract sig Action    { ... }
```

Apps can communicate both virtually within the cloud backend and physically via the devices they control. Virtual interactions fall into two main categories: (1) direct mappings, where one app triggers another by acting directly on a virtual device/variable watched by the triggered app; or (2) scheduling, where one rule calls (e.g.) the runIn API from SmartThings to invoke a second rule after a delay. Physically mediated interactions occur indirectly via some physical *channel*, such as temperature. Our model—in contrast to others [34]—directly supports detection of violations mediated via physical channels. As part of our model of the overall SmartThings ecosystem, we include a mapping of each device to one or more physical Channels as either a sensor or an actuator (not shown in Listing 2).

4.6.2 Extracted Behavioral Rule Models

The second set of specifications required by the *Formal Analyzer* are the models generated by the *Behavioral Rule Extractor*. These specifications extend the base specifications described in Section 4.6.1 with specific relations for each individual IoT app. Listing 3 partially shows the Alloy specification generated for the MaliciousApp from Section 4.2.

Listing 3 Excerpts from the generated specification for MaliciousApp (Listing 1)

```
1  one sig MaliciousApp extends IoTApp {
2    presence : one PresenceSensor,
3    location : one Location }
4      { rules = r0 }
5  one sig r0 extends Rule {}{
6    triggers   = r0_trg0
7    conditions = r0_cnd0 + r0_cnd1
8    actions    = r0_act0 }
9  one sig r0_trg0 extends Trigger {} {
10   devices   = MaliciousApp.presence
11   attribute = PresenceSensor_Presence
12   no values }
13 one sig r0_cnd0 extends Condition {} {
14   devices   = MaliciousApp.location
15   attribute = Location_Mode
16   values    = Location_Mode.values - Location_Mode_Home }
17 one sig r0_cnd1 extends Condition {} { ... }
18 one sig r0_act0 extends Action {} {
19   devices   = MaliciousApp.location
20   attribute = Location_Mode
21   values    = Location_Mode_Home }
```

First, the new signature MaliciousApp extends the base IoTApp by adding fields for a PresenceSensor device and a Location as well as constraining the inherited rules field to contain only r0, defined on Line 5 as an extension of Rule. As described in Section 4.5, the *Behavioral Rule Extractor* generates the tuples for the triggers, conditions, and actions of each app's rules from the behavioral rule graph. In this case, the entry point node corresponding to the `presenceHandler` method is translated into the r0_trg0 signature (Line 9), while the condition nodes correspond with r0_cnd0 and r0_cnd1 (Lines 13, 17). Lastly, the action node from that path

of the BRG generates r0_act0 (Line 18). Each of the apps analyzed would be translated into a similar specification; the bundle of these specifications define all apps in the system, analyzed by the bounded model checker.

4.6.3 Safety/Security Properties

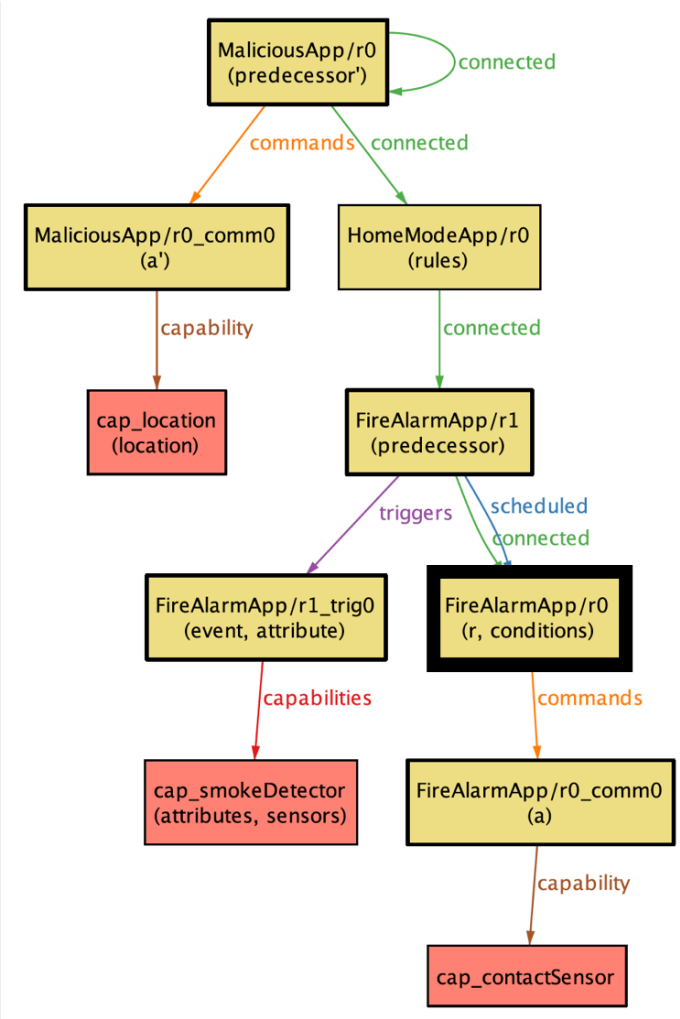


Figure 4.5: Counterexample from Alloy for running example.

To provide a basis for precise analysis of IoT app bundles against safety and security violations and further to automatically identify possible scenarios of their

Listing 4 Example Alloy assertion for property G3.12.

```
1  assert G3_12 {
2    no r : IoTApp.rules, a : r.actions {
3      // DON'T open the door...
4      a.attribute = CONTACT_SENSOR_CONTACT_ATTR
5      a.values    = CONTACT_SENSOR_OPEN
6      // ... WHEN ...
7      ((some r' : r.*are_connected, t : r'.triggers {
8        // ...smoke is detected
9        t.attribute = SMOKE_DETECTOR_SMOKE_ATTR
10       t.values    = SMOKE_DETECTOR_IS_SMOKE }) or
11      (some r' : r.*are_connected, a' : r'.actions {
12       // ...mode is away
13       a'.attribute = MODE_ATTR
14       a'.values    = MODE_AWAY })) }}
```

occurrences given particular conditions of each bundle, we designed specific Alloy assertions. These assertions express properties that are expected to hold in the extracted specifications. Specifically, each assertion captures a specific type of safety and security properties, considering our safety goals for IoT app interactions (cf. Section 4.3). In total, we define 36 safety properties, as summarized in Table 4.1. The property check is then formulated as a problem of finding a valid trace that satisfies the specifications, yet violating the assertion. The returned solution encodes an exact scenario (states of all elements, such as Devices) leading to the violation.

As a concrete example, Listing 4 formally expresses property G3.12 from Table 4.1. The assertion states that no rule (r) should have an action (a, Line 2) that results in a contact sensor (i.e., the door) being opened (Lines 4-5) while also being connected to another rule (r') that either (1) was triggered by the smoke detector (Lines 7-10) or (2) sets the home mode to *Away* (Lines 11-14). If Alloy can find a trace containing such an r and r', that trace will be presented as a counterexample, along with the information useful in finding the root cause of the violation. Given our running example, the analyzer automatically generates the counterexample

depicted in Figure 4.5. The rule FireAlarmApp/r0 (thick border) violates the assertion by opening the contact sensor (i.e., door) despite its connection to rules higher in the chain that were (1) triggered by the smoke detector (FireAlarmApp/r1) and (2) set the home mode to *Away* (MaliciousApp/r0).

Our ability to detect violations in complex chains of interaction across both cyber and physical channels sets our work apart from other research in the area, as does our ability to analyze the conditional predicates of each rule.

4.7 Evaluation

This section presents our experimental evaluation of IotCom, addressing the following research questions:

- **RQ1:** What is the overall accuracy of IotCom in identifying safety and security violations compared to other state-of-the-art techniques?
- **RQ2:** How well does IotCom perform in practice? Can it find safety and security violations in real-world apps?
- **RQ3:** What is the performance of IotCom's analysis realized atop static analysis and verification technologies?

Experimental subjects. Our experiments are all run on a multi-platform dataset of smart home apps drawn from two sources: *(1) SmartThings apps:* We gathered 404 SmartThings Classic apps from the SmartThings public repository [152]. These apps are written in Groovy using the SmartThings Classic API platform. *(2) IFTTT Applets:* We used the IFTTT dataset provided by Bastys et al. [76]. This dataset is in JSON format, with each object defining an IFTTT applet. These applets cover

a broad spectrum of services, so we filtered the dataset to extract the 55 applets specifically related to SmartThings.

Safety and Security Properties. We use a set of 36 safety and security properties for all of our experiments, each encoded as an Alloy assertion as described in Section 4.6.3. Table 4.1 defines the property set, grouped according to the corresponding goal from Section 4.3. To preserve the validity of our research, we adapted these properties from those used by other approaches in the literature [34, 35, 36, 78]. Some of these properties are general, considering the interaction between rules with no regard to specific triggers, conditions, or actions. For example, *(G1.1) NO repeated actions* considers a case where two apps both send the same command to the same device in response to a single event. Repeated actions could force the device to activate multiple times, increasing wear on the device and violating the very definition of our goal.

Others are more system- or situation-specific, such as *(G3.12) DON'T open the door WHEN smoke is detected or mode is away*. The majority of such situation-specific properties consider the values for the various state attributes of each device in the system and tend to collect under *(G3) No unsafe states*.

We performed all the experiments on a MacBook Pro with a 2.2GHz 2-core Intel i7 processor and 16GB RAM. We used Alloy 4.2 for model checking.

4.7.1 Results for RQ1 (Accuracy)

To evaluate the effectiveness and accuracy of IotCom and compare it against other state-of-the-art techniques, we used the IoTMAL [153] suite of benchmarks. This dataset contains custom SmartThings Classic apps, for which all violations, either singly or in groups, are known in advance—establishing a ground truth.

Table 4.1: Safety and Security Properties

Property	Description
Goal 1 Properties	
G1.1	NO repeated actions on a device from a single event
G1.2	NO repeated actions on a device from exclusive events
G1.3	DON'T turn on the AC WHEN mode is away
G1.4	DON'T turn on the bedroom light WHEN door is closed
G1.5	DON'T turn on dim light WHEN there is no motion
G1.6	DON'T turn on living room light WHEN no one is home
G1.7	DON'T turn on dim light WHEN no one is home
G1.8	DON'T turn on light/heater WHEN light level changes
Goal 2 Properties	
G2.1	NO action enabling a condition of another rule
G2.2	NO action disabling a condition of another rule
G2.3	NO action contradicting another action from a single event
G2.4	NO action contradicting itself from a single event
Goal 3 Properties	
G3.1	NO action triggering another unintentionally
G3.2	DON'T turn off heater WHEN temperature is low
G3.3	DON'T unlock door WHEN mode is away
G3.4	DON'T turn off living room light WHEN someone is home
G3.5	DON'T turn off AC WHEN temperature is high
G3.6	DON'T close valve WHEN smoke is detected
G3.7	DON'T turn off living room light WHEN mode is away
G3.8	DON'T turn off living room light WHEN mode is vacation
G3.9	DO set mode to away WHEN no one is home
G3.10	DO set mode to home WHEN someone is home
G3.11	DON'T turn on heater WHEN mode is away
G3.12	DON'T open door WHEN smoke is detected or mode is away
G3.13	DON'T turn off security system WHEN no one is home
G3.14	DON'T turn off the alarm WHEN smoke is detected
G3.15	DON'T unlock the door WHEN light level changes
G3.16	DON'T lock the door WHEN smoke is detected
G3.17	DON'T open the door WHEN smoke is detected and heater is on
G3.18	DON'T unlock the door WHEN smoke is detected and heater is on
G3.19	DON'T open the door WHEN motion is detected and fan is on
G3.20	DON'T unlock the door WHEN motion is detected and fan is on
G3.21	DON'T open the door/window WHEN temperature changes
G3.22	DON'T set mode WHEN temperature changes
G3.23	DON'T set mode WHEN smoke is detected
G3.24	DON'T set mode WHEN motion is detected and alarm is sounding

We faced two challenges while evaluating the accuracy of IotCom against the state-of-the-art: (1) Most analysis techniques, except IoTSAN [34], are not available. SOTERIA [35] was evaluated using the IoTMAL dataset, but the tool is not publicly available. Therefore, we rely on the results provided in the technical report [6]. (2) The violations in the IoTMAL dataset do not involve physical channels. For

Table 4.2: Safety violation detection performance comparison between SOTERIA, IoTSAN and IoTCom. True Positive (TP), False Positive (FP), and False Negative (FN) are denoted by symbols ☑, ☒, □, respectively. (*X*#) represents the number # of detected instances for the corresponding symbol *X*.

Test Cases	SOTERIA*	IoTSAN	IoTCom
Individual Apps			
ID1BrightenMyPath	☑	☑	☑
ID2SecuritySystem	☑	□†	☑
ID3TurnItOnOffandOnEvery30Secs	☑	□	☑
ID4PowerAllowance	☑□	(□2)	(☑2)
ID5.1FakeAlarm	□	□	□
ID6TurnOnSwitchNotHome	☑	☑	☑
ID7ConflictTimeandPresenceSensor	☑	□‡	☑
ID8LocationSubscribeFailure	☑	☑	☑
ID9DisableVacationMode	☒	□	☑
Bundles of Apps			
Application Bundle 1	☑	☑	☑
Application Bundle 2	☑	□†	☑
Application Bundle 3	☑	□†	☑
Application Bundle 4#	□	□‡	☑
Application Bundle 5#	□	□	☑
Application Bundle 6#	□	□	☑
Precision	90%	100%	**100%**
Recall	66.7%	25%	**93.8%**
F-measure	76.6%	40%	**96.8%**

* results obtained from [6] † IoTSAN did not generate the Promela model
‡ SPIN crashing # Benchmarks involving physical channels related violations.

evaluating this capability of the compared techniques, we developed three bundles, B4–B6, available online from the project website [151].

Table 4.2 summarizes the results of our experiments for evaluating the accuracy of IoTCom in detecting safety violations compared to the other state-of-the-art techniques. IoTCom succeeds in identifying all 9 known violations out of 10 in the individual apps, and all violations in 6 bundles of apps. Furthermore, IoTCom identifies two violations in the test case *ID4PowerAllowance*–namely, *(G1.1) NO*

repeated actions and *(G2.4) NO action contradicting itself*. Since IotCom captures schedule APIs, it can identify the second violation unlike SOTERIA and IoTSAN. IotCom misses only a single violation, in test case *ID5.1FakeAlarm*. This app generates a fake alarm using a smart device API not often used in SmartThings apps. Neither SOTERIA nor IoTSAN detected this violation.

IotCom also successfully identifies potential safety and security violations arising from interactions between apps. Test bundles $B1 - B3$ exhibit such violations using only virtual channels of interaction. Bundles $B4 - B6$ define violations due to *physical* interactions between apps. For example, B4 contains an interaction violation over the temperature channel that can result in the door being unlocked while the user is not present, violating *(G3) No unsafe behavior*, while B5 and B6 contain unsafe behavior and infinite actuation loop, respectively. SOTERIA and IoTSAN cannot detect such violations that involve interactions over physical channel.

4.7.2 Results for RQ2 (IotCom and Real-World Apps)

We further evaluated the capability of IotCom to identify violations in real-world IoT apps. We partitioned the subject systems of real-world SmartThings and IFTTT apps into 37 non-overlapping bundles, each comprised of 6 apps, in keeping with the sizes of the bundles used in prior work [34, 102]. The bundles enabled us to perform several independent experiments. IotCom detected 1332 safety/security violations across the analyzed bundles of real-world IoT apps. Figure 4.9 illustrates how the detected violations were distributed among the three goals as shown in Table 4.1. According to the results, IotCom detects violations of 20 of the safety and security properties, where 62.16% of the bundles (23 of 37) violate at least one property. In the following, we describe some of our findings.

4.7.2.1 Violation of (G1) No Unintended Behavior

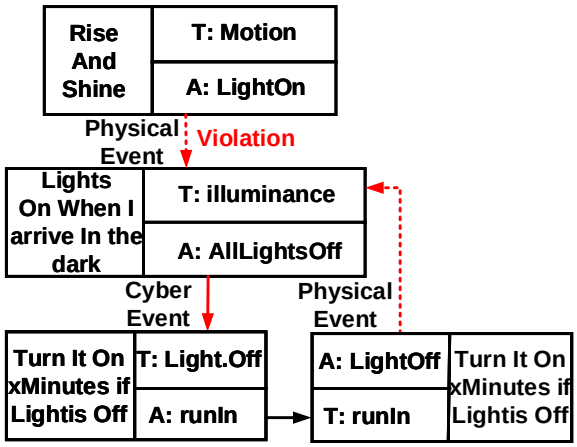


Figure 4.6: Example violation of *G1 (No unintended behavior)*: Lights continually turn off and on. The violation occurs via the *luminance* physical channel.

The chain of interactions shown in Figure 4.6 results in a loop that could continually turn a switch on and off, violating Goal 1. The loop involves three SmartThings apps: *RiseAndShine*, *TurnItOnXMinutesIfLightIsOff*, and *LightsOnWhenIArriveInTheDark*. *RiseAndShine* contains a rule activating some switch when motion is detected. *LightsOnWhenIArriveInTheDark* controls a group of switches based on the light levels reported by light sensors. *TurnItOnXMinutesIfLightIsOff* switches a switch on for a user-specified period, then turns it back off.

When *RiseAndShine* activates its switch, it could trigger *LightsOnWhenIArriveInTheDark* via the *luminance* physical channel, switching all connected lights off. This event triggers *TurnItOnXMinutesIfLightIsOff*, which may re-enable one of the lights. This changes the luminance level, entering into an endless loop between *LightsOnWhenIArriveInTheDark* and *TurnItOnXMinutesIfLightIsOff*. IotCom is uniquely capable of detecting this violation due to our support of physical channels, scheduling APIs, and arbitrarily long chains of interactions among apps.

4.7.2.2 Violation of (G2) No Unpredictable Behavior

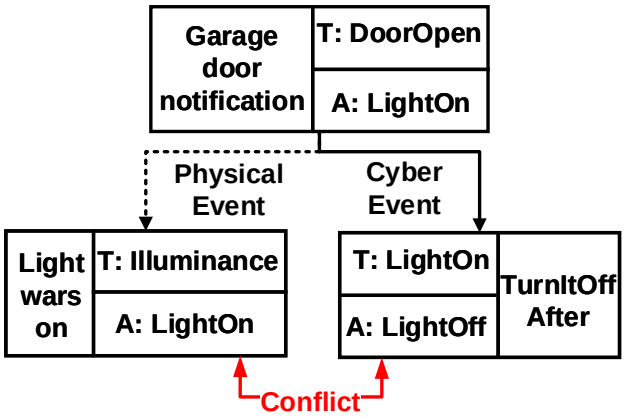


Figure 4.7: Example violation of *(G2) No unpredictable behavior*: Both "on" and "off" commands sent to the same light due to the same event. The violation happens via the *luminance* physical channel.

The three apps shown in Figure 4.7 lead to potentially unpredictable behavior due to competing commands to the same device, violating Goal 2. They also interact in part over a physical channel that could not be detected by approaches that only consider virtual interaction between apps. The IFTTT applet *Garage-DoorNotification* activates a switch when the garage door is opened. This triggers the action of SmartThings app *TurnItOffAfter*, which will turn off the light after a predefined period. At the same time, *GarageDoorNotification* may also have triggered the IFTTT applet *LightWarsOn* via a light sensor, interacting over the physical *luminance* channel. *LightWarsOn* would attempt to turn the light back on, producing an unpredictable result—a race condition—depending on which rule was executed first.

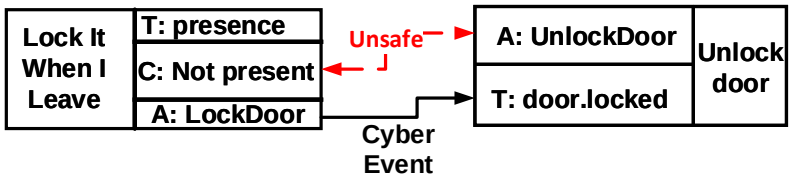


Figure 4.8: Example violation of *(G3) No unsafe behavior*: Cyber coordination between apps may leave the door unlocked when no one is home. The first rule is guarded by a condition that the home owner not be present.

4.7.2.3 Violation of (G3) No Unsafe Behavior

Figure 4.8 depicts a chain of virtual interactions that could lead to a door being left unlocked if misconfigured. The SmartThings app *LockItWhenILeave* locks the door when the user leaves the house, as detected by a presence sensor. The lock action triggers the IFTTT applet *Unlock Door*, which unlocks the door again. This violates *(G3) No unsafe behavior* by potentially leaving the door unlocked when the user leaves the house.

This example also demonstrates IotCom's unique ability to consider logical conditions when evaluating interactions. The code of *LockItWhenILeave* does not specify a particular value for the presence sensor in the trigger for its rule; the entry method is invoked by any change to the presence sensor. Instead, the rule uses a condition to ensure it is only invoked when the user is *not* present. Other tools, particularly those that require manual specification of the initial system configuration for analysis, may miss this violation by only considering the interaction when the user is present. IotCom does not have such a limitation, and correctly identifies the violation.

4.7.3 Results for RQ3 (Performance and Timing)

The last evaluation criteria are the performance benchmarks of static model extraction and formal analysis of IotCom on real-world apps drawn from the SmartThings and IFTTT repositories.

Figure 4.10 presents the time taken by IotCom to extract rule models from the Groovy SmartThings apps and IFTTT applets. This measurement is done on the datasets collected from two repositories: 404 SmartThings apps drawn from the SmartThings public repository [152] and 55 IFTTT applets from the dataset used by Bastys et al. [76]. The scatter plot shows both the analysis time and the app size. According to the results, our approach statically analyzes 98% of apps in less than one second. As our approach for model extraction analyzes each app independently, the total static analysis time scales linearly with the number of apps.

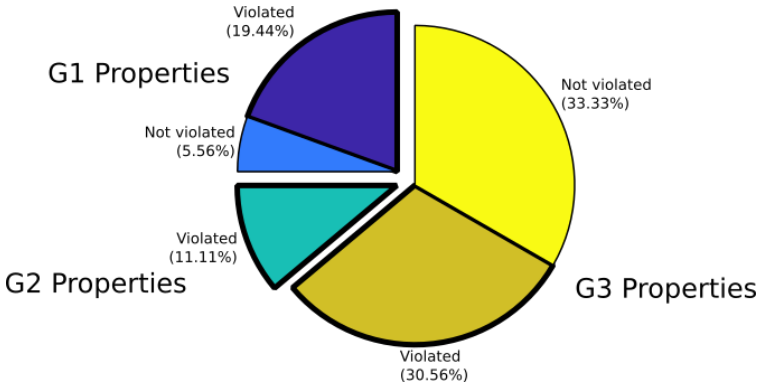


Figure 4.9: Distribution of detection violations across three goals (cf. Section 4.3).

We also measured the verification time required for detecting safety/security violations and compared the analysis time of IotCom against that required by IoTSAN [34]. We checked all 36 safety and security properties against each bundle. Based on our results, the time required by the Formal Analyzer scales based on the number of *rules* per bundle rather than the number of *apps*. This is to be

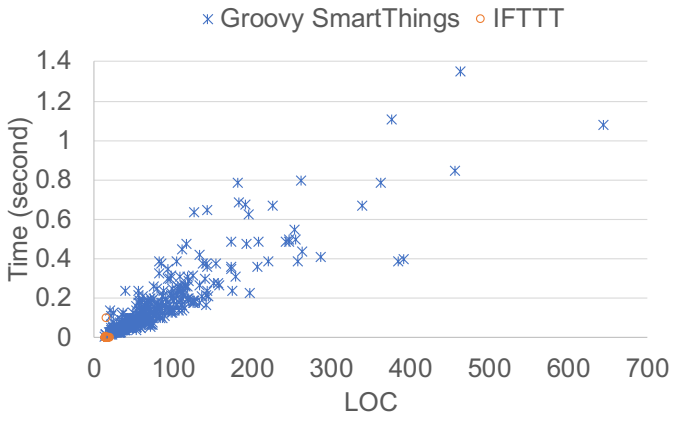


Figure 4.10: Scatter plot representing analysis time for behavioral rule extraction of IoT apps using IotCom.

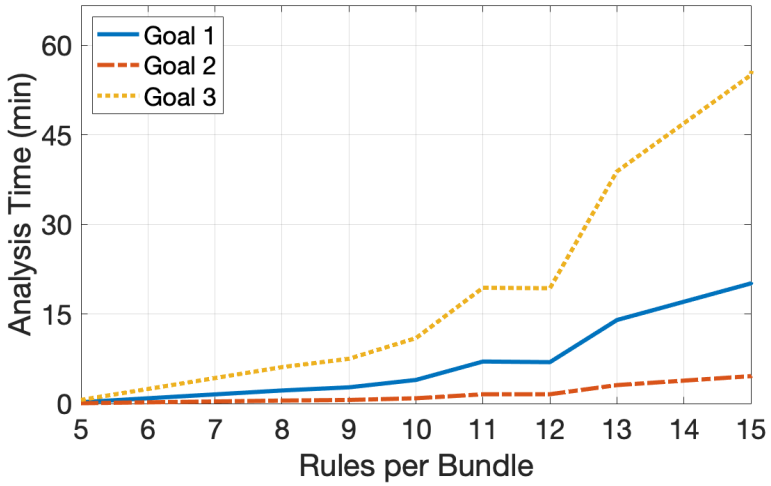


Figure 4.11: Average time required to analyze all properties related to each goal by number of rules in the analyzed bundle.

expected, given that our analysis compares fine-grained rule-to-rule interaction. Nguyen et al. [34] manually specify the initial configuration for each app in the bundle as part of the model checked by IoTSAN; IotCom does not require specification of a single initial configuration, instead exhaustively checking all configurations that fall within the scope of the app model. To perform a fair comparison between the two approaches, we generated initial configurations for

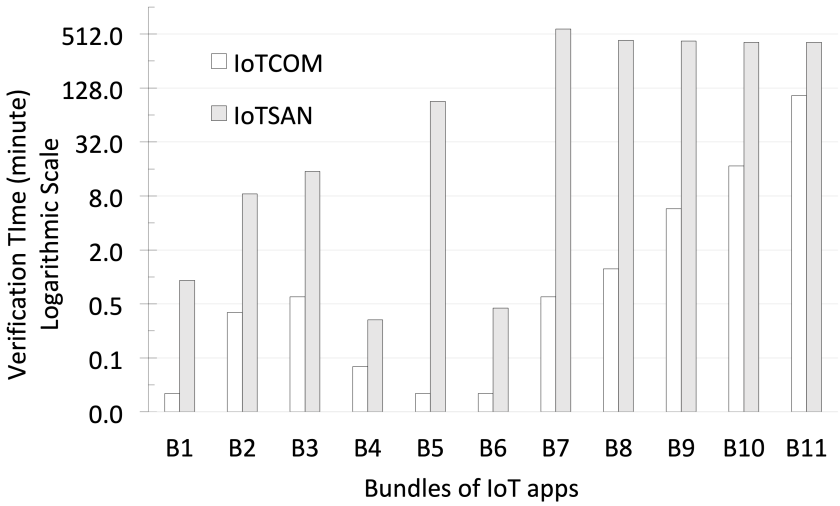


Figure 4.12: Verification time by IotCom and IoTSAN to perform the same safety violation detection in a logarithmic scale.

11 bundles of apps and converted them into a format supported by IoTSAN. We then ran the two techniques considering all valid initial configurations to avoid missing any violation.

Figure 4.11 depicts the total time taken by each approach to analyze *all* relevant configurations (rather than a single, user-selected configuration). Note that the analysis time is portrayed in a logarithmic scale. The experimental results show that the average analysis time taken by IotCom and IoTSAN per bundle is 11.9 minutes (ranging from 0.05 to 104.78 minutes) and 216.9 minutes (ranging from 0.33 to 580.91 minutes), respectively. Overall, the timing results show that IotCom reduces the violation detection time by 92.1% on average and by as much as 99.5%, and is able to effectively perform safety/security violation detection of bundles of real-world apps in just a few minutes (on an ordinary laptop), confirming that the presented technology is indeed feasible in practice for real-world usage.

4.8 Discussion

IoT apps and devices interact with each other in complex ways. Therefore, a holistic analysis is crucial to identify safety and security threats that may arise from multiple such interactions. Celik et al. [6] describe the challenges of analyzing IoT apps. These include consideration of interactions over physical channels and the capability to perform cross-platform analysis, which does not limit the analysis to a single IoT platform (i.e. IFTTT only or Groovy only). Celik et al. also emphasize the importance of performing a precise program analysis. Accordingly, IotCom has been designed and implemented to overcome those challenges. IotCom models each app individually, but composes all the models into a complete picture of the IoT system to analyze their interactions. Our analysis accounts for interactions mediated by physical channels, while other approaches focus only on interactions within the virtual system.

IotCom models time-based APIs (e.g. runIn, sunrise, sunset), but does not precisely model the relative durations requested in calls to these APIs. Our next step is to model time more precisely. IotCom does not require initial configurations, which significantly enhances its capabilities. However, our model does not account for all variables that could influence the configuration, such as spatial distance between devices [154]. Also, some SmartThings capabilities—such as switch—are very general and can be associated with many physical channels. We do not distinguish between different uses of these general devices. Considering these additional factors may improve the accuracy.

The novel graph abstraction technique proposed in IotCom makes it practical for handling on-going and future developments in the domain of IoT apps, like multiple actions and triggers for conditional triggering [155].

4.9 Summary

This chapter presents a novel approach for compositional analysis of IoT interaction threats. Our approach employs static analysis to automatically derive models that reflect behavior of IoT apps and interactions among them. The approach then leverages these models to detect safety and security violations due to interaction of multiple apps and their embodying physical environment that cannot be detected with prior techniques that concentrate on interactions within the cyber boundary. We formalized the principal elements of our analysis in an analyzable specification language based on relational logic, and developed a prototype implementation, IotCom, on top of our formal analysis framework. The experimental results of evaluating IotCom against 36 prominent IoT safety and security properties, in the context of hundreds of real-world apps, corroborates its ability to effectively detect violations triggered through both cyber and physical channels.

5 Efficient Signature Generation for Classifying Cross-Architecture IoT Malware

Internet-of-Things (IoT) devices are increasingly targeted by adversaries due to their unique characteristics such as constant online connection, lack of protection, and full integration in people's daily life. As attackers shift their targets towards IoT devices, malware has been developed to compromise IoT devices equipped with different CPU architectures. While malware detection has been a well-studied area for desktop PCs, heterogeneous processor architecture in IoT devices brings in unique challenges. Existing approaches utilize static or dynamic binary analysis for identifying malware characteristics, but they all fall short when dealing with IoT malware compiled for different architectures. In this chapter, we propose an efficient signature generation method for IoT malware, which generates distinguishable signatures based on high-level structural, statistical and string feature vectors, as high-level features are more robust against code variations across different architectures. The generated signatures for each malware family can be used for developing lightweight malware detection tools to secure IoT devices. Extensive experiments with two datasets including 5,150 recent IoT malware samples show that our scheme can achieve 85.2% detection rate with 0% false positive rate.

5.1 Motivation

IoT malware/vulnerability research. The priority of most IoT vendors are functionalities and faster pace of bringing product to market. The security of IoT systems has not received much attention. The most relevant research focuses on developing an IoT honeypot [156] called IoTPOT, used to allure malware to infect emulated IoT devices in the honeypot, which aims at collecting IoT malware binaries and the corresponding network traffic for further analysis. The malware binaries have been clustered into four distinct families based on simple command sequence and unique strings through manual analysis. Yet, they neglect the rich code-level features that facilitate a fine-grained characterization of IoT malware.

Vulnerability and bug discovery of IoT devices is a problem gaining attentions recently [157, 158, 159]. Eschweiler *et al.* [158] utilize graph matching approaches in conjunction with statistical features extracted from the disassembled binary codes to detect bugs. However, their goal is to identify similarity between individual vulnerable functions rather than matching binary files and generating detection signatures. Recently, Feng *et al.* [159] employ a scalable search method to improve the scalability and accuracy of cross-architecture bug search, where both the structural and statistical features are aggregated to create a high-level feature vector for vulnerability detection in real-time. All of the above methods use static analysis to extract features at basic block level using control flow graph (CFG). Yet, the high computational complexity of processing CFGs hinders their deployment on IoT devices.

Converting the assembly code to Intermediate Representation (IR) code has been adopted to handle syntax differences to perform cross-architecture analysis [160]. However, available IR languages/platforms are limited to handle only

a few architectures (i.e., MIPS, ARM, x86), which are not suitable for our dataset that contains malware with more diverse architectures.

IoT malware dataset. Our IoT malware dataset is provided by IoTPOT team, including two recently-collected datasets: one is collected within a three-month period between May 2016 and August 2016, and contains 1,150 malware samples/binaries; and the other one is collected within a one-year period between October 2016 to October 2017, containing 4,000 malware samples/binaries. Every sample has a MD5 name and a time label. To the best of our knowledge, this IoT malware dataset is the largest dataset currently available. To date, there are around 7,000 IoT malware samples targeting smart devices as reported by Kapersky [42]. Therefore, we believe the research on 5,150 malware set (74% of total amount) can faithfully reveal the characteristics of most IoT malware. All the malware binaries are *Linux Executable and Linkable Format (ELF) format* executable files. Figure 5.1 shows the diverse CPU architectures of the malware samples in our dataset, where ARM and MIPS are two most popular architectures for IoT malware. The detection rate of IoT malware is known to be low [161]. Therefore, *an accurate and lightweight cross-architectural detection mechanism that can be deployed on resource-constrained IoT devices is a pressing need.*

Malware statistical, string Features, and string obfuscation/encryption. As mentioned earlier, this work aims to develop lightweight IoT malware signatures, which implies the features used for generating the signatures should be easy to extract, and also the extracted features can differentiate between malicious and benign samples. In this work, we consider statistical and string features for clustering and signature generation of IoT malware families. Table 5.1 presents the statistical features extracted from exemplar benign and malicious files. It shows a significant difference between the code statistics features of benign and malicious files.

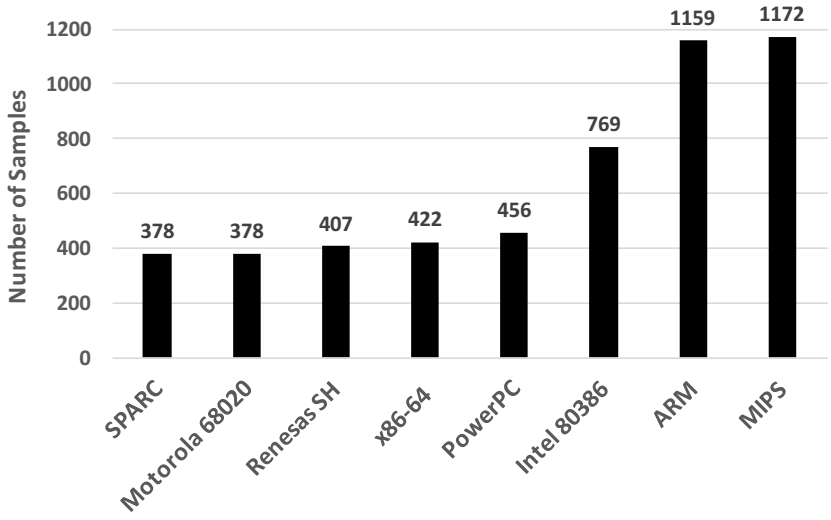


Figure 5.1: IoT malware distribution based on CPU types

Files	Redirect	Arithmetic	Logical	Transfer	Total
Benign-1	108719	23117	41817	300822	647654
Benign-2	129662	25204	57020	371085	767334
Benign-3	166767	36143	64249	487340	1025432
Malicious-1	10434	1744	2085	17087	45831
Malicious-2	13283	2104	2427	22513	58558
Malicious-3	5354	3707	408	363	31843

Table 5.1: Number of instructions for benign and malicious binaries

We also extract printable strings from the malware samples, and discover that the extracted printable strings of many malware samples contain the same string sequences, yet, they are compiled for different architectures. For instance, our experimental results show that the same printable strings such as *"busybox iptables -A INPUT -p tcp –destination-port 7547 -j DROP"* appeared in different versions of Mirai for different architecture types, such as MIPS, ARM, PowerPC and Renesas SH. This implies that IoT malware is developed to infect multiple architectures. Also, we observe printable strings contain other rich information that can be used to distinguish between different malware families (see Section 5.2.3). Such

observation and the fact that printable strings are easy to extract motivate us to consider printable strings for signature generation.

Some printable strings from malware samples are obfuscated or encrypted. However, we find that the encrypted/obfuscated printable strings of some malware samples can also be overlapped, if these samples use the same encryption/obfuscation mechanisms. For instance, we find many samples from the same malware family contain the same encrypted/obfuscated sequences "eGAIM aJPMOG qCD-CPK oMXKNNC uKLFMUQ", which can be used as signatures to identify samples from the same malware family.

5.2 Signature Generation of IoT Malware

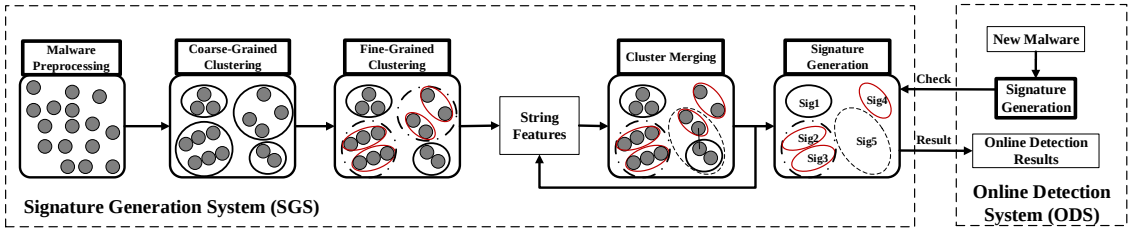


Figure 5.2: Detection system architecture

In this section, we present the design of our system that aims to generate signatures for classifying and detecting IoT malware. The proposed system consists of two major phases: *offline signature generation* and *online detection/classification*. The offline signature generation takes IoT malware samples as input, which includes the following five steps, as presented in Fig. 5.2: 1) malware preprocessing, 2) coarse-grained clustering, 3) fine-grained clustering, 4) cluster merging, and 5) signature generation for online detection.

5.2.1 System Overview

The offline signature generation can be conducted at computationally rich clouds/hubs. The malware preprocessing removes non-binary files from the dataset, and disassembles all the binary files using IDA Pro [162] to retrieve their assembly codes. After preprocessing, the number of malware samples is reduced to 4,078. We propose three stages of clustering, including coarse-grained clustering, fine-grained clustering, and cluster merging. The coarse-grained clustering utilizes statistical features, while the fine-grained clustering clusters the malware samples based on their structural similarities computed using Bindiff. The combination of coarse-grained and fine-grained clustering allows us to decrease the computational cost of the clustering process, compared to using only fine-grained clustering. Cluster merging refines the clustering results by merging clusters based on the similarity of extracted string features in an iterative manner. The cluster merging allows us to attain more generic malware signatures, thus improving the malware detection rate. Finally, we generate a succinct signature by integrating string and statistical features for each malware cluster, which can distinguish between different malware clusters. We use string and statistical features due to their capability in producing distinguishable patterns and ease of extraction. Online detection/-classification can be conducted on IoT devices by matching the signatures. In the following sections, we describe the system components.

5.2.2 Clustering IoT Malware

Instead of operating over each individual malware sample, we cluster these samples into groups, and perform group-level analysis to reduce the computational costs.

In the end, the malware clustering contains three phases: coarse-grained clustering, fine-grained clustering, and cluster merging.

Coarse-grained clustering: After generating the assembly codes of the malware files, statistical features are extracted for each malware file. The statistical features are then normalized, and used to perform the coarse-grained clustering. We extract 8 high-level statistical features from the assembly codes, including: total number of functions, total number of instructions, number of redirect instructions, number of arithmetic instructions, number of logical instructions, number of transfer instructions, number of segments, and number of call instructions. The high-level code statistics features are resilient to cross-architecture variations, as they abstract away the different code syntax.

The average and standard deviation values of these statistical features are computed for each malware sample. Among the 8 statistical features, we select the statistical features that can distinguish between different clusters with low standard deviations. In the end, we retain 6 statistical features by discarding the number of segments and number of call instructions due to their low distinguishable capability.

Finally, we use *K-means clustering* to perform coarse-grained clustering. K-means is selected due to its high efficiency. The number of clusters K is determined and validated using *DaviesâĂŞBouldin (DB) cluster validity index* [163], which is a standard metric for evaluating cluster results. A lower DB index denotes a better separation of the clusters and the better tightness inside the clusters. Therefore, the number of clusters with lowest DB index is selected as the best K for coarse-grained clustering.

Fine-grained clustering: In the fine-grained clustering phase, we consider code structural similarity between malware binaries computed using Bindiff. We iter-

atively compute the pairwise structural similarity between every malware pair within a cluster derived from coarse-grained clustering. The intuition is that high-level structural similarity generated by Bindiff is more resilient to cross-architecture variations [106], and can attain high accuracy in matching functions. This process yields an $N \times N$ similarity matrix (N is the number of malware samples), where the values in each row represent the similarity scores computed by Bindiff for a single malware sample against all other malware samples in the dataset.

Here, we utilize a popular binary similarity analysis tool, Bindiff [164], for computing the similarity between the malware samples in our dataset. Bindiff is a popular tool for computing structural similarity. It reconstructs Control Flow Graph (CFG) of each binary file to perform function and basic block matching, and then compares functions and basic blocks by extracting the graph-based features such as number of incoming/outgoing edges, the position of basic blocks in the CFG, etc. In order to tolerate the code differences brought by cross-architecture compilations, Bindiff abstracts the structural features of a binary file, while ignoring the specific assembly-level instructions. It retains a trade-off between similarity analysis accuracy and efficiency by applying a multi-level matching strategy based on function and basic block level structural attributes. The final result of Bindiff is a list of matched and unmatched functions from both binaries, based on which the similarity score (ranging in $[0, 1]$) is computed [164]. Bindiff is fairly efficient, and the matches it produces are proven accurate [106]. Therefore, in this clustering stage, we assign a relatively large cluster number to ensure every cluster is compact enough to contain all the similar malware samples.

In the fine-grained clustering, we partition the malware samples within each coarse-grained cluster into multiple fine-grained clusters using the single-linkage hierarchical clustering. We choose hierarchical clustering, because of its ability

to find clusters of arbitrary shapes with arbitrary distance metrics. The hierarchical clustering takes a matrix of pairwise distances among malware samples and generates a *dendrogram*, which is a tree-like data structure to represent the clustering outcome. Dendrogram cutoff determines the number of clusters. Distance measurement is critical for performing hierarchical clustering, and we derive the distance measurements through binary similarity analysis, which identifies common characteristics of malware samples at different levels including basic block, function, and file levels.

Rather than converting the similarity score to distance measurement which may lose accuracies, we propose to utilize similarity scores as features. The rationale lies on the fact that similar malware samples will have comparative similarity scores with other samples. Therefore, among N malware samples, each sample will have N similarity scores as a feature vector, which contains the malware's similarity score with itself (i.e., 100%) and with all other malware samples in the dataset. In order to minimize the impact of this high and ineffective self-similarity score, for malware A, we replace this self-similarity score with the highest similarity score of malware A compared with all other samples. Using similarity scores as features, we compute the distance measurements using Euclidean distance. The hierarchical clustering is conducted using the calculated distances among all samples. Similar to the coarse-grained clustering, the best number of fine-grained cluster is determined using DB cluster validity index for every coarse-grained cluster.

5.2.3 Cluster Merging

After splitting the coarse-grained clusters into the fine-grained clusters, some of the generated clusters may actually share a high similarity, which can then be merged together. Consequently, we use string features to merge clusters and refine clustering results. The cluster refinement involves two steps: 1) string feature analysis: N-gram text analysis is used to extract distinguishable string features from the printable strings; and 2) merging clusters: clusters are merged based on the similarity analysis of string features.

String feature analysis: The goal of string feature analysis is to find the string features that represent all malware samples of each cluster, since string features exhibit *rich contextual information that is suitable for fine-grained analysis*. String feature analysis facilitates the detection of cross-architecture IoT malware, as printable strings likely remain the same for binaries even when they are compiled differently. To this end, printable strings are extracted from each malware sample, which are used as inputs to generate N-gram string vectors, capturing the sequential order of strings. Punctuation marks, such as ":", "//", ";", are used to segment the strings. For example, a string vector "wget http://198.12.97.79/bins.sh; chmod 777 bins.sh; sh bins.sh" is segmented into "wget http 198.12.97.79 bins.sh chmod 777 bins.sh sh bin.sh". In order to avoid the overfitting issue, we replace the ip address with a special word "reIPaddress". Using N-gram, we are able to extract meaningful word sequences, e.g., "wget http reIPaddress bins.sh", "chmod 777 bin.sh sh" (with 4-gram). For improving the effectiveness of N-gram string feature, we remove any printable strings that contain less than three characters. We select N value according to experimental analysis performed to retain a balance between signature matching accuracy and efficiency, as described in Section 5.3.2.

Fig. 5.3 illustrates the string feature analysis. For each malware sample, we extract the N-gram string vectors, and remove the duplicate N-gram string vectors. Then, we combine the generated N-grams of all malware samples within a single cluster. Frequency analysis is carried out to identify the most common N-gram string vectors in each cluster. Consequently, we generate string features for each cluster, consisting of the top K N-gram strings with the highest appearances among all the N-gram strings in the combined string vector. The selection of K is explained in Section 5.3.2, which aims at identifying the distinguishable N-gram strings while minimizing computational costs. Thus, the top K N-gram strings are used as features of each cluster to perform cluster merging.

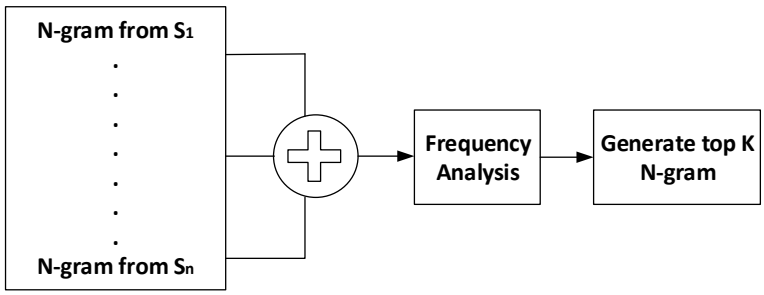


Figure 5.3: String feature analysis (S_1,$\cdots$, S_n are n samples in a cluster)

Merging clusters: Cluster merging is performed iteratively to refine the clustering results, which guarantees the malware clusters are both compact and well-separated from each other. Algorithm 6 illustrates the cluster merging procedure. After generating the top K N-gram strings for each cluster, we use Jaccard similarity to compute the *inter-cluster similarity* scores between different clusters based on the generated top K N-gram strings for each cluster. Clusters with a high string similarity score (i.e., higher than a predefined *merging threshold*) will be merged.

After merging clusters, we evaluate the merged clusters again by recomputing their top K N-gram string features, and the corresponding inter-cluster similarity

Algorithm 6 Cluster Merging

Required: τ = *merging threshold*, $|C|$ is the current number of clusters, JS represents Jaccard Similarity. c_i, c_j are two clusters under evaluation, and $SF(c_i)$, $SF(c_j)$ are their top K N-gram string features, respectively.

for *(each pair of* c_i, c_j*)* **do**
  if *(JS(*$SF(c_i)$, $SF(c_j)$*)* $\geq \tau$*)* **then**
    Merge clusters c_i, c_j $|C| = |C| - 1$ Generate new string feature for every cluster
  end
end

scores. The cluster merging process can be iterated multiple times in sequence until different clusters bearing low similarities (i.e., lower than the merging threshold), which indicates a set of well-separated and distinguishable clusters. After performing cluster merging, we can perform lightweight signature generation for each cluster.

5.2.4 Signature Generation and Online Detection/Classification

The complete signature of each merged cluster contains the top-K N-gram string feature (SF) extracted using the aforementioned method, and statistical feature (ST) that represents the average values of each statistical feature. Both SF and ST can be easily extracted from malware files, making the signature generation fairly efficient.

The online detection/classification of IoT malware is a signature matching process, where the matching is performed by computing the similarity between the extracted signature from the suspicious file and a set of cluster signatures. *Euclidean distance* $d(ST_i, ST_j)$ is used for measuring similarity of the ST. To facilitate similarity analysis, we convert the Euclidean distances into similarity scores [165],

named as Statistical Similarity (SS) and formalized as follows:

$$SS(ST_i, ST_j) = \frac{1}{1 + d(ST_i, ST_j)}. \tag{5.1}$$

On the other hand, *Jaccard Similarity (JS)* is used for computing similarity of the SF, denoted as $JS(SF_i, SF_j)$. The *Overall Similarity (OS)* score for the signature matching will be a weighted sum of JS and SS, written as follows:

$$OS(i, j) = w_1 \cdot JS(SF_i, SF_j) + w_2 \cdot SS(ST_i, ST_j), \tag{5.2}$$

where $w_1 + w_2 = 1$, and $OS(i, j)$ represents the signature matching score between file i and cluster j. In this research, we give a equal weight (i.e., 0.5) to SF and ST by default, but the weight can be tuned according to analysis results, e.g., if string obfuscation is identified, a higher weight can be assigned to ST. After computing the OS scores between a file and all cluster signatures, we identify the highest OS score as the file's suspicion level. Meanwhile, the file can be classified into the corresponding malware cluster or marked as benign. In our experiment in Section 5.3, we show that the file's suspicion level can be either a high value or a low value, which makes it straightforward to classify a suspicious file as IoT malware or benign samples.

The YARA tool [166] can be used for generating static signatures based on a sequence of specific printable strings or bytes belonging to a malware family. YARA signature for Mirai malware is shown in Listing 5.1, which includes the printable string signature. While most YARA signatures are manually identified, the proposed system can facilitate the automated identification of string signatures

for YARA. Therefore, we can easily incorporate YARA signatures in our system for malware detection.

```
rule Mirai_1
{
  meta:
    description = "Mirai Variant 1"
    author = "Mohannad / @moh"
    date = "2017-04-16"
  strings:
        $dir1 = "/dev/watchdog"
        $dir2 = "/dev/misc/watchdog"
  condition:
        $dir1 and $dir2
}
```

Listing 5.1: YARA Signature for Mirai

5.3 Evaluation

In this section, we evaluate the performance of our solution using the IoT malware dataset. We first discuss our methodology for selecting the values of K and N, and then evaluate the multi-stage clustering with cluster refinement method. The malware detection performance is evaluated in terms of malware detection rate and false positive rate. We further evaluate our system's performance in classifying the testing dataset, and benign linux firmware gleaned from various commercial product websites.

5.3.1 Selecting Parameters K and N

Similar to other empirical approaches for selecting N-gram parameter [107, 167], we also adopt an experimental approach driven by the data to select the best set of parameters. In our approach, we use a set of values {90, 100, 150, 200, 250} for selecting K, and a set of values {3, 4, 5, 6, 7} for selecting N, which are the key parameters for defining top K N-gram string feature. Our intuition is that the best K and N pair should produce the best clustering results, i.e., the samples in a cluster should bear high similarity with each other, and different clusters should be well separated. Thus, different combinations of K and N are considered with the goal of maximizing the similarity within the same cluster (*Intra-cluster similarity*), and minimizing the similarity among clusters (*Inter-cluster similarity*). Specifically, the inter-cluster string similarity is defined as the average Jaccard similarity of string features among different clusters. For intra-cluster string similarity, we collect the top-K N-gram string features of all malware samples inside each cluster, and compute the average Jaccard similarity of cluster string features with its enclosed samples.

Determining best K: We examine the *inter-cluster* and *intra-cluster* string similarity with different K values and fixed N value in order to determine the best K. Fig. 5.4 shows the string similarity results with different K values (when N is fixed as 4), from which we can see there is a slight increase of both inter-cluster and intra-cluster string similarity with the increase of K. To strike a balance between the intra-cluster similarity (the higher the better) and the inter-cluster similarity (the lower the better), we measure the difference between inter and intra-cluster string similarity, i.e., the gap between two lines, and select the K with the maximal gap. In the end, we select the best $K = 100$. For validation, we evaluate the performance

Table 5.2: Inter-cluster string similarity with different N values (K=100)

N	3	4	5	6	7
Inter-Cluster	0.162	0.120	0.171	0.162	0.164

by fixing N as other values, and $K = 100$ always performs best. This process can be fully automated by measuring the difference between inter-cluster and intra-cluster similarity.

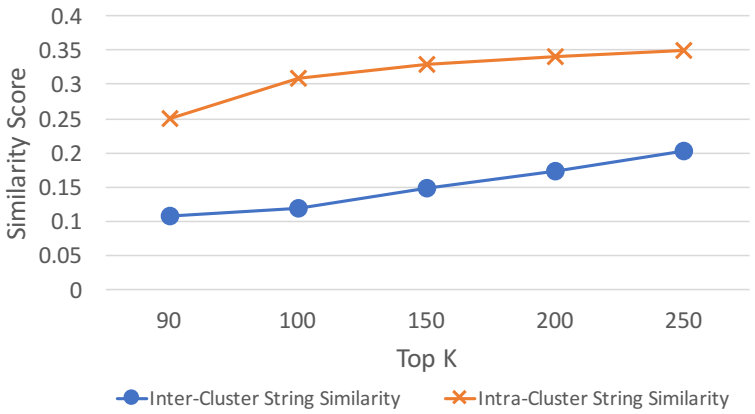


Figure 5.4: Inter-cluster and Intra-cluster string similarity with different K values ($N = 4$)

Determining best N: By fixing the value of $K = 100$, we use different N values to evaluate the inter-cluster string similarity. Table 5.2 shows $N = 4$ yields the lowest inter-cluster similarity. Note that we omit the measurement of intra-cluster string similarity to reduce the computational costs. Thus, we select the best N as 4. Finally, the string feature of each cluster is generated based on the ***top-100 4-gram*** string vectors. The selection of N is also an automated process by measuring the inter-cluster similarity w.r.t. different N values.

5.3.2 Evaluating Malware Clustering

Several mechanisms presented in the literature for evaluating clustering [168]. As mentioned earlier, DaviesâĂŞBouldin index is used in this work for validating number of cluster [168]. Because DaviesâĂŞBouldin reflects the ratio between inter and intra cluster similarity, and the smaller DB value is better. However, after performing several experiments, we tried to generate clusters contain at least two malware files. This aims to avoid generating tight clusters that contain only one file [111]. Fig. 5.5 illustrates the evaluation of coarse-grained clustering based on DB index, where 10 clusters represents the lowest DB index value 0.77.

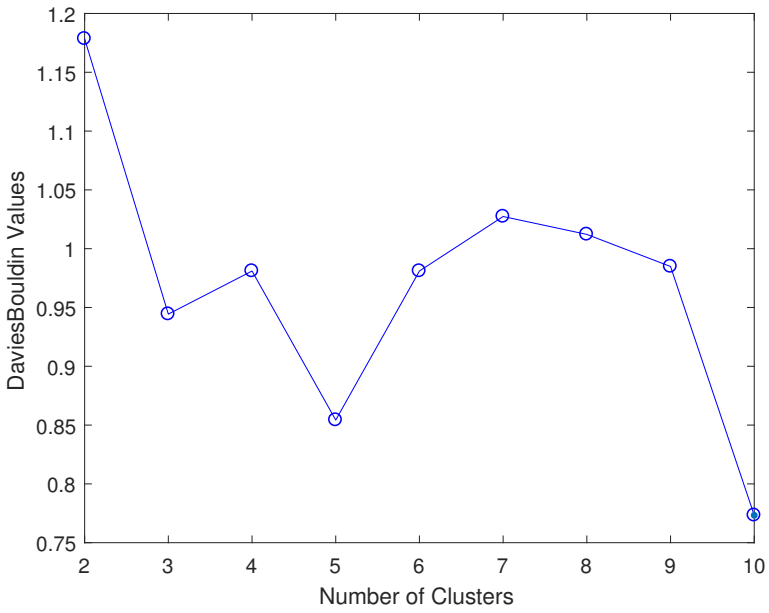


Figure 5.5: DaviesâĂŞBouldin index for evaluating the number of coarse-grained clusters

The same approach has been also followed to validate fine-grained clustering. On average DB index 0.6 is used for identifying the number of fine-grained clusters in each coarse-grained cluster.

Evaluating cluster merging using string feature: For merging clusters, we compute the similarity scores using cluster string features. Recall that the cluster string feature represents the top-100 4-gram string vectors of a cluster. Two clusters will be merged, if the Jaccard similarity score of their cluster string features is higher than a *merging threshold*. The merging threshold should be set sufficiently high to avoid merging dissimilar clusters, but should not be set too high that may prevent appropriate cluster merging. In this work, we empirically set the merging threshold as 0.7 [111] to merge clusters that resemble each other. In the end, 153 original clusters are merged into 110 clusters, which are re-evaluated to make sure they cannot be further merged.

Table 5.3: Summary of Clustering Results. The number of samples that have been used for performing the clustering is 2000 files (training dataset). Therefore, all clustering and processing time measurements are based on the training dataset

Entire Dataset			**Clustering (Training Dataset)**			**Processing Time (sec)**		
# of samples	undetected by all AV scanners	undetected by best AV scanner	Coarse	Fine	After Merge	Coarse	Fine	After Merge
4078	2 (%0.49)	45 (%1.1)	10	153	110	0.01	2.48	2.85

Clustering Coherence: The compact of our clustering approach has been also evaluated based on Virus Total detection results. We selected top-3 scanners that have high detection rate. Namely, AVG, DrWeb and McAfee. Then, we followed similar approach to [111] for generating malware families based on the generated labels by each Virus Total scanner. The malware families are generated by removing the last section of the generated label string, which is separated by $dot(.)$. For example, *Linux.BackDoor.Fgt* is the malware family that will be generated for the following labels generated by DrWeb *(Linux.BackDoor.Fgt.373, Linux.BackDoor.Fgt.578, Linux.BackDoor.Fgt.11, Linux.BackDoor.Fgt.229)*.

Then we check the consistency of each cluster, generated after merging clusters, by computing the distribution of malware family in each cluster, where it is expected to have a dominant malware family. The results show cohesion clusters, as the average malware family distribution is %92 for all clusters among the top-3 Virus Total scanners, as presented in Fig. 5.6, which shows the cohesion of the generated clusters after performing the merge.

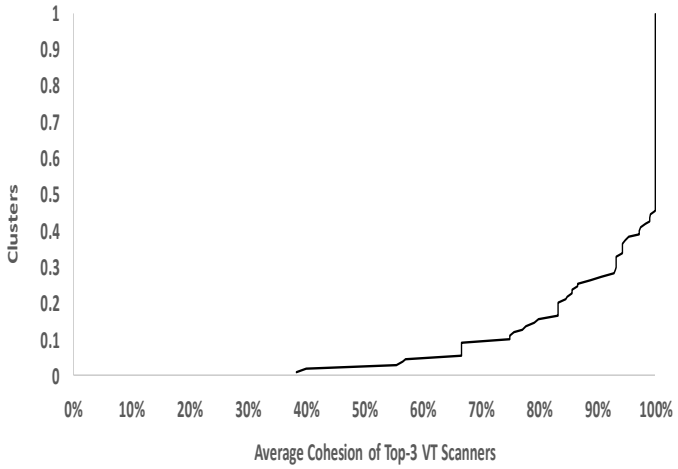


Figure 5.6: Distribution of cluster cohesion

5.3.3 Evaluating Signature Detection

The cluster signature will include the string feature and statistical feature, generated using our IoT malware dataset. In this section, we evaluate the detection accuracy and effectiveness of our cluster signature. A malware sample is detected if its maximum *OS* value (i.e., overall similarity in Eq. 5.2) is higher than a *detection threshold*. The detection threshold is set as a high value (i.e., 0.7) to reduce false positive rate.

For conducting the evaluation of clusters' signatures, we download a set of benign firmware binaries from openwrt, while the second part of the IoT malware dataset (testing dataset) is used for evaluating our approach. All the tested files are in Linux ELF format. The benign firmware dataset contains 130 samples, while the testing dataset contains 2078 malware samples. We generate the string and statistical features for these benign and malware samples. Table 5.4 reports the evaluation results, it shows the average statistical similarity of the testing dataset 94%, which is much higher than the average statistical similarity of the benign ELFs. Also, the detection rate based on string signature is 0% for the benign ELFs, while our solution can successfully detected malcious ELFs with 85.2% detection rate.

Table 5.4: Statistical similarity of new benign/malicious samples with clusters' statistical signature and detection rate based on string signatures

Source	# of Samples	Average statistical similarity	String Signature Detection Rate
Benign Firmware	130	41%	0%
Testing Dataset	2078	94%	85.2%

Performance comparison: We also conduct performance comparisons with two existing works based on API call sequences [103] and operation code (OpCode) N-grams [107]. The results are shown in Table 5.5, and our detection method can achieve significant performance improvement by capturing the unique characteristics of IoT malware.

Table 5.5: Performance comparison

Comparison	Detection Rate	False Positive Rate
API Calls	64.8%	5.1%
OpCode N-gram	66.0%	10.0%
Our solution	**85.2%**	**0%**

5.3.4 Evaluating Runtime Performance

Table 5.3 presents the processing time required for processing and generating the clusters. Clearly, our approach does not pose overhead, this is the result of performing the clustering on multi-stages. The merging process took longer time in comparison with coarse-grained and fine-grained clustering. This is expected, because the merging process performs the iteration several times until no similarity score exists above the threshold, and in every iteration N-gram string analysis is performed again. We also evaluate the runtime performance of our signature matching mechanism on an ARM platform using QEMU [169]. We run experiments inside an emulator with ARM Cortex-A9 CPU (0.8GHz to 2GHz) and 256MB of RAM. The running time is 15ms for matching/classifying a new binary file. Although many IoT devices have lower configurations than our emulator, we believe the running time performance indicates the efficiency of our mechanism. In future, we will evaluate our mechanism on real IoT devices.

5.4 Discussion

Evasive techniques: The proposed approach for generating lightweight detection signatures utilizes printable strings as string features. As a result, our approach is susceptible to string obfuscation and encryption techniques. To date, the IoT malware samples are still very premature compared with their sophisticated PC counterpart, and we have not observed any IoT malware employing code obfuscation/encryption techniques. We believe the proposed system addresses a timely need to provide an effective first-line defense on IoT devices, and it also contributes to a better understanding of IoT malware.On the other hand, we envision that the sophistication level of IoT malware will definitely grow.

Unknown malware: Another caveat is that our system *cannot deal with unknown IoT malware*, so that we need to constantly update the signatures as new IoT samples are discovered. But the update can be conducted offline on a computationally rich hub. For instance, we can generate updated signatures everyday to keep up the rapid change of IoT malware. Moreover, as shown in [170], the structural features suffer from the variations caused by different compilation options, which may induce false classification results.

Threshold setting: There are multiple thresholds in our system, including: merging threshold (set as 0.7), sample matching threshold (set as 0.9), and detection threshold (set as 0.7). Currently, we use empirical approaches to identify an appropriate threshold by evaluating over two opposite training datasets, e.g., one contains the malware belonging to a family called “insider", and one contains the samples outside the family called “outsider". The minimum value of all insiders and maximum value of all outsiders can be identified, and the threshold is set to the mean of these two values that optimizes the separation of the two different worlds. This process can be automated to relieve the manual burden. It is evident that for different datasets, we may need to adjust these threshold accordingly.

5.5 Summary

This chapter investigated the emerging IoT malware detection problem, and proposed an efficient signature generation and classification mechanism for cross-architecture IoT malware. Based on static analysis, the proposed mechanism utilizes string, statistical and structural features for classifying IoT malware, where Bindiff is used for computing structural similarities, and N-gram printable string vectors and statistical features are extracted for characterizing the malware families.

The experimental results show the effectiveness and efficiency of our signature generation system.

6 Towards Best Secure Coding Practice for Implementing SSL/TLS

Developers often make mistakes while incorporating SSL/TLS functionality in their applications due to the complication in implementing SSL/TLS and their fast prototyping requirement. Insecure implementations of SSL/TLS are subject to different types of Man in The Middle (MiTM) attacks, which ultimately makes the communication between the two parties vulnerable to eavesdropping and hijacking attacks, thereby violating confidentiality and integrity of the exchanged information. This chapter aims to support developers in detecting insecure SSL/TLS implementation in their codes by utilizing a *low-cost cross-language* static analysis tool called PMD. In the end, two insecure implementations of SSL/TLS have been identified, and subsequently a new PMD rule set is created. This rule set consists of three rules for addressing *hostname validation vulnerability* and *certificate validation vulnerability*. The rules have been evaluated over 1,517 code snippets obtained from Stack Overflow, and the results show that 71% of the code snippets contain insecure SSL/TLS patterns. The detection rate of our approach is 100%, while it detects 165 violations inside the vulnerable code snippets in total.

6.1 Background

This section describes background knowledge about static analysis tools for detecting bugs, and introduces our criteria for selecting the tool to implement our detection rules. Static analysis and dynamic analysis solutions have been introduced for detecting vulnerability in the applications. Since this work aims at assisting developers in detecting insecure implementation of SSL/TLS, we will review and compare some state-of-the-art solutions proposed for detecting programming bugs using static analysis techniques.

Several open source static analysis tools are presented for detecting bugs in Java programs, including:

1. FindBugs [171]: is an open source tool for detecting bugs in Java code. It is a static analysis tool on Java bytecode, and can be used via command line and integrated into different IDEs. FindBugs can discover various types of bugs including problematic coding practice and vulnerabilities. FindBugs rules can be created using Visitor pattern (Java API). However, this tool does not detect insecure SSL/TLS implementation patterns.

2. Hammurapi [172]: is an open source tool for analyzing Java source code. It can be integrated to IDEs, and is developed with scalability in mind. Hammurapi employs Abstract Syntax Tree (AST), where new rules can be added to this tool, using java code or XML rules. However, this tool is rather complicated [173], and does not focus on detecting security vulnerabilities and insecure implementation patterns.

3. Jlint [174]: is written in C++ for detecting common programming errors in Java (e.g., race condition). Jlint performs semantic and syntax analysis on

Java bytecode for accomplishing its duties. Therefore, Jlint is not intended for the check and validation of insecure SSL/TLS implementation, nor any kind of other security checks. Although new rules can be integrated into Jlint, it will require modifying Jlint's source code [173], which makes Jlint difficult to expand.

4. PMD: is an open source tool, which is written in Java and it checks Java source code for a set of predefined bugs. PMD can be used through command line, and graphical user interface via the available plugins for various IDEs. PMD constructs Abstract Syntax Tree (AST), and then examines the constructed AST for detecting bugs. PMD checks for some security bugs, but it neither checks insecure cryptographic mechanisms, nor examines SSL/TLS implementations. PMD rules can be defined using Java code (Visitor pattern) or XPath queries. This provides more flexibility and makes it easier for extension.

We define two selection criteria for identifying the optimal tool to develop our detection rules. The tool should be:

1. open source and is still actively supported by the community.

2. easy-to-use and facilitating the integration of new rules.

Accordingly, PMD has been selected for implementing our new rules to detect insecure SSL/TLS implementations, because PMD is an open source tool, and can be easily expanded with new rule sets. Unlike other tools that require changing the source codes of the tools, or are limited to a specific method for adding new rules, PMD is flexible, easy-to use, and deemed as a cross-architectural analysis tool, as it can analyze different programming languages.

6.2 Insecure SSL/TLS Patterns

This section explains the commonly identified SSL/TLS vulnerabilities, and describes the justification behind selecting those vulnerabilities. Then, we present the code snippets that represent each vulnerability. Two insecure implementations of SSL/TLS have been widely discussed and reported in the literature [113, 54, 175, 116, 176].

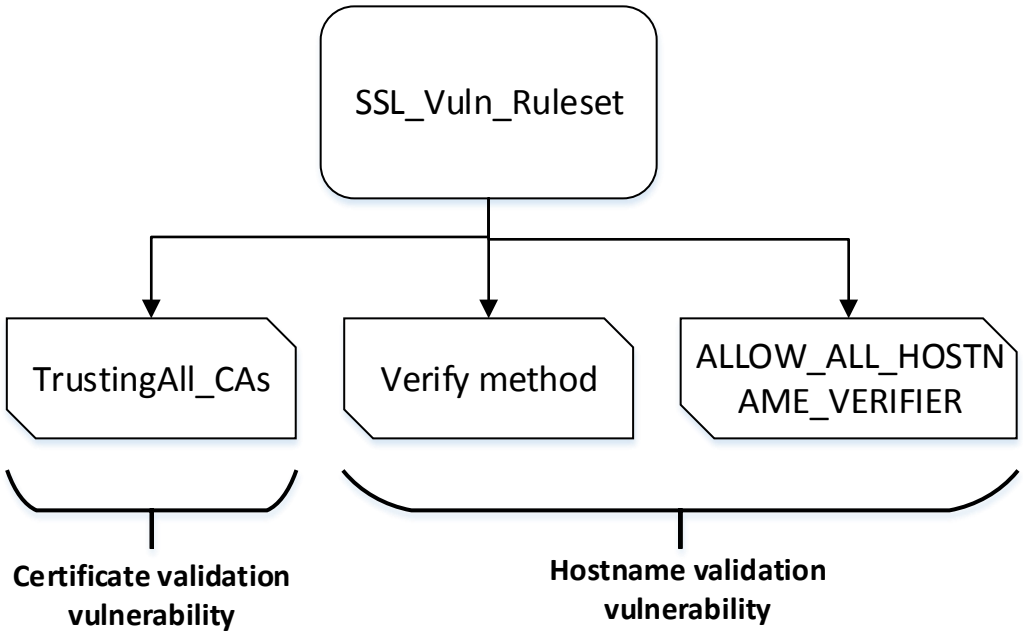


Figure 6.1: Insecure SSL/TLS implementation patterns

Figure 6.1 summarizes these insecure patterns and a detailed description about each pattern is as follows:

1. Certificate validation vulnerability: the certificate and all Certificate Authorities (CAs) in the certificate chain of CAs are trusted and not being verified. As illustrated in Listing 6.1, method (*checkServerTrusted*) does not perform

any verification. To fix the vulnerability, it should go over the chain of CAs that are included in the certificate, and verifies the validity of each CA in the chain until reaching the root CA. Otherwise, an attacker can replace the original certificate of the server with a self-signed certificate to be accepted by the client, since the certificate chain is not verified. As a result, MiTM attack can be established.

2. Hostname validation vulnerability: two insecure patterns have been identified under this vulnerability. The last line in Listing 6.1 shows the case when the developer not only fails to validate the hostname, but he/she also allows trusting all hostnames. In Listing 6.1, host verification is not performed at all, because the method (*verify*) does nothing and always returns true. These are two most commonly observed vulnerabilities related to hostname validation, the existence of which allows MiTM attackers to eavesdrop and hijack the communications, by allowing an attacker to impersonate the host.

```
1  //Trusting all  Certificates  Pattern
2  public void checkServerTrusted(X509Certificate[] chain, String  authType)
3   throws CertificateException {
4    //do nothing
5  }
6
7  //Allowing all Hostnames Pattern #1
8  SSLSocketFactory sf = new MySSLSocketFactory(trustStore);
9  sf.setHostnameVerifier(SSLSocketFactory.
10 ALLOW_ALL_HOSTNAME_VERIFIER);
11
12 //Allowing all Hostnames Pattern #2
13 HostnameVerifier hostnameVerifier = new HostnameVerifier() {
14  @Override
15  public boolean verify(String hostname, SSLSession session) {
16   return true;
17  }
18 }
```

Listing 6.1: Insecure SSL/TLS Patterns

6.3 Proposed PMD Rulesets

The goal of this work is to create new rules for detecting insecure SSL/TLS implementation patterns. In this section, we describe the architecture of PMD and the supported methods for creating new PMD rules, introduce our assumption, and demonstrate the proposed PMD rulesets for accurately detecting the insecure SSL/TLS implementation patterns.

6.3.1 PMD Rulesets and Rules

Figure 6.2 illustrates the architecture of PMD, which includes the newly proposed ruleset (described in Section 6.2). A Java class is analyzed by generating its Abstract Syntax Tree. The analyzer then examines the generated AST against a set of predefined rules, and finally a report will be generated that displays the detected bugs. Even though Data Flow Analysis (DFA) has been integrated into PMD, PMD has not supported creating rules based on DFA yet. PMD rules are organized based on different categories (formally known as Rulesets), while each ruleset contains several rules that address a single bug. Therefore, each rule possesses several properties like a description of the bug, the priority, and the detection rule.

We extend the ***PMD rules*** by adding a novel ruleset, which consists of three rules for detecting the selected insecure SSL/TLS patterns. Figure 6.3 depicts the structure of PMD rules.

As mentioned earlier, one of the main advantages of using PMD is the support for different methods to create new rules. In this work, two methods can be used for creating new PMD rule set and rules:

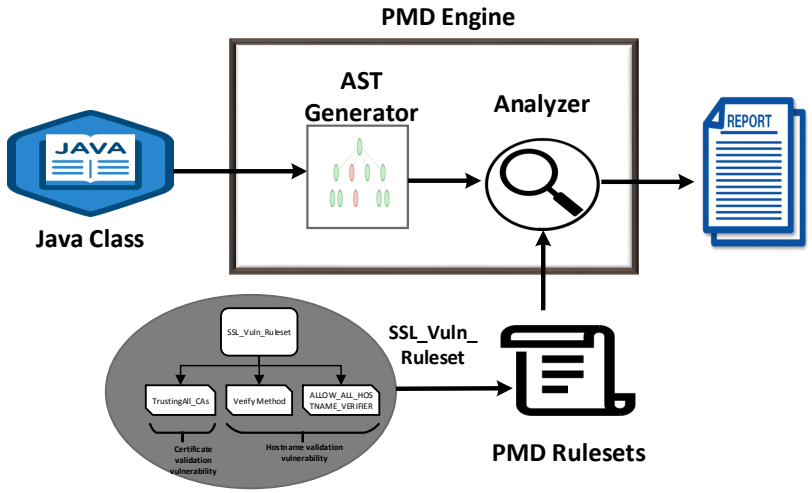


Figure 6.2: PMD architecture and the proposed PMD rulesets (*SSL_Vuln_Ruleset*)

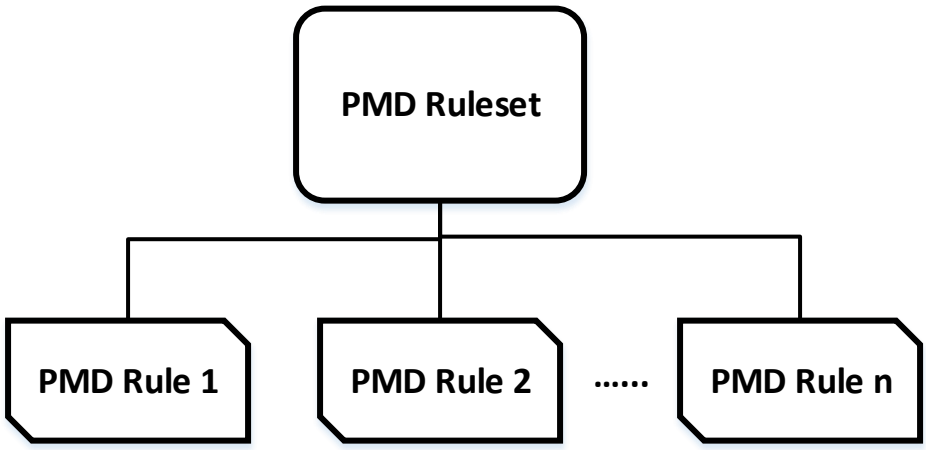


Figure 6.3: PMD ruleset structure

1- Java class: PMD rule can be written as a Java class that extends *Abstract-JavaRule*, and Visitor API can then be used for inspecting some properties in the generated AST of the class under analysis. Then, this rule class can be declared under a specific PMD ruleset.

2- XPath quires: this method treats the generated AST as an XML file, then we can write XPath queries to find specific patterns. PMD provides a handy tool for designing XPath queries called *PMD rule designer*,which can be used for generating the AST for the targeted pattern and creating the XPath query. Listing 6.2 presents an XPath that have been created using *PMD rule designer* for the insecure pattern presented in Listing 6.1.

```
1  //MethodDeclaration[@Name='checkServerTrusted'
2  and
3  Block[count(*) = 0]]
```

Listing 6.2: Allowing all Hostnames Pattern #2

In this work, XPath method is utilized for creating the rules, and PMD rule designer has facilitated and simplified the rule creation process. The designer tool contains four windows, namely the source code (top-left), XPath query (top-right), AST & DFA (bottom-left), and the result of XPath query (bottom-right). *Our main assumption here is that the developers strive to detect any insecure implementations, and develop more secure applications.* This is a reasonable assumption as most developers have already recognized the importance of the security of their applications. Therefore, the developers apply PMD and the corresponding rulesets to detect the security vulnerabilities in their applications.

Here are the detailed steps for the developers to construct the *SSL_Vuln_Ruleset* to detect SSL/TLS implementation vulnerabilities:

1. Obtaining the source code of PMD, as we want to add new rules, it should be rebuilt again using Maven after adding new rules.

2. Using the aforementioned insecure patterns (Listing 6.1) in the source code window of PMD rule designer to generate new rules.

3. Generating the AST for the provided source code. As depicted in the AST window, AST is treated as XML file, which consists of nodes and each node owns specific properties. Accordingly, the XPath query can be created.

4. The XPath query is then generated (buttom-right window), which relates to the matched pattern in the source code XPath query in this example (Listing 6.2) is simplified for clarity, but more involved matching criteria can be integrated for deriving more accurate results and avoid false positive results. For instance, *checkServerTrusted()* contains two parameters, and the data type of each parameter needs to be identified. The developer can definitely fool this XPath query by adding useless statements (e.g., print statements) within the body of *checkServerTrusted()*. However, this contradicts our assumption that developers have the intention to identify insecure implementations (i.e., the developer has no malicious intent).

5. After making sure the XPath query works as intended, a new rule can be added to the *SSL_Vuln_Ruleset*. The ruleset is included in an XML file that contains the definition of a set of rules. The default location of all Java rulesets is under the following directory `PMD-java/src/main/resources/rulesets/java`.

6. The new *SSL_Vuln_Ruleset* location should be declared in the text file `rulesets.properties`, which instructs PMD about the location of all existing rulesets.

Eclipse PMD plug-in is another easier way for creating the ruleset and its rules. But this approach limits the usage of the rule into a dedicated machine,

and reduces automation capabilities for running the evaluation, especially over a large number of Java classes. In our experiment, we add a single rule using Eclipse plug-in, and the detection result is presented in Figure 6.4. The error message displays "Consider verifying the intended certificates and not allowing all certificates by updating checkServerTrusted() method", which is in fact the suggestion for resolving the SSL/TLS vulnerability. PMD has successfully detected *checkServerTrusted()* is implemented in an insecure manner. PMD also shows other details about the detected violations, such as the line number, the name of the violated rule, etc. Suggestions for fixing this error can be also incorporated within the details of this alert, which would greatly assist the developers not only in detecting insecure patterns, but also in resolving them.

Figure 6.4: PMD analysis results on Eclipse after adding a new rule

Listing 6.3 presents the definition of one of the detection rules in our *SSL_Vuln_-Ruleset*. This rule detects insecure implementations of *checkServerTrusted()*. Line 3 shows the definition of the ruleset, which includes the the name. The actual rule is defined between Lines 9-29, and Line 15 states the priority of this rule. Finally, (Lines 18-22) contain the location where the XPath query (generated using PMD designer) is defined. To this end, we prove that PMD can tremendously facilitate the process of creating new rules for detecting new bugs, including SSL/TLS implementation bugs.

```
1 <?xml version="1.0"?>
2
```

```
3 <ruleset name="SSL_Vuln_Ruleset">
4
5   <description>
6     This ruleset detects insecure implementation of SSL/TLS
7   </description>
8
9   <rule name="TrustingAllCAs"
10    language="java"
11    message="Consider verifying the intended certificates and not allowing all
          ↪  certificates"
12  <description>
13    This is an insecure implementation of SSL/TLS, which trusts ALL
          ↪ certificates.
14  </description>
15  <priority>3</priority>
16  <properties>
17  <property name="xpath">
18  <value>
19    <![CDATA[
20    //MethodDeclaration[@Name='checkServerTrusted'
21    and Block[count(*) = 0]] ]]>
22  </value>
23  </property>
24  </properties>
25  <example>
26    <![CDATA[
27    ]]>
28  </example>
29  </rule>
30 </ruleset>
```

Listing 6.3: Definition of SSL_Vuln_Ruleset

6.4 Evaluation

This section describes our evaluation approach, including two research questions, and the results we get to answer each research question.

We conducted the evaluation over a dataset obtained from [54]. This dataset consists of 1,517 code snippets extracted from Stack Overflow website. However, these codes cover all cryptographic implementations and are not only limited to SSL/TLS implementations. Hence, we conducted data filtration over two phases. In the first phase, codes that contain these keywords (SSL, TLS, ssl, tls, X509 and x509) are shortlisted. In the end, 597 code snippets have be shortlisted after this phase. This phase provides us all code snippets that contain SSL and TLS implementation. In the second phase, 263 files are obtained, which contain the following keywords (verify, checkServerTrusted, ALLOW_ALL_HOSTNAME_-VERIFIER). The purpose of this filtration phase is shortlisting the code snippets that are related to the insecure patterns. We focus on answering the following two research questions:

- **RQ1:** How well do our detection rules perform in practice, and can they effectively detect the identified insecure patterns in real-world applications?
- **RQ2:** What is the runtime performance of PMD after using our rules?

All experiments have been performed on Ubuntu 16.04 virtual machine and 4GB memory. The modifications have been performed on the source code of PMD version 5.8.1.

6.4.1 Results for RQ1

The total code snippets that have been analyzed are 263, but 76 snippets could not be parsed correctly by PMD (will be discussed in Sec 6.5). For the rest of the code snippets ($263 - 76 = 187$), 54 files do not contain any insecure patterns. We manually investigate some of these files, and find that they are correctly bypassing our detection rules. This means the number of True Negative is 54. Therefore, the total number of the detected (True Positive) insecure SSL/TLS implementation patterns is ($187 - 54 = 133$), which reflects that %71.12 of the code snippets in our dataset contain insecure patterns. Figure 6.5 shows the number of vulnerable snippets and non-vulnerable snippets.

We also have randomly investigated several code snippets that have been detected by one of our rules to verify if they really contain insecure patterns.

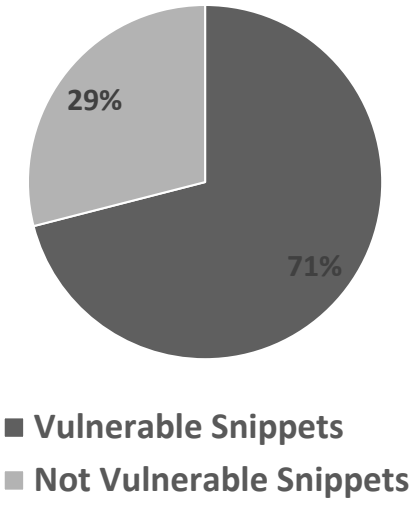


Figure 6.5: Distribution of vulnerability detection using proposed PMD rulesets

Table 6.1 lists the detection results of the proposed *SSL_Vuln_Ruleset* in Figure 6.1. The most common insecure patterns are *"Trusting All CAs"* and *"Allowing All Hostname Verifier"*. We discover that several code snippets even contain more than one insecure patterns.

Table 6.1: Detection results

Matching Insecure Patterns	Matched Code Snippets
TrustingAll_CAs	43
Verify Method	18
ALLOW_ALL_HOSTNAME_VERIFIER	40
TrustingAll_CAs & Verify Method	24
TrustingAll_CAs & ALLOW_ALL_HOSTNAME_VERIFIER	8
Verify Method & ALLOW_ALL_HOSTNAME_VERIFIER	0

Figure 6.6 presents the detection results based on the identified two categories of SSL/TLS vulnerabilities. The number of detection alarms does not match the number of vulnerable code snippets, because as mentioned earlier a single vulnerable code snippets can contain more than one insecure patterns.

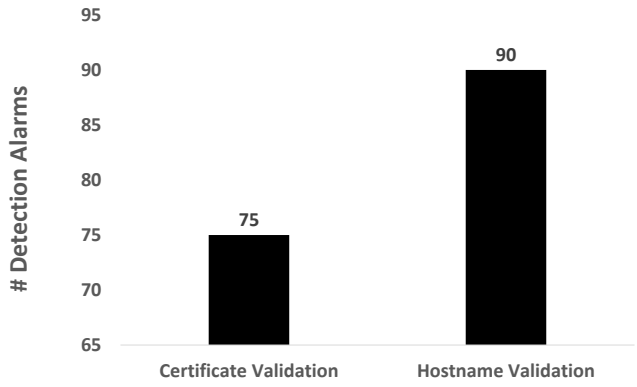


Figure 6.6: Detection results according to the types of SSL/TLS Vulnerabilities

The results show the proposed detection rules have correctly identified the insecure code snippets, and no code snippets have been misclassified (no False

Positive or False Negative). Therefore, the both detection precision and recall of our approach are 100%.

6.4.2 Results for RQ2

Measuring the overhead that might be introduced after using the new rules is crucial. Therefore, we compute the required time for analyzing the code snippets, which includes the required time for identifying which rule has been violated, and the time for parsing the generated XML report for each code snippet. The total analysis time is 144 seconds for the dataset generated after the two phases of filtration (263 code snippets). On average, the required time for analyzing each code snippet against our three rules and parsing its XML report is 0.55 second, which shows the efficiency of the proposed method.

6.5 Discussions

In this section, we provide a discussion on three limitation of our approach for detecting the insecure patterns. First, after the filtration, we have 187 code snippets, while some of the snippets cannot be analyzed. Although the current dataset is sufficient for validating our new rules, in future, we need a larger dataset for drawing more affirmed conclusions. Also, we observe the duplications in the code snippets while performing the manual investigation. Furthermore, we performed a quick validation over the code snippets that have not been parsed, and our preliminary analysis shows that the AST of those file cannot be generated.

Second, even though the discussed tools in Section 6.1 does not consider the particular problem that have been addressed in this work, we need to adapt

and then evaluate these other tools to compare their performance, efficiency and usability against our proposed approach.

Finally, as discussed in Section 6.3, we assume the developers have the motivation to find any bugs in his/her code, which is a valid assumption. But there is a possibility that the developers unintentionally inserts meaningless or debugging statements, which invalidates our rules. However, this situation can be handled by adding more conditions to the XPath query to avoid being inappropriately bypassed. There are also some cases such as the one presented in Listing 6.4, where a boolean variable holding a *"true"* value is returned rather than an explicit *"true"* value. In this case, PMD Data Flow Analysis should be explored to handle such cases.

```
boolean isTesting = true;
HostnameVerifier hostnameVerifier = new HostnameVerifier() {
   @Override
   public boolean verify(String hostname, SSLSession session) {
      return isTesting;
   }
}
```

Listing 6.4: Our rule fails to detect this insecure pattern that is similar to Listing 6.1

6.6 Summary

This chapter sheds light on a vital implementation issue: insecure coding practices while implementing SSL/TLS APIs in Java applications. Two common vulnerabilities have been identified, while three insecure patterns that represent each

vulnerability have been defined. We employ PMD static analysis tool for implementing our detection rules. After comparing it with other existing open source tools, we adopt the XPath approach for creating the new rules. In our evaluation with 187 code snippets from Stack Overflow website, we show that 71% of these code snippets are vulnerable, as they are discovered to contain various insecure patterns, which validates the effectiveness of our detection rules.

7 Conclusion and Future Research

This dissertation contributes to the body of knowledge by combining software analysis techniques and vulnerability analysis mechanisms. In this dissertation, we considered three key attributes of the emergent ecosystems that hinder traditional security analysis. We then study the attributes in a certain software ecosystem, each study aims to understand the security consequences and challenges, and finally formalize our solution overcome the challenges. The three security challenges that we considered are: detecting unsafe interactions between emergent apps, detecting cross-architecture IoT malware, and propagation of insecure patterns resulted by code reuse from StackOverflow. We proposed three security analysis frameworks that can systemically and efficiently detect sophisticated unsafe interactions and detect cross-architecture IoT malware. Lastly, we promote the best practices of security APIs such as SSL/TLS. This chapter summarizes our contributions and discusses potential future research directions:

7.1 Research Summary

The findings of the works conducted in this dissertation are summarized as follows:

- We develop Dina, the first inter-app vulnerability detection tool with the capability of analyzing dynamically loaded code, to pinpoint the stealthy inter-app communications that are concealed using reflection and DCL. Dina

combines static IAC analysis with incremental dynamic analysis to identify potential IAC vulnerabilities within dynamically loaded code at runtime. We analyze 3,000 popular benign apps and 14,000 malicious apps to identify their reflection usage and IAC communications via reflection/DCL. Our results confirm the prevalent usage of reflection and DCL in popular real-world apps, wherein surreptitious IAC behaviors concealed by reflective calls have been observed. We provide detailed case studies to assess how vulnerable apps can be exploited to launch stealthy attacks through reflection and DCL. Therefore, we believe further efforts are required to better regulate the usage of reflection and DCL calls to close the attack avenues without undermining their utilities.

- We proposed a novel approach and accompanying tool suite, called IotCom, for compositional analysis of such hidden and unsafe interaction threats in a given bundle of cyber and physical components co-located in an IoT environment. IotCom first utilizes a path-sensitive static analysis to automatically generate an inter-procedural control flow graph (ICFG) for each app. It then applies a novel graph abstraction technique to model the behavior relevant to the devices connected to the app as a *behavioral rule graph (BRG)*, which derives rules from IoT apps via linking the triggers, actions, and logical conditions of each control flow in each app then automatically generates formal app specifications from the BRG models. Lastly, it uses a lightweight formal analyzer [150] to check bundles of those models for violations of multiple safety and security properties arising from interactions among the app's rules. The experimental results of evaluating IotCom against 36 prominent IoT safety and security properties, in the context of hundreds of real-world

apps, corroborates its ability to effectively detect violations triggered through both cyber and physical channels.

- We observe the cross-architectural similarity among malware samples from the same family by investigating two real-world IoT malware datasets consist of 5,150 malware samples. Based on this keen observation, we propose a multi-stage clustering mechanism to cluster these IoT malware samples into multiple families. We then design an efficient signature generation scheme to create signatures using reliable and easily extractable string and statistical features. The string feature is extracted using N-gram text analysis, while the statistical feature contains the code-level statistics. The experimental results show the effectiveness and efficiency of our signature generation system.
- We shed the light on a vital implementation issue, insecure coding practices while implementing SSL/TLS APIs in Java and Android applications. Two common vulnerabilities have been identified, while three insecure patterns that represent each vulnerability have been defined. Therefore, we contributed towards establishing secure coding practice for developers by developing practical and ready to use rule sets (consisting of three rules) using PMD to detect vulnerable SSL/TLS implementations. These rules can accurately and efficiently identify potential SSL/TLS vulnerabilities, and help raise developers' awareness of insecure SSL/TLS implementation patterns.

7.2 Future Research Directions

The security analysis approaches contributed to this dissertation opens the horizon for a range of new research opportunities. These research directions include: (1) Performing cross-platform and cross-domain security analysis, in which unsafe

interactions can be resulted due to the interactions between IoT apps, IoT devices and mobile apps; (2) Analyzing the propagation of vulnerabilities in the evolved Android applications and identifying its correlation with the code quality; (3) Investigating security weakness in emergent platforms like robotics platforms. In the robotics area, Robotic Operating System (ROS) a prominent framework, which lacks from the security absence; (4) Considering enforcement mechanisms to block unsafe interactions and allow only safe behaviors. In the rest of this section, we discuss in more detail some of these potential future work directions.

7.2.1 Cross-platforms interactions

Analyzing the interaction across various platforms, as in this dissertation, we considered the interaction within the same platform. In Chapter 3, the considered interactions are within the Android platform, while in Chapter 4, IotCom analyzes the interactions between IoT apps. However, we partially considered the cross-platform interaction between IFTTT and Samsung SmartThings platforms in IotCom. As a future research direction of this work, investigating the security consequences of the whole chain of interactions between Android apps, IoT apps, and IoT devices. Essentially, applications inter-dependency [177] reflects the presence of shared resources and services that lead to hazards. For example, SmartThings provides an Android app, known as a companion app, to install and manage IoT apps. This companion app can be a valuable target because it constitutes a centralized point that is trusted by IoT apps and devices [178, 72]. While in the Robotics area, Android apps can be leveraged to create nodes and manage robots[1].

[1]http://wiki.ros.org/android

7.2.2 Smelling the Vulnerability in Open Source Android Applications

In emergent software ecosystems, applications evolve to accommodate new services and repair bugs [179]. These updates lead to code smells that can propagate in the evolved versions of the application [180]. The goal of this work is to perform correlation analysis to understand the relationship between the evolution of vulnerabilities and the quality of the code. This understanding will ultimately support developers in fixing their code and promoting secure code implementations. Conducting the correlation analysis entails specifying a list of insecure patterns, which can be accomplished in a similar way to our work [58] discussed in Chapter 6. The vulnerable code patterns can be obtained from security communities such as the Common Vulnerability Exposures (CVE), the National Vulnerability Database (NVD), and the Common Weakness Enumeration (CWE).

7.2.2.1 Motivation

Code Smell in Android: the vast majority of existing work focus on detecting code smells that affect code quality and violate best coding practices. Habchi et. al, [181, 180] develop Sniffer for detecting only 8 code smells. Sniffer analyzes the source code at each commit after processing open source projects. This analysis aims to identify the lifespan of code smell in evolved projects. While PAPRIKA [182] can analyze binary APKs without the need for the source code. PAPRIKA considers only 17 code smells. aDOCTOR [183] another code smell detection tool, and can identify 15 code smells. All prior tools do not consider the detection of security code smells. Another research streamline aims to identify vulnerabilities in open source software projects [184, 185]. Both tools perform their

empirical analysis by leveraging Snyk [186] to identify vulnerable dependencies in various open-source projects. While the former performs the analysis on Java projects, the latter analyzes JavaScript projects. However, none of these works study the propagation of security vulnerabilities in the context of Android.

Detecting vulnerabilities in Android: The Android vulnerability has been widely explored [56, 3, 187, 188, 189, 190], but the evolution of vulnerabilities in the Android platform did not get sufficient attention and the existing work have examined Android vulnerabilities in isolation of code smell. For example, Wu et al., [191] does not investigate the evolution of vulnerabilities in Android apps, instead, this work focuses on studying the propagation of vulnerabilities in the Android framework based on published patching reports (known as Android Security Bulletin[192]).

Correlation analysis in Android: In this domain of research, the security aspects have not been studied on a large scale. Sultana et al., [193] perform a correlation analysis between code smells and the existence of vulnerabilities. But the experimental analysis is limited to few case studies, where vulnerable and non-vulnerable versions of the same project are analyzed concerning the detected code smells. Also, the evolution of these projects has not been considered. Another study [194] explores the relation between software quality and security. This work does not consider the evolution of the apps and does not assess the likelihood of apps to be vulnerable. A limited investigation on the impact of three code smells memory and CPU has been studied in [195]. While [196] investigates the relation between code smells and architectural smells. This study studies the correlation between 19 code smells and 4 architectural smells using 111 Java projects.

7.2.2.2 Proposed Approach

This section introduces the experimental approach to perform the correlation analysis. The approach consists of three phases, as depicted in Fig. 7.1. The *pre-processing* phase applies selection criteria to identify the Github projects that will be considered in the analysis. *Evolution Tracking* phase tracks the evolution of vulnerabilities and code smells. The tracking phase is performed at the commit level, for both vulnerabilities and code smells. The *Analysis Engine* analyzes the history information generated in the previous phase. The analysis aims to understand the propagation of code smells and determine the relationship between the code smells and vulnerabilities in the evolved projects.

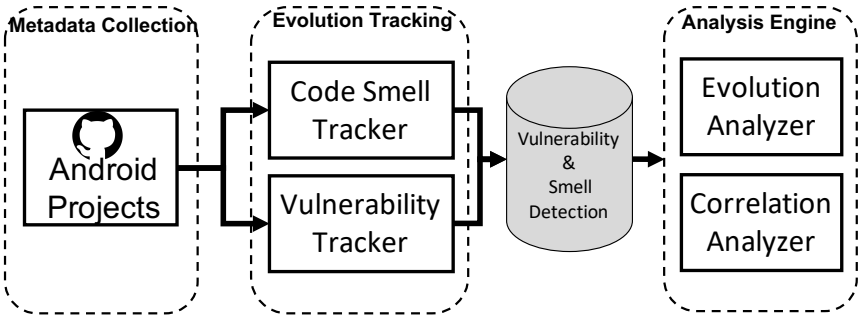


Figure 7.1: Analysis Workflow.

1. **Project Metadata Collection:** In this step we collect metadata information about the GitHub projects that will be analyzed. The collected metadata is leveraged to filter out toy projects. The metadata is identified based on the criteria used in this related work [197].

2. **Evolution Tracking:** this phase comprises two main steps: code smell tracker and vulnerability tracker. In this phase, a set of code smells and vulnerabilities will be tracked by iterating all the projects' commits.

3. **Analysis Engine:** this phase performs the analytical aspects, which involve the evolution of analyzer and correlation analyzer. The evolution analyzer identifies the introduction, survival, and removal of code smells and vulnerabilities. But the correlation analyzer determines the relation between code smells and vulnerabilities.

7.2.3 Feature Interaction in Robotics Ecosystem

In Chapters 3 and 4, we address the challenge of detecting unsafe interactions in the context of Android and Smart home. This challenge can be studied in the robotics ecosystem. As robots comprise a set of sensing and actuation components that interact with each other. The robot operating system (ROS) is one of the prominent frameworks that are used in the robotics ecosystem. Therefore, the usage of ROS is expected to be growing in industrial applications and academic research. The security of ROS constitutes a major concern that can dismiss the development of robotics systems.

The security aspect is not part of ROS's goals, even security is overlooked in the next version of ROS (ROS2), except a few security extensions that are provided for optional use [198]. Therefore, ROS suffers from significant security weaknesses including plaintext communications, open ports, and unencrypted storage [199, 200, 201]. The state-of-the-art [202, 199, 203, 204, 205] show the communication between ROS nodes is a major concern. Therefore, many of the proposed solutions consider and demonstrated attacks target this limitation. Open source penetration testing tools have been leveraged to perform the attacks on a cyber-physical security honeypot developed on top of ROS [199]. The conducted attacks show ROS suffers from major weaknesses, which allowed performing

man-in-the-middle attacks [206]. To overcome this challenge, a security layer is proposed to be deployed on top of the ROS framework in [207]. This security layer provides integrity and confidentiality by maintaining an authorization server to enable secure communication between ROS nodes. Similarly, Breiling et al., [200] proposes a secure communication channel for ROS to handle the communication between two nodes.

Another experiment discovers over 100 publicly-accessible hosts running a ROS master, after scanning the whole IPv4 scope [203]. The ability to perform this experiment using a free network scanning tool represents a major risk, as ROS master should not be made available on the public Internet. Where accessing the master node allows the attacker to take control of the connected nodes. This work takes a further step by attacking some of the discovered ROS nodes and shows how this attack can have the potential to cause physical harm if used inappropriately. However, none of these efforts have performed a systematic analysis to explore the weaknesses of ROS, even none of these approaches have assessed the security of ROS2. The future research directions in this area are:

- Conducting security analysis for understanding the safe and unsafe behaviors of ROS nodes. A thorough static analysis can be performed similarly to [208].

- Analysing the usage of ROS APIs and identifying how these APIs can be abused or misused. Dieber et al., [202] illustrates how some ROS APIs that are used either for the communication between ROS nodes or ROS nodes with the master node can be abused to add a fake ROS node.

7.2.4 Enforcement of Safe Interactions

In Chapters 3 and 4, we present mechanisms for detecting unsafe and undesired interactions between apps. Both works can be extended by examining enforcement mechanisms to strengthen detection solutions.

- **Enforcement in the context of Android**: DINA identifies vulnerable IAC. This work can be extended by applying a real-time enforcement mechanism similar to [29, 209]. Where the former requires performing formal verification to synthesize the enforcement policies, while the latter applies the principle of least-privilege.

- **Enforcement in the context of Smart Home**: IOTCOM can be strengthened by blocking unsafe interactions in real-time. Several approaches have been introduced in the smart home area. AutoTap [141] assists end-users in defining safety properties, it applies a formal method approach to synthesize the safety properties. Therefore, AutoTap is not intended to perform real-time enforcement. IoTGUARD [147] enforces a set of predefined policies based on the run-time model that is generated based on the interaction between apps at run time. However, IOTGUARD requires instrumenting the apps before the installation. IoTGUARD does not generate the safety properties automatically, it assumes the properties given by the user. This is not a practical approach because the pre-defined properties cannot accommodate all potential interactions. Therefore the enforcement can be applied to IOTCOM by combining the synthesis approach used in AutoTap and the runtime model used in IOTGUARD.

Bibliography

[1] A. I. Wasserman, "Software engineering issues for mobile application development," in *Proceedings of the FSE/SDP Workshop on Future of Software Engineering Research*, FoSER '10, (New York, NY, USA), pp. 397–400, ACM, 2010.

[2] A. Taivalsaari and T. Mikkonen, "On the development of iot systems," in *2018 Third International Conference on Fog and Mobile Edge Computing (FMEC)*, pp. 13–19, April 2018.

[3] Y. Acar, M. Backes, S. Bugiel, S. Fahl, P. McDaniel, and M. Smith, "Sok: Lessons learned from android security research for appified software platforms," in *2016 IEEE Symposium on Security and Privacy (SP)*, pp. 433–451, May 2016.

[4] R. R. Filho, *Emergent Software Systems*. PhD thesis, School of Computing and Communications, Lancaster University, 01 2018.

[5] D. Octeau, P. McDaniel, S. Jha, A. Bartel, E. Bodden, J. Klein, and Y. L. Traon, "Effective Inter-Component Communication Mapping in Android with Epicc: An Essential Step Towards Holistic Security Analysis," in *Proc. of USENIX Security*, 2013.

[6] Z. B. Celik, P. McDaniel, and G. Tan, "Soteria: Automated iot safety and security analysis," 2018.

[7] M. Abomhara and G. M. Kien, "Cyber Security and the Internet of Things: Vulnerabilities, Threats, Intruders and Attacks," *Journal of Cyber Security and Mobility*, vol. 4, no. 1, pp. 65–88, 2015.

[8] S. Sicari, A. Rizzardi, L. A. Grieco, and A. Coen-Porisini, "Security, privacy and trust in internet of things: The road ahead," *Computer Networks*, vol. 76, pp. 146–164, 2015.

[9] D. Navarro, F. Mieyeville, W. Du, M. Galos, and I. O'Connor, "Towards a design framework for heterogeneous wireless sensor networks," in *2011 1st International Symposium on Access Spaces (ISAS)*, pp. 83–88, June 2011.

[10] S. Wang, A. Prakash, and T. Mitra, "Software support for heterogeneous computing," in *2018 IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, pp. 756–762, July 2018.

[11] Y. J. Jia, Q. A. Chen, S. Wang, A. Rahmati, E. Fernandes, Z. M. Mao, and A. Prakash, "ContexIoT: Towards Providing Contextual Integrity to Appified IoT Platforms," in *Proceedings of the 21st Network and Distributed System Security Symposium (NDSS'17)*, (San Diego, CA), February 2017.

[12] Y. Mehmood, F. Ahmad, I. Yaqoob, A. Adnane, M. Imran, and S. Guizani, "Internet-of-things-based smart cities: Recent advances and challenges," *IEEE Communications Magazine*, vol. 55, pp. 16–24, Sep. 2017.

[13] W. Enck, M. Ongtang, and P. McDaniel, "On lightweight mobile phone application certification," in *Proceedings of the 16th ACM Conference on Computer and Communications Security*, CCS '09, pp. 235–245, 2009.

[14] M. Nakamura, H. Igaki, and K.-i. Matsumoto, "Feature interactions in integrated services of networked home appliances: An object-oriented approach.," pp. 236–251, 01 2005.

[15] S. Apel, J. M. Atlee, L. Baresi, and P. Zave, "Feature interactions: the next generation (dagstuhl seminar 14281)," in *Dagstuhl Reports*, vol. 4, Schloss Dagstuhl-Leibniz-Zentrum fuer Informatik, 2014.

[16] S. Nguyen, "Feature-interaction aware configuration prioritization," in *Proceedings of the 2018 26th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*, ESEC/FSE 2018, (New York, NY, USA), pp. 974–976, ACM, 2018.

[17] T. Pedersen, T. Le Guilly, A. P. Ravn, and A. Skou, "A method for model checking feature interactions," in *2015 10th International Joint Conference on Software Technologies (ICSOFT)*, vol. 1, pp. 1–10, July 2015.

[18] S. Apel, S. Kolesnikov, N. Siegmund, C. Kästner, and B. Garvin, "Exploring feature interactions in the wild: The new feature-interaction challenge," in *Proceedings of the 5th International Workshop on Feature-Oriented Software Development*, FOSD '13, (New York, NY, USA), pp. 1–8, ACM, 2013.

[19] P. Leelaprute, T. Matsuo, T. Tsuchiya, and T. Kikuno, "Detecting feature interactions in home appliance networks," in *2008 Ninth ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing*, pp. 895–903, Aug 2008.

[20] W. Ahmad, C. Kästner, J. Sunshine, and J. Aldrich, "Inter-app communication in android: Developer challenges," in *Proceedings of the 13th International Conference on Mining Software Repositories*, MSR '16, (New York, NY, USA), pp. 177–188, ACM, 2016.

[21] E. Chin, A. P. Felt, K. Greenwood, and D. Wagner, "Analyzing inter-application communication in android," in *Proc. of MobiSys'11*, pp. 239–252, 2011.

[22] L. R. Soares, J. Meinicke, S. Nadi, C. Kästner, and E. S. de Almeida, "Exploring feature interactions without specifications: A controlled experiment," in *Proceedings of the 17th ACM SIGPLAN International Conference on Generative Programming: Concepts and Experiences*, GPCE 2018, pp. 40–52, 2018.

[23] B. J. Muscedere, R. Hackman, D. Anbarnam, J. M. Atlee, I. J. Davis, and M. W. Godfrey, "Detecting feature-interaction symptoms in automotive software using lightweight analysis," in *2019 IEEE 26th International Conference on Software Analysis, Evolution and Reengineering (SANER)*, pp. 175–185, Feb 2019.

[24] W. Enck, M. Ongtang, and P. McDaniel, "Understanding android security," *IEEE Security Privacy*, vol. 7, pp. 50–57, Jan 2009.

[25] L. Li, T. F. Bissyandé, D. Octeau, and J. Klein, "DroidRA: Taming reflection to support whole-program analysis of android apps," in *Proc. of ISSTA*, pp. 318–329, 2016.

[26] Y. Zhauniarovich, M. Ahmad, O. Gadyatskaya, B. Crispo, and F. Massacci, "Stadyna: Addressing the problem of dynamic code updates in the security analysis of android applications," in *Proc. of CODASPY '15*, pp. 37–48, 2015.

[27] D. Landman, A. Serebrenik, and J. J. Vinju, "Challenges for static analysis of java reflection - literature review and empirical study," in *Proc. of ICSE*, pp. 507–518, May 2017.

[28] Y. Tsutano, S. Bachala, W. Srisa-an, G. Rothermel, and J. Dinh, "An efficient, robust, and scalable approach for analyzing interacting android apps," in *Proc. of ICSE*, pp. 324–334, May 2017.

[29] H. Bagheri, A. Sadeghi, R. Jabbarvand, and S. Malek, "Practical, formal synthesis and automatic enforcement of security policies for android," in *Proc. of DSN*, pp. 514–525, June 2016.

[30] M. Hammad, H. Bagheri, and S. Malek, "Determination and enforcement of least-privilege architecture in android," in *Proc. of ICSA*, pp. 59–68, April 2017.

[31] Y. K. Lee, J. y. Bang, G. Safi, A. Shahbazian, Y. Zhao, and N. Medvidovic, "A sealant for inter-app security holes in android," in *Proc. of ICSE*, pp. 312–323, May 2017.

[32] E. Bodden, A. Sewe, J. Sinschek, H. Oueslati, and M. Mezini, "Taming reflection: Aiding static analysis in the presence of reflection and custom class loaders," in *Proc. of ICSE*, pp. 241–250, 2011.

[33] Z. Qu, S. Alam, Y. Chen, X. Zhou, W. Hong, and R. Riley, "Dydroid: Measuring dynamic code loading and its security implications in android applications," in *Proc. of DSN*, pp. 415–426, June 2017.

[34] D. T. Nguyen, C. Song, Z. Qian, S. V. Krishnamurthy, E. J. M. Colbert, and P. McDaniel, "Iotsan: Fortifying the safety of iot systems," in *Proceedings*

of the 14th International Conference on Emerging Networking EXperiments and Technologies, CoNEXT '18, (New York, NY, USA), pp. 191–203, ACM, 2018.

[35] Z. B. Celik, P. McDaniel, and G. Tan, "Soteria: Automated iot safety and security analysis," in *2018 USENIX Annual Technical Conference (USENIX ATC 18)*, (Boston, MA), pp. 147–158, USENIX Association, 2018.

[36] W. Ding and H. Hu, "On the safety of iot device physical interaction control," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, CCS '18, (New York, NY, USA), pp. 832–846, ACM, 2018.

[37] "SmartThings Classic documentation." `https://docs.smartthings.com/en/latest/ref-docs/reference.html`, 2018.

[38] "Do more with smartthings - ifttt." `https://ifttt.com/smartthings`, 2019.

[39] Y. Hu, Y. Zhang, J. Li, and D. Gu, "Cross-architecture binary semantics understanding via similar code comparison," in *2016 IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER)*, vol. 1, pp. 57–67, March 2016.

[40] M. Antonakakis, T. April, M. Bailey, M. Bernhard, E. Bursztein, J. Cochran, Z. Durumeric, J. A. Halderman, L. Invernizzi, M. Kallitsis, D. Kumar, C. Lever, Z. Ma, J. Mason, D. Menscher, C. Seaman, N. Sullivan, K. Thomas, and Y. Zhou, "Understanding the mirai botnet," in *26th USENIX Security Symposium (USENIX Security 17)*, (Vancouver, BC), pp. 1093–1110, USENIX Association, 2017.

[41] B. Herzberg, D. Bekerman, and I. Zeifman, "Breaking Down Mirai: An IoT DDoS Botnet Analysis." https://www.incapsula.com/blog/malware-analysis-mirai-ddos-botnet.html, Accessed at Feb 21, 2017.

[42] "Amount of malware targeting smart devices more than doubled in 2017." https://www.kaspersky.com/about/press-releases/2017_amount-of-malware-targeting-smart-devices-more-than-doubled-in-2017, 2017. Accessed at July 21, 2017.

[43] A. Taivalsaari and T. Mikkonen, "A roadmap to the programmable world: Software challenges in the iot era," *IEEE Software*, vol. 34, pp. 72–80, Jan 2017.

[44] T. Mikkonen and A. Taivalsaari, "Software reuse in the era of opportunistic design," *IEEE Software*, vol. 36, pp. 105–111, May 2019.

[45] S. K. Datta and C. Bonnet, "Easing iot application development through datatweet framework," in *2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, pp. 430–435, Dec 2016.

[46] P. Rosenkranz, M. Wählisch, E. Baccelli, and L. Ortmann, "A distributed test system architecture for open-source iot software," in *Proceedings of the 2015 Workshop on IoT Challenges in Mobile and Industrial Systems*, IoT-Sys '15, pp. 43–48, 2015.

[47] Matt Asay, "Open source near ubiquitous in IoT, report finds." https://readwrite.com/2016/05/04/open-source-near-ubiquitous-iot-report-pl1/, Accessed at Oct 10, 2019.

[48] "About security alerts for vulnerable dependencies." `https://help.github.com/en/articles/about-security-alerts-for-vulnerable-dependencies`, Sep. 2019.

[49] N. Neshenko, E. Bou-Harb, J. Crichigno, G. Kaddoum, and N. Ghani, "Demystifying iot security: An exhaustive survey on iot vulnerabilities and a first empirical look on internet-scale iot exploitations," *IEEE Communications Surveys Tutorials*, vol. 21, pp. 2702–2733, thirdquarter 2019.

[50] S. Baltes, R. Kiefer, and S. Diehl, "Attribution required: Stack overflow code snippets in github projects," in *2017 IEEE/ACM 39th International Conference on Software Engineering Companion (ICSE-C)*, pp. 161–163, May 2017.

[51] A. Lotter, S. A. Licorish, B. T. R. Savarimuthu, and S. Meldrum, "Code reuse in stack overflow and popular open source java projects," in *2018 25th Australasian Software Engineering Conference (ASWEC)*, pp. 141–150, Nov 2018.

[52] W. Bai, O. Akgul, and M. L. Mazurek, "A qualitative investigation of insecure code propagation from online forums," in *2019 IEEE Cybersecurity Development (SecDev)*, IEEE.

[53] M. Verdi, A. Sami, J. Akhondali, F. Khomh, G. Uddin, and A. K. Motlagh, "An empirical study of c++ vulnerabilities in crowd-sourced code examples," *arXiv preprint arXiv:1910.01321*, 2019.

[54] F. Fischer, K. BÃűttinger, H. Xiao, C. Stransky, Y. Acar, M. Backes, and S. Fahl, "Stack overflow considered harmful? the impact of copy paste on android application security," in *2017 IEEE Symposium on Security and Privacy (SP)*, pp. 121–136, May 2017.

[55] N. Meng, S. Nagy, D. Yao, W. Zhuang, and G. Arango-Argoty, "Secure coding practices in java: Challenges and vulnerabilities," in *2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE)*, pp. 372–383, May 2018.

[56] M. Alhanahnah, Q. Yan, H. Bagheri, H. Zhou, Y. Tsutano, W. Srisa-an, and X. Luo, "Detecting vulnerable android inter-app communication in dynamically loaded code," in *IEEE INFOCOM 2019 - IEEE Conference on Computer Communications*, pp. 550–558, April 2019.

[57] M. Alhanahnah, Q. Lin, Q. Yan, N. Zhang, and Z. Chen, "Efficient signature generation for classifying cross-architecture iot malware," in *2018 IEEE Conference on Communications and Network Security (CNS)*, pp. 1–9, May 2018.

[58] M. Alhanahnah and Q. Yan, "Towards best secure coding practice for implementing ssl/tls," in *IEEE INFOCOM 2018 - IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, pp. 1–6, April 2018.

[59] A. Sadeghi, H. Bagheri, J. Garcia, and S. Malek, "A taxonomy and qualitative comparison of program analysis techniques for security assessment of android software," *IEEE Trans. Software Eng.*, vol. 43, no. 6, pp. 492–530, 2017.

[60] L. Li, A. Bartel, J. Klein, Y. L. Traon, S. Arzt, S. Rasthofer, E. Bodden, D. Octeau, and P. McDaniel, "I know what leaked in your pocket: Uncovering privacy leaks on Android apps with static taint analysis," *CoRR*, vol. abs/1404.7431, 2014.

[61] H. Bagheri, A. Sadeghi, J. Garcia, and S. Malek, "Covert: Compositional analysis of android inter-app permission leakage," *IEEE Transactions on Software Engineering*, vol. 41, no. 9, pp. 866–886, 2015.

[62] L. Li, A. Bartel, T. F. Bissyandé, J. Klein, and Y. L. Traon, "Apkcombiner: Combining multiple android apps to support inter-app analysis," in *Proceedings of the IFIP TC 11 International Conference*, pp. 513–527, 2015.

[63] H. Bagheri, A. Sadeghi, R. Jabbarvand, and S. Malek, "Automated dynamic enforcement of synthesized security policies in android," tech. rep., Department of Computer Science, George Mason University, 2015.

[64] B. Schmerl, J. Gennari, A. Sadeghi, H. Bagheri, S. Malek, J. Camara, and D. Garlan, "Architecture Modeling and Analysis of Security in Android Systems," in *Software Architecture*, pp. 274–290, Nov. 2016.

[65] H. Bagheri, J. Wang, J. Aerts, and S. Malek, "Efficient, evolutionary security analysis of interacting android apps," in *Proceedings of the 34th IEEE International Conference on Software Maintenance and Evolution (ICSME)*, pp. 357–368, 2018.

[66] V. B. Livshits and M. S. Lam, "Finding security vulnerabilities in java applications with static analysis," in *Proc. of USENIX Security*, 2005.

[67] A. P. Felt, E. Chin, S. Hanna, D. Song, and D. Wagner, "Android permissions demystified," in *Proceedings of the 18th ACM Conference on Computer and Communications Security*, CCS '11, (New York, NY, USA), pp. 627–638, ACM, 2011.

[68] P. Barros, R. Just, S. Millstein, P. Vines, W. Dietl, M. dAmorim, and M. D. Ernst, "Static analysis of implicit control flow: Resolving java reflection and android intents (t)," in *2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pp. 669–679, Nov 2015.

[69] B. Davis and H. Chen, "Retroskeleton: Retrofitting android apps," in *Proc. of MobiSys '13*, (Taipei, Taiwan), 2013.

[70] J. Sawin and A. Rountev, "Improving static resolution of dynamic class loading in java using dynamically gathered environment information," *Automated Software Engg.*, vol. 16, pp. 357–381, June 2009.

[71] S. Poeplau, Y. Fratantonio, A. Bianchi, C. Kruegel, and G. Vigna, "Execute this! analyzing unsafe and malicious dynamic code loading in android applications.," in *Proc. of NDSS*, vol. 14, pp. 23–26, 2014.

[72] E. Fernandes, J. Jung, and A. Prakash, "Security analysis of emerging smart home applications," in *2016 IEEE Symposium on Security and Privacy (SP)*, pp. 636–654, IEEE, 2016.

[73] Y. Tian, N. Zhang, Y.-H. Lin, X. Wang, B. Ur, X. Guo, and P. Tague, "Smartauth: User-centered authorization for the internet of things," in *Proceedings of the 26th USENIX Conference on Security Symposium*, SEC'17, (Berkeley, CA, USA), pp. 361–378, USENIX Association, 2017.

[74] Z. B. Celik, L. Babun, A. K. Sikder, H. Aksu, G. Tan, P. McDaniel, and A. S. Uluagac, "Sensitive information tracking in commodity iot," in *Proceedings of the 27th USENIX Conference on Security Symposium*, SEC'18, (Berkeley, CA, USA), pp. 1687–1704, USENIX Association, 2018.

[75] Q. Wang, W. U. Hassan, A. M. Bates, and C. A. Gunter, "Fear and logging in the internet of things," in *25th Annual Network and Distributed System Security Symposium, NDSS 2018, San Diego, California, USA, February 18-21, 2018*, 2018.

[76] I. Bastys, M. Balliu, and A. Sabelfeld, "If this then what?: Controlling flows in iot apps," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, CCS '18, (New York, NY, USA), pp. 1102–1119, ACM, 2018.

[77] M. Surbatovich, J. Aljuraidan, L. Bauer, A. Das, and L. Jia, "Some recipes can do more than spoil your appetite: Analyzing the security and privacy risks of ifttt recipes," in *Proceedings of the 26th International Conference on World Wide Web*, WWW '17, (Republic and Canton of Geneva, Switzerland), pp. 1501–1510, International World Wide Web Conferences Steering Committee, 2017.

[78] H. Chi, Q. Zeng, X. Du, and J. Yu, "Cross-app interference threats in smart homes: Categorization, detection and handling," *CoRR*, vol. abs/1808.02125, 2018.

[79] N. Apthorpe, D. Reisman, and N. Feamster, "Closing the blinds: Four strategies for protecting smart home privacy from network observers," *arXiv preprint arXiv:1705.06809*, 2017.

[80] B. Lagesse, K. Wu, J. Shorb, and Z. Zhu, "Detecting spies in iot systems using cyber-physical correlation," in *2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*, pp. 185–190, IEEE, 2018.

[81] A. Rahmati, E. Fernandes, K. Eykholt, and A. Prakash, "Tyche: A risk-based permission model for smart homes," in *2018 IEEE Cybersecurity Development (SecDev)*, pp. 29–36, IEEE, 2018.

[82] J. Chen, W. Diao, Q. Zhao, C. Zuo, Z. Lin, X. Wang, W. C. Lau, M. Sun, R. Yang, and K. Zhang, "Iotfuzzer: Discovering memory corruptions in iot through app-based fuzzing.," in *NDSS*, 2018.

[83] A. Acar, H. Fereidooni, T. Abera, A. K. Sikder, M. Miettinen, H. Aksu, M. Conti, A.-R. Sadeghi, and A. S. Uluagac, "Peek-a-boo: I see your smart home activities, even encrypted!," *arXiv preprint arXiv:1808.02741*, 2018.

[84] F. Xiao, L. Sha, Z. Yuan, and R. Wang, "Vulhunter: A discovery for unknown bugs based on analysis for known patches in industry internet of things," *IEEE Transactions on Emerging Topics in Computing*, 2017.

[85] B. Ur, M. Pak Yong Ho, S. Brawner, J. Lee, S. Mennicken, N. Picard, D. Schulze, and M. L. Littman, "Trigger-action programming in the wild: An analysis of 200,000 ifttt recipes," in *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pp. 3227–3231, ACM, 2016.

[86] C. Busold, S. Heuser, J. Rios, A.-R. Sadeghi, and N. Asokan, "Smart and secure cross-device apps for the internet of advanced things," in *International Conference on Financial Cryptography and Data Security*, pp. 272–290, Springer, 2015.

[87] C.-J. M. Liang, L. Bu, Z. Li, J. Zhang, S. Han, B. F. Karlsson, D. Zhang, and F. Zhao, "Systematically debugging iot control system correctness for building automation," in *Proceedings of the 3rd ACM International Conference on Systems for Energy-Efficient Built Environments*, pp. 133–142, ACM, 2016.

[88] T. Yu, V. Sekar, S. Seshan, Y. Agarwal, and C. Xu, "Handling a trillion (unfixable) flaws on a billion devices: Rethinking network security for the

internet-of-things," in *Proceedings of the 14th ACM Workshop on Hot Topics in Networks*, HotNets-XIV, pp. 5:1–5:7, 2015.

[89] W. Zhang, Y. Meng, Y. Liu, X. Zhang, Y. Zhang, and H. Zhu, "Homonit: Monitoring smart home apps from encrypted traffic," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, CCS '18, pp. 1074–1088, 2018.

[90] B. Ali and A. Awad, "Cyber and physical security vulnerability assessment for iot-based smart homes," *Sensors*, vol. 18, no. 3, p. 817, 2018.

[91] H. Thapliyal, N. Ratajczak, O. Wendroth, and C. Labrado, "Amazon echo enabled iot home security system for smart home environment," in *2018 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS)*, pp. 31–36, Dec.

[92] C. Davidson, T. Rezwana, and M. A. Hoque, "Smart home security application enabled by iot:," in *Smart Grid and Internet of Things* (A.-S. K. Pathan, Z. M. Fadlullah, and M. Guerroumi, eds.), (Cham), pp. 46–56, Springer International Publishing, 2019.

[93] A. Goudbeek, K. R. Choo, and N. Le-Khac, "A forensic investigation framework for smart home environment," in *2018 17th IEEE International Conference On Trust, Security And Privacy In Computing And Communications/ 12th IEEE International Conference On Big Data Science And Engineering (TrustCom/BigDataSE)*, pp. 1446–1451, Aug 2018.

[94] M. B. Yassein, W. Mardini, and A. Khalil, "Smart homes automation using z-wave protocol," in *2016 International Conference on Engineering MIS (ICEMIS)*, pp. 1–6, Sep. 2016.

[95] J. Wilson, R. S. Wahby, H. Corrigan-Gibbs, D. Boneh, P. Levis, and K. Winstein, "Trust but verify: Auditing the secure internet of things," in *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*, pp. 464–474, ACM, 2017.

[96] A. Tekeoglu and A. Tosun, "A testbed for security and privacy analysis of iot devices," in *2016 IEEE 13th International Conference on Mobile Ad Hoc and Sensor Systems (MASS)*, pp. 343–348, Oct 2016.

[97] J. L. Newcomb, S. Chandra, J.-B. Jeannin, C. Schlesinger, and M. Sridharan, "Iota: A calculus for internet of things automation," in *Proceedings of the 2017 ACM SIGPLAN International Symposium on New Ideas, New Paradigms, and Reflections on Programming and Software*, pp. 119–133, 2017.

[98] E. Fernandes, A. Rahmati, J. Jung, and A. Prakash, "Decentralized action integrity for trigger-action iot platforms," in *22nd Network and Distributed Security Symposium (NDSS 2018)*, 2018.

[99] M. Balliu, M. Merro, and M. Pasqua, "Securing cross-app interactions in iot platforms," in *IEEE Computer Security Foundations Symposium*, 2019.

[100] "SmartThings Classic capabilities reference." `https://docs.smartthings.com/en/latest/capabilities-reference.html`, 2018.

[101] I. Agadakos, C.-Y. Chen, M. Campanelli, P. Anantharaman, M. Hasan, B. Copos, T. Lepoint, M. Locasto, G. F. Ciocarlie, and U. Lindqvist, "Jumping the air gap: Modeling cyber-physical attack paths in the internet-of-things," in *Proceedings of the 2017 Workshop on Cyber-Physical Systems Security and PrivaCy*, CPS '17, (New York, NY, USA), pp. 37–48, ACM, 2017.

[102] K. Hsu, Y. Chiang, and H. Hsiao, "Safechain: Securing trigger-action programming from attack chains," *IEEE Transactions on Information Forensics and Security*, pp. 1–1, 2019.

[103] M. Alazab, "Profiling and classifying the behavior of malicious codes," *Journal of Systems and Software*, vol. 100, pp. 91–102, 2015.

[104] I. Santos, F. Brezo, J. Nieves, Y. K. Penya, B. Sanz, C. Laorden, and P. G. Bringas, "Idea: Opcode-sequence-based malware detection," in *Engineering Secure Software and Systems: Second International Symposium, ESSoS 2010*, pp. 35–43, 2010.

[105] H. Flake, "Structural comparison of executable objects," *DIMVA 2004, July 6-7, Dortmund, Germany*, 2004.

[106] M. Bourquin, A. King, and E. Robbins, "Binslayer: Accurate comparison of binary executables," in *Proc. of PPREW '13*, pp. 4:1–4:10, 2013.

[107] A. Shabtai, R. Moskovitch, C. Feher, S. Dolev, and Y. Elovici, "Detecting unknown malicious code by applying classification techniques on opcode patterns," *Security Informatics*, vol. 1, no. 1, p. 1, 2012.

[108] X. Hu, K. G. Shin, S. Bhatkar, and K. Griffin, "Mutantx-s: Scalable malware clustering based on static features.," in *USENIX Annual Technical Conference*, pp. 187–198, 2013.

[109] D. Kong and G. Yan, "Discriminant malware distance learning on structural information for automated malware classification," in *Proc. of SIGKDD*, pp. 1357–1365, 2013.

[110] A. Costin, A. Zarras, and A. Francillon, "Towards Automated Classification of Firmware Images and Identification of Embedded Devices," in *32nd International Conference on ICT Systems Security and Privacy Protection (IFIP SEC)*, May 2017.

[111] R. Perdisci, W. Lee, and N. Feamster, "Behavioral clustering of http-based malware and signature generation using malicious network traces," in *Proc. of NSDI*, (Berkeley, CA, USA), pp. 26–26, USENIX Association, 2010.

[112] M. Z. Rafique and J. Caballero, "Firma: Malware clustering and network signature generation with mixed network behaviors," in *Proc. of RAID*, pp. 144–163, 2013.

[113] D. C. Nguyen, D. Wermke, Y. Acar, M. Backes, C. Weir, and S. Fahl, "A stitch in time: Supporting android developers in writing secure code," 2017.

[114] S. Krüger, S. Nadi, M. Reif, K. Ali, M. Mezini, E. Bodden, F. Göpfert, F. Günther, C. Weinert, D. Demmler, *et al.*, "Cognicrypt: supporting developers in using cryptography," in *Proceedings of the 32nd IEEE/ACM International Conference on Automated Software Engineering*, pp. 931–936, IEEE Press, 2017.

[115] S. Sivakorn, G. Argyros, K. Pei, A. D. Keromytis, and S. Jana, "Hvlearn: Automated black-box analysis of hostname verification in ssl/tls implementations," in *Proceedings of the 38th IEEE Symposium on Security & Privacy*, 2017.

[116] B. He, V. Rastogi, Y. Cao, Y. Chen, V. N. Venkatakrishnan, R. Yang, and Z. Zhang, "Vetting ssl usage in applications with sslint," in *2015 IEEE Symposium on Security and Privacy*, pp. 519–534, May 2015.

[117] D. Sounthiraraj, J. Sahs, G. Greenwood, Z. Lin, and L. Khan, "Smv-hunter: Large scale, automated detection of ssl/tls man-in-the-middle vulnerabilities in android apps," in *Proceedings of the 21st Annual Network and Distributed System Security Symposium*, 2014.

[118] E. Bodden, A. Sewe, J. Sinschek, H. Oueslati, and M. Mezini, "Taming reflection: Aiding static analysis in the presence of reflection and custom class loaders," in *Proceedings of the International Conference on Software Engineering*, pp. 241–250, May 2011.

[119] "Soot – a framework for analyzing and transforming java and android applications." `http://sable.github.io/soot/`, May 2018.

[120] Y. Xue, G. Meng, Y. Liu, T. H. Tan, H. Chen, J. Sun, and J. Zhang, "Auditing anti-malware tools by evolving android malware and dynamic loading technique," *IEEE Transactions on Information Forensics and Security*, vol. 12, pp. 1529–1544, July 2017.

[121] A. Bosu, F. Liu, D. D. Yao, and G. Wang, "Collusive data leak and more: Large-scale threat analysis of inter-app communications," in *Proc. of ASIA CCS'17*, pp. 71–85, 2017.

[122] S. Rasthofer, S. Arzt, and E. Bodden, "A machine-learning approach for classifying and categorizing android sources and sinks.," in *Proc. of NDSS*, 2014.

[123] "Boost c++ library." `http://www.boost.org/`, May 2018.

[124] O. Corp., "Java debug wire protocol (jdwp)." `https://docs.oracle.com/javase/7/docs/technotes/guides/jpda/jdwp-spec.html`, May 2018.

[125] J. Blasco and T. M. Chen, "Automated generation of colluding apps for experimental research," *Journal of Computer Virology and Hacking Techniques*, pp. 1–12, 2017.

[126] L. Li, A. Bartel, T. F. Bissyandé, J. Klein, Y. Le Traon, S. Arzt, S. Rasthofer, E. Bodden, D. Octeau, and P. McDaniel, "IccTA: Detecting inter-component privacy leaks in Android apps," in *Proc. of ICSE*, pp. 280–291, 2015.

[127] S. Rasthofer, S. Arzt, M. Miltenberger, and E. Bodden, "Harvesting runtime values in android applications that feature anti-analysis techniques," in *Proc. of NDSS*, 2016.

[128] R. Hay, O. Tripp, and M. Pistoia, "Dynamic detection of inter-application communication vulnerabilities in android," in *Proceedings of the 2015 International Symposium on Software Testing and Analysis*, pp. 118–128, ACM, 2015.

[129] R. Juzenaite, "Security vulnerabilities of voice recognition technologies." `https://resources.infosecinstitute.com/security-vulnerabilities-of-voice-recognition-technologies/#gref`, Accessed on July 2019.

[130] Y. Chen, W. You, Y. Lee, K. Chen, X. Wang, and W. Zou, "Mass discovery of android traffic imprints through instantiated partial execution," in *Proceedings of the 2017 ACM SIGSAC Conference on Computer and Communications Security*, CCS '17, pp. 815–828, 2017.

[131] S. R. Choudhary, A. Gorla, and A. Orso, "Automated test input generation for android: Are we there yet? (e)," in *Proc. of ASE*, pp. 429–440, IEEE Computer Society, 2015.

[132] A. Machiry, R. Tahiliani, and M. Naik, "Dynodroid: An input generation system for android apps," in *Proceedings of the 2013 9th Joint Meeting on Foundations of Software Engineering*, pp. 224–234, 2013.

[133] S. Hao, B. Liu, S. Nath, W. G. Halfond, and R. Govindan, "PUMA: Programmable ui-automation for large-scale dynamic analysis of mobile apps," in *Proceedings of the 12th annual international conference on Mobile systems, applications, and services*, pp. 204–217, 2014.

[134] M. Y. Wong and D. Lie, "Intellidroid: A targeted input generator for the dynamic analysis of android malware," in *Proc. of NDSS*, 2016.

[135] "Google Home." `https://store.google.com/us/product/google_home?hl=en-US`, 2018.

[136] Amazon, "Understanding the smart home skill API." `https://developer.amazon.com/docs/smarthome/understand-the-smart-home-skill-api.html#prerequisites-to-smart-home-skill-development`, 2019.

[137] W. Zhou, Y. Jia, Y. Yao, L. Zhu, L. Guan, Y. Mao, P. Liu, and Y. Zhang, "Discovering and understanding the security hazards in the interactions between iot devices, mobile apps, and clouds on smart home platforms," in *28th USENIX Security Symposium (USENIX Security 19)*, (Santa Clara, CA), pp. 1133–1150, USENIX Association, Aug. 2019.

[138] Z. B. Celik, E. Fernandes, E. Pauley, G. Tan, and P. McDaniel, "Program analysis of commodity iot applications for security and privacy: Challenges and opportunities," *arXiv preprint arXiv:1809.06962*, 2018.

[139] O. Alrawi, C. Lever, M. Antonakakis, and F. Monrose, "Sok: Security evaluation of home-based iot deployments," in *IEEE S&P*, pp. 208–226, 2019.

[140] M. Mohsin, Z. Anwar, G. Husari, E. Al-Shaer, and M. A. Rahman, "Iotsat: A formal framework for security analysis of the internet of things (iot)," in *2016 IEEE Conference on Communications and Network Security (CNS)*, pp. 180–188, 2016.

[141] L. Zhang, W. He, J. Martinez, N. Brackenbury, S. Lu, and B. Ur, "Autotap: Synthesizing and repairing trigger-action programs using ltl properties," in *Proceedings of the 41st International Conference on Software Engineering*, ICSE '19, (Piscataway, NJ, USA), pp. 281–291, 2019.

[142] S. Lee, J. Choi, J. Kim, B. Cho, S. Lee, H. Kim, and J. Kim, "Fact: Functionality-centric access control system for iot programming frameworks," in *Proceedings of the 22Nd ACM on Symposium on Access Control Models and Technologies*, SACMAT '17 Abstracts, pp. 43–54, 2017.

[143] R. Schuster, V. Shmatikov, and E. Tromer, "Situational access control in the internet of things," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, CCS '18, pp. 1056–1073, 2018.

[144] M. Mohsin, Z. Anwar, F. Zaman, and E. Al-Shaer, "Iotchecker: A data-driven framework for security analytics of internet of things configurations," *Computers & Security*, vol. 70, pp. 199 – 223, 2017.

[145] L. Li, T. F. Bissyand, M. Papadakis, S. Rasthofer, A. Bartel, D. Octeau, J. Klein, and L. Traon, "Static analysis of android apps: A systematic literature review," *Information and Software Technology*, vol. 88, pp. 67 – 95, 2017.

[146] "IFTTT platform documentation." https://platform.ifttt.com/docs, 2019.

[147] Z. B. Celik, G. Tan, and P. McDaniel, "IoTGuard: Dynamic enforcement of security and safety policy in commodity IoT," in *Network and Distributed System Security Symposium (NDSS)*, (San Diego, CA), February 2019.

[148] Garageio, "IFTTT applet: If i arrive at my house then open my garage door." https://ifttt.com/applets/213296p, 2019.

[149] E. M. Myers, "A precise inter-procedural data flow algorithm," in *Proceedings of the 8th ACM SIGPLAN-SIGACT Symposium on Principles of Programming Languages*, POPL '81, (New York, NY, USA), pp. 219–230, ACM, 1981.

[150] D. Jackson, "Alloy: A lightweight object modelling notation," *ACM Trans. Softw. Eng. Methodol.*, vol. 11, pp. 256–290, Apr. 2002.

[151] "IotCom project website." https://sites.google.com/view/iotcom/home, 2019.

[152] "SmartThings Community repository." https://github.com/SmartThingsCommunity/SmartThingsPublic, 2018.

[153] "IoTMAL benchmark app repository." https://github.com/IoTBench/IoTBench-test-suite/tree/master/smartThings/smartThings-Soteria, 2019.

[154] J. Choi, H. Jeoung, J. Kim, Y. Ko, W. Jung, H. Kim, and J. Kim, "Detecting and identifying faulty iot devices in smart home with context extraction," in *2018 48th Annual IEEE/IFIP International Conference on Dependable Systems and Networks (DSN)*, pp. 610–621, June 2018.

[155] "Share your applet ideas with us! survey." https://www.surveymonkey.com/r/2XZ7D27, 2019.

[156] Y. M. Pa Pa, S. Suzuki, K. Yoshioka, T. Matsumoto, T. Kasama, and C. Rossow, "IoTPOT: Analysing the rise of IoT compromises," in *9th USENIX Workshop on Offensive Technologies (WOOT 15)*, (Washington, D.C.), 2015.

[157] J. Pewny, B. Garmany, R. Gawlik, C. Rossow, and T. Holz, "Cross-architecture bug search in binary executables," in *2015 IEEE Symposium on Security and Privacy*, pp. 709–724, May 2015.

[158] S. Eschweiler, K. Yakdan, and E. Gerhards-padilla, "discovRE: Efficient Cross-Architecture Identification of Bugs in Binary Code," in *Proc. of NDSS*, pp. 21–24, February 2016.

[159] Q. Feng, R. Zhou, C. Xu, Y. Cheng, B. Testa, and H. Yin, "Scalable graph-based bug search for firmware images," in *Proc. of CCS*, pp. 480–491, 2016.

[160] M. Chandramohan, Y. Xue, Z. Xu, Y. Liu, C. Y. Cho, and H. B. K. Tan, "Bingo: Cross-architecture cross-os binary search," in *Proc. of FSE*, pp. 678–689, 2016.

[161] "Google's VirusTotal puts Linux malware under the spotlight." http://www.zdnet.com/article/googles-virustotal-puts-linux-malware-under-the-spotlight/, 2014. Accessed at July 21, 2017.

[162] "Ida." https://www.hex-rays.com/products/ida/, Accessed at Feb 21, 2017.

[163] A. K. Jain and R. C. Dubes, *Algorithms for clustering data*. Prentice-Hall, Inc., 1988.

[164] "BinDiff Manual." https://www.zynamics.com/bindiff/manual/, Accessed at July 21, 2017.

[165] T. Segaran, *Programming Collective Intelligence*. O'Reilly, 2007.

[166] "Welcome to YARAâĂŹs documentation." http://yara.readthedocs.io/en/v3.7.0/index.html, Accessed at Dec 21, 2017.

[167] E. B. Karbab, M. Debbabi, and D. Mouheb, "Fingerprinting Android packaging: Generating DNAs for malware detection," *Digital Investigation*, vol. 18, pp. S33–S45, Aug. 2016.

[168] M. Halkidi, Y. Batistakis, and M. Vazirgiannis, "On clustering validation techniques," *Journal of Intelligent Information Systems*, vol. 17, no. 2, pp. 107–145, 2001.

[169] "Qemu: the fast processor emulator." http://www.qemu-project.org/, Accessed at Feb 21, 2017.

[170] M. Egele, M. Woo, P. Chapman, and D. Brumley, "Blanket execution: Dynamic similarity testing for program binaries and components," in *Proc. of USENIX Security*, (San Diego, CA), pp. 303–317, 2014.

[171] "Jlint - find bugs in java programs." http://findbugs.sourceforge.net/, accessed at Dec. 2017.

[172] "Jlint - find bugs in java programs." http://www.hammurapi.biz/hammurapi-biz/ef/xmenu/hammurapi-group/products/hammurapi/index.html, accessed at Dec. 2017.

[173] M. Aderhold and A. Kochtchi, "Tailoring pmd to secure coding." Tech. Rep., 2013.

[174] "Jlint - find bugs in java programs." `http://jlint.sourceforge.net`, accessed at Dec. 2017.

[175] N. Meng, S. Nagy, D. Yao, W. Zhuang, and G. A. Argoty, "Secure coding practices in java: Challenges and vulnerabilities," *arXiv preprint arXiv:1709.09970*, 2017.

[176] S. Fahl, M. Harbach, T. Muders, L. Baumgärtner, B. Freisleben, and M. Smith, "Why eve and mallory love android: An analysis of android ssl (in)security," in *Proceedings of the 2012 ACM Conference on Computer and Communications Security*, CCS '12, (New York, NY, USA), pp. 50–61, ACM, 2012.

[177] I. S. Udoh and G. Kotonya, "Developing iot applications: challenges and frameworks," *IET Cyber-Physical Systems: Theory & Applications*, vol. 3, no. 2, pp. 65–72, 2018.

[178] X. Wang, Y. Sun, S. Nanda, and X. Wang, "Looking from the mirror: Evaluating iot device security through mobile companion apps," in *28th USENIX Security Symposium (USENIX Security 19)*, (Santa Clara, CA), pp. 1151–1167, USENIX Association, Aug. 2019.

[179] A. E. Hassan and R. C. Holt, "Predicting change propagation in software systems," in *20th IEEE International Conference on Software Maintenance, 2004. Proceedings.*, pp. 284–293, Sep. 2004.

[180] S. Habchi, R. Rouvoy, and N. Moha, "On the survival of android code smells in the wild," in *Proceedings of the 6th International Conference on Mobile Software Engineering and Systems*, MOBILESoft '19, (Piscataway, NJ, USA), pp. 87–98, IEEE Press, 2019.

[181] S. Habchi, N. Moha, and R. Rouvoy, "The rise of android code smells: who is to blame?," in *Proceedings of the 16th International Conference on Mining Software Repositories*, pp. 445–456, IEEE Press, 2019.

[182] G. Hecht, O. Benomar, R. Rouvoy, N. Moha, and L. Duchien, "Tracking the software quality of android applications along their evolution (t)," in *2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pp. 236–247, IEEE, 2015.

[183] F. Palomba, D. Di Nucci, A. Panichella, A. Zaidman, and A. De Lucia, "Lightweight detection of android-specific code smells: The adoctor project," in *2017 IEEE 24th International Conference on Software Analysis, Evolution and Reengineering (SANER)*, pp. 487–491, Feb 2017.

[184] B. Carlson, K. Leach, D. Marinov, M. Nagappan, and A. Prakash, "Open source vulnerability notification," in *IFIP International Conference on Open Source Systems*, pp. 12–23, Springer, 2019.

[185] A. Decan, T. Mens, and E. Constantinou, "On the impact of security vulnerabilities in the npm package dependency network," in *Proceedings of the 15th International Conference on Mining Software Repositories*, MSR '18, (New York, NY, USA), pp. 181–191, ACM, 2018.

[186] "Snyk." `https://docs.smartthings.com/en/latest/ref-docs/reference.html`, Accessed on July 2019.

[187] X. Wei, L. Gomez, I. Neamtiu, and M. Faloutsos, "Permission evolution in the android ecosystem," in *Proceedings of the 28th Annual Computer Security Applications Conference*, ACSAC '12, (New York, NY, USA), pp. 31–40, ACM, 2012.

[188] A. P. Felt, E. Chin, S. Hanna, D. Song, and D. Wagner, "Android permissions demystified," in *Proceedings of the 18th ACM Conference on Computer and Communications Security*, CCS '11, (New York, NY, USA), pp. 627–638, ACM, 2011.

[189] T. Nafees, N. Coull, I. Ferguson, and A. Sampson, "Vulnerability anti-patterns: A timeless way to capture poor software practices (vulnerabilities)," in *Proceedings of the 24th Conference on Pattern Languages of Programs*, PLoP '17, (USA), pp. 23:1–23:16, The Hillside Group, 2017.

[190] L. Wu, M. Grace, Y. Zhou, C. Wu, and X. Jiang, "The impact of vendor customizations on android security," in *Proceedings of the 2013 ACM SIGSAC Conference on Computer & Communications Security*, CCS '13, (New York, NY, USA), pp. 623–634, ACM, 2013.

[191] D. Wu, D. Gao, E. K. T. Cheng, Y. Cao, J. Jiang, and R. H. Deng, "Towards understanding android system vulnerabilities: Techniques and insights," in *Proceedings of the 2019 ACM Asia Conference on Computer and Communications Security*, Asia CCS '19, pp. 295–306, 2019.

[192] "Android security bulletins." `https://source.android.com/security/bulletin`, Accessed on Sept 2019.

[193] K. Z. Sultana, A. Deo, and B. J. Williams, "Correlation analysis among java nano-patterns and software vulnerabilities," pp. 69–76, 2017.

[194] A. Peruma and D. Krutz, "Understanding the relationship between quality and security: A large-scale analysis of android applications," in *2018 IEEE/ACM 1st International Workshop on Security Awareness from Design to Deployment (SEAD)*, pp. 19–25, 2018.

[195] J. Oliveira, M. Viggiato, M. F. Santos, E. Figueiredo, and H. Marques-Neto, "An empirical study on the impact of android code smells on resource usage.," in *SEKE*, pp. 314–313, 2018.

[196] F. A. Fontana, V. Lenarduzzi, R. Roveda, and D. Taibi, "Are architectural smells independent from code smells? an empirical study," *Journal of Systems and Software*, vol. 154, pp. 139 – 156, 2019.

[197] U. A. Mannan, I. Ahmed, R. A. M. Almurshed, D. Dig, and C. Jensen, "Understanding code smells in android applications," in *Proceedings of the International Conference on Mobile Software Engineering and Systems*, MOBILESoft '16, (New York, NY, USA), pp. 225–234, ACM, 2016.

[198] J. Kim, J. M. Smereka, C. Cheung, S. Nepal, and M. Grobler, "Security and performance considerations in ros 2: A balancing act," *arXiv preprint arXiv:1809.09566*, 2018.

[199] J. McClean, C. Stull, C. Farrar, and D. MascareÃśas, "A preliminary cyber-physical security assessment of the Robot Operating System (ROS)," in *Unmanned Systems Technology XV* (R. E. Karlsen, D. W. Gage, C. M. Shoemaker, and G. R. Gerhart, eds.), vol. 8741, pp. 341 – 348, International Society for Optics and Photonics, SPIE, 2013.

[200] B. Breiling, B. Dieber, and P. Schartner, "Secure communication for the robot operating system," in *2017 Annual IEEE International Systems Conference (SysCon)*, pp. 1–6, April 2017.

[201] C. Cerrudo and L. Apa, "Hacking robots before skynet," *IOActive Website*, 2017.

[202] B. Dieber, R. White, S. Taurer, B. Breiling, G. Caiazza, H. Christensen, and A. Cortesi, *Penetration Testing ROS*, pp. 183–225. Cham: Springer International Publishing, 2020.

[203] N. DeMarinis, S. Tellex, V. P. Kemerlis, G. Konidaris, and R. Fonseca, "Scanning the internet for ros: A view of security in robotics research," in *2019 International Conference on Robotics and Automation (ICRA)*, pp. 8514–8521, May 2019.

[204] R. White, G. Caiazza, H. Christensen, and A. Cortesi, *SROS1: Using and Developing Secure ROS1 Systems*, pp. 373–405. Cham: Springer International Publishing, 2019.

[205] A. Giaretta, M. De Donno, and N. Dragoni, "Adding salt to pepper: A structured security assessment over a humanoid robot," in *Proceedings of the 13th International Conference on Availability, Reliability and Security*, ARES 2018, pp. 22:1–22:8, 2018.

[206] F. Callegati, W. Cerroni, and M. Ramilli, "Man-in-the-middle attack to the https protocol," *IEEE Security Privacy*, vol. 7, pp. 78–81, Jan 2009.

[207] B. Dieber, S. Kacianka, S. Rass, and P. Schartner, "Application-level security for ros-based applications," in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 4477–4482, Oct 2016.

[208] P. Tsankov, A. Dan, D. Drachsler-Cohen, A. Gervais, F. Bünzli, and M. Vechev, "Securify: Practical security analysis of smart contracts," in *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, CCS '18, (New York, NY, USA), pp. 67–82, ACM, 2018.

[209] M. Hammad, H. Bagheri, and S. Malek, "Deldroid: An automated approach for determination and enforcement of least-privilege architecture in android," *Journal of Systems and Software*, vol. 149, pp. 83 – 100, 2019.