On The (In)Effectiveness of Static Logic Bomb Detection for Android Apps

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Abstract—Android is present in more than 85\% of mobile devices, making it a prime target for malware. Malicious code is becoming increasingly sophisticated and relies on logic bombs to hide itself from dynamic analysis. In this paper, we perform a large scale study of TSOPEN, our open-source implementation of the state-of-the-art static logic bomb scanner TRIGGERSCOP\textsubscript{E}, on more than 500k Android applications. Results indicate that the approach scales. Moreover, we investigate the discrepancies and show that the approach can reach a very low false-positive rate, 0.3\%, but at a particular cost, e.g., removing 90\% of sensitive methods. Therefore, it might not be realistic to rely on such an approach to automatically detect all logic bombs in large datasets. However, it could be used to speed up the location of malicious code, for instance, while reverse engineering applications. We also present TRIGDB a database of 68 Android applications containing trigger-based behavior as a ground-truth to the research community.

Index Terms—Logic bombs, Trigger Analysis, Static Analysis, Android Applications Security.

I. INTRODUCTION

Android is the most popular mobile operating system with more than 85\% of the market share in 2020 \cite{1}, which undoubtedly makes it a target of choice for attackers. Fortunately, Google set up different solutions to secure access for applications in their Google Play. It ranges from fully-automated programs using state-of-the-art technologies (e.g., Google Play Protect \cite{2}) to manual reviews of randomly selected applications. The predominant opinion is that the Google Play market is considered relatively malware-free. However, as automated techniques are not entirely reliable and manually reviewing every submitted application is not possible, they continuously improve their solutions’ precision and continue to analyze already-present-in-store applications.

Consequently, the main challenge for attackers is to build malicious applications that remain under the radar of automated techniques. For this purpose, they can obfuscate the code to make the analysis more difficult. Example of obfuscation includes code manipulation techniques \cite{3}, use of dynamic code loading \cite{4} or use of the Java reflection API \cite{5}. Attackers can also use other techniques such as packing \cite{6} which relies on encryption to hide their malicious code. In this paper, we focus on one type of evasion technique based on logic bombs. A logic bomb is code logic which executes malicious code only when particular conditions are met.

A classic example would be malicious code triggered only if the application is not running in a sandboxed environment or after a hard-coded date, making it invisible for dynamic analyses. This behavior shows how simple code logic can defeat most dynamic analyses leading to undetected malicious applications.

In the last decade, researchers have developed multiple tools to help detecting logic bombs \cite{7} \cite{8} \cite{9}. Most of them are either not fully automated, not generic or have a low recall. However, one approach, TRIGGERSCOP\textsubscript{E} \cite{10} stands out because it is fully automated and has a false positive rate close to 0.3\%. In this paper, we try to replicate TRIGGERSCOP\textsubscript{E} and perform a large-scale study to show that the approach scales. Furthermore, we identify specific parameters that have a direct impact on the false positive rate.

As TRIGGERSCOP\textsubscript{E} is not publicly available and the authors cannot share the tool, we implement their approach as an open-source version called TSOPEN. Although TSOPEN has been implemented by faithfully following the details of the approach given in TRIGGERSCOP\textsubscript{E} paper, we did not use the same programming language, i.e., C++. We used Java to reuse publicly available and well tested state-of-the-art solutions. Indeed, our solution relies on the so-called Soot framework \cite{11} to convert the Java bytecode into an intermediate representation called Jimple \cite{12} and to automatically construct control flow graphs. Also, to model the Android framework, the life-cycle of each component and the inter-component communication, TSOPEN relies on algorithms from FlowDroid \cite{13}.

We use TSOPEN to conduct a large-scale analysis to see if such a static approach is scalable. We ran TSOPEN over a set of 508 122 applications from a well-known database of Android applications named ANDROZOO \cite{14}. This experiment shows that the approach is scalable but yields a high false-positive rate. Hence, because of this high false-positive rate, the approach might not be suitable to detect all logic bombs automatically. More than 99 651 applications were flagged with 522 300 triggers supposedly malicious, yielding a false-positive rate of more than 17\%.

Since we obtain a false-positive rate which is much higher than in the literature, we investigate the discrepancies. We construct multiple datasets to consider the concept drift effect, which could affect the results shown by Jordaney et al. \cite{15}. Moreover, we also investigate multiple aspects of the implementation, such as the list of sensitive methods, the call-graph construction algorithm or the timeout threshold. Furthermore, we applied additional two filters not mentioned in the literature: (1) Purely symbolic values removal and (2) Different package name removal. Results indicate that to get close to a false positive rate of 0.3\%, either aggressive filters

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should be put in place or a short list of sensitive methods should be used. In both cases, the impact on the false-negative rate is considerable. This means that if the approach is usable in practice with a low false-positive rate, it might miss many applications containing logic bombs.

We have sent the paper to the TRIGGERScope’s authors, who gave us positive feedback and did not see any significant issue regarding our approach nor on TSOOpen’s design.

In summary, we present the following contributions:

- We implement TSOOpen, the first open-source version of the state-of-the-art approach for detecting logic bombs and show that this approach might not be appropriate for automatically detecting logic bombs because it yields too many false-positives.
- We conduct a large-scale analysis over a set of more than 500 000 Android applications. While the approach is theoretically not scalable because it relies on NP-hard algorithms, we find that, in practice, 80% of the applications can be analyzed.
- We conduct multiple experiments on the approach’s parameters to see the impact on the false positive rate and identify that a low false-positive rate can be reached but at the expense, for instance, of missing a large number of sensitive methods.
- We experimentally show that TRIGGERScope’s approach might not be usable in a realistic setting to detect logic bombs with the information given in the original paper. We empirically show that using TRIGGERScope’s approach, trigger analysis is not sufficient to detect logic bombs.
- We publicly release a database of Android apps containing logic bombs as a ground-truth for future research.

We make available our implementation of TSOOpen and TRIGDB with datasets to reproduce our experimental results: [https://github.com/JordanSamhi/TSOpen](https://github.com/JordanSamhi/TSOpen)

The remainder of the paper is organized as follows. First, a motivation example is given in Section II in order to clarify the reason we are studying logic bombs. Afterward comes the overview of TRIGGERScope in Section III in which we give an overview of its structure. We evaluate TSOOpen in Section IV. Subsequently, in Section V, we discuss the limitations of our work and the reference paper [10]. Section VI relates similar state-of-the-art works in the context of detecting anti-reverse-engineering practices. Finally, in Section VIII we present the direction in which we will continue our research.

II. MOTIVATION

We consider two motivating examples. The first one is an application that seems legit but embeds a time-bomb that is triggered at a specific date: let’s say two weeks after the installation date. This would mean that the malicious code will remain silent for some time before being triggered. Listing 1 is a concrete example of such a logic bomb. It is located at line 4 within the onStart() method, and it triggers the malicious code when a user opens the application and the date is reached.

We can see that with a minimum of effort, a malware developer can bypass most of the dynamic analyses which study the behavior of applications by monitoring them. Petsas & al. [16] give interesting results regarding simple solutions to bypass state-of-the-art dynamic analyses like Andrubis [17] and CopperDroid [18]. The idea is to keep the malicious code dormant during dynamic analyses by hiding it behind unexplored branches. Nevertheless, recent works show that dynamic analyses improve code coverage during the execution of an application by forcing path exploration. They do so by instrumenting the application to modify the control flow. However, these approaches face several limitations, e.g., GRODDROID [19] does not force all branches but only those that guard malicious code which they have to detect beforehand, reducing the problem to detecting malicious code. Likewise, X-FORCE [20] does not force all branches and can force unfeasible paths, making it unsound for analyses.

The first example in Listing 1 was not part of a targeted attack but more in the idea of a widespread malicious application. Let’s now consider a State-Sponsored Attack or an Advanced Persistent Threat [21] which targets specific devices. Those devices could embed seemingly legitimate applications that contain, e.g., an SMS-bomb and remain undetected by most of the analysis tools.

Such a logic bomb could be used as a backdoor to steal sensitive user data. Indeed, if it is a well prepared targeted attack, the attacker could send an SMS with a specific string recognized by the application. Then the application would leak wanted information and stop the broadcast of the SMS to other applications supposed to receive it. This example shows how important it is to detect as many logic bombs as possible in applications, especially in mobile devices, which nowadays store a lot of personal information.

Listing 2 shows an implementation of such a threat in the method onReceive(Context c, Intent i) of BroadcastReceiver class which is triggered when, in this case, an SMS is received by the device. First, the body of the SMS is retrieved in line 3. Then, at line 4, it is compared against "!CMD:" which is a hardcoded string matched against the body of an SMS. This check is considered suspicious because the application can match a hardcoded string against any incoming SMS. Hence it can wait for external commands to be executed by the malicious part of the application. Note that it could be harmless. That is why it is suspicious and not malicious. If the condition is satisfied, the command is retrieved from the SMS, and the malicious code is activated at line 5.

```
1 protected void onStart() {
2     new Date();
3     installDate_plusDays{14};
4     if (now.after(installDate)){attack();}
5 }
```

```
1 public void onReceive(Context c, Intent i) {
2     SmsMessage sms = getIncomingSms(i);
3     String body = sms.getMessageBody();
4     if (body.startsWith("!CMD:"))
5         processCmd(getCmdFromBody(body));
6 }
```

Listing 1: Time-bomb example

Listing 2: SMS-bomb example
III. OVERVIEW

In this section, we explain TSOpen, an open-source implementation of TRIGGERSCOPE, at the conceptual level. The approach is summarized in Figure 1.

A. Applications representation

Android apps do not have a single entry point like usual Java programs. They are made of components, each one having its life-cycle managed by the Android framework.

Modeling life-cycles and how components are connected is not trivial. That is why TSOpen relies on FLOWDROID [13]. Indeed, FLOWDROID handles intra-component communications by introducing dummy main methods and opaque predicates to guarantee that any execution order would not influence any static analysis over the model. FLOWDROID also relies on IcCTA [22] to model the inter-component communications thanks to EPICC [23]. Using state-of-the-art solutions allowed us to avoid reimplementing the Android framework modeling reducing implementation errors. Thus, we retrieve an interprocedural control flow graph on which we can run static analysis algorithms (step A in Figure 1).

Now that we have a model of the application that can be seen in Appendix 1, we can run our analysis, starting with the symbolic execution.

B. Symbolic execution

When classifying predicates, the program has to make decisions depending on the type of objects in conditions, i.e., the condition’s semantics. Therefore, this analysis models, using symbolic execution (step B in Figure 1), the values and the operations performed over Java objects. More precisely, as we faithfully implemented TRIGGERSCOPE, we focus on modeling strings, integers, location, SMS, and time-related objects. Also, these interesting objects are annotated in order to ease the classification.

Furthermore, the classification cannot be done without retrieving the instructions guarded by a condition, that is why the next step, i.e., the predicate recovery, is essential.

C. Predicate recovery

An essential step of the analysis is to construct the intra-procedural path predicate related to each instruction to build the logical formula leading to the instruction. For this, we operate as follows:

Let $ICFG = (I_r, E_r)$ the directed graph describing the interprocedural control flow graph given by FLOWDROID where, $I_r$ represents the set of reachable instructions of the program and $E_r \subseteq I_r \times I_r$ corresponds to the set of reachable directed edges of the program represented by a pair of instructions $(i_a, i_b)$ indicating that the flow goes from $i_a$ to $i_b$. Let $C_r$ the set of reachable conditions of the program and $\Gamma^-(i) = \{x \mid (x, i) \in E_r\}$ the predecessor function.

The algorithm to retrieve the full path predicate of each instruction is described as follows:

1) $\forall i \in I_r, \forall e = \{(x, i) \mid x \in \Gamma^-(i)\} \in E_r$, annotate $e$ with the closest preceding condition $c \in C_r$ (step C.1 in Figure 1).

2) $\forall i \in I_r$, annotate $i$ with $p = getFormula(i) = \{\forall (getFormula(x) \land c) \mid x \in \Gamma^-(i), e \text{ the condition annotated on edge } (x, i)\}$ (step C.2 in Figure 1).

3) $\forall i \in I_r$, simplify the formula $p$ with the basic laws of Boolean algebra, $p$ is the full intra-procedural path predicate annotated on $i$ (step C.3 in Figure 1).

The last step is essential in order to remove false dependencies of instructions. Indeed, consider the following formula: $(p \land q) \lor (\neg p \land q)$ which could have been calculated after step 2. The instruction annotated with this formula would have a false dependencies on predicate $p$ because $(p \land q) \lor (\neg p \land q) = q \land (p \lor \neg p) = q \land 1 = q$ as defined by the distributive and complementation laws of boolean algebra. Hence, the elimination of false dependencies.

Now that we have retrieved path predicates and eliminated false dependencies, we can classify predicates.

D. Predicate classification

In order to classify predicates, i.e., their potential suspiciousness, two essential characteristics are taken into account (step D in Figure 1). Firstly, we verify that the predicate involves a previously computed time-, SMS- or location-related object. Secondly, we verify the type of check performed over the object. The focus is set to comparisons with relevant previously modeled objects and hardcoded values/constants in the application. If a condition corresponds to these criteria, it is flagged as suspicious. Note that the Jimple intermediate representation of the Java bytecode is convenient for this stage as it allows analysts to access explicit object types. This step
acts as a filter for the final control dependency step as it reduces the conditions to analyze by ruling out not suspicious conditions.

We can now perform the last step to check if a sensitive method is called within the guarded instructions of a suspicious condition.

### E. Control dependency

The last step of the approach consists in characterizing whether a condition is defined as a logic bomb (step E in Figure 1). For this, every guarded instruction of a considered condition is checked to verify if it invokes a sensitive method. Also, TRIGGERSCOPE’s developers had the idea to check whether a variable would be modified and later involved in another check, which, in turn, its guarded instructions would be similarly checked. This idea extends the range of possibilities regarding the search for logic bombs. Our implementation takes all these steps into account.

The interested reader can find further details about the implementation in Appendix A. Furthermore, Appendix H shows an execution example of the analysis.

### IV. Evaluation

In this section we evaluate TSOOPEN and address the following research questions:

- **RQ1:** Does TSOOPEN’s approach scale?
- **RQ2:** What parameters can impact the false positive rate?
- **RQ3:** Is it possible to locate the malicious code with logic bomb detection?
- **RQ4:** Do benign and malicious applications use similar behavior regarding the approach under study and why?
- **RQ5:** Are TRIGGERSCOPE’s results reproducible?

Our analyses were run on a server with an Intel Xeon E5-2430 2.20GHz processor with 24 cores, and 95GB of RAM and the High-Performance Computing equipment available at the University of Luxembourg.

### A. RQ1: Does TSOOPEN’s approach scale?

We perform the large scale analysis on a large dataset containing 508 122 applications. This dataset has been created by randomly extracting applications from the 10 million applications of AndroZoo. This analysis is necessary to understand why it could or could not be deployed in real-world analyses, e.g., before being accepted into a store. Analyzing millions of applications with a 1-hour timeout has to be parallelized to take as short a time as possible. For this purpose, we took advantage of the High-Performance Computing equipment available at the University of Luxembourg.

We took into consideration 508 122 benign and malicious applications. In fact, out of 508 122 considered applications, 405 810 (79.9%) were successfully analyzed with an average of 21 seconds per analysis (e.g., timeout). The proportion of applications with detected triggers with this approach is 19.6% (99 651) and 34.9% (177 112) without library filter (The library filter is further explained in Section IV-B5). Also, 522 300 (791 364 without library filter) triggers are detected by TSOOPEN among which 0.48% of SMS-related triggers, 1.35% location-related triggers, and 98.17% of time-related triggers.

Our default threshold for the timeout is one hour. Some applications cannot be analyzed within one hour. A malware developer could simply use techniques, such as obfuscation, to slow down static analysis tools to prevent the application from being analyzed. To understand how an attacker could bypass the analysis, we measured the execution time of the analysis in function of four features: (a) the size of dex files, (b) the number of classes, (c) the number of objects, and (d) the number of branches.

In Figure 2 we can intuitively assume that there is no correlation between the size of the dex file or the number of classes in the app with the duration of the analysis. In fact, when measuring the Pearson Correlation Coefficient (PCC), computed based on Equation 1 we can state that there is no correlation.

$$ r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} $$

In Equation 1 $n$ is the number of data pair, $x_i$ and $y_i$ are data points, $\bar{x}$ and $\bar{y}$ respectively correspond to $\frac{1}{n} \sum_{i=1}^{n} x_i$ and $\frac{1}{n} \sum_{i=1}^{n} y_i$.

The correlation coefficient computed for the data corresponding to the duration as a function of the dex size is equal to 0.152.

With its value close to 0, we can say that the size of the bytecode of an application does not influence the duration of the analysis, this means that even if an attacker naively introduces libraries or code to bring noise in the analysis, e.g., with dead code, it will not force the analysis to reach the timeout. Similarly, this type of analysis does not seem to be sensitive about the number of classes in an application as the PCC computed for the data corresponding to the duration as a function of the number of classes is equals to 0.153. The same conclusion can be done as for the dex file size, even with a lot of noise, meaning many classes brought by obfuscation, for example, the analysis still stays efficient.

On the other hand, other features directly influence the duration of the analysis. In Table I representing the correlation coefficients of Figure 3 we can see that the more objects in an application, the more time it will take to analyze the application. Indeed, while the Pearson correlation coefficient does not indicate any linear correlation (we can intuitively see the exponential correlation in Figure 3) due to the PCC value of 0.359, the Spearman Correlation Coefficient computed based on Equation 2 assures us that the relationship between...
the variables observed can be represented using a monotonic function due to a coefficient of 0.908.

\[ r_s = \frac{cov(r_{gx}, r_{gy})}{\sigma_{rg_x} \sigma_{rg_y}} \]  

(2)

In Equation \( r_{gx} \) and \( r_{gy} \) respectively represent the rank variables of \( x \) and \( y \). Similarly, \( \sigma_{rg_x} \) and \( \sigma_{rg_y} \) respectively represent the standard deviations of \( r_{gx} \) and \( r_{gy} \).

Better, as exponential functions can be approximated into linear functions by taking the logarithm of both sides, we can compute a linear correlation coefficient on \( (x_i, log(y_i)) \) for \( i \in \{0,1,...,n\} \) (\( n \) being the number of pairs of data) and extrapolate the results for the original data. We obtain a score of 0.795, which is a strong linear correlation, assuring us that the original data is positively correlated following an exponential function.

The explanation for this exponential correlation is simple: to understand and detect logic bombs, this approach aims at retrieving the semantic of objects of interest. This means that the more objects to model, the more statements to take into account while modeling, therefore the more time the analysis will take. This can be problematic for an application with many objects or an application where the developer deliberately introduces useless objects to introduce noise in the analysis.

Additionally, we can see in Table 1 that the number of reachable branches and the duration of the analysis is, similarly to the number of objects and the duration of the analysis, positively correlated following an exponential function. Indeed, it introduces new paths, meaning many values to remember depending on the path during the symbolic execution. Regarding the approach used in this analysis, the most troublesome consequence of having many branches (path minimization is an NP-hard problem) is that it considerably slows down the analysis.

Furthermore, as the path predicate recovery is not necessary over the entire code of an application, we collected, afterward, on a subset of the large-scale study’s applications the average time taken by the predicate recovery step. It revealed that it is responsible for 22.2% of the analysis time of an application on average and also responsible, in 35.3% of the cases, for reaching the timeout. In contrast, the symbolic execution is responsible for 61.7% of the analysis time on average, but it has to be performed over the entire application to decide to classify predicates. It must be taken into account for future work in order to optimize the number of successfully analyzed applications.

For understanding the general scheme in which the logic bombs, even false-positives, are triggered we extracted for each detected trigger the type of component in which the method triggering the logic bomb is located as well as the component where the call stack starts for reaching this method, referred to as starting component.

In Figure 4 we can see that in a large number of cases, components containing the method triggering the logic bomb are non-Android classes (49.44%).

Also, 43.1% are located in Activities, meaning that the trigger can also be directly embedded in the user code interface. It makes sense since many applications use time-related triggers for user interfaces (e.g., games).

If we take into account the starting components, it becomes more evident. In fact, almost 80% of the starting components are Activities. Many of these are likely to call a method of another class to trigger the logic bomb. Another interesting fact in starting components is that, despite the low proportion, the process of triggering often starts in a BroadcastReceiver or a Service. BroadcastReceivers are, in this case, mostly linked to SMS-related triggers. Regarding Services, we can assume that this method is likely to be used to monitor the device and trigger code at the right moment.

We also extracted two other features to understand the form of the check when detected. We wanted to know if the intra-procedural logic formula extracted during the analysis was complex or not in the general case. We can see in Figure 5 that in the majority of the cases, there is only one predicate in the formula, which means that the triggered behavior, in the case of this particular analysis, is generally isolated not part of a multiple branch decision.

Furthermore, the density of instructions dominated by a trigger is interesting to study. Indeed, we can see that in the majority of cases, the number of guarded instructions by a trigger is lesser than 10 (JIMPLE instructions). As the number of instructions is small, we can assume that those instructions represent different calls to other classes’ methods to perform a useful action. This assumption correlates with the fact that in most cases, the component in which is the trigger is a basic class (see Figure 4), that is to say, a non-Android component.

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**Table 1** Correlation coefficients of the data of Figure 3 (PCC: Pearson Correlation Coefficient, SCC: Spearman Correlation Coefficient)

|                      | PCC | SCC | PCC \((x_i, log(y_i))\) |
|----------------------|-----|-----|--------------------------|
| # of objects to time | 0.349 | 0.908 | 0.795                   |
| # of branches to time | 0.331 | 0.859 | 0.624                  |

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**Fig. 4** Rate of components (A: Activities, BC: BasicClass, BR: BroadcastReceivers, S: Services, CP: ContentProviders)

**Fig. 3** Evolution of the duration of the analysis depending on the number of objects and branches in the applications considered.
class. In fact, in 55.29% of the cases, one of the instructions is a method call, which confirms our previous data records of Figure 4.

To retrieve the rate of false-positives among the 99,651 detected applications, we based ourselves on VirusTotal [26]. However, the VirusTotal score is challenging to trust for qualifying an application as malware. That is why we decided to classify these applications by detection rate. Table II shows that the rate of false-positives reaches a lower bound of 17.2% and an upper bound of 24.6%.

Table II: VirusTotal (VT) detection rate of TSO\(^\text{\textregistered}\) PEN flagged applications (October 2019).

| VT Apps | >0   | >10  | >20  | >30  | >40  | >50  |
|---------|------|------|------|------|------|------|
| FF Rate | 17.2%| 20.6%| 22.6%| 24.2%| 24.5%| 24.6%|

On a dataset with two orders of magnitude smaller than in RQ1, we find that the false positive rate still reaches a high value of more than 27%.

2) Sensitive Methods Filter: In this experiment, we randomly remove methods in the list of sensitive methods, one after the other, to observe the impact on the false positive rate. We perform this experiment 32 times to see if the results converge. Figures 6 shows the results of this experiment. Each curve represents an experiment. We see that in order to reach a low false-positive rate (e.g., 0.38%, represented by the dotted line), we have to remove, on average, more than 11,500 methods (> 90%) from the list of sensitive methods, which will be missed during the analysis.

We can also see a curve diving fast on the leftmost side of the graph of Figure 6. It represents the same filter for which the most used sensitive methods are removed first. The sensitive methods are ordered by their occurrence in logic bombs based on the results of the control experiment in Section IV-B1.

We observe that to reach a low false-positive rate represented by the dotted line, removing the 68 most-used methods is enough. This means a concentrated number of sensitive methods are used to qualify a trigger as a logic bomb. Those methods mostly allow one to read device information, write into logs/files, and communicate with the external world.

We provide in Table VIII the list of sensitive methods, each present in at least 1% of logic bombs detected in the control experiment of Section IV-B1. Those 15 methods represent 80.7% of the total of potential logic bomb yielded by our tool. Although some of these methods can be omitted in a definitive list, others like TelephonyManager.getDeviceId, which is considered sensitive as it can be leaked and deliver information to the attacker, have to appear in the list of sensitive methods considered. This method alone corresponds to 0.4% of the rate of false-positive. We observe that each method in the list can have a considerable impact on the false-positive rate.

From the definition of a false-positive in the literature, we can deduce that a false-negative, in this case, it is a malicious application not flagged by the tool. Therefore, to measure the rate of false-negative in our study, we use a dataset containing only malicious apps. As before, we randomly remove methods from the list of sensitive methods. Figure 7 details our findings. We can first see that the false-negative rate starts from 45.7%, then we can see that removing sensitive method increases the rate of false-negative (while decreasing the rate of false-positive, see Figure 5). We have seen previously that removing about 11,500 sensitive methods could be helpful to reach a

out of 11,338 (i.e., 64.4%) with an average of 24 seconds per application. A success means that the analysis for an application did not reach the timeout nor crashed.

The analysis found 9,355 suspicious triggers, 4,824 applications with a suspicious check, 3,636 applications with suspicious triggered behavior and 3,099 applications after post-filters (see Table VIII for more information) yielding a false-positive rate of 27.3%.

| Size of logical formula / Number of guarded instructions | Guarded instructions | Size of formulas |
|----------------------------------------------------------|----------------------|-----------------|
| 0%                                                       | 0%                   | 0%              |
| 10%                                                      | 10%                  | 10%             |
| 20%                                                      | 20%                  | 20%             |
| 30%                                                      | 30%                  | 30%             |
| 40%                                                      | 40%                  | 40%             |
| 50%                                                      | 50%                  | 50%             |

Fig. 5: Size of logical formula and count of guarded instructions
TABLE III: Experimental results with Timeout variation (cols. 2 and 3), Symbolic Filter (col. 4), Package Filter (col. 5).

| # apps analyzed | Original results | Timeout 2h | Timeout 3h | Symbolic values filter | Package filter |
|-----------------|------------------|------------|------------|------------------------|----------------|
| # apps analyzed | 7297             | 9884       | 9897       | 9880                   | 10133          |
| # of suspicious triggers | 5391            | 7723       | 7727       | 1033                   | 83             |
| # of apps with triggers | 1701 (23.3%)   | 2373 (20.9%) | 2376 (21%) | 381 (3.4%)             | 31 (0.3%)      |

TABLE IV: Top 15 sensitive methods considered order by number of occurrence in the default experiment of Section IV-B1

| Sensitive Methods | Occurrences | Percentage | False-positive rate induced |
|-------------------|-------------|------------|-----------------------------|
| TextView.setText  | 688         | 12.8%      | 1.6%                        |
| ConnectivityManager.getActiveNetworkInfo | 600 | 11.1% | 1.2% |
| File.<init>       | 544         | 10.1%      | 1.2%                        |
| Log.v             | 436         | 8.1%       | 1.6%                        |
| URL.openConnection | 361         | 6.7%       | 1.3%                        |
| ContextWrapper.startActivity | 361 | 6.7% | 1.3% |
| Location.getLatitude | 280       | 5.2%       | 0.9%                        |
| Log.println       | 241         | 4.5%       | 1.0%                        |
| ActivityCompat    | 196         | 3.5%       | 0.9%                        |
| NotificationManager.notify | 163 | 3.0% | 0.6% |
| File middlet      | 118         | 2.2%       | 0.5%                        |
| Handler.sendMessageDelayed | 112 | 2.1% | 1.3% |
| Handler.sendMessage | 90          | 1.7%       | 0.6%                        |
| Handler.sendMessage | 85          | 1.6%       | 0.6%                        |
| TelephonyManager.getDeviceId | 77 | 1.4% | 0.4% |

3) **Trigger Filter:** In this experiment, we modify TSOPEN in order not to take into account any potential trigger if the values retrieved during the symbolic execution attributed to the test were purely symbolic or unknown. In Table III we can see that the number of suspicious triggers drops to 1033 and the number of applications with suspicious triggers to 381. This minor change produces results with a factor 5 change regarding the detection rate. Also, it allows our tool to get a false positive rate close to 3.4%. Unfortunately, the analysis misses all logic bombs where triggers are derived from purely symbolic values.

Using the trigger filter can have a significant impact on the false positive rate.

4) **Package Filter:** In this experiment, we modify TSOPEN in order to only take into account methods that are in the same package as the application under analysis. This filter is stronger than the library filter of Section IV-B5 as it constrains more the analysis. The results of Table III shows that the number of methods analyzed is significantly reduced. Indeed, the time taken for the analysis is shallow compared to the other analyses. Also, the number of triggers yielded by TSOPEN reaches 83 in 31 different apps. The rate of false-positive is almost equal to the original one. This heuristic has a significant drawback, and an attacker could easily bypass this filter by changing the package name of classes implementing the triggered behavior. Unfortunately, the analysis does not take into account all the code outside of the package. In some applications this accounts for more than 93% of the code.

Using the package filter can have a significant impact on the false positive rate.

5) **Library Filter:** In this experiment, we filter out well-known libraries in order to remove noise from the results. For this, we used a list that was made in a study about common libraries [27] used in Android applications. We manually

Changing the list of sensitive methods can significantly impact the false-positive rate and the false-negative rate, at least up to two orders of magnitude.

Fig. 6: Evolution of the false-positive rate as a function of the number of sensitive methods randomly removed from the list of sensitive methods considered.

Fig. 7: Evolution of the false-negative rate as a function of the number of sensitive methods randomly removed from the list of sensitive methods considered.

low false-positive rate close to 0.3%. In Figure 7 we can see that doing so would set the false-negative rate between 70% and 95%, which would be unacceptable to detect malicious applications.
Triggers are still commonly used in benign applications. We can say that even with an efficient library filter, time-related triggers are still used. Besides, we have already said that suspicious triggers. It shows that common libraries make great use of time-related behavior. We acknowledge that even being relatively free from a logic bomb. This can be explained since a logic bomb does not necessarily make the difference between malicious and benign behavior. This shows the need for a more in-depth analysis of the guarded behavior of the triggers.

We started from the premise that a permission-based method is not necessarily sensitive. Therefore, we used a list of sink methods from FlowDroid [13] as they can leak data, which is considered sensitive. The new list features 130 methods. Nevertheless, the number of triggers flagged by our tool (after re-running the experiment) stays relatively high by reaching 2855. They are distributed in 956 applications (11.5%, see Table VI). Even with a reduced list of methods considered for the control dependency step, the tool cannot make the difference between malicious and benign behavior. This shows the need for a more in-depth analysis of the guarded behavior of the triggers.

Using a reduced list of sensitive methods which are all involved in data leak does not have a significant impact on the false positive rate.

| # apps w/ LB       | 3099   | 1701 (−45.1%) |
|--------------------|--------|---------------|
| # Suspicious LB    | 9535   | 5391 (−43.3%) |
| # Time-related     | 9909   | 5034 (−44.0%) |
| # SMS-related      | 132    | 117 (−11.3%)  |
| # Location-related | 304    | 240 (−21%)   |

TABLE V: Comparison between TSOOPEN’s results before and after filtering common libraries (LB: Logic Bomb)

Table VI: Experimental results with different list of sensitive methods.

| # apps analyzed | 8285 |
|-----------------|------|
| Mean time of analysis | 21.1s |
| # of suspicious triggers | 2855 |
| # of apps with triggers | 956 (11.5%) |

TABLE VI: Experimental results with different list of sensitive methods.

Analyzed 35 of them and confirmed that they contain only false-positives.

After having filtered common libraries from the triggers found beforehand, our results reveal that a scaling approach with this analysis would still not be conceivably concerning the still high number of triggers detected. Indeed, Table V shows that even with a reduction of 43.5% of the number of suspicious triggers, there are 5391 suspicious triggers. Also, the number of applications flagged as containing a logic bomb goes from 3099 to 1701, a reduction of 45.1% for the tool but still greater by two orders of magnitude compared to the state-of-the-art. It means that among 11338 unique benign applications there are potentially 1701 false-positives (23.3%).

Note that, despite being conservative, the false-positive rate calculated during this experiment is obtained by counting the number of benign applications flagged by our tool containing a logic bomb. This can be explained since a logic bomb necessarily contains malicious code, otherwise, it is triggered behavior. We acknowledge that even being relatively free from malicious applications, picking applications from Google Play is not sufficient to qualify the dataset’s applications as benign.

Note that, despite being conservative, the false-positive rate calculated during this experiment is obtained by counting the number of benign applications flagged by our tool containing a logic bomb. This can be explained since a logic bomb necessarily contains malicious code, otherwise, it is triggered behavior. We acknowledge that even being relatively free from malicious applications, picking applications from Google Play is not sufficient to qualify the dataset’s applications as benign.

Nevertheless, to stay in line with the literature, we use the same evaluation process.

The majority of detected triggers filtered by the common libraries are time-related triggers. Out of the 4144 suspicious triggers filtered, 4065 (98.1%) are time-related whereas only 15 (0.36%) are SMS-related and 64 (1.54%) are location-related. It shows that common libraries make great use of time-related triggers. Besides, we have already said that suspicious time-related triggers definition was not narrow enough to detect it compared to SMS-related and location-related. We can say that even with an efficient library filter, time-related triggers are still commonly used in benign applications.

The library filter does not have a significant impact on the false positive rate.

6) Different list of sensitive methods: To build the list of sensitive methods, we reused the results of Pscout [28] and SuSi [29], as in the literature. The constructed list contains 12755 methods. Nevertheless, we have seen that with this list, we obtain a high false-positive rate. That is why we decided to verify the impact if we were to use another, shorter list of sensitive methods.

7) Concept Drift: Differences in results between TSOOPEN and existing experiments of the literature could be due to concept drift [15], i.e., the fact that applications used in the experiments of existing papers are older than the ones used in our paper. We launched experiments on multiple datasets of 10k apps from 2013 to 2016 and have the following results for the false positive rate: 2013: 18.5%, 2014: 15.7%, 2015: 21.1% and 2016: 22.6%. We observe no significant impact on the results.

8) Timeout variation: Experiments in the literature could have been conducted a couple of years ago. To simulate the hardware available at the time, we performed the experiments with shorter timeouts. We launched experiments on multiple datasets of 10k applications and have the following results for the false-positive rate: 2013: 15.7%, 2014: 15.8%, and 5min: 15.7%. We observe no significant impact on the result.

9) Call-graph construction algorithm: The literature might be imprecise and might not always provide all information regarding the implementation of the tool they developed. Mostly, a crucial part of performing inter-procedural analyses is the call-graph construction algorithm. Therefore, as we do not always know which call-graph algorithm is used, we renewed our previous experiment by varying the algorithm. For this, we used the following call-graph construction algorithms: SPARK [30], CHA [31], RTA [32] and VTA [33].

Table VII reveals our experimental findings. First, we can see that none of these algorithms allow us to get a low false-positive rate close to 0.3%. It can be deduced that having the correct algorithm will not suffice to have a perfect implementation. Second, even though the results with Spark algorithm...
and VTA algorithm are close, we can see that changing the call-graph construction algorithm leads to different results (i.e., false-positive rates of 12.6% for VTA, 11.4% for CHA, 13.6% for RTA, and 11.5% for SPARK).

Besides, we run the same experiment by increasing the timeout to 2h and 3h. Table III shows the results of these experiments. We can see that there is almost no difference between a timeout of 2h and 3h. However, considering the initial timeout of 1h, the results obtained here are different. Indeed, the timeout of 1h yielded 1701 applications with triggers, against 2373 and 2376, respectively 2h and 3h. Likewise, the number of triggers detected increases from 5391 with 1h to 7724 and 7727 with respectively 2h and 3h.

We have experimentally seen that minor changes in the implementation can have an important impact on the results. Using heuristics allows the approach to get a false-positive rate similar to the literature (0.3%). However, this result has a significant impact on the recall, the false-negative rate being raised between 70% and 95%.

C. RQ3: Is it possible to locate the malicious code with logic bomb detection?

This is by far the most interesting question for this research area. Indeed, detecting malicious code is a difficult problem per se, that is why if this approach could help in this direction, it could be promising. In fact, TSOPEN’s approach is efficient for this purpose for applications taken individually. Indeed, we manually analyzed 200 apps, and we were able to locate quickly (i.e., in less than 2 minutes on average) the malicious code with the results yielded by TSOPEN. When a true-positive is encountered, we were able to directly inspect the method in which the logic bomb was. Consequently, we had malicious code at hand. Note that these manual analyses allowed us to construct TRIGDB, in Section IV-D0c we give more details.

During our numerous manual analyses, we were able to locate/track the malicious code easily. The condition of the logic bomb playing the role of the malicious code entry-point.

D. RQ4: Do benign and malicious applications use similar behavior regarding the approach under study and why?

In this section, we analyze randomly chosen malicious and benign Android applications containing a trigger.

a) Malicious: The first malicious application we present is called “LittlePhoto” and allows a person with malicious intents to install third party applications and receive information about the device via HTTP by sending an SMS with "$$@@&&$$" or "$$@@&&$$" as the content. It can be viewed as a targeted attack which uses a logic bomb detected as #sms/#body.equals(’$$@@&&$$’). This kind of SMS-related logic bomb is usual in remote administration tool (RAT) or SMS-based backdoors.

The second one is called "com.allen.mp" and this time relies on a time-related triggered behavior: "#now cmp 14400000L". After decompiling the application and analyzing it (see Appendix F for an example of the code), we found that it checks if there is a ten days period between the current time and a pre-defined value. If the condition is satisfied, the application retrieves information about the type of operating system, the version of the Android framework, the model of the device, the number of the device, the operator, the type of network, and information about the storage. Then it sends all this information to a C&C server: http://search.gongfu-android.com:8511/search/sayhi.php.

b) Benign: The first benign application we present is called "Exam Tool". It allows students to cheat during an exam without looking at the phone but get the answer from a friend by the number of vibrations the phone would make depending on the received SMS. TSOPEN flagged this application with this logic bomb: #sms/#body.equals("zebinjo"). It is clear that it is suspicious according to the definition of a logic bomb. However, is it malicious? Even if it calls a method categorized as sensitive (on the list of sensitive methods), the answer is no. Indeed, depending on the SMS received, the phone will vibrate according to a particular protocol defined in the application. But, a hard-coded response is in the onReceive method of the BroadcastReceiver receiving the SMS. And when receiving exactly the string "zebinjo" it will trigger the vibration according to the following scheme: "abacadacdadacdadacdc–da–dca–dca–aca–aca–aca–a–dca–caca–a–ad", the code can be seen in Appendix F.

This example shows why TSOPEN’s approach cannot be entirely reliable because of the trigger’s focus and not the triggered behavior itself. It implies detecting malicious code, i.e., the problem reduces to detecting malicious code.

Another example of SMS-related triggered behavior is the family of tracker applications allowing users to get information about the device via HTTP by sending an SMS with intents to install third party applications and receive information about the device via HTTP by sending an SMS with "$$@@&&$$" or "$$@@&&$$" as the content. It can be viewed as a targeted attack which uses a logic bomb detected as #sms/#body.equals(’$$@@&&$$’). This kind of SMS-related logic bomb is usual in remote administration tool (RAT) or SMS-based backdoors.

The next benign application named "TrackMe" makes the use of a time-related triggered-based behavior, which is part of the definition of TSOPEN’s approach but is clearly legitimate. The detected logic bomb is #now cmp 15L which is a
If the behaviors matched, obviously or otherwise, we kept the behavior of the code guarded by the trigger found by our tool. (also in databases like [26]) in order to compare it with the we tried to understand what was the purpose of the malware the tool was not triggering the malicious code per se. Second, applications respecting this constraint, but the trigger found by like VirusTotal [26]. It is not sufficient. Indeed we found many checked if the application was a known malware in databases had a starting point to track the malicious code. First, we first is a dataset of malicious applications, and the second is a dataset of benign applications. To faithfully reproduce the experiments, we wanted to use the datasets of the experiments in the original paper. Unfortunately, the list of benign applications has been lost. Hence, we created a new dataset which has the same properties as the original dataset. Concerning malicious applications, 3 out of the 14 considered in their experiments were shared with us.

1) Malicious applications: We have executed TSOPEN over the three malicious applications TRIGGERSCOPE’s authors were willing to share to check if the same logic bombs described in their paper could be found. The first one is called Holy Colbert, the second one comes from the Zitmo malware family, and the last one is the RCSAndroid malware.

First, when executing TSOPEN over the application called "Holy Colbert" coming from the so-called MalGenome dataset we effectively find the same time-bomb as they did, but not only, we also discovered an SMS-bomb, see Appendix C for more details. The SMS-bomb revealed by our tool is \#sms/\#body.matches("health") which represents a suspicious narrow check against the body of an incoming SMS. It is triggered if the time-bomb is satisfied, meaning at a specific date, here the May, 21st 2011. It triggers the deletion of data through the content resolver. This implies that our implementation is not entirely identical to the original. We do not claim that this additional finding makes our implementation more precise because it may introduce more false-positives in other applications.

Finally, regarding the "Zitmo" and "RCSAndroid" malicious applications they provided us, TSOPEN was able to extract the same logic bombs as TRIGGERSCOPE.

2) Reproducibility of TRIGGERSCOPE’s results: In this section, we further investigate the discrepancies between TSOPEN’s results and TRIGGERSCOPE’s.

In the original paper, they had a total of 9582 unique benign applications due to overlap between categories. We made the list of the 11383 applications public in the project repository for reproducibility purposes.

First, we observe in Table VIII a considerable difference between our analysis and TRIGGERSCOPE’s: while TSOPEN identified 3099 suspicious apps, TRIGGERSCOPE identified only 35\(^6\). While it is true that the two datasets are different, we did not expect to find a two order of magnitude difference between the results.

Second, we extracted, from each application, and each

| Domain | # Apps | w/ SC | w/ STB | After PF |
|--------|--------|-------|--------|----------|
| Time   | 2987 (4950) | 1719 (302) | 1263 (30) | 1094 (10) |
| Location | 3305 (4440) | 2366 (71) | 1817 (25) | 1716 (8) |
| SMS    | 1025 (1158) | 759 (89) | 586 (64) | 489 (19) |
| Total  | 7297 (9018) | 4824 (462) | 3636 (117) | 3099 (35) |

Our manual investigations have shown that benign and malicious applications can use the same code for benign and/or malicious behavior. Therefore, in this case, the problem of qualifying malicious code remains. We make available a list of malicious/benign applications that make a similar usage of trigger-based behavior in TRIGDB in the repository of TSOPEN project.

E. RQ5: Are TRIGGERSCOPE’s results reproducible?

The experiments have been conducted on two datasets: the first is a dataset of malicious applications, and the second is

| # apps analyzed | CHA | RTA | VTA |
|-----------------|-----|-----|-----|
| Mean time of analysis | 35.4s | 35.1s | 34.5s |
| # of suspicious triggers | 817 | 2270 | 1687 |
| # of apps with triggers | 275 (11.4%) | 506 (13.6%) | 957 (12.6%) |

TABLE VII: Experimental results with different call-graph construction algorithms and a reduced list of sensitive methods considered. (CHA: Class Hierarchy Analysis, RTA: Rapid Type Analysis, VTA: Variable Type Analysis)

| Domain | # Apps | w/ SC | w/ STB | After PF |
|--------|--------|-------|--------|----------|
| Time   | 2987 (4950) | 1719 (302) | 1263 (30) | 1094 (10) |
| Location | 3305 (4440) | 2366 (71) | 1817 (25) | 1716 (8) |
| SMS    | 1025 (1158) | 759 (89) | 586 (64) | 489 (19) |

TABLE VIII: Result of our analysis on the 11383 benign applications. The values in parenthesis represent TRIGGERSCOPE’s results for the original dataset. (SC: Suspicious Checks, STB: Suspicious Triggered Behavior, PF: Post-Filters).

Unfortunately, TRIGGERSCOPE authors were unable to run their tool on our dataset to compare the results, so we reused the results of their paper on their original dataset to compare our results.

11383 - 9582 = 1801

1801 / 9582 * 100 = 18.73%
The reader may have noticed the structure of the previous application flagged). In a recent analysis, Stone found a malicious application using multiple evading techniques[36]. The malware will first check if the device has a Bluetooth adapter and a name, which is important as emulators use default names. Then it would check if the device has a sensor and verify the content of /proc/cpuinfo to find both intel and amd strings. As most devices use ARM processors, those strings should not appear. It also checks the appearance of any Bluestacks files, which is an emulator solution and other emulation detections. Finally, this application would deliberately throw an exception and check the content to find any matching string that would show an emulator’s existence.

Predicate Minimization. The next limitation lies in the fact that predicate recovery and predicate minimization are performed systematically, which increases the probability of running into a complicated formula for which the minimization step would never end. Besides, this step is responsible for 22.2% of the analysis time and responsible, in 35.3% of the cases, for reaching the timeout of the analysis. Unlike the symbolic execution step, which is responsible for the largest part of an application’s analysis time (61.7%), the path predicate recovery and minimization are not necessary for the entire application. Indeed, the symbolic execution phase is necessary to decide on the suspiciousness of conditions. A countermeasure would be to locate interesting checks and then perform the full path predicate recovery and minimization.

Maliciousness. The most critical weakness of TRIGGER-SCOPE approach is the control dependency step, which compares method calls dominated by suspicious triggers with a list of sensitives methods. This phase requires more attention as it is used to qualify the maliciousness of a condition. Indeed, a suspicious check can be harmless due to the same usage benign and malicious applications make of trigger-based behavior. We were able to construct a dataset with the same properties as the one used in the original paper. However, TSOPEN yielded a high false-positive rate by detecting 3099 potential apps with logic bombs (> 27%). We see the importance of having the original list for reproducing this experiment as it can significantly impact the false-positive rate. Therefore, with the information that has been provided to us and the description of the approach made in the original paper, we conclude that the approach might be used in a realistic setting to detect logic bombs.
Nevertheless, we recognize the difficulty of this step, given the lack of a formal definition of malware. Despite having considerable resources, major companies also realize the difficulty to automatically qualify malicious code, e.g., Google still accepts malicious applications in its PlayStore [37].

**Implementation Errors.** Even though we reproduced faithfully the approach described in TriggerScope paper and reused available and well-tested state-of-the-art code when possible, we are not immune from implementation errors.

**Implementation Unknowns.** Given the details in the original paper, we are not able to reproduce the results. Therefore, we tried to vary parameters and implementation details to get as close as TriggerScope’s results. However, it is challenging to test all the combinations of implementation/parameters to get the original results.

VI. RELATED WORK

In 2008, Brumley & al. [7] developed Minesweeper, which is an interesting approach to assist an analyst. Their solution worked directly at the binary level of an executable application. Their goal was to uncover trigger-based behavior by constructing conditional paths and input values to execute the application. The next step was to ask a solver whether the path is feasible or not. If not, they would not explore this path. On the contrary, they would explore this path and ask the solver to construct -if possible- input values to satisfy the formula. They would then execute the application with the computed trigger input values to inspect the behavior, and if a malicious behavior were encountered, they would know the conditional path leading to this behavior, thus detecting if a logic bomb exists. They conducted their experiments on four real-world applications and succeeded in finding trigger-based behavior in less than 30 minutes per application with less than 14 potential logic bombs per application. Unlike TSOpen, the process is not entirely static nor fully automatic and requires a human to infer the logic bomb.

Four years later, Zheng & al. [8] focused on finding a user interface-based trigger that could be used to hide malicious code to traditional analysis in Android applications. They construct what they call the FCG (Function Call Graph) to retrieve call paths to sensitive Android APIs. The next step is constructing what they call the ACG (Activity Call Graph) to have the relationship between the application activities, i.e., how to go from one activity to another via user interface methods. Having those details, they run the application by triggering user interface elements to go to the sensitive activity, which calls a sensitive API and monitors the behavior to check if anything suspicious happens. That way, they can deduce if the user interface triggering process is used to trigger malicious code. Their approach is not generic and focuses on one single type of logic bomb. Also, we note the use of dynamic analysis of their approach again.

Pan & al. [38] presented a new machine-learning based technique to detect Hidden Sensitive Operations in Android apps. They do not specifically focus on malicious behavior contrary to TriggerScope’s approach, which targets malicious activities. Their approach is composed of a pre-processing part where lightweight data-flow and control-flow analysis are performed to extract a condition-path graph. This latter is then used to extract features that will feed the SVM classification. Doing so, HSOMiner performs a precision of 98.4% (based on 125 randomly chosen apps from a set of 63,372) and a recall of 94%. Though the approach is interesting (SVM is resistant to overfitting), it does not fit the goal of detecting logic bombs hidden in Android apps.

In 2017, Papp & al. tried to work directly at the source code level to detect trigger-based behavior in legitimate applications [9]. Their goal is not to work on a malicious application. They want to emphasize triggered behavior or backdoor behavior in legitimate open-source applications. For this purpose, they use KLEE [39] to perform mixed concrete and symbolic execution (also called concolic execution). However, first, they have to instrument the considered application to add specific library calls to use these existing tools. Then they execute the concolic execution and based on the result, and they generate different test cases. Out of these test cases, some can be highlighted by their program to be verified by an analyst to check whether it is a trigger-based behavior or not. Though it is promising for a semi-automatic detection tool, their approach can take a large amount of time to generate test cases and lead to a large number of false-negatives.

We now present a more advanced and promising method developed by Bello and Pistoia [40]. Their approach aims at exposing evading techniques that sophisticated malware use. Nevertheless, they do not stop at the detection, as we will see. Their work is divided into three parts, the first one being the detection of evasion point candidate by using information flow analysis. They use the notion of source and sink, that is to say, detecting information going from a source and going to a sink. Once detected, they step into stage two, it is simply the instrumentation of the Java bytecode to force the untaken branch during the following analysis. The last stage is precisely the execution of the instrumented application in a controlled environment to monitor the malicious code’s behavior. According to the authors, their approach is unsound but a stepping stone toward detecting new malware behavior. The first stage of their work is related to our work, except that they follow the flow of fingerprinting methods to branches.

Logic bombs can be used for venerable purposes, indeed in a recent study, Zeng & al. [41] presented an approach to detect repackaging using triggers. Indeed, their approach consists of instrumenting a legitimate app that could be repackaged by an attacker and adding an instruction to make the app "repackage-proof". They introduce graphically obfuscated trigger conditions that, when triggered, can detect if the program has undergone a repackaging process. The term "logic bomb" specifically means triggering malicious code under specific circumstances. However, the code triggered is not malicious but preventive. Therefore, although they use the same mechanism as malware developers, the authors should talk about Hidden Preventive Code. Nonetheless, their approach is resilient since we assume the condition has been detected, which is already a challenging problem. One cannot resolve the condition due to its cryptographic properties (using hash functions). Therefore the guarded code cannot be decrypted and executed. Inserting checks in legitimate apps is promising for protecting Android
apps from malware developers and has well been studied in the literature [42].

VII. CONCLUSION

In this paper, we have implemented TSOOPEN, the first open-source version of the state-of-the-art approach for detecting logic bombs in Android applications. We first conducted a large-scale analysis over a set of more than 500,000 Android applications and observed that the approach scales.

However, the approach is not appropriate for automatically detecting logic bombs because the false-positives rate of 17% is too high. We conducted multiple experiments on the approach’s parameters to understand the impact on the false positive rate and identify that a low false-positive rate could be reached but at the expense, for instance, of missing a large number of sensitive methods. That is to say, the approach with a low false-positive rate misses a large number of logic bombs. We experimentally show that TSOOPEN’s approach might not be usable in a realistic setting to detect logic bombs with the original paper’s information.

Moreover, we have seen that TSOOPEN’s approach is not sufficient to detect logic bomb because benign and malicious apps can use the same code for benign and/or malicious behavior. This is a direct consequence of the lack of a formal definition of what a malware is. We empirically show that using TSOOPEN’s approach, trigger analysis is not sufficient to detect logic bombs. Indeed, dissociating the trigger condition and the guarded behavior produces false-positives. Thus, an analyst is necessary to verify the behavior. Nevertheless, when manually inspecting malicious applications containing logic bombs, provided by TSOOPEN, we were quickly able to verify if the triggered code is malicious. We did not have to search through all the code, which saved us a lot of time. Hence, TSOOPEN’s approach seems promising to locate the malicious code using logic bombs in applications being reverse engineered.

We created TrigDB, a database of 68 applications containing localized trigger behavior. We manually analyzed and classified each logic bomb. We make it publicly available for future research as a ground-truth promised to evolve.

In a nutshell, our work shows that, even though TSOOPEN’s approach is interesting, it is not suitable for automatically detecting logic bombs. Indeed, the control dependency step is not sufficiently representative of malicious behavior. Our results contradict state-of-the-art by two orders of magnitude regarding the rate of false-positives. We have identified several parameters, such as the list of sensitive methods, which could have a two-order magnitude impact on the false positive rate. These parameters should be detailed in every paper tackling the challenging task of detecting logic bombs in Android applications. Our hope is that future publications do not omit this information to make their experiments reproducible.

VIII. FUTURE WORK

We have seen that if an application uses trigger-based behavior combined with malicious code, they are inseparable, sophisticated techniques should be used to qualify the behavior as malicious to flag it as a logic bomb. TRIGGERSCOPE checks if a sensitive method is called, but an in-depth analysis of the guarded behavior is to be preferred to understand the triggered behavior. Because a sophisticated analysis of the guarded behavior reduces to detecting malicious code, the difficulty remains due to the lack of a formal definition of what malware is. We aim at going further by linking the guarded code with its condition. The trigger would somehow be the entry point for the code. Hence we would be able to locate the malicious code, or at least be able to track it. We also want to verify if the guarded code is enough to execute a behavioral study and qualify the application’s maliciousness.

We do not just want to focus on the internal context of the application. Indeed, the external context, i.e., the application description or the application reviews, can be processed by applying NLP algorithms ([43], [44]). Existing techniques such as [45] and [46] already use the application descriptions to compare it with the permissions or the application’s behavior.

Finally, we aim to build a classification of types of triggers to understand their use in malicious applications. This would help build a detector that could take into account those classes and study their use in the wild.

IX. ACKNOWLEDGMENTS

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Any implementation is subject to erroneous code. In order to reduce the number of errors in TSO\textsc{pen}, we rely on well-tested state-of-the-art publicly available Java frameworks. TRIGGER\textsc{scope}, on the other hand, is written from scratch in C++ which increases the risks of introducing numerous implementation errors \cite{47}.

TRIGGER\textsc{scope} has originally been developed in C++ with full management of the transformation of the Dalvik bytecode in a custom intermediate representation on which is performed the control flow analysis and the analysis. The modeling of Android applications has well been explored in state-of-the-art, that is why we did not re-implement those aspects.

TSOPEN consists of more than 5K Java SLOC (18.6K for TRIGGER\textsc{scope}) which, provides better results in term of execution time than the C++ version of TRIGGER\textsc{scope}. This is probably due to the choice, on their side, to implement the control flow analysis from scratch. Also, we parallelized, using multi-threading when it was possible, e.g., the symbolic execution and the path predicate recovery.

Besides using FLOWDROID for modeling Android applications, our implementation is built on top of SOOT \cite{11} which is the state-of-the-art solution regarding static analysis over Java and Android \cite{48} programs, initially described in 1999 and since used by researchers around the world.

Note that we do not possess the information about the call-graph construction algorithm used by the authors of TRIGGER\textsc{scope}. Therefore, even though we try to faithfully implement the tool with the details of the paper, we cannot have a 100% similar tool. TSOPEN relies on Flowdroid to construct the call-graph used for the inter-procedural analysis. Flowdroid, in turn, relies by default on the Spark call-graph analysis framework \cite{30}. We evaluate TSOPEN using different call-graph construction algorithms as discussed in section \ref{sec:implementation}.

### A. Symbolic execution

Similarly to TRIGGER\textsc{scope}, our symbolic execution engine models numeric, string, time, SMS, and location-related objects. The J\textsc{imple} intermediate representation is, again, convenient for recognizing objects and operation performed over those objects thanks to its flat representation of operations and its explicit typed variables. Furthermore, as our approach is built over Soot which allows optimizing the analyzed code, numeric and string constants are easily propagated which facilitates the predicate classification.

Modeling string objects is important for the detection of suspicious checks against any string value/field of an object, e.g., the body of an incoming SMS. For this purpose, our analysis models as faithfully as possible string values propagated along the graph. When dealing directly with concrete values, the analysis recognizes the operations performed and executes it directly, e.g., append(), format(), subString(), otherwise if it is a symbolic value it records the operation.

Regarding time-related objects, TSOPEN keeps track of a list of time-related classes (e.g., Calendar, Date, LocalDateTime, SimpleDateFormat, etc.) and annotates each one with the tag \#now when it recognizes that it has been instantiated with the current date in the program. Also, TSOPEN keeps track of related methods that narrow the circumstances of the potential check performed on such values like Date.getHour() would be annotated with \#now/\#hour which eases the future classification.

Equivalently, TSOPEN records every location-related objects like android.location.Location and annotates it with the \#here tag when it is instantiated to represent the current location. Fields of those objects can be accessed to represent more precise values like the longitude or the latitude. TSOPEN annotates those values with respectively \#here/\#longitude and \#here/\#latitude.

Furthermore, the analysis does the same approach for the SmsMessage object, i.e. it annotates it with the \#sms tag and records, as strings, values retrieve from the received SMS. In this case, it keeps track of the use of the getMessageBody(), getDisplayMessageBody(), getOriginatingAddress() and getDisplayOriginatingAddress() methods and annotates them with \#sms/\#body or \#sms/\#sender.

TSOPEN also models boolean values to keep track of methods returning a boolean value used in conditions.

For the context of this analysis, TSOPEN annotates methods like Date.after(), Date.before(), String.contains(), String.startsWith(), etc.

### B. Predicate recovery

This step aims at getting rid of false dependencies while retrieving instructions dominated by the trigger condition which will be used for the control dependency. For this purpose, the analysis first begins with a forward intra-procedural analysis and it extracts simple predicates from each check and annotates the edge corresponding with the predicate. An edge annotated with a predicate $p$ means that the target of the edge must be executed if and only if $p$ is satisfied.

The next step is the real predicate recovery as it, for each node retrieves the list of predicates to be satisfied to reach this node. To this end, TSOPEN performs a backward intra-procedural analysis and combines, recursively, the previous simple predicates together. More precisely, a boolean formula is built following two rules: 1) if the node in question has one predecessor, it is combined using a logical AND; 2) if the node in question has more than one predecessor, it is combined using a logical OR between every possible path predicate.

Finally, the last step, without which the analysis would lead to a significant increase of false positives due to false dependencies, is the minimization of boolean formulas.

### C. Predicate classification

Hitherto TSOPEN has modeled interesting objects related to the purpose of this analysis and has propagated their values. It has also removed false dependencies, it now needs to decide whether a check is considered as suspicious.
a) Time-related objects: TSO\textsc{pen} verifies that (1) one of the operands is the result of the invocation of a comparison between two date/time objects such as \texttt{after()} or \texttt{before()} and (2) one of them representing the current date and the other being built with a constant value. Similarly, it verifies that, in the check, some primitive numeric types representing the current date/time are compared with a constant. In these cases, it flags the check as suspicious.

b) Location-related objects: Our tool verifies if one of the operands is a value derived from an object related to the current location and if the other operand represents a constant value. Also, it checks if one of the operands is the result of the invocation of a method such as \texttt{distanceBetween()} to check if the device is in a specific area. In these cases, it also flags the check as suspicious.

c) SMS-related objects: TSO\textsc{pen} verifies if one of the operands represents a value from the body of an SMS or the sender of an incoming SMS. Then, if it is the case, it verifies if these values, which are strings, are matched against specific patterns or constants through the invocation of methods such as \texttt{startsWith()}, \texttt{endsWith()}, \texttt{contains()}, \texttt{matches()}, etc. These checks are also flagged as suspicious because they encode tight conditions which could be used to exfiltrate data surreptitiously.

Furthermore, to set aside obvious non-suspicious checks like null check reference or the comparison of a number with "-1" (e.g., is the size of the body of an SMS greater than -1 ?), we apply a post-filter step as described in \textsc{TriggerScope} paper.

D. Control dependency

Finally, we have a reduced list of suspicious checks, we also have the list of instructions that are guarded by each check, the analysis can now determine if any of these checks contain an invocation to a sensitive Android API.

For this purpose, TSO\textsc{pen} iterates over guarded instructions of previously flagged suspicious trigger conditions and checks if they contain an invocation to a method, if it is the case, it verifies if this method appears in the list of sensitive methods considered in the paper of \textsc{TriggerScope}. The list is not public and not shared but the researchers wrote that they used the result of \textsc{PScout} \cite{28} and \textsc{SuSi} \cite{29}. We retrieved these lists as well and used them to classify a method as sensitive. If a match is found, the check is flagged as a potential logic bomb.

Additionally, this approach is inter-procedural, meaning that the analysis will propagate to analyze the content of any method invocation to check if, in the call stack, a match can be found. Also, some malware does not invoke a sensitive method directly. Indeed, the logic bomb could be used to turn a switch (e.g., a boolean) and a check could be performed on this switch elsewhere in the code. That is why the analysis follows these updated fields between methods and checks whether they are guarded by a check which would invoke a sensitive method.

\section*{Appendix B
\textsc{Holy Colbert} decompiled}

\begin{lstlisting}[language=Java]
StringBuilder date = new StringBuilder(new SimpleDateFormat("MMddyyyy").format(new Date()));
SmsMessage sms = SmsMessage.createFromPdu((byte[])((Object[])intent.getExtras().get("pdus")).get(0));
if (date.toString().matches("05212011")) {
    int nextInt = new Random().nextInt(4) + 1;
    if (sms.getMessageBody().matches("health")) {
        deleteContent();
    }
    SmsManager.getDefault().sendTextMessage(sms.getOriginatingAddress(), null, new String[]{"Cannot talk right now, the world is about to end", "Jebus is way over due for a come back", "Its the Raptures, praise Jebus", "..."}[nextInt], null, null);
}
\end{lstlisting}

Listing 4: Holy Colbert application decompiled (simplified)

\section*{Appendix C
\textsc{Time-related trigger in tracking application}}

\begin{lstlisting}[language=Java]
if ((System.currentTimeMillis() - Config.Review) / 86400000 < 15) {
    builder = new Builder(MainActivity.this);
    builder.setTitle("Trial expired");
    builder.setPositiveButton("Yes", new DialogInterface.OnClickListener() {
        public void onClick(DialogInterface dialogInterface, int i) {
            Intent intent = new Intent(MainActivity.this, BillingActivity.class);
            MainActivity.this.startActivity(intent);
        }
    });
}
\end{lstlisting}

Listing 5: Track Me application decompiled (simplified)
Fig. 8: The left diagram represents the dummy main method of the entire application constructed by FLOWDROID with each opaque predicate $p_a, \ldots, p_d$ in gray. Opaque predicates will not be evaluated during analysis, hence both branches would be considered equally. Each component life-cycle is modeled after the corresponding life-cycle. For instance, if Component X is an Activity component, FlowDroid models it according to the Activity life-cycle presented on the right hand side of the figure. As for the dummy main, FlowDroid’s concrete implementation of the component life-cycle (middle) contains opaque predicates.

### APPENDIX D

**ANDROID FRAMEWORK MODEL CONSTRUCTED BY FLOWDROID**

### APPENDIX E

**TIME-BOMB EXAMPLE**

```java
public void onCreate() {
    long j = sharedPreferences.getLong("start", 0);
    long currentTimeMillis = System.currentTimeMillis();
    if (currentTimeMillis - j < 14400000) {stopSelf();}
    else {
        if (Utils.isConnected(this)) {doSearchReport();}
        getPermission();
        provideService();
    }
}
```

Listing 6: Time-bomb in com.allen.mp application (simplified)

### APPENDIX F

**BENIGN SMS TRIGGER**

```java
public void onReceive(Context context, Intent intent) {
    SmsMessage[] smsMessageArr = (SmsMessage[])null;
    String str = getMessageBody(smsMessageArr);
    String code = "sbacdacdacdacdacdcacdcacdcadca-cc-c-da-dca-cda-c-adc-a-c-adc-a-c-dca-cac-a-dc-ad";
    if (str.equals("zebinjo")) {
        CrnacVibrator crnacVibrator = new CrnacVibrator();
        crnacVibrator.odgovor(code);
        abortBroadcast();
    }
}
```

Listing 7: Exam tool decompiled (simplified)
APPENDIX G
TRACKING APPLICATION

Listing 8: My Car Tracks decompiled (simplified)

APPENDIX H
EXAMPLE OF THE APPROACH

Fig. 9: Example of the different steps of the analysis

We explain the process of the approach with Figure 9. First, we describe the symbolic execution step with the example of Listing 9a. The first value modeled is at line 2, a new incoming SMS is being stored in variable sms and is represented by the tag #sms. In line 4 the body of the SMS is retrieved, thus the instruction is tagged with #sms/#body as our symbolic execution engine recognizes it. Some values cannot be resolved during this step, hence they are assigned symbolic values, e.g. at lines 6 and 10. Those modeled values are useful to describe the semantic of the condition at line 8 which is represented by the tag #sms/#body.startsWith("!CMD:"). This value will be used during the path predicate classification to qualify the suspiciousness of the condition.

Now that the analysis has tagged some interesting values, it retrieves the path predicate for each instruction in the code, as illustrated in Listing 9b. This simple example shows that outside any conditions, intra-procedural instructions are not annotated with any logical formula (lines 3, 5 and 7). However, instructions guarded by a condition are annotated with the predicate representing this condition. Both branches are considered, that is why the instruction at line 9 is annotated with predicate p and any instruction under the else instruction is annotated with ¬p. Those formulas are then subjected to minimization in order to rule out false dependencies. It is now possible to classify predicates and to check if they guard sensitive operations.

The next phase, shown in Listing 9c, allows classifying predicates thanks to the results of the previous symbolic execution. Indeed, decisions about the suspiciousness are taken according to the results of the symbolic execution. That is why the condition at line 5 is considered suspicious because the body of an incoming SMS is being matched against a hard-coded string. Once the suspicious conditions memorized, the analysis retrieves the instructions guarded by those conditions thanks to the path predicate recovery step. For each guarded instruction, the analysis checks if the instruction is a method call and, if it is the case, the called method is being matched against a list of sensitive methods. If no match is found, as it is the case in 9c, the inter-procedural mechanism takes place, meaning the analysis dives into application method calls to check if they use a sensitive method. In this example, the processCmd(String) method at line 9 contains such a method call. According to TRIGGERSCOPE’s approach, it is sufficient to qualify this sequence as a logic bomb.