Towards Accurate Labeling of Android Apps for Reliable Malware Detection

Aleieldin Salem
Technische Universität München
Garching bei München, Germany
salem@in.tum.de

Abstract—In training their newly-developed malware detection methods, researchers rely on threshold-based labeling strategies that interpret the scan reports provided by online platforms, such as VirusTotal. The dynamicity of this platform renders those labeling strategies unsustainable over prolonged periods, which leads to inaccurate labels. Using inaccurately labeled apps to train and evaluate malware detection methods significantly undermines the reliability of their results, leading to either dismissing otherwise promising detection approaches or adopting intrinsically inadequate ones. The infeasibility of generating accurate labels via manual analysis and the lack of reliable alternatives force researchers to utilize VirusTotal to label apps. In the paper, we tackle this issue in two manners. Firstly, we reveal the aspects of VirusTotal’s dynamicity and how they impact threshold-based labeling strategies and provide actionable insights on how to use these labeling strategies given VirusTotal’s dynamicity reliably. Secondly, we motivate the implementation of alternative platforms by (a) identifying VirusTotal limitations that such platforms should avoid, and (b) proposing an architecture of how such platforms can be constructed to mitigate VirusTotal’s limitations.

Index Terms—Software Reliability; Android Security; Malware Detection; Machine Learning

I. INTRODUCTION

The generation of reliable ground truths for malicious and benign applications (hereafter apps) is fundamental for implementing and evaluating effective malware detection methods. Assigning apps inaccurate labels (e.g., labeling malicious apps as benign) might impact the reliability of studies that inspect trends adopted by malicious apps, and, more importantly, might impede the development of effective detection methods [1]–[4]. Manual analysis and labeling of apps is arguably the most reliable method to label apps. However, it can neither cope with the frequent release of malware nor the requirement of some detection methods (e.g., Machine Learning (ML)-based methods) of large numbers of labeled apps for training and validation. Consequently, researchers turn to online platforms, such as VirusTotal [5], to label apps in their datasets as malicious and benign.

VirusTotal does not label apps as malicious and benign. Given the hash of an app or its executable, the platform provides the scan results from about 60 different commercial antiviral software [6]–[10]. So, it is up to the platform’s user to decide upon strategies to interpret such information to label apps as malicious and benign. Unfortunately, there are no standard procedures for interpreting the scan results acquired from VirusTotal to label apps, which leads researchers to use their intuitions and adopt ad hoc threshold-based strategies to label the apps in the datasets used to train and evaluate their detection methods. In essence, threshold-based labeling strategies deem an app as malicious if the number of antiviral scanners labeling the apps as malicious meets a certain threshold. For example, based on VirusTotal’s scan reports, Li et al. labeled the apps in their Piggybacking dataset as malicious if at least one scanner labeled them as malicious [7]. Pendlebury et al. labeled an app as malicious if four or more scanners did so [11], and Wei et al. labeled apps in the AMD dataset as malicious if 50% or more of the total scanners labeled an app as such [9].

Some of the aforementioned threshold-based labeling strategies may indeed accurately label apps better than others and should be standardized. Nonetheless, researchers have found VirusTotal to be dynamic in terms of the labels given by the scanners it uses [3], [12], [13], which affects threshold-based labeling strategies as follows. Threshold values that used to yield the most accurate labels might change in the future as VirusTotal changes the scanners it includes in its scan reports. Using out-of-date or inaccurate thresholds alters the distribution of malicious and benign apps in the same dataset, effectively yielding different detection results as revealed by recent results [11], [14]. On the one hand, researchers might dismiss promising detection approaches, because they underperform on a dataset that utilizes a labeling strategy that does not reflect the true nature of the apps in the dataset. On the other hand, developers of inadequate detection methods might get a false sense of confidence in the detection capabilities of their detection methods because they perform well, albeit using an inaccurate labeling strategy [15], [16].

Until a more stable alternative to VirusTotal is introduced, the research community will continue to use VirusTotal to label apps using subjective thresholds. So, the overarching objective of this paper is to provide the research community with actionable insights about VirusTotal’s dynamicity, its limitations, and how to optimally interpret its scan reports to label apps accurately using threshold-based labeling strategies. To achieve this objective, we focus on Android apps as a case study and utilize four datasets of 53K Android malicious and benign apps. Furthermore, based on the identified limitations of VirusTotal, we provide a blueprint for a platform that mitigates the limitations...
of VirusTotal and provides the research community with a more stable, reliable alternative to VirusTotal.

The contributions of this paper, therefore, are:

- The dynamicity of VirusTotal is common knowledge within the research community and has been mentioned in previous research without, to the best of our knowledge, being adequately discussed. In this paper, we reveal the details of such dynamicity and how it manifests, how it projects an improper image of the performance of otherwise competent scanners, and how it undermines the performance of threshold-based labeling strategies over time (Section III-B).
- We provide the research community with actionable insights about how to use threshold-based labeling strategies to label Android apps in a manner that copes with VirusTotal’s dynamicity and limitations (Section III-C). We demonstrate that the optimal thresholds that yield the best labeling accuracies change over time and, hence, advise researchers to find the current optimal threshold(s) to use prior to labeling apps in datasets they use to train and evaluate malware detection methods.
- There are voices within the research community that call for the replacement of VirusTotal. However, without a clear enumeration of the shortcomings of VirusTotal, we risk implementing alternative labeling platforms that suffer from the same shortcomings of VirusTotal. We identified four limitations of VirusTotal that undermine its reliability and usefulness. Those limitations are (a) frequent inclusion and exclusion of scanners in the scan reports of apps, (b) using inadequate versions of scanners that are designed to detect malicious apps for other platforms, (c) refraining from frequently and automatically reanalyzing and re-scanning apps, and (d) denying access to the history of scan reports.
- Based on the identified limitations, we provide the community in Section IV with a blueprint of how to build alternatives to VirusTotal that mitigate the platform’s limitations.

II. PRELIMINARIES

To motivate the need for our paper and its line of research, in this section, we give an example of how the dynamicity of VirusTotal impacts the labeling accuracy of threshold-based labeling strategies that are commonly used within the research community. This example also demonstrates the impact of inaccurate labeling on the reliability of malware detection methods and their results. Based on this example, we postulate research questions meant to reveal insights about detection methods and their results. Based on this example, we give an example of how the dynamicity of VirusTotal impacts the labeling accuracy of threshold-based labeling strategies.

A. Motivating Example

In this example we focus on ML-based detection methods given their popularity within the academic community [8], [10], [15], [17], [18]. Researchers devise new techniques to extract features from Android apps and use those features to train ML models. The trained models are evaluated by assessing their abilities to recognize the malignancy of apps not used during the training process (i.e., out-of-sample apps), by deeming them as malicious or benign. This process requires datasets of Android Android Package (APK) archives that researchers often acquire from online repositories, such as Androzoo [19] or VirusTotal itself. To simulate this process, we downloaded a random collection of 6,172 apps developed in between 2018 and 2019 from Androzoo. We refer to this dataset as Androzoo throughout this paper.

The acquired APK archives and their corresponding apps need to be labeled either as malicious and benign or in terms of the malware families and types they belong to [2], [9]. Since manually analyzing thousands of apps is infeasible, researchers usually download the scan reports of apps in their training datasets from VirusTotal and label them according to some labeling strategy they deem accurate. The features extracted from the downloaded apps are used alongside their labels to train ML models. As an example of an ML-based Android malware detection method, we utilize a detection method that is renowned in the research community and has been used by different researchers as a benchmark [11], namely Drebin [20]. In this example, we use different threshold-based labeling strategies that have been utilized by researchers in the past, viz. we use thresholds that deem any given app as malicious if the number of scanners in its VirusTotal scan report deeming it malicious (i.e., positives) is at least one scanner [7], four scanners [3], [11], ten scanners [6], 50% of scanners (i.e., positives total ≥ 50%) [9], and the strategy adopted by Arp et al. in [20]. We refer to those strategies as vt≥1, vt≥4, vt≥10, vt≥50%, and drebin, respectively.

To test the ability of the trained Drebin classifiers to classify out-of-sample apps accurately, we use two small datasets that we refer to as Hand-Labeled and Hand-Labeled 2019. Both datasets comprise 100 Android apps that were downloaded from Androzoo and manually analyzed and labeled, to acquire reliable ground truth. The primary difference between both datasets is that apps in the latter were developed in 2019. Furthermore, we ensured that apps in both datasets do not overlap with apps in the Androzoo dataset.

In Figure 1 we plot the classification accuracy of the Drebin classifiers whose feature vectors were labeled using different threshold-based labeling strategies over a period of four months. Each point on the X-axis refers to a point in time in which we re-scanned all apps in the Androzoo, Hand-Labeled, and Hand-Labeled 2019 datasets on VirusTotal, downloaded their up-to-date scan reports, re-trained the Drebin classifiers using all the different labeling strategies, and re-tested the trained classifiers. We use the MCC score [21] to

\[ \text{MCC} = \frac{TP 	imes TN - FP 	imes FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \]

An app is deemed as malicious if at least two out of the following ten VirusTotal scanners label it as such: AVG, Avira (formerly AntiVir), BitDefender, ClamAV, ESET-NO32, F-Secure, Kaspersky, McAfee, Panda, and Sophos.

2http://tiny.cc/95bhaz

3http://tiny.cc/a7bhaz
represent the classification accuracy of the Drebin classifiers instead of conventional metrics, such as accuracy \cite{22}, that are unable to capture or penalize bias towards certain classes in imbalanced datasets. The MCC values range from -1 (i.e., all apps were misclassified) to 1 (i.e., perfect classification), with the value of 0 indicating a classification ability similar to random classification.

We are not concerned with the absolute performance of the Drebin classifiers. With this example, we wish to demonstrate two issues. Firstly, despite all being utilized within previous research efforts, it appears that some labeling strategies (e.g., vt ≥ 4), contribute to training Drebin classifiers that generalize better to out-of-sample Android apps than other strategies. That is using the exact same feature set and ML algorithm, different labeling strategies significantly alters the performance of the same detection method, which leads to two different answers to the question: Is the Drebin methods a reliable Android malware detection method? A researcher that opts to use the vt ≥ 50% labeling strategy will deem the Drebin method as unreliable and dismiss it, whereas one that uses the vt ≥ 4 strategy might deem it as potentially reliable and continues to refine it. In general, having multiple perspectives on the reliability of a detection method might either force researchers to dismiss promising methods that underperform during the evaluation, or adopt ones that are mediocre yet perform well during the evaluation phase. Secondly, the MCC scores of the Drebin classifiers appear to fluctuate from one scan date to another, although they are merely two weeks apart. So, depending on the scan date of the VirusTotal scan reports used to label apps in the training and test datasets, researchers might get different classification accuracies from their detection methods. For example, during the period between September 13th, 2019, and October 11th, 2019, using the labeling strategy vt ≥ 2 led to training Drebin classifiers that performed better than other labeling strategies on the Hand-Labeled dataset.

B. Research Questions

In the previous example, we learned that some threshold-based labeling strategies contribute to training ML models that can classify out-of-sample Android apps more accurately, despite the fact that all of the strategies that we used in the example were devised by researchers and utilized within the literature. Furthermore, we found that the labeling accuracy of most labeling strategies seems to fluctuate over time, due to some unknown aspect of VirusTotal’s dynamicity. This fluctuation means that threshold-based labeling strategies cannot be permanently and universally utilized to label Android apps and train ML-based detection methods. In this paper, as mentioned in \textsection 1, we aim to provide the research community with actionable insights about the impact of VirusTotal’s dynamicity on the labeling strategies they utilize to label Android apps used to train and evaluate their malware detection methods, and how this dynamicity might impact the reliability of their methods. We provide those insights by (1) identifying the aspects of VirusTotal’s dynamicity and how it manifests, (2) finding methods to workaround such dynamicity given the lack of better alternative platforms to VirusTotal and the infeasibility of manually-analyzing apps, (3) pinpointing the limitations of VirusTotal that cannot be mitigated, and finally (4) using the identified limitations to sketch a blueprint for a more reliable alternative platform. We attempt to address these issues by answering the following research questions:

\textbf{RQ1} How does VirusTotal’s dynamicity impact the performance of threshold-based labeling strategies?

\textbf{RQ2} Which labeling strategy should be used to label apps based on their VirusTotal scan reports accurately?

\textbf{RQ3} What are the limitations of VirusTotal and how can they be addressed?
III. THRESHOLD-BASED LABELING STRATEGIES

A. Accuracy of Threshold-Based Labeling Strategies

In this section, we discuss the ability of different threshold-based labeling strategies to accurately label apps in our test datasets, namely Hand-Labeled and Hand-Labeled 2019. Using the scan reports of apps in the aforementioned datasets downloaded at different points in time, we label the apps use different labeling strategies and compare them against the ground truth we generated by manually analyzing those apps. In addition to the labeling strategies we used in Section II-A we use all thresholds between one and ten scanners and the threshold of 25% of scanners.

In Figure 2 we plot the performance of each labeling strategy on the Hand-Labeled and Hand-Labeled 2019 datasets between July 6th, 2019 and November 8th, 2019 in terms of the MCC score. We attempted to gain access to the VirusTotal scan reports of apps in both datasets that pre-dates July. Unfortunately, access to such reports is not available under academic licenses and requires the purchase of costly commercial ones, which we consider the first limitation of VirusTotal.

One can notice that some threshold-based labeling strategies are more accurate than others over time. Starting with the performance of $vt \geq 1$, while the labeling strategy managed to achieve a decent MCC score on apps in the Hand-Labeled dataset, its performance noticeably decreased against apps in the newer Hand-Labeled 2019 dataset. Low threshold values, such as one or two scanners, might result in false positives, especially against new apps whose VirusTotal scan reports are not mature enough. In most cases, if an app has one or two VirusTotal scanners deeming it as malicious, it is a case of a subjective definition of malignancy. For example, we noticed that some scanners such as Tencent consistently label any apps (e.g., ed23237e34ff47580a99ac70f35e84b32c05ab1d), that utilize App Inventor as malicious apps belonging to the A.gray.inventor.a malware family.

As for ($vt \geq 50\%$), pushing the threshold that high might prevent recently-developed malicious apps and apps that belong to ambiguous malware types (e.g., Adware) from being labeled as malicious, resulting in a high number of false negatives. Similar to $vt \geq 1$, the older the app and its VirusTotal scan report, the better the performance of $vt \geq 50\%$ and the newer the app, the worse the performance, especially since the malicious apps were not deemed labeled by enough VirusTotal scanners to make the 50% mark required by the strategy to deem them as malicious successfully.

Another aspect of how the age of apps and, in turn, the maturity of their VirusTotal scan reports impacts the performance of different threshold-based labeling strategies can be seen in the proximity of different MCC lines in Figure 2. In particular, in Figure 2a, the lines of almost all threshold-based labeling strategies are close to one another and exhibit a relatively steady performance (i.e., the performance does not noticeably fluctuate). However, the MCC lines in Figure 2b are more dispersed across the figure and exhibit more fluctuations in performance. For example, on the Hand-Labeled 2019 dataset, the MCC score of drebin sharply decreased from a little above 0.3 on August 30th, 2019 to almost 0.0 on September 13th, 2019 only to sharply increase to around 0.45 two weeks later. The reason behind the proximity in the case of apps in the Hand-Labeled dataset is that their positives values are high enough to accommodate threshold values up to at least 15 scanners, which is represented by the $vt \geq 25\%$ labeling strategy. The novelty of malicious apps in the Hand-Labeled 2019 means that their positives values are much lower in comparison, which prevents thresholds higher than six scanners from achieving high MCC scores.

To corroborate this argument, we calculated the mean, median, and standard deviation of the positives attribute for apps in both datasets over the same period of time. The results in Figure 3 show that the positives attribute of malicious apps in the Hand-Labeled dataset stays within the range of 15 to 20. Even with a standard deviation of ten scanners, the range of scanners needed to label malicious apps in this dataset correctly remains between 7 and 20 scanners. As for the malicious apps in the Hand-Labeled 2019 dataset, their positives values have mean and median values around seven, ranging between 2.89 scanners and 10.91 scanners. The benign apps in both datasets have mean and median values that are almost zero with a negligible standard deviation of at most one scanner. So, any threshold values above three are guaranteed to avoid false positives resulting from deeming benign apps as malicious. The aforementioned values of the positives attribute allows the labeling strategies using thresholds between three and six VirusTotal scanners (i.e., $vt \geq 3, vt \geq 4, vt \geq 5,$ and $vt \geq 6$), to outperform all other threshold-based labeling strategies on both datasets in terms of the MCC.

What we can conclude from this measurement is that the thresholds that result in decent labeling accuracy differ from one dataset to another depending on one the age of apps in the dataset and the maturity of their VirusTotal scan reports. To generalize those thresholds to multiple datasets, one must possess a diverse dataset that includes Android apps of different ages, which is a concept we discuss in detail in Section III-C.

B. Sensitivity to VirusTotal’s Dynamicity

In the previous section, despite finding that a range of thresholds between three and six yields the best MCC scores on the Hand-Labeled and Hand-Labeled 2019 datasets, we...
noticed that the performance of labeling strategies utilizing these thresholds fluctuates at different points in time especially against the latter dataset. This fluctuation is largely attributed to VirusTotal’s dynamicity and the immaturity of the scan reports of recently-developed Android apps. In this section, we analyze (a) whether the reason behind such fluctuation is indeed the dynamicity of VirusTotal, and (b) the aspects of such dynamicity that cause this fluctuation. In this analysis, we focus on the performance of threshold-based labeling strategies on the Hand-Labeled 2019 dataset on two dates, namely September 27th, 2019 and November 8th, 2019.

We found that the labeling accuracy of threshold-based labeling strategies using thresholds between three and six on benign apps in the Hand-Labeled 2019 dataset did not change, according to their specificity scores \(\frac{TN}{N}\). Focusing on their performance on the malicious apps, we found that they respectively had recall scores \(\frac{TP}{F}\) of 0.7, 0.6, and 0.6 on November 8th, 2019 instead of 0.8, 0.8, 0.8, and 0.7 on September 27th, 2019. Since the total number of malicious apps in this dataset is ten, we can investigate the differences in \(\text{positives}\) values in their scan reports and the different VirusTotal scanners that deemed them malicious on both dates. In Table I we detail the change in the \(\text{positives}\) values in terms of the VirusTotal scanners that deemed the apps as malicious which (a) were added to the scan reports on November 8th, 2019, (b) were removed from the September 27th, 2019 scan reports, and (c) changed their verdicts between both dates.

Three apps out of ten did not encounter any change in their \(\text{positives}\) values. Nonetheless, one of these apps maintained the same value of \(\text{positives}\) because two VirusTotal scanners changed their verdicts, namely Zillya changed its verdict from benign to malicious and Trustlook changed its verdict vice versa. However, VirusTotal contributed to altering the performance of all labeling strategies by removing scanners that correctly deemed two apps malicious from their scan reports. In particular, the scanners ESET-NOD32, Fortinet, and Ikarus were removed from one app’s scan report, effectively reducing its \(\text{positives}\) value from five on September 27th, 2019 to only three on November 8th, 2019; this prevented the \(vt \geq 4\), \(vt \geq 5\), and \(vt \geq 6\) labeling strategies from correctly deeming the app as malicious. The same scanners along with Yandex were not included in the

![Fig. 2: The labeling accuracy of different threshold-based labeling strategies against apps in Hand-Labeled and Hand-Labeled 2019 datasets based on their VirusTotal scan reports downloaded between July 5th, 2019 and November 8th, 2019. Accuracy is calculated in terms of the MCC of each labeling strategy.](image)

![Fig. 3: The mean, standard deviation, and median of the \(\text{positives}\) attributed found in scan reports of apps in the Hand-Labeled and Hand-Labeled 2019 datasets between July 5th, 2019 and November 8th, 2019.](image)
TABLE I: The evolution of positives for apps in the Hand-Labeled 2019 dataset that we deemed malicious after manual analysis and a detailed view of the VirusTotal scanners that were added/removed or changed their verdicts between September 27th, 2019 and November 8th, 2019 and how that affected the performance of vt\(\geq 3\), vt\(\geq 4\), vt\(\geq 5\), and vt\(\geq 6\). The check mark (✓) depicts whether the threshold-based labeling strategy managed to detect the malicious app on November 8th, 2019.

| App's SHA1 Hash | positives (September 27th, 2019) | positives (November 8th, 2019) | Added Positives | Removed Positives | Flipped to Positive | Flipped to Negative | \(\frac{\text{Precision}}{\text{Recall}}\) | \(\frac{\text{Recall}}{\text{MCC}}\) | \(\frac{\text{MCC}}{\text{Test}}\) |
|------------------|----------------------------------|----------------------------------|-----------------|-------------------|--------------------|--------------------|-----------------|-----------------|-----------------|
| 906e6ac481fd497f152234f1cd5bec6d4050037 | 0 | 0 | – | – | – | – | 0.70 | 0.82 | \(\approx 0.76\) |

VirusTotal Limitation 2

VirusTotal changes the set of scanners it includes in the scan reports of apps over time by including and excluding the verdicts of scanners regardless of the quality of those verdicts.

During this analysis, we noticed that the VirusTotal version of some of the renowned scanners, such as BitDefender and Panda, fail to recognize the malignancy of any of the malicious apps in either dataset. Both of those scanners continue to be given good reviews by users on the Google Play marketplace and, more importantly, on platforms that assess the effectiveness of antiviral software such as AV-Test [24]. VirusTotal states that the versions of scanners it uses "may differ from commercial off-the-shelf products. The [antivirus software] company decides the particular settings with which the engine should run in VirusTotal" [5]. In fact, we found that the version used by VirusTotal's for BitDefender, for instance, is 7.2, whereas the versions available on Google Play have codes between 3.3 and 3.6. The 7.2 version of BitDefender corresponds to a free edition version developed for Windows-based malware that targets older versions of Windows, such as Windows XP [25] and, hence, is inadequate to use to detect Android malware. The positive reputation that BitDefender has in the market suggests that using its adequate version (i.e., the one that is designed to detect Android malware), would yield a detection performance better than the version on VirusTotal. To verify this hypothesis, we downloaded and installed the latest version of the BitDefender scanner from the Google Play marketplace, installed it on an Android Virtual Device (AVD) and used it to scan the malicious apps in both the Hand-Labeled and Hand-Labeled 2019 datasets. We also downloaded ten apps randomly sampled from the AMD [9] dataset to test BitDefender’s accuracy. Unlike the results obtained from VirusTotal that the scanner detected none of those malicious apps, we found that BitDefender detects 56.5% of the malicious apps in the Hand-Labeled dataset, 20% of those in the Hand-Labeled 2019 dataset, and 70% of those in the sampled AMD dataset. Figuring out the reason why antiviral software companies opt to provide VirusTotal with older, inadequate versions of their scanners is not in the scope of this paper and, in fact, impossible to answer on behalf of antiviral software companies. However, it leads us to identify the third limitation of VirusTotal:
C. Finding the Optimal Threshold

In the previous section, we found that VirusTotal changes the set and versions of scanners it includes in the scan reports of apps. This change impacts the long term labeling accuracy of threshold-based labeling strategies. For example, while the dynamicity of VirusTotal has caused the MCC score of vt≥4 to decrease against the Hand-Labeled 2019 dataset from 0.89 to 0.76 (i.e., a decrease of 14.61%), it did not have an impact on the MCC scores of vt≥2 yet caused the scores of vt≥1 to decrease. Effectively, the previously-discussed aspects of VirusTotal’s dynamicity cause threshold-based labeling strategies to trade places in terms of the most accurate ones. In other words, at any given moment in time, a (different) subset of threshold-based labeling strategies will depict the most accurate labeling strategies (i.e., optimal thresholds). So, before labeling apps in their training and evaluation datasets, researchers must identify the most accurate threshold(s) at that particular point in time. Given a reference set of Android apps whose ground truth is known, one straightforward method to identify the currently accurate thresholds is to download the apps’ latest VirusTotal scan reports, compare the labeling accuracy of all thresholds between one and 60 (i.e., average total number of scanners), and choose the thresholds that yield the best scores. In this section, we investigate the feasibility of this brute force approach to identifying the optimal thresholds of VirusTotal scanners at any point in time.

Algorithm 1 depicts a simple algorithm to find the current optimal threshold of VirusTotal scanners that yields the most accurate labels. To assess the quality of labels given by different threshold-based labeling strategies, this algorithm requires the presence of a dataset (A) of pre-labeled Android malicious and benign apps. As mentioned earlier in this paper, the most reliable ground truth (γ) can be generated using manual analysis and labeling of apps. Without such a reliable ground truth (γ) that acts as a reference to compare against, one has to choose a subjective threshold (σ) that one believes represents the nature of apps in (A) and use it as ground truth (γσ). If so, the only threshold that would generate labels mimicking (γσ) would be (σ) itself. Effectively, we end up with the same problem we are attempting to avoid, namely that of choosing subjective thresholds based on personal views. Relying on manual analysis already introduces infeasibility to the algorithm. However, assuming the existence of pre-labeled apps, another problem arises. As discussed earlier, the immaturity of newly-developed Android malware and the dynamicity of VirusTotal lowers the values of the positives attribute in the scan reports of those apps which, in turn, lowers the thresholds needed to label them accurately. Without access to newly-developed Android malware, researchers risk choosing thresholds based on the scan reports of old malicious apps, which are usually higher than the thresholds required to detect new malware. For example, in Figure 2 if a researcher only has access to the Hand-Labeled dataset, on October 11th, 2019, they might opt to use the drebin labeling strategy because it exhibits stable performance of high MCC scores. However, this labeling strategy will perform much worse on newer apps in the Hand-Labeled 2019 dataset (i.e., it does not generalize to newer malicious apps). Consequently, researchers adopting this brute force approach to finding the currently optimal thresholds need to continuously update their reference datasets with newly-developed and discovered Android (malicious) apps.

If the reference dataset (A) satisfies the previous condition, identifying the currently optimal threshold can be performed as follows. For each app in the dataset (α ∈ A), the latest scan report of (α) needs to be acquired. Firstly, the user has to issue a rescan request to VirusTotal, which takes around four minutes to complete (line 5) As discussed earlier, this request can be issued using the platform’s web interface or using the Application Programming Interface (API) interface. In general, under the academic license, a total of 20K requests can be issued per day. So, depending on the size of the reference dataset (A), the process of rescanning all apps might take several days or even months. Furthermore, we recently were forbidden from issuing this type of request using our academic license. As of the date of writing this paper, we are unaware of whether VirusTotal prevents academic licenses from issuing this type of requests, or whether we are encountering an individual technical difficulty. We consider the decision of VirusTotal not to automatically and regularly rescan apps

### Algorithm 1

**An algorithm to find the current optimal threshold of VirusTotal scanners to use in labeling Android apps.**

```
1: procedure FINDCURRENTOPTIMALTHRESHOLD(A, γ)
2:   tmpResults = {}
3:   for all α ∈ A do
4:     response = VirusTotal.rescanApp(α)
5:     if response == True then
6:       report = VirusTotal.downloadReport(α)
7:       if report != Null then
8:         positivesα = report["positives"]
9:         for all σ ∈ {1, 2, 3, ..., 60} do
10:          if positivesα ≥ σ then
11:            labelα = malicious
12:          else
13:            labelα = benign
14:          tmpResults[vt ≥ σ].append(labelα)
15:       end
16:     bestThreshold = ""
17:     bestScore = 0.0
18:     for all σ ∈ {1, 2, 3, ..., 60} do
19:       currentScore = calculateScore(tmpResults[vt ≥ σ], γ)
20:     if currentScore ≥ bestScore then
21:       bestScore = currentScore
22:       bestThreshold = vt ≥ σ
23:   return bestThreshold, bestScore
```
as another limitation of the platform:

| VirusTotal Limitation 4 |
|-------------------------|
| VirusTotal does not rescans the apps it possesses on a regular basis and delegates this task to manual requests issued by its users. One direct consequence of this decision is prolonging the process of acquiring up-to-date scan reports of apps. |

In line 7, after the rescan requests are completed, researchers need to download the up-to-date scan reports from VirusTotal. Similar to the rescan API requests, download requests are limited to 20K requests per day, which might add a few more days to the process. Between lines 8 and 23, the process becomes straightforward. Using thresholds ($\sigma$) between one and 60, the labels of apps in (A) are calculated and stored in a temporary structure under the key $\text{vt} \geq \sigma$ (line 15). The stored labels are then compared against the ground truth ($\gamma$), and a score is calculated, say MCC. The threshold-based strategy that yields the best score is returned to the user.

IV. AN ALTERNATIVE TO VirusTotal

In this section, we discuss how the limitations we discussed above can be addressed upon building alternative platforms. We do this by describing the architecture of a hypothetical new platform, called Eleda\(^8\) that is designed to mitigate VirusTotal’s limitations. An overview of Eleda’s modules and operations can be seen in Figure 4.

**Data Acquisition.** The first operation of Eleda is to acquire APK archives of Android malicious and benign apps to scan and analyze (step (1)). AndroZoo \([19]\) automates the process of crawling different app marketplaces and continuously downloads their APK archives. Access to such a platform is granted to researchers via an API key that can be used to download apps using cURL. Using this module, Eleda can frequently query AndroZoo for newly-crawled and downloaded apps, which is indicated using the looped arrow.

\(^8\)Eleda is one of the mirror twins in Sharon Shinn’s novel *The Truth-Teller’s Tale*, who is a truth-teller incapable of telling lies, earning her the society’s trustworthiness. With Eleda’s proposed design, we aspire to provide the research community with an alternative to VirusTotal that is more stable and reliable.

**Scanner Acquisition and Update.** This module is responsible for analyzing and scanning the acquired apps. In step (2), the module retrieves the names of antiviral scanners and queries app marketplaces, such as Google Play, for their latest versions. This list can be manually populated at first to include the list of VirusTotal scanners that are designed to detect Android malware and are available on Google Play. As of March 2020, 38 ($\approx$63\%) out of around 60 scanners on VirusTotal are available on Google Play. After downloading the latest version of each scanner in the list, Eleda updates an AVD that is used to scan APK archives (step (3)). The process of acquiring and updating new versions of antiviral scanners from Google Play—and possibly third-party Android app marketplaces—is meant to mitigate the third limitation of VirusTotal, namely using inadequate scanners and scanner versions not designed to scan Android apps. Moreover, using a pre-populated list of scanners is meant to keep the set of antiviral scanners used to scan APK archives constant (i.e., mitigating the second limitation).

**App Scanning.** To address the fourth limitation of VirusTotal that it only re-scans Android apps upon request, in step (4), Eleda’s App Scanning module retrieves the set of APK archives available in the platform’s app repository, scans them using the AVDs set up by the Scanner Acquisition and Update module, builds the latest scan reports of those apps, and stores them in another repository (e.g., in JavaScript Object Notation (JSON) format). In order to make the transition from VirusTotal to Eleda seamless, the scan reports can contain the same information contained in VirusTotal scan reports. For example, static information about the app components can also be extracted using analysis tools, such as Androguard \([26]\), and the API calls issued by the app during runtime can also be monitored and recorded \([27]\). The frequency of the re-scan operation can be set by the users of Eleda. Given that the platform is expected to store a large number of APK archives, it need not re-scan all apps at the same time. Instead, each app can be scanned every constant interval (e.g., two weeks), starting from its initial acquisition date.

**User Interaction.** The last operation of Eleda is user interaction. In step (6), the platform receives a query from a remote user in the format of a hash of an Android app’s APK or the archive itself. If the app is not already in the platform’s app repository, the App Scanning module can add the app’s APK archive to the repository. The APK archive is then scanned using the platform’s AVDs, and its scan report can be displayed to the user. Eleda can mimic the design of VirusTotal by offering users to interact with the platform using a web-based interface or using API-requests. However, to address VirusTotal’s first limitation, Eleda can provide the users with all scan reports of the queried app.

V. DISCUSSION

In this section, we discuss the insights we gained from our experiments, the limitations of our work, and how we (plan to) address them.
Aspects of VirusTotal’s dynamicity. In answering RQ1, we attempted to (a) reveal the aspects of VirusTotal’s dynamicity that are not clearly documented within the literature, and (b) study the impact of such dynamicity on the labeling performance of threshold-based labeling strategies. In Section III-A, we found that VirusTotal regularly manipulates the set of scanners it includes in the scan reports of apps by adding/removing scanners from such reports, including ones that correctly label the apps. This leads to changing the number of scanners that deem an app as malicious (i.e., positives), which is what threshold-based labeling strategies hinge on to discern an app’s malignancy. While this change has a negligible impact on the labels of benign apps, we found that malicious apps—especially those recently developed—suffer the most from this frequent manipulation of scanners. So, to answer RQ1, the regular manipulation of scan reports means that thresholds that proved to be accurate at one point in time cannot be used over an extended period.

Optimally using VirusTotal to label apps. Given the aforementioned dynamicity of VirusTotal, the concern of RQ2 is to find a workaround for the platform’s dynamicity to be able to label (Android) apps based on their scan reports. We found in Section III-A that, at any point in time, there are thresholds that provide the most accurate threshold-based labeling strategies. So, instead of relying on a fixed threshold to label apps (e.g., four scanners), for prolonged periods, researchers should identify the current optimal thresholds based on the latest scan reports of the apps they wish to label (i.e., after re-scanning the apps on VirusTotal). In Section III-C, we propose an algorithm to identify such thresholds with the help of a diverse, pre-labeled dataset of apps, and detail the possible challenges that might face researchers adopting this algorithm.

VirusTotal’s Limitations. The research community has long aspired to replace VirusTotal with a more reliable alternative. However, without pinpointing the shortcomings of VirusTotal, we risk constructing a platform that suffers from the same limitations. So, it is imperative to identify those limitations, which is the concern of RQ3. In this paper, we identified four limitations of VirusTotal that jeopardizes its usefulness. First, the platform does not grant access to the history of scans, effectively preventing researchers from studying the performance of scanners over extended periods of time. Second, the platform changes the set of scanners it uses to scan the same apps over time, which undermines the sustainability of threshold-based labeling strategies. Third, the platform uses scanners or versions of scanners that are not suitable to detect Android malware. Fourth, the platform does not automatically re-scan apps and relies on manually re-scanning apps either via its web-interface or via remote API requests. In Section IV, we give an example of how such limitations can be mitigated upon constructing an alternative platform.

A. Limitations and Threats to Validity

Internal validity is concerned with actions or factors that could influence our results. In this paper, we relied on ground truth for the Hand-Labeled and Hand-Labeled 2019 datasets that were generated after manually analyzing their apps. The intrinsic subjectivity of manually deeming apps as malicious can threaten the reliability of this ground truth. In the process of manually labeling apps in those two datasets, we complemented our process of static and dynamic analysis of apps with consulting the VirusTotal scan reports of those apps. We opted to ignore the verdicts of VirusTotal’s scanners vis-à-vis the verdicts of a few apps that we clearly observed their malicious behavior despite being labeled as benign by all scanners. In fact, it is not uncommon for antivirus scanners to be oblivious to the malignancy of malicious apps. For example, over the past three years, we tracked the verdicts given by VirusTotal scanners to a repackaged, malicious version of the K9 Mail open source app that has been developed by one of our students during a practical course. Despite being a malicious app of type Ransom, the scanners continued to unanimously deem the app as benign since February 8th, 2017, even after analyzing and re-scanning the app. Another example is an app that we repackaged three years ago; the app continued to be labeled as benign by all scanners until only K7GW recognized the app’s malignancy in July 2019 and labeled it as a Trojan.

External validity focuses on the possibility of generalizing our results. There are two main aspects of generalization in our case. Firstly, our results are confined to two small datasets of Android apps. We chose to limit the size of our datasets to ensure rigorous analysis of their codebases and runtime behaviors in order to generate as reliable ground truth as possible. To compensate for their small size, we randomly downloaded 100 apps from AndroZoo that should act as a random sample of Android apps without bias towards malignancy, category, or marketplace. The second aspect of generalization is the confinement to Android, which we adopted as a case study in this paper. So, are our results transferrable to other domains (e.g., Windows)? Concerning the first and fourth limitations of VirusTotal, we found that the platform implements the same policies regardless of the domain researchers wish to focus on. As for the second and third limitations, using ten randomly sampled Windows-based malicious apps that we acquired from VirusTotal (e.g., [[1]]), we found that VirusTotal uses the same versions of scanners for apps belonging to different domains. We also found that VirusTotal changes the set of scanners it includes in the apps’ scan reports at different scan dates. So, it seems that our insights might also generalize to domains beyond Android.

aa0d0f82ca84b8dfc4edca89a83f171cf675a9a
bb5d253c4a60261f73ae0485fa3ae6c54b2
bb5d253c4a60261f73ae0485fa3ae6c54b2
0b3beb6080bb63154ab7491046528be0054e10

9
**Reliability validity** is concerned with the possibility of replicating our findings. To replicate our results using the same datasets, we offer the scan reports of apps in the **Hand-Labeled** and **Hand-Labeled 2019** datasets, the Drebin feature vectors used in Section II-A, and the tools we used to carry out our measurements and experiments to the research community.

### VI. Related Work

We can categorize the insights and results of this paper into two categories. Firstly, we study VirusTotal and its dynamicity, detail how this dynamicity manifests itself, and demonstrate how it impacts threshold-based labeling strategies commonly used within the research community. Secondly, based on our findings from studying VirusTotal, we attempt to provide the research community with actionable insights about how to optimally utilize VirusTotal until a valid alternative is implemented. In this context, we surveyed the literature to find related work that fall under the categories of (a) studying VirusTotal, and (b) using it for accurate labeling.

#### Studying VirusTotal

The research community has studied different aspects of VirusTotal and its scanners. In [29], Mohaisen et al. inspected the relative performance of VirusTotal scanners on a small sample of manually-inspected and labeled Windows executables. The authors introduced four criteria, called correctness, completeness, coverage, and consistency, to assess the labeling capabilities of VirusTotal scanners and demonstrated the danger of relying on VirusTotal scanners that do not meet such criteria. The main objective of this study is, therefore, to shed light on the inconsistencies among VirusTotal scanners on a small dataset. In [13], Mohaisen and Alrawi built on their previous study and attempted to assess the detection rate, the correctness of reported labels, and the consistency of detection of VirusTotal scanners according to the aforementioned four criteria. They showed that in order to obtain complete and correct (i.e., in comparison to ground truth) labels from VirusTotal, one needs to utilize multiple independent scanners instead of hinging on one or a few of them. Similarly, within the domain of Android malware, Hurier et al. studied the scan reports of VirusTotal scanners to identify the lack of consistency in labels assigned to the same app by different scanners and proposed metrics to quantitatively describe such inconsistencies [2]. More recently, Peng et al. [12] showed that VirusTotal scanners exhibit similar inconsistencies upon deeming Uniform Resource Locator (URL) as malicious and benign. The authors also showed that some VirusTotal scanners are more correct than others, which requires a strategy to label such URLs that does not treat all scanners equally. While these studies revealed inconsistencies in the verdicts given by VirusTotal, they did not delve into the possible reasons behind such inconsistencies (i.e., whether they are indeed due to the scanners’ incompetences or due to VirusTotal’s dynamicity). In this paper, we build on the insights in [2], [13], [29] to highlight the aspects of VirusTotal’s dynamicity that impact the verdicts given by scanners and how this impacts the performance of threshold-based labeling strategies and, in turn, the reliability of malware detection methods built on top of their labels.

#### Accurate Labeling Strategies

Aware of their sensitivity to VirusTotal’s dynamicity, researchers have attempted to replace threshold-based labeling strategies with more sophisticated labeling strategies, primarily based on ML. In [4], Kantchelian et al. used the VirusTotal scan reports of around 280K binaries to build two ML-based techniques to aggregate the results of multiple scanners into a single ground-truth label for every binary. In the first technique, Kantchelian et al. assume that the ground truth of an app (i.e., malicious or benign), is unknown or hidden, making the problem of estimating this ground truth is that of unsupervised learning. Furthermore, they assumed that the verdicts of more consistent, less erratic scanners are more likely to be correlated with the correct, hidden ground truth than more erratic scanners. Thus, more consistent scanners should have larger weights associated with their verdicts. To estimate those weights and, hence, devise an unsupervised ML-based labeling strategy, the authors used an Expectation Maximization (EM) algorithm based on a Bayesian model to estimate those models. The second technique devised by Kantchelian et al. is a supervised one based on regularized logistic regression. However, the authors did not describe the nature of the features they use to train such an algorithm. To devise an automated method to label apps based on different verdicts given by antiviral scanners, Sachdeva et al. [30] performed measurements to determine the most correct VirusTotal scanners using scan reports of a total of 5K malicious and benign apps. Using this information, they assign a weight to each scanner that they use to calculate a malignancy score for apps based on their VirusTotal scan reports. Depending on manually-defined thresholds, the authors use this score to assign a confidence level of Safe, Suspicious, or Highly Suspicious to test apps.

The works in [4] and [30] seem to dismiss threshold-based labeling strategies and go for sophisticated labeling methods that may be difficult to comprehend and utilize. In our paper, we studied the reasons behind the fluctuating performance of this type of labeling strategies and found that, despite their simplicity, they can be effectively utilized to accurately label Android apps based on their VirusTotal scan reports. Furthermore, we provide the research community with an algorithm to workaround VirusTotal’s dynamicity and yield the current optimal thresholds that would yield accurate labels.

### VII. Conclusion

The infeasibility of manually analyzing and labeling Android apps and the lack of more stable alternatives forces the research community to use the online platform, VirusTotal, to label apps they use in training and evaluating malware detection methods. Although VirusTotal is known to be dynamic and volatile, previous research neither delved into the aspects of the platform’s dynamicity, how it
impacts the threshold-based labeling process, and how to work around it nor implemented alternatives to VirusTotal.

With a focus on Android apps, in this paper, we studied VirusTotal to identify how its alleged dynamicity manifests itself and how it impacts threshold-based labeling strategies that are widely-adopted within the research community. Using our findings, we provided a method that bypasses the aspects of VirusTotal’s dynamicity to find the thresholds of scanners that would yield the best labeling accuracies and more effective and reliable malware detection methods. Despite this method, we realize that VirusTotal’s limitations ultimately calls for the replacement of the online platform with more reliable alternatives. In order not to implement alternative platforms that suffer from the same shortcomings of VirusTotal, we discussed the four limitations of VirusTotal that we identified through our measurements and analysis and how to avoid them in building alternative platforms.

REFERENCES

[1] M. Hurier, G. Suarez-Tangil, S. K. Dash, T. F. Bissyandé, Y. L. Traon, J. Klein, and L. Cavallaro, “Euphony: Harmonious unification of cacophonous anti-virus vendor labels for android malware,” in Proceedings of the 14th International Conference on Mining Software Repositories. IEEE Press, 2017, pp. 425–435.

[2] M. Hurier, K. Allix, T. F. Bissyandé, J. Klein, and Y. Le Traon, “On the lack of consensus in anti-virus decisions: Metrics and insights on building ground truths of android malware,” in International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment. Springer, 2016, pp. 142–162.

[3] B. Miller, A. Kantchelian, M. C. Tschantz, S. Afroz, R. Bachwani, R. Faizullahlooy, L. Huang, V. Shankar, T. Wu, G. Yiu et al., “Reviewer integration and performance measurement for malware detection,” in International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment. Springer, 2016, pp. 122–141.

[4] A. Kantchelian, M. C. Tschantz, S. Afroz, B. Miller, V. Shankar, R. Bachwani, A. D. Joseph, and J. D. Tygar, “Better malware ground truth: Techniques for weighting anti-virus vendor labels,” in Proceedings of the 8th ACM Workshop on Artificial Intelligence and Security. ACM, 2015, pp. 45–56.

[5] VirusTotal. Virustotal. [Online]. Available: http://tiny.cc/jxj9v6 (2019)

[6] H. Wang, Z. Liu, J. Liang, N. Vallina-Rodriguez, Y. Guo, L. Li, J. Tapiador, J. Cao, and G. Xu, “Beyond good play: A large-scale comparative study of chinese android app markets,” in Proceedings of the Internet Measurement Conference 2018. ACM, 2018, pp. 293–307.

[7] L. Li, D. Li, T. F. Bissyandé, J. Klein, Y. Le Traon, D. Lo, and L. Cavallaro, “Understanding android app piggybacking: A systematic study of malicious code grafting,” IEEE Transactions on Information Forensics and Security, vol. 12, no. 6, 2017, pp. 1269–1284.

[8] G. Suarez-Tangil, S. K. Dash, M. Ahmadi, J. Kinder, G. Giacinto, and L. Cavallaro, “Droidiesieve: Fast and accurate classification of obfuscated android malware,” in Proceedings of the Seventh ACM on Conference on Data and Application Security and Privacy. ACM, 2017, pp. 309–320.

[9] F. Wei, Y. Li, S. Roy, X. Ou, and W. Zhou, “Deep ground truth analysis of current android malware,” in International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment. Springer, 2017, pp. 252–276.

[10] W. Yang, D. Kong, T. Xie, and C. A. Gunter, “Malware detection in adversarial settings: Exploiting feature evolutions and confusions in android apps,” in Proceedings of the 33rd Annual Computer Security Applications Conference. ACM, 2017, pp. 288–302.

[11] R. J. J. K. Feargus Pendlebury, Fabio Pierazzi and L. Cavallaro, “Tesseract: Eliminating experimental bias in malware classification across space and time,” in 28th USENIX Security Symposium. Santa Clara, CA: USENIX Association, 2019.

[12] P. Peng, L. Yang, L. Song, and G. Wang, “Opening the blackbox of virustotal: Analyzing online phishing scan engines,” in Proceedings of the Internet Measurement Conference. ACM, 2019, pp. 478–485.

[13] A. Mohaisen and O. Alrawi, “As-meter: An evaluation of antivirus scans and labels,” in International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment. Springer, 2014, pp. 112–131.

[14] A. Salem and A. Pretschner, “Poking the bear: Lessons learned from probing three android malware datasets,” in Proceedings of the 1st International Workshop on Advances in Mobile App Analysis. ACM, 2018, pp. 19–24.

[15] F. Pendlebury, F. Pierazzi, R. Jordaney, J. Kinder, and L. Cavallaro, “Enabling fair ml evaluations for security,” in Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security. ACM, 2018, pp. 2264–2266.

[16] H. Sanders and J. Saxe, “Garbage in, garbage out: how purportedly great ml models can be screwed up by bad data,” Technical report, 2017.

[17] K. Tam, A. Feizollah, N. B. Anuar, R. Salleh, and L. Cavallaro, “The evolution of android malware and android analysis techniques,” ACM Computing Surveys (CSUR), vol. 49, no. 4, 2017, p. 76.

[18] S. Arshad, M. A. Shah, A. Khan, and M. Ahmed, “Android malware detection & protection: a survey,” International Journal of Advanced Computer Science and Applications, vol. 7, 2016, pp. 463–475.

[19] K. Allix, T. F. Bissyandé, J. Klein, and Y. Le Traon, “Androzoos: Collecting millions of android apps for the research community,” in Mining Software Repositories (MSR), 2016 IEEE/ACM 13th Working Conference on. IEEE, 2016, pp. 468–471.

[20] D. Arp, M. Spreitzenbarth, M. Hubner, H. Gascon, and K. Rieck, “Drebin: Effective and explainable detection of android malware in your pocket.” in NDSS, 2014.

[21] sklearn. sklearn.metrics.matthews_corrcoef. [Online]. Available: http://tiny.cc/8gbb7y (2019)

[22] sklearn.metrics.matthews_corrcoef. [Online]. Available: http://tiny.cc/x65xiz (2019)

[23] M. A. Inventor. About us - explore mit app inventor. [Online]. Available: http://tiny.cc/9v99z9 (2019)

[24] A.-T. T. I. S. Institute. The best antivirus software for android. [Online]. Available: http://tiny.cc/1k66az (2019)

[25] P. Magazin. Bidefender free edition. [Online]. Available: http://tiny.cc/8vx9az (2008)

[26] androguard. androguard: Reverse engineering, malware and goodwill analysis of android applications ... and more (ninja !). [Online]. Available: https://goo.gl/6o936b (2018)

[27] J. N. Aleleidin Salem, Michael Hesse and A. Pretschner, “Towards empirically assessing behavior stimulation approaches for android malware,” in The 13th International Conference on Emerging Security Information, Systems and Technologies. International Academy, Research and Industry Association (IARIA), 2019.

[28] K-9 mail - advanced email for android. [Online]. Available: http://tiny.cc/1fbb7y (2019)

[29] A. Møhaisen, O. Alrawi, M. Larson, and D. McPherson, “Towards a methodical evaluation of antivirus scans and labels,” in International Workshop on Information Security Applications. Springer, 2013, pp. 231–241.

[30] S. Sachdeva, R. Jolivet, and W. Choensawat, “Android malware classification based on mobile security framework,” IAENG International Journal of Computer Science, vol. 45, no. 4, 2018.