

# Mistakes and Malware: A Large Scale Analysis of Benign and Malicious Android Apps

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**Abstract.** Android applications (apps) are not immune to the problems which also plague conventional software including security vulnerabilities, quality defects, permission misuse, and numerous other issues. Many developers even intentionally create vulnerable or malicious apps (malware) for often highly lucrative purposes. We need to better understand current trends in app quality and security order to create higher quality software, and more effectively battle malware. In order to gather this critical information, we collected and reverse engineered 70,785 Android apps from the Google Play store, along with 1,420 malicious apps from other sources. Each app was analyzed using several static analysis tools to record a variety of information about each of them including requested permissions, size (LOC), possible defects and permission misuse. Our findings conclude that: 1) app categories substantially differ in terms of permissions misuse; 2) that there is no significant correlation between an app's quality and security; 3) that malware typically requests more permissions and suffers in several quality related metrics in comparison to benign apps; 4) that malware and benign apps are annually growing both in terms of LOC and requested permissions. We also present an easy to use, robust website and dataset for others to use in their own research.

## 1 Introduction

Android is the world's most popular mobile operating system with over 1.8 million apps available from Google Play alone [2]. In order to create better apps, we need to better understand the current trends in development, and what some of the most profound issues from a security and quality perspective are. A few areas which should be examined include permissions misuse, security vulnerabilities, defects, and adherence to coding standards. In recent academic studies, static analysis tools have been used as one method of measuring the quality and security of mobile software [9, 14, 15, 28]. *An empirical analysis of a large body of malicious and benign Android applications over time can therefore provide insights into these apps, and their trends.*

The goal of this work is to better understand benign and malicious Android apps through the use of static analysis. We collected and reverse engineered 70,785 Android applications (APK files) in 41 different categories from Google Play, along with 1,420 malware samples from the Contagio Mobile Mini Dump [1] and the Malware Genome Project [31]. Each app was analyzed using five static analysis tools: Stowaway [9],

Androrisk<sup>1</sup>, CheckStyle<sup>2</sup>, Jlint<sup>3</sup>, and APKParser<sup>4</sup>. We examined application size, rate of potential defects, adherence to coding standards, rate of permissions misuse, and security risk level. We have also created a publicly available dataset and robust website which may be used by researchers, developers, students, and general Android users to better understand these apps. Our work is guided by the following research questions:

**RQ1:** *How do app categories compare in terms of several security metrics?* We found that app categories significantly differ in terms of size, and other permissions based security metrics. Some of the evaluated areas include number of requested permissions, and permission gap.

**RQ2:** *What are the most pervasive over-permissions?* We found that some of the most common over-permissions in Google Play apps include `GET_ACCOUNTS`, `CALL_PHONE`, `READ_EXTERNAL_STORAGE`, and `ACCESS_WIFI_STATE`.

**RQ3:** *Is there a correlation between quality & security?* We found only a weak association between the quality and security of apps in the several evaluated comparisons.

**RQ4:** *How do benign & malicious Android apps compare in terms of several security based metrics?* Our results indicate that malicious apps typically contain more over-permissions, and total requested permissions, while Google Play apps have a larger rate of under-permissions and Androrisk score.

**RQ5:** *How are apps changing over time?* We found that both malicious and benign apps are annually growing in terms of both LOC and requested permissions.

The rest of the paper is organized as follows: Section 2 discusses related works, while Section 3 describes the Android permissions model. Section 4 provides details of how we collected the apps and conducted our static analysis on them. Section 5 discusses the results of our research questions and analyzes our findings. Section 6 presents information regarding our public dataset. Section 7 discusses limitations of our research and future work to be conducted, while Section 8 concludes our study.

## 2 Related Work

There have been several studies which analyzed mobile apps on a large scale. Sarma *et al.* evaluated several large data sets, including one with 158,062 Android apps in order to gauge the risk of installing the app, with some of the results broken down by category. However, this work did not analyze the apps using the range of static analysis tools which we used. Viennot *et al.* developed a tool called ‘PlayDrone’ which they used to examine the source code of over 1,100,000 free Android apps. While the authors studied a very large number of apps, they largely only used existing information which could be gathered from Google Play and only examined features such as library usage and duplicated code. They did not study areas such as security risk levels, quality attributes, or the permission gap, which were a part of our analysis. Felt *et al.* described some common developer errors found using their tool Stowaway, including confusing permission names, the use of depreciated permissions, and errors due to copying and

<sup>1</sup> <https://github.com/androguard/androguard>

<sup>2</sup> <http://checkstyle.sourceforge.net/>

<sup>3</sup> <http://jlint.sourceforge.net/>

<sup>4</sup> <https://github.com/joakime/android-apk-parser>

pasting existing code [9]. In another work, Felt *et al.* very briefly described some inclinations they had for why developers gave too many permissions to applications, but this was largely based on assumptions and not necessarily data [10].

Grace *et al.* [12] conducted work on permissions probing, which is when a 3rd party component attempts to use a permission in the hope that the attached app has requested it from the user. If the attached app has requested a permission, then the component will also have access to that permission as well. This is often done to collect, and transmit potentially sensitive information which should not be normally available to the 3rd party component. They found that more than half of all ad libraries try to probe for open permissions. This could often be the cause of an under-permission in an app since the ad library will try to use a permission which the developer did not request.

Stevens *et al.* [25] analyzed 10,000 free Android apps and found a strong sub-linear relationship between the popularity of a permission and the frequency of its misuse. They found that developers were more likely to misuse a permission when they did not understand it, and that the popularity of a permission is strongly associated with its misuse. A powerful method of avoiding permission misuse is through developer education and community support. Krutz *et al.* [14] created a public dataset of over 1,100 Android apps from the F-Droid<sup>5</sup> repository. This research analyzed a much smaller number of apps than our study and focused more on the life cycle of the apps and how each iteration of the app evolved with every version control commit.

There are several other websites which gather metrics about Android apps. One of the most popular is AppAnnie<sup>6</sup> which collects Android apps and performs several types of analysis on each of them including downloads of the app over time and advertising analytics. However, no known services perform the same types of static analysis and comparisons on apps that we do.

A substantial amount of research has been conducted on Android malware ranging from various detection techniques [11, 20, 26] to reconstructing malware behavior [21]. Zhou *et al.* [32] analyzed a large number of malware samples and characterized them in several areas including installation techniques, activation methods, and nature of malicious payloads. Unfortunately, the newest of these malware samples was only from 2011, and did not compare malicious and benign apps against one another, or use the range of static analysis tools as in our work.

### 3 Android Permissions

Android apps operate under a permission-based system where an app requires specific permissions to carry out specific functionality. In Android versions <6.0, the user is asked to accept or reject the requested permissions when installing the app. Beginning with Android 6.0, users may be asked for these permissions during runtime. Unfortunately, developers often request more permissions than they actually need, as there is no built in verification system to ensure that they are only requesting the permissions their application actually uses [9]. In this study, we use the term *over-permission* to describe a permission setting that grants more than what a developer needs for the task.

<sup>5</sup> <https://f-droid.org/>

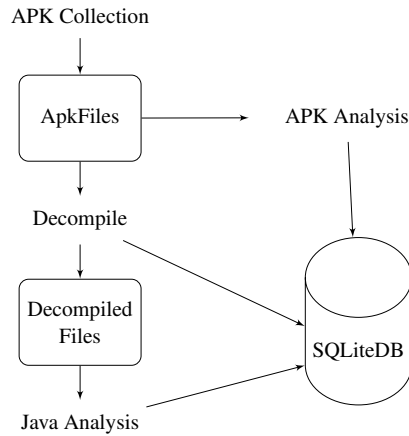
<sup>6</sup> <https://www.appannie.com>

Likewise, an *under-permission* is a setting for which the app could fail because it was not given the proper permissions. If not properly handled, an application, could throw a *SecurityException* when it attempts to perform an operation which it does not have permission to conduct.

Over-permissions are considered security risks since they do not adhere to the *principle of least privilege* and unnecessarily increase an app's attack surface. Under-permissions are considered quality risks, with a possible indication of permission probing. The primary difference between requested permissions and over-permissions is that requested permissions are merely those that the app asks to use, and does not take into consideration if the app actually needs them or not. While largely a quality concern, under-permissions can represent a possible security concern as well. One example of this is when permissions are, unknowingly to the developer, misused in a variety of ways by 3rd party libraries or even by associated ad networks which may collect and transmit potentially sensitive user data [12].

## 4 Collection & Static Analysis

We analyzed apps collected from Google Play and several malware sources using a variety of different tools. The results of this analysis have been stored in a publicly accessible database located on our project website<sup>7</sup>. An overview of the collection and analysis process is shown in Figure 1.



**Fig. 1.** APK Analysis Process

<sup>7</sup> <http://darwin.rit.edu>

#### 4.1 Step 1: Collect APK files

Android APK files were pulled from Google Play with a custom-built collector, which uses *Scrapy*<sup>8</sup> as a foundation. To limit the impact of seldom-downloaded applications, we divided our results into two groups: applications with at least 10,000 downloads, and those with less than 10,000 downloads. Of the 70,785 apps downloaded, 31,234 had at least 10,000 downloads. The creation date of the collected apps ranged from 2011, to late 2015. We assume that these apps from Google Play are not malicious, and will often refer to them as benign apps when comparing them with malware. We only used free apps in our analysis. Malware was collected from two well known sources, the Contagio Mobile Mini Dump [1] and the Malware Genome Project [31]. The Contagio Mobile Mini Dump has been collecting malware affecting many platforms, including Android, for several years. We used a total of 1,420 malware examples from 49 malware families in our analysis.

#### 4.2 Step 2. Execute static analysis tools

After reverse engineering the apps using a process established in previous works [15, 30], the next phase was to analyze them for a variety of security and quality metrics. In addition to using the tools below, we also recorded other metrics about each application including total lines of code, number of Java files, application version, target SDK, and minimum SDK.

**Stowaway:** Reports the under-permissions and over-permissions of an application. Similar to previous work [25], we made slight modifications to Stowaway to accommodate our process and stay current with updated Android permissions.

**Androrisk:** Determines the security risk level of an app by evaluating several criteria. The first is the presence of permissions which are deemed to be more dangerous. These include the ability to access the internet, manipulate SMS messages, or the rights to make a payment. The second is the presence of more dangerous sets of functionality in the app including a shared library, use of cryptographic functions, and the presence of the reflection API.

**CheckStyle:** Measures how well developers adhere to coding standards such as annotation usage, size violations, and empty block checks. We recorded the total number of violations of these standards. Default application settings for Android were used in our analysis. While adherence to coding standards may seem to be an overly fastidious thing to measure, compliance to coding standards in software development can enhance team communication, reduce program errors and improve code quality [16, 17].

**Jlint:** Discovers bugs, inconsistencies, and synchronization problems by conducting a data flow analysis and building lock graphs. We recorded the total number of discovered possible defects. This tool was selected over FindBugs since it was able to analyze the applications much faster, while still providing accurate results [22].

**APKParser:** Reads various information from Android APK files including the version, intents, and requested permissions.

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<sup>8</sup> <http://scrapy.org>

## 5 Evaluation

In the following sections, we describe our findings and answer our research questions.

### 5.1 RQ1: How do app categories compare in terms of several security metrics?

Android apps are separated into different groups known as categories, some of which include ‘Communication’, ‘Education’, ‘Lifestyle’, and ‘Tools’. These different app groups all have different focuses, likely different target audiences, and very often different developers. We sought to better understand how apps from different categories compare in terms of several metrics including use of permissions, rate of permissions misuse, and app size. Table 1 shows the top 10 collected categories, and an aggregate of all collected apps from Google Play (not just from the top categories) along with malicious apps.

**Table 1.** Comparison of App Groups

Group	LOC	Over-Permissions	Under-Permissions	Requested Permissions
Arcade	152,563	2.3	3.8	6.6
Books & Reference	123,600	2.6	2.7	5.4
Casual	150,396	2.2	4	6.5
Communication	166,083	5.2	3.6	14.6
Education	131,615	2.2	3.3	5.8
Entertainment	138,229	2.6	2.8	6.3
Lifestyle	166,114	2.9	3	8.2
Music & Audio	146,211	2.5	2.7	6.7
Personalization	113,539	3.8	2.5	8.3
Puzzle	142,998	2	3.8	5.6
Tools	106,131	4.1	2.9	8.4
Avg Google Play	158,689	3.0	3.3	7.8
Malware	32,373	6	1.9	12.4

We found a large variation in the rate of over-permissions for each category with ‘Casual’ and ‘Education’ apps having the fewest with 2.2 per app and ‘Communication’ having the largest with 5.2 for each app. ‘Personalization’ apps had the fewest number of under-permissions (2.5), while ‘Casual’ apps had the highest rate with 4 per app. The ‘Books & Reference’ category requested the fewest permissions per app, while ‘Communication’ apps requested the most permissions with an average of 14.6. ‘Lifestyle’ apps were narrowly the largest with an average 166,114 LOC per app, while ‘Tools’ apps were the smallest with 106,131 LOC.

**Analysis:** These findings are important for a variety of reasons. The results show a wide disparity among the various categories in terms of app size and security concerns. Developers may use this information to devote more resources to specific categories in

the identified permissions based issues, while for researchers it demonstrates the wide disparity in terms of size, requested permissions and the permission gap between various categories. Over-permissions are a possible security vulnerability, so app categories with more over-permissions should be given more focus from security researchers from both the perspective of why they occur, to what their negative implications may be for these categories. With the introduction of Android 6.0, future work should be done to examine the rate of change in over-permissions in the different categories with this new permissions model. Also, since over-permissions are often caused by lack of developer understanding with the abused permissions [25], these categories with the most over-permissions require the most developer education.

## 5.2 RQ2: What are the most pervasive over-permissions?

A basic security principle is the granting of the least amount of privileges to an application that it needs to properly function. Granting extra privileges creates unnecessary security vulnerabilities by allowing malware to abuse these unused permissions, even in benign apps while also needlessly increasing the app's attack surface [5]. Based on our analysis, Table 2 shows the top ten commonly occurring over-permissions in Google Play apps.

**Table 2.** Top Occurring Over-permissions in Google Play Apps

Permission	Rate %
GET_ACCOUNTS	10
READ_EXTERNAL_STORAGE	9
CALL_PHONE	7
ACCESS_WIFI_STATE	7
SYSTEM_ALERT_WINDOW	6
READ_PHONE_STATE	6
WRITE_EXTERNAL_STORAGE	4
WRITE_CONTACTS	4
GET_TASKS	4
CHANGE_NETWORK_STATE	4

**Analysis:** These top occurring over-permissions can be dangerous for a variety of reasons. For example, GET\_ACCOUNTS, permits access to the list of accounts in the accounts service, READ\_EXTERNAL\_STORAGE, allows the application to read from an external storage device and CALL\_PHONE, allows an app to start a phone call without the user confirming it through the dialer interface [3]. Research has shown that developers typically abuse permissions due to not properly understanding it, and that developer education and community support is paramount for eliminating permission abuse [25]. Based on our observations, we believe that these ten permissions require the most attention and education in order to reduce their rate of abuse.

All of the apps we analyzed were Android version  $<6.0$ , and therefore did not use the new Android permission structure which permits apps to ask for permissions at runtime. Future work could be conducted to examine the possible implications of this new permission structure on app over-permissions. From a technical perspective, will the new version of Android reduce the number of over-permissions, and will developers pay more or less attention now to possible app over-permissions?

### 5.3 RQ3: Is there a correlation between quality & security?

When developing software, there are several primary concerns of developers, two of which include the security and the quality of the application. We next sought to determine if there was a frequent correlation between the security of an application, and its quality. We measured quality by adherence to coding standards (Checkstyle) and detected possible bugs (Jlint), while security was measured by the Androrisk score and number of detected over-permissions. Both Jlint and Checkstyle values were normalized by the app's LOC to limit the effects of an app's size on the results. We used the Spearman rho and Kendall correlation metrics to determine if there was a correlation between quality and security. Using these correlation metrics, we evaluated the relationship strength of quality (Coding Standards Defects & Jlint Errors) and security (Androrisk & over-permissions). The results of this analysis are shown in Table 3.

**Table 3.** Correlation Metrics for Quality & Security

Area		Correlation	
Security	Quality	Spearman	Kendall
OPriv	Jlint	.18249	.13764
OPriv	CSDefect	.12584	.10128
Androrisk	CSDefect	.14305	.11481
Androrisk	Jlint	.38502	.29424

**Analysis:** Based on our analysis, we found only a weak association between the quality and security of applications in the several evaluated comparisons. This indicates that there is no significant correlation between the security and quality of an app. These findings are somewhat surprising since previous research has discussed the importance of adhering to coding standards as a way for developers to avoid mistakes and improve overall application security [8, 13]. Our findings demonstrate the need for further research and analysis in this area.

### 5.4 RQ4: How do benign & malicious Android apps compare in terms of several security based metrics?

In 2013 alone, there were at least 1,800 new mobile malware families, with over 96% of malware targeting Android [4]. In order to better understand Android malware, we compared the static analysis results from apps collected from the Google Play store



against 1,417 malware examples taken from the Contagio Mobile Mini Dump [1] and the Malware Genome Project [31]. We evaluated the malware samples against those collected from Google Play in a variety of areas including Andorisk score, under & over-permissions, and the requested app permissions. The results of this analysis are shown at the bottom of Table 1.

**Table 4.** MWU Results for Malicious & Benign Apps

Area	Greater In		P-value
	Malware	GP	
Over-permissions/App	✓		2.7002e-142
Under-permissions/App		✓	3.0972e-30
Permissions/App	✓		3.0872e-121
Andorisk		✓	2.1298e-32

In order to test the statistical significance of our results, we used Stowaway, Andorisk and APKParser to check if the values of permission and risk-based metrics are different in malicious and benign apps. Our null hypothesis is that there is no difference in the distribution of the security metrics between the malicious and benign apps. Our alternate hypothesis is that malicious and benign apps have different distributions for each of the security and quality related metrics. We use the one tailed Mann Whitney U (MWU) test for the hypothesis testing, since it is non-parametric and we can find out if the malicious apps indeed have higher or lower values for each of the evaluated metrics. In our analysis, we used an  $\alpha$ -value of .05 to determine if the null hypothesis can be rejected or not. As shown Table 4, the results of this analysis further validate our findings displayed in Table 1.

We next compared the requested permissions for all malicious and benign apps using APKparser. The primary difference between requested permissions and over-permissions is that requested permissions are merely those that the app asks to use, and does not take into consideration if the app actually needs them or not. We compared the top ten rates of requested permissions for the malicious apps against those recorded from Google Play. The results of this comparison are shown in Table 5. The Android Malware Repository<sup>9</sup> used a different malware oracle and found similar permissions results to what we discovered, which provides confidence to our findings. Unfortunately, they do not appear to have analyzed any apps since 2012.

**Analysis:** Our results in Table 4 indicate that malicious apps typically contain more over-permissions, and total permissions, while Google Play apps have a larger rate of under-permissions and Andorisk score. Under-permissions are a quality concern since an app will likely crash if it requests a permission which it was not granted. What is somewhat surprising is that malicious apps actually have fewer under-permissions per app compared to apps from Google Play. An explanation for this could merely be that the permissions in malicious apps are more often being used, unfortunately for disruptive activities. We also found that malicious apps request more permissions

<sup>9</sup> <https://sites.google.com/site/androidmalrepo/permission-stats>

**Table 5.** Permissions Usage

Permission	Malware %	G-Play %
INTERNET	98	94
READ_PHONE_STATE	93	45
ACCESS_NETWORK_STATE	81	84
WRITE_EXTERNAL_STORAGE	68	62
ACCESS_WIFI_STATE	61	36
READ_SMS	60	4
RECEIVE_BOOT_COMPLETED	56	1
WRITE_SMS	49	2
SEND_SMS	45	4
RECEIVE_SMS	42	5

than benign apps with an average of 12.4 permissions compared with 7.8 permissions for those collected Google Play. Malware is more likely to request these additional permissions to perform malicious activities [23].

The knowledge of what permissions have a higher prevalence in malware has several possible uses. Apps which request these permissions could be noted to have a higher probability that they are malicious. Since many benign apps have legitimate uses for these permissions, they cannot be the sole indicator, but can be an sign of a possibly malicious application. Understanding what permissions malware requests may be useful for understanding how current and future malware spreads and affects devices.

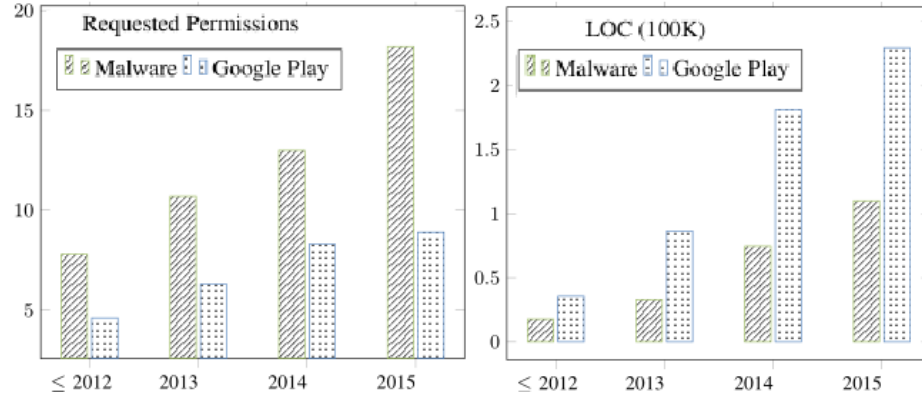
### 5.5 RQ5: How are apps changing over time?

We next sought to understand how apps are evolving on an annual basis. We first grouped the collected Google Play apps into the year they were created by using the *Date Published* value for the app from Google Play. We next found the average size (LOC), under & over-permissions, and requested permission for all apps in each age range. The results are shown in Table 6. We found that benign apps are growing in terms of size (LOC), and in the number of requested permissions. Unfortunately, the amount of under & over-permissions are growing as well.

**Table 6.** Evolution of Google Play Apps By Year

Year	Collected App Count	LOC	Opriv	UPriv	Requested Permissions
2011	2,898	25,549	2.1	2.3	3.9
2012	6,020	38,183	2.3	2.4	4.8
2013	17,466	83,445	2.3	2.9	5.9
2014	32,351	206,903	3.3	3.3	9.2
2015	5,382	248,802	3.6	5.3	10

We next compared how Android malware and Google Play apps are evolving on an annual basis in terms of size (LOC) and requested permissions. We separated the apps collected from the Contagio Mobile Mini Dump into those created in or before 2012, 2013, 2014, and 2015. The results of this analysis are shown in Figure 2.



**Fig. 2.** Evolution of Apps by Permissions & LOC

**Analysis:** We found that malicious apps are growing on an annual basis in both LOC and requested permissions. An interesting discovery is that although both are consistently growing, Google Play apps are larger in terms of LOC, but are smaller in the number of requested permissions. Our findings have several important implications for both general app development, and malware research. For developers of benign apps, indications are that apps will continue to grow in terms of LOC and in requested permissions. This is significant for several reasons. The first is that with more permissions, developers will need to be better educated about the permissions they use and diligent to ensure that they are properly using them. This will be further complicated by Google’s move to a new permission structure in Android 6.0 which will allow apps to request permissions at runtime instead of only upon installation of the app.

Benign Apps are becoming larger in terms of LOC, which likely means that teamwork will be increasingly more important since more developers will be needed to create and maintain the apps. With more developers being involved in the app, fundamental software engineering skills such as communication, documentation, diverse team roles, testing and adhering to coding standards will become increasingly important [19]. On average, malware is smaller in terms of LOC in comparison to benign apps, but is growing and requesting more permissions on an annual basis. There are a variety of current malware detection techniques including API tracing [29], behavioral based techniques [6, 24], permission based systems [27], and signature based approaches [11]. Larger software will make many of these processes more difficult and time consuming, leading for the need for different and more efficient processes.

We next chose to examine the usage rate in several of the permission requests which were growing at the most substantial rate between 2012 and 2015 in malware. The results of this are shown in Table 7. These results indicate that malware is using these

**Table 7.** Malware Permission Growth By Year

Permission	% Occuring			
	2012	2013	2014	2015
RECEIVE_BOOT_COMPLETED	55	52	71	86
READ_CONTACTS	36	55	41	68
SYSTEM_ALERT_WINDOW	1	16	27	61
WAKE_LOCK	34	19	41	54
GET_TASKS	17	25	43	39

permissions much more frequently now, than even a few years ago. For instance, the usage of `SYSTEM_ALERT_WINDOW` has gone from appearing in 1% of malware in 2012, to 61% in 2015. This permission allows an app to create new windows on the Android UI, and may often be used by malware to display a message in an attempt to convey misinformation to the user. Security researchers can analyze these trends to see how malware is evolving over time and the different types of attacks they are attempting to perform using these extra permissions. This information could prove to be invaluable for both detecting and countering the negative effects of malware.

## 6 Public Dataset & Website

**Dataset:** Our dataset is available from our publicly accessible GitHub repo<sup>10</sup>, which includes the scripts used for collecting apps and invoking the static analysis tools. The SQLite database with our complete results is updated on a regular basis from our collection and analysis software. The goal of this dataset is to allow future researchers to both learn from and expand upon our work. This dataset contains the information collected from Google Play, and the results of our static analysis tools. The raw data used in our analysis is available in three SQLite databases from our public GitHub repository, with one each for the malware data from Contagio and the Malware Genome projects, and a third for the collected information from Google Play. Unfortunately, the actual malicious APK files may only be obtained from the Contagio and Genome websites due to usage agreements.

**Website:** Our project website (<http://darwin.rit.edu>) contains information about our project, links to our GitHub repository, and a robust reporting tool which will allow users to create their own datasets from over 70,000 analyzed applications. New apps will be added on a regular basis as they are collected and analyzed from Google Play.

## 7 Limitations & Future Work

While static analysis tools have demonstrated their value in numerous previous works [9, 18], it is unreasonable to expect that any tool will ever be flawless and that no static analysis tool is perfect and generally inherently contains limitations [7]. Although Stow-away is a powerful static analysis tool which has been used in previous research [9, 18],

<sup>10</sup> <https://github.com/DroidDarwin>

it does suffer from drawbacks. Stowaway’s own authors state that the tool only achieves 85% code coverage [9], so the under & over-permissions reported by this tool are imperfect. Additionally, any reported vulnerabilities or defects by a static analysis tool should be deemed as *possible* vulnerabilities or defects, not necessarily actual ones. There is also the possibility of issues in the reverse engineering process of the apps, but we are confident in the process due to its demonstrated effectiveness and accuracy in existing research [14, 15], and due to our manual verification of some of the apps.

We only analyzed apps from Google Play and not other sources such as the Amazon Appstore<sup>11</sup> or F-Droid, which would have led to more varied application origins. However, we feel the diversity of our apps was already quite robust since we collected 70,785 applications from 41 categories. We also only examined free applications in our research due to cost constraints. Thus, the measurements comparison of apps is not representative of the entire Google Play market. Our results only apply as an evaluation of free apps, not paid apps.

We analyzed 1,420 malicious Android apps in a variety of areas. Although this represents a substantial number of malicious apps, it obviously represents only a minor portion of all Android malware. Attaining Android malware samples is a difficult task since they are often difficult to identify, and are often not widely publicized or shared for a variety of reasons, including the fear that this may only lead to them spreading.

While we have demonstrated profound results through the collection of over 70,000 Android apps, future work may be conducted in several key areas. An interesting topic would be to analyze how apps evolve over time through the examination of numerous released versions of the same app, and not through the aggregate values of apps as we have done. Android 6.0 received a massive permissions overhaul and work may be done to see how this new release affects how developers use permissions. Naturally more apps can always be examined, and with new apps being released on a daily basis the process is never ending.

## 8 Conclusion

In this paper, we described our collection and analysis process used to examine over 70,000 malicious and benign Android apps from several security and quality perspectives. Some of the primary discoveries include significant differences in permissions usage across app categories and malware, a comparison of the top over-permissions in benign and malicious apps, the discovery of only a weak correlation between an app’s quality and security, a comparison benign and malicious apps in terms of several security based metrics, and that both benign and malicious apps are growing on an annual basis. Our work has laid the foundation for important future research in analyzing both quality and security issues in Android apps, along with providing an invaluable dataset for other researchers to use in their own studies.

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<sup>11</sup> <http://www.amazon.com/mobile-apps/b?node=2350149011>

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