Android Device Risk Assessment Tool:

Using Common Permissions to Identify Applications Used in Intimate Partner Violence

Kathryn Reardon

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Abstract

Intimate partner violence affects millions of people in the United States every day. With the rising popularity of social media and smart phones, abusers have leveraged technology to control and harm their victims. One such method is through surveillance spyware applications downloaded on the victim’s phone. This project uses application permission analysis, application data gathering, and a risk assessment algorithm to detect spyware applications installed on a victim’s device. The risk assessment is based on the principle of guilt by association whereby any application that uses the same permissions used in a known spyware application is likely to be spyware itself. While analyzing the permissions of spyware and non-spyware applications, I found patterns in the permissions that did indicate spyware usage, particularly in the case of permissions designated by Android as “dangerous” or “signature.” These patterns were used for heuristic weights in the risk assessment algorithm, which correctly identifies spyware between 80 and 100% of the time while identifying non-spyware applications as only slightly likely to be spyware between 10 and 50%. These results imply that with further work, the AssessAppRisk tool could be used in conjunction with existing tools and security practices to better detect spyware applications used in intimate partner violence and help victims understand and respond to the threat.

1 Introduction

Intimate partner violence (IPV) is considered a public health concern in the United States by the CDC. This fact can be shocking for the uninformed whose idea of a public health concern is heart disease or a viral pandemic, but the four abusive behaviors of physical violence, sexual violence, stalking, and psychological aggression can lead to injury and death as assuredly as any disease [1]. The statistics differ slightly depending on the source, but approximately 1 in 4 women and 1 in 10 men have reported experiencing some form of IPV. One method that abusers use to control, manipulate, and harm their victims is surveillance spyware installed on their victim’s devices. This topic has only recently been researched, but it is a security issue of great importance because the abusers do not have to be technologically savvy to employ their attacks. Additionally, many victims are uninformed about the abuser’s tech capabilities and do not know how to deal with it even once the surveillance is suspected or discovered.

This project aims to continue the burgeoning research and security solutions begun by students and faculty primarily at Cornell Tech and New York University [2, 3, 4, 5, 6, 7]. The work done by Sam Havron et al. in creating a clinical computer security procedure and IPV Spyware Discovery tool (ISDi) is the major inspiration for the project [5]. Further work by Kevin Roundy et al. also provided ideas during the research phase [7]. I had several goals for the project, the first of which was to improve ISDi’s efficacy with a sort of “signature”-based spyware detection, as ISDi relies on blacklisting. The second goal was to obtain the permissions of known Android spyware applications and analyze them for commonalities in a guilt by association approach where any permission that was frequently used in spyware was more likely to indicate that an unknown application was also spyware. The third goal was to inspect victim devices without arousing suspicion of the attacker. The fourth goal was to programmatically assess the likelihood of an application being spyware with accuracy, as false negatives can be dangerous for the client (victim) while false positives obfuscate the danger. The final goal was to do everything in a way that is easy for a client to understand, leading to informed decision making regarding their device.

To accomplish these goals, I have designed three separate pieces, two support tools and a graphic user interface to display the findings. The first tool, AnalyzeAndroidPermissions, is Java code used to read the permissions from the AndroidManifest.xml files of a group of sample applications. It categorizes and sorts them according to Android protection level, number of times used, and whether they are present in spyware or popular, non-spyware applications. The second tool, Horoscope, is an Android application that on its face appears to be a simple daily horoscope. However, when the application is launched, it also gathers installation data of the applications on the device and saves them to a file to be used with the third tool. This final tool, AssessAppRisk, is a Java Swing application which lists every installed application with the data taken from the Horoscope application, and also displays a risk value decided by heuristic weights, a risk assessment, and descriptions of the permissions’ capabilities. AssessAppRisk includes a whitelist of 17 of the most popular applications on the Google Play Store, so the risk assessment ranges from whitelisted, very unlikely, unlikely, slightly likely, likely, and very likely to be spyware. If these tools were to be used in a real situation, it would follow the example of the field study introducing ISDi: a technician works with the client to run the tools on their device and go over the results with them.

Since IPV has evolved into a computer security problem, it is important to create a threat model that contextualizes the roles of attacker and victim and answers the questions of what the attacker knows, has access to, and can do. We must have a model both for the initial attack on the victim device and in the use of project’s tool. In the first case, these questions have been answered by the previous researchers [3]. As an aside, we use the terms attacker and victim here in the sense of an adversary model, though they align with the role of abuser and the target of abuse. “Victim” is not meant to be a slight or implication toward any person who is a target of or survivor of abuse. As for who the attacker and victim are, they tend to be intimate partners—spouses, boyfriends or girlfriends, exes, etc. There are other types of relationships, such as that of parent and child (where either party may play either role depending on age and circumstances) or even platonic friendships [8], but the relationships described in anecdotes by clients of IPV studies were only those of a romantic partner, ex-partner, and/or parent of their child(ren). The attacker and victim may live together, have lived together in the past, or never together at all. This is an important distinction for this threat model; while there are insider attacks wherein the attacker uses their organizational status to carry out an attack on that organization, it is easier to imagine a hacker thousands of miles away carrying out a remote attack. This is also not an attack on some faceless corporation, but one on a specific individual, and one whom the attacker knows very well.

What the attacker knows in this situation is both much and very little. On the social engineering side, the attacker may know many secrets that allow them to compromise the victim’s devices or accounts. Over the course of their relationship with the victim, they may come to know or compel the victim to tell them answers to security questions, like favorite color or birthday; they can watch or compel the victim to type passwords and PINs. On the other hand, it has been found that these attackers are not technically sophisticated, and Freed et al. go so far as to term them “UI-bound adversaries,” as they employ their attacks through a standard user interface with which they can be authenticated, or download the applications examined in this project to do their surveillance [3].

Another drastic difference from the typical adversary model is the attacker’s access to the victim device since most, if not all, assume the attacker’s target is someone else’s device [11]. One commonly reported scenario in cases of IPV is the device or its service is bought or paid for by the attacker. This gives the attacker control in innumerable ways, with such examples as the attacker confiscating or destroying the device, controlling associated digital accounts such as the mobile family plan or iCloud, and even manipulating relationships by giving a child a device with the intention to harass the adult target through it. Physical access to the device is key, especially since many of the spyware applications marketed towards these attackers require it.

Finally, what the attacker can do varies and has changed over time. In the past, an attacker could search for simple terms on the Google Play store like “track my girlfriend’s phone without them knowing” or “read SMS from another phone” and find many applications to choose from [4]. Following the warnings of security researchers, Google has removed many spyware applications from its store and filtered out IPV-related search terms, and it seems Android also has made changes to its APIs to make certain features of spyware applications unusable. Still, there were and are applications that can be found from a Google search, and it is simple to disable a device’s protections, e.g., Google’s Play Protect, to install such off-store applications. One particularly nasty application called Cerberus boasts of uninstall protection, remote wipe, lock with password, blocking the power menu, and those are only the capabilities that prevent the victim from reclaiming their privacy. Applications claim they can track the device’s location, take pictures, record video and audio, forward text messages, read deleted messages, and practically any other type of privacy breach one can imagine. This makes them powerful and scary tools indeed. On the other hand, some applications are not as they appear. Some applications tested for this project did not work past an introductory screen, and others triggered anti-virus software which flagged the application as a phishing attack. The Zscaler research term confirmed another case when analyzing the code of the keylogger application SPYMIE, finding a hard-coded email address with a timer to send surveilled data every minute [12]. Additionally, while some applications are free to download, most can only be used after purchasing a subscription plan.

I had to evaluate a threat model when designing my project as well. Many aspects from the previous threat model remain. I kept many design considerations from Sam Havron et al. when they were creating ISDi. First we had to consider if the attacker would know that a spyware scanning tool was being used on the victim device, and the following consideration was what they would do upon learning of the tool’s use or the victim’s participation in a security clinic. I will discuss the implications of these considerations on both projects in later sections.

Given that the main goal of my project is to identify Android spyware used in IPV, I would evaluate my project’s success by the accuracy with which it does so. I would like to see AssessAppRisk flag 75% of known spyware applications as some degree of likely to be spyware while flagging only 25% of non-spyware applications higher than slightly likely (false positives). I will show an evaluation in a following section.

2 Background and Related Work

The groundwork for this project was laid by an interdisciplinary group of researchers at Cornell Tech, Cornell University, and New York University in a series of studies beginning in 2017 and continuing today. The first study largely identifies IPV as a security issue through interviews with 40 IPV professionals and nine focus groups with 32 survivors of IPV. These interviews revealed how abusers use technology, what clients and professionals understand about said technology, how professionals advise clients about technology, and how the law understands technology used in IPV [2]. The next paper was another qualitative study with 89 participants to detail exactly how abusers use technology in IPV, which discovered technologically unsophisticated methods, such as social engineering and downloaded applications. Most importantly, they began to consider how to mitigate these types of attacks [3]. This led to an investigation of spyware used in intimate partner surveillance (IPS) which revealed both spyware and what they termed dual-use applications which have legitimate uses but can be exploited by abusers, such as Find My Friends or anti-theft applications. In this study, they also found that existing anti-virus and anti-spyware tools did not consistently catch dual-use applications [4].

The next study, mentioned earlier, produced a consultation service for IPV victims. In this service, a trained technologist worked with the client and an IPV professional to answer a standardized technology assessment questionnaire, create a diagram summarizing the client’s digital assets, manually check the client’s device for security configurations, and scan the device using ISDi [5]. ISDi is a Python application that does not require installation on the client’s device. This is to avoid notifying the abuser that the device is being investigated, since some spyware applications keep track of application installations or take screenshots while the device is being used. Instead, the technologist uses a USB connection to a laptop where ISDi is run in a browser. The researchers tested a USB connection on devices with six more capable spyware applications installed and were reasonably confident that the applications would not pick up on ISDi. ISDi’s major limitation is that its spyware detection is rather simple, using a blacklist of application names that were found using machine learning [4].

The next paper published in 2019 examined the findings of the clinical computer security approach and was more focused on sociology than computer science, reiterating some of the ideas from previous papers about the security needs and understandings of IPV victims [6]. The last study used the spyware applications unearthed by Chatterjee et al. as a seed set to discover “creepware,” applications similar to the surveillance-based spyware previously discussed but used more generally for interpersonal attacks. This paper is as important to this project as the paper concerning ISDi as it provided a method for spyware detection beyond blacklisting. The researchers developed an algorithm called CreepRank which uses the principle of guilt by association to identify applications as creepware [7].

3 Dataset Description

The first step in researching the permissions used in IPV-related applications was to obtain a representative sample of spyware applications, as well as “safe” popular applications for comparison. Most of the spyware applications (listed in Table II of Appendix section A) were referenced in previous work, while the popular applications (listed in Table III) were chosen either because they were suggested on the Google Play store, deemed the most downloaded, or reported on in the media recently. It is necessary to examine the permissions of both spyware and popular applications because there is bound to be overlap. For example, one of the features nearly every application used for IPS has is location tracking; it goes without saying that applications like Lyft and Google Maps also require location. Then there is the matter of applications which realistically should not need your location but ask for it anyway, like Facebook and TikTok. Therefore, to reach the goal of successfully identifying spyware applications while not falsely identifying popular applications, both sets of permissions needed to be analyzed.

I chose only applications available on Android devices for several reasons: it is easier to get Android application information, I was anticipating using Android Studio for part of the project, and I could readily install applications on a physical Android device via USB and Windows 10. When initially researching the possibilities for this project, I found lots of discussion about programmatically mining the data of installed applications on an Android device and little about iOS devices. What little I found implied that it was impossible. Since I had a little experience with Android Studio, I wanted to use it for the Horoscope application; additionally, although iOS applications can be written in Java, Java is better supported for Android applications, and I have most of my programming experience in that language. Lastly, when testing USB connections on my development PC, I successfully connected an Android phone in a plug-and-play manner but no success with an iPhone. I also felt that developing for iOS devices was better suited as a future work endeavor given the confines of the project timeline.

The program AnalyzeAndroidPermissions produced the data needed to develop the AssessAppRisk program. By design, every Android application must include an *AndroidManifest.xml* file. This file describes essential information about the application, including its package name and permissions that the application will request [15]. The package name is important because some spyware applications hide their nature by pretending to be system services named, for example, “Update manager” or “Sync Service.” A user granting permissions is what allows an application to access otherwise protected parts of the system, such as the camera, contacts, or external media. When I found a small sample of applications, I downloaded their APK files to my computer, APK being how Android packages applications. These files are not readable without reverse engineering, so I used the open-source Apktool to extract the AndroidManifest files and save them in a resources folder for AnalyzeAndroidPermissions [16]. I later used my own Horoscope application to get data from more applications that were installed on an emulated device, so the resource files are mixture of extracted XML and handwritten text files.

To begin, the program reads all of the files in the spyware or popular folder. It searches for the prefix *<uses-permission android:name=*, which is found before every permission, and adds it to a new line in a text file (*spywarePermissions.txt* or *popularPermissions.txt*). Repeated permissions between files are included because I want to see which permissions are requested most frequently. With all of the permissions consolidated, I first referenced the Android permissions documentation to determine if a permission was install-time (normal and signature) or runtime (dangerous) [17]. These protection levels indicate the scope of data accessed and actions performed by the application, so I hoped different levels would correlate with the permissions used in spyware or popular applications. Install-time permissions are automatically granted when the user installs the application, which means they are considered minimally risky for other applications, the system, or the user, so many permissions are considered normal. The system grants signature permissions only if the requesting application is signed with the same certificate as the application that declared the permission, and some signature permissions are not meant for third party use. Dangerous runtime permissions, however, must be explicitly granted by the user when first opening the application. They allow an application to access a higher level of private user data or control over the device. Unfortunately, Android’s documentation is not comprehensive. It was difficult to find information about permissions that were deprecated or removed in previous versions of the API, and these difficult-to-find permissions were categorized using other sources [18]. I labeled permissions that are not in the current API as “removed.” Permissions that seem to have similar purposes but which I could not find clear documentation for were classified as “other,” while some permissions are developer-specified, which I classified as “unknown” by default since I cannot predict the naming scheme or usage.

The next step was to place each permission in a hash map with its name as the key and the number of times it appeared in applications and its protection level as the value, then sort the map by protection level and count. This was done separately for the spyware and popular permissions. The final function of AnalyzeAndroidPermissions was to create lists of permissions unique to spyware, unique to popular, and shared between the two. These lists also included the permission’s protection level and the percent of applications which used it. I then copied this data to Microsoft Excel to do some additional sorting and see the data side by side, which helped me to better notice patterns or interesting outliers. This data is in section B of the Appendix.

4 Using Guilt by Association

As mentioned earlier, the CreepRank algorithm developed by Roundy et al. informed the design of AssessAppRisk’s risk assessment algorithm. CreepRank uses graph mining to compute scores using maximum a posteriori (MAP) estimation so that the higher the score, the more the application is associated with known creepware [7]. The algorithm takes a seed set of applications discovered by Chatterjee et al. as input and a dataset of installed applications and outputs the CreepRank for each application. AssessAppRisk’s algorithm is similar, taking the set of permissions discovered by AnalyzeAndroidPermissions and a set installed applications and outputs a rank for each application. The CreepRank algorithm is much more sophisticated, however, as the researchers used bipartite graphs to represents applications and devices as nodes and edges to represent installation. They then estimated the probability *p* that a particular application appears on a spyware-infected device using a binomial distribution and maximum likelihood estimation (MLE); they later incorporated MAP probability estimates when the MLE method proved to suffer from high false positive rates.

Although I would have preferred AssessAppRisk to have a mathematically-driven algorithm, I instead decided on a heuristic approach based on what I saw in the permission analysis. The first decision was that permissions of different protection levels would be more or less indicative of spyware use. This is obvious in the case of dangerous permissions; indeed, you can see in Table V and Table VI that the spyware applications use more unique dangerous permissions than the popular applications, and in Table IV that the spyware applications use more dangerous applications at a slightly higher frequency than the popular applications. I ignored the normal permissions in the assessment because of the high overlap between spyware and popular applications and the fact that they have little use for attackers.

I made two other decisions based on intuition. The first was noticing that some spyware applications used five unique removed permissions while some popular applications used only two. The difference is small, but I considered how the spyware applications are used in practice: an attacker installs the application on the victim’s device while they have physical access to it, and they may not have access to that device again. This could mean the spyware application, while running on the victim’s device, is never or rarely updated. It is also possible that the developers do not update the application frequently, unlike big-name development companies like Facebook and Twitter. Both of these theories could mean that spyware contains removed permissions at a higher rate. The second decision I made was about signature permissions. I noticed that a substantial number of signature permissions were used by spyware applications, with only three permissions shared between spyware and popular applications and popular applications using only two unique permissions. This imbalance combined with the fact that many signature applications are not to be used by third parties made signature permissions a red flag for spyware.

Based on these observations, I separated the permissions into nine groups and assigned a different weight.

|  |  |
| --- | --- |
| Category | Weight |
| Very Dangerous | 3 + frequency |
| Moderately Dangerous | 2 + frequency |
| Less Dangerous | 1 + frequency |
| Only Spyware Dangerous | 1.5 + frequency |
| Only Popular Dangerous | 1 |
| Shared Signature | 1 + frequency |
| Only Spyware Signature | 3 + frequency |
| Only Popular Signature | 1 |
| Removed | 0.3 |

Table I: Heuristic values for risk assessment.

The frequency value is the fraction of spyware applications that use a particular permission. Very Dangerous includes dangerous permissions that were included in a large majority (over 70%) of spyware applications, with the reasoning that if most spyware applications used them, they must be important to the basic surveillance functionality of the applications. Moderately Dangerous includes dangerous permissions used by fewer than 70% and more than 30% of the spyware applications, while Less Dangerous includes the remaining dangerous permissions. The rest of the categories are as they are named. When the risk value is calculated for an individual application, the total number of permissions is also accounted for. As you can imagine from such a simple weight scheme, an application with many weighted permissions will have a higher score than an application with only a few, and some applications in the sample only used around 10 total permissions. This does not exclude them from being spyware, so I added a modifier to the risk score. This modifier is the ratio of weighted permissions used in the application to the total number of permissions. If this ratio is greater than 0.4, then the risk score is increased by 1 + ratio, which helps to normalize the risk score.

5 The Risk Assessment Tool

As mentioned earlier, the Horoscope application and AssessAppRisk program are meant to be used to investigate the victim device with the help of a technician to run and interpret the programs. The technician would have Android Studio installed on a laptop which also has the project files for Horoscope and AssessAppRisk. The technician would put the victim device into debugging mode and connect it to the laptop via USB. The Horoscope application can then be installed on the device through Android Studio. After obtaining the application data from the device, the technician saves the output file to the resources folder in AssessAppRisk’s source folder. After running AssessAppRisk, the technician and client can view the results together with the technician providing explanation and advice. The tools are not meant to be used alone by victims of IPV for several reasons. The first is releasing either the Horoscope application or AssessAppRisk program to the public would make abusers equally aware of its use as survivors, and knowing that their attacks have been thwarted could cause them to change their methods or escalate their violent behavior. Another reason is that the clients surveyed in earlier studies were not typically knowledgeable about technology and may have trouble understanding the results. Finally, the way this project is designed prohibits the average non-programmer from using it; this is because the project is experimental, not because this is the best design.

The Horoscope application is an Android application with two parts: the front-facing daily horoscope and the backend application listing function. Horoscope uses Android’s *PackageManager* class to retrieve information about the application packages installed on the device including the application name, package name, installation date, last modified date, and permissions [9]. It also filters system applications and Horoscope itself since we are only interested in applications that were user-installed. Horoscope writes to file the application information, and the file is accessible in Android Studio by clicking *View > Tool Windows > Device File Explorer > data/data/net.sleepinginthevoid.horoscope > appdata.txt*. This file can then be saved to AssessAppRisk’s resources folder.

Horoscope is designed to meet the goal of inspecting the victim device without alerting the abuser. Unlike ISDi, this approach does involve installing an application, so I have taken some efforts to make up for this. I feel that if the application looks innocuous, it is less likely to arouse suspicion. If one were to search the Google Play or iTunes store, they would find many similarly titled and themed applications, and it is easy to imagine anyone downloading such an application for fun or out of boredom. The application also does what it says—it displays a daily horoscope for each astrological sign, which makes it more believably innocent. The text is hardcoded as Horoscope can be uninstalled as soon as it runs; it is not meant to stay on the device longer than necessary. On the backend, the package name keeps with the horoscope theme; unlike the spyware applications which fake their name and reveal their true nature with their package name, Horoscope maintains its disguise rather than being named something like “applist.” Finally, the actual application listing and risk assessment happens off of the victim device. This is so any spyware installed on the device does not report the assessment, and even if an attacker were to reverse engineer Horoscope’s code, they would not know the purpose of the application data being gathered.

The final piece of the project is the main feature, AssessAppRisk. The file *appdata.txt* is saved to the project files and run from the IDE, which creates a Java Swing application window with four panels (shown in section D, Figure III of the Appendix). The top left panel displays a list of installed applications and their package name. Clicking on an item changes the appearance of the other three panels [10]. The bottom left panel displays the risk score, first installation date, last modified date, and permissions. The bottom right panel again lists the permissions, but with details about their protection level and a brief description of their use (mostly taken from the Android documentation). The top right panel displays a qualitative risk assessment with a description of what that assessment could mean.

The program works by first creating a hash map to store the permission weights described in section 4. It also reads from the *whitelist.txt* file in the resources folder, which contains 19 very popular applications. This whitelist is intended to lower the number of false positives AssessAppRisk returns. When the user clicks on an application in the list, the program calculates the risk score and returns it along with the other information displayed in the bottom left panel. The risk score is calculated by comparing the application’s permissions to the weighted permissions in the permission weight map, adding the values for all weighted permissions, and adjusting the total score by the ratio discussed earlier.

The risk assessment follows another simple heuristic evaluation. Any whitelisted application is noted as such, while any other application may be rated as very unlikely, unlikely, slightly likely, likely, or very likely to be spyware, which is decided on the range in which the application’s risk score falls. The ranges are 0, greater than 0 and less than 20, greater than or equal to 20 and less than 50, greater than or equal to 50 and less than 70, and greater than 70. These ranges were determined by observing the risk scores from the sample applications and how they roughly broke down among the spyware and popular applications. Obviously the higher the risk score, the more likely the application is to be spyware. If an application were to use every single weight permission, its score would be 129.05; this is extremely unlikely since many of the permissions are used in only one or two applications, but it does show the relative severity of some applications over others.

6 Evaluating Efficacy

To evaluate AssessAppRisk’s efficacy, I downloaded 10 spyware and 10 non-spyware applications to an emulated device and ran Horoscope to get the application data. These 20 applications were not members of the sample applications used to create the guilt by association algorithm. The results are shown in Table VIII in the Appendix, and Table VII shows the assessment for the seed applications for reference. The identification rate for the spyware applications exceeded expectations with 100% being identified as slightly likely to be spyware or more. No applications were deemed unlikely to be spyware in this test, although four known spyware applications were flagged as unlikely out of the seed set. This is due to those applications using a relatively small number of weighted permissions, especially those that overlap with popular applications like *android.permission.ACCESS\_FINE\_LOCATION* and *android.permission.WRITE\_EXTERNAL\_STORAGE*. As for the non-spyware applications, the assessment met expectations for them as well. Again, those applications deemed slightly likely to be spyware use the most popular dangerous permissions to access location and camera, amongst others.

An assessment of an actual user’s device produced similar results on a larger scale. My husband has a habit of downloading lots of applications and never uninstalling them, so I gathered the application data from his Samsung phone (the results of which are shown in Table IX and Table X). Assuming none of the applications are known spyware, AssessAppRisk labeled 38.2% as unlikely or very unlikely to be spyware. The largest group of applications (47.2%) were labeled slightly likely. This number is higher than desired, but not unexpected given the limitations of the heuristic assessment.

7 Discussion

I believe that I accomplished all of the goals I established when beginning this project. The overarching goal was to improve on ISDi’s blacklisting assessment by judging applications based on their permissions. To reach this goal, I first needed to learn how to get the permissions of applications, which I accomplished in developing Horoscope. I then needed to analyze the data, which I accomplished in developing AnalyzeAndroidPermissions and finding patterns in popularity of usage and unique usage. I partially fulfilled my goal of using guilt by association to judge the applications using certain permissions as spyware. My third goal (to not alert an abuser to any anti-spyware inspection) would need to be tested on a real person, but I believe the precautions I took in concealing Horoscope’s purpose and doing the actual risk assessment on a separate device are enough to fool the average person while not leaving evidence for a spyware application to forward to the abuser later. I accomplished the fourth goal of programmatically assessing risk with AssessAppRisk, and by my efficacy evaluation, did so successfully with few false negatives or false positives. The final goal was for the entire process of inspecting the device to be easy for a client to understand; since I am not using the tool with an actual client, I cannot say for sure if they would understand it. I designed the risk assessment application window for understanding and included verbal descriptions of what the assessment and permissions mean, aimed to help a trained technician explain the results to a client. Overall, I am fairly satisfied with what I have developed.

I faced several limitations while creating this project. The first was difficulty finding spyware applications to study. Although there are supposedly thousands of them, the ones I found were inaccessible. Some were non-functional, not accepting user credentials or crashing on boot (the best and brightest do not make their careers off harming others, it seems). Many of the more sturdy-looking applications required payment before they could even be downloaded. I refused to pay for them because the prices were exorbitant, I did not want to reward developers who are actively and knowingly facilitating harm [4], and if I were foolish enough to use my own credit card, I would be at risk of having it stolen. I assume the researchers in New York have more resources to work around these problems.

Another limitation involved the ISDi tool. Originally, I wanted to work with the program and add functionality since ISDi’s code is available on GitHub [13]. However, it was designed for Linux and Mac computers, so I had a lot of trouble using workarounds for my Windows 10 computer. Even when I solved that problem, I could not use the tool because I lacked the blacklist (kept secret by the researchers so neither abusers nor developers learn of it and evolve their methods in response). I created my own placeholder blacklist just to get the program to run, but I found there must be some other files I was missing. Additionally, I could not get ISDi to recognize that a device was connected, a function that apparently works natively on Mac, but not Windows. These obstacles meant my project would have to be a spiritual successor rather than an increase in functionality.

A final limitation was in my implementation of the guilt by association algorithm. When I first read the paper discussing it, I thought it was a very smart and intuitive approach to take, and I wanted to mimic it. I spent time on other parts of the project, intending to come back to the algorithm later on. When I reread the paper, I realized the algorithm was much more complicated than I remembered, involving math concepts that I have little to no experience with. I knew it would take a lot of research for me to even understand their approach, let alone implement it with my project, and unfortunately time was now an issue. This led to my decision to take a heuristic approach, similar to ISDi. If I had more time, I would like to go back and learn about the probability estimation referenced by Roundy et al. and implement a data-driven algorithm, which I think would improve both my results and credibility of the tool.

My research and development has uncovered many implications. I believe it is possible for spyware, dual-use, and creepware applications to be detected with a more dynamic tool than a blacklist, and that is through permission analysis. My research also emphasizes something that I think should be common knowledge: popular applications can be predatory, and users should not blindly trust developers because they are well-known. When I was analyzing the permissions I had gathered, I worried that my project would be meaningless—that it would think everything was spyware because so many highly-downloaded applications used just as many dangerous permissions as known spyware did. I joked to friends and family that my program would not be entirely wrong to judge Facebook or Amazon as dangerous. That was why these applications had to be whitelisted. Uber has a risk score of 60.28, which would otherwise deem it likely to be spyware, and far too many non-spyware applications fall into the slightly likely range. This is of course a limitation of my analysis, but it is also the result of far too many applications requesting the user’s private data, like location, camera, audio, and storage. This is a takeaway not just for users, but for developers as well. It behooves application developers to ask themselves if they really need to ask for a particular permission for their application to function, or if they are overreaching and creating an avenue for abuse.

If this project were to be continued into the future, the first thing to do would be gather more sample applications for their permissions. This may reinforce the trends I noticed in my original sample, uncover new ones, or actually debunk them, but large sample sizes are important for accurate statistical analysis. The next task would be to refine the permission analysis with more research on the permissions that were not easily classified, which again could provide more insight into what differentiates the spyware applications for others. As I mentioned earlier, the algorithm used for the risk assessment could be improved to be more rigorous, providing better, more meaningful results. Once the tool was improved and tested, it could be integrated into already existing spyware detection like ISDi and used during security clinics to assist and advise clients.

8 Conclusion

In developing this project, I learned about a real security threat that affects many people in the United States and the current methods developed to prevent it. I also learned about Android applications and permissions, including how an application requests them, how they are categorized, and what kinds of actions they allow an application to take. I created my first Android application with interactive buttons, which also involved learning about *PackageManager* and saving files to the Android device. The research and work that I have done was in the name of an important societal cause, which is my major motivation in life. I am happy that the end result of my work pretty closely resembles how I had imagined it when first setting out and that it could be of actual use to someone who needs it.

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APPENDIX

1. *Sampled Applications*

|  |  |
| --- | --- |
| Application Name | Package Name |
| AllTracker Anti-Theft [14] | city.russ.alltrackercorp |
| Android Monitors [14] | com.ibm.fb |
| Cell Tracker Kids | us.cell.tracker.kids.locator |
| Cerberus [4] | com.lsdroid.cerberuss |
| Clone WhatsWeb Pro [7] | clone.whatsapp.pro |
| Control by SMS [7] | smartmob.com.controller |
| FamiSafe | com.wondershare.famisafe |
| Girlfriend Cell Tracker [7] | com.omrup.cell.tracker |
| Highster Mobile | com.highstermobile.main |
| Hoverwatch | com.android.core.mntg |
| iKeyMonitor [4] | com.sec.android.internet.im.service.im20190419 |
| IP Webcam [7] | com.pas.webcam |
| iSpyoo [14] | com.systemservice |
| Mrecorder [7] | com.mobileservice.sync |
| Screen Recorder [7] | net.example.hatiboy.gpcapture |
| SMS Forwarder [7] | cz.psencik.smsforwarder |
| Spy GPS SMS Call Controller [7] | com.dspark.phone.modefind |
| Spy To Mobile [7] | com.spy2mobile.light |
| TrackView [4] | com.trackview |
| Unseen – No Last Seen [7] | com.tda.unseen |

Table II: Set of IPS-related apps (more simply called spyware) used for permission analysis. Applications without a reference were found by searching online for IPS-related terms.

|  |  |
| --- | --- |
| Application Name | Package Name |
| Amazon | com.amazon.mShop.android.shopping |
| Among Us | com.innersloth.spacemafia |
| Cash App | com.squareup.cash |
| Facebook | com.facebook.katana |
| Gmail | com.google.android.gm |
| Google Maps | com.google.android.apps.maps |
| Instagram | com.instagram.android |
| Lyft | me.lyft.android |
| Facebook Messenger | com.facebook.orca |
| Netflix | com.netflix.mediaclient |
| Pokemon GO | com.nianticlabs.pokemongo |
| Seamless | com.seamlessweb.android.view |
| Snapchat | com.snapchat.android |
| Spotify | com.spotify.music |
| TikTok | com.zhiliaoapp.musically |
| Twitter | com.twitter.android |
| Uber | com.ubercab |
| Weather Channel | com.weather.Weather |
| WhatsApp | com.whatsapp |
| YouTube | com.google.android.youtube |

Table III: Set of non-IPS-related apps (more simply called popular) used for permission analysis.

1. *Sampled Permissions*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Shared | | Spyware | Popular | Combined |
| dangerous | android.permission.WRITE\_EXTERNAL\_STORAGE | 0.85 | 0.8 | 0.83 |
| dangerous | android.permission.ACCESS\_FINE\_LOCATION | 0.75 | 0.7 | 0.73 |
| dangerous | android.permission.READ\_EXTERNAL\_STORAGE | 0.75 | 0.7 | 0.73 |
| dangerous | android.permission.ACCESS\_COARSE\_LOCATION | 0.7 | 0.6 | 0.65 |
| dangerous | android.permission.READ\_CONTACTS | 0.7 | 0.65 | 0.68 |
| dangerous | android.permission.READ\_PHONE\_STATE | 0.7 | 0.65 | 0.68 |
| dangerous | android.permission.RECORD\_AUDIO | 0.55 | 0.5 | 0.53 |
| dangerous | android.permission.CAMERA | 0.5 | 0.7 | 0.6 |
| dangerous | android.permission.READ\_SMS | 0.5 | 0.1 | 0.3 |
| dangerous | android.permission.RECEIVE\_SMS | 0.5 | 0.15 | 0.33 |
| dangerous | android.permission.GET\_ACCOUNTS | 0.45 | 0.7 | 0.57 |
| dangerous | android.permission.CALL\_PHONE | 0.35 | 0.25 | 0.3 |
| dangerous | android.permission.ACCESS\_BACKGROUND\_LOCATION | 0.3 | 0.15 | 0.23 |
| dangerous | android.permission.ACCESS\_MEDIA\_LOCATION | 0.25 | 0.15 | 0.2 |
| dangerous | android.permission.READ\_CALENDAR | 0.25 | 0.2 | 0.23 |
| dangerous | android.permission.SEND\_SMS | 0.25 | 0.15 | 0.2 |
| dangerous | android.permission.RECEIVE\_MMS | 0.1 | 0.05 | 0.08 |
| dangerous | android.permission.WRITE\_CONTACTS | 0.05 | 0.2 | 0.13 |
| normal | android.permission.ACCESS\_NETWORK\_STATE | 0.95 | 1 | 0.98 |
| normal | android.permission.INTERNET | 0.95 | 1 | 0.98 |
| normal | android.permission.WAKE\_LOCK | 0.95 | 1 | 0.98 |
| normal | android.permission.ACCESS\_WIFI\_STATE | 0.75 | 0.8 | 0.78 |
| normal | android.permission.RECEIVE\_BOOT\_COMPLETED | 0.7 | 0.85 | 0.78 |
| normal | android.permission.CHANGE\_WIFI\_STATE | 0.45 | 0.4 | 0.43 |
| normal | android.permission.MODIFY\_AUDIO\_SETTINGS | 0.4 | 0.5 | 0.45 |
| normal | android.permission.VIBRATE | 0.35 | 0.85 | 0.6 |
| normal | android.permission.BLUETOOTH | 0.3 | 0.55 | 0.43 |
| normal | android.permission.FOREGROUND\_SERVICE | 0.25 | 0.7 | 0.48 |
| normal | android.permission.CHANGE\_NETWORK\_STATE | 0.2 | 0.25 | 0.23 |
| normal | android.permission.GET\_TASKS | 0.2 | 0.15 | 0.18 |
| normal | android.permission.BLUETOOTH\_ADMIN | 0.1 | 0.45 | 0.28 |
| normal | com.android.launcher.permission.INSTALL\_SHORTCUT | 0.1 | 0.35 | 0.23 |
| normal | com.android.launcher.permission.UNINSTALL\_SHORTCUT | 0.1 | 0.15 | 0.13 |
| normal | android.permission.BROADCAST\_STICKY | 0.05 | 0.15 | 0.1 |
| normal | android.permission.CHANGE\_WIFI\_MULTICAST\_STATE | 0.05 | 0.2 | 0.13 |
| normal | android.permission.DISABLE\_KEYGUARD | 0.05 | 0.05 | 0.05 |
| normal | android.permission.GET\_PACKAGE\_SIZE | 0.05 | 0.05 | 0.05 |
| normal | android.permission.NFC | 0.05 | 0.4 | 0.23 |
| normal | android.permission.READ\_SYNC\_SETTINGS | 0.05 | 0.25 | 0.15 |
| normal | android.permission.READ\_SYNC\_STATS | 0.05 | 0.1 | 0.08 |
|  | Shared | Spyware | Popular | Combined |
| normal | android.permission.USE\_BIOMETRIC | 0.05 | 0.35 | 0.2 |
| normal | android.permission.USE\_FINGERPRINT | 0.05 | 0.45 | 0.25 |
| normal | android.permission.USE\_FULL\_SCREEN\_INTENT | 0.05 | 0.2 | 0.13 |
| other | com.google.android.c2dm.permission.RECEIVE | 0.65 | 0.9 | 0.78 |
| other | com.google.android.finsky.permission.BIND\_GET\_INSTALL\_REFERRER\_SERVICE | 0.4 | 0.6 | 0.5 |
| other | com.android.vending.BILLING | 0.3 | 0.35 | 0.33 |
| other | com.google.android.gms.permission.ACTIVITY\_RECOGNITION | 0.1 | 0.2 | 0.15 |
| other | com.android.launcher.permission.READ\_SETTINGS | 0.05 | 0.1 | 0.08 |
| other | com.google.android.providers.gsf.permission.READ\_GSERVICES | 0.05 | 0.55 | 0.3 |
| removed | android.permission.READ\_PROFILE | 0.15 | 0.4 | 0.28 |
| removed | android.permission.USE\_CREDENTIALS | 0.15 | 0.5 | 0.33 |
| removed | android.permission.FLASHLIGHT | 0.1 | 0.15 | 0.13 |
| removed | android.permission.WRITE\_SMS | 0.1 | 0.05 | 0.08 |
| removed | android.permission.AUTHENTICATE\_ACCOUNTS | 0.05 | 0.35 | 0.2 |
| removed | android.permission.MANAGE\_ACCOUNTS | 0.05 | 0.45 | 0.25 |
| signature | android.permission.SYSTEM\_ALERT\_WINDOW | 0.45 | 0.25 | 0.35 |
| signature | android.permission.WRITE\_SETTINGS | 0.3 | 0.05 | 0.18 |
| signature | android.permission.REQUEST\_INSTALL\_PACKAGES | 0.1 | 0.1 | 0.1 |

Table IV: Shared permissions (unknown omitted) with fraction of apps that included them.

|  |  |  |
| --- | --- | --- |
| Spyware Only | | |
| dangerous | android.permission.READ\_CALL\_LOG | 0.5 |
| dangerous | android.permission.PROCESS\_OUTGOING\_CALLS | 0.45 |
| dangerous | android.permission.ACCESS\_SUPERUSER | 0.15 |
| dangerous | android.permission.READ\_PHONE\_NUMBERS | 0.1 |
| dangerous | android.permission.WRITE\_CALL\_LOG | 0.1 |
| dangerous | android.app.action.DEVICE\_ADMIN\_ENABLED | 0.05 |
| normal | android.permission.REQUEST\_IGNORE\_BATTERY\_OPTIMIZATIONS | 0.35 |
| normal | android.permission.REQUEST\_DELETE\_PACKAGES | 0.2 |
| normal | android.permission.ACCESS\_LOCATION\_EXTRA\_COMMANDS | 0.1 |
| normal | android.permission.RESTART\_PACKAGES | 0.1 |
| normal | android.permission.ACCESS\_NOTIFICATION\_POLICY | 0.05 |
| normal | android.permission.KILL\_BACKGROUND\_PROCESSES | 0.05 |
| normal | android.permission.PERSISTENT\_ACTIVITY | 0.05 |
| normal | android.permission.SET\_ALARM | 0.05 |
| removed | com.android.browser.permission.READ\_HISTORY\_BOOKMARKS | 0.25 |
| removed | com.android.browser.permission.WRITE\_HISTORY\_BOOKMARKS | 0.1 |
| removed | android.permission.READ\_HISTORY\_BOOKMARKS | 0.05 |
| removed | android.permission.READ\_USER\_DICTIONARY | 0.05 |
| removed | android.permission.WRITE\_USER\_DICTIONARY | 0.05 |
| signature | android.permission.PACKAGE\_USAGE\_STATS | 0.2 |
| signature | android.permission.READ\_PRIVILEGED\_PHONE\_STATE | 0.15 |
| signature | android.permission.INTERACT\_ACROSS\_USERS | 0.1 |
| signature | android.permission.INTERACT\_ACROSS\_USERS\_FULL | 0.1 |
| signature | android.permission.READ\_LOGS | 0.1 |
| signature | android.permission.WRITE\_SECURE\_SETTINGS | 0.1 |
| signature | android.app.action.BIND\_DEVICE\_ADMIN | 0.05 |
| signature | android.permission.BIND\_ACCESSIBILITY\_SERVICE | 0.05 |
| signature | android.permission.BIND\_NOTIFICATION\_LISTENER\_SERVICE | 0.05 |
| signature | android.permission.CAPTURE\_AUDIO\_OUTPUT | 0.05 |
| signature | android.permission.CHANGE\_CONFIGURATION | 0.05 |
| signature | android.permission.MANAGE\_DEVICE\_ADMINS | 0.05 |
| signature | android.permission.MANAGE\_USERS | 0.05 |
| signature | android.permission.MODIFY\_PHONE\_STATE | 0.05 |
| signature | android.permission.OVERRIDE\_WIFI\_CONFIG | 0.05 |
| signature | android.permission.REBOOT | 0.05 |
| signature | android.permission.STATUS\_BAR | 0.05 |
| signature | android.permission.TETHER\_PRIVILEGED | 0.05 |
| signature | android.permission.UPDATE\_APP\_OPS\_STATS | 0.05 |
| signature | com.android.launcher.permission.WRITE\_SETTINGS | 0.05 |

Table V: Permissions unique to spyware (unknown omitted).

|  |  |  |
| --- | --- | --- |
| Popular Only | | |
| dangerous | android.permission.ACTIVITY\_RECOGNITION | 0.15 |
| dangerous | android.permission.WRITE\_CALENDAR | 0.1 |
| normal | android.permission.WRITE\_SYNC\_SETTINGS | 0.3 |
| normal | android.permission.DOWNLOAD\_WITHOUT\_NOTIFICATION | 0.15 |
| normal | android.permission.MANAGE\_OWN\_CALLS | 0.1 |
| normal | android.permission.INSTALL\_SHORTCUT | 0.05 |
| normal | android.permission.REORDER\_TASKS | 0.05 |
| other | com.htc.launcher.permission.READ\_SETTINGS | 0.4 |
| other | com.htc.launcher.permission.UPDATE\_SHORTCUT | 0.4 |
| other | com.sec.android.provider.badge.permission.READ | 0.35 |
| other | com.sec.android.provider.badge.permission.WRITE | 0.35 |
| other | com.sonyericsson.home.permission.BROADCAST\_BADGE | 0.35 |
| other | com.huawei.android.launcher.permission.CHANGE\_BADGE | 0.3 |
| other | com.amazon.device.messaging.permission.RECEIVE | 0.25 |
| other | com.huawei.android.launcher.permission.READ\_SETTINGS | 0.2 |
| other | com.huawei.android.launcher.permission.WRITE\_SETTINGS | 0.2 |
| other | com.sonymobile.home.permission.PROVIDER\_INSERT\_BADGE | 0.2 |
| other | com.oppo.launcher.permission.READ\_SETTINGS | 0.15 |
| other | com.oppo.launcher.permission.WRITE\_SETTINGS | 0.15 |
| other | com.anddoes.launcher.permission.UPDATE\_COUNT | 0.1 |
| other | com.facebook.katana.provider.ACCESS | 0.1 |
| other | com.facebook.mlite.provider.ACCESS | 0.1 |
| other | com.facebook.orca.provider.ACCESS | 0.1 |
| other | com.facebook.permission.prod.FB\_APP\_COMMUNICATION | 0.1 |
| other | com.facebook.receiver.permission.ACCESS | 0.1 |
| other | com.majeur.launcher.permission.UPDATE\_BADGE | 0.1 |
| other | com.nokia.pushnotifications.permission.RECEIVE | 0.1 |
| other | me.everything.badger.permission.BADGE\_COUNT\_READ | 0.1 |
| other | me.everything.badger.permission.BADGE\_COUNT\_WRITE | 0.1 |
| removed | android.permission.SUBSCRIBED\_FEEDS\_READ | 0.05 |
| removed | android.permission.SUBSCRIBED\_FEEDS\_WRITE | 0.05 |
| signature | android.permission.BATTERY\_STATS | 0.05 |
| signature | android.permission.MANAGE\_DOCUMENTS | 0.05 |

Table VI: Permissions unique to popular apps (unknown omitted).

1. *Evaluation*

|  |  |  |  |
| --- | --- | --- | --- |
| Known Spyware | | Not Spyware | |
| AllTracker Anti-Theft | Very Likely | Amazon | Whitelisted |
| Update manager | Likely | Among Us | Very Unlikely |
| Cell Tracker Kids | Slightly Likely | Cash App | Slightly Likely |
| Cerberus | Very Likely | Facebook | Whitelisted |
| Clone WhatsWeb Pro | Slightly Likely | Gmail | Whitelisted |
| Control by SMS | Unlikely (5) | Google Maps | Whitelisted |
| FamiSafe | Slightly Likely | Instagram | Whitelisted |
| Girlfriend Cell Tracker | Likely | Lyft | Whitelisted |
| Highster Mobile | Unlikely (4) | Facebook Messenger | Whitelisted |
| Hoverwatch | Very Likely | Netflix | Whitelisted |
| iKeyMonitor | Very Likely | Pokemon Go | Slightly Likely |
| IP Webcam | Slightly Likely | Seamless | Unlikely |
| iSpyoo | Very Likely | Snapchat | Whitelisted |
| Mrecorder | Likely | Spotify | Whitelisted |
| Screen Recorder | Slightly Likely | TikTok | Whitelisted |
| SMS Forwarder | Slightly Likely | Twitter | Whitelisted |
| Spy GPS SMS Call Controller | Likely | Uber | Whitelisted |
| Spy To Mobile | Likely | Weather Channel | Whitelisted |
| TrackView | Unlikely (6) | WhatsApp | Whitelisted |
| Unseen – No Last Seen | Unlikely (3) | YouTube | Whitelisted |
| 80% correct | | 0% incorrect; 10% slightly likely | |

Table VII: AssessAppRisk’s assessment of the seed applications. The number in parentheses denotes the small number of weighted permissions used in incorrectly labeled spyware applications.

|  |  |  |  |
| --- | --- | --- | --- |
| Known Spyware | | Not Spyware | |
| Cloud backup | Likely | Discord | Unlikely |
| Android System4 | Very Likely | Duolingo | Unlikely |
| Google Settings | Very Likely | Reddit | Slightly Likely |
| Settings | Likely | Zoom | Likely |
| System Service (xno) | Very Likely | Wish | Slightly Likely |
| Update Manager | Likely | Twitch | Unlikely |
| Backup | Very Likely | DoorDash | Slightly Likely |
| Easy Logger | Very Likely | Venmo | Slightly Likely |
| System Service | Very Likely | GPay | Slightly Likely |
| Find My Friends | Slightly Likely | SoundCloud | Unlikely |
| 100% correct | | 10% incorrect; 50% slightly likely | |

Table VIII: AssessAppRisk’s assessment of the test applications.

|  |  |  |  |
| --- | --- | --- | --- |
| Application | Assessment | Application | Assessment |
| Amazon Shopping | Slightly Likely | Drive | Unlikely |
| Skype for Business | Slightly Likely | Currents | Slightly Likely |
| McDonald’s | Slightly Likely | Uber Eats | Whitelisted |
| Ring | Slightly Likely | Word | Slightly Likely |
| Tuesdays | Unlikely | Taco Bell | Unlikely |
| Duke Energy | Unlikely | Burger King | Slightly Likely |
| 1Password | Unlikely | Twitch | Very Unlikely |
| T-Mobile Pay | Unlikely | Google Pay | Likely |
| Navy Federal | Slightly Likely | AppSelector | Unlikely |
| MyFitnessPal | Slightly Likely | hum | Unlikely |
| Authenticator (Google) | Slightly Likely | Google Play Movies & TV | Slightly Likely |
| Target | Unlikely | Pokemon HOME | Slightly Likely |
| My Spectrum | Unlikely | DoorDash | Whitelisted |
| Facebook Ads | Unlikely | Photos | Slightly Likely |
| PayPal | Slightly Likely | Uber | Slightly Likely |
| Discord | Unlikely | Trails End | Whitelisted |
| eBay Partner Attribution | Unlikely | MapMyWalk | Slightly Likely |
| Content Transfer | Likely | Facebook | Slightly Likely |
| Excel | Slightly Likely | Business Suite | Unlikely |
| Samsung Time Zone Data | Slightly Likely | Messenger | Likely |
| myScouting | Slightly Likely | JetBlue | Unlikely |
| Android Accessibility Suite | Unlikely | SmartThings | Very Unlikely |
| Reddit | Slightly Likely | TCGplayer | Unlikely |
| Zoom | Likely | Calculator | Slightly Likely |
| GoToWebinar | Slightly Likely | SmartNews | Slightly Likely |
| D&D Beyond | Unlikely | Samsung Health | Likely |
| Lyft | Whitelisted | Venmo | Slightly Likely |
| HomeAdvisor | Slightly Likely | Samsung Pay | Unlikely |
| Amazon Alexa | Slightly Likely | Samsung Notes | Likely |
| Instagram | Whitelisted | Google Play Books | Unlikely |
| GIPHY | Slightly Likely | Smart Switch | Unlikely |
| Flipboard | Unlikely | Inkpad NotePad | Slightly Likely |
| Alarmy | Slightly Likely | ParkMobile | Unlikely |
| Patreon | Slightly Likely | Sport Clips | Slightly Likely |
| Pokemon GO | Slightly Likely | Audio Recorder | Unlikely |
| Outlook | Slightly Likely | Authenticator (Azure) | Slightly Likely |
| Google Play Music | Slightly Likely | Postmates | Very Unlikely |
| myAT&T | Slightly Likely | Name ID | Very Unlikely |
| Yelp | Slightly Likely | SlowCOVIDNC | Unlikely |
| American Airlines | Unlikely | One Night | Unlikely |
| RAR | Unlikely | WEBTOON | Unlikely |
| PNC | Slightly Likely | Google Play Games | Unlikely |
| Twitter | Whitelisted | Google News | Slightly Likely |
| Square Point of Sale | Slightly Likely | Chick-fil-A | Unlikely |
| Softcard | Likely |

Table IX: AssessAppRisk’s assessment of a real user’s device.

|  |  |
| --- | --- |
| Assessment | Percent |
| Whitelisted | 6.7% (6/89) |
| Very Unlikely | 4.5% (4/89) |
| Unlikely | 33.7% (30/89) |
| Slightly Likely | 47.2% (42/89) |
| Likely | 7.9% (7/89) |
| Very Likely | 0% (0/89) |

Table X: Assessment percentages for Table IX.

1. *Program Screenshots*

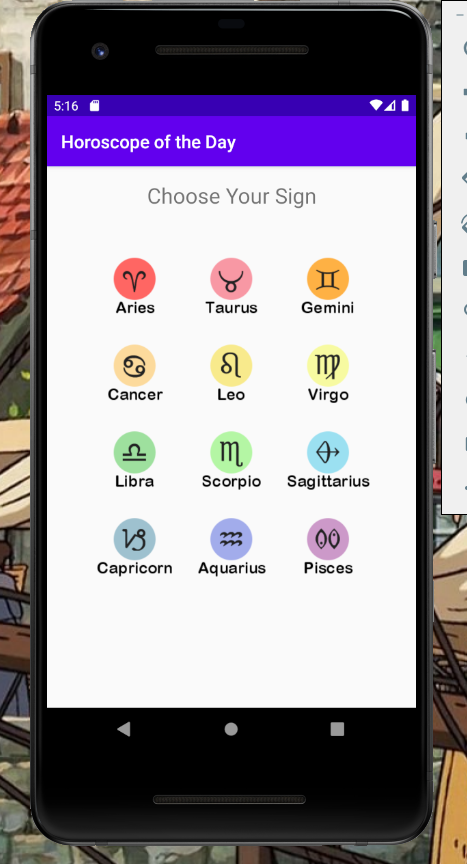


Figure I: The Horoscope application’s main screen.

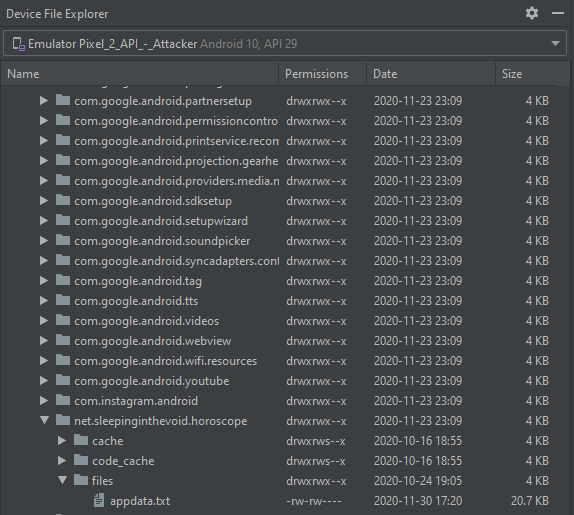


Figure II: The Device File Explorer in Android Studio.

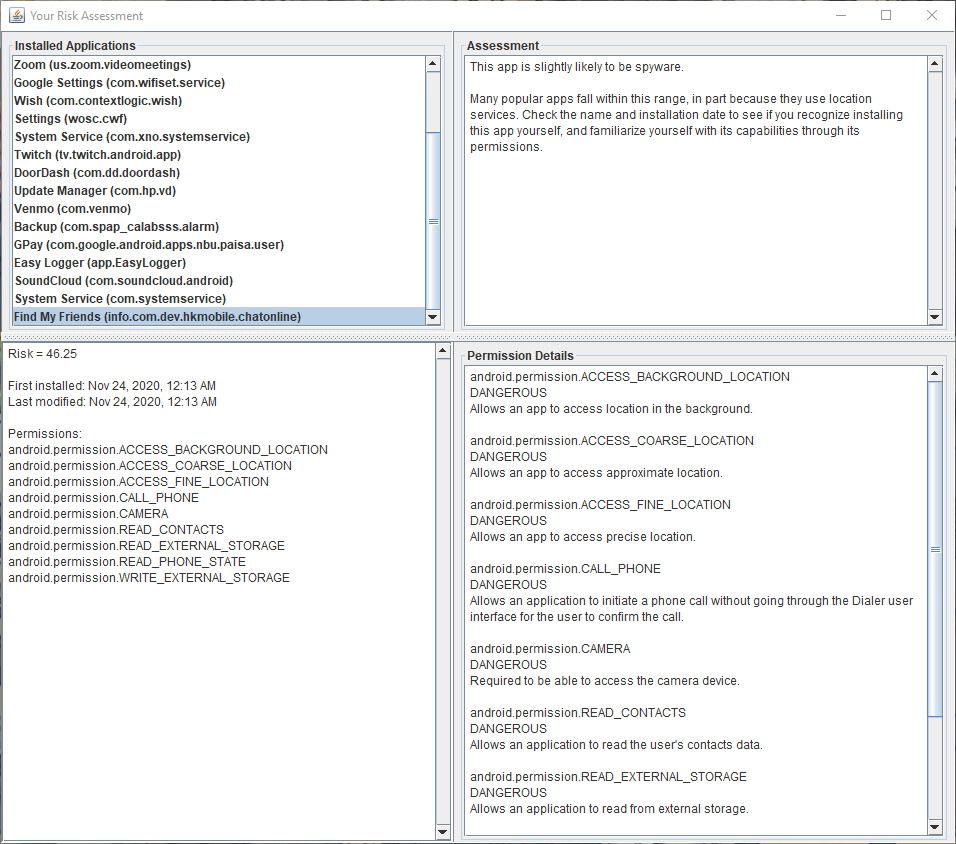


Figure III: The AssessAppRisk application window.