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MobSafe: Cloud Computing based Forensic Analysis for Massive Mobile Applications using Data Mining

Jianlin Xu, Yifan Yu, Zhen Chen*, Bin Cao, Wenyu Dong, Yu Guo and Junwei Cao

Abstract: With the explosive increase in Mobile apps, more and more threats migrate from traditional PC client to mobile device. Compared with traditional Win+Intel alliance in PC, Android+ARM alliance dominates in Mobile Internet, the apps replace the PC client software as the major target of malicious usage. In this paper, to improve the security status of current mobile apps, we propose a methodology to evaluate mobile apps based on Cloud Computing platform and data mining. We also present a prototype system named MobSafe to identify the mobile app's virulence or benignancy. Compared with traditional method, such as permission pattern based method etc., MobSafe combines the dynamic and static analysis method to comprehensively evaluate a android app. In the implementation, we adopt ASEF and SAAF framework, the two representative dynamic and static analysis method, to evaluate the android apps and estimate the total time needed to evaluate all the apps stored in one mobile app market. Based on the real trace from a commercial mobile app market called AppChina, we can collect the statistics that the number of active android apps, the average number apps installed in one android device and the expanding ratio of mobile apps. As mobile app market serves as the main line of defence against mobile malwares, our evaluation results shown that it is practical to use cloud computing platform and data mining to verify all stored apps routinely to filter out malware apps from mobile app markets. As the future work, MobSafe can extensively use machine learning to conduct automotive forensic analysis of mobile apps based on the generated multifaceted data in this stage.

Key words: Android Platform, Mobile Malware Detection, Cloud Computing, Forensic Analysis, Machine Learning, Reddis Key-Value Store, Big Data, Hadoop Distributed File System, Data Mining

1 Introduction

1.1 Mobile Threats

These years witness an explosive increase in mobile apps. According to Mary Meeker's report[1] on Mobile Internet trends. More and more PC client software are migrating to the mobile device[2−3]. According to Gartner's statistical prediction[4], the amount of total downloads of mobile apps in 2013 will be about 81 billion. Among these, there are about 800,000 Android apps in Google Play market, and the total download is about 48 billion as of May 2013[5]. In contract with Apple AppStore, there are different sources for android apps download, such as wandoujia, AppChina, Baidu mobile assistant etc. While these markets give a good supply and bring more convenience for android users, they will also bring mobile threats as different market place has different malware detection utility and methods. Some sophisticated malwares can escape from detection and spread even via such android markets.

1.2 Some root causes for malware origins

It needs some discussions about the malware's origins, provenances and spreading.

(1) Android platform allows users to install apps from the third-party marketplace that may make no efforts to verify the safety of the software that they distribute.

(2) Different market place has different defense

• Jianlin Xu is with Department of Computer Science and Technologies and Tsinghua National Laboratory for Information Science and Technology (TNList), Tsinghua University, Beijing 100084, China.
E-mail:xjl11@mails.tsinghua.edu.cn
• Yifan Yu is with Department of Electronic Engineering and Tsinghua National Laboratory for Information Science and Technology (TNList), Tsinghua University, Beijing 100084, China.
E-mail:yuyf10@gmail.com
• Zhen Chen and Junwei Cao are with Research Institute of Information Technology and Tsinghua National Laboratory for Information Science and Technology (TNList), Tsinghua University, Beijing 100084, China.
E-mail:zhenchen, jcao@tsinghua.edu.cn
• Bin Cao, Wen-Yu Dong and Yu Guo are with Department of Computer Science & Technologies, Research Institute of Information Technology and Tsinghua National Laboratory for Information Science and Technology (TNList), Tsinghua University, Beijing 100084, P. R. China.
E-Mail: jiangxin_thu@sina.cn
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utility and revocation policy for malware detection.

(3) It is easy to port an existing Windows-based botnet client to android platform.

(4) Android application developers can upload their applications without any check of trustworthiness. The applications are self-signed by developers themselves without the intervention of any certification authority.

(5) A number of applications have been modified, and the malware have been packed in and spread through unofficial repositories.

Some sophisticated malware detect the presence of an emulated environment and change their behavior, create hidden background processes, scrub logs, and restart on reboot.

1.3 Some known malware in Android platform

There are a lot of already discovered malwares which include: Drad.A, Fake Player, Geinimi, PJApps, HongToutou, DroidDream trojan, DroidKungFu, SteamyScr, Bgyoulu.A, Cabir, HippoSMS, Fake Netflix, Walk & Text, Dog Wars, DroidDreamLight, BaseBridge, Zsone, jSMSHider, Rageagainstthecage, Zimperlich, Exploid, Plankton, DougaLeaker.A, Rufraud, Gone in 60s etc.

1.4 Some malicious behaviors of Android malware

Malware is usually motived by controlling mobile device without user intervention, such as:

1) Privilege escalation to root,
2) Leak private data or exfiltrate sensitive data,
3) Dial premium numbers,
4) Botnet activity,
5) Backdoor triggered via SMS.

1.5 Our Work

In this paper, based on home-brewed Cloud Computing platform and data mining, we propose a methodology to evaluate mobile apps for improving current security status of mobile apps, MobSafe, a demo and prototype system, is also proposed to identify the mobile app's virulence or benignancy. MobSafe combines the dynamic and static analysis method to comprehensively evaluate a android app, and reduce the total analyse time to a acceptable level. In the implementation, we adopt the two representative dynamic and static analysis method, i.e. ASEF and SAAF framework, to evaluate the android apps and estimate the total time needed to evaluate all the apps stored in one mobile app market, which provide useful reference for a mobile app market owner to filter out the mobile malwares.

This paper is organized as follows: Section 2 provides an overview of related works of static analysis and dynamic analysis methods, Section 3 introduces infrastructure Cloud Computing platform, MobSafe frontend and backend's design, ASEF and SAAF framework respectively. Section 4 presents the performance evaluation based on real trace data, including the experiments' result and analysis, and Section 5 makes a brief conclusion of this paper, and Section 6 discusses the future work using Machine Learning to further evaluate the android apps.

2 Related work

Security analysis of Android apps is a hot topic. More and more researchers use static analysis and dynamic behavior analysis, and even integrate it with machine learning techniques to identify malware.

2.1 Static analysis methods

David Barrera et al.[6] make an analysis on permission-based security models and its applications to android through a novel methodology which applies

Self-Organizing Map (SOM) algorithm preserving proximity relationships to present a simplified, relational view of a greatly complex dataset. The SOM algorithm provides a 2-dimensional visualization of the high dimensional data, and the analysis behind SOM can identify correlation between permissions. They discover insights on how the developers use the allowed permission model in developing and underlines the permission model's strengths as well as its shortcomings through their methodology. Based on their results, they propose some enhancements to the android permission model.

Enck et al.[7] (TaintDroid) build a tool that warns users about applications that request blacklisted sets of permissions. They take both dangerous functionality and vulnerabilities into consideration and apply a wide range of analysis techniques. They design and implement a Dalvik decompiler, ded, which can recover application's Java source code only using its installation image. Besides, they analyze 21 million LOC retrieved from the top 1,100 free applications in the Android Market using automated tests and manual inspection. Consequently they identify the essential causes of android application security problems and show the severity of discovered vulnerabilities. Their results show the wide misuse of privacy sensitive information, the evidence of telephone misuse, wide including of ad libraries in android application, and the failing to securely use android APIs of many developers.

Adrienne Felt et al.[8] develop Stowaway, a tool to detect overprivilege in Android applications, and use this tool to evaluate 940 applications from Android Market, finding that about one-third are overprivileged. Additionally, they identify and quantify developer's patterns leading to overprivilege. Moreover, they determine android's access control policy through automatic testing techniques. Their results present a fifteen-fold improvement over the android documentation and reveal that most developers are trying to follow the principle of least privilege but fail due to the lack of reliable permission information.

Karim O. Elish et al.[9] implement an analysis tool to construct data dependence graphs statically with inter-procedural call connectivity information that capture the data consumption relations in programs through identifying the directed paths between user inputs (e.g., data and actions) and entry points to methods providing critical system services. Furthermore, they conduct an initial set of experiments to characterize the data consumption behaviors of legitimate and malicious Android apps with this tool, specifically on how they respond to user inputs and events. Nevertheless, some malware may attempt to circumvent their data dependence checking by misusing the user's inputs while performing malicious activities, so their work need to be improved in these conditions.

Iker Burguera et al.[10] propose Crowdroid, which finds that open(), read(), access(), chmod() and chown() are the most frequently used system calls by malware.

Johannes Hoffmann et al.[11] present SAAF (a Static Android Analysis Framework), which provides program analysis such as data-flow analysis and visualization of control flow graph. They analyze about 136,000 benign apps and 6,100 malicious apps, and their results confirm the previous observations for smaller app sets; what's more, their results provide some new insights into typical Android apps.

Yacin Nadji et al.[12] propose airmid, which uses collaboration between in-network sensors and smart devices to identify the provenance of malicious traffic. They create three mobile malware samples, i.e. Loudmouth, 2Faced and Thor, to testify the correctness of airmid. Airmids remote repair design consists of an on-device attribution and remediation systema an server-based infection detection system. Once detected, the software executes repair actions to disable malicious activity or to remove malware entirely.

2.2 Dynamic behavior analysis

Portokalidis et al.[13] propose Paranoid Android, a system where researchers can perform a complete malware analysis in the cloud using mobile phone replicas.

Zhou et al.[14] propose DroidMOSS which take advantage of fuzzy hashing technique to effectively localize and detect the changes from app-repackaging behavior.

2.3 Machine learning

A. D. Schmidt et al.[15] propose a solution based on monitoring events occurring on Linux-kernel level. They apply the tool, readelf, to read static information held by executables and use the output of readelf to classify android software. After applying readelf to both normal apps and malware apps, they use the names of the functions and calls appearing at the output of readelf to form their benign training set and malicious training set. Furthermore, they apply three classifiers, PART (extracting decision rules from the decision tree learner C4.5), Prism (a simple rule inducer which covers the whole set by pure rules), and nNb (a light-weight version of the well-known Nearest Neighbour algorithm), to predict whether an android software is normal or malicious. The testing result shows that their approach is effective. Additionally, they build a system which provides three main functionalities: on-device analysis, collaboration, and remote analysis, to detect malware apps on android.

Mario Frank et al.[16] investigate the difference between high-reputation and low-reputation applications, and further to identify malware. Their method only uses the permission requests, and don't statically analyze applications to extract features when there is no available code.

Shabtai et al.[17] similarly build a classifier for Android games and tools, as a proxy for malware detection.

Sanz et al.[18] apply several types of classifiers to the permissions, ratings, and static strings of 820 applications to see if they could predict application categories, using the category scenario as a stand-in for malware detection.

Zhou et al.[19] find real malware in the wild with DroidRanger, a malware detection system that uses permissions as one input.

3 MobSafe

3.1 Infrastructure Cloud Platform

3.1.1 CloudStack

Saturn-cloud[20−21], a home-brewed cloud computing platform, is used to conduct security analysis task. Saturn-storage, NFS storage with ZFS file system (openindiana+napp-it)[22], is used to accommodate the virtual machines. It can scale to 16 hard disks, each with 2TB SATA storage, totally achieve 32TB store volume. Cloudstack[23] is used to manage a VMware vshphere based computing servers. The whole cloud infrastructure is shown in Figure 1.

3.1.2 Hadoop Storage for Mobile apps

There are about 40 servers and 40TB storage in our experimental research platform which based HDFS.

3.2 Work principle

MobSafe is a system to check whether an android app is virulence or benignancy based some customized tool in cloud platform. The procedure of mobsafe is shown in Figure 2.

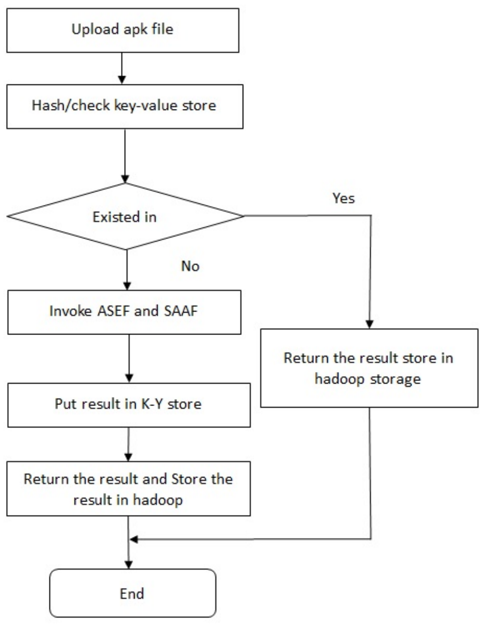
Upload apk file
Hash/check key-value store
Existed in
Yes
No
Invoke ASEF and SAAF
Return the result store in hadoop storage
Put result in K-Y store
Return the result and Store the result in hadoop
End

Fig. 2 The procedure of android app analysis in mobsafe

MobSafe is a automatize system which can be used to analyze android apps. When you submit an unknown apk file to MobSafe for analysis, it will check the key-value store whether the apk is already analyzed and its result is store in hadoop storage. This comparison based on the hashing of the apk file as the key to query the reddis key value store. In this implementation, the redis version is 2.1.3. If the key is matched in reddis, then the result is returned as response to submitter. If the key is not matched, it indicts a new apk file. In such case, the apk is stored in hadoop storage. After that, a daemon invoke the automatize tool, such as ASEF and SAFF, to collect the log and store in hadoop specified directory. Also the daemon inserts the key to reddis and updates the value with the result directory in hadoop storage.

3.3 Frontend

Mobsafe has a web frontend, which is based on SpringSource's Spring framework, and Twitter Boostrap. It provides suspect apps upload function and return the analysis result demonstrated in web page.

3.4 Backend

3.4.1 ASEF

ASEF(Android Security Evaluation Framework)

ASEF[24] is a automatize tool which can be used to analyze android application. When you submit an unknown apk file to ASEF for analysis, firstly it

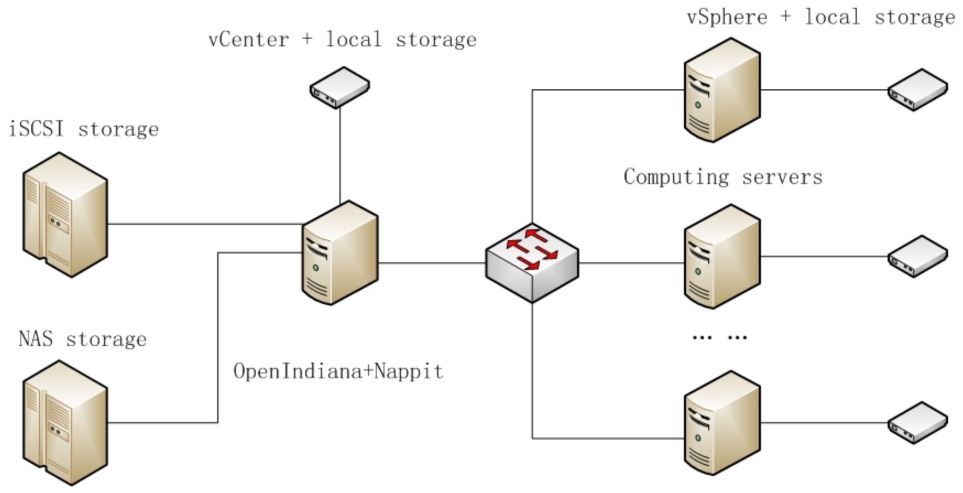

Fig. 1 Infrastructure cloud platform based on CloudStack.

will start the ADB logging and traffic sniffing using TCPDUMP, then launch an android virtual machine (AVD) and installs the application on it. After that ASEF begins to launch the application to be analyzed and send a number of random gestures to simulate human integration on the application. Meanwhile, ASEF also compare the log of android virtual machine with a CVE library, and its internet activity with Google Safe browser API[27]. After a certain number of gestures are sent to virtual machine, the test circle is end and the application will be uninstalled. Then ASEF will begin to analyze the log file and the Internet traffic the apps generated. ASEF uses Google Safe Browsing API to find out whether the URLs the app try to reach is malicious or not. ASEF also checks the existed vulnerability with a known vulnerability list to find out whether the application has some serious vulnerability.

3.4.2 SAAF

SAAF(Static Android Analysis Framework)

SAAF[26] is a static analyzer for Android apk files. It is the acronym of Static Android Analysis Framework. It can extract the content of apk files, and then decode the content to smali code, then it will apply program slicing on the smali code, to analyse the permissions of apps, match heuristic patterns, and perform program slicing for functions of interest.

3.4.3 Other tools

There are also a lot of other assistance static analysis tools, such as readelf[27], ded[28], apktool[29], androguard[30] and soot[31], to help us analyse the android apps. Most of these tools are based on reversing engineering. some dynamic analysis tools like Strace[32] and randoop[33] to detect android apps based on runtime behaivor. Strace watches system call in Linux kernel while randoop stimulates the android apps by random inputs and watches the output messages.

4 Evaluation

4.1 Global Statistics of the Dataset

We have collected data set from AppChina, a china android market with own Android app installation tool. This assistance tool help user to install, upgrade and remove android apps quickly and logging such operations for analysis. The data set is collected during the three-month period from May 1st to July 31st in 2012. The size of data set is about 1 TB zipped logs (expanded size above 10 TB). Totally there are about 100 K active Android apps in logs. We downloads android apps from AppChina to verify based on MobSafe. Each downloaded Android app has its web page on the Market website. We also crawled the web version of the Android Market to supply android app with text description. We also conduct some correct proof by self-written malware verification.

Figure 3 shows the total number active apps in AppChina keep steadily increase during these three months. it maintained a growth rate above 10%.

From Table 1, all these resolution android devices account for the about 90% of total android devices. We also notice that high resolution display android device users are increased steadily while some middle resolution display android device users are decreased steadily.

We classify the android devices into three categories:

Table 1 Different display resolution with different portion account for all android devices in year 2012

Display resolution	240x320	320x480	480x800	480x854	540x960	720x1280	800x1280
May	5.40%	26.45%	37.60%	13.00%	7.11%	1.22%	4.30%
June	4.12%	29.41%	35.31%	12.88%	5.99%	1.93%	5.54%
July	3.77%	31.76%	35.1%	11.83%	5.39%	2.73%	5.47%

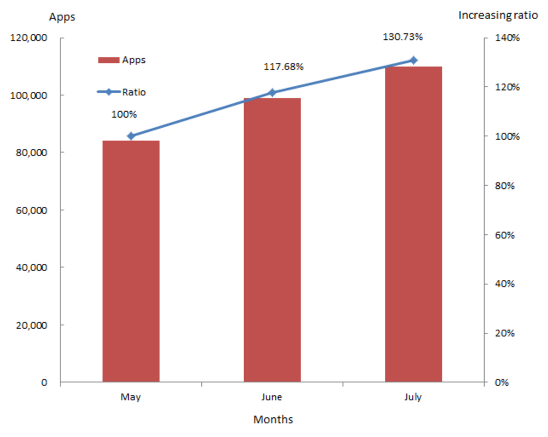

Fig. 3 The trend of android mobile apps in AppChina in one quarter (in year 2012)

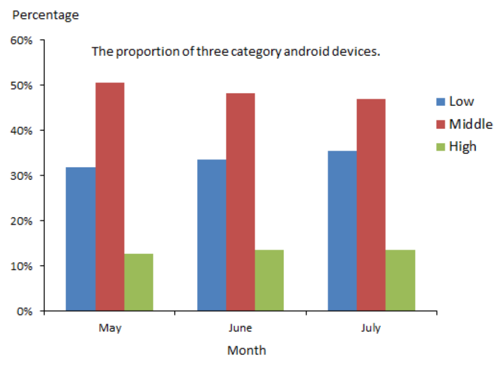

Fig. 4 The portion of three different display's resolutions varied in three month in year 2012

Low class, Middle class and High class according to the display resolution. It seems that the display resolution of android devices is increased steadily in these three months as shown in Figure 4.

It also needs to notice that the number of apps installed in mobile android devices is about 30 according to three months' statistics in Figure 5. But as more and more user choice high resolution android device, the number of apps installed in device is increased too.

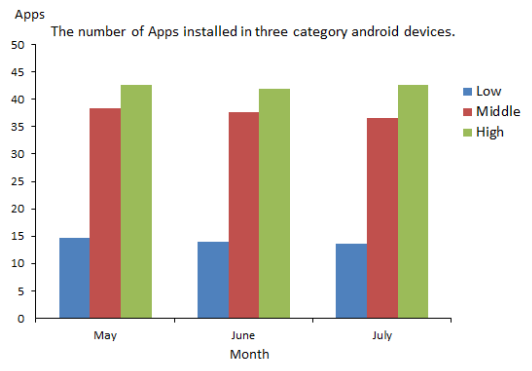

Fig. 5 The average number of apps installed in three category android devices in year 2012

4.2 Performance metrics

4.2.1 ASEF

In order to measure how much time ASEF takes to analyse an app, we write a script which can record the timestamp of the beginning of running a program and use ASEF to analyse 20 different android apps downloaded from AppChina. The results is shown in Figure 6, where the time it takes to analyse one application varies from 64 seconds to 150 seconds, and the average time is about 100 seconds. It means that we can finish the analysis and acquire the result in less than 2 minutes on average.

When we look up the whole analysis procedure in detail, we can find out that there are 6 steps during analyzing one app. And the preparing step, the starting log service step, the ending process step and analyzing step take up 3%,3%,5%,10% of total time separately. About 80% of time is consumed on the installing and testing stage, shown in Figure 7. So if we want to reduce the total time, we should try to speed up these two steps.

In the analysis step, the time it takes depends on the random gestures we input. The more gestures, the longer it takes. Figure 8 presents the result of reduced time by cutting down some gestures. We decrease the number of gestures sent to android virtual machine(AVD) so that the testing time will be shortened. After we decrease the number of gestures from 1000 to 200, the total time decreases in 20

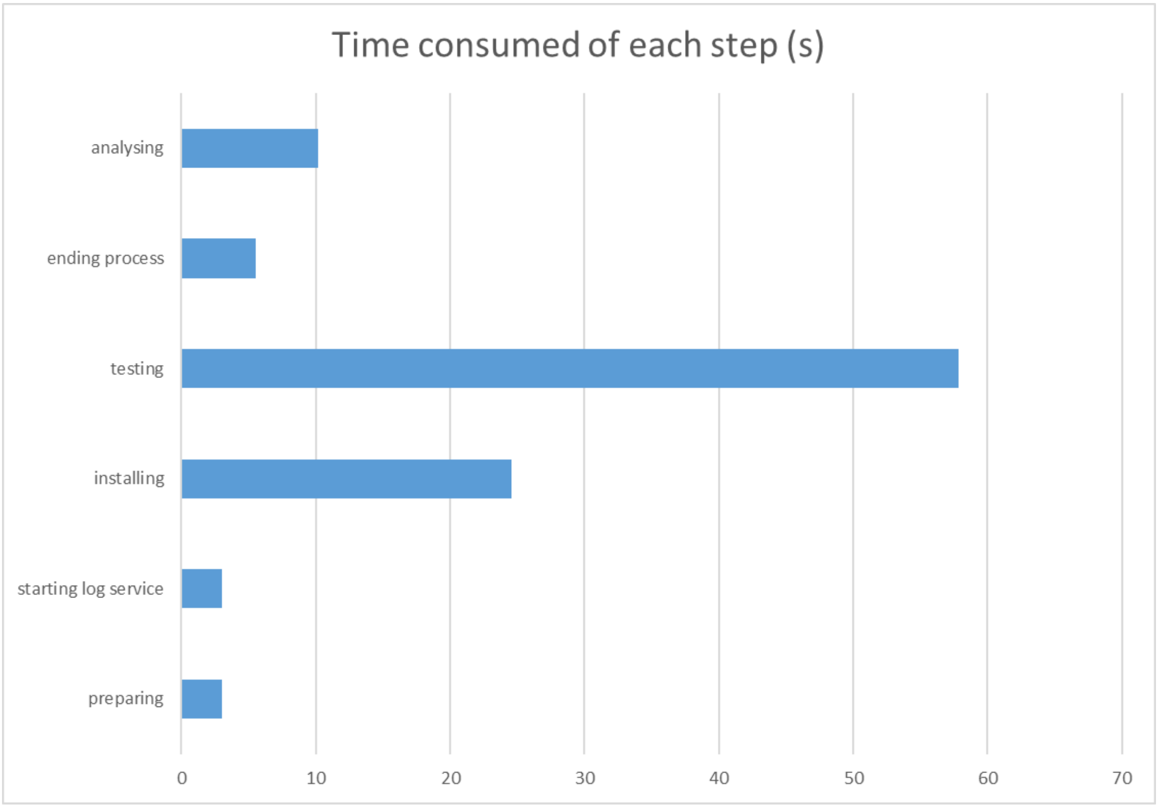

Fig. 6 ASEF: The total consumed time of each app (s)

seconds, which accounts for 20% of the total time. This method is effective and we can also use it to improve user's experience.

4.2.2 SAAF

We apply SAAF to 25 android apps downloaded from AppChina for static smali code analysis, to evaluate the performance of this tool. From the Figure 9 below, we can see that the most time consuming step of SAAF is the slicing step, and the second is the permission categorizing step. The average time of analysing one app consumed by SAAF in one Linux virtual machine, which runs on Intel-i5 four core CPU with 4 GB of memory, is about 33.93 seconds.

From Figure 10, we know that the analysing of different app will consume different time, and the total time depends on the complexity of apps, such as the amount of methods etc. But for most apps, SAAF will finish the analysis in a acceptable period.

4.3 Estimated instances

That means if we apply ASEF to all the apps in Google Play market, which has 800,000 apps in total, it will consume about 450 hours by 50 such virtual machines, which runs on Intel-i5 four core CPU with 4 GB of memory.

If we apply SAAF to all the apps in Google Play market too, it will consume about 151 hours by 50 such virtual machines.

From the above calculation, it also needs to notice that the dynamic method(such as ASEF) costs more time than the static one(such as SAAF) as the former one needs to monitor app's system call and network behaviour.

According to average number of apps installed in one android device is about 30 shown above, it costs about 1 hour to use ASEF and SAAF to finish the analysis in one virtual machine and android AVD. But if we can distribute the installed apps into separated individual VMs or AVDs, the whole time can be lesser than one minute, which is acceptable for user's experience in security check.

5 Conclusion

In this paper, we propose a methodology to evaluate the security of android mobile apps based on cloud computing platform. We also implement a prototype system, i.e., MobSafe, for automation forensic analysis of mobile apps' static code and dynamical behavior.

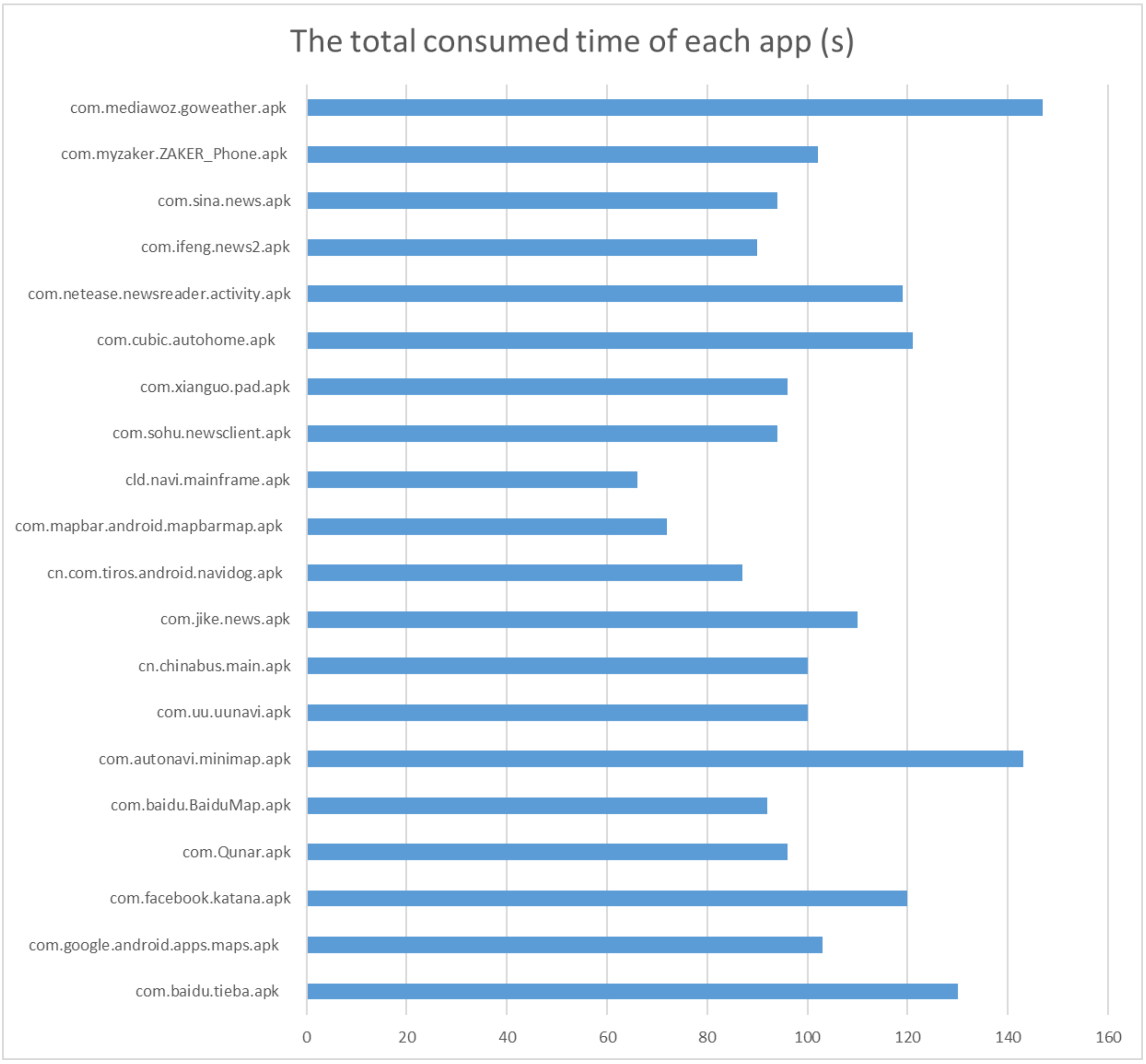

Fig. 7 ASEF: Time consumed of each step (s)

Based on the real trace from AppChina, a mobile app market, we can estimate that the number of active android apps and the average number apps installed in one android device, and the increasing ratio of mobile apps. We adopt ASEF and SAAF, the two representative dynamic analysis method and static analysis method, to evaluate the android apps and estimate the total time needed to evaluate all the apps stored in a mobile app market. As mobile app market serves as the main line of defence against mobile malwares, it is practical to use cloud computing platform to defence malware in mobile app markets as shown in the results.

6 Future Work

Machine Learning(ML)[34] is a promising technology to identify mobile app's virulence or benignancy based on data mining. As we collect more and more app's logging and network behaviour data, we can further use K-means method to classify apps after training a classifier. In this case, the well-known accuracy metrics includes precision and recall can be measured to evaluate the calssifier agorithm. other method such as PCA (primary component analysis) and Matrix Factorization also can be try and test.

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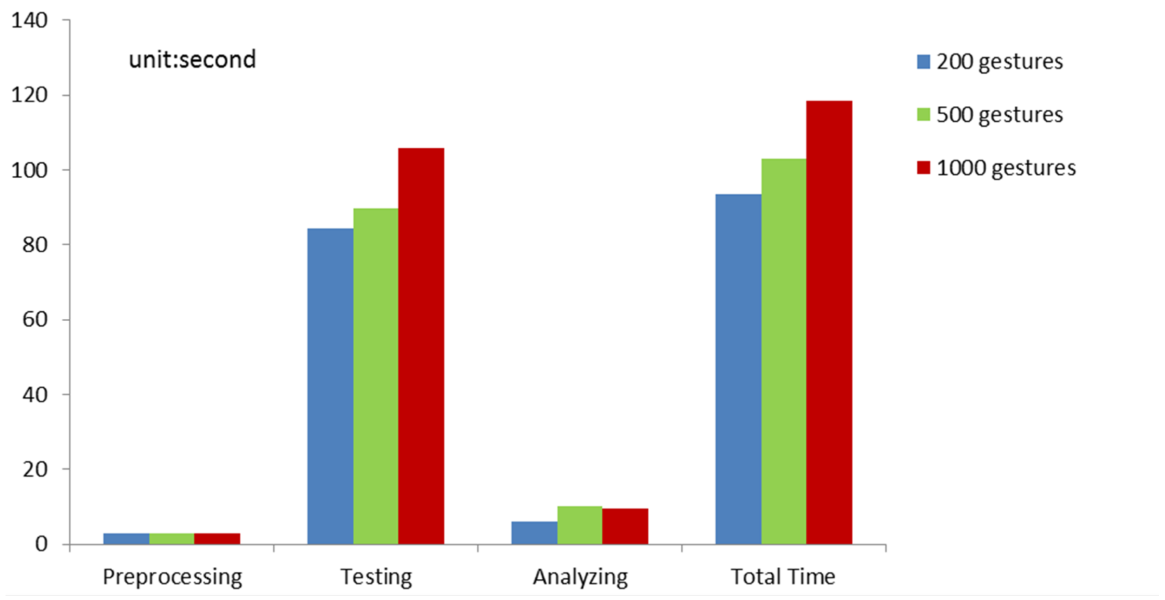

Fig. 8 The time consumption analysis of ASEF framework

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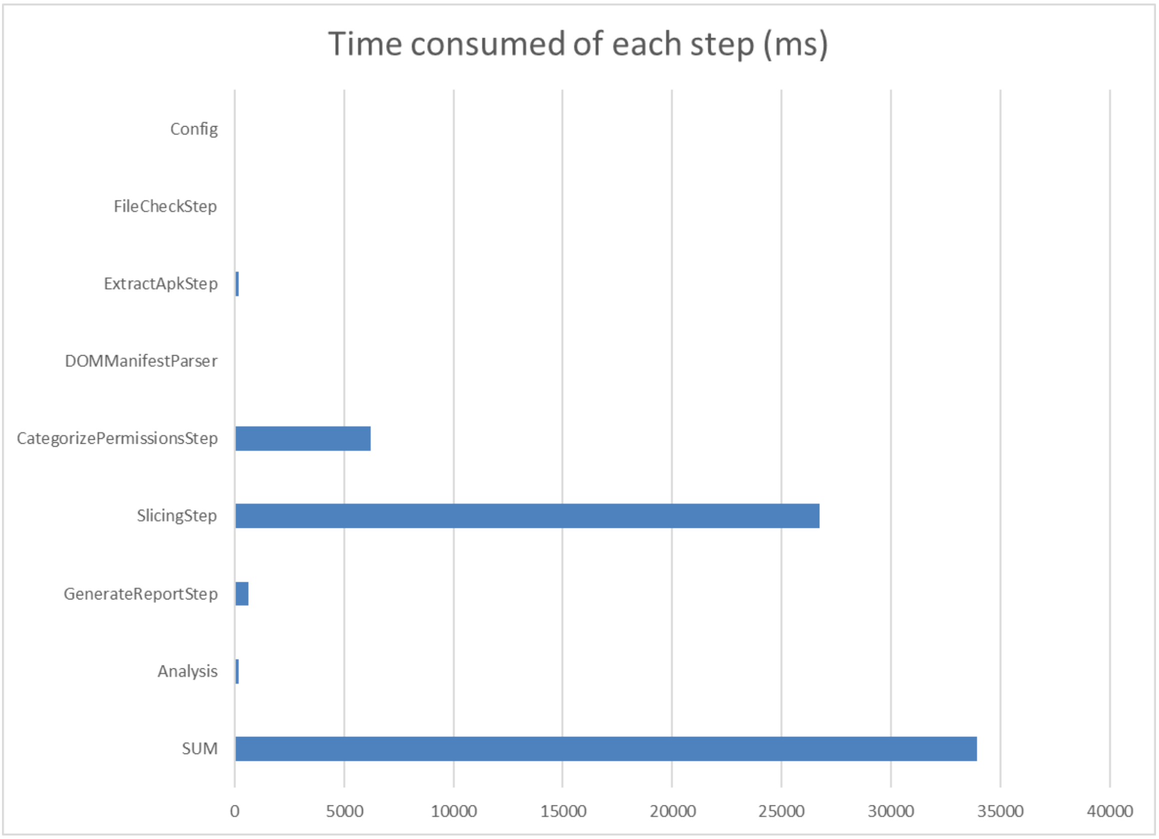

Fig. 9 SAAF: Time consume of each step (ms)

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Jianlin Xu is an undergraduate student working in Department of Computer Science and Technologies at Tsinghua University. His research interests include network security and network structure.

Yifan Yu is an undergraduate student working in Department of Electronic Engineering at Tsinghua University. His research interests include network security and mobile safety.

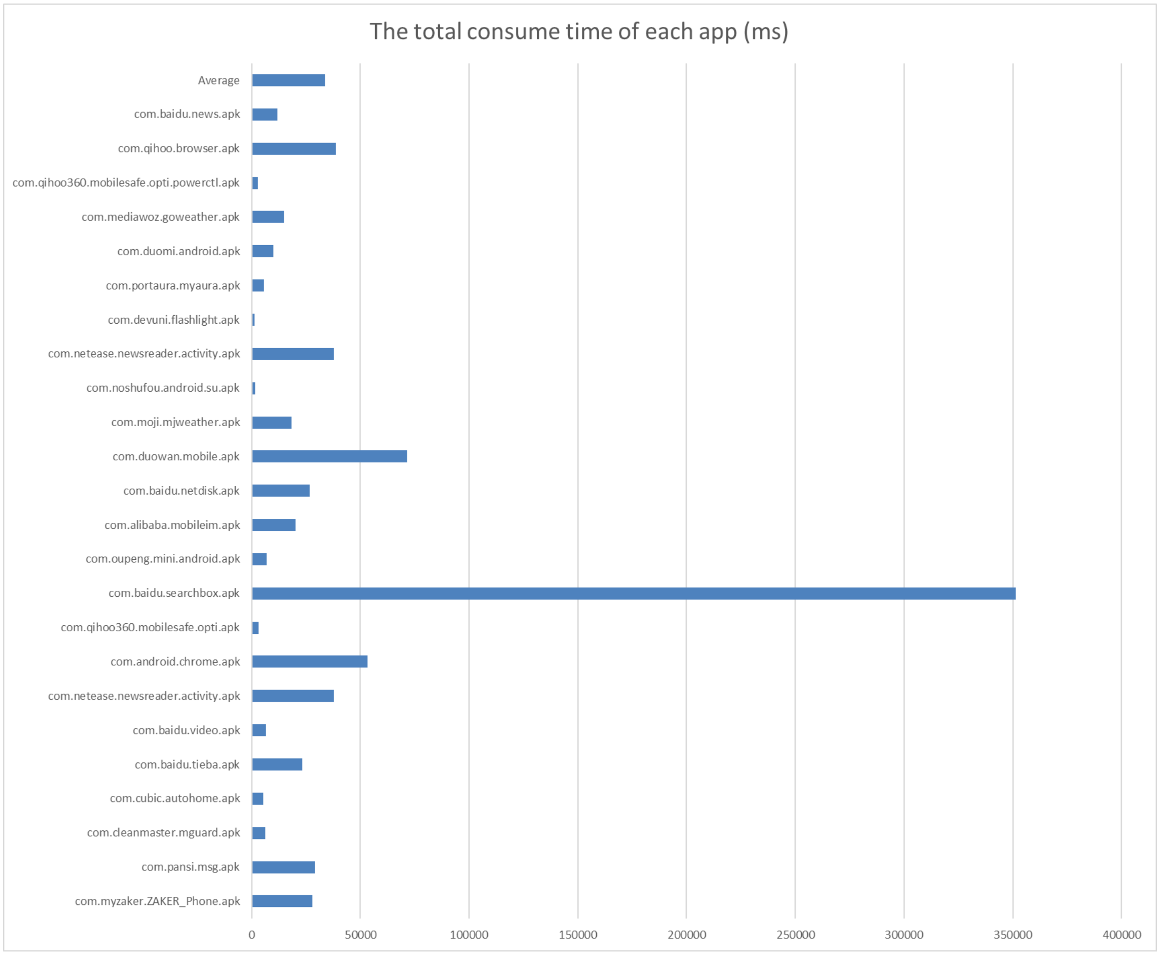

Fig. 10 SAAF: The total consume time of each app (ms)

Zhen Chen is an associate professor in Research Institute of Information Technology in Tsinghua University. He received his B.E. and Ph.D. degrees from Xidian University in 1998 and 2004. He once worked as postdoctoral researcher in Network Institute of Department of Computer Science in Tsinghua University during 2004 to 2006. He is also a visiting scholar in UC Berkeley ICSI in 2006. He joined Research Institute of Information Technology in Tsinghua University since 2006. His research interests include network architecture, computer security, and data analysis. He has published around 80 academic papers.

Bin Cao is an postgraduate student working in Department of Computer Science and Technology at Tsinghua University. He got his bachelor's degree in PLA Information Engineering University in 2005. His research interests include computer network security and mobile safety.

WenYu Dong is working as computer security researcher. He is a postgraduate student working in Department of Computer Science and Technology at Tsinghua University. He got bachelors degree in PLA Univ. of Info. & Engi in 2009. Currently his main research interests focus on computer network security and mobile safety.

Yu Guo is working as computer security researcher. He got bachelors degree in PLA Univ. of Info. & Engi in 2005. He is studing in Department of Computer Science and Technology at Tsinghua University for the graduate degree .His main research interests include network and information security, computer software performance, wireless network.

Junwei Cao is currently Professor and Deputy Director of Research Institute of Information Technology, Tsinghua University, China. He is also Director of Open Platform and Technology Division, Tsinghua National Laboratory for Information Science and Technology. His research is focused on advanced computing technology and applications. Before joining Tsinghua in 2006, Junwei Cao was a Research Scientist of Massachusetts Institute of Technology, USA. Before that he worked as a research staff member of NEC Europe Ltd., Germany. Junwei Cao got his PhD in computer science from University of Warwick, UK, in 2001. He got his master and bachelor degrees from Tsinghua University in 1998 and 1996, respectively. Junwei Cao has published over 130 academic papers and books, cited by international researchers for over 3000 times. Junwei Cao is a Senior Member of the IEEE Computer Society and a Member of the ACM and CCF.