An Empirical Study on Quality of Android Applications written in Kotlin language

Bruno Gois Mateus · Matias Martinez

Abstract Context: During the last years, developers of mobile applications have the possibility to use new paradigms and tools for developing their mobile applications. For instance, since 2017 Android developers have the official support to write their Android applications using Kotlin language. Kotlin is a programming language 100% interoperable with Java that combines Object-oriented and functional features.

Objective: The goal of this paper is twofold. First, it aims to study the degree of adoption of Kotlin language on development of Android applications and to measure the amount of Kotlin code inside Android application. Secondly, it aims to measure the quality of Android applications that are written using Kotlin and to compare it with the quality of Android application purely written using Java.

Method: We first define a method to detect Kotlin applications from a dataset of open-source Android applications. Then, we analyze those apps to detect instances of code smells and compute an estimation of quality of the apps. Finally, we study how the introduction of Kotlin code impacts on the quality of an Android application.

Results: Our experiment found that 11.78% of applications from a dataset with 925 open source apps have been written (partially or fully) using Kotlin language. We found that after the introduction of Kotlin code in existing Android application written in Java, the quality of the majority of such applications increase.
1 Introduction

In 2017, Smartphone companies shipped a total of 1.46 billion devices. The vast majority of them (85%) run one platform, Android from Google which is much more adopted than the second most used platform, iOS from Apple, with the 14.7% of the worldwide smartphone volume (IDC, 2017).

For developing a mobile application capable of running on devices with Android, Google provides official IDEs and SDKs (software development toolkit). Android allows running native applications originally written in Java. The SDK compiles the Java code into Dalvik bytecode, which is packaged on .apk. Then, developers submit those .apks to applications stores, such as the official one named Google Play Store. Android users can install applications by downloading those .apks directly from the apps stores. The Android platform includes a virtual machine capable of running .apks.

During the last years, different development approaches and frameworks have emerged for ease the development of mobile applications (Nagappan and Shihab, 2016; Martinez and Lecomte, 2017). For instance, two emerged development approaches focus on multi-platforms: their goal is the developer writes one application once, and then to obtain a version for each different mobile platforms including Android and iOS. The first one aims at building hybrid mobile applications: apps built coding both non-native (e.g., HTML for Phonegap/Cordova) and native code. The non-native code is shared across all the platforms’ implementations, whereas the native is written for a particular platform. The second kind of frameworks targets the creation of cross-compiled apps. Their receive as input an application written in a not-native language and transform into native code for a particular platform. Xamarin from Microsoft and React-Native from Facebook are two them. Those two kinds of development frameworks aim developer to write less code and consequently, to reduce the development cost.

Meanwhile, Google and Apple continue evolving their development toolkits for building native applications with the goal of avoiding mobile developers migrate to such three-party development framework Xamarin Visual Studio from their competitor Microsoft. Apple gave the first step to provide a new programming language into iOS platforms by releasing in June 2014 Swift, a modern, multi-paradigm language that combines imperative, object-oriented and functional programming.

In 2017 Google has announced that the Kotlin programming language was chosen as an officially supported language for Android development. Kotlin is a pragmatic programming language that runs on Java virtual machine and Android. It combines Object-oriented and functional features and, as it has 100% interoperability with Java, then it is possible to mix Kotlin and Java code in the same application. Android official blog states that, by the end of 2017, Kotlin is used in more than 17% of projects in Android Studio 3.0 (La, 2017).
The goal of this paper is twofold. First, to study the adoption of Kotlin language on Android applications and the amount of Kotlin code written on Android applications. Secondly, to measure the quality of Android applications that are written using Kotlin.

Our motivation is to know whether the Android applications written using Kotlin language have better quality than the applications written using the traditional approach for developing native Android apps, that means, to use Java language.

Several previous works have studied the quality of mobile applications, focusing on presence of code smells, aka antipatterns (Reimann et al., 2014a; Hecht et al., 2015a,b; Palomba et al., 2017), energy consumption (Morales et al., 2016, 2017; Cruz and Abreu, 2017; Carette et al., 2017; Saborido et al., 2018), performance (Hecht et al., 2016; Carette et al., 2017; Saborido et al., 2018), and hybrid applications (Malavolta et al., 2015a,b). However, to our best knowledge, neither the adoption of Kotlin language for developing Android apps nor the quality of Android apps written using Kotlin language has been studied.

To carry out our experiment, we start by building a dataset of Kotlin applications for Android platform. Then, we calculate the amount of Kotlin code that each has and we later analyze how the amount of that code varies along the history of Android applications. After that, we focus on the quality of Android applications. As proposed by Hecht et al. (2015a), we measure the quality of an Android application regarding the presence of code smells in that app. We first carry out an experiment for detecting instances of ten code smells proposed by the literature (Hecht et al., 2015a; Hecht, 2016) from two datasets of Android apps: one dataset with apps that were built using Kotlin code, the other with apps without Kotlin code. Then, we compare the presence of smell between the two datasets. Finally, we study how the introduction of Kotlin code impacts on the quality of an Android application.

The research of this paper is guided by the following research questions.

- **RQ 1:** What is the degree of adoption of Kotlin in mobile development?
  
  We inspect a dataset of open-source Android application, named F-Droid, and we filter those that were built, at least partially, using Kotlin.
  
  Finding 1: The 11.78% of the open-source Android applications from F-droid (i.e., 109 out of 925) contain Kotlin code;

- **RQ 2:** What is the proportion of Kotlin code in mobile application?
  
  We analyze every filtered application and we compute the proportion of code that is written in Kotlin language.
  
  Finding 2: The 35% of the apps that include Kotlin (i.e., 35 out of 109) are completely written in Kotlin, i.e., those do not include Java code.

- **RQ 3:** How do code evolve along the history of an Android application after the introduction of Kotlin code?
  
  We compute the amount of Kotlin code for each version of an Android application to analyze the evolution trends of the Kotlin code inside applications along their history.

1. [https://f-droid.org/](https://f-droid.org/)
Finding 3: For the 67.9%, the amount of Kotlin code increases over the evolution whereas the amount of Java code is reduced.

- **RQ 4:** Is there a difference between Kotlin and pure Java Android apps in terms of code smells presence?
  
  We compare the smells found in two Android apps datasets: one with Kotlin code, other without any line of Kotlin. For that, we replicate the experiment done by Habchi et al. (2017) which compares iOS and Android apps.

Finding 4: Oriented object smells affect more Kotlin that Java applications, but for 3 out of 4 oriented objected smells Java applications have in median more entities affected by them with statistically relevance.

- **RQ 5:** How frequent does the introduction of Kotlin positively impact on the quality of the versions of an Android application? We first compute the quality of each version of Kotlin applications based on the quality models from Hecht et al. (2015a) and then we measure the impact over the quality of introducing Kotlin code in applications initially written in Java.

Finding 5: The introduction of Kotlin code in Android applications initially written in Java increases the quality of, at least, the 50% of the apps.

The contributions of this paper are:

- A methodology for detecting applications written in Kotlin;
- A dataset with 109 open-source Android applications written partially or totally with Kotlin;
- An analysis of the validity of Android-related code smells presented by the literature;
- A study that compares the presence of smells in Kotlin apps and Java apps;
- A study about the measurement of the impact over the software quality of introducing Kotlin code in Android applications.

The paper continues as follows. Section 2 presents the related work. Section 3 describes Kotlin and the development of Android applications using Kotlin language. Section 4 introduces the methodologies used to respond the research questions. Section 5 presents the results and the answers to the research questions. Section 6 presents the threats to the validity. Section 7 concludes the paper.

2 Related Work

Kent Beck coined the term *code smell* in the context of identifying quality issues in code that can be refactored to improve the maintainability of a software (Fowler et al., 1999). Since there, the software engineering community has explored various associated dimensions that include proposing a catalog of smells, detecting smells using a variety of techniques, exploring the relationships among smells, and identifying the causes and effects of smells (Sharma and Spinellis, 2018). However, according to Aniche et al. (2017), the traditional code smells capture very general principles of good design. Moreover, they suggested that specific types of code smells are needed to capture “bad practices” on software systems adopting a specific platform, architecture or technology. In this context, researchers have been working in smells specific to the usage of object-relational mapping frameworks (Chen et al., 2014), Android apps (Verloop, 2013; Reimann et al., 2014a).
In this section, we discuss the relevant literature about code smells detection and fixing in mobile apps and related works on software evolution.

2.1 Detection of anti-patters (code smells) on mobile app

Mannan et al. (2016) compared the presence of well-known Oriented Object code smells in 500 Android apps and 750 desktop applications in Java. They concluded that there is not a major difference between these two types of applications concerning the density of code smells. However, they observed that the distribution of code smells on android applications is more diversified than for desktop applications. Khalid et al. (2016) conducted a study about the relation of presence of code smells and applications’ rating. They analyzed 10,000 Android applications using the tool Findbugs\(^8\) and their reviews at Google Play Store. They found that there is correspondence between these three categories of warnings and the complaints in the review-comments of end users.

Reimann et al. (2014a) propose a catalog of 30 quality smells dedicated to Android. These code smells are mainly originated from the good and bad practices documented online in Android documentations or by developers reporting their experience on blogs. Hecht et al. (2015b,a) have proposed a tooled approach, called Paprika, to identify object-oriented and Android-specific anti-patterns from binaries of mobile apps. Palomba et al. (2017) proposed a detection tool, called aDoctor, to detect 15 android anti-patterns using static analysis code techniques. They tested aDoctor on a testbed of 18 android apps and attained a detection precision close to 100%.

While Mannan et al. (2016) and Khalid et al. (2016) focused on detection of oriented-object smells in mobile apps, Reimann et al. (2014a) proposed a catalog of smells dedicated to Android. Moreover, Hecht et al. (2015a,b) and Palomba et al. (2017) proposed tools to identify android smells.

To the best of our knowledge, nobody has studied code smells on applications written with Kotlin.

2.2 Code evolution

Object-oriented metrics have gained popularity to assess software quality, since their definition by Chidamber and Kemerer (1994).

Li et al. (2017a) conducted an empirical study on long spans in the lifetime of 8 typical opensource mobile apps to have a better understanding of the evolution of mobile apps. The tried to verify whether Lehman’s laws (Lehman 1980) still apply to mobile apps. Their results indicated that a subset of Lehman’s laws still applies to open source mobile apps. Moreover, they found that the growth of mobile apps is non-smooth and the software instability increases with the addition of thirdparty libraries.

To the best of our knowledge, no works studied the evolution of Kotlin applications.

\(^8\) http://findbugs.sourceforge.net
2.3 Presence of code smells (Anti-patters) throughout the software evolution

To assess software quality other works focus on the presence of code smells. Palomba et al. (2015) presented HIST (Historical Information for Smell Detection), an approach aimed at detecting five different code bad smells by exploiting information extracted from versioning systems. They compared their approach over a manually-built oracle of smells identified in twenty Java open source projects, with traditional approaches, based on the analysis of a single project snapshot. They found that HIST can identify code smells that cannot be identified by traditional approaches. Also, they confirmed that there is a potential to combine historical and structural information to achieve a better smell detection.

Tufano et al. (2015) conducted a sizable empirical study over the change history of 200 open source projects from different software ecosystems, including Android applications. They investigated when bad smells are introduced by developers and the circumstances and reasons behind their introduction. They found that most times code artifacts are affected by bad smells since their creation. Moreover, they observed that the main activities which developers tend to introduce smells are implementing new features and enhancing existing ones.

Hecht et al. (2015b,a) have proposed a tooled approach, called Paprika, to identify object-oriented and Android-specific anti-patterns from binaries of mobile apps, and to analyze their quality along evolution. They considered 106 Android applications that differ both in internal attributes, such as their size and external attributes from the perspective of end users. They collected several versions of each application to form a total of 3,568 version to estimate software quality during their evolution. They found that mobile app developers need to allocate more quality assurance efforts. Palomba et al. (2018) presented a large-scale empirical study on the diffuseness of code smells and their impact on code change- and fault-proneness. The study analyzed a total of 395 releases of 30 open source projects and considering 13 different code smells. The found that smells characterized by long and/or complex code (e.g., Complex Class) are highly diffused, and that smelly classes have a higher change- and fault-proneness than smell-free classes.

In fact, Tufano et al. (2015) and Palomba et al. (2015) focused on code smells, but none of them have investigated the presence of Android-specific smells during the software evolution. On the other hand, Hecht et al. (2015b,a) proposed a tool capable of identifying both type of smells, oriented object, and android and they evaluated the evolution of software quality.

However, none of these works studied the presence of smells on the mobile application written in Kotlin.

2.4 Relation between code smells and programming languages in mobile apps

Habchi et al. (2017) studied code smells in the iOS ecosystem, considering Swift and Objective-C languages and how it is compared with Android smells. They proposed a catalog of 6 iOS-specific code smells that they identified from developers feedbacks and the platform official. To identify those code smells they extended Paprika (Hecht et al. 2015a,b). Then, they analyzed 103 Objective-C apps and 176 Swift apps hosted on Github and discovered that code smells tend to appear with the same proportion or only a slight difference in Objective-C and Swift and
that the apps written in Objective-C and Swift are very different concerning OO metrics. Furthermore, they analyzed 1,551 Android open-source application from F-Droid and found that Android apps tend to contain more code smells than iOS apps in both languages, except for the SAK code smell, which appears in the same proportion for all languages.

Although Habchi et al. (2017) focused on the relation between code smells and programming languages in the context of mobile apps, they did not consider applications written in Kotlin.

2.5 Studies that measure the impact on code smells on runtime.

Besides some works with the focus on identify code smells, other authors have focused on better understanding the impact of code smells on runtime. Hecht et al. (2016) conducted an empirical study with different versions of open source Android apps to determine if the correction of Android anti-patterns had a significant impact on the user interface (number of delayed frames) and memory usage. They reported that correcting these android code smells effectively improves the user interface and memory usage in a significant way.

Cruz and Abreu (2017) studied whether or not eight best performance-based practices. They realized an empirical study with 6 applications from F-droid and manual refactoring were applied for each detected pattern in those applications. They found that fixing ViewHolder, DrawAllocation, WakeLock, ObsoleteLayout-Param, and Recycle improved energy efficiency. However, fixing UnusedResources and UselessParent did not provide any significant change in energy consumption while fixing Overdraw increase energy consumption by 2.2%.

Saborido et al. (2018) performed a study about the use of Java implementation HashMap and the Android API that offers different implementations of the map data structure. They analyzed 5,713 Android apps in GitHub and available in Google Play. They found that SparseArray variants should be used instead of HashMap and ArrayMap when keys are primitive types because it is more efficient in terms of CPU time, memory and energy consumption, disagreeing partially with the Android documentation.

These works focus on oriented object and Android smells and how they impact on different runtime aspects. Nevertheless, these experiments did not consider Kotlin applications.

2.6 Approaches that automatically correct code smells

The previous works from Mannan et al. (2016); Khalid et al. (2016); Papadakis et al. (2017); Palomba et al. (2017); Hecht et al. (2015b,a); Habchi et al. (2017); Hecht et al. (2016); Cruz and Abreu (2017); Saborido et al. (2018) focused on studying (detecting) code smells. Other words focus on applying “correction” action to overcome the code smells. Carette et al. (2017) proposed a toolled and reproducible approach, called Hot-Pepper, to automatically correct code smells and evaluate their impact on energy consumption. Hot-Pepper relies on Paprika. They conducted an empirical study on five Android apps to assess the energy impact of Android performance. Their
results confirm that Android anti-patterns have an impact on the energy consumption of apps.

Morales et al. (2016, 2017) introduced a novel approach for refactoring mobile apps while controlling for energy consumption, EARMO that uses evolutionary multiobjective techniques. They evaluated it on a benchmark of 20 free and open-source Android apps. The results have shown that EARMO can propose solutions to remove a median of 84% of anti-patterns, with a median execution time of less than a minute. Concerning the difference in energy consumption after refactoring, they observed that for three apps improved their energy consumption with statistically significant results.

Cruz and Abreu (2018) presented a tool capable of identifying and applying automatic refactoring of five energy code smells: View Holder, Draw Allocation, Wake Lock, Recycle and ObsoleteLayoutParam (Cruz and Abreu 2017). They analyzed 140 free and open-source Android apps collected from F-droid. Their experiment yielded a total of 222 refactorings in 45 apps, which were submitted to the original repositories as PRs. 18 apps had successfully merged their PR. These works (Morales et al. 2016, 2017; Cruz and Abreu 2017, 2018; Carette et al. 2017) applied refactoring at Java code level to remove code smells.

As far as we know, no studies focused on apply refactoring on Kotlin applications.

3 Brief Introduction to Mobile Development using Kotlin Language

In this section, we briefly describe Kotlin and Android application development using writing Kotlin code.

3.1 Kotlin programming languages

Kotlin is a statically typed programming language that reduces language verbosity relative to Java (e.g., semicolons are optional as a statement terminator ‘;’). Furthermore, Kotlin applications run on top of the Java Virtual Machine (JVM). The Kotlin compiler kotlinc compiles Kotlin code to Java bytecode, which can be executed by that JVM. This implies that Kotlin is interoperable with Java and other JVM languages as well (e.g., Scala or Groovy).

Regarding the development of mobile applications, this interoperability can be seen in two manners. First, Kotlin developers can use libraries (e.g., jars) written in another language such as Java, and secondly, developers can create applications using Kotlin together with other JVM languages.

3.2 Kotlin for Mobile development

To develop a mobile application using Kotlin languages, developers can use the same tools that Google provides for developing Android apps using Java language. Those tools are: a) the Software Development Kit (SDK) and b) Integrated De-

https://developer.android.com/about/
An Empirical Study on Quality of Android Applications written in Kotlin language

Development Environment (IDE). For instance, Android Studio +3.0 fully supports the development of Android apps using Kotlin code and provides features such as autocomplete, debugging, refactoring, lint check. Using Android Studio, it is possible to: 1) start a new Android project for developing an app using Kotlin from scratch, 2) add new Kotlin files to an existing project already written in Java, or 3) converts existing Java code to Kotlin.

During the development, Java and Kotlin code are compiled (translated) to Dalvik bytecode and stored .dex files (those are similar to .class file for Java VM). Dex files run on top of the adapted JVM for Android devices named Dalvik or Art (according to the Android version). Finally, Dalvik bytecode is packaged in a file named Application Package Kit (APK), which groups the bytecode of a mobile app (similarly to jar files for class files in Java). Moreover, it is possible to inspect these files using a tool present in the Android SDK, named apkanalyzer.

3.3 Advantages claimed by Kotlin community

First of all, as far as we know, nobody has studied the advantages of using Kotlin. However, the community of Kotlin developers enumerate some features in favor of Kotlin, suggesting, that mobile developers should change from Java to Kotlin. Vinther (2017) suggests 17 reasons why developers should totally switch to Kotlin: 1) Java Interoperability, 2) Familiar Syntax, 3) String Interpolation, 4) Type Inference, 5) Smart Casts, 6) Intuitive Equals, 7) Default Arguments, 8) Named Arguments, 9) The When Expression, 10) Properties, 11) The Data Class, 12) Operator Overloading, 13) Destructuring Declarations, 14) Ranges, 15) Extension Functions, 16) Null Safety, and 17) Better Lambdas. To the best of our knowledge, no work has empirically validate those reasons in the context of mobile development.

4 Methodology

In this section, we present the methodology used in this paper for studying Android mobile applications written with Kotlin language. In Section 4.1 we describe the method to collect mobile applications and to define the dataset of Android application we use in this paper. Section 4.2 presents the heuristics for classifying Kotlin apps from the mentioned dataset, used to respond to RQ 1. Section 4.3 presents the method to obtain the proportion of Kotlin code, used to respond RQ 2. Section 4.4 presents the different evolution trends of code source, used to respond to RQ 3. Section 4.5 describes the code smells from the bibliography, used to respond RQ 4. Finally, section 4.6 describes the technique to calculate the quality score of Android applications and the process to measure the impact of introducing Kotlin code, used to respond to RQ 5.

10 https://developer.android.com/studio/
11 https://developer.android.com/studio/build/apk-analyzer
4.1 Creation of a dataset of Kotlin applications

4.1.1 Selecting dataset of Android applications

To study the using of Kotlin in the context of mobile development, we need first to select a dataset of mobile applications. We selected the F-droid, an open-source Android app repository. The main reasons for that decision are: 1) it contains only open-source apps, then it is possible to analyze the source code; 2) for each application it has a link to a public available source code repository (e.g., to GitHub) and the bytecode (apks) from different released versions; 3) it stores the previous versions of each app, which is necessary for studying the app evolution. 4) it is used by the Software Engineering community in previous works (Wang and Godfrey, 2013; Krutz et al., 2015; Morales et al., 2016; Karim et al., 2016; Chen, 2016; Allix et al., 2016; Cruz and Abreu, 2017; Grano et al., 2017; Hassan et al., 2017; Li, 2017; Kessentini and Oum, 2017; Abdalkareem et al., 2017; Ciurumelea et al., 2017; Carette et al., 2017; Li et al., 2017b; Cruz and Abreu, 2018).

In total, F-droid has 1,509 applications. Note that one mobile application has one or more versions, each of them represented by an apk. F-droid provides the apks of an application via a web page, so we built a web crawler to download all of apk. F-droid provides on the main page of each application a link to download its last three versions and a link for another page with some technical information that contains all versions. Our crawler is able to visit both pages for each application and retrieves the link to the apk for every version available. F-droid provides the upload date only for the last three version, but every version has a version number (e.g., 1.1, 1.2, 3), allowing to sort the versions chronologically.

4.1.2 Filtering applications from F-Droid

In this work, we are interested in a subset of mobile applications from F-droid: those that contain Kotlin code. As Kotlin was announced as an official language for Android development in 2017 before that date, Android developers did not have support from Google for developing Android apps using Kotlin language. For that reason, we consider that apps which the last versions date from 2016 or earlier could not give us much information about the use of Kotlin language in the Android domain. As consequence, the criterion we used for building our dataset of mobile apps is to select every application which its last version was released in 2017 or later.

The total number of applications retrieved by the date of June 4th, 2018 that fulfill our selection criterion is 925. The total number of versions (i.e., apks) found corresponding to those applications was 13,094. We finally downloaded 12,175 apks (93%), corresponding around of 54 GBs. However, for the 7% of apks files, the F-droid server answered with a HTTP error: those apks are not available anymore.

12 https://f-droid.org
13 Last visit: 06/04/2018.
14 https://android-developers.googleblog.com/2017/05/android-announces-support-for-kotlin.html
Fig. 1: Pipeline to classify Android applications (Section 4.2.). First we download applications from F-droid using our web crawler. Then, we classify them between Kotlin and Java in three steps. First, in step (a), heuristic $H_{\text{apk}}$ considers the content of apk. Second, in step (b), heuristic $H_{\text{gh}}$ uses the Github API to get information about the programming languages used by every application of our dataset hosted there. Third, in step (c), heuristic $H_{\text{sc}}$ analyzes the partial dataset to verify presence of Kotlin source code.

4.2 Detecting Kotlin apps

For responding our RQ$_1$ (What is the degree of adoption of Kotlin in mobile development?), we build a process to classify both the applications and apks retrieved in Section 4.1 in two categories of applications: 1) written (partially or totally) with Kotlin, and 2) written with Java (not include any line of Kotlin code). Note that we only focus on the code of the application (source or bytecode), discarding analyzing their dependencies.

Figure 1 shows the process for classifying applications between Kotlin and Java based, which has 3 main steps.

We first apply an heuristic $H_{\text{apk}}$, Figure 1(a), that consists on looking for a folder called kotlin inside the apk file. Having such folder is an evidence of having Kotlin code inside the application. To automatize this task, we use an Android developer tool provided by the Android SDK, named apkanalyser. Using this heuristic, we first classify each version (apk) of an application. Then, if at least one apk of an application is classified as Kotlin, the heuristic classifies the application as ‘Kotlin’. Otherwise, it classifies it as ‘Java’. The $H_{\text{apk}}$ provides a cheap and fast approach to get an initial guess about the presence of Kotlin code.

At the same time, we apply our the second $H_{\text{gh}}$, Figure 1(b), which leverages on the Github API: for each application hosted on Github, we query the Github API to retrieve the amount of code (expressed in bytes) from the most recent version (i.e., the HEAD) grouped by the programming language. We classify the app as ‘Kotlin’ if Kotlin language is present in the response of the API. The input of this heuristic is a URL to a Github repository.
Finally, once we retrieve a set of candidate Kotlin applications using $H_{apk}$ and $H_{gh}$, we apply the heuristic $H_{sc}$, Figure 1(c), to assert the presence of Kotlin code in, at least, one commit. $H_{sc}$ inspects every version of the source code repository of an application, which URL is available in the F-droid web page. An application is classified as Kotlin if the heuristic finds, at least, one commit that introduces Kotlin code. To carry out this task, the heuristic used the tool CLOC which returns a list with the languages used in an application and the amount of code regarding no-blank lines. $H_{sc}$ is time-consuming because it requires to analyze the source code of each revision of an application. Hence, to execute $H_{sc}$ for every application from F-droid is prohibitive.

Note that, differently of $H_{sc}$, heuristic $H_{gh}$ only focuses on the most recent version hosted on Github (the API only retrieves that information). Consequently, it cannot detect applications that: a) do not contain Kotlin code in the most recent version, but b) contain Kotlin code in older versions.

4.3 Analyzing the proportion of Kotlin code

For responding the RQ 2 (What is the proportion of Kotlin code in mobile application?), we first retrieve the code of the last version of each application classified as ‘Kotlin’ using the heuristics presented in Section 4.2. For each application under analysis, we retrieve the corresponding code repository, information available on F-droid website. We found that all the selected applications have a GIT repository. We execute the tool CLOC over the most recent version of each application, and we then calculate the proportion of Kotlin code (excluding blanks and comments) with respect to the total code of the application. Note that we discard analyzing files that do not contain JVM bytecode, such as XML, CSS, JavaScript and others.

4.4 Analyzing the code evolution of Android applications

For responding the RQ 3 (How do code evolve along the history of an Android application after the introduction of Kotlin code?), we inspect the source code repository of one application to analyze the evolution trend of Kotlin code along the history of the application.

For each code repository associated to one application, we visit each commit in chronological order (starting from the oldest one) for calculating the amount of code (also using CLOC) of the version related to the commit. In this experiment, we focus on analyzing the evolution trend of two particular languages: Java (i.e., the traditional used for developing Android apps) and Kotlin.

We define 9 cases that represent different evolution trends of Kotlin and Java code. They are:

ET 1: Kotlin is the initial language and the amount of Kotlin grows along the history.

ET 2: Kotlin code replaces all Java code between two consecutive versions.

15 http://cloc.sourceforge.net/
16 http://cloc.sourceforge.net/
ET 3: Kotlin code replaces some Java in consecutive versions (i.e., amount of Java code drops), but after the drop, the amount of Java continues growing.

ET 4: Kotlin increases together with Java.

ET 5: Kotlin grows and Java decrease and last version of the app has both languages.

ET 6: Kotlin grows and Java decrease until the amount of Java code is 0.

ET 7: Kotlin grows and Java remains constant.

ET 8: Kotlin is constant and Java grows.

ET 9: Kotlin introduced in the app but lately disappears (amount is 0).

Note that it could exist more evolution trends that we have not included in the previous list. We include only those we have observed during our experiment and are particularly interesting for this paper.

To classify each Kotlin application according to evolution trend, we first plot the amount of code (line of code) of Kotlin and Java for each commit (Figure 4 shows some of such plots). Then, we manually select the evolution trend that is most representative (i.e., that better fits) to the code evolution of that application.

4.5 Analyzing the difference between Kotlin and Java applications and the quality of Android application

For responding the RQ 4 (Is there a difference between Kotlin and pure Java Android apps in terms of code smells presence?), we run a code smells detection tool over Android applications from the dataset presented in Section 4.2. In this paper we focus on two kinds of smells: Object-oriented and Android-related code smells.

4.5.1 Selection code smells detecting tool

To detect code smells from Android Applications we select the tool Paprika [Hecht et al., 2015a, b, c, d, e, f, g].

The reasons for selecting Paprika are: a) it can detect oriented-object and android specific code smells; b) it was designed for detecting code smell on Android applications without requiring code source: the input of Paprika is the apk of one Android application; c) as it works at JVM bytecode level (i.e., an apk contains bytecode), it can analyze Android application written on Java and/or Kotlin; d) it is open-source and code hosted on GitHub; e) it is customizable: a user can add new code smell to detect; f) previous works have extensively used Paprika for analyzing mobile apps [Hecht et al., 2015a, b, 2016; Habchi et al., 2017; Carette et al., 2017; Grano et al., 2017]; g) the tool implementation was deeply validated by carrying out, for instance, a validation with Android developers [Hecht, 2016].

Table 1 shows the code smell that Paprika is able to identify: 4 are object-oriented and 13 are android code smells. Moreover, Table 1 also presents the entities that are related to each code smell. Some entities are related to Object-Oriented smells (Classes, Methods), others to Android smells (Activities, Async Task).

17 https://github.com/GeoffreyHecht/paprika
18 Version of Paprika used: commit 5ebd34 https://github.com/GeoffreyHecht/paprika/commit/5ebd349ed3067914386e8c6a05e87ff161f9edd1
Table 1: Paprika supported code-smells. The column ‘Considered’ shows the 10 code smells studied in our work (✓) and the 7 not studied (X).

| Type                   | Code smell name             | Entity          | Considered |
|------------------------|-----------------------------|-----------------|------------|
| Object-Oriented        | Blob Class (BLOB)           | Classes         | ✓          |
|                        | Swiss Army Knife (SAK)      | Interface       | ✓          |
|                        | Complex Class (CC)          | Classes         | ✓          |
|                        | Long Method (LM)            | Method          | ✓          |
| Android-Specific       | Hashmap Usage (HMU)         | Class           | X          |
|                        | Unsupported Hardware Acceleration (UHA) | Class | X          |
|                        | Leaking Inner Class (LIC)   | Inner classes   | X          |
|                        | Member Ignoring Method (MIM) | Methods       | X          |
|                        | Internal Getter/Setter (IGS) | Methods       | X          |
|                        | No Low Memory Resolver (NLMR) | Activities   | ✓          |
|                        | Heavy AsyncTask (HAS)       | Async Tasks     | ✓          |
|                        | Heavy Service Start (HSS)   | Services        | ✓          |
|                        | Heavy Broadcast Receiver (HBR) | Broadcast Receivers | ✓          |
|                        | Init OnDraw (IOD)           | View            | ✓          |
|                        | Invalidate Without Rect (IWR) | View        | X          |
|                        | UI Overdraw (UIO)           | View            | ✓          |
|                        | Bitmap Format Usage (BFU)   | -               | X          |

The input of Paprika is an apk (i.e., a version of an Android application) and returns a list with all instances of the smells found in that apk. Moreover, for each instance of some smells (incl. BLOC, CC and HSS), Paprika returns a fuzzy value between the two extreme cases of truth (0 and 1) which represent the degree of truth or certainty of the detected instance (Habchi et al., 2017; Hecht, 2016).

To detect occurrences of code smells, Paprika uses metrics associated to entities. For example, the code smell Long Method (LM) is an object-oriented smell, and it is related to methods: an instance of LM are methods which the number of instructions is higher to a given threshold.

In addition to the identification of code smell instances, Paprika produces as output the metrics associated with the entities that it uses for detecting smells, for example, the number of methods, activities, services. These entities-associated metrics are later used to calculate the software quality score (Section 4.6).

4.5.2 Code Smells considered in our study

We now describe the smells that we selected as the target in our study. Table 1 shows them with ✓ in column “Considered”.

First, we consider the four oriented object smells (BLOB, SAK and CC, related to classes, LM related to methods) because they can also exist on Kotlin applications. Let us briefly describe each of them. A Blob class (BLOB), also known as a God class, is a class with a large number of attributes and/or methods (Brown et al., 1998). A Swiss army knife (SAK) is an interface with a large number of methods (Hecht, 2016). A complex class (CC) is a class containing complex methods. These classes are hard to understand and maintain and need to be refactored (Fowler et al., 1999). Long methods (LM) have much more lines than other methods, becoming complex, hard to understand and maintain.

Secondly, we consider 6 Android platform related code smells that Paprika can detect, and we discard 7. Those Android smells we consider are: 1) NLMR (related
with activities), 2) HAS (async taks), 3) HSS (async taks), 4) HBR (broadcast receivers), 5) UIO (views), and 6) IOD (views)

Let us briefly describe each of them. No Low Memory Resolver (NLMR) ([Hecht et al., 2015b]) occur when activities do not have the method onLowMemory() overridden, that are supposed be called to free resources. If this method is not implemented by the activity, the Android system could kill the process to free memory, and can cause an abnormal termination of programs ([Reimann et al., 2014b]).

Heavy ASynctask (HAS) ([Hecht, 2016]), Heavy Service Start (HSS) ([Hecht, 2016]) and Heavy BroadcastReceiver (HBR) ([Hecht et al., 2015a]) are similar: they occur when heavy operations are executed at the main thread in different Android components, Async Task, Service and BroadcastReceiver, respectively ([Mariotti, 2013a,b,c]).

UI Overdraw (UIO) ([Hecht et al., 2015a]) and Init OnDraw (IOD) ([Hecht, 2016]) are related to custom views. The smell UIO produces overdraw views due there are missing method invocations such as clipRect and quickReject ([McAnlis, 2015]), which avoid the overdraw. IOD happens when new objects are created inside onDraw method that could be executed many times by second, result in many object allocations ([Ni-Lewis, 2015a]).

4.5.3 Code Smells ignored in our study

We ignore 7 Android-related code smells that Paprika can identify. Table 1 shows them with a “X” in column “Considered”. Those smells are: MIM, LIC, IGS, BUF, HMU, UHA and IWR. In the remainder of this section, we describe them and explain why we decided to exclude them.

Member Ignoring Method (MIM) ([Reimann et al., 2014b]) occurs when a method does not access any object attribute. In Android, it is recommended to use a static method instead because of the static method invocations are about 15%-20% faster than a dynamic invocation ([AndroidDoc, 2018a]). The smell Leaking Inner Class (LIC) ([Hecht et al., 2015b]) occur when an application uses non-static inner and anonymous classes as in Java this type of inner class holds a reference to the outer class, and this could provoke a memory leak in Android systems ([Reimann et al., 2014b]; [Lockwood, 2013]). We decided to discard MIM and LIC because Kotlin does not have static methods ([KotlinDoc, 2018]).

Internal Getter/Setter (IGS) ([Reimann et al., 2014b]) impacts on the performance and energy consumption of applications ([Hecht et al., 2016]; [Morales et al., 2016]; [Kessentini and Ouni, 2017]; [Grano et al., 2017]; [Palomba et al., 2017]; [Carette et al., 2017]). However, this code smell only impacts when an application runs on Android platforms 2.3 or less ([Cruz and Abreu, 2018]). The discard the smell because the number of active Android devices that run those platform versions is less than 0.5%.[19]

Bitmap Format Usage (BFU) is related with image format ([Carette et al., 2017]). We discard it because it is related to neither Kotlin nor Java code, i.e., the smell is independent of the programming language used.

HashMap Usage (HMU) ([Carette et al., 2017]) occurs when developers use small HashMap instances instead of using ArrayMap or SimpleArrayMap, both pro-

[19] https://developer.android.com/about/dashboards/ Last visit: 06/11/2018
vided by the Android framework (Haase, 2015; AndroidDoc, 2018b). However, the results found by Saborido et al. (2018) show that ArrayMap is generally slower and less efficient regarding energy consumption than HashMap. Moreover, they show that if the keys used are primitive types, developers should adopt SparseArray variants, because they are more efficient concerning CPU time, memory and energy consumption. We discard this smell because of: a) the mentioned finding from Saborido et al. (2018), and b) the Paprika’s mechanism used to identify HMU occurrence does not take into account the key type.

Finally, we focus on 2 smells related to custom views. Unsupported Hardware Acceleration (UHA) (Hecht, 2016) occurs when developers call a method that is not hardware accelerated, so it runs on the CPU instead of GPU impacting on performance and energy consumption (Ni-Lewis, 2015b). We discard it because the occurrences of the smell depend neither on the developer nor programming languages. The smell Invalidate Without Rec (IWR) (Hecht, 2016) appears when the onDraw method is not implemented properly, resulting in overdraw views (Ni-Lewis, 2015b). When developers do not specify the rectangle area that should be updated, the whole view is redraw, even some area that is not visible, resulting in performance problems. Ni-Lewis (2015b) indicated that developers should call the method invalidate(Rect dirty), specifying the area to be drawn, to avoid this smell. However, this method is deprecated in API 28 and since API 21 its calls is ignored. Consequently, we discard this smell.

4.5.4 Analyzing the difference between Kotlin and Java applications in terms of presence of code smells

First, we analyze the Kotlin and Java applications in our dataset to identify the OO and Android smells listed in Section 4.5.2. We run Paprika for all version of each application (i.e., apks). Then, we compute the percentage of Android applications affected by each code smell. An application $a$ is affected by a code smell $s$ if $a$ has at least one instance of $s$. This approach splits applications into two groups: affected by $s$ and not affected by $s$.

However, the number of instances of a smell can vary across an application. Thus, for each affected app, we compute the ratio between the number of instances of each code smell and the number of concerned entities related to the smells (Habchi et al., 2017). For each application $a$, the ratio of a smell $s$ (Habchi et al., 2017) is defined as:

$$ratio_s(a) = \frac{fuzzy\_value_s(a)}{number\_of\_entities_s(a)}$$

where $fuzzy\_value_s(a)$ is the sum of the fuzzy values of the detected instances of the smell $s$ in the app $a$ and $number\_of\_entities_s(a)$ is the number of the entities concerned by the smell $s$ in the app $a$.

As done by Habchi et al. (2017), we use the ratio to quantify the importance of the difference in proportions of the smells. Based on the ratio, we compute Cliffs $\delta$ (Romano et al., 2006), which indicates the magnitude of the effect size (Cliff, 2014) of the treatment on the dependent variable. According to Romano et al. (2006), the effect size is small for $0.147 \leq \delta < 0.33$, medium for $0.33 \leq \delta < 0.474$, and large for $\delta \geq 0.474$. We opted for the Cliffs $\delta$ test since it is suitable for
non-normal distributions. Moreover, Cliffs $\delta$ is also recommended for comparing samples of different sizes (Macbeth et al., 2011).

4.6 Calculating quality scores of Android applications

For responding the last RQ 5 (How frequent does the introduction of Kotlin positively impact on the quality of the versions of an Android application?), we use the technique presented by Hecht et al. (2015a) for scoring each version (apk) of the mobile application. The score serves as an estimation of the mobile app quality in a particular version (apk) and is based on the consistency between applications size and the number of detected code smells.

4.6.1 Defining a quality model

To compute the software quality score based on one type of smell code $sc$, the technique from Hecht et al. (2015b) first builds an estimation model using linear regression, which represents the relationship between the number of code smells of type $sc$ and the size of an application. The size of the application is a metric related to the entity associated to $sc$ (presented in Table 1), e.g., for smell BLOB, it is the total number of classes of an app. Then, the software quality score of an application at a particular version, the techniques takes as input the number of code smells and a value of size, and produces a score based on the additive inverse of the residual. A higher positive score implies better quality: as described by Hecht et al. (2015a) larger positive residual value suggests worst software quality because it means the apk has more smells with respect to its size than the norm (i.e., linear regression), whereas a larger negative residual value implies better quality because of the lower number of smells.

4.6.2 Training a quality model

We created a quality score model, i.e., a linear regression, for each code smell that we consider in Section 4.5.2. We trained the linear model using a dataset defined by Hecht et al. (2015a) which contains 3,568 Android versions (apk) extracted from the Google Play store between June 2013 and June 2014. First, we created the training set from the output of Paprika given as input the mentioned dataset. Each element of the training dataset (a row) corresponds to a single apk $a$ and has $a)$ the number of instance of $s$ in $a$, and $b)$ the value associated to the entity of smell $s$ in $a$. For example, for smell Long Method (LM), we compute the linear regression between: 1) the number of instances of smell LM and 2) the total number of methods.

4.6.3 Using the a quality model for measuring quality of Kotlin apps

Once trained, we compute the quality scores (one per code smell) for each apk from the F-droid applications that we classified as ‘Kotlin’ (Section 4.2). Those apks conform our test dataset. Note that the training dataset does not include any

Hecht (2016) considers that a method is “long” (LM) if it has more than 17 instructions.
Table 2: Classification of F-Droid applications according to the programming language.

| Information | Available | Downloaded |
|-------------|-----------|------------|
|             | Kotlin    | Java       |
| Unique apps | 928       | 109        |
| Versions    | 13,094    | 1081       |

We measure the impact on the quality of introducing Kotlin code as follows. For each application that has both Java and Kotlin apk and for each code smell $cs$, we first compare the quality scores of $cs$ between the apk that introduces Kotlin code and the previous apk (i.e., which has Java code and no Kotlin). Then, we compare the quality score between the last Java apk (i.e., the version just before to the introduction of Kotlin code) and the most recent Kotlin version available. These two comparisons have different goals: the first one aims at measuring the impact just after the introduction of Kotlin in an app; the second one aims at studying the impact after the application (that now includes Kotlin code) has evolved.

4.6.5 Detecting changes in the quality evolution trends after introducing Kotlin

Hecht et al. (2015a) have established 5 major quality evolution trends. Each trend describe how the quality scores from the versions of an application $a$ change along the evolution of $a$. They are: A) Constant Decline, B) Constant Rise, C) Stability, D) Sudden Decline, and E) Sudden Rise.

In this paper we want to study whether the introduction of Kotlin code into an app $a$ produces a positive change in the quality evolution trend. For that, for each application $a$, we manually classify the quality evolution trend before and after the introduction of Kotlin on $a$. Then, we consider that Kotlin produce a positive change if: 1) the trend before the introduction is ‘Decline’ or ‘Stability’ (trends A, C or D); and 2) the trend after the introduction is exclusively ‘Rise’ (trends B or E). Note that we discard analyzing those apps whose trends (before or after) do not fit any of the defined major trends.

5 Results

5.1 RQ1: What is the degree of adoption of Kotlin in mobile development?

Table 2 summarizes the classification of applications done using the methodology presented in Section 4.2. Our dataset has 925 applications: 109 (11.78%) of them contain, at least, one version (apk) that includes Kotlin code. The rest of the applications, 816 (88.22%), do not have any version that contain Kotlin code. Figure 2(a) shows these percentages. Considering the number of versions (apk),
we found 1081 apks (8.88%) with Kotlin code and 11094 (91.12%) without Kotlin code.

Over a total of 109 Kotlin applications: a) $H_{apk}$ classified 97 app ‘Kotlin’, i.e., those with at least one ‘Kotlin’ apk. For 43 all them, all apks are classified as ‘Kotlin’ apk; b) $H_{gh}$ classified 16 additional applications as ‘Kotlin’ which were added to our dataset, resulting 109 application (93 + 16).

Response to RQ 1: What is the degree of adoption of Kotlin in mobile developing?
We found that 109 out of 925 applications from the dataset F-Droid has, at least, one version released between the years 2017 and 2018 written (total or partially) using the Kotlin language.

5.2 RQ2. What is the proportion of Kotlin code in mobile application?

For computing the percentage of Kotlin code, we executed the methodology presented in Section 4.3 over the 109 apps that contain at least one version with Kotlin code.

Figure 3 shows the distribution of Kotlin applications according to the percentage of Kotlin code. We found that 39 out of 109 (35.78%) applications have only Kotlin code, i.e., 64.22% of Kotlin applications are partially written in Java. Furthermore, we found that 58 out of 109 (53.21%) applications have more at least 80% of Kotlin code. Moreover, 21 out of 925 (19.27%) applications, have less than 10% of Kotlin code.

Response to RQ 2: What is the proportion of Kotlin code in mobile application?
Considering the last version of each application, the majority of Kotlin applications have at least 80% of lines of code written in Kotlin.

$^{21}$ Note that those 16 apps correspond to the cases that Kotlin code is added into the application, but since that moment, it could happen that: 1) the developers have not released any version (i.e., created an apk), or 2) the released versions are not available on F-droid.
Fig. 3: Distribution of applications according their percentage of Kotlin code. 53% of Kotlin applications have more than 80% of source code written in Kotlin.

Table 3: Classification of Android applications according to the evolution trend of Kotlin and Java source code.

| Source Code Evolution Trend                                      | # Apps | % |
|------------------------------------------------------------------|--------|---|
| ET 1 Kotlin is the initial language and the amount of Kotlin grows | 10     | 9.2|
| ET 2 Kotlin code replaces all Java code                         | 21     | 19.3|
| ET 3 Kotlin code replaces some Java then Java continues growing | 4      | 3.7|
| ET 4 Kotlin increase together with Java                         | 11     | 10.1|
| ET 5 Kotlin grows and Java decrease (but never is zero)         | 22     | 20.2|
| ET 6 Kotlin grows and Java decrease until the Java code is 0   | 16     | 14.7|
| ET 7 Kotlin grows and Java remains constant                     | 15     | 13.8|
| ET 8 Kotlin is constant and Java grows                         | 8      | 7.3|
| ET 9 Kotlin introduced but lately disappears                    | 2      | 1.8|
| Total applications                                              | 109    | 100%|

Note that, by analyzing the source code of the applications, the number of apps with only Kotlin code is lower (39) than the number of application with apks only classified as ‘Kotlin’ (43 apps found in Section 5.1). This makes sense since classifying an apk as ‘Kotlin’ happens in two cases: when the apk was written 1) mixing Java and Kotlin code; 2) the apk was written only Kotlin code.

5.3 RQ3 How do code evolve along the history of an Android application after the introduction of Kotlin code?

Table 3 shows the results and Figure 4 displays, for each code evolution trend, the code evolution of one particular application as example.
Fig. 4: Evolution trends of Kotlin and Java code. The figure presents one graphic per evolution trend described in Section 4.4. Each graphic presents the evolution of Kotlin and Java code along the history (i.e., commits) of one single application. The x-axis corresponds to the commits and the y-axis corresponds to the amount of code (i.e., lines).
The most frequent code evolution trend we found is ET 5, with 22 out of 109 (20%) Kotlin applications. This evolution trend represent the cases that, after the first version (i.e., commit) that introduces Kotlin code, the amount of Kotlin code tends to grow, whereas the amount of Java code decreases. Sub-figure 4(e) shows the code evolution of app Openlinkwith, which corresponds to that evolution trend. Still, the last version of Openlinkwith has more lines of code (LOC) of Java than Kotlin. Another application classified as ET 5 is Poet-Assistant (sub-figure 4(f)). However, unlike Openlinkwith, the amount of Kotlin code in the last version is larger than the amount of Java code. In the mentioned applications, the lines that represent the evolution of Kotlin code seem to be symmetric w.r.t those of Java. We suppose that some components of the application written in Java code are gradually migrated to Kotlin code.

A similar trend to ET 5 is ET 6: 16 Android apps (14.7%) exhibit that trend. As the difference with ET 5, the amount of Java code gradually decreases until arriving to zero LOC. Since that moment, those applications do not contain Java code any more. The sub-figure 4(g) shows one application, Simple-Calendar, which first versions were written in Java. Then, the versions from commit 09ef99 to 206dfe, introduce Kotlin code and remove Java code. Finally, from commit eee184 the application is composed by only Kotlin code.

The second most frequent code evolution trend is ET 2, with 21 applications over 109 (19.3%). Sub-figure 4(b) shows the code evolution of the application Simple-Flashing, initially written in Java. One commit (1bb5c9) migrates the complete code base from Java to Kotlin. However, unlike with ET 5 and 6, in ET 2 there is not any version that shares Java and Kotlin code.

There are two trends ET 7 and 8 (with 15 and 8 applications, resp.) of which amount of code of a given language is almost constant since its introduction. For example, the sub-figure 4(i) shows the code evolution of Talk-Android, classified as ET 8. One commit (7f12) introduces a portion of Kotlin code (105 lines). Since then: a) the amount of Kotlin code remains constant along the evolution (the last commit e724 has 106 LOC), b) the amount of Java code constantly grows. The sub-figure 4(h) shows an inverted case (app Bimba): the amount of Java code is constant while the amount of Kotlin grows.

Moreover, there are 11 Android apps (10.1%) that correspond to trend ET 4: the amount of both Java and Kotlin grows. The sub-figure 4(d) shows the amount of code of the app Android USB MSD: here, the introduction of code written in one language does not produce a decrease of the amount of code written in the other language. Also, evolution trend ET 1 has 11 applications: those, such as app Vpnhotspot sub-figure 4(a) were initially written in Kotlin and did not include Java code in any version.

Another evolution trend is ET 3: when Kotlin code is introduced, the amount of Java code decreases (in similar proportions), but then, Java amount start growing again. Sub-figure 4(c) shows the code evolution of app Home-Assistant one of the 4 apps (3.7%) classified as ET 3. Here, we suspect that developers migrate only a portion of code.

Finally, there are two applications that evolution trends are ET 9: Kotlin code is introduced at some time, but some version later it disappears. The sub-figure 4(j) shows the code evolution of Freeotpplus application. Here, the ends of the evolution trends of Java and Kotlin code are symmetric: we suspect that the Kotlin code
Table 4: Percentage of Android apps affected by code smell. An app \( a \) is affected by a code smell \( s \) if \( a \) has at least one instance of \( s \).

| Lang  | Object-oriented smells | Android smells |
|-------|-------------------------|----------------|
|       | LM  | CC  | BLOB | SAK | NLMR | UIO | HBR | HSS | HAS | IOD |       |
| Kotlin| 99.99 | 99.30 | 97.72 | 79.96 | 98.71 | 55.87 | 46.10 | 14.41 | 16.17 | 14.61 |
| Java  | 99.73 | 96.85 | 92.51 | 60.21 | 99.25 | 38.38 | 42.19 | 21.50 | 22.79 | 06.03 |
| K - J | 0.17 | 2.45 | 5.21 | 19.75 | -0.34 | 17.49 | 3.91 | -7.09 | -6.61 | 8.58 |

Response to RQ 3: How do code evolve along the history of an Android application after the introduction of Kotlin code?

For the 67.9% of the Kotlin applications, the amount of Kotlin code increases along the Android app evolution and, at the same time, the amount of Java code decreases or remains constant (cases ET 2, 5, 6 and 7).

For the 34% of the apps, the Kotlin code replaces the totality of the Java code written on those apps (cases ET 2 and 6).

5.4 RQ 4: Is there a difference between Kotlin and pure Java Android apps in terms of code smells presence?

We applied the methodology presented in Section 4.4. We executed Paprika on all apks from our dataset of 925 applications which most recent version date from 2017 or 2018. Paprika successfully analyzed 881 (95%) applications and threw an error over 44 apps. We removed from our analysis 68 apks from 6 different applications with Paprika returned that they have 0 classes and 0 methods. In total, Paprika analyzed with success 875 (94%) applications, 785 Java applications and 90 Kotlin applications (over a total of 93 Kotlin apps with 1+ apks as presented in Section 5.1 Paprika failed at analyzing every apk from 3 apps).

First, we focus on computing the number of affected applications. Then, we focus on the number of affected entities.

5.4.1 Number of Affected Applications

Table 4 shows the percentages of Android applications analyzed with success affected by each code smell grouped by the programming language.

We found that 3 out of 4 (75%) oriented object smells affect more than 92% of applications considering both languages, Kotlin and Java. LM is the most frequent smell, affecting approximately 99% of the apps of both languages. SAK is the least frequent smell, but it still affects the majority of applications, around 79% Kotlin applications and 60% of Java applications. We conclude that 4 out of 4 (100%) of oriented object code smells are more present in Kotlin applications.

Table 4 also shows differences between the percentages of applications written in Java and Kotlin (row K - J): for 3 out of 4 OO smells (LM, CC and BLOB),

the differences are small: 0.17%, 2.45% and 5.21% respectively. We conclude that in general, LM, CC and BLOB affect a similar proportion of both Kotlin and Java application. However, this is not valid for SAK, since the difference between the percentage of applications affected by this smells is around 19% further in Kotlin applications.

Our results agree with previous work [Hecht et al. 2015a; Habchi et al. 2017] showing that LM, CC, BLOB and SAK—in that order—are most frequent OO smells in Android applications. Thus, we confirm that this is also valid for Kotlin applications.

Regarding Android smells, we observed that NLMR is the most frequent smell, affecting 98% and 99% of Kotlin and Java applications, respectively. Otherwise, the second most present android smell, UIO, affect 55% of Kotlin and only 38% of Java applications. Other 3 smells (HSS, HAS, IOD) are present in, at most, the 23% of all apps. Note that as difference with oo smells, there are 3 Android smells that affect more in proportion, more Java apps, while the other 3 smells affects more Kotlin apps.

Response to RQ 4: Is there a difference between Kotlin and pure Java Android apps in terms of code smells presence?
In terms of affected applications: All OO smells affect, proportionally, more applications with Kotlin code than apps without Kotlin, even the difference is small for 3 out of 4 smells (between 0.17 and 5.21%). On the contrary, 3 out of 6 Android smells affect, proportionally, more Java apps than Kotlin apps.

5.4.2 Number of Affected Entities

Now, we study the proportion of entities affected by smells using the methodology presented in Section 4.5.4. Table 5 shows, for each smell and programming language, the median (med) of the ratios of smells (Formula 1) in the apps and the Cliff’s $\delta$ effect sizes.

First, we observe that the most frequent smells (LM, CC and BLOB) have a small median ratio. This means that, although they are present in most applications, only a few entities are affected by these smells. Moreover, the Cliff's $\delta$ values show that the difference between the smell median ratio of Kotlin and Java applications are statistically significant for three smells: ‘small’ difference for CC, medium for BLOB and ‘large’ difference for LM. We conclude that despite of the fact that oriented object smells affect more Kotlin applications, our results show that for LM, BLOB and CC, Java applications have in median more entities affected by them with statistically relevance.

Concerning Android smells, we observe that the median ratio for 4 out of 6 smells (HBR, HSS, HAS and IOD) are null for Java and Kotlin application, which is consistent with the Table 4 since less than 50% of applications for both languages are affected by these smells. Furthermore, Cliff’s $\delta$ shows no significant difference for these smells. We conclude that very few entities are affected by these smell, even for HBR that affect more than 40% of Android applications. Concerning UIO and NLMR, we observe significance statistically. Despite the small
Table 5: Ratio comparison between Kotlin and Java. The column ‘Cliffs’ δ’ shows the difference between the smell median ratio of Kotlin and Java applications: negative values mean that a smell affects less entities in Kotlin than in Java.

| Smell | Lang | Median Ratio | Cliff’s δ | Significance of difference |
|-------|------|--------------|-----------|---------------------------|
| LM    | Kotlin | 0.0556      | -0.4807   | Large                     |
|       | Java  | 0.0779      |           |                           |
| CC    | Kotlin | 0.0614      | -0.2096   | Small                     |
|       | Java  | 0.0769      |           |                           |
| BLOB  | Kotlin | 0.00173     | -0.3483   | Medium                    |
|       | Java  | 0.0261      |           |                           |
| SAK   | Kotlin | 0.0019      | -0.0355   | Insignificant             |
|       | Java  | 0.0026      |           |                           |
| NLMR  | Kotlin | 0.3076      | -0.4285   | Medium                    |
|       | Java  | 1.0000      |           |                           |
| UIO   | Kotlin | 0.0769      | 0.1499    | Small                     |
|       | Java  | 0.0000      |           |                           |
| HBR   | Kotlin | 0.0000      | 0.0084    | Insignificant             |
|       | Java  | 0.0000      |           |                           |
| HSS   | Kotlin | 0.0000      | -0.0641   | Insignificant             |
|       | Java  | 0.0000      |           |                           |
| HAS   | Kotlin | 0.0000      | -0.0711   | Insignificant             |
|       | Java  | 0.0000      |           |                           |
| IOD   | Kotlin | 0.0000      | 0.0921    | Insignificant             |
|       | Java  | 0.0000      |           |                           |

median ratio of entities affected by UIO, Kotlin applications have more entities affected by UIO with ‘Small’ significant difference. Regarding NLMR, we find that Java applications have more entities affected with a ‘Medium’ significant difference. This result agrees with the result from [Habchi et al., 2017] and shows that NLMR affects all activities of most Java applications.

Response to RQ 4 (cont.): Is there a difference between Kotlin and pure Java Android apps in terms of code smells presence?

In terms of affected entities: despite the fact that oriented object smells affect more Kotlin applications, our results show that for 3 out of 4 (LM, CC, BLOB), oriented smells and for 1 out of 6 (NLMR) android smells Java applications have in median more entities affected by them with statistically relevance.

5.5 RQ5: How frequent does the introduction of Kotlin positively impact on the quality of the versions of an Android application?

Table 6 shows, for each type of smell, the number of Kotlin applications whose quality scores increase after the introduction of Kotlin code. The increase of one quality score associated with one type of smell implies fewer instances of that smell and, consequently, better quality of the application.
Table 6: Changes on quality scores after introducing Kotlin. The table shows the number of applications that have improved a quality score associated to a smell. The column ‘First Kotlin’ shows the comparison between the quality score of the last version without Kotlin and the first version with Kotlin. The column ‘Last Kotlin’ compares the the quality score of the last version without Kotlin and the last version with Kotlin. The column ‘Positive Change on Evolution Trend’ counts the number of apps where the introduction of Kotlin produces a change in the quality evolution trend from ‘Decline’ or ‘Stability’ to ‘Rise’. 

| Code Smell | # Apps Kotlin Improves Quality Score | Positive Change on Evolution Trend |
|------------|-------------------------------------|-----------------------------------|
|            | First Kotlin                        | Last Kotlin                        |
| LM         | 24 (51.06%)                         | 18 (38.30%)                        | 2/18 (11%) |
| CC         | 30 (63.83%)                         | 31 (65.96%)                        | 9/31 (29%) |
| BLOB       | 32 (68.09%)                         | 33 (70.21%)                        | 10/33 (30.3%) |
| SAK        | 38 (80.85%)                         | 39 (82.98%)                        | 17/39 (43.6%) |
| HBR        | 37 (78.72%)                         | 31 (65.96%)                        | 5/31 (16%) |
| HAS        | 31 (65.96%)                         | 26 (55.32%)                        | 2/26 (7.7%) |
| HSS        | 43 (91.49%)                         | 35 (74.47%)                        | 1/35 (2.8%) |
| JOD        | 33 (70.21%)                         | 34 (72.34%)                        | 6/34 (17.6%) |
| NLMR       | 31 (65.96%)                         | 32 (68.09%)                        | 4/32 (12.5%) |
| UIO        | 33 (70.21%)                         | 30 (63.83%)                        | 6/30 (20%) |

Fig. 5: Evolution of quality scores based on CC smell along the version history.
The results show that for the 10 smells, at least the 50% of the applications that introduced Kotlin code (47 in total, see Section 5.1), their quality scores increase between the last Java version and the first version that introduce Kotlin (see Table 3 column ‘First Kotlin’). That means, for such applications the introduction of Kotlin code has a positive impact on the quality scores. Furthermore, for 9 out of 10 smells, at least the 50% applications have an improvement of the quality score between the last Java version and the most recent (i.e., the last) Kotlin version (see Table 3 column ‘Last Kotlin’).

For instance, let us focus on smell CC (complex-class) at the second row of Table 5. As column “First Kotlin” shows, for 30 applications out of 47 (63.83%), the version \( v_k \) that introduces Kotlin code has larger (i.e., better) quality score associated to smell CC than the last version without Kotlin \( v_{k-1} \) (i.e., the previous version of \( v_k \)). Figure 5(a) shows the quality score associated to the smell CC of each version of “DuckDuckGo” app. The last version that does not contain Kotlin code corresponds to \( X=6 \) in that figure. We observe that the first version that has Kotlin code (\( X=7 \)) increases the quality score, as well as all the subsequent versions (\( X=\{7..11\} \) do.

Furthermore, as column “Last Kotlin” shows, for 31 applications (65.96%), the most recent version with Kotlin code has larger (i.e., better) quality score associated to smell CC than the version before the introduction of Kotlin. Again, “DuckDuckGo” is one of those apps: the last version (\( X=11 \)) has a higher score than the last Java version (\( X=6 \)). Note that, for the CC smell, there is 1 application (\( X=31-30 \)) whose quality scores: a) decrease in the version that introduces Kotlin, but b) increase in the most recent Kotlin versions. The evolution of the quality score of one of those applications, named “Draw”, is displayed in sub-figure 5(b).

We also observe in Table 5 that for 5 out of 10 smells, the number of apps with quality improvements after the first Kotlin version (column “First Kotlin’) is larger than the number of apps with quality improvements over the last Kotlin version (column “Last Kotlin’). This means that the quality scores from some Kotlin applications decrease between the first and the last Kotlin versions. For instance, sub-figure 5(c) shows the evolution of quality score of “Davdroid” application: the first Kotlin version increases the score w.r.t the last Java version. However, during the subsequent versions, the quality scores drop, even lower than the last Java version. Finally, sub-figure 5(d) shows the evolution of the quality score of one application, named “Icsdroid”, whose quality score constantly decreases after the introduction of Kotlin code. This finding shows that also the quality of Kotlin applications can be degraded along the app evolution.

Response to RQ 5: How frequent does the introduction of Kotlin positively impact on the quality of the versions of an Android application?

The introduction of Kotlin code in Android applications initially written in Java produces a rise in the quality scores from, at least, the 50% of the Android apps.

---

22 We recall that the score quality is calculated using the output of Paprika, which takes as input `.apk` files. In our experiment, we first got 93 applications with 1+ `.apk` classified as ‘Kotlin’ (Section 5.1). Paprika could successfully analyze 90 (Section 5.4): 47 of them with ‘Java’ and ‘Kotlin’ `.apks`, 43 with only ‘Kotlin’ `.apks`. 
Finally, last column from Table 6 shows the number of applications where the introduction of Kotlin has changed the quality evolution trend from ‘Decline’ or ‘Stability’ to ‘Rise’ (Section 4.6.5). We call those Positive changes on quality evolution changes. For the oriented object smells, Kotlin produces a positive change on between the 11% and 43.6% of the applications that present an improvement of quality between the last version of Java and the last of Kotlin. For the Android smells, the number of apps with positive change is lower between the 2.8% and 20%.

Figure 6 shows three cases. The first one, displayed in sub-figure 6(a), corresponds to a positive change in the quality evolution trend. Before the introduction of Kotlin, the quality scores were constantly declining. The introduction of Kotlin has positively changed the evolution trend: after that, the quality scores constantly rise. The second case, sub-figure 6(b) shows that the introduction of Kotlin does not change the trend: the quality score before and after the introduction is stable. Note that, over the end of the evolution, the quality score suddenly rise. However, we do not associate this rise with the introduction of Kotlin, which was done much before. Finally, the third cases, sub-figure 6(c) does not present a change on the trend: the quality score was rising before the introduction of Kotlin and continues rising after that.

In conclusion, the study about the changes of quality evolution trend shows that some applications: a) stop having a constant degradation of the quality of the app written in Java, and b) present an improvement of quality that even rises after the introduction of Kotlin code.

6 Threats to Validity

6.1 Internal

Classification of Android apps. In section 4.2 we defined a procedure for classifying Android apps in ‘Kotlin’ and ‘Java’ based on three heuristics that inspected both source code and apk. By applying those heuristics we assure the absence of false-positives in our dataset, i.e., apps classified as ‘Kotlin’ but without Kotlin code
An Empirical Study on Quality of Android Applications written in Kotlin language

along with their life-cycle. However, it could exist some false negatives, i.e., apps that had Kotlin code in a version (but, by mistake, not detected by the heuristic $H_{apk}$), but they do not have any more in the most recent version (by definition, not detected by the heuristic $H_{gh}$). The heuristic $H_{sc}$ can detect such apps in case that $H_{gh}$ fails, but it is expensive to execute $H_{sc}$ over the complete F-droid dataset considering our current infrastructure (remember that $H_{sc}$ analyzes the code of each version of each application).

**Modelisation of software quality models.** There is a risk that the training dataset could not be representative of Android application. Thus, the quality models produce incorrect estimation. We consider the same training dataset that previous works have used for creating quality models as our and for detecting smells on Android apps (Hecht et al. 2015a,b, 2016). Furthermore, the use of that dataset allows having a training dataset and a validation dataset without any intersection, avoiding the generation of an overfitted model.

6.2 External

**Validity of Paprika.** It could exist the risk that Paprika has a) false positives, i.e., it detects smells instances that are not correct, and b) false negatives, i.e., it does not detect smell instances. However, Paprika has been exhaustively evaluated through different experiments (Hecht 2016).

**Representative of F-droid.** It could be the case that the applications from F-droid do not correctly represent the universe of Android apps. However, to our knowledge this F-droid is the largest Android repository that has both binary and source code of each app. Our experiment needs to analyze such kinds of artifacts.

**Size of F-droid.** The current version of F-droid has 1,509 Android applications. To our knowledge, it is the largest repository of open-source Android apps. It exists other Android repositories such as AndroZoo (Allix et al. 2016; Li et al. 2017b), much larger than F-droid, but, unfortunately, it does not contain the source code of the apps and contains apps that are not open-source.

**Missing versions (apks) on F-droid.** There are some apks that are listed on the F-droid page, but their apk files are not available. Consequently, we could not analyze them. Moreover, there is a risk that F-droid does not contain all the released versions of an application. Consequently, this missing data could affect our analysis of the application quality, which is based on the analysis of all apks available of F-droid.

7 Conclusion and Future work

During the last years, different development approaches have emerged for developing mobile applications. In this context, Google has announced that Kotlin became officially supported language for Android development in 2017. Almost one year since the announcement, we conducted an empirical study verify whether
the produced Android apps with this new program language have better quality than the applications written using the traditional approach for developing Android apps, that means, to use Java language.

To realize our empirical study, we first created a dataset of Kotlin and Java open-source applications. We downloaded from F-droid 925 applications, corresponding 12,175 different version in total, and their link to the source-code repository. Then, we applied three heuristics to classify these applications between Kotlin and Java applications, to allow us to analyze these applications separately. Our resultant dataset contains 109 out 925 applications that have at least, one version between the years 2017 and 2018 written using Kotlin. Moreover, considering the most recent version of each Kotlin applications, we observed that 35% of them are written exclusively using Kotlin.

Regarding the evolution of Kotlin code during the application lifecycle, we found that for 67.9% of the Kotlin applications, the amount of Kotlin code increases along the app evolution and the amount of Java code decreases or remains constant. Furthermore, for 34% of the apps, the Kotlin code replaces totality of the Java code written on those apps.

To observed the differences between Kotlin and Java application regarding presence of code smells, we used the tool Paprika to identify 10 smells, 4 oriented object smells and 6 android specific smells. We found that the 3 out of 4 oriented object (OO) smells (LM, CC and BLOB) are present, at least, in the 92% of both Java and Kotlin application. In percentage, OO smells are more frequent in Kotlin apps. However, we found that Java applications have more entities affected by 4 out of 10 code smells (incl. the mentioned 3 OO smells), whereas Kotlin apps have more by only 1 out of 10.

We concluded our study analyzing the impact of Kotlin on the quality of an Android application. Regarding the immediate impact of introducing Kotlin on Android applications, i.e., the first version that has Kotlin code, we found that the adoption of Kotlin produces a rise of the quality from, at least, 50% of the applications.

As future work, we plan to empirically verify if the advantages claimed by Kotlin develops community (Section 3.3) are true in the context of mobile development and to investigate more code smells and anti-patters related, for instance, with the performance and energy consumption.

References

IDC. Smartphone os market share, 2017 q1, 2017. URL https://www.idc.com/promo/smartphone-market-share/

Meiyappan Nagappan and Emad Shihab. Future Trends in Software Engineering Research for Mobile Apps. 2016 IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER), pages 21–32, 2016. ISSN 9781509018550. doi: 10.1109/SANER.2016.88. URL http://ieeexplore.ieee.org/document/7476770/

Matias Martinez and Sylvain Lecomte. Towards the quality improvement of cross-platform mobile applications. In Proceedings of the 4th International Conference on Mobile Software Engineering and Systems, MOBILESoft ’17, pages 184–188,
An Empirical Study on Quality of Android Applications written in Kotlin language 31

James La. Update on kotlin for android, 2017. URL https://android-developers.googleblog.com/2017/11/update-on-kotlin-for-android.html.

Jan Reimann, Martin Brylski, and Uwe Aßmann. A tool-supported quality smell catalogue for android developers. In Proc. of the conference Modellierung 2014 in the Workshop Modellbasierte und modellgetriebene Softwaremodernisierung–MMSM, volume 2014, 2014a.

G. Hecht, O. Benomar, R. Rouvoy, N. Moha, and L. Duchien. Tracking the software quality of android applications along their evolution (t). In 2015 30th IEEE/ACM International Conference on Automated Software Engineering (ASE), pages 236–247, 2015a. doi: 10.1109/ASE.2015.46.

Geoffrey Hecht, Romain Rouvoy, Naouel Moha, and Laurence Duchien. Detecting Antipatterns in Android Apps. Proceedings - 2nd ACM International Conference on Mobile Software Engineering and Systems, MOBILESoft 2015, pages 148–149, 2015b. doi: 10.1109/MobileSoft.2015.38.

Fabio Palomba, Dario Di Nucci, Annibale Panichella, Andy Zaidman, and Andrea De Lucia. Lightweight detection of Android-specific code smells: The aDoctor project. SANER 2017 - 24th IEEE International Conference on Software Analysis, Evolution, and Reengineering, pages 487–491, 2017. doi: 10.1109/SANER.2017.7884659. URL https://dibt.unimol.it/staff/fpalomba/documents/C18.pdf.

Rodrigo Morales, Ru En Saborido, Foutse Khomh, Francisco Chicano, and Giuliano Antoniol. Anti-patterns and the energy efficiency of Android applications. page 12, 2016.

Rodrigo Morales, Ruben Saborido, Foutse Khomh, Francisco Chicano, and Giuliano Antoniol. EARMO: An Energy-Aware Refactoring Approach for Mobile Apps. IEEE Transactions on Software Engineering, X(X):1–31, 2017. ISSN 00985589. doi: 10.1109/TSE.2017.2757486.

Luis Cruz and Rui Abreu. Performance-Based Guidelines for Energy Efficient Mobile Applications. 2017 IEEE/ACM 4th International Conference on Mobile Software Engineering and Systems (MOBILESoft), pages 46–57, 2017. doi: 10.1109/MOBILESoft.2017.19. URL http://ieeexplore.ieee.org/document/7972717/.

Antonin Carette, Mehdi Adel Ait Younes, Geoffrey Hecht, Naouel Moha, and Romain Rouvoy. Investigating the energy impact of Android smells. SANER 2017 - 24th IEEE International Conference on Software Analysis, Evolution, and Reengineering, pages 115–126, 2017. doi: 10.1109/SANER.2017.7884614.

Rubén Saborido, Rodrigo Morales, Foutse Khomh, Yann Gaël Guéhéneuc, and Giuliano Antoniol. Getting the most from map data structures in Android. Empirical Software Engineering, pages 1–36, 2018. ISSN 15737616. doi: 10.1007/s10664-018-9607-8.

Geoffrey Hecht, Naouel Moha, and Romain Rouvoy. An empirical study of the performance impacts of Android code smells. Proceedings of the International Workshop on Mobile Software Engineering and Systems - MOBILESoft '16, pages 59–69, 2016. ISSN 9781450321389. doi: 10.1145/2897073.2897100. URL http://dl.acm.org/citation.cfm?doid=2897073.2897100.

I. Malavolta, S. Ruberto, T. Soru, and V. Terragni. End users’ perception of hybrid mobile apps in the google play store. In 2015 IEEE International Conference on Mobile Services, pages 25–32, June 2015a. doi: 10.1109/MobServ.2015.14.
Ivano Malavolta, Stefano Ruberto, Tommaso Soru, and Valerio Terragni. Hybrid mobile apps in the google play store: An exploratory investigation. In Proceedings of the Second ACM International Conference on Mobile Software Engineering and Systems, MOBILESoft ’15, pages 56–59, Piscataway, NJ, USA, 2015b. IEEE Press. ISBN 978-1-4799-1934-5. URL http://dl.acm.org/citation.cfm?id=2825041.2825051

Geoffrey Hecht. Detection and analysis of impact of code smells in mobile applications. Phd thesis, Université Lille 1 : Sciences et Technologies ; Université du Québec à Montréal, November 2016. URL https://tel.archives-ouvertes.fr/tel-01418158

Sarra Habchi, Geoffrey Hecht, Romain Rouvoy, and Naouel Moha. Code Smells in iOS Apps: How Do They Compare to Android? Proceedings - 2017 IEEE/ACM 4th International Conference on Mobile Software Engineering and Systems, MOBILESoft 2017, pages 110–121, 2017. doi: 10.1109/MOBILESoft.2017.11.

Martin Fowler, Kent Beck, John Brant, William Opdyke, and Don Roberts. Refactoring: improving the design of existing code. Addison-Wesley Professional, 1999.

Tushar Sharma and Diomidis Spinellis. A survey on software smells. Journal of Systems and Software, 138:158–173, 2018. ISSN 01641212. doi: 10.1016/j.jss.2017.12.034. URL https://doi.org/10.1016/j.jss.2017.12.034

Maurício Aniche, Gabriele Bavota, Christoph Treude, Aric Van Deursen, and Marco Aurélio Gerosa. A validated set of smells in model-view-controller architectures. Proceedings - 2016 IEEE International Conference on Software Maintenance and Evolution, ICSME 2016, pages 233–243, 2017. doi: 10.1109/ICSME.2016.12.

Tse-Hsun Chen, Weivi Shang, Zhen Ming Jiang, Ahmed E Hassan, Mohamed Nasser, and Parminder Flora. Detecting performance anti-patterns for applications developed using object-relational mapping. In Proceedings of the 36th International Conference on Software Engineering, pages 1001–1012. ACM, 2014.

Daniël Verloop. Code smells in the mobile applications domain. Master thesis, TU Delft, Delft University of Technology, 2013. URL https://repository.tudelft.nl/islandora/object/uuid:bcba7e5b-e898-4e59-b636-234ad3fd4327?collection=education

Davood Mazinanian, Nikolaos Tsantalis, and Ali Mesbah. Discovering refactoring opportunities in cascading style sheets. In Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering, pages 496–506. ACM, 2014.

Umme Ayda Mannan, Iftekhar Ahmed, Rana Abdullah M. Almurshed, Danny Dig, and Carlos Jensen. Understanding code smells in Android applications. International Workshop on Mobile Software Engineering and Systems (MOBILESoft ’16), pages 225–234, 2016. doi: 10.1145/2897073.2897094. URL http://dl.acm.org/citation.cfm?doid=2897073.2897094

Hammad Khalid, Meiyappan Nagappan, and Ahmed E. Hassan. Examining the relationship between FindBugs warnings and app ratings. IEEE Software, 33(4): 34–39, 2016. ISSN 07407459. doi: 10.1109/MS.2015.29.

S R Chidamber and C F Kemerer. A metrics suite for object oriented design. IEEE Transactions on Software Engineering, 20(6):476–493, 1994. ISSN 0098-5589 VO - 20. doi: 10.1109/MS.1994.295895.

Denguang Li, Bing Guo, Yan Shen, Junke Li, and Yanhui Huang. The evolution of open-source mobile applications: An empirical study. Journal of Software:
An Empirical Study on Quality of Android Applications written in Kotlin language

Evolution and Process, 29(7):1–18, 2017a. ISSN 20477481. doi: 10.1002/smr.1855.

Meir M Lehman. Programs, life cycles, and laws of software evolution. Proceedings of the IEEE, 68(9):1060–1076, 1980.

Fabio Palomba, Gabriele Bavota, Massimiliano Di Penta, Rocco Oliveto, Denys Poshyvanyk, and Andrea De Lucia. Mining version histories for detecting code smells. IEEE Transactions on Software Engineering, 41(5):462–489, 2015. ISSN 00985589. doi: 10.1109/TSE.2014.2372760.

M. Tufano, F. Palomba, G. Bavota, R. Oliveto, M. Di Penta, A. De Lucia, and D. Poshyvanyk. When and Why Your Code Starts to Smell Bad. In 2015 IEEE/ACM 37th IEEE International Conference on Software Engineering, volume 1, pages 403–414, 2015. ISBN 0270-5257 VO - 1. doi: 10.1109/ICSE.2015.59.

Fabio Palomba, Gabriele Bavota, Massimiliano Di Penta, Fausto Fasano, Rocco Oliveto, and Andrea De Lucia. On the diffuseness and the impact on maintainability of code smells: a large scale empirical investigation. Empirical Software Engineering, 23(3):1188–1221, 2018. ISSN 15737616. doi: 10.1007/s10664-017-9535-z.

Mike Papadakis, Siegfried Rasthofer, Alexandre Bartel, Li Li, Jacques Klein, Yves Le Traon, and Mountain View. Static Analysis of Android Apps : A Systematic Literature Review. Information and Software Technology, pages 1–22, 2017. ISSN 09505849. doi: 10.1016/j.infsof.2017.04.001.

Luis Cruz and Rui Abreu. Using Automatic Refactoring to Improve Energy Efficiency of Android Apps. In Proceedings of the CiBe XXI Ibero-American Conference on Software Engineering, 2018. URL http://arxiv.org/abs/1803.05889

Magnus Vinther. Why you should totally switch to kotlin, 2017. URL https://medium.com/@magnus.chatt/why-you-should-totally-switch-to-kotlin-c7bbde9e10d5

Wei Wang and Michael W. Godfrey. Detecting API usage obstacles: A study of iOS and android developer questions. IEEE International Working Conference on Mining Software Repositories, pages 61–64, 2013. ISSN 21601852. doi: 10.1109/MSR.2013.6624006.

Daniel E. Krutz, Mehdi Mirakhorli, Samuel A. Malachowsky, Andres Ruiz, Jacob Peterson, Andrew Filipski, and Jared Smith. A dataset of open-source android applications. IEEE International Working Conference on Mining Software Repositories, 2015-August(i):522–525, 2015. ISSN 21601860. doi: 10.1109/MSR.2015.79.

Md. Yasser Karim, Huzefa Kagdi, and Massimiliano Di Penta. Mining Android Apps to Recommend Permissions. 2016 IEEE 23rd International Conference on Software Analysis, Evolution, and Reengineering (SANER), pages 427–437, 2016. doi: 10.1109/SANER.2016.74. URL http://ieeexplore.ieee.org/document/7476663/

Zhiyuan Chen. Helping Mobile Software Code Reviewers : A Study of Bug Repair and Refactoring Patterns. pages 3–4, 2016.

Kevin Allix, Tegawendé F. Bisseyandé, Jacques Klein, and Yves Le Traon. AndroZoo: Collecting Millions of Android Apps for the Research Community Kevin. Proceedings of the 13th International Workshop on Mining Software Repositories - MSR '16, pages 468–471, 2016. doi: 10.1145/2901739.2903508. URL http://dl.acm.org/citation.cfm?doid=2901739.2903508

Giovanni Grano, Andrea Di Sorbo, Francesco Mercaldo, Corrado A. Visaggio, Gerardo Canfora, and Sebastiano Panichella. Android apps and user feedback: a dataset for software evolution and quality improvement. Proceedings of the
Safwat Hassan, Weiyi Shang, and Ahmed E. Hassan. An empirical study of emergency updates for top android mobile apps. *Empirical Software Engineering*, 22(1):505–546, 2017. ISSN 15737616. doi: 10.1007/s10664-016-9435-7. URL http://dx.doi.org/10.1007/s10664-016-9435-7

Li Li. Mining AndroZoo: A retrospect. *Proceedings - 2017 IEEE International Conference on Software Maintenance and Evolution, ICSME 2017*, pages 675–680, 2017. doi: 10.1109/ICSME.2017.49.

Marouane Kessentini and Ali Ouni. Detecting Android Smells Using Multi-Objective Genetic Programming. *Proceedings - 2017 IEEE/ACM 4th International Conference on Mobile Software Engineering and Systems, MOBILESoft 2017*, pages 122–132, 2017. doi: 10.1109/MOBILESoft.2017.29.

Rabe Abdalkareem, Emad Shihab, and Juergen Rilling. On code reuse from StackOverflow: An exploratory study on Android apps. *Information and Software Technology*, 88:148–158, 2017. ISSN 09505849. doi: 10.1016/j.infsof.2017.04.005.

Adelina Ciurumelea, Andreas Schaufelbuhli, Sebastiano Panichella, and Harald C. Gall. Analyzing reviews and code of mobile apps for better release planning. *SANER 2017 - 24th IEEE International Conference on Software Analysis, Evolution, and Reengineering*, pages 91–102, 2017. doi: 10.1109/SANER.2017.7884612.

Li Li, Jun Gao, Médéric Hurier, Pingfan Kong, Tegawendé F. Bissyandé, Alexandre Bartel, Jacques Klein, and Yves Le Traon. AndroZoo++: Collecting Millions of Android Apps and Their Metadata for the Research Community. 2017b. doi: 10.1145/2901739.2903508. URL http://arxiv.org/abs/1709.05281

William H Brown, Raphael C Malveau, Hays W McCormick, and Thomas J Mowbray. *AntiPatterns: refactoring software, architectures, and projects in crisis*. John Wiley & Sons, Inc., 1998.

Jan Reimann, Martin Brylski, and Uwe Aßmann. Android smells catalogue, 2014b. URL http://www.modelrefactoring.org/smell_catalog [Online; accessed 17-July-2018].

Gabriele Mariotti. Antipattern: freezing the ui with an asynctask, 2013a. URL http://gmariotti.blogspot.com/2013/02/antipattern-freezing-ui-with-asynctask.html [Online; accessed 17-July-2018].

Gabriele Mariotti. Antipattern: freezing the ui with a service and an intentservice, 2013b. URL http://gmariotti.blogspot.com/2013/03/antipattern-freezing-ui-with-service.html [Online; accessed 17-July-2018].

Gabriele Mariotti. Antipattern: freezing a ui with broadcast receiver, 2013c. URL http://gmariotti.blogspot.com/2013/02/antipattern-freezing-ui-with-broadcast.html [Online; accessed 17-July-2018].

Colt McAnlis. Android performance patterns: Overdraw, cliprect, quickreject, 2015. URL https://www.youtube.com/watch?v=vkTn3Ule4Ps [Online; accessed 17-July-2018].

Ian Ni-Lewis. Avoiding allocations in ondraw() (100 days of google dev), 2015a. URL https://www.youtube.com/watch?v=HAK5acHQ53E [Online; accessed 17-July-2018].
An Empirical Study on Quality of Android Applications written in Kotlin language

AndroidDoc. Performance tips — android developers, 2018a. URL https://developer.android.com/training/articles/perf-tips#PreferStatic [Online; accessed 17-July-2018].

Alex Lockwood. How to leak a context: Handlers & inner classes, 2013. URL https://www.androiddesignpatterns.com/2013/01/inner-class-handler-memory-leak.html [Online; accessed 17-July-2018].

KotlinDoc. Classes and inheritance - kotlin programming language, 2018. URL https://kotlinlang.org/docs/reference/classes.html#companion-objects [Online; accessed 17-July-2018].

Chet Haase. Developing for android ii google developers medium, 2015. URL https://medium.com/google-developers/developing-for-android-ii-bb9a51f8c8b9 [Online; accessed 17-July-2018].

AndroidDoc. Array map — android developers, 2018b. URL https://developer.android.com/reference/android/support/v4/util/ArrayMap [Online; accessed 17-July-2018].

Ian Ni-Lewis. Custom views and performance (100 days of google dev), 2015b. URL https://youtu.be/zK2i7ivzK7M?t=4m57s [Online; accessed 17-July-2018].

Jeanine Romano, Jeffrey D Kromrey, Jesse Coraggio, Jeff Skowronek, and Linda Devine. Exploring methods for evaluating group differences on the nsse and other surveys: Are the t-test and cohensd indices the most appropriate choices. In annual meeting of the Southern Association for Institutional Research. Citeseer, 2006.

Norman Cliff. Ordinal methods for behavioral data analysis. Psychology Press, 2014.

Guillermo Macbeth, Eugenia Razumiejczyk, and Rubán Daniel Ledesma. Cliff’s Delta Calculator: A non-parametric effect size program for two groups of observations. Universitas Psychologica, 10:545 – 555, 05 2011. ISSN 1657-9267. URL http://www.scielo.org.co/scielo.php?script=sci_arttext&pid=S1657-92672011000200018&nrm=iso.