On the adoption, usage and evolution of Kotlin Features on Android development

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Abstract Context: Currently, more than 2 million applications are published on Google Play, the official store of Android applications, which makes the Android platform the largest mobile platform. Although the majority of Android applications have been written in Java, since 2017 when Google announced Kotlin as an official programming language of the Android platform, developers have an option of write applications using Kotlin, that combines object-oriented and functional features.

Objective: The goal of this paper is to understand the usage of Kotlin features. Particularly, we interested in four aspects of features usage: i) which features are adopted, ii) what is the degree of adoption, iii) when these features are added into the Android applications for the first time, iv) which are the features first introduced, and v) how the usage of features evolves along with applications’ evolution.

Method: To analyze the usage of Kotlin features, we inspect the source code of Kotlin application. To study how a feature is used along the life-cycle of a given mobile application, we identify the Kotlin features used on each version of that application. We also compute the moment that each feature is used for the first time. Finally, we identify the evolution trend that better describes that usage of a given feature.

Results: Our experiment showed that 15 out of 19 features are used on at least 50% of Android applications written in Kotlin. Moreover, we found that type inference, lambda and safe call are the most used features, being found on 98%, 93% and 84% of applications, respectively. Also, we observed that the most used Kotlin features are those first used on Android applications. Finally, we reported that the majority of applications tend to increase the number of instances of 18 out of 19 studied features along with the evolution of Android applications.

Keywords: Android; Mobile development; Kotlin; Feature evolution; Evolution trends; Features adoption; Open-Source applications
1 Introduction

Currently, the Android platform is the largest mobile platform, with more than 2 million applications published in the official store, Google Play. Since the first release of the Google’s operational system, developers have been developing application mostly using Java, and in some specific scenarios, using in C++. However, in 2017, when Google announced Kotlin as an official programming language of the Android platform, developers earned another option of programming language to write applications. Kotlin is an open-source statically typed programming language that targets the Java Virtual Machine (JVM) and Android.

The announcement made by Google had a significant impact on the popularity of Kotlin. After became an official Android language, the Stack Overflow Annual Developer Survey reported Kotlin between the technologies that developers most wanted and most loved in 2018 and 2019. Moreover, an empirical study of 2,167 open-source Android applications showed that 11.26% have been written (partially or fully) using Kotlin language. Furthermore, Google recently announced that Android development will become increasingly ‘Kotlin-first’, which means that many new APIs and features will be offered in firstly Kotlin. As a consequence, they advise developers that are starting a new project, to write it in Kotlin.

Kotlin provides a different approach to write mobile applications because it combines object-oriented and functional features, some of them not present in Java or not available for Android development. We hypothesize is that features provided by a new programming language (in this case Kotlin) can seduce developers to starting using it. Therefore, we conjecture that the usage of Kotlin features, especially, the first added features and their degree of adoption, can explain the motivation behind the decision of using Kotlin to develop Android applications. However, to the best of our knowledge, there is no study in the literature about the adoption of Kotlin features by Android developers.

The goal of this paper is to understand the usage of Kotlin features. Particularly, we interested in four aspects of features usage: i) which features are adopted, ii) what is the degree of adoption, iii) when these features are added into the Android applications for the first time, iv) which are the features first introduced, and v) how the usage of features evolves along with applications’ evolution.

To carry out our experiment, we used the largest publicly available dataset with open-source Android applications written in Kotlin. To study the adoption of Kotlin features, we extracted features from the source code of those applications and we identified when these features were used for the first time in a project. To understand how the use of features evolves along the history, we analyzed the code repository of each application (i.e., Git) with the goal of mining the features used on each version (commit). Then, we automatically assigned to each pair application-feature \((a, f)\) an evolution trend that better describe the use of \(f\) along the evolution of \(a\). As difference with other studies that focus on manual classification of evolution trends, our method is completely automated.

1 https://insights.stackoverflow.com/survey/2017
2 https://insights.stackoverflow.com/survey/2018
3 https://insights.stackoverflow.com/survey/2019
4 https://android-developers.googleblog.com/2019/05/google-io-2019-empowering-developers-to-build-experiences-on-Android-Play.html
5 https://kotlinlang.org/docs/reference/comparison-to-java.html
Finally, we computed which is the most frequent evolution trend associated to a feature.

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

- **RQ1**: What features of Kotlin are adopted by Android developers?
  **Finding**: We found that the most used features are *type inference, lambda* and *safe call* being identified in 98%, 93% and 84% of applications, respectively. On the contrary, we found that features *overloaded operator* and *super delegation* are the least used, being observed in 21% and 6% of applications respectively.

- **RQ2**: When do Android developers introduce Kotlin features during applications’ evolution?
  **Finding**: We found that the most used Kotlin features are introduced just after the first commit that has Kotlin code. Moreover, we observed that the least used Kotlin features tend to be introduced later on the Kotlin history.

- **RQ3**: What is the order of addition of Kotlin features and in what proportion these features are added together?
  **Finding**: Type inference is always one of the first three added features and the same is valid to Lambda considering 75% of applications. Moreover, these two features are introduced on the same commit in 69% of applications.

- **RQ4**: How the usage of Kotlin features evolves along the evolution of Android applications?
  **Finding**: We found that 9 features which predominant evolution trend characterized by a linear increasing of the number of instances along applications’ evolution. Moreover, we observed that 11 features presents a period of stability followed by a period of increase and after the increasing period remains stable again. Finally, we found 1 feature that presents a unstable behavior, the number of instances of a feature varies between periods of increase, decrease, and stability.

The contributions of this paper are:

- A study about the adoption of Kotlin’s features in the development of Android mobile applications.
- A study that shows when those features are first used by Android developers during application’s evolution.
- A study that shows how Kotlin’s features evolve during the applications’ evolution.
- A methodology to automatically identify and classify trends of features adoption during application’s evolution.

The paper continues as follows. Section 2 introduces Kotlin and its features. Section 3 describes the methodologies used to respond to the research questions. Section 4 presents the results and the answers to the research questions. Section 5 outlines threats of the validity. Section 6 presents the related work. Finally, we conclude in Section 7. All the data presented in this paper is publicly available in our appendix: [https://github.com/UPHP/kotlin_features](https://github.com/UPHP/kotlin_features).
2 Description of Kotlin’s Features

2.1 What is Kotlin?

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, developers can use it to write few files in an existing project or to write a whole application from scratch.

Kotlin was announced as an official programming language for Android development in 2017. The official IDE for Android development, Android Studio, provides first-class support for Kotlin, including a built-in tool to help the conversion of Java-based code to Kotlin. Moreover, using the Android Studio 3.0 or later, developers can use any feature for Java 7 and some features from Java 8, for example Java lambdas. However, it impacts on the choose of the minimum target Android SDK version. On the other hand, Java 6 is full compatible with Android development. For this reason, Kotlin generates bytecode compatible with Java 6 bytecode.

Therefore, the announcement made by Google brought the possibility for developers to use Kotlin instead of Java to write code for Android and, consequently, to use Kotlin’s features not supported by Java.

2.2 Kotlin Features

In the following subsections, we present some Kotlin features that are not present in Java. Note that Lambdas is present in Java, but to use it in Android development, developers have to deal with a constraint of minimum Android SDK target.

2.2.1 Type inference

Kotlin is a strongly typed language, but developers do not always need to declare types explicitly. The compiler attempts to infer the type of an expression based on information that it includes. Type inference can happen in different situations, for instance, when a return type of a function can be inferred, so it is not necessary to declare the return type or in a variable declaration, based on the assignment.

2.2.2 Lambda expressions and Anonymous functions

Lambda expressions and Anonymous functions are both ‘function literals’, i.e., functions that are not declared, but passed as an expression. Using Lambda developers makes the code more succinct and readable by introducing more concise expressions. Furthermore, since the application and the Android platform interacts through a variety of callbacks, lambda functions are useful in Android development, fitting with the use of callback to handle user events perfectly.

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6 https://developer.android.com/studio/write/java8-support
7 https://kotlinlang.org/docs/reference/comparison-to-java.html
8 https://kotlinlang.org/docs/reference/lambdas.html
2.2.3 Inline Function

Using inline function developers can eliminate certain runtime penalties imposed by higher-order functions due to memory allocations and virtual calls, by inlining the lambda expressions.

The runtime overhead is a consequence of the fact that in Kotlin functions are high-order functions, consequently, they are object, and they capture a closure, i.e., those variables that are accessed in the body of the function.

2.2.4 Null-safety

In Kotlin, the type system distinguishes between references that can hold null (nullable references) and those that can not (non-null references). If a developer wants to access a property of one object that has no guarantee safe (i.e., could be null) the compiler reports an error. Thus, the developer has three options. First, developers can explicitly check whether a object is null, as we usually would do in Java. Second, the Kotlin’s safe operator represented by symbol "?" could be used. In this case, the property is returned if the object is not null, otherwise null is returned. The third option is the not-null assertion operator '!!', that converts any value to a non-null type and throws an exception if the value is null.

Although Kotlin’s type system is aimed to eliminate NullPointerExceptions (NPE), it is possible that Kotlin programs suffer with NPE and the possible causes are: 1) An explicit call to throw NullPointerException; 2) Usage of the not-null assertion operator '!!' 3) Java interoperation; 4) Some data inconsistency with regard to initialization.

2.2.5 When expression

When expression replace switch operator of C-like languages and provides flexibility: 1) if many cases should be handled in the same way, the branch conditions may be combined with a comma; 2) developers can use arbitrary expressions (not only constants) as branch conditions; 3) branch conditions can contain an expression that check a value for being in or !in a range or a collection; 4) also, branch conditions can be used to check whether a value is (is) or is not (!is) of a particular type. Furthermore, it can be used as an expression. In this case, the value of the satisfied branch becomes the value of the overall expression.

2.2.6 Default argument

Default argument allows developers to write methods or constructors with optional arguments, i.e., that when it was not passed in the method call, it receives a default value. Thus, instead of write multiple constructors or overload multiple methods, developers could use default arguments. Furthermore, this feature allows developers to write more concise, more expressive, more readable and consequently more maintainable code.

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9 https://kotlinlang.org/docs/reference/null-safety.html
10 https://kotlinlang.org/docs/reference/control-flow.html
2.2.7 Named argument

Named argument is an argument passed in a method call with its name specified. In that way, developers do not need to follow the same order of arguments found in the method declaration. Moreover, named argument can increases readability, since it provides more information about the arguments on the function call.

2.2.8 Smart cast

Smart cast makes possible to avoid the use of explicit cast operators because the compiler tracks is-checks (instanceof equivalent) and explicitly casts for immutable values, which means no more instanceof checked followed by explicit casts.\footnote{https://kotlinlang.org/docs/reference/typecasts.html}

2.2.9 Data classes

Data classes comes to replace the Plain Old Java Object (POJO) and, consequently, its boilerplate code. In Java, to create a POJO, a developer needs to define a class with constructor(s), fields to store data, getters and setters for each field, equals(), etc. Using data class, the Kotlin compiler performs all of this work.

2.2.10 Range expression

Range expression makes the syntax of for loop iteration and control flow statements more readable. It implements a common interface in the library: ‘ClosedRange\(<\;T\;>\)’ that denotes a closed interval in the mathematical sense, defined for comparable types. It has two endpoints: start and endInclusive, both included in the range. The main operation is contains, usually used in the form of ‘in’/’!in’ operators. Furthermore, they are formed with rangeTo functions that have the operator form ‘..’.\footnote{https://kotlinlang.org/docs/reference/ranges.html}

2.2.11 Extension function

Extension function provides the ability to extend a class with new functionality without having to inherit from that class or use any design pattern such as Decorator. Using special declarations called extensions, it possible to add functions and properties extensions.

2.2.12 String template

String template may contain pieces of code that are evaluated and whose results are concatenated into the string.

\footnote{https://kotlinlang.org/docs/reference/typecasts.html} \footnote{https://kotlinlang.org/docs/reference/ranges.html}
2.2.13 Delegation

Inheritance in object-oriented programs establishes a strong coupling between classes [10], and for this reason developers should favor object composition over class inheritance [11]. One approach to reach this goal is to replace inheritance with delegation [8], which is natively supported by Kotlin (Super delegation). Kotlin also supports delegation at the level of properties. This type of delegation aims to avoid code duplication like the setters and getters of different properties [14].

2.2.14 Destructuring declaration

Destructuring declaration makes possible to break down an object into multiple variables at once. For instance, it can be used to return multiple values for a function or to traverse a map [14].

2.2.15 Operator overloading

Operator overloading allows developers to provide implementations for a predefined set of operators. These operators have fixed symbolic representation (like + or *) and fixed precedence. However, changing the meaning of an operator could result in obfuscated code. In Kotlin, to overload an operator, developers should provide a function defined inside a class or an extension function. Moreover, functions that overload operators need to be marked with the operator modifier [15].

2.2.16 Singleton

Singleton is a design pattern that restricts the instantiation of a class to one single instance. Kotlin provides an easy way to declare singletons using object declaration. An object declaration always has a name following the object keyword. Just like a variable declaration, an object declaration is not an expression, and cannot be used on the right hand side of an assignment statement [16].

2.2.17 Companion Object

Companion Object is an alternative to static methods since, unlike Java, Kotlin classes do not support static methods. Declaring a companion object inside a class, developers are able to call its members with the same syntax as calling static methods in Java, using only the class name as a qualifier. However, even though the members of companion objects look like static members in other languages, at runtime those are still instance members of real objects [17].

13 https://kotlinlang.org/docs/reference/delegated-properties.html
14 https://kotlinlang.org/docs/reference/multi-declarations.html
15 https://kotlinlang.org/docs/reference/operator-overloading.html
16 https://kotlinlang.org/docs/reference/object-declarations.html
17 https://kotlinlang.org/docs/tutorials/kotlin-for-py/objects-and-companion-objects.html
2.2.18 Coroutine

A Coroutine is a operation that can be suspended without blocking a thread. This feature aims at simplifying asynchronous programming. Using coroutines, the logic of the program can be expressed sequentially and the underlying library will figure out the asynchronous. This is a particular advantage for Android developers since Android is single-threaded by default.

3 Methodology

In this section, we present the methodology applied to respond to the research questions. First, we present a method to detect features from source code (Section 3.1). Second, we present a method to identify when features are used for the first time (Section 3.2). Finally, we present a method to classify the behavior of features along with the application’s evolution (Section 3.3).

3.1 Identification of Kotlin features from a Koltin source code file

For responding to all our research questions, we need to identify the use of Kotlin features from the applications’ source code. For that, we built a tool that given as input a Kotlin source code file (.kt file), it returns a list of all features found in that file.

Our feature detection tool was built by extending Detekt\(^{18}\) an open-source static analyzer of Kotlin code. Detekt operates on the abstract syntax tree (AST) provided by the Kotlin compiler and provides a mechanism to visit the AST of a Kotlin file.

For each feature that we presented in Section 2.2, we first investigated their structures, i.e., which are the AST nodes related to. Then, we encoded different analyzers for detecting feature instances from ASTs based on those nodes. We could successfully encode analyzers for 17 features, all present in Table 1. We built 19 analyzers because we encoded two analyzers for two features: Safety and Delegation. We split the Safety feature in two: 1) Safe call, that gives us information about the usage of the safe operator ‘?’ and 2) Unsafe call, that give us information about whether developers use the unsafe operator ‘!!’. Since Kotlin provides two types of delegation, we also split Delegation in two features: 1) Super Delegation and 2) Property Delegation. Nevertheless, due to the limitation of our AST-based approach, we could not encode analyzers for detecting Coroutines. The usage of Coroutine is characterized by the use of functions as launch, delay and others from the package kotlinx.coroutines. However, they cannot be distinguished easily from functions defined by the developers because the AST provided by the Kotlin compiler API represents these functions as a regular functions.

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\(^{18}\) https://arturbosch.github.io/detekt/
Table 1: Kotlin features and normalization criteria

| ID | Feature                                      | Normalization Criteria       |
|----|----------------------------------------------|------------------------------|
| 1  | Type inference                               | # of properties              |
| 2  | Lambda                                       | LOC                          |
| 3  | Inline function                              | # of named functions         |
| 4  | Safety (Safe and Unsafe calls)               | # of qualified expressions   |
| 5  | When expressions                             | LOC                          |
| 6  | Function w/arguments with default value      | # of functions               |
| 7  | Function w/ named arguments                  | # of function calls          |
| 8  | Smart casts                                  | LOC                          |
| 9  | # of data classes                            | # of classes                 |
| 10 | Range expressions                            | LOC                          |
| 11 | Extension Functions                          | # of named functions         |
| 12 | String template                              | # of properties              |
| 13 | Delegation (Super and Property delegation)   | # of Properties              |
| 14 | Operator Overloading                         | # of named function          |
| 15 | Singleton                                    | # of object declaration      |
| 16 | Companion Object                             | # of object declaration      |
| 17 | Destructuring Declaration                    | # of properties              |

3.2 Mining Kotlin Features from Applications

3.2.1 Analyzing Feature Evolution by Inspecting Commits

For analyzing the use of features along with the history of one application, we created another tool which takes as input one Git repository and produces, for each version $v$ (i.e., commit) the number of features that the version $v$ has. The tool navigates the commits from a Git repository, starting from the oldest one, and for each of them computes the number of features by invoking our feature detection tool described in Section 3.1. Note that our tool computes the features from the complete version related to a commit $c$, not only from the files affected by $c$. Our tool is built over Coming [21], a framework for navigating Git repositories which allows users to plug-in their source code analyzers.

After navigating through all commits, the tool stores the results in a JSON file which has, for each commit, the number of features of each type. The results are also grouped by file, for example, file ‘FileX.kt’ has eight instances of lambda feature, and file ‘FileY.kt’ has four. Moreover, for each version, we computed and stored additional metrics such as lines of code (LOC) per programming language used in the project, number of files per program language, and number of Kotlin classes. Note that, the generated output could have entries related to versions that do not include Kotlin code. In those cases, we computed the previously mentioned metrics (the metric ‘number of Kotlin files’ will be zero), but, however, we don’t trigger our Kotlin feature detection tool.

3.2.2 Summarizing use of Kotlin features

For responding to our first research question (RQ1), we processed the output of our feature evolution tool (Section 3.2.1), i.e., the JSON file produced for each
application. We counted, for each feature $f$, the number of applications whose last version have at least one instance of $f$.

Furthermore, we counted the total number of instances of each feature in every application. As the applications can have different sizes and characteristics, we normalized the total number of instance following the criteria presented in Table 1. For 4 features, we decided to normalized by the number of lines of code, which gives a measure of the size of an app in line of code. For other features we decided to use other metric as normalization, which could give us a better idea about how much those features are being used. For instance, we normalized data class by number of classes, because every data class is a class. Thus, using this criteria of normalization we observe the percentage of class defined as data class.

### 3.2.3 Identifying first use of Kotlin features

For responding to RQ2, we computed for each application $a$ and for each feature $f$ the first commit $C_{fa}$ that introduces an instance of $f$ into $a$. Then, we calculated the index $i$ of $C_{fa}$, i.e., the position of that commit inside a list with all commits from $a$, chronologically ordered. Finally, we defined a metric, named Introduction moment, $m_{af} \in [0, 1]$, that normalizes the index $i$ by the total number of commits from $a$. For instance, $m_{af} = 0$ means that feature $x$ was introduce into $a$ in the first commit, $m_{af} = 0.5$ was introduced in the commit number $0.5 \times (\# \text{ commits in } a)$, and $m_{af} = 1$ introduced in the last commit $(\# \text{ commits} − 1)$.

### 3.2.4 Identifying the order which Kotlin features are first used and when two features are introduced together

For responding to RQ3, we calculated for each application $a$ the order of Kotlin features introduction. The goal is to rank each feature $f$ used in an application $a$ according with their first use. The ranking $r$ of feature $f$ means that $f$ is the $r$-th feature to be used in $a$. Consequently, there are $r − 1$ features that were introduced in $a$ in previous commits. Note that $r \in [1, \# \text{ features}]$ and if two features are introduced for a first time in the same commit, they share the same $r$ values.

For computing those rankings, we first computed, for each feature $f$, the metric $m_{fa}$ (explained in Section 3.2.3). Then, we sorted the features according to their values of $m_{fa}$, in an ascending way. The position of a feature in that sorted list corresponds to its ranking. Finally, once we computed the rankings for each applications, we calculated the distribution of rankings of each feature.

Using the ranking of features of each application, we counted when a feature is introduced with another feature on the same commit comparing their position in the ranking. Then, we counted for each feature in how many applications it was added together and before the others features.

### 3.3 Classifying the use of features along the application’s evolution

In our last research question we study how features are used along the history of an application. The goal of $RQ4$ was to detect trends that describe the evolution of the use of each feature along with the applications’ history. For example, we
wanted to detect the applications where the use of a particular Kotlin feature is constant or increases or even decrease along with the applications’ histories.

### 3.3.1 Feature evolution on applications

To study the use of a feature along with the history of one application, we counted the number of instances present on each version. An instance of a feature is a particular use of that feature in the code.

### 3.3.2 Classification of feature evolution trend

Our goal was to classify each pair of application-feature \((a,x)\) with a trend that best describes the evolution of feature \(x\) in the history of application \(a\). In this work, we considered 11 evolution trends of features along with an application’s history. After executing the classification, we are able to identify the most frequent evolution trends that we observe for each feature and, using that explanation, to conclude how do developers use features during the evolution of Kotlin applications.

### 3.3.3 Considered trends

We have established 11 major feature evolution trends to answer RQ3. An example of each of them are showed in Figure 1. Those trends are:

- **Constant Rise (CR):** describes features that once they are introduced (i.e., used for a first time in an application), developers tend to add more instances of this feature in future applications’ versions. Therefore, the number of instances of a feature increases in a constant rate, i.e., linearly, along with the application’s evolution.

- **Constant Decline (CD):** describes features that once they are introduced, developers tend to remove them gradually in future applications’ versions. In other words, the number of instances of a feature has the opposite behavior of the constant rise trend. Therefore, along with the application’s evolution, the number of features instances decreases at a constant rate.

- **Stability (S):** describes features whose the number of instance remains the same after it introduction, during the whole application’s evolution.

- **Sudden Rise (SR):** describes those features which the number of occurrences grows suddenly after relative stability along with the history. Using this trend, we are able to identify those features that present small number of instances in the firsts commits and then, at the following commits, on each commit, developers introduce significantly more instances of a feature.

- **Sudden Decline (SD):** analogously, this trend describes the opposite behavior of SR, those features which the number of occurrences decreases suddenly. Features that present many instances since the first commits then suddenly, they start to be removed and this behavior continues in the next consecutive commits.
Fig. 1: Example of evolution trends studied. The x-axis represents the evolution of an application, i.e., commits, and the y-axis show that number of occurrence of a feature.

**Sudden Rise Plateau (SRP):** describes feature which most of its instances are introduced in the firsts commits of an application and then, during the rest of the application’s history, only a few instances are introduced.

**Plateau Gradual Rise (PGR):** describes those feature which once they are introduced, the number of instances tends to remains the same during an interval of commits and then, presents a sudden increase in few consecutive commits, and finally presents a stable behavior again.

**Plateau Gradual Decline (PGD):** similar to the trend PGR, this trend describes those features which the number of instances starts and ends stable. However, as the opposite of PGR, in this trend, the change that happens between the periods of stability has marked a decrease in the number of instances, in a few consecutive commits.

**Plateau Sudden Rise (PSR):** is similar to PGR. However, using this trend, we aim to detect features that present: a) a stability period in the beginning application’s evolution b) a transition period containing only one commit and c) stability period in the end of application’s evolution.

**Plateau Sudden Decline (PSD):** analogously to PSR, this trend is a special case of PGD where the change between the two periods of stability has marked a decrease in the number of instances, in two consecutive commits.

**Instability (I):** describes features which the number of instances alternates, between an increase and a decrease rates, during the application’s evolution. For example, one case that could be represented by this trend is when the number of a feature increases in a version, then suddenly decreases in the following version, and finally increases again during the lasts versions of the app.

In the literature, other authors have studied similar trends. However, they have not target the evolution of the adoption of programming languages features. Hetcht et al. [15] studied the evolution of the applications’ quality. Malavolta et
al. [18] investigated the evolution of maintainability issues along the evolution of Android applications and Mateus et al. [13] studied the evolution of the amount of Kotlin code on Android applications.

### 3.3.4 Considered formulas

To model the 11 major evolution trends presented in Section 3.3.3, we considered six formulas and Figure 2 shows an example of each formula. We chose them according to different scenarios that we wanted to detect, previously described in Section 3.3.3. Furthermore, our processes of classification is automated, differently from the classification done in previous studies [15, 18].

**Linear function** The linear function is given by the formula $y = ax + b$.

An example is presented in Sub-Figure 2(a). Using this formula, we aim to detect those features which the number of added (or removed) instances of a feature by version are constant along with every version from an application. In linear function, the rate of change (given by coefficient $a$) is always constant. Therefore, investigating the value of the coefficient $a$ we classify the application’s trend into: a) (CR), when $a > 0$ which implies on constant increase b) (CD), when $a < 0$ which implies on constant decrease and c) (S), when $a = 0$ which determines a constant behavior.

**Exponential function** The Exponential function is given by the formula $y = ab^x + c$.

An example is presented in Sub-Figure 2(b). Using this formula, we aim to detect those features which the number of occurrences exponentially increase (or decrease) along with the history. Unlike a linear function, the number of added (or removed) instances of a feature always grow (or decreases, resp.) along with the application’s history. Here, the rate of change (given by coefficient $b$). When $b$ is greater than 1, the value of $y$ increase as $x$ increases (SR). On the other hand, if $b$ is $0 < b < 1$, the value of a function increases as the value of $x$ decrease (SD). Then, considering the value of $b$ we can split the applications better described by an exponential function in two trends; SR and SD.

**Logarithmic function** The Logarithmic function is given by the formula $y = a \log_b(x) + c$.

An example is presented in Sub-Figure 2(c). Using this formula, we aim to detect those features which the number of added instances always grows along with the application’s history. However, contrary to the exponential formula, the rate of change always decreases with time. Therefore, the logarithmic function represents the trend SRP.
Sigmoid function The Sigmoid function, which is a special case of the logistic function, is given by the formula $y = \frac{L}{1 + e^{-k(x-x_0)}} + b$.

An example is presented in Sub-Figure 2(d). A sigmoid a bounded function and in our case, $L$ and $b$ determine these boundaries. Thus, $y$ can assume values from $-L + b$ to $L + b$. Additionally, when $L \cdot b > 0$, $y$ approaches $L + b$ as $x$ approaches $+\infty$ and approaches $-L + b$ as $x$ approaches $-\infty$. On the other hand, we observe the opposite behavior, when $L \cdot b < 0$. Moreover, $x_0$ is sigmoid’s midpoint, which marks the middle of the S-curve. Finally, $k$ determine the steepness of the curve.

Therefore, using this formula, we model the trends PGR and PGD. The PGR trend is characterized by a lowest the number of instances $(-L + b)$ at the beginning of the application history and the highest value $(L + b)$ of the number of instances in the end. Moreover, the transition between the lowest and the highest values is characterized by a gradual rise, in 1 or few consecutive commits, when developers introduce a considerable number of instances. The PGD trend follows the opposite behavior, starting from the highest number of instances and finishing with the lowest number of instances.

**Binary Sigmoid function** We considered a special case of the previous defined Sigmoid function: the slope of the function is completely vertical (given by a large value of coefficient $k$). An example is presented in Sub-Figure 2(e). Therefore, using this formula we can identify the trends PSR and PSD.

**Polynomial function** The polynomial function is given by the formula $a_n x^n + a_{n-1} x^{n-1} + \ldots + a_2 x^2 + a_1 x + a_0$, where $n$ is the degree of the polynomial and $a_n > 0$. Moreover, the degree of a polynomial determines the number of minimum and maximum (at most degree $-1$) given an open interval. Therefore, using these formulas we detect those features which the number of instances along the application’s evolution form a curve with two or more minimum or maximum, considering the input domain, that corresponds the number of commits [1, #commits]. Consequently, using this formula, we classify applications that present the trend I. Figure 2(f) shows a polynomial example.

### 3.3.5 Finding the formula that better describes the feature evolution

To match a feature evolution trend with one of the studied trends, we applied the following methodology:

*Obtaining series of number of instances per application* As explained in Section 3.2, the execution of our tool given one application results in the number of instances of each feature that each application’s version (i.e., commit) has. From this result generated for each application $a$, we generated a series of values $y_{xa} = \{vax_1, vax_2, \ldots, vax_n\}$ where $vax_i$ corresponds to the number of instance of feature $x$ detected in the $i$-version of $a$ (corresponding to the $i$-th commit considering chronological order, starting with the first version that introduces $x$). That is, the first element contains the number of features in the first version that introduces $x$, the third element those from the third version $x$ after the introduction of $x$, etc.

For example, Figure 3 shows an application named ‘Hand and Foot Scores’ and the evolution of two Kotlin features, *Lambda* and *When Expression*. We observed
that 3 instances of *when expression* were introduced in the first Kotlin commit, $v_{a0} = 3$ and $v_{a4} = 5$, where $x = whenExpression^{19}$ On the other hand, *lambda* was introduced in the fifth commit. It is important to note that, Figure 3 does not show all application’s commits, since it shows only Kotlin commits and, in contrast, Kotlin was introduced in the third commit.

**Computing formulas’ coefficients by fitting the series** For each series $y_{xa}$ from a pair application-feature $(a, x)$, and for each formula $f$ presented in 3.3.4 we used non-linear least squares to fit function $f$ to data $y_{xa}$. This gives as result a set of coefficients $\alpha_1, \ldots, \alpha_n$ for $f$ that correspond to the optimal values so that the sum of the squared residuals $SS_{reg}$ (Formula 1) is minimized.

$$SS_{res} = \sum_{i}^{[\text{versions}a]} (y_{xa_i} - f_i)$$ (1)

The number of coefficients generated varies according to the formula $f$: for linear, the number of coefficients is two, whereas for a polynomial of 4 degrees is 5. For executing the fitness of data, we used the function ‘curve_fit’ for library scipy\(^{20}\) Then, we consider applications with at least 5 versions, since to use ‘curve_fit’ need at least as many data points as you have parameters, 5 for polynomial of 4 degree.

**Post-Processing formulas and coefficients** This step has two goals: a) simplify some polynomial formulas and b) discard some Sigmoid function which does not have a clear S-shape considering the domain applied \([1, \#\text{commits}]\).  

First, we simplify those polynomial formulas whose highest coefficients $n$ is close to zero (i.e., $< 0.0001$). The reason is that the evolution trend can be similarly described with a polynomial formula with degree $n - 1$ or by linear.  

Second, we discard Sigmoid which do not have a clear S-shape. For example the Sigmoid function with coefficients $K = 0.1, X_0 = -9.2, L = 7.5$ in the domain $X \in [0, 15]$ has not a S-shape but a straight line.  

Third, we classify as binary sigmoid those functions that produce only to two values in the considered domain that correspond to trend PSR or PSD.

\(^{19}\) All information is available in our Appendix: [https://github.com/UPHF/kotlin_features](https://github.com/UPHF/kotlin_features)\(^{20}\) [https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.curve_fit.html](https://docs.scipy.org/doc/scipy/reference/generated/scipy.optimize.curve_fit.html)
Choosing the formula that best represents a feature evolution trend Once we computed the coefficients for each formula, we chose, for each pair \((a, x)\), the formula that yields less error to predict the values of \(y_{xa}\). We call it \(f_{\text{best},ax}\). Thus, this formula is considered as that one that best represents the feature evolution trend among all formulas we consider in this experiment (Section 3.3.4). We based our choice in a statistical measure named R-square (Coefficient of Determination) which measures how close the data are to the fitted formula. R-squared \((R^2)\) is always between 0 (bad) and 1 (good) and is given by the Formula 2:

\[
R^2 \equiv 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} 
\]

(2)

where \(SS_{\text{tot}}\) is:

\[
SS_{\text{tot}} = \sum_{i}^{\text{versions, a}} (y_{xa_i} - \bar{y}_{xa})^2
\]

(3)

An important observation is that two formulas \(f_1\) and \(f_2\) could have very close \(R^2\) values or even equals considering a small threshold\(^{21}\). In those cases, we chose the simplest one i.e., which one that simplifies the description of a trend. The priority order, arbitrary chosen by ourselves, is: \(\text{Linear} \gg \text{Exponential} \gg \text{Logarithmic} \gg \text{Sigmoid} \gg \text{Sigmoid} \gg \text{Polynomial}\).

Summarizing of best formulas Finally, for each feature \(x\) and formula \(f\) we count the number of applications that have \(f\) as the best formula (Section 3.3.5). The result from this step helps us to explain the most frequent evolution trend associated with each feature.

3.4 Evaluation dataset

To answer our research questions, we need a dataset of applications that include Kotlin code.

3.4.1 Dataset selection criterion

The goal of this work is to know how the Android developers use Kotlin features during the development of Android applications. Many of them are not available in Java for developing Android applications. Therefore, we decided to study on Android applications (partially or totally) written in Kotlin.

3.4.2 Dataset of Android Applications written in Kotlin

In this work, we used the second version of the FAMAZOA dataset\(^{13}\), which has 269 applications\(^{22}\). This dataset combines applications from three different sources, AndroidTimeMachine\(^{12}\), AndroZoo\(^{11}\) and F-Droid\(^{23}\). It contains open-source

\(^{21}\) We chose 0.01 as threshold value.
\(^{22}\) https://uphf.github.io/FAMAZOA/versions/v2
\(^{23}\) http://f-droid.org
Android applications with different portions of Kotlin code: some completely written in Kotlin, others using both Kotlin and Java languages. To the best of our knowledge, this is the largest dataset of open-source Android applications written in Kotlin.

Figure 4(a) gives us the order of magnitude of our analysis, showing the distribution of FAMAZOA’s applications according to their number of commits. As it shows, in the median, an application of our dataset has 277 commits and 50% of the applications have between 96 and 817 commits. Moreover, the number of applications decreases as long the number of commits increases, as Figure 4(a) shows. In figure 4(b), we observe the distribution of applications regarding the number of commits done before and after the introduction of Kotlin. In the left part of the plot, we observe the distribution of applications according to the number of commits inserted before the introduction of Kotlin whereas on the right side, we observe the opposite. Moreover, the medians of the number of commits before and after introduction are close, 90 and 113, respectively. However, the plot shows that as long the number of commits increase, the probability of an application having more commits before the inclusion of Kotlin increases as well.

4 Results

4.1 RQ1: What features of Kotlin are adopted by Android developers?

Figure 5 summarizes the result of our experiment described in Section 3.2. For each feature, it shows the percentage of applications that use that feature. Figures 6(a) and 6(b) show the distribution of the number of occurrences of each feature by application. In addition, Figure 7 shows the distribution of the number of occurrences of each feature by application (normalized by the criteria presented in Table 1). All features presented in this section are introduced and described in Section 2.

24 We are not plotting the outliers to keep a better visualization. To see the full version of those figure access: https://github.com/UPHF/kotlin_features/tree/master/appendix/dataset
Fig. 5: Percentage of applications that uses a specific Kotlin feature. Each bar corresponds to a feature and contains in the top the number of applications that use that feature.

Fig. 6: Distribution of the number of instances of the studied features in FAMA-ZOA’s applications.
We identified 265 applications whose last version has Kotlin code. Considering these applications, we observed that the most used feature is type inference with 261 out of 265 (98%) applications having at least one instance of this feature, as Figure 5 shows.

Finding 1: we found that in a median 70% of the variable declarations do not have their type explicitly declared, as Figure 7 displays. In these cases, the types are inferred by the Kotlin compiler.

However, we also noticed some applications whose all variables have their type inferred, for instance, Geocaching4Locus which has 54 variable declared. The fact that the Kotlin compiler can infer the type from assignments might explains this situation, because using this feature developers can write a more concise code.

Lambda is the second most used feature, being found in 249 out of 265 (93%) applications with a median of 51 instances by application, as Figure 6(a) shows. One possible reason to justify the amount of instances found, it is the fact of Android applications rely on callbacks to interact with the Android platform and because Kotlin provides a more concise and straightforward way to implement these callback when compared with Java. Also, we noted that the number of lambdas varies between applications as the number of Kotlin file as well. However, when the number of lambdas is normalized by the number of lines of code, we noted that most applications have the same proportion of lambdas by the number of lines of code since we found a small InterQuartile Range (IQR) as Figure 7 shows.

The third most used feature is safe call. We found 224 out of 265 (84%) applications where safe calls were found, with a median 21 occurrences per application. Another feature related to safety, unsafe call, it is used in 213 out of 265 (80%)
applications. As the opposite of safe calls, unsafe calls could result in `NullPointerException`. Our finding suggests that:

**Finding 2:** despite the fact of Kotlin providing a safer type system, most of Kotlin applications rely on code that could be affected by `NullPointerException`, since we found in a median, 11 occurrences of unsafe calls by application.

The possible reasons for the usage of the unsafe operator are: 1) due to interoperability with Java, e.g., Kotlin code calling to a method defined in a Java file or dependency (jar file), 2) the limitations of the Kotlin’s type inference mechanism, and 3) by an explicit decision of developers. Furthermore, as the Figures 6 shows, we found a smaller IQR of the distribution of unsafe calls than the distribution of safe calls. We found smaller values of outliers as well, as Figure 7 displays.

Two features share the position of the fourth most used feature: when expressions and companion objects. 218 out of 265 (82%) contains at least one occurrence of when expressions and 7 occurrences in the median. However, there are some applications with a higher occurrence of this feature. We found 3 applications with more than 300 occurrences of this feature. Finally, we conclude that the number of when expressions is strongly related with the number of lines, since we found a small IQR and a few outliers values, as we can see in Figure 7.

Considering companion objects we observed 6 occurrences in the median per application. Furthermore, Figure 7 displays that 45% of the object declared are companion object. We conclude that:

**Finding 3:** although Kotlin does not have static methods, developers take advantage of use companion object to call its members with the same syntax as calling static methods in Java since 82% of applications have at least one instance of this feature.

Furthermore, as Figure 8 shows, function calls with named arguments and function definition with arguments with a default value are used in more than 60% applications of our dataset and, for both features, we found in the median 2 occurrences per application. We normalized the number of instances by the number of function calls and the number of function definitions, respectively, as Figure 7 shows. We found that:

**Finding 4:** less than 1% of function calls has a named argument. Similarly, we observed also that less than 2% of function definitions have at least one argument with a default value.

Moreover, we found that 157 out of 265 (59%) uses data classes, with a median of 1 instance by application, as in Figure 9 shows. We normalized the number of data classes by the number of regular classes, as shown in Figure 7. Then, we concluded that:

**Finding 5:** in the median, less than 4% of applications’ classes are data classes. Although for 25% of applications that have data class, the number of data classes are more than 10% of the total number of classes.

Kotlin provides simple approaches to use two well-known design patterns, singleton and delegation. Regarding the usage of singleton, we observed 172 out of
265 (64%) applications have at least one class that implements the singleton pattern. Furthermore, as Figure 6(b) shows an application has in median 2 occurrence of this feature, although 12% of objects declared in Kotlin application are singletons, as displayed in Figure 7. Considering properties delegation, we observed it in 134 out of 265 (50%) applications. Normalizing the number of properties delegated by the number of properties for each application, we found that:

Finding 6: despite the fact of the Kotlin standard library provides factory methods for several useful kinds of delegation, such as lazy and observable, less than 1% of properties defined in Kotlin applications are delegated, as we can see in Figure 7.

The last four features are those used for less than 40% applications in our dataset. We observed 106 out of 265 (40%) applications that declare multiple variables at the same time using destructuring declaration.

Figure 5 displays that overloaded operator is found in 56 out of 265 (21%) applications. Also, we found two application, ‘Mahougen’ and ‘DroidComplex’, whose more than 10% of their functions are implementations of overloaded operators.

Finally, the least used feature is super delegation, which we found in only 18 out of 265 (6%) applications. Although it has proven to be a great alternative to implementation inheritance [8], we found that Kotlin applications have in median 0 occurrences of super delegations. However, the fact of the use of inheritance is essentially absent in mobile applications [23] can explain this finding.

Response to RQ 1: What features of Kotlin are adopted by Android developers?
We studied 19 Kotlin features in our experiment, and as a result, we found three groups of features: i) 6 features used on at least 80% of applications; ii) 9 features used in more than 50% and less than 80% of applications; iii) 4 features used in less than 40%. Furthermore, we found that type inference, lambdas and safe calls are the most used features, being found on 98%, 93% and 84% of applications, respectively.

4.2 RQ2: When do Android developers introduce Kotlin features during applications’ evolution?
To answer this research question, we used a metric defined in Section 3.2.3 named introduction moment. We observed that 15 out of 19 features presented an introduction moment smaller than 0.1, as Figure 8 displays, which means that these features tend to be introduced in the first 10% of Kotlin commits. However, comparing the introduction moment of the most and the least used features, it turned out distinct behaviors. The most used features (type inference, lambda and safe call) presented in median an introduction moment smaller than 0.01. Data class is not one of the most used features, but it also presented a small introduction time, 0.04 in the median. However, in this case, we believe that this value is a consequence of the fact that, in general, data classes are used to model domain classes which is one of the first activities during the development. On the other hand,
Fig. 8: Distributions of the number of commits that introduce the first instance of a Kotlin feature. The number of commits is normalized: 0 means the first commit, 1 means the last commit.

the least used features as inline functions, overloaded operator and super Delegation presented higher values of the introduction moment, 0.27 for inline functions, 0.14 for overloaded operator and 0.32 for super delegation.

Furthermore, we found that all features present cases of late introduction, i.e., after of the firsts 85% of Kotlin commits. This situation happens because none of these features are mandatory to write Kotlin code.

Response to RQ 2: When do Android developers introduce Kotlin features during applications’ evolution? The most used Kotlin features (Lambda, Safe Calls, When Expressions and Unsafe calls) are introduced in the very beginning of Kotlin’s history. On the other hand, we found that the least used Kotlin features tend to be introduced later on the Kotlin history.

4.3 RQ3: What is the order of addition of Kotlin features and in what proportion these features are added together?

Beyond the moment of introduction of a feature, we study the order of addition in applications of Kotlin features. For that, we ranked all the studied features, as discussed in Section 3.2.4 Figure 9 summarizes the results. It shows that type inference, lambda, when expression, companion object and unsafe call, tend to be the first-introduced feature in at least 50% of the applications. Comparing their ranking of introduction, we noted that:

Finding 7: type inference is always one of the first three features added into Android applications.

Furthermore, lambdas are also added as the first three features considering 75% of applications that has lambdas. Besides that, we noted that when expressions,
Fig. 9: Ranking of introduction of Kotlin features studied. The first violin (left) shows that type inference is one of the first 3 added features and that mostly, it is the first added feature. The width of the violins is scaled according to the number of observations in each position.

companion object and unsafe call are added later in some applications, as the max values show, 11th, 9th and 10th respectively. Regarding the least used features, destructuring declaration, inline functions, overloaded operator and super delegation, we found that they have the highest median position among all features, 5th for destructuring declaration and overloaded operator, and 6th for inline function and super delegation. Moreover, overloaded operator and super delegation appeared in the last two position of the ranking 14th and 15th, respectively.

We compared the ranking introduction of two features to know which are the features that are commonly used for the first time together (i.e., share the same introduction moment) and to know whether a particular feature $f_1$ is commonly used before than another one $f_2$ (i.e., ranking of $f_1$ is lower than that one from $f_2$). As described in Section 3.2.4, for each a pair of features $(f_1, f_2)$ we calculate the proportion of applications that introduce $f_1$ and $f_2$ in the same commit. This result is summarized in Figure 10 that shows the percentage of applications where a feature $f_1$ (row) is introduced on the same commit that a feature $f_2$ (column). Analogously, Figure 11 shows the percentage of applications where a feature $f_1$ (row) is introduced before a feature $f_2$ (column).

We found that the sixth most used features, type inference, lambda, safe call, when expression, companion object and unsafe call, are introduced together in at least 40% of all applications, considering any pair of these features. Particularly, we noted that:

Finding 8: in 69% of applications type inference and lambda (the two most used features) are introduced into the applications on the same commit.
However, as Figure 11 shows, \textit{lambda} is introduced before \textit{type inference} only in 3\% of applications, whereas for 28\% of applications \textit{type inference} is introduced before \textit{lambda}. We observed similar behavior when comparing the introduction of \textit{type inference} and \textit{companion object}. Furthermore, Figure 10 shows that \textit{inline function} and \textit{super delegation} were never added together.

Moreover, we observed a contrast between two regions of Figure 11, top right and left bottom. The first region presents a higher concentration of numbers close to the maximum value observed, 87, whereas the second region presents number close to the minimum value, 0. Therefore, we concluded that the most used features (top left) are in general introduced \textit{before} the least used features (bottom right). We noted for instance that \textit{safe call} is introduced before \textit{inline function} in 81\% of applications. The result is aligned with the finding presented in Section 4.2 where we showed that in general the \textit{introduction moment} of the most used features are smaller than the \textit{introduction moment} of the least used features.
response to RQ 3: What is the order of addition of Kotlin features and in what proportion these features are added together? We found that 5 features, type inference, lambda, when expression, companion object and unsafe call, tend to be the first introduced feature in at least 50% of the applications. Moreover, type inference is always one of the three first introduced features and 69% of applications introduced it together with lambdas. Regarding lambda, it is one of the three first introduced features in 75% of applications. Also, we observed that in 69% of applications type inference and lambda are introduced into the applications on the same commit and that the most used features are often added together.
4.4 RQ4: How the usage of Kotlin features evolves along the evolution of Android applications?

Table 2 presents the results of this research question obtained using the methodology presented in Section 3.3. Each cell shows the number and the percentage of applications whose the evolution of a feature $f$ (a row) is better described by trend $t$ (a column). Additionally, the number of applications analyzed that have a feature $f$ is displayed in the column Total applications.

For 9 out of 19 (47%) features studied are better described by CR, a constant rise trend. Moreover, 7 of 19 (36%) features presented stability intervals separated by a gradual rise. We also observed that two features have the same quantity of better described by CR and PGR. Other 4 features (21%) presented a behavior of stability intervals separated by a sudden rise (trend PSR Figure 1(i)). Additionally, the instability trend better describes 1 feature (5%). Finally, we did not find any feature better described by stability.

In Table 2, the column Inc shows the total of applications and the percentage of applications which are better described by any trend that shows an increasing in the number of instances of features (i.e., CR, SR, SRP, PGR, PSR). Similarly to the column Inc, the column Dec, shows the sum of CD, SD, PGD, PSD, that give us the total of applications and the percentage of applications which are better described by a trend that shows a decrease of usage of a feature. Furthermore, column I represents the Instability trend, i.e., applications that varies between increase and decrease behavior. Consequently, 100% of applications are represented by column I, Inc and Dec.

Now we explain our results for the three most used Kotlin features according to the results presented in Section 4.1, type inference, lambda, and safe call. We found that the majority of applications presented a behavior of increasing the number instances along the applications’ evolution. Table 2 shows that 71% of applications containing type inference, 81% of applications containing lambda and 80% of applications containing safe calls. Moreover, the constant rise trend, CR, better describes the evolution of these features in 36%, 39% and 32% of applications, respectively. In addition, Table 3 shows for each feature one application better described by each trend that has an increasing behavior.

Considering the usage of type inference, we found 64 (27%) of applications whose number of type inference varies between increase and decrease intervals along applications’ evolution. On the other hand, we observed only 5 (2%) applications whose the number of type inference decreases during applications’ evolution. We observed a similar behavior for the fifth most used features, type inference, lambda, safe call, when expression and companion object, except for when expression. In this case, the number of applications that show a decrease of instances along the applications’ evolution is equal to the number of applications better described by the instability trend.

Another interesting finding is that the sixth most used features, unsafe call, does follow the same behavior of the fifth most used features. It is the only feature better describe by Instability. Figure 12 shows the evolution of the usage of unsafe call in 3 applications whose evolution trend was classified as instability. We suppose this behavior is a consequence of developers concerned with the usage of unsafe call which it might cause a NullPointerException. The instability found
| Revolution Trends | CR  | SD  | SH  | SS  | SHR | FGR | PGR | PSGD | PSGD | I  | Inc | Dec | Total |
|-------------------|-----|-----|-----|-----|-----|-----|-----|------|------|----|-----|-----|-------|
| Type Inference    | 44  | 11  | 55  | 23  | 15  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Lambda            | 36  | 16  | 25  | 10  | 38  | 22  | 10  | 50   | 20   | 12 | 10  | 6   | 139   |
| Safe Call         | 68  | 24  | 44  | 17  | 34  | 14  | 10  | 50   | 20   | 12 | 10  | 6   | 139   |
| When Exp          | 19  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Companion Object  | 39  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Oncall Call       | 44  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| String Template   | 44  | 14  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Func With DefVal  | 39  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Singleton         | 37  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Smart Cast        | 40  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Range Else        | 42  | 14  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Func and With     | 39  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Named Arg         | 39  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Data Prv          | 41  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Extension Function| 38  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Property Decl     | 28  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Destructor Decl    | 13  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Inline Func       | 38  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Overloaded Op      | 41  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Type Conversion   | 40  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Exception Prop     | 41  | 13  | 22  | 15  | 11  | 10  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
| Total             | 90  | 30  | 60  | 24  | 30  | 12  | 5   | 50   | 20   | 12 | 10  | 6   | 139   |
Table 3: Examples of applications better described by each trend that presents an increase of the number of instances along applications’ evolution. The rows represent features: *lambdas* (top), *safe call* and *when expressions* respectively. The columns represent evolution trends.

| Features                  | Constant Rise | Sudden Rise | Sudden Rise Plateau | Plateau Gradal Rise | Plateau Sudden Rise |
|---------------------------|---------------|-------------|---------------------|---------------------|---------------------|
| Lambdas                   |               |             |                     |                     |                     |
| Safe calls                |               |             |                     |                     |                     |
| When Expresions           |               |             |                     |                     |                     |

Fig. 12: Examples of applications better described by each trend that presents an increase of the number of instances along applications’ evolution.

could be related to the fact that developers remove instances of *unsafe call* that cause *NullPointerException*.

Response to RQ 4: *How the usage of Kotlin features evolves along the evolution of Android applications?* Developers tend to more instances along the evolution of Android applications of 18 out of 19 (94%) features studied. The only exception is the feature *Unsafe call* that was better described by the instability trend. Moreover, we found that 9 out of 19 features are better described by the trend *Constant rise*.

Finally, as we described in Section 3.2.4 to identify the trend that better describe the evolution trend of a feature, we used R-squared, which measures how close the data are to the fitted formula. The R-squared assumes values between 0 and 1, and 1 means a perfect fitting.
Fig. 13: Distribution of the coefficient of determination, R-square, considering the best function fitted for each feature. The median value is 0.89 (R-square equal to 1 means a perfect fitting).

Figure 13 shows the distribution of the R-squared obtained from the chosen formula (i.e., best fit functions for each feature) The median R-square is 0.89, which means that the 50% the selected formulas describe almost perfectly the evolution trends. Moreover, we found that 75% of evolution trends fitted presented an R-Squared greater than 0.78, and only outliers have R-Squared values lower than 0.5.

5 Threats to Validity

5.1 Internal

Selection of features In this work, we investigated the adoption and evolution usage of a subset of Kotlin features. Therefore, the criteria used to select the target features impact our results. For that reason, we chose the features listed in the official Kotlin documentation.

Feature identification Our results depend on how precisely we identify the target features. However, we were not able to write a detector of instances of Coroutines. Furthermore, we manually checked a sample of commits to validate the results given by our tool.

Evolution trend identification One of the goals of our work is to identify evolution trends. To avoid any bias, we established 11 evolution trends (See Section 3.3.3) similarly used in other studies present in the literature. Moreover, to match a feature evolution with one of the studied trends, we defined 6 formulas (described in Section 3.3.4). However, it is possible that other formulas, not used in this paper, fit better with any evolution trend. To fit a formula with a feature

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25 https://kotlinlang.org/docs/reference/comparison-to-java.html
evolution trend, we applied a well-known algorithm (‘curve_fit’) from the Scipy, a Python-based ecosystem of open-source software for mathematics, science, and engineering. Moreover, we considered the R-Square, a statistical measure, that measures how close the data are to the fitted formula. The goal of the formulas is not to predict the number of features that future versions of an application could have. Our goal is to fit the evolution trends to understand how the usage of features has evolved.

5.2 External

Representativeness of FAMAZOA Our work relies on FAMAZOA [13], a dataset of open-source mobile applications written in Kotlin. Considering the number of applications published on Google Play, FAMAZOA represents a small parcel since it only contains open-source applications, and that can limit the generalization of our findings. However, to the best of our knowledge, it is the largest dataset of Android open-source applications written in Kotlin and it was already used for studying Android kotlin applications [13]. Moreover, our experiments are based on source code analysis and unfortunately, applications stores such Google Play, only provides the compiled code.

Developer’s experience In our work, we analyzed the source code of different Android applications. Considering the usage of the studied features, it is possible that some of them require more experience from developers to be used properly. However, we did not consider information about developers’ experience. Nevertheless, all applications analyzed are published on F-droid or Google Play, then it represents a current snapshot of Android development. We intend to consider this aspect in future work.

6 Related Work

We group the related work into three areas: 1) empirical studies on language features 2) empirical studies on the usage evolution of language features and 3) evolution of Android open-source applications.

Empirical studies on adoption of language features Several empirical studies about programming language features of different languages have been done. Some of these studies focused on feature identification.

Surton et al. [31] developed and validated a tool to identify the use of generic libraries in C++ projects to support a programmer’s comprehension. In another work, Uesbeck et al. [32] investigated the impact of lambda expressions on the development, debugging, and testing effort in C++. Pinto et al. [28] studied the energy efficiency of Java’s Thread-Safe Collections. They empirically investigated 16 collection implementations (13 thread-safe, 3 non-thread-safe) using micro- and real world-benchmarks and observed that simple design decisions can greatly impact energy consumption.

26 https://scipy.org
In the meantime, Chapman [6] studied the usage of regular expressions by Python developers conducting an empirical study over nearly 4,000 open-source Python projects from GitHub. They found six common behavioral that describe how regular expressions are often used in practice.

JavaScript features were also the target of studies. Since JavaScript is a prototype-based language, Silva et al. [30] developed a tool, JSCLASSFINDER, to investigate how class emulation is employed in JavaScript applications. Finally, they observed that 26% of 50 most popular applications from Github does not use class and that 9 out of 50 applications that use inheritance. Gallaba et al. [10] focused on the usage of asynchronous callbacks in JavaScript. They present a set of program analysis techniques to detect instances of asynchronous callbacks and to refactor such callbacks using promises, a language extension that provides an alternative to the asynchronous callbacks. They evaluated their tool, called PROMISESLAND, and found that it refactors substituting callbacks to promise correctly.

More recently, Casse et al. [5] focused their study on Swift exception handling mechanism. Their goal was to know what the extension developers adhere to good practices exemplified by guidelines and tutorials and to identify what are the common bad practices related to exception handling particularly relevant to Swift code. To answer these questions, they combined ten semi-structured interviews with Swift developers, and they conducted a quantitative analysis of 78,760 Swift files extracted from 2,733 open-source GitHub repositories. They concluded that there is ample opportunity to improve the way Swift developers use error handling mechanisms.

Although these studies applied different techniques in empirical studies of different sizes, all of them focused on only one feature and they did not investigate their adoption over time as we do in this paper. Moreover, nobody has studied features of Kotlin language.

Empirical studies on the usage evolution of language features Studies about the adoption of features over time has been done as well.

Parnin et al. [26, 27] conducted the first empirical study to understand how Java generics have been integrated into open-source software by automatically mining the history of 40 popular Java programs and traversing more than 650 million lines of code. They found that generics can reduce the number of type casts in a project and are usually adopted by one or two contributors, rather than all committers.

Donnghoon et al. [17] replicated the experiment done by Parnin et al. [26, 27] to investigate the claimed benefits of C# generics and to compare the use of generics in C# and Java. They conclude that generics are more readily used in C# than in Java and the benefits of generics are manifested more clearly in C#.

More recently, Pinto et al. [29] and Wu et al. [33] performed large empirical studies to investigate the usage of concurrency constructs in open-source applications in Java and C++, respectively. Pinto et al. [29] found more than 75% of 2227 project projects either explicitly create threads or employ some concurrency control mechanism. Moreover, they found that only 23% of concurrent projects adopted the java.util.concurrent library. Wu et al. [33] found that developers in most projects do not move from third-party concurrency constructs to standard concurrency constructs and small-size applications introduce concurrency constructs
more intensively and more quickly than medium-size applications and large-size applications.

Java exception handling mechanism was also the target of several studies [2, 25, 24]. Asaduzzaman et al. [2] investigated the use of exception handling analyzing 274,000 Java projects from GitHub. They found that bad practices of exception handling are common in open-source Java projects and that regardless of experience, all developers use bad practices exception handling. However, they do not consider adoption over time. On the other hand, Osman et al. [25, 24] conducted empirical studies on long-lived Java systems. They observed that the amount of error-handling code, the number of custom exceptions and their usage in catch handlers and throw statements increase as projects evolve. Moreover, they observed that applications have significantly more error handling code than libraries.

Since annotations have been widely used by the Java community for different purposes, Yu et al. [35] conducted a empirical study to evaluate the usage, evolution and impact of Java Annotations.

Although these studies focused in adoption of features considering the software evolution, they investigated particularly one selected feature and none of them aimed Kotlin features.

Differently, to the previous studies, Malloy [19, 20] and Dyer et al. [7] conducted empirical studies considering a set of programming language features.

Malloy [19, 20] investigated the degree to which Python software developers are migrating from Python 2 to Python 3 by measuring and quantifying the adoption of Python 3 features. They found that Python software developers are choosing to maintain the backward compatibility with Python 2 instead of exploiting the new features and advantages of Python 3.

To identify uses of new Java language features over time, Dyer et al. [7] analyzed over 23k open-source Java projects containing more than 7 million Java files, which when parsed resulted in over 14 billion AST nodes. They observed that all features are used even before their release date, but there are still millions of more places where they could potentially be used. Also, they concluded that features tend to be adopted by committers on an individual basis rather than as a team.

These studies considered the adoption of a set of features over time, however only Dyer et al. [7] studied how the usage of a feature evolves along with software evolution. On the other hand, Mazinanina [22] focused on the evolution trend of only one feature, investigating the usage of Lambda in Java. They conducted a large-scale empirical study, statically analyzing the source code of 241 open-source projects, to study the format of 100,540 lambda expressions and to investigate the historical trends and adoption rates of lambdas. Furthermore, to understand the reasons why developers introduce lambda expressions, they surveyed 97 developers who are introducing lambdas in their projects. As a result, they revealed an increasing trend in the adoption of lambdas in Java.

In contrast with the previous studies, our work focus on a set of Kotlin feature, their adoption and their evolution trend along with applications’ version.

Evolution of Android open-source applications

As a consequence of the explosion of the number of mobile applications, several aspects of the evolution of Android applications were investigated.

Hetcht et al. [15] presented an approach for performing static code analysis on Android applications’ bytecode and detecting software code smells, object-oriented
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and Android-specific. Analyzing the evolution of the quality across 3,568 versions of 106 different Android applications based on the presence of the studied smells, they identified five different quality evolution trends.

Calciati and Gorla [3] investigated the evolution of permission requests analyzing more than 14,000 applications. They found that applications tend to add permissions over time and that when a permission request is removed from an application, it does not necessarily imply the removal of the corresponding functionality.

Mateus et al. [13] conducted the first empirical study about Android applications written in Kotlin. Applying their approach to detect Kotlin applications on three well-known datasets of Android applications, AndroidTimeMachine [12], AndroZoo [1] and F-Droid, they presented FAMAZOA, a dataset containing 244 Kotlin applications. Using this dataset, they analyzed source code evolution of Android applications, observing the behavior of the amount of Kotlin and Java code and considering 12 evolution trends. They found that for the 63.9% of the Kotlin applications, the amount of Kotlin code increases along with the Android application evolution and, at the same time, the amount of Java code decreases or remains constant.

Malavolta et al. [18] investigated the evolution of 6 maintainability issues along with the evolution of Android applications. They conducted an empirical study using static analysis on 434 GitHub repositories containing applications published in the Google Play store and actively maintained. They inspected the evolution trend of the density for each type of maintainability issues and identified 12 different possible trends. They concluded that, independently from the type of development activity and notwithstanding the issue type, maintainability issue density grows until it stabilizes, but issues are seldom fully resolved.

Habchi et al. [14] presented the first large-scale empirical study that investigates the survival of Android code smells. This study covers eight types of Android code smells, 324 Android applications, 255k commits, and the history of 180k code smell instances. They reported that while in terms of time Android code smells can remain in the codebase for years before being removed, it only takes 34 effective commits to remove 75% of them. Also, Android code smells disappear faster in bigger projects with higher releasing trends.

Calciati et al. [4] proposed a framework to analyze the evolution of Android applications. Their framework extracts plenty of information, such as how an application uses sensitive data and which third-party libraries it relies on. Analyzing 235 applications with at least 50 releases, they found that Android applications tend to have more leaks of sensitive data over time and that the majority of API calls relative to dangerous permissions are added to the code in releases posterior to the one where the corresponding permission was requested.

These studies tie into our research because they focus on the evolution of Android applications. Some of them [15] [19] [16] applied a similar methodology, identifying evolution trends of different aspects of Android applications. However, they used a manual approach to classify application according to the identified trends. Differently, in our work, we applied a method that automatically classifies features evolution behavior into evolution trends. Furthermore, to the best of our knowledge, this work is the first empirical study about the adoption and evolution of Kotlin features.
7 Conclusion

Since Kotlin became an official programming language to develop Android applications in 2017, the number of applications written with Kotlin is increasing. One possible reason for this fact is features provided by Kotlin, most of them not present in Java. In this context, we conducted the first empirical study exploring different aspects of the adoption and evolution of Kotlin features as: which features are adopted, what is the degree of adoption, when these features are added into the Android applications for the first time, which are the features first introduced, and how they evolve along with applications’ evolution. To perform our empirical study, we used FAMAZOA, a dataset of open-source Android applications written in Kotlin. Then, we extracted features from the source code of those applications. We also identified when these features were used for the first time in a project. In total, we studied 19 features and their evolution trend. To classify the evolution trends of these features, we defined 11 evolution trends modeled by 6 functions and we created an automated method of classifying.

We found that 15 out of 19 features are used by the majority of Android applications. We also found that type inference, lambda and safe call are the most used features presented 98% in 92% and 83% of applications respectively. Regarding the introduction time of Kotlin features into Android applications, we observed that the most used features are just after the first Kotlin commit. On the other hand, we observed that the least used features are introduced later. Moreover, we noted that the most used features are the first feature added. Particularly, we observed that type inference is always one of the first three feature introduced. Finally, we found that 18 out of 19 features presented increasing of features instances along the applications’ evolution.

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