An experience-based recommendation system to support migrations of Android applications from Java to Kotlin

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Abstract—In 2017, Google announced Kotlin as an official Android programming language, and more recently, as the preferred programming language to build applications. These facts motivated developers to migrate their applications, which is challenging because each migrated piece of code must be tested after the migration to ensure it preserves the expected behavior. Due to the interoperability between Java and Kotlin, most developers decided to migrate their applications gradually. Thus, developers have to decide which file(s) to migrate first on each migration step. However, there are no tools available to help developers make these choices. This paper presents an approach to support a gradual migration of Android applications that given a version of an application written in Java and eventually, in Kotlin, it suggests the most convenient files to migrate. To this end, we built a large-scale corpus of open-source projects that migrated Java files to Kotlin. Then, we trained a learning to rank model using the information extracted from these projects. To validate our model, we verify whether these recommendations made by them correspond to real migrations. The results showed our approach modestly outperforms random approaches. Since most Android applications are written in Java, we conclude that our approach may significantly impact Android applications’ development. Therefore, we consider this result is the first step into long-term research towards a model capable of predicting precisely file-level migration, establishing the initial baseline on file migrations.

I. INTRODUCTION

In 2017, Google promoted Kotlin, a programming language that combines functional and object-oriented features, as an official Android language. More recently, in 2019, Google declared that Android became ‘Kotlin-first’, which means that new API, libraries, documentation will target Kotlin and eventually Java [1]. Since then, Google has advised developers to create new applications using Kotlin instead of Java [2].

Kotlin is compiled to Java byte-code, which means that it is interoperable with Java, i.e., Kotlin code can invoke code written in Java and vice-versa, both running on the same underlying JVM. Thanks to this interoperability, developers of Java-based Android applications can: i) adding new Kotlin code and maintaining the existing Java code, and/or ii) migrating some parts of their apps written in Java code to Kotlin. Recent research has shown that the 19% of Android applications completely migrated from Java to Kotlin were gradually migrated [3].

Moreover, some popular commercial Android applications also gradually migrated from Java to Kotlin. For instance, Duolingo, a free science-based language education platform [5], was completely migrated in 2 years. Figure 1 shows the evolution amount of Java and Kotlin code from Duolingo. During that period, Java files were progressively migrated to Kotlin, i.e., a commit migrated a subset of Java files, leaving other files in Java.

The gradual migration allows developers to: a) migrate a subset of Java files, b) exhaustively test the migrated code to verify that the migrated code preserves the expected behaviour, and c) commit (and eventually release) a new version of their app before continue with the migration of other files. As Duolingo’s developers report [6], gradual migration allowed them to apply strict testing, code review and code style of each part of the application that was migrated.

Gradual migration faces several challenges. This paper focuses on particularly in one: given a version of the program to migrated (composed by no migrated and, eventually, some migrated code), a developer should select a set of files that she/he wants to migrate on that migration step. This selection could be complex as: a) it could exist several candidate files to migrate, and b) the wrong selection of files to be migrated could increase the migration effort due to emerging errors [7].

Fig. 1: Evolution of the number of lines (LOC, axis X) of Java and Kotlin along with the Duolingo application’s migration process [4] since 2014 (Axis Y).
starting the migration slowly, and also it indicates possible paths to start (model, test, utility functions) \[9\].

In this paper, we present a novel approach, named MigrationEXP, that assists developers during the migration process by recommending a set of candidate Java files that could be migrated in the next migration step. This work is novel: to our knowledge, no previous work has focused on the automated recommendation of migration. This approach could complement the other tool used by developers during migration \[10\]: the automated file converter tool provided by Android Studio IDE.

We build our approach applying learning to rank to create a model based on migration performed by developers in open-source projects. It considers different aspects of the source code from the application under migration. Our intuition is that using information from these migrations, our model captures the rationale behind these migrations. We trained and evaluated our commits that migrated Java code to Kotlin on 1 457 open-source applications. To the best of our knowledge, no work has proposed a machine learning based approach in the context of Android application migration.

The result of this paper is: our approach outperforms the random approach by at least 38%, considering the Mean Average Precision (MAP). We consider that this resulting model is an initial step towards a fully automated recommendation system to support applications’ migration.

The contributions of this paper are:

- An approach that recommends migrations at file level from one programming language to another.
- A static analyzer tool that identifies 12 metrics exclusive to Android applications \[11\]
- A benchmark of projects that performed migrations from Java to Kotlin.

The paper continues as follows. Section II explains the terminology used along the paper. Section III characterizes our approach. Section IV outlines the methodology used to evaluate our approach. Section V reports the evaluation results. Section VII discusses the consequences of our results and future work. Section VI presents the threats to the validity. Section VIII presents the related work. Section IX concludes the paper. All the data presented in this paper is publicly available in our appendix: https://anonymous.4open.science/r/fe5cf980-060b-49ad-81b5-28dc22f26360

II. TERMINOLOGY

In this section, we present the terminology we used in this paper.

Language interoperability: the ability of two or more software components to cooperate despite differences in language, interface, execution platform \[11\].

Migration: the process of translating software from its source programming language to the target programming language.

Migration step: A set of translations on the code written in the source language to the target language that generates a new version (commit) of a software.

Gradual migration: a migration process that has more than one migration step. Along this process, some versions have code written in both source and target language.

One-step migration: a migration process that fully migrates a software in one migration step. In one-step migration, no version has code written in both source and target language.

File migration: a file translated from the source language to the target language in one migration step.

Commit with File migration: a commit that has one or more file migrations.

III. OUR APPROACH: MIGRATIONEXP

This section presents an approach named MigrationEXP, which supports the gradual migration of projects by suggesting files that could be migrated from one programming language to another.

A. Overview

We build our approach MigrationEXP using information from projects that have done file migrations from one programming language to another. Our intuition is that by analyzing those migrations, we can create a model that captures the rationale behind these migrations, i.e., the developers’ experience on migrations. Then we can use it to recommend files to be migrated.

Our approach consists of two phases as Figure 2 illustrates: a) the development phase, and b) the serving phase. In the development phase, our approach learns a model from migrations of projects from language $\text{lang}_1$ (e.g., Java) to $\text{lang}_2$ (e.g., Kotlin), done by developers on open-source projects. Then, in the serving phase, given a project $P$ as input, the model generated in the development phase is used to recommend file-level migrations: the model produces a list of candidate files to be migrated. Now, we give a summary of both phases from our approach.

1) Development phase: MigrationEXP is built using learning to rank, a supervised machine learning algorithm. Consequently, we need to provide example data to train our model. Each example is described by a vector of measurements or features and a label that denotes the category or class the example belongs to \[12\]. In our case, we use data from projects that have migrated from one programming language to another to create MigrationEXP’s training set. To this end, for each commit of these projects, we analyze their files to create a vector of features that describe them by extracting a set of metrics and classifying them as migrated or not migrated (label). These vectors are the training data used by our approach to learning a model. Finally, once we trained our model, it is deployed, and it is ready to be used in the serving phase.
Fig. 2: Our approach, MigrationEXP, has two phases: development and serving phase.

2) Serving phase: In the serving phase, our approach takes as input a program $P$, written partially or totally using $\text{lang}_1$, which developers aim to migrate to $\text{lang}_2$. As done in the development phase, our approach extracts features from the project’s files, i.e., candidates files to migrate, and creates for each file one vector of features, as done during the development phase. These vectors are given as input to our model. Finally, using this information, the model learned in the development phase sorts the project’s files according to their relevance and returns the list of recommended files to be migrated.

Figure 3 shows an example of this phase. The approach takes as input a project composed of 5 files where 4 files ($A.\text{lang}_1, B.\text{lang}_1, C.\text{lang}_1$, and $E.\text{lang}_1$) need to be migrated, and one $D.\text{lang}_2$ already migrated. The learned rank model ranks the 4 files based on the experience of developers by migrating similar files (i.e., with similar vector features). In this example, the developer could start migrating the files at the top of the recommendation, e.g., $E.\text{lang}_1$ and, eventually, $C.\text{lang}_1$, then testing the migrated app, committing the changes, and generating a new version to publish. Note that thanks to the interoperability, the migrated files (e.g., $E.\text{lang}_1$) could continue interacting with the no migrated (e.g., $B.\text{lang}_1$).

B. Instantiating MigrationEXP for supporting Java to Kotlin migration

The approach described in Section III is language independent. In this work, we instantiate and evaluate the approach in the context of migrations of Java to Kotlin. This instance of our approach aims to help Android developers to migrate from Java to Kotlin.

Given an application that should be migrated to Kotlin, our approach generates a rank with all candidate Java files to be migrated, where the top files are the recommendations to be migrated first. To create such an approach, we created a ranking model using a learning to rank algorithm, which solves a ranking problem by sorting objects according to their degrees of relevance, preference, or importance [13].

In this section, first, we present how we use the information extracted from projects with file migration from Java to Kotlin to collect the data needed to build our ranking model (Section III-B1). Then, in Section III-B3, we explain how we transform this data according to the representation used in learning to rank. Finally, in Section III-B4, describe the list of features extracted during the feature extraction process.

1) Learning process for Java to Kotlin migration model:
Our intuition is that we can build a learning-to-rank model that is able to capture from developers the knowledge to decide which file(s) migrates first given an app to be migrated. A simplified illustrative example: if we train a model with projects in which developers have migrated first short files (expressed in SLOC), then our ranking model, given as input an app $A_m$ to be gradually migrated, will propose to first migrate the shortest files from $A_m$.

In this work, we automatically create a ranking model by feeding it with information from real migrations done by developers. To this end, we used a learning-to-rank algorithm. In learning-to-rank, the training data consists of queries and documents where each query is associated with a set of documents. The relevance of the documents concerning the query is represented by a label [13]. In our context, each commit with at least one file migration from the training dataset becomes a query. A document associated with a query (and transitivity to a commit $C$) corresponds to a file $f$, which
belongs to the commit $C$. Each query’s documents are labeled with 1 if the document (file) was migrated in the commit associated with the query. Otherwise, a document is labeled with 0 (when a file is not migrated in that commit).

To illustrate how we transform the information extracted from commit with migration in our training dataset, let us imagine an application with 3 Java files ($File_1.java$, $File_2.java$, $File_3.java$). Consider a commit that performs these actions: i) removes “$File_1.java$” ii) updates “$File_2.java$” and iii) adds “$File_3.kt$”. This commit has a file migration ($File_1.java$ was migrated from Java to Kotlin). Consequently, we label these documents as follows: $File_1.java$ as migrated (1), $File_2.java$, $File_3.java$ as not migrated (0). From that information, we create a query.

To prepare the data used to train the model, we create one query per each commit that migrated code from our training set. Finally, the set of queries is the input of the training process of the ranking model, which generates as output a learned ranking model.

2) Using Java to Kotlin migration model to support migration: The learned ranking model is used in the serving phase (Section III-A) for recommending migrations. In that phase, the input is a query composed of files (documents) that belong to the application to be migrated. In fact, for obtaining one recommendation, we create a query composed of those documents. Note that those documents are not labeled. Then, giving a query as input, the model outputs, for each document, a Predicted relevance value. By sorting these documents according to their values, from the most relevant to the less relevant, we obtain the ranking of recommendations, where the documents in the first positions are the ones to be prioritized during the migration.

3) Representing documents and queries: We now focus on the representation of files from a commit as documents belonging to a query. Each file from a commit is represented by a vector of features. Consequently, a query is a set of vectors. The process of learning the model, which receives as inputs queries with labeled documents, will learn the relation between the features that represent the files and the labels (two in this paper: 1 for migrated and 0 for no migrated).

In the serving phase, we create a vector for each file of the application to be migrated. We create a query composed of a set of vectors, which is the input of the model. The model then ranks each vector (file) according to the features’ value and the label contained in all vectors.

4) Feature extraction for Java and Android apps: During feature extraction, measurements are extracted from the data given as input to our approach to create vectors of features that compose our model’s input. To the best of our knowledge, no study establishes a relationship between metrics or measurements and source code file migrations. For that reason, we decided to use 54 metrics as the features used by our approach to create a vector that represents a file from a project under migration. These metrics are listed in Table I.

First, we use 42 source code metrics that have been defined and used in previous experiments related, for instance, to the assessment of the overall quality of the software [15], [16], [17], [18], [19], [20], [21], [22]. These metrics are grouped in different categories like inheritance, communication, and complexity and readability. They include the object-oriented metrics proposed by Chidamber and Kemerer [23], such as Weighted Methods per Class (WMC), readability metrics such as the number of loops and the number of comparisons proposed by Buse et al. [24] and Salabrino et al. [25] and other source code metrics like the number of Sources Line Of Code (SLOC).

Secondly, we define 12 Android metrics to capture characteristics exclusive to Android applications. These metrics are:

- isActivity: a binary feature that informs whether a class extends the Activity class from the Android API.
- isView: a binary feature that informs whether a class extends the View class from the Android API.
- isBroadcastReceiver: a binary feature that informs whether a class extends the BroadcastReceiver class from the Android API.
- isService: a binary feature that informs whether a class extends the Service class from the Android API.
- isContentProvider: a binary feature that informs whether a class extends the ContentProvider class from the Android API.
- isFragment: a binary feature that informs whether a class extends the Fragment class from the Android API.
- isBuildingBlock: a binary feature that informs whether a class extends one of the essential building blocks (Activity, Service, BroadcastReceiver and ContentProvider) of an Android application.
- isInAndroidHierarchy: a binary feature that informs whether a class extends any class from the Android API.
- Number of parameters coupled: The number of methods parameters whose type is an object from the Android API.
- Number of return coupled: The number of methods whose the return type is an object from the Android API.
- Number of methods coupled: The number of methods whose at least one parameter or return type is an object from the Android API.
- hasAndroidCoupling: a binary feature that informs whether a class has at least one method coupled.

IV. Methodology

This paper aims to evaluate the feasibility of using MigrationEXP to help developers gradually migrate Android applications. The following research questions guide our study:

- RQ1: To what extent a learning-to-rank model learned from migrations done in real projects may recommend migration of files precisely?

In this section, we present the methodology applied to respond to this research question. First, we present the method applied to collect open-source applications that have performed migration of files from Java to Kotlin (Section IV-A). Then, we describe how we learn a model from information about migrations performed by developers in these projects.
Our model works at the level of file-level migrations, but to the best of our knowledge, there is no dataset of file migration from Java to Kotlin. Therefore, to conduct our study, we create two datasets with Java to Kotlin migrations to train and evaluate our approach. First, we collect migrations from an existing dataset of open-source applications written, partially or totally, in Kotlin. However, we need to filter projects that contain Java as well, since this is a requirement to have migrations. For that reason, we select all projects with at least one commit with Java (i.e., a commit that introduces Java code). At the end of this procedure, we identified 5,126 repositories.

### Step 2. Identification of projects that used Java at its lifecycle.

The previous step is necessary to identify projects that have Kotlin. However, we need to filter projects that contain Java as well, since this is a requirement to have migrations. For that reason, we select all projects with at least one commit with Java (i.e., a commit that introduces Java code). At the end of this procedure, we identified 5,126 repositories.

### Step 3. Identification of file migration.

In order to find real cases of migrations, we navigate through all commits of 5,126 repositories identified in step 2. Then, we apply the following procedure: consider that a repository is a set of versions (commits) $C_r = \{c_1, c_2, ..., c_n\}$ where $i$ determines the commit number, i.e., $c_1$ is the first commit and $c_n$ is the last commit. Then, to find migrated files, we compare consecutive commits, $c_i, c_{i+1}$ to extract a pair of files, $f_i$, $f_{i+1}$, that should respect the following conditions: i) $f_i$ is a Java file from $c_i$ and it was removed in $c_{i+1}$, ii) $f_{i+1}$ is a Kotlin file added on $c_{i+1}$, and iii) $f_i$ and $f_{i+1}$ share the same filename ignoring the file extension (.java, .kt). In this step, we stop once a migration is found. The rationale behind this step, is to keep only repositories with migrations, to save computation time and storage resources. Applying this strategy, we identified 1,357 repositories with migrations. We identified 7,275 commits with migration that migrated 27,375 files from 1,179 projects, as Table II shows.

A. Data acquisition for training and evaluation

Our model works at the level of file-level migrations, but to the best of our knowledge, there is no dataset of file migration from Java to Kotlin. Therefore, to conduct our study, we create two datasets with Java to Kotlin migrations to train and evaluate our approach. First, we collect migrations from an existing dataset of open-source applications written, partially or totally, in Kotlin published on apps Stores such as F-droid and Google Play. Then, to obtain more data about migrations, not only from Android applications, we analyze additional applications hosted on GitHub.

The usage of these two datasets allows us to evaluate our model in the wild, which is different from the in the lab (i.e., using one dataset to train and test our model applying 10-Fold cross-validation), because it does not assumes that 90% of the domain knowledge is known beforehand.  

We now detail how we build the two datasets of migrations.

a) **GitHub$_{2k}$:** dataset of open-source projects with migrations: We followed 3 steps to create our GitHub$_{2k}$ dataset: i) identification of open-source projects hosted on GitHub that use Kotlin, ii) filtering projects that have Java code at any version, i.e., commits, and iii) filtering projects that have migrated files from Java to Kotlin.

#### Step 1. Identification of open-source projects written in Kotlin hosted on GitHub.

This step aims at finding all repositories on GitHub potentially written in Kotlin. Our search was performed on the publicly-available GitHub mirror available on Google BigQuery. This mirror offers a full snapshot of the content of more than 2.8 million open-source repositories and almost 2 billion files. Moreover, it provides information about the use of programming languages in last commit of each repository. Therefore, we performed a query looking for projects that have Kotlin. As a result, it returned 7,119 repositories.

#### Step 2. Identification of projects that used Java at its lifecycle.

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b) **Android$_{2k}$:** dataset of Android applications with migrations: To build our dataset of Android applications with migrations, we mined the repositories of FAMAZOA v3. FAMAZOA is the largest publicly available dataset of open-source repositories written in Kotlin, and it contains 387 applications written partially or totally in Kotlin collected from 3 dataset of Android open-source applications: Android-TimeMachine, AndroZoo and F-Droid. We applied steps 2 and 3 presented in Section IV-A and we identified 270 out of 387 (69%) applications with at least one migration from Java to Kotlin. Since FAMAZOA includes applications hosted on the GitHub, to avoid duplicates, we removed 170 applications from GitHub$_{2k}$ that are present in Android$_{2k}$.

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**TABLE I: List of collected features grouped by category.**

| Subcategory | Metric name |
|-------------|-------------|
| **Size**    | Source Lines Of Code (SLOC), Number of methods, Number of fields |
| **Complexity** | Weight Method Class (WMC), Max nested blocks |
| **Coupling** | Coupling between objects (CBO), Response for a Class (RFC) |
| **Encapsulation** | Number of public fields, Number of public methods |
| **Cohesion** | Lack of Cohesion of Methods (LCOM), Tight class cohesion (TCC), Loose Class Cohesion (LCC) |
| **Inheritance** | Depth Inheritance Tree (DIT) |
| **Readability** | Number of unique words, Number of loops, Number of assignments, Number of comparisons, Number of string literals, Number of math operations, Quantity of numbers |
| **Android**  | isActivity, isView, isBroadcastReceiver, isService, isContentView, isFragment, isBuildingBlock, isInAndroidHierarchy, hasAndroidCoupling, Number of methods coupled, Number of parameters coupled, Number of returns coupled |
| **Java-specific** | Number of default fields, Number of default methods, Number of final fields, Number of final methods, Number of static fields, Number of static methods, Number of private fields, Number of private methods, Number of protected fields, Number of protected methods, Number of abstract methods, Number of anonymous classes, Number of inner classes, Number of lambdas, Number of static invocation (NOSI), Number of synchronized fields, Number of synchronized methods, Number of parentheses expressions, Number of returns, Number of try catches, Number of log statements, Number of variables |

(Section IV-C). Finally, in Section IV-D, we explain how we evaluated this model.

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**TABLE II: List of collected features grouped by category.**

| Subcategory | Metric name |
|-------------|-------------|
| **Size**    | Source Lines Of Code (SLOC), Number of methods, Number of fields |
| **Complexity** | Weight Method Class (WMC), Max nested blocks |
| **Coupling** | Coupling between objects (CBO), Response for a Class (RFC) |
| **Encapsulation** | Number of public fields, Number of public methods |
| **Cohesion** | Lack of Cohesion of Methods (LCOM), Tight class cohesion (TCC), Loose Class Cohesion (LCC) |
| **Inheritance** | Depth Inheritance Tree (DIT) |
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| **Android**  | isActivity, isView, isBroadcastReceiver, isService, isContentView, isFragment, isBuildingBlock, isInAndroidHierarchy, hasAndroidCoupling, Number of methods coupled, Number of parameters coupled, Number of returns coupled |
| **Java-specific** | Number of default fields, Number of default methods, Number of final fields, Number of final methods, Number of static fields, Number of static methods, Number of private fields, Number of private methods, Number of protected fields, Number of protected methods, Number of abstract methods, Number of anonymous classes, Number of inner classes, Number of lambdas, Number of static invocation (NOSI), Number of synchronized fields, Number of synchronized methods, Number of parentheses expressions, Number of returns, Number of try catches, Number of log statements, Number of variables |

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*We queried the GitHub mirror at 25 of January of 2020.*

[http://f-droid.org](http://f-droid.org)
TABLE II: Results of the data extraction.

| Dataset      | #Projects w/ migration | Files in commits w/ migration Total | Migrated |
|--------------|------------------------|------------------------------------|----------|
| GitHub 2k    | 1179/1187 (99%)        | 1495734                            | 27375 (1.8%) |
| Android 2k   | 266/270 (98%)          | 497635                             | 8754 (1.7%) |

We ended with 270 applications in Android 2k and 1187 projects in GitHub 2k. Finally, we found 3118 commits with migration that migrated 8754 files, as Table II shows.

B. Feature extraction

MigrationEXP relies on 54 metrics extracted from the source code of open-source projects with file migrations from Java to Kotlin. To extract 12 exclusive Android metrics, we built a static analysis tool using Spoon [30]. The remaining 42 source code metrics are extracted using CK [31], which also applies static analysis to calculate code metrics.

To extract these metrics from files of each commit with migration in our datasets, we created a tool that takes as input a Git repository and the list of commits with migration. This tool relies on jGit, a pure Java library implementing the Git version control system[4].

The tool clones the software repository, then it navigates through all commits. Let $C_r = \{c_1, c_2, ..., c_n\}$ be the set of commits with migrations of a given repository. ∀$c, c \in C$ the tool checkout the source code, then it extracts the metrics by calling CK [31] and our Android features detector. When a repository is analyzed, our tool generates a JSON file. This file has, for each commit, the values for feature extracted grouped by file.

C. Model training

The existing learning-to-rank algorithms are categorized into three approaches: pointwise, pairwise, and listwise [13]. In the pointwise approach, the input is a single document. Consequently, it does not consider the inter-dependency among documents [13]. On the other hand, pairwise and listwise algorithms consider the inter-dependency among documents.

In the pairwise approach, the ranking problem is reduced to a classification problem on document pairs, whereas the listwise approach addresses the ranking problem by taking ranking lists as instances in both learning and prediction [14].

In the context of gradual migration that we target in this paper, we hypothesize that the decision to migrate or not one file is made considering a project’s context and not a file individually. For instance, in a migration step S given by commit C, a developer chooses a set of files FM (one or more) to be migrated over other files NFM that are not migrated in that step. Thus, to capture that decision between files to migrate, we decided to use the pairwise approach. During model training, that approach considers that, in the query associated with commit C, file $f_i$ from FM was ranked higher than a file $f_j$ from NFM.

D. Evaluation

To evaluate the performance of our model, we use Android 2k as the testing dataset. Moreover, due to the absence of a benchmark of file migrations using file ranking, we measure our model’s improvement over random guesses. We compute our approach’s performance improvement by comparing our approach’s performance with the random ranking using the formula: Improvement = $\frac{O - B}{O}$, where O denotes the ranking performance of our approach, B means the ranking performance of a baseline ranking schema.

Figure 4 illustrates a hypothetical scenario that shows how our evaluation works. Given as input a project which in its last version (commit #2) has 4 Java files ($A, C, D$ and $E$), since commit #2 migrates one file ($A$), it becomes a query that contains one document per file. Then, our model generates a ranking of files containing all project files on that version (commit #2), i.e., a ranking of documents composed of $A, C, D$ and $E$. This ranking is then analyzed based on the position of the relevant documents (i.e., those from migrated files such as $A$) to compute the recommendation performance.

The overall approach performance is computed using the Mean Average Precision at K (MAP@k) [35] that ranges from 0 to 1, where a perfect ranking result in MAP@1 equals 1. For each query, we compare the set of top-K results with the set of K actual relevant documents, as Figure 4 exemplifies. We recall that in this scenario, a query is a commit with migration from a project that belongs to the testing dataset, and a document is a file from that commit. As the median of files migrated per commit is 1, we considered $k$ ranging from 1 to 10.

V. RESULTS

A. RQ1: To what extent a learning-to-rank model learned from migrations done in real projects may recommend migration of files precisely?

This section presents the evaluation results of a random approach and LambdaMART applied to rank file-level migrations. Table III summarizes our results. Our results show that in particular, we trained our model using LambdaMART [32], an algorithm developed by Microsoft that applies the pairwise approach and has been shown to be among the best performing learning methods based on evaluations on public datasets [23]. We used the LambdaMART implementation provided XGBoost, a scalable machine learning system for tree boosting proposed by Chen et al. [34] Given a query done on XGBoost, this tool outputs as predicted relevant values (see Section III-B2) a float number per document, where a smaller value means higher relevant. We call those values predicted relevance XGB.

We trained our model with the information extracted from 7275 commits with at least one migration from the GitHub 2k dataset. These commits have 1495734 files where 27375 were migrated, as Table II shows.

D. Evaluation

To evaluate the performance of our model, we use Android 2k as the testing dataset. Moreover, due to the absence of a benchmark of file migrations using file ranking, we measure our model’s improvement over random guesses. We compute our approach’s performance improvement by comparing our approach’s performance with the random ranking using the formula: Improvement = $\frac{O - B}{O}$, where O denotes the ranking performance of our approach, B means the ranking performance of a baseline ranking schema.

Figure 4 illustrates a hypothetical scenario that shows how our evaluation works. Given as input a project which in its last version (commit #2) has 4 Java files ($A, C, D$ and $E$), since commit #2 migrates one file ($A$), it becomes a query that contains one document per file. Then, our model generates a ranking of files containing all project files on that version (commit #2), i.e., a ranking of documents composed of $A, C, D$ and $E$. This ranking is then analyzed based on the position of the relevant documents (i.e., those from migrated files such as $A$) to compute the recommendation performance.

The overall approach performance is computed using the Mean Average Precision at K (MAP@k) [35] that ranges from 0 to 1, where a perfect ranking result in MAP@1 equals 1. For each query, we compare the set of top-K results with the set of K actual relevant documents, as Figure 4 exemplifies. We recall that in this scenario, a query is a commit with migration from a project that belongs to the testing dataset, and a document is a file from that commit. As the median of files migrated per commit is 1, we considered $k$ ranging from 1 to 10.

V. RESULTS

A. RQ1: To what extent a learning-to-rank model learned from migrations done in real projects may recommend migration of files precisely?

This section presents the evaluation results of a random approach and LambdaMART applied to rank file-level migrations. Table III summarizes our results. Our results show that

1The this implementation can also perform listwise ranking. However, as shown in our appendix, its pairwise version outperforms its listwise version.
Fig. 4: For each commit that migrates code (e.g., commit #2), our approach generates a ranking with all project files. This is shown as the Recommendation list on the figure. This ranking is evaluated based on the relevant documents (i.e., those migrated by the developers).

when $k$ increases, $MAP$ increases for both approaches. That makes sense since a greater $k$ means that a model has more chances to select a file correctly in the ranking. For instance, consider a commit with 50 files whose ten files were migrated. When $k = 1$, the model has one chance to put 1 of the ten files migrated in the ranking. When $k = 2$, the model has two chances to put 1 of the ten files migrated in the ranking.

We also found that our approach outperforms the random approach for any value of $k$, presenting an improvement of at least 38% for any value of $k$.

Response to RQ1: To what extent a learning-to-rank model learned from migrations done in real projects may recommend migration of files precisely? The results show that the performance of our learning-to-rank approach to recommend file-level is substantially limited. Its best performance presented a $MAP@10 = 0.11$, where a perfect ranking implies $MAP = 1$. This result suggests that there is still room for improvement.

This experiment is the first attempt to apply learning-to-rank algorithms to create a recommendation system of file-level migrations to the best of our knowledge. Comparing our model with a random approach, we note that our model outperforms a random approach significantly. However, our results also show that there is room to improve our approach to get a better ranking as a result. In Section VII, we discuss more detailed perspectives to improve our results. Therefore, we consider this result establishes the initial baseline for future research.

a) Case Study: In this case study, we present how MigrationEXP performed, suggesting file-level migration when Simple Calendar Pro is given as input. Simple Calendar Pro is an application published on Google Store that has more than 100,000 downloads and its source code is hosted on GitHub. This application was initially written in Java, but it was fully migrated to Kotlin in two months. Starting in commit 09ef99, their developers performed a gradual migration that was completed in commit eee184, after 202 commits. Figure 5 shows the number of Java and Kotlin files on each commit from the app along the gradual migration.

We apply MigrationEXP on a version of Simple Calendar Pro, identified by commit faae6b. At this version, Simple Calendar has 34 Kotlin files (most of them already migrated by previous commits) and 10 Java files, i.e., 10 candidate files to be migrated. Table IV presents those Java files. Given that version of Simple Calendar, our approach generates a predicted relevance $XGB$ value (described in Section III-B2) for each file. Those are also presented in Table IV. Then, it creates a ranked list of these 10 files considering those values. Therefore, according to MigrationEXP, Formatter.java should be the first migrated because it has the lowest predicted relevance $XGB$ value (-0.03), followed by Constants.java (0.07), and so on.

Now, we compare this suggestion from MigrationEXP with the real migration done by the developer on that particular version of Simple Calendar. The developers migrated only one
file, `Formatter.java`, and that change produced a new version (commit `ab6fd0b`) of their application. In this case, the file in the first position of the list of recommendations made by MigrationEXP was exactly the same file migrated by the developers, resulting in a MAP@1 equal to 1.

VI. THREATS TO VALIDITY

In this section, we discuss the threats that could affect the validity of our results.

A. Construct validity

Threats to construct validity concern the relation between theory and observation.

a) Learning from migrations in open-source projects: To create an accurate machine learning model, a large amount of data is essential. Due to the absence of a benchmark dataset of file migration from Java to Kotlin, we mined open-source project from GitHub and FAMAZOA. We used this information to train and evaluate our model. However, there is a risk that open-source projects and not open-source projects might be migrated differently. Thus, the learned model would not adequately characterize the migration activity of those projects.

b) Automated evaluation: To have an automated evaluation process of MigrationEXP, we consider examples of file-level migrations from open-source projects as ground-truth. However, we do not consider the motivation behind these migrations because we cannot automatically retrieve this information from the project’s repositories. Consequently, our approach may suggest file-level migrations that do not reflect the decision taken by developers. Nevertheless, we affirm that this first study aimed to explore whether learning to rank can model the problem of recommending file-level migrations.

c) Feature selection: The choice of the feature set used to train our learning to rank model directly impacts its results, depending on whether these features discriminate adequately, lines migrated and non-migrated. However, to the best of our knowledge, no study establishes a relationship between any metric and source code migration. For that reason, we target source code metrics that have been used in a wide variety of experiments like fault prediction [15], [18], fault localization [20], testing [17], defect prediction [19], refactoring prediction [21] and for measuring the quality of object-oriented software [16]. Moreover, we consider 12 exclusive Android features that, according to our experience with Android development, could support the decision to perform a file migration. Nevertheless, it could exist missing features that discriminate better the migration activity.

d) Learning algorithm: In this paper, LambdaMART was the algorithm chosen to build our ranking model. However, the choice of the machine learning technique to build a prediction model has a strong impact on the performance [55]. Thus, using other existing algorithms, our approach could present different performance levels.

B. Internal validity

Threats to internal validity concern all the factors that could have impacted our results.

a) In the wild evaluation: To evaluate MigrationEXP, we did not apply any pre-processing technique in our datasets. Therefore, we trained and evaluated our model using highly imbalanced datasets, i.e., there are considerably more instances of the non-migrated files than instances of files migrated. However, some models may under-perform if trained with imbalanced data [57].

b) Training parameters: The choice of parameters for the model construction is another threat. In this work, we simply use the default parameters of XGBoost. Therefore, for different datasets or metrics, the best parameters might be different, leading to different results.

C. External validity

Threats to external validity concern the generalizability of our findings.

a) Representativeness of our datasets: Our work relies on two datasets of open-source software. However, open-source software is a small parcel of the existing software. This fact may limit the generalization of our findings.

| Candidate files          | Predicted relevance | Relevant Document | Predicted Ranking |
|--------------------------|---------------------|-------------------|-------------------|
| `Formatter.java`         | -0.03               | Yes               | 1                 |
| `Constants.java`         | 0.07                | -                 | 2                 |
| `MyViewPager.java`       | 0.14                | -                 | 3                 |
| `MyWidgetItemProvider.java` | 0.16          | -                 | 4                 |
| `BootCompletedReceiver.java` | 0.19         | -                 | 5                 |
| `LicenseActivity.java`   | 0.23                | -                 | 6                 |
| `WidgetItemConfigureActivity.java` | 0.38   | -                 | 7                 |
| `Utils.java`             | 0.54                | -                 | 8                 |
| `NotificationReceiver.java` | 0.93          | -                 | 9                 |
| `AboutActivity.java`     | 0.95                | -                 | 10                |

TABLE III: Mean Average Precision (MAP) at K of a random approach and LambdaMART.

| Algorithm         | Mean Average Precision (MAP) at K |
|-------------------|----------------------------------|
| Random            | 0.099 0.030 0.047 0.057 0.061 0.054 0.055 0.053 0.057 0.056 |
| LambdaMART        | 0.049 0.071 0.083 0.092 0.099 0.105 0.109 0.113 0.117 0.120 |
| Improvement (%)   | 81% 56% 43% 38% 38% 48% 50% 53.0% 51.0% 53.0% |
VII. DISCUSSION AND FUTURE WORK

This work presented a study investigating the feasibility of applying learning-to-rank to build an approach to recommend file-level migrations of Android applications. The results showed that although our approach overcomes random approaches, there is room for improvement. Nevertheless, we highlight our approach’s novelty and argue that these results establish a baseline for future work. Moreover, it opens directions for researchers. In this section, we list some of them.

a) Hyperparameter tuning: One strategy to potentially improve our results is to perform a hyperparameter tuning. Each algorithm has a set of parameters, each having its domain, which may have different types (i.e., continuous, discrete, boolean and nominal), making the entire set of parameters of an algorithm a large space to explore. Consequently, the search for the machine learning algorithm’s best parameters is a difficult task in terms of computation complexity, time, and efforts. In future work, we plan to explore different techniques of hyperparameter tuning.

b) Data balancing: Another aspect researchers may focus on are pre-processing techniques to handle the imbalance of our migration dataset since they can be more important than classifier choice. Despite many real-world Machine-Learning applications, learning from imbalanced data is still not trivial. However, other software engineering studies have used Synthetic Minority Over-sampling Technique (SMOTE) to fix the data imbalance. As feature work, we intend to explore pre-processing techniques to understand how they impact the recommendation of file-level migrations.

c) Feature engineering: Since our machine learning models achieve a modest performance, we intend to focus on feature engineering as future work. Adding new features or discarding existing ones could result in a better set of features that may improve our results. Therefore, more research should be conducted to i) evaluate the current set of features and possibly discard some feature, ii) verify to what extent existing metrics applied in other domains of software engineering, like process metrics, code smells, and ownership metrics, are suitable for our problem and iii) develop new metrics able to characterize better migrated or non-migrated file instances.

d) Feedback from developers: In this paper, we used a ranking metric (MAP) to automatically assess the quality of the recommendations generated by MigrationEXP. To complement our evaluation, as future work, we plan to conduct a study where developers that want to migrate their applications would evaluate the recommendations made by our approach.

e) Deploying MigrationEXP in the wild: We aim to make MigrationEXP a production-ready model to integrate it with Android Studio, the official IDE for Android development. To this end, we intend to develop a plugin for Android Studio and to make it publicly available in the official JetBrains Plugin Repository, as Iannone et al. have done. We believe that by making our approach publicly available, we can receive feedback from users to improve it.

VIII. RELATED WORK

a) The adoption of Kotlin: Olveira et al. [50] performed a study to understand how developers are dealing with the adoption of Kotlin on Android development, their perception of the advantages and disadvantages related to its usage. They found that developers believe that Kotlin can improve code quality, readability, and productivity. Gois Mateus and Martinez [53] have studied the adoption of Kotlin, the migration of Android applications from Java to Kotlin.

b) Migration of Android applications to Kotlin: Coppola et al. [51] evaluated the transition of Android applications to Kotlin to understand whether the adoption of Kotlin impacts the success of an application (i.e., popularity and reputation) of Android apps on the App Store. Martinez and Gois Mateus [10] conducted a survey to know why Android developers have migrated Java code to Kotlin to identify the main difficulties they have faced. Our work also targets the migration of Android applications to Kotlin, but from a different perspective. We focus on assisting developers in gradually migrate their applications by proposing a machine learning approach that suggests file-level migrations.

c) Empirical studies on Kotlin code: Researchers have conducted different studies about the use of Kotlin. Flauzino et al. [52] have studied 100 software repositories (not only Android apps) containing Java or Kotlin code (but not both). They found that, on average, Kotlin programs have fewer code smells than Java programs. Gois Mateus and Martinez [53] have studied the adoption of the features introduced by Kotlin. They found that some Kotlin features are more used than others. Ardito et al. [54] conducted a study with undergraduate students to assess the assumed advantages of Kotlin concerning Java in the context of Android development and maintenance. The authors found evidence that the adoption of Kotlin led to a more compact code. Other works have focused on helping developers to develop Kotlin apps. For example, Courtney and Nielsen present a tool, named j2kCLI, that allows users to translate Java code to Kotlin faster than the same functionality provided by Android Studio. From the JetBrains research group, Bryksin et al. [56] investigated code anomalies in Kotlin and whether these anomalies could improve the Kotlin compiler.

d) Programming language migration: Martin and Müller [57] presented a structured approach for migrating C source code to Java, minimizing manual intervention by software engineers. Mossienko [58] presented an automated approach for source-to-source translation of Cobol applications into Java focused on generating maintainable code. El-Ramly et al. [59] presented an experimental language transformer, J2C#, to automatically convert Java to C# using tree rewriting via functional rule-based programming.
Marchetto et al. [60] defined a stepwise approach to help developers migrating a Java application into an equivalent service-oriented system. Colosimo et al. [61] presented an Eclipse plugin to migrate legacy COBOL programs to the web. Zhong et al. [62] proposed an approach to assist code migration that automatically mines how APIs of one language are mapped to APIs of another language. Trudel et al. [63] introduced a data-driven approach that statistically learns the mappings between APIs from the source code of the same project written in C# and Java. Gu et al. [66] proposed a deep learning-based system for API migration. Malloy et al. [67], [68] created a tool for syntax and feature recognition and investigated the degree to which Python developers are migrating from Python 2 to 3 by measuring the adoption of Python 3 features. Verhaeghe et al. [69] proposed an approach to help developers migrate the Graphical User Interface of web-based software systems. Although these works target programming languages migrations, none of them have a focus on migration from Java to Kotlin.

e Learning-to-rank applied to software engineering:
Xuan et al. [70] presented a learning-based approach that combines multiple fault localization ranking metrics. The authors empirically their against seven ranking metrics and concluded that it could localize faults more effectively than the ranking metrics taken in isolation. Ye et al. [71], [72] developed a learning-to-rank approach that emulates the bug-finding process employed by developers. They trained a ranking model that characterizes useful relationships between a bug report and source code files by leveraging domain knowledge. The authors empirically evaluated their approach and conclude that it outperforms the other three state-of-the-art approaches. Zhao et al. [73] evaluated the approach created by Ye et al. [71] to verify the influence of the recommended files’ size on the efficiency in detecting bugs. Yang et al. [74] introduced a learning-to-rank approach to building software defect prediction models by directly optimizing the performance measure. Le et al. [75] proposed a fault localization approach that employs a learning-to-rank strategy, using likely invariant diffs and suspiciousness scores as features. Tian et al. [76] created a learning-to-rank model that combines location-based and activity-based information from historical bug reports to recommend developers automatically to address particular bug reports. Niu et al. [77] proposed a code example search approach based on the learning-to-rank technique. Wang et al. [78] presented a top-k learning-to-rank approach to Cross-Project Defect Prediction. Cao et al. [79] proposed a rule-based specification mining approach based on learning-to-rank. Loyola et al. [80] introduced a learning-to-rank-based model to support bug localization. Kim et al. [81] presented a learning-to-rank fault localization technique that uses genetic programming to combine static and dynamic features. Sohn et al. [20], [82] introduced a learn-to-rank fault localization approach that learns how to rank program elements based on spectrum-based fault localization formulas, code metrics and change metrics. Haas and Hummel [83] applied learning-to-rank to derive a scoring function that suggests extract method refactoring of long Java methods. Hussain et al. [84] used learning-to-rank to create a prototype of an automated recommendation system to classify and select design patterns. Different from these works, our work is the first one to apply learning to rank to suggest file-level migrations.

IX. CONCLUSION

In this work, we presented MigrationEXP, an approach to support developers in the gradual migration based on learning to rank. Despite being a language-independent approach, we evaluate its feasibility in the context of migration of Android applications from Java to Kotlin. MigrationEXP relies on migrations performed in open-source projects to recommend file-level migration. For that reason, we crawled open-source projects hosted on GitHub and Android applications written in Kotlin from FAMAZOA. Then, for every project’s file, we extracted 42 source code metrics and 12 Android metrics. Using this information, we trained a ranking model. We compared our model with the random approach, and we concluded that it outperforms the random approach by at least 38% considering the Mean Average Precision (MAP). However, this performance is still limited since our approach best performance presented a $\text{MAP@10} = 0.12$.

To the best of our knowledge, this experiment is the first attempt to apply learning to rank to create a recommendation system of file-level migrations. Thus, this work allowed us to show that there is room to improve MigrationEXP. We believe that our approach may significantly impact Android applications’ development since most Android applications are written in Java and because to keep updated with Android platform news features, applications should be written in Kotlin. Therefore, we consider this result is the first step into long-term research towards a model capable of predicting precisely file-level migration. We consider that our results establish the initial baseline on file migrations.

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