Recommending Library Migration Targets via Mining Dependency Change Sequences

***Abstract*—The wide adoption of third-party libraries in software projects is beneficial but also risky. Third party libraries may have security vulnerabilities, may be abandoned by their maintainers, or may no longer align with current project requirements. Under such circumstances, a software project needs to migrate its library to another library with similar functionalities, but it is often not easy to find good substitute libraries and make migration decisions between candidate libraries. Therefore, automated recommendation of migration target is desired to support decision making in library migration. However, existing library migration mining methods suffer from low performance and require extensive human effort to correct the results.**

In this paper, we present a recommendation approach for library migration through mining dependency change sequences of existing software repositories. Given a library to migrate, our approach first generate candidate libraries from the sequences, and then rank them using four carefully designed metrics to capture right migration targets from large number of candidates: Rule Support, Message Support, Distance Support and API Support. We evaluate our approach on 21,358 Java GitHub projects and 773 manually confirmed migration rules from previous work. The experiments show that our metrics can effectively separate real migration targets from other libraries, and our approach significantly outperforms existing works, with MRR of 0.8566, top-1 precision of 0.7947, top-10 NDCG of 0.7665 and top-20 recall of 0.8939. We also evaluate our approach on 480 libraries not included in previous work, where we successfully confirm 661 new migration rules. The demo, source code and data are provided at: [[TODO: Add a link here]]

***Index Terms*—library migration, mining software repositories, library recommendation**

I. Introduction

Modern software systems rely heavily on third-party libraries for rich and ready-to-use features, reduction of development costs and increase in productivity [1], [2]. In recent years, the rise of open source software and the emergence of package hosting platforms, such as GitHub [3], Maven Central [4] and NPM [5], has led to an exponential growth of open source libraries. For example, the number of newly published JARs in Maven Central is 86,191 in 2010, 364,268 in 2015, and over 1.2 million in 2019 [4]. Nowadays, open source libraries can satisfy a diverse spectrum of development requirements, and are widely adopted in both commercial and open source software projects [6].

However, third-party libraries are known to cause problems in software maintenance, some of which require the project to migrate to an alternative library. First, third-party libraries may have sustainability failures [7], [8]. They may be abandoned by their maintainers due to lack of time and interest, difficulty in maintenance, or being superseded by competitors [7]. Second, third-party libraries may have security vulnerabilities [9], [10].

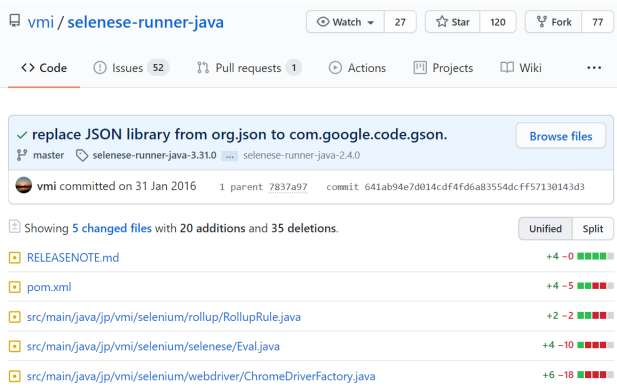


Fig. 1. An example migration between JSON libraries

Although libraries generally provide fixes to vulnerabilities in a later version, in practice fixes are not always available at certain time or context. Finally, third-party libraries may fail to satisfy new requirements when the project evolves. A Java Web application at its infancy stage may be using `org.json:json`[1] for its simplicity and ease of use, but when the application matures and scales, it often has to migrate to `gson`[2] or `jackson`[3] for their richer features and higher performance (see Figure 1 for an example). In any of the above cases, a software project needs to replace the library with another similar library, which are called *library migration* in the literature [11]–[18].

However, it is often not easy to find good substitute libraries and choose between a number of candidate libraries [11], [19], [20]. Community curated lists such as `awesome-java`[4] and AlternativeTo[5] are often non-informative and contain low quality libraries, while blog posts and articles are often opinion based and outdated [19]. The easily accessible metrics such as popularity and release frequency have limited usefulness and it varies with domain [20]. As a result, industry projects often rely on domain experts for making migration decisions [21], while open source projects only migrate libraries when core developers reach a consensus in discussions [14]. In either case, the migration decision is not guaranteed to be appropriate, cost-effective or beneficial to the project.

[1]https://mvnrepository.com/artifact/org.json/json
[2]https://mvnrepository.com/artifact/com.google.code.gson/gson
[3]https://mvnrepository.com/artifact/com.fasterxml.jackson.core/jackson-core
[4]https://github.com/akullpp/awesome-java
[5]https://alternativeto.net/

To address this situation, researchers have proposed automated library recommendation approaches based on mining of existing software data. In particular, a number of studies are conducted to mine migration rules [11], [13], [16], mine analogical libraries [19], [22], and recommend libraries [23], [24], but they all have their limitations in the context of recommending library migration targets. Existing methods for mining migration rules [11], [13] can be used for migration recommendation based on how many times a migration occurred, but suffer from either low recall [11], [16] or low precision [13], and require extensive human effort for correcting the mined results. The method of mining analogical libraries [19], [22] can accurately find semantically similar libraries, but provide no evidence on the feasibility and occurrences of migrations between them. Existing methods of library recommendation [23], [24] are designed for recommending missed reuse opportunities based on the libraries a project is using and the properties of the project, not recommending migration opportunities of a library already in use.

Built upon the works of Teyton et al. [11], [13] and Alrubaye et al. [16], in this paper, we propose a new approach for automated recommendation of library migration targets from existing software development histories. We formulate this problem as a *mining* and *ranking* problem. Given a library to be replaced, our approach first *mines* library candidates from dependency change sequences built from a large software corpus. After that, the candidates are *ranked* based on a combination of four carefully designed metrics capable of pinpointing likely migration targets from large number of candidates: Rule Support, Message Support, Distance Support and API Support. Finally, the top target libraries, their metrics, and the relevant migration instances are returned for human inspection. Our approach can be effectively implemented as a web service, which can be used by project maintainers to suggest migrations or support their migration decisions.

To implement and evaluate our approach, we collect version control data of 21,358 Java GitHub repositories from the World of Code database [25], where we successfully extract 147,220 dependency change sequences from their `pom.xml` files[6]. To support metric computation, we also collect Maven artifacts from Maven Central [4] using Libraries.io [26], and extract API information for each collected Maven artifact. During the evaluation, we first demonstrate the effectiveness of each metric by comparing metric distributions of ground truth migrations (extended from previous work [13]) with distributions of other candidates. Then, we compute Mean Reciprocal Rank (MRR) [27], top-k precision, top-k recall and top-k Normalized Discounted Cumulative Gain (NDCG) [28] for our approach along with existing works and a number of other baselines. Finally, we experiment our approach on other popular libraries both to ensure our approach is generalizable and to confirm more real world migrations. Our experimental evaluations show that the metrics can effectively separate real migration targets from other libraries, the method that combines all four metrics can reach MRR of 0.8566, top-1 precision of 0.7947, top-10 NDCG of 0.7665 and top-20 recall of 0.8939 in the ground truth dataset, and we can confirm 661 new migration rules with a comparable performance. We also extend the migration dataset in Teyton et al. [13] with both new migration rules and latest migration commits for existing rules, resulting in a total of 1,434 migration rules in 3,340 commits from 1,313 repositories. The new migration dataset can be used to facilitate further research in library migration.

The main contributions of this paper are the following.

1) We propose a new approach for migration target recommendation based on mining dependency change sequences and ranking on four metrics, which significantly outperforms existing works.
2) We implement and systematically evaluate our approach for Java and Maven. During evaluation, we extend the dataset in Teyton et al. [13] into a latest dataset of library migrations in open source Java projects.

II. Background

In this section, we first provide a brief introduction to the context of our approach. After that, we define common terminologies and a dependency model used throughout the remainder of this paper. Then, we provide our definition to the migration target recommendation problem. Finally, we introduce the most related work of Teyton et al. [11], [13] and Alrubaye et al. [16] before introducing our approach in the next section.

A. Library Migration

Migration is a common phenomenon in software maintenance and evolution, and may refer to different development activities that stem from various motivations. Common cases of migrations in software development include: migrating from an legacy platform to a modern platform [29], [30], one programming language to another programming language [31]–[37], one library version to another library version [38], [39], one API to another API [12], [15], [40]–[45], or one library to another library [11], [13], [14], [16], [46], [47]. In this paper, we use the term **library migration** to refer to the process of replacing one library with another library of similar functionalities, as in [11]–[18].

Two steps are typically needed for a library migration. The first step is to decide which library to migrate and whether a migration is worthy. The second step is to conduct the real migration by modifying API calls in source code, changing configuration files, etc. Kabinna et al. [14] studied logging library migrations in Apache Software Foundation (ASF) projects. They discovered that ASF projects conduct logging library migrations for flexibility, new features and better performance, but the code changes are hard, migrations tend to introduce post-migration bugs, and some projects fail to migrate due to absence of submitted migration patches or lack of maintainers' consensus. Given current situation, the main objective of our approach is to provide *explainable* and

[6]In a Maven managed project, a `pom.xml` file declares all libraries used in a project folder. We do not consider Gradle managed projects in the evaluation.

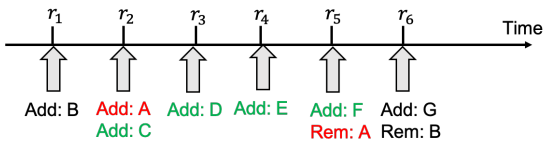


Fig. 2. An example dependency change sequence

evidence based support to the first step of migration, such that developers can make the most appropriate migration decision for their project based on our recommendation results. (See Section VIII for related work about the second step)

B. Terminologies and Dependency Model

Let $\mathcal{P}$ be the set of projects and $\mathcal{L}$ be the set of libraries to be analyzed. A project $p \in \mathcal{P}$ has a set of revisions $Rev(p) = \{r_1, r_2, ..., r_n\}$, where each revision has zero, one or more parent revisions. For each revision $r_i \in Rev(p)$, it depends on a set of libraries $L_i \subset \mathcal{L}$, which we call **dependencies** of r_i. By comparing with its parent revision(s) (e.g. r_{i-1}), we can extract the dependency changes of r_i as[7]

$$L_i^+ = L_i - L_{i-1} \tag{1}$$

$$L_i^- = L_{i-1} - L_i \tag{2}$$

where L_i^+ is the set of added libraries and L_i^- is the set of removed libraries. By sorting all revisions in topological order and aggregating dependency changes, we can build a **dependency change sequence** (or **dep seq**) D_p for project p.

$$D_p = L_1^+, L_1^-, L_2^+, L_2^-, ..., L_n^+, L_n^- \tag{3}$$

For library $a \in \mathcal{L}$ and library $b \in \mathcal{L}$, we consider (a, b) as a **migration rule** if and only if $\exists p \in P,\ r_i, r_j \in Rev(p)$, p has conducted a migration from a to b between r_i and r_j, where $b \in L_i^+$ and $a \in L_j^-$. Note that a migration may either happen in one revision ($r_i = r_j$), or spans over multiple revisions ($r_i \neq r_j$). We refer to a as **source library** and b as **target library** in the subsequent paper.

Figure 2 shows an artificial example of a dependency change sequence where a project performed a migration from library A to F in revision r_5. In this case, $L_5^+ = \{F\}$ and $L_5^- = \{A\}$, and (A, F) is a migration rule by our definition.

C. Problem Definition

Let R be the set of all migration rules. Given projects $\mathcal{P}$, libraries $\mathcal{L}$, dep seqs D_p for $p \in \mathcal{P}$, and a set of library queries (i.e. source libraries) Q, the objective of *migration target recommendation* is to identify migration rules with both high coverage (for objectivity) and accurate results (for minimizing human inspection effort). For library $a \in Q$, an approach should seek to find migration targets $T = \{b|(a, b) \in R\}$. We view this problem as a two-step mining and ranking problem. In the mining step, an approach should generate a **candidate rule** set R_c from all dep seqs. In the ranking step, for all $(a, b) \in R_c$, it should compute a confidence value $conf(a, b)$ and sort R_c by this value. It should ensure that the target libraries in top ranked candidate rules are more likely to be real migration targets.

[7]We will discuss how we deal with multi-parent revisions in Section IV.

D. Existing Approaches

Several existing approaches can be fit into this problem definition. In Teyton et al. [11], they define candidate rules as the Cartesian product of added and removed libraries in the same revision. More formally, for project p and revision r_i,

$$R_{ci}^p = \{(a, b)|(a, b) \in L_i^- \times L_i^+\} \tag{4}$$

$$R_c = \bigcup_{p \in \mathcal{P}} \bigcup_{r_i \in Rev(p)} R_{ci}^p \tag{5}$$

And they define confidence value as the number of revisions a rule occurred divides the maximum number of all rules with same source or same target:

$$conf_T(a, b) = \frac{|\{r_i|(a, b) \in R_{ci}^p\}|}{\max(|\{(a, x) \in R_c\}|, |\{(x, b) \in R_c\}|)} \tag{6}$$

Their approach also requires manual specification of a threshold t, and they consider a candidate rule (a, b) as a migration rule if and only if $conf_T(a, b) \geq t$. In their evaluation, by setting $t = 0.06$, they confirmed 80 migration rules with a precision of 0.679 in 38,588 repositories.

In their subsequent work [13], they also consider migrations that spans over multiple revisions, using the following definition of candidate rules

$$R_c^p = \{(a, b)|(a, b) \in L_j^- \times L_i^+, r_i \leq r_j\} \tag{7}$$

$$R_c = \bigcup_{p \in \mathcal{P}} R_c^p \tag{8}$$

By this definition, (A, C), (A, D), (A, E) and (A, F) in Figure 2 will all be considered as candidate rules given A as source library. In the hope of covering as much migration rules as possible, they manually verify all candidate rules, resulting in 329 migration rules identified from 17,113 candidate rules and 15,168 repositories.

Alrubaye et al. [16] propose a tool called MigrationMiner, which use the same candidate rule definition as in [11], but filter candidate rules by their relative frequency and whether API replacement really occurred in code changes. Their filtering strategy can be effectively described in our framework as Rule Support $RS(a, b) = 1$ and API Count $AC(a, b) > 0$ (See Section III for their definitions). The tool is tested on 16 repositories where 6 migration rules can be confirmed with 100% precision. Table I provides a summary and comparison of existing approaches along with ours.

III. Our Approach

In this section, we introduce our approach for recommending library migration targets at a high level. As mentioned before, we tackle this problem using a mining step and ranking step. We first describe how candidate rules are mined for each dep seq. Then we detail how we design the four ranking metrics. Finally, we describe the confidence value, ranking strategy, and the pseudo code for our final algorithm.

TABLE I
COMPARISON WITH MOST RELATED WORK [11], [13], [16]. SEE SECTION V FOR MORE PERFORMANCE COMPARISONS.

Approach	Candidate Rules for A in Figure 2	Migration Rule Selection	Performance
Teyton et al. [11]	(A, F)	$conf_T(a, b) \geq 0.06$	0.679 precision, 80 migration rules confirmed in 38,588 repositories
Teyton et al. [13]	(A, C), (A, D), (A, E), (A, F)	All candidate rules	0.019 precision, 329 migration rules confirmed in 15,168 repositories
Alrubaye et al. [16]	(A, F)	$RS(a, b) = 1 \wedge AC(a, b) > 0$	1.000 precision, 6 migration rules confirmed in 16 repositories
Our Approach	(A, C), (A, D), (A, E), (A, F)	Rank by $conf(a, b)$ (Equation 16)	0.795 top-1 precision, 1,384 migration rules confirmed in 21,358 repositories

A. Mining Candidate Rules

Given a library a, the first step of our recommendation algorithm is to find a set of candidate rules $\{(a, x)\}$, in which x may be a feasible migration target. We follow a similar process like in [13] for mining candidate rules R_c (Equation 7 and 8) for high coverage. Since it is known to generate many false positives, we will specifically consider candidate rules mined from the same revision (R^p_{ci} in Equation 4) during metric computation. We also collect all the relevant revision pairs for each candidate rule (a, b), defined as

$$Rev(a, b) = \{(r_i, r_j) | a \in L^-_j \wedge b \in L^+_i \wedge r_i \leq r_j\} \quad (9)$$

B. Four Metrics for Ranking

1) Rule Support: For each candidate rule (a, b), we define Rule Count $RC(a, b)$ as the number of times a is removed and b is added in the same revision:

$$RC(a, b) = |\{r_i | (a, b) \in R^p_{ci}, \forall p \in \mathcal{P}, r_i \in Rev(p)\}| \quad (10)$$

We define Rule Support $RS(a, b)$ as Rule Count divides the maximum value of Rule Count for all candidate rules with a as source library:

$$RS(a, b) = \frac{RC(a, b)}{\max_{(a,x) \in R_c} RC(a, x)} \quad (11)$$

This metric is basically a reuse of $conf_T(a, b)$ in Equation 6, based on the intuition that the most frequent same-revision dependency changes are more likely to be library migrations. We omit the second denominator because it can only be computed with a full-scale mining ($Q = \mathcal{L}$), which is costly given the current number of libraries.

2) Message Support: Besides the "implicit" frequency-based hint characterized by Rule Support, we observe that the "explicit knowledge" provided by developer written messages accompanying revisions (e.g. commit messages or release notes) is extremely valuable. Therefore, we design the following heuristic to determine whether a revision pair (r_i, r_j) seems to be doing a migration from a to b:

1) First, we split the names of a and b into possibly informative parts, because developers often use shortened names to mention libraries in these messages.
2) For $r_i = r_j$, we check whether its message is stating a migration from a to b.
3) For $r_i \neq r_j$, we check whether the message of r_i is stating the introduction of library b while mentioning a, and whether the message of r_j is stating the removal of a as a cleanup.

The checks are implemented via keyword matching of library name parts along with different hint verbs for migrations, additions, removals, and cleanups. For example, we consider words like "migrate", "replace", "switch" as hinting a migration. We also iteratively refined the keyword matching strategies using ground truth commits discovered in Section V.

Let $h(r_i, r_j) \mapsto \{0, 1\}$ be the heuristic function described above. We define Message Count $MC(a, b)$ as the number of revision pairs (r_i, r_j) whose messages are indicating a migration from a to b, where b is added in r_i and a in removed in r_j:

$$MC(a, b) = |\{(r_i, r_j) | (r_i, r_j) \in Rev(a, b) \wedge h(r_i, r_j)\}| \quad (12)$$

And we further define Message Support $MS(a, b)$ as

$$MS(a, b) = \log_2(MC(a, b) + 1) \quad (13)$$

3) Distance Support: The previous two metrics do not take into consideration multi-revision migrations without any meaningful messages, but such cases may still be common because not all developers write high quality messages. Based on the observation that most real target libraries are introduced near the removal of source library, we design the Distance Support metric to penalize the candidates that often occur far away. Let $dis(r_i, r_j)$ be the number of revisions between revision r_i and r_j (0 if $r_i = r_j$). We define Distance Support $DS(a, b)$ as the average of a reverse distance metric:

$$DS(a, b) = \sum_{(r_i, r_j) \in Rev(a,b)} \frac{1}{(dis(r_i, r_j) + 1)^2} \quad (14)$$

4) API Support: Another strong hint of a library migration is the real code modifications and API replacements performed between the two libraries. To capture this hint, we define API Count $AC(a, b)$ as the number of code hunks[8] in $Rev(a, b)$ where the APIs (i.e reference to public methods and fields) of b are added and the APIs of a are removed. Then, we define API Support as

$$AS(a, b) = \max(0.1, \frac{AC(a, b)}{\max_{(a,x) \in R_c} AC(a, x)}) \quad (15)$$

[8]A hunk is a group of added and removed lines extracted by the diff algorithm of a version control system.

The reason for setting a minimum threshold is that we cannot detect any code change for some migration rules, either because the code changes are performed before adding b, or because the migration does not require any code changes (e.g. the migration only need to modify configuration files or only changes the inner implementation of a specification).

C. Recommending Migration Targets

Our recommendation algorithm combines the four metrics introduced above to generate a final confidence value for all candidate rules, using a simple multiplication as follows:

$$conf(a,b) = RS(a,b) \cdot MS(a,b) \cdot DS(a,b) \cdot AS(a,b) \quad (16)$$

For each library query $l \in Q$, the corresponding candidate rules are sorted by this confidence value from the largest to smallest. If the confidence values of some candidate rules are the same, we further sort them using other metrics. Finally, the recommendation results along with the relevant revision pairs, grouped by each library query, are returned for human inspection. Algorithm 1 provides a full description of our migration recommendation algorithm. After initialization of the required data structure (line 1-5), we generate the candidate rules and accumulate necessary data for metric computation in one iteration of all projects and their dep seqs (line 6-14). After that, the metrics and confidence values are computed through another iteration of all candidate rules (line 15-24).

Several important optimizations can be applied to Algorithm 1. First, the initialization in line 2-4 can be done lazily to avoid excessive memory consumption. Second, for a project with length n dep seq, the iteration in line 6 can be efficiently done in $O(n)$ by reversely traversing through the dep seq while maintaining a set of removed libraries and relevant revisions. Finally, we can precompute $AC(a,b)$ for all $(a,b) \in \mathcal{L} \times \mathcal{L}$ through one iteration of all project diffs, to avoid costly and often repetitive on-demand computation of $AC(a,b)$.

Algorithm 1 Recommending Library Migration Targets

Input: Projects $\mathcal{P}$, libraries $\mathcal{L}$ and library queries Q.
Output: For $a \in Q$, R_c sorted by $conf(a,b)$.

1: Initialize: $Rev(a,b) \leftarrow \emptyset$
2: **for** $(a,b) \in \mathcal{L} \times \mathcal{L}$ **do**
3: Initialize: $RC(a,b) \leftarrow MC(a,b) \leftarrow DS(a,b) \leftarrow 0$
4: Initialize: $AS(a,b) \leftarrow 0.1$
5: **end for**
6: **for** $p \in \mathcal{P}, a \in Q, b \in R_c^p, (r_i, r_j) \in Rev(a,b)$ **do**
7: $Rev(a,b) \leftarrow Rev(a,b) \cup (r_i, r_j)$
8: **if** $r_i = r_j$ **then**
9: $RC(a,b) \leftarrow RC(a,b) + 1$
10: **end if**
11: $MC(a,b) \leftarrow MC(a,b) + h(r_i, r_j)$
12: $DS(a,b) \leftarrow DS(a,b) + 1/(dis(r_i, r_j) + 1)^2$
13: $AC(a,b) \leftarrow AC(a,b) +$ getAPICount(r_i, r_j)
14: **end for**
15: **for** $(a,b) \in R_c = \bigcup_{p \in \mathcal{P}} R_c^p$ **do**
16: $RS(a,b) \leftarrow RC(a,b) / \max_{(a,x) \in R_c} RC(a,x)$
17: $MS(a,b) \leftarrow \log_2(MC(a,b) + 1)$
18: $DS(a,b) \leftarrow DS(a,b) / |Rev(a,b)|$
19: $AS'(a,b) \leftarrow AC(a,b) / \max_{(a,x) \in R_c} AC(a,x)$
20: **if** $AS'(a,b) > AS(a,b)$ **then**
21: $AS(a,b) \leftarrow AS'(a,b)$
22: **end if**
23: $conf(a,b) = RS(a,b) \cdot MS(a,b) \cdot DS(a,b) \cdot AS(a,b)$
24: **end for**
25: **return** For $a \in Q$, R_c sorted by $conf(a,b)$

IV. Implementation

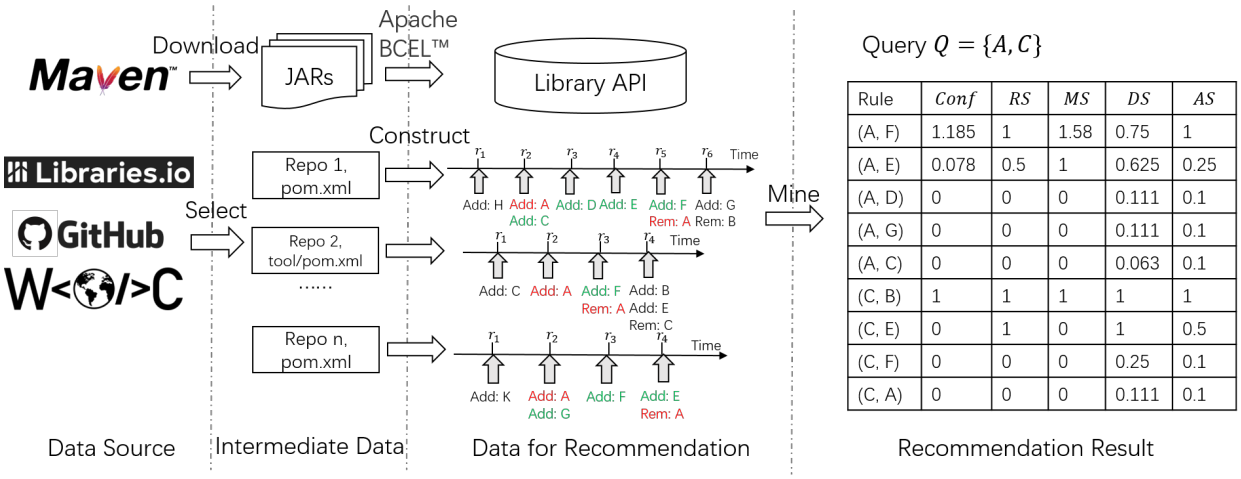
In this section, we go through the important implementation details for our approach, including design considerations, implementation environment, and the data collection process. Figure 3 provides an overview of our implementation.

A. Design Considerations

We choose to implement our approach for Java projects because of Java's popularity and industrial importance, and also because previous works [11], [13], [16] are also implemented for Java. We choose to mine dep seqs only for Maven [48] manged projects because it will make dependency extraction trivial by parsing the `pom.xml` files. Each `pom.xml` file has a dependency section where developers can declare used libraries by stating their library group IDs, artifact IDs and version numbers. During compilation, most declared libraries are downloaded from Maven Central [4], which provides a central hosting service for most Java open source libraries indexed as "artifacts." We consider artifacts with the same group ID and artifact ID as one library, and the version string as marking the different versions of a library. We do not consider version number during recommendation. Although multiple (group ID, artifact ID) may refer to the same library, we do not handle such aliases, because we observe that a renaming of group ID and artifact ID often accompanies important library changes, such as major version updates, intentional dependency shadowing, etc. Therefore, we consider the migrations between such aliases as eligible migration rules. However, we do not consider target libraries with the same group ID as source library, because we observe that they are often siblings, sub-components or auxiliary libraries that are very unlikely to be a real migration target.

B. Implementation Environment

We implement our approach on a Red Hat Linux server with 2 Intel Xeon E5-2630 v2 CPUs, 400GB RAM and 20TB storage. It has access to World of Code [25], a database for storing open source version control data including almost all repositories from GitHub. We use World of Code because it offers much higher performance when constructing dep seqs, compared with directly cloning from GitHub and analyzing with `git`. The libraries and APIs are collected using Java, and the project dep seqs are constructed using Python. They are all stored in a local MongoDB [49] instance. The final recommendation service is implemented in Java using the Spring framework [50].



Rule	$Conf$	RS	MS	DS	AS
(A, F)	1.185	1	1.58	0.75	1
(A, E)	0.078	0.5	1	0.625	0.25
(A, D)	0	0	0	0.111	0.1
(A, G)	0	0	0	0.111	0.1
(A, C)	0	0	0	0.063	0.1
(C, B)	1	1	1	1	1
(C, E)	0	1	0	1	0.5
(C, F)	0	0	0	0.25	0.1
(C, A)	0	0	0	0.111	0.1

Fig. 3. Overview of our implementation, with some example data and results.

C. Data Collection

1) Library Metadata and API Retrieval: We use the Libraries.io dataset [26] (last updated in January 2020) to get a list of Maven artifacts and their metadata. After updating the latest version information from Maven Central in October 2020, we get a total of 184,817 distinct libraries for mining candidate rules ($|\mathcal{L}| = 184,817$), and 4,045,748 distinct library versions for API extraction.

Then, we download the corresponding JAR file from Maven Central for each version, if it has one. The total size of downloaded JAR files is ∼3TB, but they can be safely deleted after the APIs are extracted. For each JAR file, we use Apache Commons BCEL™ library [51] to extract all public classes along with their fields and methods and store each class as a document in MongoDB. Each document describes a unique and compact class signature object describing its fields, methods, inheritance relationships, etc. They are indexed by SHA1 computed from all its properties. We also maintain mappings between library versions and classes. Finally, we get 25,272,024 distinct classes in total. The whole download and extraction process takes about 3 days to finish with 16 parallel threads on our server.

2) Dep Seq Construction: We use the GitHub repository list provided by the Libraries.io dataset, in which we select non-fork repositories with at least 10 stars and one `pom.xml` file, resulting in 21,358 repositories. The repository commits and blobs are then retrieved and analyzed from World of Code version R (last updated April 2020). A repository may have multiple `pom.xml` files in different paths for different sub-projects or sub-modules, so we consider each file as tracking the dependency of one project, and choose to construct one dep seq for each of the `pom.xml` files. For each `pom.xml` file, we extract all commits where this file is modified, separately parse its old version and new version to see whether any library is added or removed. For parallel branches, we sort changes by time and merge them into one dep seq. We also clean duplicate changes introduced by merge commits or parallel branches. After filtering out dep seqs with only one revision, we finally get 147,220 different dep seqs ($|\mathcal{P}| = 147,220$).

TABLE II
STATISTICS OF THE RECOMMENDATION DATABASE

Data Type	Count or Size	Time to Construct
GitHub repositories	21,358	Several minutes
Commits with diffs	29,439,998	About 1 day
Parsed `pom.xml`s	10,009,952	About 1 day
Dep seqs	147,220	Several Hours
Libraries	185,817	Several Minutes
Library versions	4,045,748	Several Hours
Java classes	25,272,024	About 3 days
Non-zero API counts	4,934,677	About 2 weeks
Database size (compressed)	∼100GB	About 3 weeks

3) API Count Precomputation: As mentioned in Section III-C, it is worthwhile to precompute an API Count table for each $(a, b) \in \mathcal{L} \times \mathcal{L}$, because on-demand computation during recommendation is not only time-consuming but also inefficient in that many Java file diffs will be analyzed multiple times for different candidate rules. Therefore, we iterate over all Java file diffs for each repository, while maintaining a set of current candidate rules, to see whether some of them should increment their API Count values. The whole computation can be done in a highly parallel manner both for each repository and for code analysis of different Java file pairs. In the end, we get 4,934,677 library pairs with non-zero AC values. The whole computation takes about two weeks to finish with 16 threads, but it only needs to be run once, because the table can be incrementally updated when new repository data come in. Table II provides an overview of the final recommendation database we use.

V. Evaluation

In this section, we first introduce three research questions for evaluation. Then, we describe how we extend the ground truth migration rules in [13], before we show the evaluation methods and results for each research question.

A. Research Questions

Our main goal is to evaluate the effectiveness of Algorithm 1 in recommending migration targets. Since the algorithm mainly relies on a confidence value computed from four metrics (Equation 16), we first verify the effectiveness of each proposed metric, forming the first research question:

- RQ1: How effective is RS, MS, DS, and AS in identifying real migration targets from other libraries?

Then, we want to show that our approach has good overall performance and outperforms existing approaches, using ground truth migration rules and common metrics for evaluating ranking problems, forming the second research question:

- RQ2: What is the performance of our approach compared with other baselines and existing approaches?

Finally, to ensure our approach is generalizable and provide a latest dataset for further library migration research, we ask the third research question:

- RQ3: What is the performance of our approach on non-ground truth queries, and how many additional migration rules can we confirm in these queries?

B. Ground Truth

We choose to build a new ground truth of migration rules based on the ground truth in [13], as the current situation may have been significantly changed since its publication. The ground truth in [13] consists of 329 library pairs with "abbreviated" library names which may correspond to multiple group IDs and artifact IDs. They manually solve the aforementioned library aliasing issue (Section IV-A) through manual verification and abbreviation, but we consider it too costly to conduct such a manual resolution on the 180k libraries we collected. Therefore, we choose to map the rules back to group IDs and artifact IDs. To cover as much migration rules as possible, we consider all pairs in Cartesian product as possible rules for multiple mappings. We also conduct reverse and transitive expansion of the rules until saturation (i.e. $(a, b) \in R \Rightarrow (b, a) \in R$, $(a, b) \in R \wedge (b, c) \in R \Rightarrow (a, c) \in R$), based on the intuition that libraries within one functionality category can be replaced with any other library in the same category. We get 3,878 "possible" migration rules after extension.

Recall in Section II-B that we define a migration rule as a rule that we can confirm at least one migration in one project, so the rules collected before may still contain many false positives by this definition. Therefore, we use all source libraries in the rules as queries to our approach, collect any relevant commits for these rules, and manually label the rules to see whether we can find at least one commit pair performing the corresponding migration. We use the following criteria to determine whether (a, b) is a migration rule:

1) If library a and library b provide obviously different functionalities, we label (a, b) as false.
2) For other rules, we manually check the "most possible" commits by applying the message matching algorithm in Section III-B2. If there exists some messages stating a migration from a to b, we label (a, b) as true.
3) Otherwise, we check the commit diffs for easily understood small commits, and only label (a, b) as true when we can find at least one understandable commit performing a migration from a to b.

The labelling process is done by three of the authors (one PhD and two undergraduates) with at least one year of Java development experiences. To mitigate threats brought by manual labelling, we adopt a conservative labelling strategy and ensure all rules with true labels are double checked by the PhD student, who has 3 years of Java experiences and 1 year of industry experiences. We also manually check the top-20 recommendation results and add any new migration rules using the same labelling process. It is worth noting that the ground truth is constructed and continuously updated when we iteratively refine our approach, so we believe it has a reasonably good coverage for the source libraries in it. Finally, we get a ground truth of 773 confirmed migration rules with 190 different source libraries, distributed in 2,214 commit pairs from 1,228 repositories. This set of migration rules are used as the ground truth, and denoted as R_t in the remainder of this section.

In RQ1 and RQ2, we use the aforementioned 190 source libraries in R_t as the query to our approach ($|Q| = 190$), which returns 243,152 candidate rules ($|R_c| = 243,152$)) along with the metrics, commits and confidence values. Note that the number of candidate rules is significantly larger than the size of ground truth rules ($|R_t| = 773$), which makes an effective ranking absolutely necessary. The recommendation only takes several minutes to finish with precomputed API Count data.

C. RQ1: How effective is RS, MS, DS, and AS in identifying real migration targets from other libraries?

To answer RQ1, we plot the percentage of rules left along the x-axis for both ground truth rules R_t and other candidate rules $R_c - R_t$ in Figure 4. We plot different figures for the confidence value in [11], the four proposed metrics, and our final confidence value, respectively. The difference in steepness for ground truth rules and other rules can be clearly observed in each plot, but some are better in term of steepness (notably, $conf$ being the steepest among all plots). We can also observe the necessity of a minimum threshold for AS, as many ground truth rules have zero API Count values.

D. RQ2: What is the performance of our approach compared with other baselines and existing approaches?

To answer RQ2, we compute common quality metrics for evaluating ranking problems: Mean Reciprocal Rank (MRR) [27], top-k precision, top-k recall, and top-k Normalized Discounted Cumulative Gain (NDCG) [28]. These metrics have also been used to evaluate other recommendation problems in software engineering [23], [24], [52], [53].

Mean Reciprocal Rank (MRR) is defined as the mean of the multiplicative inverse of the rank of the first ground truth rule for all queries:

$$MRR = \frac{1}{|Q|} \sum_{q \in Q} \frac{1}{\min_{(q,x) \in R_t} rank(q, x)} \tag{17}$$

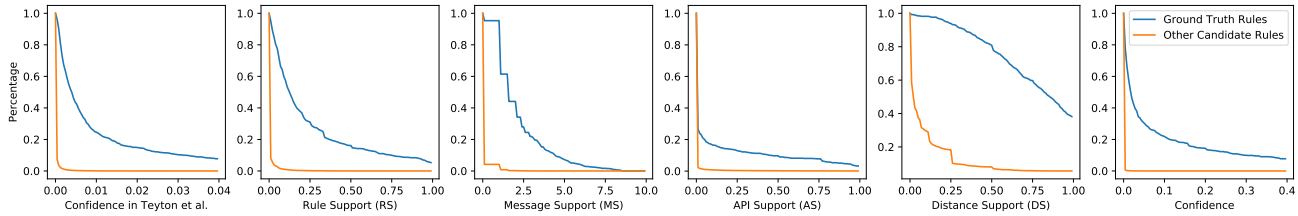


Fig. 4. The percentage of remaining ground truth rules and other rules along the x-axis. Note that the 0.1 minimum threshold is not applied for AS here.

TABLE III
PERFORMANCE COMPARISON OF DIFFERENT APPROACHES

Approach	MRR	Precision@1	NDCG@10	Recall@20
Teyton et al.	0.7133	0.6368	0.5972	0.7257
Alrubaye et al.	0.8461	0.8462	0.5440	0.0142
RS Only	0.7208	0.6474	0.6025	0.7270
MS Only	0.7619	0.6737	0.6548	0.7736
RS · MS	0.8275	0.7579	0.7481	0.8616
RS · MS · DS	0.8401	0.7737	0.7630	0.8680
RS · MS · AS	0.8379	0.7737	0.7490	0.8745
Our Approach	0.8566	0.7947	0.7665	0.8939

It ranges between $[0, 1]$, and a higher value means that the user can see the first ground truth rule more quickly in general for each query.

Let R_k be the top-k ranked candidate rules for all queries, we define top-k precision and top-k recall as:

$$Precision@k = \frac{|R_k \cap R_t|}{|R_k|} \tag{18}$$

$$Recall@k = \frac{|R_k \cap R_t|}{|R_t|} \tag{19}$$

Normalized Discounted Cumulative Gain (NDCG) measures to what extent the ranking result deviates from the ideal result. For each library $l \in Q$ and its top-k returned rules R_{lk}, let $r(i) = 1$ if the rank i is in ground truth and 0 otherwise, we can define its Discounted Cumulative Gain (DCG) and Ideal Discounted Cumulative Gain (IDCG) as:

$$DCG_l@k = \sum_{i=1}^{k} \frac{r(i)}{\log_2(i+1)} \tag{20}$$

$$IDCG_l@k = \sum_{i=1}^{|R_{lk} \cap R_t|} \frac{1}{\log_2(i+1)} \tag{21}$$

And NDCG@k is defined as:

$$NDCG@k = \frac{1}{|Q|} \sum_{l \in Q} \frac{DCG_l@k}{IDCG_l@k} \tag{22}$$

which ranges in $[0, 1]$ where 1 means a perfect match with ideal top-k ranking result and 0 means the worst.

We compare these metrics of our approach with that of [11] and [16], and also the following baselines using different confidence value alternatives:

- **RS Only**: Use only RS for ranking.
- **MS Only**: Use only MS for ranking.
- **RS · MS**: Use $RS \cdot MS$ for ranking.
- **RS · MS · DS**: Use $RS \cdot MS \cdot DS$ for ranking.
- **RS · MS · AS**: Use $RS \cdot MS \cdot AS$ for ranking.

Some metric combinations are omitted because we find DS and AS only work well in combination with RS and MS. We only show MRR, top-1 precision, top-10 NDCG and top-20 recall in our paper, due to space constraints.

The performance comparison results are shown in Table III. The performance of Teyton et al. [11] is slightly lower than their reported result (Table I), and a possible reason is that they test their approach for releases while we test their approach for commits. However, because of the significant performance gap between their approach and ours, we believe such difference is negligible. Therefore, we conclude in Table III that our approach outperforms all existing approach and baselines in terms of MRR, top-10 NDCG and top-20 recall. There is only one exception that Alrubaye et al. [16] achieves higher top-1 precision using its aggressive filtering strategy (Section II-D), but this strategy significantly impacts the recall and NDCG of its result. Consequently, we conclude that our approach achieves the best overall performance and is the most suitable one for migration recommendation, compared with the evaluated alternatives.

E. RQ3: What is the performance of our approach on non-ground truth queries, and how many additional migration rules can we confirm in these queries?

To answer RQ3, we select the most popular 500 libraries based on the number of repositories it has been added. After filtering out existing source libraries in R_t, we get 480 libraries. We use them as query to our approach and collect their recommendation output, resulting in 383,218 candidate rules. To ensure that the migration rules we confirm is valuable for a broad audience and keep a reasonable amount of human inspection effort, we only inspect candidate rules that:

1) occur in top-20 recommendation result,
2) have been added in more than 10 repositories,
3) have non-zero confidence values.

After the filtering, we need to label 4,418 candidate rules in 12,565 `pom.xml` file changes, 2,353 commit pairs and 1,313 repositories. We repeat the labelling process in Section V-B, and we successfully confirm 661 migration rules in 1,233 commits and 785 repositories, for 231 (48.125%) of the 480 queries. We further compute the quality metrics in RQ2, both *with* and *without* filtering in Table IV for the 231 queries. Note

TABLE IV
PERFORMANCE IN NON-GROUND TRUTH DATASET

Approach	MRR	Precision@1	NDCG@10	Recall@20
With filtering	0.8427	0.7565	0.7983	1.0000
No filtering	0.7881	0.6783	0.7702	1.0000

that top-20 recall is 1 because we only check top-20 results. If we only consider candidate rules after filtering, our approach achieves comparable performance on all metrics in this new dataset (Note that it is trivial for users to apply similar custom filtering rules when using our service). Even if we compute metrics for all rules (where some ground truth may be missed), we can still achieve reasonably good MRR and comparable NDCG@10 values. Therefore, we conclude that our approach generalize well in an unknown dataset.

By merging migration rules from Section V-B and RQ3, we finally get 1,384 migration rules from 14,334 `pom.xml` changes, 3,340 commit pairs and 1,651 repositories (7.73% of the 21,358 repositories). If we consider top 20% largest repositories in terms of commit numbers, 1,092 out of 4,271 repositories (25.57%) has undergone at least one library migration. Both percentages are higher than the reported percentage in [13] (5.57% and 9.95%), indicating that library migrations are more prevalent in Java open source projects since 2014. The dataset is available on our project website (see Abstract).

VI. LIMITATIONS

A. Failure Case Analysis

Cold Start. The most obvious failure case in our approach is that, it can only recommend migration targets that have been frequently migrated in the project corpus. However, this limitation can be mitigated by using a large project corpus, because the more worthy a migration is, the more common it will be in such a corpus. As shown in [14], 33 of 223 ASF projects have undergone at least one logging migration, mostly from ad-hoc logging libraries (e.g. `log4j`) to log abstraction libraries (e.g. `slf4j`) and log unification libraries (e.g. `logback`), and our apporach performs well in these popular migrations. Developers can also use other tools (e.g. [22]) or Google search to come up with some alternatives, and use our tool to make the final decision.

Data Sparsity. Other failure cases are generally caused by the sparsity of many real migrations in our data. If only one or several relevant commits can be identified for a query, other added libraries in these commits tend to occur as false positives together with the true migration target. MS and AS can handle such cases, but they sometimes fail either because developers do not write informative commit messages, or because code changes are not needed for the migration or are completed before/after the `pom.xml` changes.

Miscellaneous. Our approach will definitely fail if a library has no substitute at all, and it cannot issue any warnings or hints in such cases. Our method of matching commit messages sometimes falsely identify a migration, and can be improved by more sophisticated NLP techniques. Our approach also frequently returns Bills of Materials, libraries that warp other libraries, or "full solution" frameworks like Spring in our results. Even if they are not considered as migration targets during the labelling process, they may still be useful for developers.

B. Threat to Validity

1) Construct Validity: It is generally impossible to compute accurate recall for all possible migration targets in the wild [11], [13]. Even if we limit the evaluation on a set of ground truth libraries, we cannot guarantee completeness of the identified migration targets. To mitigate this threat, we aggressively extend the largest set of migration rules from existing work [13] and manually validate all extended rules, to present a "best effort" estimation of recall in RQ2.

2) External Validity: Our approach may not generalize to a different dataset (e.g. industry projects) and to other programming languages and library ecosystems. . We mitigate this threat by collecting a large number of open source Java projects and libraries, and testing on many library queries. Also, our approach in Section III does not make any language specific assumptions and can be easily re-implemented for other programming languages. Others can also refer to Section IV as an example of how to make implementation choices for a specific language or ecosystem context.

VII. RECOMMENDATION EXAMPLE

We present one recommendation example from the results of RQ3: `c3p0:c3p0` in Table V. It is a database connection pooling library which has been renamed to `com.mchange:c3p0` since version `0.9.2` in 2007. Many other competitors for database pooling also emerged from 2007, under different licenses or for specific scenarios. We choose `c3p0:c3p0` as an example not only because of the diversity of migration targets returned, but also because it well demonstrates common failures and peculiarities of our approach.

We can see from Table V that the top-1 recommended target is `com.mchange:c3p0`, with much higher confidence than the rest. The second result is Hikari CP, a database pooling library since 2013, which boasts its light-weight and much higher performance compared with other libraries. The 5th and 10th result is Alibaba Druid, a connection pool designed specifically for monitoring purposes. The 7th result is `c3p0` for integrated use with Hibernate. The 15th result is Apache Commons DBCP, a pooling library under the ASF license. The rest of the results are omitted in the Table because they are all false positives. Given the prevalence of migrations from `c3p0:c3p0`, a developer should also consider abandoning it for his/her project, and choose one of the above libraries instead after evaluating the migration costs, benefits, licenses and other factors through investigation of the migration commits and other available information.

Other candidates are ranked above some migration targets in Table V, either because they are added together with the migration target in some migration commits, or because their commit messages are falsely identified as stating a migration.

TABLE V
RECOMMENDATION RESULTS OF `c3p0:c3p0`

Rank	Is Correct	Library	Confidence	RS	MS	DS	AS
1	True	com.mchange:c3p0	0.4083	0.9880	4.1700	0.9910	1.0000
2	True	com.zaxxer:HikariCP	0.0124	0.0238	1.0000	0.5222	0.1000
3	False	org.jboss.jbossts.jta:narayana-jta	0.0071	0.0357	2.0000	1.0000	0.1000
4	False	org.springframework.boot:spring-boot-starter-test	0.0050	0.0595	1.0000	0.8518	0.1000
5	True	com.alibaba:druid	0.0039	0.0476	1.0000	0.8222	0.1000
6	False	org.jboss.spec.javax.servlet:jboss-servlet-api_3.0_spec	0.0038	0.0238	1.5849	1.0000	0.1000
7	True	org.hibernate:hibernate-c3p0	0.0037	0.0357	1.5849	0.5430	0.1000
8	False	org.hibernate:hibernate-core	0.0030	0.0476	1.5849	0.3870	0.1000
9	False	org.springframework.boot:spring-boot-starter-web	0.0029	0.0357	1.0000	0.7539	0.1000
10	True	com.alibaba:druid-spring-boot-starter	0.0026	0.0238	1.0000	1.0000	0.1000
11	False	org.modeshape:modeshape-web-explorer	0.0024	0.0238	1.0000	1.0000	0.1000
12	False	org.springframework.boot:spring-boot-devtools	0.0024	0.0238	1.0000	1.0000	0.1000
13	False	org.springframework.boot:spring-boot-starter-thymeleaf	0.0024	0.0238	1.0000	1.0000	0.1000
14	False	org.springframework.boot:spring-boot-starter-aop	0.0024	0.0238	1.0000	1.0000	0.1000
15	True	commons-dbcp:commons-dbcp	0.0012	0.0238	1.0000	0.3199	0.1667

VIII. RELATED WORK

In this section, we briefly go through other related works not discussed before, and we summarize the relationship, differences or improvements of our work compared with these existing works.

Bartolomei et al. [46] studied the feasibility of using API wrappers to migrate two XML libraries, and two Java GUI libraries in a subsequent study [47]. They summarized peculiarities of designing wrapper libraries and proposed a set of design patterns for wrapper libraries. However, it's generally costly to implement a wrapper and nearly impossible to implement wrappers for all possible migrations.

To recommend libraries to developers, Thung et al. [23] propose to recommend libraries based on the libraries a project is already using, through association rule mining and collaborative filtering. More approaches are proposed for this problem later, such as multi-objective optimization [24], hierarchical clustering [54], advanced collaborative filtering [55], matrix factorization [56], etc. However, their main objective is to recommend missed reuse opportunities based on the libraries a project is using and the properties of the project, not to recommend migration opportunities of a library already in use. Chen et al. [19] mine semantically similar libraries by training word embedding on Stack Overflow tags. Given a library, their method can return a list of possibly similar libraries, but their methods provide no evidence on the feasibility and prevalence of migrations between this library and the returned libraries.

A number of studies have proposed methods for mining API mappings of two similar libraries [12], [15], [18], [42], [45], [57] or even directly editing code to use the new API [58], [59]. Zheng et al. [57] use web search engines to mine alternative APIs, based on the observation that developers often share knowledge of similar APIs on blog posts. Gokhale et al. [42] build mappings by harvesting the execution traces of similar APIs. Teyton et al. [12] find API mappings by analyzing their co-occurring frequencies in existing migrations. Alrubaye et al. [15] improve their method using information retrieval techniques and a custom sorting algorithm, and they [18] later propose a better method using machine learning models. Chen et al. [45] propose an unsupervised deep learning based approach that embeds both API usage patterns and API descriptions. Xu et al. [58] propose an approach to infer and apply migration edit patterns from existing projects. Collie et al. [59] propose to model and synthesize library API behavior without prior knowledge, which can be used for identifying migration mappings and applying migration changes. The output of our approach can serve as input for any of the approaches above, because they all require manual specification of library pairs. Our new migration dataset may also be helpful in facilitating further research into this area.

Other recent works also aim to aid dependency management, but from a different perspective, such as characterizing library usage [6], versioning [60]–[62] and update behaviors [39], discovering considerations for library selection [20], [21], resolving version conflicts in dependency tree [63], [64], in multi-module projects [65], and so on.

IX. CONCLUSION AND FUTURE WORK

In this paper, we propose an approach for automated recommendation of library migration targets, through mining dependency change sequences of a large corpus of software projects. We formulate this problem as a mining and ranking problem and design four advanced metrics for ranking: Rule Support, Message Support, Distance Support and API Support. To the best of our knowledge, our approach achieves best performance in this problem domain, with MRR of 0.8566, top-1 precision of 0.7947, top-10 NDCG of 0.7665 and top-20 recall of 0.8939. We also verify and build a latest migration dataset of 1,384 rules in 1,651 repositories.

In the future, we plan to design better heuristics to deal with the failure cases mentioned in Section VI. More importantly, we plan to evaluate our tool in an industry context and collect usage feedback from industry developers, while extending the migration rule dataset in a crowd-sourced manner. Finally, we plan to systematically investigate developer considerations for library migration, using the collected migration dataset.

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