# Example-Based Automatic Migration of Continuous Integration Systems

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## ABSTRACT

Continuous Integration (CI) is a widely adopted software engineering practice for faster code change integration and testing. Developers often migrate between CI systems in pursuit of features like matrix building or easier workflow. However, this migration is effort-intensive and error-prone owing to limited knowledge of the new CI system and its syntax. Moreover, our analysis identified that these migrations require multiple iterations and significant time to achieve stability in the new CI system, and there is insufficient support for the automatic migration of CI configurations.

To mitigate this, we propose a novel approach for CI systems' automatic migration: CIMig. Our approach utilizes example-based mining, where it extracts translation rules and configuration patterns from existing migration examples, and employs them to reproduce this migration in new contexts. To empirically validate and evaluate our approach, we apply it to the migration between Travis CI and GitHub Actions. We gathered learnings from 1001 projects, and then applied them to migrate an evaluation set of 251 projects. We also performed a user study employing CIMig to migrate the CI systems of five Java projects. These analyses helped us perform a qualitative and quantitative evaluation of CIMig, and we contextualize our results by comparing them with those of the manual-rule-based *GitHub Actions Importer*. Furthermore, our tool generated files that were rated favorably by developers and saved them an average of 42.4 minutes over the manual migration of these same projects. Our example learning-based approach is also more flexible, as proven by our ability to apply it to migrate GitHub Actions files to Travis CI, which GitHub Actions Importer can not do. We believe CIMig is the first generic approach of its kind to migrate CI systems and can be applied to other software configuration system migrations. Our replication package is available at [5].

## 1 INTRODUCTION

Continuous Integration (CI) is a widely used software engineering (SE) process for automatically integrating changes in shared repositories. It has enabled drastic change and improvement in SE processes and outcomes, such as quicker issue resolution, and faster shipping [41, 84, 86]. Travis CI and GitHub Actions (GHA) are the most popular CI tools for Open Source Software (OSS) projects [35, 41, 67], and migrations occur frequently between these two tools [35]. However, these migrations are slow and error-prone due to various factors [50], and further complicated by a lack of tool-support. The only official tool, GitHub Actions Importer [32], only supports migrating to GHA, relies on manual mappings, and lacks support for features such as the migration of secrets like authorization tokens. [28]. Moreover, this tool is technology-specific and can not be applied to other CI systems.

Most existing migration research works focus on analyzing and migrating source code between programming languages [4, 25, 27, 54, 61], and few works are concerned with the analysis and migration of configuration code [34, 40, 65, 77], and none tackled the automatic migration of CI configuration code. Many differences exist between source code and configuration. Source code defines the behavior of software, relies on programming languages like Java, Python, etc., with more descriptive logic syntax, and is generally managed and documented by developers. Configuration code describes the parameters of a software application [11], relies on markup languages like YAML or domain-specific languages (DSLs) [78] with higher abstraction, and is generally maintained by DevOps engineers [78]. The migration of CI systems is challenging because of the differences between the Source and Target CI systems [50], owing to the usage of DSLs with higher abstraction. Moreover, our analysis identified that these migrations require multiple iterations and a significant time span to achieve stability in the Target CI system.

To mitigate this difficulty, we propose a novel approach *CIMig* that employs example-based mining, to migrate CI configurations between CI system. CIMig automatically learns rules from semantically-equivalent tuples of CI files originating from different tools, then applies its learnings to migrate CI files from a Source to a Target CI system. To validate and evaluate our approach, we utilized it to perform migrations between GHA and Travis CI. We assessed the results of CIMig through automatic and manual evaluations, described its cost, and analyzed some of the cases where it fails. Through this paper, we answer the following research questions:

**RQ1:** How effective is the proposed migration pipeline?
**RQ2:** What is the cost of the migration pipeline?
**RQ3:** What are the limitations of our approach ?

CIMig can translate 70.82% of a Travis CI file and 51.86% of a GHA file on average. Its translations from Travis to GHA are competitive with GitHub Actions Importer, where they had an average cosine [69] similarity of 0.51 to the developer's hand-crafted manual translations, versus 0.45 achieved by GitHub Actions Importer. Unlike the latter, CIMig also translates syntax in the opposite direction, where it generates files with an average 0.35 cosine similarity to the developer's versions.

*The research work is not related to the author's position in the affiliation.

Our main contributions through this work are:

- A novel technology-agnostic CI migration technique leveraging Apriori Rule Mining and Tree Association Rules.
- A comprehensive evaluation to evaluate the effectiveness of CIMig, and of a few important failure scenarios.
- A dataset of GitHub Actions and Travis CI configuration files from 30,543 real-world Java projects shared at [5].

We motivate our work within Section 2. We discuss its background in Section 3. We detail our approach in Section 4, and the quality, cost, and shortcomings of applying techniques to migrations between GHA and Travis CI within Section 6. Related works are detailed in Section 7, the threats to validity are discussed in Section 8, and finally, we conclude our work in Section 9.

## 2 PROBLEM CONTEXTUALIZATION

Prior research [50] has identified through qualitative analysis that migrating a CI infrastructure is a difficult process, due to technical and human hurdles. To further validate these findings, we performed an empirical study, where we analyzed 1252 projects that migrated from Travis CI to GHA, one of the most common migration patterns [35, 50]. These projects were collected through a process detailed in Section 4.1, and are manually confirmed to have created an equivalent GHA file.[1]

Through our Git and API-based analyses, we uncovered that an average 71.20 days, and 2.75 commits are needed to reach a successful build that corresponds to the equivalent GHA file, with some projects needing up to 169 commits to reach this threshold. This implies that the migration process is not self-evident and requires multiple attempts over an important span of time. Furthermore, we find that 48 projects seemingly abandoned the migration process entirely even though they implemented equivalent GHA files, as they never achieved a successful GHA workflow.

To better illustrate the complexity of the CI migration process, we present an example of a migration from Travis CI to GHA from the project `VocableTrainer-Android` in Figure 1.

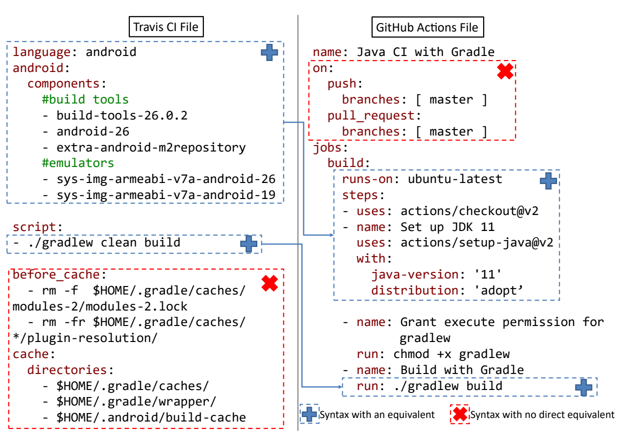



**Figure 1: Example of Migration from Travis CI to GitHub Actions**

The semantically-equivalent segments of the configuration are marked with a + sign and linked with an arrow in Figure 1. However, the sections marked with an **x** sign, have no direct equivalents between the two syntaxes.

The Travis CI configuration of this project requires specifying `android` as a language and manually configuring the different `components` required to run this project within the Travis CI environment. However, that is not necessary within GHA, as all of these components are provided by default when using the `ubuntu-latest` environment.

While Travis CI automatically performs the checkout process and makes Gradle executable, these steps need to be explicitly performed in GHA. Travis CI workflow execution triggers are configured via its website or performed via API requests [75]. But, GHA developers need to specify them within the `on` section of the GHA configuration file. In addition, while Travis CI provides a generic cache configuration mechanism, GHA does not have a workflow-wide directly equivalent syntax for caching. It relies on the configuration of job-specific caches by using `actions/cache@v3`, or package-manager-specific caching keywords. `cache:gradle` can be added to this example to ensure caching.

Overall, this example illustrated how developers need to navigate and avoid many pitfalls during the translation of a CI configuration file, and how the lack of direct equivalents of some syntaxes hinders the translation process.

## 3 BACKGROUND

### 3.1 Continuous Integration

Continuous Integration tools automate code integration by automatically validating new commits via the execution of building, testing, and other processes. Most CI tools are configured via Configuration code files, and the execution of a CI tool is referred to as a workflow.

GitHub Actions [32], Travis CI [76], Azure Pipelines [6], and Circle CI [20] are among the most popular CI tools, and have many commonalities. All four tools rely on YAML-based [72] files to store the configuration of their workflows, with each relying on its own Domain Specific Language (DSL). For all four tools, workflows can be manually or automatically triggered by Git events such as pull requests or pushes. Workflows are composed of one or more jobs, which may be configured to execute in parallel in different environments. For each of these tools, a job may be composed of one or more steps that run sequentially, and it's possible to use variables to share information between the different steps and the different jobs.

Even with the functional similarity of these tools, there are significant conceptual and syntactical differences between them. For example, while the Operating System for each GHA job may be specified using the `runs-on` [29] keyword, or the keyword `vmImage` [8] for Azure Pipelines, or the `image` [18] keyword for CircleCI, Travis CI uses the keyword `os` [73] to configure it for all stages and jobs. While Travis CI has a specific phase `install` [74] within its lifecycle to prepare the environment, GHA, Azure Pipelines, and CircleCI leave the specification of these phases to the developers. GHA makes workflows and jobs reusable with the keyword `uses` [30], so does Azure Pipelines with `task` [7], and CircleCI via `orbs` [19], but, Travis CI does not offer an equivalent function.

[1] Defined as sharing 50% or more functionality, detailed in Section 4.1

## 3.2 Example-based Learning

A plausible approach for automatic CI system migration is to learn from how prior developers migrate from source CI systems to target CI systems and how they compose the structure of the CI configurations. Such migration and composition data can be extracted from open-source projects hosted in GitHub. We utilized Association rule mining [26, 46], an ML approach for finding interesting associations among data. Specifically, we used the Apriori Rule Mining [1] and Frequent-Tree Mining [16] algorithm to generate rules for the target CI system.

### 3.2.1 *Apriori Rule Mining.*

Apriori is an Association Rule Mining (ARM) algorithm defined by Agrawal et al. [1]. It starts by finding the frequent individual items in a database, also known as transaction set, and expands them to item sets co-occurring together as long as the appearance of those item sets is larger than a minimum threshold specified by the user. Apriori then uses these frequent item sets to generate association rules that reflect general trends in the transactions set. Apriori rules are composed of a Left Hand Side (LHS), the antecedent, also referred to as pre-condition, and a Right Hand Side (RHS), the consequent. Within our work, the transaction set as well as the resulting rules, are composed of subsets of Abstract Syntax Trees (sub-ASTs).

### 3.2.2 *Frequent Tree Mining and Tree Association Rules.*

Frequent Tree mining empowers us to discover frequent maximal, induced, ordered sub-trees with a specific minimum support from a group of similar trees. We performed Frequent-Tree Mining via the `CMTreeMiner` [16] algorithm on subsets of Abstract Syntax Trees (ASTs). We grouped these sub-ASTs by their root nodes and passed them as input to `CMTreeMiner`. Frequent Trees are discussed in detail in Chi et al.'s work [17]. Using these trees, we were able to extract Tree Association Rules (TAR), which we adapted from the work of Mazuran et al. [51]. Similar to association rules, TARs are composed of an antecedent and a consequent. Within our work, we considered the antecedent to the root node as well as 50% of the branches of a Frequent Trees, and the consequent being the remaining branches of the tree. Hence, a Frequent Tree may generate multiple TARs during the execution of CIMig.

# 4 APPROACH

An overview of our approach is shown in Figure 2. We use Travis CI and GHA syntaxes in the different illustrative examples.

## 4.1 Data Preparation

The proposed approach CIMig requires three sets of configuration files. Set (1) containing Source CI files , Set (2) Target CI files, and Set (3) of Source and Target CI file-pairs, with each pair containing two files from different CI tools that implement similar functionality. To prepare these files for the analyses we aim to perform on them, we apply an abstraction process to them. This process parses these files into equivalent ASTs, then transforms their leaves by matching them with regular expressions that contain predefined keywords to preserve the commands used within the configuration code files while removing their project-specific parameters. To evaluate our approach, we chose to focus on Java projects using Travis CI or GHA as they are the most important subset of CI-using OSS projects [9, 23, 41, 67, 68]. To concertize the data preparation phase in this context, we discuss the processes we followed to create the 3 aforementioned sets in this specific context. First, we collected the projects from two sources: Google BigQuery and GitHub, the two most popular OSS repository hosting sites [31, 48], after applying criteria on activity and popularity as outlined by previous works [36, 45, 56], ensuring that these projects have a size > 0 KB, have been active in 2021, and have a popularity ≥ 5 stars or ≥ 5 forks. We collected 345228 projects after de-duplication. Then, we used Travis CI and GHA APIs to establish a project's usage of these CI tools, a more accurate method of establishing adoption [67].

This allowed us to build these three project sets:

- Travis CI-Only projects: 13403, containing Set (1) or Set (2), depending on Translation direction.
- GHA-only projects: 15888, containing Set (1) or Set (2), depending on Translation direction.
- Travis CI and GHA projects: 5138, 1252 after filtering, containing Set (3).

We used the first two projects sets to extract Set (1) and Set (2) for Task B in 4.2, to extract Frequent Trees for both Travis CI and GHA. We used the third project set to perform migration effort analysis discussed in Section 2, and to extract Set (3) of semantically equivalent configuration code file tuples for Tasks A-1 and A-2 in 4.2. It's important to note that while Travis CI uses one configuration code file, GHA may use multiple files, hence why we're extracting tuples from a project, as they contain one Travis file, and may contain more than one GHA file. We applied the following filtering process to find these tuples. First, we performed a git-history-based analysis to extract the Travis CI and GHA file tuple which contains the file pair composed of the Travis CI and one of the GHA files with the highest cosine similarity [69], a metric used within previous works [15, 81] to determine source code and configuration code similarity, and which have passing build statuses as confirmed by the GHA and Travis CI APIs. We eliminated 1748 projects as they did not have configuration files for one or both tools in their history, likely due to Git rewritings [12], and 919 projects, due to their tuples having a maximum cosine similarity of 0.1 or less.

Second, to confirm the semantic equivalence of the remaining tuples from the third set, two co-authors manually analyzed file tuples from 2471 projects. As mentioned earlier, the extracted file tuple may contain more than one GHA file. Hence, the developers performed a pairwise comparison between the Travis file and each of the GHA files in each tuple, starting with the longest GHA file. To save time, they stopped when reaching the minimum equivalency criterion. We opted for this permissive semantic equivalence criterion after perceiving that very few projects completely re-implement the same functionality between GHA and Travis CI, which is consistent with previous findings [50]. After applying these filtering processes, only 1252 projects met these criteria.

Similar to other works that tackled code translation [2, 66], we split third set into two subsets, following the 80%-20% ratio, a "training" set of file tuples from 1001 projects and a "test" set of file tuples from 251 projects. The project splitting process was random to maintain representativeness. Only the training set is used for Tasks A-1 and A2, while the testing set is reserved for the evaluation of the approach. Since Tasks A-1 and A2 of CIMig are designed to

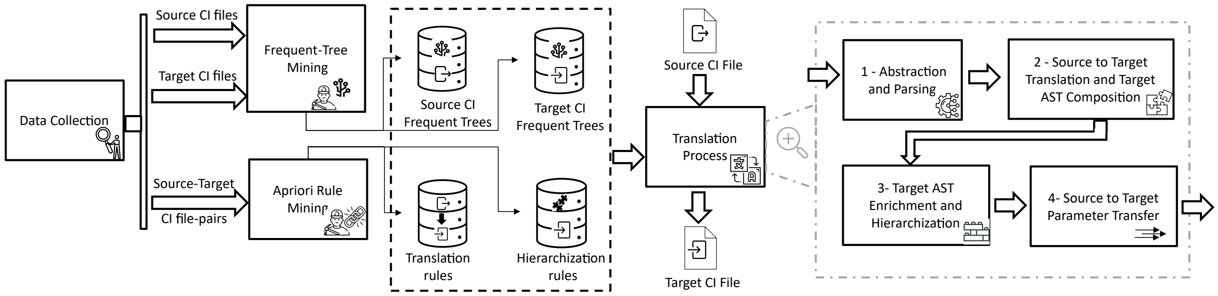
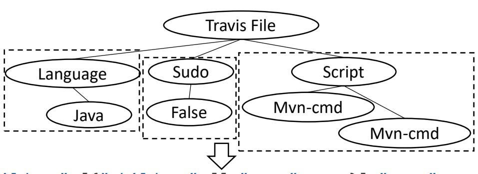



**Figure 2: Overview of CIMig when used to migrate between Travis CI and GHA**

learn on file-pairs, we transform each tuple into pairs where the same Travis CI file is paired with the multiple GHA files.

## 4.2 Training CIMig

*4.2.1* ***Task A: Apriori Rule Mining Process.*** The goal of this process is to find rules that allow us to translate Source CI syntax to Target CI Syntax, which we refer to as ① Translation Rule Mining as well as rules that link different parts of Source CI syntax to each other, referred to as ② Hierarchization Rule Mining. This process is applied to the Source-Target CI file pairs set.




```
{"children":[{"children":[],"type":Java}],"type":Language}
{"children":[{"children":[],"type":false}],"type":sudo}
{"children":[{"children":[],"type":mvn-cmd},
{"children":[],"type":mvn-cmd}],"type":script}
```

**Figure 3: Travis CI H-2 AST Extraction Example**

**Task A-1: Translation Rule Mining.** To extract translation rules to guide our translation from the Source CI to the Target CI tool, we analyze the previously-prepared file pairs.

First, after the abstraction of these files as detailed within Section 4.1, we parse them into ASTs. Then, for each pair of ASTs, we extract the sub-ASTs of height equal to 2 starting from the leaves of the ASTs, which we refer to as H-2 ASTs within this work, and we represent them in a textual format. We decided on this height after a process of parameter tuning, detailed in the Parameter Tuning paragraph of 4.2.3. An example of the application of the abstraction and H-2 collection processes is shown in Figure 3. For each file pair $i$, we obtain a set of H-2 ASTs extracted from the Source CI file: $SRC - H2_i$, and a set of H-2 ASTs extracted from the Target CI file $TGT - H2_i$

Second, for each file pair, we apply Cartesian product, used in other code-translation works [71], to create a transaction set $T_i = SRC - H2_i \bigtimes TGT - H2_i$ We chose this product since the alignment of the configuration code files from different tools is not possible in many of cases, as different configuration parameters can be at different locations within the file pairs due to some tools, such as GHA, employing a more flexible file structure than others.

Third, all the transaction sets generated from the file pairs are grouped into one large set $T_{transl} = \sum_{i=1}^{N} T_i$ on which we perform our Apriori-based Association Rule Mining (ARM) [1], previously detailed in Section 3.2. This rule-mining was used in other works tackling code translation and configuration mapping such as that of Hora et al. [42]

These rules are evaluated in terms of their support [1], confidence [1], and lift [52], with higher values indicated higher quality rules. Support reflects how often the item set appears together, $support(SRC \Rightarrow TGT) = P(SRC \cup TGT)$, where $SRC$ is a specific H-2 AST from Source CI, $TGT$ is a specific H-2 AST from Target CI. Confidence reflects how often the rule is correct, $confidence(SRC \Rightarrow TGT) = P(SRC \cup TGT)/P(SRC)$. Lift is the ratio of the actual confidence of a rule to its expected confidence, $lift(SRC \Rightarrow TGT) = confidence(SRC \Rightarrow TGT)/P(TGT)$. We specified a minimum support of $10^{-6}$, a value determined via a process detailed in the Parameter Tuning paragraph of 4.2.3.

Fourth, we filter the generated rules to keep those with the format of SRC-CI-H2-AST ⇒ TGT-CI-H2-AST, thus creating the Rule-Set $R$.

We calculate the confidence, lift and support products of these rules with their flipped counterparts, of the format TGT-H2-AST ⇒ SRC-CI-H2-AST, to substantiate the equivalence between the two H-2 ASTs. This is important since one Source CI H-2 AST may have multiple possible equivalent Target H-2 ASTs, and vice-versa.

Finally, we automatically bifurcate $R$ into two sets, based on whether the cosine similarity of the LHS's leaves and the RHS's leaves was above 0.5. These sets are:
$R_{sim}$: Similarity-Based rule-set.
$R_{stat}$: Statistical-Based rule-set.

We opted for this bifurcation as we anticipate a number of spurious rules will be present in $R$ due to the application of the Cartesian product. We choose to apply $R_{stat}$ in the translation process, after applying additional constraints, as it may still contain some useful non-textually-similar rules. We detail these constraints and the translation process in Section 4.3.

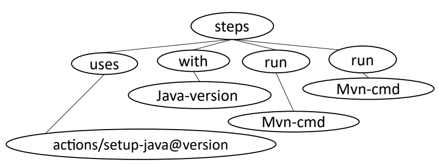
**Task A-2: Hierarchization Rule Mining.** The translation rules only capture two levels of the entire Source CI AST to find its equivalent Target CI AST. However, CI ASTs often contain 3 or more levels. Thus, multiple H-2 ASTs can be linked with a variety of intermediate nodes on multiple levels. To better infer the intermediate nodes within a Target AST, and ensure the correct composition of the generated Target CI file, we created a set of hierarchization rules via the following steps.

First, from each Target CI file $i$, we built a transaction set $TH_i$ of the extracted H-2 AST nodes and their parents, then we built $TH = \sum_{i=1}^{N} TH_i$ on which we ran the Apriori algorithm with a minimum support of $10^{-6}$ to generate the hierarchization rules.

Similar to their translation counterparts, the rules were filtered to keep those of the desired format of H-2-AST-Child ⇒ Parent. These rules allow us to find the direct parents of an H-2 AST, thus allowing us to infer some intermediate nodes within the complete generated AST of our Generated Target CI file. In addition, their confidence, lift, and support products were also calculated.

#### 4.2.2 *Task B: Frequent-Tree Mining Process.*

While our translation and hierarchization rules allow us to translate H-2 ASTs and find their direct ancestors, they do not capture patterns that link multiple H-2 CI ASTs to each other or patterns that span more than 2 levels. Such patterns may allow us to add beneficial sub-ASTs via inferring which sub-ASTs occur together, thus allowing us to address syntax that is not directly translatable from the Source CI syntax or syntax that does not have a direct equivalent. To capture these useful patterns, we perform Frequent-Tree Mining, detailed in Section 3.2, on the Source CI files set, and the Target CI files set. After abstracting these files, we extract sub-ASTs originating from each of their intermediate nodes. This mining process empowered us to discover a set of Frequent sub-ASTs, which we refer to as $FT$, where each tree has a minimum support of 5%, a value we chose via parameter tuning, detailed in the Parameter Tuning paragraph of 4.2.3.




```
Root is steps, Children contain [{"children":[],"type":mvn-cmd},
{"children":[],"type":mvn-cmd}]}

Children should contain {"children":[{"children":[],
"type":javaversion}],"type":with},{"children":[{"children":[],
"type":actions/setup-java@version}],"type":uses}
```

**Figure 4: Example of Frequent Tree mined from GHA and Generated TAR**

These Frequent Trees we extracted capture sub-ASTs which co-occur frequently within the files we used as input, and an example of such a Frequent Tree containing a beneficial pattern, which we extracted by mining GHA files, is shown within Figure 4. This tree contains the syntax used to setup and configure Java within a specific job, as well as the usage of Maven commands, signaling that these two elements are likely to occur together. As detailed in Section 3.2, these Frequent Trees generate multiple Tree Association Rules (TAR), and an example TAR is shown in the figure as well, where the antecedent is the root node steps along with the usage of Maven commands within an AST, and the consequent is the setup and configuration of Java. Such co-occurring H2-ASTs can't be be identified by translation and hierarchization rules. As illustrated by this example, the configuration of Java is a beneficial addition to our translation. Furthermore, TARs generally add more intermediate nodes to an AST file, which are useful for the hierarchization process.

#### 4.2.3 *Parameter Tuning for Task A & B.*

While designing the Apriori Rule Mining and Frequent Tree Mining processes, we followed an extensive parameter tuning process. Due to the prevalence of the migration from Travis CI to GHA, we focused on that translation scenario during this process. For the Apriori Rule Mining tasks, while deciding on the optimal number of levels to capture within our translation rules, our goal was to generate rules that strike a good balance between conservativeness and generality, as higher-order rules may less easily accommodate the migration with new CI workflow steps not seen during the training process, while lower order rules may generate too many rules that are prone to noisiness. To determine the ideal number of levels to consider, we mined rules with different sub-ASTs of different heights. We specifically evaluated 3 different types of rules: H-2 rules, with two levels on both sides of the rules, Mixed rules, with three levels on one side, two levels on the other side of the rule, and H-3 rules, with three levels on both sides of the rules. For each type of rule, we mined Travis CI => GitHub Actions rules, and then performed an evaluation of these rule sets against hand-crafted ones. While Sim-based H-2 and Stat-based H-2 rules had F-1 scores of 71.25% and 31.85%, Sim-based Mixed and Stat-based Mixed rules had F-1 scores of 60.75% and 8.10%, and Sim-based H-3 and Stat-based H-3 rules had F-1 scores of 33.33% and 10.26%. Hence, it's clear that H-2 rule-set has significantly better rules, while considering higher-level rules causes a precipitous drop in rule quality. Furthermore, while performing the rule mining process, we experimented with different values for the minimum support, and opted to use $10^{-6}$ as it allows the generation of the maximum number of rules on the development machine, described in 5.2, without causing memory consumption issues related to the Apriori algorithm [1]

Concerning Frequent Tree Mining, we again aimed to strike a balance between conservativeness and generality, and to operate within the constraints of time and memory needed for the mining process. Hence, we attempted the mining process with multiple minimum support values ranging from 1% to 75%. Of the values in this range, we found that a minimum support of 5% generated a sufficient number of trees, consisting of 2664 GHA Frequent Trees and 524 Travis CI Frequent Trees, within an amount of time detailed in 5.2, while higher support values resulted in a much smaller number of Frequent-trees, especially for Travis CI. For example, 10% minimum support resulted in the discovery of only 1006 GHA trees and 175 Travis CI trees, and 25% resulted in the discovery of only 191 GHA trees and 40 Travis CI trees, thus capturing far fewer patterns. Frequent Tree Mining with minimum support values lower than 5% either went on indefinitely, or took much longer time and resulted in few additional trees, most of which were not generalizable.

### 4.3 Using CIMig

The four steps of the approach that we follow to translate files from the Source CI syntax to the Target CI syntax are illustrated in Figure 2. Within this section, we detail the different steps of the translation process and illustrate them with an example of a translation from Travis CI to GHA. Similar to GitHub Actions Importer, we designed CIMig to use one file as input and produce one file as output, as the splitting of CI configuration across all files is optional in some CI tools such as GHA, and not at all supported by other tools such as Travis CI.

```
language: java
sudo: false
jdk:
  oraclejdk7
after_success:
  mvn clean cobertura:cobertura coveralls:report
```

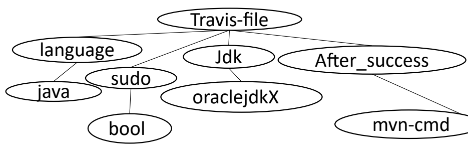



**Figure 5: Example of Travis CI File and its corresponding AST**

*4.3.1 Step 1: Abstraction and Parsing.* First, the configuration code of the source file is processed with the same abstraction process applied during the training phase, described in Section 4.1, and then parsed to an Abstract Syntax Tree (AST) from which we collect the H-2 ASTs. The parameters of the commands within these nodes, which are removed in the abstraction process, are stored for usage in a later step. An example of a Travis CI configuration file and its equivalent abstracted AST is shown within Figure 5.

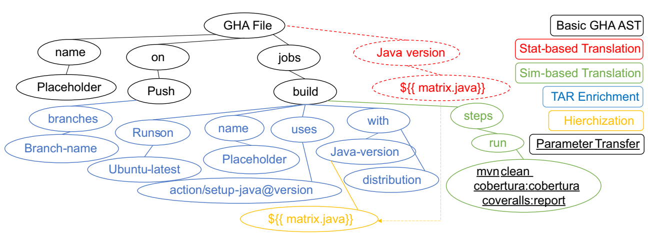



**Figure 6: Example of a translated GHA AST**

*4.3.2 Step 2: Source to Target Translation and Target AST Composition.* This step is composed of 3 phases: Initialization, Sim-based Translation, and Stat-based Translation. We also detail the Insertion Process we follow during the latter two phases.

Step 2.1: **Initialization.** First, we initialize a Target CI *seed tree* before the translation process begins. This AST is created from Frequent Trees found within the Target CI files, and that was verified to follow the correct structure of the Target CI tool. An example of a basic GHA AST composed of a seed tree is shown in black in Figure 6. This AST forms the basis of the file we're attempting to create as an end result of our translation process, and we refer to this file as generated equivalent Target CI file.

```
{"children":[{"children":[],"type":mvn-cmd}],"type":After_success}}  ➡  {"children":[{"children":[],"type":mvn-cmd}],"type":run}
```

**Figure 7: Example of Sim-based translation rule**

Step 2.2: **Sim-based Translation.** Second, we attempt a Sim-based translation, which makes use of Sim-based rules, detailed in Task A-1 of Section 4.2.1. For each Source CI H-2 AST collected within the previous step, we collect all the Sim-based rules with an LHS that matches it. Then, we extract the best rule according to its confidence product and apply it to generate the corresponding Target CI H-2 AST, which is then inserted within the AST of the generated equivalent Target CI file. Figure 7 shows an example of such a translation rule that applies to the Travis CI file shown in Figure 5. The usage of its results in a generated equivalent GHA file is shown in green in Figure 6. These rules effectively translate syntax that is directly equivalent between Source and Target CI systems and has textual similarity.

```
{"children":[{"children":[],"type":java}],"type":language}}  ➡  {"children":[{"children":[],"type":${{matrix.java}}}],"type":Java-version}
```

**Figure 8: Example of Stat-based translation rule**

Step 2.3: **Stat-based Translation.** Third, we attempt Stat-based translation. For each H-2 AST not translated within the previous step, we collect all the Stat-based rules with an LHS that matches it. However, we look for certain prerequisites before attempting to apply the Stat-based rules. For each rule, we collected the Frequent Trees of the Source CI tool, which contain the LHS of this rule, and the Target CI Frequent Trees, which contain the RHS of this rule.[2] CIMig analyzes each matched rule in descending order of their confidence product. It ascertains whether at least one Source CI Frequent-Tree, containing the LHS of the Stat-based rule, is present within the Source CI file's AST. It also verifies if a Frequent-tree from the Target CI tool, containing the RHS of the Stat-based rule, has at least 50% of its branches within this AST. If both conditions are met, the rule is applied and the corresponding Target CI H-2 AST is generated and inserted within the AST of the generated equivalent Target CI file. Figure 8 shows an example of such a translation rule that applies to the Travis CI file shown in Figure 5. The usage of its results in a generated equivalent GHA file is shown in red in Figure 6. This type of rule is especially useful for the non-directly-equivalent syntax and directly-equivalent syntax which does not have textually similar leaves, such as the translation of the `language:android` segment from the motivational example in Figure 1.

**Insertion Process.** In this paragraph, we detail the insertion process that we followed during the Sim-based Translation and the Stat-based Translation. CIMig performs a DFS-based search within the generated equivalent Target CI file AST to find the deepest node that matches the parent node of the new H-2 AST, which is then used as the point of insertion. The H-2 AST's children are inserted as the matching node's siblings. The design of this process was guided by observations of the YAML syntax, which is used by many CI tools, as intermediary nodes do not occur multiple times on the same level within a YAML file. If no matching nodes are found, the new H-2 AST is assumed to be a direct descendant of the file's root node and is accordingly inserted at the root of the file.

[2]This step is independent of the translation process, it is pre-computed to help accelerate it.

#### 4.3.3 *Step 3: Target AST Enrichment and Hierarchization.*

Step 3.1: **AST Enrichment with TARs.** to improve the structure of our generated equivalent Target CI file, we make use of TARs contained within the previously-mined Frequent Trees, detailed in Task B of Section 4.2.1. TARs can add beneficial patterns found within CI files of the same type, as well as intermediate nodes and structures that can be used to hierarchize the previously generated H-2 ASTs. We attempt to match each of the Target CI tool's TARs with the AST of the generated equivalent Target CI file. If a TAR is applicable, we insert the AST branches it generates while preserving any existing nodes within the file. an example of an AST Enrichment is shown in blue in Figure 6 .

Step 3.2: **AST Hierarchization.** The goal of the hierarchization process is to improve the placement of our H-2 ASTs, and the internal structure of our generated equivalent Target CI file's AST. We apply Algorithm 1 to achieve this process, which employs the hierarchization rules, detailed Task A-2 of in Section 4.2.1. First, as shown in lines 12-13, for each H-2-AST we inserted at the root, we attempt to apply the hierarchization process. Within this paragraph, we refer to the H-2 AST we're attempting to hierarchize as the current H-2 AST. For each current H-2 AST, we call the function DFS_Based_Insert, detailed in lines 1-11, where we perform a DFS-based search to find the deepest node that matches the current H-2 AST's parent type. If a match is found, we insert the current H-2 AST's children as children of the matching node and remove the current H-2 AST from the root node. This re-application of the same insertion process we followed in the previously-described *Step 2* allows us to take advantage of the new intermediate nodes added via the TAR enrichment process that we previously applied. If no matches are found, we collect all the Target CI hierarchization rules the LHS of which matches the current H-2 AST and we apply the hierarchical rule with the highest confidence product, as detailed in lines 14-21. Lines 22-30, show how we use this rule: we produce a new node using the new parent type, and add the current H-2 AST to its children. We then pass this new node as a search target to DFS_Based_Insert. If a node with the same type as our new parent is found within our Target CI file AST, we insert the current H-2 AST as one of its children. If no matches are found, the newly generated node is inserted a child of the root of the generated equivalent Target CI file's AST.

An example of a hierarchization rule is shown in Figure 9. It applies to the generated equivalent GHA file we're constructing in Figure 6, where the usage of this rule's results is shown in yellow. This example also illustrates how the application of TARs allowed us to add new intermediate nodes, which were then useful during the hierarchization process.

```
{"children":[{"children":[],"type":
${{ matrix.java}}}],"type":Java-version}   ➡   with
```

**Figure 9: Example of Hierarchization rule**

#### 4.3.4 *Step 4: Source to Target AST Parameter Transfer.*

Before applying the abstraction process in Section 4.3.1, we stored the parameters that correspond to the different commands contained in the H-2 ASTs we extracted. Throughout the different steps of our translation process, we keep track of which parameters correspond to each collected H-2 Source CI AST, as well as which generated H-2 Target CI AST corresponds to which H-2 Source CI AST. The generated Target CI ASTs are abstract due to the nature of the rule generation process, making the parameter transfer to them a direct process, where we copy the parameters to the new commands while preserving their order. Hence, we end up with a generated equivalent Target CI file that contains commands identical to their Source CI counterpart. An example of the results of this step is illustrated within the underlined node in the AST shown in Figure 6, where the parameters of the maven command were transferred from the original Travis CI AST. The generated equivalent Target CI file AST is finally transformed into a regular YAML file that can be used by the developers in their Target CI environment.

**Algorithm 1** Hierarchization Algorithm

```
1: function DFS_Based_Insert(CI_H2_AST,CI_AST)
2:     T ← CI_H2_AST.Parent_Node.Type
3:     Insert_Node ← DFS Based Search(CI_AST, T)
4:     if Insert_Node ≠ NULL then
5:         Insert_Node.Children ← (Insert_Node.Children_AST ∪ CI_H2_AST.Children)
6:         CI_AST.Children ← (CI_AST.Children \ CI_H2_AST)
7:         return True
8:     else
9:         return False
10:    end if
11: end function
12: for all CI_H2_AST ∈ CI_AST.Children do
13:     if DFS_Based_Insert(CI_H2_AST,CI_AST) = False then
14:         Matched_Hierarch_Rules ← ∅
15:         for all Hierarchy_Rule ∈ Hierarchy_Rules do
16:             if Hierarchy_Rule.LHS = CI_H2_AST then
17:                 Matched_Hierarch_Rules ← (Matched_Hierarch_Rules ∪ Hierarchy_Rule)
18:             end if
19:         end for
20:         if Matched_Hierarch_Rules.size > 0 then
21:             Best_Rule ← Best(Matched_Hierarch_Rules)
22:             New_CI_AST ← Init(Best_Rule.Parent_Node.Type)
23:             New_CI_AST.Children ← (New_CI_AST.Children ∪ CI_H2_AST)
24:             CI_AST.Children ← (CI_AST.Children \ CI_H2_AST)
25:             if DFS_Based_Insert(New_CI_AST,CI_AST) = False then
26:                 CI_AST.Children ← (CI_AST.Children ∪ New_CI_AST)
27:             end if
28:         end if
29:     end if
30: end for
```

## 5 EVALUATION

### 5.1 RQ1: How effective is CIMig?

To measure the effectiveness of CIMig, we performed two-pronged evaluation: automatic translation evaluation and user study.

*Automatic Translation Evaluation:* To evaluate the performance of the automatic translation, we applied CIMig on "test-set" of 251 that we discussed in Section 4.1. We evaluated two aspects of the automatic translation. First, we calculated the percentage of automated translations, which quantifies how many of the H-2 ASTs collected from each source CI file are matched and translated by CIMig. Second, we adopted Cosine similarity [69] and CrystalBLEU [24] to measure the similarity between CIMig generated CI configuration files and developer-written Target CI configuration files. We chose these two metrics due to their wide usage in literature. Cosine similarity is known for its versatility and applicability in source code migration research works [15, 59, 64, 70, 81], and CrystalBLEU is designed for source code similarity and was utilized in code generation works [21, 47, 83] and code migration works [44, 63]. For comparative analysis, we compared the performance of CIMig with that of GitHub Actions Importer, the official tool from GitHub Actions [33], using these two metrics.

*User Study:* We performed a user study to evaluate the practicality of CIMig. The study was done with five participants, out of 15 initially contacted. They had software development or research experience ranging from 3 to 7 years, CI experience including GHA ranging from 1 month to 1 year. Each participant was tasked with migrating five Travis CI projects to GHA manually. They also migrated these projects semi-automatically twice, with one migration using a configuration file generated by CIMig and another with GitHub Actions Importer. The five projects are from the Travis CI-only set, and we selected them using popularity ($\geq$ 5 stars or $\geq$ 5 forks), project activity ( $>$ 200 commits made), and project freshness ( updated June 2023 or later) following criteria in a similar works [36, 45, 56]. The five projects are `hutool` [22], `WxJava` [79], `hsweb-framework` [43], `elasticsearch-sql` [62], `TelegramBots` [10]. For the study, we only considered Travis CI to GHA migrations as GitHub Actions Importer only supports Travis CI to GHA. All configuration files generated by CIMig and GitHub Actions Importer were anonymized before being shared with the participants to avoid bias. For each migration task, the participants were asked to achieve a "First Passing Workflow", a workflow that implements minimal CI functionality, and a "Final Workflow" which implements all CI functionality that is available in Source CI configuration. During the study, we measured how much time can be saved via the semi-automatic migration approaches using CIMig and GitHub Actions Importer generated files. Also, we received ratings for the usefulness of the generated files by each tool from participants using a Likert scale [3] ranging from 1 to 5, with 1 being "not at all useful" and 5 being "incredibly useful". Our full study guide and the full reports are available at [5].

## 5.2 RQ2: What is the CIMig Execution Cost?

To estimate the time consumption of the training and translation processes, we programmatically measured the time it took to execute each training task, as well as the execution times for each translation performed on our test set, during the experiment execution. We performed our experiment on a machine running Ubuntu 22.04 and configured with an Intel Xeon CPU with 6 cores/12 threads and 32 GB of RAM.

## 5.3 RQ3: What are the Shortcomings of CIMig?

To find the shortcomings of the results of CIMig, we asked coauthors who did not work on developing CIMig to manually evaluate the results of our experiments by providing detailed reports on the different issues they noticed for the worst 25 generated translations from Travis CI to GHA, and the worst 25 generated translations from GHA to Travis CI, as determined by Cosine similarity. We then grouped similar issues into 3 main categories and reported the number of translations of each type that possessed that flaw.

# 6 RESULTS

## 6.1 RQ1: CIMig Migration Effectiveness

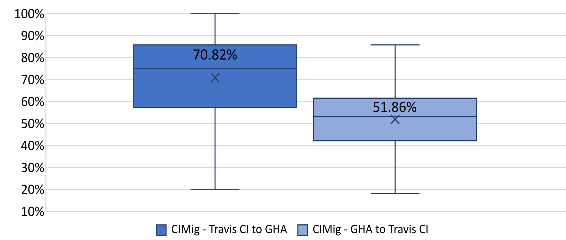



**Figure 10: Percentage of H-2 ASTs translated per-file**

*6.1.1 Automatic Translation Evaluation Results.* As the translation percentage values illustrate within Figure 10, for the 251 projects composing the test set of GHA-Travis CI equivalent set, our technique is effective at translating an average of 70.82% and a median of 75% of the H-2 ASTs extracted from a Travis CI file. Furthermore, CIMig translates an average of 51.86% and a median of 53.13% of a GHA H-2 ASTs to Travis CI syntax.

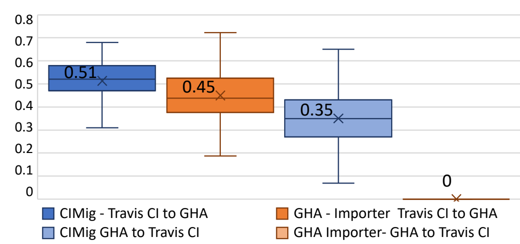



**Figure 11: Cosine Similarity score of the Generated files.**

Moving on to the translation quality, both Cosine Similarity and CrystalBLEU scores, illustrated within Figure 11 and Figure 12 respectively, and measured using the test set, display averages of 0.51 and 0.044 for the translation from Travis CI to GHA. The translation from GHA to Travis CI has averages of 0.35 and 0.036, respectively.

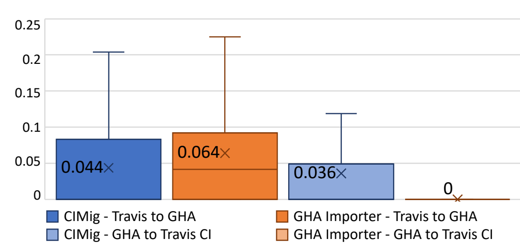



**Figure 12: CrystalBLEU score of the Generated files.**

Using the CrystalBLEU metric, it's clear that the generated equivalent GHA files and the equivalent Travis CI files show a good similarity to their developer-crafted baselines, especially when considering the works of Eghbali & Pradel. [24] For CrystalBLEU, where values around 0.05 were considered indicative of context-preservation and feature-parity between the code pairs. Furthermore, Using both Cosine Similarity and CrystalBLEU to compare the results from CIMig to those obtained by GitHub Actions Importer for the scenario of translating Travis CI files to GHA files, it's clear that CIMig's generated files are as similar to the developer-provided files. This helps substantiate the quality of our generated files, especially since the official tool relies on hand-crafted specific rules. While CIMig supports the translation from GHA to Travis CI, GitHub Actions Importer does not, nor does any current tool, hence why there is no baseline for comparison in that case.

We find it important to mention that a considerable amount of GHA syntax does not have a Travis CI equivalent, mainly because the oft-used `Actions` in GHA do not have a direct equivalent in Travis CI, as it doesn't support reusable workflows, making their translation difficult, explaining the lower results obtained when translating GHA files to Travis CI. It's also notable that GHA-Travis CI equivalent set contains GHA and Travis CI tuples that have as little as 50% functionality in common, meaning that the generated equivalent GHA file or generated equivalent Travis CI file may only achieve a maximum similarity of 50%.

Overall, our results further support the confidence in the quality of the equivalent Target CI file generated by CIMig and validate that they implement a sizeable percentage of the functionality originally found in the Source CI file. We believe the files CIMig generates can form a good basis for developers to build on and help accelerate the migration process of their infrastructure, and we attempt to confirm this in the following section.

*6.1.2 User Study.* Table 1 shows the results of the user study conducted following Section 5.1. Column 1 shows the name of projects used for the migration from Travis CI to GHA in the study. The First Workflow (column 2-6) shows the time that developers spent on Manual migration and migrations using CIMig and GitHub Actions Importer to reach a First passing workflow. For the results of CIMig and GitHub Actions Importer, we show how much time was saved in comparison to Manual migration (column 4 and column 6). Similarly, the Final Workflow (column 7-11) shows measures of developer time taken to reach a Final passing workflow for the same 3 migration types. Finally, Avg. User Rating (column 12-13) contains the average usefulness scores from 1 to 5, assigned by the developers to the files from CIMig and GitHub Actions Importer.

The results show that using the CIMig or GitHub Actions Importer helps developers reach both the First-passing workflow and the Final-passing workflow much faster than manual migrations. Indeed, CIMig reduced the Manual migration time by 16% to 86%, and GitHub Actions Importer reduced it by 22% to 84% for reaching the First-passing workflow. We see similar reductions as well in the migration time for the Final-passing workflow. In terms of user ratings, CIMig has an average of 3.04 user rating, and GitHub Actions Importer has a higher average user rating of 4.16. We notice similar user ratings for the two tools for the `Hsweb-framework` and `Telegram Bots` projects. In both projects, CIMig also provides higher reduction in migration time than GitHub Actions Importer. Two developers mentioned in their reports that the files provided by CIMig were easier to extend for these 2 projects than GitHub Actions Importer's files, where GitHub Actions Importer's attempts to translate some syntax results in more complicated configuration files. In summary, CIMig shows lower reduction rate than GitHub Actions Importer on three projects and higher reduction rate on two projects. User ratings tend to follow the reduction rates, with ratings for CIMig being lower than GitHub Actions Importer. Overall, the results confirm that the files generated by CIMig are usable in the GHA environment with minor modifications, and help save on migration time. Furthermore, CIMig leverages mining processes from existing files, making it easy to extend and adapt to new syntax, as shown via GHA to Travis CI migration. On the other hand, GitHub Actions Importer is built using manual-mapped rules, and only supports Travis CI to GHA migration, limiting its extension to other scenarios. Hence, CIMig provides more usefulness in terms of supporting more migration scenarios with comparable performance to the specialized migration tool.

## 6.2 RQ2: CIMig Execution Cost

Concerning the time needed to perform the translation of GHA files to Travis CI the average execution time of CIMig is 719.85 milliseconds, and the median is 705 milliseconds. Meanwhile, the average execution time of GitHub Actions Importer is 1553.31 milliseconds, and the median is 1503.38, for the same process. While both executions times are acceptable [60], CIMig is faster than GitHub Actions Importer . CIMig has acceptable times for translating GHA syntax to Travis CI as well, with a median execution time of 797 milliseconds, and an average translation time of 1235.46 milliseconds.

Concerning the different processes of the training phase, they are only executed once and are independent of the translation process, making their time consumption less important. During the rule mining phase, detailed in Section 4.2.1, we executed 2 Apriori-based ARM operations: Travis CI to GHA translation rules, which took 45947 milliseconds to execute, and GHA hierarchization rules which took 22022 milliseconds to execute. These times were nearly identical when mining the translation rules GHA to Travis CI, as well as the generation of Travis CI hierarchization rules. The most time-consuming process we designed was the detection of which GHA and Travis CI Frequent Trees match with the Stat-Based rules, which took 1625773 milliseconds (around 27 minutes), despite a parallelized implementation that took advantage of all CPU threads available. This is however not surprising as there is a total of 99586 Stat-Based rules for each direction, along with 524 Travis CI Frequent Trees and 2664 GHA Frequent Trees.

We performed two Frequent-Trees mining operations: one on Travis CI files, which took 1211342 milliseconds (around 20 minutes), and one on GitHub Actions files which took 257445 seconds (around 71 hours). The latter's much higher time consumption can be attributed to a bigger number of unique root nodes at which we attempted to detect Frequent-Trees, as well as the larger and more complex ASTs of GHA files. Overall, we believe CIMig time consumption during the training phase also remains within acceptable limits.

## 6.3 RQ3: CIMig Translation Failures

Although our approach generates CI files of good quality, there are certain cases where our approach fails to generate an acceptable

Table 1: User Study results on manual migration, and migrations with CIMig and with GHA Importer

| Project name | First Workflow | | | | | Final Workflow | | | | | Avg. user rating | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Manual | CIMig | | GHA Imp. | | Manual | CIMig | | GHA Imp. | | CIMig files | GHA Imp. files |
| | time (m) | time (m) | saved (%) | time (m) | saved (%) | time (m) | time (m) | saved (%) | time (m) | saved (%) | | |
| WxJava | 38.40 | 23.6 | 38.54 | 11.60 | 69.79 | 76.80 | 30.20 | 60.68 | 19.80 | 74.22 | 2.60 | 4.80 |
| hutool | 41.40 | 26.4 | 36.23 | 9.00 | 78.26 | 90.40 | 40.20 | 55.53 | 14.80 | 83.63 | 2.80 | 4.40 |
| Elasticsearch-sql | 29.00 | 24.20 | 16.55 | 4.60 | 84.14 | 46.00 | 36.20 | 21.30 | 8.00 | 82.61 | 3.40 | 5.00 |
| Hsweb-framework | 68.80 | 9.80 | 85.7 | 24.00 | 65.12 | 93.40 | 34.60 | 62.96 | 45.00 | 51.82 | 3.40 | 3.40 |
| Telegram Bots | 22.20 | 10.40 | 53.15 | 17.20 | 22.52 | 73.40 | 26.80 | 63.49 | 33.60 | 54.22 | 3.00 | 3.20 |
| Average | 39.96 | 18.88 | 46.05% | 13.28 | 63.97% | 76 | 33.6 | 52.79% | 24.24 | 69.30% | 3.04 | 4.16 |

translation. These failures are classified into three categories as follows:

**Syntax with no direct equivalent:** (5 out of 25 Travis CI ⇒ GHA translations, 22 out of 25 GHA ⇒ Travis CI translations) Although there are some similarities between Travis CI and GHA configuration syntaxes, there are certain functionalities that are supported in only one of them. For example, GHA offers the `uses` keyword that allows reuse of existing GHA workflows in the form of Actions, but Travis CI does not offer an equivalent functionality. An example of this syntax is shown in Listing 1.

```
uses: sonarsource/sonarcloud-github-action
env:
    GITHUB_TOKEN: ${{ secrets.GITHUB_TOKEN }}
    SONAR_TOKEN: ${{ secrets.SONAR_TOKEN }}
    SONAR_SCANNER_OPTS: -Dsonar.organization=albertus82-github
```

**Listing 1: GHA syntax with no Travis CI equivalent from `Albertus82/Cyclesmod`**

**Syntax that relies on more than two levels:** (7 out of 25 Travis CI ⇒ GHA translations, 2 out of 25 GHA ⇒ Travis CI translations) Since we opted to capture and translate H-2 ASTs in Travis CI, any functionalities that depend on the configuration of more than 2 levels are not captured. For example, the usage of multiple stages with different `jdk` and `language` settings in Travis.

**Unabstracted syntax and parsing issues:** (23 out of 25 Travis CI ⇒ GHA translations, 4 out of 25 GHA ⇒ Travis CI translations) Since the abstraction process was applied with the usage of the most common commands, some less common commands, such as `openssl` and `jarsigner`, are not represented within the translation rules we generated. An illustration of this is shown in Listing 2.

```
before_deploy:
    openssl aes-256-cbc -K $encrypted_key
       -iv $encrypted_iv -in release-key.jks.enc
       -out gotify-release-key.jks -d  ...
    jarsigner -verbose -sigalg SHA1withRSA
      -digestalg SHA1 -keystore release-key.jks
```

**Listing 2: Travis CI syntax from `Gotify/Android` containing unmatched commands**

## 7 RELATED WORKS

**Automatic Code Migration.** Migrating from one programming language to another is very common in large software systems due to the need for cross-platform support and language support features. However, programming language migration is effort-intensive and error-prone [13, 53, 87] due to the differences in syntax and unfamiliarity with the target programming language. To mitigate this, researchers developed tools and techniques for automatic programming language migration. For example, Java2CSharp [27] and j2swift [61] are developed for migrating from Java to C# and Swift. However, these tools and other research works [25, 38, 54] use predefined transformation rules for their migration. Creating these rules is a laborious process, and in many cases, these migrations may fail due to complex and rare syntax used by different programming languages. To resolve these limitations, Zhong et al. [87] and Nguyen et al. [57] utilized a mining-based approach for automatic migration. These approaches heavily relied on similarity-based alignment and may not correctly migrate code if the target language adopts a different naming scheme. mppSMT by Nguyen et al. [58], utilizes a divide-and-conquer approach with a phrase-based SMT engine to integrate the semantic features for automatic migration. The approach uses data and control dependency of source code, which may not be applicable to configuration code due to its higher level of abstraction. j2sInferer [4] is a recent approach that utilizes syntax and mapping rules with minimal domain logic for migration of Android Java code to Swift code with 65% cross-project accuracy. Such syntax similarity is very low among configuration code files and makes alignment infeasible. More recently, ML-based techniques [14, 37] are proposed for the automatic migration of programming languages. However, ML approaches require large corpora for model training, which may not be feasible for recently developed programming languages or DevOps configuration files where very little migration data exists.

**Configuration Maintenance.** Like source code files, the different configuration code files for CI systems, Build systems, etc., are integral parts of software projects. Prior works suggested that developers often work on maintaining and migrating configuration systems [34, 67, 80, 85] to improve performance and productivity. However, maintaining configuration code is tedious due to limited domain-specific knowledge and syntactical differences in configuration code across different tools. Gligoric et al. [34] utilized dynamic analysis and search-based refactoring techniques to automatically migrate build systems. Moreover, automated program repair-based techniques [39, 49, 55] are applied to fix build scripts. Xue et al. [82] proposed a technique for automatic migration to Docker containers. Recently, Henkel et al. [40] proposed binnacle to automatically detect bad practices in Docker files. Vassallo et al. [77] utilized program analysis techniques to detect anti-patterns in CI configuration scripts. At the same time, Rahman & Parmin [65] proposed a technique for automatically detecting security vulnerabilities in

Puppet-based IaC configurations. Although there are several techniques for the automatic migration and maintenance of different configuration systems, there is no research work on the automatic migration of CI systems.

# 8 THREATS TO VALIDITY

**Internal Validity.** The main threat is the incorrect composition of the generated CI configuration code. To mitigate this, we tested our approach thoroughly in several rounds, and we contextualized our results by comparing them to both developer-crafted and GitHub Actions Importer-generated files. We also evaluated the generated files with state-of-the-art metrics to evaluate the correctness of the approach, and further evaluated them via the user study.

**External Validity.** We evaluated our approach for migration between Travis CI and GitHub Actions. These projects are Java-based and OSS in nature. So, our approach may not work correctly on other CI systems with different programming languages and closed-source projects. Although the evaluation is CI system-specific, the proposed rule mining and composition techniques are more generic. Moreover, different CI systems support similar functionalities and similar structures, such as YAML. So, we believe that our proposed approach will work for other CI systems as well, with sufficient retraining. We attempted to approximate actual user experience via our user study by recruiting developers with varied development and CI experiences, but their experiences may not reflect every possible users'.

**Construction Validity.** For automatic rule generation, we considered two-level (H-2) level AST transition nodes. We believe these rules are a good balance between conservativeness and diversity, for reasons detailed in the Parameter Tuning paragraph of 4.2.3.

# 9 CONCLUSION AND FUTURE WORK

With the growing use of CI systems for faster code integration, migration of CI systems has become very common in development activity. However, migrating CI systems is a tedious and error-prone process [50]. We presented CIMig To assist the developers with CI migration, and help facilitate this process. In our evaluation, even with a small set of existing CI migration data, CIMig can generate CI files of good similarity to the developer-crafted versions. Furthermore, the user study also suggests that CIMig is beneficial for developers, allowing them to migrate CI systems in less time than manual migration. Moreover, the proposed approach is generic in nature and can be easily applied to other configuration systems as well. In the future, we plan to incorporate large language models (LLM), such as ChatGPT, to generate more accurate migration rules and apply the automatic migration process to other configuration systems, such as Docker, etc.

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