Characterization and Automatic Update of Deprecated Machine-Learning API Usages

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Abstract—Due to the rise of AI applications, machine learning libraries have become far more accessible, with Python being the most common programming language to write them. Machine learning libraries tend to be updated periodically, which may deprecate existing APIs, making it necessary for developers to update their usages. However, updating usages of deprecated APIs is typically not a priority for developers, leading to widespread usages of deprecated APIs which expose library users to vulnerability issues. In this paper, we built a tool to automate these updates. We first conducted an empirical study to seek a better understanding on how updates of deprecated machine-learning API usages in Python can be done. The study involved a dataset of 112 deprecated APIs from Scikit-Learn, TensorFlow, and PyTorch. We found dimensions of deprecated API migration related to its update operation (i.e., the required operation to perform the migration), API mapping (i.e., the number of deprecated and its corresponding updated APIs), and context dependency (i.e., whether we need to consider surrounding contexts when performing the migration). Guided by the findings on our empirical study, we created MLCatchUp, a tool to automate the update of Python deprecated API usage that automatically infers the API migration transformation through comparison of the deprecated and updated API signatures. These transformations are expressed in a Domain Specific Language (DSL). We evaluated MLCatchUp using a test dataset containing 258 files with 514 API usages that we collected from public GitHub repositories. In this evaluation, MLCatchUp achieves a precision of 86.19%. We further improve the precision of MLCatchUp by adding a feature that allows it to accept additional user input to specify the transformation constraints in the DSL for context-dependent API migration. Using this addition, MLCatchUp achieves a precision of 93.58%, which is a 7.39% precision improvement from our original solution.

Index Terms—Python, Program Transformation, Automatic Update, Deprecated API, Domain Specific Language

1 INTRODUCTION

The popularity of machine learning has surged in recent years, among both developers and researchers. Currently, the most popular programming language for machine learning is Python, due to the vast amount of Python libraries that support and provide machine learning capability. Furthermore, these libraries offer easy to use APIs, which allow developers to utilize machine learning without knowing the low-level implementation details.

Libraries are typically updated from time to time to add new features, fix bugs, or improve performance. With each new update, changes in the library’s APIs are inevitable, which may include API deprecations. Usages of deprecated APIs must be replaced with their corresponding updated APIs to ensure that the code works with the future version of the library. Such deprecation also occurs in Python machine learning libraries. Using the latest version of machine learning library is important for the performance and security of the program. Han et al. [1] stated that to take full advantage of deep learning libraries, users must always keep up to date with the latest library versions. A study by Wang et al. [2] supports a similar argument, stating that using an older version of deep learning library may expose library users to security issues and worse performance.

However, updating usages of deprecated APIs can be cumbersome and time-consuming. This affect some developers to prefer using the older versions of a library, as demonstrated by several studies [1], [2], [3]. Hence, providing a better alternative to manually updating the usages of Python deprecated machine learning library APIs can benefit many developers. Although deprecation of machine learning library APIs is common, each deprecation affects the API usages differently. Some deprecations can be fixed easily while others may require a deep understanding of the workflow or functionality of the API. No studies have attempted to get a better understanding on the deprecated API migration pattern for Python machine-learning libraries.

Prior to this study, several attempts have been made to automate the update of deprecated API usages in other programming languages. A4 [4] is an approach for automatic Android API migration by learning API migration patterns from code examples. AppEvolve [5], provides automated API usage update for Android by using before- and after-update code example to create an update patch. Extending AppEvolve, CocciEvolve [6] provides an automated API usage update for Android using only a single after-update example, providing an easily readable transformation expressed in the form of semantic patch language (SmPPL). NEAT [7] generates transformation rules for deprecated Android API usage replacements without any usage example. NEAT constructs signature graph to do the type conversions required by the API replacement. No previous work has targeted Python API deprecation.

In this study, we followed an “as simple as possible, but no simpler” approach — as advocated in many recent studies [8], [9], [10] — by first doing an empirical study to
Ascertaining the level of innovation needed and then designing a suitably complex solution to address the problem at hand. Through this empirical study, we aim to discover deprecated API migration dimensions in popular Python machine learning libraries. Within each dimension, we define the categories of deprecated API migrations that exist in Python machine learning libraries.

For our case study, we picked a subset of the available Python machine libraries based on the number of GitHub repositories that depend on the library (obtained through GitHub dependency graphs). According to this statistic, as of August 2020, more than 120,000 repositories utilize Scikit-learn, while more than 82,000 repositories use TensorFlow, Keras, and Pytorch each have at least 52,000 and 34,000 utilizing repositories respectively. However, since Keras is included within TensorFlow as of January 2017, we picked Scikit-Learn, TensorFlow, and Py Torch as our case study libraries. We collected API deprecation messages from the documentation and changelogs of the last two years’ (July 2018 - August 2020) major and minor releases of these libraries, where we found a total of 112 distinct APIs that were deprecated. We utilized manual thematic analysis and found three common dimensions in deprecated API migration, namely the chosen update operation (based on the type of operation done in the API migration), the API mapping (based on the number of deprecated and updated APIs), and the need for context dependency (based on whether the API migration depends on information in the surrounding usage context). We also labelled each of the collected deprecated APIs based on the categories within each dimension to learn their distribution.

Based on the findings in the empirical study, we propose a tool to automate the update of Python deprecated API usages called MLCatchUp. MLCatchUp takes as input the deprecated API signature, the updated API signature, and the file to be updated. It then automatically infers the required transformation by comparing the deprecated and updated APIs’ signatures. The inferred transformations are expressed in the form of a Domain Specific Language (DSL) that we built based on the results of our empirical study.

A comparison of features between MLCatchUp and other similar refactoring and automatic API usage update tools [1, 2, 3, 4] is shown in Table 1. Compared to the tools from previous studies, MLCatchUp is the only tool that supports the Python language along with its unique features. Python has several unique features, including parameter default values, two types of parameters (positional parameter and keyword parameter), the usage of whitespaces and indentation as separator, and dynamic typing. A keyword parameter is a type of parameter that can only be addressed through its name, which is in contrast with positional parameter that can be addressed through both its position and name. The usage of whitespaces and indentation as separator makes parsing Python code different from other languages which typically depends on a specific symbol (e.g., Java and C which use semicolons and brackets). Among the previous tools, the closest work to ours is NEAT [5]. However, the NEAT algorithm does not work well for Python. NEAT requires the parameter types of all API within a library to perform the automatic update. The need of parameter types for all API within the library means that we also need to label the type for APIs that are not deprecated. Due to the dynamic nature of Python, we would need to do this parameter types labelling manually, which renders NEAT no longer fully automatic.

We evaluated MLCatchUp using a dataset that we collected from public GitHub repositories using our prototype Python API usage GitHub search tool. Our evaluation dataset is comprised of 258 files containing 514 deprecated API usages from 66 different Python machine learning library APIs. The update results created by MLCatchUp are manually labelled by Python programmers with at least 4 years of experience who are not co-authors of this study. Based on the evaluation result, MLCatchUp achieves a precision of 86.19%. We also conducted a qualitative study on the failed update results, where we found one of the main faults to be MLCatchUp’s inability to infer transformation constraints for context-dependent deprecated API migrations. To mitigate this problem, we add a feature into MLCatchUp to accept additional user input in the form of a transformation constraint. Using this feature, we conducted a follow-up experiment where MLCatchUp achieved 93.58% precision.

MLCatchUp is beneficial for library users, library developers, and future researchers who aim to ease the process of updating deprecated API usages. For library users, MLCatchUp can be used to assist them in updating the usages of deprecated API within their codebase, significantly reducing the time required to update into a newer version of a library. Library developers can create a script that makes use of MLCatchUp to update deprecated API usages within code. This script can then be distributed alongside the update of the library, making it easier for users to update the library. For future researchers, MLCatchUp can be a foundation for studies and tools on automated deprecated API usage update, especially for the Python programming language.

In summary, the main contributions of this work are as follows:

- We collect a list of Python deprecated APIs from the releases over the last two years of Scikit-Learn, TensorFlow, and Pytorch by manually reading their dependencies.
We define the dimensions of Python deprecated API usage migrations and compute the distributions for each dimension’s categories to determine which type of API usage migration should be prioritized in the creation of an update tool.

We create MLCatchUp, an automated Python API usage update tool that can infer the required API transformation automatically. To the best of our knowledge, we are the first to create such a tool for Python.

We evaluate MLCatchUp using our manually collected dataset of 514 deprecated API usages collected from public Github repositories, where MLCatchUp achieves 86% precision.

The rest of the paper is organized as follows. Section 2 discusses our empirical study of Python deprecated API usage migrations and our findings from this study. Section 3 talks about the structure and features of our Python API usage automated update tool, MLCatchUp. Section 4 describes our evaluation of MLCatchUp, including the dataset used, the evaluation results, and our findings. Section 5 talks about the threats to validity of our work. Section 6 discusses related works on API deprecation and program transformation. Finally, Section 7 summarizes and concludes our work and talks about the possibilities for future work.

2 Empirical Study

Through this empirical study, we seek to get a better understanding of the categories of deprecated API migrations when updating usages of deprecated machine-learning APIs in Python. We also measure the distribution of these categories to better comprehend which categories are the most relevant to Python machine-learning libraries. Using these findings and analysis, our aim is to create a tool that can automate the process of updating the usage of deprecated Python machine learning APIs.

The process of our empirical study is as follows. First, we define the research questions that we attempt to answer. Second, we select the libraries and APIs that we use as our case study and define our approach in collecting those APIs. Third, we analyze the categories of deprecated API migration from our case study to answer our first research question. Finally, we measure the distribution of the deprecated API migration categories within our case study APIs to answer the second research question.

2.1 Research Questions

In this empirical study, we analyze the API migration dimensions of Python machine learning libraries and their prevalence in these libraries. We ask the following research questions:

• **RQ1** What are the dimensions of the API migrations for Python machine-learning deprecated API usages?

  Currently, the API migration dimensions in deprecated Python APIs are unknown. Understanding these dimensions and their categories would help us in designing an automatic deprecated API migration tool.

• **RQ2** What is the distribution of deprecated API migrations in Python machine-learning libraries?

Understanding the frequency of each API migration dimension and its categories will help researchers to determine the most common API migrations. Having such an understanding is beneficial in creating tools to ease the process of updating deprecated APIs. Information on the frequency of each API migration dimension’s categories will help researchers and API migration tool developers in determining what type of API migration should be prioritized in the creation of an update tool.

2.2 Case Study Data Collection

One of the main problems in collecting API deprecations from Python machine-learning libraries is that there are no clear specifications or standards on how the deprecations are documented. Each of these machine learning libraries has a different way of documenting their API deprecations. Moreover, even within the same library, the documentation for API deprecation varies. While Python provides a warning function that can be used to mark a deprecated API, it is not commonly used by API developers.

As a consequence of the varying deprecation documentation, there is no automatic approach capable of listing the deprecations of machine learning library APIs. Furthermore the documentation and changelogs of all of the libraries that we consider are in the form of unstructured text, making it even harder to automatically collect the API deprecations. Thus, we collected the API deprecations by manually reading the changelog of each library. To ease our search, we focused on looking for text containing the word “deprecate-” and “replace-”, which indicates API deprecation or replacement. For scikit-learn, the changelog is available in their official documentation page. For Pytorch and TensorFlow, the changelog can be found in their Github release page.

We thoroughly read the documentation provided by each library to collect a list of API deprecations and their updated APIs. We limit our manual collection effort to changelogs of major and minor releases in the last two years (July 2018 - August 2020). For scikit-learn, we read the changelogs of versions 0.21.0, 0.22.0, and 0.23.0. For Pytorch, our study includes the changelogs of versions 0.4.1, 1.0.0, 1.1.0, 1.2.0, 1.3.0, 1.4.0, 1.5.0, and 1.6.0. Lastly, we included the changelogs of TensorFlow versions 1.9.0, 1.10.0, 1.11.0, 1.12.0, 1.13.0, 1.14.0, 1.15.0, 2.0.0, 2.1.0, 2.2.0, and, 2.3.0.

From the documentation, we found a total of 112 pairs of deprecated APIs and their updated APIs, distributed across the libraries as shown in Table. TensorFlow has the highest number of deprecated APIs due to a significant update from version 1.x to 2.x, which introduced a compatibility API module. This compatibility module provides an interface to make use of deprecated APIs from the older version of TensorFlow. The creator of TensorFlow recommends to immediately update any use of the compatibility module API to the newer API in the 2.x versions.
2.3 RQ1: Deprecated API Migration Dimensions

In this research question, we aim to find the deprecated API migration dimensions in Python machine-learning libraries. To answer this research question, we utilized thematic analysis, which is a qualitative data analysis method for systematically identifying, organizing, and offering insight into patterns or themes across a dataset [11]. We followed the six steps of thematic analysis using the 112 deprecated APIs that we collected. These steps are as follows:

1) Familiarization with the data. Familiarization with the data is done by thoroughly reading and analyzing the deprecated API migration data that we collected. In our study, data refers to the deprecated and updated signatures of the 112 deprecated APIs that we collected.

2) Initial coding of the data. Code refers to the patterns or actions of the API migrations that are done to update the usage of deprecated APIs.

3) Searching for themes. In our study, themes are the dimensions of deprecated API migrations. In this step, we search for the common dimensions of API migration that appear in multiple different deprecated APIs.

4) Reviewing themes. We review the dimensions of API migrations that we found to ensure that all of the found dimensions are relevant. Similar dimensions are merged, while irrelevant dimensions are discarded.

5) Defining and naming themes. We define the dimensions of deprecated API migrations and provide an informative name for each dimension that reflects its themes and meaning.

6) Writing up the results. Finally, we write the result of our analysis, which is compiled in the empirical study of this paper.

We found three dimensions of deprecated API migration, which are related to the update operation required to perform the migration, the API mapping from the deprecated to the updated APIs, and the context dependence of the migration (see Section 2.4 for the distribution of these dimensions). The definitions of these dimensions and their categories are as follows:

**Update Operation.** We observe common patterns in the updates required to migrate a deprecated API to its updated APIs by looking at the differences between the signatures of the two APIs. We found the following categories of update operations:

- **Remove parameter:** This operation removes the deprecated API usage function parameter(s). An example of this update operation can be seen in Figure 1. In this example, the API sklearn.cluster.KMeans has the deprecated parameter n_jobs in line 2. After the update, the parameter is removed, with the result shown in line 3.

- **Change a parameter type:** This operation changes the type of the current API argument. The operation first checks whether the type of the current API argument matches the new type. If the current argument type does not match the new type, the deprecated API argument needs to be changed to follow

- **Rename parameter:** This operation replaces one or more deprecated parameter names with a new name. Similar to remove parameter deprecation, this update operation only affect API usages where the deprecated parameter name is explicitly declared.

- **Convert positional parameter to keyword parameter:** This operation removes the positional parameter(s) and uses their value(s) to create new keyword parameter(s) within the API usage. An example of this update operation can be seen in Figure 2. In this example, the torch.add API’s second positional parameter is deprecated and replaced with the keyword parameter alpha. The deprecated API usage can be seen in line 4, while the updated code can be seen in line 5.

- **Rename a method:** This operation renames the function and/or the module of the API that is deprecated into a new updated name. Figure 3 shows an example of this update operation for a torch.gels API usage in line 3. The torch.gels method name is deprecated and is replaced with the new name torch.lstsq.

- **Add a parameter:** This operation adds a positional/keyword parameter to an API invocation, as illustrated in Figure 4. In lines 3-5, we can see the deprecated torch.nn.functional.affine_grid API usage, in which the keyword parameter align_corners is not specified. To update this deprecated API usage, a new keyword parameter align_corners needs to be added as can be seen in lines 6-7.

- **Change a parameter type:** This operation changes the type of a deprecated API usage parameter. The operation first checks whether the type of the current API argument matches the new type of the updated API. If the current argument type does not match the new type, the deprecated API argument needs to be changed to follow
def forward(self, input_image, affine_params):
    affine_grid = affine_params.view(1, 2, 3)
    affine_grid = torch.nn.functional.affine_grid(affine_params, (input_image.size(0),
                                  input_image.size(1), *self.img_size),
                                  align_corners=True)
    return self.affine_grid

Fig. 6: Migration for deprecated API usage from PyTorch.nn.functional.affine_grid

The new type specification. In this operation, a previously valid type may no longer be usable in the parameter. The creation of new variables or values may be needed in this update operation. Figure 5 provides an example of this operation for sklearn.utils.estimator_checks.check_estimator deprecated API usage. In this example, the allowed parameter type in the updated API is changed to only the Estimator type. To update this deprecated API usage, a type check is added for the function invocation argument (lines 5-8) to ensure that its value is suitable for the updated API.

- **Add a constraint to a parameter value:** This operation adds a constraint to the value of the API parameter due to a change in the permitted value of the parameter. This operation adds a value check for the API argument to ensure that the current value of the argument fits the newly permitted range of values of the API parameter.
- **Remove API:** This operation removes the deprecated API without replacing its usage with any updated API. This is typically used when the deprecated API is no longer needed or no longer has any effect when invoked.

import torch
from sklearn.linear_model import logistic_regression_path

def KFold_Selection(seed):
    from sklearn.model_selection import KFold
    if seed is not None:
        KFold(random_state = seed, shuffle=True)
    else:
        KFold(random_state = seed)

Fig. 7: Migration for sklearn.linear_model.logistic_regression_path deprecated API usage from sklearn version 0.21.0

The type of mapping represents the ratio between the number of the deprecated and updated APIs involved in the migration. We found three types of mappings from our investigation:

- **1:1 API mapping:** It occurs when a deprecated API is modified or replaced by a single updated API.
- **1:N API mapping:** It occurs when a deprecated API is modified or replaced by at least two updated APIs.
- **1:0 API mapping:** It occurs when a deprecated API is removed without any suggested replacement.

**Context Dependency.** It indicates whether the deprecated API migration depends on the context of the deprecated API usage. This context refers to the value and type of the arguments in the deprecated API usage. We found two categories of context dependency.

- **Context-dependent update.** It is a migration where the required update depends on the value of one or more arguments of the API invocation. An example of this case is found in the sklearn.model_selection.KFold API, where the usage is only deprecated if the random_state argument is not None, in which case the shuffle argument must be set to True. Otherwise, there is no change to the API. For example, in Figure 8 the update is done by adding an if statement that checks the value of the contextual variable seed used as the random_state argument.
- **Context-independent update.** This migration is not affected by the value of the API invocation arguments.

2.4 RQ2: Migration Dimensions Distribution

In the second research question, we are interested in the distribution of deprecated API migration categories within the dimensions defined in Section 2.3 update operation, API
TABLE 3: Distribution of the case study API based on the required update operation to perform the migration

| Update Operation   | Scikit-learn | PyTorch | TensorFlow |
|--------------------|--------------|---------|------------|
| Remove Param       | 12           | 1       | 0          |
| Rename Param       | 0            | 1       | 25         |
| Post Key Param     | 0            | 8       | 0          |
| Rename Method      | 4            | 18      | 17         |
| Add Parameter      | 2            | 1       | 9          |
| Change Param Type  | 2            | 3       | 0          |
| Add Param Value Con| 1            | 4       | 0          |
| Remove API         | 1            | 0       | 3          |

TABLE 4: Distribution of the case study API based on its API mapping

| API Mapping Type | Scikit-learn | PyTorch | TensorFlow |
|------------------|--------------|---------|------------|
| 1:1               | 21           | 36      | 50         |
| 1:N               | 0            | 0       | 1          |
| 1:0               | 1            | 0       | 3          |

First we label each API based on its update operation. The results of this labelling can be seen in Table 3. The common operations vary according to the library. We found that most deprecated API migrations in scikit-learn involve removing parameter. PyTorch and TensorFlow deprecated API migrations also often rename parameters. Among the update operations, change parameter type, add constraint to parameter value, and remove API are the least commonly used, amounting to 5 or fewer APIs for each update operation.

Then, we label each API based on its update context. The results of this labelling can be seen in Table 4. The majority of the API updates are context-independent. Out of 112 APIs, only 9 API updates are context-dependent.

TABLE 5: Distribution of the case study API based on the contextual dependency of the API update

| Context Type            | Scikit-learn | PyTorch | TensorFlow |
|-------------------------|--------------|---------|------------|
| Context-independent     | 19           | 30      | 54         |
| Context-dependent       | 3            | 6       | 0          |

From these distributions within the three dimensions we found that simpler updates are preferred among different Python machine learning libraries. Rename method, rename parameter, add parameter, and remove parameter are the most commonly used, each with at least 10 APIs using the approach. 107 out of 112 APIs follow the 1:1 update mapping, suggesting a tendency towards a less complex updates. Finally, majority of API updates are context-independent, which is the case for 103 out of 112 APIs. We leverage these findings to guide our priorities in creating automated update tool for Python deprecated API usage.

3 Automated Update for Python Deprecated API Usages

Based on the findings of our empirical study and the fact that Python deprecated APIs are still being used by developers, we are interested in creating an automated approach to update the usage of Python deprecated APIs. We incorporate the findings of our empirical study in creating this update tool, mainly to direct the types of transformations that the tool should support.

We create MLCatchUp, a tool that provides automated update for Python deprecated API usage. MLCatchUp infers the required transformations for the update by comparing the difference between the deprecated API signature and the updated API signature. Using these API signatures and a code containing the usage of deprecated API as an input, MLCatchUp will automatically provide a new version of the code where all usages of the specified deprecated APIs are replaced with the corresponding updated API. During the transformation process, MLCatchUp utilizes a domain-specific language to make its transformation more readable for the users. In the following subsections, we discuss in detail on the architecture and features of MLCatchUp.

3.1 MLCatchUp Architecture

The architecture and pipeline of MLCatchUp are given in Figure 9. There are two main inputs to MLCatchUp, namely the input Python file (O-1), and the input API signatures (O-2). The input Python file is the file that is going to be updated, while the input API signatures are the deprecated API signature and the updated API signature. The input Python file is transformed into its AST using the abstract syntax tree module provided by Python. Then, MLCatchUp detects and locates the usage of the deprecated API based on the deprecated API signature. Our approach in this deprecated API detection is adapted from the work of Wang et al. [2], which is done through the normalization of all API usages into their fully qualified name, and comparisons of these names to the deprecated API signature.

Input API signatures are used in the transformation inference process (S-2) where the necessary transformations for the API migration are automatically inferred. The necessary transformations are in the form of DSL commands (O-4), containing a series of atomic operations required for the update (e.g., rename method, rename parameter, etc.) which are to be performed sequentially. The DSL is then parsed by the DSL parser (S-3) into a list of operations that can be executed by MLCatchUp. These operations are applied to the input file AST (S-4), producing the updated AST (O-5).

The updated AST is then compared with the input file AST by using the code diff checker (S-5), which lists all the code differences between the two ASTs and outputs the update diff (O-6). Finally, based on the code differences in the update diff (O-6), the update is applied to the input Python file (S-6) by making only the necessary changes to

8. https://docs.python.org/3/library/ast.html
the API usages without any modification to the original code comments and spacing. This results in the updated input file (O-7).

In the following sections, we describe in detail the main components of the MLCatchUp automated update process. Section 3.2 explains the transformation operations provided by MLCatchUp and their DSL equivalents. This section also describes the grammar of the DSL that is used by MLCatchUp. Section 3.3 discusses how our approach creates the automatic transformation based on the deprecated and updated API signatures.

### 3.2 Transformation Operations and DSL

In providing the required update to mitigate the usage of a deprecated API, MLCatchUp makes use of several basic transformation operations. We choose the required basic transformation operations based on the result of our empirical study, where we found that the varieties of deprecated API migration can be summarized into 8 different update operations, as described in Section 2.3.

We leverage these findings as the building block of the automatic update functionality provided by MLCatchUp. Each operation within MLCatchUp is paired with a corresponding construct in the domain specific language to describe the transformation. The required transformation operations for each API migration are inferred automatically, as we will discuss in Section 3.3. This transformation inference process will produce a DSL script that specifies all the required transformations between a pair of deprecated and updated API.

The grammar of the DSL in EBNF (Extended Backus–Naur Form) is shown in Figure 10.

Each transformation listed in the DSL grammar corresponds to a basic transformation operation provided by MLCatchUp. The mapping between each basic transformation operation and its DSL grammar is shown in Table 6.

### 3.3 Transformation Inference

MLCatchUp automatically infers the required change to update the usage of the deprecated API using the deprecated and updated API signatures as its inputs. Based on these signatures, MLCatchUp produces DSL commands containing the steps required to update code containing deprecated API usages.

We define an API signature as the fully qualified name of the API and the list of parameters available for the API, where each parameter consists of its name, type, and an optional default value. A fully qualified API name consists of the API module names and the API function name. This information is sufficient as Python does not provide method overloading. The API parameter definition is declared in the form of a comma separated list of positional and keyword parameters, where each parameter has a specific type and may include a default value. To separate positional and keyword parameters, the symbol * is used. The syntax that is accepted by MLCatchUp for API signatures is shown in Figure 11.

The difference between the deprecated API signature and the updated API signature is used to automatically infer the required transformation for the API usage update. The pseudocode of this transformation inference is shown in Algorithm. The transformation inference takes as inputs the deprecated API signature and the updated API signature. Using these inputs, several steps are done to produce the DSL commands to update the deprecated API usage. First, if the updated API signature is an empty string, we add a `remove_api` operation (lines 2-3). If the updated API

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**TABLE 6: Mapping between each transformation operation and its DSL grammar**

| Transformation Operation | DSL Grammar                      |
|--------------------------|----------------------------------|
| Rename Method            | <rename_method>                  |
| Rename Parameter         | <rename_parameter>               |
| Remove Parameter         | <remove_parameter>               |
| Convert Positional to Keyword Parameter | <positional_to_keyword_parameter> |
| Add Parameter Type       | <add_parameter>                  |
| Change Parameter Type    | <type_constraint>                |
| Add Constraint to Parameter Value | <value_constraint>              |
| Remove API               | <remove_api>                     |
⟨transformations⟩ ::= ⟨transformation_op⟩ [ if ⟨transformation_constraint⟩ ]; +

⟨transformation⟩ ::= ⟨rename_method⟩
                  | ⟨rename_parameter⟩
                  | ⟨remove_parameter⟩
                  | ⟨positional_to_keyword_parameter⟩
                  | ⟨add_parameter⟩

⟨rename_method⟩ ::= rename_method ⟨old_method⟩ to ⟨new_method⟩

⟨rename_parameter⟩ ::= rename_parameter ⟨old_parameter_name⟩ to ⟨new_parameter_name⟩ for ⟨old_method⟩

⟨remove_parameter⟩ ::= remove_parameter ⟨old_parameter_name⟩ for ⟨old_method⟩

⟨positional_to_keyword_parameter⟩ ::= positional_to_keyword parameter ⟨parameter_position⟩ keyword ⟨new_parameter_name⟩ for ⟨old_method⟩

⟨add_parameter⟩ ::= add_parameter ⟨new_parameter_name⟩ with value ⟨expression⟩ for ⟨old_method⟩

⟨remove_api⟩ ::= remove_api ⟨old_method⟩

⟨transformation_constraint⟩ ::= ⟨transformation_constraint⟩ and ⟨transformation_constraint⟩
                           | ⟨transformation_constraint⟩ or ⟨transformation_constraint⟩
                           | [not] ⟨old_parameter⟩ ⟨constraint_definition⟩

⟨constraint_definition⟩ ::= ⟨type_constraint⟩
                        | ⟨value_constraint⟩

⟨type_constraint⟩ ::= has type ⟨type⟩

⟨value_constraint⟩ ::= has value ⟨expression⟩

⟨old_method⟩ ∈ a set of deprecated API signature

⟨new_method⟩ ∈ a set of updated API signature

⟨old_parameter_name⟩ ∈ a set of parameter name

⟨new_parameter_name⟩ ∈ a set of parameter name

⟨parameter_position⟩ ∈ a set of positive number

⟨type⟩ ∈ a tfpdef

⟨expression⟩ ∈ a expr

Fig. 10: Grammar of the MLCatchUp domain specific language

Fig. 11: Syntax of MLCatchUp API signature

signature is not empty, we compare the fully qualified name (line 5) of the deprecated and updated API signature, and add a rename_method operation if the names differ (line 6). Then, we eliminate identical API parameters from both API signatures (line 8), as the same parameters between the two APIs will not affect the API update. Two API parameters are considered identical if they have the same keyword or position, and the same type.

After removing identical parameters, we compare the remaining API parameters from the two API signatures. Two possible actions are taken during this comparison. First, if two API parameters have the same type but different keyword names, we add a rename_parameter operation into the DSL (lines 11-14). Second, if two API parameters have the same type, but there is a positional parameter in the deprecated API signature and a keyword parameter in the updated API signature, we add a positional_to_keyword_parameter operation (lines 15-18). Then, we check whether there are any remaining API parameters in the deprecated and the updated API signatures. Each of the remaining API parameters in the deprecated API signature is added as a remove_parameter operation into the DSL commands (lines 19-21). Finally, for each remaining API parameter in the updated API signature, we add an add_parameter operation.

As an illustration, consider the TensorFlow.compat.v1.to_float() deprecated API. This API usage needs to be updated to use the TensorFlow.cast(dtype=TensorFlow.float32) API. Using these API signatures, MLCatchUp performs the transformation

9. https://docs.python.org/3.6/reference/grammar.html
These DSL commands can then be applied to files containing the deprecated `TensorFlow.compat.v1.to_float()` API usage. First, the file needs to be parsed into its AST. Then, each DSL command is parsed and translated into the corresponding transformation that is applied to the AST. After all the transformations are applied, the AST is changed back into the code form and the code differences between the updated code and the deprecated code are presented to the users. Based on these code differences, MLCatchUp applies the transformation to the original code, making only the necessary changes towards the deprecated API uses, retaining the comments and spacing of the original code. An example result of the update is shown in the code diff in Figure 13.

While MLCatchUp can infer the required transformation operations, MLCatchUp is unable to infer the required information regarding any added constraints for the transformation itself. Indeed the API signatures do not provide such information. To mitigate this problem, we allow MLCatchUp to be run with an optional argument in which the user can specify the transformation constraint as an input. This input constraint must be written using the MLCatchUp domain specific language. An example of the inferred DSL script and the provided input constraint for the `sklearn.model_selection.KFold` API update is shown in Figure 14.

In Figure 14 we see that from the API signatures, MLCatchUp is able to infer that `sklearn.model_selection.KFold` deprecated API usage needs to be updated with the addition of `shuffle:bool=True` parameter. However, MLCatchUp is unable to obtain the transformation constraint information from the API signatures, providing an incomplete inferred series of transformation commands. In actuality, the add parameter update operation should only be done if the value of `random_state` parameter is not None. This constraint is expressed through a user input constraint.

4 MLCatchUp Evaluation

To evaluate MLCatchUp, we conducted an experiment to analyze the update results. In this section, we explain the setting, data, and results of this evaluation. We also conduct a qualitative study on the kinds of deprecated API usages.
that cannot be updated successfully by MLCatchUp and discuss the possible approaches to mitigate them for future work.

4.1 Dataset Collection
Based on our empirical study, we use deprecated APIs from Scikit-learn, TensorFlow, and Keras libraries for our evaluation. We consider the 112 identified deprecated APIs from the three libraries. In order to provide a realistic evaluation, we use real API usages for our evaluation. With this in mind, we directed our API usage search towards public GitHub repositories, which contain code from developers across the globe.

At first, we tried to use the GitHub code search API\(^\text{10}\) by using the deprecated API signature as the text-based search query. However, a lot of irrelevant results were returned, as the search cannot differentiate between API usages and other code elements. Accordingly, we created a prototype GitHub search engine that is able to accurately find code containing usage of Python APIs.

We adapted the work of Wang et al.\(^\text{2}\) to build this search tool. Our search tool makes use of the GitHub search API, allowing up to 1,000 repositories to be retrieved for each search query. For the deprecated API usage detection, we utilized API normalization which rewrites all API usages in the code with their fully qualified name. Each fully qualified name is matched with the deprecated API signature to detect usages of deprecated APIs in the code. We also added multiprocessing capability to our search tool, reducing the execution time. Using the deprecated API signatures as the input, we collected our evaluation data.

4.2 Evaluation Dataset
Using our search tool, we collected code containing deprecated API usages from GitHub public repositories for the 112 case study APIs. Out of the 112 APIs, we found public code usages for only 66 APIs. For each of these 66 APIs, we collected at most five files containing deprecated API usage for our evaluation dataset. For deprecated APIs used by more than five files, we randomly selected the five files. Meanwhile, for deprecated APIs used by only five or fewer files, we used all of the files for our evaluation. In total, we collected 258 files containing 514 API usages from 66 different APIs. 45 files contain Scikit-learn API usages, 89 files contain TensorFlow API usages, and 124 files contain PyTorch API usages.

4.3 Experiment Setting
We conducted an experiment to evaluate the ability of MLCatchUp to update the usage of deprecated APIs. We aim to measure how precise the updates produced by MLCatchUp through this experiment. With this goal in mind, we calculated the precision of the update result. We define precision as the percentage of the correct updates performed during the test. The formulas for precision is shown below:

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

Instances of deprecated API usages are automatically detected and updated using MLCatchUp based on the input API signatures and the inferred transformations. For each updated API usage, there are three possible labels:
1) True Positive (TP): deprecated API usage is updated correctly
2) False Positive (FP): deprecated API usage is updated incorrectly, i.e. the updated API usage is incorrect

To label the update result, we employed the help of three Python programmers with at least four years of experience. These programmers are non-authors, and were given instruction and training before they conducted the labelling process. Each instance of the deprecated API usages is labelled by two different programmers. If any labelling disagreement arises between the two programmers, we conducted a discussion until a consensus is achieved. Throughout the labelling process, only two labelling disagreements occurred, which results in 99.61% inter-rater reliability.

4.4 Experiment Result Without User-Provided Constraints
We evaluated MLCatchUp following the scenario described in Section\(^\text{4.3}\). The transformation operations for each deprecated API usages are automatically inferred by MLCatchUp from their deprecated and updated API signatures. These transformation operations are then applied to the file containing the deprecated API usage, producing the updated file. The result of this experiment is shown in the second row of Table\(^\text{7}\).

From the experiment, MLCatchUp achieved a precision of 86.19%. There are 71 updated code that are labelled as false positives, indicating instances of deprecated API usages that were not updated correctly by MLCatchUp. One of the main reasons for the presence of false positive results is due to the transformation constraint not being present for context-dependent updates because such a constraint cannot be automatically inferred by MLCatchUp.

![Fig. 14: DSL commands with input constraint for migrating sklearn.model_selection.KFold deprecated API usage from scikit-learn version 0.23.0](image-url)
4.5 Adding Constraints to MLCatchUp’s Inferred DSL

We further improve the transformation precision of MLCatchUp by adding user-specified transformation constraints for context-dependent deprecated API usage updates. Within the evaluation dataset, we found that there are 21 files containing 49 context-dependent deprecated API usages. Failures in updating these API usages is one of the main contributors for the false positive updates produced by MLCatchUp.

While MLCatchUp is unable to automatically infer the required transformation constraint from the API signatures, MLCatchUp does provide the capability to include such constraints in its transformation. In particular, MLCatchUp accepts transformation constraint in its DSL, as shown in `<transformation_constraint>` non-terminal in Figure[10].

Using this additional input, we conducted a follow-up experiment on MLCatchUp using the same test dataset. We manually define the required transformation constraints for each context-dependent deprecated API usage migration and add them as an input to MLCatchUp. In total, we manually write 7 transformation constraints. The result of this follow-up experiment is shown in the third row of Table[7].

Using the additional input constraints, MLCatchUp achieves 93.58% precision, which is a 7.39% improvement compared to the previous experiment. From the 49 context-dependent deprecated API usages, 38 are updated successfully. While the addition of the user input constraints improves the overall precision of MLCatchUp update result, there remain some false positives. Out of the 514 deprecated API usages, 33 are updated incorrectly. To understand the reasons for these failures, we conducted a qualitative study, which we will discuss in the next sub-section.

4.6 MLCatchUp’s Failed Migrations

Based on our evaluation of MLCatchUp, we see that there are 33 instances of deprecated API usage that are updated incorrectly. We analyze these cases, aiming to find the reasons of these failed migrations. The reasons are:

1) API usage migration involving arithmetic operations. Deprecated API usage migration may involve arithmetic operations between the updated API usage and other values. This arithmetic operation is not handled by MLCatchUp. This case is found in the `torch.addcdiv` deprecated API migration, shown in Figure[15]. In this example, the deprecated API usage line 1 needs to be replaced into an arithmetic operation between the input parameter of the deprecated API usage and a `torch.floor_divide` API invocation line 2. In the future, we can add support for arithmetic operation in MLCatchUp to handle this type of API migration.

```
1 - torch.addcdiv(input, tensor, other)
2 + input + torch.floor_divide(tensor, other)
```

Fig. 15: Migration for `torch.addcdiv` deprecated API usage from Torch version 1.6.0

2) API usage migration involving 1:N API mapping. Currently, MLCatchUp only handles API usage migrations with 1:1 and 1:0 API mappings, which are the most common API mapping migration categories of Python deprecated API usage. An example of the 1:N case is found in the `tensorflow.compat.v1.sparse_to_dense` deprecated API migration, where the update requires adding an invocation of `tensorflow.sparse.SparseTensor` and changing the API name of `tensorflow.compat.v1.sparse_to_dense` to `tensorflow.sparse_to_dense`. This API migration is illustrated in Figure[16].

In the future, it is possible to extend the operations provided by MLCatchUp to include operations adding new API invocations. We would also need to enable the automatic transformation inference to infer the required transformations for a 1:N API migration mapping.

```
1 - indices_scattered = tf.compat.v1.sparse_to_dense{
2 - sparse_indices, tf.cast(tf.shape(shape),
3 - tf.int64), indices_gathered}
4 + sparse_tensor = tf.sparse.SparseTensor(sparse_indices,
5 + indices_gathered, tf.cast(tf.shape(shape),
6 + tf.int64))
7 + indices_scattered = tf.sparse.to_dense(sparse_tensor)
```

Fig. 16: Migration for `tensorflow.compat.v1.sparse_to_dense` deprecated API usage from Tensorflow version 2.0.0

3) API usage migration involving value and/or type modifications of the parameter values. MLCatchUp addresses the problem of parameter value or type change through the usage of transformation constraints. However, this approach can be insufficient as some deprecated APIs require the parameter values to be updated, which typically include constructing a new value through mathematical operations or other API invocations. An example of this case is found in the `torch.masked_select` deprecated API usage, which is shown in Figure[17]. In the deprecated version, `torch.masked_select` allows for `IntTensor` as its second positional parameter. In the updated version, the second positional parameter must be of type `BoolTensor`, hence the conversion is done using the `torch.gt` API in line 3. In the future, it is possible to add more operations into MLCatchUp that would enable modifications of the values of API parameters.

```
1 - import torch
2 - def MAPE_torch(pred, mask):
3 +   mask = torch.gt(true, mask - 0.01)
4 -   pred = torch.masked_select(pred, mask)
```

Fig. 17: Migration for `torch.masked_select` deprecated API usage from PyTorch version 1.2.0

4) API usage migration involving parameter name and position changes of multiple API parameters with the same type. In this deprecated API migration, the deprecated API parameter names are changed into the new names described in the updated API signature. However, to infer the new names for the deprecated API parame-
Threats to **internal validity** also apply to the accuracy of the labelling done in the MLCatchUp evaluation. As the update result labelling is done by humans, there exists a possibility of human error. To mitigate this problem, each instance of the deprecated API usages is labelled by two different programmers. If any disagreement occurs, a discussion is conducted to achieve a consensus.

Threats to **construct validity** relate to the suitability of the evaluation metric that we chose for MLCatchUp evaluation. We used precision as the metric to evaluate the update results of MLCatchUp by measuring the percentage of correct update produced by MLCatchUp in our test dataset of 258 files. This metric has also been used to evaluate existing tools on automatic update of deprecated APIs [7]. Thus, we believe the threats are minimal.

**6 Related Work**

**API deprecation.** API deprecation is a topic that has been studied extensively [12], [13], [14], [15], [16], [17], [18], [19], [20]. Zhou and Walker [12] created a lightweight framework to detect deprecated API usages in source code examples on the web for Android API usage. Brito et al. [13] proposed a recommendation tool to infer replacement messages by mining solutions adopted by developers. This recommendation tool aims to help developers to find deprecated API alternatives. Sawant et al. [14], [15] explored the reaction of API users towards API deprecations. They found that most developers do not update their API usages due to the cost of update not being worth it. When they do react, they prefer to fix the code by deleting the deprecated API instead of replacing it with the updated API. A similar study by Hora et al. [16] explored the impact of API evolution and found that API changes can affect the whole ecosystem. They also found that client developers need some time to discover and apply the new APIs, while the majority does not react at all. Xavier et al. [17] found that the frequency of API deprecations increase over time and systems that are more popular have higher frequency of deprecations. Li et al. [18] characterize deprecated Android APIs and found that usage of deprecated APIs are mostly found in popular libraries. Our study is focused on the API deprecation of Python machine learning libraries. We manually collected a list of 112 deprecated APIs from three popular Python machine learning libraries, namely Scikit-Learn, TensorFlow, and PyTorch. These were the most popular machine learning libraries and contain APIs that have been deprecated in the last 2 years. We made this pragmatic choice to address the recent pain points that many developers face. We designed MLCatchUp based on the results of our empirical study, which may not hold true for other libraries and APIs. There were also cases where MLCatchUp is unable to produce correct update, which we discussed in Section 4.6. In the future, we plan to extend our study to cover more recent releases of popular ML libraries – the landscape of ML libraries may continue to change and other ML libraries may become more popular than the three we investigated. We also plan to address the limitations of MLCatchUp, mainly its inability to migrate 1:N API mappings.

**API migration.** Multiple works and studies on API migration have been done [19], [20], [21], [22], [23], [24]. Bogart et al. [19] found that different programming ecosystems have different expectations towards API breaking changes. Cossette and Walker [20] conducted a retroactive study on API incompatibilities between several versions of Java.
libraries. From their manual analysis, they found that the majority of API changes cannot be automatically transformed without severe restrictions and that the majority of changes to an API were not documented properly. The tool apiwave [21] keeps track of API popularity and migration of major frameworks and libraries from top 650 GitHub Java projects. Li et al. [22] conducted an empirical study on web API evolution by analyzing the evolution of five popular web APIs. They found that web APIs evolve in limited patterns and that most of the API changes in web APIs involve refactoring. Dig and Johnson [23] study the requirements for API migration tools by analyzing the API changes of three frameworks and one library in Java. They found that from their case studies, more than 80% of the API changes are refactoring, indicating an important role of refactoring in API migration. Xia et al. [24] performs large-scale study on the current practice of handling evolution-induced compatibility issues in Android apps. They proposed RAPID, an automated tool to determine whether a compatibility issue has been addressed or not through utilization of static analysis and machine learning techniques. Our study is focused on the API migration of Python machine learning deprecated API usages. We defined the dimensions of API migration for Python machine learning deprecated API usages using the case study of 112 deprecated APIs.

Program transformation. Works on program transformation has also been done [4], [5], [6], [7], [25], [26], [27], [28], [29], [30], [31], [32]. LASE [25] is an Eclipse plug-in that provides an example-based program transformation. LASE is able to create a context-aware edit script from code examples, and uses the script to transform the code. Sydit is a program transformation tool that helps developers in systematic editing task involving similar changes in multiple places. Given a source and target method, Sydit learns and applies systematic edits which results are displayed to the programmer to review and approve. REFAZER [26] was proposed by Rolim et al. to automatically learn program transformations through observation of code edits performed by developers. REFAZER synthesizes program transformations for Python code by leveraging inductive programming using input-output examples. Coccinelle [27], [28], a program matching and transformation tool for C language, allows program developers to write code manipulation rules in terms of code structure. Transformation in Coccinelle is expressed in the form of semantic patch language (SmpL), which has a syntax similar to a code diff. A port of Coccinelle for Java language, called CoccinelleJ was also proposed by Kang et al. [29]. SPINNER [32] is capable of automatically inferring Coccinelle semantic patches from existing code change examples for the Linux kernel. SPINNER considers similar code fragments and control flows in the changes to identify the change patterns.

A4 [4] is an approach to assist developers with Android API migration by leveraging source code examples to learn the API migration patterns. A4 can either automatically migrate API calls with little to no extra modifications or provide a guidance to assist with the migration. More recently, Fazzini et al. [5] created AppEvolve which transforms the usage of deprecated Android APIs into backward-compatible updated code by learning from code examples. Haryono et al. [6] presented a new tool for automatic Android API update called CocciEvolve which is built on CoccinelleJ. CocciEvolve shows an improvement from AppEvolve in the form of readable transformations and its capability to produce working updates with only a single update example. Thung et al. [7] proposed NEAT, a tool to generate transformation rules that can assist developers in deprecated API replacement without code example for Android APIs. NEAT uses the signature graph from the source code of the API library to convert between one type and another. In our work, we proposed MLCatchUp, which automates the update of Python machine learning deprecated API usages. MLCatchUp does not require any code example to provide its transformation, but rather infers the required transformations through the difference between the deprecated and updated API signatures and presents these transformations in the form of a DSL. MLCatchUp is built for the Python programming language, bringing a set of difficulties previously unseen in other programming languages, such as positional and keyword parameters, default parameter values, usage of whitespaces as separator, and dynamic typing which allows a variable to have different types during the program execution.

7 Conclusion and Future Work

We conducted an empirical study to learn the dimensions of the API migrations required by Python deprecated APIs. We manually collected a list of 112 APIs and their updated API signatures from three popular Python machine learning libraries: Scikit-Learn, Tensorflow, and PyTorch. Using manual thematic analysis, we found three dimensions in the deprecated API migrations: update operation, API mapping, and context dependency.

Based on findings in our empirical study, we created MLCatchUp, an automated tool to update the usage of Python deprecated APIs. MLCatchUp automatically infers the transformation operations to migrate and update the usage of a deprecated API. Given the API signatures and the file containing deprecated API usages, MLCatchUp automatically lists the transformations in the form of a DSL and updates the deprecated API usage within the file. We evaluated MLCatchUp using a dataset of 258 files containing 514 API usages from 66 different APIs. MLCatchUp achieved 86.19% precision. We further improve MLCatchUp by adding transformation constraints input, allowing it to process the update for context-dependent deprecated API usage update. With this improvement, MLCatchUp achieved 93.58% precision, a 7.39% precision improvement from experiment without user-added constraint.

For future work, we plan to extend our study to other popular Python libraries, including non-machine learning libraries. By increasing the scope of the case study, we may encounter more variety of deprecated APIs and their migrations. We also plan to address the current shortcomings of MLCatchUp, namely its inability to create 1:N API mapping migration updates, etc.

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