

Insights into Deep Learning Refactoring: Bridging the Gap Between Practices and Expectations

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With the rapid development of deep learning, the implementation of intricate algorithms and substantial data processing have become standard elements of deep learning projects. As a result, the code has become progressively complex as the software evolves, which is difficult to maintain and understand. Existing studies have investigated the impact of refactoring on software quality within traditional software. However, the insight of code refactoring in the context of deep learning is still unclear. This study endeavors to fill this knowledge gap by empirically examining the current state of code refactoring in deep learning realm, and practitioners' views on refactoring. We first manually analyzed the commit history of five popular and well-maintained deep learning projects (e.g., PyTorch). We mined 4,921 refactoring practices in historical commits and measured how different types and elements of refactoring operations are distributed and found that refactoring operation types' distribution in deep learning projects is different from it in traditional Java software. We then surveyed 159 practitioners about their views of code refactoring in deep learning projects and their expectations of current refactoring tools. The result of the survey showed that refactoring research and the development of related tools in the field of deep learning are crucial for improving project maintainability and code quality, and that current refactoring tools do not adequately meet the needs of practitioners. Lastly, we provided our perspective on the future advancement of refactoring tools and offered suggestions for developers' development practices.

Additional Key Words and Phrases: Refactoring, Deep Learning, Empirical Software Engineering

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1 INTRODUCTION

As deep learning continues to evolve rapidly, deep learning projects continue to be rapidly updated to optimize model construction, improve computing, and increase algorithm performance [18, 43]. However, if maintenance activities are not conducted properly, they can lead to a decrease in quality. The complexity of deep learning models and their high dependence on data, as well as constantly updated algorithms and techniques, present unique challenges for their maintenance. These unique challenges make the development and maintenance of deep learning projects distinct from traditional software [11].

There have been significant studies [7, 10, 16, 20, 25, 27] demonstrating the benefits of refactoring for software maintenance, reuse, and code enhancement, focused on traditional software. However, few studies have investigated code refactoring in deep learning projects, and there is also a lack of research into deep learning practitioners' views on refactoring and related tools. Investigating code refactoring in deep learning projects and uncovering the reasons behind such practices can help optimize the development process, improve team productivity, and enhance code quality. Therefore, we analyzed the state of code refactoring in deep learning repositories and investigated the perceptions of deep learning practitioners on code refactoring.

Our study aims to answer the following research questions:

RQ1: How does code refactoring behave within deep learning projects?

This RQ studies code refactoring practices in deep learning projects and uncovers how it differs from code refactoring in traditional Java software. Understanding code refactoring practices in deep learning projects is crucial to enhance maintainability. We found that the most common refactoring operation types in deep learning projects are *Remove Dead Code* and *Rename*. However, the distribution of usage for refactoring operations in Java differs from that in deep learning projects. Additionally, method-level refactorings are frequently used in deep learning projects, and variable-level refactorings are often introduced as they are easily modifiable elements. These insights not only highlight the unique challenges and implications within the deep learning domain but also lay the groundwork for tailored software engineering that is crucial to the rapidly evolving field of deep learning. We further surveyed developer perspectives on refactoring in deep learning at RQ2. Furthermore, the manual examination of commit messages unveiled indications of developers employing automation tools for refactoring tasks. Based on this finding, we further surveyed the compatibility of existing tools with the unique needs of deep learning practitioners in RQ3.

RQ2: What are the perspectives of deep learning practitioners regarding code refactoring?

Building upon insights gained from RQ1, this RQ investigates into practitioners' perspectives on code refactoring, including their opinions on specific refactoring operations and elements within deep learning. Practitioners in deep learning projects prioritize *Remove Dead Code* and *API Refactoring*, while the importance of *Pull Up* and *Push Down*, which are widely studied in traditional projects is not well recognized. *Method* and *Class* are highly regarded in deep learning refactoring. Examining practitioners' perspectives on deep learning code refactoring can validate and quantify the observations from RQ1, and provide a critical understanding of their preferences, challenges, and potential unmet needs. These insights help bridge the gap between the research and practice in current AI development, thereby aiding the development of targeted refactoring techniques for this domain.

RQ3: How well do current refactoring tools meet practitioner needs?

This RQ investigates practitioners' opinions on the effectiveness of existing refactoring tools. The findings from RQ1 revealed evidence of refactoring tool utilization within commit messages, which led us to assess the suitability of existing tools for deep learning requirements.

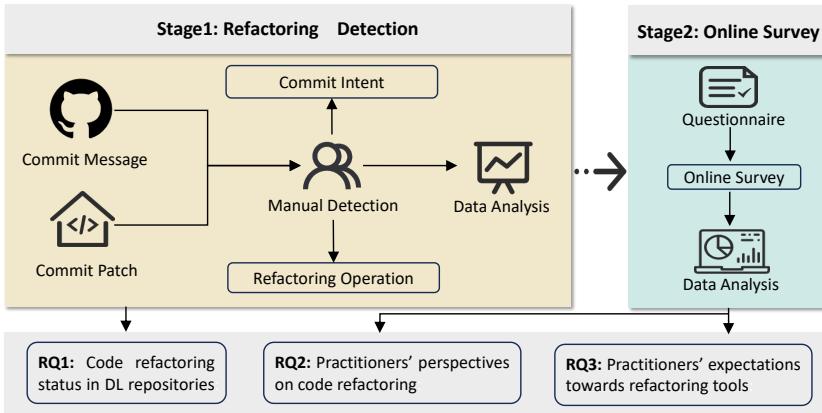


Fig. 1. Research methodology overview

Practitioners suggested combining these tools with Large Language Models to achieve more effective and context-aware results. The suggestions for improvement from deep learning practitioners emphasized user-friendliness, project-specific customization, and comprehensive testing integration. These insights aim to inform the development of future tools tailored to the distinct requirements of deep learning practitioners in the deep learning domain.

The intention behind our investigation is to facilitate consideration by researchers regarding the requirements of practitioners, thereby continuing the advancement of code refactoring for deep learning projects. Furthermore, we aim to provide new insights that can promote the development of better refactoring tools for deep learning projects. This paper makes the following contributions:

- (1) We manually analyzed five deep learning projects' commits and detected 53 types of 4,921 refactoring operations. We further analyzed the distribution of different refactoring operation types and elements in deep learning projects.
- (2) We surveyed 159 deep learning practitioners from 38 countries to shed light on practitioners' views on refactoring and their expectations of refactoring tools. To the best of our knowledge, we are the first to perform empirical study of refactoring practices in deep learning projects.

Paper Organization: Section 2 describes the methodology of our research. Section 3 shows the results of our study. We discuss the implications and threats of our results in Section 4. Section 5 discusses related work. Section 6 draws conclusions and outlines avenues for future work.

2 RESEARCH METHODOLOGY

In this section, we present the design of our empirical study. Our main goal in this study is to comprehensively understand code refactoring practices within deep learning projects, investigate practitioners' perceptions of code refactoring, and assess the alignment of current refactoring tools with the specific needs of deep learning practitioners. Our study aims to provide crucial insights for software engineering practices in the realm of deep learning and drive advancements in pertinent technologies. The overview of the methodology in our study is shown in Figure 1 and consists of two stages. **Stage 1:** Manual mining of refactoring operations from repository history commit messages manually. **Stage 2:** An online survey for confirming and extending the conclusions about the current stage of refactoring in Open Source deep learning libraries.

Table 1. Statistics of deep learning projects used in our study.

Project	Time Range	#Commits	#Star
Keras	2015/03-2023/09	8,342	60.2k
Scikit-learn	2010/01-2023/09	30,375	57k
Pytorch	2012/02-2023/09	63,722	74.3k
Transformers	2018/10-2023/09	13,900	118k
Tensorflow	2015/11-2023/09	50,863	180k
Total		167,202	

```

✓ fixing name position_embeddings to object_queries (#24652)
* fixing name position_embeddings to object_queries

* [fix] renaming variable and docstring do object queries

* [fix] comment position_embedding to object queries

* [feat] changes from make-fix-copies to keep consistency

* Revert "[feat] changes from make-fix-copies to keep consistency"

This reverts commit 56e3e9e.

* [tests] fix wrong expected score

* [fix] wrong assignment causing wrong tensor shapes

```

Fig. 2. Commit 99c3d44906ec448c4559fecdc9a63eda364db4d4

2.1 Stage 1: Refactoring Manual Detection

Since most of the deep learning projects use Python as the main programming language [23, 33, 35], we only analyzed refactoring commits that involve Python. To answer RQ1, we selected five open source deep learning projects that are widely used and well-maintained: Keras [1], Scikit-Learn [3], PyTorch [2], TensorFlow [4], and Transformer [5]. These frameworks were chosen based on their high stars and forks in GitHub. Table 1 shows statistics of deep learning projects we used in RQ1. To the best of our knowledge, there is no refactoring detection tool that can detect all common refactoring operations in Python. Additionally, some commits might contain tangled changes, making it more difficult to isolate the changes related to refactorings. Therefore, we follow previous research to mine refactoring operations from the commit [6, 13, 24, 28, 38].

2.1.1 Filter. We first crawled all commits of these five deep learning projects using the GitHub API, totaling 167,202 commits up until September 2023. However, due to the enormous amount of manual detection, we used a keyword-based filter to reduce the amount of work involved in manual detection. Developers commonly use a range of textual patterns to document their refactoring activities, including ‘extract’, ‘reorganize’, and ‘redesign’, in addition to ‘refactor’ [24]. In this part, following *Self-Affirmed Refactoring* [6], we created a keyword-based commit message filter to pre-filter potential refactoring commits. In particular, we only focused on refactoring commits in Python since the majority of the deep learning project is written in Python [33]. After the application of the keyword-based filter, we filtered 28,803 commits for manual detection.

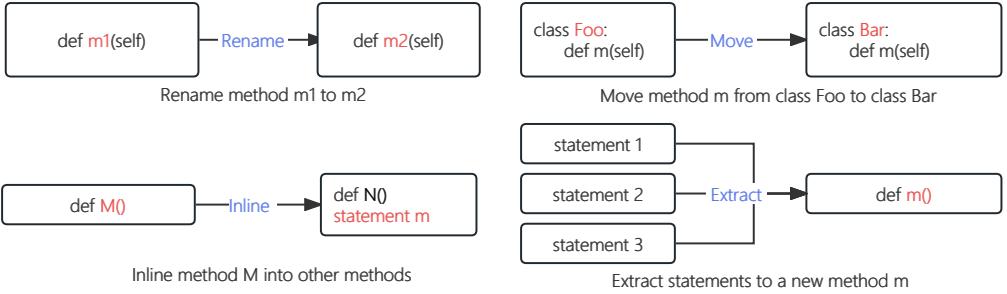


Fig. 3. Refactoring operations abstract example diagrams in method level

2.1.2 Manual Detection. After filtering all refactoring commit messages detected by keywords, We manually analyzed each commit message. This process entailed two authors analyzing the data of each code change and identifying the intent of commits. We examined each commit to identify its purpose because some commits contain refactoring-like code changes yet their actual intent is to debug or update. Commit `99c3d44906ec448c4559fecdc9a63eda364db4d4` in Figure 2 fixed the incorrect variable name, but may be mistaken for a *Rename* refactor operation. We employed a two-phase process:

(1) We first divided all the filtered commits into two bins, each evaluator independently analyzed and labeled a piece of the commit as “1” if the commit was a refactoring commit, and “0” otherwise. The evaluator further analyzed the code changes of the refactoring-related commit to determine what refactoring operation was performed by that commit, we followed Fowler’s description [16]. The evaluators ignored the tangled changes in the manual detection phase and only abstract refactoring related changes. Since refactoring practices in real-world development may differ from the description given in Fowler’s book, after each evaluator had marked 100 commits, they had a discussion to re-establish consistent refactoring classification standards. The evaluators repeated this action in all five studied projects and corrected each of the previously marked commits according to the final standards. The final standards we used differed from Fowler’s in code elements. We followed a similar information modeling approach as the one used by **REFACTORINGMINER** [39], including the following elements:

- **Module:** A module is defined as a Python file, containing classes and methods, and directly affiliated definitions and statements (i.e., those not defined within a method).
- **Class:** A class may contain definitions, methods, and statements.
- **Method:** A method contains a list of parameters (if any), and the statements it carries.
- **Statements:** A statement is the smallest unit of execution in Python and is usually terminated by a line break or a semicolon.
- **Variable:** A variable is a container for storing data and is the smallest nameable storage element in python program.

We summarized 7 most common refactoring operation types according to Fowler’s book, Figure 3 shows the abstract example diagrams of *Rename*, *Move*, *Extract*, and *Inline*.

- **Remove Dead Code:** remove invalid or redundant code fragments that are no longer being executed by the program. This type of refactoring is accompanied by “clean” and “remove unused code” in the commit message.
- **Rename:** change the name of elements for code clarity and readability. This type of refactoring consists of *Rename Module*, *Rename Class*, *Rename Method*, *Rename Variable*.

- **Move:** move code elements from one location to another. This type of refactoring consists of *Move Module*, *Move Class*, *Move Method*, *Move Statement*, and *Move Variable*.
- **Extract:** extract independent and reusable elements from larger and more complex code elements. This type of refactoring consists of *Extract Module*, *Extract Class*, *Extract Method*, and *Extract Variable*.
- **Inline:** inline a part of code directly into its place of use. This type of refactoring consists of *Inline Module*, *Inline Class*, *Inline Method*, and *Inline Variable*.
- **API Refactoring:** refactor the application programming interfaces in code. This type of refactoring usually involves parameter changes, return value changes, etc.
- **Consolidate or Decompose Conditional Expression:** refactor expressions to make them more concise, readable, and logical by consolidating or decomposing them.

There are also other unlisted refactoring operation types that rarely appear in deep learning project refactoring practices, and we identify them by following Fowler's book [16], e.g. *Pull Up* and *Push Down*. After the independent evaluation, the two evaluators checked each other's commit data that was labeled as refactoring-related. The evaluators disagreed on 439 instances out of a total of 4,921 refactoring instances. These instances were carefully discussed to reach a consensus until there was no disagreement on any code change after the second stage of refactoring operation classification. The inter-rater agreement was further quantified using Cohen's Kappa coefficient, yielding a value of 0.81, indicating substantial agreement between the evaluators in the classification of refactoring operations.

The labeled dataset is available in our replication package¹. Additionally, we also observed the usage of "Pylint", "Flake", "...Generated by Copilot." in the commit message. This indicates that developers use refactoring tools during the refactoring process, which motivated us to investigate practitioners' perceptions of current refactoring tools in **Stage 2**.

2.2 Stage 2: Online Survey

To further investigate deep learning code refactoring, we conducted an anonymous online survey with deep learning participants. The survey aimed to validate and quantify the observations from Stage 1, and to shed light on practitioners' views on refactoring and their expectations of refactoring tools.

2.2.1 Design. Combining the results of the first step and previous work [13, 14], we concluded nine refactoring operation types, five refactoring operation elements, and three types of refactoring tools to launch an online survey for deep learning practitioners. The online survey aims to provide insights into Open Source code refactoring in deep learning projects and practitioners' expectations of current refactoring tools. The refactoring operation types we employed consist of the seven most common refactoring operation types in deep learning projects from Stage 1 (*Remove Dead Code*, *Rename*, *Move*, *Extract*, *Inline*, *API Refactoring*, *Consolidate or Decompose Conditional Expression*), and two refactoring operation types that are widely studied in traditional java refactoring (*Pull Up* and *Push Down*). The elements consist of *Variable*, *Statement*, *Method*, *Class*, and *Module*. The refactoring tools consist of code smell detection tools and automatic refactoring tools.²

The survey included different types of questions, e.g., multiple-choice questions, short answer questions, and rating questions (5-point Likert scale: Strongly Disagree to Strongly Agree). We included the category "I don't know" to filter respondents who do not understand our brief descriptions. The survey consists of three sections:

¹<https://anonymous.4open.science/r/DLRF-E0C7>

²<https://forms.gle/7mFJcHXbRFGGHY9r9>

Table 2. Description of Code Refactoring Tools

Refactoring Tool	Description
Code Smell Detection Tools	Code smells are signs that your code is not as clean and maintainable as it could be. They can derive from the misuse of syntax and almost always suggest code needs to be refactored or redesigned to improve the overall quality of the program. Code smell detection tools can help developers find where to refactor to improve the quality of their code.
Automatic Refactoring Tools	Automatic refactoring tools identify problems in the code and eliminate them through refactoring. These tools reduce the effort of developers as they have very little to do during the code refactoring process.

- **Demographics:** The survey first asked for demographic information about the participants, including country/area of residence, current occupation, experience in years, and primary programming language.
- **Thoughts on Refactoring:** This section focuses on providing insights into the current state of Open Source code refactoring in deep learning projects. We started by showing clear and concise example diagrams of some of the classic refactoring operations in method level. We then invited developers to rate the nine refactoring operations and five refactoring elements in terms of importance and frequency. This section highlights practitioners' opinions towards refactoring in the deep learning software development process.
- **Tool Utilization:** The purpose of this section is to gather information about developers' usage of refactoring tools and investigate practitioners' expectations of these tools. We first provided respondents with a brief description of code refactoring tools shown in Table 2, consisting of (1) code smell detection tool [19], and (2) automatic refactoring tools [17]. Then we asked practitioners *Have you used or are you familiar with such tools?* and extended an invitation to respondents to share their observations regarding such tools. In addition, practitioners were invited to provide advice on improving refactoring tools through an open-ended question.

At the end of the survey, we allowed respondents to provide free-text comments, suggestions, and opinions about code refactoring and our survey. A respondent may or may not provide any final comments.

During the initial phase of our research, we conducted a preliminary survey with a small group of professionals who differed from our survey respondents. The purpose is to gather feedback on two key aspects: (1) the length of the questionnaire and (2) the clarity of the terms used. Based on the feedback received, we made minor modifications to the survey and finalized the questionnaire. It should be noted that the responses collected during the pilot survey were not included in the results presented in our research paper.

2.2.2 Participant Recruitment. We selected Github repositories with the top 100 popular open-source deep learning projects (based on their number of stars) and mined these repositories to extract their contributors' public email addresses. We finally mined 3,125 contributors' email addresses and sent a link to our survey. We aimed to recruit open-source deep learning practitioners who have software development experience in addition to professionals working in the industry. Out of these emails, four practitioners replied with blank responses; six practitioners replied that they would not answer any survey. Finally, we received 159 valid responses. The 159 respondents

Table 3. Participants Roles & Programming Experience

	0-1 y	2-3 y	4-5 y	6-9 y	>10 y	total
Algorithm	2	25	24	14	6	71
Development	5	14	10	15	6	50
Architect	0	1	2	3	5	10
Project Manager	1	1	0	1	1	4
Testing	0	1	0	1	1	3
Others	2	7	2	2	1	14
total	11	49	38	36	20	152

resided in 38 countries across six continents. The top two countries where the respondents came from were India and the United States.

An overview of the surveyed participants and their experience is depicted in Table 3. Most participants are engaged in Algorithm and have 2-3 years of professional experience.

2.2.3 Data Analysis.

We analyzed the survey results based on the question types.

To understand trends in the Likert-scale questions, we reported the percentage of each option selected. We dropped “I don’t know” ratings and created bar charts (many of which are shown in the remainder of this paper).

To obtain insights from responses to open-ended questions, we use open coding to analyze the survey results qualitatively by inspecting responses. The first author analyzed the interviews by transcribing them and then performed open coding to generate codes of the questionnaire contents using NVivo [32] qualitative analysis software. Then, the second author verified the initial codes created by the first author and provided suggestions for improvement.

3 RESULTS

In this section, we present the results of research questions that investigate code refactoring from commits and practitioners.

3.1 RQ1: Refactoring Practices in Deep Learning Projects

In RQ1, we explored code refactoring practices in deep learning projects, including practitioners’ practices on refactoring during development, and the distribution of different refactoring operation types and elements’ usage in their projects. We uncovered how refactoring operation types’ distribution in deep learning projects differs from code refactoring in traditional Java software [8]. In addition, we analyzed the distribution of different code elements in refactoring commits for deep learning projects.

3.1.1 Refactoring Operations. We detected 53 refactoring operations of 4,921 practices by manual detection, the complete distribution of all refactoring operations can be found in the replication package. To enhance comprehension and organization of these refactorings, we categorized common refactoring operations into seven operation types, each comprising various specific code refactoring operations shown in Figure 4. Table 4 shows the result of our manual detection, including the refactoring practice number, description, and example of each operation type. In previous research [8] of traditional Java software code refactoring, some refactoring operation types in the given table were habitually overlooked, specifically, *Remove Dead Code* and *Consolidate or Decompose Conditional Expression*.

According to the table, *Remove Dead Code* is the most frequent refactoring operation type. This phenomenon may be attributed to the rapid iteration characteristic of deep learning, resulting in code that is updated swiftly and not promptly cleaned up by developers as the commit message contains “remove the old code...”. Besides, deep learning projects usually include experiments, such as testing new models, and algorithms or tuning hyper-parameters [11] as “remove test of model...”. This leads to a large number of code snippets in the source, that ultimately become dead code when the outputs of the experiment are determined and subsequently thrown away. Nevertheless, as requirements can change over time or the originally intended functionality not be implemented, a significant amount of dead code is left behind. *Remove Dead Code* is an important step in maintaining a clear code structure and improving the maintainability of projects [34].

The frequent occurrence of *Consolidate or Decompose Conditional Expression* operations in deep learning projects can be attributed to the complexity of model structures, frequent adjustments and optimizations, and the impact of technical debt within the project. Complex models and long-term development can result in a build-up of technical debt [26], some of which could include confusing conditional logic. To enhance the maintainability and simplicity of deep learning projects, teams might engage in frequent refactoring of conditional expressions.

To investigate the differences in code refactoring between deep learning projects and traditional Java projects [8], we chose seven refactoring operation types to compare the differences in usage within deep learning projects and traditional Java projects. Five refactoring operation types (*Rename*, *Move*, *Extract*, *Inline*, *API Refactoring*) are well studied in previous work and commonly used in deep learning projects. The other two types (*Pull Up* and *Push Down*) are not common in deep learning projects but are well studied in traditional Java projects.

We extracted the commits of the above seven refactoring operations and compared their distribution on deep learning projects with traditional Java projects. The results are shown in Figure 5. *Rename* is significantly higher in deep learning projects than in Java projects, especially for *Rename Variable*. The frequency of adjustments, renaming of model layers, and naming of variables in deep learning projects are the main reasons for this phenomenon. *Move* is also commonly used

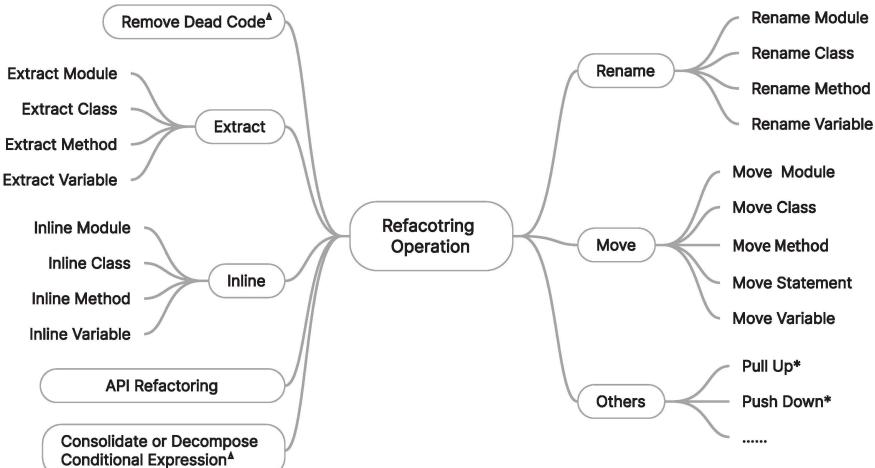


Fig. 4. Code refactoring operation types in deep learning projects. Δ: Operation commonly used in deep learning projects while overlooked in previous work; *: Operation which is uncommon in deep learning projects while being widely studied in previous work.

in the refactoring of deep learning projects, although it is less frequent than those in Java projects. As Java projects are usually developed by a large team and require a stricter code structure and specification, *Move* is more frequently adopted to ensure code tidiness and consistency [16]. Deep learning projects always prioritize rapid iteration and experimentation, featuring complex model structures and diverse code structures. Refactoring practices in these teams may allow for greater freedom, with *Move* being used less frequently in deep learning projects compared to Java. *Extract*, *API Refactoring* and *Inline* are more prevalent in deep learning projects than in traditional Java

Table 4. Code Refactoring Operations in Deep Learning Projects

Refactoring Operation	#Number	Description
Remove Dead Code	1,730 (35.16%)	Remove invalid or redundant code fragments that are no longer being executed by the program.
<pre>1 - def __getitem__(self, val: int) -> Expr: 2 - return self.shape_env.duck_int(val) 3 - def size_hint(self, expr: Expr) -> int: 4 - if not isinstance(expr, Expr): 5 - assert isinstance(expr, int)</pre>		<pre>1 + def size_hint(self, expr: Expr) -> int: 2 if not isinstance(expr, Expr): 3 assert isinstance(expr, int)</pre>
Rename	1,170 (23.78%)	Change elements' name for code clarity and readability.
<pre>1 - def rescale(self, 2 image: np.ndarray, 3 scale: Union[float, int] 4) -> np.ndarray: 5 self._ensure_format_supported(image) 6 return image * scal 7 def to_numpy_array(self, image, 8 rescale=None, 9 channel_first=True): 10 ... 11 if rescale: 12 - image = self.rescale(13 image.astype(np.float32), 14 1 / 255.0) 15 ...</pre>		<pre>1 + def rescale_image(self, 2 image: np.ndarray, 3 scale: Union[float, int] 4) -> np.ndarray: 5 self._ensure_format_supported(image) 6 return image * scal 7 def to_numpy_array(self, image, 8 rescale=None, 9 channel_first=True): 10 ... 11 if rescale: 12 + image = self.rescale_image(13 image.astype(np.float32), 14 1 / 255.0) 15 ...</pre>
Move	729 (14.81%)	Move code elements from one location to another.
<pre>1 - torch/distributed/fddp/fully_sharded_data_parallel.py 2 ... 3 def _get_shard_functional(4 tensor: torch.Tensor, 5 rank: int, 6 world_size: int, 7) -> Tuple[torch.Tensor, int]: 8 - chunk, pad_num = FullyShardedDataParallel._get_chunk(9 tensor, rank, world_size, 10) 11 shard = chunk.clone() 12 if pad_num > 0: 13 shard = F.pad(shard, [0, pad_num]) 14 return shard, pad_num 15 ...</pre>		<pre>1 + --torch/distributed/fddp/flat_param.py 2 ... 3 def _get_shard_functional(4 tensor: torch.Tensor, 5 rank: int, 6 world_size: int, 7) -> Tuple[torch.Tensor, int]: 8 + chunk, pad_num = FlatParamHandle._get_unpadded_shard(9 tensor, rank, world_size, 10) 11 shard = chunk.clone() 12 if pad_num > 0: 13 shard = F.pad(shard, [0, pad_num]) 14 return shard, pad_num 15 ...</pre>
Extract	499 (10.14%)	Extract independent and reusable elements from larger and more complex code elements.
<pre>1 - def make_buffer_allocation(self, buffer): 2 - name = buffer.get_name() 3 - device = self.codegen_device(buffer.get_device()) 4 - dtype = self.codegen_dtype(buffer.get_dtype()) 5 - size = self.codegen_shape_tuple(tuple(buffer.get_size())) 6 - stride = self.codegen_shape_tuple(tuple(buffer.get_stride()))</pre>		<pre>1 - def make_buffer_allocation(self, buffer): 2 + return self.make_allocation(3 + buffer.get_name(), 4 + buffer.get_device(), 5 + buffer.get_dtype(), 6 + buffer.get_size(), 7 + buffer.get_stride(), 8 + self.can_cache_buffer_in_thread_local(buffer)) 9 + def make_allocation(10 + self, name, device, dtype, shape, stride, 11 + can_cache_buffer_in_thread_local=False): 12 + device = self.codegen_device(device) 13 + dtype = self.codegen_dtype(dtype) 14 + size = self.codegen_shape_tuple(shape) 15 + stride = self.codegen_shape_tuple(stride)</pre>

Continue in next page.

Refactoring Operation	#Number	Description
API Refactoring	287 (5.83%)	Refactor the application programming interfaces.
<pre>1 - def _get_initial_value(self, 2 - replica_id=0, device=None, 3 - primary_var=None, **kwargs): 4 - if replica_id == 0: 5 - assert device is not None</pre>		<pre>1 - def _get_initial_value(self, 2 + replica_id, device, 3 + primary_var, **kwargs): 4 + if replica_id == 0: 5 assert device is not None</pre>
Consolidate or Decompose Conditional Expression	228	Refactor expressions to make them more concise, readable, and logical by consolidating or decomposing them.
<pre>1 - def reverse(x, axes): 2 - if isinstance(axes, int): 3 - axes = [axes] 4 - for a in axes: 5 - x = np.flip(x, a) 6 - return x</pre>		<pre>1 - def reverse(x, axes): 2 + if isinstance(axes, list): 3 + axes = tuple(axes) 4 + return np.flip(x, axes)</pre>
Inline	157 (3.19%)	Inline a part of code directly into its place of use.
<pre>1 - def _iterate_columns(X, columns=None): 2 - ... 3 - for i in columns: 4 - yield _get_column(X, i) 5 - ... 6 - def _get_column(X, i): 7 - if issparse(X): 8 - x = np.zeros(X.shape[0]) 9 - s_p, e_p = X.indptr[i], X.indptr[i + 1] 10 - x[X.indices[s_p:e_p]] = X.data[s_p:e_p] 11 - else: 12 - x = X[:, i] 13 - return x</pre>		<pre>1 - def _iterate_columns(X, columns=None): 2 - ... 3 - if issparse(X): 4 + for i in columns: 5 - x = np.zeros(X.shape[0]) 6 - s_p, e_p = X.indptr[i], X.indptr[i + 1] 7 - x[X.indices[s_p:e_p]] = X.data[s_p:e_p] 8 + yield x 9 - else: 10 + for i in columns: 11 + yield X[:, i] 12 + ...</pre>
Others	121 (2.46%)	Other refactoring operations rarely appear in deep learning project refactoring practices, e.g. Pull Up, Push Down.

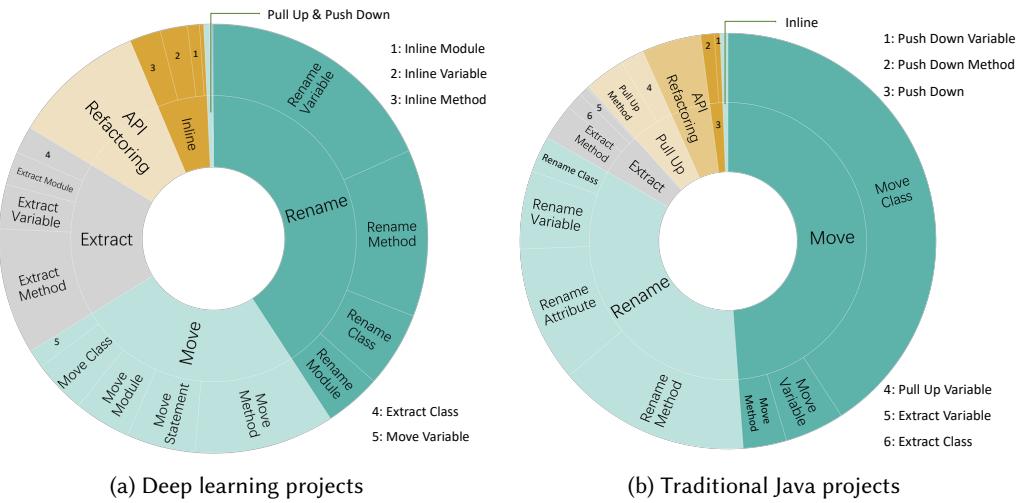


Fig. 5. Distribution of refactoring operations for deep learning projects and traditional Java projects

projects. Model structures and algorithms in deep learning projects can often be complicated, requiring more abstraction and optimization. Consequently, *Extract* is frequently employed to abstract complex methods or modules, thereby enhancing the modularity and reusability of code. Deep learning projects always need to refine and enhance their interfaces regularly to accommodate evolving needs, resulting in frequent usage of *API Refactoring*. *Inline* often occurs in pursuit of higher performance, to reduce the overhead of calls, or to revert some inappropriate extraction operation [16]. *Pull Up* and *Push Down* operations are infrequent in both types of projects but are particularly uncommon in deep learning. Deep learning projects tend to concentrate on designing model hierarchies and structures, with less emphasis on class inheritance and optimizing hierarchies.

Finding 1: *Remove Dead Code* and *Rename* are two of the most frequent operation types in deep learning repositories. *Rename*, *Move*, *Extract*, *Inline*, *API Refactoring*, *Pull Up* and *Push Down*, which are widely studied in Java, show a different distribution of usage in deep learning projects.

3.1.2 Refactoring elements. We counted the elements of all refactoring commits excluding *Remove Dead Code* (as it is usually cluttered and only involves deletion), including Variable, Statement, Method, Class, and Module. The elements' frequency of occurrences on refactoring operations in the deep learning repository is displayed in Figure 6. This distribution of refactoring operations' elements can offer insights into code optimization and project maintenance in deep learning projects.

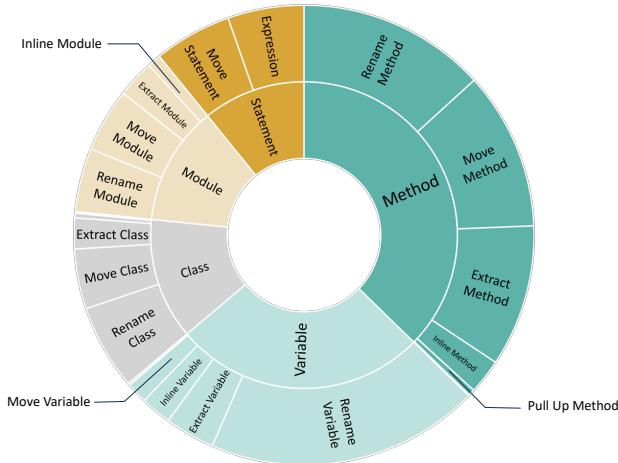


Fig. 6. Distribution of refactoring elements for deep learning project

Method (37.31%), as the element of each functional unit of the deep learning model, accounts for the largest proportion of refactoring operations. During our analysis of method-level commits, we found that the most frequently utilized refactoring operations are *Rename Method* and *Move Method*. These types of refactoring operations are relatively simple and contribute to both code readability and modularity. It is essential to consider these factors when undertaking code maintenance tasks. *Variable* (26.52%) has the second-highest percentage of refactoring operations. The most frequent of these is *Rename Variable*, which is typically linked to the “same variable name” in the commit

message to prevent “naming conflicts”. *Class* (12.80%) and *Module* (12.55%) share a similar percentage of refactoring operation elements, and are both related to the alignment of model components and structures. *Rename* and *Move* are the most prevalent actions in these two levels of operation. *Rename* helps ensure that the code structure is clear and understandable, while *Move* enhances the modularity of the code, making the entire model simpler to manage and maintain. In the context of deep learning projects, these actions are critical for model comprehension and development. The proportion of *Statement* (10.82%) level operations is comparatively low. A notable component of this percentage is the *Consolidate or Decompose Conditional Expression* operation, probably because the complex conditional logic and computation in the deep learning model require frequent refactoring of conditional expressions to improve readability and maintainability.

Finding 2: *Method*, being a more moderate element, is frequently employed in refactoring operations, while *Variable*, being easier to modify, is also frequently used in refactoring. The frequency at which refactoring operations take place for *Class* and *Module* are approximately equal. The proportion of statement-level operations is comparatively low.

3.2 RQ2: Practitioners’ Opinion on Refactoring

In RQ2, deep learning practitioners were surveyed and asked to evaluate the significance of operations or elements during the refactoring process. Of the 159 practitioners surveyed, 145 (91.2%) “Strongly Agreed” or “Agreed” that “refactoring is an important part of software development in deep learning projects”, 11 chose “Neutral”, while the remaining three practitioners “Strongly Disagree” with the importance of refactoring.

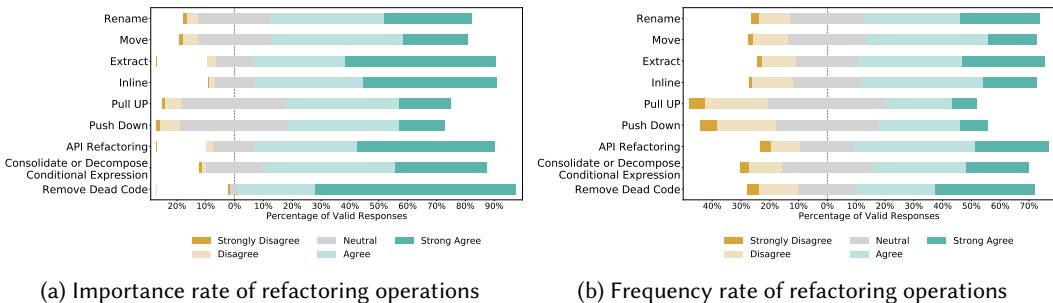


Fig. 7. Respondents’ rate of refactoring operation types’ importance and frequency

3.2.1 Refactoring Operations. We further investigated practitioners’ opinions on several common refactoring operation types. Figure 7 illustrates respondents’ rating of refactoring operation types’ importance and frequency.

In general, it is apparent that *Remove Dead Code* is the most vital refactoring operation acknowledged by practitioners, trailed by *API Refactoring*, *Extract*, *Inline*, *Consolidate or Decompose conditional Expression*, *Rename*, *Move*, *Pull Up* and *Push Down*. *Extract* and *Inline* obtain similar scores of importance, whereas *Rename* showcase no noteworthy advantage over *Move*, and *Pull Up* and *Push Down* are comparable in significance among practitioners. It is worth noting that the practitioners’ scores for refactoring operations’ frequency are not consistent with our observation

in RQ1. There are various possible explanations for this, the one that comes from our dataset used in RQ1 will be discussed in 4.2.

We can also get insights from the characterization of the rating results for each refactoring operation. As stated in RQ1, *Remove Dead Code* is the most frequent operation in refactoring commits. However, it cannot guarantee the same status in the minds of practitioners. This can be attributed to *Remove Dead Code* being a clean-up process when other code changes are made, rather than a specific intention. As a result, practitioners may be unaware of this operation. *API Refactoring* may be considered important due to the significance of code interfaces and organizational structure in deep learning projects that typically entail extensive data processing and model creation. However, we did not observe such a high frequency of API Refactoring usage in RQ1, which may be since the keyword-based filters we used screened out some of the API Refactoring by mistake. *Extract* and *Inline* refactoring operations that are important in other languages, are also of high importance in the minds of deep learning practitioners, reflecting their concern for code reusability and structural clarity. while *Move* and *Rename* received relatively low scores, perhaps because they are also relatively low in difficulty to perform, and so have received practitioner slights. *Consolidate* or *Decompose Conditional Expression* is more commonly used in the minds of practitioners than we observed in RQ1, probably because our keyword-based filter incorrectly excluding these operations. In contrast to the above refactoring operations, practitioners tend not to prioritize *Pull Up* and *Push Down*. Developers ranked these two actions lowest in terms of importance and frequency of usage, consistent with our observations and discussions in RQ1. We also found an interesting phenomenon when analyzing the data, that more experienced practitioners (who have been working for a longer period of time) are less likely to agree with the importance of these two refactoring operations for code refactoring in deep learning projects.

Finding 3: The respondents from practitioners had formed beliefs that were inconsistent with our observation in RQ1. *Remove Dead Code* and API Refactoring are more important to practitioners. The importance of *Rename* and *Move* operations which are currently more widely studied in traditional project, is not well recognized by practitioners of deep learning project. Especially *Pull up* and *Push down* receive a very low recognition rate. This also suggests that code refactoring in the deep learning project may differ significantly from traditional code refactoring.

3.2.2 Refactoring elements. As for refactoring elements in the context of refactoring in deep learning projects, we also invite practitioners to answer whether these refactoring operation elements are important and frequently used in deep learning projects. Figure 8 illustrates respondents' rating of refactoring elements' importance and frequency.

According to the results, it is evident that *Method* and *Class* rank first and second, respectively, with *Variable* and *Statement* closely following in terms of practitioners' rating for “*Do you think refactoring elements below are important to improve the quality of the code in your deep learning project?*” and “*Do you think this refactoring element is frequently used in your deep learning project?*” In comparison, *Module* falls significantly behind in importance score, but its rating for importance is similar to that of *Variable* and *Statement*.

We further analyzed the rating results of each element. *Method* is considered to be the most crucial and frequently refactoring element in both traditional software and deep learning projects. This is consistent with our observation in RQ1. *Class* comes second in rating results which could indicate that, in the area of deep learning, optimizations at the method and class level are being

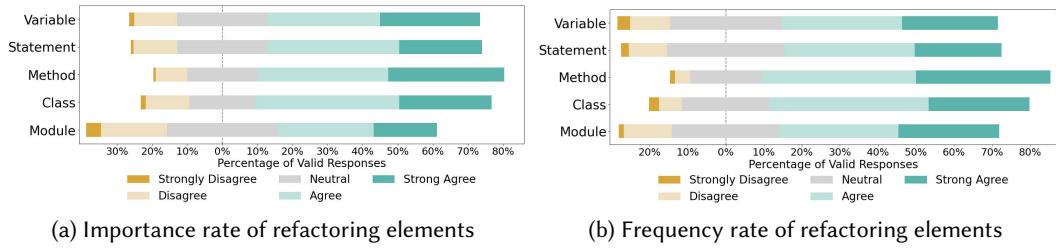


Fig. 8. Respondents' rate of refactoring elements' importance and frequency

given priority by practitioners. They not only directly affect the logic and structure of the model, but are also easier to refactor with the right level of element. *Statement* and *Variable* have comparable and relatively small ratings. This could imply that for practitioners, the impact of refactoring at the statement and variable levels on code quality in deep learning projects is deemed minimal, or might be regarded as less significant compared to the refactoring at method and class levels. However, the frequency of variable-level refactoring usage does not align with our observations in RQ1, and a possible explanation for this could be that the minuscule of its modifications causes practitioners to neglect to carry out a Variable-level refactoring operation. *Module* has a relatively low rating, this could be attributed to the fact that restructuring modules demands a comprehensive understanding of the entire project structure, which might pose a significant challenge for practitioners. Moreover, in deep learning projects, modules often emphasize model components, data processing flow, or training pipelines, requiring less frequent refactoring. We also found that more experienced practitioners are less likely to agree with the importance of Module-level code refactoring in deep learning projects.

Finding 4: The responses from practitioners indicated that they formed beliefs consistent with our observations in RQ1 on smaller elements (Method, Statement, and Variable), whereas respondents held inconsistent beliefs on larger elements (Class, Module). Method is considered to be the most crucial and frequently employed level of element in refactoring deep learning projects, while Class comes second in rating results. Variable, Statement, and Module have a similar frequency of usage in practitioners' minds, while Module has a relatively lower rating for the importance of code refactoring element in deep learning projects.

3.3 RQ3: Practitioners' Perspectives on Refactoring Tools

In RQ3, we surveyed practitioners about their use of refactoring tools consist of code smell detection tools and automatic refactoring tools. We further invite them to provide their perceptions of refactoring tools to uncover the shortcomings of existing tools.

3.3.1 Code Smell Detection Tools. Of the 156 questionnaires responding to this section, 85 respondents (54.5%) indicated that they had used or were familiar with code smell detection tools. 73 people gave valid opinions about the tool.

There are many practitioners (28) who find code smell detection tools useful but also contain many drawbacks, the biggest one is “*Too many false positives*”, which is the common view of 17 practitioners. Practitioners who do not want to use these tools in development stated “...don’t

believe the system. It annoyingly makes easy mistakes..." and said "*It never seemed worth the hassle*". There are a number of concerns that have deterred practitioners from using code smell detection tools. One is the "*who need them most can't figure out how to set them up...*", and "*sometimes you need to suppress the feedback and if the ability to filter out this feedback is too granular it leads to a lot of filler in your code, if it's too broad you may miss out on useful feedback.*" Some practitioners find "*it difficult to distinguish more semantically*", and "*... are often too pedantic and lack contextual information about the project structure*".

There are also some participants who concerned that the current tools "...are built for only traditional software eng", a participant finds the code smell detection tools "...usually aren't designed with ML projects in mind, and sometimes raise inappropriate warnings. For example, an ML algorithm may have many hyper-parameters, but a code smell detection tool will complain that a function shouldn't have so many arguments." There is also a practitioner who said "...Python is behind other languages I've used in terms of tooling for smell/refactoring".

In addition, many practitioners offered some insights into their go-to code smell detection tools, including SonarQube, Ruff, Flake8, IDE plugins, ChatGPT, and Copilot. SonarQube, the automated code review platform, has received a moderately positive response. As a practitioner said "*Sonarqube. I hate working with it. Such a clunky piece of software. I am much more a fan of linters like pylint and flake8, albeit they are sometimes not as feature complete for coding styles*". Of the code analysis tools, practitioners seem to favour Ruff, with some practitioners arguing that "...ruff has been helpful, pylint is too hard to configure and anything more complex is too annoying...". Ruff is popular for its speedy execution, as one practitioner attested "*I use Pylint, Ruff, different pre-commit hooks to find code that can be refactored, bugs in my code. They are pretty great but most are very slow. Ruff is the fastest tool I used. It'll be very good if all the tools are as fast as ruff*". Tools that combined with Large Language Models, like Copilot and ChatGPT, have recently gained popularity, that "*These have been my go-to choices for code-related tasks*".

Finding 5: Developers acknowledge the usefulness of traditional code smell detection tools but have some concerns: (1) they always appear false positive, (2) do not apply to deep learning projects, and (3) they are not user-friendly. As an alternative, combining code smell detection tools with Large Language Models is considered the future trend.

3.3.2 Automatic Refactoring Tools. Of the 155 questionnaires responding to this section, 71 respondents (%45.8) indicated that they had used or were familiar with code smell detection tools. 62 people gave valid opinions about the tool.

There are many practitioners (23) who find automatic refactoring tools useful which is "...absolutely necessary to keep the code clean and professional" but only for sample cases and also weak in accuracy. The automatic refactoring tool "...makes things faster but it usually doesn't handle heavy complexity too well..." as a practitioner thought these tools "*Very useful for variable renaming or moving around methods, breaking out chunks into methods. Haven't done anything more complex with them, complex refactor I would rather do by hand (to trust that it's done right, but also complex refactoring is done infrequently enough that it's not worth learning the tool)*". Furthermore, it has been argued that the tool does not consider the context and structure of the project as a practitioner said "*Automatic refactoring tools can do small amount of refactoring for common patterns. However they lack holistic analysis of the code and thus leaving rest to manual refactoring*".

Similar to the code smell detection tools, practitioners found that current automatic refactoring tools were not designed for deep learning. A practitioner said that "*I have found them useful for*

web server development mainly, but not so much for deep learning development". There is also a practitioner who said "I've mostly used it for strongly typed languages (Java, TypeScript), which I didn't face much challenges with since the tools were able to accurately detect usages. I would imagine it might be more challenging for loosely typed languages". The practitioners also thought these tools are hard to use, a practitioner stated "The python Rope library is where I have the most experience (outside of IDE tooling). I've found the docs to be somewhat lacking in "how to" guidance. I've had some success reviewing the unit tests and work out from that how to use specific functionality. Given the complexity of the domain having documentation that serves the purposes of being detailed and then (and perhaps separate material) is able to concisely demonstrate how to achieve refactoring operations - is needed".

As a practitioner stated that code smell detection tools "...Can introduce bugs or syntax issues", the most important concern that has deterred practitioners from working with automatic refactoring tools is their tendency to introduce bugs. Because "Sometimes wrong refactoring, takes longer to fix".

The most common tools considered by practitioners are IDE plugins and tools combined with the Large Language Model, such as Copilot and ChatGPT, which are good at code generation. In contrast to traditional tools that receive a rating of "not good, not bad", ChatGPT and Copilot have high expectations. A practitioner said "... I have had moderately good success refactoring code with a LLM and I expect to do it more often". There also had a voice that the traditional automatic refactoring tools "Great but limited - integrations with Copilot would be great". However, a practitioner said "To really trust an automatic refactoring tool, you need to have a lot of trust in your test suite", and there is also a practitioner who said "...tried chatgpt and copilot. Their suggestion is the right direction to go. However, one needs to test all the edge cases thoroughly."

Finding 6: Developers recognized the usefulness of automatic refactoring tools. But they also have many concerns about traditional tools: (1) they only work for easy cases (2) while weak in accuracy and trending to introduce bugs, (3) they lack context or project structure, and (4) are hard to not user-friendly. Besides, tools combined with Large Language Models have been well received, but the code they refactored is also considered worthy of further testing.

3.3.3 Practitioners' Advice.

There are 48 practitioners who gave valid advice for refactoring tools enhancement.

The most common view is that these tools should take more information into account, including contextual and constructive information. A practitioner who gave a proposal said "...let's imagine a tool, that takes into account project decisions, rules, conventions. moreover, tool that scans git history and 'understands' such git changes that were specifically about refactorings. and let's imagine that such tool 'understands' commands that are relevant to specific project in natural language format (please do such refactoring: make separation of <this> module, etc.)".

Another part of the practitioners advised that the current tools for deep learning should be enhanced with customization features. A practitioner stated "More configurable so that they can also be applied to libraries and frameworks". There is also a practitioner said these tools should "...learn the user's coding style and adapt to it instead of forcing a predefined standard".

The practitioners have made their own suggestions regarding the current difficulties in using the tool. A practitioner said the tools need "Documentation and tutorials. Additionally having a consistent definition of operations". While another practitioner wants these tools "Reduce configuration variability, extend the documentation". There is also a part of practitioners who hope the automatic tools do not 'force' them and easy to undo. A practitioner stated "I hope those tools are less invasive.

Sometimes I feel they ‘force’ me to refactor my code although some parts do not need a refactoring job”, and another practitioner said *“...it should always be easy to undo/have an easily navigatable history of recent changes...”*. Furthermore, it has been suggested by numerous practitioners that refactoring must be accompanied by a testing component, as a practitioner said *“The best way to refactor is by maintaining the invariant that test coverage is complete and the tests pass. test harness...”*, which is a crucial part of the refactoring process.

Finding 7: Deep learning practitioners offered their advice on how to improve current automatic refactoring tools, including (1) taking context and project structure into consideration, (2) building complete documents and configuration for ease of use, (3) adding customized features to be used in deep learning projects, (4) offering tracker of history change to rollback and (5) combining a complete test component.

4 DISCUSSION

4.1 Implications

Our results highlight a number of points to be further discussed and several implications for the research community:

4.1.1 Strengthening research on code refactoring in deep learning projects. Our research demonstrates that refactoring practices in deep learning projects differ greatly from those in traditional Java projects. Remove Dead Code, API Refactoring, and Consolidation or Decompose Expression are crucial refactoring operations in deep learning projects. Nevertheless, the current research concentrates primarily on Java refactoring, and there is still an absence of research regarding the aforementioned refactoring operations. Moreover, some developers have also made other requests for refactoring like *“Handling C++-Python FFI boundaries...”* and *“Rearchitecture”*.

4.1.2 Optimizing the development process. According to our observations in RQ1, Remove Dead Code and Rename are the two most common refactoring operation types in deep learning projects, which could be a result of inadequate code review and naming conventions. Practitioners also mentioned *“Since OSS usually has more contributors, it is more necessary to have clear guidance/configuration for those tools, as it would lead to many conflicts otherwise”*. Optimizing the development process for deep learning projects is essential, which includes establishing naming conventions, identifying and cleaning up dead code. It is important to ensure that all team members share and follow these standards to improve code readability and maintainability.

4.1.3 Improving the accuracy of refactoring tools. Among the concerns about either code smell detection tools or automatic refactoring tools, the most frequently mentioned by developers is the issue of accuracy. For small-scale refactoring, many refactoring operations have been mentioned by developers as challenges that current refactoring tools do not do a good job of dealing with, e.g., *“...it can cause troubles sometimes if you rename a variable to a name that already is taken by another variable...”*. As for large-scale refactoring operations, current refactoring tools pose difficulties in implementing as they do not adequately consider context and project structure. As a part of developers responded that refactoring tools *“...should offer detailed custom configuration to guide the tool’s task...”*, clear documentation and a guidebook should be provided to assist users in correctly utilizing the refactoring tool. Ensuring accuracy necessitates not only the functionality of the tool but also its proper usage and comprehension by users.

4.1.4 Combining refactoring with testing. Testing is a critical aspect of refactoring, which ensures code refactoring does not break existing functionality and maintains the stability and reliability of the system. However, to the best of our knowledge, none of the prevalent refactoring tools are currently supported by a testing system that meets the developer's requirements. This is also one of the main factors that prevent practitioners from using automatic refactoring tools, that a practitioner said, "*To really trust an automatic refactoring tool, you need to have a lot of trust in your test suite*". In fact, when participants were asked to provide suggestions for enhancing the tool, some suggested that "*Just a better test coverage after the automatic refactoring*".

4.1.5 Refactoring in the Era of Large Language Model. According to the respondents of our survey, current refactoring tools are "... not smart ...being inflexible", and also lack the use of code context to support a customizable refactoring tool. Large Language Model can aid in comprehending code, enhancing our understanding of the code context. By incorporating Large Language Model and code analysis techniques, automatic refactoring suggestions can be generated. This provides context-specific and personalized proposals based on the syntax rules, code context, and project structure.

4.2 Threats to Validity

Our research threats come from the two stages of our empirical study

4.2.1 Refactoring Detection. Due to the high number of project commits employed, conducting a full and detailed analysis of this data was not feasible. Therefore, following the approach of Alomar et al. [6], we utilized keyword-based filters to filter the commits initially. This approach may have lost some refactoring commits, leading to an incomplete analysis of our refactoring practices in the deep learning repository.

Furthermore, our selection comprises only five highly popular deep learning projects which possess extensive maintenance information and boast active open source communities. Nevertheless, other deep learning projects may not have reached maturity in terms of development and maintenance, and their actual implementation of code refactoring may vary from the projects we employed. To reduce these threats, we conducted a survey of deep learning practitioners to explore their real refactoring practices.

4.2.2 Online Survey. It is possible that some of our survey respondents may not have a clear understanding of code refactoring techniques or our questions, and thus their responses may introduce noise to the data that we collect. To reduce this threat, we included the category "I don't know" to filter respondents who do not understand our brief descriptions in multiple-choice questions and dropped "I don't know" ratings in data analysis. When analyzing responses to short answer questions, we eliminated responses such as "N/A". We also drop responses by respondents who complete the survey in less than two minutes. Still, we cannot fully ascertain whether participant responses are accurate reflections of their beliefs. This is a common and tolerable threat to validity in many previous studies about practitioners' perceptions and expectations [24].

Another threat is that our participants are contributors from open source deep learning repositories, who may not be representations of commercial deep learning software engineers. It is still unclear whether our insights are still suitable for commercial deep learning projects. Investigating the perspective of commercial deep learning developers is our ongoing work.

5 RELATED WORK

Refactoring is recognized as a fundamental practice for keeping software sustainable and healthy [16, 27, 37, 39]. For this reason, extensive empirical research has recently been conducted to extend

Table 5. Summary of Previous Work of Code Refactoring

Study	Content	Methodology	Summary of Findings
Murphy-Hill et al. [28]	How developers practice refactoring activities	Analyzing commit history	Developers typically perform numerous refactorings in a short period, 90% refactorings are done manually.
Negara et al. [29]	Manual and automated refactoring	Analyzing refactoring instances	Over half of refactorings are done manually, 30% of applied refactorings do not reach version control.
AlOmar et al. [9]	Refactoring activities and contributors in open source projects	Analyzing 800 open source projects using Refactoring Miner	No correlation between experience and refactoring motivation, top contributors perform more variety of refactoring operations.
Chaves et al. [15]	The impact of refactoring operations on internal quality attributes	Analyzing 29,303 refactoring operations	Over 94% refactorings applied to code elements with at least one critical internal quality attribute, and improved the internal quality.
Vassallo et al. [41]	Which refactoring operations are more prevalent, and main factors leading to refactoring	Analyzing commit history of 200 open source systems	Developers adopt refactoring mainly to improve understandability, schedule refactoring after system is stable, files likely refactored by their owners.
Wang et al. [42]	Intrinsic and extrinsic factors driving refactoring	Interviewing 10 expert developers	Identified intrinsic and extrinsic factors driving refactoring, and also identified tool availability as a prominent factor.
Vakilian et al. [40]	How programmers use refactoring tools	Collecting and analyzing Java programming interaction data	Programmers prefer lightweight ways to invoke refactorings, and make small changes using tools even if tools are occasionally buggy.
Kim et al. [24]	Microsoft engineers' view on refactoring	Surveying 328 Microsoft engineers	Developers place less importance on behavior preservation, system-wide refactoring reduced inter-module dependencies and post-release defects.
Jain et al. [22]	Refactoring trends and research opportunities	Surveying 221 IT professionals	Refactoring tools are under-used due to availability, usability, and trust issues, automated system is needed.
Oliveira et al. [30]	Relevance of refactoring customization and tool support	Analyzing 1,162 refactorings, surveying 40 developers	Developers confirmed the relevance of customization patterns and agreed that improvements in IDE refactoring support were needed.
Oliveria et al. [31]	Developers' understanding of refactoring detection tool mechanics	Surveying 53 Java project developers	Tools do not detect many refactorings expected by developers, most developers do not follow refactoring mechanisms used by refactoring detection tools.

our knowledge of this practice. The two major lines of research related to our work are (1) studies based on refactoring practices and (2) studies based on surveys and interviews. Table 5 shows an overview of empirical studies on code refactoring.

5.1 Studies based on refactoring practices

There has been much work that analyzed code changes or development documentation in repositories to gain insights related to refactoring. Murphy-Hill et al. [28] investigated how developers

practice refactoring activities by analyzing historical commits. The researchers found that programmers typically perform numerous refactorings within a brief timeframe, and 90% of refactorings are carried out manually. Negara et al. [29] presented the first comprehensive empirical study that considers both manual and automated refactoring, using a large corpus of refactoring instances detected through an algorithm that infers refactorings from fine-grained code edits. Their central findings reveal that over half of the refactorings are performed manually, and 30% of the applied refactorings do not reach the version control system. AlOmar et al. [9] analyzed 800 open-source projects by mining their refactoring activities using Refactoring Miner, and identified their corresponding contributors. They found there is no correlation between experience and motivation behind refactoring, top contributed developers are found to perform a wider variety of refactoring operations. Chaves et al. [15] analyzed the version history of 23 open source projects with 29,303 refactoring operations and found that developers apply more than 94% of the refactoring operations to code elements with at least one critical internal quality attribute, and always improved the internal quality attributes. Vassallo et al. [41] analyzed the change history of 200 open source systems at the commit level to investigate which refactoring operations are more diffused when refactoring operations are applied, and which are the main developer-oriented factors leading to refactoring. They found developers adopt refactoring mainly to improve the understandability of source code and mainly schedule refactoring after the system's structure is stable. They also found that source code files are most likely to be refactored by their owners rather than others.

There are also some studies investigating the performance of refactoring on issues such as reuse, security, and maintenance [10, 12, 20, 21, 25, 27, 36]. Nevertheless, most of studies above have focused on Java or JavaScript projects, leaving a gap in the insights of refactoring on deep learning projects.

5.2 Studies based on surveys and interviews

Wang et al. [42] conducted a study involving 10 expert software developers. They identified both intrinsic (self-motivated) and external (influenced by peers or management) factors that drive refactoring activity. The research also highlighted tool availability as a prominent factor that enables developers to translate their motivations into actions. Vakilian et al. [40] collected and analyzed interaction data from Java programming and found that programmers prefer lightweight methods of invoking refactorings, usually perform small changes using the refactoring tool. They also found that programmers use predictable automated refactorings even if they have rare bugs or change the behavior of the program by interview. Kim et al. [24] surveyed 328 engineers from Microsoft and found the findings reveal that developers place less importance on the requirement of preserving behavior within refactoring definitions. They further interviewed the Windows refactoring team to gain insights into the methods employed in system-wide refactoring. They found that binary modules refactored by the team showed a considerable reduction in inter-module dependencies and post-release defects. Jain et al. [22] surveyed 221 IT professionals to understand the trends followed by developers and what are the research opportunities in the field of refactoring and developmental challenges. They found that refactoring tools are under-used as they have availability, usability and trust issues. An automated system is the need of the hour to ensure consistency in change management, visualize the structure of code, inspect code, detect design issues, and carry out refactoring. Oliveira et al. [30] analyzed 1,162 refactorings composed of more than 100k program modifications from 13 software projects and conducted a survey with 40 developers about the most frequent customization patterns they found. Developers confirmed the relevance of customization patterns and agreed that improvements in IDE's refactoring support were needed. Oliveria et al. [31] surveyed 53 developers of popular Java projects on GitHub to gain a better understanding of the mechanics of refactoring detection tools. They found that

refactoring detection tools did not detect many refactoring operations expected by developers and most developers did not follow the refactoring mechanisms used by refactoring detection tools.

The above work conducted interviews or surveys to discover developers' perspectives about refactoring and refactoring tools. However, they are still mostly limited to developers of Java projects. The findings related to refactoring in deep learning projects, which is currently a fast-growing area and is very different from traditional Java projects in terms of development and maintenance, still need to be investigated.

6 CONCLUSION AND FUTURE WORK

Code refactoring is an important part of deep learning project development. In this work, we manually analyzed five deep learning projects' history commits to detect refactoring operation, and further surveyed 159 deep learning practitioners from 38 countries for practitioners' views on refactoring and their expectations of refactoring tools. The refactoring practices in deep learning projects are different from those in Java projects, and some of the most common refactoring operations are lack of research. Practitioners in deep learning recognized the importance of refactoring in the development of deep learning projects. They also offered comments and advice on current refactoring tools.

We highlight the limitations of current research and suggest future directions for the improvement of code refactoring in deep learning projects. Moreover, we present practitioners' expectations regarding refactoring tools and provide suggestions for their enhancements.

To further improve code refactoring practices in the field of deep learning, researchers should collaborate with deep learning practitioners continuously. Future studies could put more effort into refactoring in deep learning, and develop automation tools for deep learning projects to improve the overall efficiency of code maintenance.

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