Characterizing Performance Bugs in Deep Learning Systems

Junming Cao
School of Computer Science and
Shanghai Key Laboratory of Data
Science
Fudan University
Shanghai, China

Bihuan Chen∗
School of Computer Science and
Shanghai Key Laboratory of Data
Science
Fudan University
Shanghai, China

Chao Sun
School of Computer Science and
Shanghai Key Laboratory of Data
Science
Fudan University
Shanghai, China

Longjie Hu
School of Computer Science and
Shanghai Key Laboratory of Data
Science
Fudan University
Shanghai, China

Xin Peng
School of Computer Science and
Shanghai Key Laboratory of Data
Science
Fudan University
Shanghai, China

ABSTRACT
Deep learning (DL) has been increasingly applied to a variety of domains. The programming paradigm shift from traditional systems to DL systems poses unique challenges in engineering DL systems. Performance is one of the challenges, and performance bugs (PBs) in DL systems can cause severe consequences such as excessive resource consumption and financial loss. While bugs in DL systems have been extensively investigated, PBs in DL systems have hardly been explored. To bridge this gap, we present the first comprehensive study to characterize symptoms, root causes, and introducing and exposing stages of PBs in DL systems developed in TensorFlow and Keras, with a total of 238 PBs collected from 225 StackOverflow posts. Our findings shed light on the implications on developing high-performance DL systems, and detecting and localizing PBs in DL systems. We also build the first benchmark of 56 PBs in DL systems, and assess the capability of existing approaches in tackling them. Moreover, we develop a static checker DeepPerf to detect three types of PBs, and identify 488 new PBs in 130 GitHub projects. 62 and 18 of them have been respectively confirmed and fixed by developers.

1 INTRODUCTION
The advances in deep learning (DL) have attracted an increasing interest in applying DL to various applications in both industry and academia, e.g., image processing, machine translation, speech recognition, medical diagnosis, self-driving cars, and robotics. These DL systems adopt a data-driven programming paradigm, where developers define a desired neural network that learns the decision logic from a large amount of training data. Differently, traditional systems follow a logic-based programming paradigm, where developers directly encode the decision logic in the source code. This paradigm shift poses unique challenges to engineering DL systems [1, 7, 21, 83].

1 https://lambdalabs.com/blog/demystifying-gpt-3/
2 https://stackoverflow.com/questions/58441514/why-is-tensorflow-2-much-slower-than-tensorflow-1

∗ Bihuan Chen is the corresponding author.

In particular, performance, as an important quality requirement, is one of the challenges in engineering DL systems [83]. It has a significant impact on the time and resources (e.g., GPU memory and power) required during the process pipeline (e.g., training and inference) of DL systems [44]. For example, the language model GPT-3 costs millions of dollars for a single training run. Thus, performance bugs (PBs) can slow down DL systems, consume excessive resources, hurt user experience, cause financial loss, or threaten human lives. For example, many users suffered a significant slowdown of their DL systems after upgrading TensorFlow 1.x to TensorFlow 2.x, and hence decided to switch to PyTorch. Moreover, performance questions of DL systems are recognized as the most difficult to answer among all questions of DL systems on StackOverflow [83]. Therefore, it is necessary to study the characteristics of PBs in DL systems.

A lot of efforts have been recently made to extensively investigate the characteristics (e.g., symptoms, root causes, fixes and taxonomy) of general bugs [26–28, 86] and specific bugs [8, 68, 82, 85] in DL systems. However, these studies are not specifically designed for PBs, and thus only capture some partial characteristics of PBs in DL systems. In contrast, PBs in DL systems could be different due to the programming paradigm shift from traditional systems to DL systems. In summary, the characteristics of PBs in DL systems are under-investigated.

To bridge this knowledge gap, we present the first comprehensive study to characterize PBs in DL systems developed in TensorFlow and Keras. We collect 238 PBs from 225 StackOverflow posts, and manually analyze these PBs to answer three research questions.

• RQ1 Symptom: what are the symptoms of PBs?
• **RQ2 Root Cause**: what are the root causes of PBs?
• **RQ3 Stage**: what are the stages of introducing and exposing PBs?

Through these research question analyses, we aim to provide useful findings for developers and researchers. For example, more than half of the PBs slow down DL systems, and nearly one-third of the PBs consume either extremely low or high resources. About half of the PBs are introduced by API misuses, and root causes related to model, data and hardware introduce more than one-third of the PBs. The most bug-prone stages are data preparation, environment setting, model building and training. The most bug-affecting stages are training and data preparation. 40% of the PBs are not exposed in the introducing stage.

Our findings provide implications for developers and researchers on developing high-performance DL systems and detecting and localizing PBs in DL systems, e.g., performance-aware techniques to recommend DL library APIs and DL models, static techniques to model and estimate time cost and resource consumption of DL systems, and rule-based techniques to detect and localize PBs in DL systems.

Based on those 238 PBs, we build a benchmark of 56 PBs that cover most symptoms and root causes. For each PB, we report its environment configuration, input data, buggy version, fixed version, the performance change after fixing, and reproduction steps. Moreover, using our benchmark, we quantitatively assess the capability of a profiler in detecting PBs, the capability of a compiler in optimizing PBs, and the capability of documentation in hinting PBs. The results have indicated that all these approaches have a very limited capability.

To demonstrate the usefulness of our findings, we develop a static checker, named DeepPerf, that supports rule-based detection of three types of PBs derived from our study. We run DeepPerf against 1,108 GitHub projects with more than 100 stars. DeepPerf detects 488 new PBs in 130 of these projects with 15 false positives. 62 of these PBs have already been confirmed by the developers, and 18 of them have already been fixed. Others are still waiting for confirmation.

In summary, this paper makes the following contributions.

• We present the first comprehensive study to characterize 238 PBs in DL systems developed in TensorFlow and Keras.
• We build the first benchmark of 56 PBs in DL systems and assess the capability of existing approaches in tackling them.
• We develop a static checker, named DeepPerf, to detect three types of PBs, and detect 488 new PBs in 130 GitHub projects.

2 EMPirical STUDY METHODOLOGY

We first introduce the design of our empirical study, and then present our data collection and labeling process.

2.1 Study Design

Our goal is to characterize PBs in DL systems. As DL systems can be built on top of various DL libraries, we limit our scope to DL systems developed in TensorFlow and Keras. We select TensorFlow as it is the most popular DL library on GitHub. Specifically, TensorFlow is used in 110,641 GitHub repositories, while the second most popular DL library PyTorch is used in 69,947 GitHub repositories. We also include Keras because it is built on top of and tightly integrated with TensorFlow. We do not distinguish between TensorFlow and Keras in our analysis because they are often used together.

To achieve this goal, we propose the three research questions as introduced in Sec. 1. Our symptom analysis in RQ1 aims to understand the observable consequences of PBs. Our findings from RQ1 can characterize the significance of PBs, and provide insights for developing PB detection approaches. Our root cause analysis in RQ2 aims to characterize the fundamental reasons for the occurrence of PBs. Our findings from RQ2 can provide insights for designing PB localization approaches. Our stage analysis in RQ3 aims to locate DL pipeline stages where PBs are introduced and exposed, and measure the distance between exposing stage and introducing stage. Our findings from RQ3 can locate the bug-prone and bug-affecting stages that should be concerned, and reflect the difficulty of PB localization. Our findings can also provide hints to develop high-performance DL systems.

2.2 Data Collection

We collected PBs from a well-known Q&A site StackOverflow, where world-wide developers can discuss software development problems. Our PB collection process consists of the following three steps.

**Step 1: DL Post Selection.** We first selected posts related to DL libraries TensorFlow and Keras by checking whether the tags of a post contain the keywords “tensorflow” and “keras”. We also filtered posts that were created before 2018-01-01 to avoid usage discussions about old versions of DL libraries that are usually no longer used. At the time of selection (i.e., 2021-03-01), we obtained 61,169 DL posts. Then, we excluded posts that did not contain any source code in question descriptions for the ease of our manual analysis. To focus on high-quality posts, we also excluded posts that did not have an accepted answer or any answer whose votes were greater than two because questioners often commented that the problems had been solved, but forgot to accept the answer. After this step, we had 18,730 DL posts.

**Step 2: PB Post Selection.** Instead of directly using performance-related keywords from the existing studies on PBs in traditional systems (e.g., [30, 48, 62, 79]), we derived a keyword set in the following way to achieve a wide and comprehensive coverage of PB posts. We first randomly sampled 100 posts with a tag of “performance” from the 18,730 posts in Step 1. Then, we manually analyzed these posts to extract performance-related keywords, and added them to the set of keywords from existing studies. We continued this procedure of random sample and manual analysis for two rounds until no new performance-related keyword is found. Finally, we used the derived keyword set to search the question descriptions of the 18,730 posts in Stage 1, which resulted in a total of 742 candidate PB posts.

**Step 3: PB Identification.** We manually verified the 742 candidate PB posts to reduce noise that was not about PBs in DL systems. For example, some posts might happen to have performance-related keywords, but did not discuss PBs; some posts actually discussed the accuracy of DL models (because accuracy is often interchangeable with performance in the DL community, and we align with the SE community where performance is usually referred to as efficiency); and some posts indeed discussed performance, but did not have a correct answer, which could not be used to understand the characteristics of...
The taxonomy of PB symptoms is shown in Fig. 1. It is organized into three high-level categories (i.e., Time, Memory, and Processor) and 10 inner categories, which are exhibited by 187 (78.6%) of the 238 PBs. The remaining 51 (21.4%) PBs have no clear indication about their symptoms in the posts, and hence are included in the Unknown category. Notice that a PB can exhibit multiple symptoms.

Time. This category covers PBs exhibiting high time cost, which accounts for the largest portion of PBs, i.e., 129 (54.2%). In particular, 100 (42.0%) of the PBs manifest Slow Execution Time during the execution of DL systems, including data preparation, model building, training, evaluation, hyper parameter tuning, or prediction. Further, 16 (6.7%) of the PBs exhibit Increasing Time Over Time; e.g., the prediction time became longer and longer as the model ran. Moreover, 8 (3.4%) of the PBs manifest Slow Initialization Time when DL systems are initialized before execution; e.g., it spent more than 80 seconds to import TENSORFLOW. DL systems can still work but slowly when exhibiting the above symptoms. Differently, 8 (3.4%) of the PBs result in Program Hang that makes DL systems cease to respond to inputs, which is the most severe symptom.

Memory. This category includes PBs consuming RAM/GPU memory abnormally, accounting for 58 (24.4%) of the PBs. Specifically, Out of Memory is the most common as well as the most severe symptom, covering 42 (17.6%) of the PBs. Memory Leak, manifested in 16 (6.7%) of the PBs, occurs when the memory usage keeps increasing, and may finally lead to out of memory errors. Moreover, Abnormal GPU Memory Usage, i.e., either unexpectedly high or low GPU memory usage, is exhibited in 5 (2.1%) of the PBs.

Processor. This category consists of PBs with abnormal CPU/GPU utilization, which accounts for 16 (6.7%) of the PBs. In particular, Abnormal GPU Utilization, i.e., either unexpectedly high or low GPU utilization, is manifested in 8 (3.4%) of the PBs. For example, the GPU utilization was only around 15%, while the training time was slow (each epoch took 40 to 50 seconds). Moreover, DL systems may Not Use GPU, leading to no speedup than when running on CPU, which occurs in 4 (1.7%) of the PBs. In addition, Abnormal CPU Utilization is also exhibited in 4 (1.7%) of the PBs.

Summary. More than half of the PBs slow down DL systems, and nearly one-third of the PBs consume either extremely low or high resources like memory and processor. Such severe consequences of PBs motivate the significance of PBs. Moreover, only four of the ten symptoms, as highlighted in dotted rectangles in Fig. 1, are shared with the existing symptom taxonomies for general DL bugs. This category includes PBs consuming RAM/GPU memory abnormally, accounting for 58 (24.4%) of the PBs. Specifically, Out of Memory is the most common as well as the most severe symptom, covering 42 (17.6%) of the PBs. Memory Leak, manifested in 16 (6.7%) of the PBs, occurs when the memory usage keeps increasing, and may finally lead to out of memory errors. Moreover, Abnormal GPU Memory Usage, i.e., either unexpectedly high or low GPU memory usage, is exhibited in 5 (2.1%) of the PBs.

3.2 Root Cause Analysis (RQ2)

The taxonomy of PB root causes is reported in Fig. 2. It is grouped into five high-level categories (i.e., API, Model, Library, Data and Environment) and 15 inner categories, which cause 218 (91.6%) of the 238 PBs. The other 20 (8.4%) PBs have unclear or infrequent (which occur once) root causes, and thus are included in the Others category.

API. This category covers PBs caused by library API misuses, which is the most common category and accounts for 110 (46.2%) of the PBs. Specifically, TENSORFLOW and KERAS provide efficient APIs for achieving high performance, e.g., the t.f.data API for building efficient input pipelines, and various operation APIs for efficient computation. However, developers often write their own implementation which is
often less efficient, but do Not Use the corresponding Efficient API directly, potentially due to the unfamiliarity with APIs. This causes 50 (21.0%) of the PBs. For example, a developer wrote a for loop to perform concatenation on a set of images, which could be efficiently achieved by the map API from tf.data.Dataset. Moreover, TensorFlow and Keras provide various batch processing APIs for high performance, e.g., data loading, training, evaluation or prediction in a batch mode. However, developers might Not Use a Batch API and some even implement batch processing by themselves, which causes 16 (6.7%) of the PBs. For example, a developer loaded a large data set into GPU memory all at once, causing an out of memory error\(^6\). The flow_from_directory API in TensorFlow provides various batch processing APIs for high performance, e.g., data loading, training, evaluation or prediction in a batch mode. However, even when developers are aware of some APIs, they might not fully understand their performance characteristics, and write Inefficient API Usage, which causes 44 (18.5%) of the PBs. Fig. 3 shows an example of inefficient API usage, where a developer called the map API before the batch API, and did not pass the num_parallel_calls argument to map\(^5\), leading to a long training time. To speed up, map should be called after batch to reduce the number of times the mapped function _batch_parser is called, and num_parallel_calls should be passed to enable parallelism.

**Model.** This category consists of PBs that are related to DL models, which is the second most common category, accounting for 50 (21.0%) of the PBs. In particular, developers may have Confusion with Computation Graph because of the unfamiliarity with the programming model in TensorFlow and Keras, which causes 27 (11.3%) of the PBs. A typical confusion is with the programming model of TensorFlow 1.x, which is to first build a dataflow computation graph and then run it repeatedly with inputs being fed to and outputs being fetched from the graph. Developers often mix the graph construction into the graph execution. As a result, nodes are repeatedly added to the graph, and the graph execution becomes slower and slower. An example\(^5\) is shown in Fig. 4, where Line 14–16 builds the graph and should be moved out of the execution loop to Line 6–8. Another common confusion is with the usage of session, which owns resources like queues and variables. However, developers repeatedly create a session in the graph execution loop without reusing, or forget to close the session. The example in Fig. 4 also forgets to close the session, and the fix is to use the session as a context manager at Line 11 that will automatically close the session. A typical confusion in TensorFlow 2.x is with the @tf.function decorator, which accelerates the decorated function by running it in graph mode instead of in eager mode. However, developers often do not know where to add the decorator and how to design the decorated function to get real speedup. Further, developers design an Inefficient Model Structure (e.g., missing convolution and pooling layers before the flatten layer to have too many weights) or set Improper Model Parameter (e.g., a large kernel size in a convolution layer to cause a long training time). These two categories respectively cause 6 (2.5%) and 12 (5.0%) of the PBs. Moreover, developers also set Improper Hyper Parameter, e.g., a large batch size to cause an out of memory error or a small batch size to cause a long training time. This category causes 5 (2.1%) of the PBs.

**Library.** This category refers to PBs caused by problems of DL libraries, accounting for 24 (10.1%) of the PBs. Specifically, 15 (6.3%) of the PBs are caused by Library Bug; i.e., DL systems themselves are correctly written, but trigger the PBs in DL libraries. For example,
```
inp = tf.constant([[1., 1.]]);
out = tf.constant([[1., 8.]]);
weight = tf.Variable([[1., 1.], [1., 1.]]);

optimizer = tf.train.GradientDescentOptimizer(0.1)

* loss = (out[0][0] - y[0][0])**2 + (out[0][1] - y[0][1])**2

+ train = optimizer.minimize(loss)

- sess = tf.Session()
+ with tf.Session() as sess:
- y = tf.matmul(inp, weight)
+ loss = (out[0][0] - y[0][0])**2 + (out[0][1] - y[0][1])**2
+ y = tf.matmul(inp, weight)
```

**Figure 4: Graph Confusion Before and After Fix**

repeated calls to `model.predict` (e.g., in a loop) resulted in a memory leak, due to a memory leak persisting across multiple versions of TensorFlow. Moreover, `Wrong Library Version` causes 9 (3.8%) of the PBs, as version restrictions have to be satisfied for full GPU usage. For example, a CPU version of TensorFlow is used on a GPU machine, leading to no GPU usage; and TensorFlow 1.x is not fully supported on CUDA 11.1, resulting in a long time to start the training.

**Data.** This category covers PBs related to data processing, which accounts for 21 (8.8%) of the PBs. In particular, developers may write `Inefficient Data Transmission`, e.g., loading input data over the network during training but not directly copying them to the local storage, or storing weight data in CPU which causes the weights copied to GPU and the gradients copied back to CPU in each training iteration. This category accounts for 12 (5.0%) of the PBs. Further, developers may implement `Inefficient Data Preprocessing` (e.g., lack of image normalization before changing an image to a tensor), which causes 3 (1.3%) of the PBs. Moreover, `Improper Input Data` (e.g., improper data format or size that consumes excessive resources) causes 6 (2.5%) of the PBs. For example, images with unnecessarily high resolution were loaded, resulting in an out of memory error.

**Hardware.** This category covers PBs related to hardware issues, accounting for 13 (5.5%) of the PBs. Specifically, hardware may only support part of the DL library versions, and hence `Hardware and Library Mismatch` causes 4 (1.7%) of the PBs. For example, a GPU with compute capability 6.1 is not supported in TensorFlow 2.3 which requires a GPU with compute capability 7.0. Further, to utilize the full acceleration capability of TPU, DL systems often need specific code design. Thus, `Hardware and Code Mismatch` causes 7 (2.9%) of the PBs. For example, to use Colab TPU, the DL model need to be explicitly converted to a TPU compatible version; otherwise the training becomes extremely slow. Moreover, hardware need proper configuration to achieve full utilization, especially for distributed training. Thus, `Improper Configuration` causes 2 (0.8%) of the PBs. For example, the `tf.distribute.Strategy API should be used to properly configure and allocate multiple GPUs`.

**Summary.** About half of the PBs are introduced by API misuses. Model, data and hardware, i.e., the enabling characteristics of DL systems, introduce more than one-third of the PBs. DL libraries also introduce one-tenth of the PBs. These diverse sources of root causes increase the complexity of PB localization. Moreover, only seven of the 15 root causes, as shown in dotted rectangles in Fig. 2, are the same to the previous root cause taxonomies for general DL bugs [26, 27, 86]. These differences owe to the fact that our study is focused on the performance of DL systems, while the previous studies are mainly concentrated on the functionality of DL systems.

### 3.3 Stage Analysis (RQ3)

Islam et al. [27] classify the pipeline of DL systems into six stages, i.e., Data Preparation, Model Building, Training, Evaluation, Hyper Parameter Tuning and Prediction, in their study on general DL bugs. We consider these stages as the execution stages of DL systems, and further add two new stages, identified in our data labeling, before them. The first newly added stage is Environment Setting, where the DL environment like libraries and hardware are properly installed and configured. The second one is Initialization, where the DL system is initialized (e.g., importing libraries and initializing parameters) before starting the execution stages. For each PB, we determine the stage that introduces the PB by analyzing where its root cause is located, and decide the stage that exposes the PB by analyzing where its symptom is exhibited. We categorize the introducing stage or exposing stage of a PB as Unknown when there is no clear indication in the post.

Fig. 5a reports the number of PBs introduced and exposed in each stage, where the stage name on the x-axis is simplified to the initial letters. Data preparation is the most bug-prone stage, which is blamed in 92 (38.7%) of the PBs. Environment setting, model building and training are the second most bug-prone stages, respectively causing about 10% of the PBs. Hence, developers should pay more attention to these stages to avoid the introduction of PBs, while automated PB localization approaches should be specifically developed for these stages. The other stages are less bug-prone, respectively introducing at most 5% of the PBs. On the other hand, training and data preparation are the two most bug-affecting stages, where 99 (41.6%) and 45 (18.9%) of the PBs are respectively exposed. Thus, developers should focus more efforts on these two stages to optimize their performance, while automated PB detection approaches should be specifically developed for these two stages. Around 7% of the PBs are respectively exposed until the evaluation and prediction stages. The other stages are less bug-affecting, which respectively expose at most 3% of the PBs.

Further, data preparation introduces more PBs than exposed. This difference is even more severe in the other two earlier pipeline stages, i.e., environment setting and model building. About 61% of the PBs are introduced in the earlier four pipeline stages, around 60% of which are exposed in the later four pipeline stages. The other way around, training exposes more PBs than introduced. This difference also holds in the other two later pipeline stages, i.e., evaluation and prediction. Nearly 60% of the PBs are exposed in the later four pipeline stages. Thus, PBs should be proactively detected and localized before severe consequences occur so as to reduce time cost and resource consumption. Besides, for each PB, we measure the distance between its exposing
stage and introducing stage, which is used as an indicator of the difficulty of PB localization. Intuitively, the larger the distance, the more difficult to localize a PB from its symptom to root cause. As shown in Fig. 5b, 105 (44.1%) of the PBs are exposed and introduced in the same stage, while 93 (39.1%) of the PBs cannot be exposed in the introducing stage. Specifically, 68 (28.6%) of the PBs are exposed two stages later. Extremely, 4 (1.7%) of the PBs are exposed seven stages later; i.e., they are introduced in the first stage but exposed in the last stage. Hence, PB localization is quite challenging for a considerable amount of PBs.

Moreover, we investigate the symptom distribution of the PBs exposed in each stage, which is shown in Fig. 6a. This distribution helps pinpoint the potentially useful performance indicators for detecting PBs exposed in different stages. For example, time-related indicators can be valuable to detect PBs exposed in initialization, data preparation and prediction, because the most common symptom of the PBs exposed in these stages is under the category of Time. Similarly, we report the root cause distribution of the PBs introduced in each stage in Fig. 6b. This distribution helps hint the potential technical solutions to localize PBs introduced in different stages. For example, the most frequent root cause of the PBs introduced in most stages is under the category of API, and hence API misuse detection could be developed to localize PBs introduced in these stages.

Summary. The most bug-prone stages are data preparation, environment setting, model building and training, which introduce nearly 70% of the PBs. The most bug-affecting stages are training and data preparation, which expose around 60% of the PBs. Nearly 40% of the PBs cannot be exposed in the introducing stage. Moreover, we introduce two new stages that are not covered in the previous stage analysis for general DL bugs [27], and investigate the introducing and exposing stages that are not distinguished in the previous study [27].

3.4 Implications

We discuss the implications of our findings for developers of DL systems as well as researchers.

Developers. Our study reveals the common symptoms of PBs that developers could pay attention to when testing and running their DL systems for detecting potential PBs. Our study also identifies the common root causes of PBs that can be useful for developers to diagnose, debug or fix PBs. Our study also captures the most bug-prone or bug-affecting stages where developers could focus more efforts on to provide the most benefit for PB introduction avoidance or performance optimization. Furthermore, our findings provide some development suggestions. Developers should carefully read the release note and API documentation of DL libraries to get familiar with the rich set of library APIs and their performance characteristics. In this way, PBs caused by the most common root cause (i.e., API misuses) might be reduced. Developers should also be systematically trained to have a comprehensive understanding of computation graph to build efficient DL models. In this way, PBs caused by the second most common root cause (i.e., model construction) might be reduced.
Researchers. Our findings provide several implications on future research in three directions. First, intelligent techniques for high-performance DL system development are needed. As developers are often unaware of library APIs that are specifically designed for high performance or unaware of the performance characteristics of library APIs, DL library API recommendation techniques should be developed. To achieve performance-aware API recommendation, a knowledge graph of DL library APIs should be constructed based on release notes. API documentation and StackOverflow discussions with a specific focus on modeling performance characteristics of APIs and performance differences across library versions. To locate and replace inefficient code snippets written from scratch by developers, semantic analysis techniques should be developed to determine their semantic similarity to existing library APIs. Apart from such intelligent techniques at the code level, recommendation techniques should be developed to automatically suggest DL library versions, efficient DL models and their parameters, and environment configurations.

Second, PB detection techniques are needed. Half of the symptoms (i.e., Increasing Time Over Time, Program Hang, Out of Memory, Memory Leak, and Not Using GPU) can be regarded as a credible oracle for detecting PBs in DL systems. Therefore, proactive monitoring and prediction techniques should be developed to detect PBs as early as possible before these severe symptoms occur. DL systems exhibiting the other symptoms are not guaranteed to contain PBs as it is often not clear how much time or resources a DL system should consume to run without a PB. To solve this performance oracle problem, one potential way is to design differential testing techniques to compare the performance of DL systems running with different DL libraries, different DL models, or different hardware configurations. However, it may incur too much overhead. Hence, another potential way is to design static techniques to model and estimate time cost or resource consumption of DL systems so that performance bottlenecks can be identified in advance before execution. During our manual analysis, we find that TensorFlow has some built-in mechanism in detecting PBs and recommending fixes by throwing a warning message, e.g., “WARNING: tensorflow: multiprocessing can interact badly with TensorFlow, causing nondeterministic deadlocks. For high performance data pipelines tf.data is recommended”. However, such warning messages are only raised in 3 of the PBs, indicating the preliminary support in PB detection due to symptom and root cause diversity. Hence, built-in mechanisms in DL libraries should be further enhanced.

Third, PB localization techniques are needed. Our study reveals that the exposing stage of a PB is often not the introducing stage. For example, the location that throws the error message of an out of memory error is usually not the location of the root cause. Therefore, it is often challenging to localize PBs. During our manual analysis, we find that developers often use logs as the clue to locate PBs. Hence, automated log analysis techniques should be developed to smartly insert log statements into DL systems and locate potential PBs using log traces. Further, as API misuse is the most common root cause of PBs, mining techniques should be designed to learn frequent API usage sequences and localize potential violations in DL systems. API usage mining has been widely explored in traditional systems [57], but it is interesting to investigate how they are applicable to PBs in DL systems. Last but not the least, rule-based techniques should be developed to detect and localize PBs, considering the potentially large amount of PBs on StackOverflow or GitHub. The challenge is to automatically derive but not manually specify the rules.

4 BENCHMARK AND ASSESSMENT

We reproduce and build a benchmark of 56 PBs from the 238 PBs in our empirical study with four person-months effort, which can be used to facilitate the future research on PBs in DL systems. We also assess the capability of existing approaches in addressing them.

4.1 Benchmark Construction

We reproduce PBs on the machine with a 16-core Intel i7-7820X CPU (3.60GHz), NVIDIA TITAN Xp GPU, 128GB RAM and 1TB SSD. Different PBs require different TensorFlow versions which further require different CUDA Toolkit versions to support GPU. As it is tricky to install different CUDA versions in the same physical machine, we use TensorFlow Docker images18. As a result, only NVIDIA GPU Driver19 is installed in the physical machine, and each docker container has its own CUDA Toolkit version. Finally, TensorFlow Docker images ranging from version 1.12 to 1.15, and version 2.0 to 2.5 with GPU support are covered to build our benchmark.

We first sample some PBs from the 238 PBs in our empirical study instead of trying to reproduce all the 238 PBs due to the large manual effort involved in reproducing PBs from StackOverflow posts. To have a good coverage of symptoms and root causes, we sample 50% PBs from each set of PBs that are caused by each inner category of root causes while exhibiting each high-level category of symptoms. Then, for each sampled PB, we reproduce it with the following three steps.

Step 1: Decide TensorFlow Version. If the TensorFlow version is shown in the post, we use it. If not, we check whether APIs specific to TensorFlow 1.x (e.g., tf.Session) or 2.x (e.g., @tf.function) exist in the post. If yes, we use the latest TensorFlow version of 1.x (i.e., 1.15) or 2.x (i.e., 2.5). If not, we use TensorFlow 2.5.

Step 2: Complete Code Snippets. As developers tend to only include code fragments that are directly related to questions, code snippets in the post are often incomplete. Specifically, if the buggy (or fixed) version is executable, we complete the fixed (or buggy) version based on it. Otherwise, we manually write missing code fragments for both buggy and fixed versions based on question description and answer.

Step 3: Reproduce Symptoms. We execute the buggy and fixed version to reproduce symptoms described in the post. We may change input data size, model parameters, etc. to reproduce described symptoms as our hardware environment might be different from the post. For PBs with out of memory errors, we set the maximum GPU memory limit with tf.GPUOptions such that the out of memory errors can be reproduced even on GPUs with a larger memory.

We successfully reproduce 56 PBs. The first six columns of Table 1 present the number of reproduced PBs across root causes and symptoms, where the number in parentheses is the number of PBs used in our empirical study. Overall, they cover all the root causes except for Wrong Library Version and the three hardware relevant root causes.

https://tensorflow.org/install/docker

https://github.com/NVIDIA/nvidia-docker
They also cover all high-level symptoms, but achieve a relatively low coverage of processor relevant symptoms. The main reasons for failed reproduction are two-fold: i) developers provide very incomplete code snippets in the posts, and hence it is difficult to complete the buggy or fixed version, and ii) some PBs require specific hardware environments that are different from our machine. To foster future research on PBs in DL systems, we record for each of the PB in our benchmark its environment configuration, input data, buggy version, fixed version, performance change after fixing, and reproduction steps.

### 4.2 Approach Assessment

A potential application of our PB benchmark is to assess the capability of existing approaches in detecting and localizing PBs. To the best of our knowledge, there is no PB detection and localization approach for DL systems. Hence, we select and assess the following three typical performance analysis techniques, which can be used by developers to improve the performance of DL systems, with our benchmark.

- **TensorFlow Profiler**\(^{20}\): It is built on top of NVIDIA CUDA Profiling Interface to track the performance of TensorFlow models. It visualizes the time cost and resource consumption of various TensorFlow operations in the model, finds performance bottlenecks, and recommends best practices to improve performance.

- **XLA (Accelerated Linear Algebra)**\(^{21}\): It is a domain-specific compiler that can accelerate TensorFlow models. Each TensorFlow operation is executed by a precompiled GPU kernel implementation. XLA can compile the TensorFlow graph into a sequence of computation kernels generated specifically for the given model, and fuse the kernels to avoid memory operations during the execution of different kernels to improve the performance [37].

- **TensorFlow Documentation**: It includes all TensorFlow API documentation\(^{22}\) and performance guide\(^{23}\) where developers can find hints about performance problems and optimization solutions.

Generally, we assess each technique in two dimensions: i) whether a technique is applicable to a PB (or whether a PB is in the capability scope of a technique), and ii) whether a technique can solve a PB. The assessment results are shown in the last five columns in Table 1.

As shown in the seventh column of Table 1, TensorFlow Profiler is only applicable to 15 (26.8%) PBs, but is not applicable to the others for two reasons. First, TensorFlow Profiler requires a TensorFlow version of at least 1.14. However, some PBs are reproduced with a lower version. Second, TensorFlow Profiler requires a full training or evaluation process to track the performance, which is not always available for the PBs in our benchmark. Moreover, of these 15 PBs, TensorFlow Profiler fails to finish profiling because of out of memory errors for 9 PBs, and does not raise any warning or raises a false warning for 4 PBs. Hence, we consider these 13 PBs as not solved by TensorFlow Profiler. For the remaining 2 PBs, TensorFlow Profiler either raises a warning but suggests a fix that achieves a smaller performance improvement than our fixed version in the benchmark, or helps detect the PB by reporting the most time-consuming operation but fails to raise a warning and suggest a fix. Thus, we consider these 2 PBs as partially solved by TensorFlow Profiler, as reported in the eighth column of Table 1. These results demonstrate that TensorFlow Profiler has limited capability in tackling PBs.

As presented in the ninth column of Table 1, XLA is applicable to 23 (41.1%) PBs. There are two reasons that XLA is not applicable to the others. First, XLA uses just-in-time (JIT) compilation. However, compilation errors might occur for some PBs in our benchmark. Second, XLA is designed for optimizing the performance of TensorFlow models. Thus, it is not applicable to PBs whose root causes are

---

\(^{20}\)https://tensorflow.org/guide/profiler

\(^{21}\)https://tensorflow.org/xla

\(^{22}\)https://www.tensorflow.org/versions/r2.5/api_docs

\(^{23}\)https://www.tensorflow.org/guide
The default graph optimizer in TensorFlow runtime, cannot eliminate this type of PBs although it has the loop optimizer.

To implement the checker, we first extract TensorFlow APIs that may add computation graph nodes by parsing the @tf_export decorators in the source code of TensorFlow Python APIs. Then, we manually review these APIs to exclude APIs that actually do not add nodes (e.g., tf.assign) or APIs that produce different values given the same inputs (e.g., tf.random.uniform). Finally, we obtain 356 APIs.

Our checker determines whether these 356 APIs are called with the same argument values among loop iterations. To this end, it tracks variables that are changed among loop iterations, including the loop control variable, variables that are assigned in the loop body but are defined outside the loop, and any variables that depend on them. It identifies APIs called without using changed variables as arguments as PBs. Our analysis is inter-procedural. If there are functions called in the loop, it passes changed variables to callee functions, analyzes changed variables in callee functions, and identifies APIs called without using changed variables as arguments in callee functions.

**Checker 2: Inefficient Order of map and batch.** As showed in Fig. 3, calling map before batch is not efficient, and hence batch is suggested to be called before map to reduce the number of times the mapped function is called. To detect such API misuse of batch and map, our checker first identifies t. Dataset object, and then analyzes the call sites to check whether batch is called after map.

**Checker 3: Disabled Parallelism of map and interleave.** As showed in Fig. 3, calling map without setting its num_parallel_calls argument disables parallelism. This also holds for interleave. To detect such API misuse of map and interleave, our checker identifies t. Dataset object, and then analyzes the call sites to check whether map and interleave are called without setting num_parallel_calls.

### 5.2 Evaluation
To evaluate the effectiveness of the three checkers in DeepPerf, we use PyGitHub to crawl 1,108 GitHub repositories that use TensorFlow and Python and have at least 100 stars, and run DeepPerf on these repositories. We also report detected PBs as issues to developers. The results are shown in Table 2, where the statistics about detected, confirmed and fixed PBs are reported for each checker.

Specifically, **Checker 1** detected 77 PBs in 49 projects. It detected 15 false positives (i.e., the fourth column in Table 2). The reason is that we use lightweight heuristics to decide loop invariants based on AST and Jedi, but do not use heavy-weight data/control flow analysis, for the scalability of our checker. 20 PBs in 14 projects have been confirmed by developers, and 6 of them in 3 projects have been fixed.

---

**Table 2: PB Detection Results of DeepPerf**

| Checker   | Detected | Confirmed | Fixed |
|-----------|----------|-----------|-------|
|           | PB  | Proj. | FP | PB  | Proj. | PB  | Proj. |
| Checker 1  | 77  | 49  | 15 | 20  | 14  | 6   | 3    |
| Checker 2  | 195 | 68  | 0  | 16  | 9   | 0   | 0    |
| Checker 3  | 216 | 66  | 0  | 26  | 15  | 12  | 6    |
| Total      | 488 | 130 | 15 | 62  | 35  | 18  | 9    |

---

24https://docs.python.org/3/library/ast.html
25https://github.com/davidhalter/jedi/
26https://tensorflow.org/api_docs/python/ops
27https://github.com/tensorflow/tensorflow/tree/r1.15/tensorflow/python/ops
28https://github.com/PyGithub/PyGithub

---

not related to TensorFlow operations or computation graphs. Furthermore, of these 23 PBs, XLA only improves the performance for 4 PBs but still achieves a smaller performance improvement than our fixed version in the benchmark. This is reasonable because XLA is actually not aware of the PBs, but optimizes performance by fusing nodes in computation graphs, while our fixed version reduces the number of nodes in computation graphs. Hence, we consider these 4 PBs as partially solved by XLA, as reported in the tenth column of Table 1. For the other 19 PBs, XLA does not have any performance improvement because of the small number of nodes in computation graphs. Thus, we consider these 19 PBs as not solved by XLA. These results indicate that PBs in DL systems often cannot be eliminated by the compilation optimization techniques in XLA.

As shown in the last column of Table 1, TensorFlow documentation is only applicable to 9 (16.1%) PBs. We consider TensorFlow documentation as applicable as long as the documentation mentions the optimization solution of a PB. There are two main reasons that TensorFlow documentation is applicable to a small portion of PBs. The first is that performance characteristics, especially non-time characteristics, are hardly described in API documentation. The second is that many PBs are caused by inefficient usages of multiple APIs, but API documentation is often focused on individual API usages. Although performance guide covers usages of multiple APIs, they only cover limited APIs such as tf.data. We consider these 9 PBs as solved by TensorFlow documentation. These results show that TensorFlow documentation provides limited support for PBs.

**Summary.** Efforts like profiling, compilation optimization and documentation have been devoted to optimizing the performance of DL systems from different perspectives. However, they provide limited capability in tackling PBs, potentially due to the lack of a comprehensive understanding of PBs in DL systems.

### 5 DETECTION
To demonstrate the usefulness of our findings, we implement a rule-based static checker, named DeepPerf, to detect PBs in DL systems. DeepPerf is implemented with two analysis tools, AST and Jedi. It currently supports three types of PBs whose detection rules are manually derived from our empirical study (Sec. 3).

#### 5.1 Approach
We design static checkers for the following three types of PBs.

**Checker 1: Repeated Node Creation.** Creating the same nodes repeatedly to a computation graph is one of the common types of PBs under the root cause category of Confusion with Computation Graph. DeepPerf is designed to detect node creation APIs that are called in loops with the same argument values; e.g., the two APIs tf.matmul and optimizer.minimize in Fig. 4. Actually, it is similar to Loop Invariant Computation and Code Motion (LICM) optimization, which has been well studied in classic compilers [3]. However, Grappler showed in Fig. 3, calling map after batch is not efficient, and hence batch is suggested to be called before map to reduce the number of times the mapped function is called. To detect such API misuse of batch and map, our checker first identifies tf.Dataset object, and then analyzes the call sites to check whether batch is called after map.

**Checker 2: Inefficient Order of map and batch.** As showed in Fig. 3, calling map before batch is not efficient, and hence batch is suggested to be called before map to reduce the number of times the mapped function is called. To detect such API misuse of batch and map, our checker first identifies tf.Dataset object, and then analyzes the call sites to check whether batch is called after map.

**Checker 3: Disabled Parallelism of map and interleave.** As showed in Fig. 3, calling map without setting its num_parallel_calls argument disables parallelism. This also holds for interleave. To detect such API misuse of map and interleave, our checker identifies tf.Dataset object, and then analyzes the call sites to check whether map and interleave are called without setting num_parallel_calls.

---

24https://docs.python.org/3/library/ast.html
25https://github.com/davidhalter/jedi/
26https://tensorflow.org/api_docs/python/ops
27https://github.com/tensorflow/tensorflow/tree/r1.15/tensorflow/python/ops
28https://github.com/PyGithub/PyGithub

---
We discuss the closely related work in understanding and analyzing deep learning bugs and performance bugs. The recent success in applying deep learning techniques to a variety of domains has gained increasing interest in understanding characteristics of bugs in deep learning systems. Zhang et al. [86] collected 175 bugs in deep learning systems developed in TensorFlow from StackOverflow posts and GitHub commits. They analyzed the symptoms and root causes of these bugs, and explored the challenges and strategies in bug detection and localization. Islam et al. [27] and Humbatova et al. [26] expanded the scope of Zhang et al.’s study to include more deep learning libraries. Islam et al. [27] analyzed the types, root causes, impacts and pipeline stages of 970 bugs in deep learning systems written in CAFFE, KERAS, TensorFlow, Theano and Torch, while Humbatova et al. [26] constructed a taxonomy of bugs in deep learning systems that use TensorFlow, Keras and PyTorch based on manual analysis of 375 bugs and interviews with 20 developers. In their follow-up work, Islam et al. [28] analyzed bug fix patterns. Kim et al. [33] built a benchmark of 4,577 bugs from 193 deep learning systems. Differently, Jia et al. [29] explored the symptoms, root causes and locations of 202 bugs in the TensorFlow library.

Apart from these studies that are focused on a general scope of bugs in deep learning systems, several recent studies have targeted more specific bugs. Zhang et al. [82] studied failures of deep learning jobs that are running on a remote, shared platform in Microsoft. Chen et al. [8] investigated faults related to the deployment of deep learning models to mobile devices. Zhang et al. [85] summarized five common training problems in deep learning systems, and developed a tool to automatically detect and repair training problems. Wan et al. [68] studied API misuses when deep learning systems use cloud AI services, summarized eight misuse patterns, and developed static checkers to automatically detect some of the misuse patterns.

Some of these existing studies reveal some partial characteristics of performance bugs in deep learning systems. For example, Zhang et al. [86] and Islam et al. [27] respectively recognized low efficiency and hang as a symptom of deep learning bugs. Zhang et al. [82] identified GPU out of memory as a failure category of deep learning jobs. Chen et al. [8] recognized memory and speed issues as two types of faults in the inference stage of deployment process. Wan et al. [68] derived four performance-related API misuse patterns of cloud AI services. Despite these efforts, there still lacks a comprehensive study to understand the characteristics of performance bugs in deep learning systems, and thus our study aims to bridge this knowledge gap and raise the awareness of PBs in DL systems.

Besides, some studies have investigated general problems and challenges in developing and deploying deep learning systems. For example, Guo et al. [19] measured the accuracy and and performance differences across four deep learning libraries. Zhang et al. [83] identified seven kinds of frequently asked deep learning questions in StackOverflow, and analyzed their resolution difficulty and root causes. Han et al. [21] investigated the topics that developers discuss when developing deep learning systems. Chen et al. [7] built a taxonomy of challenges in deploying deep learning systems to different platforms through manual analysis of StackOverflow posts. Pham et al. [54] measured accuracy variance in training deep learning systems. Cumaudo et al. [11] studied the pain-points that developers face when using cloud services of computer vision by mining StackOverflow posts.
Although these studies are not designed for deep learning bugs, they shed light on debugging and bug detection in deep learning systems. Specifically, Guo et al. [19] reported performance differences in terms of time cost and memory consumption when trained deep learning models are migrated or quantized to different mobile devices and web browsers, and called for performance optimization and testing techniques. Zhang et al. [83] summarized performance as a category of frequently asked deep learning questions in StackOverflow, and recognized that performance questions are the most difficult to answer. Our study is inspired by these studies to systematically characterize performance bugs in deep learning systems.

Moreover, some advances have been made to detect deep learning bugs. For example, Zhang et al. [87] developed a static analysis approach to detect numerical bugs in neural architectures based on abstract interpretation. Lagouvardos et al. [34] proposed a static analysis to detect shape incompatibility errors in TensorFlow programs, while Verma and Su [67] proposed a dynamic abstract interpreter to catch such errors. Wardat et al. [72] developed a dynamic analysis approach to locate faults in deep neural networks. In addition, great efforts have been devoted to testing deep learning systems (e.g., [32, 42, 50, 51, 64, 65, 74]) and deep learning libraries (e.g., [20, 45, 53, 70, 71, 84]) for quality assurance. Zhang et al. [81] presented a comprehensive survey of work in this direction. However, little attention has been received to detecting and testing performance bugs in deep learning systems, and our study sheds light on this area.

### 7.2 Performance Bugs

A lot of empirical studies have characterized performance bugs from different perspectives (e.g., root causes, discovery, diagnosis, fixing and reporting) for desktop or server applications [30, 48, 62, 79, 88], highly configurable systems [24, 25], mobile applications [38, 40], database-backed web applications [77, 78], and JavaScript systems [59]. They shed light on potential directions on performance analysis (e.g., detection, profiling and testing). Our study is the first to understand performance bugs in deep learning systems, which differs from traditional systems on the programming paradigm.

Several advances (e.g., [2, 9, 12, 22]) have been made to detect general performance bugs using dynamic profiles from production runs. A large body of work has proposed pattern-based techniques to detect specific performance bugs such as reusable/cacheable data (e.g., [5, 13, 46]), inefficient/redundant loops (e.g., [14, 47, 49, 63]), and inefficient collections (e.g., [31, 60, 75]). Besides, a lot of techniques have been proposed for performance testing, i.e., generating test cases to trigger worst-case performance (e.g., [6, 36, 41, 52, 73]) and find performance bugs (e.g., [18, 61, 66]). Another line of work is focused on performance profiling techniques to identify hot paths (e.g., [4, 15, 35]) and fit a performance model to the input size (e.g., [10, 17, 80]). These performance analysis approaches are designed for traditional systems, and cannot be directly applied to deep learning systems.

Recently, some performance analysis approaches have been proposed for deep learning systems. For example, Qi et al. [55] modeled and estimated time cost of training deep neural networks, while Gao et al. [16] estimated GPU memory consumption. These estimation techniques are useful to identify potential performance bugs in advance. Liu et al. [39] measured the performance of training deep learning models on mobile devices, while Ma et al. [43] compared time cost of Java-based deep learning libraries when running deep learning tasks in browsers. These studies empirically demonstrate the performance differences. To reduce the memory usage of deep neural networks, Rhu et al. [56] developed a dynamic memory manager to virtualize memory usage, while Wang et al. [69] proposed a dynamic GPU memory scheduler. To make deep learning models efficient, Han et al. [23] used pruning and quantization to compress models, Yan et al. [76] used a performance model to estimate the time of distributed model training and find the optimal distributed configuration, and Menghani [44] presented a survey in this area. These approaches are system-level performance optimization techniques, while our detection approach is at the source code level. Despite these efforts, the characteristics of performance bugs in deep learning systems are still unclear, and thus our study motivates new directions on performance analysis.

### 8 CONCLUSIONS

In this paper, we present the first comprehensive study to characterize PBs in DL systems developed in TensorFlow and Keras. Moreover, we build the first benchmark of PBs in DL systems, and assess the capability of existing approaches in tackling them. Further, we develop a static checker DeepPerf to detect three types of PBs, and detect many new PBs in GitHub projects. The significance of our study, benchmark, and detection approach is that we raise the awareness of PBs in DL systems and shed light on the implications for both developers and researchers on developing high-performance DL systems as well as detecting and localizing PBs in DL systems. All the study data and the source code of DeepPerf is available at https://dlperf.github.io to foster future research.

### REFERENCES

[1] Saleema Ameri, Andrew Begel, Christian Bird, Robert DeLine, Harald Gall, Ece Kamar, Nachiappan Nagappan, Besmira Nushi, and Thomas Zimmermann. 2019. Software engineering for machine learning: A case study. In Proceedings of the IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice. 291–300.

[2] Glenn Ammons, Jong-Deok Choi, Manish Gupta, and Nikhil Swamy. 2004. Finding and removing performance bottlenecks in large systems. In Proceedings of the European Conference on Object-Oriented Programming. 172–196.

[3] David F. Bacon, Susan L. Graham, and Oliver J. Sharp. 1994. Compiler Transformations for High-Performance Computing. ACM Comput. Surv. 26, 4 (1994), 345–420.

[4] Thomas Ball and James R Larus. 1996. Efficient path profiling. In Proceedings of the 29th Annual IEEE/ACM International Symposium on Microarchitecture. 46–57.

[5] Suparna Bhattacharya, Mangala Goweri Nanda, Kanchi Gopinath, and Manish Gupta. 2011. Reuse, recycle to de-bloat software. In Proceedings of the European Conference on Object-Oriented Programming. 408–432.

[6] Jacob Burnim, Sudeep Javekar, and Koushik Sen. 2009. WISE: Automated test generation for worst-case complexity. In Proceedings of the IEEE 31st International Conference on Software Engineering. 463–473.

[7] Zhenpeng Chen, Yanbin Cao, Yuanqiang Liu, Haoyu Wang, Tao Xie, and Xuanzhe Liu. 2020. A comprehensive study on challenges in deploying deep learning based software. In Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering. 750–762.

[8] Zhenpeng Chen, Huihan Yao, Yiling Lou, Yanbin Cao, Yuanqiang Liu, Haoyu Wang, and Xuanzhe Liu. 2021. An empirical study on deployment faults of deep learning based mobile applications. In Proceedings of the IEEE/ACM 43rd International Conference on Software Engineering. 674–685.
[9] Jürgen Cito, Philipp Leitner, Martin Rinard, and Harald C Gall. 2019. Interactive production performance feedback in the IDE. In Proceedings of the IEEE/ACM 41st International Conference on Software Engineering. 971–981.

[10] Emilio Coppa, Camil Demetrescu, and Irene Finocchi. 2012. Input-Sensitive Profiling. In Proceedings of the 33rd ACM SIGPLAN Conference on Programming Language Design and Implementation. 89–98.

[11] Alex Cummard, Rajesh Vasa, Scott Barnett, John Grundy, and Mohamed Abdelrazek. 2020. Interpreting Cloud Computer Vision Pain-Points: A Mining Study of Stack Overflow. In Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering. 1584–1596.

[12] Charlie Curtsinger and Emyr D Berger. 2015. Coz: Finding code that counts with causal profiling. In Proceedings of the 25th Symposium on Operating Systems Principles. 184–197.

[13] Luca Della Toffola, Michael Pradel, and Thomas R. Gross. 2015. Performance Problems You Can Fix: A Dynamic Analysis of Memoization Opportunities. In Proceedings of the ACM SIGPLAN International Symposium on Foundations of Software Engineering. 895–907.

[14] Evelyn Duesterwald and Vasanth Bala. 2000. Software Profiling for Hot Path Prediction. Less is More. In Proceedings of the Ninth International Conference on Architectural Support for Programming Languages and Operating Systems. 202–211.

[15] Monika Dhok and Murali Krishna Ramanathan. 2016. Directed test generation to detect loop inefficiencies. In Proceedings of the 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering. 16–28.

[16] Charlie Curtsinger and Emyr D Berger. 2015. Coz: Finding code that counts with causal profiling. In Proceedings of the 25th Symposium on Operating Systems Principles. 184–197.

[17] Alex Cummard, Rajesh Vasa, Scott Barnett, John Grundy, and Mohamed Abdelrazek. 2020. Interpreting Cloud Computer Vision Pain-Points: A Mining Study of Stack Overflow. In Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering. 1584–1596.

[18] Charlie Curtsinger and Emyr D Berger. 2015. Coz: Finding code that counts with causal profiling. In Proceedings of the 25th Symposium on Operating Systems Principles. 184–197.
