Automated Generation and Evaluation of JMH Microbenchmark Suites from Unit Tests

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Abstract—Performance is a crucial non-functional requirement of many software systems. Despite the widespread use of performance testing, developers still struggle to construct and evaluate the quality of performance tests. To address these two major challenges, we implement a framework, dubbed ju2jmh, to automatically generate performance microbenchmarks from JUnit tests and use mutation testing to study the quality of generated microbenchmarks. Specifically, we compare our ju2jmh generated benchmarks to manually-written JMH benchmarks and to automatically generated JMH benchmarks using AutoJMH framework, as well as directly measuring system performance with JUnit tests. For this purpose, we have conducted a study on three subjects (RxJava, Eclipse-collections, and Zipkin) with ∼454K source lines of code (SLOC), 2,417 JMH benchmarks (including manually-written and generated AutoJMH benchmarks) and 35,084 JUnit tests. As a result, the ju2jmh generated JMH benchmarks consistently outperform using the execution time and throughput of JUnit tests as a proxy of performance and JMH benchmarks automatically generated using AutoJMH framework while being comparable to JMH benchmarks manually written by developers in terms of tests’ stability and ability to detect performance bugs. Nevertheless, ju2jmh benchmarks are able to cover more of the software applications than manually-written JMH benchmarks during the microbenchmarking execution. Furthermore, ju2jmh benchmarks are generated automatically, while manually-written JMH benchmarks requires many hours of hard work and attention, therefore our study can reduce developers’ effort to construct microbenchmarks. In addition, we identify three factors (too low test workload, unstable tests and limited mutant coverage) that affect a benchmark’s ability to detect performance bugs. To the best of our knowledge, this is the first study aimed at assisting developers in fully automated microbenchmark creation and assessing microbenchmark quality for performance testing.

Index Terms—Performance, Performance Testing, Performance Microbenchmarking, JMH, Performance Mutation Testing

1 INTRODUCTION

PERFORMANCE is a crucial non-functional requirement of software systems. Performance can directly impact user-perceived software quality while using systems. Performance testing [1] aims to assess several non-functional attributes of systems, such as the execution duration of a process, response time, stability, and resource usage. However, in order to evaluate overall software systems, state-of-the-art performance testing practices typically involve relatively large-scale and long-running tests [2], which are time-consuming, difficult to be fully automated, and not easy to reconcile with continuous integration (CI) practices [3]. To address these issues, several approaches of performance unit testing, such as performance microbenchmarking, have been proposed for the precise performance evaluation of small-scale and isolated source code segments. Performance microbenchmarking is executed at a similar level of granularity as unit tests, e.g., method level or even a statement level [4], [5]. The goal of performance microbenchmarking frameworks is to detect performance bugs as early as possible by, for example, checking and testing each system build [6]–[8]. Due to the numerous challenges of performance microbenchmarking, such as unreliable results [9], [10], the need for in-depth knowledge of methodology [11], [12], and a lack of appropriate tooling [3], [13], [14], several performance microbenchmarking frameworks, including JMH in the Java ecosystem, have been proposed to automate performance microbenchmarking.

However, developers still encounter a number of difficulties when implementing performance microbenchmarking. On the one hand, developers struggle to construct correct microbenchmarks. Prior studies [14], [15] reveal that, as opposed to JUnit functional tests, only a few open-source projects use microbenchmarking frameworks to assess performance. The challenges of microbenchmark design [16] and configuration [17]–[19] (e.g., microbenchmarks may be “over-optimized” by JIT, resulting in muddled time measures) hinder developers from effectively exploiting performance microbenchmarks [4], [16], [20], [21]. On the other hand, assuring microbenchmark quality is a significant concern. Microbenchmarks can be rendered ineffective and error-prone due to a variety of causes. For example, a prior study [5] highlights five problematic JMH practices which are common in open-source software.

In light of the fact that many projects lack microbenchmarks but do have unit tests [14], [15], we propose automatically deriving performance microbenchmarks from JUnit tests for performance testing, and speculate that such derived performance microbenchmarks are preferable to using JUnit tests directly to measure system performance (e.g., by measuring the execution duration of unit tests, as currently practiced in some related work [3], [15]). Specifically, we implement a framework dubbed ju2jmh that developers...
can use to automatically obtain a performance test suite, without manual development effort. To assuage developers’ concerns about microbenchmark quality assurance (as mentioned above) and validate our hypothesis that derived microbenchmarks are superior to JUnit tests to measure system performance directly, we then use mutation testing to examine our produced microbenchmarks and compare them to manually-written JMH benchmarks, automatically generated JMH benchmarks using AutoJMH framework, and directly measuring the execution time and throughput of JUnit tests. We design and implement a microbenchmark evaluation framework dubbed Performance Mutation Testing (PMT) framework, which includes five performance mutation operator APIs for reproducing performance bugs (i.e., inject performance bugs into the source code), based on five common performance bug patterns highlighted in recent studies [22], [23]. The framework enables us and developers to automatically reproduce performance bugs in any desired source code location and evaluate any specific performance microbenchmark.

We evaluate the quality of microbenchmark suites generated from ju2jmh by using PMT, and based on three projects with ~454K source lines of code (SLOC), 2,417 JMH benchmarks (2,262 manually-written and 155 generated using AutoJMH) and 35,084 JUnit tests: Rxjava1, Eclipse-collections2, Zipkin3.

Our study addresses the following research questions:

- **RQ1: How stable are automatically generated performance microbenchmarks?**
  We use two metrics to assess microbenchmark stability, and both reveal that JMH benchmarks generated by ju2jmh (hereafter abbreviated as ju2jmh benchmarks) significantly outperform JUnit tests in all studied cases and are comparable to human-written JMH benchmarks and AutoJMH benchmarks. Because ju2jmh benchmarks are fundamentally JMH benchmarks, the conclusion that ju2jmh benchmarks are comparable to manually-written JMH benchmarks is reasonable. However, ju2jmh benchmarks are generated automatically, while JMH benchmarks are typically written by developers, therefore our tool can reduce developers’ effort to construct microbenchmarks.

- **RQ2: Can performance microbenchmarks detect artificial performance bugs from mutation testing?**
  Generated ju2jmh benchmarks outperform JUnit tests and AutoJMH benchmarks in artificial performance bug detection, but only in some cases outperform manually-written JMH benchmarks. However, ju2jmh benchmarks are able to cover (execute) more mutants (100%) than manually-written JMH benchmarks (66%) during the microbenchmark execution, suggesting that ju2jmh benchmarks can cover more of the applications. In general, ju2jmh benchmarks can detect a higher proportion of mutants exclusively than other tests.

- **RQ3: Can performance microbenchmarks detect real performance bugs?**
  According to our experiment of a real-world performance bug and a similar artificially generated bug, ju2jmh performs better than JUnit in detecting the real bug and artificial bug. Furthermore, the artificial bug and real-world bug affect benchmarks in a very similar way.

- **RQ4: What are the major factors affecting a microbenchmark’s ability to detect performance bugs?**
  We identify three common factors that jeopardize a benchmark’s ability to identify performance bugs: (1) Too low workload (this applies to generated ju2jmh and JUnit tests, but not to manually-written JMH benchmarks). (2) Unstable benchmarks. (3) Limited mutant coverage as a result of inappropriate execution times (neither too low nor too high).

In conclusion, we compare our generated ju2jmh benchmarks with manually-written JMH benchmarks and with automatically generated JMH benchmarks using AutoJMH framework, as well as using the execution time and throughput of JUnit tests as a proxy of performance. The ju2jmh benchmarks consistently outperform JUnit tests while being comparable to manually-written JMH benchmarks and AutoJMH benchmarks in terms of microbenchmarks’ stability and ability to detect performance bugs. However, the generated ju2jmh benchmarks can cover more of the applications than manually-written JMH benchmarks. In addition, we automate our approach for creating and assessing ju2jmh benchmarks, whereas human-written JMH benchmarks require a considerable amount of human effort. Moreover, although ju2jmh benchmarks and AutoJMH benchmarks are both generated automatically, AutoJMH has several serious restrictions. As a result, our technique successfully aids developers in the microbenchmark construction, and microbenchmark quality is assured. To further assess microbenchmark quality, we also reveal three factors that affect microbenchmarks’ ability to detect bugs for future microbenchmark enhancement.

**Paper organization**

Section 2 introduces background on performance microbenchmarking, while Section 3 discusses the related studies on generating, assessing, and improving performance microbenchmarks. In Section 4, we present the overview of our study, which is comprised of two phases discussed in Section 5 and Section 6, respectively. Section 7 presents the experiments for our study. In Section 8, we clarify threats to the validity of our study. We conclude our study and discuss future work in Section 9.

**2 BACKGROUND**

This section provides an overview of the performance microbenchmarking in the Java ecosystem and terminology used throughout this paper.

**2.1 Performance Microbenchmarking in Java.**

Performance testing [1] aims to assess several non-functional attributes of systems, such as the execution duration of a process, response time, stability, and resource

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1. [https://github.com/ReactiveX/RxJava](https://github.com/ReactiveX/RxJava)
2. [https://github.com/eclipse/eclipse-collections](https://github.com/eclipse/eclipse-collections)
3. [https://github.com/openzipkin/zipkin](https://github.com/openzipkin/zipkin)
usage. In this study, we focus on unit-level (e.g., method) performance testing of systems, known as performance microbenchmarking. In contrast to system-level testing, which is for assessing the overall performance, and load (or stress) testing, which is an end-to-end testing approach, performance microbenchmarking aims to evaluate small units of systems, like the throughput of a method, or the performance of an algorithm.

Over the past few years, many Java frameworks such as Caliper [24], JMH [25], AutoJMH [16], or JUnitPerf [26] have provided microbenchmarking tooling. However, evidence [14] in practice confirms that performance microbenchmarking is not yet as established as functional unit testing or system performance testing. Users of these frameworks must either create their own performance microbenchmarks from scratch (e.g., JMH benchmarks), automatically generate and run JMH benchmarks by using an existing tool (e.g., AutoJMH benchmarks), which works only under certain situations, or scaffold existing microbenchmarks (e.g., JUnitPerf that applied on JUnit test cases). Only a few open-source projects deploy any microbenchmarking frameworks, and the projects often use JUnit functional tests repeatedly to evaluate performance [14], [15]. Specifically, they execute JUnit tests for a specific number of times or a duration for an effective measurement of elapsing time or throughput.

2.2 Java Microbenchmarking Harness (JMH)

Due to the numerous challenges of performance microbenchmarking, such as unreliable results [9], [10], the need for in-depth knowledge of methodology [11], [12], and a lack of appropriate tooling [3], [13], [14], several performance microbenchmark frameworks, including JMH in the Java ecosystem, have been proposed to automate performance microbenchmarking. JMH is a framework developed under the OpenJDK umbrella that enables users to design and run repeatable performance microbenchmarks. JMH, similar to JUnit, uses Java annotations to prepare the testing environment for evaluating specific payloads (i.e., a self-contained program that wraps the code segment that is essential to system performance [16]) through several metrics, such as the throughput of a method. A JMH benchmark class can contain several benchmarks, each of which is tagged by an annotation @Benchmark and is usually designed to test the methods of related source code classes.

Figure 1 depicts an example of a JMH benchmark class from Eclipse-collections project. The methods with annotations @Setup and @TearDown are used to prepare and clean up the microbenchmarking environment respectively (equivalent to JUnit test fixtures), while the method with @Benchmark (that is equivalent to @Test in JUnit) is used to evaluate the performance of a functionality of MaxByIntTest class. Benchmark fixtures can be optionally executed in either the class scope or the benchmark scope to prepare or clean up microbenchmarking environment. Methods tagged by @Setup, such as the method setUp() in the Figure 1, are executed before running the benchmarks (tagged by @Benchmark), and similarly, methods tagged by @TearDown, like the method tearDown() in the figure, are executed after running the benchmarks.

JMH benchmarks can be designed to measure performance, such as throughput or execution time, with flexible and different configurations. However, a single JMH benchmark iteration can encompass repetitive workload executions. As a result, to facilitate the evaluation of microbenchmark quality, we use workload throughput over a particular time period (designated "measurement time" and set to 1 second by default, i.e., @Measurement(time = 1)) as a metric for further study, rather than focusing on the details of repetitive control flow in the benchmarks. Accordingly, the execution time of benchmarks is calculated by average execution time = \frac{1}{\text{throughput}}. In our experiments, specifically, the metric is the number of operators executed per second for a microbenchmark.

In general, JMH benchmarks have more advantages than JUnit tests for evaluating performance. As previously mentioned, one common performance testing practice is to run JUnit in a loop to measure performance [14], [15]. Although JMH benchmarks also use a loop to execute the payload repeatedly, the elegant features provided in JMH benchmarks lead to more accurate performance measurement results. For example, JMH benchmarks perform warm-up iterations to stabilize the system in order to avoid data noise caused by the execution environment, can have benchmark fixtures to prepare and clean-up the testing environment, and easily handle running benchmarks through multiple iterations, threads, and forks.

2.3 Mutation Testing

Mutation testing is a technique that aims to assess and improve the efficacy of test suites in discovering faults [27]. This technique reproduces artificial bugs through several predefined rules (i.e., mutation operators) that help in measuring the efficiency of a test suite in detecting them [22]. Mutation testing for performance purposes, so-called performing mutation testing, is a novel practice that raises
many open challenges and questions to address. Recent studies [3], [22] deploy mutation testing to address the efficiency of performance benchmarks in discovering performance bugs.

2.4 Detecting Real-world Performance Bugs

A performance bug could be detected by the covering performance tests by searching for degradation in their test results. For example, if we measure throughput of the covering performance test and the throughput is decreased significantly enough (e.g., 1%, 5%, and 10%), we consider that the test detects some performance bugs. For mutation testing, the test is run on both the system version with and without artificial performance bugs, and the results from the two versions are compared to determine whether performance degradation exist or not (i.e., the mutant is killed or not). For real-world performance bug detection, the test is run on the parent system that is assumed to contain a bug and the child system with new source code changes where the bug fixes are applied. After comparing two versions of test results, we can detect the existence of the performance degradation as well (i.e., the real-world performance bug is presented in the parent system).

3 RELATED WORK

In this section, we provide an overview of the related work through three different perspectives.

Performance microbenchmarking. Recent studies deem that performance testing frameworks should concentrate on integrating with standard CI tooling and facilitating effective testing construction techniques [3], [15], [28]. Performance microbenchmarking is a software solution for short-term performance testing by integrating CI techniques, however, it is less established and commonly used than unit testing or system performance testing. Only a few open-source projects use performance unit testing frameworks, whereas many others rely on JUnit functional tests to assess performance [14], [15]. Design [16] and configuration [17]–[19] challenges (e.g., microbenchmarks may be “over-optimized” by JIT, resulting in muddled time measures) hinder developers from effectively exploiting performance microbenchmarks [4], [16], [20], [21]. To reduce difficulties, Ding et al. [8] utilize JUnit tests to assess the performance properties of systems. Rodriguez-Cancio et al. [16] propose AutoJMH, an automated approach that can take one source code segment and one covering unit test as input and generates a full JMH microbenchmark for that segment [16]. However, AutoJMH is limited to manually configuring specific single statements and has preconditions that prevent developers from testing a large portion of the source code. In addition, the tool is obsolete because it has not been maintained or updated since August 12, 2016. In this study, we implement an automated tooling framework, ju2jmh, for widely exploiting JMH performance microbenchmarks.

Empirical studies on performance bugs. Performance-related bugs are well-known as a threat to users’ positive perception of software systems. Moreover, since performance bugs are usually difficult to reproduce, it takes a long time to detect and fix them, such as 1,075 days on average to discover and fix 36 performance bugs in Jin et al. [29]. Nistor et al. [13] disclose that, compared to reasoning about functional bugs, developers have little support for reasoning about performance bugs. In addition, more experienced developers are required to address performance bugs [30].

Recent studies have identified commonly reported performance bugs, which can serve as a guideline for reproducing and fixing bugs. Radu and Nadi [23] provide a dataset, NFbugs, including eight performance bug patterns from a total of 138 non-functional bug fixes in 67 open-source projects in Java or Python. Delgado-Pérez et al. [22] review prior empirical studies on performance bugs [31]–[36] and summarize seven performance anti-patterns. Laaber and Leitner [3] insert slowdowns (i.e., Thread.sleep(...)) into the most used API(s) of subjects to pause execution of the program and to simulate the presence of a performance bug.

Assessing the quality of performance tests. Leitner and Bezemer [15] and Stefan et al. [14] study Java open-source systems in terms of the quality and quantity of systems’ JMH benchmarks. Recent studies [3], [37], [38] claim stability is a crucial quality attribute of performance tests. In addition, prior work [3], [22] deems the bug detection ability of performance tests as another essential quality factor. Ding et al. [8] discuss the ability of readily available unit tests in detecting reported performance issues. As a result, they reveal eight factors to make a (unit) test effective at discovering performance bugs in a release pipeline.

Recent studies [3], [22] deploy mutation testing to address the ability of JMH microbenchmarks in discovering reproduced performance bugs. Laaber and Leitner [3] propose an approach to assess JMH microbenchmarks in discovering injected slowdowns. Delgado-Pérez et al. [22] use seven performance anti-patterns as means to assess JMH microbenchmarks in discovering performance bugs. However, both studies have limited flexibility with several manual actions that hinder followers from effectively performing their approaches in practice. In this study, we propose the first performance mutation framework to assess the quality and efficiency of performance tests automatically.

4 STUDY OVERVIEW

This section provides an overview of our study methodology, which primarily consists of two phases: (1) generating microbenchmarks using ju2jmh, (2) evaluating microbenchmarks using mutation testing. In the next two sections, we discuss each phase in detail.

Figure 2 depicts an overall workflow of our methodology. To prepare our experiment, we begin by searching through test packages to extract desired JMH microbenchmarks and JUnit test suites, as well as setting up the performance (unit) testing environment. We then deploy ju2jmh to generate JMH microbenchmarks from JUnit test suites. In addition, we also deploy AutoJMH framework to generate JMH benchmarks for performance testing evaluation. Given the produced microbenchmarks, we use our

4The data and scripts of our study are shared at https://github.com/senseconcordia/JUnit2JMH-PMT-TSE-2021.
5The tool is publicly available at: https://github.com/alniniclas/junit-to-jmh/
PMT framework to inject performance bugs into the source code, and evaluate the microbenchmarks’ quality in terms of result variability and bug-detection ability. To further study the microbenchmarks’ ability to detect performance bugs, we also investigate the factors that may affect the microbenchmarks’ detection of them.

Figure 2: Our methodology to address the quality of performance microbenchmarks

Prior to beginning an experiment, preparation is needed. It necessitates the extraction of JMH microbenchmarks and JUnit test suites from the studied subjects for subsequent analysis.

Human-written JMH microbenchmarks. JMH is a Java microbenchmarking framework that has shown promise in properly scaffolding payloads [16]. Existing JMH microbenchmarks of systems are usually developed under the careful effort of the same developers who designed the system. Since designing JMH benchmarks necessitates deep knowledge of both system and the framework, developers are hesitant to exploit and maintain them. In this study, we have investigated existing human-written JMH microbenchmarks of systems. After building the systems, an executable jar is created by automated building tools to assist testers in executing JMH benchmarks of the system.

JUnit test suites. JUnit tests are designed to assess whether unit elements of the software system are functionally correct. Generally, JUnit tests do not tend to help measure the performance, as they are highly vulnerable to noisy environments. Ding et al. [8] utilize JUnit tests to evaluate the performance of tests. Therefore, to assess the performance of JUnit tests in our study, we measure test throughput by repeatedly executing unit tests for a given duration (e.g., one second). To do so, we deploy JUnit @Rule to monitor individual test execution and quantify the elapsed time in nanoseconds, allowing us to determine the throughput of a test method (i.e., @Test). In our experiments, we use a nested loop to measure the throughput of a JUnit test method 30 times to serve as a baseline for comparing different tests. The inner loop is used to measure the throughput of the test by executing the test as many times as the specific duration is reached. The outer loop is used to measure the throughput of the test multiple times, providing multiple data-points for the test.

AutoJMH microbenchmarks. Rodriguez-Cancio et al. [16] propose AutoJMH, an automated approach that can take one source code segment and one unit test that covers the segment as input and generates a full JMH microbenchmark for it [16]. Only single statements can be supplied as the source code segment input for AutoJMH and the input statements should be executed by at least one unit test.

The JMH benchmarks generated by AutoJMH, also known as AutoJMH benchmarks, require a collection of variables as input and the variable values are extracted from the execution of covering unit tests from which the benchmarks were derived. The purpose of AutoJMH benchmarks is to measure the performance of input statements without running the entire program. In addition, the tool is obsolete because it has not been maintained or updated since August 12, 2016.

Regarding the similarities of AutoJMH and ju2jmh, they both use JUnit tests as input and then automatically generate JMH benchmarks. However, AutoJMH and ju2jmh have major differences. As defined above, AutoJMH executes JUnit tests for one time to gather required data for building JMH benchmarks, while ju2jmh benchmarks are designed to repeatedly execute JUnit tests, as payload, to measure their performance. Furthermore, AutoJMH benchmarks execute input statements without executing the entire program, while ju2jmh benchmarks execute input statements (i.e., JUnit tests) by actually executing the program. Lastly, AutoJMH requires manually specifying single statements as input for JMH benchmark building, which means that the number of generated JMH benchmarks is limited by the number of input statements. However, ju2jmh benchmarks are built on existing JUnit tests of programs, and the number of JUnit tests of a well-known program is usually quite large. As a result, in our experiment, the number of JMH benchmarks generated by AutoJMH is significantly lower than ju2jmh, which results in a much lower coverage of the program for AutoJMH.

5 Generating Microbenchmarks Using ju2jmh

To demonstrate the feasibility of generating JMH benchmarks from unit tests, we implement a tool dubbed ju2jmh that can automatically generate ready-to-execute JMH benchmarks from JUnit test suites. The main goal of ju2jmh’s design is to be able to generate functionally correct benchmarks from a wide variety of real-world unit tests while minimizing performance overhead and complexity.

Figure 3 depicts the basic benchmark generation procedure of ju2jmh. The procedure consists of two main steps: (1) Analysis step: the ju2jmh tool analyzes the existing unit test classes in order to identify individual JUnit test classes.

![Figure 3: Overview of the ju2jmh approach and its inputs and outputs](image-url)
methods and other relevant test features; (2) Benchmark generation step: the tool generates JMH benchmarks with each benchmark method responsible for repeatedly executing (a copy of) a single unit test method as its payload. For example, as shown in Figure 3, if ju2jmh is applied to a unit test class called UnitTestClass, which contains two unit test methods named testCase1 and testCase2, ju2jmh first generates a copy of the UnitTestClass class, and then generates a JMH benchmark class called _Benchmark that is placed within this copy. The new benchmark class contains two JMH benchmark methods, testCase1_benchmark and testCase2_benchmark, whose responsibilities are to repeatedly execute testCase1 and testCase2 as their payloads.

In the analysis step, ju2jmh first identifies the individual JUnit test methods that are expected to be converted to JMH benchmarks. Next, ju2jmh detects any other features of the test methods that are required for proper execution, such as fixture methods, test rules, and expected exceptions, all of which should be handled explicitly by the generated benchmarks. The analysis is performed using Apache Commons BCEL\(^6\) to statically inspect the bytecode of all relevant JUnit test classes (specified as input for the tool) in order to find test methods (annotated by org.junit.Test), fixture methods (annotated by org.junit.Before, org.junit.After, org.junit.BeforeClass, or org.junit.AfterClass), test rules (annotated by org.junit.Rule or org.junit.ClassRule), expected exceptions (extracted from the arguments of the org.junit.Test annotation), and ancestor classes containing any of the above.

In the benchmark generation step, ju2jmh uses the JavaParser\(^7\) library to parse Java source code and generate the Abstract Syntax Tree (AST). This step consists of the following activities: (1) copying the AST of each relevant JUnit test class, (2) generating the AST for a corresponding _Benchmark class that is customized based on the information gathered in the analysis step, (3) inserting the generated benchmark class into the AST of the copied JUnit test class as a static member class, and (4) printing the results via a Java source file. The generated benchmark class contains a JMH benchmark method for each of the JUnit test methods in the JUnit class.

Each generated benchmark inherits the same superclass, which implements the functionality required to execute JUnit tests properly through the benchmark. The ju2jmh benchmark superclass contains methods to help instantiate and access a JUnit test class instance, methods to invoke fixture methods of JUnit test class (including all fixture methods from the superclasses), methods to apply all rules of the JUnit test class and its superclasses, and a benchmark execution method to execute the JUnit test methods. In the cases with the expected exceptions, the ju2jmh benchmark superclass executes a different benchmark execution method with the expected exceptions as an additional parameter.

In terms of the way ju2jmh works, class copies are preferred over direct accessing the classes due to subtle considerations. First, in the case where the tool creates a copy of the JUnit test class rather than directly referencing the original class, this processing allows future versions

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\(^6\)A Java bytecode analysis tool from The Apache Software Foundation: https://commons.apache.org/proper/commons-bcel/

\(^7\)A tool for analyzing, transforming and generating Java codebase: https://javaparser.org/
of ju2jmh to make changes to the JUnit test methods in order to improve the generated benchmarks, for example by preventing optimizations such as dead code elimination. Moreover, rather than making the generated benchmark class a separate top-level class, it is inserted as a static member of the copy to reduce the risk of naming conflicts and to keep the benchmarks organized closely with the tests they use as payloads.

Our approach ju2jmh has been implemented in Java and integrated into the Gradle build system. JavaParser and Apache Commons BCEL are the primary libraries used for the unit test analysis and benchmark generation. The generated benchmarks are dependent on JMH [25] and JUnit4 libraries.

6 Evaluating Microbenchmarks Using Mutation Testing

In this section, we present the workflow of our PMT framework for evaluating unit-level performance tests (microbenchmarks). First, the framework implements and employs five performance mutation operators that are derived from common real-world performance bugs [3], [12], [22]. Second, it automatically injects performance bugs (based on the five mutation operators) into the analyzed software system and generates performance mutants (i.e., artificial performance bugs). Then, the generated performance mutants are executed against the to-be-evaluated performance microbenchmarks. Furthermore, to better classify between an actual slowdown (i.e., a performance bug) and a performance fluctuation, we leverage hierarchical re-sampling [9], [17] and two statistical measures, namely, Relative Standard Deviation (RSD) [17], [37], [38] and Relative Confidence Interval of means (RCI) [9], [17]. Last, the PMT framework computes the mutation score, which is defined as the proportion of the killed (detected) performance mutants, to assess the effectiveness of performance microbenchmarks in detecting performance bugs.

![Figure 5: Overview of our Performance Mutation Testing framework.](image)

6.1 Designing Mutation Operators for PMT

Our study aims at assisting developers in alleviating the challenges of constructing and evaluating performance tests rather than detecting performance bugs. To achieve our study goal, we use PMT to inject artificial performance bugs for further analysis. We evaluate performance tests by comparing the test results on the systems with and without performance bugs. Performance tests can help developers reveal the effects that mutants have on the systems, detect performance bugs and complement the omission of static tools that may treat some code as syntactically correct but cannot reveal its negative impact on performance.

A PMT framework requires specialized mutation operators for generating performance mutants (i.e., software versions with artificial performance bugs or slowdowns). In this study, we expose five performance mutation operators based on previous research on summarizing performance anti-patterns [3], [22], [23], which we then implement in our PMT framework.

In particular, Delgado-Pérez et al. [22] review prior empirical studies on performance bugs [31]–[36] and summarize seven performance anti-patterns, of which we employ two patterns for designing our performance mutation operators and exclude five others (three memory-related bug patterns and two for future work). Radu and Nadi [23] present the NFBugs dataset, which contains eight performance bug patterns discovered after analyzing 36 performance bug fixes from a total of 138 non-functional bug fixes in 67 open-source Java or Python projects. We adopt three performance anti-patterns from NFBugs and leave the remaining five as future work. Furthermore, Laaber and Leitner [3] propose inserting Thread.sleep(...) into source code to slow down program execution for performance mutation testing, which we also accept for the design of our performance mutation operators. We selected the five performance bug patterns because of the high availability of source code statements that a pattern can be applied to. Moreover, the five patterns do not require manipulating multiple lines of source code, and generated bugs scarcely tend to endanger the overall functionality.

In summary, we introduce a total of five performance mutation operators based on prior studies on analyzing performance bugs and implement them in our PMT framework. Such performance mutation operators are not specific to certain software systems and can be applied to any Java system without manual effort. Moreover, the PMT framework is extensible, allowing for the easy integration of new performance mutation operators.

Below we describe the five performance mutation operators in detail, with a summary in Table 1.

- **Primitive to Wrapper (PTW).** Replacing a primitive type (e.g., long) with its corresponding wrapper class (i.e., Long) can lead to performance bug [23], since primitive types are stored on the stack and provides faster access. We include the built-in wrapper classes for all primitive types, i.e., Byte, Boolean, Short, Integer, Long, Float, Double, and Character.

- **StringBuilder to StringBuffer (STS).** Replacing a java.lang.StringBuilder object with a java.lang.StringBuffer object can result in performance bug because StringBuffer is not synchronized [23]. Apart from the difference in performance, functionalities of these two classes are equivalent. Therefore, we perform the operator only on method-level to prevent propagation of changes.

- **Enhanced For Loops (EFL).** Replacing a traditional for-loop with a for-each loop to iterate over an array or a Collections class can introduce performance bug because of extra calls. The semantics of
the code is usually unaffected by such replacements. However, if the loop counter is used in the for-loop, the replacement may cause performance bug due to the additional cost of calculating it.

- **Swap of Operands in Condition (SOC).** Reordering the two operands in a compound OR condition if the left operand is a variable or a Boolean literal (i.e., True and False), and the right operand is a method invocation. Forcing the evaluation of the right operand (i.e., a method invocation) by placing it as the left operand in a compound OR condition may introduce slowdown since the method invocation may not be executed originally as the right operand [22].

- **Simulation of Heavy-Weight Operations (HWO).** Injecting a delay (e.g., Thread.sleep(t)) can slow down the program execution. In our study, we consider injecting a delay as the first statement of each JMH microbenchmark (annotated by \@benchmark). We chose the first statement as the candidate injection location since we expect to see that the delay is executed definitively, i.e., the injected delay cannot be affected by the data-flow and control-flow for the code in this method. For example, if a delay is injected into a branching statement, the delay may never be executed depending on the branching conditions. The HWO has been used in prior studies [3], [22] to simulate slowdowns, however, it does not represent real-world performance bugs. Nevertheless, we believe the HWO complements the other mutation operators based on real-world performance bugs and thus include HWO in this study.

### 6.2 Generating and Validating Performance Mutants

The PMT framework parses the source code of a target system into Abstract Syntax Trees (ASTs) and looks for opportunities to apply the five performance mutation operators on the parsed ASTs. For each applicable AST location and each mutation operator, the PMT framework generates one performance mutant. For example, the EFL mutation operator can be applied to a subset of traditional for-loop in one system, in RxJava, the PMT framework finds 682 applicable locations and generates a total of 62 performance mutants.

Note that if a mutant is killed by any functional test, it is an invalid performance mutant since it breaks functionality. The system’s regular behavior could be disrupted by the presence of such mutants, which leads to the system’s performance not being properly measured. Therefore, in this study, we only consider performance mutants that do not change system functionality and require performance tests to detect. As a result, we introduce a validation step in the PMT framework: All the generated performance mutants are executed against the functional unit tests and are excluded from the further step (i.e., calculating mutation score) if one cannot make all the functional tests pass.

### 6.3 Calculating Mutation Score

Relying on the purpose of mutation testing in performance that is introducing performance bugs deliberately, we looked over the benchmark’s results against a valid mutant to find significant differences. Recent studies [3], [22] have been advocating statistical hypothesis tests (e.g., Wilcoxon rank-sum test) to label a significant difference in results as a performance bug, slow down, or the presence of artificial bugs. However, prior studies [37] concluded that testing with Wilcoxon rank-sum tests is not a suitable vehicle for detecting performance degradation in cloud environments due to high false-positive reported.

To better classify between an actual performance slowdown and a performance fluctuation, we leverage hierarchical re-sampling [9], [17] and a statistical measure, i.e., Relative Confidence Interval of means (RCI) [9], [17].

For a benchmark that covers and executes any of generated performance bug, the PMT framework deploys pa [39] to estimate the throughput’s RCI (of before and after the bug injection) with bootstrap (i.e., re-samples) [40], [41] using 10,000 bootstrap iterations [42]. Respectively, the size of a performance bug can be defined as \[1 – Upper_{RCI}\] (in %), which reflects the effectiveness of mutant against the benchmark. If the bug size is significant enough (e.g., \[\geq 5\%\]), we can consider that the benchmark could detect the injected performance bug (i.e., a killed mutant).

Last, the PMT framework calculates the mutation score of performance microbenchmarks as the percentage of the killed performance mutants. The calculated mutation score helps evaluate the quality of one or a group of microbenchmarks. The microbenchmarks’ quality (and efficiency) in discovering bugs increases as their mutation score rises.

One of the advantages of mutation testing is to find deficiencies in tests and improve them, and improved tests can be further utilized to detect real-world bugs [43]. That is, we use artificial performance bugs to build and enhance the tests, and such tests could be used in the future to detect real-world performance bugs. If a performance test can detect an artificial performance bug, it is more likely to detect a real-world version of that bug.

### 6.4 Preliminary Analysis of PMT

To investigate the impacts of the five mutation operators, we devise a preliminary analysis based on five JMH benchmarks. We define the hitting_count as the total number of times that a benchmark executes (hits) a mutant statement. Furthermore, the hitting_ratio is the total number of times that a mutant statement is executed per second.

To investigate how large the effect of each mutation operator is when increasing hitting_ratio, we designed five JMH benchmarks. Each related benchmark is executed for 20 iterations against original source code and mutant version five times, yielding 100 data points containing measured throughput for one second. If differences between original results and mutant results increase, we assume that the effect of the performance bug is increased.

Figure 6 presents box plots of the five benchmarks’ results for original and mutant executions, across increasing the hitting_ratio. To study the difference between the original microbenchmark execution and the microbenchmark executions after bug injections, we present the upper bound of estimated RCI in Table 2. The upper bound of RCI reflects the minimum performance degradation caused by bugs.
In general, for all five mutation operators, when we increased hitting_ratio, differences between original results and mutant results become more significant (the upper bound of RCI decreases). However, we also observed that the RCI upper bound of HWO (0.824) for 10^6 in Table 2 is greater than 10^3 (0.771), indicating that this conclusion may not be applicable to a very high hitting_ratio for a certain operator and the results may be limited by some external factors, such as overheads and variations occur due to hardware specific limitations. When hitting_ratio is lower than 10^3 times, differences are not significant in PTW, STS, and EFL with less than 1% performance degradation in all cases. On the other hand, in SOC and HWO, differences are significant in all hitting_ratio. In SOC and HWO, hitting_count is fixed while hitting_ratio is increased. This conveys that the effect of the two operators is high, even with one execution.

To summarize, when a benchmark executes a buggy statement (i.e., mutant statement) more times, the observed difference in results generally increases. In addition, differences are significant in all hitting_ratio in SOC and HWO.

### Table 1: Examples of the five mutation operators.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Conditions</th>
<th>Example</th>
</tr>
</thead>
</table>
| PTW      | Candidate expression should be a variable from any primitive types; i.e., byte, boolean, short, int, long, float, double, and char. | - return this.count;  
+ return ((Long)(this.count)).longValue(); |
| STS      | This operator should manipulate one method at a time to prevent propagation of changes. | - StringBuilder result = new StringBuilder();  
+ StringBuffer result = new StringBuffer();  
...  
return result.toString(); |
| EFL      | Candidate loop should be a traditional for-loop that contains a loop counter. | int i = 0;  
for (; i < subscribers.length; i++) {  
+ for (Subscriber<? super R> o : subscribers) {  
+ i = subscribers.getIndekOf(o);  
... |
| SOC      | 1) The left operand should be a variable or a Boolean literal.  
2) The right operand should be a method invocation that never return Null. | - if (done || emitter.isCancelled())  
+ if (emitter.isCancelled() || done) |
| HWO      | This pattern is not subject to any conditions. | + Thread.sleep(0,1);  
...  
return TreeBag.newBag(); |

### Table 2: The upper bound of RCI for the five mutation operators with the increasing of hitting_ratio.

<table>
<thead>
<tr>
<th>Operator</th>
<th>1</th>
<th>10</th>
<th>10^2</th>
<th>10^3</th>
<th>10^4</th>
<th>10^5</th>
<th>10^6</th>
</tr>
</thead>
<tbody>
<tr>
<td>PTW</td>
<td>0.999</td>
<td>0.999</td>
<td>0.998</td>
<td>0.997</td>
<td>0.957</td>
<td>0.736</td>
<td>0.379</td>
</tr>
<tr>
<td>STS</td>
<td>1.0</td>
<td>1.0</td>
<td>0.998</td>
<td>0.990</td>
<td>0.932</td>
<td>0.959</td>
<td>0.687</td>
</tr>
<tr>
<td>EFL</td>
<td>0.997</td>
<td>1.0</td>
<td>0.998</td>
<td>0.998</td>
<td>0.986</td>
<td>0.967</td>
<td>0.920</td>
</tr>
<tr>
<td>SOC</td>
<td>0.843</td>
<td>0.848</td>
<td>0.847</td>
<td>0.847</td>
<td>0.854</td>
<td>0.840</td>
<td>0.826</td>
</tr>
<tr>
<td>HWO</td>
<td>0.878</td>
<td>0.877</td>
<td>0.864</td>
<td>0.820</td>
<td>0.800</td>
<td>0.771</td>
<td>0.824</td>
</tr>
</tbody>
</table>

In this section, we introduce the three study subjects involved in this study. We experimented and evaluated our derived microbenchmarks to human-written microbenchmarks to evaluate if the derived ones are superior than human-written ones. Moreover, we compare our derived microbenchmarks with those microbenchmarks automatically generated by AutoJMH to evaluate if ju2jmh outperforms the existing framework.

#### 7.1 Study Subjects

In this section, we introduce the three study subjects involved in this study. We experimented and evaluated our derived microbenchmarks to human-written microbenchmarks to evaluate if the derived ones are superior than human-written ones. Moreover, we compare our derived microbenchmarks with those microbenchmarks automatically generated by AutoJMH to evaluate if ju2jmh outperforms the existing framework.

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8 [https://github.com/DIVERSIFY-project/autojmh-source-code](https://github.com/DIVERSIFY-project/autojmh-source-code)
Figure 6: Preliminary analysis of the five mutation operators. Each of paired boxes contains obtained 100 data points for two cases of original source code executions and mutant executions, from each of five designed JMH benchmarks, across increasing hitting_ratio. Each box contains 100 data points obtained from a relevant benchmark. Black boxes represent data from original source code executions, and white boxes represent data from mutant executions.

two frameworks, i.e., ju2jmh and PMT, on three open-source Java projects, Rxjava, Eclipse-collections, and Zipkin, which have readily available JUnit test cases and JMH microbenchmarks. The selected three open-source projects are well-known, well-maintained, and were widely studied in prior studies on performance microbenchmarking [3], [5], [15], [17], [22], [37]. In addition, a recent study [5] lists the three subjects among the top 25 projects with the highest number of JMH micro-benchmarks.

Table 3 describes the detailed information of our studied subjects: the studied version (“Version”) (i.e., the most recent version at the time our study began), the extracted metadata from Github including the numbers of stars (column Stars) and the number of contributors (column Contr.), the number of the source lines of code (column SLOC), the total number of JMH benchmarks (column # JMH) and selected JUnit test cases (column # JUnit).

### Table 3: Overview of the studied subjects.

<table>
<thead>
<tr>
<th></th>
<th>Version</th>
<th>Stars</th>
<th>Contr.</th>
<th>SLOC</th>
<th># JMH</th>
<th># JUnit</th>
</tr>
</thead>
<tbody>
<tr>
<td>RxJava</td>
<td>3</td>
<td>44.7k</td>
<td>379</td>
<td>135K</td>
<td>1217</td>
<td>9K</td>
</tr>
<tr>
<td>Ec-collections</td>
<td>10.4.0</td>
<td>1.7k</td>
<td>88</td>
<td>88</td>
<td>1217</td>
<td>9K</td>
</tr>
<tr>
<td>Zipkin</td>
<td>2.7</td>
<td>14.4k</td>
<td>145</td>
<td>7467</td>
<td>59</td>
<td>501</td>
</tr>
</tbody>
</table>

7.2 Experiment Settings

We deployed ju2jmh on three subjects’ JUnit test suites to build 171,366 ju2jmh benchmarks, of which 35,084 were evaluated in this study, accounting for 48% of total 72,430 tests evaluated. Our PMT framework analyzed a total of ~454K SLOC and generated ~149K artificial performance mutants, each of which was executed in a single position of the source code. During the validation procedure, ~99% of the generated mutants were recognized as possibly valid mutants.
Table 4: Overview of the selected mutants and covering tests that are involved in our experiment.

<table>
<thead>
<tr>
<th>Mutation Operator</th>
<th>RsJava</th>
<th>Eclipse-collections</th>
<th>Zipkin</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># Mutants</td>
<td>JMH</td>
<td>ju2jmh*</td>
</tr>
<tr>
<td>PTW</td>
<td>42</td>
<td>147</td>
<td>3074</td>
</tr>
<tr>
<td>STS</td>
<td>2</td>
<td>0</td>
<td>205</td>
</tr>
<tr>
<td>HWO</td>
<td>9</td>
<td>193</td>
<td>337</td>
</tr>
<tr>
<td>EFL</td>
<td>8</td>
<td>121</td>
<td>573</td>
</tr>
<tr>
<td>SOC</td>
<td>5</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Total</td>
<td>66</td>
<td>461</td>
<td>4199</td>
</tr>
</tbody>
</table>

* equals to the number of JUnit tests
† AutoJMH benchmarks that is equal to the number of Mutants

Eclipse-collections includes a significant number of JUnit tests that take roughly four months to run once; as a result, we randomly selected ∼15% of them for examination while studying all tests from two other subjects. Afterward, in order to have a fair and feasible evaluation approach, we selected a subset of the generated mutants with a wide variety of characteristics while considering all possible tests that cover them. To increase the chance of evaluating more tests against a specific mutant, we selected each mutant from the set of a class’s mutants in different packages of the source code, as well as selecting mutants that are covered by more JMH benchmarks and ju2jmh/JUnit tests.

Table 4 provides an overview of the mutants and tests involved in our measurements. For each of five designed mutation operators and across the three study subjects, we present the number of selected mutants (column # Mutants), all contained JMH benchmarks (column JMH), ju2jmh/JUnit tests that cover any of the mutants (column JUnit/ju2jmh), and generated AutoJMH benchmarks (column Auto.).

Our study establishes three performance oracles: (1) If there is no source code update, the performance tests results should remain relatively unchanged; (2) If the existence of a performance bug is confirmed and covered by a performance test, there should be a variation in the testing results and such variation should be consistent with the characteristics of the performance bug; (3) If a mutation is injected and covered by a performance test, the testing results should vary, and the magnitude of the results should follow the same trend as the mutation triggered times.

7.3 Execution environment

To perform the execution procedure, we benefited from the power of cloud computing resources as a real-world environment. To have a consistent measurement process, for all the experiments in this study, we deployed c2-standard-4 (4 vCPUs, 16 GB memory) instances provided by Google Cloud.\(^{10}\) Instances are run on Debian GNU/Linux 10 (buster) and OpenJDK 1.8. In total, our experiment consists of 99, 406 measurements, each containing 30 data points measured, i.e., each data point is the number of executions of one JMH microbenchmark case (annotated by #benchmark) in one second. It took ∼1656 machine hours to complete all the experiments in this study.

7.4 Results

We aim to answer three research questions. For each RQ, we present the motivation to answer the RQ, our approach to addressing the RQ, and the corresponding results.

**RQ1: How stable are automatically generated performance microbenchmarks?**

**Motivation**

A very first question arising while adopting a performance microbenchmarking is whether microbenchmarks (JMH, AutoJMH, JUnit, or microbenchmarks from ju2jmh) are stable enough to detect meaningful variations in microbenchmarking results. In recent studies, non-determinism has been identified as the main barrier to obtaining repeatable measurements in performance microbenchmarking. If a performance microbenchmark is not stable enough, it can report deceptive variations in microbenchmarking results when there are not any. Various tools and techniques aim at minimizing the effect of non-determinism at each level of abstraction [9], [44], [45]. JMH has recently become popular with achieving relatively stable performance results, while any form of using JUnit tests as benchmarks has been usually challenging and unstable. To evaluate the quality of performance microbenchmarks, we first measure their stability.

**Approach**

To answer RQ1, we studied the benchmarks in terms of their result variability. We executed all benchmarks of subjects individually in isolation. Each measurement consists of 30 iterations’ result of a benchmark, similar to the number of trials in recent study [22].

To measure the stability of a benchmark, we have taken two steps: one encloses the stability in comparison with other benchmarks, while the other presents how soon a benchmark becomes stable (see Section 6.3 for more details).

1. **Benchmark’s stability in comparison.** In this step, for each measurement, we compute the relative standard deviation (RSD) across 30 iterations’ results to statistically compare the benchmark’s stability with others. We assume that benchmarks with RSD less than 1% are stable enough for detecting performance bugs [17], while benchmarks with RSD greater than 5% are unstable because it represents a relevant and clear variability in performance [38]. Due to the relatively large variation of benchmarks with RSD between 1% and 5%, they are not stable enough for

\(^{10}\)https://cloud.google.com/
detecting small-size bugs, while they are still useful for detecting large-size bugs. However, most of the generated performance bugs do not have a large size and they might not be detected by benchmarks with RSD between 1% and 5%.

(2) Benchmarks’ stability tendencies. If a performance benchmark reaches a stable stage sooner than others, it produces valuable results sooner. In this step, we devised a heuristic statistical strategy to determine which benchmark becomes stable first [37].

For each benchmark, we select $i$ data points out of 30 iterations’ result to form an original set ($P_{\text{original}}$), and similarly, we select another $i$ different data points to form a microbenchmarking set ($P_{\text{microkm}}$). The selection size, $i$, ranges from 2 up to 15 data points ($i \in \{2, 3, ..., 15\}$). We repeat our selection strategy for 100 times, providing 100 pairs of ($P_{\text{original}}, P_{\text{microkm}}$). Following prior study’s approach [17] and by deploying $\mu$ [39], we estimate the confidence interval for the ratio of means with bootstrap [41], using 100 bootstrap iterations for each of 100 pairs (that resembles to the suggested 10,000 bootstrap iterations [42]). Therefore, the width of estimated relative confidence interval (RCIW) computed for each benchmark with $i$ iterations, that indicates how a benchmark’s results are spread and variable around the mean.

Results

(1) Benchmark stability in comparison. Figure 7 is a box-plot chart representing the distribution of RSD calculated (in %) for all benchmarks, across three testing frameworks and three subjects.

![Figure 7: Distribution of the variability, using RSD (in %)](image)

According to Figure 7, the box-and-whisker of RSD of ju2jmh benchmarks range from 0% to 4.52% in Rxjava with a median of 1.16%, while the box-and-whisker of RSD of JUnit tests range from 0.01% to 7.24% with a median of 2.04% in the same subject. As we can see, JUnit tests have a higher median and maximum of RSD than JMH and AutoJMH benchmarks in Rxjava. Zipkin faces the same situation. For Eclipse-collections, JUnit tests have a higher median RSD (1.84%) than ju2jmh benchmarks (0.45%) and a higher maximum value in the box-and-whisker (3.34% vs. 0.96%), respectively. Because a larger RSD indicates that a benchmark is more unstable, these results imply that ju2jmh benchmarks are much more stable than JUnit tests in three studied subjects.

Likewise, we can also compare the stability of ju2jmh benchmarks and manually-written JMH benchmarks based on Figure 7. The median RSD of JMH benchmarks (0.57%) in Rxjava is smaller than ju2jmh benchmarks (1.16%), however, it is greater than ju2jmh benchmarks in Eclipse-collections (1.98% vs. 0.45%) and Zipkin (0.72% vs. 0.49%), as shown in this figure. If only the Eclipse-collections and Zipkin are considered, it appears that ju2jmh benchmarks are more stable than manually-written JMH benchmarks. However, when all three subjects are considered, we can only conclude that ju2jmh benchmarks beat JMH benchmarks in terms of stability in some subjects and not in others. As a result, ju2jmh benchmarks and manually-written JMH benchmarks are comparable.

Lastly, the stability of ju2jmh benchmarks can be also compared with AutoJMH benchmarks according to Figure 7. In terms of the median RSD, in Rxjava, AutoJMH benchmarks has a smaller value (0.37%) than ju2jmh benchmarks (1.16%). However, in Eclipse-collections, the median RSD of ju2jmh benchmarks (0.45%) is smaller than AutoJMH benchmarks (0.99%), and the box-and-whisker length of ju2jmh benchmarks (0.96%) is also smaller than AutoJMH benchmarks (3.05%), indicating that most of ju2jmh benchmarks are more stable than AutoJMH benchmark in this study subject. In Zipkin, the stability of most of ju2jmh benchmarks and most of AutoJMH benchmarks are comparable because of the close median RSD values (0.49% vs. 0.48%). Therefore, the stability of ju2jmh benchmarks are comparable to AutoJMH benchmarks based on the evaluation of these three subjects.

In conclusion, based on the comparisons between automatically generated ju2jmh benchmarks and the other three microbenchmarks, we can infer that, although ju2jmh leverages JUnit tests to generate microbenchmarks, the ju2jmh microbenchmarks are more stable than the original JUnit tests and their stabilities are comparable to manually-written JMH benchmarks and AutoJMH benchmarks.

In Table 5, we focus on how benchmarks stable and unstable are in detecting performance bugs. The table presents the proportion of benchmarks that are stable enough ($RSD \leq 1\%$) or unstable ($RSD \geq 5\%$).

<table>
<thead>
<tr>
<th>Table 5: Stable and unstable benchmarks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject</td>
</tr>
<tr>
<td>---------------------------</td>
</tr>
<tr>
<td>JMH</td>
</tr>
<tr>
<td>ju2jmh</td>
</tr>
<tr>
<td>JUnit</td>
</tr>
<tr>
<td>Auto†</td>
</tr>
<tr>
<td>JMH</td>
</tr>
<tr>
<td>ju2jmh</td>
</tr>
<tr>
<td>JUnit</td>
</tr>
<tr>
<td>Auto†</td>
</tr>
<tr>
<td>Eclipse-collections</td>
</tr>
<tr>
<td>Zipkin</td>
</tr>
</tbody>
</table>

In Eclipse-collections and Zipkin, 91.5% and 84.6% of ju2jmh benchmarks are recognized stable, significantly higher than 5.0% and 58.4% for JUnit tests, 29.0% and 61.0% for JMH benchmarks, and 51.0% and 82.5% for AutoJMH benchmarks. In Rxjava, both ju2jmh and JUnit microbenchmarks produced equal number of stable benchmarks, but 9.5% of the JUnit tests are recognized unstable, higher than 3.9% for ju2jmh benchmarks. Despite the fact that JMH benchmarks (77.2%) and AutoJMH benchmarks (81.1%) are
more stable than ju2jmh benchmarks (43.8%), but in terms of unstable benchmarks, ju2jmh benchmarks and JMH benchmarks have very close values (3.9% vs. 2.3%) and ju2jmh benchmarks are better than AutoJMH benchmarks (3.9% vs. 7.5%). Based on these results, we can infer that ju2jmh benchmarks are generally more stable than JUnit tests and comparable to (or slightly more stable) manually-written JMH benchmarks and AutoJMH benchmarks.

Furthermore, we also check whether JUnit tests remain stable after being converted to ju2jmh benchmarks. In Rxjava, both ju2jmh and JUnit have the same amount of stable tests. Specifically, 86.4% of JUnit tests that recognized stable remain stable after being converted to ju2jmh benchmarks, 0.9% of JUnit tests that recognized unstable become stable, and 0.6% of JUnit tests that recognized stable become unstable. For the unstable JUnit tests that become stable, we rerun the associated ju2jmh benchmarks without warm-up iterations, and all of the new results achieve a higher RSD (%) ranging from 0.2% to 7.1% than the results with warm-up iterations, thus the test stability has deteriorated in all cases. As a result, warming up the system before running the benchmark is critical to achieve the stability of ju2jmh benchmarks in comparison to JUnit tests without warm-up iterations. For the stable JUnit tests that become unstable, we manually checked the source code and found that all of these tests contain tasks that deal with asynchronous executions, multiple threads or multiple processors, which are restricted in ju2jmh benchmarks. Moreover, all the JUnit tests in Eclipse-collections and Zipkin remain stable in form of ju2jmh benchmarks, none of JUnit tests that recognized unstable become stable, and none of JUnit tests that recognized stable become unstable. In conclusion, a high portion of JUnit tests remains stable after being converted to ju2jmh benchmarks.

(2) Benchmarks’ stability tendencies. Figure 8 presents the results of the second step, which encloses how benchmarks grow more stable as the number of iterations increases. Every box represents the distribution of calculated RCIWs for all benchmarks of a testing framework with i iterations. The greater the RCIW, the more variation (less stability) there is in the result set. Accordingly, the larger the box-and-whisker, the more variation of stability there is between benchmarks of one type. For example, according to Figure 8, a benchmark usually produces more variable results through two iterations than a larger number of trials, such as 15 iterations. It is noted that, to facilitate a better comparison and clarification, we zoom in the chart so that a few whiskers and one box are shown out of the presenting range, but this does not affect the conclusion.

As illustrated in Figure 8, the median RCIW of JUnit tests is always greater than ju2jmh, JMH, and AutoJMH benchmarks, implying that JUnit tests are generally more unstable than the other three types of microbenchmarks. Furthermore, based on the following analysis, we can conclude that JMH, ju2jmh, and AutoJMH RCIWs are comparable among these three studied subjects. The median RCIW of ju2jmh benchmarks is always greater than JMH in Rxjava and Zipkin, but their differences are significantly smaller than the RCIW differences between JUnit tests and JMH/ju2jmh benchmarks, indicating that although ju2jmh benchmarks are more unstable than JMH benchmarks in these two subjects, their difference is very limited. Rxjava faces the same conclusions when ju2jmh is compared with AutoJMH. In addition, the median RCIW of ju2jmh benchmarks is lower than JMH and JUnit in Eclipse-collections, suggesting that those benchmarks are more unstable than ju2jmh benchmarks in this subject. Moreover, the median RCIW of ju2jmh benchmarks is always comparable with AutoJMH benchmarks in two subjects of Eclipse-collections and Zipkin. Lastly, in all three subjects, ju2jmh benchmarks’ RCIWs are converging with JMH and AutoJMH benchmarks’ RCIWs to a higher level of stability, with a very near level of stability after 15 iterations.

In conclusion, regarding stability assessing, both steps yield identical results: (1) in all three studied subjects, the generated ju2jmh benchmarks outperform JUnit tests; (2) ju2jmh and manually-written JMH benchmarks are comparable, but ju2jmh benchmarks outperform manually-written JMH benchmarks in two out of three studied subjects. (3) ju2jmh benchmarks are also comparable to AutoJMH benchmarks.

RQ1: Can performance microbenchmarks detect artificial performance bugs from mutation testing?

Motivation
While executing performance microbenchmarking, a performance bug can make developers question whether it comes from a noisy environment [37], [38], the benchmark’s unstable quality [9], or even a bug. In RQ1, we assessed the stability of benchmarks. However, the stability itself is not sufficient for detecting performance bugs. A further evaluation of benchmarks is needed on their ability to detect performance bugs.

Approach
To address benchmarks’ ability in detecting bugs, we leverage the PMT framework presented in Section 6 to inject artificial performance bugs into the source code. An artificial performance bug could be observed by a covering performance test by searching for degradations in its results. If the performance test can detect an artificial bug, it is more likely that the test can also detect a real-world similar performance bug.

First, to generate artificial performance bugs, we applied the PMT framework to the subject’s source code. We build up a large number of systems versions, each containing one performance bug injected setting at a single source code location. Then, we extract all benchmarks that cover any of the selected mutants. Afterwards, we execute benchmarks that cover an injected performance bug, before and after
Note the minimum bug occurring in the target system. We bound of estimated RCI, opposite to its lower bound, de-
U

O

by a performance bug can be defined as,

\[ \text{mutant if the throughput of the benchmark with the mutant is significantly lower than the throughput in the original system. For a studied benchmark, we estimate its confidence interval for the ratios of means (RCI), and the ratios are calculated based on the benchmark's throughputs (of before and after the bug injection) and by deploying bootstrap technique [40], [41], using 10,000 bootstrap iterations [42] with confidence level of 99%.

Therefore, the size of performance degradation caused by a performance bug can be defined as,

\[ \text{bug size} = [1 - U_{RCI}] \]

calculate the bug size in % and it reflects the effectiveness of mutant against the benchmark. We then assume three different thresholds as the minimum performance degradation that bugs produce, namely 1%, 5%, 10%, which has been used in prior study [22]. The thresholds are chosen from 1% to 10% because: (1) According to the preliminary analysis results of PMT in Table 2, bug size in the mutation operators SOC and HWO are always greater than 10%, which is why we set a 10% threshold for them. Although PTW, STS, and EFL, mutation operators can/may achieve a bug size of 10% as the hitting ratio increases by a large value, for consistency among different mutation operators, we still keep 10% as upper bound for all mutations. (2) In terms of selecting the lowest threshold, 1% is the lowest threshold used in the prior work [22], and the bugs with bug sizes less than 1% are difficult to detect. The three thresholds are chosen from 1% with a high falsely reported positive (bugs not caused by mutants) to 10% with a low falsely reported positive. If a bug size is greater than the threshold, there is a significant variation in results, which conveys that the benchmark could kill the mutant (detect the injected bug), and vice versa. The mutation score is then calculated to compare ju2jmh benchmarks to manually-written JMH benchmarks, JUnit tests, and AutoJMH benchmarks.

Results

Table 6 presents the percentage of tests that kill any of mutants and Table 7 presents the calculated mutation score over the three thresholds (columns 1%, 5% and 10%), for the four testing frameworks (column FW) and the five mutation types (columns PTW(%), STS(%), EFL(%), SOC(%) and HWO(%)).

\[ \frac{\text{Number of iterations}}{15} = \{2, 3, \ldots, 15\} \]
Comparing ju2jmh benchmarks and JUnit tests: According to column Total (%) in Table 6, across the three subjects and for all three thresholds, more ju2jmh benchmarks kill a mutant than JUnit tests. In total, from 4.2% to 34.6% of all ju2jmh benchmarks kill a mutant, significantly higher than 3.5% to 15.7% for JUnit. Furthermore, over large degradations (≥10%), low and equivalent percentage of ju2jmh and JUnit kill a mutant, while in small degradations (≥1%), ju2jmh significantly outperforms JUnit.

Furthermore, according to column Total (%) in Table 7, ju2jmh achieves a higher mutation score than JUnit, with the exception of Eclipse-collections and the threshold of 1%. In total, ju2jmh achieves the mutation score from 29.7% to 80.0%, higher than JUnit with the mutation score of 23.9% to 69.0%. In Eclipse-collections and over the threshold of 1%, the difference between ju2jmh benchmarks and JUnit tests is slight (87.8 vs. 91.8). In other cases, ju2jmh outperforms JUnit.

In conclusion, while both Ju2jmh and JUnit tests cover all of the mutants in the study, the percentage of ju2jmh benchmarks that kill a mutant is higher than JUnit tests, implying that for a given mutant operator, it is more likely to be killed by ju2jmh benchmarks than JUnit tests. In addition, ju2jmh benchmarks generally achieve higher mutation scores than JUnit tests. Therefore, ju2jmh is more effective in detecting performance bugs, regardless of the analysis perspective of mutation operators or tests.

Comparing ju2jmh and JMH benchmarks: We first compare percentage of ju2jmh and JMH benchmarks that kill a mutant using the analysis of column Total (%) in Table 6. In some cases, the percentage of ju2jmh benchmarks is greater than that of JMH benchmarks, while in other cases, it is lower. For example, 37.1% and 21.0% of ju2jmh benchmarks in Eclipse-collections and Zipkin kill a mutant with bug size ≥1%, higher than 28.9% and 18.4% of JMH benchmarks. However, in other cases, ju2jmh benchmarks achieve a smaller percentage.

We then compare the mutation scores of ju2jmh and
JMH benchmarks according to Table 7. Column Total (%) illustrates that **ju2jmh** benchmarks are more efficient than JMH benchmarks in killing mutants in general. On average, 29.7% to 80.0% of mutants are killed by **ju2jmh** benchmarks, higher than 30.4% to 60.9% by JMH benchmarks. In more than half of the cases, **ju2jmh** benchmarks achieve higher mutation scores than JMH benchmarks. Moreover, although manually-written JMH benchmarks are not far behind **ju2jmh** benchmarks in terms of mutation scores, they cover far fewer mutants (29.7% vs. 100%).

As presented in Table 6 and Table 7, although there are more percentages of JMH benchmarks that kill mutants than **ju2jmh** benchmarks, the overall coverage of all JMH benchmarks is much less than **ju2jmh**, implying that **ju2jmh** benchmarks have more coverage diversity, whereas manually-written JMH benchmarks are more specific to certain mutants with less coverage diversity. The manually-written JMH benchmarks would produce more accurate results if they could achieve higher coverage. However, this necessitates a great deal of manual effort, which is impractical in real-life development. Therefore, we can deduce that **ju2jmh** benchmarks cover more mutants than manually-written JMH benchmarks, and that the JMH benchmarks necessitate proper enhancements, such as higher mutant coverage, in order to achieve better results.

**Comparing AutoJMH benchmarks with other tests:** Similarly, when the percentage of AutoJMH benchmarks that kill a mutant is compared to those of other tests, AutoJMH benchmarks can have higher percentages than **ju2jmh** benchmarks, according to column Total (%) in Table 6. However, both benchmarks can generally achieve 100% mutant coverage, as presented in Table 7. In addition, AutoJMH benchmarks have limitations that prevent them from being trusted and valuable. First, according to Table 4, the number of generated AutoJMH benchmarks is significantly lower than the other tests, resulting in a limited data set for study. Second, AutoJMH is obsolete as we mentioned in Section 4. Third, AutoJMH is limited to manually configuring specific single statements. Such reasons limit the spread and application of AutoJMH.

Moreover, **ju2jmh** benchmarks achieve a higher mutation score than AutoJMH benchmarks in all cases across the three subjects and for all three thresholds, according to column Total (%) in Table 7. In total, **ju2jmh** achieves the mutation score of 29.7% to 80.0%, significantly higher than 12.2% to 58.0% for AutoJMH. In particular, in Rxjava and Eclipse-collections, **ju2jmh** benchmarks have mutation scores of at least 20.4% higher than AutoJMH benchmarks.

In conclusion, while both **ju2jmh** and AutoJMH benchmarks cover all mutants, **ju2jmh** benchmarks achieve higher mutation scores than AutoJMH benchmarks, indicating that **ju2jmh** benchmarks are more effective than AutoJMH benchmarks in detecting performance bugs.

**Different effect of mutation operators’ diversity:** According to row Total (%) in Table 6, which presents the percentage of benchmarks that kill a mutant, across the threshold of 1%, 61.2% of JMH benchmarks, 65.4% of **ju2jmh** benchmarks, 84.3% of JUnit tests, and 41.3% of AutoJMH benchmarks failed in killing mutants. The highest percentage of benchmarks kill mutants from SOC (the total mutation score in column SOC) with the percentage of 3.6% to 38.9%, and the smallest percentage of benchmarks kill mutants from PTW (column PTW) with the percentage of 0.5% to 19.5%. Moreover, mutants from HWO (column HWO) have a strong effect on benchmarks, particularly where 11.7% of benchmarks with a large bug size 10% is significantly greater than 0.5% of benchmarks that kill a mutant from PTW.

Table 7 yields the same finding, proving that different mutation operators have different effects on microbenchmarks. According to row Total (%), which presents the calculated mutation score across all tests of the three study subjects, 35.5% to 89.0% of mutants are killed by the tests in total. The highest mutation score is achieved by HWO (column HWO) with the percentage of 0.5% to 100% of mutants are killed. The smallest mutation score is for SOC (column SOC) with the percentage of 37.5% to 62.5% of mutants are killed. Such large variations in the results illustrate the diversity of mutant operators.

**Exclusive mutation score:** In order to provide more insight into **ju2jmh** benchmarks, we define the exclusive mutation score, which is the percentage of mutants that are exclusively killed by a framework and not by others. We calculate the exclusive mutation score for the four frameworks, across the three subjects, for the five mutation operators, and over the three thresholds. In total, over the threshold of 1%, **ju2jmh** benchmarks achieve the exclusive mutation score of 3.2%, higher than 2.2% for JMH benchmarks and 0.6% for JUnit tests, but less than 6.5% for AutoJMH benchmarks. Over the threshold of 5%, **ju2jmh** benchmarks achieve the exclusive mutation score of 9.0%, considerably higher than 2.2% for JMH, 0.6% for JUnit, and 6.5% for AutoJMH. Over the large threshold of 10%, **ju2jmh** benchmarks achieve the exclusive mutation score of 5.8%, higher than 0.6% for JUnit and 3.6% for AutoJMH, but less than 8.7% for JMH. In conclusion, most mutants are covered by multiple tests, with **ju2jmh** benchmarks covering more mutants exclusively than JUnit tests in all cases and JMH and AutoJMH benchmarks in the majority of cases.

**RQ2 Takeaway**

**ju2jmh** benchmarks are more effective in detecting performance bugs than JUnit tests and AutoJMH benchmarks. **ju2jmh** benchmarks cover more mutants than manually-written JMH benchmarks and JMH benchmarks necessitate proper enhancements, such as higher mutant overage, to achieve better results. Furthermore, we discover that different mutation operators can have various effects on benchmarks. In general, **ju2jmh** benchmarks can detect a higher proportion of mutants exclusively than other tests.

**RQ3: Can performance microbenchmarks detect real-world performance bugs?**

**Motivation**

One of the advantages of mutation testing is to find deficiencies in tests and improve them, thus improved tests can be further utilized for detecting real-world bugs [43]. We are motivated to know if benchmarks with higher performance mutation score can detect real-world performance bugs.
better. On the other hand, we tend to know how similarly the generated mutants and real-world performance bugs behave in affecting a covering performance test.

**Approach**

To answer the motivation questions, we check whether a performance test is more likely to detect a similar real-world performance bug if it is able to detect a mutant.

For a specific real performance bug inside a system’s source code, we first find all JUnit tests and JMH benchmarks that cover it. Next, we deploy *ju2jmh* to build benchmarks from JUnit tests and deploy the PMT tool to generate a mutant similar to the bug on the same source code location. Last, we execute covering *ju2jmh* and JMH benchmarks 30 times against the original system where the bug is fixed, the parent system that still contains the bug, and the system where the bug is replaced with a generated mutant. Then, we compare mutation results with real bug results. Accordingly, the tendency of performance tests in detecting a mutant is compared with the tendency of them in detecting real bugs.

Similar to previous research question, we predict the RCI for both the original system and the system containing real-world bugs (RCI_{bug}) and predict the RCI for the original system and its mutant version (RCI_{mutant}). Then, we compare both calculated RCIs to find similarities between them.

The real-world explored performance bugs are extracted from NFBugs dataset [23]. NFBugs is a dataset of 138 non-functional bug fixes in 67 open-source projects in Java or Python. NFBugs contains eight common performance bugs patterns from performance bugs that are already fixed by the projects’ community. The building of our PMT tool is based on the real-world performance bugs collected from NFBugs dataset.

In total, there are 13 fixing of real-world performance bugs from 11 different projects in NFBugs dataset that are supported in our PMT tool (i.e., the bug can be reproduced by one of the five developed patterns). The 13 bug fixes are from three bug patterns of PTW, EFL, and STS. However, only one bug fix can be studied through this research question’s experiment. For the rest of 12 bug fixes, in 11 of them, there is either no JMH/JUnit test in the system or there is no JMH/JUnit test that covers any of fixed bugs, and for the last bug fix, the corresponding system is no longer available in public.

The performance bug exists in Storio and is fixed through commit of #566d3e9. There are 21 Junit tests in the system that cover the bug. Accordingly, we build 21 *ju2jmh* microbenchmarks and a mutant associated with the bug. Lastly, we compare the mutation score of *ju2jmh* benchmarks and JUnit tests.

**Results**

Figure 9 presents the calculated $U_{RCI}$ for each of numbered 21 *ju2jmh* benchmarks and numbered 21 JUnit tests, against the mutant and the real bug. Similar to the previous research question, three thresholds (1%, 5% and 10%) are marked as three minimum bug size that trigger the detection of bug. If calculated $U_{RCI}$ is below each of the three thresholds’

Table 8 summarizes Figure 9.

<table>
<thead>
<tr>
<th></th>
<th>Mutant</th>
<th>Bug</th>
<th>Mutant</th>
<th>Bug</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>ju2jmh</em></td>
<td>1%</td>
<td>5%</td>
<td>10%</td>
<td>5%</td>
</tr>
<tr>
<td>66.7</td>
<td>42.8</td>
<td>4.7</td>
<td>66.7</td>
<td>42.8</td>
</tr>
<tr>
<td>JUnit</td>
<td>0.0</td>
<td>19.0</td>
<td>0.0</td>
<td>19.0</td>
</tr>
</tbody>
</table>

According to Figure 9 and Table 8, *ju2jmh* appears to performs better than JUnit in either killing the mutant or detecting the real-world bug. For the three thresholds of bug sizes 1%, 5% and 10%, the percentage of *ju2jmh* benchmarks that kill the mutants are 4.7% (benchmark #1), 42.9% (benchmarks #1 to #9), and 66.7% (benchmarks #1 to #14) respectively, better than JUnit tests with the percentage of 0.0%, 19.0% (benchmarks #1 to #4), and 61.9% (benchmarks #1 to #13), indicating that *ju2jmh* benchmarks can detect the mutant better than JUnit tests. Similarly, *ju2jmh* performs better than JUnit in detecting real-world bugs. Over smaller degradations (1% and 5%), 66.6% and 42.8% of *ju2jmh* microbenchmarks detect the presence of the bug, higher than 61.9% and 23.8% for JUnit tests. None of the *ju2jmh* or JUnit tests can detect real-world bugs with a larger bug size threshold (10%). As a result, *ju2jmh* performs better than JUnit in both killing the mutant and detecting the bug.

According to Figure 9, both *ju2jmh* benchmarks and JUnit tests produce results with a similar distribution against the mutant and the bug. On average, the differences of calculated $U_{RCI}$ between the mutant and the bug is 0.36% for *ju2jmh* benchmarks and 0.26% for JUnit tests, enclosing the similarities between results of benchmarks against the mutant and results of benchmarks against the bug. However, in all cases, the tendency of *ju2jmh* benchmarks in killing the mutant or detecting the bug is higher than JUnit tests. *ju2jmh* benchmarks have a lower calculated $U_{RCI}$ value (higher tendency) than JUnit tests from 0.3% to 2.98% in killing the mutant, and from 0.23% to 2.63% in detecting the bug. In conclusion, the distribution of *ju2jmh* benchmarks’ results and JUnit test results is similar, but the tendency of *ju2jmh* benchmarks in both killing the mutant and detecting the bug is higher than JUnit tests.

**RQ3 Takeaway**

According to our experiment of a real-world performance bug and a similar generated mutant, *ju2jmh* performs better than JUnit in killing the mutant and detecting the bug. Furthermore, the mutant and real-world bug affect benchmarks in a very similar way.

**RQ4: What are the major factors affecting a microbenchmark’s ability to detect performance bugs?**

**Motivation**

To determine a performance microbenchmark is effective or unsatisfactory, there are a number of metrics that require
further investigation and comparisons. In this section, we highlight three causes that significantly affect the ability of microbenchmarks to detect bugs. The causes $c1$ and $c3$ in the following are derived from prior research [8]. We examine three of the eight causes they identified and merge two of them into $c1$. In addition, $c2$ is derived based on both the prior work [3] and the aforementioned analysis of RQ results.

$c1$. Too low workload: performance bugs could not be detected in benchmarks with a modest workload of payloads. In other words, most of mutants are killed by the benchmarks with relatively large workload.

Ding et al. [8] point out that not enough microbenchmark execution repetition could have a significant impact on a performance microbenchmarks’ ability to find bugs. During a microbenchmark execution, if we raise the number of iterations of a microbenchmark code, the workload can be increased without exceeding the hardware limit. As a result, we have combined these two reasons into one.

$c2$. Unstable microbenchmarks: Laaber and Leitner [3] reveal that the variability of a benchmark has an impact on benchmarking results. Furthermore, both RQ1 and RQ2 indicate that ju2jmh benchmarks outperforms JUnit tests in all studied subjects and is comparable to JMH benchmarks when two separate aspects are taken into account (i.e., the microbenchmark stabilities and microbenchmark ability to detect bugs). The same conclusions may imply that microbenchmark stability affects microbenchmark ability to detect bugs, which could be of interest.

$c3$. Limited mutant coverage: performance bugs are generated by the PMT framework, however they only affect one point in the source code (mostly one line of source code). Therefore, to investigate this cause, we considered the total number of times that the source code line containing bugs (mutants) was hit during the microbenchmark execution as a coverage metric. We claim that the more times a benchmark hits the buggy line, the more significant performance degradation in microbenchmarking results exists.

Other causes: there are other known/unknown causes for future study that might impact benchmarks in exposing bugs. For example, benchmarks may access to IO/network/resource [8], natural internal and external noises [37], [38], ideal during execution [8], and the design of the benchmark itself [5]. These other causes are not evaluated here, and are left for future research.

Approach

To answer RQ4, we examined each of the three aforementioned causes against all of the RQ2’s benchmark tests that killed a mutant. Since there were not many benchmarks that killed a mutant with the bug size ≥ 5% and 10%, we only studied on the threshold of 1% as the minimum bug size.

To examine workload ($c1$), we take the throughput (ops/s) of benchmarks as the metric. In addition, we take the RSD (%) of benchmarks and the hitting_count (/s) to study on the second ($c2$) and third ($c3$) causes respectively. For each metric (i.e., throughput/RSD/hitting_ratio), we calculate the number of benchmarks that could kill the mutant with different values of metrics for subsequent analysis. Specifically, we split the range of all measurements (of a testing framework and across all five mutant types) into four equal-size groups from the minimum value to the maximum value in the data-set. Then, we count the total number of benchmarks that kill a mutant in each group.

In prior RQs, we compare ju2jmh to other testing frameworks and find that ju2jmh outperform other testing frameworks in general. Therefore, the question of why ju2jmh outperforms other testing frameworks arises. The ju2jmh benchmarks achieve 100% mutant coverage, which means that each mutant must be executed. For mutants merely covered by ju2jmh benchmarks, it is obvious that ju2jmh benchmarks perform better due to mutant coverage. For mutants covered by multiple tests, we perform a study on them. We first select all mutants that are covered by all four types of tests. We choose the top mutant cases where ju2jmh benchmarks outperform other tests the most and conduct manual analysis on them. For each of the five mutation types, we extract a ranking list of the mutants for which ju2jmh outperforms the other three frameworks in terms of killing the mutants. The ranking is determined by the largest
Table 9: The number of tests that killed any of mutants, according to the three causes with four groups of the related metric, for the three testing frameworks, and across three studied subjects.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Framework</th>
<th>c1: too low workload</th>
<th>c2: unstable tests</th>
<th>c3: limited coverage</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>g1</td>
<td>g2</td>
<td>g3</td>
<td>g4</td>
</tr>
<tr>
<td>RxJava</td>
<td>JMH</td>
<td>38</td>
<td>50</td>
<td>82</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>ju2jmh</td>
<td>32</td>
<td>115</td>
<td>193</td>
<td>1,088</td>
</tr>
<tr>
<td></td>
<td>JUnit</td>
<td>14</td>
<td>34</td>
<td>100</td>
<td>319</td>
</tr>
<tr>
<td></td>
<td>AutoJMH</td>
<td>3</td>
<td>1</td>
<td>4</td>
<td>32</td>
</tr>
<tr>
<td>Ec-col</td>
<td>JMH</td>
<td>23</td>
<td>23</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>ju2jmh</td>
<td>10</td>
<td>15</td>
<td>63</td>
<td>653</td>
</tr>
<tr>
<td></td>
<td>JUnit</td>
<td>9</td>
<td>10</td>
<td>42</td>
<td>441</td>
</tr>
<tr>
<td></td>
<td>AutoJMH</td>
<td>6</td>
<td>0</td>
<td>2</td>
<td>24</td>
</tr>
<tr>
<td>Zipkin</td>
<td>JMH</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>ju2jmh</td>
<td>1</td>
<td>4</td>
<td>9</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>JUnit</td>
<td>1</td>
<td>1</td>
<td>12</td>
<td>19</td>
</tr>
<tr>
<td></td>
<td>AutoJMH</td>
<td>2</td>
<td>0</td>
<td>6</td>
<td>10</td>
</tr>
<tr>
<td>Total</td>
<td>145</td>
<td>253</td>
<td>461</td>
<td>2,651</td>
<td>3,370</td>
</tr>
</tbody>
</table>

*Eclipse-collections

bug size difference between ju2jmh benchmarks and the tests from the other three frameworks. If a mutant is covered by multiple tests that are specific to a type, we choose the best result as a representation of this test type. Then top five mutants with the largest bug size difference between ju2jmh benchmarks and the other tests are then selected. Lastly, we manually inspect the top five cases, such as static analysis, to determine why ju2jmh benchmarks outperform other tests.

Similarly, we follow the procedure from the manual analysis above to study the reasons why the mutants can only be killed by ju2jmh benchmarks but not by other tests. We first extract all mutants that can only be killed by ju2jmh benchmarks with three various thresholds for throughput reduction (1%, 5%, and 10%). For each threshold and mutation operator type, after ranking ju2jmh benchmarks by comparing the maximum difference of bug size between them and the other tests, we choose the top cases to perform the manual analysis.

Results

Table 9 presents the number of microbenchmarks that killed a mutant according to each of four groups of the three causes.

**c1. Too low workload:**

In total, 74.4% of mutants are killed by benchmarks with the largest workload (column c1.g4), significantly higher than three other groups. In all cases of column c1, ju2jmh, JUnit, and AutoJMH significantly confirms our claim that benchmarks with the largest workload are better in detecting bugs, while JMH is against our claim.

In RxJava, 1,088 (76.2%) ju2jmh benchmarks, 319 (68.3%) JUnit tests, and 32 (80.0%) AutoJMH benchmarks belong to the largest workload group (g4), while JMH benchmarks are normally distributed among four groups and the largest workload’s group contain only 16.3% of the benchmarks. Furthermore, in Eclipse-collections and Zipkin, similar findings are obtained in comparing ju2jmh, JUnit, and AutoJMH. However, JMH completely stands against our claim in these two subjects where 23 (46%) Eclipse-collections benchmarks and 6 (85.7%) Zipkin benchmarks belong to the smallest workload’s group (g1).

In conclusion, ju2jmh, JUnit, and AutoJMH all confirm that benchmarks with the largest workload are better in detecting performance bugs, but JMH does not necessarily support this claim.

**c2. Unstable microbenchmarks:**

Column c2 of table 9 depicts a highly significant effect on stability, with the most stable benchmarks (column c2.g1) killing 94.6% of mutants. All four test frameworks confirm that most of mutants are killed by the most stable benchmarks. Specifically, across the three subjects, 71.4% to 96.1% of JMH benchmarks, 90.7% to 96.8% of ju2jmh benchmarks, 93.9% to 97.0% of JUnit tests, and 61.1% to 96.9% of AutoJMH benchmarks belong to the most stable benchmarks that killed a mutant.

In conclusion, microbenchmark stability has a significant impact on detecting performance bug. The more stable benchmarks can better detect performance bugs.

**c3. Limited mutant coverage:**

In general, results do not necessarily confirm that benchmarks need higher hitting_ratio (e.g., column c3.g4) to detect performance bugs. However, if the benchmark hit the buggy statement with lower ratio (e.g., column c3.g1), the mutant could not be killed by the benchmark. In total, two middle groups (c3.g2 and c3.g3) killed 89.4% of all mutants, and only 4.7% of mutants are killed in a situation with the lowest hitting_ratio (c3.g1). As a result, we can conclude that in order to detect performance bugs, microbenchmarks require appropriate hitting_ratio values (not too high or too low). In other words, mutants with too low hitting_ratio cannot sufficiently degrade microbenchmarks. Moreover, microbenchmarks rarely hit a mutant with a large hitting_ratio to make significant degradations. The data trend indicating the number of microbenchmarks detecting bugs decreases in an interval with a high hitting_ratio reinforces the view stated in section 6.4, implying that some external factors, such as hardware limitations, may have an impact on microbenchmarks results.

According to Table 9, we can conclude that the positive effect of each of the three discussed causes can result in better detection of the performance bug. We conclude that benchmarks with sufficient workload, higher stability, and
appropriate coverage can better kill the mutant. The three approaches of ju2jmh, JUnit, and AutoJMH confirm our claim that benchmarks with the largest workload can better detect bugs, while JMH does not necessarily confirm it. In all cases, all four approaches confirm that the most stable benchmarks can better detect bugs. Lastly, results do not confirm that benchmarks need high coverage, but they need an appropriate coverage of the bug to be able to detect the bug.

Our manual study identified three reasons why ju2jmh benchmark outperforms others. In particular, the experiment yields five top-five cases (out of a total of 25) in which the ju2jmh benchmark outperforms other tests the most based on bug size. The maximum bug size difference between ju2jmh benchmarks and other tests ranges from 0.5% to 97.2%. Among the 25 cases, AutoJMH benchmarks are involved in the majority of cases (16 of 25), while JMH benchmarks are involved in the fewest (4 of 25 cases). In addition, we manually analyze another 27 cases where mutants that can only be killed by ju2jmh. Based on the total 52 (i.e., 25 + 27) cases, we found the reasons why ju2jmh benchmarks outperform other tests, which can be summarized as follows: (1) In 28 cases, ju2jmh benchmarks hit the mutants more often than the other frameworks (more than 4× to 400,000×); (2) In 22 cases, ju2jmh benchmarks have higher stability (lower RSD) than the other frameworks; (3) In 13 cases, ju2jmh benchmarks have a more proper workload size (not too high or too low) than the other frameworks. The detailed experiment results are attached to Table 10 in the Appendix section.

In summary, to answer this RQ4, we used prior work to derive three causes and conducted three experiments to measure these three causes. The results indicate that (1) Too low workload can prevent ju2jmh benchmarks from detecting performance bugs effectively. The same conclusion applies to JUnit tests and AutoJMH benchmarks, but not to JMH benchmarks. (2) Unstable microbenchmarks can also impede microbenchmarks from detecting bugs, and this finding is not limited to a particular testing framework. (3) Performance bugs are more likely to be detected in microbenchmarks with appropriate execution times for bugs during the microbenchmarking period. Too low or too high execution times can cause microbenchmarks to fail to detect performance bugs.

8 Threats to Validity

In this section, we discuss the threats to the validity of our study.

8.1 External Validity

We performed our evaluations on three popular open-source Java software systems from a limited system set that extensively deploys JMH along with JUnit. However, the subjects’ JMH benchmarks are actively maintained by professional development teams and include sufficient microbenchmarks, thus they are suitable to be used in our experiments.

We developed five mutation operators in our PMT framework, but there would be many other known/unknown performance bug patterns in real-world systems. We randomly selected our study mutants from a broad set of generated mutants. Various mutants can have a wide range of characteristics that our chosen mutants may not cover. In the future, we will explore more mutants and extend our framework to support more mutant types.

During our study, we found that some JUnit tests are performance unit tests rather than functional unit tests. At the time of writing, our tool does not distinguish them since it is tricky to do so through static analysis of source code. Future work may consider addressing this issue to improve our existing approach.

8.2 Internal Validity

Monitoring performance is always challenging with noises [9]. To minimize such errors as much as possible, (1) for each measurement, we executed benchmarks for 30 iterations each, (2) in isolated, controlled, and large-scale cloud computing resources provided by Google Cloud, and (3) we reduced random bias by performing an evaluation strategy, i.e., bootstrapping.

Performance testing is vulnerable to environmental noises and running performance tests on virtual computing instances might affect the reliability of results more than on bare-metal computing servers. However, bare-metal servers are more expensive than cloud environments, and the data noise produced by cloud-based studies is usually acceptable. There exist many prior studies [3], [8], [22], [28], [37], [38] that have been conducted on cloud environments for performance testing. In addition, although the variability of cloud environment can affect statistical analysis, we repeat each test 30 times to mitigate data noise caused by such variability.

9 Conclusion

The goal of performance microbenchmarking is to catch degradations (e.g., slowdowns) as early as possible, such as checking (and microbenchmarking) every build of the system. In this paper, we look into how to help with microbenchmark construction and quality assurance. On the one hand, our ju2jmh tool can automatically construct ready-to-execute JMH benchmarks from a wide set of readily available JUnit tests, that potentially relieve developers from designing challenges and costs. One the other hand, we implement a PMT framework to automatically assess the quality of microbenchmarks in detecting bugs.

To further assess the quality of our automatically generated ju2jmh benchmarks, we devise a study to compare the ju2jmh benchmarks to manually-written JMH benchmarks.
and using JUnit tests directly as performance proxies in terms of microbenchmark stability and ability of performance bug detection. For microbenchmark stability, generated ju2jmh benchmarks have been proven to be comparable with manually-written JMH benchmarks, while they significantly outperform JUnit tests in all analyzed subjects. For microbenchmark efficiency, we can similarly conclude that ju2jmh benchmarks outperform JUnit benchmarks and are comparable with manually-written JMH benchmarks. However, ju2jmh benchmarks are able to cover more of the software applications than JMH benchmarks during the microbenchmarking execution. In addition, when compared to developing human-written JMH benchmarks, our automated tool can save developers time and effort in microbenchmark construction.

In future, we aim to extend the ju2jmh by handling two common noises of dead code elimination and constant folding [16]. Furthermore, our PMT framework is developed with five operators, while there would many other performance bug patterns in reality. In future works, we aim to advance the PMT with more mutation operators. In addition, we would like to investigate and evaluate other factors that may affect microbenchmarks’ ability to detect performance bugs.

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