SJFuzz: Seed & Mutator Scheduling for JVM Fuzzing

Anonymous Author(s)

ABSTRACT

While Java Virtual Machine (JVM) plays a vital role in ensuring correct executions of Java applications, testing JVMs via generating and running class files on them can be rather challenging. The existing techniques, e.g., *ClassFuzz* and *Classming*, attempt to leverage the power of fuzzing and differential testing to cope with JVM intricacies by exposing discrepant execution results among different JVMs, i.e., inter-JVM discrepancies, for testing analytics. However, their adopted fuzzers are insufficiently guided since they include no well-designed seed and mutator scheduling mechanisms, making differential testing essentially ineffective. To address such issue, in this paper, we propose *SJFuzz*, the first JVM fuzzing framework with seed and mutator scheduling mechanisms for automated JVM differential testing. Overall, *SJFuzz* aims to mutate class files via control flow mutators to facilitate the exposure of inter-JVM discrepancies. To this end, *SJFuzz* schedules seeds (class files) for mutations based on the discrepancy and diversity guidance. *SJFuzz* also schedules mutators for diversifying class file generation. To evaluate *SJFuzz*, we conduct an extensive study on multiple representative real-world JVMs, and the experimental results show that *SJFuzz* significantly outperforms the state-of-the-art mutation-based JVM fuzzer in terms of the inter-JVM discrepancy exposure and the class file diversity. Moreover, *SJFuzz* successfully reported 46 JVM bugs where 20 have been confirmed and 16 have been fixed by the JVM developers.

1 INTRODUCTION

Java Virtual Machine (JVM) refers to the virtual machine which interprets and executes Java bytecode compiled from various high-level programming languages, e.g., Java, Scala, and Clojure [17]. Typically, after source code files are compiled to bytecode class files, JVM first leverages class loaders to load such class files, in terms of the strict order of loading, linking, and initialization. Then, JVM directly executes the bytecode, or transforms the loaded bytecode into machine code for actual execution via Just-in-Time (JIT) or Ahead-of-Time (AOT) compilers for optimization purposes.

Multiple JVM implementations, such as Oracle's HotSpot [13], Alibaba's DragonWell [10, 11], IBM's OpenJ9 [14], Azul's Zulu [20], and GNU's GIJ [12], have been widely applied in support of a variety of Java-bytecode-based applications. While ideally they are expected to implement the same JVM specification and conform to consistent cross-platform robustness, they are usually implemented by different groups for different platforms and thus may cause de facto inconsistencies which are likely to indicate JVM defects, e.g., the same class file may run smoothly on one JVM but trigger verifier errors on another JVM.

Testing JVMs via manually designing tests based on analyzing JVM semantics can be extremely challenging due to their intricacies, e.g., it can be rather hard to check the correctness of JVM outputs (i.e., the test oracle problem). To address such challenge, prior research work attempts to integrate fuzzing [40] and differential testing [37] for automated JVM testing, i.e., designing fuzzers to generate class files as tests for executing different JVMs such that their discrepant execution results (defined as *inter-JVM discrepancies* in this paper) can be used for testing analytics. For instance, *ClassFuzz* [32] fuzzes Java class files by mutating their modifiers or variable types to test the loading, linking, and initialization phases in JVMs. More recently, *Classming* [31] fuzzes live bytecode to mutate the control flows in class files to test deeper JVM execution phases (e.g., bytecode verifiers and execution engines) across multiple JVMs.

However, the power of the existing JVM fuzzers may not be fully leveraged since they fail to apply seed scheduling and mutator scheduling mechanisms which have become vital in enhancing fuzzing effectiveness. In particular, seed scheduling refers to aggressively selecting and mutating seeds to facilitate program vulnerability exposure. Many coverage-guided fuzzers [7, 24, 46, 49, 53, 54] schedule seeds for mutation simply when executing them can increase code coverage. The existing JVM fuzzers, on the contrary, fail to leverage code coverage as seed scheduling guidance because they can hardly exploit the runtime coverage information for fuzzing since JVMs are likely to cause non-deterministic coverage at runtime due to their adopted mechanisms, e.g., parallel compilation and on-demand garbage collection [32]. Specifically, *ClassFuzz* only collects coverage information for initializing JVMs and *Classming* even exploits no coverage for fuzzing. Similarly, while scheduling mutators guided by code coverage has been proven effective recently [49, 62], the existing JVM fuzzers are restrained by selecting mutators uniformly under no guidance.

In this paper, we present *SJFuzz* (***S**cheduling for **J**VM **Fuzz**ing*, in our *GitHub* repository [18]), a JVM fuzzing framework which applies seed and mutator scheduling mechanisms to facilitate the exposure of discrepant execution results among different JVMs, i.e., inter-JVM discrepancies, for JVM differential testing. Specifically, *SJFuzz* schedules seed class files under two types of guidance—discrepancy and diversity. On one hand, *SJFuzz* retains the class files that can be executed to directly incur inter-JVM discrepancies or used to generate mutants for being executed to cause inter-JVM discrepancies, as seeds for further mutations. On the other hand, assuming that increasing code coverage can be reflected by diversifying test case (class file) generation, *SJFuzz* applies a coevolutionary algorithm [9] to filter the remaining class files to augment class file diversity for further mutations. Moreover, *SJFuzz* also iteratively schedules mutators to augment the overall distances between seed and mutant class files. In particular, for a given seed class file, *SJFuzz* estimates the diversity expectation of each mutator and selects a mutator to optimize the class file diversity.

To evaluate *SJFuzz*, we conduct a set of experiments upon various popular real-world JVMs, e.g., OpenJDK, OpenJ9, DragonWell, and OracleJDK. In particular, we apply *SJFuzz* and *Classming*, the state-of-the-art mutation-based JVM fuzzer, to generate class files via seed class files selected from popular open-source Java projects, which are then executed in the studied JVMs to expose their discrepancies.

```
 1   protected Enumeration<URL> findResources(...){
 2 +    i0 = 5
 3      ...
 4      r4 = r1.parent
 5      ...
 6 +    i0 = i0 + -1
 7 +    if i0 <= 0 goto line 9
 8 +    lookupswitch(i0) { case 4: goto line 4; default: goto line 13; }
 9      r3 = $r5
10      ...
11      $z0 = r1.ignoreBase  // r1.ignoreBase is always 0
12      if $z0 == 0 goto line 19
13      $r7 = specialinvoke r1.getRootLoader()
14      if $r7 != null goto line 16
15      ...
16      $r8 = specialinvoke r1.getRootLoader()
17      $r9 = virtualinvoke $r8.getResources(r2)
18      ...
19      $r6 = staticinvoke CollectionUtils.append(r3, r14)
20      return $r6
21   }
```

Figure 1: A class file generated under diversification guide.

The results suggest that *SJFuzz* significantly outperforms *Classming* in terms of inter-JVM discrepancy exposure, e.g., exposing 3.6×/5.5× more total/unique discrepancies on average. Moreover, 46 previously unknown bugs were reported to their corresponding developers after analyzing the inter-JVM discrepancies incurred by *SJFuzz* while none can be detected by *Classming*. As of submission time, 20 bugs have already been confirmed by the developers.

In summary, this paper makes the following main contributions:

- **Technique.** We introduce *SJFuzz*, which to the best of our knowledge is the first JVM fuzzing framework that applies seed and mutator scheduling mechanisms to test JVMs.
- **Implementation.** We implement our JVM testing approach as a practical system based on Jimple-level mutation via the Soot analysis framework [58].
- **Evaluation.** We conduct an extensive set of experiments based on four popular JVMs and various real-world benchmark projects. The experimental results demonstrate that *SJFuzz* significantly outperforms the state-of-the-art mutation-based JVM fuzzer. Notably, we reported 46 previously unknown bugs found by *SJFuzz*, out of which 20 have been confirmed and 16 have been fixed by the developers.

2 MOTIVATING EXAMPLE

In this section, we introduce a real-world JVM bug exposed by applying differential testing via mutating program control flows to illustrate the potential issues of state-of-the-art *Classming* and motivate *SJFuzz*. Specifically, Figure 1 shows a simplified Jimple code snippet of a mutated method `findResources()` in `AntClassLoader.class` from project `Ant`, where the Jimple code representation refers to a Soot-based intermediate representation of Java programs for simplifying Java bytecode analysis [59]. Running such class file exposes an execution discrepancy between OpenJDK (1.8.0_232) and OpenJ9 (1.8.0_232). Specifically, in the original seed class file, after `z0` is assigned with the value of member `ignoreBase` of `r1`, i.e., 0 (line 11), line 12 is immediately executed, followed by line 19. However, inserting the `lookupSwitch` instruction changes the control flow to be from line 8 to line 13. Next, method `getResources()` of the root class loader is invoked (line 17). As

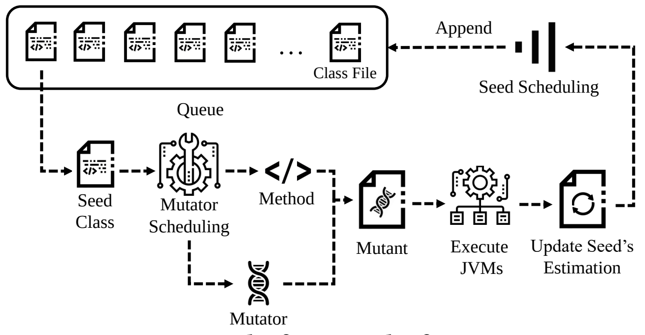


Figure 2: The framework of *SJFuzz*.

a result, by passing parameter `META-INF/MANIFEST.MF` to `getResources()`, OpenJDK8 (1.8.0_232) returns nothing while OpenJ9 (1.8.0_232) returns the paths of the `MANIFEST.MF` files in its lib JARs. We further found such discrepancy was triggered as OpenJDK8 failed to find the existing resources.

Although this discrepancy can be exposed by simply inserting a `lookupSwitch` instruction to the seed class file, *Classming* failed to expose such discrepancy under multiple runs in practice. Specifically, we found that for the example class file, *Classming* updated new seed class files after iteratively generating mutants via uniformly selected mutators, and failed to reproduce the discrepancy-inducing execution path under a fair time limit. Such fact suggests that adopting similar seed class files via only uniformly selected mutators may hinder the effective exploration of discrepancy-inducing mutants. Furthermore, we also observe that while *Classming* typically adopted similar seed class files mutated from one root throughout causing inefficient usage of computing resources, which can be leveraged to explore other promising seed class files, e.g., the ones that can expose multiple discrepancies [5, 6] simultaneously. Such fact also leads to a demand of scheduling multiple seed class files other than only one in one run based on their discrepancy-guided potentials.

These insights motivate the development of our proposed approach *SJFuzz*, which effectively schedules seed class files and diversifies their mutations, and successfully exposes the inter-JVM discrepancy in the example under just one run.

3 THE APPROACH OF *SJFUZZ*

The framework of *SJFuzz* is demonstrated in Figure 2. Overall, *SJFuzz* enables iterative mutation-based class file generation. In particular, given a seed class file, *SJFuzz* adopts the control flow mutation strategy to generate its mutant class file (Section 3.1). Accordingly, for each iteration, *SJFuzz* schedules seed class files (Section 3.2) under the diversity and discrepancy guidance. *SJFuzz* also schedules mutators deterministically or randomly to augment class file diversity (Section 3.3) for further iterations.

Algorithm 1 shows the details of *SJFuzz*, which is initialized by adding one `seedClass` into the `queue` and assigning the `seedClass` to be *optional* (defined in Section 3.2). Under each iterative execution (line 6), *SJFuzz* schedules control-flow mutators for each class file in the `queue` to facilitate the class file diversity (lines 8 to 10). A class file can be identified whether to be *primary* (defined in Section 3.2) after running on the adopted JVMs (lines 13 to 17). For any valid mutant class file, *SJFuzz* updates its distance to its seed class file to

Algorithm 1 The framework of *SJFuzz*

```
Input: seedClass, budget, bound
Output: queue
1:  function FUZZING_FRAMEWORK
2:      iteration ← 0
3:      queue ← list()
4:      queue.add(seedClass)
5:      seedClass.primary ← False
6:      while iteration < budget do
7:          children ← list()
8:          for class in queue do
9:              method ← randomlySelectMethod()
10:             mutantClass ← SCHEDULE_MUTATOR(class, method)
11:             mutantClass.primary ← False
12:             iteration ← iteration + 1
13:             runJVMs(mutantClass)
14:             if mutantClass incurs new DISCREPANCIES then
15:                 class.primary ← True
16:                 if mutantClass is VALID then
17:                     mutantClass.primary ← True
18:             if mutantClass is VALID then
19:                 distance ← Levenshtein(class, mutantClass)
20:                 updateEstimation(class, distance)
21:                 children.add(mutantClass)
22:             else
23:                 updateEstimation(class, -1)
24:         merge(queue, children)
25:         queue ← SCHEDULE_SEEDS(queue, bound)
26:     return queue
```

guiding further mutator scheduling (lines 18 to 23). At last, all the *primary* class files and filtered *optional* class files are retained for future mutations (lines 24 to 25). After each iteration, the updated seed class files are used for JVM differential testing. Such iterations are terminated when hitting the `budget`. Note that *SJFuzz* only enables valid class files for mutations because mutating an invalid class file tends to cause exceptional program behaviors rather than unexplored inter-JVM discrepancies.

3.1 Control Flow Mutation

Prior research work on fuzzing compilers including JVMs tend to mutate program control flows via a set of corresponding mutators for exposing vulnerabilities in their "deep" execution stages [26, 31, 35, 42]. Following such prior work (and also for a fair comparison with them), *SJFuzz* also adopts such control flow mutation with representative mutators. Specifically in source code level, *SJFuzz* randomly selects two original instructions, and creates a directed transition between them. If such transition is a loop, the corresponding iteration will be limited to 5 times. Correspondingly, *SJFuzz* implements the mutators with the Jimple-level instructions `goto`, `lookupswitch`, and `return` provided in *Soot* [58].

SJFuzz iteratively selects random positions from randomly selected methods to apply the control-flow mutators. Specifically, *SJFuzz* establishes an instruction list which contains the instructions executed by the adopted JVMs under their execution order. Next, *SJFuzz* selects and inserts a control flow mutator into a random spot of the instruction list under each iteration.

3.2 Seed Scheduling

Since it is difficult to directly apply coverage guidance for fuzzing JVMs, we adopt two alternative types of guidance for our seed scheduler. In particular, we develop a discrepancy-guided seed scheduler which retains discrepancy-inducing class files for further mutations. We also develop a diversity-guided seed scheduler which filters other class files to augment the overall class file diversity via coevolutionary algorithm [9].

Discrepancy-guided seed scheduling. Intuitively, if running a mutant of a class file can cause inter-JVM discrepancies, such class file is likely to generate more discrepancy-inducing mutants than other class files as it implies a potential connection with program bugs or vulnerabilities [5, 6]. Therefore, such class file and its mutant (if valid, i.e., successfully running in at least one JVM under test without unexpected behaviors such as verifier errors or crashes) are defined as *primary* class files and are retained for future iterative executions. This seed scheduler is essentially similar to many coverage-guided seed schedulers [7, 24, 46, 53, 54], which tend to retain seeds when running them can increase code coverage.

Diversity-guided seed scheduling. When running a mutant of a class file does not instantly cause inter-JVM discrepancies, it does not necessarily suggest that no discrepancy-inducing mutants can be generated in future iterative executions. In other words, leveraging such class file can also possibly advance the inter-JVM discrepancy exposure. In this paper, such class files are characterized as *optional*. Note that differential testing usually enables vast space for generating test cases, which indicates that the total number of class files that cause discrepancies between sophisticated JVMs can be rather limited. We can then infer that the *optional* class files may significantly outnumber the primary class files. Therefore, *SJFuzz* should filter the *optional* class files to ensure fuzzing efficiency.

We consider that increasing code coverage can be essentially reflected as diversifying execution paths on the same JVMs and thus demands diverse test cases (i.e., class files). Therefore, our seed scheduler for *optional* class files is guided by class file diversity, so that the *optional* class files are filtered to augment the class file diversity. In particular, how to measure class file diversity should be resolved in the first place. To accurately reflect the fine-grained differences between class files, an ideal metric is expected to reflect their instruction-by-instruction comparisons. Therefore, we adopt the executed instructions of a given class file, namely *EntryInstruction*, as the representative instructions to efficiently measure the diversity between JVM class files. Note that *EntryInstruction* reflects the instruction-level execution order and retains only the unique executed instructions to reduce the ambiguity of diversity measurement caused by repeated instructions, e.g., in loops. Eventually, we measure the diversity between a pair of class files by deriving differences between their associated *EntryInstructions*.

In this paper, *SJFuzz* applies edit distance, i.e., Levenshtein Distance [45], a metric widely used to derive the "minimum number of single-character edits (insertions, deletions, or substitutions)" between two strings, to measure the difference between *EntryInstructions* because the mutation-based class file generation can analogize the single-character string edits as demonstrated in [28].

Algorithm 2 The Fitness Function for Seed Scheduling

```
Input: queue
Output: queue
1:  function CALCULATE_DIVERSE_FITNESS
2:      classes ← list()
3:      for class in orignalQueue do
4:          if class.primary is False then
5:              classes.add(class)
6:      for target in classes do
7:          distance ← 0
8:          for class in classes do
9:              if class equals target then
10:                 continue
11:             distance ← distance + Levenshtein(class, target)
12:         target.setFitness(distance / length(classes))
13:     return queue
```

To be specific, *SJFuzz* generates class files by mutating the selected seed class files, i.e., inserting the instructions with the adopted control flow mutators. The resulting iterative single-point mutations between the seed and mutant class files can be modeled as inputs for Levenshtein-Distance-based computation when such class files are all modeled as "strings". For instance, assume two *EntryInstructions* of their corresponding class files $C_1 : \{i_1, i_2, i_3, i_4, ..., i_n\}$ and $C_2 : \{i_1, i_3, i_4, ..., i_n\}$. We can observe that C_1 can be transformed from C_2 by only inserting one instruction i_2 between i_1 and i_3. Therefore, their Levenshtein Distance is computed as 1. We also adopt other distance metrics for evaluation, but the detailed results (available on our GitHub page [18]) are not discussed here due to the space limit. In general, we find no significant difference in utilizing different distance metrics according to our results.

Accordingly, *SJFuzz* adopts the coevolutionary algorithm [9] to efficiently evaluate the individual *optional* class files out of their group by constructing its fitness function to reflect their average distances with other *optional* class files. Specifically, the fitness computation details are presented at Algorithm 2. For each *optional* class file, *SJFuzz* calculates its total Levenshtein Distance with other *optional* class files. Subsequently, the average Levenshtein Distance is calculated as the fitness score of the given class file. By sorting all the derived fitness scores, *SJFuzz* retains the top-N corresponding *optional* class files for further mutation-based class file generation, where N is predefined as the bound variable in Algorithm 1.

To illustrate, we incorporate the discrepancy- and diversity-guided seed schedulers to facilitate code coverage and inter-JVM discrepancies when differentially testing JVMs.

3.3 Mutator Scheduling

Since it is challenging to derive the exact diversity of the overall class files on the fly, *SJFuzz* schedules mutators to diversify the seed and mutant class files under each iteration to approximate the overall class file diversity instead. In particular, *SJFuzz* first applies the edit distance, i.e., Levenshtein Distance [45] in this paper, to delineate the diversity between a pair of class files. Accordingly, *SJFuzz* establishes a *deterministic mutator scheduling mechanism* for estimating the mutator that can optimize the seed-mutant distance. Meanwhile, *SJFuzz* also develops a *random mutator scheduling mechanism* to prevent the potential local optimization that can derive local optimal mutators caused by the *deterministic mutator scheduling mechanism*. As a result, *SJFuzz* derives a mutator for a given class/method by combining the two mechanisms.

Deterministic mutator scheduling. Note that any mutator selected from one iteration can incur cumulative impact on the mutations of the subsequent iterations. To capture such cumulative impact from the previous mutations, *SJFuzz* adopts the *Monte Carlo method* [19] to develop the *deterministic mutator scheduling mechanism*, where given a selected method m_p, *SJFuzz* develops a value function, represented as $V(c_i, a_j, m_p)$, to determine the mutation opportunity of class file c_i by applying a mutator a_j as demonstrated in Equation 1. Such value function can reflect the resulting diversity of the overall class files under the mutation, i.e., the cumulative diversity expectation between the seed and mutant class files under all the iterations.

$$V(c_i, a_j, m_p) = \mathbb{E}[\frac{1}{N}\sum_{k=0}^{N} Distance_k] \quad (1)$$

Here *Distance* refers to the Levenshtein Distance between the seed class file c_i and its mutant class file by applying mutator a_j. $Distance_k$ refers to their Levenshtein Distance in the k_{th} iteration which can be dynamically updated since the mutation spot is randomly selected in m_p under each iteration. $\mathbb{E}$ refers to expectation. It can be easily derived that $V(c_i, a_j, m_p)$ for c_i is incrementally updated and inefficient to be directly computed. Therefore, we further enable dynamic updates on $V(c_i, a_j, m_p)$ as presented in Equation 2 to approximate its value, where α is a constant. Note when one class file c_i fails to generate a valid class, its *Distance* is set to -1.

$$V(c_i, a_j, m_p) = V(c_i, a_j, m_p) + \alpha(Distance - V(c_i, a_j, m_p)) \quad (2)$$

As a result, we select a mutator a_j corresponding to the largest $V(c_i, a_j, m_p)$ for c_i. Typically, *SJFuzz* allows computing $V(c_i, a_j, m_p)$ after running the mutant class files on JVMs such that it can be used for mutator selection of the subsequent iteration when needed (as in line 20 of Algorithm 1).

Random mutator scheduling. Only maximizing $V(c_i, a_j, m_p)$ tends to cause local optimization, i.e., $V(c_i, a_j, m_p)$ is likely to converge to one mutator after iteratively selecting it, while the actual optimal mutator cannot be derived until later iterations. To address such issue, *SJFuzz* further leverages a *random mutator scheduling mechanism* to reduce its possibility to select a sub-optimal mutator under early-terminated executions by randomly selecting one mutator for class file generation under the ongoing iteration. As a result, by properly combining such mechanism with the *deterministic mutator scheduling mechanism*, it can potentially extend the *Monte Carlo* process until convergence for enhancing the selection probability of the optimal mutator, i.e., preventing the local optimization.

The overall mutator scheduling mechanism is presented in Algorithm 3. We first set an `explorationRate` and generate a random value for comparison (line 2). Next, if such random value is less than the `explorationRate`, *SJFuzz* chooses the *random mutator scheduling mechanism* that returns a random mutator under the ongoing iteration (lines 3 to 5). Otherwise, *SJFuzz* derives the mutator

Algorithm 3 Mutator Scheduling

```
Input : class, method
Output: mutantClass
1: function SCHEDULE_MUTATOR
2:     rand ← Random()
3:     if rand < explorationRate then
4:         mutator ← selectRandomMutator(class, method)
5:         return mutatedClass ← mutator.mutate(class)
6:     bestMutator ← selectDeterministicMutator(method)
7:     return mutatedClass ← bestMutator.mutate(class)
```

by applying the *deterministic mutator scheduling mechanism* (lines 6 to 7).

4 EVALUATION

We conduct a set of experiments on various popular JVMs. Overall, we aim to compare *SJFuzz* with the state-of-the-art *Classming* in terms of their resulting inter-JVM discrepancies, the class file generation efficiency, and the reported bugs/defects by answering the following research questions:

- **RQ1:** Is *SJFuzz* effective in exposing inter-JVM discrepancies?
- **RQ2:** Are the seed and mutator schedulers effective?
- **RQ3:** Is the diversity guidance effective?

Furthermore, we report and analyze the bugs detected by *SJFuzz* with all the evaluation details presented in our GitHub page [18].

4.1 Benchmark Construction

We adopt multiple widely-used real-world JVMs, i.e., OpenJDK, OpenJ9, DragonWell, and OracleJDK, for running *SJFuzz* to expose their execution discrepancies. Note that their detailed versions are available on our GitHub page [18] since multiple versions of each JVM are used in our evaluation. We also adopt state-of-the-art *Classming* as the baseline for comparison as it outperformed other existing JVM differential testing approaches [31]. Specifically, for a fair comparison with *SJFuzz* which integrates differential testing and test generation, we also run *Classming* on all studied JVMs in parallel.

To launch *SJFuzz*, we adopt 26 class files from 7 well-established open-source projects as the seed class files for mutation-based class file generation. To construct such benchmarks, we first attempt to collect all available class files originally adopted for evaluating *Classming*, for approaching a fair performance comparison. As a result, `Eclipse`, `Jython`, `Fop`, and `Sunflow` are selected due to their availability while others incur stale configurations, JAR incompatibility, mismatched `main` declarations, etc. Moreover, we also adopt `Ant` and `Ivy` (two popular command-line applications from Apache Projects [8]) and `JUnit` [16] (a widely used unit testing framework) to expand our benchmark diversity.

Note that while the existing approaches, e.g., *Classming*, are designed to only launch mutations for the entry methods corresponding to the `main` methods, in this paper, we attempt to adopt diverse “entry” modes, i.e., diverse method types (entries) for mutation. Particularly, we adopt two such modes: *main-entry* and *JUnit-entry*. More specifically, in addition to *main-entry* adopted by [31, 32], the new *JUnit-entry* mode, on the other hand, refers to mutating other entry methods associated with JUnit tests.

JUnit-entry can benefit the class file generation with the following reasons. First, *JUnit-entry* supplements *main-entry* on the mutation space for a class file which cannot be explored by *main-entry* only, since a large amount of JUnit test classes are designed for non-main methods in practice. Next, the execution discrepancies between JVMs are likely to be better presented in *JUnit-entry*, since assertions examine different JVM executions upon class files and thus enable smaller scope in exposing discrepancies and easier analytics than *main-entry*.

In this paper, for *main-entry*, we select seed class files as the class files containing the `main` methods. For *JUnit-entry*, since each project contains various test classes, we randomly adopt 4 class files under test for each project with more than 5 corresponding test methods from the projects `Fop`, `Jython`, `Ant`, `Ivy`, and `JUnit` which all use the JUnit framework with available test source files on the corresponding GitHub repositories. Note that `Fop`, `Jython`, `Ant`, and `Ivy` are chosen as both the *main-entry* and *JUnit-entry* benchmarks for straightforward performance comparison between the two modes within one project.

4.2 Environmental Setups

We perform our evaluation on a desktop machine, with Intel(R) Xeon(R) CPU E5-4610 and 320 GB memory. The operating system is Ubuntu 16.04. The `exploreRate` for Algorithm 3 is set to 0.1 and the bound for Algorithm 1 is set to 20 by default.

We observed that *SJFuzz* has rather stable performance across different configurations where the detailed experimental results can be found on our GitHub page [18] due to space limit. Similar as prior work [23, 24, 32, 53, 54], all benchmarks are executed by all the studied approaches for 24 hours to generate class files to reflect a large enough testing `budget`. Note that we run each experiment five times for obtaining the average results to reduce the impact of randomness.

4.3 Result Analysis

4.3.1 RQ1: The inter-JVM discrepancy exposure effectiveness of SJFuzz. The inter-JVM discrepancy results (both the total and the unique discrepancies) after executing the generated class files are presented in Table 1. For instance, for benchmark `Jython.class`, *SJFuzz* exposed a total of 826.2 discrepancies and 7.4 unique discrepancies averagely. Note that in this paper, to identify unique discrepancies, we first summarize the symptoms of the discrepant JVM behaviors, including assertions in Junit tests, exceptions, and the results printed in standard output. Then we compare such symptoms with the previously recorded unique discrepancies to distinguish whether they are unique or not.

We can observe that overall, *SJFuzz* can significantly outperform *Classming* in terms of the inter-JVM discrepancy exposure. To be specific, *SJFuzz* can expose averagely 1233.9 total discrepancies and 8.5 unique discrepancies, while *Classming* can expose averagely 267.1 total discrepancies and 1.3 unique discrepancies, i.e., over 3.6×/5.5× more total/unique discrepancies. Moreover, we can further find that for all the adopted benchmark projects, *SJFuzz* can significantly outperform *Classming* in terms of both the total and unique discrepancy exposure. Note that *SJFuzz* also exposes

Table 1: Discrepancies exposed by *SJFuzz* and *Classming*.

Project	Benchmark(.class)	*SJFuzz*		*Classming*		p-value
		Total	Unique	Total	Unique	
Eclipse	EclipseStarter	2773.8	10.0	247.2	1.0	0.0033
Fop	Fop	24.2	2.2	1.0	1.0	0.0121
Jython	Jython	826.2	7.4	14.2	1.0	0.0036
Sunflow	Benchmark	1856.8	9.8	341.8	1.0	0.0036
Ant	Launcher	2684.6	11.8	503.2	1.0	0.0036
Ivy	Main	5020.0	19.0	1537.4	3.4	0.0053
Fop (JUnit-entry)	FopConfParser	1602.4	10.2	83.6	1.8	0.0052
	FopFactoryBuilder	1685.2	10.4	367.6	3.2	0.0057
	ResourceResolverFactory	212.8	3.8	23.6	1.0	0.0036
	FontFileReader	787.4	6.4	115.0	1.0	0.0033
Jython (JUnit-entry)	PyByteArray	2234.8	10.2	878.0	2.0	0.0055
	PyFloat	947.0	4.0	255.6	1.0	0.0037
	PySystemState	233.0	4.2	57.6	1.0	0.0033
	PyTuple	1623.4	7.0	304.0	1.8	0.0046
Ant (JUnit-entry)	AntClassLoader	301.0	11.6	6.2	1.0	0.0037
	DirectoryScanner	75.8	9.6	2.8	1.0	0.0036
	Project	54.8	2.8	0.0	0.0	0.0035
	Locator	1786.4	9.2	442.6	1.0	0.0035
Ivy (JUnit-entry)	ResolveReport	210.0	5.6	0.0	0.0	0.0036
	ApacheURLLister	649.0	8.0	205.2	1.0	0.0036
	Configurator	498.8	7.8	61.6	1.0	0.0036
	IvyEventFilter	1262.6	9.8	393.6	2.4	0.0053
JUnit (JUnit-entry)	RuleChain	997.2	14.2	263.8	1.0	0.0036
	TestWatcher	810.2	2.8	224.6	1.0	0.0035
	ErrorReportingRunner	2029.4	11.2	524.2	1.0	0.0036
	Money	894.6	11.6	91.2	1.0	0.0037
Average		1233.9	8.5	267.1	1.3	N/A

all the discrepancies found by *Classming* in our evaluation. Furthermore, we apply the Mann-Whitney U test [50] to illustrate the significance of *SJFuzz*. It can be seen in Table 1 that the p-value of *SJFuzz* comparing with *Classming* in terms of the average unique discrepancies is far below 0.05 in each benchmark, which indicates that *SJFuzz* outperforms *Classming* in each benchmark significantly ($p < 0.05$). Such results can reflect that our adopted discrepancy guidance mechanism, including diversifying and filtering class file generation, can be quite effective.

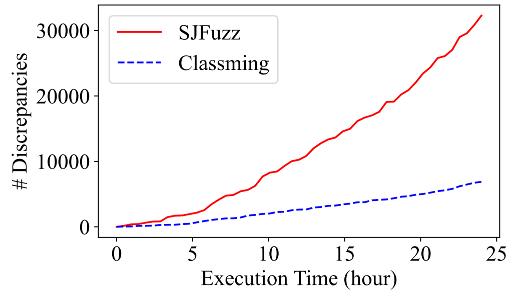
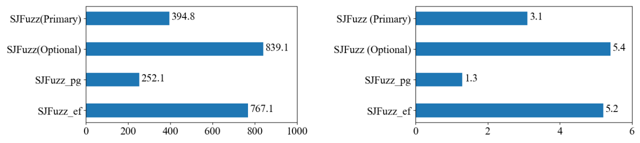


Figure 3: *SJFuzz*/*Classming* efficiency in 24 hours.

We further investigate the impact of the execution time on discrepancy exposure by *SJFuzz* and *Classming*. Figure 3 shows how the total exposed discrepancies on all the benchmarks by the two approaches vary over time. We can observe that although we enhanced the differential testing efficiency by running JVMs in parallel for *Classming* (as in Section 4.1), *SJFuzz* can still significantly outperform *Classming* by exposing 32081.4 vs. 6944.6 discrepancies in total. We can also observe that *SJFuzz* consistently outperforms *Classming* in finding JVM discrepancies all the time before terminating the executions. Such result can further indicate the power of the discrepancy guidance mechanism of *SJFuzz*.



(a) All discrepancies. (b) Unique discrepancies.

Figure 4: Average number of discrepancies found by *SJFuzz*, *SJFuzz*$_{pg}$ and *SJFuzz*$_{ef}$ in all benchmarks.

Finding 1: *SJFuzz is effective by exposing 3.6× more discrepancies than Classming (32081.4 vs. 6944.6) under the same evaluation setups.*

We also investigate the discrepancies exposed by our adopted entry modes for class file mutations: *main-entry* and *JUnit-entry*. Specifically, *SJFuzz* can significantly outperform *Classming* under both the entry modes, i.e., *SJFuzz* can expose 60.2 unique discrepancies in 6 *main-entry* benchmarks and 160.4 unique discrepancies in 20 *JUnit-entry* benchmarks, while *Classming* can only expose 8.4 and 24.2 unique discrepancies under such two entry modes respectively. Additionally, for the projects which enable both *main-entry* and *JUnit-entry* (i.e., `Fop`, `Jython`, `Ant`, and `Ivy`), *SJFuzz* exposes 120.6 unique discrepancies in total under *JUnit-entry* and 40.4 under *main-entry*. Such result indicates the effectiveness of our newly proposed *JUnit-entry* mode for JVM testing. We highly encourage future researchers/practitioners to look into such *JUnit-entry* mode for advancing JVM testing.

Finding 2: *JUnit-entry is more effective than main-entry in exposing inter-JVM discrepancies.*

4.3.2 *RQ2: Effectiveness of the seed and mutator schedulers.*

In this section, we investigate the effectiveness of the seed and mutator schedulers respectively.

Effectiveness of the seed scheduler. To investigate the effectiveness of the adopted seed scheduler of *SJFuzz*, we record the number of discrepancies exposed by the *primary* and *optional* class files of the original *SJFuzz* approach, denoted as *SJFuzz*(primary) and *SJFuzz*(optional), respectively. Furthermore, we also build the two variant techniques of *SJFuzz*: (1) *SJFuzz*$_{pg}$, which only activates discrepancy-guided seed scheduling for *SJFuzz*, and (2) *SJFuzz*$_{ef}$, which equally filters the class files regardless whether they are *primary* or *optional*. Note that *SJFuzz*$_{pg}$ retains the initial class file for further mutations until it explores a *primary* class file given that the initial class file is not *primary*.

In general, we can observe from Figure 4 that *SJFuzz*$_{pg}$ can be effective by exposing 252.1 toal discrepancies and 1.3 unique discrepancies on average. Interestingly, only *SJFuzz*$_{pg}$ itself can enable quite close performance with state-of-the-art *Classming* (267.1 toal discrepancies and 1.3 unique discrepancies on average as in Table 1). Such results can indicate the effectiveness of our "discrepancy-guided" intuition, i.e., exploiting the power of discrepancy-inducing class files can advance JVM differential testing.

We can also observe from Figure 4 that *SJFuzz*$_{ef}$ can be effective by exposing 767.1 total discrepancies and 5.2 unique discrepancies.

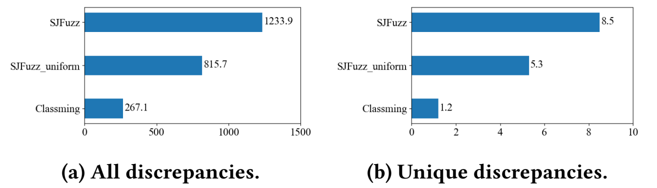


Figure 5: Average number of discrepancies found by *SJFuzz*, *SJFuzz$_{uniform}$* and *Classming* in all benchmarks.

Since *SJFuzz$_{ef}$* essentially refers to equally filtering all the class files to facilitate their seed-mutant distance, i.e., diversity, for further mutation-based class file generation, the fact that *SJFuzz$_{ef}$* outperforms *SJFuzz$_{pg}$* implies that such diversity-guided class file filtering mechanism makes a vital contribution to exposing inter-JVM discrepancies.

Interestingly, Figure 4 demonstrates that by integrating *SJFuzz$_{pg}$* and *SJFuzz$_{ef}$*, i.e., applying the original *SJFuzz*, mutating *primary* class files can incur significantly more inter-JVM discrepancies, i.e., 394.8 vs. 252.1 total discrepancies with 3.1 vs. 1.3 unique discrepancies between *SJFuzz*(primary) and *SJFuzz$_{pg}$*. Such results indicate that injecting *optional* class files for test case generation can advance the *primary* class files to generate more discrepancy-inducing class files. To illustrate, when mutating *optional* class files generate discrepancy-inducing mutant class files, they are all converted to be *primary*. Thus, *primary* class files are increasingly adopted for further mutations such that their chances to expose discrepancies can be augmented. Furthermore, the fact that *SJFuzz*(optional) outperforms *SJFuzz$_{ef}$* suggests that directly retaining *primary* class files for further mutations can also advance the *optional* class files to expose inter-JVM discrepancies. We can infer that by independently mutating *primary* class files via revoking their filtering process, more *optional* class files can be retained for further mutations because the *primary* class files no longer compete against them for being selected. To summarize, *SJFuzz$_{pg}$* and *SJFuzz$_{ef}$* can mutually advance each other to optimize the performance of *SJFuzz*.

Finding 3: *As different components of the seed scheduling mechanism, SJFuzz$_{pg}$ and SJFuzz$_{ef}$ are both effective and integrating them can further advance each other in terms of exposing inter-JVM discrepancies.*

Effectiveness of the mutator scheduler. To investigate the effectiveness of the mutator scheduler of *SJFuzz*, we build a variant technique *SJFuzz$_{uniform}$* of the original *SJFuzz* by selecting mutators uniformly. Overall, we can observe from Figure 5 that *SJFuzz$_{uniform}$* can expose 815.7 total discrepancies and 5.3 unique discrepancies averagely. Although *SJFuzz$_{uniform}$* still outperforms *Classming* 2.1×/3.4× averagely in exposing total/unique discrepancies, the exposed discrepancies decrease significantly after disabling mutator scheduling, i.e., 33.9%/37.6% averagely in exposing total/unique discrepancies compared to *SJFuzz*. Such results indicate that applying the mutator scheduler in *SJFuzz* can make significant contributions in terms of inter-JVM discrepancies.

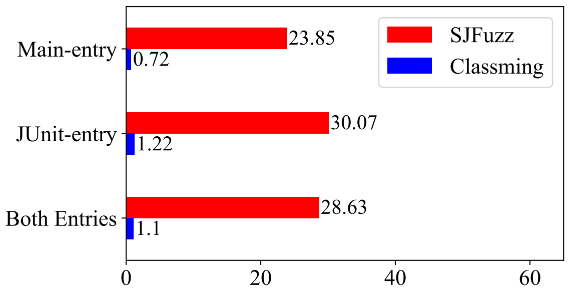


Figure 6: Average seed-mutant levenshtein distance.

Finding 4: *Applying the mutator scheduling mechanism can significantly improve the power of exposing discrepancies for JVM fuzzers.*

4.3.3 *RQ3: Effectiveness of the diversity guidance.*

The previous findings of the effectiveness of different *SJFuzz* components can imply their underlying mechanism of diversifying class file generation can be potentially effective. However, accurately measuring data diversity can be rather challenging. In this paper, we delineate the class file diversity in terms of the average seed-mutant Levenshtein Distance of the collected class files.

The diversity results of the class file generation are presented at Figure 6. We can observe that *SJFuzz* incurs much larger average seed-mutant Levenshtein Distance compared with *Classming*, i.e., overall 25.0× larger and 32.1×/23.6× larger under *main-entry*/*JUnit-entry*. It can be inferred that *Classming* tends to generate similar mutants, which also indicates the effectiveness of *SJFuzz*'s diversity-guided class file generation mechanism.

We further attempt to infer the possible reasons behind the diversity performance difference between *SJFuzz* and *Classming* in terms of the seed-mutant Levenshtein Distance. Assume a mutated class file (simplified version) in Figure 7 with only one executed instruction (line 4). Initially, *Classming* would select and insert the `return` mutator (line 5) because other mutators can result in the potential def-use violation of the `r0`-exclusive variables and thus the verification error. Such error can hinder the detection of "deep" bugs, e.g., bugs incurred in execution engine. However, under such circumstance, the class file in Figure 7 is likely to be retained as the seed to repeatedly select the `return` mutator under each iterative execution for further class file generation. As a result, all the mutant class files realize single-mutation difference with their respective seeds, i.e., leading to potential short seed-mutant Levenshtein Distance. In contrast, *SJFuzz* is free from such constraints because it can diversify seed *optional* class files with best effort. Moreover, even when a seed *optional* class file generates a similar mutant class file, they together are hardly retained for further mutations under the diversity-guided class file filtering mechanism.

Finding 5: *Diversifying class file generation is advanced in testing the "deep" bugs in execution engine by retaining sufficient valid class files.*

```
class A {
    ...
    public void someFunction() {
        r0=<java.lang.System: java.io.PrintStream out>;
        return; // inserted by return mutator
        ......
    }
}
```

Figure 7: An example of mutating paradox for *Classming*.

Table 2: Issues found by *SJFuzz*.

JVMs	# Reported				# Confirmed			
	Loading Phase	Linking Phase	Run-time	Crash	Loading Phase	Linking Phase	Run-time	Crash
OracleJDK	0	0	3	0	0	0	2	0
OpenJDK	2	3	3	3	0	0	2	0
Dragonwell	1	2	2	0	0	0	0	0
OpenJ9	6	7	12	2	0	4	10	2
TOTAL	9	12	20	5	0	4	14	2

4.4 Bug Report and Discussion

We manually analyze all the collected discrepancies to derive potential defects. Note that in this paper, we define a defect as an error or an unexpected behavior for a specific JVM version. As a result, we report 46 potential defects from the discrepancies found by *SJFuzz* (*Classming* fails to expose any of these bugs), as in Table 2, to their corresponding developers. As of today, 20 of them have been confirmed while 16 of them have been fixed by the developers. The remaining 4 confirmed defects are marked as "won't fix" as they do not affect JDK9 or later versions. We present some example bug reports as follows.

4.4.1 Resource retrieval bug. We have reported an OpenJDK bug on retrieving JAR information which has been confirmed by the OpenJDK developers and assigned a bug ID `JDK-8244083`. This bug was exposed by the execution discrepancy between OpenJ9 and OpenJDK. To be specific, they both executed one class file from `AntClassLoader.class`, where OpenJDK failed to retrieve the JAR information from given resources while OpenJ9 succeeded. The developers inferred that certain side effect changed the behaviors of the original method.

4.4.2 Runtime inconsistency bug. We have reported an OpenJ9 bug on issuing a runtime erroneous return under the mutated classes from `Money.class`, as shown in Figure 8. We applied its original JUnit tests on all the class files mutated from `Money.class` which resulted in multiple errors/discrepancies. In particular, OpenJ9 reported an `AssertionError` while OpenJDK passed the test. However, when we further removed one JUnit test which caused `StackOverflowError`, both OpenJ9 and OpenJDK passed the test. Accordingly, we summarized that such discrepancy may be caused by the unresolved dependency between JUnit tests and reported it to the corresponding developers [1].

To tackle such issue, developers applied option `optlevel` at the `warm` level and inferred this as a JIT issue. After checking the `tree simplification` (an optimization feature in OpenJ9), developers found that OpenJ9 made a wrong assumption to the `nodeIsNonZero` flag set. As a result, the instruction `ificmpne` was changed to `goto` by OpenJ9 and it caused the associated branch to be always executed, even when the value of the associated variable did not meet the branch conditions. Eventually, they fixed this issue as follows:

```
class A {
    ...
    public boolean isZero() {
        int var1 = this.amount();
        // OpenJ9 and OpenJDK get var1 = 0 here
        boolean var2;
        if (var1 == 0) {
            var2 = true; // OpenJDK executed here
        } else {
            var2 = false; // OpenJ9 executed here
        }
        return var2;
    }
}
```

Figure 8: Runtime inconsistency bug in OpenJ9.

> *It looks like the `nodeIsNonZero` flag was set because IL gen assumed that slot 0 was still being used to store the receiver and thus the flag did not need to be reset. There is a method that is supposed to check if slot 0 was re-used so that flags can be reset. This problem can be fixed by adding cases to handle other types of stores to slot 0... I will open a pull request to make this change.*

4.4.3 Verifier bug. A verifier bug usually is derived by analyzing the discrepancies about throwing a `verifyError` or not. In particular, verifier bugs are perceived typical "deep" bugs, i.e., bugs that are tricky to be detected and debugged.

By executing the mutated `ErrorReportingRunner.class` from project `JUnit`, we discovered that OpenJDK (1.8.0_232), OpenJDK (9.0.4), and OpenJDK (11.0.5) threw `VerifyError`, while OpenJ9 (1.8.0_232) and OpenJ9 (11.0.5) wrongly took it as a valid class file for execution. Moreover, there even incurred a discrepancy among multiple OpenJ9 versions, i.e., OpenJ9 (9.0.4) threw a `VerifyError`. Accordingly, we inferred that OpenJ9 (1.8.0_232) and OpenJ9 (11.0.5) were buggy and reported them to developers.

Interestingly, it took the developers quite a while to understand the cause of such bugs. At first, they speculated this issue as an "out of sync" problem:

> *It seems the code in verifier is likely out of sync or some new changes related to verifier were only merged for OpenJDK8 & OpenJDK11 given that only OpenJDK9/OpenJ9 captured VerifyError. Need to further analyze to see what changes in verifier caused the issue.*

When they attempted to locate the issue by checking the exception table, they found no exception table for the associated method of the mutated class file. Next, they divided the issue into two different checking branches: one was investigating the `simulateStacks` for how it propagated the `uninitalizedThis` (a variable to mark the status of `simulateStacks`) which may or may not be launched in the `mergeStacks` code; the other was comparing the differences in `rtverify.c` for different JVM releases. Finally, by comparing different versions of `rtverify.c`, the developers have identified that a checking mechanism on `uninitializedThis` was disabled in `matchStack()` when creating the `stackmap`. Accordingly, OpenJ9

```
1 if (!verifyData->createdStackMap) { // enable to fix another issue
2   if (liveStack->uninitializedThis
3   && !targetStack->uninitializedThis) {
4     rc = BCV_FAIL;
5     goto _finished;
6   }
7 }
```

Figure 9: OpenJ9 buggy code in rtverify.c.

```
        ...
66      return0  // return without exitmonitor
        ...
265     monitorenter  // enter the monitor
        ...
709     invokestatic 911 Print.logPrint
712     iload 5
714     iconstm1
715     iadd
716     istore 5
718     iload 5
720     ifle 66  // go to line 66
        ...
```

Figure 10: The IllegalMonitorStateException issue of OpenJ9.

(1.8.0_232) and OpenJ9 (11.0.5) were confirmed to fail to capture the `VerifyError`.

The buggy instructions of `rtverify.c` are demonstrated in Figure 9. OpenJ9 (1.8.0_232)/OpenJ9 (11.0.5) were allowed to correctly throw `VerifyError` when enabling the checking mechanism on `uninitializedThis` by removing line 1 in Figure 9. However, since such checking mechanism was designed to prevent a Spring verifier issue [2], it could not be removed simply. Meanwhile, even though the `VerifyError` could be correctly captured on OpenJ9 (9.0.4), its associated `VerifyError` message was rather out-dated. Such issues together deliver a potential demand on upgrading the verification logic of OpenJ9. At last, the developers have stated that they intend to generate a patch to fix all of the exposed issues [4].

4.4.4 Bug under discussion (unconfirmed yet).

In addition to assisting developers in exploring the "deep" bugs, we even triggered an in-depth discussion and revisit to the validity of well-established JVM mechanisms via a potential defect reported by *SJFuzz*.

We have found an issue that OpenJ9 could break the structured locking. In particular, when executing the corresponding mutated class `DirectoryScanner.class`, OpenJDK threw an `IllegalMonitorStateException` because the executing thread accessed a method and executed `entermonitor`, but simply returned without executing `exitmonitor`. However, OpenJ9 did not throw `IllegalMonitorStateException`. Accordingly, we inferred that OpenJ9 allowed returning a method under mismatching `entermonitor` and `exitmonitor` (which broke structured locking) and have reported it to the OpenJ9 developers [3]. Figure 10 refers to the partial class file that exposed such issue.

At first, the developers denied the potential violation of structured locking, i.e., they analyzed our submitted class file and claimed no violation of structured locking. However, during our further investigation, we discovered that while `exitmonitor` has not been executed from line 265 to line 720 in Figure 10, line 720 was executed followed by a `return` instruction (line 66) where `IllegalMonitorStateException` should have been thrown. Correspondingly, the developers reconsidered this issue and finally agreed on the violation of structured locking.

Since the developers still insisted on the legitimacy of their development schemes, they further questioned and inspected the validity of the structured lock mechanism.

> *We may end up with cleaner locking code if we enforced structured locking. This also came up recently in a discussion on how to handle OSR points for inlined synchronized methods. We should investigate the benefits/costs of adopting Structured Locking.*

By tracing back to the JVM specification [15] on the structured locking mechanism, the developers argued that structured locking could be allowed, yet not required. As a result, they considered revoking structured locking to be more as an domain-specific adaptation, rather than a bug, controversially.

In summary, *SJFuzz* is capable of detecting multiple types of "deep" bugs via exposing inter-JVM discrepancies for testing analytics. Furthermore, the bugs detected by *SJFuzz* can be rather tricky to be explored by the existing approaches, e.g., the bug incurred by unresolved JUnit test dependency and the bug that urged developers to trace back to JVM specifications.

5 THREATS TO VALIDITY

The threats to external validity mainly lie in the subjects and faults used in our benchmark. To reduce the threats, we determine to select all the possible projects from *Classming*. Moreover, we extend our selections of seed class files to complicated and popular Java projects such as *Ant*, for evaluating the scalability of our approach.

The threats to internal validity mainly lie in the potential faults in our implementation (including dependent libraries). To reduce such threat, we apply mature libraries, such as Soot, to implement *SJFuzz*. We also carefully review and test our implemented code and the library code. As a result, we even detected a defect in our adopted Soot version which injected unexpected string into the output class files such that a valid class file was presented as invalid. Correspondingly, we hacked Soot's source code and fixed this issue.

The threats to construct validity mainly lie in the metrics used. To reduce the threats, we leverage various widely used metrics for JVM testing, including the number of discrepancies, as well as the class file diversity and unique bugs found.

6 RELATED WORK

JVM and Compiler Testing. In addition to the aforementioned *ClassFuzz* and *Classming*, Sirer et al. [56] first proposed a grammar-based approach to generate class files by randomly changing a single byte in a seed input which can be hardly applied for deeply testing JVMs. Yoshikawa et al. [65] developed a type system that generates Java class files, which are random, executable, and finite, and then tested them on selected JIT compiler or other Java runtime environments. Freund et al. [39] developed a type system specification for a subset of the bytecode language with type checking and prototype bytecode verifier implementation. Savary et al. [52] derived an abstract model from formal specifications to test the Java byte code verifier. Calvagna et al. [25] proposed an automated conformance testing approach to model JVM as a finite state machine and derive test suites to expose their unexpected behaviors. More recently, Padhye et al. [51] automatically guided QuickCheck-like random input generators to semantically analyze test programs for generating test-oriented Java bytecode.

Yang et al. [64] proposed a random test generation tool for open-source C compilers, which crashed every compiler they tested and found 325 previously unknown bugs in three years. A recent work by Le et al. [41] leveraged equivalence modulo inputs (EMI) to validate different C compilers. Furthermore, they also introduced a guided and advanced mutation strategy based on Bayesian optimization for compiler testing [43]. Chowdhury et al. [33] developed novel techniques for EMI-based mutation of CPS modelsincluding dealing with language features that do not exist in procedural languages. More recently, Cummins et al. [34] developed DeepSmith for accelerating compiler validation via deep learning to model the real-world code structures and generate vast realistic programs to expose compiler bugs. Similarly, Liu et al. [48] automatically generated well-formed C programs to fuzz off-the-shelf C compilers based on generative models.

Compared to the existing JVM and compiler testing approaches either performing worse or requiring extra knowledge in addition to a single seed class file, *SJFuzz* adopts seed and mutator schedulers based on easy-to-catch runtime discrepancy/diversity information, i.e., acquiring no extra knowledge of bytecode constraints or JVM specifications.

Seed Scheduling in Fuzzing. Many coverage-guided fuzzers adopt seed scheduling mechemisms to enhance their effectiveness. AFL [7] typically schedules seeds whenever executing them can increase code coverage. Bohme et al. [24] developed AFLFast to construct a Markov chain model by utilizing coverage feedback, and then scheduled the seeds according to the probability generated from the model for further exploration. They also proposed AFLGo [23] to reach a given program location by scheduling the most related seeds (i.e., the seeds closer to the target location) for mutation. She et al. [55] proposed K-scheduler to schedule the seeds based on all reachable and feasible edges by using the graph analysis of control flow graph. Wang et al. [60] proposed TortoiseFuzz to schedule seeds according to function, loop, and basic block in the target program. Li et al. [47] proposed Cerebro to schedule seeds based on the code complexity, execution time, and coverage information balanced by an online multi-objective-based algorithm. Woo et al. [61] schedules the seeds in fuzzing by modeling the fuzzing process as a multi-armed bandit problem. Chen et al. [29] leveraged the power of different fuzzers by merging seeds generated from them into one corpus and scheduling seeds among various fuzzers. Li et al. [46] proposed Steelix, which utilizes comparison progress information and coverage feedback for scheduling seeds to facilitate the fuzzing efficacy. To bias input generation towards rare branches, Lemieux et al. [44] proposed FairFuzz to schedule the seeds that hit rare branches for mutation. To facilitate the hybrid fuzzing efficiency, Chen et al. [27] proposed MEUZZ to schedule the seeds between a coverage-guided fuzzer and a concolic execution engine via machine learning. Chen et al. [30] proposed SAVIOR, which schedules the seeds that can reach more sanitizer instrumentation (i.e., a potential buggy point) to expose vulnerabilities of the target program. Zhao et al. [67] proposed DigFuzz to schedule seeds based on the difficulty of their corresponding paths and prioritize them for concolic execution via a Monte-Carlo-based probabilistic path prioritization model. Zhang et al. [66] developed TRUZZ, which schedules the seeds based on the coverage feedback in a newly discovered execution path, i.e., a seed increasing more code coverage has a higher priority to be selected. However, Such existing seed scheduling mechanisms can hardly be used for JVM fuzzing because they are widely guided by code coverage. In this paper, *SJFuzz* adopts diversity and discrepancy as alternative guidance to alleviate the impact of lacking code coverage information for seed scheduling.

Mutator Scheduling in Fuzzing. Similar to the above-mentioned seed scheduling mechanisms, many mutator scheduling mechanisms tend to select mutators to increase code coverage during fuzzing. Stephens et al. [57] developed Driller, which selects the symbolic executor to mutate a seed if it fails to increase code coverage under a given time budget. Lyu et al. [49] proposed MOPT, which utilizes Particle Swarm Optimization (PSO) algorithm [36] to find the optimal scheduling probability distribution of mutators via historical code coverage for enhancing fuzzing effectiveness. Fioraldi et al. [38] proposed AFL++ to facilitate fuzzing efficacy by scheduling different mutators from different fuzzers, e.g., mutators from AFL [7] and RedQueen [21]. Wu et al. [62] conducted a study on the havoc fuzzing strategy widely adopted by many coverage-guided fuzzers, and found that applying different mutators leads to different code coverage among various projects. Next, they proposed an improved mutator scheduling mechanism based on a multi-armed bandit algorithm [22] according to the real-time coverage feedback. Xie et al. [63] proposed DeepHunter by scheduling Affine Transformation mutator and Pixel Value Transformation mutator to a given seed via their reference images.

Although failing to exploit code coverage as the existing mutator schedulers, *SJFuzz* still schedules mutators in a lightweight manner by diversifying class file generation via *Monte Carlo method*.

7 CONCLUSION

In this paper, we proposed *SJFuzz*, the first fuzzing framework using seed and mutator scheduling for automated JVM differential testing. Specifically, *SJFuzz* employs a discrepancy-guided seed scheduler which retains discrepancy-inducing class files and class files that generate discrepancy-inducing mutants. It also employs a diversity-guided seed scheduler which filters other class files via a coevolutionary mechanism to augment class file diversity for further mutations. Moreover, *SJFuzz* applies a mutator scheduler based on the *Monte Carlo method* to diversify the class file generation. To evaluate the efficacy of *SJFuzz*, we performed an extensive study to compare *SJFuzz* with *Classming*, the state-of-the-art mutation-based JVM fuzzer, on various real-world benchmarks. The results show that overall, *SJFuzz* significantly outperforms *Classming* in terms of exposing inter-JVM discrepancies for JVM differential testing, e.g., *SJFuzz* exposes 8.5 unique discrepancies while *Classming* only exposes 1.3 unique discrepancies averagely on all the studied benchmarks. To date, we have reported 46 previously unknown bugs discovered by *SJFuzz* to the JVM developers where 20 have been confirmed and 16 have been fixed.

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