DSpot: Test Amplification for Automatic Assessment of Computational Diversity

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ABSTRACT
In this work, we characterize a new form of software diversity: the existence of a set of variants that (i) all share the same API, (ii) all behave the same according to an input-output based specification and (iii) exhibit observable differences when they run outside the specified input space. We quantify computational diversity as the dissimilarity between execution traces on inputs that are outside the specified domain. Our technique relies on test amplification. We propose source code transformations on test cases to explore the input domain and systematically sense the observation domain. We run our experiments on 472 variants of 7 classes from open-source, large and thoroughly tested Java classes. Our test amplification multiplies by ten the number of input points in the test suite and is effective at detecting software diversity.

1. INTRODUCTION
Since a couple of years, many works have investigated the phenomenon of different pieces of software having the same computational effect. They have called this phenomenon in different ways: computational “sameness” [8], computational “equivalence” [10], computational “redundancy” [4] or computational “diversity” [2]. Despite different goals, they all explore the same idea: how similar or different is the computation of two different pieces of code?

All these works rely on white-box techniques to assess the similarity between two different pieces of code. By white-box, we mean that those techniques intrusively observe the program execution through profiling, logging or instrumentation. For example, Jiang and colleagues [9] automatically extract code fragments from function bodies and use random test values to assess the input/output similarity of the fragments. Very recently, Carzaniga and colleagues [4] run randomly generated test cases on redundant code snippets to observe dissimilarities between traces of internal computation events. White-box assessment of computational diversity is useful to detect semantic clones.

The main usage of computational diversity is for fault tolerance using n-version systems [14] [11]. The essence of n-version systems is as follows: given n versions of the same program, say p1 and p2, if one observes a difference in the output for an input x the program p1(x) ≠ p2(x) – then a fault is detected. In this example, white-box computational diversity means that p1 and p2 have differences in their internal computation (e.g., different control flow). However, despite different internal computations, p1(x) may always be equal to p2(x), which is useless from the viewpoint of n-version programming. N-version systems require computational diversity that is observable from the outside, at the boundary of the program under usage. We call such diversity “black-box computational diversity”. Two program variants are computational diverse in a black-box manner if and only if there exists certain inputs values for which the variants expose different observable behaviors. How to detect black-box computational diversity?

In this paper, we propose an approach, called DSpot for assessing the presence of black-box computational diversity. DSpot takes as input a test suite and a set of n program variants. The n variants have the same application programming interface (API) and they all pass the same test suite (i.e. they comply with the same executable specification). DSpot consists of two steps: (i) automatically transforming the test suite; and (ii) running this larger test suite, that we call “amplified test suite” on all variants to reveal visible differences in the computation.

The first step of DSpot is an original technique of test amplification [15] [18] [13] [17]. Our key insight is to combine the automatic exploration of the input domain with the systematic sensing of the observation domain. The former is obtained by transforming the input values and method calls of the original test. The latter is the result of the analysis and transformation of the original assertions of the test suite, in order to observe the program state from as many observation points visible from the public API as possible. The second step of DSpot runs the augmented test suite on each variant. The observation points introduced during amplification generate traces of observable points on the program state (from a black-box perspective). If there exists a difference between the trace of a pair of variants, we say that these variants are computationally diverse. In other words, two variants are considered diverse if there exists at least one input outside the specified domain that triggers different behaviors on the variants which can be observed through the public API.

1DSpot stands for diversity spotter

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To evaluate the ability of DSpot at observing computational diversity, we consider 7 open-source software applications. For each of them, we create 472 program variants, and we manually check that they are computationally diverse, they form our ground truth. We then run DSpot for each program variant. Our experiments show that DSpot detects 100% of the 472 computational diverse program variants. In the literature, the technique that is the most similar to test amplification is by Yoo and Harman [17], called “test data regeneration” (TDR for short), we use it as baseline. We show that test suites amplified with DSpot detect twice more computationally diverse programs than TDR.

To sum up, our contributions are:

• an original set of test cases transformations for the automatic amplification of an object-oriented test suite.
• a validation of the ability of amplified test suite to spot black-box diversity in 472 variants of 7 open-source large scale programs.
• a comparative evaluation against the related work [17]
• original insights about the natural diversity of computation due to randomness and variety of runtime environments.
• a publicly available implementation² and benchmark³

The paper is organized as follows: section 2 expands on the background and motivations for the paper; section 3 describes the core technical contribution of the paper: the automatic amplification of test suites; section 4 presents our empirical findings about the amplification of 7 real-world test suites and the assessment of black-box diversity among 472 program variants.

2. BACKGROUND

We aim at detecting the computational diversity among a set of program variants. In this section, we dwell on our motivation and the concepts behind our approach.

2.1 Our Previous Work

In our previous work presented at ISSTA’14 [2], we introduced a technique to automatically create program variants. We call those program variant “sosies”² they all pass the same test suite while having variations in their source code. This technique takes place in our global research agenda about automated software diversification [3].

In this work, we did preliminary experiments to assess the actual computational diversity of sosies. We logged each method entry and the values of all data at each control point, incl. objects. For object variables, we collected their string representation. That way, we produced one execution trace for each test case execution. Running the same test suite on different variants with this kind of log produced traces inside which we could look for dissimilarities that indicated behavioral differences.

This experiment to assess computational diversity revealed several challenges about this logging technique. The first challenge is scalability: running the complete test suite of Apache commons.math with this kind of log produces traces of 10 gigabytes. The second challenge is about the synchronization of traces. Quantifying computational diversity is about spotting the differences and the overlaps between two traces. It is easy to spot the point at which two traces diverge, i.e. when one trace has a method call and the other does not or when they both call different methods. However, it is very difficult to re-synchronize the traces, i.e. to find the spot in both traces when they become the same again. This is a critical problem to quantify the exact amount of difference (instead of just spotting a divergence). The third and most important challenge: we realized that even if two program variants have different traces, they may not result in any computational diversity that is visible from their interface.

2.2 Why White-Box Computational Diversity is not Enough?

In testing, a technique is said white-box if there is access or manipulation of a program’s source code or execution. Hence, white-box computational diversity is observed on the internals of a software module, through instrumentation and logging (“white” refers to transparency). On the contrary, black-box computational diversity is observed at the level of a program’s public API (the program and its execution remain a black and closed box). White-box diversity is internal (implementation), black-box is external (observable behavior).

The difference between white-box computational diversity and black-box computational diversity is related to the essence of software modularity: black-box computational diversity is observable at the interface of the software module under analysis (i.e. it’s API), while white-box computational diversity requires to break the encapsulation (i.e. opening the box to observe or modify the module’s internals). There is an implication relation between the two concepts: black-box diversity implies white-box diversity (but not the opposite).

Let us consider the example of Listing 1. It shows three implementations of a subtraction. subtract1 and subtract2 can not be shown computationally diverse from its programming interface, while subtract1 and subtract3 expose black-box computational diversity for specific points of the input space.

Listing 1: Three subtraction functions. subtract1 and subtract2 can not be shown computationally diverse from its programming interface, while subtract1 and subtract3 expose black-box computational diversity for specific points of the input space.

```java
1  public int subtract1 (int a, int b) {
2    return a-b;
3  }
4  public int subtract2 (int a, int b) {
5    return -(a+b);
6  }
7  public int subtract3 (int a, int b) throws
8    OverflowException {
9    BigInteger bigA = BigInteger.valueOf(a);
10   BigInteger bigB = BigInteger.valueOf(b);
11   BigInteger result = bigA.subtract(bigB);
12   if (result.lessThan(BigInteger.MIN_VALUE)) {
13     throw new DoNotFitIn32BitException();
14   }
15   // the API requires an 32-bit integer value
16   return result.intValue();
17 }
```

²http://diversify-project.github.io/
³http://diversify-project.eu/data/
⁴sosie is the French word for look-alike
do not unify both implementations). However, from the interface of the function, it is impossible to observe any difference in function’s behavior. On the contrary, `subtract1` and `subtract3` expose some black-box computational diversity. Calling `subtract1(MINVALUE+1, 2)` will yield 2147483645 while `subtract3(MINVALUE+1, 2)` will trigger an exception. This difference, observable from outside the module, is what we call black-box computational diversity.

Why white-box computational diversity is not enough? The archetypal usage of computational diversity is fault tolerance and recovery blocks [14, 1]. N-version systems embed N variants of certain modules, as well as a voting mechanism built at the interface of the variants. By construction, white-box computational diversity is not necessarily visible from the interface, and cannot be considered by the voting mechanism. In other words, for n-version systems to be useful, black-box computational diversity is required.

In our example of Listing 1, having a N-Version architecture on top of `subtract1` and `subtract2` would not detect the potential overflowing bug. On the contrary, running in parallel `subtract1` and `subtract3` would enable to observe a difference when the overflow happens, and hence to detect the bug.

2.3 Input and Observation Spaces

In this work, we consider programs written in mainstream programming languages (such as an object-oriented program written in Java).

The input space `I` of a program `P` is the set of all possible stimuli for `P`. These can be values or method calls. For example, the input space of `subtract1` is the cartesian product of 32-bit encoded integers, but the input space of `BigInteger` consists of all combinations of method calls on `BigInteger` objects.

The observation space `O` is the set of all the observation points that can be triggered from the public interface. They are typically composed of public fields and any value that can be retrieved through a public method.

The link with standard test cases is direct and is illustrated in figure 1. The first part of a test case, incl. creation of objects and method calls, constitutes a point in the program’s input space (black diamonds in the figure). An oracle in the form of an assertion invokes one method and compares the result to an expected value: this constitutes an observation point on the program state that has been reached when running the program with a specific input (observation points of a test suite are black circles in the figure). This view is shared by other authors, e.g. Harman et al. [2]. We say that a test suite specifies a set of relations between points in the input and observation spaces. Points that are not in the test suite, form the unspecified domain.

All non-trivial programs contain unspecified parts, which relate to specific inputs and error cases (such as the overflow in our example) and irrelevant observation points in `O`. In the subtraction example, if one assumes that the specified input space is \([-2^{16}, 2^{16}]\) all three implementations are functionally equivalent.

By construction, black-box computational diversity happens on the unspecified points in the input space or on unexplored observation points in `O`.

3. OUR APPROACH TO DETECT COMPUTATIONAL DIVERSITY

We present DSpot, our approach to detect computational diversity. This approach is based on test suite amplification through automated source code transformations on test case code.

3.1 Overview

The global flow for DSpot is illustrated in figure 2. It takes as inputs a set of variants of a program `P`, which all pass the same test suite `TS`. Let us consider two of them `P1` and `P2`. First, DSpot amplifies the test suite to explore the unspecified input and observation spaces (as defined in Section 2.3). As illustrated in figure 1 amplification generates new inputs and observations in the neighbourhood of the original points (new points are orange diamonds and green circles). This cartesian product of the amplified set of input and the complete set of observable points forms the amplified test suite `ATS`.

Figure 2 shows an additional step “observation point selection”: this step removes the naturally random observations. Indeed, as discussed in more details further in the paper, some observations points produce diverse outputs between different runs of the same test case on the same program. This natural randomness comes from randomness in the computation and from specificities of the execution environment (addresses, file system, etc).

Once DSpot has generated an amplified test suite, it runs it on a pair of program variants to compare their visible behavior, as captured by the observation points. If some points reveal different values on each variant, they are considered as computationally diverse.
3.2 Test Suite Transformations

Our approach for amplifying test suites systematically explores the neighbourhood of the input and observation points of the original test suite.

3.2.1 Exploring the Input Space

Literals and statement manipulation: The first step of amplification consists in transforming all test cases in the test suite with the following test case transformations. Those transformations operate on literals and statements:

Transforming literals: given a test case tc, we run the following transformations for every literal value: a String value is transformed in three ways: remove, add a random character, and replace a random character by another one; a numerical value i is transformed in four ways: $i + 1$, $i - 1$, $i \times 2$, $i ÷ 2$; a boolean value is replaced by the opposite value.

Transforming statement: given a test case tc, for every statement s in tc we generate two test cases: one test case in which we remove s and another one in which we duplicate s.

Given the transformations described above, the transformation process has the following characteristics: (i) each time we transform a variable in the original test suite, we generate a new test case (i.e., we do not ‘stack’ the transformations on a single test case); (ii) the amplification process is exhaustive: given s the number of String values, n the number of numerical values, b the number of booleans and st the number of statements in an original test suite $TS$, DSpot produces an amplified test suite ATS of size: $|ATS| = s \times 3 + n \times 4 + b + st \times 2$.

These transformations, especially the one on statements, can produce test cases that cannot be executed (e.g., removing a call to add before a remove on a list). In our experiments, this accounted for approximately 10% of the amplified test cases.

Assertion removal: The second step of amplification consists of removing all assertions from the test cases. The rationale is that the original assertions are here to verify the correctness, which is not the goal of the generated test cases. Their goal is to assess computational differences. Indeed, assertions that were specified for test case ts in the original test suite are most probably meaningless for a test case that is variant of ts. When removing assertions, we are cautious to keep method calls that can be passed as a parameter of an assert method. We analyze the code of the whole test suite to find all assertions using the following heuristic: an assertion is a call to a method which name contains either assert or fail and which is provided by the JUnit framework. If one parameter of the assertion is a method call, we extract it, then we remove the assertion. In the final amplified test suite, we keep the original test case, but also remove its assertion.

Listing 2 illustrates the generation of two new test cases. The first test method testEntrySetRemoveChangesMap() is the original one, slightly simplified for sake of presentation. The second one testEntrySetRemoveChangesMap_Add duplicates the statement entrySet.remove and does not contain the assertion anymore. The third test method testEntrySetRemoveChangesMap_DataMutator replaces the numerical value 0 by 1.

```java
public void testEntrySetRemove() { // #1
....
for (int i = 0; i < sampleKeys.length; i++) {
    entrySet.remove(new DefaultMapEntry<K, V>(
        sampleKeys[i], sampleValues[i]));
    assertFalse(
        "Entry should have been removed from the underlying map.");
    getMap().containsKey(sampleKeys[i]);
} // end for
....
}

public void testEntrySetRemove_Add() { // #2
....
// call duplication
entrySet.remove(new DefaultMapEntry<K, V>(
    sampleKeys[i], sampleValues[i]));
entrySet.remove(new DefaultMapEntry<K, V>(
    sampleKeys[i], sampleValues[i]));
getMap().containsKey(sampleKeys[i]);
....
}

public void testEntrySetRemove_Data() { // #3
....
// integer increment
// int i = 0 -> int i = 1
for (int i = 1; i < (sampleKeys.length) ; i++) {
    entrySet.remove(new DefaultMapEntry<K, V>(
        sampleKeys[i], sampleValues[i]));
    getMap().containsKey(sampleKeys[i]);
} // end for
....
}
```

Listing 2: A test case testEntrySetRemoveChangesMap (#1) that is amplified twice (#2 and #3)

3.2.2 Adding Observation Points

Our goal is to observe different observable behaviors between a program and variants of this program. Consequently, we need observation points on the program state. We do this by enhancing all the test cases in ATS with observation points, that are responsible for collecting pieces of information about the program state during or after the execution of the test case. In this context, an observation point is a call to a public method, which result is logged in an execution trace.

For each object o in the original test case (o can be part of an assertion or a local variable of the test case), we do the following:

- we look for all getter methods in the class of o (i.e., methods which name starts with get, that takes no parameter and whose return type is not void, and methods which name starts with is and return a boolean value) and call each of them. We also collect the values of all public fields.
- if the toString method is redefined for the class of o, we call it (we ignore the hashcode that can be returned by toString)
- if the original assertion included a method call on o, we include this method call as an observation point.

Filtering observation points: This introspective process provides a large number of observation points. Yet, we have noted in our pilot experiments that some of the values that we monitor change from one execution to another. For instance, the identifier of the current thread changes between two executions. In Java, Thread.currentThread().getId()
is an observation point that always needs to be discarded for instance.

If we keep those naturally varying observation points, DSpot would say that two variants are different while the observed difference would be due to randomness. This would be spurious results that are irrelevant for computational diversity assessment. Consequently, we discard certain observation points as follows. We instrument the amplified tests ATS with all observation points. Then, we run ATS 30 times on \( P_1 \) and \( P_2 \), the number of observation points which have a different values on each variant accounts for visible computational diversity. When we compare a set of variants, we use the mean number of differences over each pair of variants.

### 3.3 Detecting and Measuring the Visible Computational Diversity

The final step of DSpot, runs the amplified test suite on pairs of program variants. Given \( P_1 \) and \( P_2 \), the number of observation points which have a different values on each variant accounts for visible computational diversity. When we compare a set of variants, we use the mean number of differences over each pair of variants.

### 3.4 Implementation

Our prototype implementation amplifies Java source code.\(^{3}\) The test suites are expected to be written using the JUnit testing framework, which is the \#1 testing framework for Java. It uses Spoon\(^{12} \) to manipulate the source code in order to create the amplified test cases. DSpot is able to amplify a test suite within minutes.

The main challenges for the implementation of DSpot were as follows: handle the many different situations that occur in real-world large test suites (use different versions of JUnit, modularize the code of the test suite itself, implement new types of assertions, etc.); handle large traces for comparison of computation (as we will see in the next section, we collect hundreds of thousands observations on each variant); spot the natural randomness in test case execution to prevent false positives in the assessment of computational diversity.

### 4. EVALUATION

To evaluate whether DSpot is capable of detecting computational diversity, we set up a novel empirical protocol and apply it on 7 large-scale Java programs. Our guiding research question is: **Is DSpot capable of identifying realistic large scale programs that are computationally diverse?**

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3\(^{7}\) the prototype is available here: [http://diversity-project.github.io/test-suite-amplification.html](http://diversity-project.github.io/test-suite-amplification.html)

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### 4.1 Protocol

First, we take large open-source Java programs that are equipped with good test suites. Second, we manually forge variants of those programs using a technique from our previous work\(^{2}\). With manual analysis, we ensure that they all indeed expose some black-box computational diversity.

Third, we amplify the original test suites using our approach and also using a baseline technique by Yoo and Harman\(^{17}\) presented in\(^{13}\). Finally, we run both amplified test suites and measure the proportion of variants that are detected as computationally different. We also collect additional metrics to further qualify the effectiveness of DSpot.

### 4.2 Dataset

We build a dataset of subject programs for performing our experiments. The inclusion criteria are the following: 1) the subject program must be real-world software; 2) the subject program must be written in Java; 3) the subject program’s test suite must use the JUnit testing framework; 4) the subject program must have a good test suite (a statement coverage higher than 80% with standard conditional negation mutation).

This results in Apache Commons Math, Apache Commons Collections, Apache Commons Codec and Google Gson and Guava. The dominance of Apache projects is due to the fact that they are among the very rare organizations with a very strong development discipline.

In addition, we aim at running the whole experiments in less than one day (24 hours). Consequently we take a single class for each of those projects as well as all the test cases that exercise it at least once.

Table 1 provides the descriptive statistics of our dataset. It gives the subject program identifier, its purpose, the class we consider, the number of tests that execute at least once one method of the class under consideration, the statement coverage and the total number of program variants we consider (excluding the original program). We see that this benchmark covers different domains, such as data encoding and collections, and is only composed of well-tested classes. In total, there are between 12 and 145 computationally diverse variants of each program to be detected. This variation comes from the relative difficulty of manually forging computationally diverse variants depending on the project.

### 4.3 Baseline

In the area of test suite amplification, the work by Yoo and Harman\(^{17}\) is the most closely related to our approach. Their technique is designed for augmenting coverage but can be directly applied to detecting computational diversity. Their algorithm, called test data regeneration – TDR for short – is based on four transformations on numerical values in test cases: data shifting (\(\lambda x + 1\) and \(\lambda x - 1\))
Table 2: The performance of DSpot on amplifying 7 Java test suites.

| Test Suite       | Static #TC | Static #TC amplified in TS | Static #assert in TS | Static #obs. | Static #disc. in obs. | Dynamic #TC | Dynamic #TC amplified in TS | Dynamic #assert in TS | Dynamic #obs. | Dynamic #disc. in obs. |
|------------------|------------|----------------------------|----------------------|--------------|----------------------|-------------|----------------------------|----------------------|--------------|----------------------|
| commons-codec    | 72         | 672 (x9)                   | 509                  | 10597 (x20)  | 12                   | 72          | 672                        | 3528                 | 16920        | 10597                |
| commons-collections | 111       | 1291 (x12)                 | 433                  | 14772 (x34)  | 0                    | 768         | 9202                       | 7035                 | 973096       | 14772               |
| commons-io       | 221        | 2518 (x11)                 | 1330                 | 20408 (x15)  | 54313                | 262         | 2661                        | 1346                 | 209911       | 20408               |
| commons-lang     | 233        | 988 (x4)                   | 2206                 | 12854 (x6)   | 18                   | 233         | 12854                      | 2266                 | 57856        | 12854               |
| guava            | 35         | 625 (x18)                  | 84                   | 6834 (x81)   | 0                    | 14110       | 624565                     | 20190                | 9464         | 6834                |
| gson             | 684        | 4992 (x7)                  | 1125                 | 26869 (x24)  | 144                  | 671         | 4772                        | 1127                 | 167150       | 26869               |
| JGit             | 138        | 2152 (x16)                 | 176                  | 90828 (x516) | 13377                | 138         | 2089                        | 185                  | 92856        | 90828               |

4.4 Research Questions

We first examine the results of our test amplification procedure

RQ1a: what is the amount of generated test cases? We want to know whether our transformation operators on test cases enable us to create many different new test cases, i.e. new points in the input space. Since DSpot systematically explores all neighbors according to the transformation operators, we measure the number of generated test cases to answer this basic research question.

RQ1b: what is the amount of additional observation points? In addition to creating new input points, DSpot creates new observation points. We want to know the order of magnitude of the number of those new observation points. To have a clear explanation, we start by performing only observation point amplification (without input point amplification) and count the total number of observations. We compare this number with the initial number of assertions, which exactly corresponds to the original observation points.

Then, we evaluate the ability of the amplified test suite to assess computational diversity.

RQ2a: does DSpot identify more computationally diverse programs than TDR? Now, we want to compare our technique with the related work. We count the number of variants that are identified as computationally different using DSpot and TDR. The one with with the highest value is better.

RQ2b: does the efficiency of DSpot come from the new inputs or the new observations? DSpot stacks two techniques: the amplification of the input space and the amplification of the observation space. To study their impact in isolation, we count the number of computationally diverse program variants that are detected by the original input points equipped with new observation points and by the amplified set of input points with the original observations.

The last research questions digs deeper in the analysis of amplified test cases and computationally diverse variants.

RQ3a: What is the amount of natural randomness in computation? Recall that DSpot removes some observation points that naturally varies even on the same program. This phenomenon is due to the natural randomness of computation. To answer this question quantitatively, we count the number of discarded observation points, to answer it quantitatively, we discuss one case study.

RQ3b: what is the richness of computational diversity? Now, we really understand the reasons behind the computational diversity we observe. We take a random sample of three pairs of computationally diverse program variants and analyze them. We discuss our findings.

4.5 Empirical Results

We now discuss the empirical results obtained on applying DSpot on our dataset.

4.5.1 # of Generated Test Cases

Table 2 presents the key statistics of the amplification process. Each line is a subject program. The columns are grouped in two. The first group gives a static view on the test suites (e.g. how many test methods are declared). The second group draws a dynamic picture of the test suites under study (e.g. how many assertions are executed).

Indeed, in real large-scale programs, test cases are modular. Some test cases are used multiple times because they are called by other test cases. For instance, a test can specify all contracts of a collection and thus be called when testing all implementations of collections (ArrayList, LinkedList, etc.). We call them generic tests.

Let’s first concentrate on the static values. The first four numerical columns give the number of original test cases, the number of original assertions, the number of generated test cases by amplification, the number of generated observation points obtained after amplification. The fifth column gives the number of the discarded observation points because of natural variations (discussed in more details in section 4.5.2).

For instance, the test suite considered for commons.codec contains 72 test cases. DSpot produces an amplified test suite that contains 672 test methods: 9x more than the original test suite. The original test suite observes the state of the program with 509 assertions, while DSpot employs 10597 observations points to detect computational differences.

In Table 2, one can see that our amplification process is massive. We create between 4x and 12x more test cases than the original test suites. Each new test case represents a new rich input point defined by a set of method calls together with the literals used as parameters and the variables of the test case (cf. figure 2). Consequently, our test case transformations yield a rich exploration of the input space.
Let us now consider the dynamic part of the table at the right hand side. The four columns respectively give the number of original tests executed (#TC exec.), the number of synthesized tests executed (#ATC exec.), the number of assertions executed, and the number of observation points executed. As we can see, the number of generated tests (#ATC exec.) is impacted by amplification. For instance, for commons.collection there are 1291 tests in the amplified test suite, but altogether, 9202 test cases are executed. The reason is that we synthesize new test cases that use other generic test methods. Consequently, this increases the number of executed generic test methods, which is included in our count.

### 4.5.2 # of Generated Observation Points

Now we focus on the observation points. The fourth column of Table 2 gives the number of assertions in original test suite. This corresponds to the number of locations where the tester specifies expected values about the state of the program execution. The fifth column, gives the number of observation points in the amplified test suite. We do not call them assertions since they do not contain an expected value, i.e., there is no oracle. Recall that we use those observation points to compare the behavior of two program variants in order to assess the computational diversity.

As we can see, we observe the program state on many more observation points than the original assertions. As discussed in Section 2.2, those observations points use the API of the program under consideration, hence allow to reveal visible and exploitable computational diversity. However, this number also encompasses the observation points on the new generated test cases.

If we look at the dynamic perspective (second part of Table 2), one observes the same phenomenon as for test cases and assertions, there are many more points actually observed during test execution than statically declared ones. The reasons are identical, many observations points are served during test execution than statically declared ones.

We run DSpot and TDR to see whether those two techniques are able to detect the computationally diverse programs. Table 3 gives the results of this evaluation. The first column contains the name of the subject program. The second column gives the number of variants detected by DSpot. The third column gives the number of variants detected by TDR. The last three columns explore more in depth whether computational diversity is revealed by new input points or new observation points or both, we will come back to them later.

As we can see, DSpot is capable of detecting all computationally diverse variants of our benchmark. On the contrary, the baseline technique, TDR, is always worse. Either it detects only a fraction of them (e.g., 10/12 for commons.codec) or even not at all. The reason is that TDR, as originally proposed by Yoo and Harman, focuses on simple programs with shallow input spaces (one single method with integer arguments). On the contrary, DSpot is designed to handle rich input spaces, incl. constructor calls, method invocations and strings. This has a direct impact on the effectiveness of detecting computational diversity in program variants.

Our technique is based on two insights: the amplification of the input space and the amplification of the observation space. We now want to understand the impact of each of them. To do so, we disable one or the other kind of amplification and measure the number of detected variants. The result of this experiment is given in the last two columns of Table 3. Column “input space effect” gives the number of variants that are detected only by the exploration of the input space (i.e. by observing the program state only with the observation method used in the original assertions). Column “observation space effect” gives the number of variants that are detected only by the exploration of the observation space (i.e. by observing the result of method calls on the objects involved in the test). For instance, for commons.codec, all variants (12/12) are detected by exploring the input space, and 10/12 are detected by exploring the observation space.

This means that 10 of them are detected are detected either by one exploration or the other one. On the contrary for guava, only the exploration of the observation space enables DSpot to detect the three computationally diverse variants of our benchmark.

By comparing columns “input space effect” and “observation space effect” one sees that our two explorations are not mutually exclusive and are complementary. Some variants are detected by both kinds of exploration (as in the case of commons.codec). For some subjects, only the exploration of the input space is effective (e.g. commons-lang), while for others (guava), this is the opposite. Globally, the exploration of the input space is more efficient, most variants are involved in the test). For instance, for commons-codec, all variants (12/12) are detected by exploring the input space, and 10/12 are detected by exploring the observation space.

Let us now consider the last column of Table 3. It gives
void testCanonicalEmptyCollectionExists() {
    if (((supportsEmptyCollections()) && (
        isTestSerialization()) && ((
            skipSerializedCanonicalTests()))) ) {
        Object object = makeObject();
        Logger.logAssertArgument(f.getAbsolutePath());
    // observation on f
    File f = new java.io.File(name);
    // observation on f
    Logger.logAssertArgument(f.getCanonicalPath());
    Logger.logAssertArgument(f.getAbsolutePath());
    }
}

Listing 3: An amplified test case with observation points that naturally vary, hence are discarded by DSpot

the mean number of observation points for which we observe a difference between the original program and the variant to be detected. For instance, among the 12 variants for commons.codec, there is on average 21.9 observation points for which there is a difference. Those numbers are high, showing that the observation points are not independent. Many of the methods we call to observe the program state inspect a different facet of the same state. For instance, in a list, the methods isEmpty() and size are semantically correlated.

4.5.4 Natural Randomness of Computation

When implementing DSpot, we discovered that some observation points naturally vary even when running the same test case several times on the same program. For instance, a hashcode that takes into account a random salt can be different between two runs of the same test case. We call this effect, the “natural randomness” of test case execution.

We discovered two kinds of natural variations in the execution of test suites. First, some observation points vary over time when the test case is executed several times on the same environment (same machine, OS, etc.). This is the case for the hashcode example. Second, some observation points vary depending on the execution environment. For instance, if one adds an observation point on a file name, the path name convention is different on Unix and Windows systems. If method getAbsolutePath is an observation point, it may return “/tmp/foo.txt” on Unix and “C:\tmp\foo.txt” on Windows. While this first example is pure randomness, the second only refers to variations in the runtime environment.

Interestingly, this natural randomness is not problematic in the case of the original test suites, because it remains below the level of observation of the oracles (the test suite assertions in JUnit test suites). However, in our case, if one keeps an observation point that is impacted by some natural randomness, this would produce a false positive for computational diversity detection. Hence, as explained in Section 4.5, one phase of DSpot consists in detecting the natural randomness first and discarding the impacting observation points.

Our experimental protocol enables us to quantify the number of discarded observation points. The 6th column of Table 2 gives this number. For instance, for commons-codec, DSpot detects 12 observation points that naturally vary. This column shows two interesting facts. First, there is a large variation in the number of discarded observation points, it goes up to 54313 for commons-io. This case, together with JGIT (the last line), is due to the heavy dependency of the library on the underlying file system (commons-io is about IO – hence file systems – operations, JGIT is about manipulating GIT versioning repositories that are also stored on the local file system).

Second, there are two subject programs (commons-collections and guava) for which we discard no points at all. In those programs, DSpot does not detect a single point that naturally varies by running 100 times the test suite on three different OSES. The reasons is that the API of those subject programs does not allow to inspect the internals of the program state up to the naturally varying parts (e.g. the memory addresses). We consider this good as this, it shows that the encapsulation is good: more than providing an intuitive API, more than providing a protection against future changes, it also completely encapsulates the natural randomness of the computation.

Let us now consider a case study. Listing 5 shows an example of an amplified test with observation points for Apache Commons Collection. There are 12 observation methods that can be called on the object f instance of File (11 getter methods and toString). The figure shows two getter methods that return different values from one run to another (there are 5 getter methods with that kind of behavior for a File object). We ignore these observation points when comparing the original program with the variants.

4.5.5 Nature of Computational Diversity

Now we want to understand more in depth the nature of the black-box computational diversity we are observing. Let us discuss three case studies.

Listing 6 shows two variants of the writeStringToFile() method of Apache Commons IO. The original program calls openOutputStream, which checks different things about the file name, while the variant directly calls the constructor of FileOutputStream. These two variants behave differently outside the specified domain: in case writeStringToFile() is called with an invalid file name, the original program handles it, while the variant throws a FileNotFoundException. Our test transformation operator on String values produces such a file name, as shown in the test case of listing 6: a “.” is changed into a star “/”. This made the file name an invalid one. Running this test on the variant results in a FileNotFoundException.
Listing 5: Amplified test case that reveals computational diversity between variants of listing 4

Listing 6: Two variants of toJson in GSON

Listing 7: Two variants of decode in commons.codec

Listing 8: Amplified test case that reveals the computational diversity between variants of listing 6

4.6 Threats to Validity

DSpot is able to effectively detect black-box computational diversity using test suite amplification. Our experimental results are subject to the following threats.

First, this experiment is highly computational, a bug in our evaluation code may invalidate our findings. However, since we have manually checked a sample of cases (the case studies of Section 4.5.4 and Section 4.5.5) we have a high confidence in our results. Our implementation is publicly available.

Second, we have forged the computationally diverse program variants. Eventually, as shown on Table 3, our technique DSpot is able to detect them all. The reason is that we had a bias towards our technique when forging those variants. This is true for all self-made evaluations. This threat on the results of the comparative evaluation against TDR is mitigated by the analytical comparison of the two approaches. Both the input space and the output space of TDR (respectively an integer tuple and a returned value) are simpler and less powerful than our amplification technique.

Third, our experiments consider one programming language (Java) and 7 different application domains. To further assess the external validity of our results, new experiments are required on different applications and more application domains.

5. RELATED WORK
The work presented is related to two main areas: the identification of similarities or diversity in source code and the automatic augmentation of test suites.

**Computational diversity** The recent work by Carzaniga et al. [4] has a similar intent as ours: automatically identifying dissimilarities in the execution of code fragments that are functionally similar. They use random test cases generated by Evosuite to get execution traces and log the internals of the execution (executed code and the read/write operations on data). The main difference with our work is that they assess white-box computational diversity and they do it with random testing instead of test amplification in our case.

Koopman and DeVale [14] aim at quantifying the diversity among a set of implementations of the POSIX operating system, with respect to their responses to exceptional conditions. Diversity quantification in this context is used to detect which versions of POSIX provide the most different failure profiles and should thus be assembled to ensure fault tolerance. Their approach relies on Ballista to generate millions of input data and the outputs are analyzed to quantify the difference. This is an example of black-box diversity assessment with intensive fuzz testing and observation points on crashing states.

Many other works look for semantically equivalent code fragments through static or dynamic analysis. Gabel and Su [5] investigate the level of granularity at which diversity emerges in source code. Their main finding is that, for sequences up to 40 tokens, there is a lot of redundancy. Beyond this (of course fuzzy) threshold, the diversity and uniqueness of source code appears. Higo and Kusumoto [8] investigate the interplay between structural similarity, vocabulary similarity and method name similarity, to assess functional similarity between methods in Java programs. They show that many contextual factors influence the ability of these similarity measures to spot functional similarity (e.g., the number of methods that share the same name, or the fact that two methods with similar structure are in the same class or not). Jiang and Su [9] extract code fragments of a given length and randomly generate input data for these snippets. Then, they identify the snippets that produce the same output values (which are considered functionally equivalent, w.r.t the set of random test inputs). They show that this method identifies redundancies that static clone detection does not find. Kawaguchi and colleagues [10] focus on the introduction of changes that break the interface behavior. They also use a notion of partial equivalence, where “two versions of a program need only be semantically equivalent under a subset of all inputs”.

**Test suite amplification** In the area of test suite amplification, the work by Yoo and Harman [17] is the most closely related to our approach, and we used as the baseline for computational diversity assessment. They amplify test suites only with transformations on integer values, while we also transform boolean and String literals, as well as statements test cases. Yoo and Harman also have two additional parameters for test case transformation: the interaction level that determines the number of simultaneous transformation on the same test case, and the search radius that bounds their search process when trying to improve the effectiveness of augmented test suites. Their original intent is to increase the input space coverage to improve test effectiveness. They do not handle the oracle problem in that work.

Xie [15] augments test suites for Java program with new test cases that are automatically generated and he automatically generate assertions for these new test cases, which can check for regression errors. He seeds faults in subject programs to demonstrate the improved fault-detection capability of the augmented test suite, vs. the original test suite Harder et al. [6] propose to retrieve operational abstractions, i.e., invariant properties that hold for a set of test cases. These abstractions are then used to compute operational differences, which detects diversity among a set of test cases (and not among a set of implementations as in our case). While the authors mention that operational differencing can be used to augment a test suite, the generation of new test cases is out of this work’s scope. Zhang and Elbaum [18] focus on test cases that verify error handling code.

Instead of directly amplifying the test cases as we propose, they transform the program under test: they instrument the target program by mocking the external resource that can throw exceptions, which allow them to amplify the space of exceptional behaviors exposed to the test cases. Pezze et al. [13] use the information provided in unit test cases about object creation and initialization to build composite test cases that focus on interactions between classes. Their main result is that the new test cases find faults that could not be revealed by the unit test cases that provided the basic material for the synthesis of composite test cases. Xu et al. [16] refer to “test suite augmentation” as the following process: in case a program P evolves into P’, identify the parts of P’ that need new test cases and generate these tests. They combine concolic and search-based test generation to automate this process. This hybrid approach is more effective than each technique separately, but with increased costs.

6. **CONCLUSION**

In this paper, we have presented DSpot, a novel technique for detecting black-box computational diversity between a pair of programs. This technique is based on test suite amplification: the automatic transformation of the original test suite. DSpot uses two kinds of transformations, for respectively exploring new points in the program’s input space and exploring new observation points on the execution state. after execution with the given input points.

Our evaluation on large open-source projects shows that test suites amplified by DSpot are capable of assessing computational diversity and that our amplification strategy is better than the closest related work, a technique called TDR by Yoo and Harman [17]. We have also presented a deep qualitative analysis of our empirical findings. Behind the performance of DSpot, our results shed an original light on the specified and unspecified parts of real-world test suites and the natural randomness of computation.

This opens avenues for future work. There is a relation between the natural randomness of computation and the so-called flaky tests (those tests that occasionally fail). To use, the assertions of the flaky tests are at the border of the natural undeterministic parts of the execution: sometimes they hit it, sometimes they don’t. With such a view, we imagine an approach that characterizes this limit and proposes an automatic refactoring of the flaky tests so that they get farther from the limit of the natural randomness and enter again into the good, old and reassuring world of determinism.
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