Demystifying the Combination of Dynamic Slicing and Spectrum-based Fault Localization

Sofia Reis¹, Rui Abreu¹ and Marcelo d’Amorim²
¹IST, University of Lisbon & INESC-ID, Portugal
²Federal University of Pernambuco, Brazil
sofia.o.reis@tecnico.ulisboa.pt, rui@computer.org; damorim@cin.ufpe.br

Abstract
Several approaches have been proposed to reduce debugging costs through automated software fault diagnosis. Dynamic Slicing (DS) and Spectrum-based Fault Localization (SFL) are popular fault diagnosis techniques and normally seen as complementary. This paper reports on a comprehensive study to reassess the effects of combining DS with SFL. With this combination, components that are often involved in failing but seldom in passing test runs could be located and their suspiciousness reduced. Results show that the DS-SFL combination, coined as Tandem-FL, improves the diagnostic accuracy up to 73.7% (13.4% on average). Furthermore, results indicate that the risk of missing faulty statements, which is a DS’s key limitation, is not high — DS misses faulty statements in 9% of the 260 cases. To sum up, we found that the DS-SFL combination was practical and effective and encourage new SFL techniques to be evaluated against that optimization.

1 Introduction
Software debugging is important and challenging. The task of locating the faulty code (i.e., fault localization) is particularly challenging. As such, countless automated techniques have been proposed in the past to reduce the cost of fault localization [Wong et al., 2016]. Model-based software diagnosis (MBSD) [Reiter, 1987; de Kleer and Kurien, 2003] and Spectrum-Based Fault Localization (SFL) [Harrold et al., 2000] are two popular techniques that leverage different principles to automate fault isolation [Abreu et al., 2008]. At a high-level, MBSD techniques [Wotawa et al., 2002; Mayer and Stumptner, 2008; Mayer et al., 2008; Perez and Abreu, 2018; Ko and Myers, 2008] attempt to eliminate non-suspicious components whereas SFL techniques attempt to rank suspicious components with the goal of reducing fault diagnosis cost.

Dynamic Slicing (DS) [Agrawal and Horgan, 1990] is an instance of MBSD that has attracted huge attention in research over the last decades [Silva, 2012]. The technique traces back the statements in the code that influence a given point of interest, such as the evaluation of a failing assertion. Similarly to DS, SFL [Harrold et al., 2000] received tremendous attention in research over the years [Wong et al., 2016]. It computes suspiciousness values associated with program components (e.g., statements) based on coverage information gathered during the execution of test cases. More precisely, SFL uses coverage information of passing and failing test cases to identify likely faulty statements and produces on output a list of program components ranked in decreasing order of suspiciousness.

Intuitively, DS identifies irrelevant parts of the code (i.e., parts that do not contribute to the fault) whereas SFL ranks the relevant parts of the code. It is conceivable, therefore, to combine these two techniques based on the intuition that highly ranked statements (as per SFL), albeit covered by failing executions, could be in fact unrelated to the fault (as per DS). In fact, prior work reported promising preliminary results on this combination [Wotawa, 2010; Alves et al., 2011; Hofer and Wotawa, 2012; Lei et al., 2012; Guo et al., 2018]. Unfortunately, they used a small set of subjects in their evaluation or over optimistic methods to evaluate fault localization improvement [Wu et al., 2014; Lucia et al., 2014b; Wen et al., 2016].

Given the importance of fault localization, this paper revisits the problem of assessing the effectiveness of combining DS and SFL, addressing the key issues of prior work. We conducted a comprehensive study involving 260 faults from 5 different programs from the Defects4J benchmark [Just et al., 2014], which is frequently used to evaluate fault localization research. Results show that DS misses faulty statements in 9% of the 260 faults analyzed. Furthermore, we found that the combination of the two approaches improves fault localization up to 73.7% (13.4% on average). To sum up, results indicate that the risk of applying the technique is relatively low for the positive impact it may bring; and, the tool implementing the technique works out-of-the-box, i.e., it puts no requirements on the running environment, subject programs it can be used, and requires no special setup.

The contributions of this work are:

1) An empirical study, using real-world applications and bugs, on the combination of DS-SFL for bug localization of Java faulty programs.

2) A tool¹, dubbed Tandem-FL, implementing the DS-SFL combination.

¹Tool and dataset available at/through https://github.com/damorim/lithium-slicer (Accessed June 22, 2019)
2 Dynamic Slicing (DS)

Model-based diagnosis is a well-known approach that has been proposed by the DX community, a sub-field of AI that develops algorithms and techniques to determine the root-cause of observed failures. [Reiter, 1987; de Kleer and Kurien, 2003]. Applications of model-based diagnosis to localize software faults have demonstrated that it can be framed as dynamic slicing [Mayer and Stumptner, 2008; Mayer et al., 2008].

Dynamic slicing [Agrawal and Horgan, 1990] is an instance of model-based software diagnosis that has been shown useful in automated software debugging where the region of interest is restricted to what can be reached from failing tests. Several dynamic slicing techniques exist. This paper uses Critical Slicing (CS) [DeMillo et al., 1996] for its simplicity generality. Critical Slicing prescribes a black-box language-semantics-agnostic recipe to computing executable slices. Critical Slicing simplifies the original program such that the resulting program preserves critical observations, such as assertion violations. More precisely, the simplification mechanism consists of deleting statements on the original program and checking if the output of the original and modified program are the same.

Our implementation of Critical Slicing is based on the Mozilla Lithium tool\textsuperscript{2}. It takes as input a file and produces as output a simplified version of that file that satisfies a user-defined oracle. In our case, the oracle is defined such that the test produces the same failure manifestation as the one observed with the test execution on the original program. The Lithium minimization process starts by determining the initial size—in number of lines—of chunks to delete from the input file. For that, it chooses the highest power of two number smaller than the file size. For example, if the file has 1,000 lines, Lithium sets the initial chunk size to 512 lines. Then, the tool starts a local search looking for chunks to exclude from the file. If the chunk satisfies the oracle it is removed. When no more chunks of that given size can be removed, Lithium divides the chunk size by two and repeats the search. This iterative process continues until no more lines can be removed. If \( n \) is the size of the input file and \( m \) is the size of the 1-minimal file found by Lithium, then Lithium usually performs \( O(m \cdot \log(n)) \) iterations.

**Claim 1** The faulty statement may not be included in the critical slice of failing test cases.

If test oracles are too general, it is possible, conceptually, that the critical slicing algorithm produces slices without the faulty code. Suppose that a test fails with a Null-Pointer Exception (NPE) and the criterion used to slice the code in that case (i.e., the oracle) is the presence of NPE in the output, regardless of the position that raises that exception. It is therefore possible that the slice obtained at some iteration of the aforementioned algorithm raises NPE, but it does so in a different part of the code. If that happens, the critical slicing algorithm would consider that as an acceptable simplification—as it satisfied the criterion—and would continue. As the algorithm does not backtrack, it would be impossible, to obtain a slice containing the faulty component from that point on.

It is worth noting that this is not a problem that afflicts only CS; all purely dynamic slicing techniques manifest this problem [Lin et al., 2018]. To mitigate the issue in CS, it is necessary to make oracles more specific. For that, our approach was to use as the slicing criterion the stack trace associated with the test failure. That decision increases the chances that the sliced program will follow a path to the error similar to that followed by the original program. In addition, there are faults whose outputs may slightly differ from one execution to another. For example, exceptions including memory address identifiers, which change on each execution. For these cases, it was developed a mechanism to compare the rest of the output ignoring the identifier of the memory address.

3 Spectrum-based Fault Localization (SFL)

Spectrum-based fault localization is a statistical fault localization technique that takes as input a test suite including at least one failing test and reports on output a ranked list of components likely to be in fault [Wong et al., 2016; Jones and Harrold, 2005; Lucia et al., 2014a; Abreu et al., 2009]. The following are given in SFL: a finite set \( C = \{c_1, c_2, ..., c_M \} \) of system components\textsuperscript{3}; a finite set \( T = \{t_1, t_2, ..., t_N \} \) of N system transactions, which correspond to records of a system execution, such as test cases; the error vector \( e = \{e_1, e_2, ..., e_N \} \), where \( e_i = 1 \) if transaction \( t_i \) has failed and \( e_i = 0 \) otherwise; and an \( N \times M \) coverage matrix \( A \), where \( A_{ij} \) denotes the coverage of component \( c_j \) in transaction \( t_i \). The pair \((A,e)\) is commonly referred to as spectrum [Harrold et al., 2000]. Figure 1 shows an example spectrum.

Several types of spectra exist. The most commonly used is called hit-spectrum, where the coverage matrix is encoded in terms of binary \( \text{hit} \) (1) and \( \text{not hit} \) (0) flags, i.e., \( A_{ij} = 1 \) if \( t_i \) covers \( c_j \) and \( A_{ij} = 0 \) otherwise. SFL takes as input the pair \((A,e)\) and produces on output a list of components ranked by their faulty suspiciousness. To that end, the first step of the technique consists of determining what columns of the matrix \( A \) resemble the error vector \( e \) the most. For that, an intermediate component frequency aggregator \( n_{pq}(j) \) is computed \( n_{pq}(j) = |\{i | A_{ij} = p \land e_i = q \}| \). \( n_{pq}(j) \) denotes the number of runs in which the component \( j \) has been active during execution \((p = 1)\) or not \((p = 0)\), and in which the runs failed \((q = 1)\) or passed \((q = 0)\). For instance, \( n_{12}(j) \) counts the number of times component \( j \) has been involved \((p = 1)\) in failing executions \((q = 1)\), whereas \( n_{10}(j) \) counts the number of times component \( j \) has been involved in passing executions. We then calculate similarity to the error vector by means of applying fault predictors to each component to produce a score quantifying how likely it is to be faulty. Components are then ranked according to such likelihood scores and reported.

\textsuperscript{2}Lithium details available at https://github.com/MozillaSecurity/lithium (Accessed June 22, 2019)

\textsuperscript{3}A component can be any code artifact of arbitrary granularity such as a class, a method, or a statement [Harrold et al., 2000]
to the user. Ochiai is one of those fault predictors that has shown to perform well [Wong et al., 2016; Pearson et al., 2017]. The Ochiai formula is given by the following equation: \( ochiai = \sqrt{n_{11}(j)} / \sqrt{(n_{11}(j) + n_{01}(j)) \times (n_{11}(j) + n_{10}(j))} \).

4 The Tandem-FL Approach

This section describes Tandem-FL, a technique where DS and SFL work in tandem to solve the fault localization problem. To illustrate the idea behind Tandem-FL, consider a debugging scenario with five components \( c_{1..5} \) and five transactions \( t_{1..5} \), two of which are failing. Consider, additionally, that the component \( c_2 \) is faulty. Figure 2 shows, at the left-hand side of the arrow (\( \Rightarrow \)), an hypothetical spectra and its corresponding ranking, produced with the Ochiai predictor. Each line in the ranking shows, respectively, the rank/position, the component label, and the Ochiai score (in parentheses).

We illustrate the workflow of the Tandem-FL approach for this scenario in the following. Let us analyze components at the granularity of statements. First, Tandem-FL picks the first two statements at the top of the ranking, \( c_4 \) and \( c_3 \), for further analysis. (The cutoff point is user-defined.) Second, the technique picks a failing test to slice the code, say \( t_2 \). A slice is a set of statements. Let us assume that the slice obtained for the transaction \( t_2 \) is \( \{c_2, c_5\} \), i.e., it excludes statements \( c_4 \) and \( c_3 \) that were previously covered by the test. Finally, the spectra and ranking are updated. The right-side of Figure 2 shows the modified spectra and ranking after slicing the code against \( t_2 \). It is worth noting that the technique slices the code for every failing tests. Intuitively, slicing enables the identification of statements in the spectra whose values can be set to zero, i.e., the components marked with 0 are irrelevant to determine the test output.

Let us now observe the effect of this spectra modification on the ranking. Analyzing the Ochiai formula, one observes that, for the components \( j \), which are not part of the slice of a failing test, the combination reduces the value of \( n_{11}(j) \) and increases the value of \( n_{01}(j) \). Therefore, suspiciousness of those components decrease. Similar argument applies to other fault predictors. In the running example from Figure 2, the components \( c_3 \) and \( c_4 \), which are not in the slice of \( t_2 \), have their suspiciousness reduced, enabling the faulty component \( c_2 \) to rise from the third to the first position in the ranking.

Let us now observe the effect of this spectra modification on the ranking. Analyzing the Ochiai formula, one observes that, for the components \( j \), which are not part of the slice of a failing test, the combination reduces the value of \( n_{11}(j) \) and increases the value of \( n_{01}(j) \). Therefore, suspiciousness of those components decrease. Similar argument applies to other fault predictors. In the running example from Figure 2, the components \( c_3 \) and \( c_4 \), which are not in the slice of \( t_2 \), have their suspiciousness reduced, enabling the faulty component \( c_2 \) to rise from the third to the first position in the ranking.

Briefly, the workflow of Tandem-FL consists of four steps:

1. Compute spectra \( S \) and ranking \( R \) for the input test suite;
2. Select top \( k \) most suspicious classes, according to \( R \);
3. Compute slicer for every suspicious file, obtained in Step 2, and every failing test;
4. Assemble all the resulting slicers of each failing test;
5. Adjust spectra \( S \), from step 1, with the slices of each failing test, from step 4, and then recompute the ranking.

Claim 2 The rank of faulty statements cannot decrease if the slice includes the faulty statements.

The proof is based on the outlined argument that irrelevant components \( j \) have their ranks reduced as \( n_{11}(j) \) decreases and \( n_{01}(j) \) increases. If those irrelevant components appear at positions above the faulty component, it is possible that

\[
\begin{array}{c|cccccc|c}
T & c_1 & c_2 & c_3 & c_4 & c_5 & e \\
\hline
1 & 1 & 0 & 1 & 1 & 0 & \checkmark \\
2 & 0 & 1 & 1 & 1 & 1 & \times \\
3 & 1 & 0 & 1 & 0 & 0 & \times \\
4 & 0 & 1 & 0 & 0 & 1 & \checkmark \\
5 & 1 & 0 & 0 & 1 & 1 & \checkmark \\
\end{array}
\]

(a) Spectra update.

\[
\begin{array}{c|cccc}|c|c|c|c|}
& 1 & c_4 (0.59) & 1 & c_2 (0.35) \\
2 & c_3 (0.55) & 2.5 & c_1 (0.32) \\
3 & c_2 (0.35) & 2.5 & c_5 (0.32) \\
4.5 & c_1 (0.32) & 4 & c_3 (0.29) \\
4.5 & c_5 (0.32) & 5 & c_4 (0.00) \\
\end{array}
\]

(b) Ranking update.

Figure 2: Modifications on spectra and ranking as result of slicing code against test \( t_2 \). Double arrow (\( \Rightarrow \)) indicates before and after.

the faulty component becomes more suspicious relative to \( j \), i.e., the ranking of the faulty component increases. If those components appear at positions below the faulty components, the ranking of the faulty components is unaffected.

5 Evaluation

We studied the following research questions:

**RQ1. How effective is DS in eliminating code?**

**RQ2. How often does DS miss faulty statements?**

**RQ3. How effective is Tandem-FL for bug localization?**

The first question evaluates the ability of dynamic slicing to reduce the size of application code. Improvements on fault localization depend on that ability. The second question addresses the problem that affects all dynamic slicing techniques [Lin et al., 2018]—that of missing faulty statements (see Claim 1). Developers would not be able to successfully debug code for the cases that issue is manifested. The third research question evaluates the impact of the combination, as substantiated by Tandem-FL, to fault localization.

5.1 Objects of Analysis

We used subject programs from the Defects4J benchmark [Just et al., 2014] in our evaluation. Table 1 shows size, number of tests, and number of faults, for each considered program. Two faults from Apache commons-lang were not considered because we were unable to reproduce them in our environment. Apache commons-lang is a library providing utility functions for the java.lang API. Apache commons-lang is a library of self-contained mathematics and statistics components. JFreechart is a Java library for creating charts. Joda-Time is a library for manipulating date and time. Mockito is a mocking testing framework.

As to quantify complexity of fault localization on this benchmark, we measured the frequency of “faults of omission” (FOO), which is a fault whose fix is materialized only with the addition of new code [Pearson et al., 2017]. Intuitively, the ability of techniques to produce accurate diagnostic reports in those cases might be poorer as existing statements are not problematic. We found that this dataset has a total of 59.7% of FOOs, making it challenging for techniques to perform well.
A fundamental issue of purely dynamic slicing techniques will be analyzed. These files are selected from the SFL ranking (see Section 2). We control the scope of analysis through the variable $k$, denoting the number of most-suspicious files that will be analyzed. These files are selected from the SFL ranking as follows. First, we build a ranking of files by determining, for each ranked statement, the file that declares it. Then, we select the top-$k$ distinct files from such file ranking.

The techniques we evaluate in this study are Tandem-FL$^k$ and SFL$^k$, which is the comparison baseline. Tandem-FL$^k$ is as defined in Section 4 (see Step 2 of the workflow) whereas SFL$^k$ is as SFL, but it produces a ranking only including the statements from the top-$k$ ranked files. In this study, we used 5 and 10 as the values of $k$, following the same choice as in previous fault localization studies [Ang et al., 2017].

### 5.2 Techniques

One important independent variable for this study is the scope of analysis for the techniques. Analyzing long rankings would be unacceptably expensive not only for humans [Parnin and Orso, 2011] but also for machines. For example, Critical Slicing needs to re-compile the affected file at every iteration, i.e., after deleting statements and before checking the oracle (see Section 2). We control the scope of analysis through the variable $k$, denoting the number of most-suspicious files that will be analyzed. These files are selected from the SFL ranking as follows. First, we build a ranking of files by determining, for each ranked statement, the file that declares it. Then, we select the top-$k$ distinct files from such file ranking.

The techniques we evaluate in this study are Tandem-FL$^k$ and SFL$^k$, which is the comparison baseline. Tandem-FL$^k$ is as defined in Section 4 (see Step 2 of the workflow) whereas SFL$^k$ is as SFL, but it produces a ranking only including the statements from the top-$k$ ranked files. In this study, we used 5 and 10 as the values of $k$, following the same choice as in previous fault localization studies [Ang et al., 2017].

### 5.3 Results and Discussion

This section discusses and answers the research questions.

**RQ1: How effective is DS in eliminating code?**

A necessary but insufficient condition for improvement of fault localization with Tandem-FL is that dynamic slicing eliminates a high amount of code from the best ranked files. Table 2 shows, as percentages, the size reduction of the top files obtained with dynamic slicing for different values of $k$. Overall, results indicate that dynamic slicing substantially reduces the size of highly-ranked files.

**RQ2: How often does DS miss faulty statements?**

A fundamental issue of purely dynamic slicing techniques is the risk of discarding faulty statements (see Section 2). This research question evaluates the practical impact of this conceptual issue. Table 3 shows the number of cases dynamic slicing captures at least one of the faulty statements among the sliced files for different values of $k$. These numbers indicate that in 87.3% of the cases, on average, dynamic slicing finds at least one faulty statement in the top 5 of the highest-ranked faulty classes. This number is slightly improved to 91.2% if we consider the top 10 of the highest-ranked faulty classes.

To analyze the impact of dynamic slicing in context, we also compared Tandem-FL$^k$ and SFL$^k$ considering the number of cases where the fault is captured by the technique within a certain bound $k$. Note that the reason SFL$^k$ misses the fault is different compared to Tandem-FL$^k$. SFL$^k$ captures the fault if it is included within the top $k$ files; it misses the fault otherwise. Table 4 shows results, indicating that Tandem-FL$^k$, typically, captures more faults compared to SFL$^k$. In only two cases, highlighted in gray color, SFL$^k$ outperformed Tandem-FL$^k$. These results show that the majority of faulty statements are found on the 5 highest ranked faulty classes and that Tandem-FL$^{10}$ is the technique that performs better, missing only 23 out of the 260 (~8.8%) faults.

**RQ3: How effective is Tandem-FL for bug localization?**

In RQ3, we evaluate the impact of combining DS with SFL to improve fault localization. The first experiment we ran consists of measuring the difference of diagnosis cost between the two fault localization techniques. This metric has been previously used in other studies [Wong et al., 2016; Ang et al., 2017; Pearson et al., 2017; Perez and Abreu, 2018]. More specifically, we computed $\Delta C = C(\text{SFL}^k) - C(\text{Tandem-FL}^k)$, where $C$ denotes the diagnosis cost and is obtained by computing the mean position in the ranking of all buggy statements. $\Delta C < 0$ means that Tandem-FL$^k$ performs worse compared to its baseline. That could happen if dynamic slicing misses the faulty statement. $\Delta C = 0$ means that the faulty statement remained in the same position. $\Delta C > 0$ means that Tandem-FL$^k$ outperformed the baseline, i.e., the mean position of the faulty statements is smaller in Tandem-FL$^k$ compared to that of the baseline. It is worth noting that we assume perfect bug
understanding [Parnin and Orso, 2011], i.e., if the developer sees the bug in the ranking, he is able to precisely determine if it is the faulty one. Figure 3 summarizes the performance of Tandem-FL\(^k\) relative to SFL\(^k\). The figure shows a histogram over \(\Delta C\) for different values of \(k\). Note that (1) the number of cases where the baseline outperforms Tandem-FL\(^k\) is small (e.g., 33 of the 260 faults for \(k = 10\)) and that (2) the number of cases Tandem-FL\(^k\) outperforms the baseline is significant (e.g., 117 of the 260 faults for \(k = 10\)). One of the following reasons justifies the baseline outperforming Tandem-FL\(^k\): (1) a fault of omission or (2) the test has design limitations which DS is not capable of handling (mentioned in Section 2).

Figure 4 shows the distributions of \(\Delta C\) considering all cases where Tandem-FL\(^k\) outperformed the baseline.

In the following, we present statistical analysis of the techniques. Table 5 reports descriptive statistics about the distributions of \(C\) for the techniques under different values of \(k\). In bold, we present the results for the 227 faults corresponding to the cases where \(\Delta(C) \geq 0\). The number in parentheses are relative to the dataset including all faults. We observe the following when considering the faults which can benefit from Tandem-FL (numbers in bold). For \(k = 5\), Tandem-FL achieves a mean improvement of 41.1 (9.57% on average) statements on the ranking and an impressive maximum ranking improvement of 3171 (96.7% on average) statements. For \(k = 10\), Tandem-FL\(^k\) achieves a mean improvement of 19 (13.35% on average) statements on the ranking and a maximum ranking improvement of 209 (73.7% on average) statements. Such difference is justified by the fact that entire files are discarded in Tandem-FL\(^k\), whose statements are included in the ranking of Tandem-FL\(^k\). Consequently, the improvements obtained by the technique will not be as high if slicing on these additional files is unable to aggressively and safely discard statements. This also shows that slicing files, in addition to slicing statements from those files, is very beneficial for fault localization performance.

Table 5 presents the statistics to determine if the observed results are statistically significant. Shapiro-Wilk tests the null hypothesis that results are drawn from a normal distribution. The test is performed for all techniques and values of \(k\). With 99% confidence, the results tell us that the distributions are not normal. Given that \(C\) is not normally distributed, we used Friedman, a non-parametric statistical test of hypothesis. The null hypothesis is that the rankings obtained with all techniques and variants are the same. With 99% confidence, the results show that the distributions are distinct. To understand which techniques perform differently, i.e., to answer the question Does Tandem-FL\(^k\) perform differently than SFL\(^k\), we performed a Siegel post-hoc analysis. Figure 5 reports results. Each square shows the statistical significance of the difference in diagnostic accuracy amongst the different techniques—the lighter color means no statistical significance and smaller values of \(p\) indicates higher significance. Based on these results, it is possible to determine with 95% confidence that the performance of each pair of techniques is different (except for Tandem-FL\(^5\) versus Tandem-FL\(^10\), where there is no significance).

As the results are statistically significant, it is possible to state that Tandem-FL\(^k\) has a positive effect on the localization of some types of bugs. There is indeed a problem on using slicing on fault of omission bugs that needs further research. Although, this dataset has more than 50% of fault of omissions, our simple slicing approach was capable of improving the ranking of 95 faults for \(k = 5\) and 115 faults for \(k = 10\). These may be promising results from what Automated Pro-

<table>
<thead>
<tr>
<th>(k = 5)</th>
<th>(k = 10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(SFL)</td>
<td>(Tandem-FL)</td>
</tr>
<tr>
<td>Mean</td>
<td>779.3 (584.3)</td>
</tr>
<tr>
<td>Median</td>
<td>187.7 (49.4)</td>
</tr>
<tr>
<td>Variance</td>
<td>1218.3 (1223.1)</td>
</tr>
<tr>
<td>Shapiro-Wilk</td>
<td>(W = 0.67)</td>
</tr>
<tr>
<td></td>
<td>(p = 9.64 \times 10^{-15})</td>
</tr>
<tr>
<td>Friedman</td>
<td>(\chi^2 = 175.18)</td>
</tr>
<tr>
<td></td>
<td>(p\text{-value} = 9.71 \times 10^{-38})</td>
</tr>
</tbody>
</table>
A potential threat to 

5.4 Threats to Validity
A potential threat to external validity relates to the set of programs used in our study. When choosing the projects for our study, our aim was to opt for projects that resemble a general and large-sized application. To reduce selection bias and facilitate the comparison of our results, we decided to choose a benchmark that is popular in the community [Just et al., 2014]. Our study did not evaluate the faults from the Closure compiler benchmark that is popular in the community [Just et al., 2014].

7 Conclusions and Future Work
Several approaches have been proposed in the literature to reduce software debugging costs through automated fault diagnosis with the goal of improving productivity in software development. In this domain, Dynamic Slicing (DS) and Spectrum-based Fault Localization (SFL) are very popular techniques and normally seen as complementary.

This paper reports the outcome of a comprehensive study using real-world applications with the goal of demystifying the impact of combining DS with SFL. The results of our empirical study show that, in practice, DS misses faulty statements infrequently 9% (23 misses in 260 cases) and that the DS-SFL combination, coined as Tandem-FL, improves the diagnostic accuracy up to 73.7% (15.4% on average).

Despite tacit opinions of the research community about the usefulness of DS in automated debugging, we found the DS-SFL combination practical (as per the relatively low number of misses) and effective (as per the improvements of ∆(C) on the relevant cases), and encourage new SFL techniques to be evaluated against that optimization. Future work includes 1) improving our oracle heuristics to handle more exceptions, 2) conducting experiments in more Defects4j faults and other datasets, and 3) handling cases of faults of omission.

Acknowledgments
This material is based upon work supported by Fundação para a Ciência e a Tecnologia (FCT), with the reference PTDC/CCI-COM/29300/2017, and by national funds also through FCT with reference UID/CEC/50021/2019. This research was partially funded by INES 2.0, FACEPE grants PRONEX APQ 0388-1.03/14 and APQ-0399-1.03/17, and CNPq grant 465614/2014-0.


