Automatically Repairing Programs Using Both Tests and Bug Reports

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Abstract*—The success of automated program repair (APR) depends significantly on its ability to localize the defects it is repairing. For fault localization (FL), APR tools typically use either spectrum-based (SBFL) techniques that use test executions or information-retrieval-based (IRFL) techniques that use bug reports. These two approaches often complement each other, patching different defects. No existing repair tool uses both SBFL and IRFL. We develop RAFL (Rank-Aggregation-Based Fault Localization), a novel FL approach that combines multiple FL techniques. We also develop Blues, a new IRFL technique that uses bug reports, and an unsupervised approach to localize defects. On a dataset of 818 real-world defects, SBIR (combined SBFL and Blues) consistently localizes more bugs and ranks buggy statements higher than the two underlying techniques. For example, SBIR correctly identifies a buggy statement as the most suspicious for 18.1% of the defects, while SBFL does so for 10.9% and Blues for 3.1%. We extend SimFix, a state-of-the-art APR tool, to use SBIR, SBFL, and Blues. SimFix using SBIR patches 112 out of the 818 defects; 110 when using SBFL, and 55 when using Blues. The 112 patched defects include 55 defects patched exclusively using SBFL, 7 patched exclusively using IRFL, 47 patched using both SBFL and IRFL and 3 new defects. SimFix using Blues significantly outperforms iFixR, the state-of-the-art IRFL-based APR tool. Overall, SimFix using our FL techniques patches ten defects no prior tools could patch. By evaluating on a benchmark of 818 defects, 442 previously unused in APR evaluations, we find that prior evaluations on the overused Defects4J benchmark have led to overly generous findings. Our paper is the first to (1) use combined FL for APR, (2) apply a more rigorous methodology for measuring patch correctness, and (3) evaluate on the new, substantially larger version of Defects4J.

I. Introduction

Automated program repair tools aim to reduce the cost of manually fixing bugs by automatically producing patches [1]. Repair tools have been successful enough to be used in industry [2], [3]. These tools typically follow a three step process: identifying the location of bug, producing candidate patches, and validating those patches. The method used for each of these steps can significantly affect the tool's success. To improve the three steps of the repair process, researchers have proposed to use different kinds of fault localization strategies [4]–[9], patch generation algorithms (e.g., heuristic-based [10]–[14], constraint-based [15]–[18], and learning-based [19]–[21]), and patch validation methodologies [22], [23]. Our study focuses on improving fault localization, which was recently identified as a key aspect of program repair that affects patch correctness [4], [5], [8], [15], [24], [25].

Most repair tools use SBFL, which uses developer-written test-execution coverage to compute the suspiciousness scores of the program's elements, such as classes, methods, and statements. The elements are ranked based on these scores and repair tools use top-ranked elements as candidate locations to patch bugs. To the best of our knowledge, only two repair tools, R2Fix [26] and iFixR [7], use IRFL, which ranks suspicious program elements based on their similarity with bug reports. Using SBFL and IRFL can be complementary. For example, iFixR patches defects that 16 SBFL repair tools cannot, and vice versa [7].

Because combining FL techniques that use different information sources (e.g., SBFL, mutation-based fault localization, and IRFL) can significantly outperform individual FL techniques in terms of localizing bugs [27]–[29], we hypothesize that using combined SBFL and IRFL can enable repair tools to patch all the defects that they can patch when using the underlying SBFL and IRFL alone, and perhaps some others. To the best of our knowledge, this is the first investigation of the effect of combined FL on automated program repair.

To combine FL techniques, we develop RAFL, a novel approach that uses rank aggregation algorithms [30] to combine the top-k ranked statements produced using different FL techniques. RAFL measures the similarity of the two ranked lists using the Spearman footrule distance [31] and runs the cross-entropy Monte Carlo algorithm [32] to produce a super list of top-k statements while maximizing the similarity to the individual lists. RAFL can combine FL results obtained using any set of techniques; in this paper, we specifically focus on combining SBFL and IRFL, as these have been used in program repair.

Existing IRFL techniques [33]–[37] are not well suited for program repair because they localize defects at the file or method level, whereas repair tools need statement-level granularity. We develop Blues, a statement-level IRFL technique based on BLUiR [34], an existing file-level IRFL technique. Blues considers abstract syntax tree (AST) representations of program statements as a collection of documents, and bug report as a query, and uses a structured information retrieval technique to rank the statements based on their similarity with the bug report. Blues is the first unsupervised statement-level IRFL technique. The prior statement-level IRFL technique, D&C [38] used by iFixR [7], required supervised training.

We implement an SBFL technique using the latest version (v1.7.2) of GZoltar, and the Ochiai ranking strategy, which is one of the most effective ranking strategies in object-oriented programs [27], [39]. We evaluate this SBFL technique, Blues, and their RAFL-enabled combination SBIR, on 818 real-world defects in the Defects4J v2.0 benchmark.

> (RQ1) We find that SBIR outperforms SBFL and Blues, for all sizes of suspicious statement lists we investigated (1, 10, 50, 100). For example, SBIR correctly identifies a buggy statement as the most suspicious for 148 of the 818 (18.1%) defects, whereas SBFL does so for 89 (10.9%) and Blues for 25 (3.1%).

To test if the combined FL improves repair performance, we use SimFix [14], a state-of-the-art repair tool. We chose SimFix because a recent study [7] found that it outperforms a suite of 16 other repair techniques, including iFixR, kPAR [24], AVATAR [40], and LSRepair [41], as well as others. We run SimFix on 818 defects in Defects4J v2.0 for which bug reports are available using our SBFL implementation, Blues, and SBIR.

> (RQ2) Using SBIR enables SimFix to patch marginally more defects (112 out of 818) than using SBFL (110) and significantly more than using Blues (55). With SBIR, SimFix produces patches for most of the defects patched using SBFL or Blues, as well as 3 new defects that could not be patched previously. Further, with SBIR, SimFix is able to produce all but one (29 out of 30) of the correct patches it produces with SBFL, and all (16 out of 16) of the correct patches with Blues. Additionally, SimFix with our FL implementations produces patches for 10 defects that none of 14 state-of-the-art repair tools can patch [24]. Finally, using Blues, SimFix significantly outperforms iFixR, the state-of-the-art IRFL-based repair tool [7], patching 19 out of 156 defects (7 correctly) while iFixR patches only 4 defects (3 correctly).

To evaluate the correctness of patches, there exist two established methods: using automatically generated, independent, high-quality evaluation test suites not used during the repair process [42]–[44], and manually comparing the patches against developer-written solutions [45], [46]. While manual inspection can be subject to subconscious bias, especially if the inspectors are authors of the tools being evaluated [47], using evaluation tests is inherently partial, as generated tests may not fully cover the modified program [44]. Our patch evaluation methodology combines these methods, producing more precise and complete results.

Our evaluation uses the Defects4J [48] benchmark. A recent study [49] compared the repair performance of 11 repair tools on a diverse set of benchmarks and found that repair tools patch significantly more defects in versions of Defects4J prior to 2, than in other benchmarks (47% of Defects4J defects, while 10–30% of the other benchmarks' defects). This suggests that research has overfit to the older versions of the Defects4J benchmarks, and results presented on that benchmark are too optimistic. Defects4J v2.0 has significantly more defects from more diverse projects (835 defects from 17 large open-source Java projects, as opposed to 395 defects from 6 projects) and provides bug report information for most (818 out of 835) defects. To the best of our knowledge, no FL technique or repair tool has been evaluated on this Defects4J version, to date, allowing us gain insight into how results of prior evaluations generalize.

> (RQ3) Past program repair evaluations do, in fact, fail to generalize to new defects. For example, SimFix correctly patches 3–6% (6% when using SBFL, 3% Blues, 6% SBIR) of the defects in the older version of Defects4J, but only 1–2% (2% SBFL, 1% Blues, 2% SBIR) of the *new* defects. Of the patches SimFix produces for the old defects, 39–40% are correct; for the new defects, only 13–19% are correct.

We make the following contributions:

- Blues: A novel statement-level, unsupervised IRFL technique, the first to require no training.
- RAFL: A novel unsupervised approach to combine multiple FL techniques.
- The first investigation of the effect of combining IRFL and SBFL on automated program repair.
- An open-source fault localization toolkit that implements: (1) Blues, (2) an SBFL technique using the latest version of GZoltar (v1.7.2) and Ochiai, and (3) SBIR, which combines the SBFL and Blues using RAFL.
- An evaluation of SBIR, Blues, and SBFL on the 818 defect subset of Defects4J (v2.0) showing that SBIR significantly outperforms the other techniques.
- An evaluation of program repair using SBIR, Blues, and SBFL, showing that when using SBIR, program repair can produce patches for most of the defects it can using other FL techniques, and some others.
- A replication package containing all artifacts to replicate our evaluation. This is the first evaluation of either fault localization or program repair on such a large subset of Defects4J (v2.0).

The rest of this paper is organized as follows. Section II provides background on FL techniques and their use in automated program repair. Section III describes RAFL, Blues, SBIR, and our approach to use combined FL in program repair. Section IV details our evaluation's dataset and metrics, and evaluates combining SBFL and IRFL and that combination's effect on program repair. Section V places our work in the context of related research, and Section VI summarizes our contributions.

II. Fault Localization Background

Fault localization research focuses on developing automated techniques to identify program elements (such as source code files, methods, and statements) that are likely to contain the underlying defect that cause software failures. Most automated FL techniques use dynamic analysis and runtime information of the defective program to compute the suspiciousness score, the probability of being defective, of the program elements. These techniques produce a ranked list of program elements based on the suspiciousness score. FL techniques can be classified based on the source of the information they use. For example, SBFL techniques use test coverage information [50]–[52], mutation-based fault localization (MBFL) techniques use test results collected from mutating the program [53], [54], (dynamic) program slicing techniques use the dynamic program dependencies [55], [56], stack trace analysis techniques use error messages [35], [57], predicate switching techniques use test results from mutating the results of conditional expressions [58], IRFL techniques use bug report information [33]–[37], and history-based techniques use the development history to identify the suspicious program elements that are likely to be defective [59], [60]. A recent survey details advantages and disadvantages of the existing FL techniques [61].

No one class of the FL techniques outperforms the others in terms of their ability to localize defects. And combining multiple types of FL techniques can often outperform individual underlying techniques [27]–[29], [62].

Most automated program repair tools use SBFL or IRFL (e.g., [7], [10]–[21], [26]). The intuition behind SBFL is that the more frequently an element is executed by failing tests, and the less frequently it is executed by passing tests, the more suspicious that element is. Meanwhile, IRFL works on the assumption that the terms used in bug reports, even if filed by users, will be found in the buggy source files. IRFL techniques consider the source files to be a collection of documents and use IR-based models to rank the documents based on their estimated relevance to the bug report (which, in IR terminology, acts as a query).

Repair tools often use different versions of off-the-shelf frameworks to implement SBFL techniques (e.g., ACS [63] uses GZoltar (v0.1.1), while SimFix uses GZoltar (v1.6.0)), make assumptions (e.g., HDRepair [64] assumes that faulty method is known), and adapt FL results (e.g., ssFix [65] prioritizes the statements from the stack trace of crashed program before the statements obtained using the FL technique) to improve the repair performance of their tool. Such assumptions and tweaks can significantly affect repair tools performance and are often elided while presenting the results of repair tools [24]. Further, the implemented FL strategies are hard to isolate from repair tools' implementations, preventing researchers from reusing the implemented FL strategies across different repair tools. This also leads to potential biases in comparing repair tools, even when they use same FL technique [24].

III. Combining FL for Program Repair

This section describes RAFL, Blues, SBFL, and using these FL strategies for program repair.

A. RAFL: Rank-Aggregation-Based Fault Localization

Existing approaches [27]–[29], [39], [66] to combine multiple FL techniques, are based on *learning to rank* [67], supervised deep machine learning techniques. These techniques consider suspiciousness scores of program elements as *features* and implement pairwise learning to train a model that ranks defective elements higher than non-defective elements. Such approaches require a training dataset of program elements annotated with suspiciousness scores computed using different FL techniques; each elements needs to be labeled as "defective" or "not-defective". The trained model then predicts if a new program element is defective. The performance and generalizability of such models depends heavily on the dataset and features used for training.

We propose to use an unsupervised approach that requires no training. We formulate the problem of combining multiple FL techniques as a rank aggregation (RA) [30] problem. The RA problem involves combining multiple ranked lists (base rankers) into one single ranked list (aggregated ranker), which is intended to be more reliable than the base rankers [68]. The RA problem has been studied extensively in information retrieval [69], marketing and advertisement research [30], social choice (elections) [69], and genomics [70]. We propose to use RA algorithms for combining multiple FL techniques' ranked lists of suspicious statements.

We implement RAFL using the RankAggreg [71] package in R, which implements several RA algorithms (cross-entropy Monte Carlo algorithm (CE), genetic algorithm (GA), and a brute force algorithm) and provides distance metrics (Spearman footrule distance [31], and Kendall's tau distance [72]) to produce an aggregated ranker from base rankers. Based on the specified distance metric, the algorithms create an objective function that encodes the distance between the aggregated ranker and base rankers. The algorithms then attempt to minimize the value of the objective function by updating the sampled aggregated ranker iteratively until convergence. The convergence criteria is the repetition of the same minimum value of the objective function in *convIn* consecutive iterations. In practice, both CE and GA produce similar lists; however, CE is typically more efficient and converges more quickly. Similarly, there is no clear winner between the Spearman footrule distance and the Kendall's tau distance; however, computing the former is faster. Accordingly, RAFL uses CE with the Spearman footrule distance. We set *rho* ("quantile" of candidate lists sorted by the function values) to 0.1 and *convIn* to 7, as suggested in the RankAggreg documentation [73].

We use RAFL to implement SBIR, which combines the top-k ranked statements produced using Blues (Section III-B) with the ones produced using our SBFL (Section III-C) to produce a combined list of top-k ranked statements.

B. Blues: Bug Report Fault Localization

IRFL techniques use source code information and bug report text to rank suspicious source files using IR models, such as latent Dirichlet allocation [74], vector space model [75], and latent semantic analysis [76]. Existing IRFL techniques [33]–[37] are ill-suited for program repair because these techniques localize bugs at either file or method level, while repair requires statement-level localization. iFixR [7], an IRFL-based repair technique localizes bugs at the statement level by extending

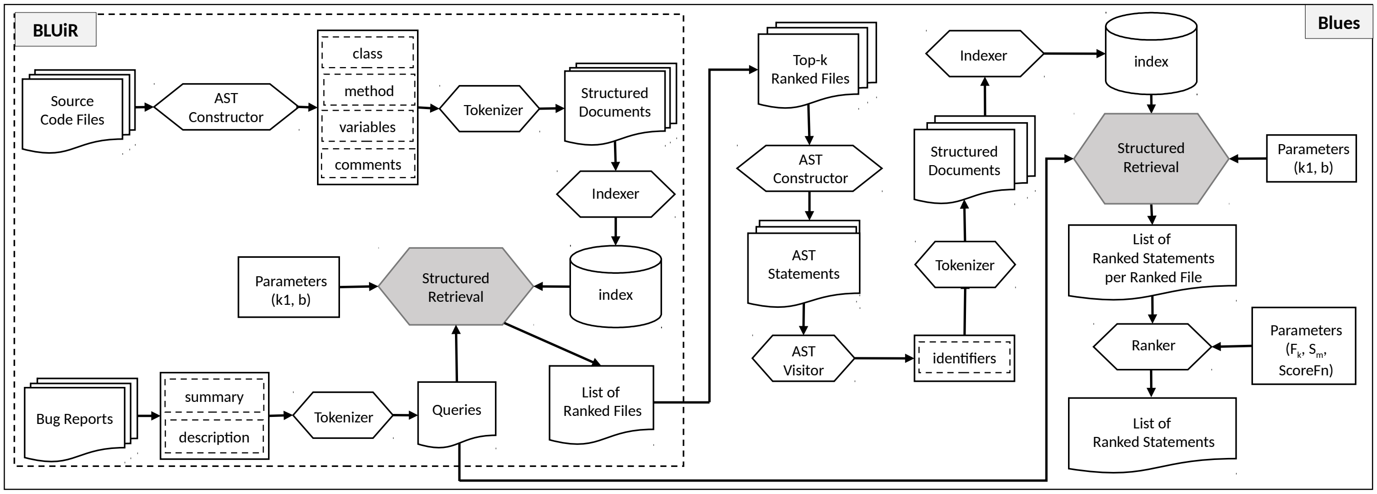

Fig. 1. The Blues architecture builds on BLUiR to produce a ranked list of suspicious statements using structured information retrieval.

the D&C pre-trained models' file-level results [38], an existing file-level IRFL technique. D&C uses a supervised machine learning approach to train multiple classifier models on the bug-location pairs to predict the buggy files. The models are trained on Bench4BL [77] benchmark that includes five projects (Codec, Collections, Csv, Lang, and Math) that are also part of Defects4J (v2.0) benchmark. The approach and implementation are not general enough to be retrained with other projects, and because these models are trained on the projects in the evaluation dataset, it is inappropriate to use D&C's pre-trained models in our study.

Instead, we propose a novel, unsupervised, statement-level IRFL technique, Blues, based on BLUiR [34], an existing file-level IRFL technique. We select BLUiR because it uses an unsupervised approach (it does not require training) and performs comparably to the other state-of-the-art IRFL techniques [77]. Figure 1 shows the Blues architecture to produce a ranked list of suspicious statements, described next.

1) Blues's Ranking of Suspicious Files: For each defect, Blues's inputs are the source files and bug report. Blues builds the AST of each source file using Eclipse Java Development Tools (JDT). Next, Blues traverses the AST to extract identifiers associated with each program construct, such as class names, method names, variable names, and comments. It then splits the extracted identifiers into tokens using *CamelCase* splitting, which improves the matching recall. Blues then parses the bug report to extract identifiers from the *summary* and *description* fields, storing the information in separate structured XML documents. The XML documents created from source files and bug report are then fed into Indri toolkit [78] for efficient indexing and for developing the retrieval model. Indri pre-processes the XML documents using text normalization (remove punctuation, perform case-folding, tokenize terms), stopword removal (remove extraneous terms such as "a", "the", "be", etc.), and stemming (conflate variants of the same underlying term (e.g., "ran", "running", "run"). Next, it indexes the pre-processed documents by collecting and storing statistics, such as term frequency (TF) (the number of times a term occurs in a given document), document frequency (DF) (the number of documents in which a given term appears), and Inverse Document Frequency (IDF), which is formulated as $log(\frac{N}{DF})$, where N is the total number of documents in the collection. Finally, Blues uses an IR model (TF-IDF formulation based on the BM25 (Okapi) model [79]) to search and rank the documents based on their similarity with the given bug report. The TF-IDF-based IR model uses two tuning parameters: the term weight scaling parameter k_1 and the document normalization parameter b, which are provided as input (along with XML documents) to the Indri toolkit. We set $k_1 = 1.0$ and $b = 0.3$, as suggested in the original BLUiR study [34]. The output of the IR model is the ranked list of source files along with similarity scores for the bug report.

2) Blues's Ranking of Suspicious Statements: To identify the suspicious statements from the top ranked suspicious files, Blues takes the top-k ranked files, uses Eclipse JDT to create the AST of each source file, and then uses AST Visitor to parse and extract AST statements from the source file ASTs. For each AST statement, Blues extracts the identifier terms and the line number of that AST statement. Extracting AST statements instead of natural language text from source files enables Blues to: (1) fetch compilable code statements (a single code statement may span across multiple lines in source file), which can be considered for replacement by repair tools, and (2) compute separate suspiciousness scores for nested AST statements that exist on the same line of the source file. Next, for each of the AST statements, Blues creates an XML document that contains the identifiers extracted from that statement along with the information of its source file and line number. Blues then feeds these XML documents, along with the tuning parameters ($k_1 = 1.0$ and $b = 0.3$), to the Indri toolkit to perform the same processing as for ranking source files, and uses the same IR model to produce a ranked list of AST statements along with their similarity scores with the bug report. Blues extracts the source file and line number information from ranked AST statement results to produce a ranked list of suspicious statements per file.

As real-world projects may contain many source files, it may be ineffective to consider all lines in a higher-ranked source file to be more suspicious than lines in other files. Instead, Blues' ranker module uses the following input configuration parameters to produce a final list of ranked statements:

1) F_k: Number of top-k suspicious files to be considered to produce the final ranked list of suspicious statements.
2) S_m: Number of top-m suspicious statements per suspicious file to be considered to produce the final ranked list of suspicious statements.
3) $ScoreFn$: Function to combine the suspiciousness scores of ranked files and statements. This can be either $Score_{high}$ or $Score_{wt}$, as defined next.

To incorporate the suspiciousness scores of ranked files (S_{file}) in the scores of ranked statements (S_{line}), Blues provides following two scoring functions.

1) $Score_{high}$: Rank highest the m most suspicious statements in the most suspicious file, followed by the m most suspicious statements in the next most suspicious file, and so on.
2) $Score_{wt}$: Assign each statement a weighted suspiciousness score, weighing the file's and statement's scores using the weights α and β: $\alpha \cdot S_{file} + \beta \cdot S_{line}$.

In our experiments, we set $F_k = 50$ based on the recommendation of a prior study [7]. We experiment with using different S_m values and scoring mechanisms. We run Blues using six different configurations: five ($S_m \in \{1, 25, 50, 100, all\}$) with $Score_{high}$, and one ($S_m = all$) with $Score_{wt}$. For $Score_{wt}$, we empirically set $\alpha = 0.8$ and $\beta = 0.2$, which localized maximum number of bugs when compared to using other combinations. Using different configurations gives complementary results by localizing different defects. Therefore we create an *Blues ensemble* that combines the FL results of these six different configurations and localizes all of the defects that underlying Blues configurations localize. RQ1 in Section IV-D describes the detailed comparison of FL results obtained using different configurations of Blues and the Blues Ensemble.

C. Spectrum-Based Fault Localization

A program spectrum is a measurement of runtime behavior of a program, such as code coverage of developer-written tests [52]. Comparing program spectra on passing and failing tests can be used to rank program elements (e.g., class, method, statement). SBFL techniques calculate the suspiciousness score of an element using some ranking strategy that considers the following four values collected from the test execution coverage on that element: (1) number of failing tests that execute element (e_f), (2) number of failing tests that do not execute element (n_f), (3) number of passing tests that execute element (e_p), and (4) number of passing tests that do not execute element (n_p). While there are multiple ranking strategies proposed for SBFL, including Ochiai [51], DStar [80], and Tarantula [81], many empirical studies [27], [39] have shown that Ochiai is more effective for object-oriented programs. Thus, most SBFL-based repair tools use Ochiai, and so does our study.

There exists multiple open-source testing and debugging frameworks, including JaCoCo [82], GZoltar [83], and Cobertura [84], that repair tools use to compute the test execution coverage on source code. To implement SBFL, our study uses the GZoltar framework because it is the framework most repair tools use, and a recent study comparing 14 repair tools on Defects4J (v1.2.0) used multiple GZoltar versions, showing that the latest-at-the-time version (v1.6.0) significantly improves FL results and repair performance [24]. Therefore, we use the latest version (v1.7.2) of GZoltar to implement SBFL. Section IV-D compares the FL results obtained when using different versions of GZoltar to implement SBFL.

GZoltar's inputs are the source code and test suite; it executes tests to produce coverage matrices on passing and failing tests. Next, it processes the coverage matrices to compute e_f, n_f, e_p, and n_p for each source code statement, then computes the suspiciousness scores of statements using the Ochiai ranking formula: $Score = e_f((e_f + n_f)(e_f + e_p))^{-1/2}$. As SBFL-based repair tools often use Gzoltar, our SBFL implementation and FL results can be directly used by future repair tools.

D. Program Repair Using Different FL Strategies

Instead of developing a new repair tool, we use SimFix [14], a state-of-the-art program repair tool because it outperforms a suite of 16 other repair techniques [7], including the state-of-the-art IRFL-based tool iFixR, as well as kPAR [24], AVATAR [40], and LSRepair [41], and others. Unlike many repair tools, SimFix' FL implementation is not tightly coupled to repair mechanism, which allows us to extend its implementation to use different FL strategies.

The SimFix implementation [85] is coded to work with the Defects4J benchmark. Its input is a project name and bug id (associated with each defect in Defects4J), and, optionally, precomputed statement-level FL results. SimFix considers the top-k (we set $k = 100$) ranked statements from the FL result to attempt to produce a patch. (Without provided FL results, SimFix runs SBFL with Ochiai (implemented using GZoltar (v1.6), employing a test purification technique [86] to improve FL accuracy). To patch a defect, SimFix uses code patterns mined from frequently occurring code changes in developer-written patches. SimFix identifies code snippets similar to the suspicious code, defining similarity using structural properties, variable names, and method names. SimFix ranks the code snippets by the number of times the mined patterns have to be applied to replace the buggy code, and then selects the snippets (one at a time) from the ranked list of top 100, applies the pattern-based modifications to produce a candidate patch, and validates the patch against the purified failing tests. SimFix can stop once a patch passes the test suite [14] but its implementation [85] generates all the patches that pass at least one of the purified failing tests. In this study, we use only the patch that passes all of the developer tests provided with the defect.

identifier	project	description	defects
Chart	jfreechart	framework to create charts	8
Cli	commons-cli	API for parsing command line options	39
Closure	closure-compiler	JavaScript compiler	174
Codec	commons-codec	implementations of encoders & decoders	18
Collections	commons-collections	extensions of the Java Collections Framework	4
Compress	commons-compress	API for file compression utilities	47
Csv	commons-csv	API to read and write CSV files	16
Gson	gson	API to convert Java Objects into JSON	18
JacksonCore	jackson-core	core part of the Java JSON API (Jackson)	26
JacksonDatabind	jackson-databind	data-binding package for Jackson	112
JacksonXml	jackson-dataformat-xml	data format extension for Jackson	6
Jsoup	jsoup	HTML parser	93
JxPath	commons-jxpath	interpreter of XPath, an expression language	22
Lang	commons-lang	extensions to the Java Lang API	65
Math	commons-math	library of mathematical utilities	106
Mockito	mockito	a unit-test mocking framework	38
Time	joda-time	date and time processing library	26
total			818

Fig. 2. The 818 defects from the 17 large real-world Java projects that have bug reports associated with in Defects4J (v2.0) benchmark.

IV. Evaluation

This section describes the data and methodology used to evaluate our techniques, and the evaluation results.

A. Dataset and Metrics

Defects4J (v2.0) targets Java 8 and consists of 835 reproducible defects from 17 large open-source Java projects. Each defect comes with (1) one defective and one developer-repaired version of the project code with the changes minimized to those relevant to the defect; (2) a set of developer-written tests, all of which pass on the developer-repaired version and at least one of which evidences the defect by failing on the defective version; (3) the infrastructure to generate tests using modern automated test generation tools; and (4) the summarized information for each defect that includes the bug report URL. Out of the 835 defects, 818 have the bug report URL available, making IRFL possible. We use these 818 defects. Figure 2 describes these 818 defects and the projects they come from.

We use the following two metrics, which are commonly used to evaluate the performance of FL techniques [27]:

1) $\mathbf{E_{inspect}}$**@k**: counts the number of defects successfully localized within the top-k ranked statements.
2) **EXAM**: computes the fraction of statements that have to be inspected until finding a defective statement.

$E_{inspect}$@k can tell us how useful an FL technique is for a repair tool that only considers the top k ranked statements. Higher value of $E_{inspect}$@k provide repair tools an opportunity to patch more defects. The EXAM score measures the relative position of defective statement in the ranked list. Smaller value of EXAM score means the defective statement is ranked higher.

To be consistent with the prior studies [7], [24], [27], we consider a defect to be successfully localized when at least one of the defective statements (statement modified by developer) is covered in the top-k ranked statements. Unlike previous studies that break ties between statements having same suspiciousness scores by reassigning ranks using their average rank [87] or expected rank [27], we rank such statements in the order of their appearance in the FL results, as this is how repair tools process these results.

B. SimFix Execution Methodology

We use SimFix to repair each of the 818 defects in the Defects4J (v2.0) benchmark using the developer-written tests to validate the produced patches and top-100 suspicious statements obtained using the SBFL, Blues Ensemble, and SBIR Ensemble to localize the defects. We do not make any modification to the originally released implementation of SimFix except reducing the number of suspicious statements it uses to localize the defects from 200 to 100 to improve experimental execution speed, and increasing the timeout per attempt from 5 hours to 24 hours. We make these modifications because the focus of this study is repair performance and not the repair efficiency. The modifications ensure that SimFix gets an opportunity to try all of the top-100 ranked statements to produce a patch instead of timing out.

SimFix uses a deterministic patch generation algorithm. (Many other tools are nonderministic and require multiple repair attempts per defect.) Thus we execute SimFix once for each defect, for each of the three FL strategies, resulting in a total of 3 × 818 = 2,454 repair attempts. We ran our experiments using a cluster of 50 compute nodes, each with a Xeon E5-2680 v4 CPU with 28 cores (2 processors, 14 cores each) running at 2.40GHz. Each node had 128GB of RAM and 200GB of local SSD disk. We launched multiple repair attempts in parallel, each requesting 2 cores on one compute node. The computational requirements are significant: Repairing a single defect 3 times with a 24-hour timeout can take 72 hours per defect, and 6.7 CPU-years for 818 defects. Overall, all the experiments combined took six weeks of wall-clock time to execute: three weeks to compute the fault localization results using all the different configurations, and three more weeks for program repair experiments.

C. Evaluating Patch Correctness

Prior repair tools' evaluations measure frequency of patch production [49], types of defects patched [88], and quality or correctness of the produced patches [46], [47], [63], [89]. Evaluations that measure patch correctness use either manual inspection [46], [47], [89] or automatically-generated evaluation test suites [15], [44], [47], [63], [90]. While manual inspection is subjective and could be biased, using low-quality evaluation test-suites could inaccurately measure patch correctness [47]. Therefore, we propose a new patch evaluation methodology that uses both of these methods to evaluate the patch correctness.

For each patch, we consider the developer-written patch (available for all Defects4J defects) as an oracle, and use EvoSuite [91] to generate 10 test-suites using 10 seeds, a search budget of 12 minutes per seed, and a coverage criterion of maximizing line coverage. As patches may not modify the same classes as the oracle patches, we generate evaluation tests for all of the developer and evaluation-patch modified classes. This methodology is the state-of-the-art objective (but potentially incomplete [47]) automated test-driven patch correctness methodology [44]. To evaluate the correctness of a patch, we first execute the evaluation tests on the patch. If it fails any tests, we annotate such patch as *plausible* (the term used for a patch

SBFL (E_{inspect}@k)						
	$k =$	1	25	50	100	all
		89	398	470	550	726
Blues (E_{inspect}@k)						
S_m	ScoreFn	$k = 1$	25	50	100	all
1	$Score_{high}$	25	62	68	68	68
25	$Score_{high}$	25	145	206	254	380
50	$Score_{high}$	25	145	192	275	479
100	$Score_{high}$	25	145	192	240	532
all	$Score_{high}$	25	145	192	240	637
all	$Score_{wt}$	25	145	192	240	637
Blues Ensemble		25	178	273	366	637

Fig. 3. SBFL and Blues performance, in terms of E_{inspect}@k, on the 818 defects. For Blues, we test six configurations and their ensemble.

S_m	ScoreFn	$k = 1$	25	50	100
1	$Score_{high}$	60	287	333	333
25	$Score_{high}$	81	337	397	437
50	$Score_{high}$	73	328	380	432
100	$Score_{high}$	75	330	387	429
all	$Score_{high}$	75	331	388	430
all	$Score_{high}$	95	348	405	461
SBIR Ensemble		148	458	534	601

Fig. 4. SBIR performance, in terms of E_{inspect}@k, on the 818 defects. Each SBIR version combines SBFL and one of six configuration of Blues, and the Blues ensemble.

that passes developer-written tests but is incorrect [45]). Otherwise, we manually inspect the patch and compare it against the developer's patch. If the patch is semantically equivalent to the developer's patch, we annotate it as *correct*. If it is not, we annotate it as *plausible*. If a patch is partially correct or we cannot determine its semantic equivalence because it requires extensive domain knowledge, which often happens when the modifications are made in different methods, we conservatively annotate it as *plausible*, but keep a record of such scenarios. Thus, our patch evaluation methodology is conservative as we only consider a patch to be *correct* if it passes all evaluation tests and is also semantically equivalent to the developer's patch.

D. Evaluation Results

RQ1: Does SBIR localize more defects than the underlying SBFL and Blues techniques?

Figure 3 shows the $E_{\text{inspect}}@k$ localization results for SBFL, six configurations of Blues, and an ensemble of those Blues configurations. SBFL outperforms Blues for each k. We use these baseline results to later compare to SBIR. From here on, we use Blues Ensemble as our representative Blues technique, and refer to it as such.

Figure 4 shows the performance (in terms of $E_{inspect}@k$ for $k \in \{1, 25, 50, 100\}$) of SBIR that combines the top-k ($k \leq 100$) suspicious statements obtained using SBFL and various configurations of Blues (Figure 3). SBIR Ensemble outperforms all of its individual versions. From here on, as

	$E_{\text{inspect}}@k$			EXAM		
k	SBFL	Blues	SBIR	SBFL	Blues	SBIR
1	89	25	148	0.888	0.969	0.819
25	398	178	458	0.625	0.829	0.574
50	470	273	534	0.533	0.712	0.459
100	550	366	601	0.440	0.356	0.231

Fig. 5. SBFL, Blues, and SBIR comparison on the 818 defects, measuring E_{inspect}@k, the number of defects successfully localized in top k statements, and EXAM, the mean fraction of statements inspected before a defective statement is found. SBIR outperforms SBFL and Blues for all k and both measures.

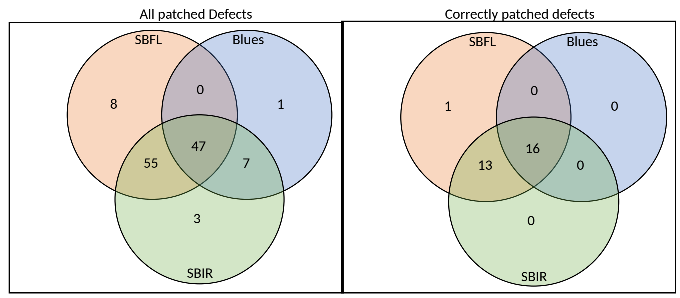

Fig. 6. Distribution of defects patched by SimFix when using SBFL, Blues, and SBIR FL techniques. In total, SimFix with SBIR produces 112 patches, 29 of which are correct. With SBFL, 110 patches (30 correct), and with Blues, 55 patches (16 correct).

with Blues, we consider SBIR Ensemble as our representative SBIR technique, and refer to it as such.

Figure 5 compares the performance of SBFL, Blues, and SBIR in terms of $E_{\text{inspect}}@k$ and EXAM scores averaged over the 818 defects. SBIR consistently outperforms both SBFL and Blues. SBIR localizes more defects and ranks the correct defective statements higher in the ranked list compared to the underlying SBFL and Blues techniques. These results confirm prior findings suggesting that combining FL techniques leads to better FL [27]–[29], [39], [66], [92].

RQ2: Does using SBIR in program repair improve repair performance?

Figure 6 shows a Venn diagram of the defects SimFix with our FL strategies repairs. Overall, SimFix patches a total of 121 out of 818 defects, and 30 of these are patched correctly. SimFix using SBIR patches 112 defects, 110 when using SBFL, and 55 when using IRFL. Thus, using SBIR enables SimFix to patch marginally more defects than SBFL and significantly more defects than Blues. The 112 defects patched using SBIR include 55 of the 63 defects patched exclusively using SBFL, 7 of the 8 patched exclusively using IRFL, all of the 47 defects patched using both SBFL and IRFL, and 3 new defects. These results show that SBIR enables SimFix to patch a majority of defects it patches exclusively using SBFL or Blues, as well as new defects. Considering correctly patched defects, SimFix using SBIR correctly patches 29 out of the 818 defects and these defects include all but one defect correctly patched using SBFL and all defects patched using IRFL. Section IV-E describes why SimFix using SBIR sometimes fails to patch defects that it patches using SBFL or Blues.

defect	Eval. Test Cov. method	Eval. Test Cov. class	SBFL automated	SBFL manual	Blues automated	Blues manual	SBIR automated	SBIR manual
47 defects patched using SBFL, Blues, and SBIR								
Chart-1	0.400	0.746	✔	✔	✔	✔	✔	✔
Chart-12	1.000	0.963	✔	‡	✔	‡	✔	‡
Cli-18	1.000	0.970	✘	✘	✘	✘	✘	✘
Cli-19	1.000	0.969	✘	✘	✘	✘	✘	✘
Closure-14	0.583	0.708	✔	✔	✔	✔	✔	✔
Closure-73	0.970	0.205	✔	✔	✔	✔	✔	✔
Closure-113	0.000	0.164	✔	‡	✔	‡	✔	‡
Closure-126	0.478	0.440	✔	✔	✔	✔	✔	✔
Codec-8	1.000	0.974	✔	✔	✔	✔	✔	✔
Compress-38	1.000	0.615	✘	✘	✘	✘	✘	✘
Csv-14	0.981	0.991	✘	✘	✘	✘	✘	✘
Csv-15	0.962	0.991	✔	‡	✔	‡	✔	‡
Gson-15	0.833	0.970	✔	✔	✔	✔	✔	✔
JacksonCore-15	0.655	0.720	✘	✘	✘	✘	✘	✘
JacksonCore-17	0.511	0.791	✘	✘	✘	✘	✘	✘
JacksonDatabind-1	0.037	0.791	✔	‡	✔	‡	✔	‡
JacksonDatabind-8	1.000	0.931	✘	✘	✘	✘	✘	✘
JacksonDatabind-28	0.500	0.600	✔	✘	✔	✘	✔	✘
JacksonDatabind-48	1.000	1.000	✔	✘	✔	✘	✔	✘
JacksonDatabind-53	0.815	0.959	✔	✘	✔	✘	✔	✘
JacksonDatabind-54	0.024	0.359	✔	✔	✔	✔	✔	✔
JacksonDatabind-75	—	—	-	✘	-	✘	-	✘
JacksonDatabind-83	0.781	0.881	✔	‡	✔	‡	✔	‡
JacksonDatabind-87	1.000	0.995	✔	‡	✔	‡	✔	‡
JacksonDatabind-101	0.000	0.113	✔	✘	✔	✘	✔	✘
JacksonDatabind-107	0.176	0.76	✔	‡	✔	‡	✔	‡
Jsoup-39	0.412	0.68	✔	✔	✔	✔	✔	✔
Jsoup-57	1.000	0.95	✔	‡	✔	‡	✔	‡
JxPath-12	1.000	0.857	✔	✔	✔	✔	✔	✔
Lang-10	0.938	0.957	✔	✘	✔	✘	✔	✘
Lang-43	0.647	0.761	✔	✔	✔	✔	✔	✔
Lang-45	1.000	0.993	✘	✘	✘	✘	✘	✘
Lang-58	0.882	0.961	✔	✔	✔	✔	✔	✔
Lang-63	0.813	0.915	✔	✘	✔	✘	✔	✘
Math-8	1.000	0.974	✘	✘	✘	✘	✘	✘
Math-28	1.000	1.000	✔	✘	✔	✘	✔	✘
Math-40	0.989	0.992	✘	✘	✘	✘	✘	✘
Math-41	1.000	0.991	✔	✔	✔	✔	✔	✔
Math-50	0.943	0.957	✔	✔	✔	✔	✔	✔
Math-53	1.000	0.987	✔	✔	✔	✔	✔	✔
Math-57	1.000	0.974	✔	✔	✔	✔	✔	✔
Math-70	1.000	1.000	✔	✔	✔	✔	✔	✔
Math-73	1.000	1.000	✘	✘	✘	✘	✘	✘
Math-80	1.000	0.966	✘	✘	✘	✘	✘	✘
Math-84	1.000	1.000	✔	✘	✔	✘	✔	✘
Math-85	0.944	0.903	✘	✘	✘	✘	✘	✘
Time-11	1.000	0.855	✘	✘	✘	✘	✘	✘
7 defects patched using Blues and SBIR but not using SBFL								
Closure-18	0.694	0.845	-	-	✔	‡	✔	‡
JacksonDatabind-112	0.889	0.523	-	-	✔	‡	✔	‡
Jsoup-45	1.000	0.979	-	-	✘	✘	✘	✘
Jsoup-67	0.857	0.979	-	-	✘	✘	✔	✘
JxPath-22	1.000	0.878	-	-	✔	✘	✔	✘
Lang-27	0.956	0.987	-	-	✘	✘	✘	✘
Math-82	1.000	0.983	-	-	✔	✘	✔	✘
1 defect patched exclusively using Blues								
Closure-107	0.000	0.086	-	-	✔	‡	-	-
3 defects patched exclusively using SBIR								
JacksonCore-11	1.000	0.957	-	-	-	-	✘	✘
JacksonDatabind-20	0.739	0.891	-	-	-	-	✔	‡
Jsoup-90	0.318	0.704	-	-	-	-	✔	✘
55 defects patched using SBFL and SBIR but not using Blues								
Cli-22	1.000	1.000	✘	✘	-	-	✘	✘
Closure-21	0.935	0.970	✔	✘	-	-	✔	✘
Closure-22	0.886	0.771	✘	✘	-	-	✘	✘
Closure-38	0.000	0.018	✔	✘	-	-	✔	✘
Closure-46	0.000	0.917	✔	‡	-	-	✔	‡
Closure-57	0.300	0.508	✔	✔	-	-	✔	✔
Closure-62	0.600	0.737	✔	✔	-	-	✔	✔
Closure-68	0.535	0.291	✔	✔	-	-	✔	✔
Closure-84	0.000	0.349	✘	✘	-	-	✘	✘
Closure-109	0.000	0.303	✔	✘	-	-	✔	✘
Closure-115	0.033	0.293	✔	✘	-	-	✔	✘
Closure-152	1.000	0.987	✔	‡	-	-	✔	‡
Closure-160	0.955	0.488	✔	‡	-	-	✔	‡
Closure-161	0.000	0.348	✔	✔	-	-	✔	✔
Closure-162	1.000	0.974	✔	✘	-	-	✔	✘
Closure-168	0.08	0.324	✔	✘	-	-	✔	✘
Codec-9	1.000	0.995	✔	✘	-	-	✔	✘
Collections-28	0.000	0.369	✔	✘	-	-	✔	✘
Compress-16	0.730	0.857	✘	✘	-	-	✘	✘
Compress-18	1.000	0.990	✘	✘	-	-	✘	✘
Compress-25	1.000	0.233	✔	‡	-	-	✔	✘
Compress-27	1.000	0.931	✔	✔	-	-	✔	✔
JacksonCore-9	0.000	0.474	✔	✘	-	-	✔	✘
JacksonDatabind-3	0.929	0.836	✔	✔	-	-	✔	✔
JacksonDatabind-5	1.000	0.893	✘	✘	-	-	✘	✘
JacksonDatabind-29	0.077	0.292	✔	‡	-	-	✔	‡
JacksonDatabind-35	0.136	0.406	✔	✘	-	-	✔	‡
JacksonDatabind-43	0.778	0.903	✔	‡	-	-	✔	‡
JacksonDatabind-51	0.000	0.000	✘	✘	-	-	✘	✘
JacksonDatabind-64	0.500	0.634	✘	✘	-	-	✘	✘
JacksonDatabind-71	0.974	0.907	✘	✘	-	-	✘	✘
JacksonDatabind-84	1.000	1.000	✘	✘	-	-	✘	✘
JacksonDatabind-86	1.000	1.000	✘	✘	-	-	✘	✘
JacksonDatabind-90	1.000	0.715	✔	✘	-	-	✔	✘
JacksonDatabind-103	0.000	0.000	✔	✘	-	-	✔	✘
Jsoup-23	1.000	1.000	✔	✘	-	-	✔	✘
Jsoup-64	0.000	0.000	✔	✘	-	-	✔	✘
JxPath-6	0.882	0.958	✘	✘	-	-	✘	✘
JxPath-10	1.000	0.857	✘	✘	-	-	✘	✘
JxPath-14	1.000	0.886	✘	✘	-	-	✘	✘
Lang-16	0.957	0.992	✘	✘	-	-	✘	✘
Lang-33	0.875	0.929	✔	✔	-	-	✔	✔
Lang-39	0.965	0.976	✔	✘	-	-	✔	✘
Lang-44	0.957	0.984	✘	✘	-	-	✘	✘
Math-5	1.000	0.990	✔	✔	-	-	✔	✔
Math-6	1.000	0.923	✘	✘	-	-	✘	✘
Math-20	0.000	0.979	✔	‡	-	-	✔	‡
Math-33	1.000	0.963	✔	✔	-	-	✔	✔
Math-59	1.000	0.986	✔	✔	-	-	✔	✔
Math-63	1.000	0.986	✔	✔	-	-	✔	✔
Math-75	1.000	0.984	✔	✔	-	-	✔	✔
Math-79	1.000	0.990	✔	✔	-	-	✔	✔
Math-81	0.980	0.975	✘	✘	-	-	✘	✘
Math-88	1.000	0.954	✔	‡	-	-	✔	‡
Math-104	1.000	0.955	✘	✘	-	-	✘	✘
8 defects patched exclusively using SBFL								
Closure-19	0.583	0.729	✘	✘	-	-	-	-
Closure-48	0.256	0.300	✔	✘	-	-	-	-
Closure-59	0.880	0.484	✔	✘	-	-	-	-
Closure-92	0.081	0.233	✔	‡	-	-	-	-
JacksonDatabind-4	0.542	0.567	✔	✘	-	-	-	-
Math-58	1.000	0.667	✔	‡	-	-	-	-
Math-74	1.000	1.000	✘	✘	-	-	-	-
Time-7	1.000	1.000	✔	✔	-	-	-	-

Fig. 7. The 121 defects from Figure 6. "Eval. Test Cov." shows the mean statement coverage of evaluation tests on developer-modified methods and classes. A patch is *correct* (✔) if it passes all of the evaluation tests and manual inspection finds it semantically equivalent to the developer's patch. A patch is *plausible* (✘) if it fails at least one evaluation test or if it passes all of the evaluation tests but manual inspection determines the patch is incorrect; the patches are labeled (‡) if a determination could not be made. The highlighted defects are part of the Defects4J (v1.2.0) benchmark, for which our repair techniques find patches but 14 existing repair tools (including the previous version of SimFix), do not.

project	#defects	SimFix (SBFL)	SimFix (Blues)	SimFix (SBIR)
Chart	8	1/2	1/2	1/2
Closure	133	6/18[a]	3/6[b]	6/15
Lang	65	3/9[a]	2/6[b]	3/10
Math	106	11/25[a]	5/13	11/25
Mockito	38	0/0	0/0	0/0
Time	26	1/2[a]	0/1	0/1
total	376	22/56 (39%)	11/28 (39%)	21/53 (40%)
↓ new projects added in Defects4J (v2.0.0) ↓				
Cli	39	0/3[a]	0/2	0/3
Closure	41	1/5	0/0	1/5
Codec	18	1/2[a]	1/1	1/2
Collections	4	0/1[a]	0/0	0/1
Compress	47	1/5[a]	0/1	1/5
Csv	16	0/2	0/2	0/2
Gson	18	1/1	1/1	1/1
JacksonCore	26	0/3[a]	0/2	0/4[c]
JacksonDatabind	112	2/24[a]	1/12[b]	2/25[c]
JacksonXml	6	0/0	0/0	0/0
Jsoup	93	1/4[a]	1/4[b]	1/7[c]
JxPath	22	1/4[a]	1/2[b]	1/5
total	442	8/54 (15%)	5/27 (19%)	8/60 (13%)
all defects	818	30/110 (27%)	16/55 (29%)	29/112 (26%)

[a] includes defects that could not be patched using Blues .
[b] includes defects that could not be patched using SBFL.
[c] includes defects that could neither be patched using SBFL nor Blues.

Fig. 8. SimFix repair performance on the 818 defects using SBFL, Blues, and SBIR as its FL strategy. Each cell shows the number of correctly patched defects and plausibly patched defects: correct/plausible. The techniques perform much better on the older defects than the newer ones. For example, 39–40% of the patches produced on the older defects are correct, but only 13–19% of the patches produced on the new defects are.

For each defect in the Venn diagram in Figure 6, Figure 7 shows the mean statement execution coverage of the evaluation tests ("Eval. Test Cov.") on the developer-modified methods and classes, and the patch correctness results obtained using evaluation tests ("automated") and manual inspection ("manual").

Comparing our SimFix against the results for 14 state-of-the-art repair tools [24], including the original SimFix, on the six projects used in that evaluation (Chart, Closure, Lang, Math, Mockito, and Time) in Defects4J v1.2.0, reveals that SimFix using our implemented FL techniques produced patches for 10 new defects that none of the 14 repair tools patch. Figure 7 highlights these defects with a grey background.

Comparing the repair performance of SimFix using Blues against iFixR on the 156 defects from Lang and Math projects (the only ones used in iFixR's original evaluation [7]) shows that SimFix using Blues significantly outperforms iFixR. Considering only the top patches produced, SimFix patches 19 out of 156 defects and 7 are patched correctly while IFixR patches 4 defects, out of which 3 are patched correctly. Considering all the patches produced, for 7 of the 19 defects (Lang-27, Math-41, Math-50, Math-53, Math-73, Math-84, Math-85) patched by SimFix, iFixR does not produce a patch; 3 out of these 7 defects (Math-41, Math-50, Math-53), SimFix patches correctly. For 2 defects (Lang-43 and Lang-58), iFixR produces plausible patches while SimFix using Blues produces correct patches. These results show that our Blues outperforms iFixR's IRFL, which extends D&C [38].

RQ3: How does the repair performance vary across the new and old versions of Defects4J benchmark?

project	Closure	Lang	Math	Mockito	Time	Total
#defects	133	65	106	38	26	368
GZ v0.1.1	78	29	91	21	22	241
GZ v1.6.0	95	57	100	23	22	297
GZ v1.7.2	115	54	100	33	22	324

Fig. 9. Comparison of our SBFL to prior SBFLs used for repair based Ochiai and older versions of Gzoltar [24].

Figure 8 compares the repair performance of SimFix using different FL techniques on defects that are newly added in Defects4J (v2.0) against the ones that are part of the older versions. SimFix correctly patches 3–6% (6% when using SBFL, 3% Blues, 6% SBIR) of the defects in the older version of Defects4J, but only 1–2% (2% SBFL, 1% Blues, and 2% SBIR) of the *new* defects. Of the patches SimFix produces on the old defects, 39–40% are correct; for the new defects, only 13–19% are correct. These results shows that SimFix overfits to the defects that are part of older versions and more specifically, to the Closure, Lang, and Math projects' defects.

Comparing the total defects patched using SBFL on Defects4J (v2.0) with the originally reported results that use Defects4J (v1.0) [14] also shows that SimFix overfits to Defects4J (v1.0). On Defects4J (v1.0), SimFix patches 56/357 (16%) of the defects, 34/56 (61%) correctly. Meanwhile, on Defects4J (v2.0), it patches 110/818 (13%) of the defects, 30/110 (27%) correctly. Considering the repair performance on newly added defects in Defects4J (v2.0), SimFix using SBFL patches 54/442 (12%) of the defects, only 8/54 (15%) correctly. The repair performance of SimFix on Defects4J (v2.0) is comparable to the performance of 11 repair tools evaluated on 4 other defect benchmarks, patching 10–30% of the defects [49].

RQ4: Do our techniques outperform the state of the art? Figure 9 compares our SBFL implementation to the results reported for Defects4J (v1.2.0) for SBFL implemented using Ochiai and older versions of Gzoltar [24]. Our SBFL implementation localizes 27 more defects than v1.6.0.

We compare the performance of Blues against the state-of-the-art IRFL technique used by iFixR [7] on the defects that technique was evaluated on (171 defects from Lang and Math projects in Defects4J v1.2.0). Blues outperforms iFixR when considering top 200 suspicious statements, with Blues localizing 130 defects, and iFixR 121. Similarly, when considering all statements the techniques dub suspicious, Blues localizes 153 and iFixR 139. For the top 100 statements, iFixR does better, localizing 117 while Blues 110.

E. Discussion and Threats to Validity

Automated patch correctness evaluation. Our methodology uses automatically generated evaluation tests and revealed that such tests are ineffective for defects the developers repaired by adding new methods, classes, parameters to existing data structures, or arguments to existing methods. For example, for *JacksonDatabind-75*, the patch adds arguments to a buggy method. The evaluation tests generated using the developer-repaired version invoke the updated method, and so do not compile on the SimFix-patched version because the method signature in that version does not match the signature expected by the tests.

Our patch correctness evaluation methodology (Section IV-C) is conservative. Out of the 185 (74 using SBFL, 37 using Blues, and 74 using SBIR), 48 (18 using SBFL, 11 using Blues, and 19 using SBIR) patches were either partially correct or we could not determine the semantic equivalence to the developers' patches because these patches inserted new code or replaced existing code in classes and methods that are different from developer-modified classes. Hence, we annotated them as plausible while keeping a record of such scenarios.

Impact of fault localization success on repair performance. Although studies have shown that being able to patch defects is correlated with being able to localize defects [24], we found that SimFix patched some defects even if they were not localized and failed to patch defects even if they were localized. The former happened when SimFix modified parts of the program other than developer-modified code and the produced a patch that passed all of the tests. For example, *Closure-107* defect was not localized by any FL technique but SimFix using Blues patched the bug. The latter happens when SimFix' repair algorithm was not able to construct a faulty code snippet that covered all of the defective statements using the statements from the ranked list of suspicious statements. For each suspicious statement, SimFix expands the statement (at most by ± 5 lines) to construct multiple faulty code snippets and computes their similarity with the candidate code snippets (mined from elsewhere). A pair of faulty and candidate code snippets with highest similarity score is then used to construct a patch. If a defect involves non-contiguous faulty statements and SimFix is unable to construct a faulty code snippet that covers all of the faulty statements, then it failed to patch that defect. For example, for *Time-7* defect, both SBIR and Blues identify the correct faulty statements (lines #708, 710 in class `org.joda.time.format.DateTimeFormatter`) as suspicious and do not identify the non-faulty statement (line #709) while SBFL identifies all three statements as suspicious (because all of them are executed by same tests). It turns out that SimFix needs line #709 to construct a faulty code snippet that covers both of the faulty statements (line #708 and line #710) which can be replaced by a candidate code snippet. Thus, SimFix using SBFL patches Time-7 defect while SimFix using SBIR and Blues does not even though all three FL techniques correctly identify defective statements. This behavior is specific to the way SimFix uses the FL results to construct a patch. Thus, to improve repair performance, just using a better FL technique may not suffice as the performance also depends on the way repair tools process the FL results to construct patches. While we wanted to consider more repair tools in our study, we found that FL implementation is often tightly coupled to the tools' implementation and requires substantial engineering effort for experimental adaptation. Besides, different tools generally use different methods to process the FL results which are hard to isolate and control for to perform study on multiple tools.

V. Related Work

Statement-level IRFL. Existing IRFL techniques, produce a ranked list of suspicious files instead of suspicious statements [33]–[37]. iFixR [7] produces ranked statements from ranked suspicious files using pre-trained D&C models [38]. We do not extend D&C in our study because the training dataset of the pre-trained model overlaps with our evaluation dataset (recall Section III-B). By contrast, our Blues uses an unsupervised approach and therefore does not require training to produce ranked statements.

Combining FL techniques. Existing techniques that combine multiple FL techniques, such as CombinedFL [27], DeepFL [28], Fluccs [66], Savant [29], MULTRIC [39], and TraPT [62], use *learning to rank* [67] algorithms that consider the suspiciousness scores from multiple FL techniques as features, and train a model to predict if a given program element is defective based on those features. PREDFL, the most recent technique, combines SBFL and statistical debugging using a unified model that combines runtime statistics computed by the two techniques [92]. By contrast, RAFL uses a generic, unsupervised approach to combine multiple FL techniques.

Fault Localization in Program Repair. Most repair tools use SBFL implemented using off-the-shelf coverage tracking tools and the Ochiai ranking strategy [10]–[21]. R2Fix [26] and iFixR [7] are the only two IRFL-based repair tools, and no prior repair tool uses combined SBFL and IRFL. Although, using patch-execution results from repair tools to refine FL results can outperform state-of-the-art SBFL and MBFL techniques [9]. Recent studies have shown the effect of using different technologies, assumptions, and adaptations of test-suite-based FL techniques on the performance of repair tools [4]–[6], [8], [15], [24], [25]. Often, program repair researchers omit FL tuning used by their repair tools while presenting repair performance, which leads to bias in comparing performance of different repair tools [24]. Further, the FL implementations are often tightly coupled to the repair tool implementations, which makes it hard to use the FL for other repair tools, or improve the FL. Our FL toolkit can be used to mitigate this bias as it can serveas a plugin by future repair tools to decouple their FL implementations from their repair algorithm implementation, as is done in some frameworks, including JaRFly [44].

VI. Contributions

We have investigated the effect of combining SBFL and IRFL on automated program repair. We presented RAFL, a novel unsupervised approach to combine multiple FL techniques, and Blues, a statement-level IRFL technique. SBIR, which combines an SBFL technique and Blues, localizes more defects and ranks defective statements higher than the underlying SBFL and Blues. SimFix, using SBIR, produces patches for more defects than the underlying SBFL and Blues, while retaining almost all of the correct patches. Our results demonstrate that combining SBFL and IRFL leads to better fault localization, and enables program repair to benefit from the complementary benefits of the two approaches, warranting further research into improving program repair by combining SBFL and IRFL.

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