UNIVERSITY OF CALIFORNIA,
IRVINE

Towards Parallelization of Regression Test Selection

THESIS

submitted in partial satisfaction of the requirements
for the degree of

MASTER OF SCIENCE

in Software Engineering

by

Maruf Hasan Zaber

Thesis Committee:
Professor Cristina V. Lopes, Chair
Associate Professor James A. Jones
Assistant Professor Joshua Garcia

2021

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ALGORITHMS

ACKNOWLEDGMENTS

I could not have accomplished this research and thesis without the continuous support and encouragement of many people who are close to me professionally and personally. More precisely, I would like to express my gratitude to my dissertation committee members, colleagues, friends, and family.

First and foremost, I want to thank my advisor, Professor Cristina Videira Lopes for her valuable guidelines and continuous support. My journey in graduate school has been particularly nuanced and oftentimes, difficult for various professional and personal reasons. Crista always encouraged me to freely pursue projects that I am interested in and make career moves as I deem suitable for me. I think her research insights, engineering acumen, and career guidelines will always help me to be a better engineer.

I want to thank my thesis committee members, Prof. James A. Jones and Prof. Joshua Garcia for their valuable comments and suggestions. I was a teaching assistant for Prof. Jones for two quarters. I learned a lot about Software Testing, the overarching theme of this very thesis, by working with him in the Software Test Debug course. Josh was my de-facto co-advisor on this research on regression test selection. This work would not have been possible without his valuable, in-depth, and domain-specific advice. Josh went above and beyond in helping me write papers for ASE and ISSTA. Josh, thank you very much!

I want to thank my colleagues in the Mondego Lab, Farima FarmahiniFarahani, Vaibhav Saini,Di Wang, Rohan Achar, and Pedro Martins for their insightful questions and intellectual company. I enjoyed so much working with you all and I wish you all great success in your career. I want to thank the Informatics department manager, Marty Beach, ICS student counselor Julie Oh, Kaelyn Costa, and Leslie Escalante, and international student advisor Ruth Ortega for making my time in the department and in UCI so seamless.

Big shout out to my friends in UC Irvine, Pedro Matias, Sumaya Almanee, Janus Vermanken, Nil Mamano, Sameera Ghayyur, Efi Karra, Ned Beigi, Evita Bakopolou, Prabhu Rajasekaran, Ke Jing, Ted Grover, Syed Andalib, Wahiduzzaman Khan, and Rufaida Anagh. Thank you for keeping me sane in this long and arduous endeavor. Big thanks to my friends Sakib Malek, Mehrab Morshed, Sakib Sauro, Abdul Mumit, and Prithvi Zareen, Adij Khan, Habib Tawhid, and Shuvo Mahmud for always being in touch while being so far geographically.

Big shout out to my family. I am what I am today because of the dream that was instilled in me by Ammu and Abbu. The amount of support, dedication, and courage they have shown in every step of my life is monumental. Ammu and Abbu, you are the champions. Big shout-out to my sisters, Ummul Mahfuza and Ummul Mahmuda. Both of you are my role models and will always remain so.

ABSTRACT OF THE THESIS

Towards Parallelization of Regression Test Selection

By

Maruf Hasan Zaber

Master of Science in Software Engineering

University of California, Irvine, 2021

Professor Cristina V. Lopes, Chair

Regression Test Selection (RTS) is a set of techniques for selecting a subset of test cases from the test suite based on the changes in source code. RTS tools may select tests in different granularity, namely file-level, class-level, or method-level. File- and class-level tools are less precise than method-level tools, but they are simpler, and carry considerably less execution overhead in test selection. In this thesis, we show how method-level test selection can be made efficient by appropriate use of inverted indexing and parallel processing. We present a static method-level RTS tool, TLDR – a Maven plugin for unit testing with JUnit 4.x. Like other static RTS approaches, TLDR extracts the firewall of each changed method or field to compensate for dynamic dispatch. The main difference with other RTS tools is that it has a configurable and multi-threaded *Pipe and Filter* architecture, with several in-memory inverted indexes for fast lookup. We conducted 23.5 hours of experiments on 20 popular open-source Java projects where we compared TLDR with state-of-art RTS tools like Ekstazi, STARTS, and HyRTS, and traditional unit testing methods like retest-all and parallel retest-all. Our evaluation has shown that TLDR is both more precise and more efficient than contemporary RTS techniques like Ekstazi, STARTS, HyRTS, retest-all, and parallel retest-all.

Chapter 1

Introduction

Software artifacts evolve throughout their life-cycle—undergoing changes, additions, and deletions. These software modifications often result in errors or unintended behaviors in portions of the software. Therefore, robust unit and integration testing are warranted to maintain integrity and coherence in iterative software development. The safest method to identify bugs, errors, and faults is to run a set of tests that covers the entire software artifact i.e the complete test suite. This practice is referred to as *Retest-all* in the literature [35, 63, 42]. Unfortunately, Retest-all is time-consuming and computing-intensive, hence impractical for large-scale repositories. For example, the complete test suite of Apache Hadoop takes approximately 17 hours to complete [20]. Furthermore, the resulting test reports from Retest-all are often too large for manual inspection and intervention. For example, Microsoft Windows 8.1 had more than 30 million tests [28], which made it impractical to tackle all at once. For these reasons, in projects with large test suites it is desirable to perform *regression test selection (RTS)*, i.e., select and run a subset of the complete test suite that assesses only the code that is affected by changes to the software [41, 12, 51].

RTS has been the target of extensive research spanning decades [49, 35, 63, 42, 52, 65, 29].

Despite an abundance of techniques reported in the literature, this form of software testing is still not prevalent in practice. To a large extent, this lack of adoption occurs because (1) the overhead of selecting a subset of tests can be more expensive than just running the entire test suite [68]; (2) the inability of RTS to scale to large programs [42]; and (3) the risk of missing required tests [50].

In object-oriented languages, one important dimension of variability among RTS tools is the granularity of test selection. RTS tools can select tests at file-level (all tests in a test file), class-level (all tests in a test class), or method-level (individual unit tests). Method-level RTS is more precise than the coarser variants, and therefore it might seem the most desirable approach to RTS, as it might result in faster test execution time (fewer tests). However, research has shown that the existing method-level RTS techniques are slower than class- and even file-level RTS because of the large overhead involved in tracking dependencies at such fine granularity [32, 68]. This is the problem targeted by our work.

In this thesis, we present TLDR, a static and method-level RTS tool for Java that is both precise and efficient. TLDR simulates the polymorphism principle of OOP, using static analysis. TLDR achieves safety by selecting all tests that correspond to an entity's *firewall*, the set of entities which may be impacted given a change to an entity [61, 60, 58]. To improve the precision of RTS, TLDR selects tests at the method-level like *FaultTracer* [68]. However, unlike other RTS tools, TLDR leverages a novel multi-threaded *pipe-and-filter* architecture [56].

Most RTS techniques follow a common sequence of steps: identifying changes in source artifacts (e.g, source code, machine code, jars, etc.), constructing dependency graphs, traversing the graphs to find impacted entities, and finally mapping the impacted entities to one or more test cases in the test suite [67, 20, 19, 33, 34, 68]. In all existing RTS tools, these steps are performed sequentially. However, the pipeline is such that some of these steps can be executed in parallel. The efficiency of TLDR comes from two aspects of its design. First, selecting

tests at the method-level makes it more precise, reducing the number of tests to be retested, as well as the test execution time. This is theoretically true for all method-level RTS tools, but it has been difficult to achieve in practice. Second, and most importantly, parallelizing some steps of the test selection pipeline increases the throughput of the dependency analysis process, making test selection faster. These aspects, together, result in reduced end-to-end testing time for TLDR.

In this thesis, we empirically show that through the adoption of parallelism, method-level RTS can be efficient compared to class-level RTS. In summary, this thesis makes the following novel contributions:

- We propose a multi-threaded pipe-and-filter architecture for RTS tools that reduces test selection overhead.
- We construct a precise RTS technique, TDLR, that operates at a finer-granularity (i.e., the method-level) and utilizes the proposed pipe-and-filter architecture to achieve major reductions in the time needed to actually execute test cases.
- We evaluate TLDR on 20 open source Java projects. We also compare the performance in terms of times with state-of-the-art RTS techniques, Ekstazi, STARTS, HyRTS as well as more conventional testing techniques like retest-all and parallel-retest-all. We show that TLDR is 2.7 times more precise than STARTS, 2.1 times more precise than Ekstazi, and 1.4 times more precise than HyRTS. Due to its better precision and more efficient test selection technique, TLDR is 1.5 times faster than Ekstazi, 1.7 times faster than STARTS, and 1.2 times faster than HyRTS.

The remainder of the thesis is organized as follows: In Chapter 2, we discuss the core concept of regression test selection and contemporary RTS tools. In chapter 3, we discuss relevant literature on regression test selection. In chapter 4, we discuss the theoretical concept of our

approach to RTS and compare TLDR with other state-of-art RTS tools with an example. In chapter 5, we present our main contributions, i.e., the design and implementation of TLDR. In chapter 6, we discuss the theoretical proof of TLDR's correctness and completeness. In chapter 7, we discuss the empirical evaluation of TLDR. In chapter 8, we discuss the limitations of TLDR and threats to the validity of our evaluation. Finally, in chapter 7, we discuss the future work and concluding remarks.

Chapter 2

Background

The idea of selecting a smaller set of regression tests based on what parts of the code changed is at least three decades old [35]. Since its introduction, numerous techniques and tools have been proposed. We focus on recent techniques that target Java programs in this thesis. In this chapter, we lay the theoretical background of regression test selection along with examples and discuss several contemporary RTS tools.

2.1 Regression Test Selection

Regression test selection (RTS) is a technique of selecting and executing a subset of tests instead of the complete test suite in a way that is still safe i.e achieves the same test result in each iteration [13, 21, 22]. A high-level overview of RTS is shown in figure 2.1. There are two main steps of RTS, namely, *analysis phase* and *execution phase*. In the analysis phase, the tests that are affected by the current change are identified. This step requires storing information about the latest iteration i.e. commit of the repository, for example, state of each source-code files and external files, dependency graph, and test-to-source map. In each

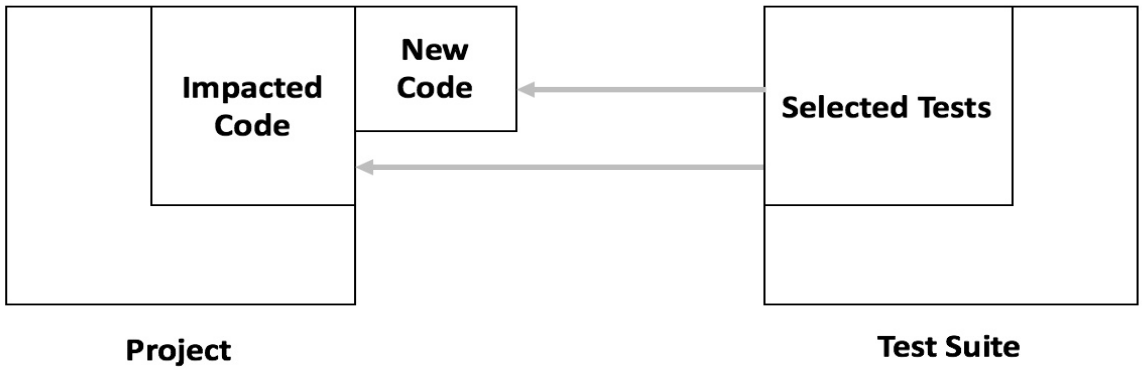


Figure 2.1: High-level overview of Regression Test Selection.

iteration, the repository is parsed statically and compared with the stored state to analyze the change in the current iteration. Once the changes are identified, the stored dependency graph is updated. In some RTS tools this stage is considered as a separate phase of analysis i.e. *Collection Phase* [22]. Then from the nodes that correspond to the changed entities i.e. packages or classes or methods, the dependency graph is traversed to find out all the entities that are impacted by the changes in the current iteration. This set of entities is called *firewell*. In the second step of RTS, each test function that covers the entities that belong to the *firewell* is selected and run.

The analysis required for RTS can be expensive. However, the efficiency of RTS stems from the minimization of the test suite. It selects and runs significantly fewer number of tests compared to the entire test-suite, therefore, incurs less end-to-end testing time. RTS can result in larger end-to-end time for smaller test suites or iterations where a substantial among of code refactoring has been done. However, RTS guarantees that the average end-to-end time for a series of iterations is always less than the *retest-all*. Oftentimes, RTS is combined with test prioritization for better efficiency. For example, instead of the complete project, RTS can be run only on the parts of the project that are visible to the user, bug- or error-prone, critical to the business requirement, or complex. Other optimization approach involves parallelly running the selected tests [8]. However, no prior work has explored the scope of parallelization

in the test selection process. In this thesis, we explore the application of parallelization in test selection as well as test run to achieve better optimization.

2.2 Types of RTS

RTS tools vary along three overarching dimensions: (i) the granularity of test selection, (ii) the granularity of change impact analysis, and (iii) how dependencies are collected.

2.2.1 Granularity of Test Selection

In Java programs, test suites are encapsulated in a set of test classes, each one containing one or more test methods. These test classes are placed within test packages. RTS tools can select tests by package i.e. all test methods within the selected package, by classes i.e. all test methods within the selected test classes, by methods i.e. precisely selected test methods. The test methods in a test class often rely on common setup and tear-down code, but good practices dictate that each test method be independent of the others, which does not always happen. Therefore, the first decision an RTS technique for Java programs must make is the granularity of test selection. Because test methods are supposed to be independent of each other, in theory, method-level test selection allows us to identify exactly the least amount of tests to be selected for a given change. However, it has been observed that sometimes projects do not follow the principle of test method independence [39]. Therefore, the extra complexity and runtime overhead associated with selecting individual methods instead of classes may not be justified in practice. This is a design decision that benefits from collecting empirical data about how Java developers write test suites. Nevertheless, if the overhead of selecting test methods is low, and assuming that at least some test suites follow test method independence, it will always be desirable to select individual tests.

2.2.2 Granularity of Change Impact Analysis

Another dimension of variance is the granularity of change impact analysis. Source code can be analyzed at four different levels of granularity: file-level, class-level, member-level (i.e. methods and fields), and statement-level. On the one hand, the smaller the granularity of analysis, the more precise RTS can be. For example, if only the name of a local variable changed, statement-level change impact analysis should be able to infer that no regression testing would be necessary for that change because it had no impact; member-level analysis would identify that particular method as the only entity that needs retesting; class-level analysis would select that entire class as the entity to be retested; and finally, file-level analysis would select that file, possibly with many classes, as the entity to be retested. On the other hand, the smaller the granularity of analysis, the more complex RTS becomes, and that often comes with additional runtime overhead that may not compensate for the increased precision of test selection. Particularly, for larger projects, small granularity can be impractical because building precise dependency graph will be prohibitively expensive. Contrarily, coarser granularity is less precise. For example, a class-level RTS tool would select all the test methods within an impacted test class even if only one out of many test methods was impacted by the latest change. The inefficiency induced by the imprecision is compensated by the efficient test selection process as it is significantly less expensive to build and traverse class-level or file-level dependency graph. However, if the change in the source-code is distributed across many files coarser-granularity RTS tool can be impractical because it will select a significantly large number of unwanted test methods.

2.2.3 Dependency Collection

Change impact analysis requires the construction of a dependency graph among entities – files, classes, methods, and even statements – of the subject project. The third dimension

along which RTS techniques differ is in how they build the dependency graphs. There are two main ways of gathering dependencies: static analysis [17, 34], and dynamic analysis [20, 68]; a third approach is to use both [67]. Dynamic analysis of dependencies is particularly desirable for object-oriented languages because of their dynamic binding features [53]. Dynamic dependency graph generation is prohibitively expensive for finer granularity, such as member-level, making such RTS techniques impractical [14]. However, dynamic RTS is safe as it captures the actual firewell. Static RTS tools, contrarily, captures dependency by static analysis of the source offline. Safety is maintained by traversing the entire class-hierarchy of the impacted members. However, if the repository makes use of reflection, instrumentation, or if any external resources, for example, external files, database are used static RTS can be unsafe.

2.3 Regression Test Selection Techniques and Tools

In this section, we describe four contemporary RTS tools for Java projects, namely, FaultTracer [68], Ekstazi [20], STARTS [34], and HyRTS [67]. Among these four tools, FaultTracer and HyRTS are not open-source. We collected HyRTS from the author of the tool. However, we could not collect FaultTracer's artifact. Hence, STARTS, Ektazi, and HyRTS are used as baselines to evaluate the proposed RTS tool, TLDR.

2.3.1 FaultTracer

FaultTracer is one of the earliest RTS tools written in Java [68]. FaultTracer is a dynamic RTS tool that analyzes changes in statement-level and selects tests at method-level. Given two versions of a program, in order to find all atomic changes in the program, it builds an enhanced call graph called *Extended Call Graph (ECG)* that augments the traditional

method call graph with field access information. ECG is built by statement-level analysis of the source-code. Furthermore, in order to reduce manual inspection, FaultTracer combines change-analysis-based test selection with a fault localization component. For each failed test in the current iteration, it ranks the atomic changes based on their suspiciousness. To calculate the suspicious score of a particular edit, it adapts four spectrum-based fault location techniques. These techniques are based on the following heuristics (i) statements that are only covered by failed tests are more suspicious, (ii) statements that are executed by more number of failed tests than passed tests are statistically more suspicious, (iii) statements whose Jaccard Similarity Coefficient [1] i.e. ratio between the number of associated failed tests and the summation of the number of all failed tests and number of associated passed tests, are higher, are more suspicious, and (iv) statement whose Ochiai coefficient [1, 66] is higher, is more suspicious.

2.3.2 Ekstazi

Ekstazi is the most popular open-source RTS tool for Java. This is a Maven plugin that runs RTS for Java unit tests [20, 19]. Ekstazi is a dynamic RTS tool that analyzes changes by file-level granularity and selects tests by class-level granularity. Since Ekstazi has coarser granularity, it selects higher number of tests. However, due to its efficient test selection technique, it incurs less end-to-end testing time. Ekstazi runs into three phases, namely, *analysis phase*, *execution phase*, and *collection phase*. In the analysis phase, Ekstazi calculates the checksum of each file in the repository and compares with previously-stored checksum to find out the changed files. After that, it selects the tests that cover these files. In the execution phase, it dynamically updates the list of tests to be run by the Maven test executor i.e. *Surefire* to run only the selected tests. In the collection phase, Ekstazi instruments the stack-trace of the selected tests to collect dynamic dependencies. Since Ekstazi collects file-level dependencies dynamically, it is safe even if the repository uses external resources.

The artifact publicly available in this URL - https://github.com/gliga/ekstazi.

2.3.3 STARTS

STARTS is a class-level static RTS tool [34]. Like Ekstazi, this is also a Maven plugin for Java unit tests. STARTS efficiency stems from efficient compile-time code analysis as it does not involve instrumentation or reflection which are computationally expensive. Like Ekstazi, STARTS also stores and compares the checksum of each class for change analysis. STARTS computes the firewall of each changed class by traversing the transitive closure in the static dependency graph. In object-oriented programming language like Java, dependencies are resolved in run-time. Therefore, in order to uphold safety, STARTS adds redundant edges to all the classes in the class hierarchy. Therefore, the firewall of each changed class includes all the classes that are impacted or may have been impacted by the recent change. The inefficiency, induced by the selection of higher number of tests is compensated by the efficient test selection. STARTS is publicly available in this URL - https://github.com/marufzaber/STARTS-Fork.

2.3.4 HyRTS

HyRTS is a class-level dynamic RTS tool [67]. However, unlike Ekstazi and STARTS, HyRTS implements a hybrid-granularity change impact analysis, therefore, combines the strength of both class-level and method-level RTS techniques. HyRTS performs method-level analysis for method-level changes like addition, deletion, and edition of statements, addition, and deletion of methods, etc., and class-level analysis for class-level changes like addition and deletion of files, class header change. HyRTS performs these two different granular analyses in two separate phases and finally, combines the selected tests. Like Ekstazi, HyRTS has a separate collection phase that collects dependencies by instrumenting the

stack-trace of the selected tests. However, a hybrid RTS tool that collects dependencies offline has been documented to be more efficient than the one that collects dependencies online due to the overhead of instrumentation. HyRTS is publicly available in this URL - https://github.com/marufzaber/HyRTS-Fork.

Chapter 3

Related Work

A plethora of research on incremental testing of software repository can be found in the literature [35, 26, 25, 51]. The core concept of regression testing can be generalized across languages [27, 26]. Nonetheless, implementation of RTS tool largely varies across platforms i.e. build tools, environments, or even requirements. Despite this research literature spanning decades, RTS techniques are not used in mainstream software-development practice. Also, a bulk of RTS tools are not safe [25]. Even for intuitively safe RTS tools, proving safety is difficult. However, RTS tools still hold promises. This is evident from, Ekstazi, which has been adopted in several open-source projects. In this section, we describe previous work on RTS, including the use of change impact analysis in the context of RTS, the granularity at which RTS operates, and the use of static and dynamic information for RTS.

3.1 Change Impact Analysis

Change impact analysis (CIA) [36] is critical for RTS, allowing techniques to determine which tests should be selected for re-execution. Li et al. propose a framework for change impact

analysis with nine overarching characteristics, namely, object i.e. input-output, impact set, type of analysis i.e. static or dynamic, intermediate representation, language support, tool support, and empirical evaluation. Acharya et al. [2] found that static slicing-based CIA does not scale for larger projects. *PathImpact* uses dynamic slicing to perform CIA [31]. However, the technique was reported to be unsafe as it depends on the operational behavior of the software. Gethers et al. [18] found that a combination of information retrieval, data mining, and source code analysis yields better precision and recall for CIA. Ren et al. [48] introduced *Chianti*, a fine-grained change impact tool for Java. Chianti can isolate all semantically meaningful atomic changes that can potentially impact a test. Buckner et al. proposed *JRipples*, an eclipse plugin that assists developers with debugging and relies on CIA at the class level [7]. Goknil et al. [24] propose a technique for CIA at the architecture-and-design level.

Static CIA can be imprecise for object-oriented languages due to dynamic binding. However, static code analysis can be more efficient than dynamic analysis. Bacon proposed a fast algorithm for virtual method call resolution in C++ [4]. Dean et al. used proposed a fast static analysis algorithm for class hierarchy in OOP [11]. These techniques can be leveraged to optimize software where throughput is an important performance metric [9], such as operating systems and compilers.

3.2 Granularity of Regression Test Selection

The granularity of RTS has been studied extensively where different studies have found contradictory results. Bible et al. conducted a comparative study among RTS at varying granularity [5]. They compared TestTube [10], a coarse-grained RTS tool with DejaVu, a fine-grained RTS tool, in terms of precision and analysis times required by the techniques. They argue that a hybrid approach is more promising, which contradicts Legunsen et al.'s

recommendation of a coarse-grained approach [33]. In their evaluation, method-based RTS selects more tests, making it less precise than class-based RTS [33]. RTS at a coarser granularity, although less precise, has been shown to be effective nonetheless through the RTS technique Ekstazi [20] [20].

Method-based RTS tends to be more precise while incurring a greater cost (e.g., computational cost) for analyzing code. For example, Gligoric et al. propose RTS++, a call-graph-based RTS tool for C++ which runs at the function level. This tool was evaluated to be on average 38% faster than re-test all. Method-level RTS selects fewer tests compared to coarser-grained RTS tools [68, 67, 17]. However, reducing the test execution time might not necessarily yield shorter end-to-end testing times because the overhead of CIA for method-level RTS can be substantial. For example, in certain cases, *FaultTracer* can be more expensive than retest-all [68]. Whether the cost stems from implementation issues or only from the computational load is not apparent [68].

Our evaluation of TLDR demonstrates that by incorporating parallelism across the RTS pipeline, careful selection of checksum algorithms, and efficient database design, method-level RTS can outperform coarser-grained RTS.

3.3 Dependency Collection in RTS

Ekstazi selects tests at the class level based on dynamic dependencies at the file level [20]. However, dynamic RTS is not always faster than static RTS [68]. To optimize the efficiency of dynamic test selection, RTS techniques are often designed to run in different phases. Orso et al. first proposed an RTS technique that involves two phases: a partition phase and selection phase [43]. Ekstazi runs in three phases: analysis, execution, and collection phases [20].

Static RTS has been studied for decades but has achieved little industry adoption. STARTS is

a static RTS technique that selects tests at the class level [34]. Legunsen et al. [33] conducted a comprehensive study of static RTS tools at different granularities and found that the safety issue of static RTS mainly arises from dynamic dispatch. They evaluated Ekstazi and STARTS [34] with a method-level RTS technique [32] and found that the method level is an order of magnitude more expensive than class-level static and dynamic RTS. Contrary to their results, we have observed that TLDR, a method-level technique, takes less time for end-to-end testing than coarser-grained RTS tools. We believe this performance gain stems from the application of parallelism, the selection of an efficient checksum algorithm, and our efficient database schema design.

Hybrid approaches have also been proposed by researchers. Chen et al. [10] proposed TestTube, an RTS tool for C that utilizes both static and dynamic analysis of source. Static analysis is performed to detect source code change while dynamic analysis is conducted for dependency resolution [10]. Panigrahi et al. proposed a hybrid RTS for object-oriented language [46]. This tool extracts control and data dependency from dynamic dependency graph and extracts program change by analyzing UML state machine models of the changed code.

Overall, TLDR and its evaluation demonstrate that using static information without dynamic information can result in an RTS technique that is precise. safe with respect to all changes in source files of projects that do not involve reflection, and highly efficient in terms of end-to-end testing time. However, further improving RTS through a hybrid static-and-dynamic RTS technique is an interesting avenue for future work.

Chapter 4

Parallelization of Regression Test Selection

In this chapter, we propose a novel, method-level, and static RTS tool, TLDR. We discuss how TLDR compensates the computational expense of finer-granularity change impact analysis by the application of parallelism. We then compare TLDR with other contemporary RTS tools through a synthetic example.

4.1 Concept

We saw in chapter 2 that properties of RTS tool have a varying degree of performance implications. Table 4.1 shows how each category of RTS tools varies in terms of precision, test selection time, and test execution time. As we can see, finer granular RTS tools have shorter test execution time because they select fewer tests. However, they incur large test selection time because change impact analysis in finer granularity is more expensive. Again, Static RTS tools have shorter test selection time, thus have shorter end-to-end time. Therefore, an

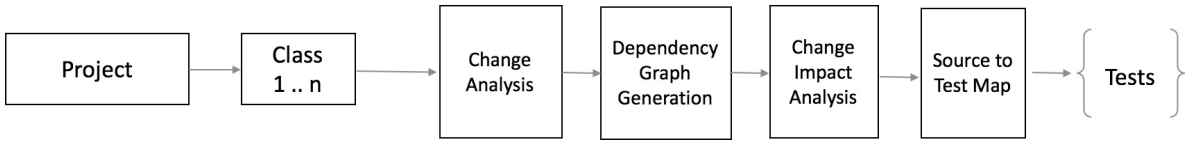
efficient RTS tool that incurs lesser end-to-end time should be static. Moreover, it should combine the benefits of finer- and coarser-granularity RTS tools. As mentioned earlier, a finer granularity RTS tool incurs more test selection time. In this thesis, we explore the application of parallelism in the change impact analysis technique of a finer-granularity RTS tool to reduce the test selection time as well which will, in turn, reduce the end-to-end time. Therefore, we design TLDR, a method-level and static RTS tool that leverages an efficient and parallel *pipe-and-filter* architecture [23, 47] along with a set of in-memory inverted and forward indices.

Figure **??** shows the pipeline of a sequential RTS tool which includes four modules, namely, Change Analysis, Dependency Graph Generation, Change Impact Analysis, and Source to Test Map. In contemporary RTS tools, these phases are completed sequentially [20, 34, 67, 68]. A key observation is these modules are partially independent for each class. For example, while we are analyzing recent changes in one class, we can analyze another class parallelly in the pipeline. Dependency graph construction must be synchronized among the classes as they are interdependent. However, after the dependency graph has been constructed, change impact analysis and source to test map are independent steps for each class. Therefore, given appropriate synchronization, we can employ multiple worker threads among each module and dramatically reduce the throughput of the pipeline. The core concept of TLDR is based on

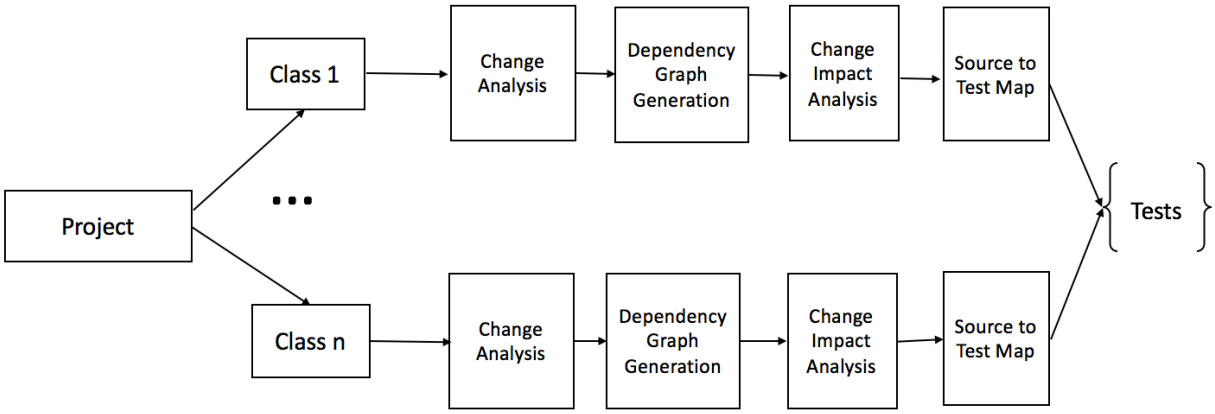
Table 4.1: Categorization of RTS Techniques

Property	**Category**	**Precision**	**Test Selection Time**	**Test Execution Time**
Granularity of Test Selection	Package Class Member	Very Imprecise Imprecise Precise	Small Moderate Large	Very Large Large Small
Granularity of Change Analysis	File Class Member Statement	Very Imprecise Imprecise Precise Very Precise	Small Moderate Large Very Large	Very Large Large Small Very Small
Dependency Collection	Static Dynamic	NA NA	Small Large	NA NA

this parallel pipe-and-filter architecture. It parallelly passes each class of the project in the pipeline. In each module, a worker thread consumes the outputs of the preceding module. The worker threads that are not currently busy consume the outputs from a blocking queue. Ultimately the pipeline outputs a set of tests. We will discuss the design and implementation of TLDR in chapter 6.



(a) Sequential RTS pipeline



(b) Parallel RTS pipeline

Figure 4.1: Generic pipeline of regression test selection.

4.2 Example

Table 4.1 summarizes the similarities and differences among four recent techniques, as well as our own, i.e., TLDR. What follows is an explanation of this table, followed by one concrete example of how three of these tools behave in the presence of a given change.

Below, we explain the functionality of TLDR compared Ekstazi, STARTS, and HyRTS to

illustrate how these three approaches differ along the dimensions of Table 4.1. Table 4.3 shows an example Java project. Column *Source* shows the source code and column *Test* shows the test suite of the project. For each method in the source code, there is a test method in the test suite. Class `A` is extended by classes `B, D` and class `B` is extended by class `C`. Each of the sub-classes overrides method `A.f2`. Method `A.f1` is overridden by `C` and `D`.

The test selection sets when method `B.m1` changes are:

- Ekstazi: all test methods in `TestA, TestB`, and `TestC` – 6 tests.
- STARTS: all test methods in `TestA, TestB, TestC`, and `TestD` – 8 tests.
- HyRTS: test methods `TestB.tM1, TestA.tF1, TestC.tF1` – 3 tests.
- TLDR: test methods that reach, or might reach, `B.m1`, specifically `TestB.tM1, TestA.tF1, TestC.tF1`, and `D.tF1` – 4 tests.

Both Ekstazi and STARTS select tests at class level, so if any one test method needs to be retested, the entire class where that method is declared will be retested. TLDR selects tests at individual method level, so it can be more precise, as this example shows – 4 test methods instead of 6 (Ekstazi) or 8 (STARTS). However, since this is an atomic change within the class, HyRTS only selects 3 methods. STARTS and TLDR use static analysis for tracking dependencies, while Ekstazi and HyRTS use dynamic analysis. Therefore, Ekstazi and HyRTS are more precise with respect to inheritance and method overriding. Let's look

Table 4.2: Categorization of RTS Tools

Technique	**Granularity of Test Selection**	**Granularity of Change Analysis**	**Dependency Collection**
Ekstazi [20]	Class	File	Dynamic
STARTS [34]	Class	Class	Static
HyRTS [67]	Class/Method	Class/Method	Static+Dynamic
FaultTracer [68]	Method	Statement	Dynamic
TLDR	Method	Member	Static

Table 4.3: An Example Java Project

Source

```
class A {
  String f1() { return new B().m1() +
      "a";}
  String f2() { return "a1";}
}
class B extends A {
  String m1() { return "b";}
  String f2() { return "b1";}
}
class C extends B {
  String f1(){ return super.f1() + "c";}
  String f2(){ return "c";}
}
class D extends A {
  String f1(){ return "d";}
  String f2(){ return "d";}
}
```

Tests

```
class TestA {
    A obj = new A();
    void tF1(){ assert(obj.f1() !=
        null);}
    void tF2(){assert(obj.f2() !=
        null);}}
class TestB {
    B obj = new B();
    void tM1(){assert(obj.m1() != null);}
    void tf2(){assert(obj.f2() !=
        null);}}
class TestC {
    C obj = new C();
    void tF1(){assert(obj.f1() != null);}
    void tF2(){assert(obj.f2() != null);}
class TestD {
    A obj = new D(); // <--- note the
        declaration as A
    void tF1(){assert(obj.f1() != null);}
    void tF2(){assert(obj.f2() != null);}
```

at the consequences of static vs. dynamic analysis for the test method `TestD.tF1`. That method instantiates a `D` object, but statically declares it as type `A`. Being an instance of `D`, and given that `D` overrides `A.f1`, the test method `TestD.tF1` does not need to be selected when `A.f1` changes. In this case, Ekstazi is able to identify that the `A`-object created in `TestD.tF1` is an instance of subclass `D`, while both STARTS and TLDR are unable to do so.

Now let us consider another scenario where `Class D` is made to extend `Class C` but no method is changed. The test selection sets for this change are:

- Ekstazi: all test methods in `TestD` – 2 tests.
- STARTS: all test methods in `TestA, TestD`, and `TestD` – 4 tests.
- HyRTS: test methods `TestD` – 2 tests.
- TLDR: No test method is selected – 0 tests.

Even if no method was changed, `ClassD` will have different checksum, therefore, Ekstazi will select `TestD` and STARTS will select `TestA, TestD`. HyRTS considers class hierarchy change as class header change, thus it will perform file-level analysis and test selection. Therefore, it will select `TestD`. However, TLDR detects that even though the class hierarchy has been modified, no method was updated. Therefore, it will not select any test method.

Chapter 5

TLDR Design and Implementation

In this section, we discuss the design and implementation of TLDR. We first discuss the main algorithms of TLDR, and show how they can be parallelized. Then we describe the architecture of the implementation and each module in detail.

5.1 Test Selection and Dependency Extraction

Algorithm 1 describes the test selection algorithm underlying TLDR. The procedure takes two versions of a project as input – $project_n$ and $project_{n-1}$ – and returns the set of selected tests, *selected*. It does so by iterating through all class files of the latest version, checking for new, modified, and deleted ones. For new and modified classes, it then iterates through their declared members (methods and fields), checking for new, modified, and deleted members. For new and modified members, it extracts their static dependencies – an algorithm explained next. Changes in classes and members are calculated by the checksum of their corresponding byte code using *BLAKE2B* [3], an efficient checksum algorithm.

After updating the dependency graph, algorithm 1 then generates *goldset*, which is a set of

all members that may have indirectly been affected by changes in $project_{n-1}$, by performing a depth-first search (DFS) over the dependency graph (line 30 of the algorithm). Each method or field in *goldset* is mapped to one or more tests that have dependencies on those entities. Test methods may have dependencies on other test methods and fields. Therefore, in order to select all impacted tests, transitive dependents of each test method in *mapped* are collected. Finally, the set of tests, *selected*, is generated by another DFS in the dependency graph, but this time only traversing test-test dependency edges.

For each changed or new $file$, Algorithm 1 finds all new and changed members, and updates the dependency graph of changed methods by calling Algorithm 2, our dependency extraction algorithm. This algorithm takes a method that has been changed and updates the global dependency graph by processing the bytecode of that method looking for instructions that establish dependencies to other methods and fields. Those dependencies may be direct (e.g. *putfield* establishes a dependency to the immediate target of the invocation) or indirect, which may involve polymorphic relations (e.g. *invokevirtual* involves dynamic dispatch, meaning that the exact type of the target is only known at runtime). Since JVM specification allows static methods to be polymorphic as well, we consider *invokestatic* as polymorphic method invocation as well. In the case of a polymorphic target, we conservatively traverse the class hierarchy of that target either up or down, in search of all possible polymorphisms. For example, when the target is a method that is overridden in one or more subclasses of its class, we include all those overridden methods as dependencies, because we don't know the exact method that will be called at runtime; similarly, when the target is missing the method, it means that the method is inherited from a superclass. In this case, we have to traverse up in the class hierarchy and include the superclass method as a dependency.

Algorithm 1 Test Selection pseudo-code

```
1: function TLDR(project_n, project_{n-1})
2:     new, changed, goldset, mapped, selected ⇐ φ
3:     for all file_n ∈ project_n do
4:         if file_n ∉ project_{n-1} then
5:             insert(file_n, blk2b(file_n))
6:         end if
7:         if blk2b(file_n) ≠ blk2b(file_{n-1}) then
8:             update(file_n, blk2b(file_n))
9:             for all member_n ∈ file_n do
10:                extract = false
11:                if member_n ∉ project_{n-1} then
12:                    insert(member_n, blk2b(member_n))
13:                    new = new ∪ {member_n}
14:                    extract = true
15:                else if blk2b(member_n) ≠ blk2b(member_{n-1}) then
16:                    update(member_n, blk2b(member_n))
17:                    changed = changed ∪ {member_n}
18:                    extract = true
19:                end if
20:                if extract ∧ isMethod(member_n) then
21:                    DEPEXTRACTION(member_n)
22:                end if
23:                for all member_{n-1} ∈ project_{n-1} − project_n do
24:                    remove(member_{n-1})
25:                end for
26:            end for
27:        end if
28:    end for
29:    for all member ∈ new ∪ changed do
30:        goldset = goldset ∪ dfs(member)
31:    end for
32:    for all member ∈ goldset do
33:        mapped = mapped ∪ testmap(member)
34:    end for
35:    for all test ∈ mapped do
36:        selected = selected ∪ dfs(test)
37:    end for
38: return selected
39: end function
```

Algorithm 2 Dependency Extraction pseudo-code

```
1: function DEPEXTRACTION(entity)
2:     direct ⇐{ "putstatic", "putfield", "getstatic", "getfield"}
3:     polymorphic ⇐{"invokevirtual", "invokeinterface", "invokestatic",
   "invokespecial"}
4:     dependencies ⇐ φ
5: [11.5em]Extract dependencies from method bytecode
6:     for all instruction ∈ entity.bytecode do
7:         if instruction.type ∈ (direct ∪ polymorphic) then
8:             dependencies = dependencies ∪ instruction.callee
9:         end if
10:    end for
11:    for all member ∈ dependencies do
12:        if dep_type(entity, member) ∈ direct then
13:            insert_in_db(entity, member)
14:        else if dep_type(entity, member) ∈ polymorphic then
15:            hierarchy ⇐ classHierarchy(member)
16:            if isOverridden(member, hierarchy) then
17:                nodes ⇐ getOverrides(member, hierarchy)
18:            else if isMissing(member, class(member)) then
19:                nodes ⇐ getInherited(member, hierarchy)
20:            end if
21:            for all e ∈ nodes do
22:                insert_in_db(entity, e)
23:            end for
24:        end if
25:    end for
26: end function
```

5.2 Safety

An RTS technique is *safe* iff it selects all tests that are impacted by a change in the projects' files [62]. As currently implemented, TLDR is not entirely safe, because it does not track dependencies resulting from (a) the use of Java reflection, and (b) the use of external jars. This is not an inherent problem of TLDR; it is simply a limitation of its current implementation, which we plan to improve. This limitation affects other RTS tools that are based on static analysis [34, 67, 17]. TLDR is safe for all other cases, i.e. for *all* changes in the *source files* of the projects, as long as they don't involve reflection. In broad strokes, an RTS technique is safe when (1) it correctly captures all dependencies of all code entities down to the desired level of granularity; (2) it correctly slices the dependency graph for the set of entities that change from a version to another; and (3) it correctly identifies the tests that reach any part of those slices. For performance purposes, and as explained above, TLDR uses a static dependency graph. Because of dynamic dispatch, static analysis of object-oriented programs needs to take inheritance relations into account. Algorithm 2 describes the construction of this static extended dependency graph, which is complete, with the two exceptions: reflection and external jars. While constructing the static extended call dependency graph, it considers both direct (line (12)) and polymorphic (line (14)) dependencies.

5.3 Parallelism in TLDR

The algorithms described above are not particularly new – similar techniques for change analysis were used by other RTS tools [68, 67, 20, 34]. However, in TLDR, we leverage the potential that Algorithm 1 has for parallelism to reduce test selection overhead. Specifically, instead of sequentially executing the entire algorithm, we parallelize lines (3), (9), (29), (32), and (35) – these are portions of the algorithm that map certain processing functions to

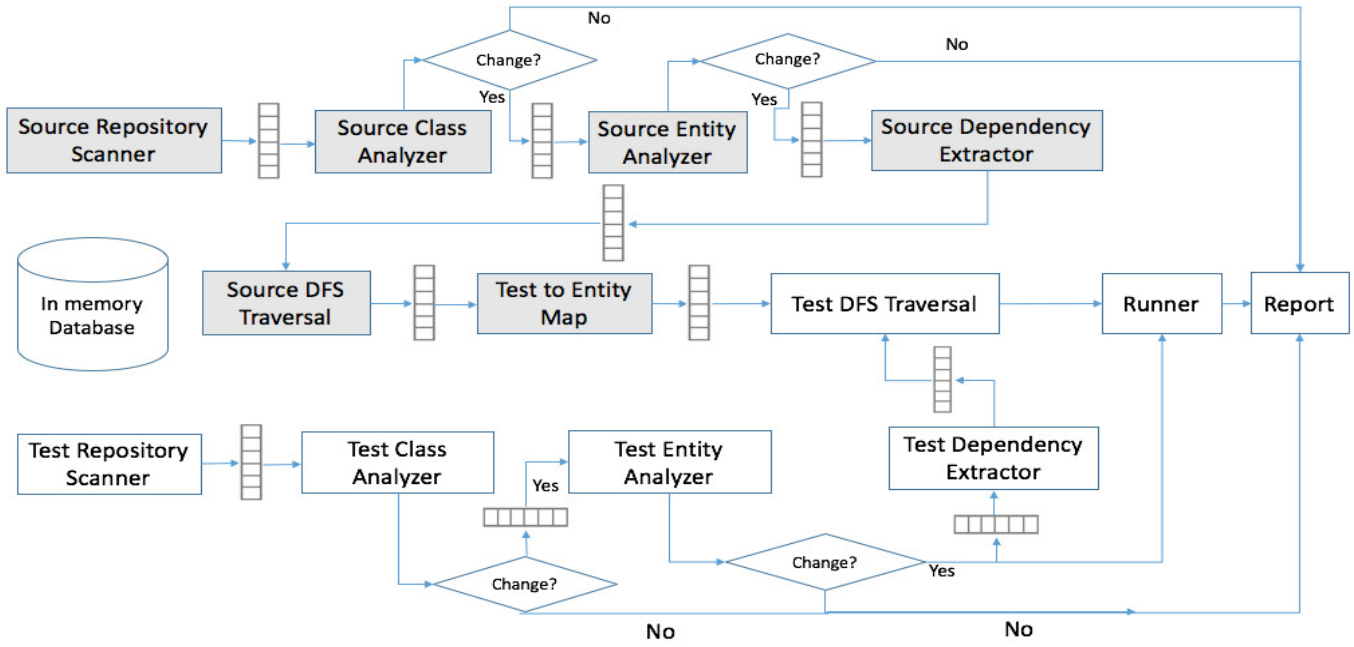


Figure 5.1: Pipe-and-filter architecture of TLDR. The architecture contains two partially-independent pipelines, one for the source-code (marked as grey) and one for the test-code (marked as white).

potentially large numbers of classes and their members.

Figure 5.1 depicts the pipe-and-filter architecture of TLDR, which fully leverages parallelism for test selection and implements Algorithm 1. The data elements of the pipeline are the absolute paths of the class files – and the fully qualified name of the classes, methods, and fields. The pipeline takes as input the absolute path of each class file and outputs a set of selected tests. Components in the pipeline are multi-threaded and interact with each other through queues. The number of worker threads between two components is configurable, so to better take advantage of the hardware. As a result, TLDR can use the full computational power of each machine where it runs.

TLDR's architecture contains two sub-pipelines: one associated with the source code under test – which we refer to as the *source pipeline* and whose constituent components are colored in grey – and another associated with test code of the project – which we refer to as the *test pipeline* and whose constituent components are filled in white. These two

Table 5.1: Hashtables used by TLDR's In-Memory Database

Hashtable No.	Key	Value
1	class absolute path	checksum
2	FQN of entity	checksum
3	FQN of entity	set of FQN of dependent entity
4	FQN of entity	set of FQN of dependency entity
5	FQN of Class	set of FQN of super class and interfaces
6	FQN of Class	set of FQN of the subclasses
7	FQN of entity	set FQN of test methods
8	FQN of test entity	Boolean

pipelines operate in parallel and either asynchronously or synchronously, depending on which component is currently operating. Broadly, each of these two sub-pipelines has the following four components in common: *Repository Scanner, Class File Analyzer, Entity Analyzer, Dependency Extractor*. Ultimately, these two sub-pipelines merge in the *Test DFS Traversal* component, followed by execution of tests by the *Runner* module. In the remainder of this section, we describe the functionality of each component.

5.4 In-Memory Database

Deductive databases are often used to store program information as relations for numerous program analyses [30]. Similar to other RTS tools, we store program-specific information for incremental change analysis, dependency graph traversals, and mapping entities to a test method [68, 67, 34, 20, 32].

Data storage and retrieval are expensive processes. If nothing changes in the project, TLDR at a minimum needs to retrieve previously stored checksums of each class file for *change impact analysis*, i.e. determining the entities affected by a change to another entity. Therefore, performance of RTS greatly depends on the database schema as well as storage technology. To achieve high performance, we use an in-memory database server, *Redis*. We implemented a customized *database handler* which is available to all the components in the pipeline. The database handler provides thread-safe APIs to read, update, and delete values.

Conceptually, Redis tables are hashtables, i.e. key-value pairs. In TLDR, the keys are the fully qualified name (FQN) of the entities and the values are either a hashcode, i.e. checksum, or a set of FQNs. Table 5.1 shows the 8 hashtables used by TLDR, each identified with a table ID. Hashtable 1 and 2 store the checksum of each file and entity i.e. field and method respectively. These two hashtables used for change analysis. Hashtable 3 stores the set of dependents of each field and method. This table is the dependency graph of the project. It is used by the DFS algorithm to traverse the firewall of each changed field and method. Hashtable 4 is the inverse of hashtable 3. It stores the set of dependencies of each field and method. This table is needed for faster update of hashtable 3 when a method is no longer another method's or a field's dependent. Hashtable 5 stores class-hierarchy information. This table is used by algorithm 2 to construct polymorphic edges in the dependency graph. Hashtable 6 is the inverse of hashtable 5 and facilitates faster update of hashtable 5 when the class hierarchy of the projects changes. Hashtable 7 stores entity to test mapping information. This is used in mapping tests to each field and method in *goldset* in algorithm 1. Hashtable 8, stores all test methods and fields. This table is used along with table 3 to traverse within the test suite.

5.5 Repository Scanner

Both the source and test pipelines start by scanning the repository of the project using a recursive depth-first search algorithm that locates all class files in the repository. In a Maven project, source classes reside on **/target/classes/* directory and test classes reside on **/target/test-classes/* directory. Source Repository Scanner collects all source classes and Test Repository Scanner collects all test classes from the above-mentioned directories

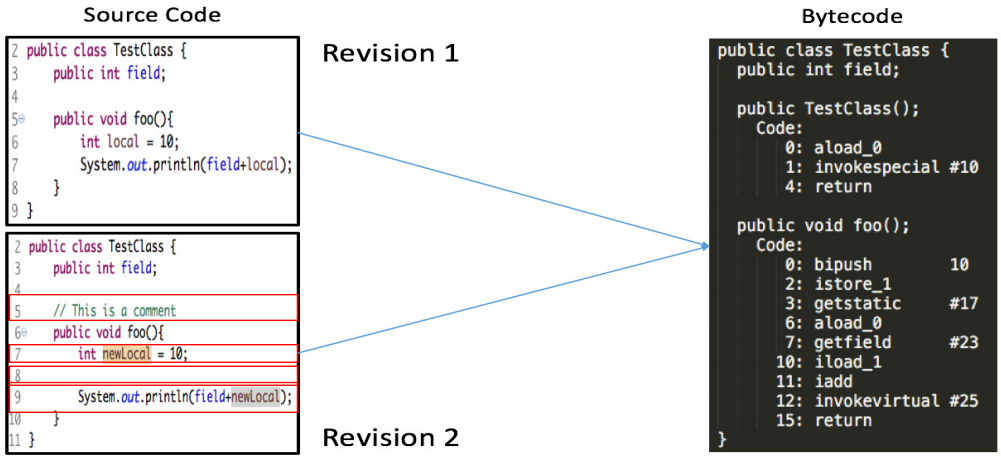


Figure 5.2: Two revisions of the same program. Revision 2 includes a new variable name, black line, and a comment. Revision 1 and Revision 2 results in the same bytecode.

respectively. A Maven project can be hierarchical with multiple modules. Each module can have its own independent source and test directory. Each Repository Scanner can discover all such source and test directories.

5.6 Class Analyzer and Entity Analyzer

TLDR performs change impact analysis during two subsequent stages: one for the class level and another for the method- and field-level. TLDR analyzes change at the bytecode level. We choose this level because many changes that do not affect tests can be filtered out when analyzing bytecode but would result in unnecessary test selection at the source code level. For instance, new or changed comments or equivalent code at the statement level (e.g., *var++* instead of *var = var + 1*), etc. yields the same checksum. For example, in figure 5.2, two versions of the same program results in the same bytecode upon compilation. Therefore, analysing bytecode instead of source-code is more efficient. Previous regression test selection approaches have followed a similar practice [20, 67, 34, 64, 16].

Broadly, TLDR can detect 16 types of changes, shown in Table 5.2. Altogether, these 16

Table 5.2: Changes detected by TLDR

	Type of Change
1	Addition of a new class
2	Addition of a new method
3	Addition of a new field
4	Addition of a new static initializer
5	Change of a method definition
6	Change of a field value
7	Change of the class hierarchy
8	Change of a class signature
9	Change of a field signature
10	Change of a method signature
11	Change of a static initializer
12	Deletion of a class
13	Deletion of a method
14	Deletion of a field
15	Deletion of a test case
16	Deletion of a static initializer

change types cover a wide variety of possible changes in object-oriented languages and at least the same type of changes handled by state-of-the-art RTS techniques [20, 67, 34].

TLDR uses a 16 character-long alpha-numeric checksum as part of its change impact analysis. The efficiency of the test selection pipelines also depends on checksum calculation. To maximize efficiency of checksum usage, TLDR uses *BLAKE2B* [3], which is 4 to 8 times faster than *SHA256, BLAKE, and SHA-1*.

For each *Class File Analyzer*, i.e., source and test, TLDR calculates the checksum of bytecode. Only the class files whose checksums are different than the previously computed value are forwarded to the next component in the pipeline for field- and method-level change analysis as shown in figure5.3.

For both source and test *Entity Analyzer* components, TLDR splits the class file into methods and fields using *Apache Common BCEL* library. The checksum is calculated by concatenating the entity's (i.e., method's or field's) modifier, signature, and body. We omit *StackMap Table* of the methods. The offset delta of StackMap of a method depends on the overall offset of the class file. Addition or deletion of a statement in the preceding method can possibly change the offset information of the subsequent methods' StackMap Table. This can cause changes in the checksum of a method even though that method did not change in code.

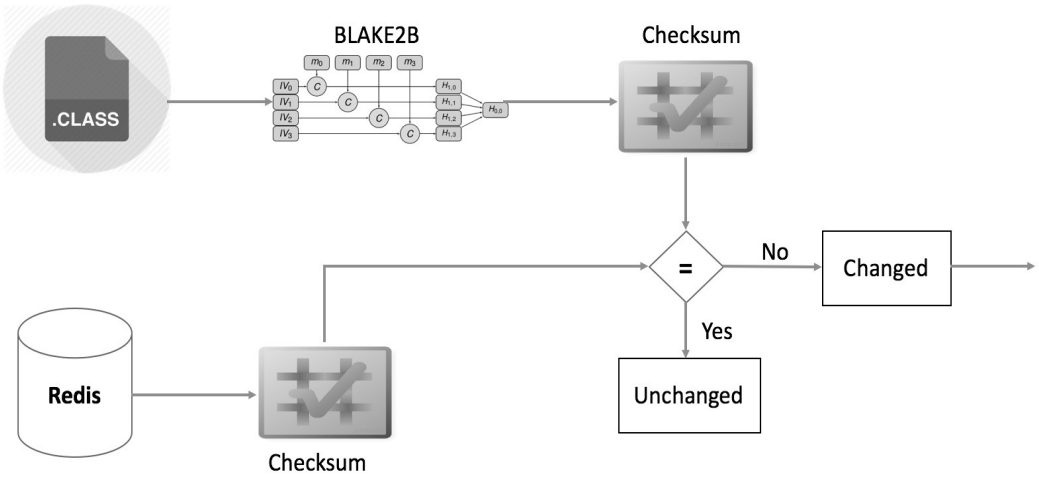


Figure 5.3: Change analysis of class files. Only the changed class files are passed to the next module.

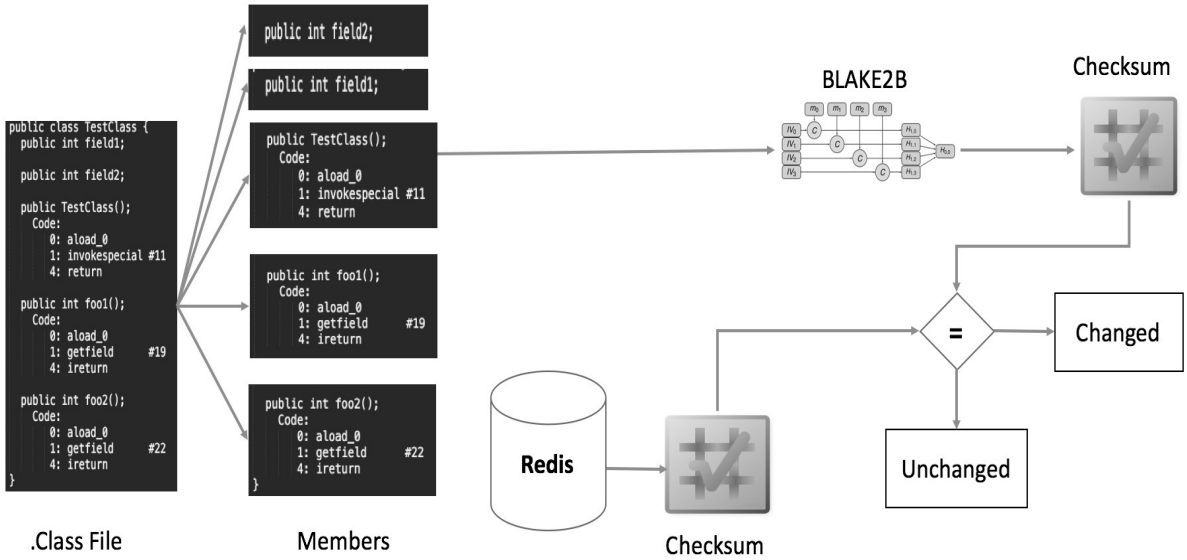


Figure 5.4: Change analysis of methods and fields. Each changed class file is split into methods and fields and fed to the change analysis module.

For fields, we calculate the checksum of the signature of the field. In addition to change analysis, we perform three tasks in Entity Analyzer: (1) extracting the class-hierarchy information, i.e., super-class and interfaces of the class; (2) update the class-hierarchy information in the database if the class hierarchy is changed; (3) update and sync the dependency information if a method or field has been deleted.

5.7 Dependency Extractor

Algorithm 2 implements Dependency Extractor. For each method including constructors (`<init>`) and static initializer (`<clinit>`), both source and test, we extract dependencies by parsing the operands of the following 13 bytecode instructions: i) `invokestatic`, ii) `invokespecial`, iii) `invokevirtual`, iv) `invokeinterface`, v) `getstatic`, vi) `getfield`, vii) `putstatic`, viii) `putfield`, ix) `checkcast`. For `invokevirtual`, `invokeinterface`, `invokestatic`, and `invokespecial` we retrieve all overridden versions of the dependency method by traversing the class hierarchy.

The extracted dependency information is inserted in both a forward and inverted index of dependencies. The inverted index is being used to formulate the transitive dependents of the changed methods, while the forward index is being used to update and synchronize the database in case a dependency is deleted in a particular revision. For the test pipeline, dependency information is indexed into two tables: (1) Hashtable 3 and (2) Hashtable 7. Test dependencies on source methods are used to map a source entity to a test method. Test methods have dependencies to other test members. To select all impacted test methods, we have to find the transitive dependents of each test that mapped to a method or field in *goldset*.

5.7.1 DFS Component

This component is a Depth-first search algorithm that traverses the transitive dependency of each changed or newly added entity. DFS Traversal of the source pipeline is synchronized with the Dependency Extractor of the test pipeline. Algorithm 1 waits for Test Dependency Extractor to finish for all data elements in the test pipeline before forwarding each member in *goldset* to Test to Entity Map component. This is because in order to map the source members to test methods, all test methods must be parsed and their updated dependency to the source methods must be indexed. Source DFS Component collects the firewall of each changed or new member.

The DFS component of the test pipeline gets input from both Test Dependency Extractor of the test pipeline and Test to Entity Map component of the source pipeline. This module is the meeting point of the two sub-pipelines. Test methods might have dependencies on other test fields, parameterized test methods, or helper methods. Test DFS component allows traversing these transitive dependencies for each new or mapped test method. This component is customized to traverse transitive dependency within the test suite.

5.8 Test to Entity Map

This component is only present in the source pipeline. This is a mapping function that maps each entity in the transitive dependent set of each changed or newly added method and field to a test method, i.e., a test method which has a direct dependency on one or more entities in the transitive dependent set. Mapped tests are then forwarded to test DFS Traversal to form a transitive set of impacted changed methods.

5.9 Runner

TLDR extends `Maven SureFire` which is a plugin to run JUnit tests in Maven projects. TLDR runs the only the selected tests by dynamically updating the `test` field of `SureFire` by Java instrumentation. In order to run the selected tests parallelly, TLDR updates `SureFire` configuration values – `forkCount` and `reuseForks`. These flags enable Surefire to spawn a specified number of JVM processes and distribute test run load among the processes parallelly.

5.10 TLDR Artifact

TLDR is an open-source project. TLDR's source-code can be found in this GitHub repository : http://www.github.com/Mondego/TLDR. The tool has not been released in the Maven Central Repository yet. Therefore, it needs to be installed in the local maven repository. To do so, the source-code needs to be cloned into the local machine and within the repository, the following maven command is needed to be executed *mvn clean compile install*. After installing TLDR in the local maven repository, the following XML snippet needs to be added in the *<plugins>* block of the *pom.xml* file of the project which is to be tested through TLDR.

```
<plugin>
   <groupId> com.mondego.ics.uci </groupId>
   <artifactId> tldr-plugin </artifactId>
   <version> 1.0.2-SNAPSHOT </version>
   <configuration>
      <goalPrefix> tldr </goalPrefix>
      <skipErrorNoDescriptorsFound> true </skipErrorNoDescriptorsFound>
   </configuration>
</plugin>
```

Before running the plugin, a Redis server must be started locally. Finally, the following command should be executed - *mvn com.mondego.ics.uci:tldr-plugin:1.0.2-SNAPSHOT:tldr -Dmultimodule.projectname=<project-name>*. This will invoke Maven surefire and the test report will be placed inside the *Target* folder of the repository. TLDR provides several optional command-line options. Some relevant command-line options are as follows -

- -Ddebug.flag: turns on the debug prints during different stages of the pipeline.
- -Dlog.directory: specifies the location of log files that are generated during analysis and testing.
- -Dcommit.hash: specifies the hashcode of a particular commit on which TLDR is to be run.
- -Dcommit.serial: specifies the serial number of the project iteration. This flag is useful in iterative evaluation of TLDR.
- -Dfork.count: specifies the number of process forks test runner should use.
- -Dthread.count: specifies the number of threads the test runner should use.

Chapter 6

Safety of TLDR

6.1 Safety of TLDR

An RTS technique is *safe* iff it selects all tests that are impacted by a change in the projects' files. As currently implemented, TLDR is not entirely safe, because it does not track dependencies resulting from (a) the use of Java reflection, and (b) the use of external jars. This is not an inherent problem of TLDR; it is simply a limitation of its current implementation, which we plan to improve. TLDR is safe for all other cases, i.e. for *all* changes in the *source files* of the projects, as long as they don't involve reflection.

In broad strokes, an RTS technique is safe when (1) it correctly captures all dependencies of all code entities down to the desired level of granularity; (2) it correctly slices the dependency graph for the set of entities that change from a version to another; and (3) it correctly identifies the tests that reach any part of those slices. We use the concept of *Static Extended Dependency Graph* to capture (1), and the concept of *Firewall* to capture (2).

6.1.1 Static Extended Dependency Graph

Zhang et al. presented extended dependency graphs for RTS tools [33] in the context of dynamic dependency tracking. Extended dependency graphs model methods and fields as vertices in the graph, and the edges are the dependencies. For a set of methods, M and a set of fields, F, extended dependency graph, G in an OO language is defined as follows [**?**]:

Definition 6.1.1. *Dynamic Extended Dependency Graph:* $G =< V, E >$ *where* $V = M \cup F$ *and* $E =< v, v' >$ *where* $v \in M, v' \in calledBy(v) \wedge V$

In this definition $calledBy(v)$ denotes the set of members (methods or fields) that the method v refers to at runtime. It is worth noting that G is dynamic in nature. This means G has edges that correspond to dependencies among members that are resolved at runtime. For performance purposes, and as explained before, TLDR uses a static dependency graph. Because of dynamic dispatch, static analysis of object-oriented programs needs to take inheritance relations into account. Algorithm 2 describes the construction of the static extended dependency graph. Formally, we define the static extended dependency graph SG as follows:

Definition 6.1.2. *Static Extended Dependency Graph:*

$SG = (V, E)$ where $V = M \cup F$, $E = (v, v')$ where $v \in M$, $v' \in V \wedge (referencedBy(v) \cup (overridden(referencedBy(v)) \vee inherited(referencedBy(v))))$

In the definition, E is the set of edges (dependencies) that are direct or indirect via polymorphism. $referencedBy(w)$ is the set of members that method w calls or refers to. $overridden(w)$ is the set of all methods that override method w, and $inheritedBy(w)$ is the set of methods inherited from superclasses. In Java, all the non-reflective dependencies among members can be captured by the following byte code instructions: `invokevirtual, invokeinterface, invokestatic, invokespecial, getstatic, getfield, putstatic, put-`

`field`. SG thus, includes all types of dependencies in Java bytecode, except reflective dependencies.

6.1.2 Firewall

The concept of firewall in software testing was first discussed by White et al. [61] and has since been adopted into object-oriented testing as well [58, 59, 60, 34, 67]. The firewall of a given code entity (i.e. file, class, method, field, or statement) is the set of entities that can be impacted by a change in that entity. Finding the firewall of a changed entity requires traversing transitive dependents of that entity. In a static RTS, such traversal involves traversing both direct and polymorphic edges. Class firewall has been proposed by Legunsen et al. for a static class-level RTS [32]. A class-level RTS selects all test classes that have dependency on any class in the class firewall of a changed class. Similarly, a method-level RTS selects all test methods that have dependency on any method or field in the method or field firewall of a changed method or field. Formally, the firewall of a member in a static graph, SG can be defined as follows:

Definition 6.1.3. *Firewall:* $F(w) = \bigcup_{\forall v} DFS(v, SG), w \in M, v \in V \wedge calledBy(w)$

In this definition, $DFS(v, SG)$ returns a set of members that are connected to node v in a static graph SG. Definition 6.1.3 defines firewall of a member as the union of firewall of all dependent members.

6.1.3 Proof of Safety of TLDR

A safe static method-level RTS tool captures both static and polymorphic dependencies among fields and methods. To prove the safety of TLDR we need to prove that TLDR captures all types of dependency in Java bytecode i.e. creates a static extended dependency

graph. Also, we need to prove that it collects all members that may be impacted by a given change in source code. Therefore, to prove the safety of TLDR, we prove that – (1) TLDR constructs a static extended dependency graph SG (2) TLDR selects all tests that map to $firewall(v)$ where v is a changed entity.

Theorem 6.1.1. *TLDR constructs static extended dependency graph SG*

Proof: Function $DEPEXTRACTION$ is being called for each changed or new $v \in M \cup F$. It takes the dependent entity v and extracts the set of its direct dependencies, *dependency*. Let us consider that $DEPEXTRACTION$ only captures static edges. Line(13) inserts each *member* $\in$ *dependency* as v's dependency with which v has `invokestatic, invokespecial, getstatic, getfield, putfield, putstatic` relation. These are static edges. However, line (22) inserts the overridden and inherited versions of each *member* with which v has `invokeinterface, invokevirtual` relations. Since the edges are between the dependent and all the overridden and inherited versions of the dependency members, they are polymorphic edges according to [54]. Contradiction.

Therefore, $DEPEXTRACTION$ captures both static and polymorphic edges, thus according to definition 6.1.2 constructs SG.

Theorem 6.1.2. *TLDR selects all tests t that has either direct or polymorphic dependency to $firewall(v)$ where v is a changed entity.*

Proof: For a changed $v \in M \cup F$, let us assume algorithm 1 returns a set of tests *selects* that does not include one t which has edge to a $v^{'} \in V \cup F$ and $v^{'} \in firewall(v)$. For each new and changed v, TLDR calls $DFS(v)$ on SG created by $DEPEXTRACTION$. According to [55], $DFS(v)$ returns a set of all entities reachable from v in SG. Therefore, $DFS(v)$ returns $firewall(v)$. This set is included in *goldset*. Line (25) adds each t that maps to any $v^{'} \in$ *goldset* in *mapped*. Each t in *mapped* is impacted by change in source code. Line (28), then calls $DFS(t)$ for each t in mapped to collect all t' that is impacted by t and adds them

to *select*. Contradiction. Therefore, *select* includes all test methods that map to $firewall(v)$ for each changed entity v.

Chapter 7

Evaluation

In this chapter, we discuss the evaluation of TLDR. Regression test selection tools are primarily evaluated based on their precision and efficiency [20, 67, 34, 68]. We evaluated TLDR in terms of the number of selected tests (precision) and end-to-end testing time (efficiency). As mentioned earlier, the baseline RTS techniques of our evaluation are Ekstazi, STARTS, and HyRTS. Before discussing the findings of our evaluation, we discuss our research questions, the projects that serve as subjects for our experiments, and the experiment setup.

7.1 Research Questions

For our evaluation, we answer the following two research questions:

1. **RQ1: To what extent does TLDR reduce the number of tests selected for re-execution compared to the baseline RTS techniques?**
   As demonstrated in the previous section, TDLR is safe for all changes in source files that do not involve reflection, similar to state-of-the-art approaches [34, 20]. However, one of TLDR's goals is to maintain precision, i.e., select as few tests as possible for re-execution

while still identifying all possible faults that the original test suite can reveal. We assess TLDR's ability to reduce tests selected while maintaining safety for this research question in contrast to the baselines.

2. **RQ2: What is the end-to-end testing time of TLDR as compared to retest-all, and the baseline RTS techniques?**

   One major contribution of TLDR is to significantly reduce end-to-end testing time compared to the state-of-the-art techniques, i.e., Ekstazi, STARTS, HyRTS, re-running all the tests from the original test suite, i.e., retest-all, and re-running all the tests from the original test suite with parallelization. As a result, we evaluate each of these six techniques in terms of end-to-end testing time for our experiments.

7.2 Data Collection

Table 7.1: Meta-information of the study projects

Project	**#Class**	**SLOC**	**#Tests**	**#Commit**	**#Star**
Asterisk-java	839	111721	260	2004	340
Commons-dbutils	96	14836	307	783	272
Commons-jxpath	232	40128	386	601	150
Commons-validator	150	33880	544	1543	127
Compile-testing	49	10389	221	354	570
Invokebinder	26	7878	99	163	95
Chronicle-Map	453	59294	1036	2935	2200
Retrofit	283	36610	694	1865	37900
Logstash-encoder	227	26682	320	829	1800
Jfreechart	1022	283820	3182	4179	683
Commons Collections	856	62858	2884	3094	347
Commons IO	321	26882	1468	2158	574
Chronicle Map	424	28697	665	2492	1648
Commons Cli	58	12326	310	915	144
Joda Time	530	86184	5332	2104	4036
Commons Email	47	12474	209	839	60
Commons Fileupload	64	10385	113	954	104
Commons Lang	714	74934	3749	5434	1628
Commons Math	1941	174505	6065	6402	263
Commons Pool	179	14337	570	1908	245

We selected 20 open-source Java projects from GitHub to evaluate TLDR against the baselines.

These projects were either single or multi-modular. These projects were used in the evaluation of prior RTS techniques [19, 67, 34, 32]. TLDR's implementation supports Maven and JUnit 4.x but not other build automation tools or unit-testing frameworks. As a result, we excluded projects that had the following characteristics -

(1) use Gradle, Ant, or other build tools and testing frameworks other than JUnit 4.x,

(2) have test suites that could not be executed by either Ekstazi, STARTS, HyRTS, or TLDR. For example, running the test suite of *Guava* caused our Java Virtual Machine to crash even after setting up the maximum heap size possible in our machine. While all large projects can benefit from RTS tools, we excluded these projects due to resource and implementation limitations. Some projects had external environment dependencies, for example, database server, socket connection, etc. Therefore, those projects could not be run without externally setting up environment dependencies. For example, in order to execute the test suite of Apache Common Net, a WebSocket connection between two machines is needed to be established.

(3) are active and popular. Projects' activity and liveliness are measured by the number of commits and popularity is measured by the number of stars. We excluded projects that had less than 500 commits and less than 50 stars.

These project exclusion criteria enable a fairer and accurate comparison among the RTS techniques in our evaluation.

Table 7.1 shows the list of projects; project size in terms of number of classes, and source lines of code (SLOC); test-suite size in terms of number of test methods; and project metadata, i.e., number of commits and the number of stars in the latest commit from GitHub using *Sourcerer* [37], a static code analysis infrastructure.

7.3 Experiment Setup

Table 7.2: Projects and Sampled Commits

Project Name	**Commit Hash**
Asterisk-java	44aee1b44afbb1e4dc518ad8ea32126291318c32
Commons-cli	De5f2b46fa952a69a8819b60d60a03eac1154282
Commons-collections	Fa11e5702bafb392b20633a0e8c9617cab9a0276
Commons-dbutils	2ed6a127bd830adbe2b385d9ee62ead2f0e61fc5
Commons-email	77ac7bcd01f558eaeeecf50e478e939d74293942
Commons-fileupload	f4cab5702b6e7d6c019c9fec29357ad2b552783d
Commons-functor	049e4fbdd987a405f2fcc1b97e6c7903db068965
Commons-jxpath	07b898f72113be256ecc1420f5388261d951c547
Commons-math	b95a43fa9af718899d03bbc2c10587c069c707f0
Commons-pool	c9f61e36b119a824c6c02ee6009eddae47bfecef
Commons-validator	dcf935a9ef9909e59f631ecbda6d00e2a8ac8450
Compile-testing	7e2b01560666ba10b330f1984fdbb3251f2548a1
Invokebinder	d539764d7ebb26edc5080a2ecd642d483bcb6030
Chronicle-Map	857f544a26e21e169280089b5f8d24b3b880782f
Retrofit	bf9f11430de52b13f2f3f1aa2be4b64d6471a46d
Commons-lang	efbfd2de9765bc01e4916b16e8eb82370f25ff82
Commons-io	724125eff6608884b0ac1c59f62695ecf43e5c8a
Joda-time	7b549b1d9ad88be845e469222c57c144ae1b7da1
Logstash-encoder	73437e6a3212985eeb55bcb9047c6def74161800
Jfreechart	9d7887f00218d39b63f209e86e248f895b10cb87

For each project, we collected hashcodes for the latest 30 commits that compile from the git log of the corresponding projects. The sampled hashcodes are shown in table 7.2. For evaluating the RTS techniques, we installed TLDR, Ekstazi[1], STARTS[2], and in our local machine. HyRTS is not open-source. We collected the HyRTS artifact from the authors of the tool [67]. STARTS had logs of test selection time and test runtime. For Ekstazi and HyRTS, we modified the plugin code to log test selection and run time individually at the end of test selection and test execution phase respectively. It should be noted that we did not modify any existing code, therefore, the core functionalities of these tools remained the same. We implemented a bash script to automatically run the experiment. For each project in our evaluation, the script retrieves the commit in the project's corresponding commit sequence

[1]collected from *https://github.com/gliga/ekstazi*
[2]collected from *https://github.com/TestingResearchIllinois/starts*

C', using the `git reset` command and each commit's corresponding hashcode. The script then uses Maven to clean out the project, compile its source code, and compile its test code without running it. Cleaning the project out before compiling it reduces any potential errors arising from residual files remaining in the project's directories that were produced during previous runs of the project. Some projects had release audit plugin, for example, *Apache Rat* and style formatting plugin, for example, *Maven Checkstyle*. We turned these plugins off because, for some projects, they caused errors while running TLDR as well as the other three RTS plugins.

For each commit, we ran the test once for each of the six techniques we evaluate, i.e., TLDR, Ekstazi, STARTS, HyRTS, retest-all, and parallel retest-all. To run parallel retest-all, we set `forkCount` and `reuseForks` flag of Maven Surefire so that it spawns a specified number of JVM processes concurrently to execute the tests. For our experiment, we used 8 JVM forks to run tests in parallel. Note that, TLDR's test runner also had 8 JVM forks. For each of these runs, we collected the test reports generated by *Maven Surefire*. The generated report is in HTML format. We implemented our own parser to collect the number of tests run from the Surefire HTML reports and test selection and test execution time from the log files generated by our custom code.

The experiment was conducted using a remote server with 256 GB (1867 MHz) DDR3 RAM, a 112-core *Intel(R) Xenon(R) E5-4650* CPU, Linux 3.10.0 operating system, and 500G of solid-state disk. We used a local server of *Redis 3.2.8* as our in-memory database.

Table 7.3: Number of tests run for Retest-All, Parallel Retest-All, TLDR, STARTS, Ekstazi, and HyRTS

Project	Commit	$\sum Test_{all}$	$\sum Test_{par}$	**TLDR**		**STARTS**		**Ekstazi**		**HyRTS**	
				$\sum Test$	$\%tests$	$\sum Test$	$\%tests$	$\sum Test$	$\%tests$	$\sum Test$	$\%tests$
asterisk-java	44aee1b	7771	7771	1157	14	2121	26	1962	24	1877	24
commons-cli	de5f2b4	12480	12480	615	4	1200	8	879	6	739	4
commons-collections	fa11e57	749910	749910	23606	2	89161	10	36914	4	25746	2
commons-dbutils	2ed6a12	9210	9210	512	4	1830	18	1142	12	925	10
commons-email	77ac7bc	5700	5700	245	2	1710	30	380	6	219	2
commons-fileupload	f4cab57	2760	2760	334	12	1622	58	1104	40	412	14
commons-functor	049e4fb	32370	32370	1318	4	3744	10	3729	10	3632	10
commons-jxpath	07b898f	11580	11580	1079	8	1900	16	1307	10	1211	10
commons-math	b95a43f	125460	125460	6685	4	8514	6	7593	6	7577	6
commons-pool	c9f61e3	8790	8790	323	2	865	8	579	6	569	6
commons-validator	dcf935a	16320	16320	1190	6	1410	8	1387	8	1201	6
compile-testing	7e2b015	6630	6630	950	14	1947	28	1675	24	1722	24
invokebinder	d539764	2970	2970	689	22	1039	34	1025	34	725	24
Chronicle-Map	857f544	31080	31080	4816	14	14752	46	13593	42	6428	20
retrofit	bf9f114	20280	20280	2567	12	3164	14	5105	24	3682	18
commons-lang	efbfd2d	140250	140250	7659	4	19558	12	12072	8	9391	6
commons-io	724125e	41040	41040	974	2	5894	14	4410	10	-	-
joda-time	7b549b1	127140	127140	11354	8	33795	26	33795	26	13795	10
logstash-encoder	73437e6	9600	9600	342	2	725	6	416	4	234	2
jfreechart	9d7887f	95460	95460	29763	30	80306	84	63392	66	33392	34
$\sum\sum Test$		**1456801**	**1456801**	**96178**		**275257**		**192459**		**113477**	
%					**8.5**		**23.1**		**18.5**		**12.2***

7.4 Results

7.4.1 RQ1: Number of Selected Tests

One of the major goals of RTS techniques is to select as few tests as possible given a change in a software under test, while maintaining safety. To assess TLDR's ability to achieve this goal, we assess TLDR with respect to Ekstazi, STARTS, HyRTS, and retest-all in terms of the number of tests each technique selects.

Table 7.3 shows the number of tests selected by each technique: *Commit* is the hashcode of the starting commit from which the baselines were evaluated for each project; $\sum Test$ is the total number of tests run for retest-all across all sampled commits; Column (4),(6), (8), and (10) i.e. $\sum Test$ show the total number of tests selected and run by TLDR, STARTS, Ekstazi, and HyRTS respectively; and Column (5), (7), (9), and (11) i.e *%tests* is the percentage of tests run by each technique across all sampled commits.

Note that sample commits are commits for which the project compiled, at least one of the baseline RTS techniques (i.e., Ekstazi or STARTS) ran, and at least one test was affected by changes in the source code.

Table 7.3's two bottom-most rows aggregate results across projects for each RTS technique and retest-all. Row $\sum\sum Test$ (second from the last) of Table 7.3 displays the total number of tests run by each technique across the projects in our experiment for which a technique can successfully run, 19 projects for HyRTS and 20 projects for the remaining RTS techniques and retest-all. For *commons-io*, HyRTS was not able to run since it threw a Maven-based exception that remains unresolved at the time of this thesis' submission. The last row of Table 7.3 displays the percentage ratio of $\sum\sum Test$ for each tool to $\sum\sum Test$ for retest-all. We can see that TLDR, STARTS, Ekstazi, and HyRTS ran 8.5%, 23.1%, 18.5%, and 12.2% of all tests across all samples for which the tools ran. TLDR is the most precise RTS tool

compared to Ekstazi, HyRTS, and STARTS. STARTS is the least precise tool. This result is intuitive because STARTS is a static and class-level RTS. For *commons-email*, TLDR was less precise than HyRTS. This occurs whenever a method is (1) overridden by many other subclasses of that method's owner class and (2) those subclasses change to a large degree. This case occurs very rarely. Note that TLDR is always more precise than STARTS and Ekstazi.

7.4.2 RQ2: End-to-End Testing Time

Table 7.4 shows the end-to-end testing time of each technique: $\sum T_{all}$ shows the total time across all sample commits in seconds ([s]) for each RTS technique for retest-all; $\sum T_{par}$ shows the total time across all sample commits in seconds ([s]) for each RTS technique for parallel retest-all; Column (4), (7), (10), (13) i.e. $\sum T_s$ show total test selection time across all commits for TLDR, STARTS, Ekstazi, and HyRTS respectively; Column (5), (8), (11), (14) i.e. $\sum T_t$ show total test execution time across all commits for TLDR, STARTS, Ekstazi, and HyRTS respectively; Column (6), (9), (12), (15) i.e. $\sum T_e$ show total end-to-end test time across all commits for TLDR, STARTS, Ekstazi, and HyRTS respectively. It should be noted that $\sum T_e$ is derived by adding $\sum T_s$ with $\sum T_t$.

Table 7.4's four bottom-most rows aggregate testing time results across projects for each RTS technique, retest-all, and parallel retest-all. Similar to Table 7.3, we exclude *Commond-IO* from any average and summation calculation for HyRTS, which could not run on the projects. Row $\sum T[sec]$ shows total test selection, test execution, and end-to-end time across all sample commits in the experiment. Row $\sum T[min]$ and $\sum T[hour]$ display this summation in minutes and hours respectively. The $\%T_{all}$ row displays the percentage ratio of $\sum\sum Time$ for each tool to $\sum\sum Time$ for retest-all for all projects. The $\%T_{par}$ displays the percentage ratio of $\sum\sum Time$ for each tool to $\sum\sum Time$ for parallel retest-all for all projects.

Table 7.4: Test run times for Retest-All, Parallel Retest-All, TLDR, STARTS, Ekstazi, and HyRTS in seconds, unless noted otherwise.

Project	$\sum T_{all}$	$\sum T_{par}$	**TLDR**			**STARTS**			**EKSTAZI**			**HyRTS**		
			$\sum T_s$	$\sum T_t$	$\sum T_e$	$\sum T_s$	$\sum T_t$	$\sum T_e$	$\sum T_s$	$\sum T_t$	$\sum T_e$	$\sum T_s$	$\sum T_t$	$\sum T_e$
asterisk-java	984	770	31.1	172.3	203.4	34.5	245.9	280.4	14.1	224.1	238.2	27.4	217.7	245.1
commons-cli	294	210	11.6	21.8	33.4	26.4	44.5	70.9	10.7	37.7	48.4	26.1	29.9	56
Commons-collections	1050	630	36.5	69.2	105.7	42.8	122.7	165.5	22.3	93.5	115.8	35.1	73.1	108.2
commons-dbutils	330	158	15.7	29.8	45.5	25.1	88.2	113.3	16.8	78.9	95.7	17	61.3	78.3
commons-email	720	480	11.2	61.1	62.3	21	141.5	162.5	27.3	67.6	94.9	33.1	56.5	89.6
Commons-fileupload	682	437	14.2	63.8	78	23.2	158	181.2	14.2	107.2	121.4	27.4	96.4	123.8
commons-functor	378	325	10.9	25.6	36.5	10.8	82.5	93.3	14.1	63.1	77.2	13.7	73.1	86.8
commons-jxpath	495	201	20.5	33.8	54.3	28.9	44.4	73.3	12.5	39.7	52.2	21.7	38	59.7
commons-math	1740	1095	68.7	246.5	315.2	26.8	289.9	316.7	11.2	281.3	292.5	54.1	282.2	336.3
commons-pool	8100	5052	22.2	605.2	627.4	20.8	1075.1	1095.9	12.3	752.7	765	18.7	761.5	780.2
commons-validator	345	258	23.9	50.9	74.8	40.2	61.1	101.3	14.4	60.1	74.5	19.9	57.4	77.3
compile-testing	306	229	30.7	69.8	100.5	37.5	93.7	131.2	13	91.5	104.5	18.4	133.5	151.9
invokebinder	165	105	20.1	29.1	49.2	22.4	39.4	61.8	9.6	36.9	46.5	16.3	35.1	51.4
Chronicle-Map	5700	3350	40.2	3092.3	3132.5	52.2	5848.7	5900.9	24.7	5484.7	5509.4	30.2	3781.3	3811.5
retrofit	1920	1632	25.4	26.9	52.3	10.3	57.7	68	6.5	62.2	68.7	13.3	33.1	46.4
commons-lang	1440	960	44	177.3	221.3	46.3	327.4	373.7	8.7	282.1	290.8	34.3	211.5	245.8
commons-io	5400	5100	15.5	37.4	52.9	32.2	52.6	84.8	12.8	47.2	60	-	-	-
joda-time	378	334	33.5	34.1	67.6	27.3	53.5	80.8	14.2	55.9	70.1	32.1	38.1	70.2
logstash-encoder	429	369	33.1	74.9	108	30.1	135.4	165.5	22.6	99.4	122	21.2	71.1	92.3
jfreechart	585	496	56.7	81.8	138.5	57	146.9	203.9	8.5	118.8	127.3	50.4	96.6	147
$\sum T[sec]$	31441	22191	565.7	4983.6	5549.3	615.8	9109.1	9724.9	290.5	8084.6	8375.1	510.4	6147.4	6657.8
$\sum T[min]$	524.1	369.8	9.4	83.0	92.4	10.2	151.8	162.0	4.8	134.7	139.5	8.5	102.4	110.9
$\sum T[hour]$	8.7	6.1	0.2	1.4	1.6	0.2	2.5	2.7	0.1	2.3	2.4	0.2	1.7	1.9
% T_{all}		70.1			18.3			31.0			27.5			21.8 *
% T_{par}					26.2			44.2			39.3			31.1*

In total, the complete experiment took 23.4 hours to complete. To perform testing of all sampled commits for 20 projects, retest-all took 8.7 hours, parallel retest-all took 6.1 hours, TLDR took 1.6 hours, STARTS took 2.7 hours, Ekstazi took 2.4 hours. HyRTS took 1.9 hours for the 19 test projects it could run on.

Overall, parallel rest-all, TLDR, STARTS, Ekstazi, and HyRTS takes 70.1%, 18.3%, 31%, 27.5%, and 21.8% of the retest-time, respectively. Thus, each tool makes the testing process 29.9%, 81.7%, 69%, 72.5%, and 78.2% faster. Therefore, on average, TLDR is faster than STARTS, Ekstazi, HyRTS, and parallel retest-all. Ekstazi is more efficient in test selection. However, due to its coarser granularity, its end-to-end time is more than TLDR. STARTS is the slowest RTS tool among the four RTS techniques under evaluation.

However, for *logstash-encoder* and *commons-emails*, TLDR is slower than HyRTS. For *commons-emails*, HyRTS is more precise than TLDR due to the aforementioned case. Therefore, for this project TLDR incurs more test execution time, thus, incurs more end-to-end time than HyRTS. For *logstash-encoder*, even though TLDR incurs less test execution time, it incurs more test selection time. Therefore, TLDR incurs more end-to-end time than HyRTS.Overall, TLDR improves upon Ekstazi's end-to-end testing time by a factor of 1.5, STARTS' end-to-end testing time by a factor of 1.7, and HyRTS's end-to-end testing time by a factor of 1.2.

TLDR is never slower than retest-all and parallel retest-all; however, this is not the case for Ekstazi, HyRTS, and STARTS. For example, For *Chronicle Maps*, Ekstazi and HyRTS are slower than parallel retest-all, STARTS is slower than retest-all and parallel retest-all.

Chapter 8

Limitations and Threats to Validity

There are several conceptual and implementation limitations of TLDR as well as potential threats to the validity of the evaluation of TLDR. In this chapter, we discuss these limitations and threats to the validity.

8.1 Reflection and Instrumentation

Reflection is a technique to analyze and modify the behavior of programming construct i.e. statements, methods, classes, and interfaces at runtime [15]. Thus dependencies that are injected by reflection can only be parsed in the runtime. Like STARTS and HyRTS, TLDR does not track dependencies resulting from the use of Java reflection API. It should be noted that reflection is not a common phenomenon in Java programs as it is computationally expensive and pose security and privacy threats. To further assess the prevalence of reflection in open-source Java projects, we statically parsed the bytecode of 50 thousand popular and buildable open-source Java projects. These projects were collected from an open-source dataset named 50k-C [40]. JDK exposes *java.lang.reflect* package that includes APIs to

read or write bytecode in runtime. Before the read/write operations, the corresponding programming construct i.e. class, method, field, etc. are needed to be loaded by a set of API that belong to *java.lang.Class* and *java.lang.Object* package. Therefore, we statically parsed the bytecodes of the projects in 50k-C to find the use of the following APIs -

- java.lang.reflect.*
- java.lang.Object.getClass
- java.lang.Class.getMethods
- java.lang.Class.getFields
- java.lang.Class.getMethod
- java.lang.Class.getField
- java.lang.Class.getConstructors
- java.lang.Class.getConstructor

In addition to reflection, another way to inject runtime dependency is instrumentation. A java program i.e. Java Agent can utilize JVM's Instrumentation API to edit bytecodes that are already loaded in a JVM [6]. A Java agent must have two public methods named *premain* and *agetmanin* who are responsible to load the agent itself statically and dynamically respectively. Therefore, we searched for the two mentioned APIs among the study bytecode.

We found that out of the 50,000 projects, only 4382 (8.7%)projects had reflection or instrumentation. This result shows that a vast majority of the open-source Java projects do not use reflection. It should be noted that this limitation is not a threat to the validity of our approach, it is simply an implementation shortcoming of TLDR. Reflective dependencies can be added by performing a more sophisticated analysis of the bytecode [38]. Since TLDR

does not capture dependencies injected by reflection, we did not include any project that has reflection in our evaluation dataset.

8.2 External Dependency

In addition to reflection, we did not incorporate external jars in the dependency extractor. This decision was carried out because we focused primarily on intra-project change impact propagation. Nonetheless, changes in external dependency artifacts may cause unanticipated changes in the project codebase. We plan to add external jar dependency tracking to TLDR.

8.3 Test Failure

By analyzing the generated test reports, we noticed that some of the selected tests fail. This happened for all three tools. However, those tests pass when the complete test suite is run. Unreliable behavior of unit testing has been documented in the literature [45, 57] [44]. These tests are known as flaky tests [39], and some causes for them include concurrency issues, test order dependency, resource leak, time, randomness, etc. Particularly problematic for RTS, in general, are test order dependencies. Although developers are encouraged to follow a set of conventions while writing unit tests, these conventions are not syntactically enforced by the test libraries. Therefore, bad implementations create the above-mentioned issues, thus seriously undermining the outcome of RTS. In TLDR, we consider intra-test dependency – dependency to static initializer, fields, helper methods, and parameterized tests within the test suite. However, test order dependency is not currently addressed. This limits the applicability of TLDR (and all other RTS tools we are aware of, including Ekstazi, STARTS, and HyRTS) to test suites that follow recommended guidelines for writing unit tests.

8.4 Average Error

Our performance evaluation suffers from the same shortcomings of other similar performance evaluations published in recent RTS literature [17, 34, 20, 68]. Specifically, the processing of each commit was done only once. We are aware that execution times for the exact same commits vary, depending on many external factors of the machine where the experiment was run. As such, in order to get statistically more reliable time values, we should run each experiment multiple times, and report the average. The reason for not doing that is that these experiments take a long time to complete; repeating them multiple times would severely slow down the reporting of these results, forcing us to reduce either the number of projects in our experimental dataset or the number of commits sampled in each project. The absence of repeated experiments is mitigated by sampling multiple commits, and having a substantially high total experiment time (roughly, 37 hours of compute time). Since the main goal of this study is to compare TLDR with 3 baselines, and given that all experiments were run in the exact same machine, the reported results are statistically valid, at least in comparison to each other.

Chapter 9

Future Work and Conclusion

9.1 Future Work

Currently, TLDR is compatible with Java projects that use Maven as build system. In chapter 8, we have discussed several implementation and conceptual limitations of the tool. In the future, we would like to advance our work on regression testing in the following directions -

9.1.1 Ground Truth and Benchmark

The baseline for the safety in all RTS tools is that the tools select all the tests that are impacted by the change in the current iteration. The baseline for the precision in all RTS tools is that the tools must select only the tests that are impacted by the change in the current iteration. In order to completely evaluate the absolute safety and precision of TLDR and other RTS tools, i.e. Ekstazi, STARTS, and HyRTS, we need to know the ground truth that is the exact set of tests that are impacted by a given set of changes. Such ground truth can be found by implementing a dynamic and method-level RTS tool which is computationally

expensive. In the future, we plan to develop a benchmark that contains the precise set of the tests that must be run for a set of the given change. Such a benchmark can be developed for a set of commits for popular open-source project.

9.1.2 Robust Artifact

A robust artifact will enable us to conduct a robust evaluation. Currently, TLDR is a Maven plugin that works for single- and multi-module Maven projects. In the future, we will make the tool compatible with projects that use Ant, Gradle, and Bazel, three of the most popular build systems. Also, external and environment dependencies are not encapsulated within TLDR. For example, running the tool requires running a local redis server. In the future, we plan to make all TLDR-specific and project-specific environment dependencies encapsulated in containers like Docker. These improvements will enable us to evaluate the tool for projects with a wide-range of variety.

9.1.3 External Dependency

Currently, TLDR analyzes dependencies within the source-code of the subject projects. However, projects often involve dependencies to external files and resources like database, shared memory, etc. Oftentimes, these dependencies are non-trivial to parse and analyze. For example, projects can have dependency on a file or a database table that is hosted in one or many remote machines. Projects can have dependencies on external files that are owned by different entities with regulated access privileges. In the future, we seek to explore how these external and nuanced dependencies affect regression testing and how to incorporate these dependencies within TLDR.

9.2 Conclusion

In this thesis, we presented TLDR, a static method-level RTS technique. TLDR selects and runs fewer tests than state-of-the-art RTS approaches Ekstazi, HyRTS, and STARTS because it performs change impact analysis and test selection at the method level. TLDR gains this improved precision of test selection while significantly reducing end-to-end testing time since TLDR leverages parallelism, and efficient checksum algorithm usage and in-memory database-schema design to improve the throughput of the test selection process. We evaluated TLDR for 20 projects. Our evaluation shows that TLDR is 2.7 times more precise than STARTS, 2.1 times more precise than Ekstazi, and 1.4 times more precise than HyRTS, while also being 1.5 times faster than Ekstazi, 1.7 times faster than STARTS, and 1.2 times faster than HyRTS. Overall, our evaluation demonstrates that method-level RTS can be made both precise and efficient. In future work, we aim to make TLDR safe for reflection and external libraries.

Bibliography

[1] R. Abreu, P. Zoeteweij, and A. J. Van Gemund. On the accuracy of spectrum-based fault localization. In *Testing: Academic and Industrial Conference Practice and Research Techniques-MUTATION (TAICPART-MUTATION 2007)*, pages 89–98. IEEE, 2007.

[2] M. Acharya and B. Robinson. Practical change impact analysis based on static program slicing for industrial software systems. In *Proceedings of the 33rd international conference on software engineering*, pages 746–755. ACM, 2011.

[3] J.-P. Aumasson, S. Neves, Z. Wilcox-O'Hearn, and C. Winnerlein. Blake2: simpler, smaller, fast as md5. In *International Conference on Applied Cryptography and Network Security*, pages 119–135. Springer, 2013.

[4] D. F. Bacon and P. F. Sweeney. Fast static analysis of c++ virtual function calls. *ACM Sigplan Notices*, 31(10):324–341, 1996.

[5] J. Bible, G. Rothermel, and D. S. Rosenblum. A comparative study of coarse-and fine-grained safe regression test-selection techniques. *ACM Transactions on Software Engineering and Methodology (TOSEM)*, 10(2):149–183, 2001.

[6] W. Binder, J. Hulaas, and P. Moret. Advanced java bytecode instrumentation. In *Proceedings of the 5th international symposium on Principles and practice of programming in Java*, pages 135–144, 2007.

[7] J. Buckner, J. Buchta, M. Petrenko, and V. Rajlich. Jripples: A tool for program comprehension during incremental change. In *13th International Workshop on Program Comprehension (IWPC'05)*, pages 149–152. IEEE, 2005.

[8] J. Candido, L. Melo, and M. d'Amorim. Test suite parallelization in open-source projects: a study on its usage and impact. In *2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pages 838–848. IEEE, 2017.

[9] C. Chambers, J. Dean, and D. Grove. Whole-program optimization of object-oriented languages. *University of Washington Seattle, Technical Report 96-06*, 2, 1996.

[10] Y.-F. Chen, D. S. Rosenblum, and K.-P. Vo. Testtube: A system for selective regression testing. In *Proceedings of 16th International Conference on Software Engineering*, pages 211–220. IEEE, 1994.

[11] J. Dean, D. Grove, and C. Chambers. Optimization of object-oriented programs using static class hierarchy analysis. In *European Conference on Object-Oriented Programming*, pages 77–101. Springer, 1995.

[12] S. Elbaum, G. Rothermel, and J. Penix. Techniques for improving regression testing in continuous integration development environments. In *Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 235–245, 2014.

[13] E. Engström, P. Runeson, and M. Skoglund. A systematic review on regression test selection techniques. *Information and Software Technology*, 52(1):14–30, 2010.

[14] R. E. Fairley. Tutorial: Static analysis and dynamic testing of computer software. *Computer*, 11(4):14–23, 1978.

[15] I. R. Forman, N. Forman, and J. V. Ibm. Java reflection in action. 2004.

[16] G. Fraser and A. Arcuri. Evosuite: automatic test suite generation for object-oriented software. In *Proceedings of the 19th ACM SIGSOFT symposium and the 13th European conference on Foundations of software engineering*, pages 416–419. ACM, 2011.

[17] B. Fu, S. Misailovic, and M. Gligoric. Resurgence of regression test selection for c+.

[18] M. Gethers, B. Dit, H. Kagdi, and D. Poshyvanyk. Integrated impact analysis for managing software changes. In *2012 34th International Conference on Software Engineering (ICSE)*, pages 430–440. IEEE, 2012.

[19] M. Gligoric, L. Eloussi, and D. Marinov. Ekstazi: Lightweight test selection. In *2015 IEEE/ACM 37th IEEE International Conference on Software Engineering*, volume 2, pages 713–716. IEEE, 2015.

[20] M. Gligoric, L. Eloussi, and D. Marinov. Practical regression test selection with dynamic file dependencies. In *Proceedings of the 2015 International Symposium on Software Testing and Analysis*, pages 211–222. ACM, 2015.

[21] M. Gligoric, R. Majumdar, R. Sharma, L. Eloussi, and D. Marinov. Regression test selection for distributed software histories. In *International Conference on Computer Aided Verification*, pages 293–309. Springer, 2014.

[22] M. Z. Gligoric. *Regression test selection: Theory and practice*. PhD thesis, University of Illinois at Urbana-Champaign, 2015.

[23] S. S. Gokhale and S. M. Yacoub. Reliability analysis of pipe and filter architecture style. In *SEKE*, pages 625–630. Citeseer, 2006.

[24] A. Goknil, I. Kurtev, and K. v. d. Berg. A rule-based change impact analysis approach in software architecture for requirements changes. *arXiv preprint arXiv:1608.02757*, 2016.

[25] T. L. Graves, M. J. Harrold, J.-M. Kim, A. Porter, and G. Rothermel. An empirical study of regression test selection techniques. *ACM Transactions on Software Engineering and Methodology (TOSEM)*, 10(2):184–208, 2001.

[26] M. J. Harrold, J. A. Jones, T. Li, D. Liang, A. Orso, M. Pennings, S. Sinha, S. A. Spoon, and A. Gujarathi. Regression test selection for java software. In *ACM Sigplan Notices*, volume 36, pages 312–326. ACM, 2001.

[27] M. J. Harrold, J. A. Jones, T. Li, D. Liang, A. Orso, M. Pennings, S. Sinha, S. A. Spoon, and A. Gujarathi. Regression test selection for java software. *ACM Sigplan Notices*, 36(11):312–326, 2001.

[28] K. Herzig, M. Greiler, J. Czerwonka, and B. Murphy. The art of testing less without sacrificing quality. In *Proceedings of the 37th International Conference on Software Engineering-Volume 1*, pages 483–493. IEEE Press, 2015.

[29] J.-M. Kim and A. Porter. A history-based test prioritization technique for regression testing in resource constrained environments. In *Proceedings of the 24th international conference on software engineering*, pages 119–129. ACM, 2002.

[30] M. S. Lam, J. Whaley, V. B. Livshits, M. C. Martin, D. Avots, M. Carbin, and C. Unkel. Context-sensitive program analysis as database queries. In *Proceedings of the twenty-fourth ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*, pages 1–12, 2005.

[31] J. Law and G. Rothermel. Whole program path-based dynamic impact analysis. In *Proceedings of the 25th international conference on software engineering*, pages 308–318. IEEE Computer Society, 2003.

[32] O. Legunsen, F. Hariri, A. Shi, Y. Lu, L. Zhang, and D. Marinov. An extensive study of static regression test selection in modern software evolution. In *Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 583–594. ACM, 2016.

[33] O. Legunsen, F. Hariri, A. Shi, Y. Lu, L. Zhang, and D. Marinov. An extensive study of static regression test selection in modern software evolution. In *Proceedings of the 2016 24th ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 583–594. ACM, 2016.

[34] O. Legunsen, A. Shi, and D. Marinov. Starts: Static regression test selection. In *2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE)*, pages 949–954. IEEE, 2017.

[35] H. K. Leung and L. White. Insights into regression testing (software testing). In *Proceedings. Conference on Software Maintenance-1989*, pages 60–69. IEEE, 1989.

[36] B. Li, X. Sun, H. Leung, and S. Zhang. A survey of code-based change impact analysis techniques. *Software Testing, Verification and Reliability*, 23(8):613–646, 2013.

[37] E. Linstead, S. Bajracharya, T. Ngo, P. Rigor, C. Lopes, and P. Baldi. Sourcerer: mining and searching internet-scale software repositories. *Data Mining and Knowledge Discovery*, 18(2):300–336, 2009.

[38] B. Livshits, J. Whaley, and M. S. Lam. Reflection analysis for java. In *Asian Symposium on Programming Languages and Systems*, pages 139–160. Springer, 2005.

[39] Q. Luo, F. Hariri, L. Eloussi, and D. Marinov. An empirical analysis of flaky tests. In *Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*, pages 643–653. ACM, 2014.

[40] P. Martins, R. Achar, and C. V. Lopes. 50k-c: A dataset of compilable, and compiled, java projects. In *2018 IEEE/ACM 15th International Conference on Mining Software Repositories (MSR)*, pages 1–5. IEEE, 2018.

[41] A. Memon, Z. Gao, B. Nguyen, S. Dhanda, E. Nickell, R. Siemborski, and J. Micco. Taming google-scale continuous testing. In *2017 IEEE/ACM 39th International Conference on Software Engineering: Software Engineering in Practice Track (ICSE-SEIP)*, pages 233–242. IEEE, 2017.

[42] A. K. Onoma, W.-T. Tsai, M. Poonawala, and H. Suganuma. Regression testing in an industrial environment. *Communications of the ACM*, 41(5):81–86, 1998.

[43] A. Orso, N. Shi, and M. J. Harrold. Scaling regression testing to large software systems. In *ACM SIGSOFT Software Engineering Notes*, volume 29, pages 241–251. ACM, 2004.

[44] F. Palomba and A. Zaidman. Does refactoring of test smells induce fixing flaky tests? In *2017 IEEE International Conference on Software Maintenance and Evolution (ICSME)*, pages 1–12. IEEE, 2017.

[45] F. Palomba and A. Zaidman. The smell of fear: on the relation between test smells and flaky tests. *Empirical Software Engineering*, pages 1–40, 2019.

[46] C. R. Panigrahi and R. Mall. A hybrid regression test selection technique for object-oriented programs. *Proc. Int. J. Softw. Eng. Appl*, 6(4), 2012.

[47] J. Philipps and B. Rumpe. Refinement of pipe-and-filter architectures. In *International Symposium on Formal Methods*, pages 96–115. Springer, 1999.

[48] X. Ren, F. Shah, F. Tip, B. G. Ryder, and O. Chesley. Chianti: a tool for change impact analysis of java programs. In *ACM Sigplan Notices*, volume 39, pages 432–448. ACM, 2004.

[49] G. Rothermel and M. J. Harrold. A safe, efficient regression test selection technique. *ACM Transactions on Software Engineering and Methodology (TOSEM)*, 6(2):173–210, 1997.

[50] G. Rothermel and M. J. Harrold. Empirical studies of a safe regression test selection technique. *IEEE Transactions on Software Engineering*, 24(6):401–419, 1998.

[51] G. Rothermel, M. J. Harrold, and J. Dedhia. Regression test selection for c++ software. *Software Testing, Verification and Reliability*, 10(2):77–109, 2000.

[52] G. Rothermel, R. H. Untch, C. Chu, and M. J. Harrold. Prioritizing test cases for regression testing. *IEEE Transactions on software engineering*, 27(10):929–948, 2001.

[53] A. Rountev, S. Kagan, and M. Gibas. Static and dynamic analysis of call chains in java. In *ACM SIGSOFT Software Engineering Notes*, volume 29, pages 1–11. ACM, 2004.

[54] V. Sundaresan, L. Hendren, C. Razafimahefa, R. Vallée-Rai, P. Lam, E. Gagnon, and C. Godin. *Practical virtual method call resolution for Java*, volume 35. ACM, 2000.

[55] R. Tarjan. Depth-first search and linear graph algorithms. *SIAM journal on computing*, 1(2):146–160, 1972.

[56] R. N. Taylor, N. Medvidovic, and E. M. Dashofy. *Software Architecture: Foundations, Theory, and Practice*. Wiley Publishing, 2009.

[57] A. Vahabzadeh, A. M. Fard, and A. Mesbah. An empirical study of bugs in test code. In *2015 IEEE international conference on software maintenance and evolution (ICSME)*, pages 101–110. IEEE, 2015.

[58] L. White, H. Almezen, and S. Sastry. Firewall regression testing of gui sequences and their interactions. In *International Conference on Software Maintenance, 2003. ICSM 2003. Proceedings.*, pages 398–409. IEEE, 2003.

[59] L. White, K. Jaber, and B. Robinson. Utilization of extended firewall for object-oriented regression testing. In *21st IEEE International Conference on Software Maintenance (ICSM'05)*, pages 695–698. IEEE, 2005.

[60] L. White, K. Jaber, B. Robinson, and V. Rajlich. Extended firewall for regression testing: an experience report. *Journal of Software Maintenance and Evolution: Research and Practice*, 20(6):419–433, 2008.

[61] L. J. White and H. K. Leung. A firewall concept for both control-flow and data-flow in regression integration testing. In *Proceedings Conference on Software Maintenance 1992*, pages 262–271. IEEE, 1992.

[62] D. Willmor and S. M. Embury. A safe regression test selection technique for database-driven applications. In *21st IEEE International Conference on Software Maintenance (ICSM'05)*, pages 421–430. IEEE, 2005.

[63] W. E. Wong, J. R. Horgan, S. London, and H. Agrawal. A study of effective regression testing in practice. In *PROCEEDINGS The Eighth International Symposium On Software Reliability Engineering*, pages 264–274. IEEE, 1997.

[64] G. Xu and A. Rountev. Regression test selection for aspectj software. In *Proceedings of the 29th international conference on Software Engineering*, pages 65–74. IEEE Computer Society, 2007.

[65] S. Yoo and M. Harman. Regression testing minimization, selection and prioritization: a survey. *Software Testing, Verification and Reliability*, 22(2):67–120, 2012.

[66] Y. Yu, J. Jones, and M. J. Harrold. An empirical study of the effects of test-suite reduction on fault localization. In *2008 ACM/IEEE 30th International Conference on Software Engineering*, pages 201–210. IEEE, 2008.

[67] L. Zhang. Hybrid regression test selection. In *2018 IEEE/ACM 40th International Conference on Software Engineering (ICSE)*, pages 199–209. IEEE, 2018.

[68] L. Zhang, M. Kim, and S. Khurshid. Faulttracer: a spectrum-based approach to localizing failure-inducing program edits. *Journal of Software: Evolution and Process*, 25(12):1357–1383, 2013.