SHF: Small: Feedback-Driven Mutation Testing for Any Language

1 Overview and Objectives

1.1 Problem Statement

The core problem this project aims to address is making the use of program mutants practical in non-research settings, in a way that meets developers' or test engineers' needs; that is, making it possible for someone creating or enhancing a test suite, or developing code and test suite in tandem, to (1) use "just enough" mutation testing for their needs, maximizing benefit gained in exchange for work performed, and to (2) work in any programming language without worrying about the quality of tool support provided for mutation testing, and without sacrificing the ease of understanding of source-based mutants, while easily adding custom mutation operators that target their specific software development task. More generally, this project aims to make use of the insights of Test-Driven-Development (TDD), and proposes using mutation testing to move beyond a paradigm where developers build a series of tests narrowly tailored to steps in development, and use Mutation-Driven-Development (MDD) to build automated test generators or verification harnesses that handle not only anticipated problems imagined during development, but problems not anticipated by human insight, discovered using mutation-based analysis. In addition to traditional manual testing, this proposal targets both highly-general property-driven testing and even full formal verification of software components, in order to be practical in the future, where software systems will often be so safety- or mission- critical that even "good" manual testing is not an acceptable approach to ensuring correctness, security, and reliability.

1.1.1 Just Enough Mutation Testing: Feedback-Driven Mutation Testing

Most previous mutation testing research focuses on computing a mutation score or, at least, the set of unkilled (and perhaps non-equivalent) mutants. Using mutation testing tools involves running many tests on many modified versions of a software system, and, for larger projects or more expensive test suites, requires substantial computing resources, making reducing that need a major thrust of mutation testing research [70]. However, as useful as knowing the overall quality of a test suite may be, the most practical goal of mutation testing is to improve a test suite. For this purpose, an expensive-to-generate list of all unkilled mutants is not really what users need — or want. A list of unkilled mutants contains uninteresting mutants (many, but not all, equivalent mutants), numerous redundant mutants (that can be killed by the same extension of the test suite, or rejected as uninteresting for the same reason), and a smaller number of actionable, representative mutants that are maximally effective in guiding improvement of a testing effort. Examining all unkilled mutants is only practical for formal verification efforts or very high-powered test suites and critical software systems that motivate such efforts. In previous work on using mutants to drive formal verification and automated testing [52, 56, 3] PI Groce and co-authors noted that examining surviving mutants was a time-consuming and unpleasant task, even in these settings. With a larger number of unkilled mutants, the problem becomes one very much like the bug triage or "fuzzer taming" problem in random testing/fuzzing [21, 126]: a user wants to quickly find mutants that indicate the most important "holes" in a testing or verification effort, and act on those most-critical gaps, possibly revealing faults in the System Under Test (SUT).

What a user really wants is a tool that presents a few very different, ranked, mutants, all likely to be of interest, and revises the presented mutants and their ranking based on actions taken by the user — adding tests, fixing faults, marking certain mutants as equivalent or uninteresting, and perhaps assigning a priority and severity to both killed or dismissed mutants and any remaining un-handled mutants. However, current mutation testing approaches make no real effort, with few exceptions [109, 18] to prioritize mutants, and none are based on a user-centered feedback loop, where the user and mutation testing framework interact to improve a test suite, automated test generator, or verification harness — and, of course, improve the SUT as well. Other than (arguably) some efforts to incorporate dominance results [105], no mutation testing

approaches currently suggest any more sophisticated way to maximize the novelty of presented mutants than stratified sampling [39]; stratified sampling does not really aim at semantic novelty, and can present many mutants from the same class together, if applied at the method level, even if those mutants are really quite similar in impact on the software system. In fact, some work [34] suggests random sampling as the most effective way to select a small set of mutants. Unfortunately, when an important class of unkilled mutants has only a few members, random sampling is almost guaranteed to fail to present one of those mutants. A user's feedback about the most critical-to-test aspects of the code, or hard work examining some mutants, simply has no influence on the kinds of sampling currently proposed in the mutation testing literature. Even creating simple clusters of mutants that are not killed due to the same underlying omission in tests requires manual effort, with users, e.g., writing a Python script scanning mutants for certain strings and assuming all mutated code with that string is part of the same "equivalence class." This is a tedious and error-prone process, and only even possible once a "kind" of unkilled mutant is discovered, largely by ad hoc scanning of the list of unkilled, uncategorized, mutants. A constantly-updated ranking of mutants likely to be useful to examine also helps provide a stopping rule other than patience, time available, or "every last mutant": since mutants are ranked by likely payoff, once a user has examined several mutants in a row without benefit, or mutants are highly similar in behavior to other mutants, a user may reasonably stop, knowing that the low-hanging fruit have probably all been picked. Finally, a feedback-driven mutation testing approach provides a simple way to improve the efficiency of mutation testing: even for a very large project, it only has to build and execute a small set of mutants, because it only runs the test suite on mutants currently predicted to be of likely interest to the user. Many mutants will be killed before they are ever executed, and others will be omitted because they are ranked too low for the user to ever consider.

Problem: Develop highly automated methods and tools that allow the practical application of mutation testing in a feedback-driven way, where user and mutation testing framework cooperate to improve testing efforts, while minimizing user effort and maximizing the ability to quickly find the most important weaknesses of a test suite, automated test generation system, or formal verification effort.

1.1.2 Any-Language Mutation Testing

One ongoing limitation of mutation testing is that tools are often research projects, and eventually become unusable due to lack of support, even in mainstream languages such as Java and C [38]. This is because mutation tools that parse a language and guarantee generation of valid programs in the source language are complex, hard-to-maintain-and-extend systems; language complexity makes such a tool for C++, for example, an extremely daunting task. The most widely used mutation tool in the real world is PIT [22], which targets Java bytecode. There are recent attempts to provide the same kind of support for other languages, especially C, by targeting LLVM IR [60].

The problem with bytecode-level mutation is that while an arguably excellent choice if the goal of mutation testing is to compute a score for a test suite, bytecode-level mutants are themselves not suitable for presentation to most users; Java developers think in terms of Java, not compiled bytecode, and C and C+++ developers certainly do not generally understand LLVM IR; test engineers are even less likely to appreciate such low-level descriptions of testing omissions. Even when possible, translation may not help: a bytecode-level mutation may not have a source-level equivalent that is conceptually simple, especially if the bytecode has been optimized, and some obvious source-level mutations (such as statement deletion) are known to be difficult to precisely implement in bytecode. Moreover, targeting bytecode only helps with languages that compile to Java bytecode or LLVM IR, which leaves out Python, Ruby, Go, and numerous other popular languages, and certainly means that supporting project-specific Domain Specific Languages (DSLs) [29] is out of the question. Finally, at the bytecode level, features that might help identify mutants with similar or very different semantic effects may be obscured; at the source level, often the simple context of the line of code modified can provide considerable information. Even if the mutant is, for example, a

```
\+ ==> -            == ==> !=          (\D )(\d +)(\D ) ==> \1(\2+1)\3
\+ ==> *            == ==> <           (\D )(\d +)(\D ) ==> \1(\2-1)\3
\+ ==> /            == ==> >           (\D )(\d +)(\D ) ==> \g <1>0\3
".+" ==> ""         while ==> if       (^\s *)(\S +.*)\n ==> \1\2\n \1break;\n
```

Figure 1: Some universal mutation rules

constant replacement in one case and an arithmetic operator replacement in another, the fact that both take place inside an argument to a logging function, or an insertion to the same linked list, may be enough to predict that their effects on the code are likely to be related.

PI Groce recently proposed [57] an approach to mutant generation that does not attempt to parse source code, but simply defines mutation operators by a set of regular-expression-defined text transformations. These are organized into a hierarchy, so that if a program is, e.g., written in Swift, the "universal" mutation operators that apply to all programming languages are first applied, then operators for "C-like" languages, and finally a set of Swift-specific rules are applied. Figure 1 shows some of the current set of "universal" rules applied to all languages. Adding a new language, even a custom DSL, or a new set of project-specific rules for an existing language, in this approach, simply requires writing a new rule file and defining where it lies in the language hierarchy. This approach is also attractive in the feedback-based setting, since the problem of generating "too many" mutants is irrelevant if only a small set of highly diverse and likely-actionable mutants is ever presented to the user, and a novelty-estimator helps a user stop examining new mutants when the payoff is likely to be low.

There are significant limitations to this approach, however. Because the source code is not parsed, and applies the regular expressions to lines of code, not larger blocks, the technique generates many mutants that are not valid programs, and cannot be compiled, or that are trivially equivalent because they, e.g., mutate "source code" in a large comment block. Integrating mutation generation with execution is currently supported, but extending it to new languages or build systems is hard for users, requiring writing considerable Python code or complex shell scripts. It is currently impossible to define mutation operators that apply to blocks of code rather than text within a single line, and standard regular expressions are not really suited to describing code constructs such as blocks, functions, classes, or structs. Natural formatting of, e.g., an s-expression in a LISP-family language can hide opportunities for mutation, such as switching argument orders.

Problem: Provide high-quality mutation generation support to be used in a maximally flexible but still efficient mutation testing framework that can be applied to (essentially) any language, such that adding project-specific novel mutation operators, or even adding support for a new language (e.g. a DSL used in a single project) is possible for non-expert users.

1.1.3 Mutation-Driven-Development

The primary focus of this project is to develop the algorithms and methods required for feedback-driven mutation testing, a process in which a user improves a verification or testing effort using a small number of well-selected mutants. However, the ideas of Test-Driven Development (TDD) [11, 67], which repeatedly turns requirements into specific test cases, then implements just enough functionality to pass the current tests (and assumes the previous implementation will not pass those tests), can be translated into a falsification-driven/mutation-driven form. A potential weakness (and, of course, an actual goal) of TDD is that the code will be narrowly tailored to the requirements, which produce the tests, which means that missing requirements will almost always be omitted both from the tests and the code. For "shall" type behaviors [64], this is not a key problem; missing "shall" requirements will likely be omitted in any case. But for security and safety, "shall not" requirements that are omitted can be deadly. Mutation-Driven-Development (MDD) in its

simplest form would require an application of feedback-driven mutation to the test suite at each development step or at least at major milestones, to ensure that code not only does what the tests require, but that the tests also sufficiently constrain the code to capture at least many implicit shall-nots. Since such a process implemented by modifying TDD-driven tests would likely break the clean and appealing mapping between tests and requirements, and manual tests are inherently limited in effectiveness, for high-criticality systems, MDD should focus on augmenting TDD-driven tests with falsification-driven formal verification or at least automated testing. One way to do this would be to "elaborate" TDD-produced unit tests into parameterized unit tests [123, 122], perhaps using a tool like DeepState [32] for C/C++. In such a process, weakness exposed by feedback-driven mutation testing would normally be addressed by taking an existing unit test and generalizing some parameters and assertions to kill the relevant mutants, letting AFL [134], libFuzzer [116], or a symbolic execution tool [119, 120, 92] identify specific inputs. The focus of the MDD process would be on producing the test generator, test harness [41, 62], or parameterized version of unit test that allows an automated tool to quickly kill mutants covered by additional specification. More radically, MDD could be interpreted as a radical departure from normal TDD practice, where a single model checking or testing harness or parameterized unit test is iteratively enhanced with assertions and checks drawn from more requirements, always requiring the ability to kill (most) mutants of the current implementation that implements those requirements. This does not produce the large set of tests in TDD, but instead produces a single, monolithic, high-powered test generator or formal specification.

1.2 PI Qualifications

PI Groce has been a user of, and contributor to, mutation testing tools for many years. He combines a long research track record in software testing, including mutation testing, with actual experience testing critical software systems at NASA's Jet Propulsion Laboratory. PI Groce's long-running interest in improving the state-of-the-art in mutation testing dates from frustration in his efforts to apply mutation tools to the testing and verification effort for the Mars Science Laboratory's flight software, in particular to the file system [45, 46, 50]. This practical orientation informs recent work on using mutation testing in a falsification-driven approach to improving high-end verification and automated testing efforts [52, 56, 3]. PI Groce has extensive experience in developing mutation tools for new languages [80, 85, 57], including the first reliable tools for mutation of Haskell, Python, and Swift, as well as in user-facing (vs. researcher-oriented) automated software testing tools [62, 32].

1.3 Intellectual Merit

This project addresses core problems not limited to practical application of mutation testing to improve test efforts in a user-centered way, but generalizable to fundamental issues in software engineering and program semantics, e.g., how to represent program changes and (mostly statically) predict the similarity of their impact on program semantics, and predict which tests are likely to detect these changes. How can novelty of information presented to a user be effectively balanced with a-priori predictions of the utility of that information, where likely-high-utility data points may also be unfortunately similar to each other? How can user feedback be incorporated into such efforts without over-burdening human users? This project also considers connections raised by preliminary work, concerning effective methodologies for program and testing/verification effort development. Can theoretical ideas about the nature of scientific discovery [110, 111, 77] be applied to such efforts? Is falsification by alternative hypotheses about the correctness of a system or power of a testing/verification effort translatable to an actionable, effective approach for building systems [52, 56]? The work on any-language mutation testing looks at syntactic patterns common to almost all programming languages, and relies on categorizing languages into families based on similarity, and how they share common meaningful syntactic changes that translate to interesting semantic changes.

2 Background and Preliminary Research

2.1 Falsification-Driven Verification and Testing

PI Groce and colleagues recently proposed a novel approach to organizing and evaluating formal verification, automated testing, and, more generally, any testing efforts aiming at very-high-quality fault detection based on combining the insight's of Popper's falsification-based notion of scientific discovery [110, 111] with mutation based methods [52, 56, 3]. The heart of the idea is (1) the proposition that a surviving mutant that is not equivalent (or at least equivalent with respect to a given specification of correctness) *falsifies* the claim that a given formal verification or test effort captures the full notion of correctness for a system and (2) the proposal that refining a verification or test effort by repeated efforts at falsification is an effective method for ensuring the quality of verification and testing efforts. This line of work work resulted in the identification of multiple previously unknown faults in the Linux kernel's RCU [27, 58, 91] module and the `pyfakefs` Python mock file system [93], despite the existence of very-high-quality automated test generation efforts for these systems [90, 54]. This preliminary work on falsification-driven methods proposed a number of algorithms and methods for using unkilled mutants to guide model checking efforts, estimate needed random testing budgets and loop-bounds in bounded model checking [74, 13], and find bugs in testing and verification harnesses, rather than the code under test. At a high level, however, the core concept was simple: users should examine all unkilled mutants of a program, and for each mutant either understand why it is equivalent or uninteresting, or actually construct (with automated help) a way to kill it. In a sense, this simply harkens back to the earliest ideas about mutation testing, but with the addition of considerable automated support, at least for verification and automated testing efforts.

Unfortunately, the methods proposed were, while useful, limited in applicability. These early efforts simply assumed that the number of unkilled mutants to be examined was small, and focused on solving the problem of helping a developer or test engineer move from an unkilled mutant to an improvement of an already very-high-quality model-checking harness or automated test generator. Human attention does not scale to analyzing large numbers of unkilled mutants without further assistance in "triaging" the mutants, however. The process of manually examining mutants bears a resemblance to the problem of manual confirmation of results from a machine-learning classifier [51, 75], where even highly-motivated scientific users are typically unwilling to examine more than a few tens of potentially problematic results [115]. The manual mutant-examination process, even aided by tools for handling individual mutants, was simply not feasible unless the number of unkilled mutants was relatively small, because the testing was already very high quality. Moreover, for a sufficiently large software system, even a very high quality verification or testing effort may fail to kill a large absolute number of mutants. The original approach simply provided no way to scale human efforts to such a needle-in-a-haystack setting.

This project aims to make the falsification-driven approach to verification and testing feasible for larger projects, or those with less effective testing or verification, and extremely easy for smaller projects with already-high-quality testing or verification. Moreover, because this proposal's feedback-driven approach no longer requires small absolute numbers of unkilled mutants, it extends the applicability of the approach to manual construction of tests to kill mutants, which was not usually in scope when extremely high kill-rates were required.

2.2 Furthest Point First and Fuzzer Taming

An unkilled mutant is, conceptually, very similar to a failing test. It presents information of possible relevance to a developer or test engineer. The mutant or test *may* indicate the presence of a previously unknown fault that needs to be fixed, either in the SUT or in the test suite/test generator. It may indicate the presence of a previously unknown fault of less importance. It may also indicate an even less interesting result: an equivalent mutant or a "failure to fail" of an inherently flaky test. Or, in many cases, an unkilled mutant or failing test may contain information that is either important or unimportant, but is uninteresting

because *it duplicates information already presented for understanding.* While examining an equivalent mutant is not always useless (e.g., it may indicate an opportunity for refactoring or improving the efficiency of code [66, 56]), examining a mutant that is equivalent to or extremely similar to an already-understood mutant is almost never worthwhile — even if the original mutant provided important, actionable information. That information has already been incorporated into the development or testing process.

Fuzzer taming [21] was a solution PI Groce and colleagues proposed to the problem of triaging test failures in automated test generation [126]. In compiler testing and other fuzzing applications, a core usability issue is that tools tend to produce very large numbers of failing tests for a much smaller number of distinct bugs. Finding the set of distinct bugs, and identifying important bugs that need to be fixed immediately is difficult, because the important bugs may be represented by only one or two failing tests in a set of thousands of failing tests, most of which are duplicates. The fuzzer taming work proposed that rather than highly imprecise clustering, which does not work well in practice, and handles outliers in a way that does not match the "power law" distribution of bugs, an algorithm matching the goal of ranking maximally-different test failures highly was appropriate. Users do not (usually) care much about finding the group of all tests failing due to a fault, or the set of all mutants killable by the same extension to a test suite or generator, but about seeing *many very different test failures* or *many different unkilled mutants* quickly, to maximize the chance of discovering the most important faults or holes in a testing effort. The *furthest-point-first* (FPF) algorithm of Gonzalez [31] does precisely this. FPF, beginning with any randomly chosen test (or mutant, in the present setting), always ranks next the point in a metric-defined space that has the *greatest distance from the previously ranked point to which it is closest.* That is, for each point (test or mutant) not yet presented to the user, FPF finds the closest among all already-ranked points, and associates each unranked point with the distance to that closest point. The unranked point with the largest such distance is then added to the ranking, and the process is repeated. FPF can be computed by a greedy algorithm, and is known to approximate novel-item discovery for an optimal clustering [31]. Preliminary work on the fuzzer taming problem using FPF-based techniques [21, 61] can be directly applied to the similar (but operationally quite different) problem of ranking unkilled mutants such that novel mutants are presented to a user. The research plan (Section 3.1.1), discusses the key *differences* between novelty ranking for mutants and the fuzzer taming problem.

2.3 Any-Language Regular-Expression Based Mutation

As discussed in the problem statement, PI Groce and colleagues released a functional, regular-expression-based mutant generator [57, 44], and demonstrated that it generated numbers of mutants and kill ratios for Java code comparable to PIT [22] and Major [72], despite not parsing the Java program at all, or acting at the bytecode level. Furthermore, for falsification-driven verification, the regular-expression-based approach produced mutants of equal value to those produced by Andrews' tool [6] and Muupi [85] for C and Python, respectively. As it stands, the `universalmutator` tool is usable for real-world mutation (in fact, it is being considered for use by NASA/JPL engineers in testing the C code for upcoming CubeSat [99] missions) for languages including: C, C++, Java, Python, Swift, Rust, Go, and the Solidity smart-contract language. The `universalmutator` allows easy definition of new rules, and supports automated analysis of mutants, coverage-based pruning of mutants, and (in some languages) trivial compiler equivalence [106] checks. As it stands, the tool and approach form a suitable platform for generating mutants to be used in this project's early phases. The research plan (in Section 3.1.4) discusses enhancements to the approach and tool that will be required to better support robust, flexible, efficient feedback-driven mutation testing.

3 Research Plan

3.1 Overview

Figure 2 shows the basic outline of a proposed workflow and components needed to support feedback-driven mutation testing. These components serve to organize the research plan.

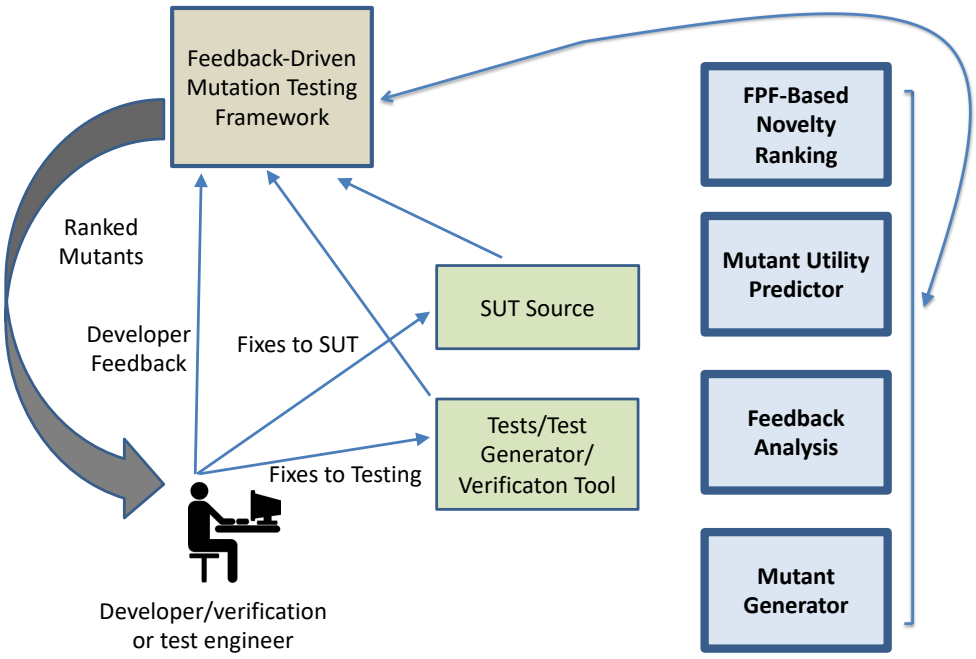

Figure 2: Basic flow of feedback-driven mutation testing.

3.1.1 FPF-Based Novelty Ranking

Ranking unkilled mutants according to how much "new" information they might provide to users requires more than simply using the FPF algorithm as in fuzzer taming. The key difference is the problem of determining how similar two mutants are; in fuzzer taming, it is possible to extract a large amount of information about similarity of failing tests from executing the tests, and, in fact, from executing the tests on program mutants [21, 61]. There is no obvious equivalent to "just run the test" for mutants, and in fact avoiding the expense of running the test suite on uninteresting mutants is one of the goals of feedback-driven mutation testing in the first place.

FPF requires a distance metric, and a distance metric requires a *representation* of mutants. Mutants can be similar because they modify the same line, function, class, or module, but also because, despite being located in very different parts of a program, they are very semantically similar. E.g., a mutant to the parser of a compiler, to an I/O error-handling routine in the code generator, and to a complex optimization pass may all be very "similar" in the only meaningful sense if all three mutants modify logging statements that don't have any actual effect on the state of the compiler. Figure 3 shows the fundamental problem. It is not, a-priori, obvious which mutants here are most (dis-)similar. Every mutant has multiple plausible "nearest neighbors" — another mutant in the same file (likely to impact the same aspects of correctness), another mutant with very similar code (likely to have the same kind of semantic impact on the local context), or another mutant with the same operator (perhaps likely to have some similarity, though probably of a lower importance than the previous two types of similarity). Are all logging statements equivalent, or are only `INFO` logging calls similar, while every `WARNING`, `ERROR` or `FATAL` is unique? Some of these decisions are unlikely to be project-independent, and so a good metric may well change during feedback-driven mutation testing, in response to information from users (see Section 3.1.3 below).

Elements of the distance metric obviously include, at minimum, mutant location, mutation operator, and some representation of the code element modified — language construct, functions called, variables modified,

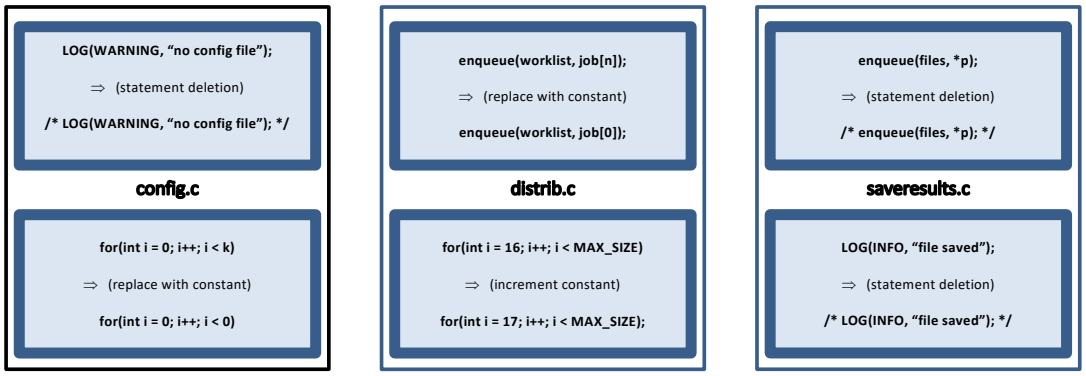

Figure 3: Which mutants are most similar? If the user marked the mutant in the upper left corner as uninteresting and added a test to kill the mutant in the upper middle, which mutant should she examine next?

and so forth. These static aspects may also be augmented with user feedback (as noted above), but also with dynamic information obtained during the process, such as frequency with which tests cover the mutated statements/modules, or the way the mutant changes the program path from the unmutated code in tests. In fact, there may need to be two distance metrics: one for selecting likely candidate mutants to execute, that uses only static information and user feedback, and one that uses dynamic results from compiling and testing mutants to refine the notion of similarity for likely-novel mutants. This is therefore a quite complex problem in representation and weighting of elements of a representation, especially for a language- and project- agnostic metric, that is also open to tuning via feedback analysis. One approach to the problem is to exploit metric learning methods [76], which was used in some of PI Groce's previous work [108], but in order to avoid over-fitting to even a set of good examples, the final metric may have to be largely hand-tuned, and designed to incorporate feedback and dynamically extracted information, which is not easily handled with learned metrics. In part this is due to the difficulty of establishing large amounts of ground truth data, and the expectation that cross-project data will be less valuable than project-specific data extracted during the process itself; although there are unsupervised approaches to metric learning [114, 124], the most popular approaches require supervision.

3.1.2 Mutant Utility Predictor

Novelty with respect to previously analyzed mutants is not the only important characteristic of a mutant. Presenting a novel, but likely equivalent mutant is often a waste of time, though some equivalent mutants can be useful for identifying optimization opportunities or refactorings. Furthermore, of two similar mutants next to be presented, it is better to present one that is higher in the mutant dominance hierarchy (the one such that its tests will kill more other mutants). There has been some initial work on predicting mutant quality attributes and utility [105, 18], including estimating how hard mutants will be to kill, statically. In addition to advancing the state-of-the-art in that respect, feedback-driven mutation testing also requires determining how to balance the need for novelty and the predicted utility of a mutant. For example, a utility-driven ranking might suggest avoiding a highly novel mutant because it is likely equivalent; however, it may be that labeling this mutant as equivalent lets the FPF ranking avoid numerous other similar mutants — e.g., postponing labeling a logging statement as confirmed equivalent by the user may not be a good idea. Also, if the mutant is *not* equivalent (perhaps the user decides this kind of logging needs to be tested), then the information obtained may be high-value.

3.1.3 Feedback Analysis

The "feedback-driven" aspect of feedback-driven mutation analysis requires that information from the user be given high priority in the process, a process with no clear equivalent in any previously proposed mutation

testing work. The most straightforward example is that if a user adds a test to kill a mutant, and marks that as a "high impact" action (the omitted testing was potentially allowing serious faults to pass without detection) or even "fault-revealing" (the new test detected a real fault in the system), then it may be most effective to abandon the search for novelty and instead search for very similar mutants still not killed by any test, in the expectation that these may also result in high impact or fault-revealing tests. If a user marks a mutant as "equivalent, but indicative of a refactoring opportunity", the same logic may apply: similar mutants in other parts of the code base may show the same problem with code quality, even if they are predicted to be equivalent, and are not highly novel. In addition to informing the system of how useful various analyzed mutants were, a user should also be able to inform the system about correct and incorrect novelty rankings: if the system presents a mutant that is, from the user's POV, a (near-)duplicate of an already handled mutant, the user should be able to express this fact, and avoid future similar bad novelty estimates.

While large-scale crowdsourcing of user feedback is likely only possible in some unusual industrial settings [109, 66], it may also be possible to apply mini-crowdsourcing techniques developed in the context of testing machine-learning classifiers to mutant ranking and analysis [118]. For high-visibility, high-criticality code such as, e.g., Linux kernel modules, this may be a very powerful tool. The challenge in such a case is to allow communication between feedback-driven mutation efforts, splitting work both so as to minimize duplication and to target developers most familiar with different aspects of the code base, as done in automated assignment of bug reports [12, 71].

3.1.4 Mutant Generator

The source of all mutants to be presented to the user is the mutant generator, and in order to maximize the effectiveness of the approach, this proposal aims to allow effective generation of mutants for any programming language or DSL, with minimal additional effort. The `universalmutator` provides an initial source of mutants that satisfies this requirement for initial experimentation, but for long-term effectiveness is both inefficient and inexpressive. The current implementation avoids parsing to such an extent that it generates numerous useless mutants embedded in code comments, or that are obviously syntactically invalid. While avoiding a parser-based approach, simple additional constraints could avoid this, without adding burden on users, such as allowing the definition of a language's comment mechanisms, and not producing mutants inside comments. More generally, a mechanism for disabling mutation in contexts defined in the same way as mutation operators would handle other, even project-specific, constraints (e.g., never mutate inline assembly in C/C++). A problem with the current representation of mutation operators and such contexts is that regular expressions are currently applied only at the line level, and in any case are not effective for defining such fundamentally non-regular aspects of code as blocks and nested delimiters. A key goal in this project is to enhance the regular-expression language (without losing its simplicity for "normal" operators) with the ability to express, in a language-independent, syntactic form, such context-dependent aspects of code; the Cobra code-checking tool's language [63] is an example of the kind of approach desired, though the language itself must be different, since transformation, not just detection, is the expressive content of a mutation operator. Moreover, the generator will also need to be improved to allow users to easily specify novel build environments and plug-ins for checking Trivial Compiler Equivalence [106] to make the entire feedback-driven mutation process workable. To some extent, an efficient mutation generator needs to incorporate aspects of mutation execution and even post-mortem analysis of the results of a mutant. Finally, for extremely large projects, simply generating and storing all mutants may be inefficient, and rather than processing the entire source code and applying all mutation rules, a demand-driven mode that only produces new mutants likely to be novel and of high utility may be required.

3.2 Mutation-Driven-Development

Rather than a separate research focus, the idea of mutation-driven-development will be a goal that informs the other research topics covered in this proposal. In particular, once tools reach sufficient maturity, they will

be used to conduct preliminary experiments in MDD as a methodology. In a sense, MDD is more central to the evaluation of this proposal's results than a separate research thrust, as discussed in the Evaluation Plan (Section 3.5.1).

3.3 Core Research Questions

The component-focused sections above provide an overview of the research problems to be addressed by this proposal, but it is also useful to consider the high-level research questions to be addressed, some of which are cross-cutting concerns independent of any single component, but potentially important to the development of a practical, maximally efficient, feedback-driven mutation approach.

3.3.1 Research Questions for Feedback-Driven Mutation Testing in General

1. What is a good generalized, language-agnostic representation of and distance metric for program mutants for use in FPF?
2. How can FPF-based selection of mutants for novelty best incorporate predictions of mutant equivalence, outcome, dominance, and productivity? Is novelty or expected utility more important?
3. How should feedback-driven mutation testing actually incorporate feedback from users into the ranking of mutants? What feedback should users be able to express, and how strongly should it be weighted?
4. Can mini-crowds be effectively leveraged to enhance the utility of user feedback?
5. Is it possible to identify outliers in otherwise similar groups of mutants, (e.g. one killed mutant in a cluser of unkilled mutants) and is such identification useful to users?
6. How should budgets for automated test generation and timeouts for verification efforts be chosen so as to quickly estimate whether a mutant is killable?
7. Is it possible to predict whether a mutant's unkillability is due to poor test generation (hard to reach error states), oracle weakness (unidentified error states), or likely real semantic equivalence?
8. How can feedback-driven mutation testing most effectively use already generated killing tests and counterexamples to prune mutants?
9. Is distance-based clustering plus timing information useful for quickly eliminating killable mutants similar to already-killed mutants? How does this relate to Predictive Mutation Testing (PMT)?

3.3.2 Research Questions Specific to Any-Language Mutation

1. What advances are required in order to maximize the efficiency and usability of a fundamentally language-agnostic regular-expression-based approach to mutant generation?
2. How should the language of regular expressions be extended to allow for language-agnostic definition of mutation operators that require more parser-like analysis of code structure, without compromising the usability and simplicity of the approach?
3. Is it possible to perform on-the-fly mutant generation for very large projects, and reconcile this approach with FPF (e.g., generate new mutants with, possibly approximate, desired distances from already evaluated mutants)?

3.4 Work Plan

For this project, a simple plan should suffice, defined by components of Figure 2. In Year One, PI Groce and the graduate student will both focus on the FPF-Based Novelty Ranking and representation of mutants and test results. This foundational work is required before other parts of the approach can be applied. For work in the first two years, the existing mutant generation capabilities will likely suffice, although it is possible that some improvements will be discovered to provide enough benefit to merit early implementation. In Year Two, both will focus on the Mutant Utility Predictor and Feedback Analysis, and how to integrate those with the FPF-Based Novelty Ranking. In Year Three, the focus will shift to the Mutant Generator itself, and the problem of any-language mutant generation. By this time, the demands made by the feedback-driven approach on the core mutation engine will be much clearer, due to the relative maturity of the user-facing

components. The third year will also emphasize integrating the entire system and performing more thorough evaluations, including of (and using) Mutation-Driven-Development. It is likely that by the middle of Year Two, a prototype system suitable for use by real developers and test engineers not part of the project will be available, and the project plan aims for the graduate student to work in an industrial or government lab setting, and try applying the process to a real system, during the summer of Year Two.

3.5 Evaluation Plan

Evaluation for this proposal includes both human-performed assessment via trying to use feedback-driven mutation for actual test improvement tasks and automated evaluations with more objective criteria, but a weaker relationship to the actual goal of helping users quickly find the most important unkilled mutants. For the human portion, informal evaluation will be performed by the research team itself, using known programs with known testing weaknesses; this will help tune the approach and experiment with new ideas. However, for more advanced assessment, expert users outside the team will be offered the chance to use the system once it is in suitable shape. In the past, PI Groce has worked with IBM Distinguished Engineer Paul E. McKenney, a prominent Linux kernel developer, on using mutants to improve kernel test suites, and has discussed similar efforts with Richard Hipp, the lead developer of the SQLite database, a rather famously well-tested program, with some resulting improvements to both test suites. Other potential users with whom PI Groce has a working relationship include NASA/JPL engineers working on upcoming CubeSat missions, colleagues working on the DeepState [32] parameterized unit testing interface to fuzzers and symbolic execution engines, and the developers of `pyfakefs`. This type of evaluation is, of necessity, somewhat qualitative. A more unbiased retrospective version that retains the core element of human rating of the value of mutants can be performed by examining actual mutants that resulted in improvements to the rcutorture [90] tests for the Linux kernel and the `pyfakefs` tests in previous work [56], and comparing the useful mutants to the highly ranked mutants: could the highly ranked mutants have motivated the key improvements to the test suites?

Just computing a mutant kill matrix for a good test suite can also partially evaluate novelty rankings, by ranking killed, rather than unkilled mutants; the experiment even realistically represents an early stage of test suite construction by feedback-driven mutation testing, especially if the mutants are only killed by a relatively small set of tests. If mutant X and mutant Y are both highly ranked, but killed by a very similar set of tests, this indicates a possible problem with the measure. In real-world feedback-driven mutation testing, it is highly desirable not to compute the full kill matrix for all mutants, but for evaluation purposes, determining the extent to which kill bitvector similarity agrees with FPF distance metric similarity serves as a basic, if quite imperfect, sanity check on the novelty ranking. Another automated way to evaluate a novelty ranking is to use automated testing to generate multiple tests to kill each mutant in ranked order. A good ranking will mean that each additional mutant is unlikely to be killed by the killing tests for any previous mutants. A similar, but more robust, measure of mutant similarity is how much adding a test that kills one mutant as the seed in a fuzzer [134, 116] improves time required to kill the other mutant, on average. Unfortunately, these measures cannot effectively measure "real distance" if one of the mutants is equivalent.

Evaluation of the mutant generator can also be partly automated, by comparing the output set of mutants to that of other tools, to ensure no important mutants are omitted; the regular-expression based approach will probably generate valid mutants not generated by other tools, since it aims at a rich operator set, in accord with the suggestions of multiple previous papers on detecting faults via mutation [73, 39]. Efficiency gains (e.g., removal of invalid or equivalent-by-construction mutants) can be measured by simple, traditional measures.

3.5.1 Mutation-Driven-Development Evaluation

The evaluation of techniques and tools developed in this proposal will also serve a dual purpose with respect to Mutation-Driven-Development. Using an MDD approach to implement various small, but easy-to-get-wrong, code projects, such as binary search and AVL trees, will make it possible both to see how

effective the tools for feedback-driven mutation testing are, and to see how effective an MDD approach to development is. In addition, using various versions of actual TDD efforts, with the associated test suites for each step of development, it should be possible to evaluate how much additional testing power MDD would have required at each step of development.

4 Related Work

4.1 Bug Triage and Distance Metrics in Software Engineering

A fundamental insight of this proposal is that the problem of presenting mutants to a user is conceptually similar to the "fuzzer taming"/crash bucketing/bug triage problem studied in automated testing research [21, 126]. This proposal's approach is centered on the idea of computing distances between mutants. The use of distance metrics in software engineering for a variety of purposes is long-standing. Almost all such uses are essentially spectrum-based [113] (that is, using counts of coverage of code entities), except for some work in model-checking [40, 17] and some of the metrics in PI Groce's recent fuzzer taming work [21]. Reneiris and Reiss initially proposed using distance between executions to localize faults [112], and Liu and Han [84], among others have followed this line with various metrics (in their case, using the localization of a spectrum-based method to determine distance). Vangala et al. proposed using distance to cluster test cases to improve diversity and eliminate duplicates [127]. Methods for clustering to identify bugs all rely on an implicit distance determined by a feature set [30]. PI Groce's previous work has used distance metrics for a variety of purposes [21, 49, 135]. Adaptive random testing uses distances (usually between inputs, not executions, however) to choose tests [19, 20, 9]. Recently, PI Groce proposed a novel, causal metric for fuzzer taming and fault localization, itself based on mutation testing results [61]. More generally, work on presenting a few mutants to maximize human efforts to improve a testing or verification effort is related to PI Groce's own work on end-user testing of machine learning systems [75, 51], where the limits of human patience are considered as a key factor in a system for presenting actionable information to a user.

4.2 Mutation Testing

There is a vast body of work on mutation testing or analysis. Mathur attributes [87] the original idea for mutation analysis to a term paper by Richard Lipton in 1970. Foundational assumptions and theory were first proposed by DeMillo et al. [24], and the approach was first implemented by Budd et al. [16] in 1980. Mutation analysis as a theory relies on two fundamental assumptions — *the competent programmer hypothesis*, and *the coupling effect*, both of which have been widely studied [128, 129, 37, 100, 101, 79, 37, 33]. This proposal is more focused on the practical effectiveness of mutation testing than on theoretical justifications.

It has long been argued [15] that mutation analysis is *stronger* than other coverage measures. The subsumption of multiple coverage measures by mutation analysis, including all the basic coverage measures [95] was shown by Offutt [103], and data flow subsumption was demonstrated by Mathur [89]. Daran et al. [23] found that mutation analysis produces faults that are similar to actual faults in terms of the error traces produced. Andrews et al. [7, 8] found that ease of detection of mutants was similar to that of real faults when compared to manually generated faults (in that manually generated faults were harder to find). Recent research by Just et al. [73] using 357 real faults showed that in 75% of cases, mutation score and test case effectiveness improved together, which is a strong relationship compared to the same coupling for coverage (46%). More recently, Papadakis et. al [107] showed in a large scale study that while there is a real relationship between mutation, it is in some sense weak; indeed they summarize their work by stating that "mutants provide good guidance for improving the fault detection of test suites, but their correlation with fault detection [is] weak," which is a foundational assumption of this proposal. Ahmed et al., using a very different approach, reached a similar conclusion about the potentially high value for suite improvement, but weak correlation of mutation analysis results [2].

Cost of execution is often [70] considered to be the most problematic aspect of practical mutation testing. Numerous approaches exist, that seek to reduce the cost of mutation analysis. Offutt and Untch [102]

categorize these, as: do *fewer*, do *smarter*, and do *faster* approaches. Operator selection, mutant sampling, and mutant clustering fall under *do fewer* — approaches that seek to reduce the number of mutants evaluated. The *do smarter* approaches seek to reduce the time taken for the entire mutation analysis by intelligently managing the various phases. Similarly, *do faster* approaches seek to reduce the time taken for evaluation of a single mutant, and include mutant schema generation, code patching, and other methods.

The *do fewer* approaches, especially simple random sampling, debuted with the initial research in mutation analysis [15, 1], where it was noticed that even a 10% random sample of mutants can on average be almost as effective (99%) as the complete set of mutants.. Sampling was further investigated by Mathur [86], Wong et al. [130, 131], and Offutt et al. [104].

Determining relative merits of selective mutation strategies such as operator selection and random sampling has long been an active field of research [131, 94, 139] Skew in fault representativeness among mutants was initially noticed by Budd et al. [15] who found that particular types of mutants are representative for particular kinds of faults. Constrained mutation was pioneered by Mathur [86, 88] and was further investigated by Wong et al. [132]. An extension of this approach called *n*-selection was suggested by Offutt et al. [104] where the most numerous mutation operators were removed one at a time. A set of guidelines for operator selection was identified and evaluated by Barbosa et al.[10]. Namin et al. [96, 97] formulated the concept of *sufficient mutation operators*, and Untch [125] even proposed simply using statement deletion as "the" mutation operator. Deng et al. [25] extended the deletion operator for diverse language elements, and obtained an effectiveness of 92% while reducing the number of mutants by 80%.

The subsumption of individual mutants and mutation operators is also an active area of research [35, 117, 83]. Higher order mutants (HOM) aim to improve the quality of mutants by combining simpler mutants into more complex mutants. Jia et al. [69, 68], found that the number of mutants can be reduced by 50% by making use of subsumption of simpler mutants by higher order mutants. Mutation clustering[26, 121, 65] is another *do-fewer* approach where similar mutants are identified based on various properties.

There has been extensive work on comparison of mutation reduction strategies [139, 138]. Zhang et al. [136] investigated the scalability of selective mutation by considering how well a randomly sampled set of mutants represent the original population. In previous work [36] PI Groce showed that there is an upper bound on the improvement in *mean effectiveness* that is possible using even an ideal mutation reduction strategy using post-hoc oracular knowledge of mutant kills. We later extended that result by evaluating the actual improvement achieved by extant mutation reduction strategies, when they do not unrealistically have access to the mutant kills achieved [39]. Recent work on Predictive Mutation Testing (PMT) [137] applies machine learning to build a model that can predict mutation results without actually running mutation testing, a novel and promising *do-smarter* approach.

4.2.1 Practical Mutation Analysis

The above work largely focuses on computing or at least estimating the total mutation score of a test suite, efficiently. The assumption is that mutation testing is meant to be, like a coverage metric, a kind of "evaluation" of a test suite, a number used to say "this is a good test suite" or at least "this is a better test suite than that test suite." While important for some real-world purposes (evaluating QA efforts) and certainly for software testing research, that is not the focus of this proposal, which considers the problem of presenting unkilled mutations to a developer or test engineer in a way that facilitates the improvement of a test suite and the detection of faults. This is inspired by PI Groce's previous work on using mutation to find defects in formal verification and automated test generation efforts [52, 56, 3].

Very recent work by Papadakis et al. (some unpublished in a conference of journal at the time this proposal was written) has aimed, unusually, at predicting the "quality" of [105] or even prioritizing [18] mutants, to rank fault-revealing mutants highly so that users can produce tests to find faults. This work is highly relevant to this proposal's aims, but focuses on a single static pass to rank mutants by their fault-revealing potential, informed by (possibly cross-project) data on fault-revealing tests. There is no feedback loop, or

ability to indicate the importance of various faults in the program under test, and the language support issue is dodged by targeting LLVM bitcode. Nonetheless, the goals, methods, and results of this work will inform this proposal's approach, in particular in the utility estimation aspect that balances FPF-determined novelty.

The single most relevant work by others, however, is to be found in a report on actual techniques in use at Google for applying mutation testing to real-world projects [109]. Their approach also uses a notion of feedback, but this is manually handled and based on using a classification scheme to heuristically throw out "arid" (likely not to be actionable) mutants; due to the size of Google's code base and the integration of their approach in Google's code review process, there is also a decision to only allow one mutation (initially randomly decided) per line of code. While the underlying motivation, of giving developers actionable information rather than computing a mutation score, is similar, and the idea of using some form of "feedback" is common, this approach considered in this proposal targets the individual developing, testing, or verifying a particular software element (either a small project, or a component of a project), and assumes an iterative process, where developers consider one unkilled mutant at a time. The Google approach does not attempt to prioritize between the unkilled mutants it surfaces, or support custom mutation operators, or learn an individual testing effort's characteristics. It is, instead, for obvious reasons, more an attempt to select mutants in an industrial scale code review setting than an effort to propose a new way to construct or enhance test suites; e.g., it only even proposes mutants of code in a diff with a previous version of the code, which makes it completely unusable in after-the-fact testing and verification efforts that do not have code changes. Further, it uses Google-wide coding conventions and developer suggestions to fix heuristics such as "avoid mutation of logging statements" rather than trying to learn (with human assistance) such heuristics for projects that may vary widely in language and coding style. The techniques used in this proposal may be useful in generalizing or enhancing an effort such as Google's, however, and share the focus on mutants as tools for focusing developer/tester attention and producing action on the part of humans, not computing a mutation score. Indeed, the report itself allows that the current approach does not scale, since it requires extensive manual support for each heuristic and language, a problem this proposal aims to directly address.

More broadly, a paper by the authors of the Google report and a group of academic mutation testing researchers [66], uses the Google effort to propose a notion of productive and unproductive mutants. Their concepts are highly related to this proposal's goals, but again centered on a diff-focused, large-scale industrial setting, rather than an approach that, like TDD, may also be applied to smaller coding efforts in a more isolated setting, such as development of embedded software, where crowdsourcing is impractical. Another key difference is that, while their work used EvoSuite to enhance a test suite to kill additional mutants, the assumption was that most suite enhancement would be due to developers adding manual tests. Furthermore, it is generally true that mutants are neither "productive" or "unproductive" in an absolute sense, but rather the value of a mutant also depends on previous mutants a developer has manually examined, and the results of that examination; this project embodies this concept in the FPF-centric workflow.

A second thrust of the efforts in this proposal is to simplify the development, maintenance, and (especially) extension of mutation testing tools by using an extension of regular expressions to define mutation operators, and separating the generation of mutants from language or build-environment specific techniques for pruning invalid mutants. This aspect of the proposal primarily builds on PI Groce's initial work on the topic of regular-expression-based mutant generation [57] and Holzmann's work on lightweight textual code analysis with Cobra [63]. Trivial compiler equivalence [106] is a key technology for supporting effective any-language mutation; especially in the context of this proposal, where executing all mutants is not the goal, simply letting the compiler handle many validity and equivalence questions is a simple and effective approach.

5 Broader Impacts

Improving Software System Reliability: A key element of broader outreach will be to report bugs discovered during testing experiments, and contribute improved test suites to critical open source projects. To that end, this proposal will primarily target real world systems in experiments, in hopes of improving their quality,

and the quality of their testing. Infrastructure developed in preliminary work includes automated testing for the Linux kernel RCU module, Google and Mozilla JavaScript engines, a variety of C compilers (including GCC and LLVM), YAFFS2 [133] and other file systems, Google's Go compiler, a large set of Unix utilities, and a large number of Python libraries (including some of the most widely used libraries, and key scientific and numeric analysis packages). In previous work, discussions with working test engineers at Mozilla, Google, and NASA have significantly informed the PI's research efforts, and this is likely to continue. PI Groce is currently discussing plans for incorporating more advanced automated test generation into NASA's open source F Prime flight architecture [14, 98], and F Prime components, such as the auto-coder, are a likely target for evaluation efforts in this project. Such efforts are planned to result in a documented process for incorporating feedback-driven mutation testing and MDD into flight software component development. Better, cheaper, high-quality testing for small budget CubeSat [99] missions could lead to advances in various fields, especially Earth observation and space-based physics. The CubeSat initiative focuses on providing a low-cost way for educational institutions and non-profits to conduct space-based research, and thus is also related to education and outreach activities. In the long term, a mutation-driven development paradigm might result in easier development of critical software components in tandem with an extremely high-quality, specification-defining automated test suite. The existence of such suites might make modifying critical systems easier, since the in-place test suite would be likely to identify even very subtle problems introduced during changes, or at least force revision of outdated specifications. With the growing impact of embedded, cyberphysical, and Internet-of-Thing systems on the physical world, this has potentially large benefits in terms of the safety and security of the general public.

Education and Outreach: The proposed research yields several opportunities for enhancing CS education, recruiting new CS majors, and retaining CS students, particularly members of underrepresented groups. PI Groce will work with the NAU Student ACM Chapter to present a series of "excursions in testing" that introduce automated testing to students, using feedback-driven mutation testing and Mutation-Driven-Development (MDD) on real code, including code from media player libraries. The work of Guzdial [59] has shown that media computation is a potentially effective way to both recruit and retain female and under-represented minority students in computer science.

6 Results From Prior NSF Support

PI Groce has received support as PI or co-PI from three NSF grants. The most relevant and recent is "Diversity and Feedback in Random Testing for Systems Software" (CCF-1217824, $491,280, 9/2012–9/2017), a collaborative proposal with John Regehr at the University of Utah. **Intellectual Merit:** The results of CCF-1217824 included a preliminary exploration of how to "tame" fuzzer output, a problem also central to this proposal [21]. In previous work, the goal was to find an algorithm for using hand-chosen distance metrics to identify bugs in tests; in this proposal, other methods for taming fuzzers are addressed. A key result from CCF-1217824 is the development of a strategy for creating "quick tests" [49], which won the Best Paper award at ICST 2014 for showing tests thus reduced can serve as effective regression tests or seeds for symbolic execution [55, 135]. Moreover, benefits do not depend on 100% preservation of a property [5]. Other results include an overview of the value of coverage in testing experiments [48] and exploration of how individual test features impact the coverage and fault detection statistics of random tests [47]. All of these results used mutation testing. **Broader Impacts:** CCF-1217824 has contributed to the discovery of previously unknown faults in multiple open-source and commercial software systems, including core compilers and system libraries. The development of the central swarm testing techniques has furthered many efforts to improve the quality of compilers, including LLVM and GCC, and to test core language tools in general [81, 78, 28, 82]. **Research Products:** Several publications resulted from this grant, including those cited above and numerous others [48, 21, 135, 49, 47, 4, 55, 62, 53, 5, 62, 42], along with three PhD theses. Source code for software systems developed or enhanced during CCF-1217824 [43, 54] is available on GitHub.

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