Using Synthetic Test Suites to Empirically Compare Search-Based and Greedy Prioritizers

Zachary Williams
Gregory M. Kapfhammer

Department of Computer Science
Allegheny College
http://www.cs.allegheny.edu/

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Important Contributions

Synthetic Test Suites

Detailed Empirical Study

Use **synthetic test suites** to empirically evaluate the **efficiency** and **effectiveness** of search-based and greedy prioritizers

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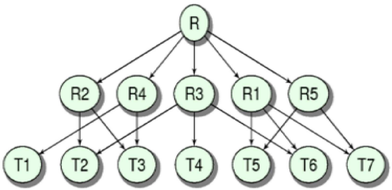

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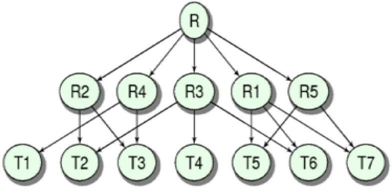

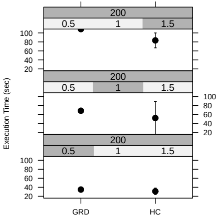

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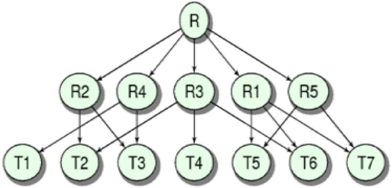

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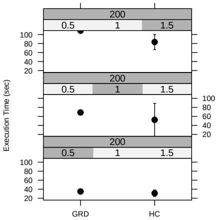

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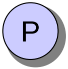

Correct programing defect

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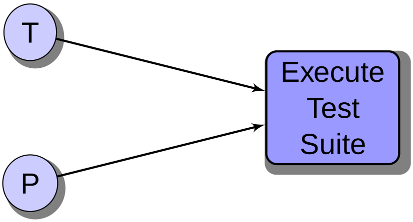

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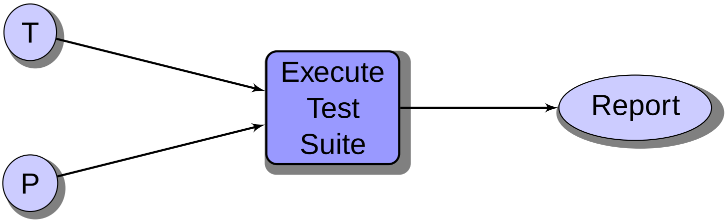

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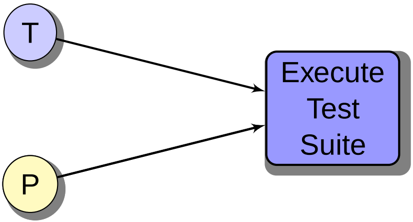

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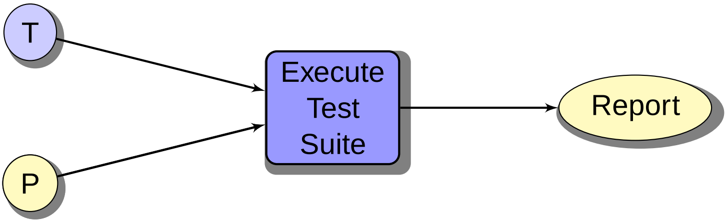

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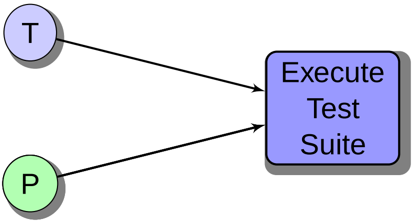

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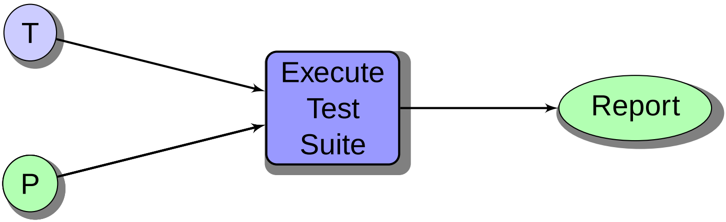

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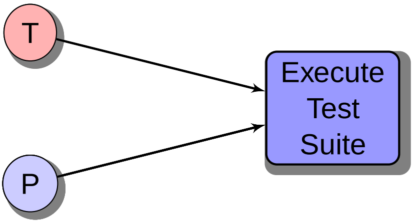

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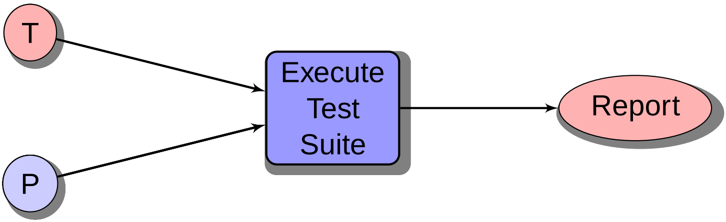

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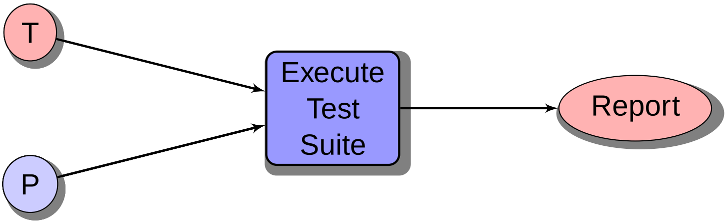
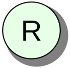


Complete retesting is often prohibitively expensive

Regression Test Suite Prioritization



Requirements necessitate the coverage of the **state** and/or **structure** of a program under test

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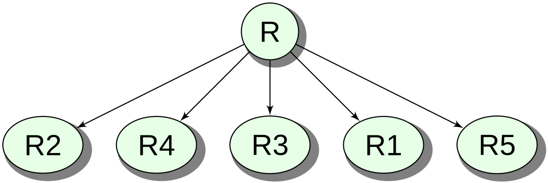

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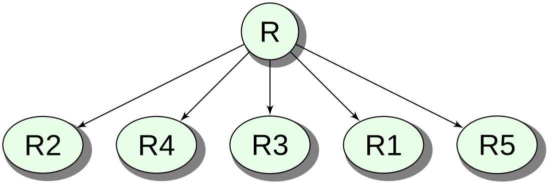

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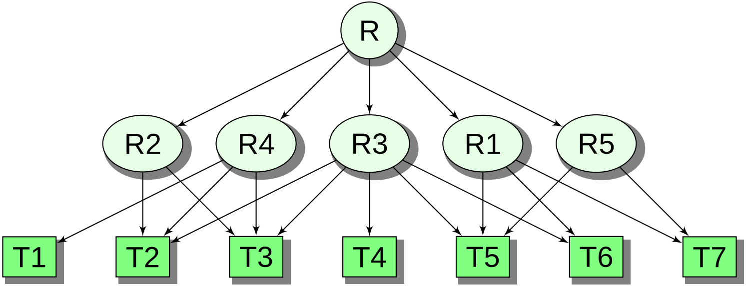

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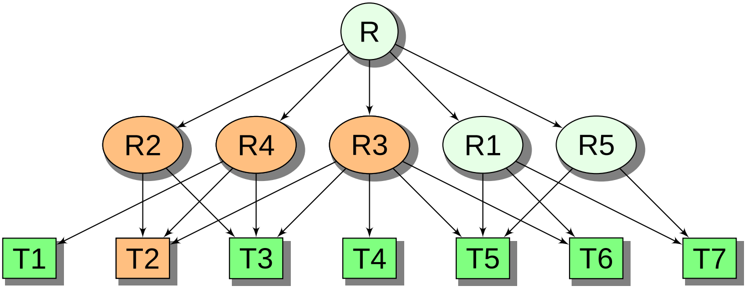

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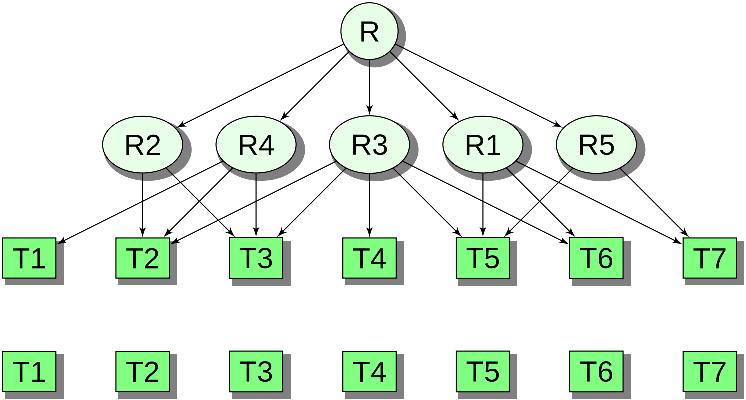

Prioritized test suites cover requirements **faster** thus enabling the **rapid** detection of defects

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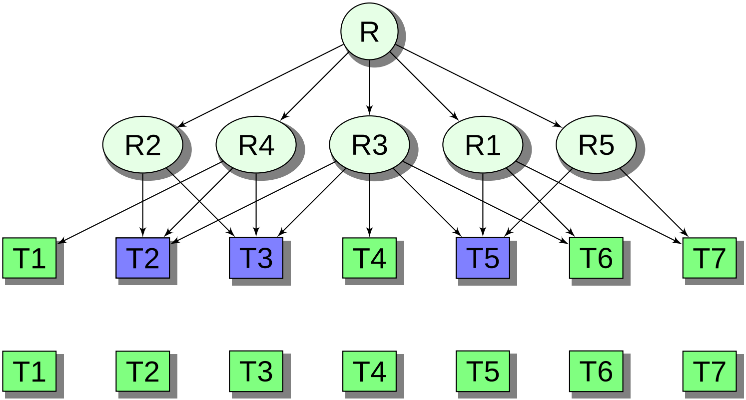

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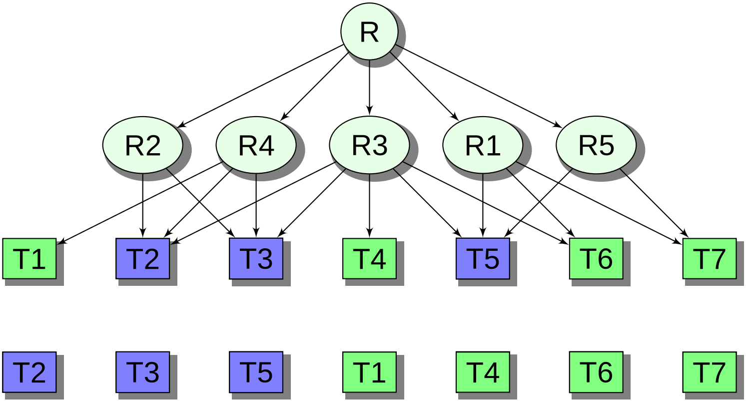

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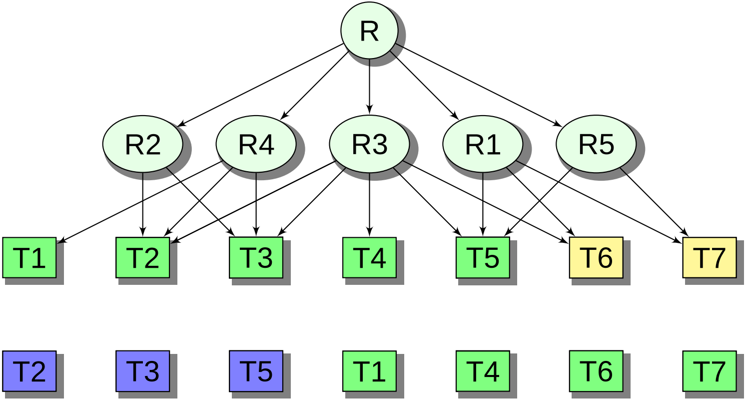

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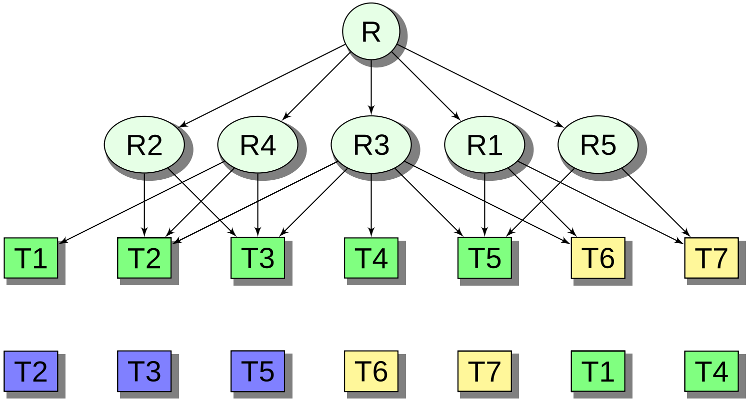

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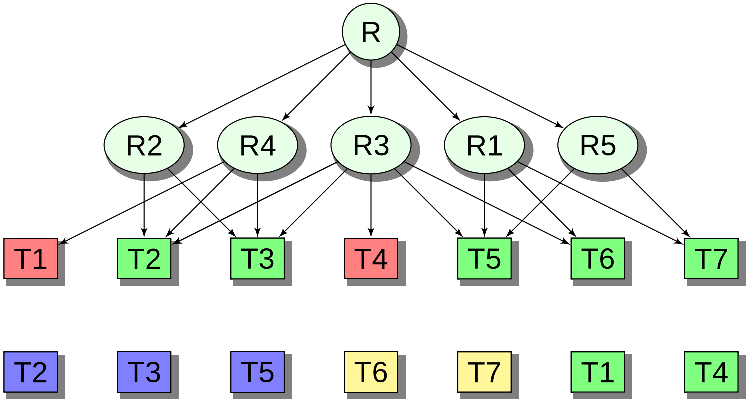

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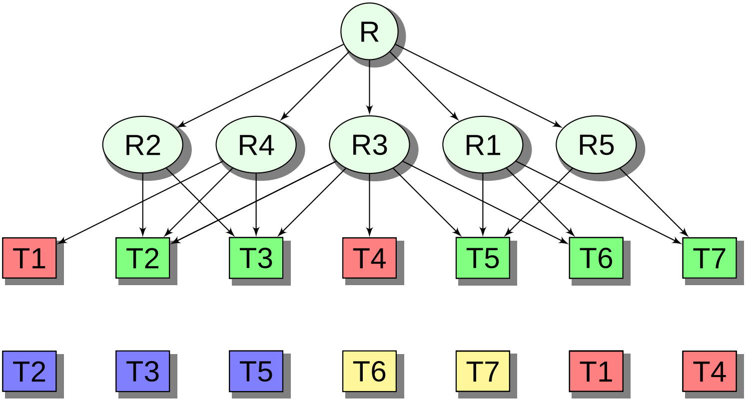

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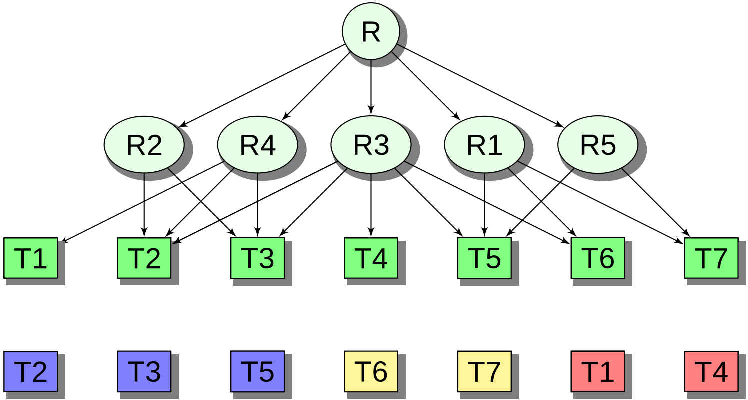

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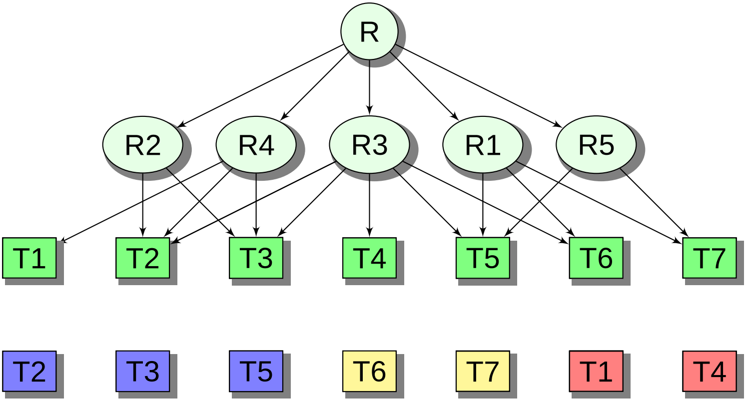

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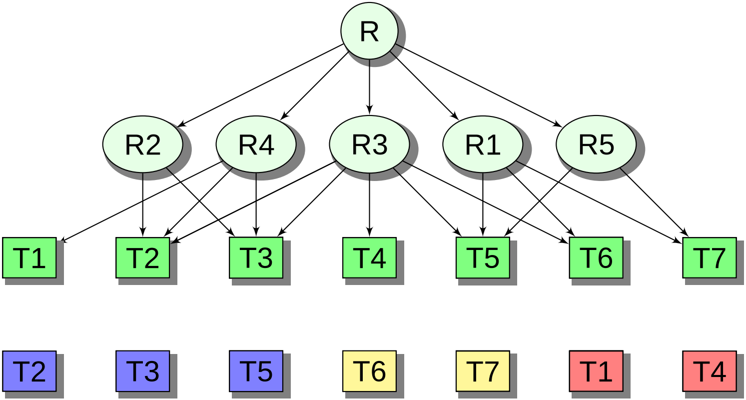
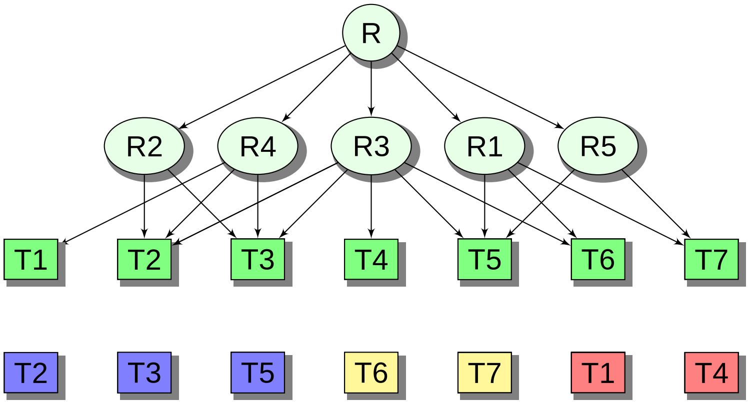


Testers can use **greedy** (Rothermel et al. TSE 2001) and **search-based** (Li et al. TSE 2007) methods to reorder suites

Regression Test Suite Prioritization



QUESTION: Which prioritization technique is the best?

Existing Prioritization Techniques

Greedy approaches select the next best test case

Hill climbers search the state space for improved orderings

Conventional wisdom dictates that greedy generally out performs hill climbing in terms of both efficiency and effectiveness

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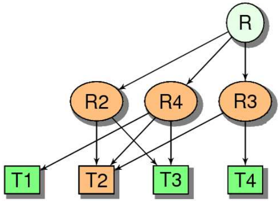

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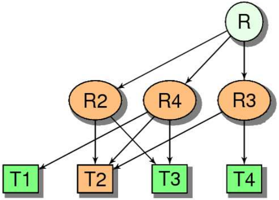

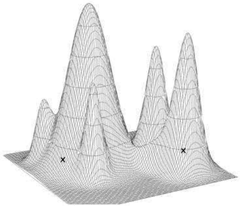

http://artedi.ebc.uu.se/course/Embo01/Phylogeny/phylogeny_readme.html

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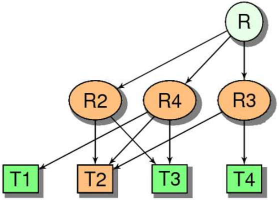

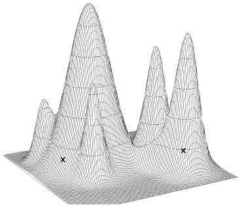

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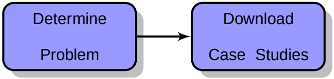
Conducting an Empirical Evaluation

Determine

Problem

These highlighted tasks are **manual**, **expensive**, and **prone to error**

Conducting an Empirical Evaluation



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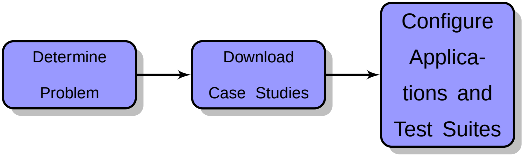

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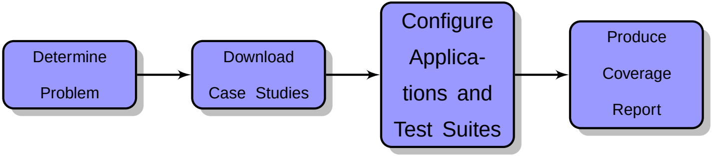

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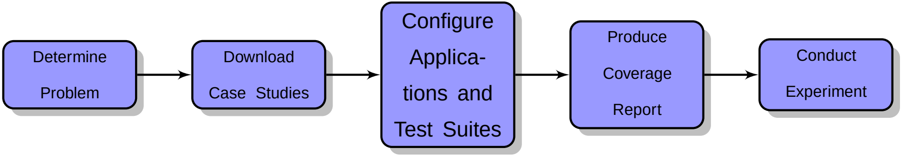

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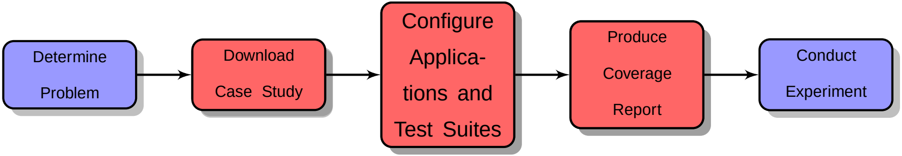

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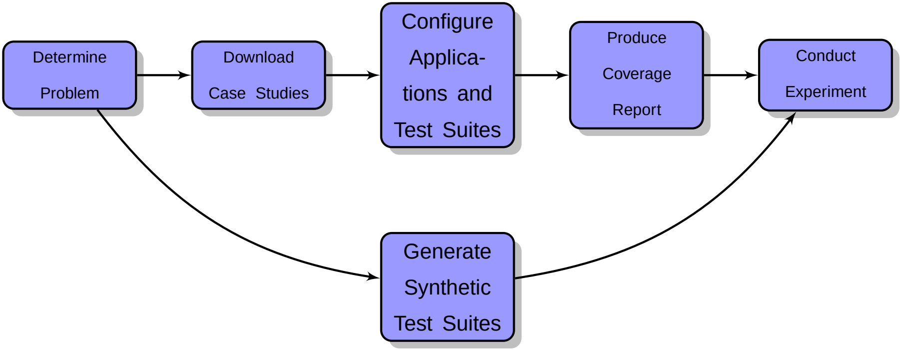

Synthetically generating a test suite is **automated**, **effective**, and **efficient**

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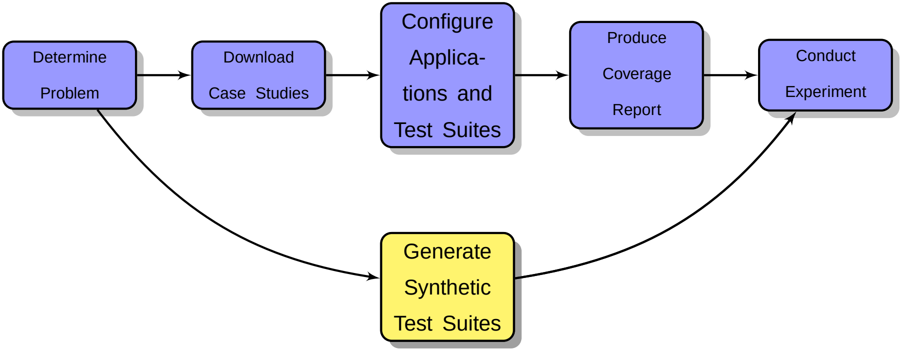

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Generating Synthetic Test Suite

The **total number of tests** controls how many tests the suite will contain

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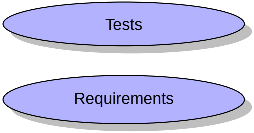
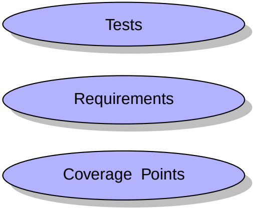


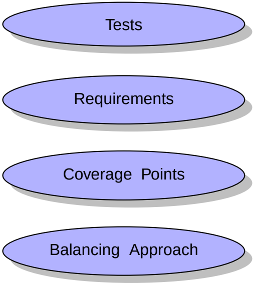
The **total number of requirements** governs how many requirements the test suite will cover

Generating Synthetic Test Suite



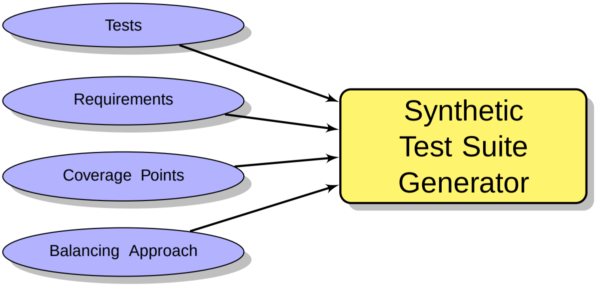
The **total number of coverage points** controls how many unique test-requirement pairs the test suite will contain

Generating Synthetic Test Suite



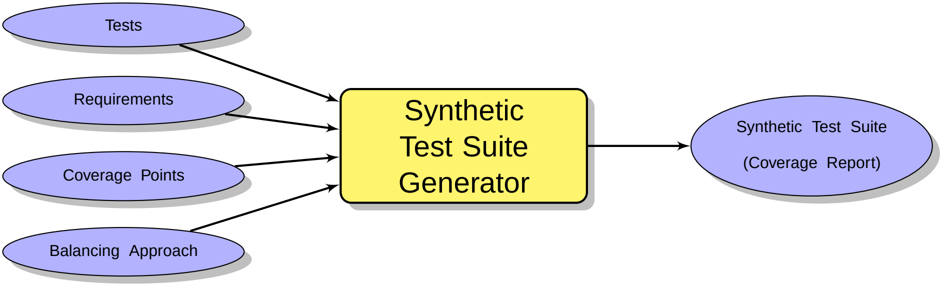
The **balancing configuration** dictates how the coverage points will be distributed in the synthetic test suite

Generating Synthetic Test Suite



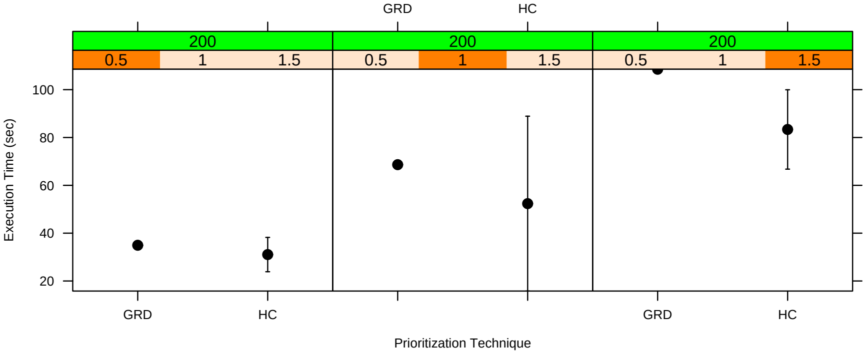
Our empirical results show that synthetic generation takes less then **0.2 seconds** for extremely large test suites

Generating Synthetic Test Suite



Contains information concerning the **requirements covered** and the **execution time** of each test

Empirical Results – Prioritizer Efficiency



HC demonstrated to be more efficient then GRD for large test suites

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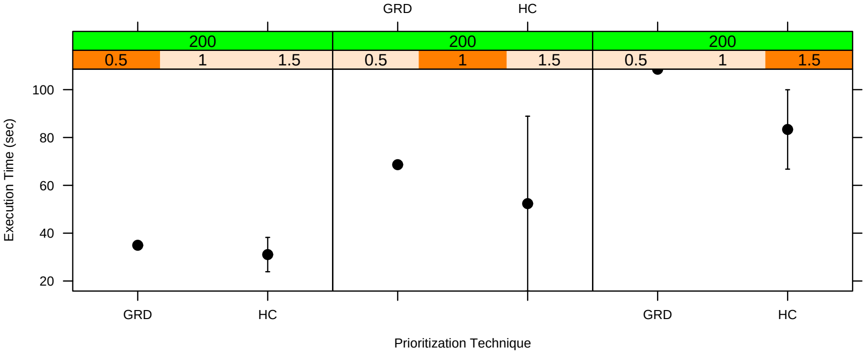

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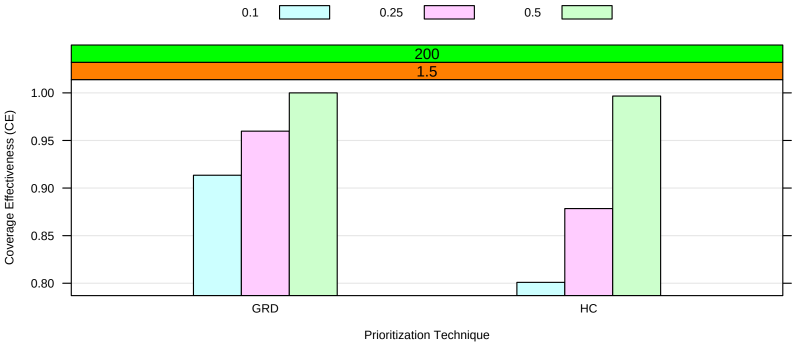

As the amount of coverage points in the test suite increases the performance of HC becomes comparable to that of GRD

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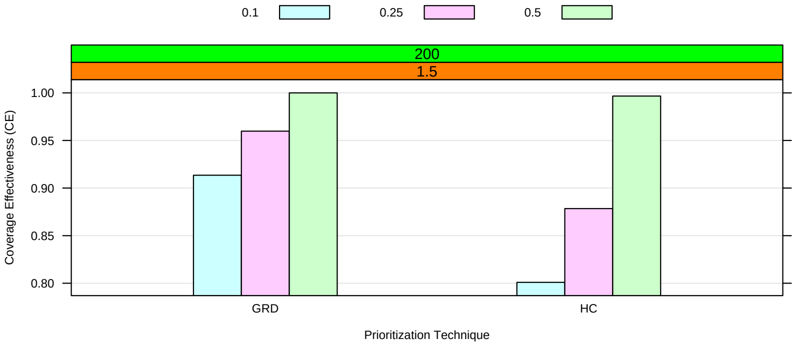

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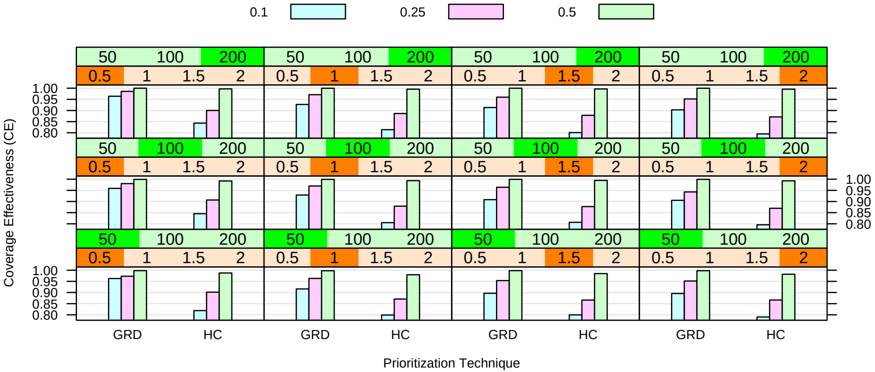

The trend is evident over a wide range of experimental configurations

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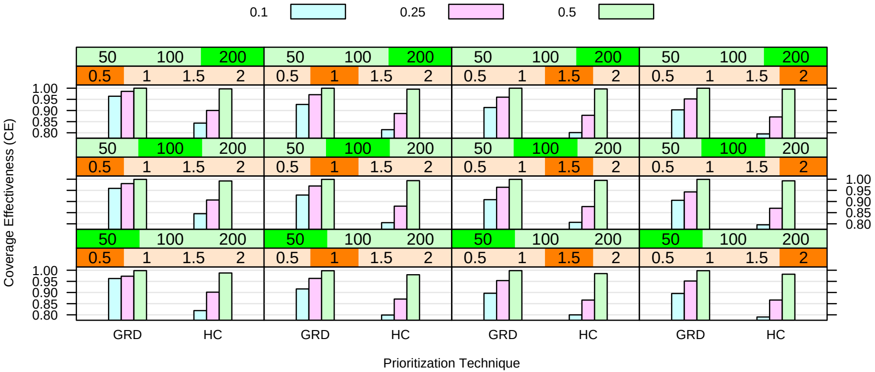

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Conclusion and Future Work

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Department of Computer Science
Allegheny College
williaz@allegheny.edu

Gregory M. Kapfhammer
Department of Computer Science
Allegheny College
gkapfham@allegheny.edu

ABSTRACT

The increase in the complexity of modern software has led to the commensurate growth in the size and execution time of the test suites for these programs. In order to address this alarming trend, developers use test suite prioritization to reorder the test cases so that faults can be detected at an early stage of testing. Yet, the implementation and evaluation of greedy and search-based test prioritizers requires access to case study applications and their associated test suites, which are often difficult to find, configure, and use in an empirical study. This paper presents two types of synthetically generated test suites that support this process of experimentally evaluating prioritization methods. Using synthetic test suites affords greater control over test case characteristics and supports the identification of empirical trends that contradict the established wisdom about search-based and greedy prioritization. For instance, we find that the hill climbing algorithm often exhibits a lower time overhead than the greedy test suite prioritizer while producing test orderings with comparable effectiveness scores.

Categories and Subject Descriptors: D.2.5 [**Software Engineering**]: Testing and Debugging

General Terms: Experimentation, Performance

Keywords: search-based and greedy test prioritization

1. INTRODUCTION

Software developers often introduce defects during the implementation process. Regression testing methods establish a confidence in the correctness of and isolate defects within a program by running a collection of tests known as a test suite. Since regression testing can be very time consuming, testers use search-based and greedy prioritization techniques to produce a test ordering that will reveal faults earlier in the suite's execution than would otherwise be possible.

Suppose that a test suite $T = \langle t_1, t_2, t_3, \ldots, t_n \rangle$ covers the set of requirements $\mathcal{R}(T) = \{r_1, r_2, r_3, \ldots, r_m\}$. Each test case $t_i \in T$ is associated with the non-empty set $\mathcal{R}(t_i) \subseteq \mathcal{R}(T)$ [1, 5]. During the empirical study of search-based

GECCO'10, July 7–11, 2010, Portland, Oregon, USA.

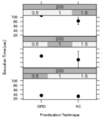

Figure 1: Execution Time - Fully Random.

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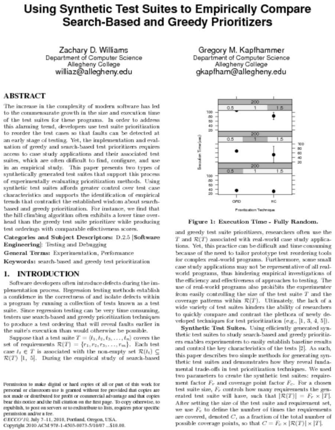

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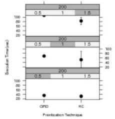

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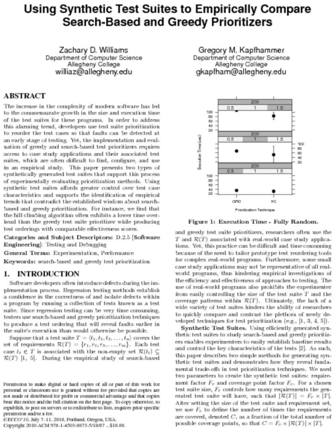

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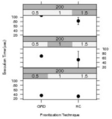

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