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An Empirical Evaluation of the Indicators for Performance Regression Test Selection

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by

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Abstract

As a software application is developed and maintained, changes to the source code may cause unintentional slowdowns in functionality. These slowdowns are known as performance regressions. Projects which are concerned about performance oftentimes create performance regression tests, which can be run to detect performance regressions. Ideally we would run these tests on every commit, however, these tests usually need a large amount of time or resources in order to simulate realistic scenarios.

The paper entitled ”Perphecy: Performance Regression Test Selection Made Simple but Effective” presents a technique to solve this problem by attempting to predict the likelihood that a commit will cause a performance regression. They use static and dynamic analysis to gather several metrics for their prediction, and then they evaluate those metrics on several projects. This thesis seeks to replicate and expand on their work.

This thesis aims in revisiting the above-mentioned research paper by replicating its experiments and extending it by including a larger set of code changes to better understand how several metrics can be combined to approximate a better prediction of any code change that may potentially introduce deterioration at the performance of the software execution.

This thesis has successfully replicated the existing study along with generating more insights related to the approach, and provides an open-source tool that can help developers with detecting any performance regression within code changes as software evolves.

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Chapter 1

Introduction

For many software projects, performance is a critical requirement. Such projects often create performance tests alongside their other tests which specifically test for performance bugs. Performance bugs are often problems with slow execution time, though other qualities like memory usage can be considered too [10].

Performance tests come with some unique constraints as opposed to automated unit testing. For performance tests to work, they typically need to use many resources, run for a long time, or execute demanding functionality, because they require a realistic scenario in order to operate. Ideally performance tests could be run for every commit, perhaps as part of a continuous integration system, similar to having your unit tests run on every commit. However, this is usually too expensive and time consuming to implement [2, 3].

Practically, as software evolves, a continuous set of code changes is being introduced, within each, one or few changes may be responsible for introducing slowdowns or speedups to the current system's execution. This is known as a performance regression. Performance regression defines any unexpected system performance in terms of runtime, when compared to its previous state, before the change, for the same set of input values, and for the same type of behavior (functional scenarios). Thus, developers are eager to detect any code changes that accidentally introduces such significant slower runtime.

Detecting code changes responsible for performance regression is challenging due to the rapidity of software evolution i.e., the number of committed changes is increasing on a daily basis [4]. And so, it is hard to individually monitor these changes while being committed to the main branch. According the recent studies [8, 11], it is impractical to separately test each code change for all possible functional test cases. Furthermore, some changes may not directly reflect performance issues since they may be only triggered by special cases (for specific type of users or workloads) and so, they may be detected later in the testing process once other changes have been also committed. So, there is a need of introducing better techniques in predicting whether a given change can be potentially hazardous to the system's performance [12].

Existing studies try to solve this issue by predicting whether or not a commit will cause a regression to occur. The hope is that by creating a system that can successfully evaluate the need to run the performance tests on a change, we can reduce the number of times we run the tests, and thus save cost. The paper ”Perphecy: Performance Regression Test Selection Made Simple but Effective” [9] presents a system that predicts whether or not a commit will cause a performance regression. Their system works by looking at 8 metrics, to predict for each benchmark whether or not a significant performance change will occur. They look at 4 different projects, for a total of 429 commits. They use metrics called hit rate (the percent of correct predictions of a performance regression) and dismiss rate (the percent of correct predictions that a regression will not occur) to evaluate their system's performance.

The 8 indicators are discussed in detail in Chapter 4, *Perphecy*. However, to help illustrate this, consider the following example. In listing 1.1, two excerpts from a diff are shown. One of the metrics used in the study is based on the percent function length change. In the first block in the example, we see that three lines from the function are deleted. The percent static function length change, therefore, is 50%. In the second block, one line of code is changed, but not added or removed. In this case, the static function length change is 0%. However, a different metric could be affected, such as ”Highest percent overhead function changed”, if this one line edit happened in a frequently called function.

Perphecy takes the calculated metrics and compares them to a predetermined threshold value. The metrics and their thresholds are called an ”indicator” in the Perphecy paper. As part of determining thresholds, the Perphecy paper selects a subset of the 8 indicators to consider. The collection of indicators is called a predictor. If any of the thresholds of the indicators in the predictor are exceeded, Perphecy predicts that a regression will occur. So, in this example, if we had these two blocks edited between commits, If the predictor that Perphecy had determined included ”static function length change”, and the threshold was 40%, Perphecy would predict a regression. Contrarily, if the threshold was 60%, it would not predict a regression unless one of the other indicators in the predictor was affected.

Listing 1.1: Descriptive Caption Text

```
static int gitdiff_oldname(const char *line, struct patch *patch)
 {
-       char *orig = patch->old_name;
        patch->old_name = gitdiff_verify_name(line, patch->is_new, patch->old_name,
                                               DIFF_OLD_NAME);
-       if (orig != patch->old_name)
-               free(orig);
        return 0;
 }

@@ -459,7 +462,7 @@ static int get_urlmatch(const char *var, const char *url)
        free(config.url.url);
        free((void *)config.section);
-       return 0;
+       return ret;
 }
```

The Perphecy paper, however, has a few limitations. First, their dataset was fairly small. As an example, one of the projects they ran on was git. They ran 5 tests on approximately 200 commits, and found 13 cases of regressions. This is a small sample size to base conclusions off of. Second, they did not show the final set of indicators that were used to give their results. They only show the method of how they obtained them.

In this paper, we attempt to replicate this study. We look at one of the studied projects: Git. We study 8596 of the more recent commits from the project, significantly more than the 201 studied in the paper. We present insights about the original study, such as a flaw in the original threshold selection algorithm and our mitigation, a more thorough analysis of the potential of each individual indicator, and the results of the predictor that was generated using the Perphecy method.

Chapter 2

Research Objective

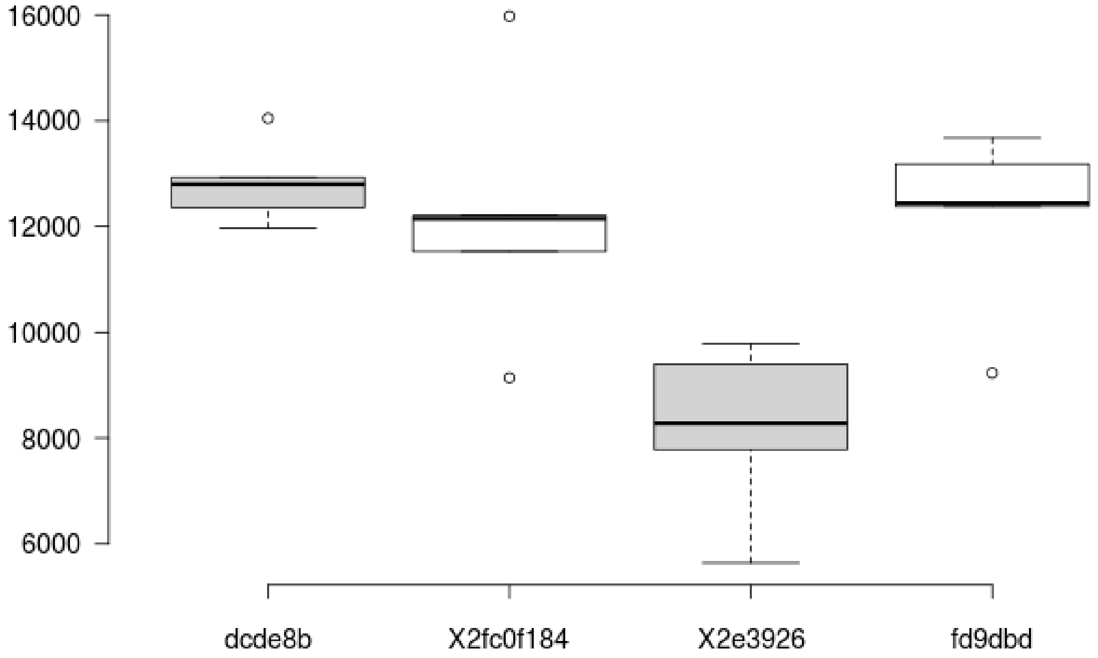
2.1 Motivation

Executing tests on every software change is a popular practice in Continuous Integration, with numerous benefits, namely the fast and continual detection of bugs throughout the development lifecycle. Performance tests, however, can not practically be run this way because it would be too expensive. The goal of this area of research is to develop techniques which decrease the cost of performance testing, while still decreasing the time it takes for developers to get feedback about whether their code has performance bugs or not.

The Perphecy study makes steps towards building a system that can predict whether a change will cause a performance regression or not. A system like that can help limit which commits need to be tested, which can save cost. If a system could be created which very reliably could predict whether a performance bug would occur or not, it could be used entirely in place of running the tests periodically, and would spend an optimal amount of time running performance tests.

A performance regression, in the context of this paper, is defined as anytime a test's execution time is longer than for the previous commit's in a statistically significant way. In the original paper, and in this one, we identify statistically significant regressions by taking 5 samples of the execution times for each commit and performing a t-test between every two commits. In figure 2.1, we show an example of these execution times. In this case, though it may be small, the t-test determined that there was a regression from commit *2d3926* to commit *fd9dbd*.

Figure 2.1: Example execution times



2.2 Contribution

Our main contribution is to replicate and extend the Perphecy paper. Our main contributions are:

1. Scalability. Since performance regression can be linked to various aspects of code changes, it is important to diversify the set of possible types of changes that may trigger situations in which the software performance deteriorates. For that reason, we examine, in this thesis, a larger dataset compared to the original study.

2. Prediction. The original study outcome was the generation of a predictor that accurately predicts the occurrence of a performance regression, for a given set of code changes. This predictor is constructed using an automatically generated combination of tuned indicators and metrics. This generation of the combination of indicators represents the main contribution of the paper, yet, the authors didn't expose any of the

generated predictors. Thus, we explore the combination of indicators for a different set of changes in order to demonstrate how the predictor is generated and provide more details about its combination.

3. Indicators. The indicators represent the building block of the predictor and so they are important in providing good prediction results, if the set of used indicators can cover all the possible performance aspects. In this context, we explore the statically and dynamically calculated indicators in terms of their performance in constructing good indicators.

2.3 Research Questions

We revisit the Perphecy experiment to further elaborate on these questions:

- **RQ1:** ***What predictors does the Perphecy approach generate when used on a larger dataset?*** In the Perphecy paper, they don't give the actual predictors (combination of indicators and thresholds) that were generated, only the hit and dismiss rates that the predictor gave.
- **RQ2:** ***What are the most useful indicators when considered independently?*** For our dataset, which of the indicators has the best combination of hit and dismiss rates for the best threshold option?

Chapter 3

Related Work

Regression Test Selection has been studied previously in many different papers . The most relevant work is the study of regression test selection. However, this research has usually been focused on correctness tests, like unit tests, rather than performance.

A study by Luo et al, ”Mining Performance Regression Inducing Code Changes in Evolving Software”, [6] investigates how to identify the code changes that induced a performance regression. The tool they create, PerfImpact, works by searching for input combinations to a program which are likely to lead to a performance regression, and then profiling the execution trace when using those inputs to estimate the impact of past code changes on the detected regression. Using execution traces / dynamic profile information as they do in this paper is a key part of the indicators used in the Perphecy study.

Alcocer et al [1] study what kinds of source code changes are responsible for performance regressions in open source software. They determine if a commit causes a performance variation with static analysis and dynamic analysis. They also show that they can get good results without running dynamic profiling for every change.

One similar study by Huang et al. [5] looks into what they call Performance Risk Analysis, or PRA. They use static analysis to estimate how expensive each function is by looking at function length, loops, and known expensive functions. Through this static analysis of a function’s ”expensiveness”, they predict the risk that a change will cause a regression. Their analysis showed they could catch 87%-95% of regressions by testing only 14%-22% of the commits.

Chapter 4

Perphecy

4.1 Summary

Perphecy is a system which ”predicts if a code commit will affect the performance of a benchmark in a benchmark suite”. Given a ”before” commit, an ”after” commit, and a performance test (also called a benchmark), Perphecy will predict whether or not that test will experience a performance regression from one commit to the other. By collecting metrics about the source code through both static and dynamic analysis, the authors of Perphecy found they were able to save as much as 83% of benchmarking time while still detecting 85% of performance affecting code changes.

Perphecy uses 8 metrics which they distill into what they call ”Indicators”. The indicators are determined to be true or false by comparing to a static threshold, which they determined using a greedy algorithm that I will explain later. Each indicator is calculated specifically for each ”old commit, new commit, benchmark” triplet that needs to be considered. These indicators, along with the rationale for each, are included below, in Table 4.1.

In order to calculate the metrics, both static and dynamic analysis is needed. Perphecy's solution for getting the dynamic results is to do a separate run of the performance tests with the dynamic analysis tool active, anytime it predicts a regression. When calculating the metrics, the most recent available dynamic analysis data for the benchmarks is used. Over time though, it is certainly possible for this information to get out of date.

Note that we did not gather indicator 6 in our study. It was unclear exactly what was

Table 4.1: Indicator Descriptions and Rationales

#	Description	Rationale
1	Number of Deleted Functions	Deleted functions indicate refactoring, which may lead to performance changes
2	Number of New Functions	Added functions indicate new functionality, which may lead to performance changes
3	Number of Deleted Functions reached by the benchmark	Deleting a function which was part of the benchmark execution could lead to a performance change
4	The percent overhead of the top most called function that was changed	Altering a function that takes up a large portion of the processing time of a benchmark has a high risk of causing a performance regression because it is such a large portion of the test
5	The percent overhead of the top most called function that was changed by more than 10% of its static instruction length	Similar to indicator 4, however this takes into account that the change affects a reasonable portion of the function in question. Bigger changes may mean higher risk.
6	The longest running function in terms of total dynamic instructions	Similar to the rationale behind indicators 4 and 5, the longest running functions likely have the highest impact on the performance of a benchmark
7	The highest percent static function length change	Large changes to functions are more likely to cause regressions than small ones
8	The highest percent static function length change that is called by the benchmark	The same as for indicator 7, but here we guarantee that the functions are actually called by the benchmark in question.

meant by ”longest running function by total dynamic instructions”, but we could interpret it two ways. Either they were referring to the total number of instructions executed in that function over the course of the entire benchmark, or they were referring to the average number of instructions executed by the function each time it was called - the average dynamic instruction length. If the former was true, this is effectively the same as indicator 4. Multiplying the percent overhead by the total number of instructions executed in the program would give you a count of dynamic instructions executed by the function. This number would be in perfect ratio relative to the other functions in the benchmark, and we only compare the functions to each other, so there would be no effective difference between these indicators. On the other hand, if the latter interpretation is true, it was unclear to us how to determine the average dynamic instruction length using the tool recommended - perf. Indicator 8 is similar, but it uses static function length instead of average dynamic function instruction count. While it is a limitation that we were unable to replicate the results of indicator 6, we believe that the other indicators provide sufficient coverage to replicate the rest of the experiment.

Chapter 5

Methodology

5.1 Data Collection

Replicating the study required first collecting all of the necessary data. There were three kinds of data needed: - Results of running each performance test - Static information for the indicators - List of functions and their start and end line in the source code - Dynamic information for the indicators - Function overhead percentage for each benchmark

We collected data for 8798 commits originally. Those commits were chosen by executing the ‘git rev-parse‘ command from the master branch at the time and going back to the first commit we could find which had performance tests. Across that range of commits, there were were 202 commits which, for various reasons, did not have any tests, so we removed them. Thus in total we considered 8596 commits.

Running all of the performance tests for a single commit takes a long time (hence the need for this study) so we parallelized the task across many machines. The results of the git performance tests are reported in wall time, which can be impacted by using different machines with different clock speeds, RAM, and such, so to mitigate this we used identical DigitalOcean virtual machine servers. These virtual servers were the standard DigitalOcean Ubuntu 16.04 x64 droplets with 1 CPU clocked at 2.2GHz and 1GB of RAM. Even after taking these precautions, there can be noise in the data. To deal with this, we ran each test five times, which is the same number of runs used in the original study.

The dynamic information was collected using linux perf which was used for some of the projects in the original paper. This was also run using DigitalOcean servers. In this case though, the similarity of the machines is not very important because we only look at which instructions are executed, which should be largely identical, especially if run on the same operating system.

The static info - the list of functions and their location in the source code - was collected by using the python lizard tool. While intended for calculating cyclomatic complexity, it easily gave us a full list of functions identified in all of the source files in the repo for that commit.

Note that all the data we gathered here is independent of the order of the commits. At this point we did not calculate the number of functions deleted between two commits, but rather the list of functions that existed in each commit. Because of this, and because of how git source control works, we could technically compare commits which were not actually developed one after the other and see whether or not the tool could predict a regression, and validate whether the performance was in fact different from commit to commit. We did not take advantage of this for the most part, but we discuss why this property is useful in the Threats and Limitations section of the paper.

5.2 Data Analysis

Analyzing the data happened in several stages. First, we determined which commits and tests experienced a performance regression. Second, we calculated the indicator metrics for each test in each pair of commits. Once we had that data, we determined the optimal thresholds for each metric using the greedy algorithm given in the original paper.

5.2.1 Determining Significant Changes

The first step was to determine the truth values for the experiment. If our tool worked perfectly, what should it predict? For the 8596 commits that we ran on, we went through each consecutive pair and for each pair, we performed a t-test with an alpha value of 0.05 between the two sets of results. If the t test showed a significant difference between the two distributions, and the mean of the old times was lower than the mean of the new times, then we declared that to be a regression for that benchmark.

5.2.2 Determining the Indicator Metrics

The indicator metrics are the numbers that matter for each of the 8 indicators used in the original paper. Unfortunately, we were unable to collect the data needed to replicate the 6th indicator from the original paper, ”Top Chg by Instruction”, using the perf tool.

As mentioned before, the values were calculated for every (commit, commit, benchmark) triplet that we ran. We used all of the data from the Data Collection stage to calculate these numbers.

The metrics for each indicator are given below:

1. Number of deleted functions
2. Number of new functions
3. Number of deleted functions reached by the benchmark
4. The highest percent called function for the benchmark that was changed
5. The highest percent called function for the benchmark that was changed by more than 10% of its static length
6. *Not Collected*
7. The highest percent of static function length change across all functions
8. The highest percent static function length change for all functions called by the benchmark

This resulted in 176,667 results in a csv file which looked like the results in Table 5.1:

Table 5.1: Example indicator results

Commit A	Commit B	Benchmark	Indicator 1	Indicator 2	Indicator 3	...
d9545c7f	8f449614	p0000-perf-lib-sanity	983	515	7	...
d9545c7f	8f449614	p0001-rev-list	983	515	16	...
...	...	...	...	...	...	...

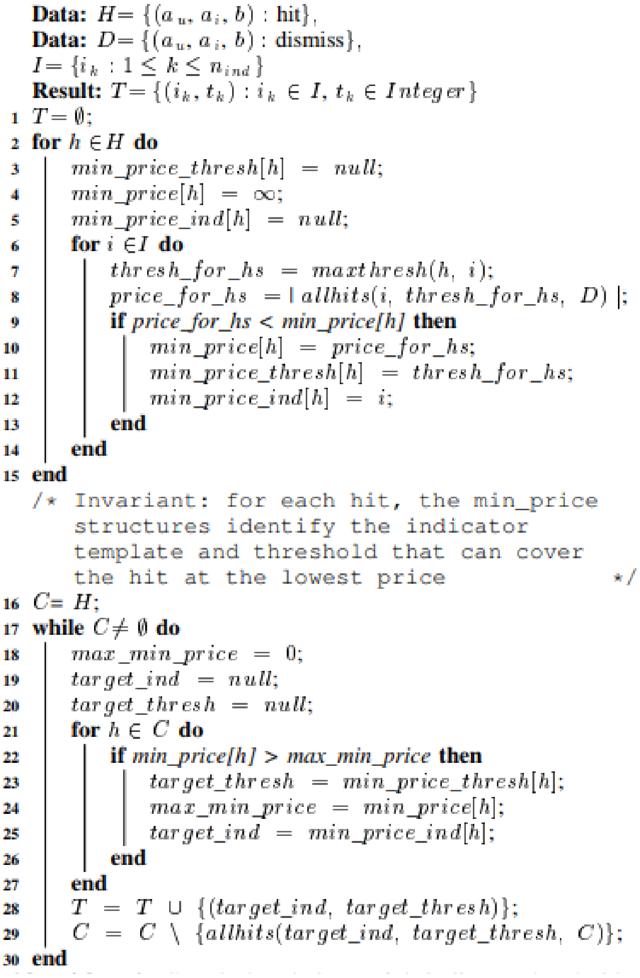
Note that these metrics are calculated assuming that dynamic profile data is available for every commit. This is the optimal situation because it has up to date data for every commit pair and benchmark. However, as described in the original paper, a dynamic profile would only be run if a hit was predicted. This would mean the dynamic data slowly becomes out of date as dismisses are accumulated.

Also note that when considering the dynamic profiling data for indicators 4 and 5, we disregarded any functions with less than 0.01% overhead.

5.2.3 Determining Thresholds

Once we had the indicator metrics calculated, we analyzed them to find thresholds using the approach in the paper. We sampled different threshold values in the range of 0 - 100 for each metric, and generated some graphs showing the hit and dismiss rates for each threshold value. We show one of these graphs for each indicator in our Analysis Section for Research Question 2.

Figure 5.1: Perphecy Threshold Algorithm



```
Data: $H = \{(a_u, a_i, b) : \text{hit}\}$,
Data: $D = \{(a_u, a_i, b) : \text{dismiss}\}$,
$I = \{i_k : 1 \leq k \leq n_{ind}\}$
Result: $T = \{(i_k, t_k) : i_k \in I, t_k \in Integer\}$
$T = \emptyset$;
for $h \in H$ do
    $min\_price\_thresh[h] = null$;
    $min\_price[h] = \infty$;
    $min\_price\_ind[h] = null$;
    for $i \in I$ do
        $thresh\_for\_hs = maxthresh(h, i)$;
        $price\_for\_hs = | allhits(i, thresh\_for\_hs, D) |$;
        if $price\_for\_hs < min\_price[h]$ then
            $min\_price[h] = price\_for\_hs$;
            $min\_price\_thresh[h] = thresh\_for\_hs$;
            $min\_price\_ind[h] = i$;
        end
    end
end
/* Invariant: for each hit, the min_price
   structures identify the indicator
   template and threshold that can cover
   the hit at the lowest price                */
$C = H$;
while $C \neq \emptyset$ do
    $max\_min\_price = 0$;
    $target\_ind = null$;
    $target\_thresh = null$;
    for $h \in C$ do
        if $min\_price[h] > max\_min\_price$ then
            $target\_thresh = min\_price\_thresh[h]$;
            $max\_min\_price = min\_price[h]$;
            $target\_ind = min\_price\_ind[h]$;
        end
    end
    $T = T \cup \{(target\_ind, target\_thresh)\}$;
    $C = C \setminus \{allhits(target\_ind, target\_thresh, C)\}$;
end
```

Our next step was to replicate the algorithm which the original paper used to determine the thresholds. The original algorithm is shown in Figure 5.1.

We did so, and realized that there is in fact a problem with the algorithm the paper used. The authors wrote a basic greedy algorithm which, to summarize in one sentence, looks at each of the hits, and finds the minimum disjunction of indicators which would have a hit rate of 1.0 with the best dismiss rate.

However, if a single hit entry has zero values for all indicators, due to how the algorithm is written, the first indicator it chooses while trying to create a predictor will be any indicator with a threshold of 0. A threshold of 0 trivially marks all commits as hits, and the predictor that is generated will simply be one indicator with a threshold of 0.

Thus, with this algorithm and our data as is, the system marks every commit as a hit, which is essentially the same as if the system had never been run in the first place.

The basic issue with the greedy approach still applies if only some of the indicators are zero and one of the indicators is very small. If for example, you have a row where every indicator metric value is set to 0, except for ”Del Func” which is set to 1, then the algorithm will pick that Del Func indicator and will wind up hitting a very large number of commits.

Due to this issue, we experiment with filtering out results with all-zero values and result with any-zero values. We show a comparison of the generated predictors in the next section.

It may seem potentially unlikely for a regression to occur when all of the indicators are zero values, but one theoretical example would be if a development team updated the version of a third party framework in a commit. If the framework caused a regression, the indicators may still be 0.

Chapter 6

Analysis & Discussion

In this chapter, we discuss the results of the study and the answers to our research questions.

6.1 RQ1: What predictors does the Perphecy approach generate when used on a larger dataset?

6.1.1 What is the potential for any test selection technique?

Before we talk about the performance of the predictors that Perphecy generates, we should put down a few statistics about the gathered data, to help characterize the data and manage our expectations.

We ran on 8596 commits. Over time, tests were added and removed to the suite of performance tests, but in general our range of commits begins with 11 tests and ends with 29 commits. Those tests are broken up into subtests, and the test result data is reported for each subtest in terms of minutes, seconds, and milliseconds it took to complete the tasks. We summed the subtest times to get a time duration for the test itself.

In all, looking at every combination of commit, commit, benchmark, we had 176,667 ”commit, commit, benchmark” results to consider. Of those, 171,656 were dismisses, approximately 97%. Thus, there were 5011 hits, or 2.84%. This seems to be in line with the results of the paper - there are proportionally very few commits that involve a significant performance regression.

Additionally worth note, there were 152,110 rows which contained an indicator metric with a value of 0, and there were 97,420 rows for which ALL of the indicator metrics had a value of 0. This means that for more than half of our ”commit, commit, benchmark” changes, no functions were added or deleted, the static instruction length of any function was unchanged, and no function that was more than .01% of the overhead for the benchmark was changed. This seemed surprisingly large, but the vast majority of these commits were either documentation changes, updates to unit tests, or involved things like changing indentation or tweaking function calls, which do not impact static function length. These findings tell us that not only do most commits not contain contain a performance regression, many are trivial changes that have no way of impacting performance tests, and many are small enough edits in non-critical sections of code that our indicators cannot pick them up.

Within the 97,420 results which had indicator metric values of all zeros, 1184 rows (approx. 1.2% of the ”all-zero” rows, and approx. 0.6% of all the rows) were actually registered as hits! Most of these changes were still of the trivial type - documentation changes, small one line edits, and the like. We attribute most of these results to noise in our data collection, however we keep them as part of our dataset because it is perfectly plausible for changes with no effect on our indicators to impact performance - for example, if a 3rd party library was updated, and the new version of that library causes a performance regression.

6.1.2 Generating and Evaluating the Predictors

In order to generate the predictor, we calculated the metrics for the indicators for each of our commit, commit, benchmark results, then ran the Perphecy threshold algorithm to output a predictor. As discussed in the Methodology section, we uncovered a problem with the original algorithm as written. So, when we ran our implementation on the 176,667 ”commit, commit, benchmark” rows, the predictor was $\{$ *Del Func* $\geq$ *X: 0* $\}$. This will trivially mark every commit as a hit, giving a Hit Rate of 1.0 and a Dismiss Rate of 0.

To get around this, we tried two changes. First, we tried removing all the entries from our results for which *every* value for the indicators was 0. This gave us a predictor of $\{$

Del Func $\geq$ *X: 1, New Func* $\geq$ *X: 1* } (Still fairly trivial). Second, we tried removing all entries for which *any* value for the indicators was 0. This gave us the most interesting predictor: { *New Func* $\geq$ *X: 44, Top Chg by Call* $\geq$ *X%: 8%, Reached Del Func* $\geq$ *X: 2, Top Reached Chg Len* $\geq$ *X%: 14%, Top Chg Len* $\geq$ *X%: 500%* } . Remember that these different values are handled as a disjunction; if any of these thresholds are met, we predict a hit for a performance regression.

We evaluated each of these predictors on the three different subsets of our data (the one with all values, the one with the rows with only zero values removed, and the one with any rows that had a single zero value removed). The results are shown in Table 6.1.

Table 6.1: Hit and Dismiss Rates for the three different predictors

Predictor	All Values (Hit, Dismiss)	No Zero Rows (Hit, Dismiss)	No Zero Values (Hit, Dismiss)
{ *Del Func* $\geq$ *X: 0* }	(1, 0)	(1, 0)	(1, 0)
{ *Del Func* $\geq$ *X: 1, ...* }	(.764, .561)	(1, 0)	(1, 0)
{ *New Func* $\geq$ *X: 44, ...*}	(.645, .804)	(.844, .553)	(1, .007)

Some interesting things to point out about these results:

- The predictor generated with all the values is, of course, trivial for all subsets
- The other two predictors have hit rates of 1 for their training set and any subsets of their training set. However, they also have dismiss rates equal or close to 0 for their training sets / subsets, which is much different than the results in the paper. When evaluating their predictor for git on the Full set of their data, they had a hit rate of 1 and a dismiss rate of .83.
- For the other two predictors, their performance on the sets that include data not trained on shows that the hit rate drops noticeably, but the dismiss rate increases dramatically.

In the original paper, they evaluate their results using K-fold cross validation - they trained their indicators on 90% of the data, then evaluated on the remaining 10%, and did that 10 times, each time for a different 10%. To gain further insight, we also tried training on a different 90% of the data, looking at just the subset of values without any zero values for any indicators. However, the predictors generated using this method were all exactly the same, except for three folds: One where Top Chg by call was 6% instead of 7%, one where Top Chg by Call was 8% instead of 7%, and one where the "New Func" indicator was gone altogether, but "Del Func $\geq$ 121" was added.

6.2 RQ2: What are the most useful indicators when considered independently?

In order to answer the question of which indicators perform the best, we plotted the hit and dismiss rate for each indicator for many different thresholds, on our full dataset of results.

We evaluated Indicators 1, 2, and 3 with threshold values from 0-1000, incrementing by 1. We evaluated Indicators 4, 5, 7, and 8 with threshold values from 0-1 (0% - 100%) incrementing by 0.01. As you can see, for each of these values the hit rate drops and the dismiss rate spikes right at the first non-zero value. For your convenience, those first points are:

Table 6.2: Hit and dismiss rates for specific indicators

Indicator	Hit Rate	Dismiss Rate
1	.728	.634
2	.749	.573
3	.553	.848
4	.597	.823
5	.555	.853
7	.682	.729
8	.600	.832

Beyond this first point, the hit rate decreases and the dismiss rate increases, and tends to level out at a certain threshold. If we define the best values for the indicators as the values that give the highest hit rate while still actually dismissing some results, then the threshold of 1 or 1% appears to be the best threshold for each of these values individually. Furthermore, the best indicator, by that definition, would be indicator 2 - New Func ≥ X. Del Func is close, but it dismisses about 6% more at the cost of about 2% of the hits. Indicator 8 dismisses about 23% more commits at that first threshold, but hits around 10% fewer regressions.

Some other observations are that indicator 3 seems to have very little room between hitting all the commits and hitting none of the commits, and that indicators 4, 5, 7, and 8 seem to quickly level out to a constant hit and dismiss rate, while for indicators 1 and 2 the hit rate seems to decrease almost linearly as the threshold increases. Also, no matter what threshold you pick, if you are using one indicator the best you can do for a hit rate with this data is 74.9%.

Figure 6.1: Indicator 1 - Del Func ≥ X

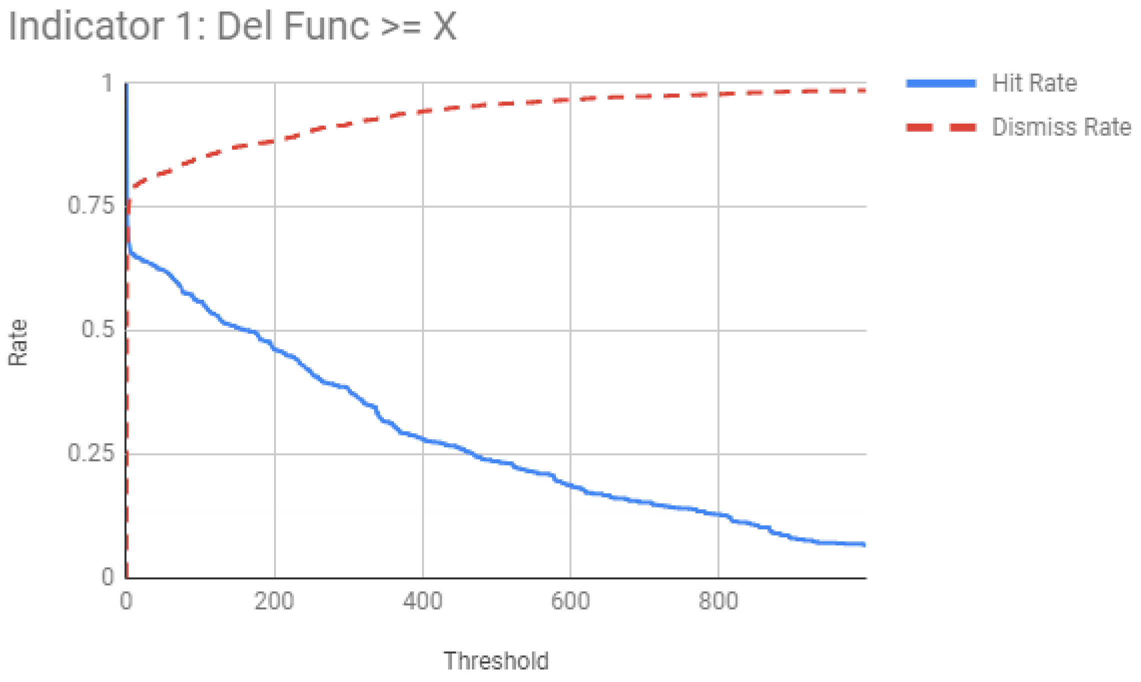


Figure 6.2: Indicator 2 - New Func ≥ X

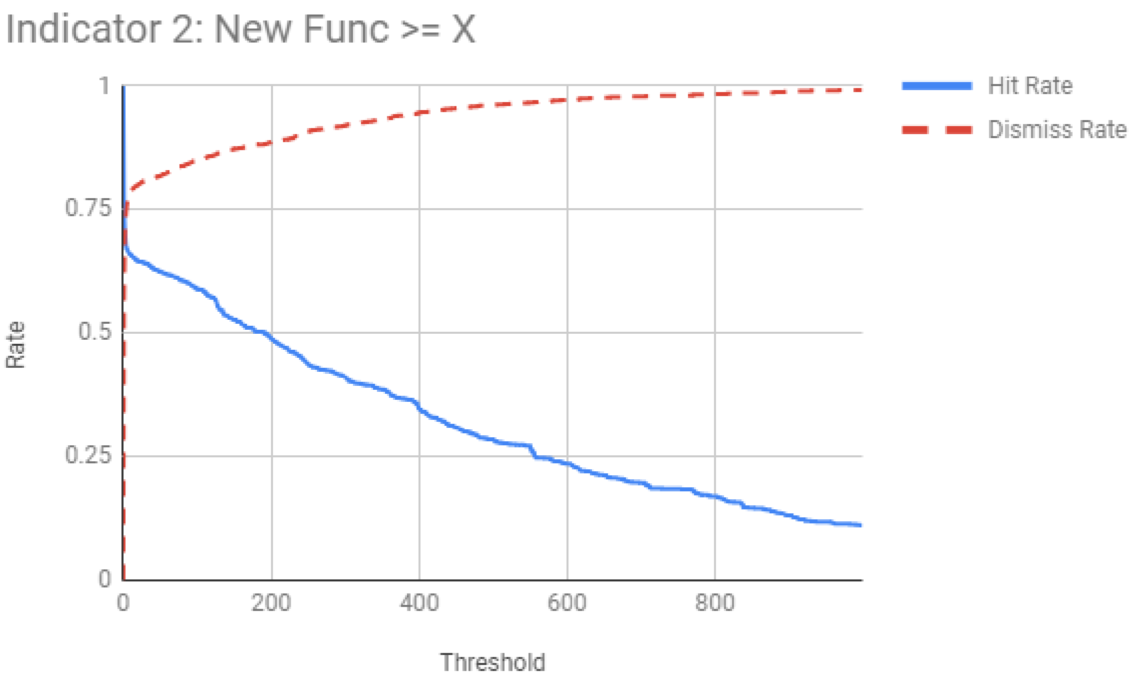


Figure 6.3: Indicator 3 - Reached Del Func ≥ X

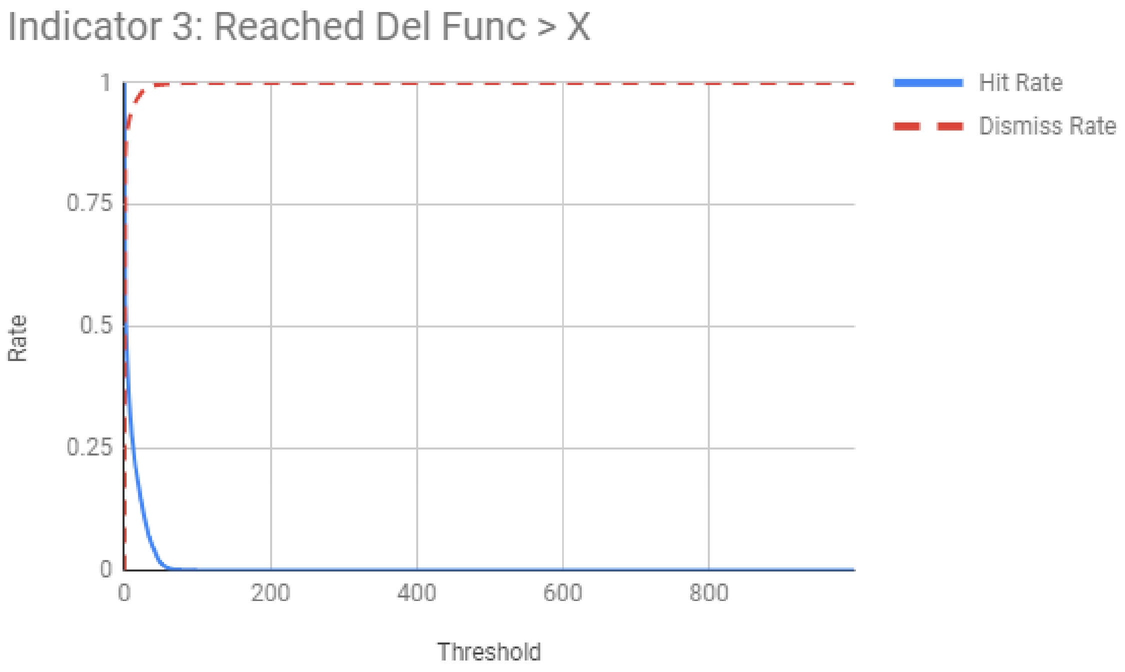


Figure 6.4: Indicator 4 - Top Chg by Call ≥ X%

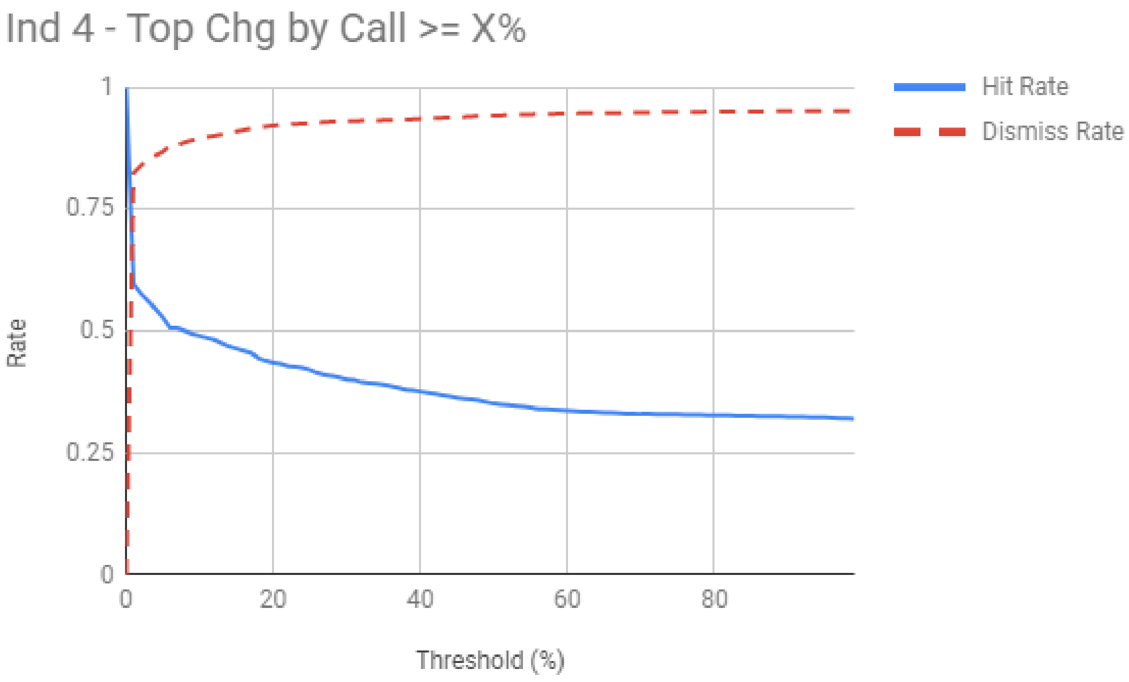


Figure 6.5: Indicator 5 - Top ≥ X% by Call Chg by ≥ 10%

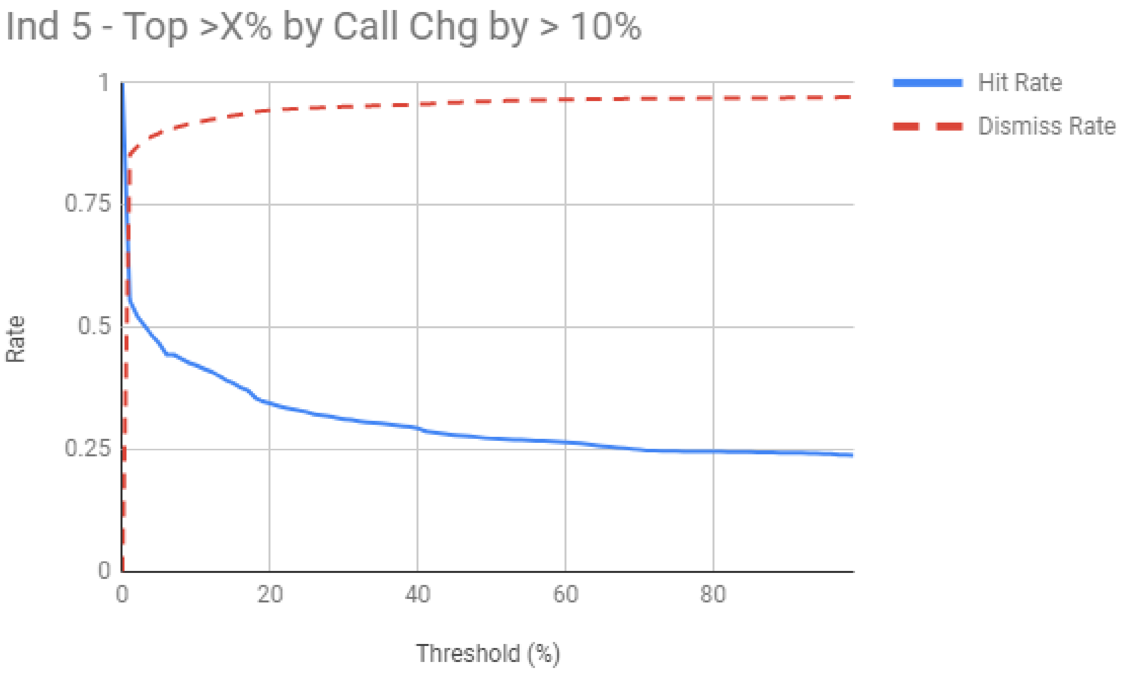


Figure 6.6: Indicator 7 - Top Chg Len ≥ X%

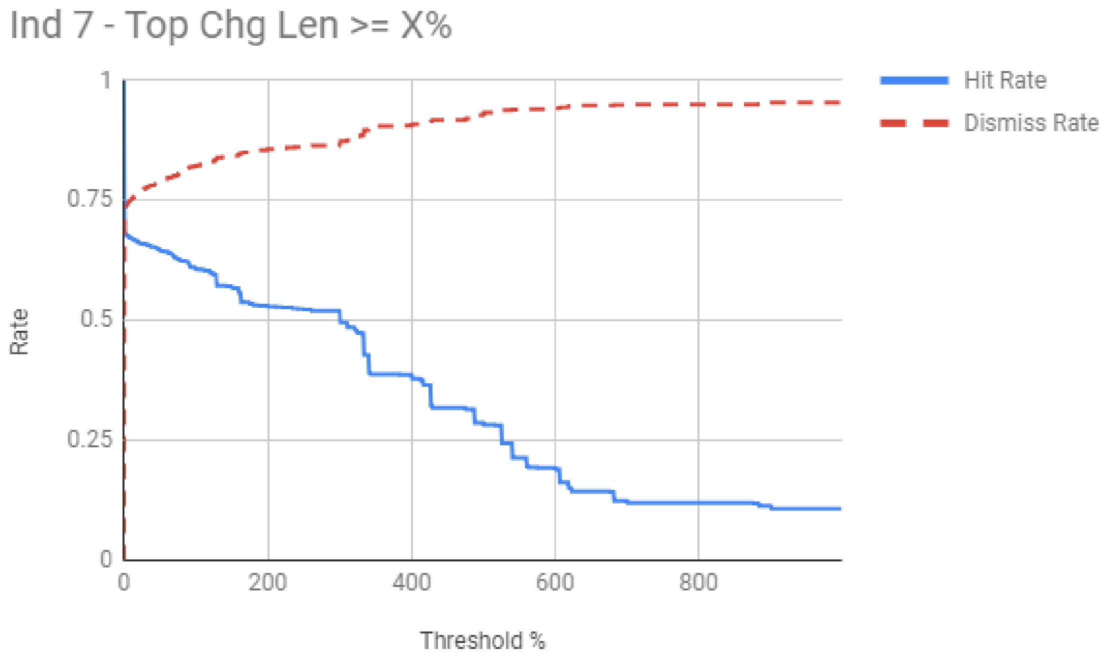
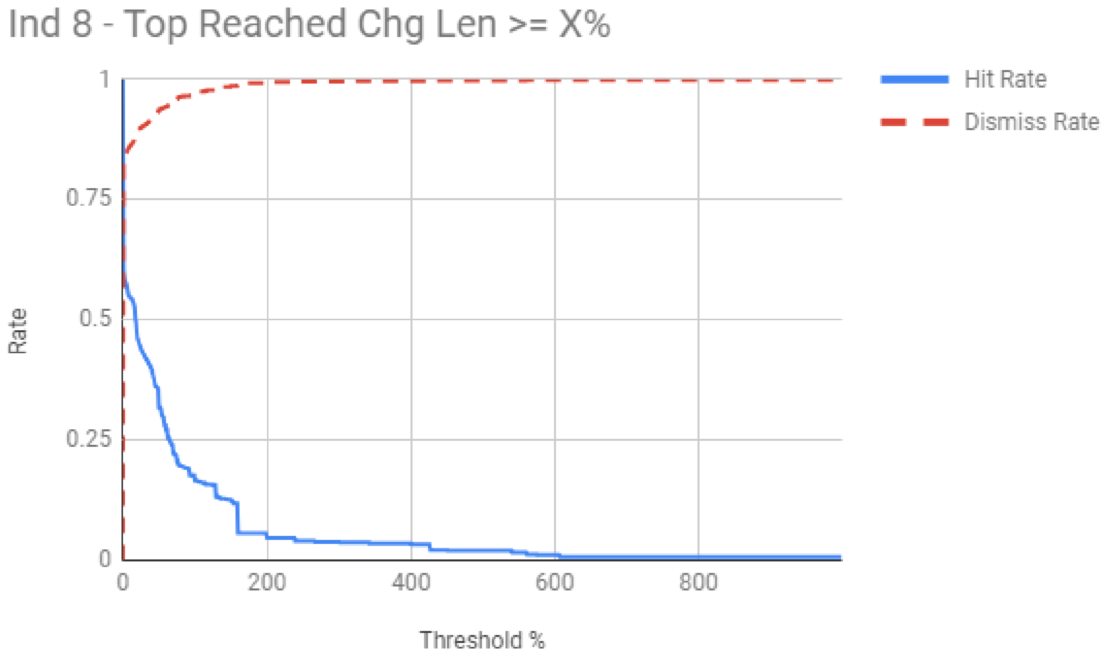


Figure 6.7: Indicator 8 - Top Reached Chg Len ≥ X%



Chapter 7

Threats to Validity

In this chapter, we present factors that may impact the applicability of our observations in real-life situations. We classify these factors into three categories [13].

Internal Validity. We report on the uncontrolled factors that interfere with causes and effects, and may impact the experimental results.

Commits not necessarily sequential: The git project itself uses git as source control, and employs a branching strategy with merges. If the project history branched and then merged, when you view the history linearly you might have two commits next to each other which technically were not developed sequentially when originally committed by the developer. However, none of our metrics are dependent on that ordering. So, even if commit A is not a direct parent to commit B in terms of how the development team wrote the code, our system can still consider them as such because it makes no difference. In fact, if desired we could jumble up the order of all the commits studied, and see if the system still works. This would not be practical, because the amount of change between commits would likely be dramatically higher, however for all our system knows the development team is just very active and makes huge changes all the time.

Neither our study nor the original study consider accumulated change over time. Both studies consider commits in pairs as they come in. If you have commits A, B, C, and D pushed, in that order, Perphecy will evaluate the changes from A to B, then B to C, then C to D. However, it may be more prudent to consider the *accumulated* change over time, until a hit occurs and we run our test again. In other words, assuming that the system predicts a dismiss for these commits, the system would consider the difference from A to B, then after marking it as a dismiss, it would consider from A to C, then again after marking it a dismiss, it would consider from A to D. With the way Perphecy works with thresholds, if the predictor was, for example, ”Del Func $\geq$ 3”, and each commit involved deleting one line, the first approach would not detect a performance hit, but the second approach would, because the accumulated change would be marked as risky. In an extreme case where a development team always limits commits to a single line of code, Perphecy would likely not function properly. Considering accumulated change would fix this issue, and may naturally decrease the need for periodic testing external to what Perphecy predicts.

Construct Validity. Herewith we report on certain challenges that validate whether the findings of our study reflect real-world conditions.

Certain git code is platform dependent. We did not perform any testing on Windows operating systems, so Windows specific code would not be executed during our dynamic profiling, and thus any indicators depending on that profiling have no chance of activating due to Windows specific changes.

The results of our experiments are influenced heavily by the definition of a performance regression. We used the same definition as in the original paper, however this definition has its limitations. For example, simply performing a t-test between two commits does not consider the history of times. One could try performing a t-test between the samples of all of the last X commits and the samples from the new commit. In a more realistic scenario, running tests more than once would be unreasonable, so another approach could be keeping a circular buffer of the last ten execution times and defining a regression as being a certain number of standard deviations away from the mean. However, evaluating different methods of defining performance regression is outside the scope of this work.

Using different computers for running performance tests: In order to execute the performance tests for over 8000 commits in a timely manner, the task was parallelized across multiple machines. This could become a threat because the results for the performance tests are given as a time duration, which can vary based on CPU speed, number of cores, and other random variables between machines. To mitigate this, identical digitalocean (citation?) VMs were used for all performance test results, which means CPU speed, RAM, and so on were identical. Additionally, we ran each test 5 separate times, such that each execution was at a different time of day on a different VM. This helps mitigate other uncontrollable random noise in the results of the testing.

External Validity. The prediction of performance regression was limited only to one project. The generated predictor does not necessarily give the best results for other projects [7]. This is due to the nature of changes performed by the developers, and so, for each set of changes, there is eventually a need to refine the predictor. We mitigate this limitation by simply re-executing our approach for the new system's changes as input and update the predictor.

Also, the diverse nature of commits may bias our results, we tired to address this limitation by analyzing a large number of diverse commits written by multiple developers to make the changes more representative. Similarly, not all projects utilize GitHub to track and manage changes; and not all projects provide a performance testing set in the publicly available source base. This may reduce the usability of our approach since is relies on executing pre-written test cases to detect any regression.

Chapter 8

Conclusion & Future Work

The goal of this work is to create a system which can accurately predict performance test regressions. We have replicated the Perphecy paper on 8596 commits of the git project and have found that the Perphecy approach does not perform as well as reported in the original paper. The original paper found that for the same project on less commits, they were able to correctly predict 85% of commits with regressions while correctly dismissing 83% of other commits. In our study, we found that with our least aggressive cleaning of the training data and our most realistic evaluation data set, a 76% hit rate with a 56% dismiss rate was more realistic. We also identify and discuss a flaw in the original paper's threshold selection algorithm, and a larger dataset with further analysis on the individual indicators used in the original study.

We plan to extend this study by adding additional indicators not considered in the original paper. We plan to add five indicators based on 3 metrics - Flux, or the number of added lines plus the number of deleted lines between two commits, Cyclomatic Complexity, and Coupling between objects. Flux would provide a similar kind of indicator as number of added functions or number of deleted functions, but it is based on lines rather than functions. Some of the results we found that had only zero values for all the indicators would have a non-zero value for flux. For cyclomatic complexity and coupling between objects, we would look at the highest changed value between two commits, and also look at the highest changed value that is also reached by the given benchmark. Though these are typically metrics used for correctness bugs, we wish to examine their impact on performance bugs as well.

This study can also be expanded to consider accumulated change, as discussed in the Threats chapter. One last extension can be to experiment with different ways of using the raw metric data other than determining static thresholds as is done in this study. For instance, the values of the metrics could be fed directly into a neural network. Depending on how the network is set up, this could lead to usage of conjunction between indicators as well as disjunction.

Chapter 9

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