quiho: Automated Performance Regression Testing Using Inferred Resource Utilization Profiles

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ABSTRACT

We introduce *quiho*, a framework for profiling application performance that can be used in automated performance regression tests. *quiho* profiles an application by applying sensitivity analysis, in particular statistical regression analysis (SRA), using application-independent performance feature vectors that characterize the performance of machines. The result of the SRA, feature importance specifically, is used as a proxy to identify hardware and low-level system software behavior. The relative importance of these features serve as a performance profile of an application (termed inferred resource utilization profile or IRUP), which is used to automatically validate performance behavior across multiple revisions of an application's code base without having to instrument code or obtain performance counters. We demonstrate that *quiho* can successfully discover performance regressions by showing its effectiveness in profiling application performance for synthetically introduced regressions as well as those found in real-world applications.

CCS CONCEPTS

• **Software and its engineering** → **Software performance**; **Software testing and debugging**; **Acceptance testing**; *Empirical software validation*; • **Social and professional topics** → *Automation*;

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1 INTRODUCTION

Quality assurance (QA) is an essential activity in the software engineering process [1–3]. Part of the QA pipeline involves the execution of performance regression tests, where the performance of the application is measured and contrasted against past versions [4–6]. Examples of metrics used in regression testing are throughput, latency, or resource utilization over time. These metrics are captured and compared for multiple versions of an application (usually current and past versions) and, if significant differences are found, this constitutes a regression.

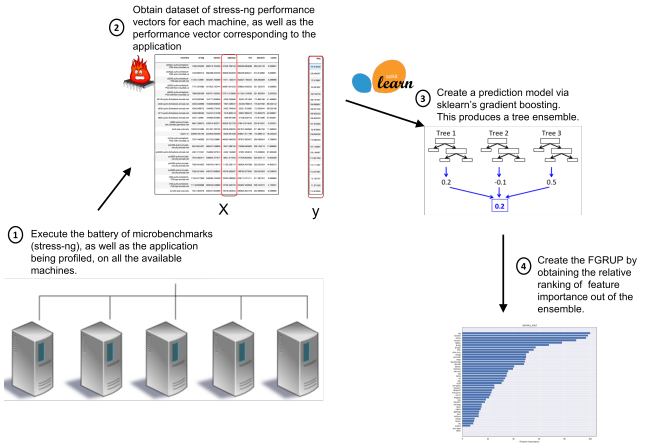

Figure 1: *quiho*'s workflow for generating inferred resource utilization profiles (IRUPs) for an application. An IRUP is used as an alternative for profiling application performance and can complement automated regression testing. For example, after a change in the runtime of an application has been detected across two revisions of the code base, an IRUP can be obtained in order to determine whether this change is significant. IRUPs can also aid in root cause analysis.

One of the main challenges in automating performance regression tests is defining the criteria to decide whether a change in application performance behavior is significant [7]. Understanding the effects in performance that distinct hardware and low-level system software[1] components have on applications demands highly-skilled performance engineering [8–10]. Traditionally, this investigation is done by an analyst in charge of looking at changes to the performance metrics captured at runtime, possibly investigating deeply by looking at performance counters, performance profiles, static code analysis, and static/dynamic tracing. One common approach is to find bottlenecks by generating a profile (e.g., using the `perf` Linux kernel tool) in order to understand which parts of the system an application is hammering on [5]. Profiling involves recording

[1]Throughout this paper, we use "system" to refer to the low-level compute stack composed by hardware, firmware and the operating system (OS).

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resource utilization for an application over time making use of tools such as `perf`. In general, this can be done in two ways: timed- and event-based profiles. Timed-based profiling samples the instruction pointer at regular intervals and generates a function call tree with each node in the three having a percentage of time associated with it, which represents the amount of time that the CPU spends within that piece of code. Event-based profiling samples at regular intervals different events at the hardware and OS level in order to obtain a distribution of events over the time that an application runs. In either case, the system needs to execute the application in a "profiling" mode, in order to have the OS enable the instrumentation mechanisms that has available to carry out this task.

Automated solutions have been proposed in recent years [11–13]. The general approach of these is to analyze runtime logs and/or metrics application in order to build a performance prediction model that can be used to automatically determine whether a regression has occurred. This relies on having accurate predictions and, as with any prediction model, there is the risk of finding false negatives/positives. In addition to striving for highly accurate predictions, one can also use performance modeling as a profiling tool.

In this work, we present *quiho* an approach aimed at complementing automated performance regression testing by using inferred resource utilization profiles (IRUP) associated to an application. *quiho* is an alternative framework for profiling an application where the utilization of one or more subsystems (e.g. virtual memory) is inferred by applying Statistical Regression Analysis[2] (SRA) on a dataset of application-independent performance vectors. The main assumption behind *quiho* is the availability of multiple machines when exercising performance regression testing, a reasonable requirement that is well-aligned with current software engineering practices (performance regression is carried out on multiple architectures and OSs).

When an application is profiled using *quiho* (Fig. 1, the machines available to the performance tests are baselined by executing a battery of microbenchmarks on each. This matrix of performance vectors characterizes the available machines independently from any application and can be used (and re-used) as the foundation for applying statistical learning techniques such as SRA. In order to infer resource utilization, the application under study is executed on the same machines from where the performance vectors where obtained, and SRA is applied. The result of the SRA for an application, in particular feature importance, is used as a proxy to characterize hardware and low-level system utilization behavior. The relative importance of these features constitutes what we refer to as an *inferred resource utilization profile* (IRUP). Fig. 4 shows an example of an IRUP for an application. Each feature in this relative ranking corresponds to a microbenchmark for a subcomponent of a system (e.g. floating point unit, virtual memory, etc.). Thus, this profile captures the resource utilization pattern of an application which can be used to automatically validate its performance behavior across multiple revisions of its code base, making *quiho* an approach to characterizing applications that is resilient to code refactoring.

[2]We use the term *Statistical Regression Analysis* (SRA) to differentiate between regression testing in software engineering and regression analysis in statistics.

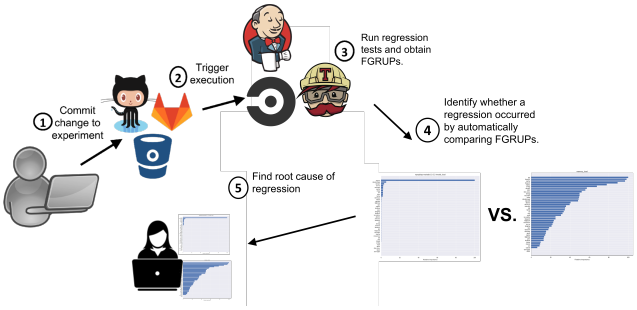


Figure 2: Automated regression testing pipeline integrating inferred resource utilization profiles (IRUP). IRUPs are obtained by *quiho* and can be used both, for identifying regressions, and to aid in the quest for finding the root cause of a regression.

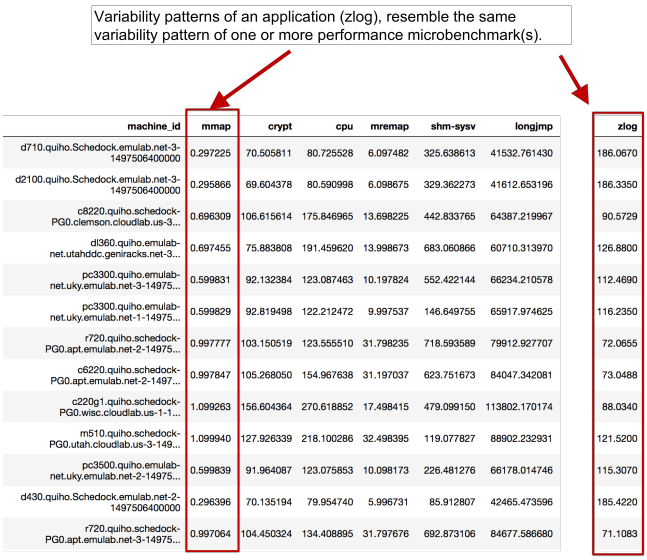
In this article, we demonstrate that *quiho* can successfully identify performance regressions. We show (Section 4) that *quiho* (1) obtains resource utilization profiles for application that reflect what their codes do and (2) effectively uses these profiles to identify induced regressions as well as other regressions found in real-world applications. The contributions of our work are:

- Insight: feature importance in SRA models (trained using these performance vectors) gives us a resource utilization profile of an application without having to look at the code.
- An automated end-to-end framework (based on the above finding), that aids analysts in identifying significant changes in resource utilization behavior of applications which can also aid in identifying root cause of regressions, and that is resilient an application code refactoring.
- Methodology for evaluating automated performance regression. We introduce a set of synthetic benchmarks aimed at evaluating automated regression testing without the need of real bug repositories. These benchmarks take as input parameters that determine their performance behavior, thus simulating different "versions" of an application.

Next section (Section 2) shows the intuition behind *quiho* and how can be used to automate regression tests. We then do a more in-depth description of *quiho* (Section 3), followed by our evaluation of this approach (Section 4). We then discuss different aspects of our work (Section 5), review (Section 6) related work and we lastly close with a brief discussion on challenges and opportunities enabled by *quiho* (Section 7).

2 MOTIVATION AND INTUITION BEHIND *QUIHO*

Fig. 2 shows the workflow of an automated regression testing pipeline and shows how *quiho* fits in this picture. A regression is usually the result of observing a significant change in a performance metric of interest (e.g., runtime). At this point, an analyst will investigate further in order to find the root cause of the problem. One of these activities involves profiling an application to see the resource utilization pattern. Traditionally, coarse-grained profiling (i.e. CPU-, memory- or IO-bound) can be obtained by monitoring



machine_id	mmap	crypt	cpu	mremap	shm-sysv	longjmp	zlog
d710.quiho.Schedock.emulab.net-3-1497506400000	0.297225	70.505811	80.725528	6.097482	325.638613	41532.761430	186.0670
d2100.quiho.Schedock.emulab.net-3-1497506400000	0.295866	69.604378	80.590998	6.098675	329.362273	41612.653196	186.3350
c8220.quiho.schedock-PG0.clemson.cloudlab.us-3...	0.696309	106.615614	175.846965	13.698225	442.833765	64387.219967	90.5729
dl360.quiho.emulab-net.utahddc.geniracks.net-3...	0.697455	75.883808	191.459620	13.998673	683.060866	60710.313970	126.8800
pc3300.quiho.emulab-net.uky.emulab.net-3-14975...	0.599831	92.132384	123.087463	10.197824	552.422144	66234.210578	112.4690
pc3300.quiho.emulab-net.uky.emulab.net-1-14975...	0.599829	92.819498	122.212472	9.997537	146.649755	65917.974625	116.2350
r720.quiho.schedock-PG0.apt.emulab.net-2-14975...	0.997777	103.150519	123.555510	31.798235	718.593589	79912.927707	72.0655
c6220.quiho.schedock-PG0.apt.emulab.net-2-1497...	0.997847	105.268050	154.967638	31.197037	623.751673	84047.342081	73.0488
c220g1.quiho.schedock-PG0.wisc.cloudlab.us-1-1...	1.099263	156.604364	270.618852	17.498415	479.099150	113802.170174	88.0340
m510.quiho.schedock-PG0.utah.cloudlab.us-3-149...	1.099940	127.926339	218.100286	32.498395	119.077827	88902.232931	121.5200
pc3500.quiho.emulab-net.uky.emulab.net-2-14975...	0.599839	91.964087	123.075853	10.098173	226.481276	66178.014746	115.3070
d430.quiho.Schedock.emulab.net-2-1497506400000	0.296396	70.135194	79.954740	5.996731	85.912807	42465.473596	185.4220
r720.quiho.schedock-PG0.apt.emulab.net-3-14975...	0.997064	104.450324	134.408895	31.797676	692.873106	84677.586680	71.1083

Figure 3: A matrix of performance feature vectors over a colection of CloudLab servers (left), and an array of a performance metric for an application on those same machines (right). Every column in the matrix comes from executing a microbenchmark on that machine. This dataset of microbenchmarks allows us to create a performance prediction model for application. Variability patterns of an application (zlog in the example), resemble the same variability pattern of one or more performance microbenchmark(s). Thus, the system subcomponent exercised by the microbenchmark is likely to be also the cause of why the application exhibits such performance behavior.

an application's resource utilization over time. Fine granularity behavior helps application developers and performance engineers quickly understand what they need to focus on while refactoring an application.

Fine granularity performance utilization behavior can better inform the regression testing pipeline. Examples of which resources are included in this type of profiling are the OS memory mapping subsystem, the CPU's cryptographic unit, or the CPU cache. This type of profiling is time-consuming and requires use of more computing resources. This is usually done offline by analysts and involves eyeballing source code, static code analysis, or analyzing hardware/OS performance counters/profiles.

An alternative is to infer resource utilization behavior by comparing the performance of an application on platforms with different performance characteristics. For example, if we know that machine A has higher memory bandwidth than machine B, and an application is memory-bound, then this application will perform better on machine A. There are several challenges with this approach:

1. Consistent Software. We need to ensure that the software stack is the same on all machines where the application runs.
2. Application Testing Overhead. The amount of effort required to run applications on a multitude of platforms is not negligible.

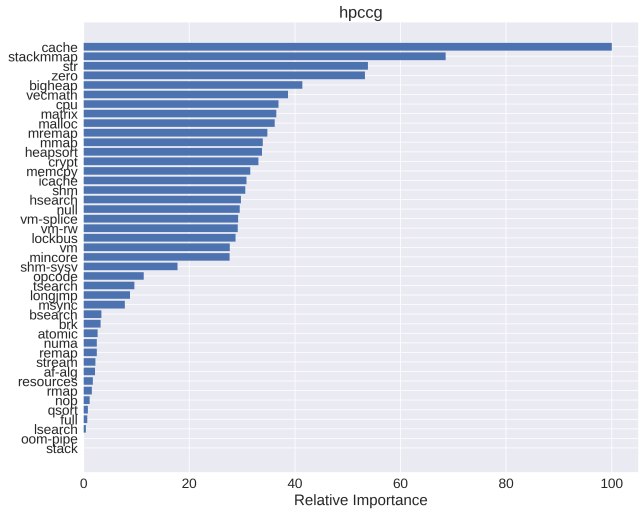


Figure 4: An example profile showing the relative importance of features for an execution of the hpccg miniapp [14]. The y-axis denotes the relative performance with respect to the most importante feature, which corresponds to the first one on the x-axis (from top to bottom).

3. Hardware Performance Characterization. It is difficult to obtain the performance characteristics of a machine by just looking at the hardware spec, so other more practical alternative is required.
4. Correlating Performance. Even if we could solve the above issue (Hardware Performance Characterization) and infer performance characteristics by just looking at the hardware specification of a machine, there is still the problem of not being able to correlate baseline performance with application behavior, since between two platforms is rarely the case where the change of performance is observed in only one subcomponent of the system (e.g., a newer machine doesn't have just faster memory sticks, but also better CPU, chipset, etc.).

The advent of cloud computing allows us to solve (1) using solutions like KVM [15] or software containers [16]. ChameleonCloud [17], CloudLab [18,19] and Grid5000 [20] are examples of bare-metal-as-a-service infrastructure available to researchers that can be used to automate regression testing pipelines for the purposes of investigating new approaches. These solutions to infrastructure automation coupled with DevOps practices [21,22] allows us to address (2), i.e. to reduce the amount of work required to run tests.

Thus, the main challenge to inferring resource utilization patterns lies in quantifying the performance of the platform in a consistent way (3,4). One alternative is to look at the hardware specification and infer performance characteristics from this, a highly inaccurate task due to the lack of correspondence between advertised (or theoretical peak throughput) and actual performance observed in reality. For example, the spec of a platform might specify that the machine has DDR4 memory sticks, with a theoretical peak throughput of 10 GB/s, but the actual memory bandwidth could be

less (usually is, by a non-deterministic fraction of the advertised performance).

quiho solves this problem by characterizing machine performance using microbenchmarks. These performance vectors are the "fingerprint" that characterizes the behavior of a machine [23]. These vectors, obtained over a sufficiently large set of machines[3], can serve as the foundation for building a prediction model of the performance of an application when executed on new ("unseen") machines [24]. Thus, a natural next step to take with a dataset like this is to try to build a prediction model.

While building a prediction model is obviously something that can be used to estimate the performance of an application, building one can also serve as a way of identifying resource utilization. If we use these performance vectors to apply SRA and we focus on feature importance [25] of the generated models, we can see that they allow us to infer resource utilization patterns. In Fig. 3, we show the intuition behind why this is so. The performance of an application is determined by the performance of the subcomponents that get stressed the most by the application's code. Thus, intuitively, if the performance of an application across multiple machines resembles the performance of a microbenchmark, then we can say that the application is heavily influenced by that subcomponent. In other words, if the variability pattern of a feature across multiple machines resembles the variability pattern of application performance across those same machines, it is likely due to the application stressing the same subcomponent that the corresponding microbenchmark stresses. While this can be inferred by obtaining correlation coefficients, proper SRA is needed in order to create prediction models, as well as to obtain a relative rank of feature importances.

If we rank features by their relative importance, we obtain what we call an inferred resource utilization profile (IRUP), as shown in Fig. **??**. In the next section we show how these IRUPs can be used in automated performance regression tests. Section 4 empirically validates this approach.

3 OUR APPROACH

In this section we describe *quiho*'s approach and the resulting prototype. We first describe how we obtain the performance vectors that characterize system performance. We then show that we can feed these vectors to SRA in order to build a performance model for an application. Lastly, we describe how we obtain feature importance, how this represents an inferred resource utilization profile (IRUP) and the algorithm (and alternative heuristics) to comparing IRUPs.

3.1 Performance Feature Vectors As System Performance Characterization

While the hardware and software specification can serve to describe the performance characteristics of a machine, the real performance characteristics can only feasibly be obtained by executing programs and capturing metrics. One can get generate arbitrary performance characteristics by interposing a hardware emulation layer and deterministically associate performance characteristics to each instruction based on specific hardware specs. While possible, this is impractical (we are interested in characterizing "real" performance). The question then boils down to which programs should we use to characterize performance? Ideally, we would like to have many programs that execute every possible opcode mix so that we measure their performance. Since this is an impractical solution, an alternative is to create synthetic microbenchmarks that get as close as possible to exercising all the available features of a system.

`stress-ng`[26] is a tool that is used to "stress test a computer system in various selectable ways. It was designed to exercise various physical subsystems of a computer as well as the various operating system kernel interfaces". There are multiple stressors for CPU, CPU cache, memory, OS, network and filesystem. Since we focus on system performance bandwidth, we execute the (as of version 0.07.29) 42 stressors for CPU, CPU cache, memory and virtual memory stressors (Tbl. 1 shows the list of stressors used in this paper). A *stressor* (or microbenchmark) is a function that loops for a fixed amount of time, exercising a particular subcomponent of the system. At the end of its execution, `stress-ng` reports the

Table 1: List of stressors used in this paper, along with the categories assigned to them by `stress-ng`. Note that some stressors are part of multiple categories.

stressor	CPU	Cache	Mem	VM
af-alg	X			
atomic	X		X	
bigheap				X
brk	X			
bsearch	X	X	X	
cache		X		
cpu	X			
crypt	X			
full			X	
heapsort	X	X	X	
hsearch	X	X	X	
icache		X		
lockbus		X	X	
longjmp	X			
lsearch	X	X	X	
malloc		X	X	X
matrix	X	X	X	
memcpy			X	
mincore			X	
mmap				X
mremap				X
msync				X
nop	X			
numa	X		X	
oom-pipe			X	
qsort	X	X	X	
remap			X	X
resources			X	
rmap			X	
shm				X
shm-sysv				X
stack			X	X
stackmmap			X	X
str	X	X	X	
stream	X		X	
tsearch	X	X	X	
vecmath	X	X		
vm			X	X
vm-rw			X	X
vm-rw				
vm-splice				X
zero			X	

[3] As mentioned in Section 7, an open problem is to identify the minimal set of machines needed to obtaining meaningful results from SRA.

Table 2: Table of machines from CloudLab. The last three entries correspond to computers in our lab.

machine	cpu	num_cpus	cores
c220g2	Intel(R) Xeon(R) CPU E5-2630 v3 @ 2.40GHz	2	8
c8220	Intel(R) Xeon(R) CPU E5-2660 v2 @ 2.20GHz	2	10
dl360	Intel(R) Xeon(R) CPU E5-2450 0 @ 2.10GHz	2	8
m510	Intel(R) Xeon(R) CPU D-1548 @ 2.00GHz	1	8
pc2400	Intel(R) Core(TM)2 Quad CPU Q9550 @ 2.83GHz	1	4
pc3000	Intel(R) Xeon(TM) CPU 3.00GHz	1	1
pc3500	Intel(R) Core(TM)2 Quad CPU Q6600 @ 2.40GHz	1	4
r720	Intel(R) Xeon(R) CPU E5-2450 0 @ 2.10GHz	1	8
scruffy	Intel(R) Xeon(R) CPU E5620 @ 2.40GHz	1	4
dwill	Intel(R) Core(TM) i5-2400 CPU @ 3.10GHz	1	4
issdm-41	Dual-Core AMD Opteron(tm) Processor 2212	2	2

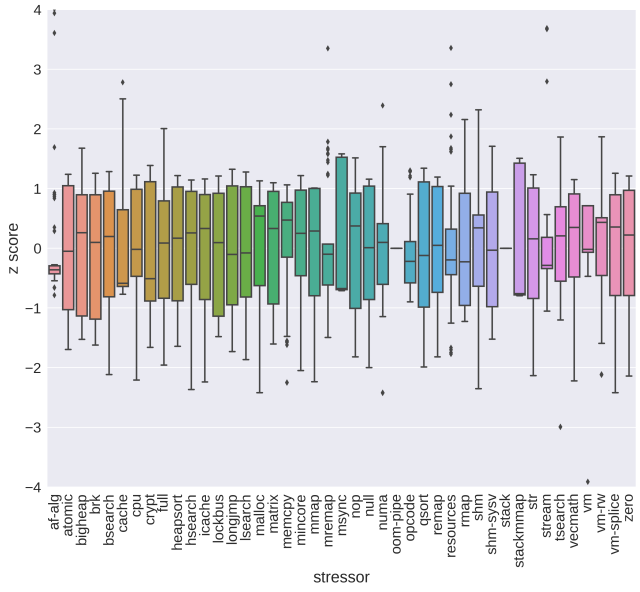


Figure 5: Boxplots illustrating the variability of the performance vector dataset. Each stressor was executed five times on each of the machines listed in Tbl. 2.

rate of iterations executed for the specified period of time (referred to as `bogo-ops-per-second`).

Using this battery of stressors, we can obtain a performance profile of a machine (a performance vector). When this vector is compared against the one corresponding to another machine, we can quantify the difference in performance between the two at a per-stressor level. Fig. 5 shows the variability in these performance vectors.

Every stressor (element in the vector) can be mapped to basic features of the underlying platform. For example, `bigheap` is directly associated to memory bandwidth, `zero` to memory mapping, `qsort` to CPU performance (in particular to sorting data), and so on and so forth. However, the performance of a stressor in this set is *not* completely orthogonal to the rest, as implied by the overlapping categories in Tbl. 1. Fig. 6 shows a heat-map of Pearson correlation coefficients for performance vectors obtained by executing `stress-ng` on all the distinct machine configurations available in

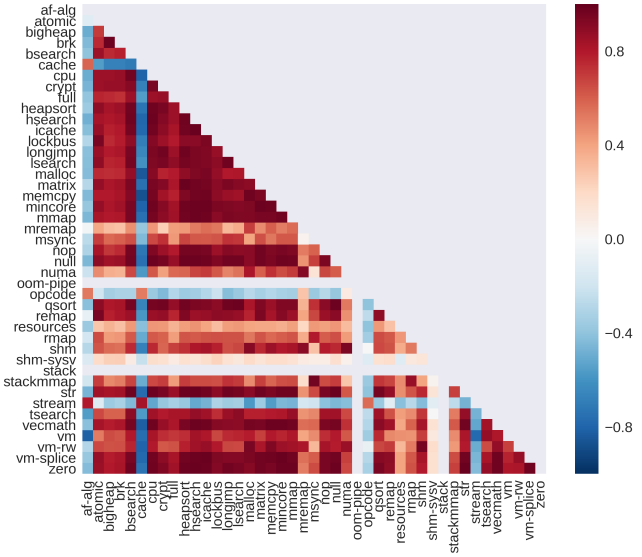


Figure 6: Heat-map of Pearson correlation coefficients for performance vectors obtained by executing `stress-ng` on all the distinct machine configurations available in CloudLab.

CloudLab [19] (Tbl. 2 shows a summary of their hardware specs). As the figure shows, some stressors are slightly correlated (those near 0) while others show high correlation between them.

In order to analyze this last point further, that is, to try to discern whether there are a few orthogonal features that we could focus on, rather than looking at the totality of the 42 stressors, we applied principal component decomposition (PCA) [27]. Fig. 7 shows the result. The figure shows the relative (blue) and cumulative (green) explained variance ratio. As we can see, having 6-8 components would be enough to explain most of the variability in the dataset. This confirms what we observe in Fig. 6, in terms of having many stressors that can be explained in function of others. However, doing so would cause the loss of information with respect to what stressors are explaining the prediction. Instead of trying to reduce the number, we decide to leave all the stressors in order to not lose this information. Part of our future work is to address whether we can reduce the number of features with the goal of improving the models, without having to lose information about which stressors are involved in the prediction.

3.2 System Resource Utilization Via Feature Importance in SRA

SRA is an approach for modeling the relationship between variables, usually corresponding to observed data points [28]. One or more independent variables are used to obtain a *regression function* that explains the values taken by a dependent variable. A common approach is to assume a *linear predictor function* and estimate the unknown parameters of the modeled relationships.

A large number of procedures have been developed for parameter estimation and inference in linear regression. These methods differ in computational simplicity of algorithms, presence of a closed-form solution, robustness with respect to heavy-tailed distributions,

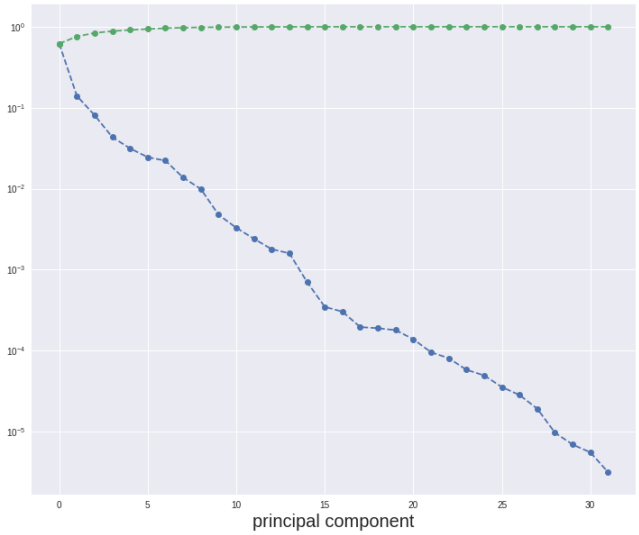


Figure 7: Principal Component Analysis for the performance vector dataset. The y-axis (log-scale) corresponds to the explained variance ratio, while the x-axis denotes the number of components. The blue line denotes the amount of variance reduced by having a particular number of components. The green line corresponds to the cumulative sum of the explained variance.

and theoretical assumptions needed to validate desirable statistical properties such as consistency and asymptotic efficiency. Some of the more common estimation techniques for linear regression are least-squares, maximum-likelihood estimation, among others.

`scikit-learn` [29] provides with many of the previously mentioned techniques for building regression models. Another technique available in `scikit-learn` is gradient boosting [30]. Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees [31]. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function. This function is then optimized over a function space by iteratively choosing a function (weak hypothesis) that points in the negative gradient direction.

Once an ensemble of trees for an application is generated, feature importances are obtained in order to use them as the IRUP for an application. Fig. 1 shows the process applied to obtaining IRUPs for an application. `scikit-learn` implements the feature importance calculation algorithm introduced in [32]. This is sometimes called *gini importance* or *mean decrease impurity* and is defined as the total decrease in node impurity, weighted by the probability of reaching that node (which is approximated by the proportion of samples reaching that node), averaged over all trees of the ensemble.

We note that before generating a regression model, we normalize the data using the `StandardScaler` method from `scikit-learn`, which removes the mean (centers it on zero) and scales the data to unit variance. Given that the `bogo-ops-per-second` metric does not quantify work consistently across stressors, we normalize the data in order to prevent some features from dominating in the process of creating the prediction models (the data for Fig. 8 has been normalized prior to being plotted). In section Section 4 we evaluate the effectiveness of IRUPs.

3.3 Using IRUPs in Automated Regression Tests

As shown in Fig. 2 (step 4), when trying to determine whether a performance degradation occurred, IRUPs can be used to compare differences between current and past versions of an application. In order to do so, we apply a simple algorithm. Given two profiles A and B, and an arbitrary ϵ value, look at first feature in the ranking (highest in the chart). Then, compare the relative importance value for the feature and importance values for A and B. If relative importance is not within $+/-\epsilon$, the importance is considered not equivalent and the algorithm stops. If values are similar (within $+/-\epsilon$), we move to the next, less important factor and the compare again. This is repeated for as many features are present in the dataset.

IRUPs can also be used as a pointer to where to start with an investigation that looks for the root cause of the regression (Fig. 2, step 5). For example, if *memorymap* ends up being the most important feature, then we can start by looking at any code/libraries that make use of this subcomponent of the system. An analyst could also trace an application using performance counters and look at corresponding performance counters to see which code paths make heavy use of the subcomponent in question.

4 EVALUATION

In this section we answer the following questions:

1. How well can IRUPs accurately capture application performance behavior? (Section 4.1)
2. How well can IRUPs work for identifying simulated regressions? (Section 4.2)
3. How well can IRUPs work for identifying regressions in real world software projects? (Section 4.3)

Note on Replicability of Results: This paper adheres to The Popper Experimentation Protocol and convention[4] [33], so experiments presented here are available in the repository for this article[5]. We note that rather than including all the results in the paper, we instead include representative ones for each section and leave the rest on the paper repository. Experiments can be examined in more detail, or even re-executed, by visiting the `[source]` link next to each figure. That link points to a Jupyter notebook that shows the analysis and source code for that graph. The parent folder of the notebook (following the Popper's file organization convention) contains all the artifacts and automation scripts for the experiments. All results presented here can be replicated[6], as long as the reader has an account at Cloudlab (see repo for more details).

[4] http://falsifiable.us
[5] http://github.com/ivotron/quiho-popper
[6] **Note to reviewers**: based on the terminology described in the ACM Badging Policy [34] this complies with the *Results Replicable* category. In the event that our paper gets accepted, we plan to submit this work to the artifact review track too.

4.1 Effectiveness of IRUPs to Capture Resource Utilization Behavior

In this subsection we show how IRUPs can effectively describe the fine granularity resource utilization of an application with respect to a set of machines. Our methodology is:

1. Given an application A, discover relevant performance features using the *quiho* framework.
2. Do manual performance analysis of A to corroborate that discovered features are indeed the cause of performance differences.

Fig. **??** shows the profile of an execution of the `hpccg` miniapp [14]. This proxy (or miniapp) application [**???**] is a "conjugate gradient benchmark code for a 3D chimney domain on an arbitrary number of processors [that] generates a 27-point finite difference matrix with a user-prescribed sub-block size on each processor." [14].

Based on the profile, `stackmmap` and `cache` are the most important features. In order to corroborate if this matches with what the application does, we profiled this execution with `perf`. The stacked profile view shows that ~85% of the time the application is running the function `HPC_sparsemv()`. The code for this function is shown in Lst. 1. As the name implies, this snippet implements a sparse vector multiplication function of the form $y = Ax$ where A is a sparse matrix and the x and y vectors are dense. By looking at this code, we see that the innermost loop iterates an array, accumulating the sum of a multiplication. This type of code is a potential candidate for manifesting bottlenecks associated with CPU cache locality [35].

Listing 1 Source code for bottleneck function in HPCCG.

```
int HPC_sparsemv(HPC_Sparse_Matrix *A,
                 const double * const x,
                 double * const y)
{

  const int nrow = (const int) A->local_nrow;

  for (int i=0; i< nrow; i++) {
    double sum = 0.0;
    const double * const cur_vals =
     (const double * const) A->ptr_to_vals_in_row[i];

    const int    * const cur_inds =
     (const int    * const) A->ptr_to_inds_in_row[i];

    const int cur_nnz = (const int) A->nnz_in_row[i];

    for (int j=0; j< cur_nnz; j++)
        sum += cur_vals[j]*x[cur_inds[j]];
    y[i] = sum;
  }

  return(0);
}
```

Table 3: Table of performance counters for the HPCCG performance test.

counter	HPCCG	stackmmap	cache	bigheap
ins. per cycle	0.78	0.18	0.25	0.39
stalled cycles p/ins.	0.53	2.29	3.52	1.44
stalled cycles (frontend)	13.51%	41.09%	89.70%	18.95%
stalled cycles (backend)	41.19%	9.23%	0.80%	56.53%
branch misses	2.87%	9.24%	0.01%	0.69%
L1-dcache misses	5.62%	5.47%	52.91%	2.75%
LLC misses	1.03%	16.41%	51.88%	5.60%

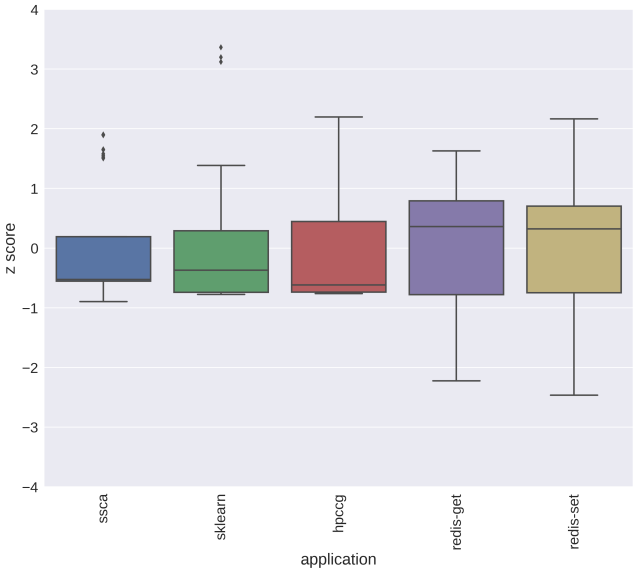


Figure 8: Variability of the five applications presented in this subsection. Y-axis has been normalized.

We analyze the performance of this benchmark further by obtaining performance counters for the application and comparing the counters with those from the top three features (Tbl. 3 shows the summary of hardware-level performance counters). Given that hardware performance counters are architecture-dependent, we can not make generalizations about given that we run an application on a multitude of machines. However, we can see that in the case of the `stackmmap` stressor, there are some similarities between the counters, specially the ones denoting stalled cycles (which significantly determine application performance [36,37]).

Next, we analyze IRUPs of other four applications[7]. These applications are Redis [38], Scikit-learn [29], and SSCA [39]. Due to space constraints we omit a similar detailed analysis as the one presented above for `hpccg`. However, resource utilization characteristics of these code bases is well known and we verify IRUPs using this high-level intuition. As a way to illustrate the variability originating from executing these applications on an heterogeneous set of machines, Fig. 8 shows boxplots of the these.

[7]For brevity, we omit other results that corroborate IRUPs can correctly identify resource utilization patterns. All these are available in the github repository associated to this article.

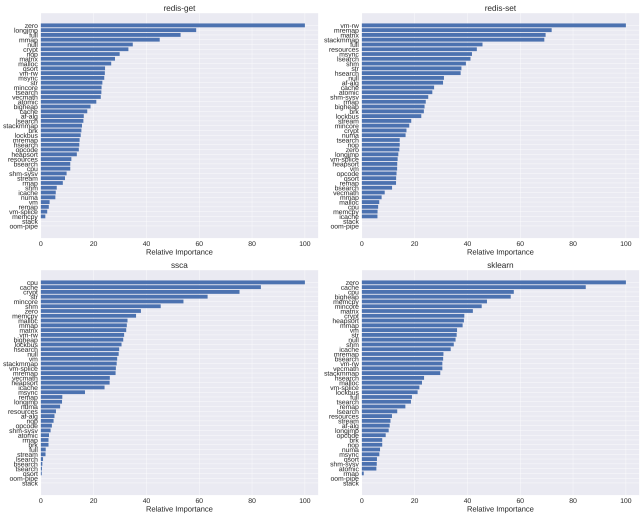


Figure 9: IRUPs for the four tests benchmarked in this section.

In Fig. 9 we show IRUPs for these four applications. The first two on the top correspond to two tests of Redis, a popular open-source in-memory key-value database. These two tests are `SET`, `GET` from the `redis-benchmark` command that test operations that store and retrieve key-value pairs into/from the DB, respectively. The resource utilization profiles suggest that `SET` and `GET` are memory intensive operations (first 3 stressors from each test, as shown in Tbl. 1), which is an obvious conclusion.

The next two IRUPs (below) correspond to performance tests for Scikit-learn and SSCA. In the case of Scikit-learn, this test runs a comparison of a several classifiers in on a synthetic dataset. Scikit-learn uses NumPy [40] internally, which is known to be memory-bound. The profile is aligned to this known behavior since the `zero` microbenchmark stresses access.

The last application is SSCA, a graph analysis benchmark comprising of a data generator and 4 kernels which operate on the graph. The benchmark is designed to have very little locality, which causes the application to generate a many cache misses. As shown in the profile, the first feature corresponds to the `cache` stressor, which as it was explained earlier, stresses the CPU cache by generating a non-locality workload.

The reader might have noticed that, regardless of how the performance of an application looks like, SRA will always produce a model with associated feature importances. Thus, one can pose the following question: is there any scenario where a IRUP is *not* correctly associated with what the application is doing? In other words, are IRUPs falsifiable? The answer is yes. A IRUP can be incorrectly representing an application's performance behavior if there is under- or over-fitting when generating the model. Fig. **??** shows the correlation matrix (left), as well as a IRUP obtained from selecting two random machines from the set of available ones. The application in question is Scikit-learn and, as the figures show, this IRUP is of little use since many features have 100% relevance. The correlation matrix shows why this is so: almost all the features are

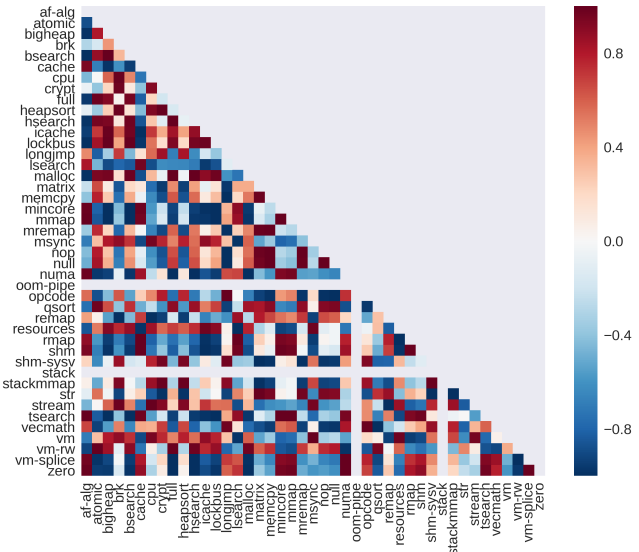


Figure 10: Correlation matrix obtained from only two randomly selected machines from Tbl. 2 (`issdm-41` and `r320` in this case).

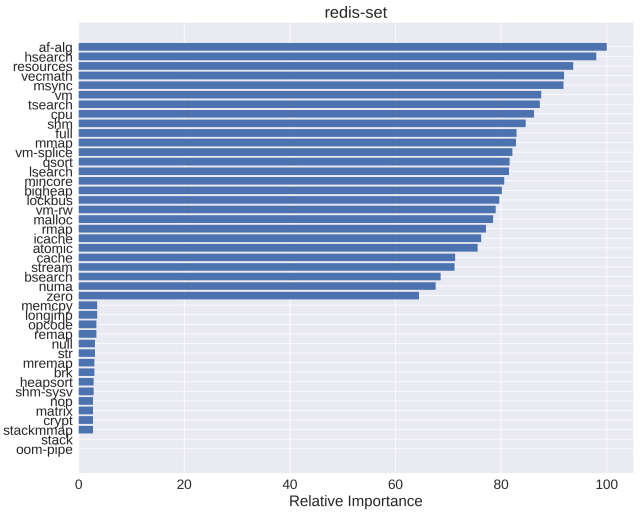


Figure 11: IRUP for `redis-set` obtained from only two randomly selected machines from Tbl. 2 (`issdm-41` and `r320` in this case).

highly correlated. As mentioned before, an open problem is that one of systematically reducing the number of required machines.

4.2 Simulating Regressions

In this section we test the effectiveness of *quiho* to detect performance simulations that are artificially induced. We induce regression by having a set of performance tests that take, as input, parameters that determine their performance behavior, thus simulating different "versions" of the same application. In total, we

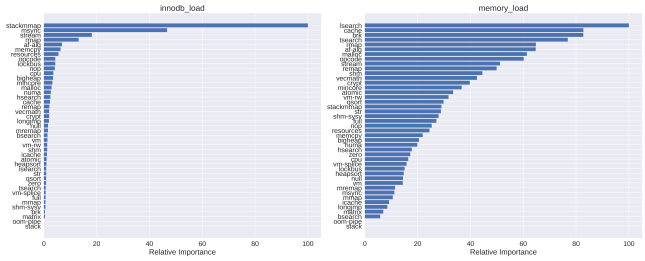


Figure 12: MariaDB with innodb and in-memory backends.

have 10 benchmarks for which we can induce several performance regressions, for a total of 20 performance regressions. For brevity, in this section we present results for two applications, MariaDB [41] and a modified version of the STREAM benchmark.

The MariaDB test is based on the `mysqlslap` utility for stressing the database engine. In our case we run the data loading test, which populates a database whose schema is specified by the user. We have a fixed set of parameters that load a 10GB database. One of the exposed parameters is the one that selects the backend (storage engine in MySQL terminology). While the workload and test parameters are the same, the code paths are distinct and thus present different performance characteristics. The two engines we use in this case are `innodb` and `memory`. Fig. 12 shows the profiles of MariaDB performance for these two engines.

The next test is a modified version of the STREAM benchmark [42], which we refer to as STREAM-NADDS (introduced in [43]). This version of STREAM introduces a `NADDS` pre-processor parameter that controls the number additions for the `Add` test of the STREAM benchmark. In terms of the code, when `NADDS` equals to 1 is equivalent to the "vanilla" STREAM benchmark. For any value greater than 1, the code adds a new term to the sum being executed. Intuitively, since the vanilla version of STREAM is memory bound, so adding more terms to the sum causes the CPU to do more work, eventually moving the bottleneck from memory to being cpu-bound; the higher the value of the `NADDS` parameter, the more cpu-bound the test gets. Fig. 13 shows this behavior.

Fig. 14 shows the IRUPs for the four tests. On the left, we see the resource utilization behavior of the "vanilla" version of STREAM (which corresponds to a value of 1 for the `NADDS` parameter). As expected, the associated features (stressors) to these are from the memory/VM category, in particular `vecmath`. As the number of terms for the sum increases, the test moves all the way to being CPU-bound (at `NADDS=30`), which can be seen by observing the `bsearch` and `hsearch` features going up in importance as the number of additions increases.

4.3 Real world Scenario

In this section we show that *quiho* works with regressions that can be found in real software projects. It is documented that the changes made to the `innodb` storage engine in version 10.3.2 improves the performance in MariaDB, with respect to previous version 5.5.58. If we take the development timeline and invert it, we can treat 5.5.58 as if it was a "new" revision that introduces a performance regression. To show that this can be captured with IRUPs, we use `mysqlslap`

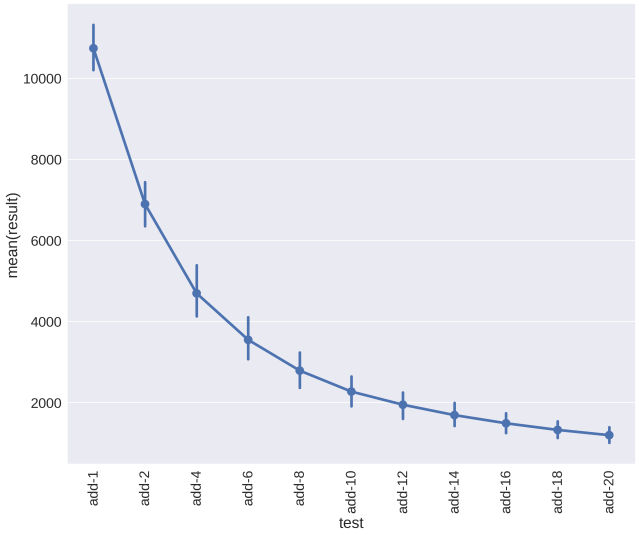


Figure 13: General behavior of the STREAM-NADDS performance test. The y-axis is the throughput of the test in MB/s. The x-axis corresponds to the number of terms in the sum expression of the `Add` STREAM subtest. The regular ("vanilla") STREAM add test is memory bound, so adding more terms to the `Add` subtest moves the performance from memory- to cpu-bound; the higher the value of the `NADDS` parameter, the more CPU-bound the test gets. This test was executed across all available machines (5 times). The bars denote standard deviation.

again and run the `load` test. Fig. 15 shows the corresponding IRUPs. We can observe that the IRUP generated by *quiho* can identify the difference in performance.

For brevity, we omit regressions found in other 4 applications (zlog, postgres, redis, and apache web server).

5 DISCUSSION

We briefly discuss some aspects related to *quiho*.

Application-Independent Performance Characterization. We used a subset of `stress-ng` microbenchmarks to quantify machine performance but the approach is not limited to this benchmarking toolkit. Ideally, we would like to extend the amount and type of stressors so that we have more coverage over the distinct subcomponents of a system. An open question is to systematically test whether the current set of stressors is sufficient to cover all subcomponents of a system, and at the same time reduce the number of microbenchmarks.

Quiho vs. other tools. The main advantage of *quiho* over other performance profiling tools is that it is automatic and 100% hands-off. As mentioned before, the main assumption being that there exist performance vectors (or they are obtained when the as part of the test) for a sufficiently varied set of machines. We see *quiho* as a complement, not a replacement of `perf`, to existing performance engineering practices: once a test has failed *quiho*'s checks, then proceed to make use of existing tools.

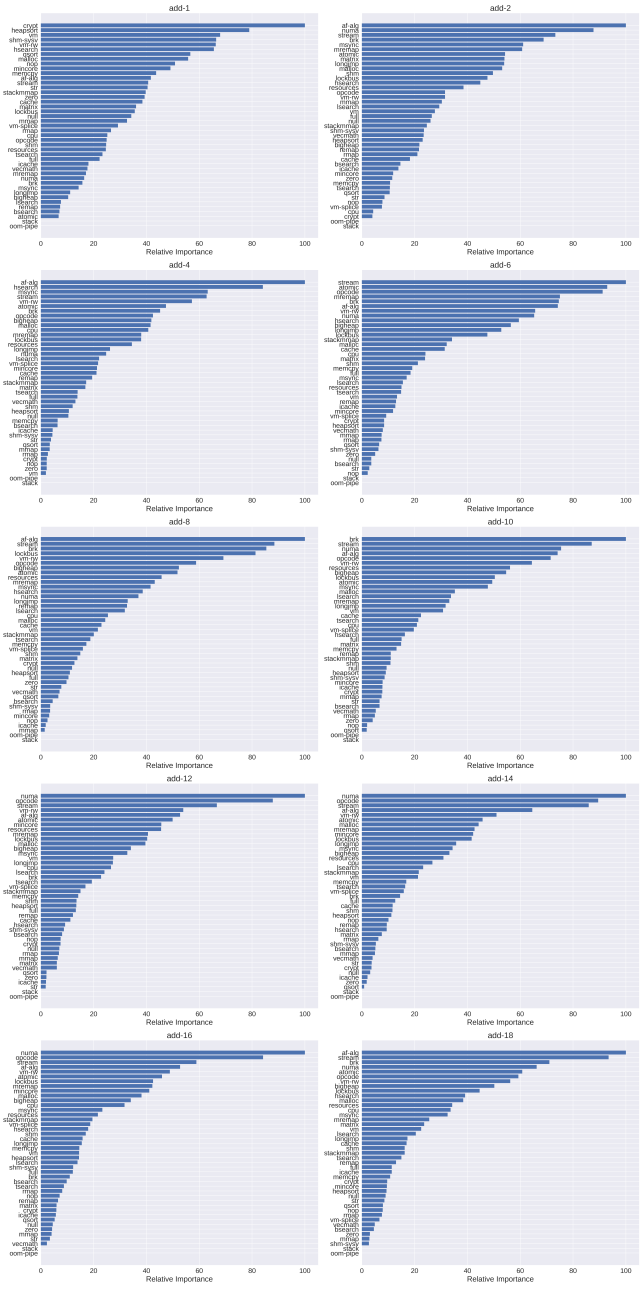


Figure 14: The IRUPs for modified version of STREAM. The parameter of `NADDS` increases by taking values of 1, 2, 4, ..., 20 and 30. We see that they capture the simulated regression which causes this application to be moving from being memory-bound to being cpu-bound.

IRUP Comparison. The algorithm specified in Section 3.3 is a straight-forward one. One could think of more sophisticated ways of doing IRUP comparison and finding equivalences. For example, using the categories from Tbl. 1, one could try to group stressors and determine coarse-grained bottlenecks, instead of fine grained

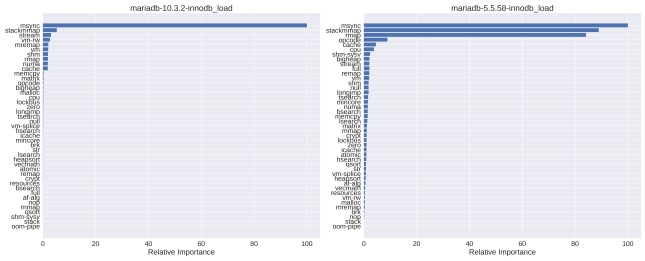


Figure 15: A regression that appears from going in the reversed timeline (from mariadb-10.0.3 to 5.5.38).

ones. Another alternative is to do reduce the number of features by applying PCA, exploratory factor analysis (EFA), or singular value decomposition (SVD), and compare profiles in terms of the mapped factors.

IRUP as a visualization tool. The reader might have noticed that IRUPs can be visually compared by the human eye (and are somewhat similar in this regard to FlameGraphs [44]). Adding a coloring scheme to IRUPs might make it easier to interpret the differences. For example, the categories in Tbl. 1 could be used to define a color palette (by assigning a color to each subset of the powerset of categories).

Reproducibility. Providing performance vectors alongside experimental results allows to preserve information about the performance characteristics of the underlying system that an experiment observed at the time it ran. This is a quantifiable snapshot that provides context and facilitates the interpretation of results. Ideally, this information could be used as input for emulators and virtual machines, in order to recreate original performance characteristics.

Reinforcement Learning. Over the course of its life, an application will be tested on many platforms. If we can have an ever-growing list of machines where an application is tested, the more we run an application in a scenario like this, the more rich the performance vector dataset (and associated application performance history). This can serve as the foundation to applycbecomes we learn about its properties. For example, if we had performance vectors captured as part of executions of the Phoronix benchmark suite (which has public data on openbenchmarking.org), we could leverage such a dataset to create rich performance models.

6 RELATED WORK

6.1 Automated Regression Testing

Automated regression testing can be broken down in the following three steps:

1. In the case of large software projects, decide which tests to execute [45]. This line of work is complementary to *quiho*.
2. Once a test executes, decide whether a regression has occurred [46]. This can be broken down in mainly two categories, as explained in [12]: pair-wise comparisons and model assisted. *quiho* fits in the latter category, the main difference being that, as opposed to existing solutions, *quiho* does not rely on having accurate prediction models since its goal is to describe resource utilization (obtain IRUPs).

3. If a regression is observed, automatically find the root cause or aid an analyst to find it [13,47,48]. While *quiho* does not find the root cause of regressions, it complements the information that an analyst has available to investigate further.

6.2 Decision Trees In Performance Engineering

In [49] the authors use decision trees to detect anomalies and predict performance SLO violations. They validate their approach using a TPC-W workload in a multi-tiered setting. In [12], the authors use performance counters to build a regression model aimed at filtering out irrelevant performance counters. In [50], the approach is similar but statistical process control techniques are employed instead.

In the case of *quiho*, the goal is to use decision trees as a way of obtaining feature performance, thus, as opposed to what it's proposed in [12], the leaves of the generated decision trees contain actual performance predictions instead of the name of performance counters

6.3 Correlation-based Analysis and Supervised Learning

Correlation-based and supervised learning approaches have been proposed in the context of software testing, mainly for detecting anomalies in application performance [47]. In the former, runtime performance metrics are correlated to application performance using a variety of distinct metrics. In supervised learning, the goal is the same (build prediction models) but using labeled datasets.

Decision trees are a form of supervised learning, however, given that *quiho* applies regression rather than classification techniques, it does not rely on labeled datasets. Lastly, *quiho* is not intended to be used as a way of detecting anomalies, although we have not analyzed its potential use in this scenario.

7 LIMITATIONS AND FUTURE WORK

The main limitation in *quiho* is the requirement of having to execute a test on more than one machine in order to obtain IRUPs. As mentioned, an open problem is to precisely quantify the minimum amount of required machines. On the other hand, we can avoid having to run `stress-ng` every time the application gets tested by integrating this into the infrastructure (e.g., system administrators can run `stress-ng` once a day or once a week and make this information for every machine available to users).

We are currently working in adapting this approach to profile distributed and multi-tiered applications. We also plan to analyze the viability of using *quiho* in multi-tenant configurations. Lastly, long-running (multi-stage) applications. e.g., a web-service or big-data application with multiple stages. In this case, we would define windows of time and we would apply *quiho* to each. The challenge: how do we automatically get the windows rightly placed.

In the era of cloud computing, even the most basic computer systems are complex multi-layered pieces of software, whose performance properties are difficult to comprehend. Having complete understanding of the performance behavior of an application, considering the parameter space (workloads, multi-tenancy, etc.) is challenging. One application of *quiho* we have in mind is to couple it with automated black-box (or even gray-box) testing frameworks to improve our understanding of complex systems.

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