Tracking Performance of the Graal Compiler on Public Benchmarks

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Disclaimer

Development Versions

Performance and other measurements used in this presentation are collected using **development** versions of the software involved. As such, they do **not** represent product performance.

Modified Benchmarks

Benchmarks used to collect the measurements were often modified to facilitate integration into the measurement infrastructure.

None of the benchmark results are standard benchmark scores.

Platform Specific

Measurements are **platform specific**. Platform information was omitted for brevity, contact us if you need more details.

... and we are only human

The data may be influenced by mistakes we are not aware of.

Outline

- Quick Platform Overview
- Handling Warm Up
- Detecting Changes
- 4 Handling More Runs
- Handling Different Metrics
- 6 Troublesome Performance Changes

About Graal Compiler

A just-in-time compiler for Java written in Java

- Functions as the last tier compiler
- Partial escape analysis and speculative optimizations

Part of a larger ecosystem surrounding the JVM

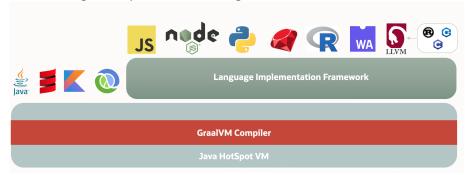
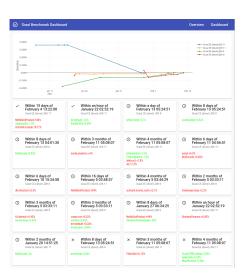
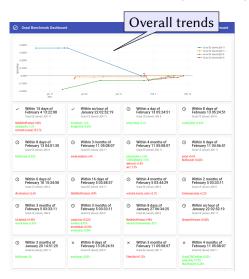
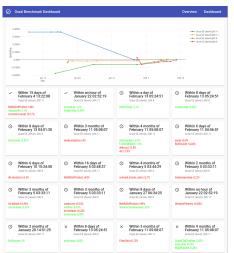


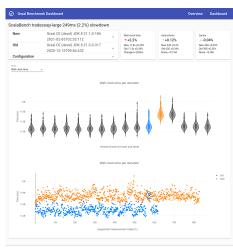
Image from https://www.graalvm.org

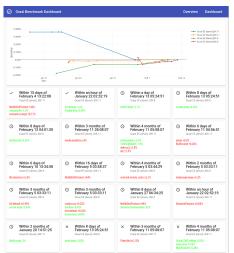


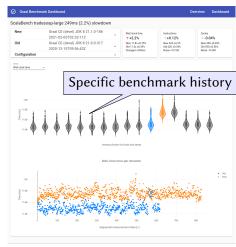


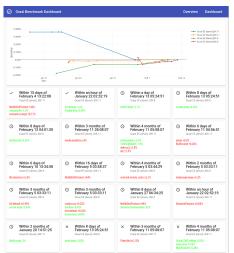


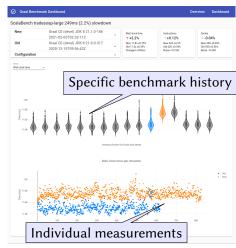












Dashboard Internals I

How to execute the measurements?

- Resource sharing and background load matter
- Repetition count is determined on the fly
- Need more than latest software version
- Faulty setup may remain invisible

What we do

- Use dedicated hardware infrastructure
 - Multiple servers with equivalent parameters
 - No other load than the benchmarks
- Proprietary software to coordinate measurements
- Iterative selection of versions to measure

Dashboard Internals II

When to fail the test?

- Noisy measurements
- Change can be legitimate
- Absolute performance requirements not given

What we do

- Compare performance of neighboring versions
- Focus on low false alarm rate
 - Iterative measurement planning
 - Observing multiple metrics together
- Alongside commit pipeline but not blocking

Dashboard Internals III

Platforms

- GraalVM CE and EE with OpenJDK and HotSpot JDK 8 and 11
- Only top level merge commits into master
- ... around 6000 versions last year

Benchmarks

- ScalaBench (includes DaCapo)
- SPECjvm2008 (non-compliant)
- Renaissance 0.10
- Plus internal microbenchmarks
- ... around 130 workloads in all

https://scalabench.org

https://spec.org/jvm2008

https://renaissance.dev

Hardware

... around 40 dedicated servers

Summary Performance History 100.00% GraalVM CE JDK 8 GraalVM EE JDK 8 Speed relative to latest version 99.00% GraalVM EE JDK 11 98.00% 97.00% GraalVM CE JDK 11 96.00% 95.00% Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021



Summary Performance History



Plot Info

Input Benchmark execution times collected across one year of compiler versions and all benchmarks.

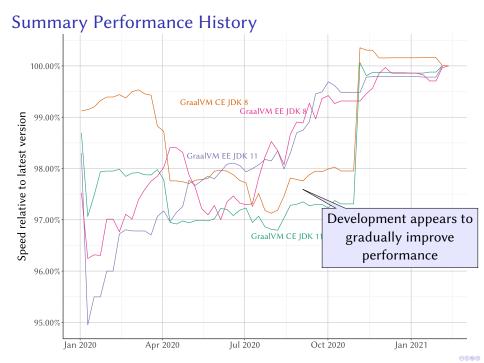
Computation Express all execution times as speed up or slow down relative to the execution times of the most recent compiler version on the same benchmark.

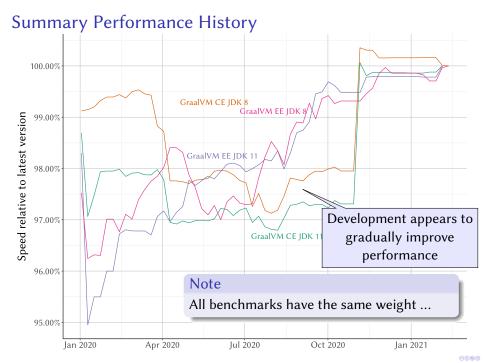
X axis Commit time of the compiler version measured.

Y axis Geometric mean of relative speed up or slow down.



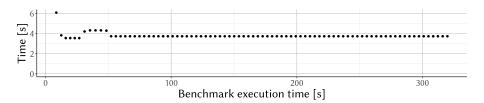
Summary Performance History 100.00% GraalVM CE JDK 8 GraalVM EE JDK 8 Speed relative to latest version 99.00% GraalVM EE JDK 11 98.00% 97.00% GraalVM CE JDK 11 96.00% 95.00% Jan 2020 Apr 2020 Jul 2020 Oct 2020 Jan 2021





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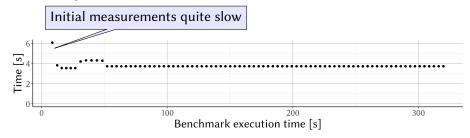


Plot Info

Input Benchmark repetition times for an arbitrarily selected benchmark and platform.

X axis Time from start of the benchmark execution.

Y axis Time of single benchmark repetition.

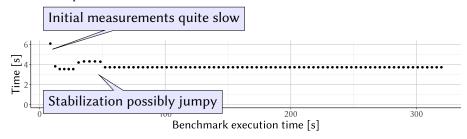


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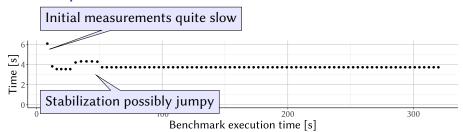


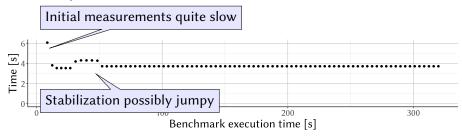
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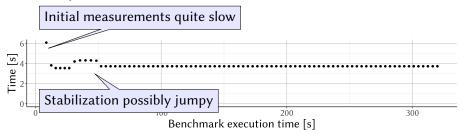
Y axis Time of single benchmark repetition.





Some reasons behind warm up eliminated in our setup

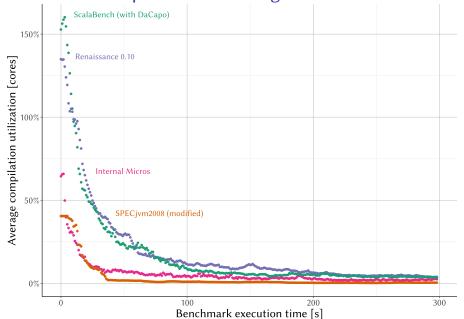
- Most power management features disabled
- Initial and maximum heap size equal and fixed
- Most (but not all) benchmarks stable after first repetition



Some reasons behind warm up eliminated in our setup

- Most power management features disabled
- Initial and maximum heap size equal and fixed
- Most (but not all) benchmarks stable after first repetition

But the elephant in the room is just-in-time compilation



Average compilation utilization [cores]

How Much Compilation On Average?



Plot Info

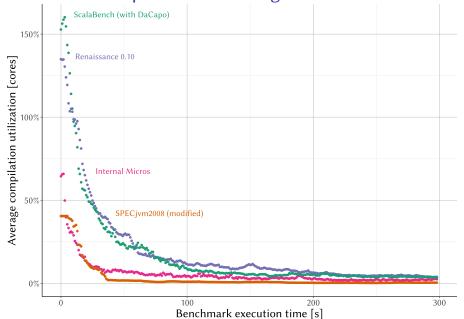
Input Cumulative compiler thread execution times collected during benchmark execution across all benchmarks.

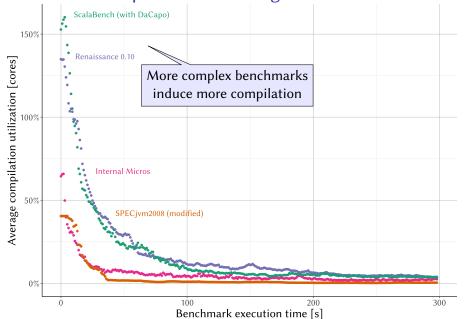
Computation Average processor utilization for compiler threads relative to single core across benchmark suites.

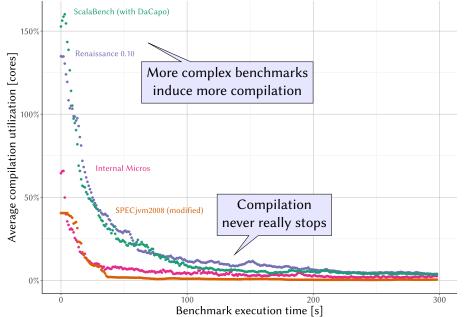
X axis Time from start of the benchmark execution.

Y axis Processor utilization for compiler threads.

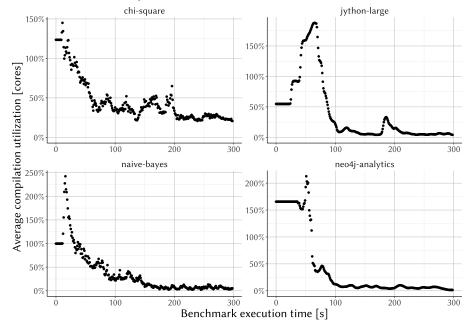








How Much Compilation Per Benchmark?



Detecting Warm Up

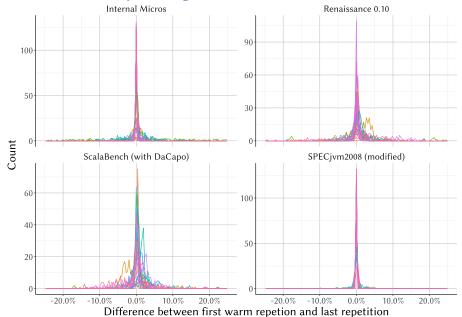
What do we want from warm up?

- Make sure we measure code produced by the last tier compiler
- Move past the most egregious performance changes
- Do not waste too much time on warm up

What we do

- Monitor activity of background compiler threads
- Establish thresholds across 60 s sliding window
- ullet The first window with activity within 10 % of minimum is warm
 - ► The algorithm is not online
 - Used with runs of 300 s to 600 s
 - Will always identify some repetitions as warm

Do We Warm Up Enough?



Do We Warm Up Enough?

Internal Micros Renaissance 0.10

Plot Info

Input Benchmark repetition times and compiler thread execution times across all benchmarks from many runs.

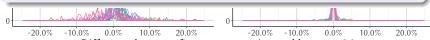
Computation Relative difference between the first repetition time considered warm and the last repetition time (which is the most warm we have).

X axis Relative difference in the repetition times.

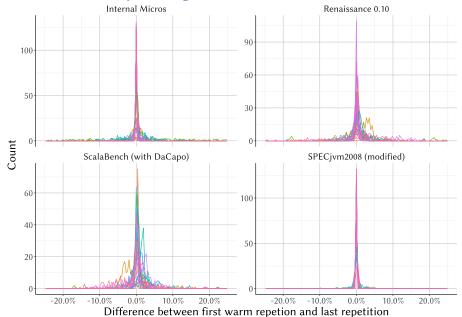
Y axis Count of runs with that difference.

Color Distinguishes benchmarks.

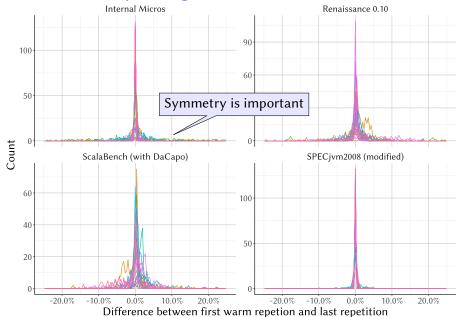
Simply How much will performance change after warm up?



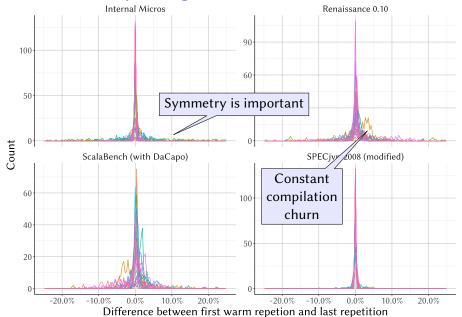
Do We Warm Up Enough?



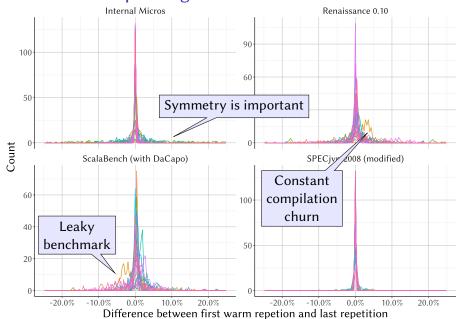
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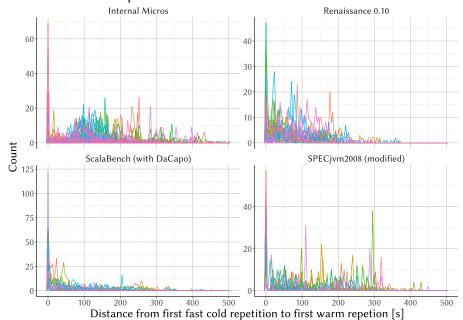
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Do We Warm Up Enough?



Do We Warm Up Too Much?



Input Benchmark repetition times and compiler thread execution times across all benchmarks from many runs.

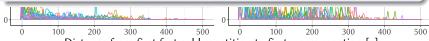
Computation How far before the first repetition considered warm did we see a repetition at least as short.

X axis Distance between the first fast cold repetition and the first warm repetition.

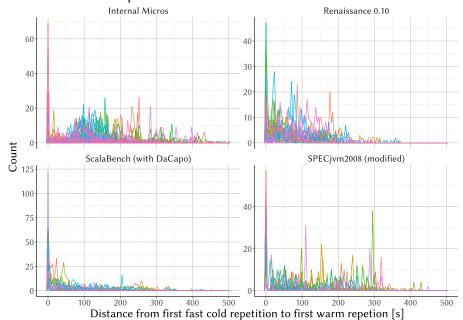
Y axis Count of runs with that distance.

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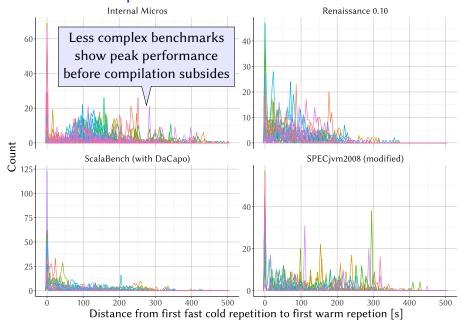
Simply How long before warm up are benchmarks already fast?

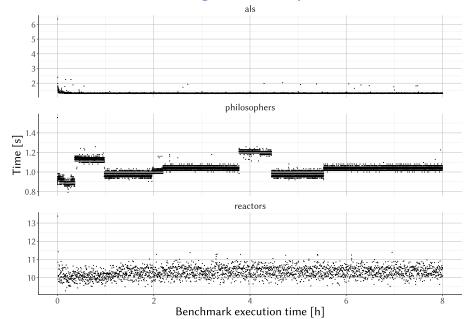


Do We Warm Up Too Much?



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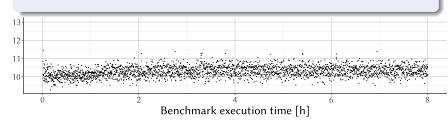


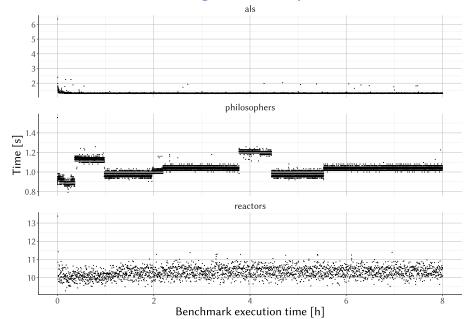


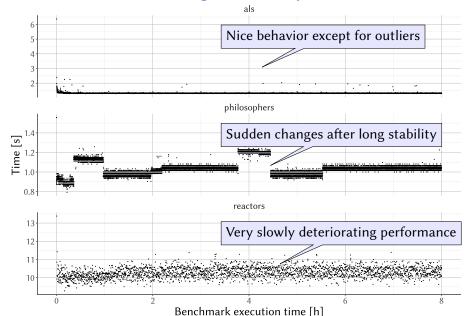
Input Benchmark repetition times for an arbitrarily selected benchmarks and platforms.

X axis Time from start of the benchmark execution.

Y axis Time of single benchmark repetition.







Take Away So Far ...

Some warm up properties complicate detection from time measurements

- Performance can change at any time into benchmark execution
- Performance changes possibly rather sudden
- Performance changes in both directions

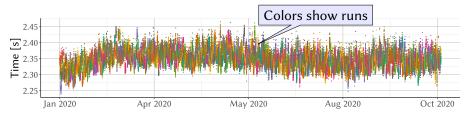
Reaching measurement stability not really the goal here

- Looking (only) at repetition times possibly wrong
- Warm up detection surprisingly important
 - Too much warmup is prohibitive resource hog
 - Too little warmup produces useless measurements

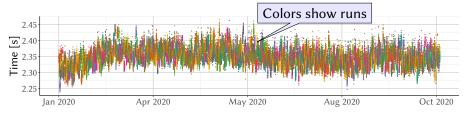
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Detecting Changes



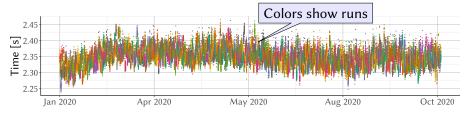
Detecting Changes



A time series change point detection problem with a few twists

- We have more correlated time series rather than just one
- We can add more data points to any version if required
- Data points are in fact hierarchical sets from runs
- We are more interested in changes near series end
- Almost no assumptions about data distribution

Detecting Changes



A time series change point detection problem with a few twists

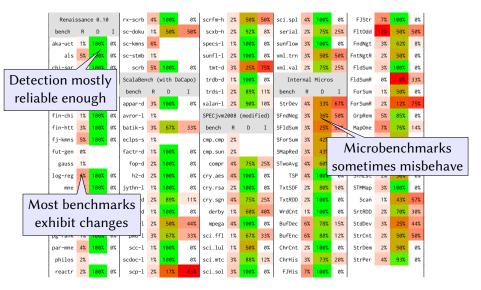
- We have more correlated time series rather than just one
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- Almost no assumptions about data distribution

We use bootstrap confidence intervals of mean differences









Manual Change Classification

We examined all detected performance changes in ad hoc version intervals

- Benchmarks not necessarily represented equally
- More measurements added when not sure

We have no classification information about false negatives

Likely impacts especially small changes relative to variance

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Plot Info

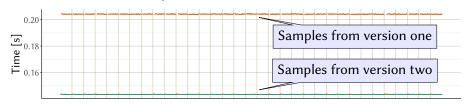
Input Benchmark repetition times for arbitrarily selected pairs of platform versions with suspected change.

X axis Benchmark repetitions and runs ordered sequentially.

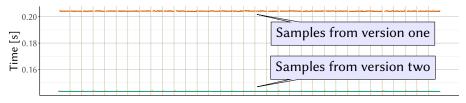
Y axis Time of single benchmark repetition.

Color Distinguishes versions.

Classification Example: Trivial



Classification Example: Trivial

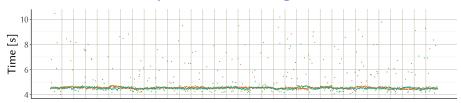


An obvious difference that is trivial to classify

- Very low variance both within run and between runs
- Difference of large relative magnitude

If all data looked like this we would have little to talk about ...

Classification Example: Small Change



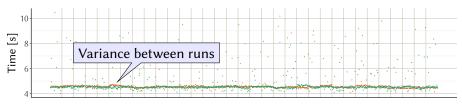
Classification Example: Small Change



Computed difference in average repetition time around $0.6\,\%$

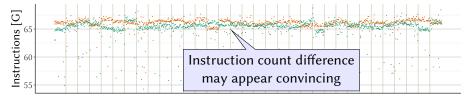
- Variance between runs large relative to the computed difference
- Outliers large relative to the computed difference
- Maybe we need more data?

Classification Example: Small Change

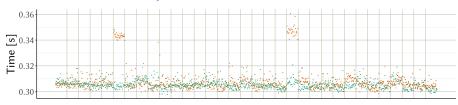


Computed difference in average repetition time around $0.6\,\%$

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Classification Example: Outlier Definition Issues



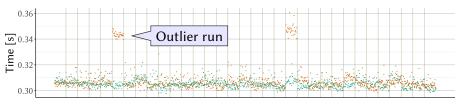
Classification Example: Outlier Definition Issues



Computed difference in average repetition time around 0.9 %

- The computed difference very much depends on outlier filtering
- Are we sure we have enough data?

Classification Example: Outlier Definition Issues



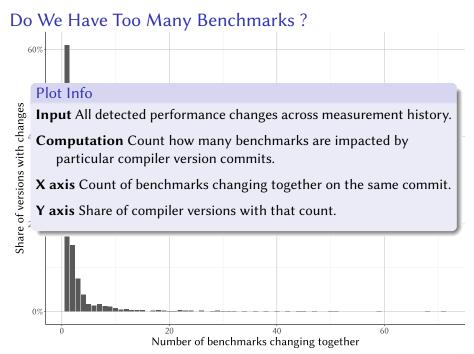
Computed difference in average repetition time around 0.9 %

- The computed difference very much depends on outlier filtering
- Are we sure we have enough data?

Assume 10 % change in outlier runs and 10 % chance of such runs

- \bullet This would result in an average repetition time change of 0.9 %
- There is around 35 % chance of getting 10 fine runs
- Obviously the example can be stretched in various directions

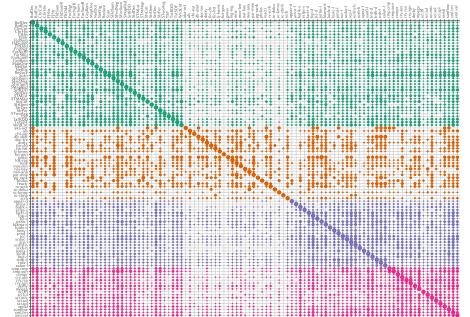
Do We Have Too Many Benchmarks? 60% Share of versions with changes 0% 60 Number of benchmarks changing together



Do We Have Too Many Benchmarks? 60% Share of versions with changes 0% 60 Number of benchmarks changing together

Do We Have Too Many Benchmarks? 60% Share of versions with changes Majority of changes limited to single benchmark 0% 60 Number of benchmarks changing together

Do Benchmarks Change Together?



Do Benchmarks Change Together?

Plot Info

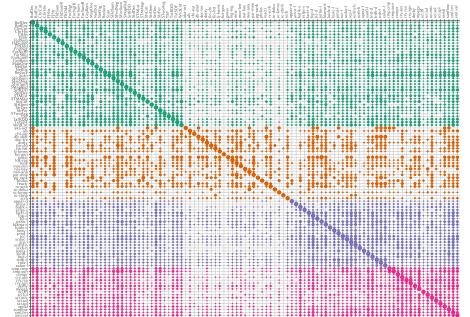
Input All detected performance changes across measurement history.

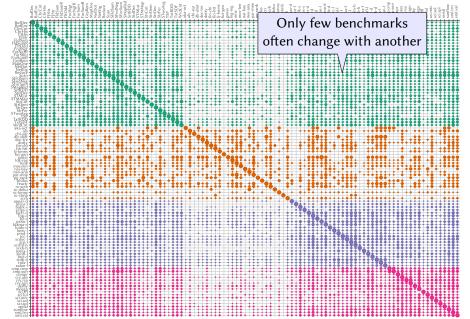
Computation Count how many times a given pair of benchmarks changed performance on the same commit.

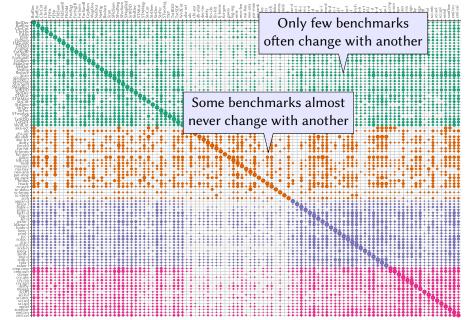
X and Y axes Individual benchmarks.

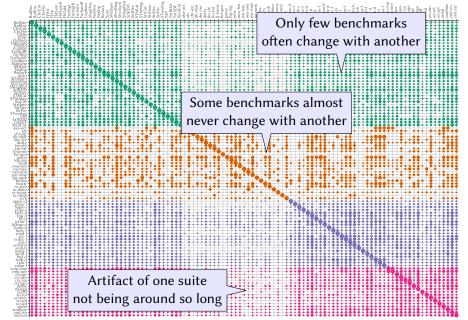
Size How often the two benchmarks changed performance together.

Color Distinguishes benchmark suites.









Take Away So Far ...

We probably do not have too many (or even enough) benchmarks

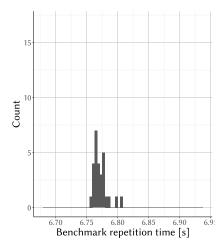
- Overlap in performance changes relatively rare
- Not really clear how to define coverage!

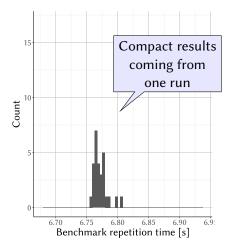
Change detection reliability per se not an issue

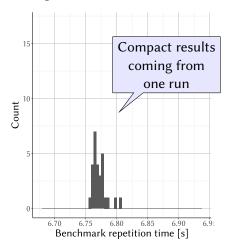
- Change definition issues beyond math
- Requires reasonable measurement procedure
- Some benchmarks may require special attention

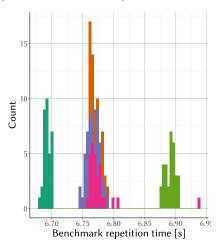
Outline

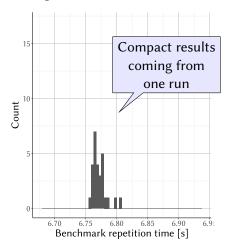
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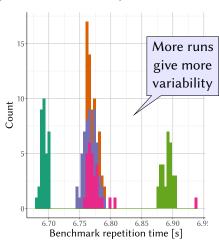






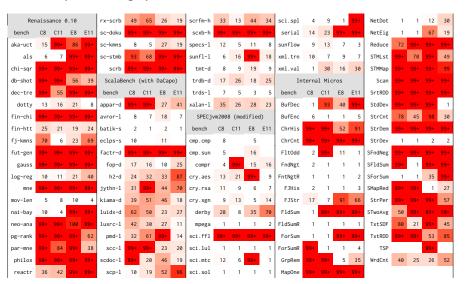






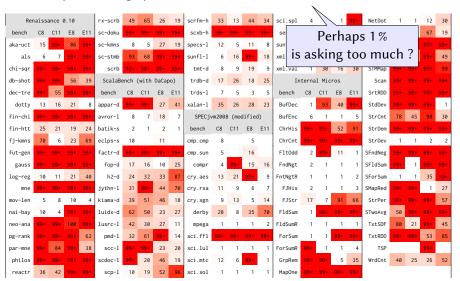
How Many Runs Needed ...

... to compute average performance with at most 1% error in 99% of cases?



How Many Runs Needed ...

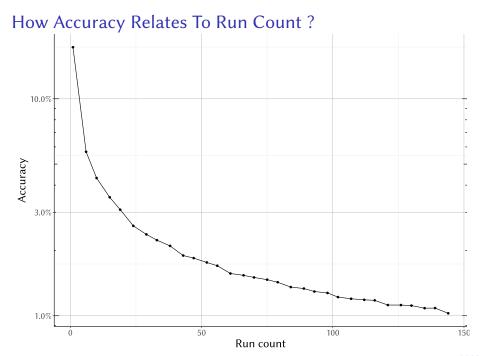
... to compute average performance with at most 1% error in 99% of cases?



How Many Runs Needed ...

 \dots to compute average performance with at most 5 % error in 99 % of cases ?

															i									
Renaissance 0.10				rx-scrb	2	2	- 1	- 1	scrfm-h	2	1	1	1	sci.spl	1	1	1	99+	NetDot	1	1	12	30	
bench	C8	C11	E8	E11	sc-doku	67	18	99+	99+	scxb-h	8	6	25	99+	serial	2	8	3	13	NetEig	1	1	2	4
aka-uct	1	4	3	4	sc-kmns	2	1	1	1	specs-1	1	1	3	1	sunflow	1	1	1	1	Reduce	14	11	8	15
als	1	2	7	14	sc-stmb	2	2	4	6	sunfl-1	1	1	2	1	xml.trn	1	1	1	1	STMLst	6	21	8	1
chi-sqr	23	22	36	26	scrb	20	10	25	42	tmt-d	1	1	2	1	xml.val	1	3	1	3	STMMap	18	99+	24	4
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dotty	1	1	1	1	appar-d	99+	99+	3	2	xalan-l	1	1	4	1	BufDec	1	5	8	2	StdDev	45	99+	99+	1
fin-chi	5	21	26	6	avror-1	2	1	1	1	SPECjvr	n2008	(mod	difie	d)	BufEnc	1	1	1	5	StrCnt	3	9	7	1
fin-htt	1	1	1	1	batik-s	1	1	1	1	bench	C8	C11	E8	E11	ChrHis	4	10	4	3	StrDem	99+	26	99+	51
fj-kmns	1	3	2	1	eclps-s	2		2		cmp.cmp	1		1		ChrCnt	11	7	3	5	StrDev	1	1	2	2
fut-gen	6	6	3	8	factr-d	6	7	38	59	cmp.sun	1		4		F1t0dd	1	45	6	1	SFndNeg	11	9	18	12
gauss	25	13	99+	99+	fop-d	1	3	1	1	compr	1	3	1	2	FndNgt	2	1	1	1	SF1dSum	34	1	99+	99+
log-reg	6	8	2	2	h2-d	1	2	1	2	cry.aes	1	1	11	4	FntNgtR	1	1	1	1	SForSum	1	1	21	44
mne	7	13	29	12	jythn-l	3	9	1	3	cry.rsa	1	1	1	1	FJHis	1	1	1	3	SMapRed	67	57	1	1
mov-len	1	1	1	1	kiama-d	1	6	2	1	cry.sgn	1	1	1	14	FJStr	1	5	3	2	StrPer	13	99+	99+	1
nai-bay	1	1	60	100	luidx-d	1	1	1	2	derby	2	1	1	2	F1dSum	1	3	73	70	STwoAvg	25	40	99+	99+
neo-ana	41	8	10	14	lusrc-l	1	1	3	1	mpega	1	1	1	1	F1dSumR	1	1	1	1	TxtSDF	3	1	8	10
pg-rank	7	5	5	2	pmd-1	1	2	13	1	sci.ffl	21	14	33	7	ForSum	1	1	81	80	TxtRDD	11	10	1	8
par-mne	8	5	99+	1	scc-1	5	11	1	1	sci.lul	1	1	1	1	ForSumR	10	1	1	4	TSP			72	
philos	10	99+	14	38	scdoc-1	4	1	1	1	sci.mtc	1	1	12	1	GrpRem	7	7	4	9	WrdCnt	1	5	2	3
reactr	2	1	23	10	scp-l	1	1	1	3	sci.sol	1	1	1	1	Map0ne	14	16	99+	99+					







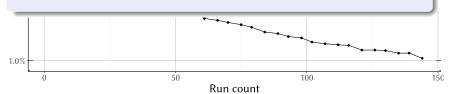
Input Benchmark repetition times for an arbitrarily selected benchmark and platform.

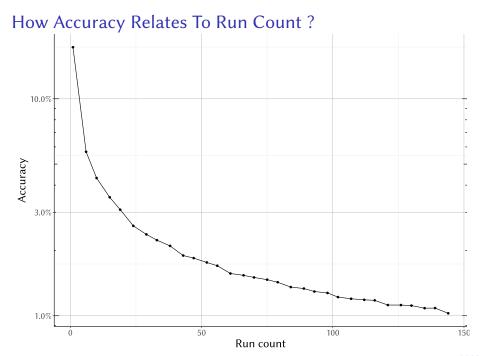
Computation Size of 99 % confidence interval for the mean relative to the mean

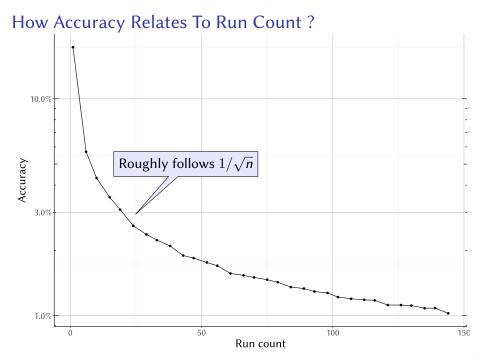
X axis How many times the benchmark was run.

Y axis Confidence interval width.

Accuracy







Take Away So Far ...

Running benchmarks only once may not be enough

- Non deterministic compilation visible especially with microbenchmarks
- But the presented tables also include simple cases of high variance

Aiming for excessive accuracy backfires quickly

Reasonable accuracy is a function of more than just the benchmark

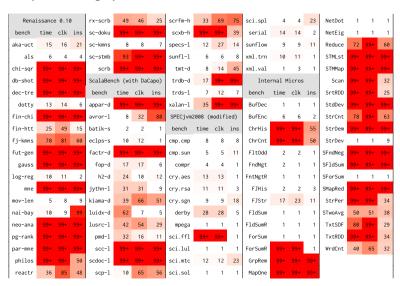
- Tooling should consider benchmarks together with platforms
- Not yet sure how often relevant parameters tend to change

Outline

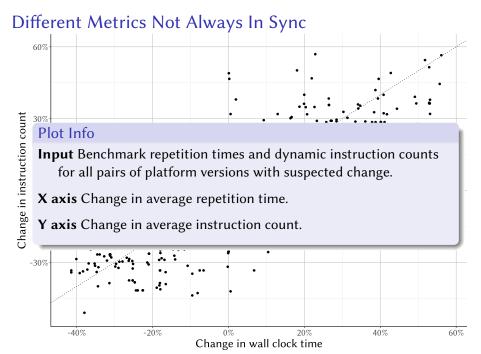
- Quick Platform Overview
- Handling Warm Up
- Detecting Changes
- 4 Handling More Runs
- 5 Handling Different Metrics
- 6 Troublesome Performance Changes

Runs Needed When Different Metrics Used ...

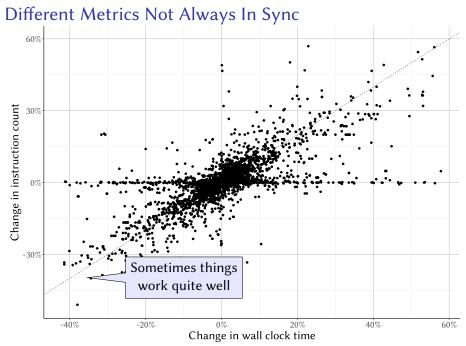
... to compute average performance with at most 1% error in 99% of cases.

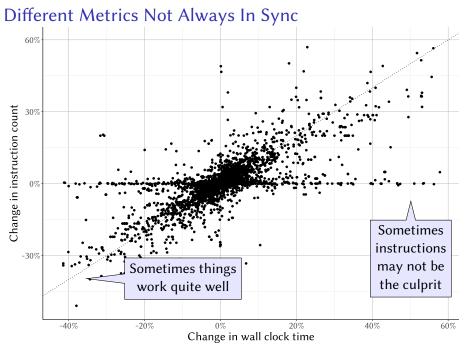


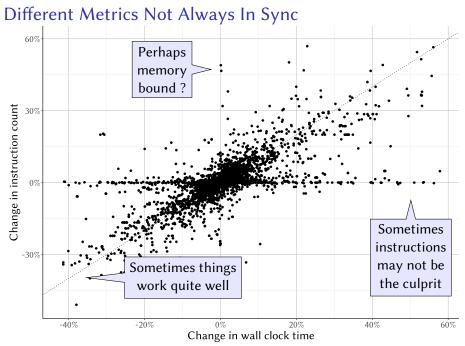
Different Metrics Not Always In Sync 60% Change in instruction count 30% 0% -30% -20% 20% 40% 60% -40% 0% Change in wall clock time



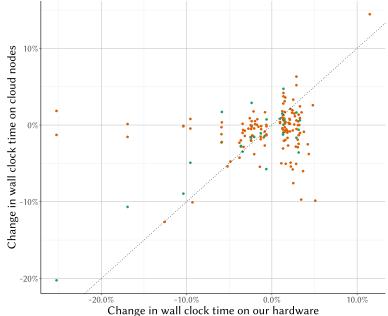
Different Metrics Not Always In Sync 60% Change in instruction count 30% 0% -30% -20% 20% 40% 60% -40% 0% Change in wall clock time







Wall Clock Time Changes Not Always Portable



Using Cores

ΑII

Wall Clock Time Changes Not Always Portable

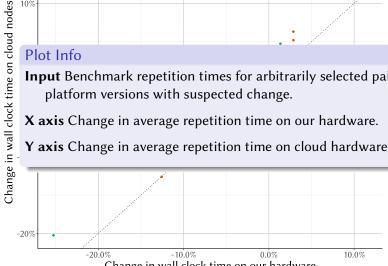


Plot Info

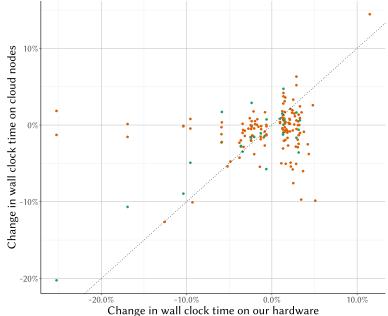
Input Benchmark repetition times for arbitrarily selected pairs of platform versions with suspected change.

X axis Change in average repetition time on our hardware.

Y axis Change in average repetition time on cloud hardware.



Wall Clock Time Changes Not Always Portable

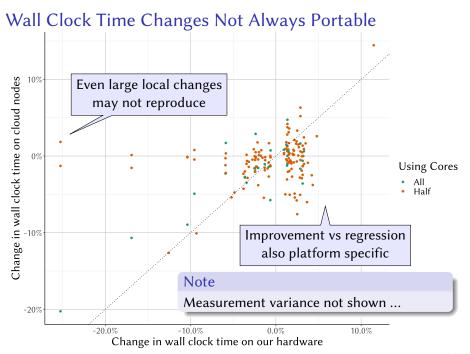


Using Cores

ΑII

Wall Clock Time Changes Not Always Portable 10% Change in wall clock time on cloud nodes Even large local changes may not reproduce 0% **Using Cores** All Half -10% -20% -10.0% 10.0% -20.0% 0.0% Change in wall clock time on our hardware

Wall Clock Time Changes Not Always Portable 10% Change in wall clock time on cloud nodes Even large local changes may not reproduce 0% **Using Cores** Half -10% Improvement vs regression also platform specific -20% -20.0% -10.0% 0.0% 10.0% Change in wall clock time on our hardware



Take Away So Far ...

Looking at more execution metrics can improve accuracy

- Can help developers trust detected time changes
- Or even direct investigation of change causes

Not really clear how to combine multiple (possibly) conflicting results

- Some metrics changing and some not
- Some platforms improving and some regressing
- Some benchmarks improving and some regressing

Outline

- Quick Platform Overview
- Handling Warm Up
- 3 Detecting Changes
- 4 Handling More Runs
- 6 Handling Different Metrics
- **6** Troublesome Performance Changes

Regression Example: Processor Scheduling I

Code

A microbenchmark that locates the first negative array item.

```
def run () {
    for (i <- 0 until REPEATS) {
        blackhole += findNegative (numbers)
    }
}
def findNegative (numbers: Array[Int]): Option[Int] = {
    numbers.find(_ < 0)
}</pre>
```

What the measurements said

Clear repetition time change between roughly 230 ms and roughly 170 ms No change in other observed counters like instruction count Observed multiple times in versions across several days Commit changes often clearly unrelated

Regression Example: Processor Scheduling II

Assembly

Compilation results in reasonably compact assembly code.

```
0x00007f115c894c00: cmp
                           %r13d.%edi
                                                     :loop iteration count test
0x00007f115c894c03: jbe
                           0x00007f115c89561c
0x00007f115c894c09: mov
                           0x10(%rdx,%r13,4),%r10d
                                                     :fetch arrav item
0x00007f115c894c0e: test
                           %r10d,%r10d
                                                     ;negative test
0x00007f115c894c11: il
                           0x00007f115c894c2a
                                                     ;found negative
0x00007f115c894c17: test
                           %eax,0x1942d3e9(%rip)
                                                     ;safepoint poll
0x00007f115c894c1d: inc
                           %r13d
                                                     ;loop iteration count test (again)
0x00007f115c894c20: cmp
                           %r13d,%edi
                           0x00007f115c894c00
0x00007f115c894c23: ig
```

Analysis

Inner loop executes at IPC 6 when fast or IPC 4.5 when slow Performance difference inflated from mere 0.5 cycle per iteration Instruction scheduler counters report different μ ops port use as the reason Actual scheduler choice only indirectly influenced by code

Regression Example: Inlining Heuristic I

Code

A microbenchmark that filters odd array items.

```
def run () {
    for (i <- 0 until REPEATS) {
        blackhole += filterOdd (numbers).length
    }
}
def filterOdd (numbers: ArrayBuffer[Int]): ArrayBuffer[Int] = {
    numbers.filter (_ % 2 == 1)
}</pre>
```

What the measurements said

Times always stable within each run
Repetition time of a run flipping between 5 s and 5.6 s
Rarely observed runs with repetition times of roughly 3.4 s
Share of runs with each time sometimes changes between versions

Regression Example: Inlining Heuristic II

Analysis

Fast and slow runs differed in what code gets inlined Inlining heuristic (also) relies on low level graph size of the callee

- If callee previously compiled, a cached value was used
- If callee not yet compiled, an estimate was made

Caller and callee invocation counters necessarily similar Hence compilation jobs launched close together in time That increases the likelihood of the inliner flipping

Take Away So Far ...

Reasons for performance change not always directly connected to committed code

- Especially microbenchmarks may exhibit fragile performance
- Responsibility for addressing changes therefore not clear

Hard to tell whether performance regression should be addressed

- Especially with benchmarks that do not represent application performance
- Effort needed to investigate reasons is not very predictable

Broader Context

Multiple testing scenarios employed

- Quick benchmark run every commit
- Thorough benchmark run every week
- Interactive performance change detection (us)

Every commit

- Fast but low detection ability
- Useful to catch major bugs fast

Every week

- Resource intensive but high detection ability
- Useful to keep track of overall development
- Significant changes investigated manually

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Contribute to Renaissance ...

... and we will start benchmarking your code too :-)