B4M36ESW: Efficient software

Lecture 3: Benchmarking

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Outline

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Benchmark

Wikipedia defines benchmark as:

1. the **act of running** a computer program, a set of programs, or other operations, in order to **assess the relative performance** of an **object**, normally by running a number of standard tests and trials against it.
2. a **benchmarking program** itself (i.e. “XY is a free benchmark that tests your computer’s performance.”)

Object examples:

- Hardware
- Compiler
- Algorithm
- ...

Types of benchmarks:

- Micro-benchmarks (synthetic)
- Application benchmarks

Types of benchmark

In most cases, we are interested in whether some change (in HW, compiler, algorithm, ...) results in **speed-up** or **slow-down**.

1. Micro-benchmark
   - Evaluates a little part of an application (e.g., one of many functions)
   - It is easy to determine source of speed-up/slow down
   - Typically, improvements in micro-benchmark do not imply improvements in application performance
2. Application benchmarks
   - Evaluates performance of the whole application
   - Performance is influenced by many real-world factors
   - For complex applications, it might difficult to determine the source of speed-up/slow-down

How to measure software performance?

- What to measure?
  - Execution time
    (important – separate part of this lecture)
  - Memory consumption
  - Energy
- How to measure?
  - Not as easy as it sounds
  - See the rest of the lecture

TL;DR: Use and understand statistics.

Outline

Measuring energy

- Connect power meter to your computer/board
- Use hardware-provided interfaces for power/energy measurement/control
  - These are more and more common these days

Example

Intel RAPL (Running Average Power Limit)

- Allows to monitor and/or limit power consumption of individual components
- Package domain, memory domain (DRAM)
- Accessible via Model-specific registers (MSRs)
- See Intel Software Developer's Manual: System Programming Guide

Outline

Measuring memory consumption

- Under modern OSes, measuring memory usage is surprisingly complex
- How programs consume memory?
  1. Program memory
     - Code, static data, heap, stack
     - Stack is allocated for each thread
     - Easy: This is what various profilers report
  2. Operating system kernel memory
     - Allocated by the OS kernel on behalf of the program
     - network buffers, disk and file system caches, system objects (timers, semaphores, ...)
     - Sometimes, it is not possible to account this memory to an individual process – e.g. network receive buffers.
  3. Shared libraries
     - How to account for memory consumed by libraries shared by multiple programs?

Basics of Linux Memory Statistics

- Tools like `top` or `htop` report several memory statistics

VIRT	Total amount of virtual memory reserved by the process. Not all this memory needs to be backed by physical memory. It does not include kernel memory.
RES	Currently resident (physical) memory (does not include swapped memory)
SHR	Memory shared with other processes (data, .so)

  - Example: Allocate 16 GiB of virtual memory without allocating physical memory immediately.

```
mmap(NULL, 1ULL << 34, PROT_READ | PROT_WRITE,
     MAP_ANONYMOUS | MAP_SHARED, -1, 0);
```

Outline

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Timestamping

1. Via system calls
   - Linux: `gettimeofday`, `clock_gettime(CLOCK_MONOTONIC)`
   - Resolution: depends on available hardware (down to 1 ns), earlier it was a system tick period (1–10 ms)
   - Overhead: hundreds of CPU cycles (but see next slide)
2. By using hardware directly (e.g. timestamp counter register)
   - TSC register on x86: resolution 1 clock cycle, overhead few (≈ 8) clock cycles
   - Similar registers on other architectures
   - Cons: **Can** be subject to CPU frequency scaling, TSC counters on different CPU cores/sockets **may not** be synchronized (can result in negative duration if OS migrates the thread)

```
static inline uint64_t rdtsc() {
    uint64_t ret;
    asm volatile ( "rdtsc" : "=A" (ret) );
    return ret;
}
```

3. Combine both: Virtual syscall

Virtual syscall for fast timestamping

- Reading TSC is fast, but HW/frequency/socket dependent
  - Problematic when two timestamps need to be subtracted
  - OS kernel knows everything about HW/frequency/socket but calling the kernel has its overhead
- Idea: OS kernel publishes enough information for user space to reliably convert TSC values to wall-clock times without calling the kernel
  - `time_ns = rdtsc() * tsc_scale + tsc_offset`
- Virtual Dynamic Shared Object – VDSO
  - Kernel memory mapped to a process address space
  - Content looks like a shared library (hence the name)
  - Application can call ordinary functions from there
  - `cat /proc/$$/maps|grep vdso`
  - `gettimeofday()`, clock_gettime() are functions implemented in VDSO (they do not call the kernel)
  - `tsc_scale` and `tsc_offset` are variables stored in VDSO and updated by the kernel when needed

VDSO inspection

```
$ gdb myprog
(gdb) run
(gdb) info proc
process 14594
(gdb) !grep vdso /proc/14594/maps
7ffff7fd1000-7ffff7fd2000 r-xp 00000000 00:00 0 [vdso]
(gdb) dump memory /tmp/vdso.so 0x7ffff7fd1000 0x7ffff7fd2000
$ objdump --disassemble /tmp/vdso.so
0000000000000700 <__vdso_gettimeofday@@LINUX_2.6-0x1c0>:
 700:     55                             push   %rbp
 701:     48 63 f6                       movslq %esi,%rsi
 704:     49 89 d2                       mov    %rdx,%r10
 707:     48 c1 e6 04                    shl    $0x4,%rsi
 ...
 741:     0f 01 f9                       rdtscp
```

Outline

Measuring execution time

- Execution time exhibits variations
- Influenced by many factors:
  - Hardware, input data, compiler, memory layout, measuring overhead, rest of the system, network load, … you name it
  - Same factors can be controlled, others cannot
- Repeatability of measurements
- How to design benchmark experiments properly?
- How to measure *speedup*?

Example

```
$ make
$ for i in $(seq 10); do \
    ./find_ellipse ../images/table.jpg 1000 no-gui|grep processImage; \
  done
processImage took 880ms
processImage took 870ms
processImage took 921ms
processImage took 876ms
processImage took 876ms
processImage took 874ms
processImage took 867ms
processImage took 875ms
processImage took 872ms
processImage took 872ms
```

Example - cont.

```
$ ./find_ellipse ../images/table.jpg 10 no-gui|grep RANSAC
RANSAC iteration took 176 µs
RANSAC iteration took 190 µs
RANSAC iteration took 127 µs
RANSAC iteration took 186 µs
RANSAC iteration took 98 µs
RANSAC iteration took 186 µs
RANSAC iteration took 146 µs
RANSAC iteration took 193 µs
RANSAC iteration took 153 µs
RANSAC iteration took 178 µs
```

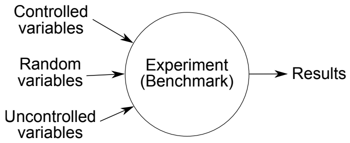
The Challenge of Reasonable Repetition

- Variations
- Measurements must be repeated
- We want to eliminate the influence of random (non-deterministic) factors
- Statistics

Controlled variables (e.g. compiler flags, hardware, algorithm changes) – we are interested how they impact the results

Random variables (e.g. hardware interrupts, OS scheduler) – we are interested in statistical properties of our results in face of these variables

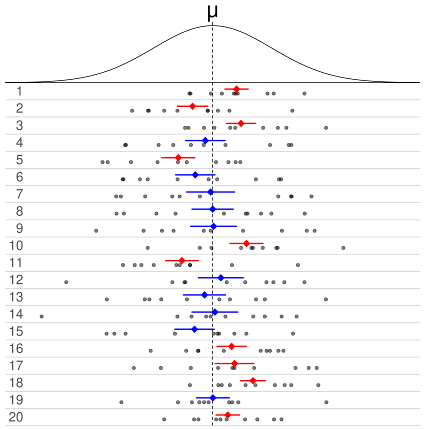
Uncontrolled variables – mostly fixed, but can cause bias of the results



Benchmark goal

- Estimate (a confidence interval for) the mean of execution time of a given benchmark on one or more platforms.
- The mean is the property of the probability distribution of the random execution times
- We can only estimate the mean value from the measurements
- Confidence interval (CI) is important
  - CI of 95% ⇒ in 95% of cases, the true mean will be within the interval.

Example: Sample means with 50% CIs



Source: By FRuDIxAFLG - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=114452600

Levels of repetition

- Results variance occurs typically at multiple levels, e.g.:
  - iteration inside a program
  - execution
  - (re)compilation (if you have a non-deterministic compiler)
- Sound benchmarking methodology should evaluate all the levels with random variations

Next slides give answers to:

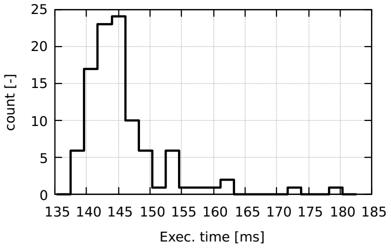
- How to summarize the results?
- How many times to repeat the experiment at each level?
  - As little times as possible to not waste time
  - As many times as possible to get reasonable confidence in results

Outline

Basic summarizing techniques

Histogram, mean, median, minimum

- Full results of the benchmark can be represented by a **histogram** of execution times. This gives us a lot of information.



- If histogram is too much information (your boss wants just a single number), we need to summarize it.
- A good summary is a **mean value with a confidence interval** (see later slides).
- If we don't have time for proper statistics (mean + CI), sometimes **median** can give us useful results too.
  - Usually not sufficient for serious research papers.
- Similarly to median, surprisingly good statistics of execution time measurement is a minimum.
  - It typically represents the situation when there was no (or little) interference to the benchmark execution.
  - See `https://easyperf.net/blog/2019/12/30/Comparing-performance-measurements`

Significance testing

Is it likely that two systems have different performance?

- Statistics can answer this with **Significance testing**
- However, this technique has **problems**, especially when used with results of computer benchmarks – see Kalibera's paper.
  - It is better to ask what is the speedup.
- Significance testing is implemented in the `ministat` tool (FreeBSD)

From ministat man page

The ministat command was written by Poul-Henning Kamp out of frustration over all the bogus benchmark claims made by people with no understanding of the **importance of uncertainty** and statistics.

ministat examples

```
+-----------------------------------------------------------------------------+
|     +++ + +   x       x    x                                               |
|   +++++ +++   x  x    x    x                                               |
|   +++++ +++   x  xx xxx x  x                                               |
|   +++++ +++   x xxxxxxx x  x x                                             |
|   +++++ +++++ xxxxxxxxx x xx x                           +                x|
|             |________MA_________|                                          |
||______M_A_______|                                                           |
+-----------------------------------------------------------------------------+
    N           Min           Max        Median           Avg        Stddev
x  40         88.92       122.527        92.594      93.34845     5.3399441
+  40        82.313       112.625         84.52     85.447325     4.6810848
Difference at 95.0% confidence
        -7.90112 +/- 2.2355
        -8.46412% +/- 2.39479%
        (Student's t, pooled s = 5.02133)
Difference at 99.5% confidence
        -7.90112 +/- 3.59073
        -8.46412% +/- 3.84658%
```

ministat examples (cont.)

Too little data with too similar distribution:

```
+---------------------------------------------------------------------------+
|                                   +  +                                    |
|+ x       +   +    +  x            +  +    * x x        x          x  xxx +|
|                          |______________________A______M_______________|  |
|          |____________________A___M________________|                      |
+---------------------------------------------------------------------------+
    N           Min           Max        Median           Avg        Stddev
x  10       151.527       155.963       154.936      154.5278     1.4673007
+  10       151.371       156.096       153.618      153.3248     1.3398755
No difference proven at 95.0% confidence
```

Confidence interval

- We want to estimate the **mean of a probability distribution**
- We only have a limited set of r measurements and know almost nothing about the distribution
- We calculate the **average value $\bar{Y}$ from the measurements**
- How is the average different from the true mean value?
- $\bar{Y} \pm \frac{S_Y}{\sqrt{r}} q_{t(r-1)}(1 - \frac{\alpha}{2})$, where
  - $q_{t(r-1)}(1 - \frac{\alpha}{2})$ is $(1 - \frac{\alpha}{2})$-quantile of the Student's t-distribution with $r - 1$ degrees of freedom.
  - α is significance level (e.g. 5%)
- We say: Execution time of our benchmark is 25.4 ± 3.2 ms with 95% confidence.
- This means that the true mean is somewhere between 22.2 and 28.6 with probability of 95%.
- `https://stackoverflow.com/questions/15033511/compute-a-confidence-interval-from-sample-data`

Visual tests

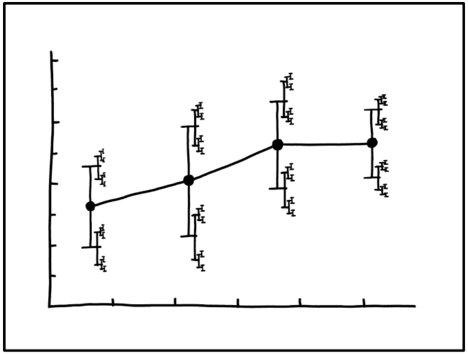
- Calculate and visualize confidence intervals.
- Do the two confidence intervals overlap?
  - No $\Rightarrow$ different performance is likely
  - Yes $\Rightarrow$ more statistics (or measurements) needed
- Hard to estimate speedup and its confidence interval
- Note: `ministat` does not calculate confidence intervals, but standard deviations, i.e. S_Y

Recommendation

Analysis of results should be statistically rigorous and in particular should quantify any variation. Report performance changes with effect size confidence intervals.

Useful tools

- ministat
- Hyperfine (`https://github.com/sharkdp/hyperfine`)
- Julia and Measurements package (`https://github.com/JuliaPhysics/Measurements.jl`)



I DON'T KNOW HOW TO PROPAGATE ERROR CORRECTLY, SO I JUST PUT

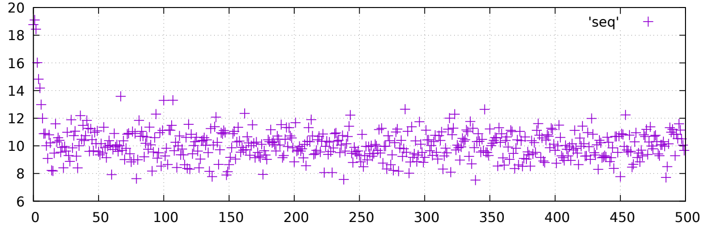
Outline

Repeating iterations

- Iteration = one execution of a loop body
- We are interested in *steady state performance*
- Initialization phase
  - First few iterations typically include the initialization overheads
  - Warming up caches, teaching branch predictor, memory allocations
- Independent state
  - Ideally, measurements should be *independent, identically distributed* (i.i.d.)
  - Independent: measurement does not depend on any a previous measurement
  - Independent $\Rightarrow$ initialized

When a benchmark reaches independent state?

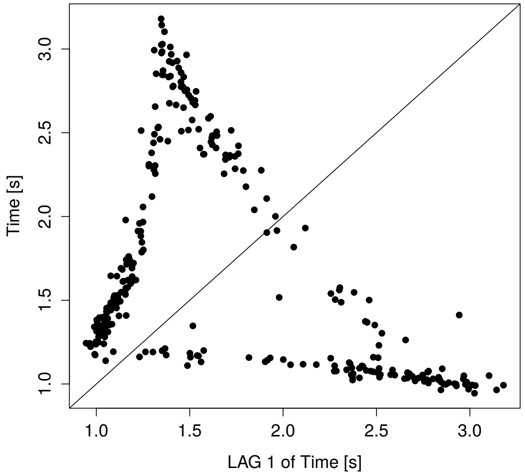
- Manual inspection of graphs from measured data
  1. run-sequence plot ⇒ easy identification of initialization phase ⇒ strip

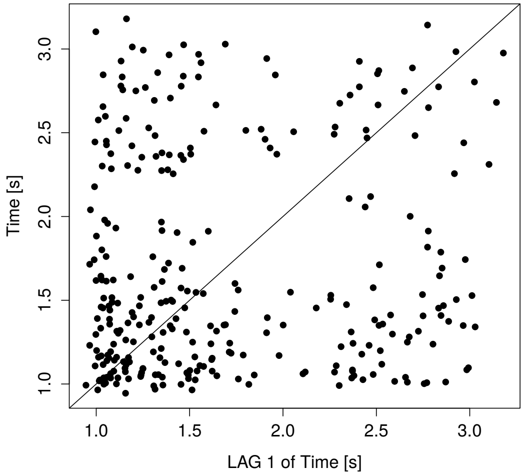


  2. Independence assessment – plot the following plots on original and randomly reordered sequence
     - lag plot (for several lags – e.g. 1–4)
     - auto-correlation function
  3. Any visible pattern suggests the measurements are not independent

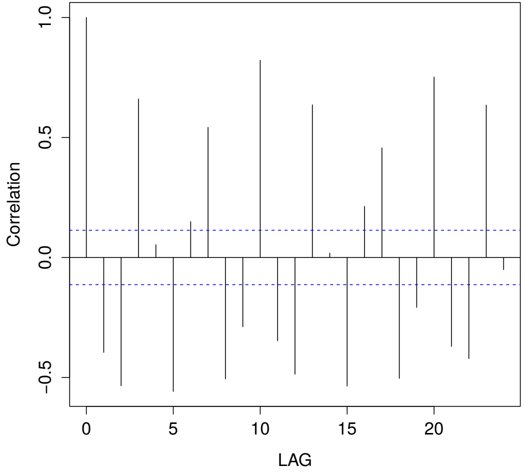
Lag plot

Dependency of a measured values on the previously measured value.

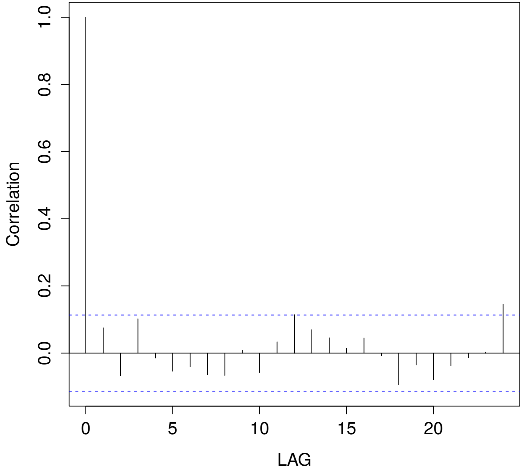




Auto-correlation function



dependent



independent

Recommendations

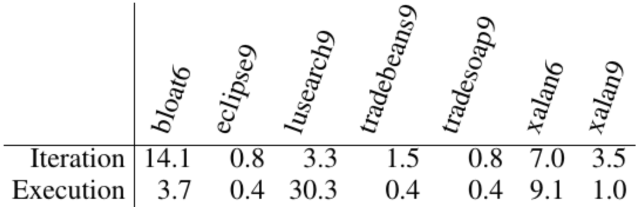
Use this manual procedure just once to find how many iterations each benchmark, VM and platform combination requires to reach an independent state.

If a benchmark does not reach an independent state in a reasonable time, take the same iteration from each run.

Outline

Repeating executions

- Running a benchmark program multiple times
  - Effect of JIT compiler etc.
- Example: Variance in % of different benchmarks from DaCapo/OpenJDK benchmark suite



	bloat6	eclipse9	lusearch9	tradebeans9	tradesoap9	xalan6	xalan9
Iteration	14.1	0.8	3.3	1.5	0.8	7.0	3.5
Execution	3.7	0.4	30.3	0.4	0.4	9.1	1.0

- What if different executions exhibit higher variance than iterations? (see lusearch9)
- Determine initialized and independent state for executions as for iterations.

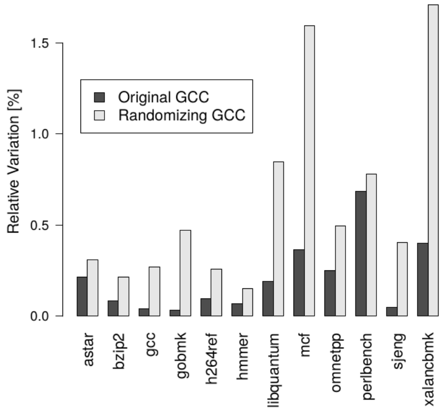
Repeating compilation

- Sometimes even a compiler can influence the benchmark results.
- Why code layout makes a difference?
    - Effects of instruction caches in the CPU – see later lecture.

Recommendation

If you cannot control the factor, make it random!

Experiment: Code layout generated by the compiler: original vs. randomized



Outline

Multi-level repetition

- We have to repeat the experiments to narrow the confidence interval
- If the variance occurs at higher levels (execution, compilation), we need to repeat at least at that level.
- Repeating at lower level may be cheaper (no execution overhead, compilation overhead, etc.)
  - Time can be saved by repeating at lower levels.
- How to find required number of repetitions at each level to reach the given confidence interval?
  - Can be formulated mathematically.
  - If you repeat too little, you have wide confidence intervals.
  - If you repeat too much, you waste your time with running unnecessary experiments.

Notation

- Levels
  - Lowest level (iteration) = 1
  - Highest level (e.g. compilation) = n
- *Initial experiment*
  - bold letters
  - $\mathbf{r_1}, \mathbf{c_1}$
- *Real experiment*
  - normal letters
  - r_1, c_1

Initial experiment

Goal is to find the required number of iterations at each level ($\mathbf{r_1}, \mathbf{r_2}, \dots$).

- Select number of repetitions (exclusive of warm-up) $\mathbf{r_1}, \mathbf{r_2}, \dots$ to be arbitrary but sufficient value, say 20.
- Gather the cost of repetition at each level (time added exclusively by that level, e.g. compile time)
  - $\mathbf{c_1}$ iteration duration
  - $\mathbf{c_2}$ time execute benchmark up to independent state
  - $\mathbf{c_3}$ compilation time
- Measurement times: $\mathbf{Y_{j_n \dots j_1}}, \quad j_1 = 1 \dots r_1, j_2 = 1 \dots r_2, \dots$
- Calculate arithmetic means for different levels:
  $\bar{\mathbf{Y}}_{j_n \bullet \cdots \bullet}$

Variance estimators

- After initial experiments, we will calculate n unbiased variance estimators $\mathbf{T_1^2}, \ldots, \mathbf{T_n^2}$
- They describe how much each level contributes independently to variability in the results
- Start with calculating $\mathbf{S_i^2}$ – biased estimator of the variance at each level i, $1 \leq i \leq n$:

$$\mathbf{S_i^2} = \frac{1}{\prod_{k=i+1}^{n} \mathbf{r_k}} \frac{1}{\mathbf{r_i} - 1} \sum_{j_n=1}^{r_n} \cdots \sum_{j_i=1}^{r_i} \left(\bar{\mathbf{Y}}_{j_n \ldots j_i \bullet \cdots \bullet} - \bar{\mathbf{Y}}_{j_n \ldots j_{i+1} \bullet \cdots \bullet} \right)^2$$

- Then obtain T_i^2:

$$\begin{aligned} T_1^2 &= \mathbf{S}_1^2 \\ \forall i, 1 < i \leq n, T_i^2 &= \mathbf{S}_i^2 - \frac{\mathbf{S}_{i-1}^2}{\mathbf{r_{i-1}}} \end{aligned}$$

- If $T_i^2 \leq 0$, this level induces little variation and repetitions can be skipped.

Real Experiment: Confidence Interval

- Optimum number of repetitions at different levels $r_1, \ldots, r_{n-1}$ can be calculated as:

$$\forall i, 1 \leq i < n, \quad r_i = \left\lceil \sqrt{\frac{c_{i+1}}{c_i} \frac{T_i^2}{T_{i+1}^2}} \right\rceil$$

- Then recalculate: S_n^2 and $\bar{Y}_{j_n \bullet \ldots \bullet}$ as before but with data from real experiment.
- Asymptotic confidence interval with confidence $(1 - \alpha)$ is:

$$\bar{Y} \pm t_{1-\frac{\alpha}{2},\nu} \sqrt{\frac{S_n^2}{r_n}}$$

where $t_{1-\frac{\alpha}{2},\nu}$ is $(1 - \frac{\alpha}{2})$-quantile of the t-distribution with $\nu = r_n - 1$ degrees of freedom.

Recommendation

For each benchmark/VM/platform, conduct a dimensioning experiment to establish the optimal repetition counts for each but the top level of the real experiment. Re-dimension only if the benchmark/VM/platform changes.

Outline

Measuring speedup

- Speedup: “With my optimization, the program runs 10% faster.”
- Speedup is the ratio of two execution times (random variables)
- What is the speedup confidence interval?
  E.g. 10%$\pm$2% faster with confidence of 99%
- How many times to repeat the speedup experiments?

Speedup confidence interval

- $\bar{Y}$ – old system execution time (average of measured times)
- $\bar{Y}'$ – new system execution time
- Speedup: $\bar{Y}'/\bar{Y}$
- Speedup confidence interval:

$$\frac{\bar{Y} \cdot \bar{Y}' \pm \sqrt{(\bar{Y} \cdot \bar{Y}')^2 - (\bar{Y}^2 - h^2)(\bar{Y}'^2 - h'^2)}}{\bar{Y}^2 - h^2}$$

$$h = \sqrt{t^2_{\frac{\alpha}{2},\nu} \frac{S_n^2}{r_n}} \quad h' = \sqrt{t^2_{\frac{\alpha}{2},\nu} \frac{S_n'^2}{r_n}}$$

Speedup confidence interval

Simplified calculation + example

- Relation of confidence interval of the speedup to confidence interval on individual measurements:

$$\mathbf{e_s} \approx \frac{\bar{Y}'}{\bar{Y}}\sqrt{e^2 + e'^2}$$

- $\mathbf{e_s}$, e, e': relative half-width of the speedup/old/new confidence intervals, i.e. $e = h/\bar{Y}$

Why is speedup confidence interval important?

- Old system: $10{\pm}1$ s, $e = 0.1$ (10%)
- New system: $9{\pm}0.9$ s, $e' = 0.1$
- Speedup: $\approx 0.9{\pm}0.13$, $e_s = 0.13$
- Outcome: Speedup can be 1, i.e. no speedup!

Calculations with confidence intervals in Julia

To type ±, write \pm and press <Tab>

```
   _       _ _(_)_     |  Documentation: https://docs.julialang.org
  (_)     | (_) (_)    |
   _ _   _| |_  __ _   |  Type "?" for help, "]?" for Pkg help.
  | | | | | | |/ _` |  |
  | | |_| | | | (_| |  |  Version 1.7.2 (2022-02-06)
 _/ |\__'_|_|_|\__'_|  |  Official https://julialang.org/ release
|__/                   |

julia> using Measurements

julia> old = 10±1
10.0 ± 1.0

julia> new = 9±0.9
9.0 ± 0.9

julia> speedup = new/old
0.9 ± 0.13
```

Recommendation

Always provide effect size confidence intervals for results.
Either for single systems or for speedups.

References

- Kalibera, T. and Jones, R. E. (2013) **Rigorous Benchmarking in Reasonable Time**. In: ACM SIGPLAN International Symposium on Memory Management (ISMM 2013), 20–12 June, 2013, Seattle, Washington, USA. `http://kar.kent.ac.uk/33611/`
  - Kalibera's paper as code: `https://github.com/softdevteam/libkalibera`
- `https://easyperf.net/blog/2019/12/30/Comparing-performance-measurements`
- `https://www.cse.unsw.edu.au/~gernot/benchmarking-crimes.html`
- Erik van der Kouwe et al. (2018) **Benchmarking Crimes: An Emerging Threat in Systems Security**, `https://arxiv.org/abs/1801.02381`