Accurate and efficient software microbenchmarks

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Background

- *Fastest JSON parser in the world* (on commodity processors): https://github.com/simdjson/simdjson
- First to parse JSON files at gigabytes per second

Where is the code ?

All code for this talk is online (reproducible!!!)

https://github.com/lemire/talks/tree/master/2023/performance/code

How fast is your disk?

PCIe 4 drives: 5 GB/s reading speed (sequential)

PCIe 5 drives: 10 GB/s reading speed (sequential)

CPU Frequencies are stagnating

architecture	availability	max. frequency
Intel Skylake	2015	4.5 GHz
Intel Ice Lake	2019	4.1 GHz

Fact

Single-core processes are often CPU bound

Solution?

Optimize the software.

Incremental optimization, how do you know that you are on the right track?

Hypothesis

This software change (commit) improves our performance.

Simple

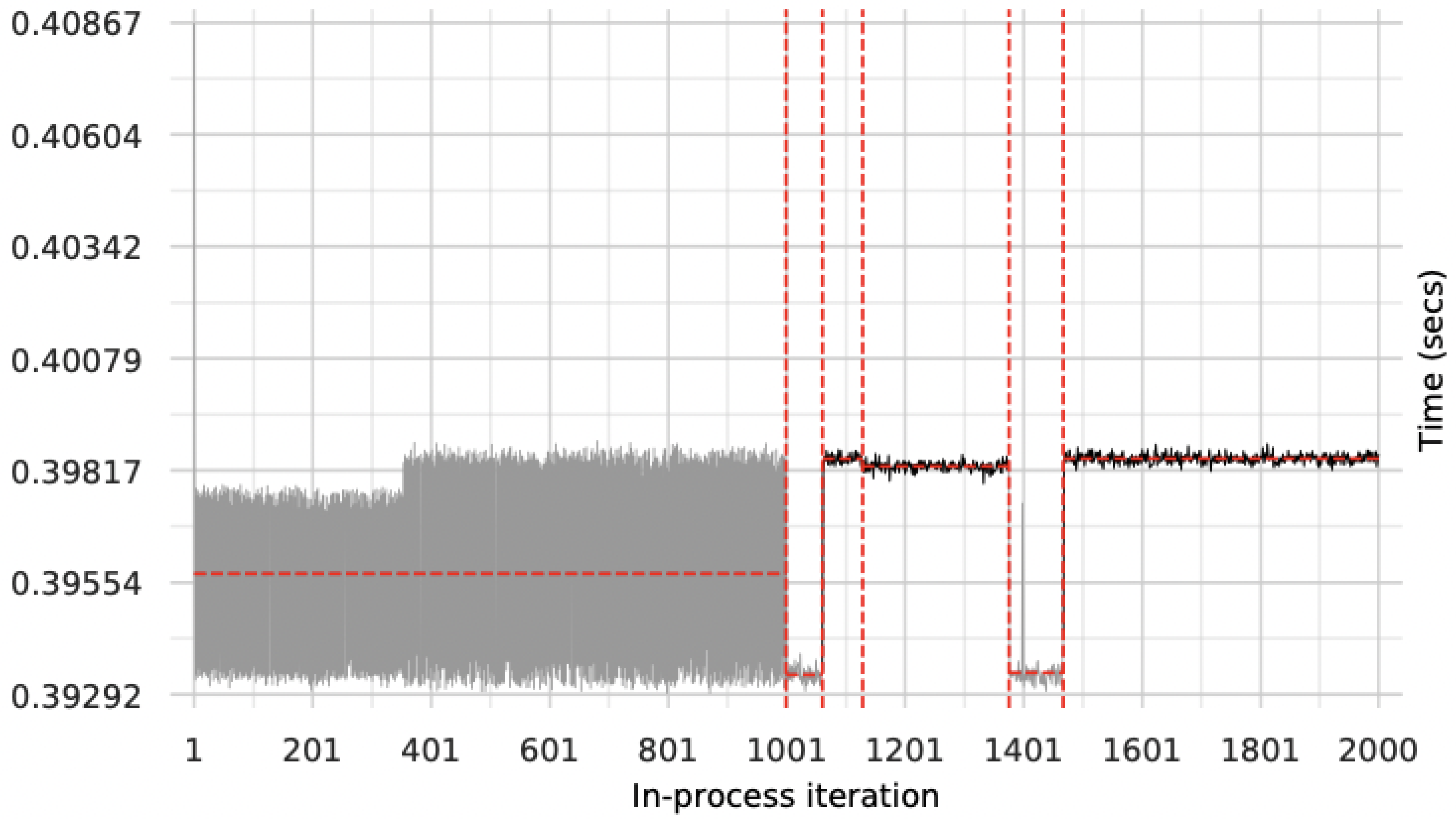
Measure time elapsed before, time elapsed after.

Complex system

Software systems are complex systems: changes can have unexpected consequences.

JIT

Virtual Machine Warmup Blows Hot and Cold



System calls

Ssystem calls (especially IO) may dominate, assume that they remain constant.

Data access

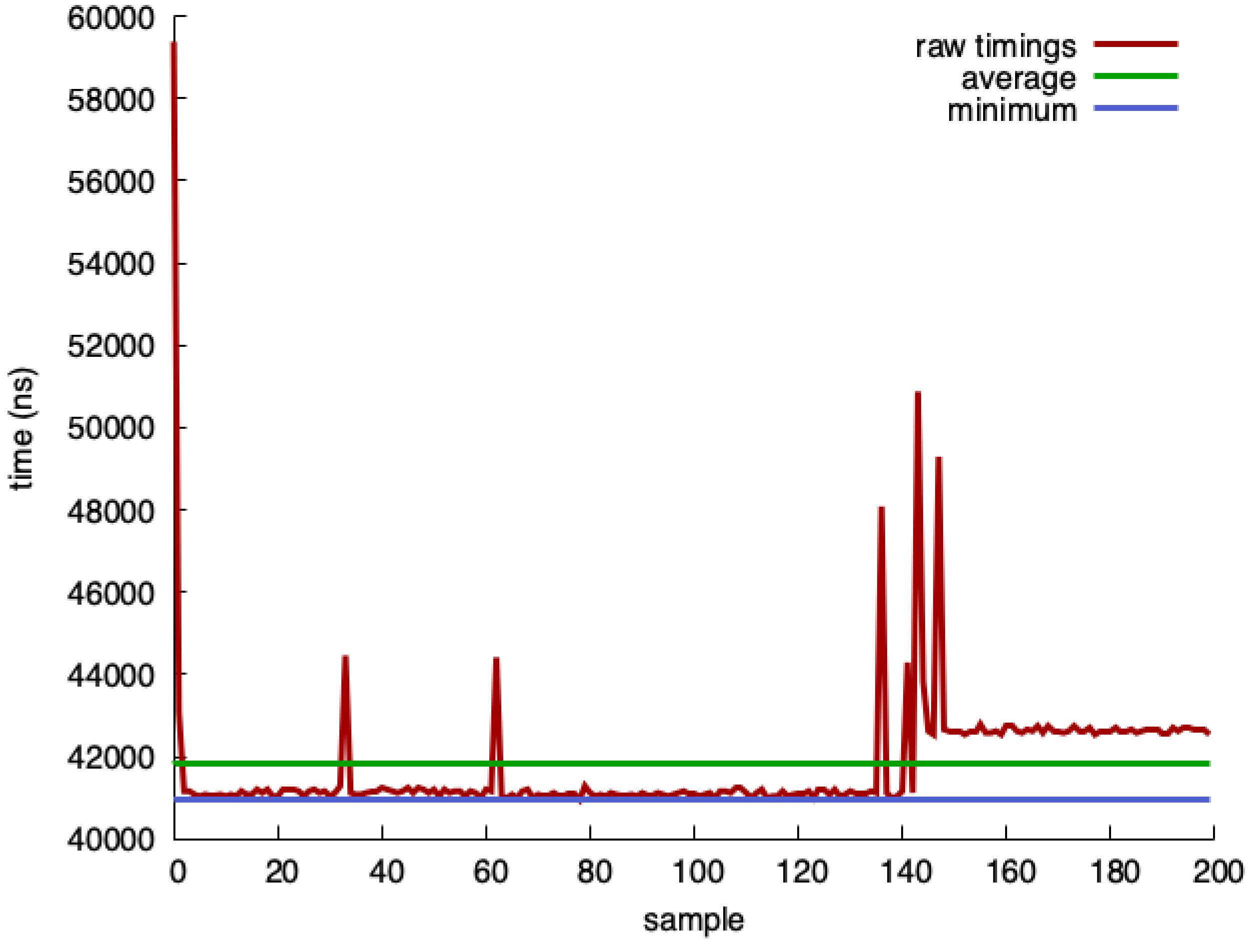
data structure layout changes can trigger expensive loads, assume that we keep that constant.

Tiny functions

Incertitude principle: by measuring you are affecting the execution so that you cannot measure safely tiny functions.

Take statically compiled code

Transcoding UTF-16 to UTF-8 of an 80kB Arabic string using the simdutf library (NEON kernel).



Use the average?

Let t be the true value and let ϵ be the noise distribution (variance σ^2).

We seek t.

Repeated measures increase accuracy

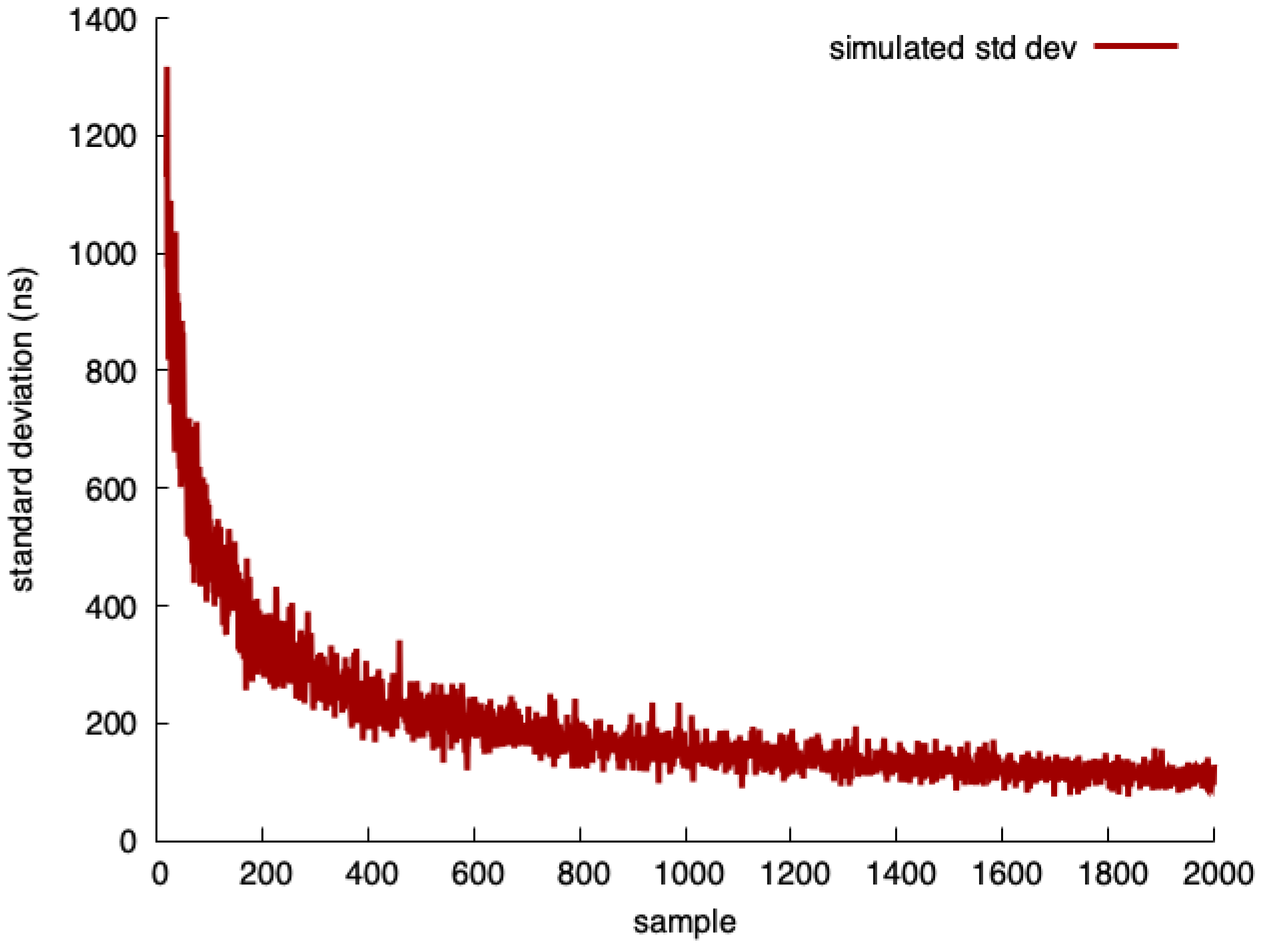
Measures are $t + \epsilon_1, t + \epsilon_2, t + \epsilon_3, \ldots$

Sum is $Nt + (\sum_i \epsilon_i)$. Variance is $N\sigma^2$.

Average is $t + (\sum_i \epsilon_i)/N$. Variance is σ^2/N. Standard deviation of $\frac{\sigma}{\sqrt{N}}$.

Simulation

```
mu, sigma = 10000, 5000
for N in range(20, 2000+1):
    s = [sum(np.random.default_rng().normal(mu, sigma, N))/N for i in range(30)]
    print(N,np.std(s))
```

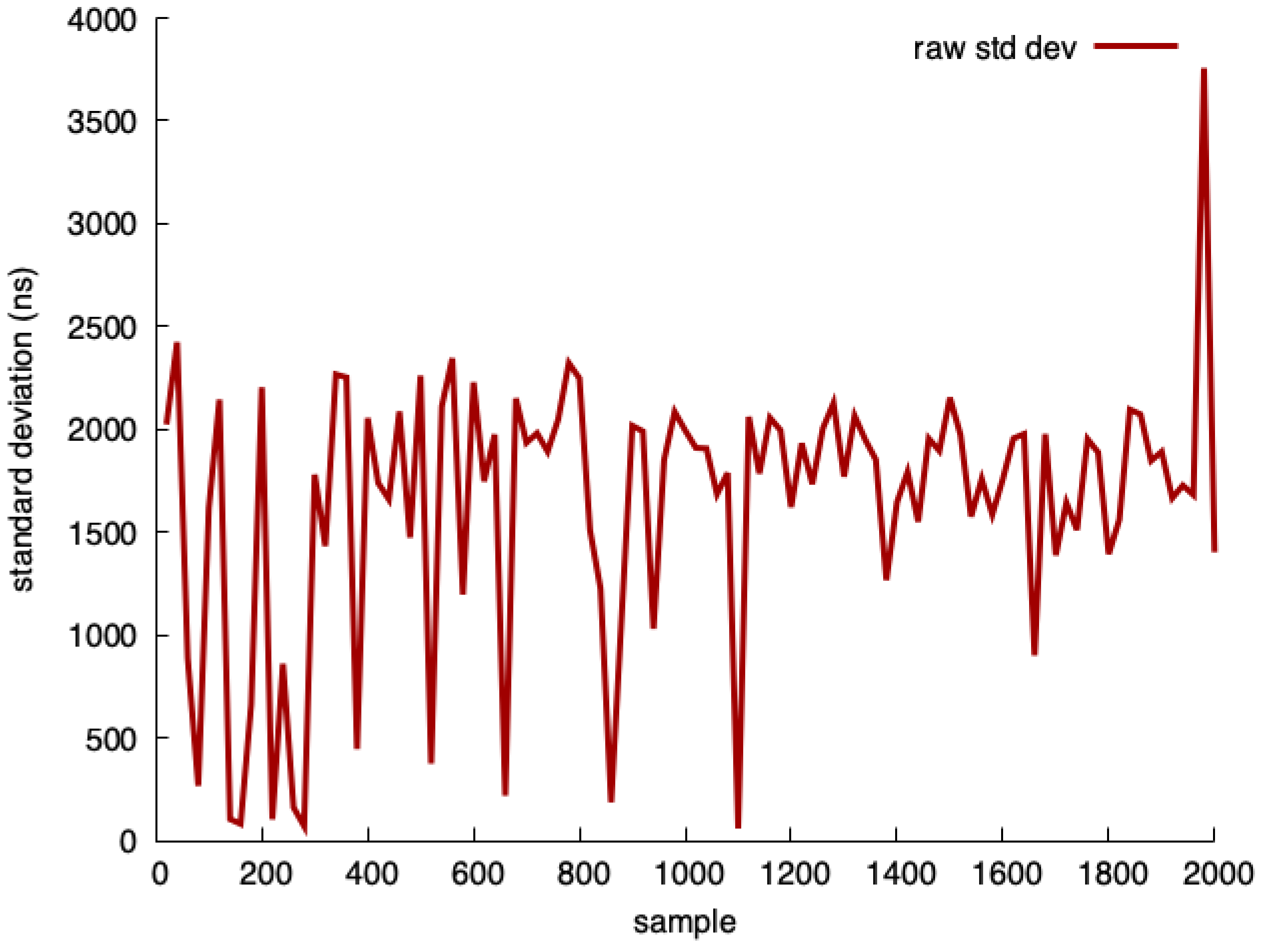

simulated std dev
standard deviation (ns)
1400
1200
1000
800
600
400
200
0
0
200
400
600
800
1000
1200
1400
1600
1800
2000
sample

Actual measurements

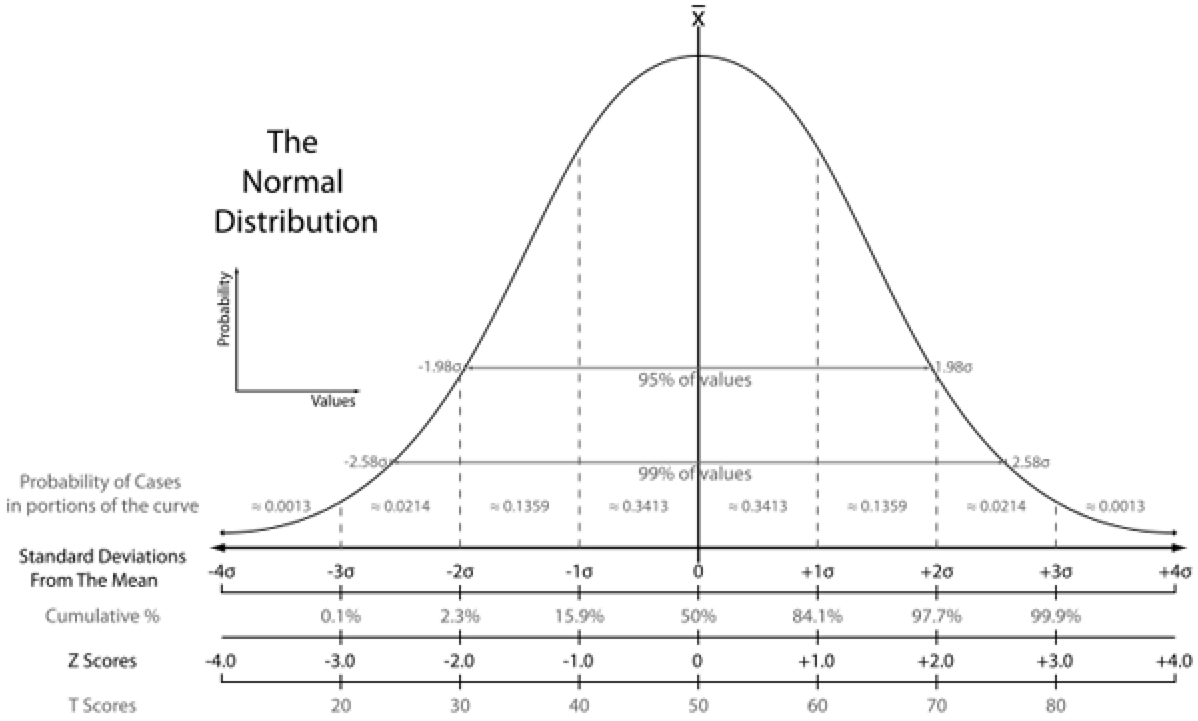
```
// returns the average
double transcode(const std::string& source, size_t iterations);


...

  for(size_t i = iterations_start; i <= iterations_end; i+=step) {
    std::vector<double> averages;
    for(size_t j = 0; j < 30; j++) { averages.push_back(transcode(source, i)); }
    std::cout << i << "\t" << compute_std_dev(averages) << std::endl;
  }
```


raw std dev
standard deviation (ns)
sample
0
500
1000
1500
2000
2500
3000
3500
4000
0
200
400
600
800
1000
1200
1400
1600
1800
2000

Sigma events



- 1-sigma is 32%
- 2-sigma is 5%
- 3-sigma is 0.3% (once ever 300 trials)
- 4-sigma is 0.00669% (once every 15000 trials)
- 5-sigma is 5.9e-05% (once every 1,700,000 trials)
- 6-sigma is 2e-07% (once every 500,000,000)

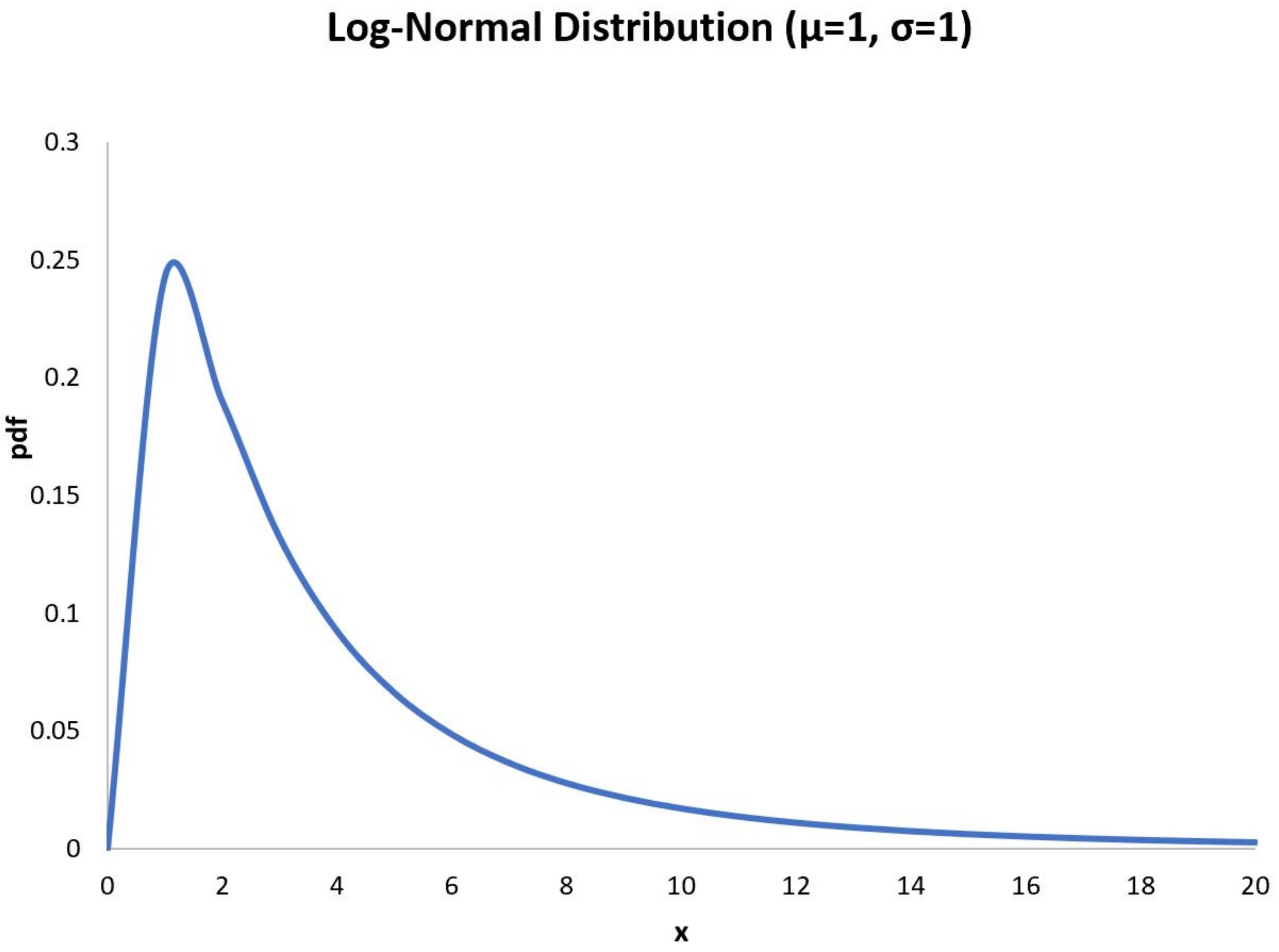
$e^{-n^2/2}/(n * \sqrt{\pi/2}) \times 100$ for $n > 3$

Measuring sigma events

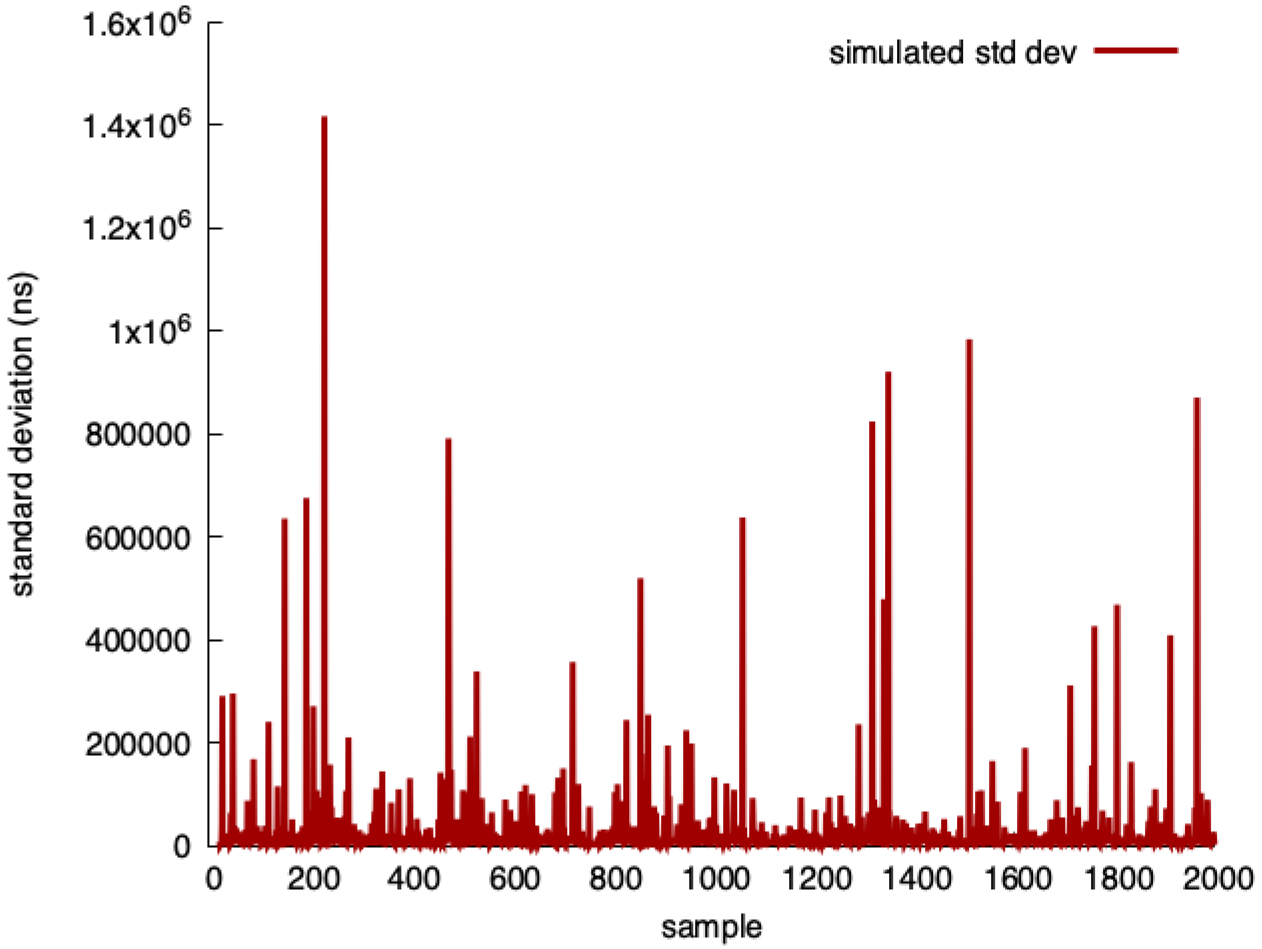
Take 300 measures after warmup, and measure the worst relative deviation

```
$ for i in {1..10}; do sudo ./sigma_test; done
4.56151
4.904
7.43446
5.73425
9.89544
12.975
3.92584
3.14633
4.91766
5.3699
```

What if we dealt with log-normal distributions?



```python
for N in range(20, 2000+1):
    s = [sum(np.random.default_rng().lognormal(1, 4, N))/N for i in range(30)]
    print(N,np.std(s))
```



simulated std dev
standard deviation (ns)
1.6x10^6
1.4x10^6
1.2x10^6
1x10^6
800000
600000
400000
200000
0
0
200
400
600
800
1000
1200
1400
1600
1800
2000
sample

What if we measured the minimum?

Relative standard deviation (σ / μ)

N	average	minimum
200	3.44%	1.38%
2000	2.66%	1.19%
10000	2.95%	1.27%

- The minimum is easier to measure to 1% accuracy.

CPU performance counters

Processors have *zero-overhead* counters recording instruction retired, actual cycles, and so forth.

No need to freeze the CPU frequency: you can measure it.

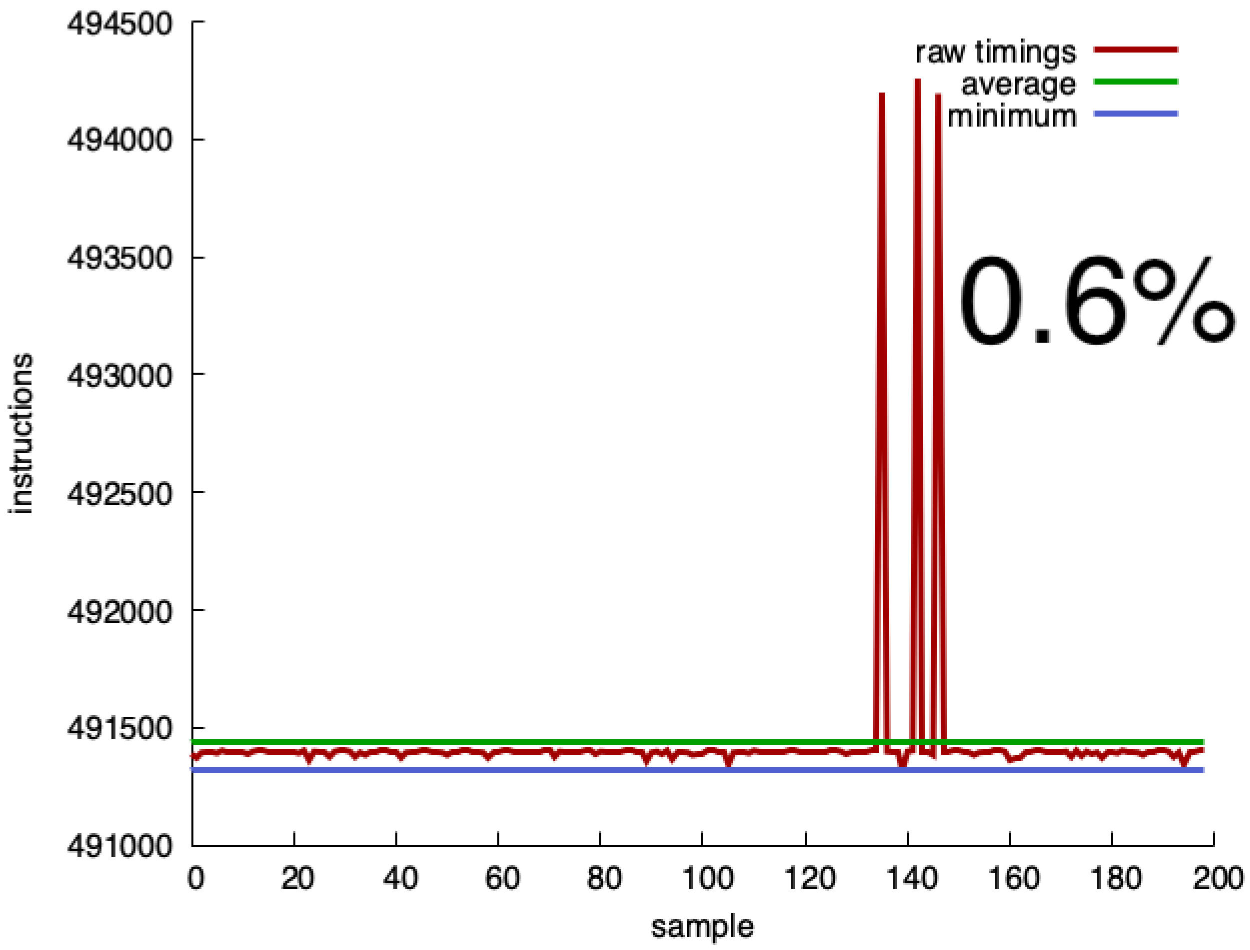
Limitations

- You can only measure so many things (2, 4 metrics, not 25)
- Required privileged access (e.g., root)

Counters in the cloud

- x64: Requires at least a full CPU
- ARM Graviton: generally available but limited number (e.g., 2 counters)

Instruction counts are accurate



Using performance counters

- Java instruction counters: https://github.com/jvm-profiling-tools/async-profiler
- C/C++: instruction counters are available through the Linux kernel
- Go instruction counters

Generally, fewer instructions means faster code

- Some instructions are more expensive than others (e.g., division).
- Data dependency can make instruction counts less relevant.
- Branching can artificially lower instruction count.

If you are adding speculative branching, make sure your test input is large.

```
while (howmany != 0) {
    val = random();
    if( val is an odd integer ) {
      out[index] =  val;
      index += 1;
    }
    howmany--;
}
```

2000 'random' elements, AMD Rome

trial	mispredicted branches
1	50%
2	18%
3	6%
4	2%
5	1%
6	0.3%
7	0.15%
8	0.15%

Take away 1

- Computational microbenchmarks can have log-normal distributions.
- Consider measuring the *minimum* instead of the *average*.

Take away 2

- Benchmarking often is good
- Long-running benchmarks are not necessarily more accurate.
- Prefer cheap, well-designed benchmarks.

Links

- Blog https://lemire.me/blog/
- Twitter: @lemire
- GitHub: https://github.com/lemire