

Timing and Benchmarking Scientific Python

EuroSciPy 2023

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2023-08-16

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How to get the slides

How to get the slides

- Available on GitHub

How to get the slides

- Available on GitHub
- `https://github.com/Kai-Striega/EuroSciPy-2023/blob/main/EuroSciPy_Speech.pdf`

What we're going to cover

Why this talk?

Why does time matter?

Thinking of measurement as an experiment

Taking a single measurement

Running a single Benchmark

What's out there?

Benchmark Design

Our benchmark

Comparing Benchmarks

Why this talk?

What this talk was supposed to be

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- Analyse the methodology of different articles & papers in the scientific Python ecosystem
- Discuss what is done well and where improvements could be made
- Apply the points learnt to *SciPy*'s benchmarking suite

That didn't happen

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- Many lack adequate analysis of their results

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- Dearth of papers looking at the performance of Scientific Python
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- Many did not even state their methodology

What this talk is

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- Advocate for a statistically rigorous approach to timing

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- Cover topics **you** should consider when timing

What this talk is not

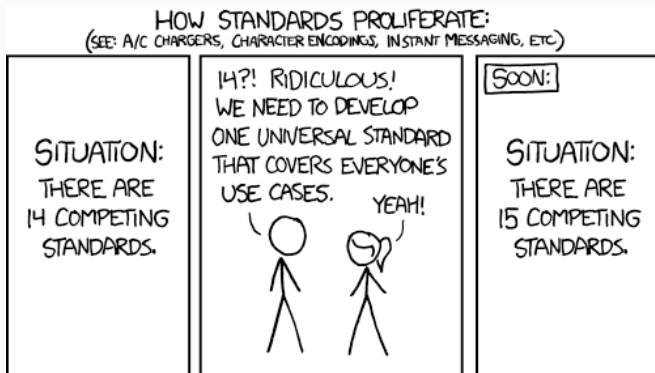


Figure 1: standards

Why does time matter?

A common problem...

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- Which is faster?
- How sure are you that it is faster?

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1 loop, best of 5: 343 msec per loop
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Which run gives the **true** time?

Variance makes time measurement hard

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- Computers can reproduce answers bit for bit

Variance makes time measurement hard

- Computers can reproduce answers bit for bit
- Computers cannot reproduce runtime

Time is an important metric

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- There are many performance metrics...
- ...many of which depend on time
- Accurate time measurement is crucial for accurate metrics

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- Many do not even state their methodologies

Thinking of measurement as an experiment

There are three kinds of lies:
lies, damned lies, and
statistics.

Unknown

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- Documented** Clearly document all aspects of the experiment, including the study design, methods, results, and limitations.

What to measure?

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- Clock cycles

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- Time

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 - Automation

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Reproducibility Well-documented benchmarking procedures enable others to replicate your experiments, ensuring that results can be verified and compared consistently

Maintenance Over time, software may undergo changes, and maintaining up-to-date documentation helps future developers understand and modify the benchmarking suite without confusion

Consistency Automation ensures that benchmarking procedures are executed consistently, minimizing human error and producing reliable and reproducible results

Reproducible Benchmarks: Automation

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Scalability As the benchmarking suite grows with new experiments and datasets, automation helps manage the complexity and handle large-scale experiments efficiently

Continuous Integration Automation can be integrated into the software's development workflow, running benchmarks automatically with each code change, ensuring that performance regressions are caught early

Taking a single measurement

You can't fix by analysis what
you bungled by design.

Light, Singer, and Willett [1990]

What effects a single measurement (not exhaustive!)

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Observer Effect

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Hardware Effects

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Warmups & Steady State

- All forms of instrumentation may change the result

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- Instrumentation normally adds overhead
- "You thought the code was slow to start with, so you made it slower to see how slow it was" - Adelstein-Lelbach [2015]

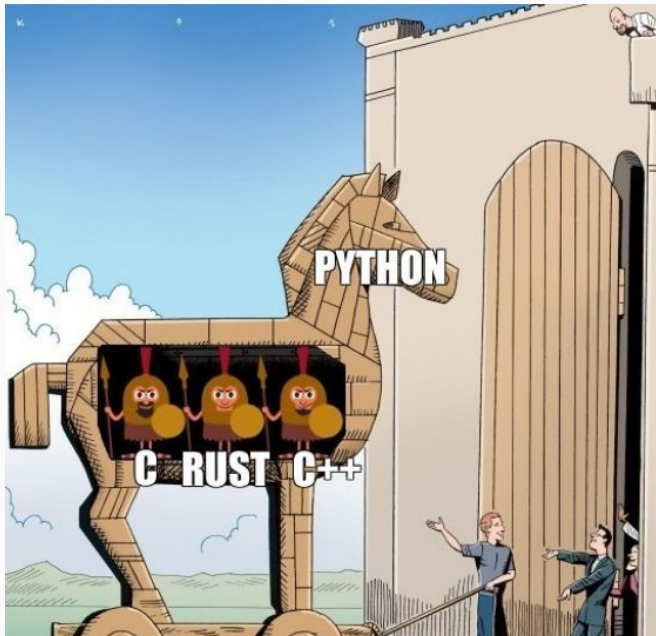
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- Mainly noticeable in low level languages

Why care in Python?

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- The `gc` module provides an interface to the garbage collector

Consider performing garbage collection then disabling the garbage collector before taking a measurement:

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```
>>> import gc  
>>> gc.collect()  
>>> gc.disable()
```


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- Overhead can vary greatly, especially when using JIT compilers
- Many benchmarking suites ignore the first n values of a run
- Warmup vs steady state is still a work in progress

Running a single Benchmark

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- May not always reflect real-world usage scenarios accurately

What's out there?

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- Returns the average of the minimum time of each run

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- Detect if a benchmark result seems unstable

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- <https://asv.readthedocs.io/en/stable/>

Benchmark Design

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- Also, which average do you use?

Average vs Minimum Time

- *Minimum* time allows us to get a "frictionless model" of performance, this is used by *timeit*
- *Average* time allows us to mathematically increase the accuracy of the measure by taking more samples, this is used by *pyperformance*
- Also, which average do you use?
- There is not yet a consensus on which measure should be used

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- In this case we must adopt different statistical tools

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Testing for a normal distribution

- It's essential to inspect the distribution of benchmark
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- Visualising with a QQ-plot
- Statistical tests can be employed to formally assess the normality assumption, such as the Shapiro-Wilk test

A simple error check

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- see Lemire [2023]

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- The minimum or the maximum is 50% smaller or greater than the mean

More error checks

- The standard deviation is greater than 10% of the mean
- The minimum or the maximum is 50% smaller or greater than the mean
- The shortest raw value takes less than 1 millisecond

Outliers and Perturbing Events

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- Perturbing events should be investigated carefully
- It is important to understand *how* it effects the benchmark result
- *pyperformance* chooses to include outliers, as it wants to reflect real world usage
- Outliers due to perturbing events may or may not be included in your analysis

Our benchmark

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- <https://github.com/python/pyperformance>

The n-body benchmark

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- Model the orbits of Jovian planets, using a simple integrator
- There does not exist an analytical solution
- Microbenchmark on floating point operations

Eyeballing the distribution

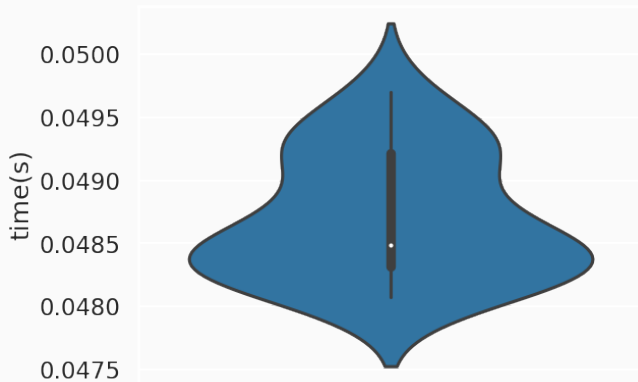


Figure 3: violinplot of n-body runtimes (s)

The summary statistics

count	20
mean	48.706
std	0.495
min	48.071
50%	48.489
max	49.701

Table 1: Summary statistics for the n-body benchmark (ms)

What about our simple error check?

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- Minimum of the runs is 48.071 ms

What about our simple error check?

- Minimum of the runs is 48.071 ms
- Mean of the runs is 48.706 ms
- ✓ Very close together

Let's look at our stability checks

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Let's look at our stability checks

- ✓ The standard deviation is 1% of the mean
- ✓ The minimum and the maximum are very close to the mean
- ✓ The shortest raw value took 48 milliseconds

Comparing Benchmarks

Does Windows or Linux run faster?

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Does Windows or Linux run faster?

- Want to compare how a change in the OS affects our runtime performance
- Ran the benchmark on Linux and Windows
- Was careful to present a fair and unbiased approach
- Let's compare the results!

Looking at the statistics

- Linux ran with a mean time of 49 ms

Looking at the statistics

- Linux ran with a mean time of 49 ms
- Windows ran with a mean time of 70 ms

For the n -body problem it's obvious...

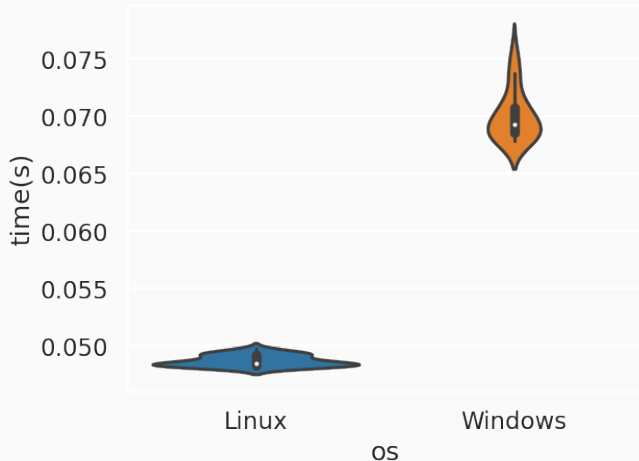


Figure 4: Runtime of the n -body benchmark

How comfortable are you saying this speedup is significant?

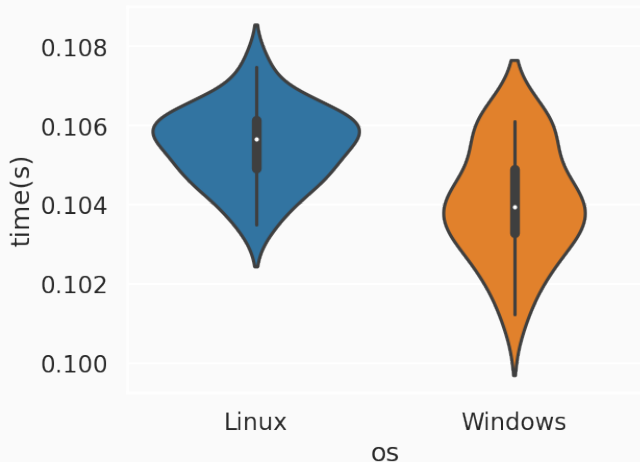


Figure 5: Runtime of the `sympy_sum` benchmark

Compare distributions, not summaries

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- Sample size and data quality

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- Distributions capture variability

Compare distributions, not summaries

- Sample size and data quality
- Distributions capture variability
- Skewness and asymmetry

References

- B. Adelstein-Lelbach. Benchmarking c++ code, 2015. URL <https://youtu.be/zWxSZcpeS8Q?t=534>.
- D. Lemire. Are your memory-bound benchmarking timings normally distributed?, 2023. URL <https://lemire.me/blog/2023/04/06/are-your-memory-bound-benchmarking-timings-normally-distributed/>
- R. J. Light, J. D. Singer, and J. B. Willett. *By Design: Planning Research on Higher Education*. Harvard University Press, 1990.

T. Mytkowicz, A. Diwan, M. Hauswirth, and P. F. Sweeney. Producing wrong data without doing anything obviously wrong! *SIGARCH Comput. Archit. News*, 37(1):265–276, mar 2009. ISSN 0163-5964. doi: 10.1145/2528521.1508275. URL <https://doi.org/10.1145/2528521.1508275>.