# Timing and Benchmarking Scientific Python

## EuroSciPy 2023

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Kai Striega

2023-08-16, 13:30 - 14:00

Software Developer & SciPy Maintainer

# How to get the slides

# How to get the slides

- Available on GitHub

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

# Disclaimer

- I am not a statistician
- Many of these techniques are rules of thumb that I work with

# 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

Comparing groups of Benchmarks

Conclusion

# Why this talk?

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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

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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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- Advocate for a statistically rigorous approach to timing
- Cover topics **you** should consider when timing

# What this talk is not

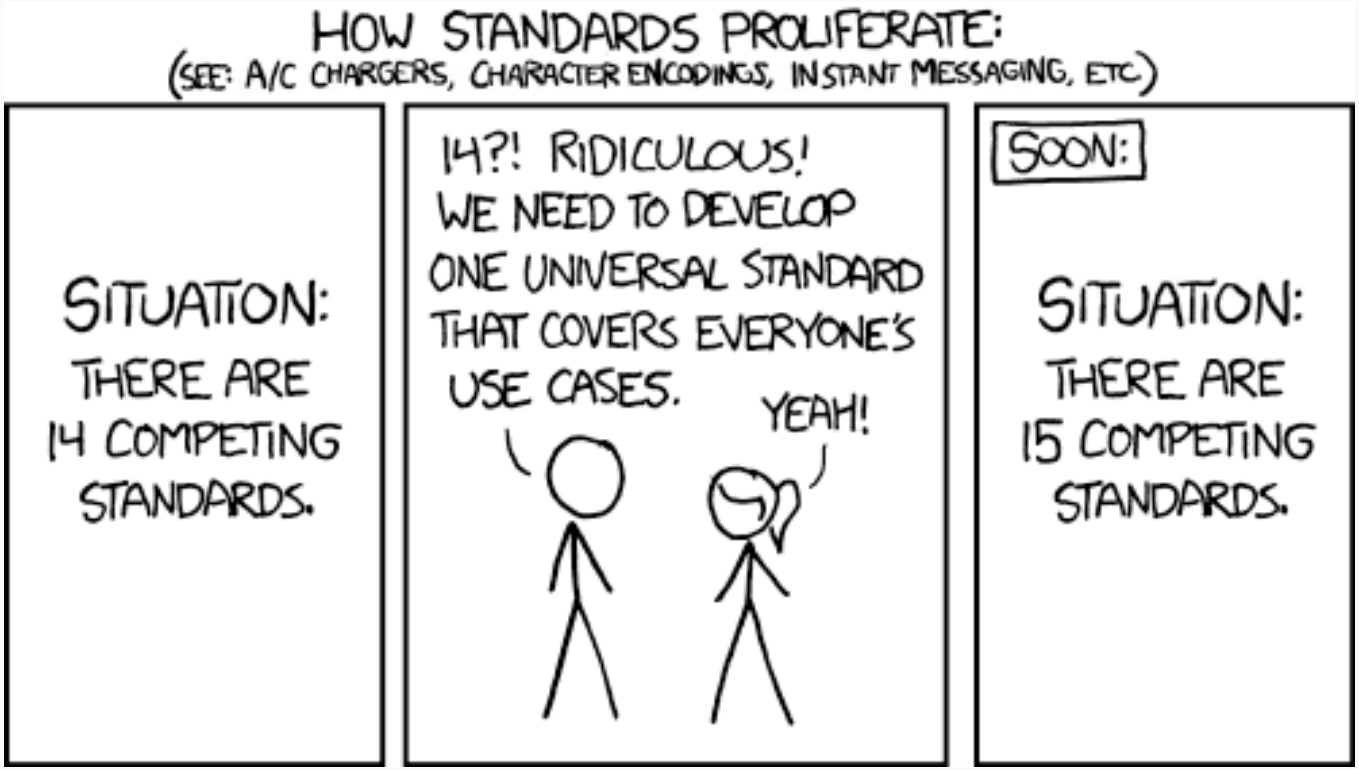


Figure 1: standards

# 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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$ python -m timeit "sum(n*n for n in range(10000000))"
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

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

# Time is an important metric

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- Who **likes** waiting?

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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

# Statistically rigorous?

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

Unknown

# Thinking of measurement as an experiment

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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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**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

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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

# Analysis of experiments

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

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Light, Singer, and Willett [1990]

# What effects a single measurement (not exhaustive!)

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Hardware Effects

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- All forms of instrumentation may change the result
- 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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- Mytkowicz et al. [2009] showed that link order and environment variable size can significantly affect measurement
- Mainly noticeable in low level languages

# Why care in Python?

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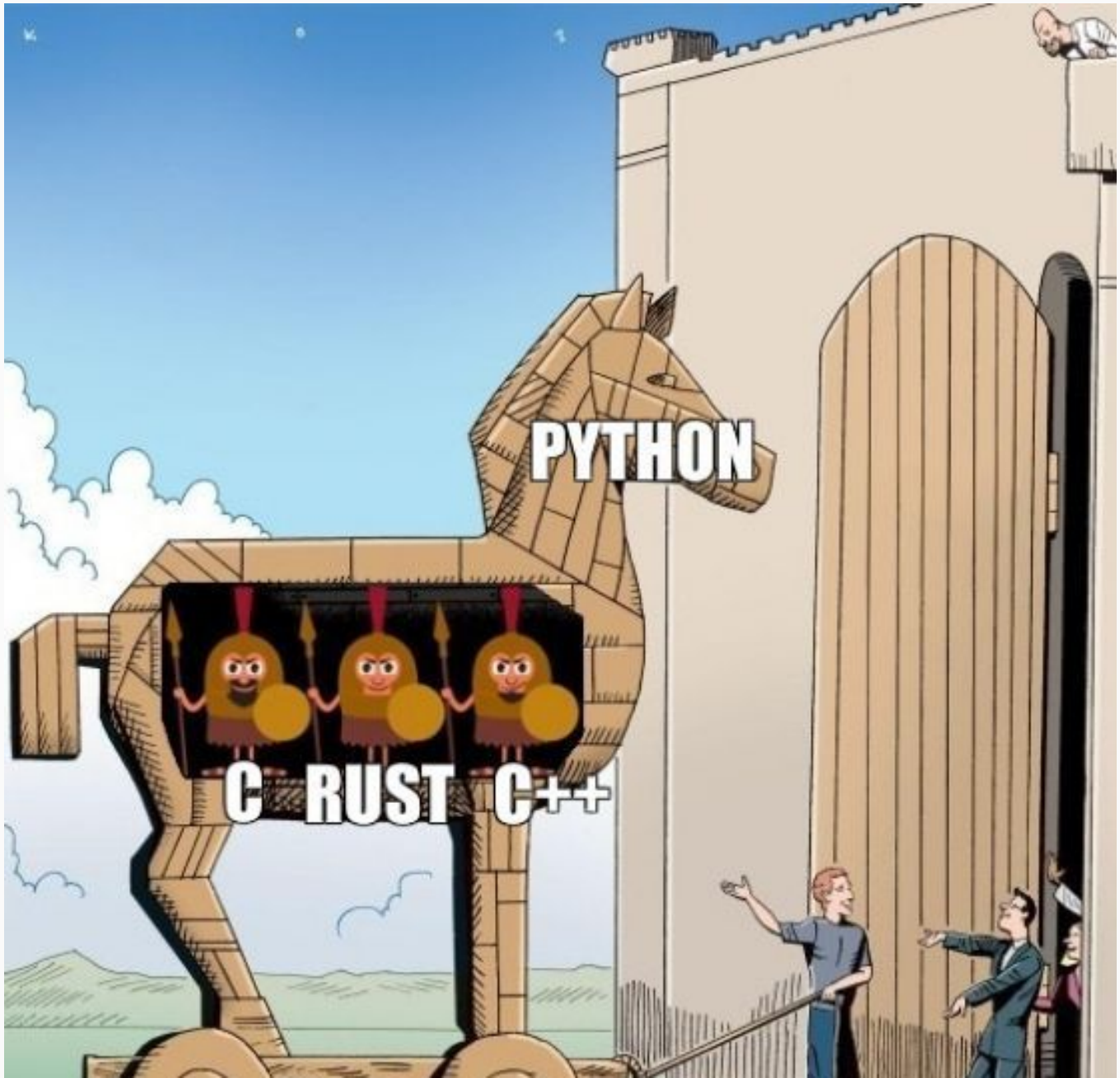

# Running a single Benchmark

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- Benchmarks are useful tools for performance analysis
- May not always reflect real-world usage scenarios accurately

# What’s out there?

# timeit

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- Returns the average of the minimum time of each run

# pyperf

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- Automatically calibrate a benchmark for a time budget

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- Automatically calibrate a benchmark for a time budget
- Detect if a benchmark result seems unstable

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

# Benchmark Design

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# 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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- The distribution of results might not always follow a normal distribution
- In this case we must adopt different statistical tools

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- It’s essential to inspect the distribution of benchmark
- Visually ”eyeballing” the test
- 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]

# More error checks

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

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- Outliers due to perturbing events may or may not be included in your analysis

# Our benchmark

# pyperformance

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

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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

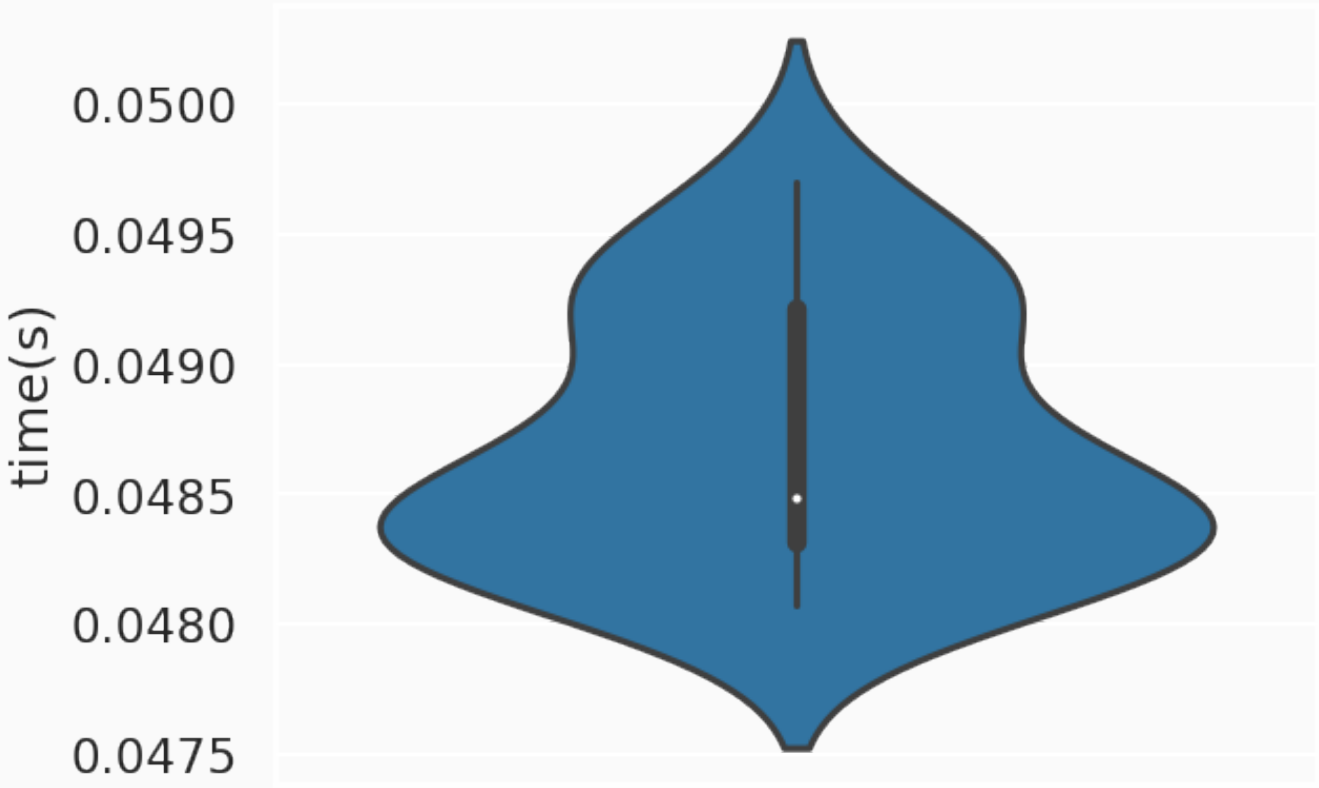


Figure 3: violinplot of n-body runtimes (s)

# 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

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- Minimum of the runs is 48.071 ms
- Mean of the runs is 48.706 ms

✓ Very close together

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- ✓ The standard deviation is 1% of the mean
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- ✓ The shortest raw value took 48 milliseconds

# Comparing Benchmarks

# Does Windows or Linux run faster?

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- Want to compare how a change in the OS affects our runtime performance
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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

# Looking at the statistics

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- 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...

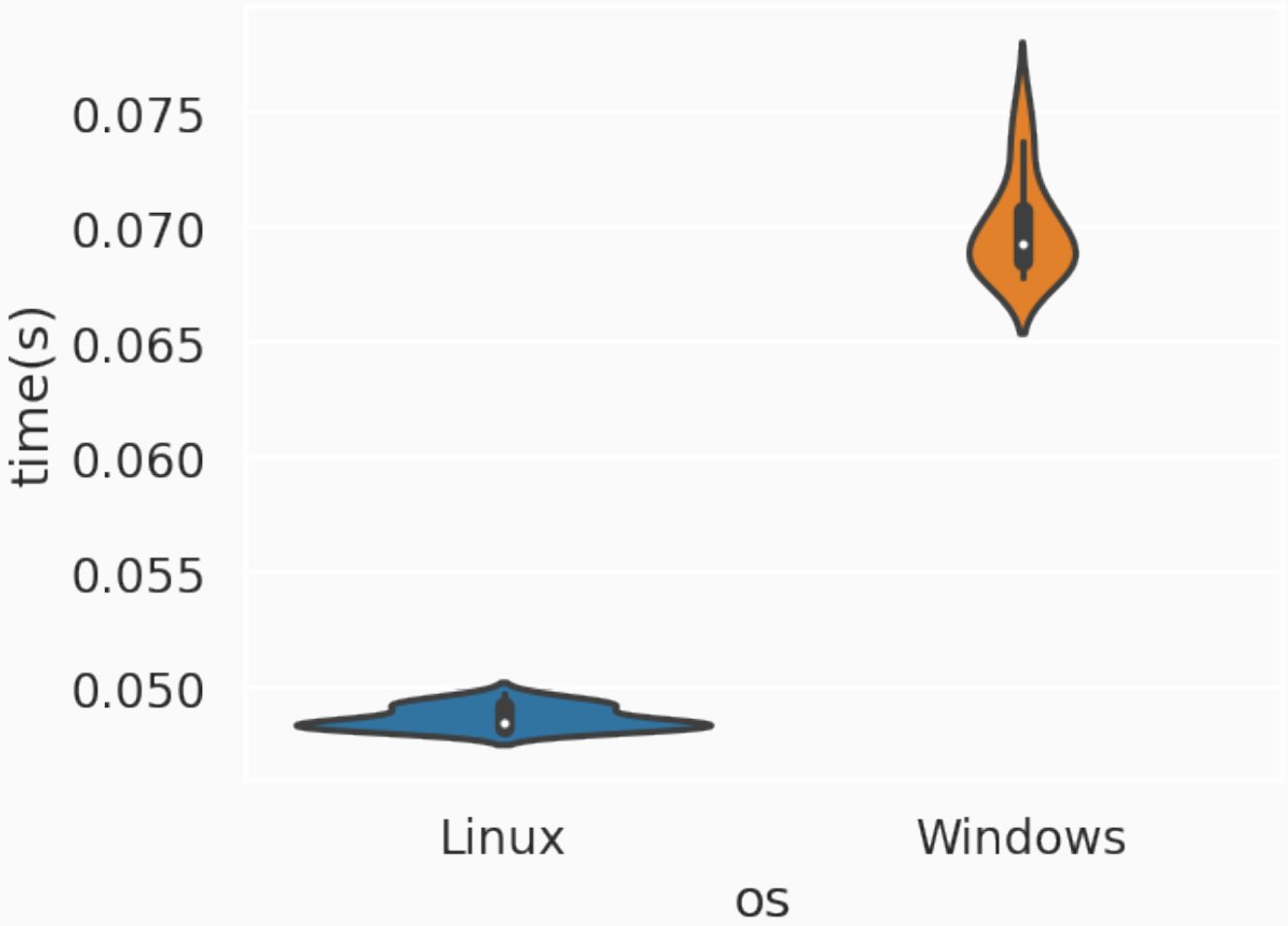


Figure 4: Runtime of the *n-body* benchmark

# How comfortable are you saying this speedup is significant?

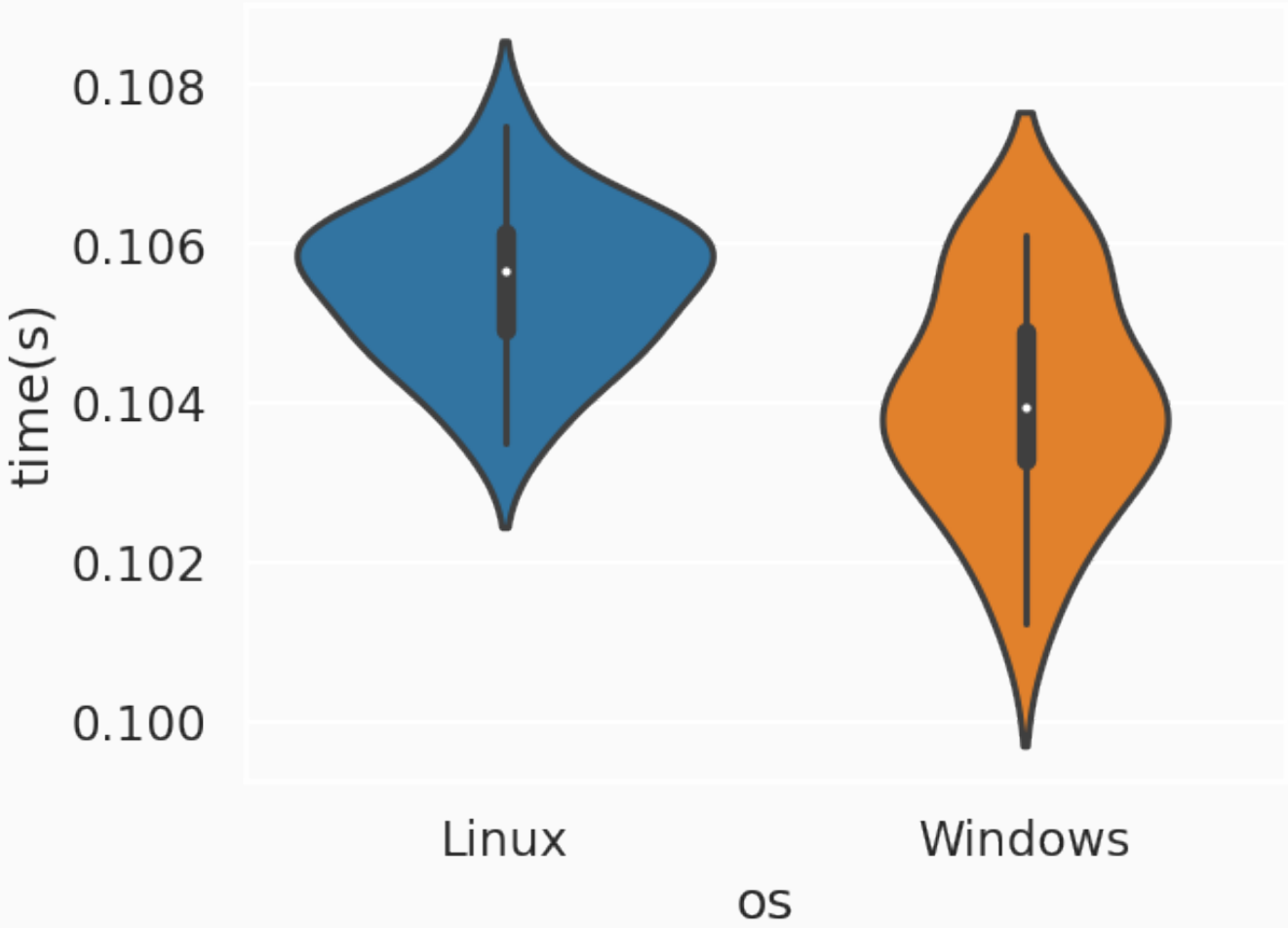


Figure 5: Runtime of the *sympy_sum* benchmark

# Compare distributions, not summaries

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- Sample size and data quality

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- Sample size and data quality
- Distributions capture variability

# Compare distributions, not summaries

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

# Comparing groups of Benchmarks

# What are we *trying* to do?

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Trying to answer a question:

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Trying to answer a question: How does our change effect the system?

# A single benchmark does not tell us much about the system

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- Want to understand how the system as a whole changes

# A single benchmark does not tell us much about the system

- A single benchmark only illuminates one facet of the system
- Want to understand how the system as a whole changes
- Need to compare multiple relevant benchmarks for each part of the system

# Back to the pyperformance benchmark

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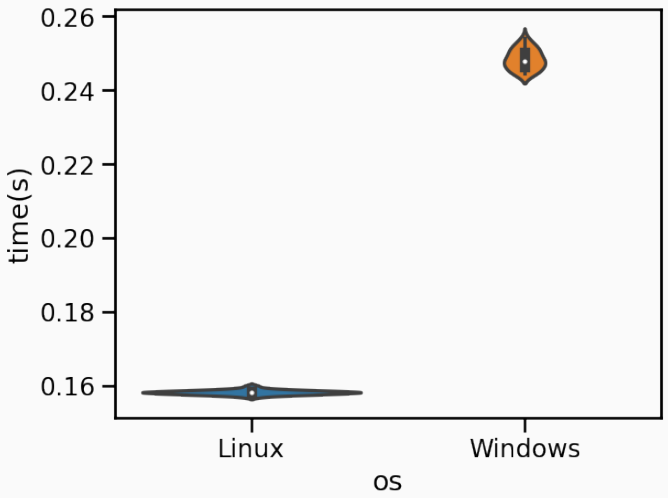
- Total of 95 benchmarks

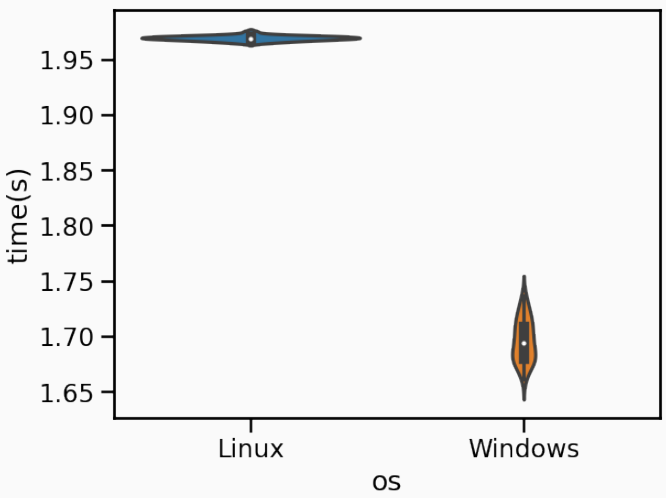
# Back to the pyperformance benchmark

- Total of 95 benchmarks
- On some of them Linux is faster, on some Windows is faster

# Back to the pyperformance benchmark




(a) 2to3




(b) mdp

**Figure 6:** Example difference in benchmark outcomes

# A simple test to see which is faster

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- Count the number of times Linux or Windows is significantly faster

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# A simple test to see which is faster

- Count the number of times Linux or Windows is significantly faster
- Compare how likely this difference is to occur due to chance
- If significant, consider the one with the higher count as faster

# Is Linux or Windows faster?

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- Linux is faster 78 times
- Windows is faster 15 times

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- The difference is statistically insignificant twice

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- The difference is statistically insignificant twice
- According to our rule of thumb, Linux is faster

# Conclusion

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- Make sure your choices are relevant to your work
- Document & Automate
- Analyse distributions, not summary statistics

# Let’s stay in touch!

- I *love* to talk about Python & Performance
- GitHub: *https://github.com/Kai-Striega*
- LinkedIn: *https://www.linkedin.com/in/kai-striega/*

Figure 7: QR code to my LinkedIn profile

# References

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