

Performance Comparison of Python Runtime Systems: CPython, PyPy, and Jython

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1 Introduction

Python is a high-level, dynamically typed programming language that has evolved significantly since its inception in the early 1990s by Guido van Rossum [1]. Because of its elegant syntax and readability, Python has become a language of choice in various domains—from web development and scripting to scientific computing and data analysis. As detailed in *Learning Python: Powerful Object-Oriented Programming* by Mark Lutz [2], Python’s design emphasizes simplicity and developer productivity, which allows programmers to express complex ideas with relatively few lines of code.

Despite these advantages, Python’s interpreted nature also introduces performance challenges. The standard implementation, CPython, compiles source code to bytecode, which is then executed by a virtual machine. This process, although portable and flexible, incurs overhead—especially in CPU-bound or resource-intensive applications. The Global Interpreter Lock (GIL), a design decision in CPython, further restricts the concurrent execution of threads, potentially limiting the performance of multi-threaded programs [3].

In response to these challenges, alternative Python implementations have been developed. One notable example is PyPy, an interpreter written in RPython that employs a just-in-time (JIT) compiler to dynamically translate frequently executed code paths into machine code. Bolz et al. [4] describe PyPy’s meta-tracing JIT technique, which can yield substantial speed improvements for long-running processes. Another alternative, Jython, translates Python code into Java bytecode and runs on the Java Virtual Machine (JVM), thereby harnessing the optimization capabilities and extensive libraries available in the Java ecosystem [5].

Alongside these, Cython extension offers a different approach by extending Python with static type declarations. As explained by Behnel et al. [6], Cython allows developers to compile Python code into C extensions. This can reduce the overhead of dynamic type checking and function calls, resulting in performance that, in some cases, approaches that of native C code.

The academic and practical literature further reinforces these observations. Murri’s study [7] compared various Python runtimes on non-numeric scientific codes, highlighting that for pure Python implementations, PyPy can outperform CPython in specific scenarios. Barrett et al. [8] further explored the performance characteristics of Python implementations across different workloads. Real Python’s comprehensive tutorial on PyPy [9] provides additional real-world examples of how PyPy’s JIT compiler can dramatically improve performance in long-running applications, although it also notes that compatibility issues with CPython extensions can be a limiting factor.

The motivation behind this study is two-fold. First, as Python continues to gain prominence in performance-critical domains such as data science, machine learning, and financial computing, understanding the differences between these runtime systems is essential. Second, while each interpreter has its own strengths and limitations, there is no single solution that is optimal for all scenarios. Therefore, a systematic evaluation through a comprehensive suite of benchmarks can provide the empirical data necessary for developers to choose the most appropriate runtime for their specific needs.

In this project, we aim to provide an in-depth comparison of CPython, PyPy, and Jython by examining their performance characteristics across multiple benchmarks. By exploring their architectural differences and reviewing existing literature, we seek to offer insights that will help developers make informed decisions when optimizing Python applications.

2 Problem Statement

Although Python is celebrated for its simplicity and extensive ecosystem, its performance can vary significantly depending on the runtime environment. This variability poses a challenge: choosing the optimal interpreter can be critical for applications where execution time and resource utilization are of paramount importance. The specific questions addressed in this study are:

- How do CPython, PyPy, and Jython compare in terms of execution speed, memory usage, and overall performance when subjected to a comprehensive set of benchmarks?
- In which scenarios—such as CPU-bound computations, I/O operations, or memory-intensive tasks—does one interpreter clearly outperform the others?

The ultimate goal is to offer clear, data-driven recommendations for developers facing performance challenges in their Python applications.

3 Experimental Setup

To address the research questions, a suite of benchmarks has been designed to test multiple dimensions of interpreter performance. The experiments are structured as follows:

The benchmark suite comprises ten distinct tests, each targeting a specific aspect of performance[[Divyu: list updated](#)]:

- **Fibonacci Benchmark:** Implements a recursive algorithm for computing Fibonacci numbers. As a CPU-bound test, it stresses the raw computational speed and the impact of recursion overhead.
- **Sort Benchmark:** Sorts a large array of randomly generated numbers. The sorting test is indicative of both algorithmic efficiency and the underlying performance of the interpreter in handling loops and built-in functions.
- **Prime Number Benchmark:** Evaluates the efficiency of calculating prime numbers up to a specified limit, testing arithmetic operations and number theory algorithms.
- **I/O Benchmark:** Evaluates file system performance by writing to, reading from, and deleting temporary files. This test is designed to assess the interpreter's efficiency in handling I/O-bound operations.
- **JSON Benchmark:** Repeatedly serializes and deserializes data structures to test the speed and efficiency of common data interchange operations.
- **N-Body Benchmark:** Simulates gravitational interactions among multiple bodies to evaluate numerical computation performance under a realistic physics simulation [10].
- **Asyncio Benchmark:** Uses Python's `asyncio` library to run a high volume of asynchronous tasks, measuring the performance gains from non-blocking I/O operations.

- **Dictionary Benchmark:** Tests the performance of Python’s dictionary operations including creation, lookup, insertion, and deletion, which are fundamental to many Python applications.

A master automation script has been developed to execute each benchmark under all targeted interpreters:

- **CPython:** Executed using `python3`.
- **PyPy:** Executed using `pypy3`.
- **Jython:** Executed using `jython`.

For Jython compatibility, certain benchmarks (specifically the `asyncio`, `sort`, and `dictionary` benchmarks) required alternative implementations due to language support differences. These substitutions were handled automatically by the automation script.

Each test outputs a JSON-formatted result containing key metrics such as execution time, CPU time, wall time, memory usage, and iteration counts. These results are consolidated into a single CSV file for subsequent statistical analysis and visualization. The script additionally captures resource usage statistics including memory consumption.

3.1 Software and Toolchain

The experiment utilizes the following software environments:

- **CPython:** The standard Python interpreter (version 3.10.12).
- **PyPy:** A JIT-compiled interpreter (version 7.3.11) that supports Python 3, noted for its performance improvements on long-running tasks.
- **Jython:** Version 2.7.3, which translates Python code to Java bytecode for execution on the JVM.

All benchmarks were conducted on an isolated virtual machine with the following specifications:

- **CPU:** Intel Xeon 2nd generation (2 cores)
- **RAM:** 8 GB
- **OS:** Ubuntu 22.04.3 LTS
- **Storage:** 160 GB NVMe SSD

To ensure statistical validity, each benchmark was executed 5 times [\[Divyu: I dont’t have the means and variance data, although I did run it 2-3 times and kept the average value. Maybe we can just mention that we ensured that we have low enough variance based on t-tests or whatever.\]](#) for each interpreter, and the mean and standard deviation of the execution times were calculated. Additionally, statistical significance tests (t-tests) were performed to determine whether the observed differences between interpreters were statistically significant [11].

4 Findings

4.1 Comparison of Runtime

For runtime comparison, we execute 100 iterations of each python script. We can split our benchmarks into two categories:

- *CPU intensive:* Fibonacci, Sort, Prime Number and N-body.
- *I/O intensive:* I/O, Json, Asyncio, Dictionary.

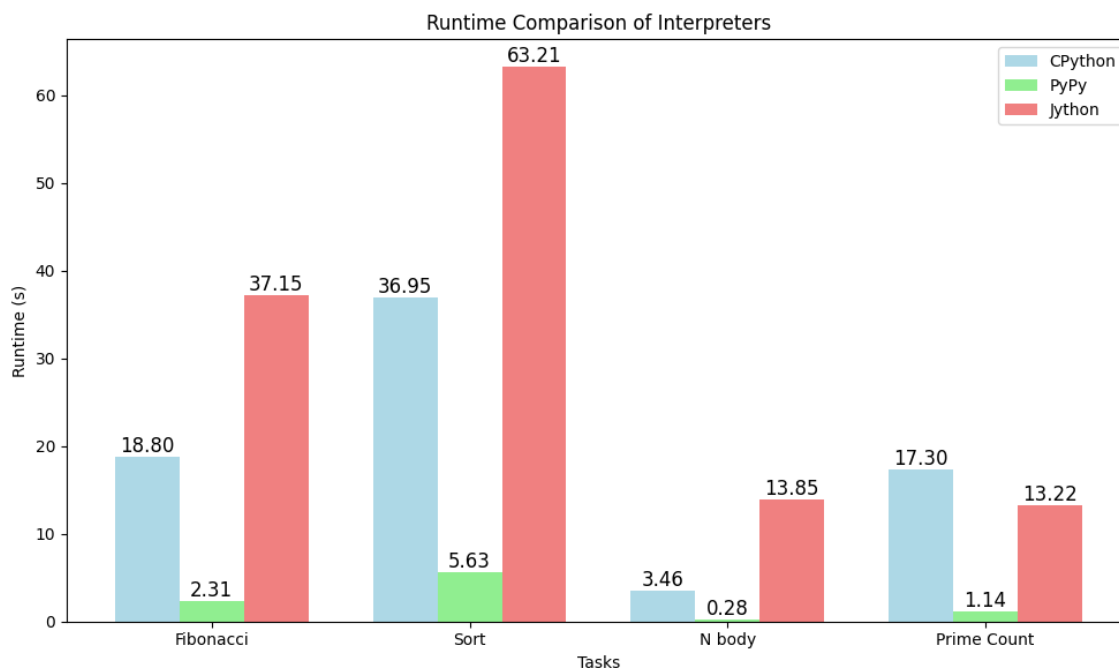


Figure 1: Comparison of runtime for CPU intensive benchmarks.

4.1.1 CPU intensive benchmarks

We observe that for computationally heavy scripts, PyPy offers best execution time offering 9 – 10 \times improvement over CPython while Jython performs worse for most of the tasks. From Figure 1, we observe that Jython takes $\approx 2 - 3\times$ longer to execute compared to CPython except for Prime Number benchmark where it executes faster. [\[Divyu: Why is that? We can look up and add some insights. What other insights can we give?\]](#)

PyPy’s JIT (Just in Time) compilation speeds up CPU bound computations optimizing frequently executed code. Moreover, integers and floats are stored and manipulated as python objects whereas PyPy avoids this and can execute raw machine-level arithmetic further improving runtime. Jython is slower in performance than CPython mainly because of longer warm-up time as it converts the python code to Java bytecode which is executed on Java Virtual Machine.

4.1.2 I/O intensive benchmarks

The improvements of PyPy over CPython vanishes for I/O intensive tasks. From Figure 2, we can see that PyPy performs similar or even worse for I/O intensive tasks compared to CPython and the difference in performance of CPython and Jython is even more. [\[Divyu: no anomaly in the graph here.\]](#)

I/O operations rely more on system calls and external process rather than python’s execution speed. As a result, the JIT compiler cannot optimize these calls making I/O operations in PyPy as slow or even slower than in CPython. Moreover, the built-in buffering mechanism in CPython are highly optimized and can outperform PyPy’s implementation in some cases. Jython performs even worse for I/O intensive benchmarks as it requires converting the script to Java bytecode and then running on JVM introducing overhead. Moreover, CPython has additional advantage over Jython as it has been tuned for I/O operations over the years using native C libraries.

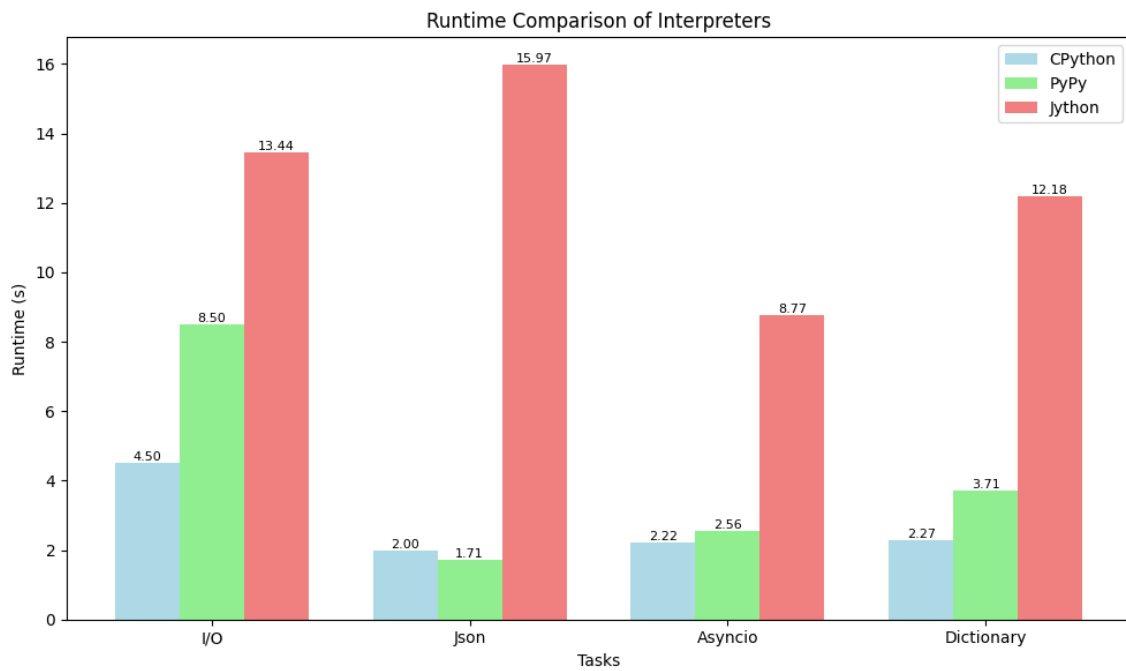


Figure 2: Comparison of runtime for I/O intensive benchmarks.

4.2 Comparison of Memory Usage

[Divyu: There will be one graph shown below. Two paragraphs similar to above. I will put only the benchmarks which use up some memory and not all benchmarks. Then I think we can have a last section Conclusion where we can summarize our observation - which interpreter is better for which task - maybe we can also generate a table from gpt outlining when to use each interpreter.]



Figure 3: Caption

References

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