Performance Profiling in Python

Network vs CPU Bottlenecks Analysis

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***Abstract*—This technical report presents a case study on Python profiling techniques to identify and distinguish between I/O-bound and CPU-bound performance bottlenecks. Two scenarios were analyzed, downloading weather station data from NOAA servers (I/O-bound) and computing distances between geographic stations (CPU-bound). Using tools such as cProfile, SnakeViz, and line_profiler, to demonstrate how proper profiling enables targeted optimization strategies.**

I Section 2.1: Network / I-O Profiling

I-A What I Did

I executed a Python script that downloads weather data from NOAA servers for multiple stations and years. I compared two versions:

- **Without cache** (`load.py`): downloads data every time from NOAA servers.
- **With cache** (`load_cache.py`): checks if file exists before downloading using `os.path.exists()`, reusing previously downloaded files.

Commands executed:

First run (without cache):

```
python3 -m cProfile -s cumulative load.py
    01044099999,02293099999 2021 2021 > profile.txt
```

Second run (with cache):

```
python3 -m cProfile -s cumulative load_cache.py
    01044099999,02293099999 2021 2021 > profile_cache.
    txt
```

I-B Results

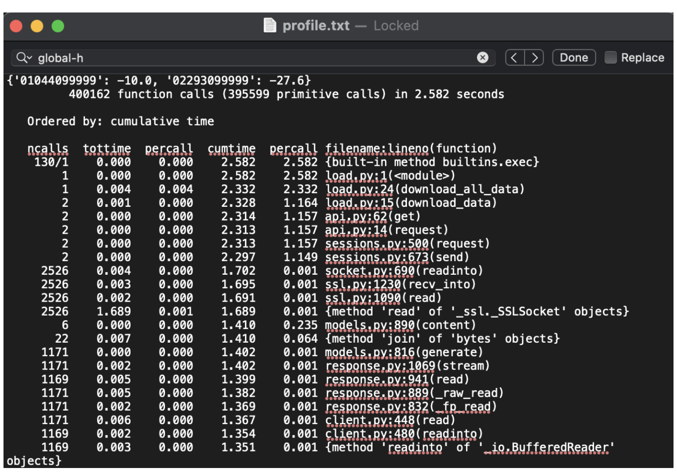

Fig. 1. cProfile results without caching - showing high requests.get time

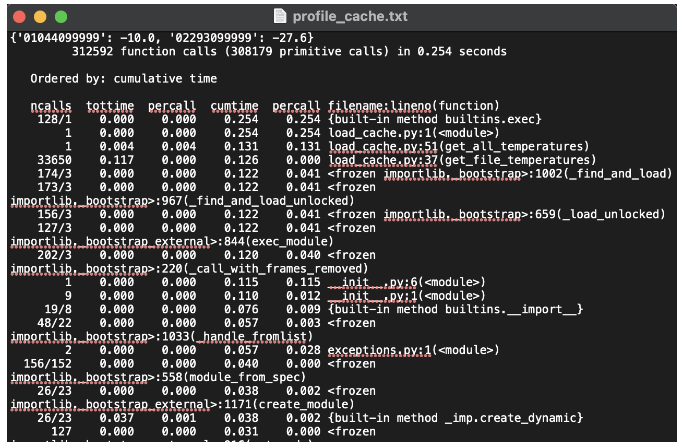

Fig. 2. cProfile results with caching - showing reduced network calls

I-C Observations and Interpretation

Most of the time was spent in:

- `requests.get()` - HTTP requests to NOAA servers
- SSL socket reads and network I/O operations

After implementing caching:

- Execution time decreased significantly on subsequent runs
- Network calls reduced to zero for already-downloaded files

This demonstrates a clear **I/O-bound process**, where performance depends primarily on network speed and latency rather than computational capacity. The simple file existence check (`os.path.exists()`) eliminated redundant downloads and dramatically improved performance.

II Section 2.2: CPU Profiling

II-A What I Did

I cloned the code repository from the book:

```
git clone https://github.com/tiagoantao/python-
    performance
```

The relevant code is located in `02-python/sec2-cpu/`.

I computed pairwise distances between weather stations using geographic coordinates with the Haversine formula. This operation has $O(n^2)$ complexity, making it computationally intensive.

Tools used:

- `cProfile`: High-level performance overview
- `SnakeViz`: Visualization of profiling results
- `line_profiler`: Per-line performance analysis

Execution steps:

Step 1: Generate profiling file

```
python3 -m cProfile -o distance_cache.prof
     distance_cache.py
```

Step 2: Visualize with SnakeViz

```
python3 -m snakeviz distance_cache.prof
```

Step 3: Line profiling

```
python3 -m kernprof -l lprofile_distance_cache.py
python3 -m line_profiler lprofile_distance_cache.py.
     lprof
```

II-B Results

Fig. 3. Terminal after running cProfile

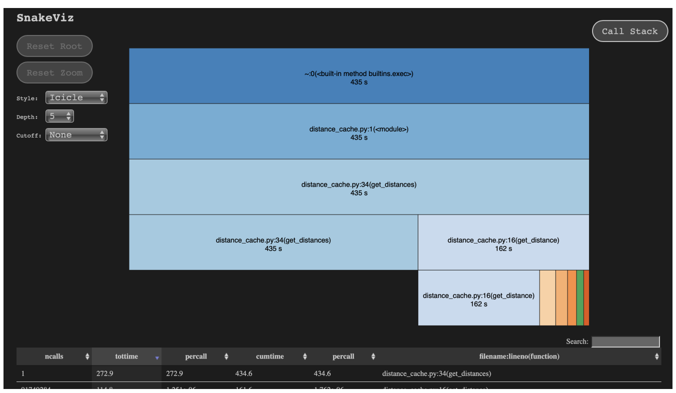

Fig. 4. SnakeViz visualization showing time distribution

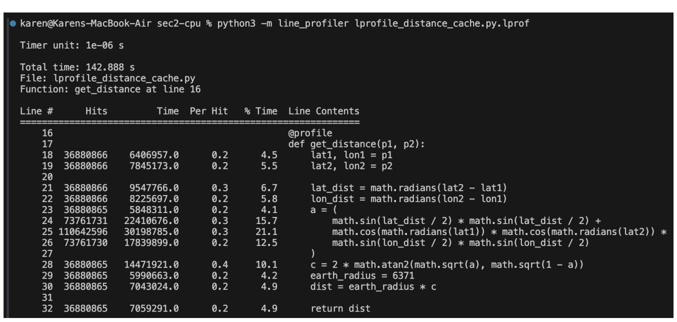

Fig. 5. Line profiler output showing bottleneck lines

Key metrics:

- Total execution time: 142.888 seconds
- Function analyzed: `get_distance()`
- Total calls per line: ∼36.8 million
- Algorithm complexity: O(n²)

TABLE I
MOST EXPENSIVE LINES IN GET_DISTANCE()

Line	Operation	% Time
24	`math.cos(radians(lat1)) * math.cos(...)`	21.1%
23	`math.sin(lat_dist / 2) * math.sin(...)`	15.7%
25	`math.sin(lon_dist / 2) * math.sin(...)`	12.5%
28	`math.atan2(...)`	10.1%

II-C Observations and Interpretation

Majority of execution time spent in mathematical operations:

- Trigonometric functions (`math.sin`, `math.cos`)
- Repeated `math.radians()` conversions
- `math.atan2()` calculations

Lines 23-25 combined account for nearly 50% of total execution time. The bottleneck is heavy computation repeated millions of times. Each operation is fast (approximately 0.2-0.4 microseconds), but 36+ million calls create significant overhead.

This confirms a **CPU-bound problem**. Unlike Section 2.1, this slowdown is not related to waiting for external resources, but to:

- Pure computation with intensive mathematical operations
- Algorithmic complexity: O(n²) means calculations grow quadratically
- Pattern: *Small cost* × *Massive repetition* = *Major bottleneck*

III Conclusions

Key findings:

- Profiling tools are essential to identify bottleneck origins before optimization
- I/O-bound tasks benefit from caching and reducing redundant operations (Section 2.1)
- CPU-bound tasks require algorithmic or implementation-level optimization (Section 2.2)
- Visual tools (SnakeViz) and line profiling provide targeted insights
- Scaling up is mostly about swapping slow O(n²)) logic for faster (O(n) solutions.

References

[1] T. Antao, *Fast Python: High Performance Techniques for Large Datasets*. Manning Publications, 2023, ch. 2, pp. 18-28.