

L4: Experimental Design, Profiling, and Performance/Energy Optimization

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1. Experimental Design, Profiling, and Performance/Energy Optimization
2. Experimental Methodology
3. Plotting Tools
4. Profiling

Experimental Design, Profiling, and Performance/Energy Optimization

In the following slides, you will be shown a series of plots; mainly taken from the PPN course reports of previous students.

For each plot:

- Try to understand what is represented
- Explain what you observe
- Give a **definitive** conclusion from the data shown

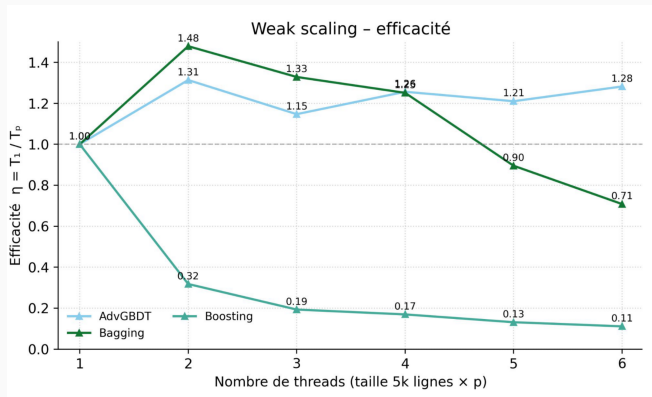
Raise your hands when ready to propose an explanation.

Plot Example (1)



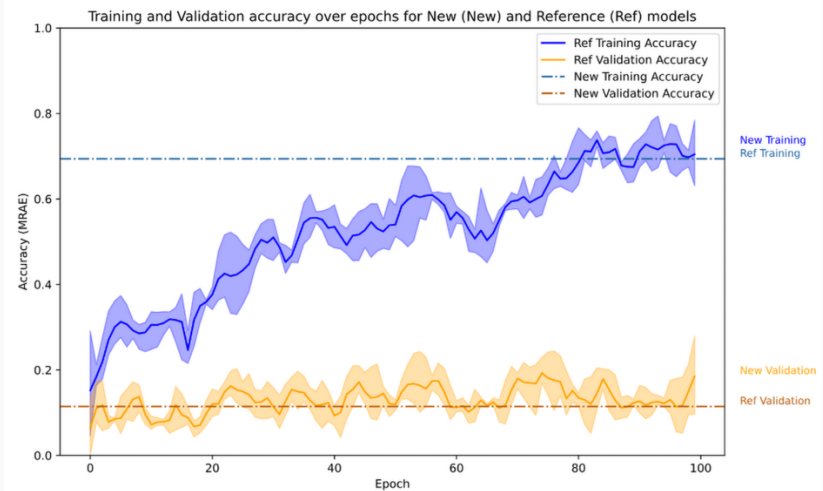
PPN Example - (No Caption)

Plot Example (2)



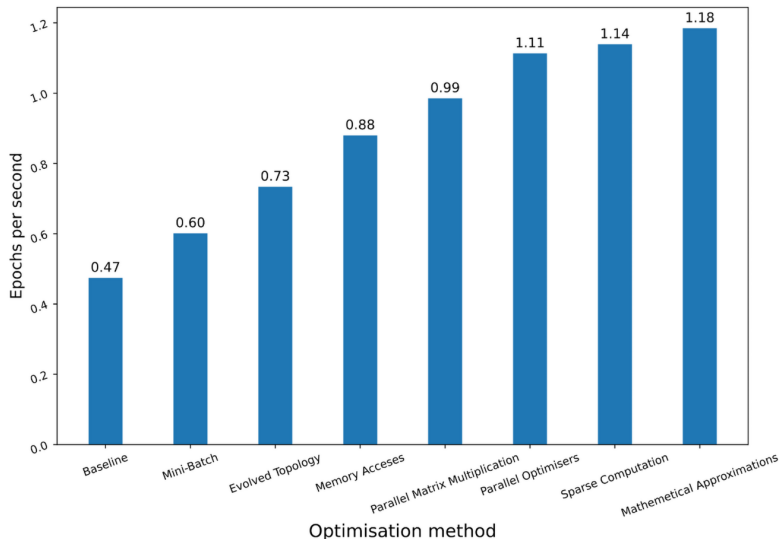
PPN Example - (No Caption)

Plot Example (3)



PPN Example - (No Caption)

Plot Example (4)



PPN Example - "Récapitulatif des optimisations faites"

Plot Example (5)



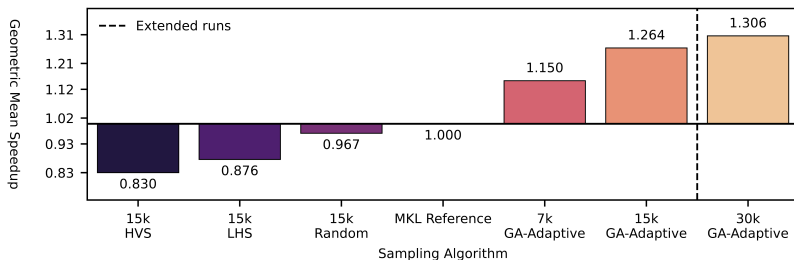
PPN Example - "Nouveau tracé de la latence cache"

Plot Example (6)



Prof Example - (KNM): (a) Speedup map of GA-Adaptive (7k samples) over the Intel MKL hand-tuning for `dgetrf` (LU), higher is better. (b) Analysis of the slowdown region (performance regression). (c) Analysis of the high speedup region. 3,000 random solutions were evaluated for each distribution.

Plot Example (7)



Prof Example - (SPR): Geometric mean Speedup (higher is better) against the MKL reference configuration on `dgetrf` (LU), depending on the sampling algorithm. 46x46 validation grid. 7k/15k/30k denotes the samples count. GA-Adaptive outperforms all other sampling strategies for auto-tuning. With 30k samples it achieves a mean speedup of $\times 1.3$ of the MKL `dgetrf` kernel.

Ask yourself:

- What do I want to communicate ?
- What data do I need ?
- Is my plot understandable in ~10 seconds ?
- Is my plot self-contained ?
- Is the context, environment, and methodology clear ?

HPC is a scientific endeavour; data analysis and plotting are essential.

- Plots drive decisions
- Plots make results trustworthy
- Plots explain complex behaviors

Datasets are large, multi-disciplinary, and often hard to reproduce.

Experimental Methodology

Experimental Methodology - Workflow



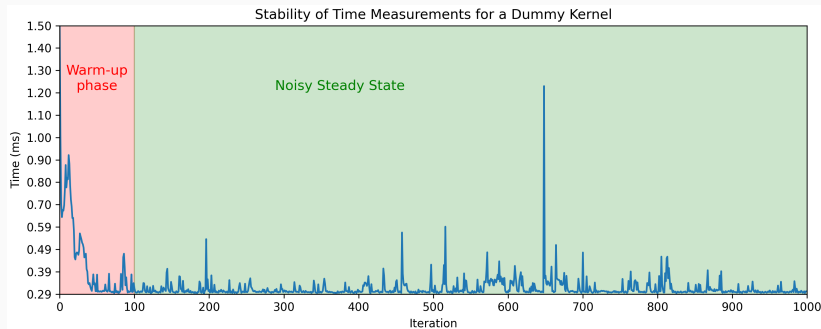
Computers are noisy, complex systems:

- Thread scheduling is non deterministic -> runtime varies between runs.
- Dynamic CPU frequency (Turbo/Boost)
- Systems are heterogeneous (CPU/GPU, dual socket, numa effects, E/P cores)
- Temperature/thermal throttling can alter runtime

How can we make sure our experimental measurements are reliable and conclusive?

Statistical significance - Warm-up effects

Systems need time to reach steady-state:



On a laptop: Mean = 0.315 ms, CV = 13.55%

We need “warm-up” iterations to measure stable performance and skip cold caches, page faults, frequency scaling.

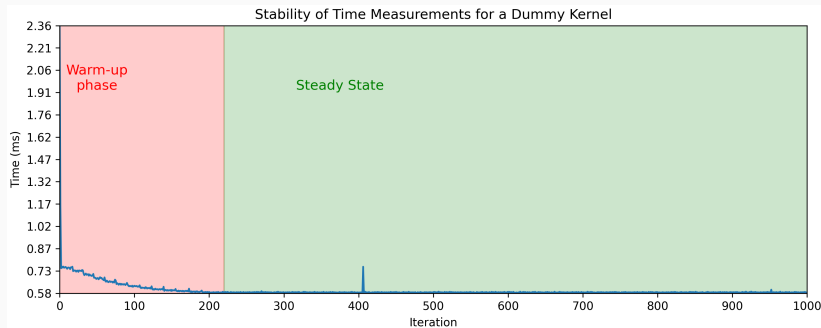
Noise can only be mitigated:

- Stop all other background processes (other users)
- Stabilize CPU Frequency (`sudo cpupower -g performance`)
 - Make sure laptops are plugged to avoid powersaving policies
- Pin threads via `taskset`, `OMP_PLACES` and `OMP_PROC_BIND`
- Consider hyperthreading
- Use stable compute nodes

Meta-repetitions are essential to mitigate noisy measurements.

Statistical significance - Example

Same experiment on a stabilized benchmarking server:



On a laptop: Mean = 0.315 ms, CV = 13.55%

Stabilized node: Mean = 0.582 ms, CV = 1.14%

Note

Timing on a laptop is always subpar

Statistical significance - Mean, Median, Variance

Single-run measurements are misleading; we need statistics.

- Mean runtime $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$
- Median: less sensitive to outliers than the mean
- Variance/standard deviation: Measure of uncertainty
- Relative metrics are useful: Coefficient of variation
($CV = \frac{\sigma}{\bar{x}} \times 100\%$)

We usually give both the mean and standard deviation when giving performance results. Plots usually show $\bar{x} \pm 1\sigma$ as a shaded region around the mean to represent uncertainty.

Note

Distribution plots can be useful: stable measurements are often close to Gaussian, even if systematic noise may lead to skewed or heavy-tailed distributions.

Statistical significance - Confidence Intervals

How to decide how many repetitions we should perform ?

- Usually, the costlier the kernels, the less meta-repetitions are expected
- Short or really short kernels should have more metas to reduce the influence of noise

Remember that:

$$CI_{0.95} \approx \bar{x} \pm 1.96 \cdot \frac{\sigma}{\sqrt{n}}$$

More repetitions increase confidence, but returns diminish:

$$\text{CI width} \propto \frac{1}{\sqrt{n}}$$

Note

Confidence intervals are a bit less common in plots than $\pm 1\sigma$ but can also be used !

Statistical significance - p -score & Hypothesis testing

In HPC, mean/median and variance often suffice, but hypothesis testing can become handy in some contexts.

- Null hypothesis (H_0): GPU and CPU have the same performance for small matrixes
 - Differences in measurements are **only** due to noise
- Alternative hypothesis: CPU is faster for small matrixes
- **p -value** is the probability that H_0 explains a phenomenon.
- If $p < 0.05$, we can safely reject H_0 (Statistically significant difference)

Example: $\bar{x}_{GPU} = 5.0s$, $\sigma_{GPU} = 0.20$, $\bar{x}_{CPU} = 4.8s$, $\sigma_{CPU} = 0.4$,
Two-sample t-test with 10 samples $p = 0.02$.

The measured differences between CPU and GPU execution time are **statistically significant**.

Reproducibility is a very hot topic (Reproducibility crisis in science):

- **Data and protocols are first-class citizens:** as important as the plots themselves
- **Transparency matters:** make data, scripts, and parameters accessible
- Enables others to **verify, build on, and trust your results**

Note

Beware of your mindset: your results should be credible and honest before being “good”.

“Our results are unstable, we have yet to understand why, this is what we tried” is a completely valid answer

Plotting Tools

Profiling
