

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

M. Jam, P. de Oliveira Castro

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

Experimental Design, Profiling, and Performance/Energy Optimization

Plot Example - Intro

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)

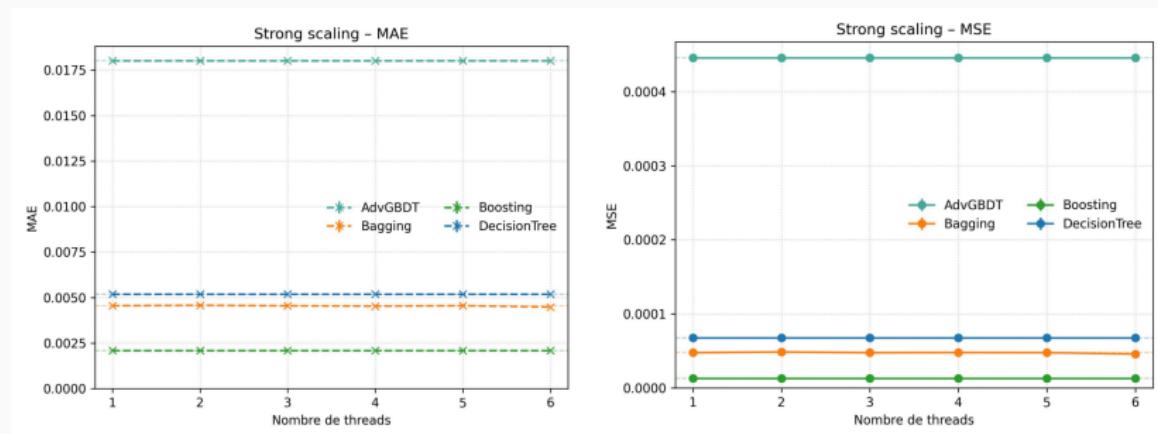


Figure 1: PPN Example - (No Caption)

Plot Example (2)

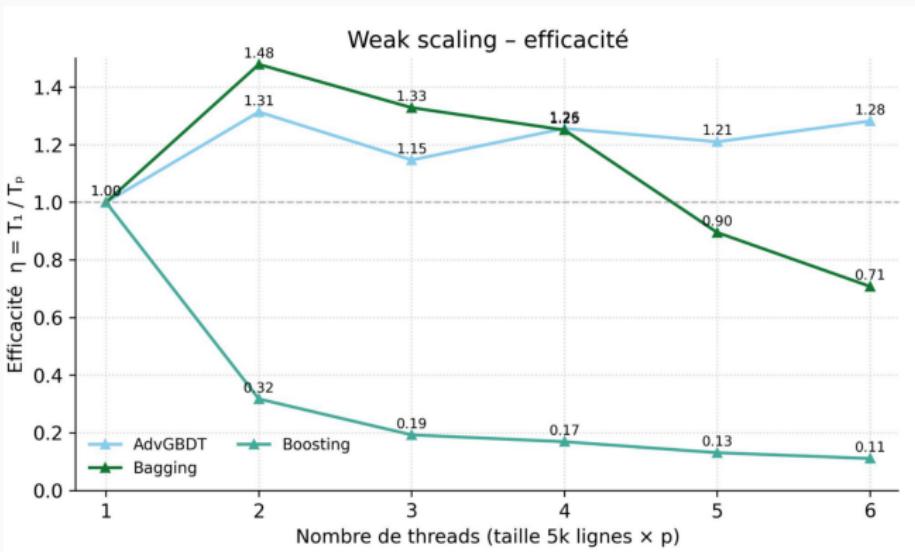


Figure 2: PPN Example - (No Caption)

Plot Example (3)

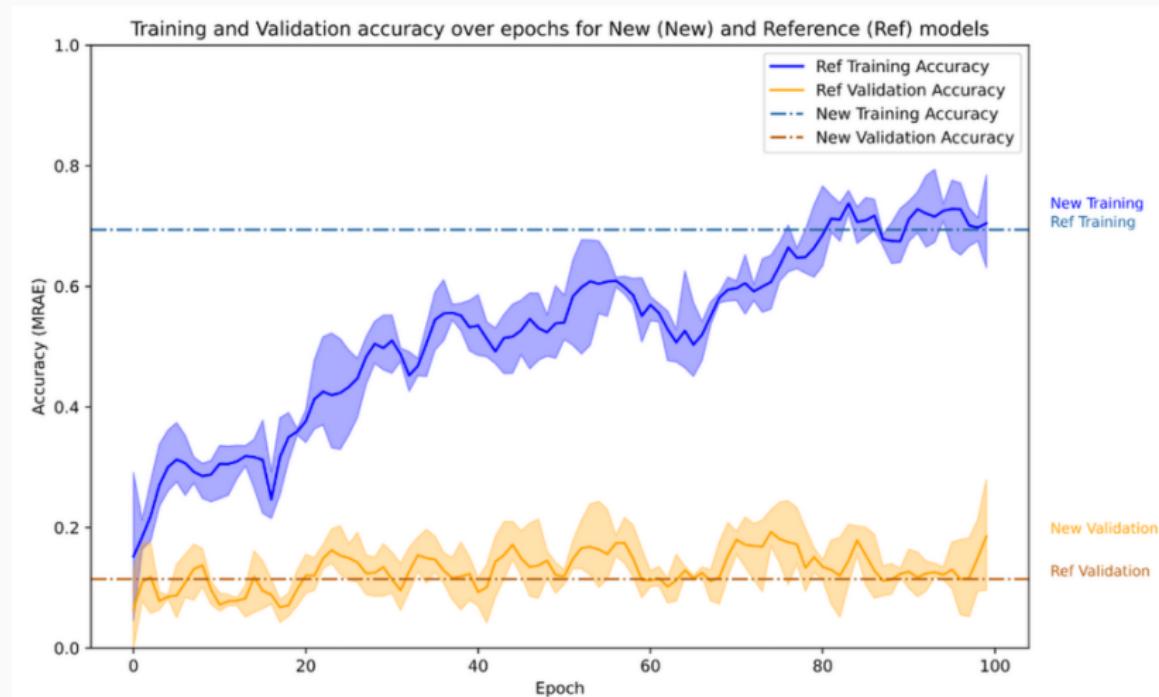


Figure 3: PPN Example - (No Caption)

Plot Example (4)

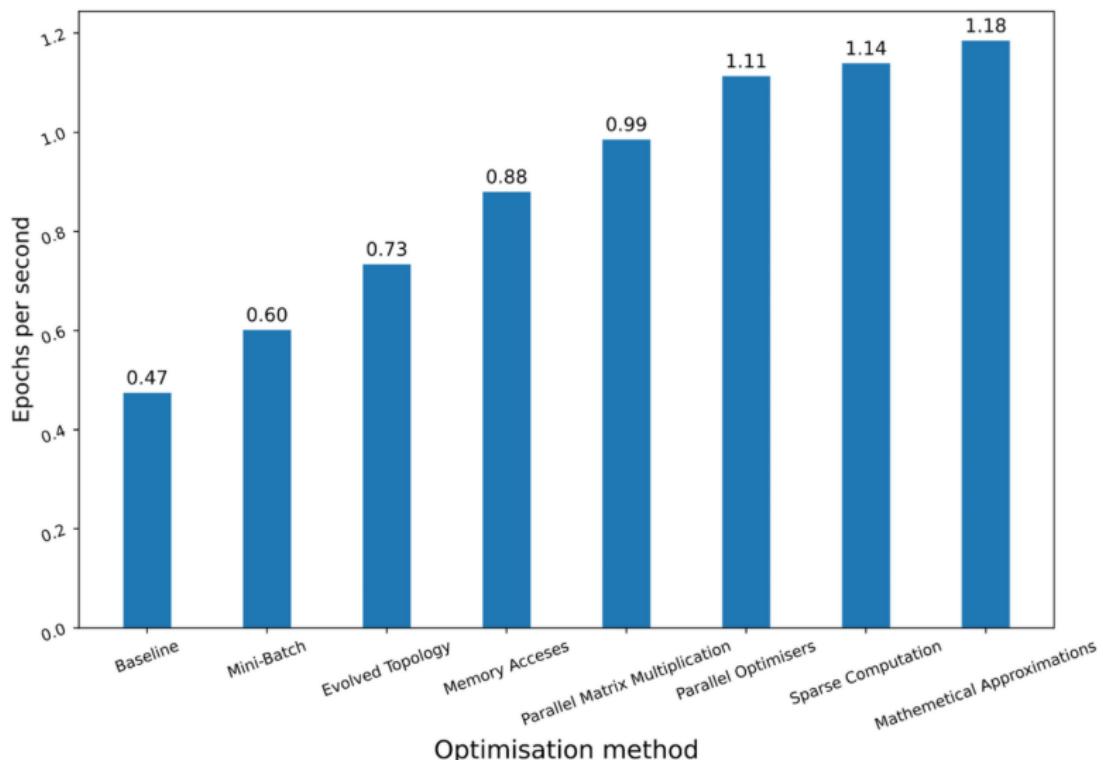


Figure 4: PPN Example - “Récapitulatif des optimisations faites”

Plot Example (5)

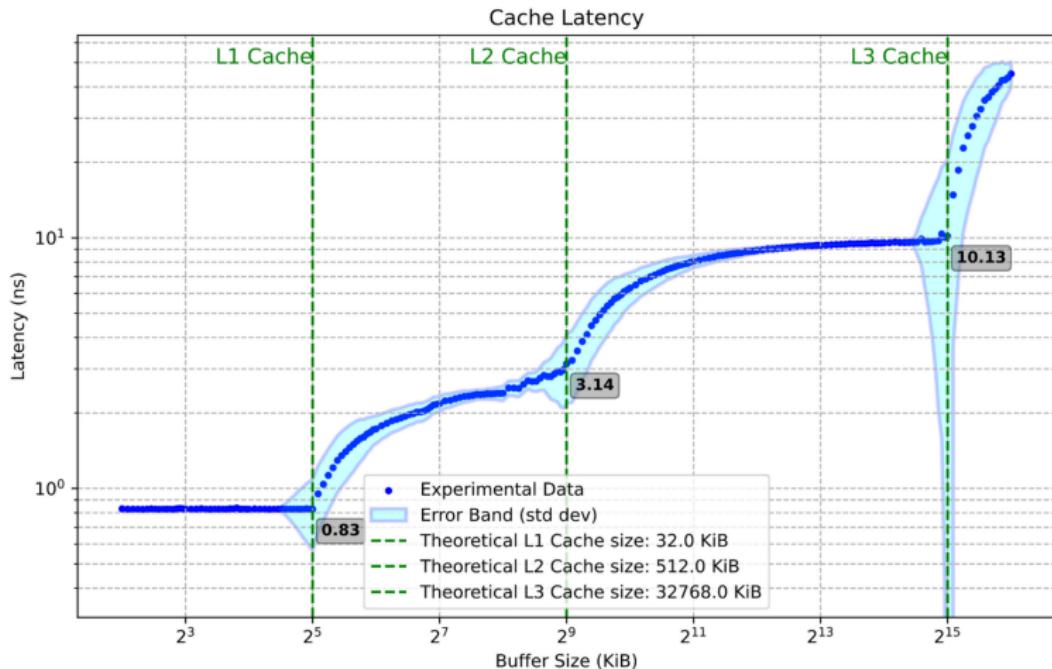


Figure 5: PPN Example - “Nouveau tracé de la latence cache”

Plot Example (6)

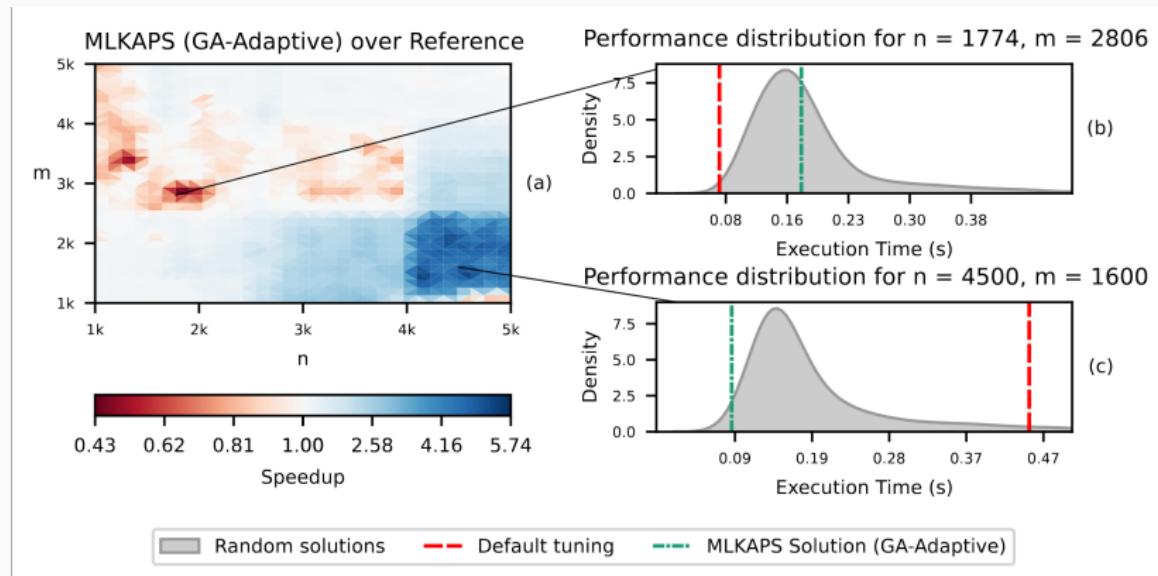


Figure 6: Prof Example - (KNM): (a) Speedup map of GA-Adaptive (7k samples) over the Intel MKL hand-tuning for `dgetrf` (LU), higher is better. (b) Analysis of the slowdown region (performance regression). (c) Analysis of the high speedup region. 3,000 random solutions were evaluated for each distribution.

Plot Example (7)

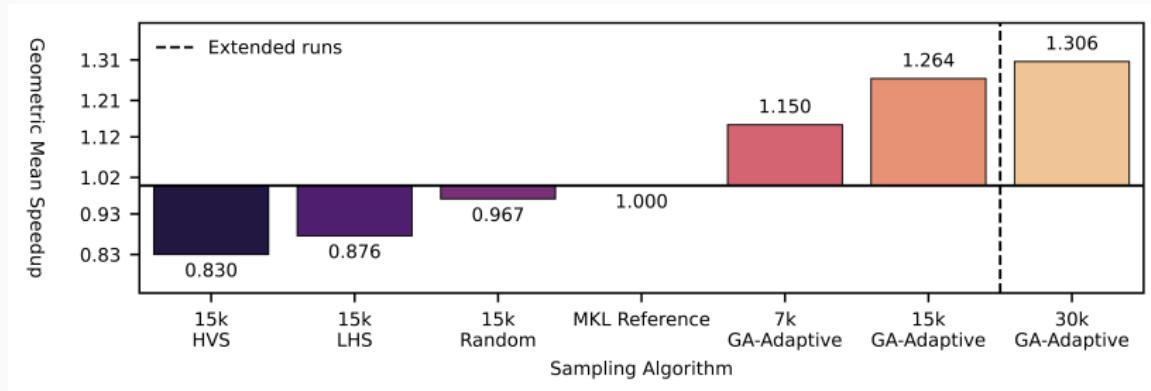


Figure 7: Prof Example - (SPR): Geometric mean Speedup (higher is better) against the MKL reference configuration on dgetrf (LU), depending on the sampling algorithm. 46x46 validation grid. 7k/15k/30k denotes the samples count. GA-Adaptive outperforms all other sampling strategies for auto-tuning. With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

Plot Example - Summary

HPC is a scientific endeavour; data analysis and plotting are first class citizens.

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

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

Plot Example - What makes a good plot

Ask yourself:

- Who am I speaking to ?
- What's my narrative?
- Is my plot understandable in ~10 seconds?
- Is my plot self-contained?
- Is the context, environment, and methodology clear?

Experimental Methodology

Experimental Methodology - Workflow



Figure 8: Typical experimental workflow

Statistical significance - Introduction

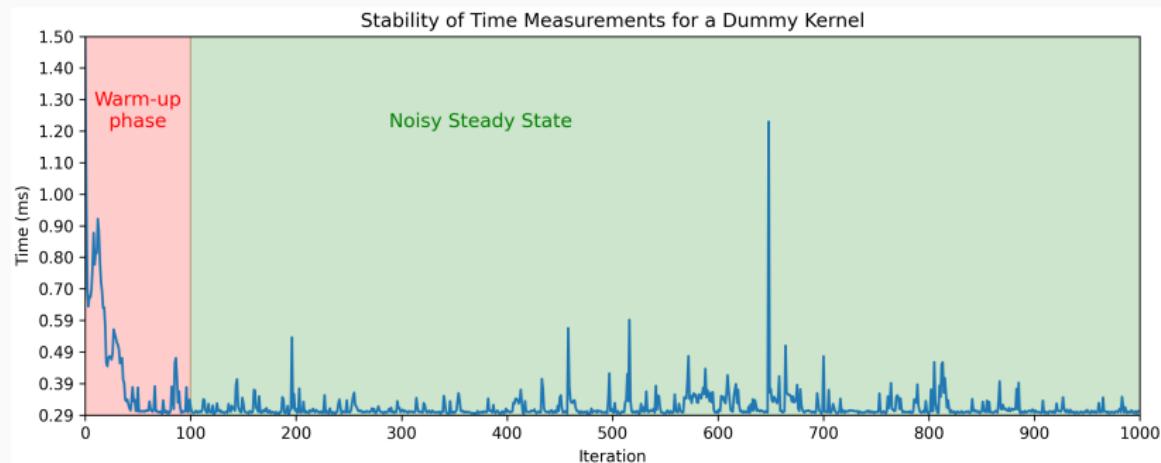
Computers are noisy, complex systems:

- 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.

Statistical significance - Noise mitigation

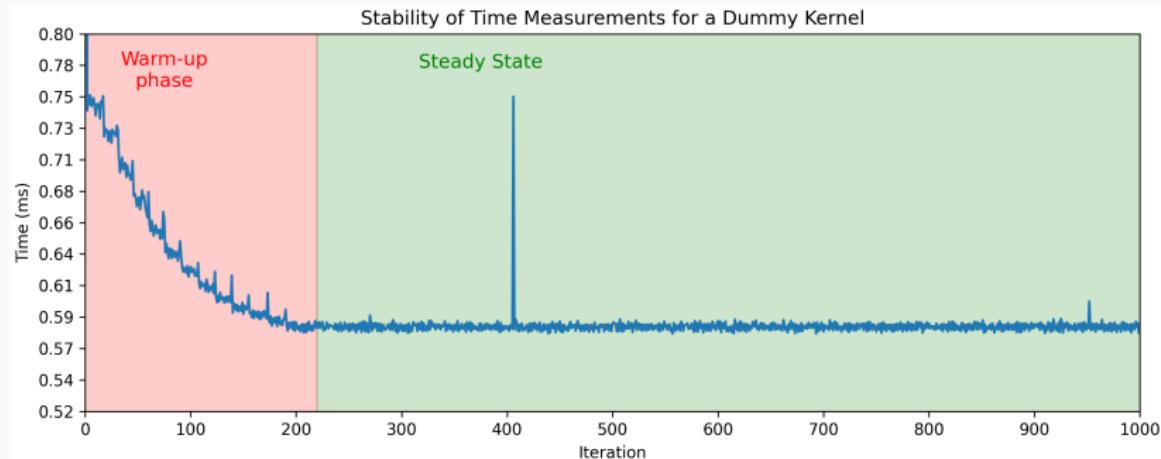
Noise can only be mitigated:

- 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.

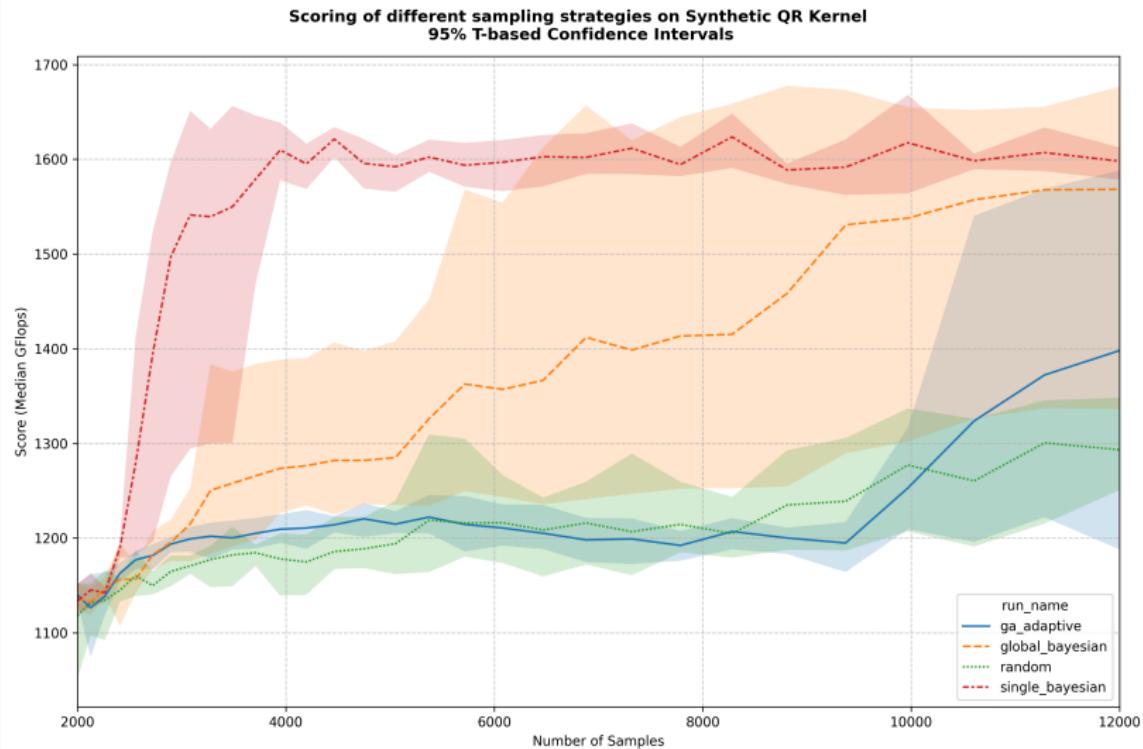
- Mean runtime $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$
- Median: less sensitive to outliers than the mean
- Variance/standard deviation: Measure of uncertainty
- Relative metrics are useful: Coefficient of variation
 $(CV = \frac{\sigma}{\bar{x}} \times 100\%)$

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



Plotting variance/uncertainty through confidence intervals can change interpretation.

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

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

Experimental Methodology – Reproducibility

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

Plotting tools - Cheetsheet

Name	Use
pandas	Storing and saving tabular data
numpy	Numerical arrays, manipulating data
matplotlib	Basic 2D plots, full control
seaborn	Statistical plots, higher-level API
logging	Logging experiment progress/results
OpenCV	Image processing, animations/videos
ffmpeg	Generating and encoding videos

Lookup the quick reference plotting gallery in the annex!
Both `matplotlib` and `seaborn` provide extensive online galleries.

[Live Example of the `matplotlib` gallery
<https://matplotlib.org/stable/gallery/index.html>]

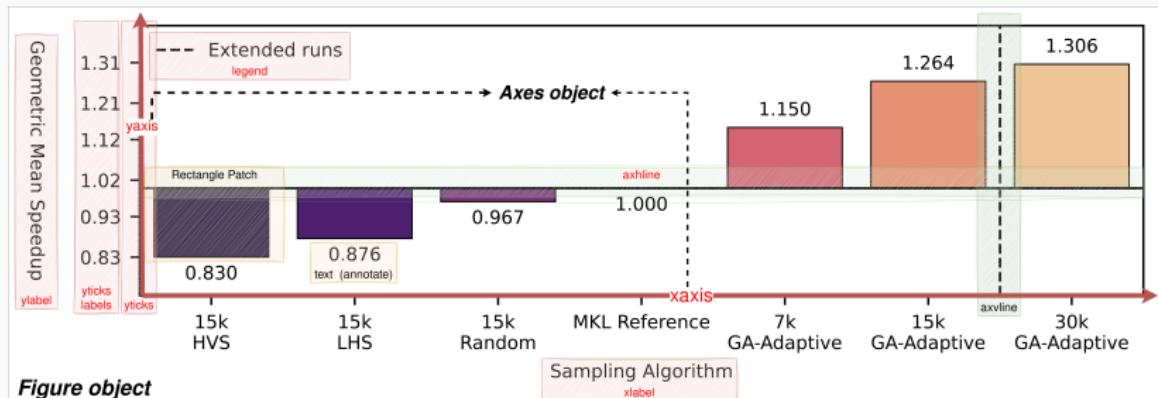
Plotting tools - Matplotlib

Matplotlib is one of the most widely used plotting libraries.
A figure is built hierarchically from nested elements:

- Figure (The canvas)
 - Subfigures
 - Axes (One or more subplots)
 - Axis (x/y/z scales, ticks, labels)
 - Artists (Lines, markers, text, patches, etc.)

- Data is plotted using axes-level functions like `ax.plot`,
`ax.histogram`
- Customization occurs at both the Figure and Axes levels
- Complex multi plots layout occur at the Figure level

Plotting tools - Matplotlib



Plotting tools - Matplotlib

```
import matplotlib.pyplot as plt

x = [0, 1, 2, 3]
y = [2.8, 5.7, 12.5, 14]

# Create a new figure, single axis
# Size is 8 inches by 8 inches, and constrained layout
fig, ax = plt.subplots(figsize=(8, 8), layout="constrained")

# Plot a simple line
ax.plot(x, y, color="red", label="My Algorithm")

# Customize the axes
ax.set_xlabel("Iteration") # Name of the X axis
ax.set_ylabel("Time (s)") # Name of the y axis
# Title of the plot
ax.set_title("Evolution of Time with the number of iteration")

ax.margins(0, 0) # Remove white spaces around the figure
ax.legend(loc="upper right") # Draw the legend in the upper right
                             corner

fig.savefig("my_plot.png", dpi=300) # Higher DPI -> bigger image
plt.close() # End the plot and release resources
```

Plotting tools - Matplotlib (Multi axis)

We can easily have multiple plots on the same figure:

```
nrows = 5, ncols = 1
fig, axs = plt.subplots(5, 1, figsize(8 * ncols, 3 * nrows))

ax = axs[0]
ax.plot()
...

ax = axs[1]
ax.plot()
...

fig.tight_layout() # Alternative to constrained layout
fig.savefig("my_muliplot.png", dpi=300)
```

Each axis is its own plot, with its own legend and artists.

Note

Use the reference (<https://matplotlib.org/stable/api/index.html>) and gallery (<https://matplotlib.org/stable/gallery/index.html>) extensively !

Plotting tools - Seaborn

Seaborn is an extension of Matplotlib dedicated to statistical visualization:

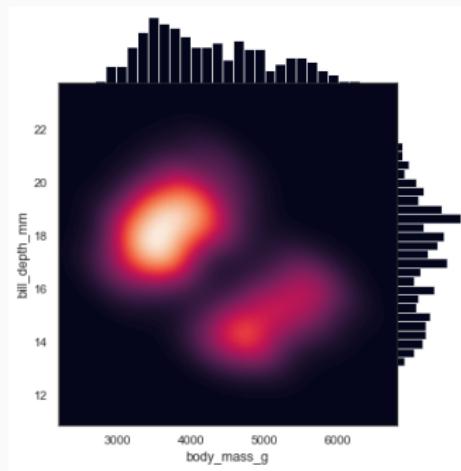


Figure 9: <https://seaborn.pydata.org/examples/index.html>

It's useful for histograms, bar charts, kdeplots, scatterplots, and is overall a very good companion library.

Plotting tools - Seaborn

```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np

df = pd.read_csv(...) # Read the dataframe from somewhere

fig, ax = plt.subplots(figsize=(8, 8), layout="constrained")

# We must pass the axis to plot on as an argument
sns.kdeplot(data=df, x="Time", label="Algorithm", color="red",
    fill=True, ax=ax)

ax.set_title("Distribution of Execution time for the algorithm")
ax.margins(0, 0)
ax.set_xlabel("Time (s)", fontweight="bold")
ax.set_ylabel("Density", fontweight="bold")

ax.set_xticks(np.linspace(df["Time"].min(), df["Time"].max(), 10)
# Format the x axis ticks: `3.25s`
ax.xaxis.set_major_formatter(StrMethodFormatter("{x:.2f}s"))

fig.savefig("my_distribution.png")
```

Profiling

Profiling - Motivation

- HPC codes are massive, complex and heterogeneous
- Humans are **bad** at predicting bottlenecks
- Don't blindly optimize everything
- Profiling guides optimization

Remember: Always profile first.

Profiling - Amdahl's law

$$\text{Speedup} = \frac{1}{1 - f + \frac{f}{S}}$$

Where f is the fraction of program improved, and S is the speedup on that fraction.

Example:

- I have optimized 80% of my application, with a speedup of x10
- In total, my application is now $\frac{1}{0.2+(0.8/10)} = 3.57 \times$ faster

The 20% are a bottleneck !

Profiling - Steps

1. Where (Hotspots) ?
 - What functions are we spending time/energy in ?
 - What call-tree are we spending time/energy in ?
2. Why ?
 - Arithmetic density, memory access patterns
 - Cache misses, branch misspredictions, vectorization efficiency (Hardware counters)
3. What goal ?
 - Should I optimize for speed ? For energy ? Memory footprint ?
 - What about cold storage size/compression ?
 - Do I have constraints (i.e. limited memory) ?
 - Should I optimize or switch algorithm ?

Profiling - Time

It's rather easy to benchmark a single function using a (high-resolution, monotonic) clock:

```
begin = time.now()  
my_function()  
end = time.now()  
elapsed = end - begin
```

Quick-and-dirty way to profile part of my program.

Profiling - Time (Stability)

But we have to account for noise:

```
for _ in range(NWarmup):
    my_function()

times = []
for i in range(NMeta):
    begin = time.perf_counter()
    my_function()
    times.append((i, time.perf_counter() - begin))

df = pd.DataFrame(times, columns=["Iteration", "Time"])

median = np.median(df["Time"])
std = np.std(df["Time"])
print(f"Time: {median} +/- {std}")

...
# Plot through seaborn !
sns.plot(data=df, x="Iteration", y="Time", ax=ax)
...
```

We must check that our measures are acceptable!

Profilers - Introduction

Full application -> Thousands of functions to measure !

- Profilers are tools to automate this
- Two main types:
 - Sampling: Pause the program and log where the program is
(Costly functions -> More samples !)
 - Instrumentation: Modify the program to automatically add timers

Profilers can also check for thread usage, vectorization, memory access, etc.

Perf - Record

Linux Perf is a powerful and versatile profiler:

```
gcc ... -g -fno-omit-frame-pointer
perf record -g -- ./mytransform ./pipelines/big.pipeline
Loaded image: images/image1.bmp (3660x4875, 3 channels)
[ perf record: Woken up 3 times to write data ]
[ perf record: Captured and wrote 0.484 MB perf.data (2941
    samples) ]
```

```
perf report
```

Children	Self	Command	Shared Object	Symbol
+	99.89%	0.00%	mytransform	mytransform [.] _start
+	99.89%	0.00%	mytransform	libc.so.6 [.] __libc_start_main@@GLIBC_2.34
+	99.89%	0.00%	mytransform	libc.so.6 [.] __libc_start_call_main
+	99.89%	0.00%	mytransform	mytransform [.] main
-	98.95%	0.00%	mytransform	mytransform [.] execute_graph
- execute_graph				
	+ 38.06%	save_image		
	+ 19.96%	load_image		
	+ 13.11%	quantize_image_naive		
	+ 10.97%	execute_node		
	+ 8.96%	convert_to_grayscale		
	5.87%	__roundf		
	2.02%	roundf@plt		
+	38.06%	2.71%	mytransform	mytransform [.] save_image
+	26.80%	13.18%	mytransform	mytransform [.] stbiw_outfile.constprop.0

Profiling - Hardware counters

In reality, perf is not just a profiler !

- The Linux Perf API can be used to access many hardware counters
- Perf record is just one usage of perf

Most CPUs/GPUs have hardware counters that monitors different events:

- Number of cycles
- Number of retired instructions
- Number of memory access
- RAPL energy counters

Profiling - Perf for Hardware counters

```
perf stat -e cycles,instructions python3 ./scripts/run_bls.py ...
...
Performance counter stats:
    749,352,412,722      cpu_core/cycles/
    3,142,707,494,308      cpu_core/instructions/      #
        4.19  insn per cycle

            32.363472139 seconds time elapsed
            225.351168000 seconds user
            0.111367000 seconds sys
```

- 4.19 instruction per cycle -> Very good vectorization
- time elapsed -> “Wall clock time”
- seconds user -> CPU time in user space -> $225/30 \approx 7$ threads !

Profiling - Perf for Hardware counters

```
perf stat -e cache-references,cache-misses python3 ./scripts/
    run_bls.py ...
...
Performance counter stats:
      394,258,269      cpu_core/cache-references/
      36,823,151      cpu_core/cache-misses/          #
  9.34% of all cache refs

      32.363472139 seconds time elapsed
      225.351168000 seconds user
      0.111367000 seconds sys
```

- 394,258,269 references to the LLC (On Intel)
- 36,283,151 LLC misses -> 9.3% miss rate

Profiling - Perf for Hardware counters

```
perf stat -e branches,branch-misses python3 ./scripts/run_bls.py
...
...
Performance counter stats:
    761,974,570,065      cpu_core/branches/
    248,674,718      cpu_core/branch-misses/      #
  0.03% of all branches

            32.363472139 seconds time elapsed
            225.351168000 seconds user
              0.111367000 seconds sys
```

- 761,974,570,065 execution flow breaks (ifs, returns, loops, etc.)
- 248,674,718 branch misses -> Good branch prediction! (0.9 miss rate)

Perf - Record with other events

We can also use `perf record` with other events !

```
perf record -e "cache-references,cache-misses,branches,branch-misses" -g -- ./mytransform ./pipelines/big.pipeline
Loaded image: images/image1.bmp (3660x4875, 3 channels)
[ perf record: Woken up 7 times to write data ]
[ perf record: Captured and wrote 1.709 MB perf.data (10260 samples) ]
```

```
perf report
```

Samples	Children	Self	Command	Shared Object	Symbol
+ 100.00%	0.00%	mytransform	mytransform	[.]	_start
+ 100.00%	0.00%	mytransform	libc.so.6	[.]	__libc_start_main@@GLIBC_2.34
+ 100.00%	0.00%	mytransform	libc.so.6	[.]	__libc_start_call_main
+ 100.00%	0.00%	mytransform	mytransform	[.]	main
- execute_graph					
		59.21%	quantize_image_naive		
+ 22.88%			load_image		
+ 9.93%			save_image		
7.82%			__roundf		
+ 59.21%	59.20%	mytransform	mytransform	[.]	quantize_image_naive

Perf is a bit “barebone”: many profilers build upon perf like Intel VTune

Hotspots

Analysis Configuration Collection Log Summary Bottom-up Caller/Callee Top-down Tree Flame Graph Platform

Elapsed Time: 2.710s

- CPU Time: 2.520s
- Total Thread Count: 1
- Paused Time: 0s

Top Hotspots

This section lists the most active functions in your application. Optimizing these hotspot functions typically results in improving overall application performance.

Function	Module	CPU Time	% of CPU Time
quantize_image_naive	mytransform	1.430s	56.7%
roundf32	ibm.so.6	0.770s	30.6%
func@0x400420	mytransform	0.190s	7.5%
_IO_fread	ibc.so.6	0.031s	1.2%
convert_interleaved_to_plane	mytransform	0.030s	1.2%
[Others]	N/A*	0.069s	2.7%

*N/A is applied to non-measurable metrics.

Effective CPU Utilization Histogram

This histogram displays a percentage of the wall time the specific number of CPUs were running simultaneously. Spin and Overhead time adds to the Idle CPU utilization value.

Effective Time

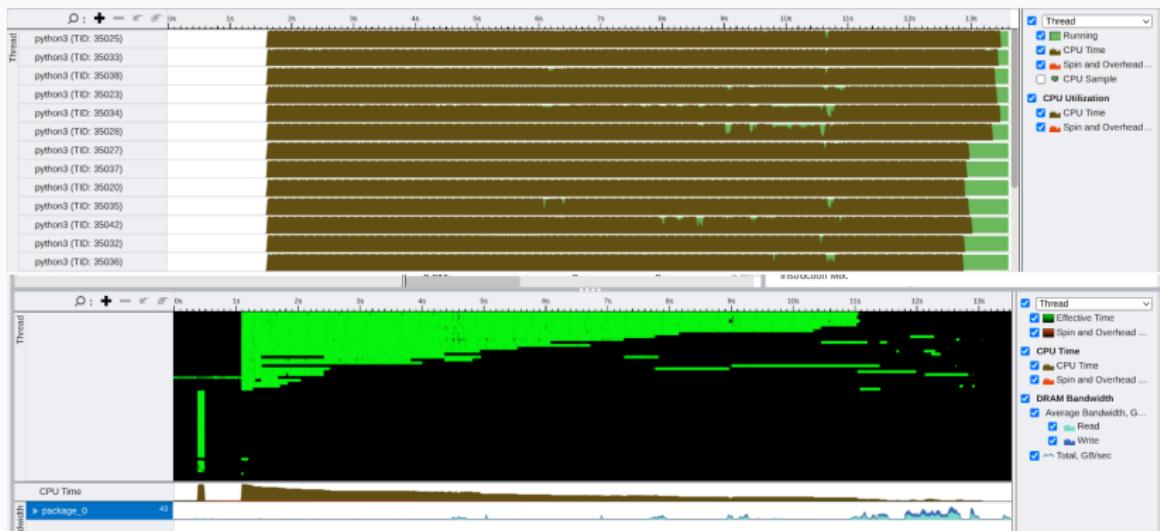
Processor

Target Utilization

Idle

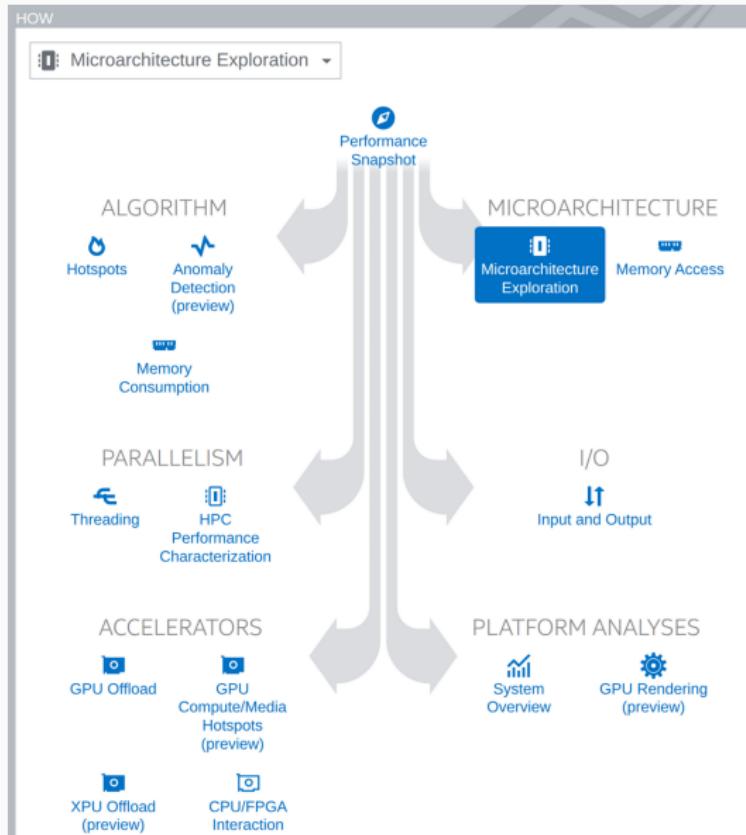
Granularity: 0.1 Millisecond (10ms)

VTune - CPU Usage



VTune - Collections Mode

VTune has multiple collection mode:



VTune - HPC Performance

VTune has multiple collection mode:

Effective Physical Core Utilization^①: 4.9% (0.973 out of 20) ↗

Effective Logical Core Utilization^②: 3.5% (0.971 out of 28) ↗

Effective CPU Utilization Histogram

Memory Bound^③: 6.4% of Pipeline Slots ↗

Performance-core (P-core):

Memory Bound^④: 6.4% of Pipeline Slots

Efficient-core (E-core):

Memory Bound^④: 0.0% of Clockticks

*N/A is applied to metrics with undefined value. There is no data to calculate the metric.

Bandwidth Utilization Histogram

Vectorization^⑤: 0.0% of Packed FP Operations ↗

Instruction Mix:

SP FLOPs^⑥: 4.7% of uOps

DP FLOPs^⑥: 0.0% of uOps

x87 FLOPs^⑥: 0.0% of uOps

Non-FP^⑥: 95.3% of uOps

Metrics were collected from Big Cores only.

Top Loops/Functions with FPU Usage by CPU Time ↗

This section provides information for the most time consuming loops/functions with floating point operations.

Function	CPU Time ^⑦	% of FP Ops ^⑧	FP Ops: Packed ^⑨	FP Ops: Scalar ^⑩	Vector Instruction Set ^⑪	Loop Type ^⑫
[Loop at line 157 in quantize_image_naive]	1.316s	4.9%	0.0%	100.0%		
roundf32	0.643s	4.9%	0.0%	100.0%	SSE2(128)	
func@0x400420	0.233s	6.3%	0.0%	100.0% ↗		

*N/A is applied to non-summable metrics.

Other profilers

- MAQAO is a profiler developed by the LIPARAD
- AMD, NVIDIA and ARM have their own profilers for their platforms
- And many, many others (likwid, gprof, etc.)

Usually, we combine a “quick” profiler like gprof/perf record with a more indepth one when needed.

Energy is a growing concern:

- One HPC cluster consume millions of dollars in electricity yearly
- ChatGPT and other LLM are computationally intensive:
 - Nvidia GPUs consumes lots of energy

On the flip side, measuring energy is harder than measuring time.

Many actors still focus on execution time only -> Energy is perceived as "Second rank"

Profiling - RAPL

Running Average Power Limit (RAPL) is an x86 hardware counter that monitors energy consumption:

- Energy is tracked at different level
 - Core, Ram, Package, GPU, etc.
- It does not account for secondary power consumers (Fans, Water cooling, etc.)
- RAPL is not event based: The entire machine is measured ! (Background processes, etc.)

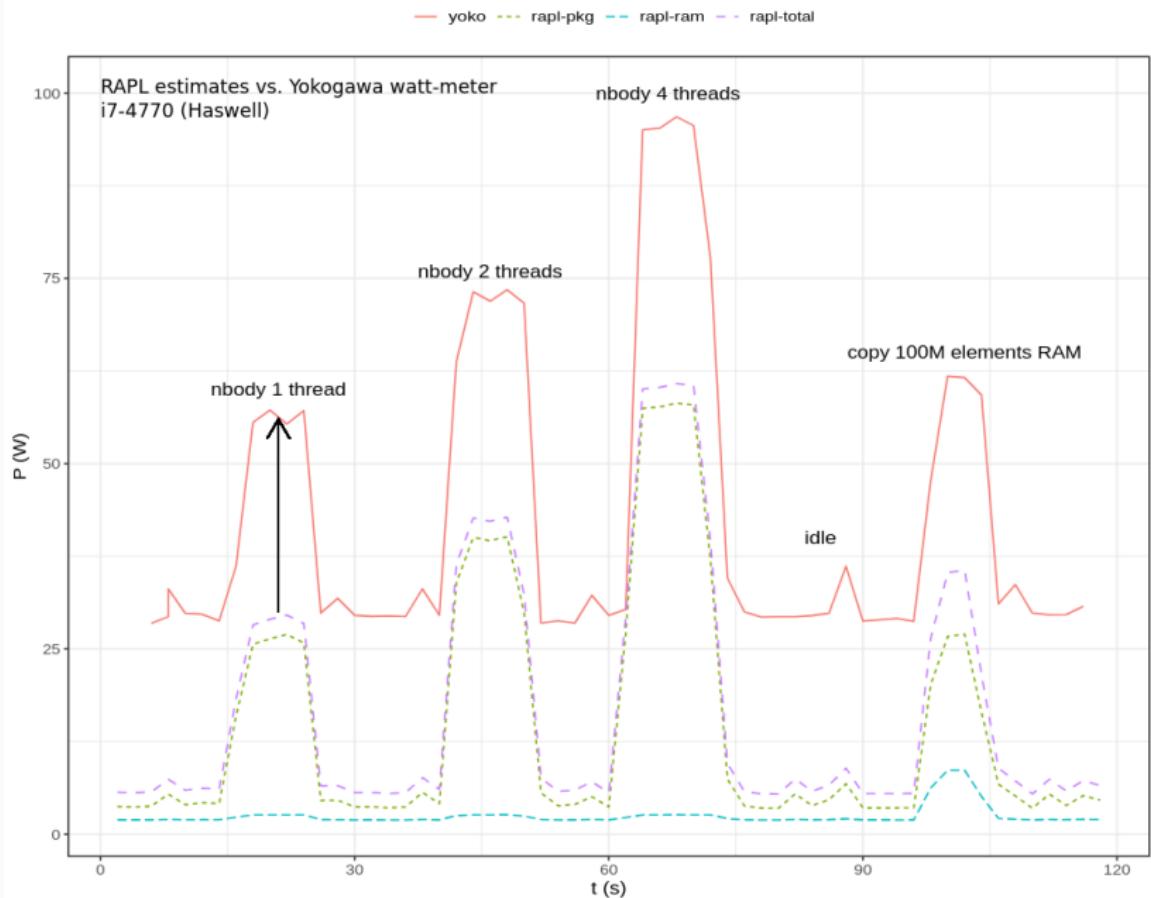
It requires sudo permissions to access (compared to a clock)

```
perf stat -a -j -e power/energy-pkg,power/energy-cores <app>
{"counter-value" : "88.445740", "unit" : "Joules", "event" : "power/energy-pkg/", "event-runtime" : 10002168423, "pcnt-running" : 100.00}
{"counter-value" : "10.848633", "unit" : "Joules", "event" : "power/energy-cores/", "event-runtime" : 10002166697, "pcnt-running" : 100.00}
```

Profiling - Watt-Meter (Yokogawa)



Profiling - RAPL accuracy



Live Demo

Experiment example

Annex/run_experiment.sh

Annex/model_convergence.py