LEAPS League of European Accelerator-based Photon Sources

European HDF User Group summit
GPU processing of HDF5 data

Jérôme Kieffer
ESRF

Introduction

- Profile of a typical data reduction workflow
- Efficient multi-threading in Python ?
- Offloading processing to GPU
- And what about compression ?

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Credit :
Marco Cammarata
ESRF ID18

Profile of a reduction workflow

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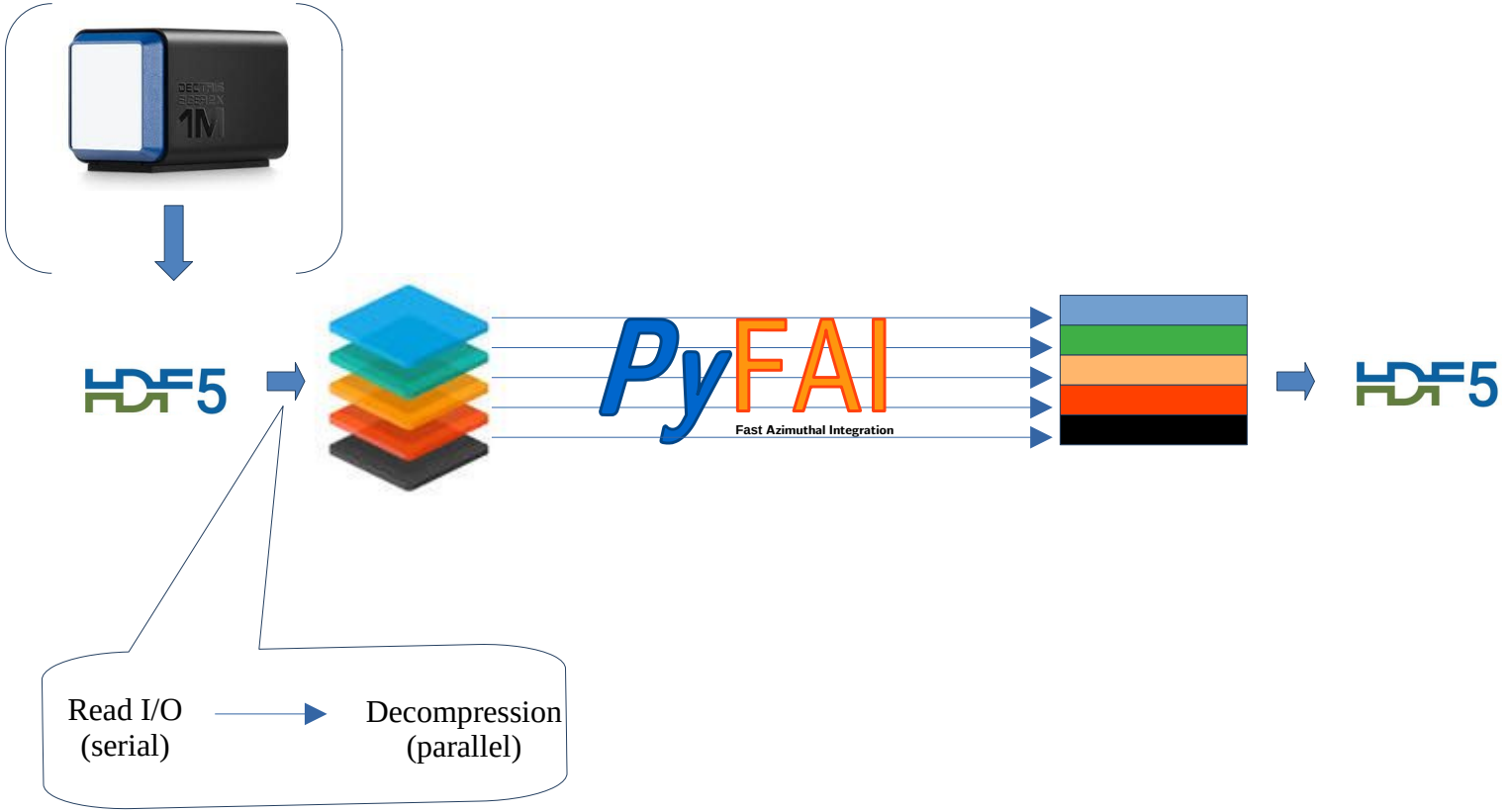

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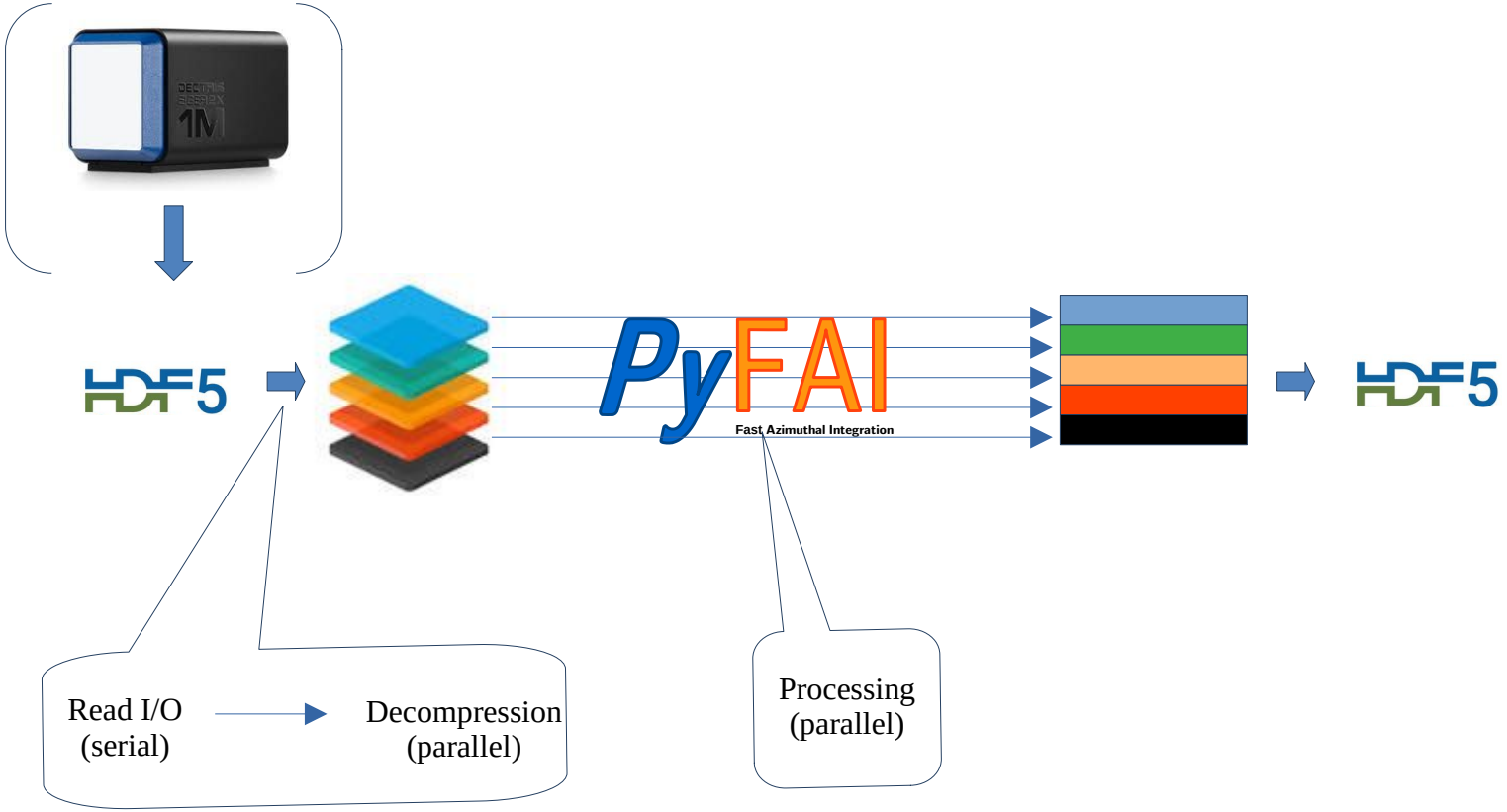

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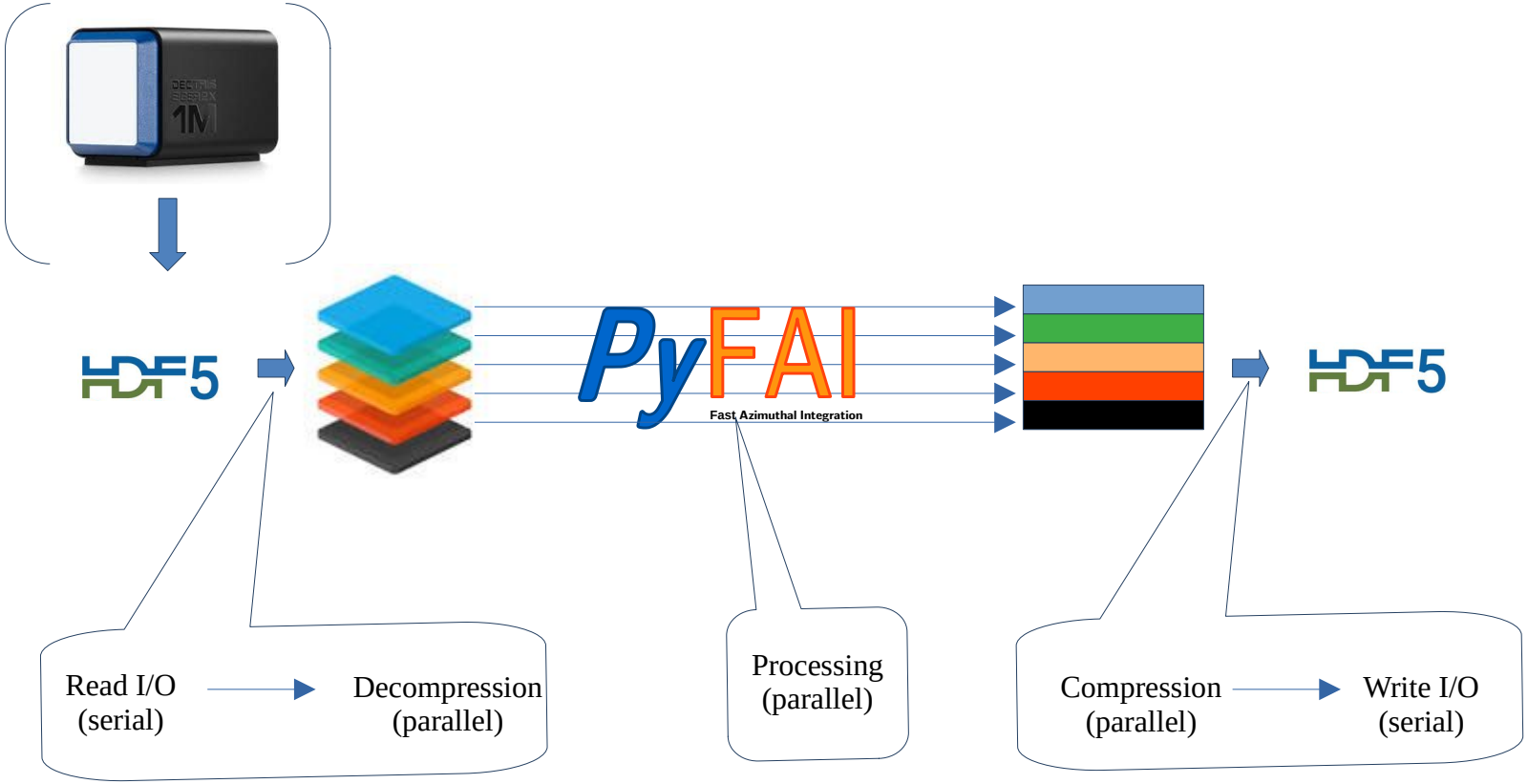

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Actual profiling from Python (h5py)

Setup:

- Computer: 2 x 32-core AMD EPYC 75F3
- Images: Eiger 4M (2070x2167, uint32), 4000 images
- Storage format: HDF5 bitshuffle-LZ4
- Reduction: 1D azimuthal integration 1000 bins (CSR, full split)

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Performances	Read	Process	Read+Process
Serial (1t)	184 fps	25 fps	14 fps
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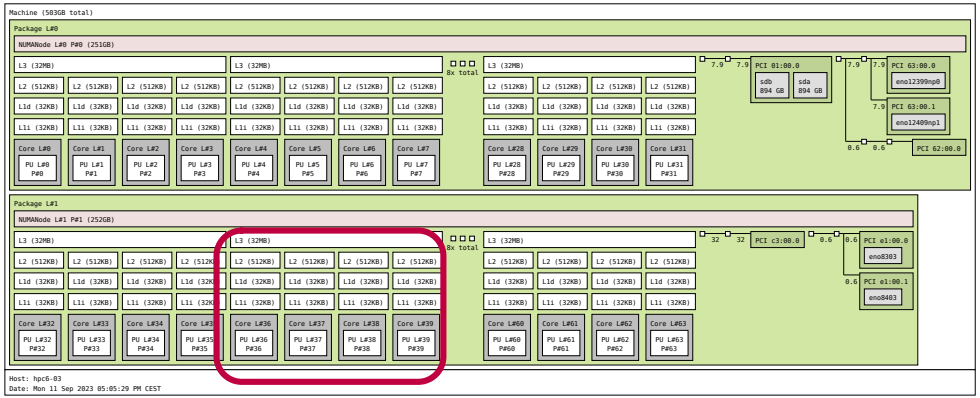

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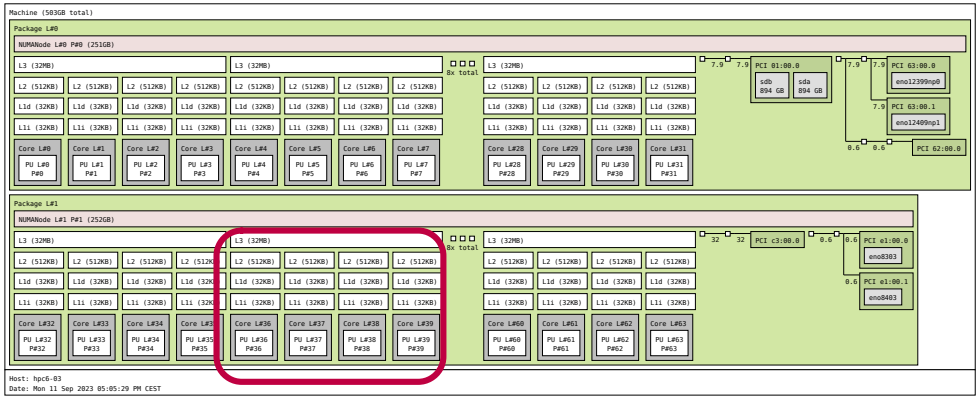

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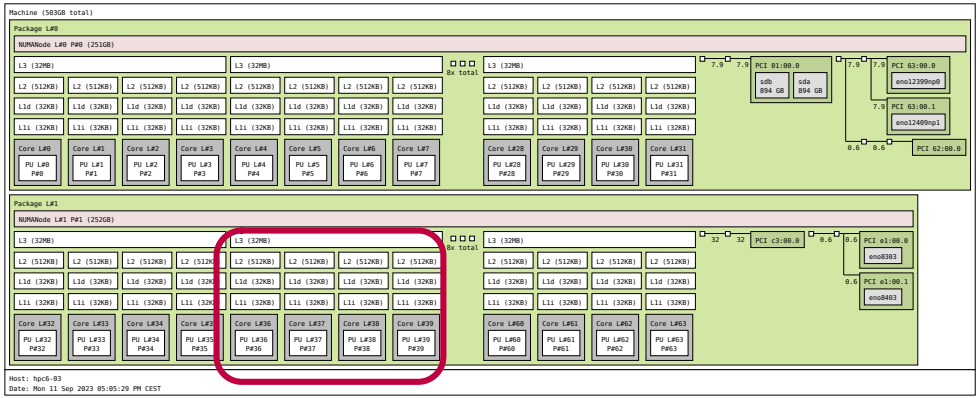

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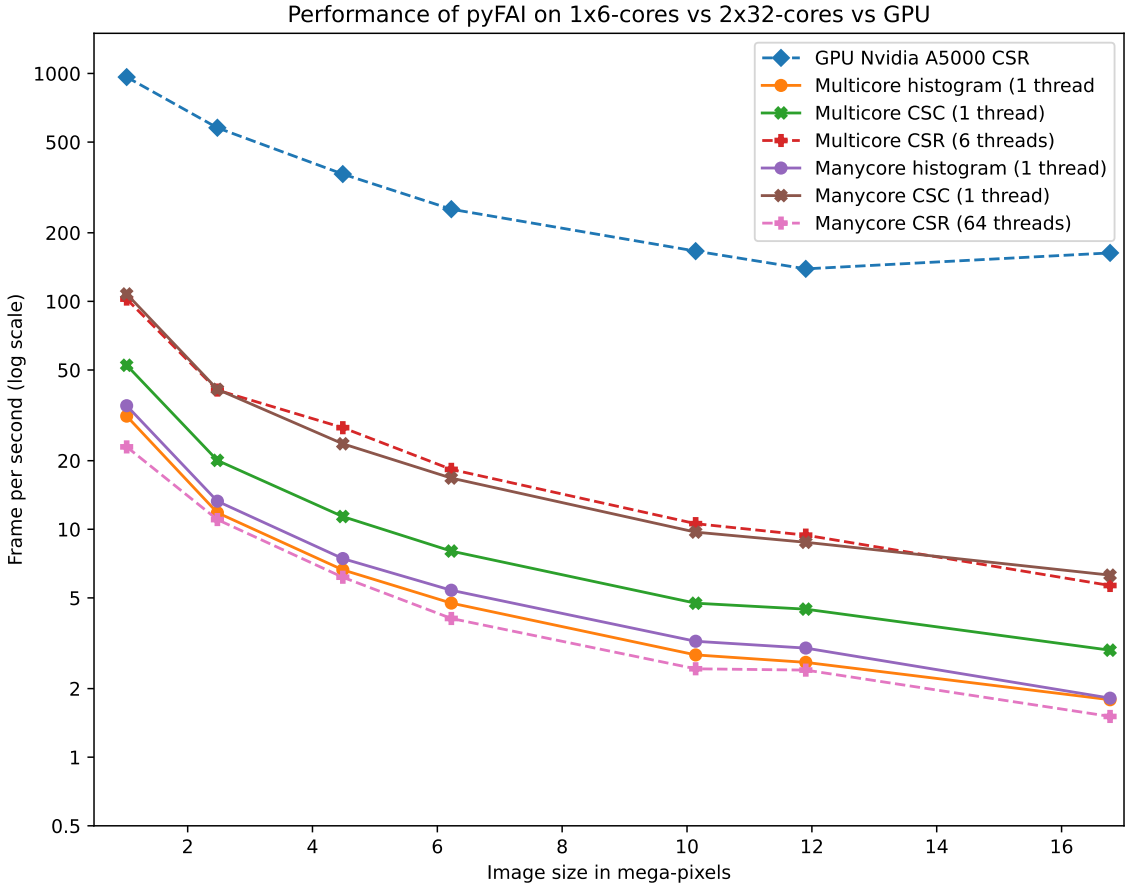

Manycore: Dual AMD EPYC 75F3, 64 cores (2021)
Multicore: Single Intel Xeon E5-1650 v4, 6 cores (2016)

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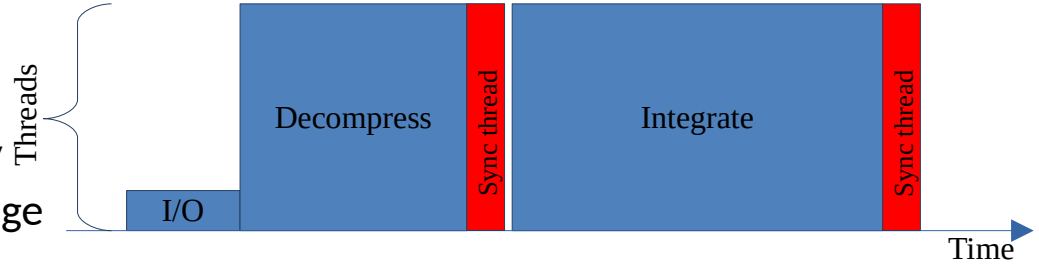

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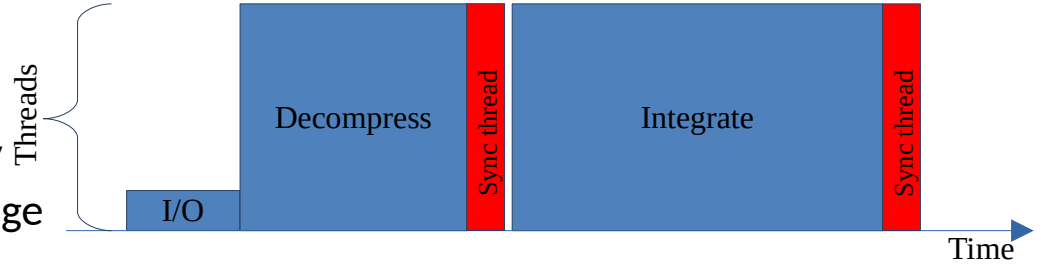

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  - One thread processes one or several images at once
    - Disable OpenMP in decompression algorithm (default in *hdf5plugin now)*
    - Decompress data and integrate image within the same thread
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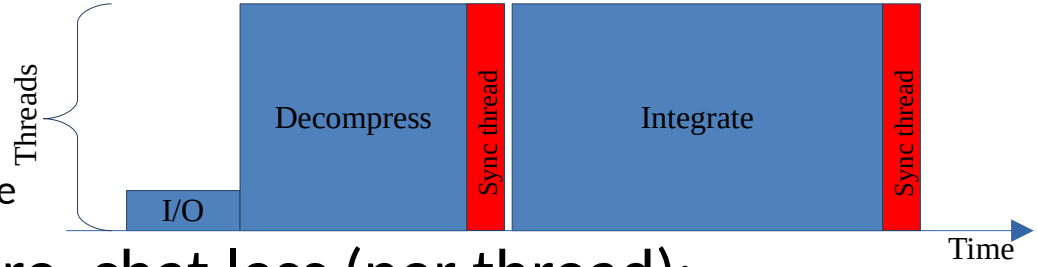

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- Issue: Python Global Interpreter Lock

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- All together:
  - In a simple python function: 22 fps

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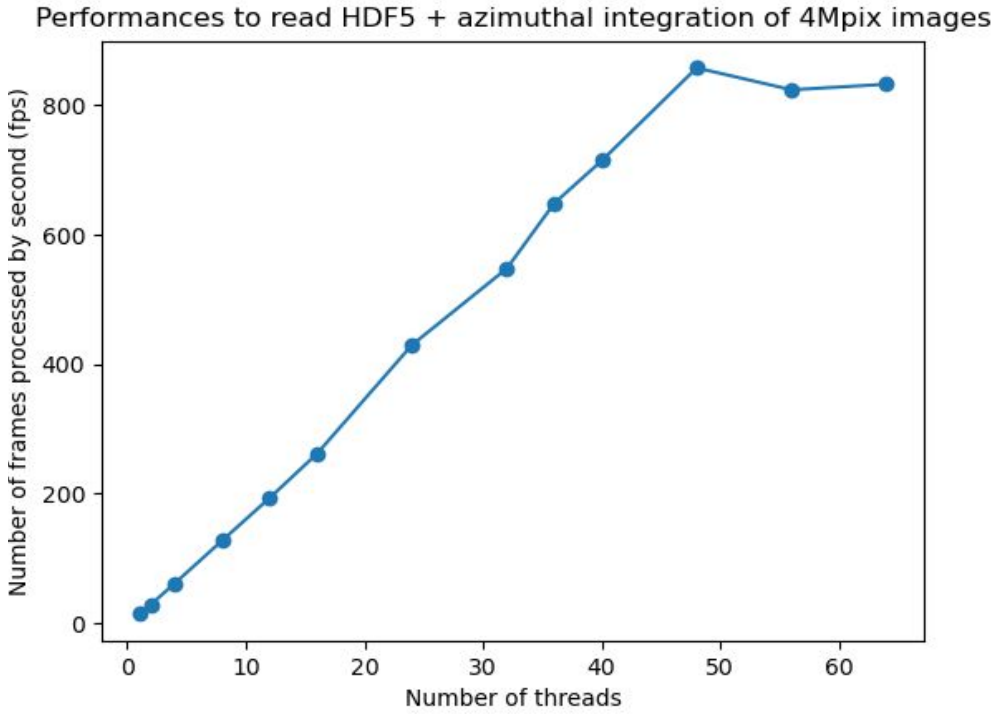

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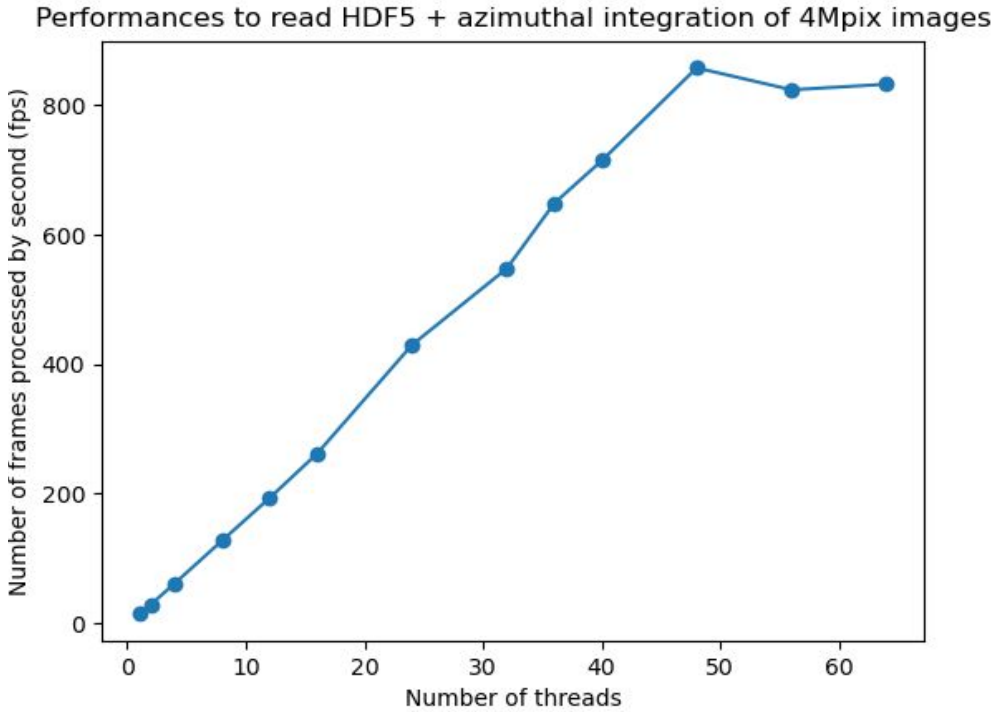

- Works efficiently when most code is GIL-free like:
  - Bitshuffle-LZ4 decompression
  - Sparse matrix multiplications

Conclusion: Multi-threading

- Many-cores do not behave nicely with OpenMP
  - Visible on multi-socket system and all AMD EPYC (NUMA)
  - Hdf5plugin has now disabled OpenMP by default !
  - Performances can be much worse than no parallelization
- A pool of thread outperforms OpenMP
  - Requires more code (100 loc instead of 10)
  - Scales linearly up to ~40 cores (22 → 850fps).
- Multi-processing is also an option
  - Serialization issue

What about GPUs ?

GPU data reduction

- Processing:
  - PyFAI runs on GPU since 2012 (published 2014)
    - Implemented in OpenCL
      - Tested on CPU & GPU Nvidia, Intel, AMD, …
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  - OpenCL
    - 2022: silx implements a LZ4 decompressor and bitshuffling
    - 2023: compressor work on LZ4 ongoing

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- CSR sparse matrix dense vector multiplication
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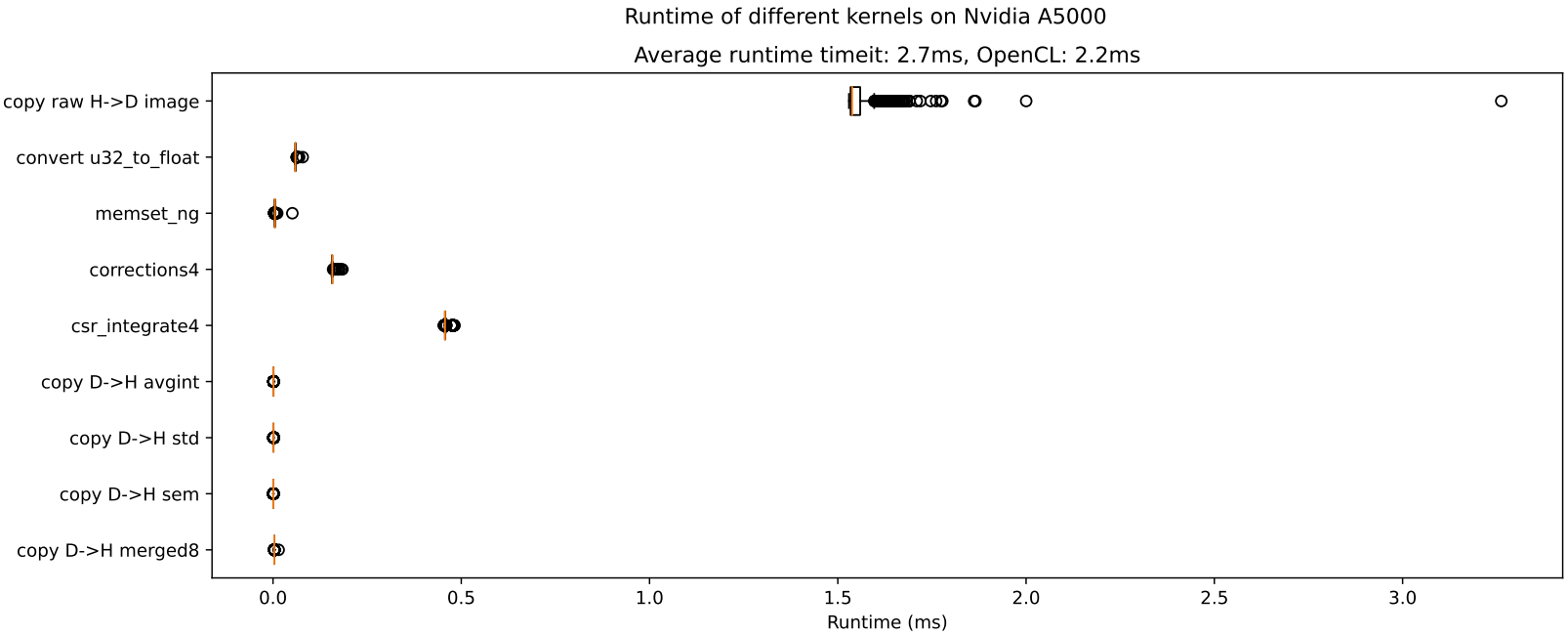
- Double precision emulated using double-float
  - http://www.theses.fr/2017LYSEN036

Profiling of GPU azimuthal integration



- Parameters:
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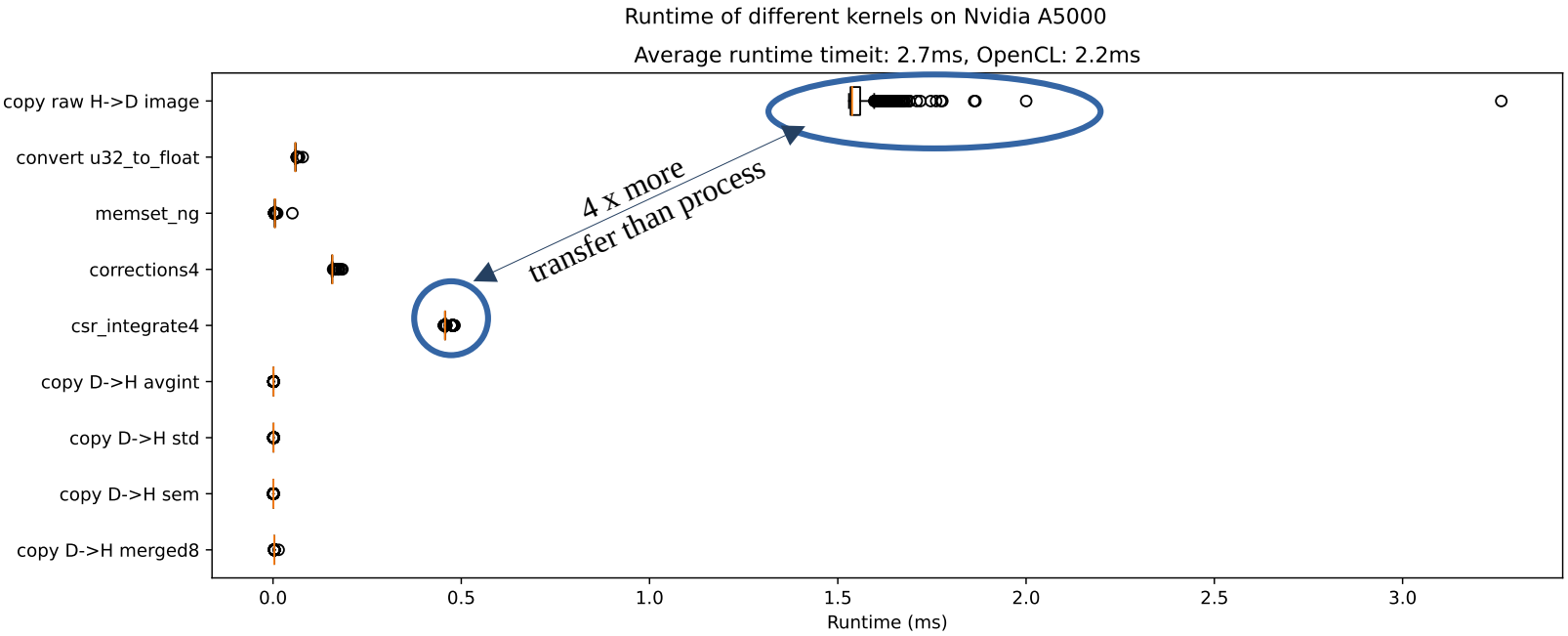

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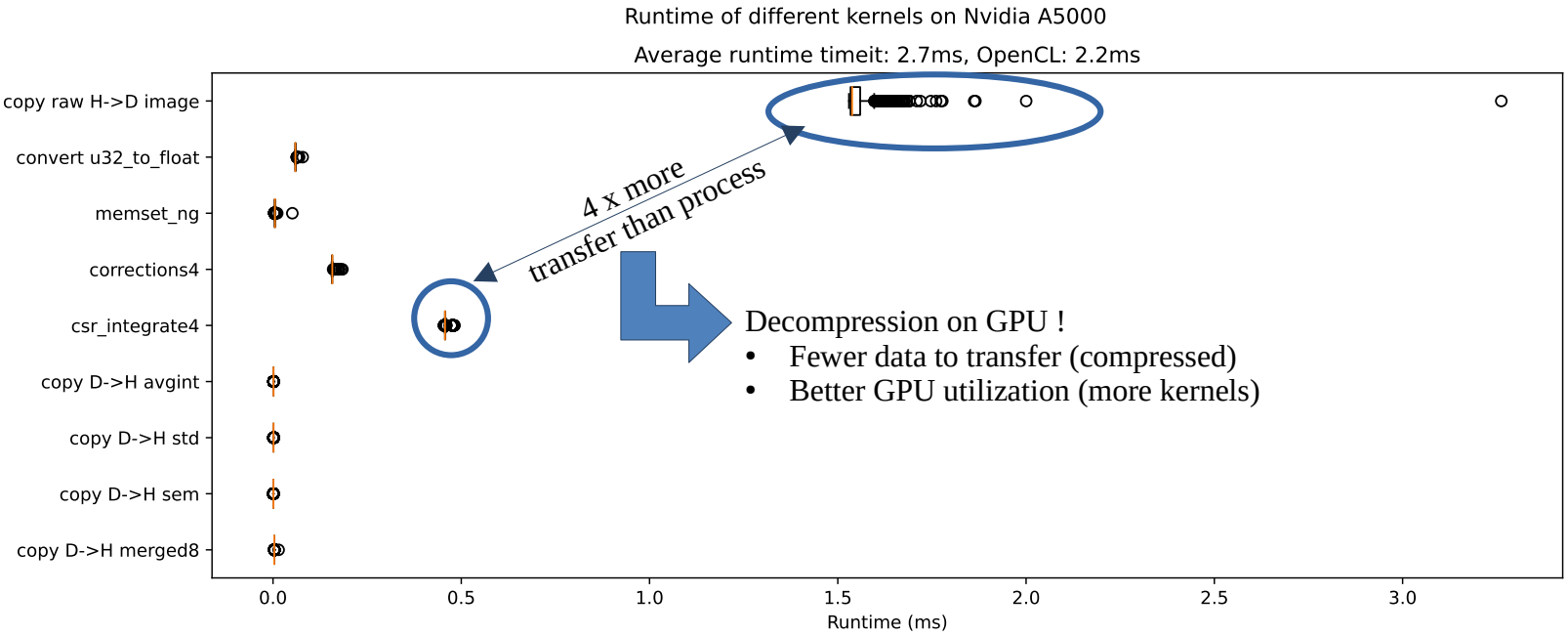

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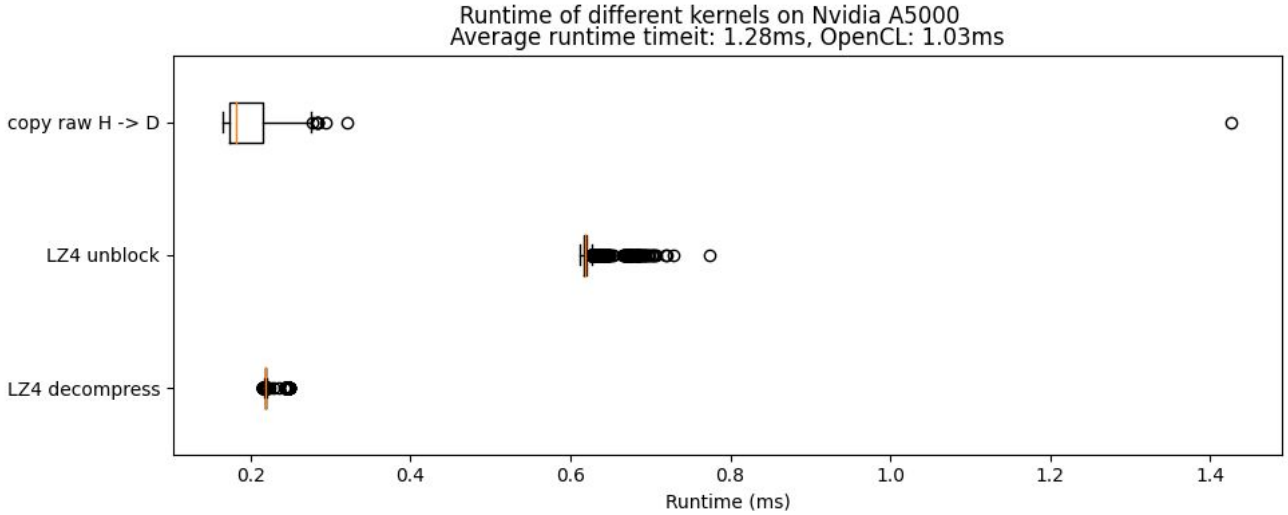

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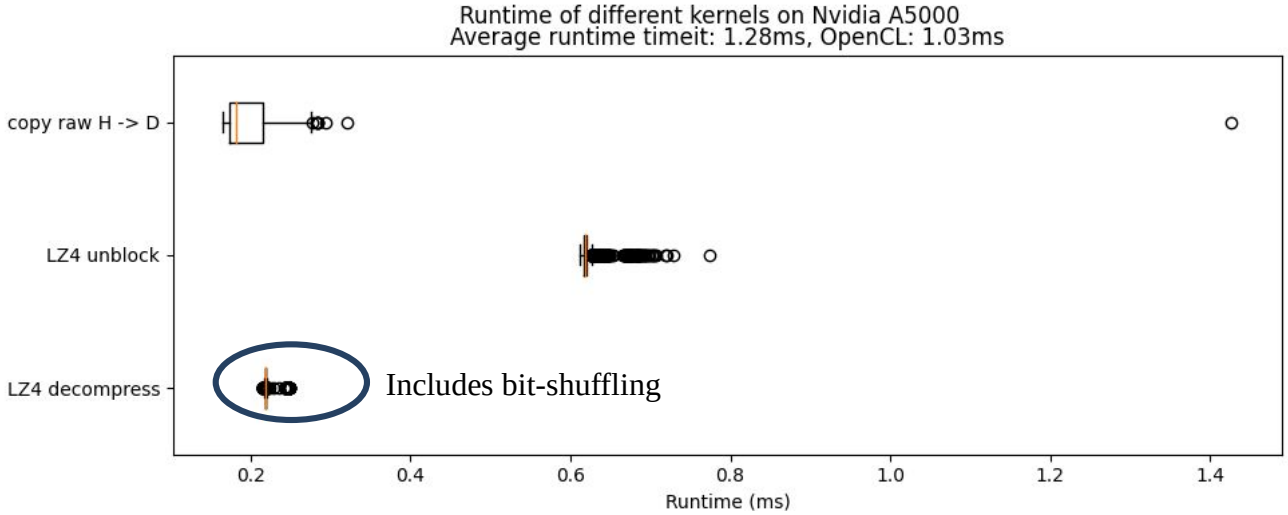

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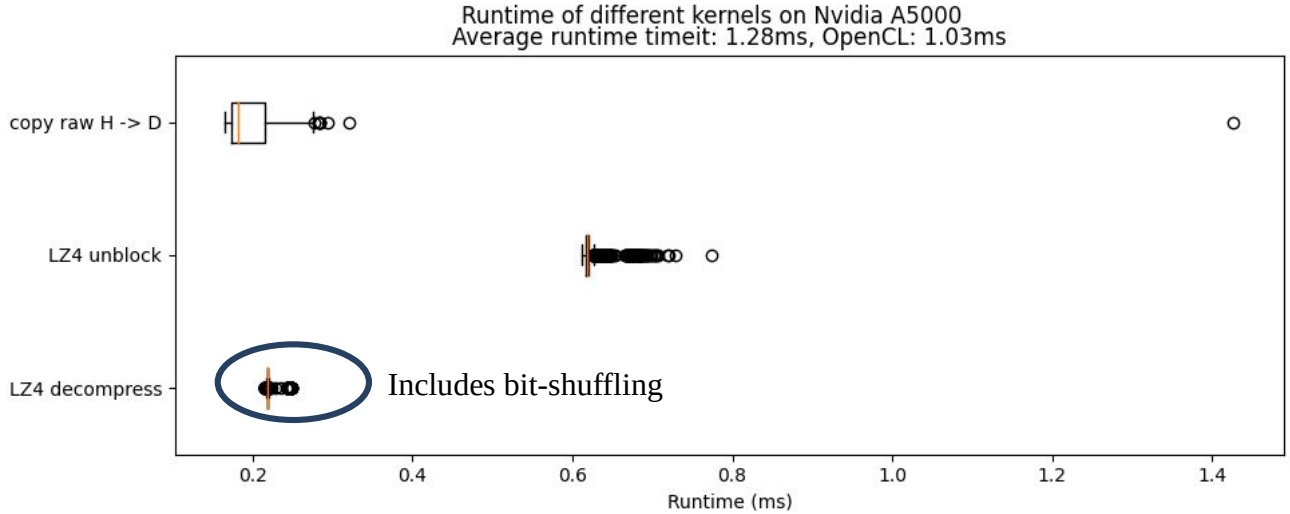

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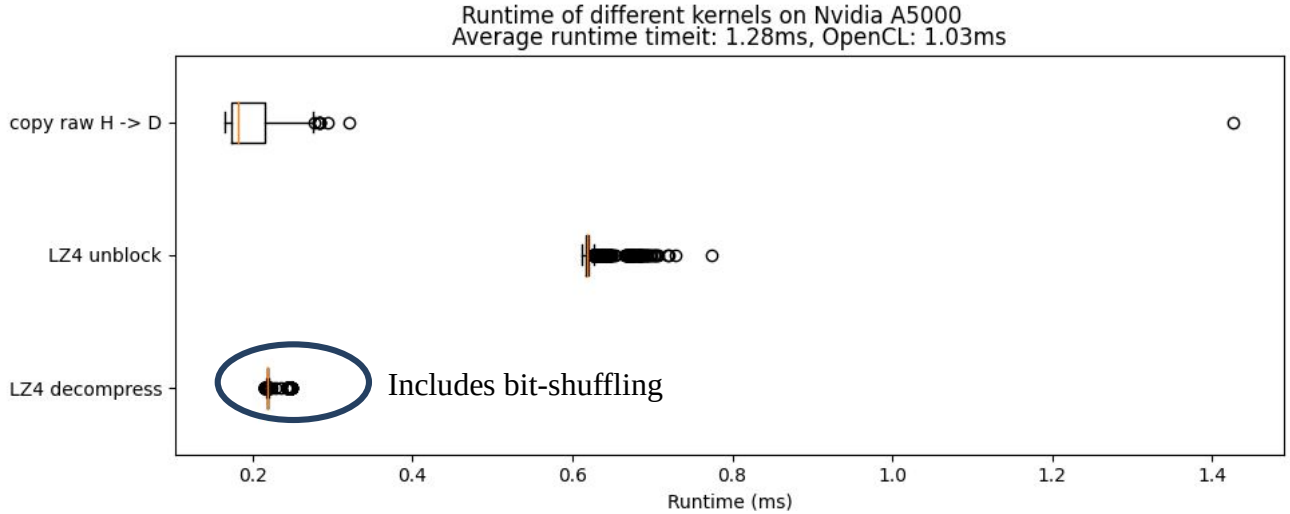
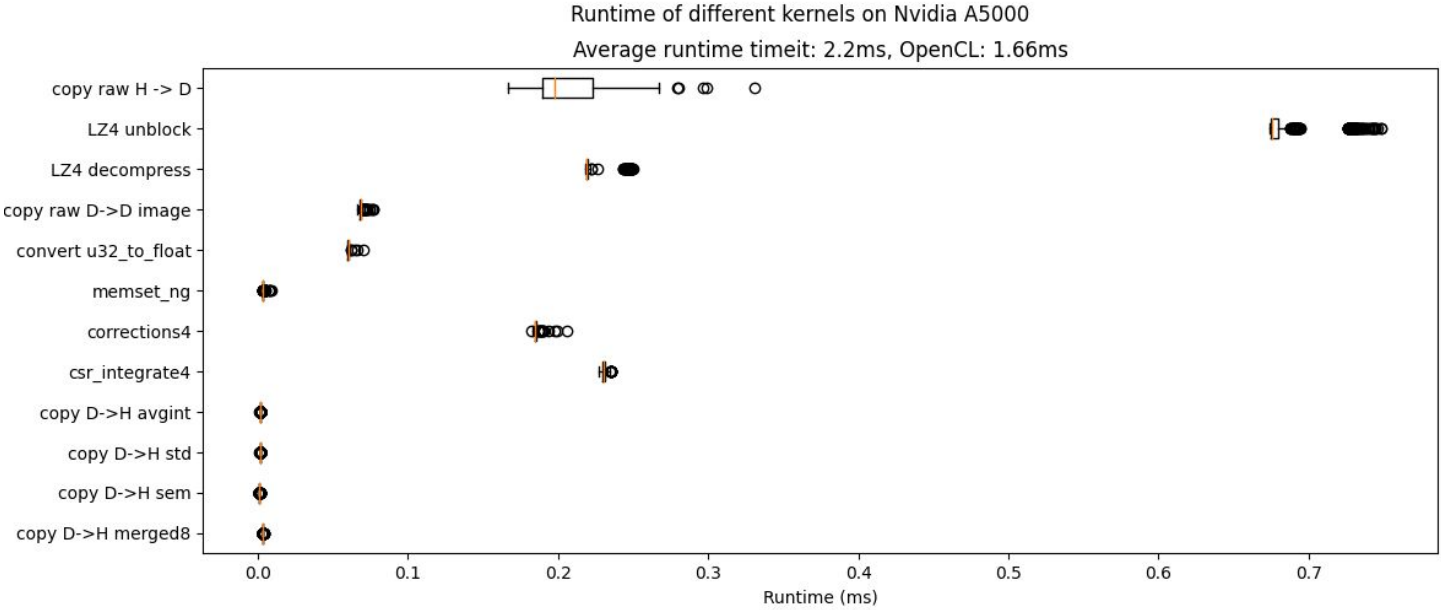


- LZ4 was designed for in-cache CPU workload:
  - → 974 fps on a Xeon (6-cores)
- Implementation by Nvidia finds blocks on CPU
- Implementation from silx finds segments on GPU:
  - →887 fps + extra savings from fewer data to send to the GPU

Profiling the complete pipeline

- Transfer → decompression → integration



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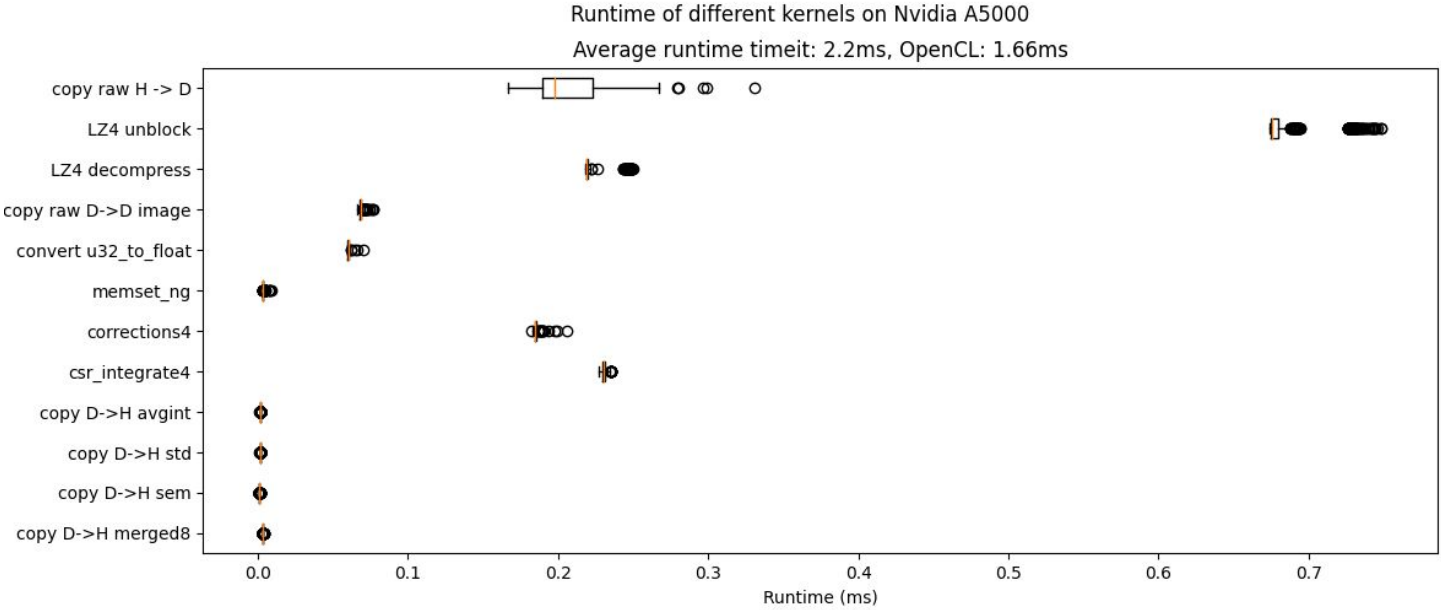

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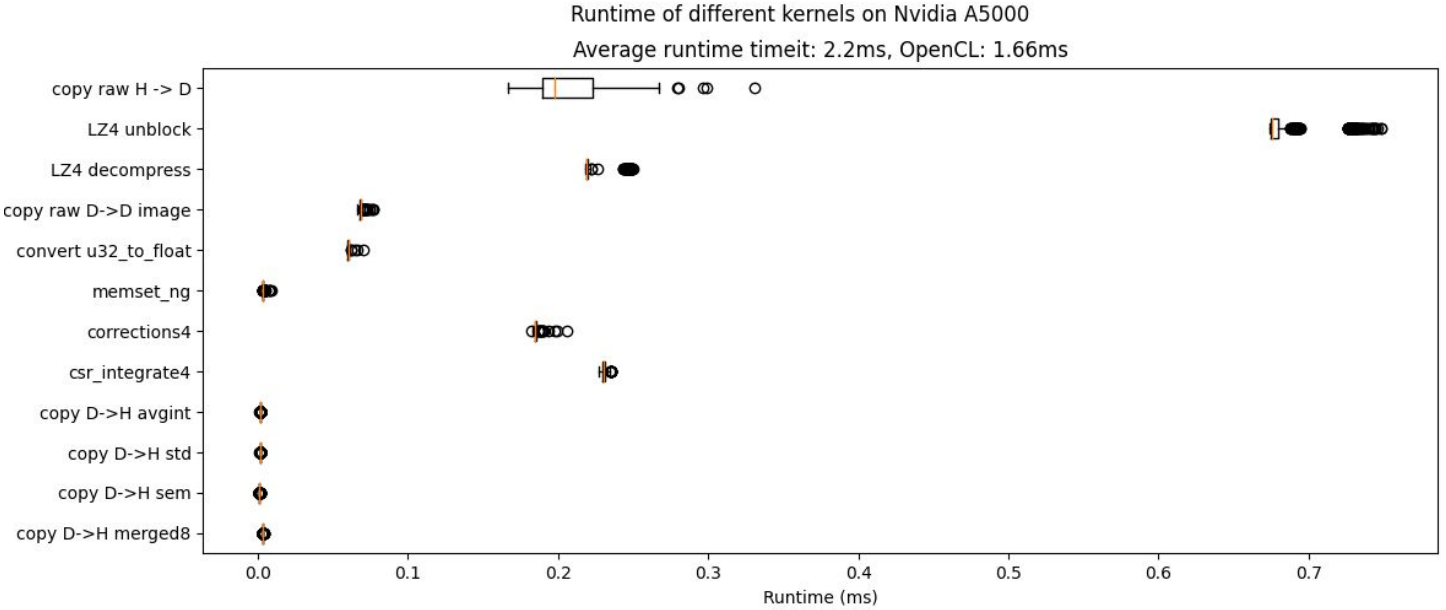
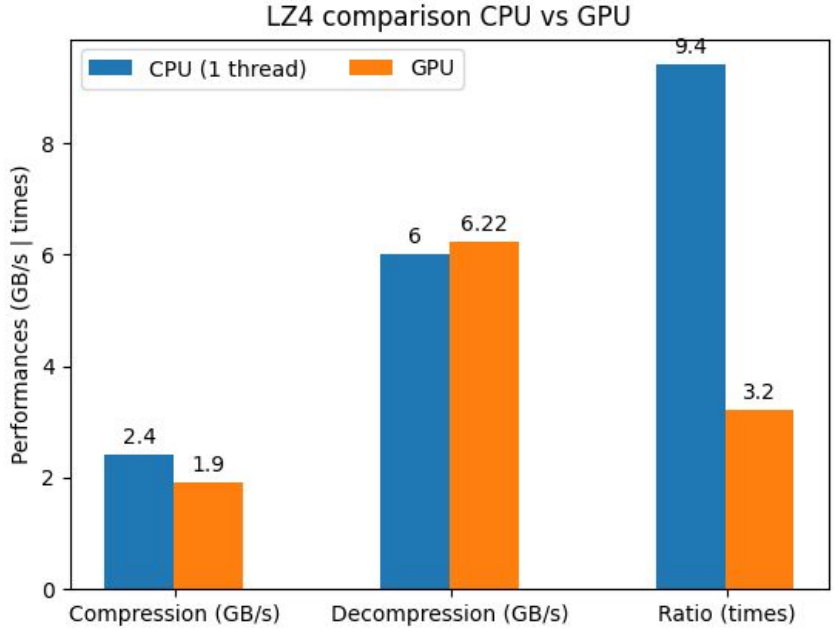


- Performances: 450 fps (single process/thread)
- Multiprocessing is possible: 568 fps with 2 workers
  - http://www.silx.org/doc/pyFAI/dev/usage/tutorial/Parallelization/MultiGPU.html

A word on LZ4 compression

- Using *nvcomp* provided by Nvidia (closed source)



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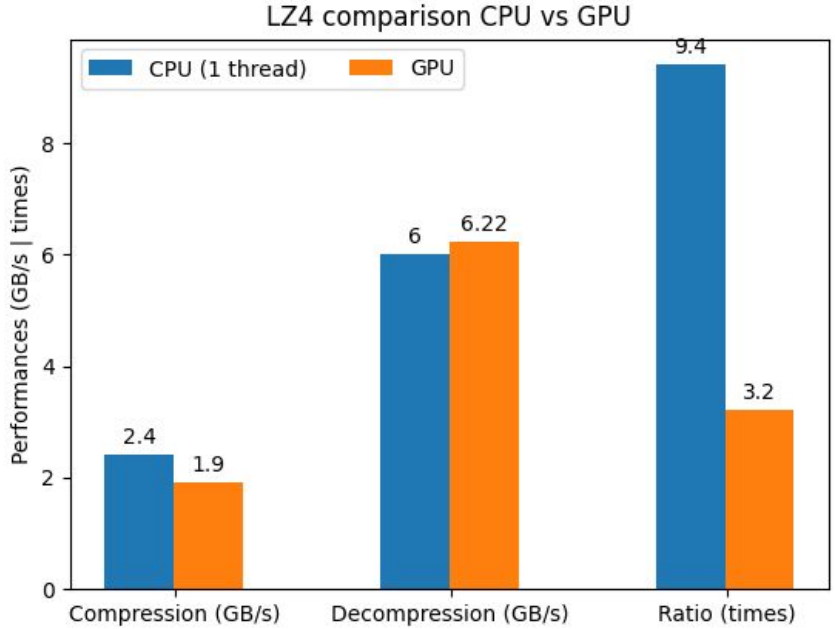

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- LZ4 algorithm is not well suited to GPU !
  - Thanks to bit-shuffling saves in BW compensates speed

Final word on energy consumption

- Workstation (from 2016)
  - Xeon E5 1650 v4 processor: 70W (measured)
  - OpenMP CSR algorithm: 35 fps
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- GPU in a workstation
  - NVIDIA RTX A5000: 215W (145W measured + 70W for the system)
  - GPU implementation: 450 fps (2 processes: 568 fps)
    - → **0.5J/frame** (0.4 J/frame with 2 processes)

Thanks to ...

- Inspiring scientists:
  - Marco Cammarata
  - Jon Wright
- Helpful colleagues:
  - Thomas Vincent
  - Armando sole (hdf5plugin)
  - Pierre Paleo
  - Alejandro Homs
  - Samuel Debionne
- Open source community:
  - HDF5
  - h5py