A performance comparison of Dask and Apache Spark for data-intensive neuroimaging pipelines

Introduction

The recent rise in data sharing and improved data collection strategies have brought neuroimaging to the Big Data era [1],[2]. Big Data frameworks can bring significant performance improvements to data-intensive neuroimaging pipelines [3].

We perform a benchmark of Dask [4] and Apache Spark [5], two Big Data engines, on neuroimaging dataset.

DASK

APACHE Spark

- Python based
- GIL limitation
- Thread based scheduler

- In-memory computing
- Data locality
- Lazy evaluation
- Fault tolerant

- Java based
- 2GB data block limitation
- Process based scheduler

Dataset

- BigBrain [6], a 81GB 3-D image of a human brain annex
- 39GB of anatomical MRI data from the Consortium for Reliability and Reproducibility (CoRR) dataset [7].

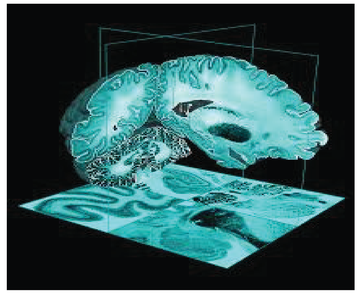


Figure 1: 3-D brain human annex

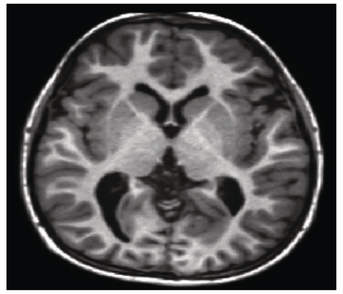


Figure 2: Anatomical MRI image

Infrastructure

- A scheduler node with a 2TB Network File System (NFS)
- Up to 8 workers with 30GB memory and 8 VCPUs each
- 10 Gbit/s network bandwidth
- Dask and Spark default configuration

Applications:

- Voxels Incrementation
- **Histogram (Python & NumPy)**
- BIDS app [8] example

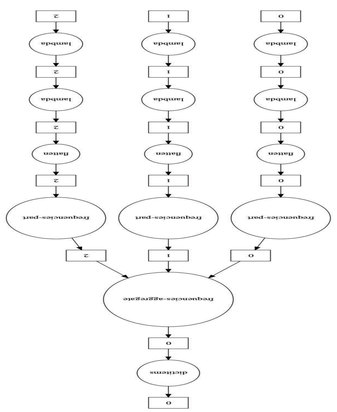


Figure 3: Histogram application flow

Results

Figure 4: Bar and Gantt charts representing the execution time of each task for the Histogram Python application.

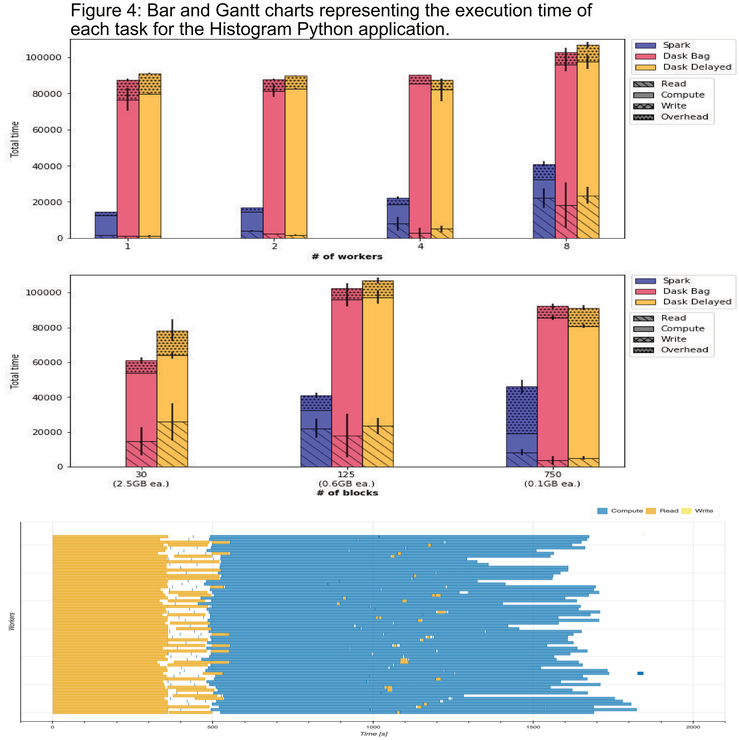
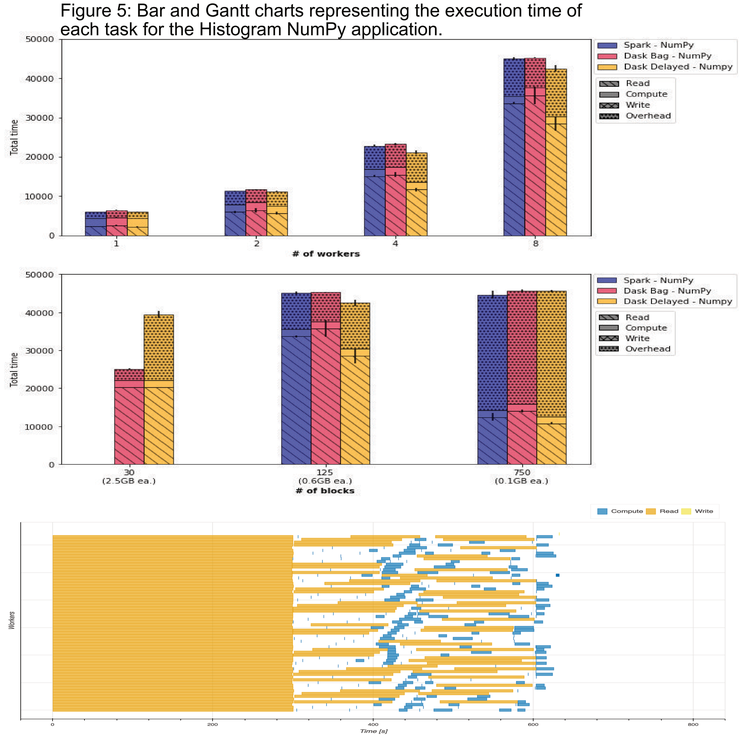


Figure 5: Bar and Gantt charts representing the execution time of each task for the Histogram NumPy application.



Discussion

Overhead / data transfer compensation:

- Almost exact compensation between differences in engine overheads and in data transfer times
- Saturated bandwidths give room for extra engine overhead as long as it desynchronizes data transfers
- Interesting idea to explore in data transfer optimization.

Effect of the share file system:

- Performance of NFS degrades substantially when accessed by concurrent tasks
- Limitations imposed by network and disk bandwidths.

Effect of Python's Global Interpreter Lock (GIL):

- Dask reduces the impact of Python's GIL on parallelism by using external C-based extensions
- Issues remain in Dask to parallelize Python functions
- Dask easily parallelize functions that release the GIL
- Need to be cautious to properly configure the workers depending on the type of functions executed in an application. i.e. multi-threading vs. multi-process workers.

Conclusion

- Our results show no substantial performance difference between the engines.
- Differences in engine overheads do not impact performance due to their impact on data transfer time: higher overheads are almost exactly compensated by a lower transfer time when data transfers saturate the bandwidth.
- These results suggest that future research should focus on strategies to reduce the impact of data transfers on applications.

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Pre-print available on arXiv.org

Code available on GitHub