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

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Abstract—In the past few years, neuroimaging has entered the Big Data era due to the joint increase in image resolution, data sharing, and study sizes. However, no particular Big Data engines have emerged in this field, and several alternatives remain available. We compare two popular Big Data engines with Python APIs, Apache Spark and Dask, for their runtime performance in processing neuroimaging pipelines. Our evaluation uses two synthetic pipelines processing the 81 GB BigBrain image, and a real pipeline processing anatomical data from more than 1,000 subjects. We benchmark these pipelines using various combinations of task durations, data sizes, and numbers of workers, deployed on an 8-node (8 cores ea.) compute cluster in Compute Canada's Arbutus cloud. We evaluate PySpark's RDD API against Dask's Bag, Delayed and Futures. Results show that despite slight differences between Spark and Dask, both engines perform comparably. However, Dask pipelines risk being limited by Python's GIL depending on task type and cluster configuration. In all cases, the major limiting factor was data transfer. While either engine is suitable for neuroimaging pipelines, more effort needs to be placed in reducing data transfer

Index Terms—Dask, Apache Spark, performance, neuroimaging

I. INTRODUCTION

The recent rise in data sharing and improved data collection strategies have brought neuroimaging to the Big Data era [1], [2]. Existing neuroimaging workflow engines, such as Nipype [3], are well suited for processing the standard compute-intensive neuroimaging pipelines, but lack incorporated Big Data strategies (i.e. in-memory computing, data locality, and lazy-evaluation) to improve performance of the increasingly prevalent data-intensive pipelines. As was noted in [4], in-memory computing, coupled with data locality, can bring significant performance improvements to data intensive neuroimaging pipelines. In this work, we investigate how performance benchmarks generalize across Big Data engines. In particular, we study the differences between Dask [5] and Apache Spark [6], for their suitability in the processing of neuroimaging pipelines. Our goal is to test whether Spark or Dask has a clear performance advantage to process Big neuroimaging Data.

Spark and Dask both offer in-memory computing, data locality, and lazy evaluation, which is common for Big Data engines. Both their schedulers operate dynamically,

which is good when task runtimes are not known ahead of time [5]. They also provide rich, high-level programming APIs, and support a variety of infrastructure schedulers, such as Mesos [7], YARN [8], or HPC clusters (Dask only). Over these similarities, the engines have differences.

First and foremost, Spark is written in Scala while Dask is in Python. Given the popularity of Python in scientific communities, this arguably gives an edge to Dask due to data serialization costs from Python to Scala. On the other hand, Python's Global Interpreter Lock (GIL) might reduce parallelism in some cases. This difference in programming languages also has qualitative implications. As part of the SciPy ecosystem, Dask provides almost transparent parallelization of applications manipulating NumPy arrays or Pandas data frames. On the other hand, Spark's Java, R and Python APIs allow to easily parallelize analyses that combine these languages, with reduced performance loss. Our study focuses on performance, although we recognize that other factors will also impact the choice of an engine in practice.

Spark and Dask were both included in the evaluation reported in [9], where a neuroimaging application processed approximately 100 GB of data. In this work, Dask was reported to have a slight performance advantage over Spark. Overall, Dask's end-to-end time (makespan) was measured to be up to 14% faster than Spark, due to "more efficient pipelining" and serialization time to Python. Dask, however, was reported to have a larger startup time than Spark. The analysis remained at a quite high level though, leaving most of the observed performance difference unexplained. In comparison, our study will provide a detailed analysis of performance differences and similarities between Spark and Dask for neuroimaging data processing.

The next section details the design of our benchmarking experiments. We consider two data-intensive neuroimaging applications: high-resolution imaging, represented by the Big-Brain data [10], and large functional MRI studies, represented by data from the consortium for reliability and reproducibility (CoRR [11]). We test application pipelines involving different patterns (map-only, map-reduce), and different types of implementations (plain Python, command-line, containerized). We evaluate performance on a dedicated cluster representative of the ones used in today's data-intensive neuroimaging studies,

using the main Dask and Spark APIs. The other sections present our results, discussion, and conclusions.

II. MATERIAL AND METHODS

A. Engines

1) Apache Spark: Apache Spark is a widely-used general-purpose Big Data engine. Its main abstraction, the Resilient Distributed Dataset (RDD) [12], is a fault-tolerant, parallel collection of data elements. It achieves fault tolerance through the recording of data lineage, the sequence of operations used to modify the original data. The RDD is the basis of Spark's other data structures, namely, Datasets and DataFrames. Datasets are similar to RDDs, but additionally use Spark SQL's optimized execution engine to further improve performance. DataFrames, used to process tabular data, are Datasets where the data is organized into named-columns. While the DataFrame API exists in all the available language APIs, Datasets are limited to Scala and Java.

As data transfers in Big Data workflows are an important source of performance bottlenecks, Spark incorporates the concepts of data locality and in-memory computing. Data locality, popularized by MapReduce [13], schedules tasks as close as possible to where the data is stored. In-memory computing ensures data is maintained in memory whenever possible, as writing large amounts of data to slower storage devices may be costly. To reduce any unnecessary communication and computation, Spark also included lazy evaluation, which builds the entire task graph prior to execution to determine what needs to be computed.

Spark is compatible with three different schedulers: Spark Standalone, YARN and Mesos. The Spark Standalone scheduler is a simple default scheduler built into Spark. In contrast, the YARN scheduler is primarily designed to schedule Hadoop-based workflows, whereas Mesos can be used to schedule a variety of different workflows. As researchers would likely be executing their workflows in HPC environments with neither YARN or Mesos installed, we limit our focus to Spark's Standalone scheduler.

The Spark Standalone scheduler is composed of three main processes: the *master*, the *workers* (*slaves*, in Spark) and the *driver*. The *master* coordinates resources provisioned by *worker* processes on the cluster. The application is submitted to the *driver* that in turn requests workers to the master and dispatches tasks to them. A job is divided into stages to be executed in a different process onto the workers. Each stage's operation is represented as a high-level task in the computation graph. The Spark standalone scheduler uses a FIFO (First-In-First-Out) job scheduling policy, and it has two execution modes: client mode, where the driver runs in a dedicated process outside of the Spark cluster, and cluster mode, where the driver runs within a worker process. Our experiments use client mode as cluster mode is not available in PySpark.

Python is commonly selected as the programming language of choice in scientific communities, and in particular, for our use case of neuroscience, where numerous specialized Python libraries exist to study the data. While serialization of Python to Java may lead to significant overheads, we chose to focus on PySpark API due to its suitability for neuroimaging research. We used Apache Spark v2.4.0.

2) Dask: Dask is a Python-based Big Data engine that is becoming increasingly popular in the scientific Python ecosystem. Like Spark, Dask avoids data transfers and needless computation and communication through in-memory computing, data locality, and lazy evaluation. Dask workflows can further reduce data transfer costs by leveraging multithreading whenever communication is not bounded by Python's GIL. Dask relies on data lineage to achieve fault tolerance, however, unlike Spark, it does not require operations to be coarsegrained. Furthermore, Dask is lightweight and modular, allowing users to only install the components they require.

Dask has five main data structures: Array, Bag, DataFrame, Delayed, and Futures. A Dask Array is used for the processing of large arrays. It provides a distributed clone of the popular NumPy library. Similar to Spark's RDD, a Dask Bag is a parallel collection of Python objects. It offers a programming abstraction similar to the PyToolz library. A Dask Dataframe is a parallel composition of Pandas Dataframes, used to process a large amount of tabular data. Dask Delayed supports arbitrary tasks that do not fit in the Array, DataFrame or Bag APIs. Finally, Dask Futures are similar to Delayed in that they support arbitrary tasks, but they operate in real-time rather than lazily. Except for Dask Bag, all APIs, by default, use the local multithreaded scheduler. Dask Bag, instead, relies on the local multiprocessing scheduler. All Dask data structures, except for Dask Array and Dask DataFrame, were used in our experiments.

The Dask graph is the internal representation of a Dask application to be executed by the scheduler. API operations generate multiple small tasks in the computation graph, allowing an easier representation of complex algorithms.

The Dask engine is compatible with numerous distributed schedulers, including YARN and Mesos, similarly to Spark. Dask also provides its own distributed scheduler, known as the Dask Distributed scheduler. Although Dask is compatible with schedulers commonly found in HPC clusters, we chose to use Dask's Distributed scheduler, to keep the environment balanced between both engines.

In the Dask Distributed scheduler, a process called *dask-scheduler* administrates the resources provided by *workers* in the cluster. The scheduler receives jobs from clients and assigns tasks to available workers. Similarly to Spark's scheduler, Dask Distributed completes the processing of a graph branch before moving along to the next one.

In our experiments, we used Dask v1.1.4.

B. Infrastructure

We used Compute Canada's Arbutus Cloud operated by the WestGrid regional organization at the University of Victoria, running OpenStack Queens release. We used c8-30gb-186 cloud instances with 8 VCPUs, an Intel Xeon Gold 6130 processor, 30 GB of RAM at 2666 MHz, 20 GB of mounted storage, and a base image running CentOS 7.5.1804 with

Linux kernel version 3.10.0862.11.6.el7.x86_64. Instances were connected by a 10 Gbit/s Ethernet network.

Cloud instances hosted a single Dask or Spark worker, configured to use 8 CPUs. We used Dask's default configuration that uses all the available memory on the instance. Its default heuristic is to: target a 60% memory load, spill to disk at 70%, pause the worker at 80%, and terminate the worker at 95%. We configured Spark to use 1 executor per worker and 25 GB of memory per executor, to leave 5 GB for off-heap. We configured the Spark driver to use 25 GB of memory, and used the default configuration for the master. We used the default configuration for worker memory management: at 60% it spills data to disk, and 50% of that amount is reserved for storage that is immune to eviction.

One cloud instance did not host any worker and had a 2 TB disk volume shared with the other instances using the Network File System (NFS) v4. This instance was also used for the Spark driver and master, for the Dask scheduler, and for job monitoring with the Spark and Dask user interfaces. For both Spark and Dask, spilled data was evicted to the NFS.

C. Dataset

We used BigBrain [10], a three-dimensional image of a human brain with voxel intensities ranging from 0 to 65,535. The original data is stored in 125 blocks in the MINC [14] HDF5-based format, available at ftp://bigbrain.loris.ca/BigBrainRelease.2015/3D_Blocks/40um at a resolution of 40 µm. We converted the blocks into the NIfTI format, a popular format in neuroimaging. We left the NIfTI blocks uncompressed, resulting in a total data size of 81 GB. To evaluate the effect of block size, we resplit these blocks into 30, 125 and 750 blocks of 2.7 GB, 0.648 GB, and 0.108 GB, using the sam library.

We also used the dataset provided by the Consortium for Reliability and Reproducibility (CoRR [11]) as available on DataLad. The entire dataset is 408.4 GB, containing anatomical, diffusion and functional images of 1,397 subjects acquired in 29 sites. We used all 3,491 anatomical images, representing 39 GB overall (11.17 MB per image on average).

D. Applications

We used three neuroimaging applications to evaluate the engines in different conditions. The first two, incrementation and histogram, are simple synthetic applications representing map-only and map-reduce applications, respectively. The third, is a real neuroimaging application representative of popular BIDS applications [15]. All scripts used for our experiments are available at https://github.com/big-data-lab-team/paper-big-data-engines

1) Incrementation: We used an adaptation of the image incrementation pipeline used in [4] (see Algorithm 1). The application reads blocks of the BigBrain image from the shared file system, increments the intensity value of each voxel by 1 to avoid caching effects, sleeps for a configurable amount of time to emulate more compute-intensive processing, repeats this process for a specified number of iterations, and finally

writes the result as a NIfTI image back to the shared file system. This application allows us to study the behavior of the engines when all inputs are processed independently, in a map-only scenario (see Figure 1). This mimics the behavior of analyzing multiple independent subjects in parallel.

- 2) Histogram: Our second application calculates the histogram of the BigBrain image (see Algorithm 2). It reads the image blocks from the shared file system, calculates intensity frequencies, aggregates the frequencies across the blocks, and finally writes the resulting histogram to the shared file system as a single 766 kB file. It follows the map-reduce paradigm, in which the final result is obtained from all the input blocks (see Fig. 2). This application requires data shuffling, incurring additional performance costs compared to Algorithm 1. The total amount of shuffled data is, however, limited to 2.62 MB per block as it only consists of image histograms. Two implementations are studied: a pure Python one, where frequencies are computed through Python dictionary manipulations, and one based on the NumPy library, that implements array computations in C.
- 3) BIDS app example: We used the BIDS app example map-reduce style application. The map phase, also called participant analysis, extracts the brain tissues of a subject's 3D MRI from the CoRR dataset using the FMRIB Software Library (FSL), and writes the resulting image (2.47 MB on average) to the NFS. The reduce phase, or group analysis, computes the volume of each brain and returns the average volume, shuffling a total of 8.6 GB image data.

While Incrementation and Histogram were implemented directly in Python, the BIDS App example requires an external set of command-line tools distributed as a Docker container

```
Algorithm 1 Incrementation (adapted from [4])
```

Require: x, a sleep delay in float

Require: file, a file containing a BigBrain block

Require: fs, NFS mount to write image to

Read block from file for each $i \in iterations$ do

for each $block \in image$ do $block \leftarrow block + 1$

Sleep x

end for

end for

Write block to fs

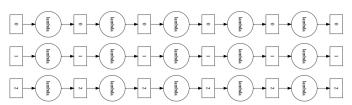


Fig. 1: Task graph for Incrementation with 5 iterations and 3 BigBrain blocks. Circles represent the incrementation and sleep function while rectangles represent data elements.

Algorithm 2 Histogram

Require: *files*, files containing BigBrain blocks **Require:** *fs*, NFS mount to save image to

for each $file \in files$ do Read block from file

Calculate frequencies in block

end for

 $histogram \leftarrow Aggregate \ frequencies \ of \ each \ file$ Write histogram to fs

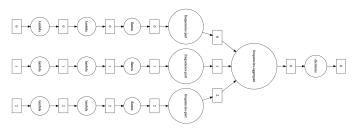


Fig. 2: Task graph for Histogram with 3 BigBrain blocks. Circles represent the functions while rectangles represent data elements.

image (bids/base_fsl on DockerHub). We converted the Docker image to a Singularity image for use in an HPC environment, using docker2singularity. The image was preloaded on the NFS and Singularity version 3.2.11.el7 was installed for all instances.

E. Experiments

Four parameters were varied in our experiments, as shown in Table I. We varied (1) the number of workers, to assess the scalability of the engines, (2) the number of BigBrain blocks in Incrementation and Histogram, to measure the effect of different I/O patterns and parallelization degrees, and (3) the number of iterations and sleep delay in Incrementation, to evaluate the effect of job length and number of tasks. It should be noted that increasing the number of blocks or iterations also increases the total compute time of the application for a given sleep delay. To avoid any potential external bias such as background load on the network, we ran the experiments in a randomized order and cleared the page cache of each worker before each execution.

For each run, we measured the application makespan as well as the cumulative data read, compute, data write, and engine overhead times across all application tasks. The overhead calculation for each CPU is the end time of its last processed task minus the total runtime of the tasks it executed. The summation of those results is the total overhead.

III. RESULTS

A. Incrementation: Number of workers

Figure 3a shows the makespan of the Incrementation application for different numbers of workers and engines. The bars show the average makespan over 3 repetitions while the error bars are the standard deviations. Overall, there is no substantial

TABLE I: Parameters for the experiments

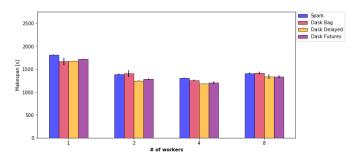
	Incrementation	Histogram	BIDS Example
# of worker	1, 2, 4, 8	1, 2, 4, 8	1, 2, 4, 8
# of blocks	30, 125, 750	30, 125, 750	-
# of iterations	1, 10, 100	-	-
Sleep delay [s]	1, 4, 16, 64	-	-

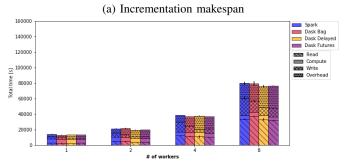
makespan difference between the engines. Dask seems to have a slight advantage over Spark, 83.61 s on average, with Delayed and Futures being slightly better than Bag.

For all engines, the makespan is far from decreasing linearly with the number of workers. The makespan even increases between 4 and 8 workers. This is due to the high impact of data transfers and engine overhead on the application.

Figure 3b shows the total execution time of the Incrementation application, broken down into data transfer (read and write), compute (sleep), and overhead time. As expected, the computing time stays similar when the number of workers increases. However, the data transfer time and overhead increase proportionally to the number of workers with regression slopes: Spark ($2337 \, \text{s/task}$), Bag ($2650 \, \text{s/task}$), Delayed ($3251 \, \text{s/task}$), Futures ($3570 \, \text{s/task}$).

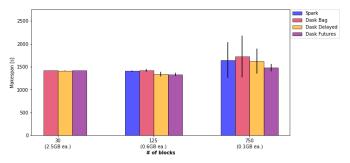
On Figure 3b, we also note that Spark's overhead is slightly lower than Dask's, particularly when the number of workers increases. Moreover, Delayed and Futures have a higher overhead than Bag. However, overhead differences are compensated by an increase in data transfer time, as a reduced overhead increases the concurrency between data transfers and the application saturates the disk bandwidth of the shared file system.

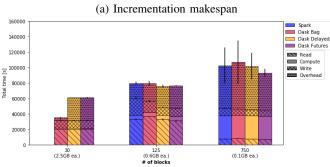




(b) Incrementation total time

Fig. 3: 125 blocks, 10 iterations, 4s delay, 8 CPUs/worker





(b) Incrementation total time

Fig. 4: 10 iterations, 4s delay, 8 workers, 8 CPUs/worker

B. Incrementation: Number of blocks

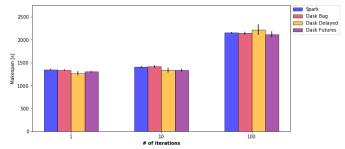
Figure 4a shows the Incrementation makespan when varying the number of image blocks for constant BigBrain image size. We were not able to run Spark for 30 blocks due to its 2 GB limitation in the task size. Once again, we do not observe any substantial difference among the engines. For all engines, makespan variability increases with the number of blocks, however, engines scale very well in general.

In Figure 4b, the total execution time of each function is shown. For 30 blocks, the increased overhead of Delayed and Futures is a calculation artifact coming from the fact that only 30 of the 64 available threads can be used concurrently. Once again, the data transfer time reduces with more blocks but the overhead time increases by a similar amount. This is not observed for 30 blocks as the workers are not used at full capacity, i.e., some threads are idle. Finally, the variability of the overhead increases with the number of blocks, which explains the makespan variability mentioned previously.

C. Incrementation: Number of iterations

Figure 5a shows the makespan of the application while varying the number of iterations. Overall, Spark and Dask APIs are once again equivalent, although Delayed and Futures are slightly faster than Bag and Spark for 1 and 10 iterations, and Futures are faster than Delayed, Bag and Spark for 100 iterations. Differences remain minor though.

In Figure 5b, the total execution time breakdown is shown. We observe the good scalability of all the engines with the number of iterations.



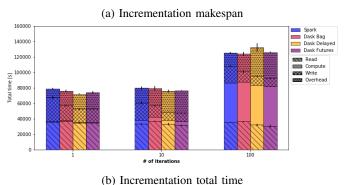


Fig. 5: 125 blocks, 4s delay, 8 workers, 8 CPUs/worker

D. Incrementation: Sleep delay

Figure 6a shows the makespan of the Incrementation application for different sleep delays. Overall, all engines again perform the same and scale well with task duration. Spark is initially slower than the Dask APIs, however, it is faster with an increased sleep delay. Also, within the Dask APIs, Dask Bag is slower than the other two, but it is not considerable.

Figure 6b shows the total execution time breakdown. Spark has the smallest overhead. As previously observed, variations in overhead time are almost exactly compensated by variations in data transfer time.

E. Incrementation: Gantt chart

Figure 7 shows the Gantt chart obtained for each engine. Gantt charts are structured in batches of up to 64 read-compute-write concurrent sequences. File reads in the first batch are much longer than the ones in the following batches: this is due to the high synchronization of data transfers that leads to a high saturation of the shared file system. We also note that overhead, represented in white, is concentrated around the data transfer tasks and the computing tasks that run concurrently with data transfers.

F. Histogram (Python): Number of workers

Figure 8a shows the makespan of the Histogram application for various amounts of workers. Spark is significantly faster than Dask APIs. The difference narrows as the number of workers increases but it remains significant. Between Dask APIs there is no substantial difference, however, Bag is slightly faster on average.

From Figure 8b, the total time spent in each function is shown. The computing time is significantly larger for Dask

than for Spark. This is presumably due to Python's GIL preventing Dask to parallelize the computation over multiple threads. Overall, the I/O and overhead times are comparable for all engines.

Figure 8b shows that Dask engines have a similar total execution time when their number of workers varies, except for 8 workers where it increases slightly due to increased read time. On the other hand, Spark total execution time keeps increasing; especially at 8 workers. This is because Dask engines benefit more from additional workers, in this GIL-bounded scenario.

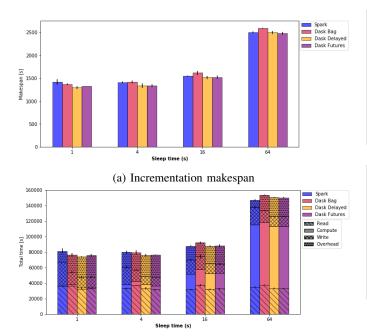
G. Histogram (Python): Number of blocks

Figure 9a shows the makespan for different block sizes. Once more, Spark is significantly faster than Dask engines and Bag is slightly faster than Delayed. Overall, the engines do not react to changes in block size.

In Figure 9b the total time for each function is shown. Note that at 30 blocks the workers' resources are not fully used since the workers can process up to 64 tasks in parallel. Moreover, the overhead for 30 blocks is erroneous due to a lower amount of block than available threads. This leads to thread based engines to have higher overhead. Given that, Spark has a much lower compute time which makes it significantly faster than Dask engines. Overall, for all engines, lower block size results in lower data transfer time but increases the overhead time. Again, this is due to large overhead desynchronizing task thus reducing the NFS bottleneck.

H. Histogram (Python): Gantt chart

Figure 10 shows the Gantt chart of the baseline Histogram experiment implemented in Python. Spark overhead is dis-



(b) Incrementation total time Fig. 6: 125 blocks, 10 iterations, 8 workers, 8 CPUs/worker

tributed through all the execution while Bag overhead happens mostly when a thread reads subsequent blocks and Delayed overhead is concentrated after reading all the blocks.

I. Histogram (NumPy): Number of workers

Figure 11a shows the makespan for various amount of workers. Overall, the makespan for all engines does not change considerably with an increase in the number of workers. This is likely a result of using a non-distributed shared file system. There is no substantial difference between all engines although Delayed is slightly faster. Figure 11b shows the total execution time breakdown. The overhead and read time increase

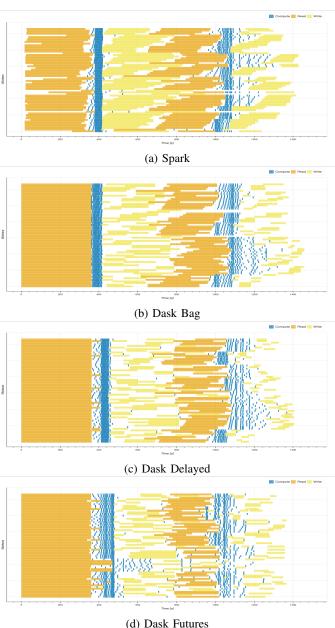
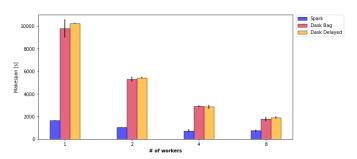


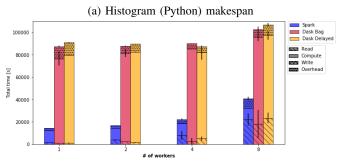
Fig. 7: Incrementation Gantt chart: 125 blocks, 10 iterations, 4s delay, 8 workers, 8 CPUs/worker. All Gantt charts are clickable and link to interactive figures with additional information.

proportionally to the number of workers thus increasing the total time.

J. Histogram (NumPy): Number of blocks

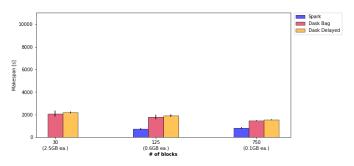
Figure 12a shows the makespan of the application for different block sizes. Overall, there is no substantial difference for all engines and block sizes.

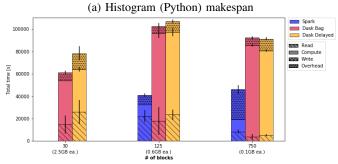




(b) Histogram (Python) total time

Fig. 8: 125 blocks, 8 CPUs/worker





(b) Histogram (Python) total time

Fig. 9: 8 workers, 8 CPUs/worker

Figure 12b shows the total time spent in each function. Once more, since Delayed is thread-based its overhead at 30 blocks is much higher. Considering the overhead error and that at 30 blocks the workers only use half their core, the total time is substantially the same for all block size. This is due to lower block sizes having a lower data transfer time, however, it balances out by the resulting increase in overhead.

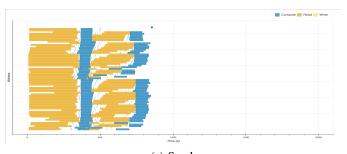
K. Histogram (NumPy): Gantt chart

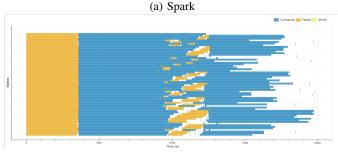
Figure 13 shows the Gantt chart of the baseline for the Histogram (NumPy) experiment. The overhead for Spark and Bag is mostly located between read and compute tasks. On the other hand, Delayed overhead is dispersed between all types of tasks. This causes Delayed to overlap more compute and read tasks simultaneously amongst different workers.

In Figure 13, read tasks are initially similar for all engines. However, when computation starts the subsequent read tasks are much shorter for Delayed. This is due to the desynchronization of the task reducing the data transfer bottleneck.

L. BidsApp example: Number of workers

Figure 14a shows the makespan of the application when varying the number of workers. Overall, there is no substantial





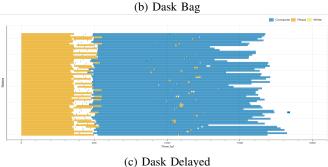


Fig. 10: Histogram (Python) Gantt chart: 125 blocks, 8 workers, 8 CPUs/worker

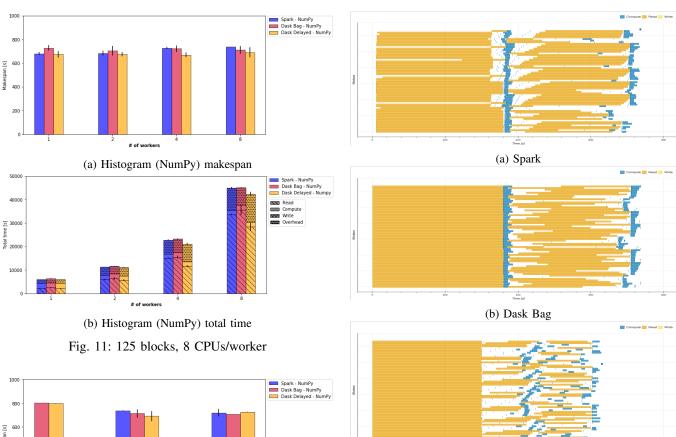


Fig. 13: Histogram (NumPy) Gantt chart: 125 blocks, 8 workers, 8 CPUs/worker

(c) Dask Delayed

Spark - NumPy

Dask Bag - NumPy

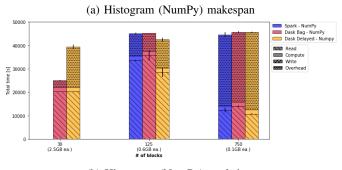
Dask Delayed - NumPy

200

200

200

(2.556 ea.) (0.656 ea.) (0.156 ea.)



(b) Histogram (NumPy) total time

Fig. 12: 8 workers, 8 CPUs/worker

difference between the engines. The makespan scales well with the increase in workers, however, the scaling reduces slightly when reaching 8 workers. This is due to an increase in I/O time caused by parallel accesses to the shared file system.

In Figure 14b, the total execution time of each function is shown. Each engine has a similar total time independently of its number of workers. This is due to the, almost, linear scaling of the engines. The overhead increases proportionally to the number of workers with regression slopes: Spark

 $(224 \, \mathrm{s/task})$, Bag $(183 \, \mathrm{s/task})$, Delayed $(173 \, \mathrm{s/task})$, Futures $(132 \, \mathrm{s/task})$. This is due to more communication between the scheduler and workers as well as intra-worker and inter-worker communication.

M. BidsApp example: Gantt chart

Figure 15 shows the Gantt chart obtained for each engine. Gantt charts are structured in two parts: participant analysis (orange) and group analysis (blue). The participant analysis tasks differ greatly in length. This is due to the unequal amount of sessions per subject processed. The group analysis is similar for all engines and APIs. Overall, most of the overhead encountered results from the transition between the two analysis. This is because the group analysis requires the results of the participant analysis to start.

IV. DISCUSSION

A. Comparison with previous studies

Overall, our experiments did not show any substantial performance difference between Spark and Dask. In contradiction with the experiments of [9], we did not observe consequential overhead differences due to serialization or startup costs. This

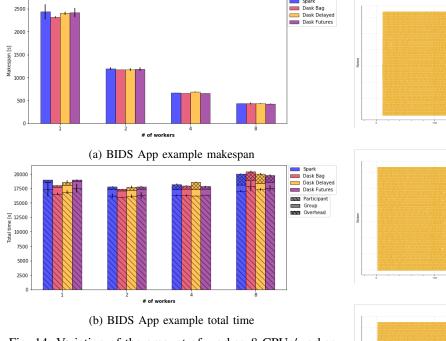


Fig. 14: Variation of the amount of worker, 8 CPUs/worker

apparent contradiction is most likely coming from differences in applications, engine parametrization, or infrastructure characteristics between the two studies. In our case, potential overhead differences were compensated by reverse trends in data transfer time. Since our focus is Big Data applications, this leads us to conclude that engines are equivalent.

B. Overhead / data transfer compensation

The observed almost exact compensation between differences in engine overheads and in data transfer times (see for instance Figure 3b) is not surprising. Indeed, when the transfer bandwidth is saturated, and in the absence of service thrashing, desynchronizing file transfers usually does not reduce the makespan of data transfers. To take an extreme example, the makespan of n concurrent file transfers of size F on a system of bandwidth B would be nF/B, as n transfers would share the bandwidth, which equals to the time required to transfer the n files sequentially. In other words, saturated bandwidths give room for extra engine overhead as long as it desynchronizes data transfers. This could be an interesting idea to explore in data transfer optimization.

C. Effect of the shared file system

We used NFS as our shared file system as it is a common and easy-to-configure solution to share data between compute nodes. The performance of NFS, however, degrades substantially when accessed by concurrent tasks, as shown in the Gantt charts in Figures 7, 10, 13 and 15. This is due to the limitations imposed by network and disk bandwidths. While network bandwidth can hardly be overcome, disk bandwidth can be increased by storing data to multiple disks addressed by a parallel file system such a Lustre [16]. Such a configuration

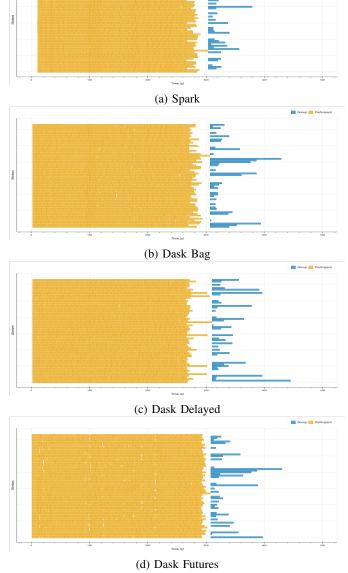


Fig. 15: BIDS App example Gantt chart: 8 workers

would likely reduce the impact of data transfers, although the main observed patterns should remain.

Throughout the applications and engines, the use of large data blocks amplified the consequences of using an NFS. Moreover, the bandwidth saturation almost neglects the scaling, from additional workers, for data-intensive applications: Incrementation and Histogram (NumPy). On the other hand, an almost linear scaling shows that it has no substantial effect on compute-intensive applications: Histogram (Python) and BIDS app example.

We suppose that using a parallel file system would allow applications to have almost linear scaling as long as they do not saturate the bandwidth of the system.

D. Effect of Python's Global Interpreter Lock

Although Dask reduces the impact of Python's GIL on parallelism by using external Python extensions, our Python histogram experiment (Figure 8 and 9) showed that issues remain in Dask to parallelize Python functions. However, Dask was easily able to parallelize the same application when implemented with NumPy (Figure 11 and 12) because in this case the computation happened in C, outside of the GIL. Similarly, the computation in command-line applications happens in a sub-process, hence outside of the GIL, which explains why the BIDS apps example application was not impacted by this issue. Although implemented in Python, Incrementation was not impacted either, as computation was only emulated through sleep time.

This behavior is also the consequence of our configuration of Dask that created 1 worker process with 8 threads. Since the Histogram Python implementation does not release the GIL it can only use one of the thread at a given time thus it slows down the computation significantly. Our results suggest configuring Dask with multi-threaded workers for application releasing the GIL and multi-process workers while the default configuration of Spark workers brings stable results across different types of applications.

E. Effect of data partitioning

The number of data partitions also has an impact on application performance. In our experiments, we set a partition for each block or subject, resulting in a maximum of 750 partitions for the BigBrain applications, and 1,397 partitions for the BIDS app. The number of partitions obeys a classical trade-off: small numbers of partitions reduce overhead, while large numbers of partitions increase parallelism. Since both Spark and Dask can work with custom partition sizes, we do not expect substantial differences coming from variations of this parameter.

V. CONCLUSION

We presented a comparison of two Big Data engines, Apache Spark and Dask. We studied the engines on three data-intensive neuroimaging applications representative of common use cases. Overall, our results show no substantial performance difference between the engines. Interestingly, 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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