OSmOSE report No 2
Development details and computational benchmarking of DEPAM
Abstract

In the big data era of observational oceanography, passive acoustics datasets are becoming too high volume to be processed on local computers due to their processor and memory limitations. As a result there is a current need for our community to turn to cloud-based distributed computing. In this paper we present a scalable computation chain for FFT (Fast Fourier Transform)-based features (e.g., Power Spectral Density) based on the Apache frameworks Hadoop and Spark. These features are at the core of many different types of acoustic analysis where the need of processing data at scale with speed is evident, e.g. serving as long-term averaged learning representations of soundscapes to identify periods of acoustic interest. In addition to a complete description of our system implementation, we also provide a computational benchmark comparing our system to different programming languages (Matlab, Python) in standalone executions, and evaluate its scalability using the speed up metric. Our current results show that our system obtains near-linear scalability in its distributed configuration for our tested dataset, and more surprisingly, is even slightly more performant with equivalent Matlab and Python-based workflows when executed on a single node.
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Chapter 1

Introduction

1.1 Context

Technological progress in observational oceanography gave rise to a two-tiered system in which major strategic investments have been put primarily in data acquisition rather than in data management and processing plans. As a result, there is currently a huge gap between in-situ small-scale data acquisition and a more integrated global knowledge that could be directly used by decision-making managers and in operational oceanography research.

The underwater Passive Acoustic Monitoring (PAM) community, which investigates both biological activities (e.g. whale census) and physical processes (e.g. wind speed and rainfall estimation) in the ocean, is a good example of ocean observing communities facing these difficulties. Especially, due to the development of cabled observatories that now provide unlimited power for high bandwidth, continuous data acquisition, and to the increase of storage capacity and life battery of temporary recorders, the volume of datasets to process has become larger and larger.

For instance, the PerenniAL Acoustic Observatory in the Antarctic Ocean (PALAOA) observatory has been recording quasi-continuously the underwater soundscape of the Southern Ocean since 2005 (Boebel et al., 2006), generating about 140 Gb per day (Kindermann et al., 2008), and the Ocean Network Canada has collected more than 300 Tb of PAM data in their database (Biffard et al., 2018). In France, governmental agencies like Service Hydrographique et Ocanographique de la Marine (SHOM) and Agence Francaise de la Biodiversit (AFB) are also facing similar challenges of processing large volume of data in the Directive Cadre Stratgie pour le Milieu Marin (DCSMM) context, where anthropogenic ambient noise analysis and marine mammal census have to be performed on a long-term continuous effort.

Several projects have started to address the question of processing high volume PAM data more efficiently by adopting distributed computing systems. Basically, it is a system whose components are located on different networked computers (or nodes), which computer communicate and coordinate their actions by passing messages to one another (Wikipedia, https://en.wikipedia.org/wiki/Distributed_computing). Each computer has its own private multiprocessor structure and memory. This makes it good for redundant storage and availability, durability. In contrast, local systems based on a single node, as usually used in the PAM community, all processors may have access to a shared memory to exchange information between processors, like when performing multiprocessor parallel computing. Among well-known distributed environments within the big data space, Apache Spark has become a prominent player. Initially open-sourced in 2012 and followed by its first stable release two years later, Spark is an open-source distributed general-purpose cluster-computing framework, providing an interface for programming entire clusters with implicit data parallelism and fault tolerance (https://en.wikipedia.org/wiki/Apache_Spark).

Although big data analytics in PAM community is only in its early stages, Thudumu et al. (2016) have already developed a distributed computing environment based on Spark Streaming for routine processing (such as spectrogram generation and filtration) of large marine bioacoustic datasets. Using Hadoop Distributed File System (HDFS) as a distributed storage system, their system resulted in better runtime performance in comparison to standalone execution, with approximately 78 % reduction in the execution time. Concurrent computational approaches have used the Matlab Parallel Computing Toolbox and Matlab Distributed
1.2 Contributions

In this paper, we wish to share these efforts by proposing a scalable computation chain for FFT (Fast Fourier Transform)-based features based on the Hadoop and Spark frameworks. These features (e.g., wideband Sound Pressure Levels) are at the core of many different types of acoustic analysis where the need of processing data at scale with speed is evident. For example, these features often serve as long-term averaged learning representations (among them, the well-known Long-Term Spectral Average (LTSA)) of soundscapes to identify periods of acoustic interest [Erbe et al., 2015, Merchant et al., 2015]. Image-based pattern recognition is also often applied to LTAS for annotation aid [Frasier et al., 2018]. Such applications, namely fast automatic content report and interactive annotation of large datasets, need fast and scalable computations of the features to be performed efficiently. Furthermore, LTSA generation relies on several processing parameters (e.g., analysis window size) that can highly modify event-specific averaged patterns and reduce the interpretability of LTSA [Hawkins et al., 2014]. To better assess this variability, systematic comparative testing of different parameter sets need to be carried out, which also requires intensive computing. Computationally, although the computation of FFT-based features for audio analysis has been highly documented and optimized, it remains very resource-intensive for high volume data, with the need of processing larger-than-memory acoustic recordings, beyond the comfort of our own laptop. Just to provide some idea of the magnitude of the problem, the space to be allocated for storing FFT results for a two-month time series is around 1 Tif.

In addition to develop a new scalable Hadoop/Spark system for high performance computing of FFT-features, we also provide a computational benchmark comparing our system to different programming languages (Matlab, Python) in standalone executions, and evaluate its scalability using the speed up metric.

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1Using a sample frequency of 48 kHz, 24000 points for each second are stored when computing an one-sided FFT up to the Nyquist frequency. If all computations are made with double (8 bytes), for 1 day of analysis, 15.45 Gb need to be stored $(24\times3600\times24000\times8 = 16588800000 \text{ bytes})$. Multiply by around 60 for two months.
Chapter 2

Methods

2.1 DEPAM workflow description

The DEPAM workflow used for the FFT-based computation is based on classical PAM analysis blocks (Merchant et al., 2015), including three main steps: short-term segmentation (e.g., 32 ms), feature computation and feature integration over longer-time windows (e.g., 1 min). A complete description of this workflow, including both theory and implementation details, is available (OSmOSE, 2019).

2.2 Implementation details of the proposed Hadoop/Spark system

Our DEPAM workflow was implemented in Scala (version 2.11.8) within the Apache Spark framework. Our proposed distributed computing system is shown Figure 2.1. It consists of a master-slave framework, using the Scala-based workflow executed within a Hadoop/Spark cluster. More specifically, Hadoop ensures both distributed storage and access to data (via Hadoop Distributed File System, HDFS) and resource management (Yet Another Resource Negotiator, YARN). Both components communicate with other machines through a master-slave model (HDFS: NameNode ↔ DataNodes, YARN: ResourceManager ↔ NodeManagers).

When Spark is used in Hadoop, the Spark Driver organizes the completion of the jobs across the cluster of executors by interacting with the ResourceManager and the NodeManagers. Moreover, this entity parses the code, and serializes the byte level code across the Spark Executors. Computations are actually done at the local level by each of them which represent processes running in a Hadoop container (container hadoop = N cores + M GB RAM). Our system is rather close to the (Thudumu et al., 2016) system, although we did not use Spark Streaming.

2.2.1 Hadoop

Hadoop enables to distribute huge volume of data across many systems and it also facilitates the cluster management. For these purposes, Hadoop relies on Hadoop Distributed File System (HDFS) for the distributed storage and access of files and Yet Another Resource Negotiator (YARN) for the resource management. Both components communicate with other machines through a master-slave model.

The main concept behind HDFS is that it divides a file into blocks. One key benefit is the distributed processing of the HDFS blocks. In HDFS, the master is the NameNode which manages the filesystem namespace and logs all modifications and the state of the filesystem. It communicates all the information about the content of a filesystem to the DataNodes. These are made up of HDFS blocks representing a piece of data. They are located locally on each machine. Regarding YARN, the Application Master (here the Spark Driver) negotiates resources to the ResourceManager which is responsible for granting containers which are the resources allocated. Containers are then supervised locally by the NodeManagers.
Figure 2.1: Implementation diagram of the proposed Hadoop/Spark system.
2.3. EXPERIMENTAL SETUP

2.2.2 Spark

Spark relies on the concept of jobs which are performed across the worker nodes (CPUs (cores) and allocated
memory) using Stages and Tasks. Two main components of the Spark architecture are:

- Spark Driver: organize the completion of the jobs across the cluster of executors by interacting with
the ResourceManager and the NodeManagers. This is the Application Master in our workflow. It
tracks all the operations by executors. Moreover, this entity parses the code, and serializes the byte
level code across the executors. Any computations is actually done at the local level by each of them.
Furthermore, the Driver aims at planning all the computation in the cluster with Directed Acyclic
Graph (DAG). Once a DAG is created, it represents a job which is divided in stages. Then, each stage
is carried out as tasks. Finally, the Driver handles fault tolerance of all performed operations;

- Spark Executors: They represent processes running in the containers in a cluster. One or more executors
could be in each worker node and multiple tasks can be run in a single executor.

2.2.3 Implementation details

Our proposed system is executed within a Spark-Hadoop cluster deployed on the DATARMOR infrastructure,
belonging to IFREMER. Each node is composed of an Intel Xeon 2X CPU E5-2680 v4 (28c / 56t), 128 Go
DDR3. When using N node cluster, one node is used as a master and remaining N-1 as slaves. Each machine
runs on SUSE with hardware specs given in the Table 1. Each node of the cluster runs latest versions of
Hadoop and Spark.

2.3 Experimental setup

2.3.1 Dataset

Computational performance of the three computing systems were evaluated using one real underwater PAM
dataset recorded at 32768 Hz near the archipelago of Saint-Pierre-et-Miquelon over the last three months of
the year 2010. It consists of 1807 45-min long wav files for a total volume of 320 GB.

2.3.2 Benchmark

Our Scala/Spark version of the DEPAM workflow was benchmarked for computational performance against
two sequential versions using Matlab (version 2016b) and Python (version 3.5) programming languages.
For both we try at best to fit with "the best practices in programming": from the PAM community (e.g.,
drawn from PAMGuide by Merchant et al. (2015)) for the Matlab implementation, and from data scientist
communities for the python implementation (e.g., drawn from the Scipy toolbox, https://www.scipy.org/).
Double-precision floating-point format has been used in all three implementations. Based on multiple unitary
tests performed on the core features of the workflow\(^1\), the three versions match with root mean square error
below \(10^{-16}\).

The two parameter sets used for our experiments are listed in table 2.1. To evaluate computational
performance of our different systems, we use execution time as evaluation measure. In order to assess
fluctuation in execution time for each set of parameters, the workflow has been executed 3 times, and
times were averaged over these executions. We paid attention that launching was taken into account in the
computation time results. We also used the Datarmor infrastructure to run our benchmark.

We run two different types of experimentations.

**Single node experimentation**  As Spark also supports a pseudo-distributed local mode, we could first
benchmark the three DEPAM versions executed in single node mode (as Spark supports a pseudo-distributed
local mode). In such a scenario, Spark is run on a single machine with one executor per CPU core.

\(^1\) See complete unitary tests here
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| Parameter             | Parameter set 1 | Parameter set 2 |
|-----------------------|-----------------|-----------------|
| nfft                  | 256             | 4096            |
| windowOverlap         | 128             | 0               |
| windowSize            | 256             | 4096            |
| recordSizeInSec       | 60              | 10              |

Table 2.1: Parameter sets of the FFT-related variables in the DEPAM workflow.

**Multi-node experimentation**  In a second experimentation, we evaluated the scalability of our Hadoop/S-park system using the speed up metric, which corresponds to the reduction of execution time due to running a fixed workload using an increased number of hardware processors.
Chapter 3

Results & Discussion

3.1 Single node experimentation

3.1.1 Numerical results

Figure 3.3 represents execution time (mins) against workload (GB) for parameter set 1. Surprisingly, although the main advantage of Apache Spark technology is to scale out processing over several nodes in a transparent way (once the Hadoop cluster is set), our current results reveal that it also performs very well in its standalone mode, outperforming both other versions of the workflow. For example, for parameter set 1 and for a workload of 135.2 GB (i.e. 800 wav files of our dataset), our standalone proposed system takes 25.8 minutes of computation time, which is approximately twice as faster as Matlab-based and python-based workflows. Due to the linearity of the workload-execution time relationships, we can expect that this time gap will increase as the dataset volume increases.

![Figure 3.1: Execution time (mins) against workload (GB) for parameter set 1.](image)

3.1.2 Technical considerations

None of our two system implementations have been optimized. For the Matlab-based workflow, more complex built-in tools could have been used such as the Parallel Computing Toolbox nor the Matlab Distributed Computing Server as in [Dugan et al., 2010]. Similarly, the Python-based workflow could have been optimized using Celeri, mpi4py or Dask libraries. However, in these implementations we try at best to fit with "the best practices in programming": from the DCLDE community in Passive Acoustic Monitoring (e.g., drawing from the Panguide by Merchant2015) for the Matlab implementation, and from data scientist communities for the python implementation (drawing from the Scipy toolbox (https://www.scipy.org/)).

Having said that, our Hadoop / Spark system has not been optimized neither. Indeed, exact split length of each audio file for each processing task, the sequence of each task and how they are distributed for linear
3.2 Multi-node experimentation

3.2.1 Numerical results

Figure 3.3 represents the speedup metric against the number of nodes for different workloads (in GB). These results show that above 200 GB, almost-linear speedup is achieved. Indeed, as the workload increases, speedup linearizes towards the ideal case of scalability represented by the dashed black curve. Reading the graph, while a 33 GB workload only increases execution time by 4 when going from 1 to 16 cluster nodes, a 300 GB workload increases it by 11. As this result has been obtained without specific optimization process, e.g. adapting the number of executors to the split length of audio file, it is very promising for further development towards a more general-purpose cloud-based analytics engine.

![Figure 3.2](image)

Figure 3.2: Speed up metric against number of cluster nodes for parameter set 1 (on the left) and 2 (on the right) for different workloads (GB), using 15 Spark executors per node.

3.2.2 Technical considerations

Our current results can be explained by the main concepts of HDFS and Spark. Indeed, HDFS store locally data as chunks of files which are distributed on the machines. This means that Spark Executors can read those HDFS blocks locally and it avoids data network transfer which can be time-consuming in the case of huge data volume. In our configuration, our block size was larger than the file size which enables to read several files in parallel. As a consequence, in this work, adding more workers allows to read more files in parallel.

Note that our workflow is trivially parallelizable, each file can be processed by avoiding Partition-Sort-Shuffle-Merge transforms except for our last step of joining timestamps. If this type of operations were used in our workflow, the runtime performances would have decreased.
Figure 3.3: Speed up metric against number of cluster nodes for parameter set 1 and for different workloads (GB), using 10 Spark executors per node.
Chapter 4

General discussion

4.1 An ode to open science: from technological innovation to standardization of best practices

In addition to this capacity of leveraging complex analytics, we believe that Hadoop and Spark should help to reshape the big data landscape in the field of PAM research for at least three other reasons. First, Spark is able to capture fairly general computations and facilitates the implementation of iterative algorithms, e.g. used for the training algorithms of machine learning systems\footnote{Spark’s machine learning library MLlib, made interoperable with NumPy} which now play an important role in most PAM applications (e.g. whale detection and classification, see workshops of DCLDE workshops). It also facilitates the implementation of interactive/exploratory data analysis (i.e., the repeated database-style querying of data), especially through its SQL-compliant query capability allowing user-defined functions (UDF) that leverage any general-purpose function to apply to the data columns (e.g. to rank or aggregate rows of data over a sliding window). Such computational functionalities, made here at scale with speed, are now crucial in the context of big ocean data where PAM metrics are processed conjointly with multiple heterogeneous time series from other sensors. As a result, although we focus in this work on simple FFT-based descriptor computations, we envision our Apache Hadoop/Spark big data ecosystem growing as a general-purpose analysis system useful for many different types of PAM analysis. Third, numerous efforts have now made to outline some best practices for PAM processing (Robinson2014, Merchant2015), in the hope of boosting standardization and interoperability. On the contrary to expensive proprietary softwares (e.g. Matlab Distributed Computing Server), we believe that open source software like Apache Spark will strongly contribute to this dynamic, and we would encourage computational scientists and researchers to leave behind them “academic” codes that are too often made unreproducible, unbuildable, undocumented, unmaintained and backward incompatible.
Chapter 5

Conclusion and Future work

The combination of Spark and Hadoop has supercharged big data analysis across many use cases by lowering the barrier of entry to advanced analytics and thereby enabling data scientists to create data-driven products that weren’t previously possible.

In this work, we focused on the issue of efficiently processed huge volume of underwater audio recordings. We investigated which framework could be an alternative to standard tools to perform distributed computations. We did this by analyzing the runtime performances of a same workflow over three different technologies. It was demonstrated that the Hadoop-Spark implementation run faster with several nodes than Matlab or Python. Increasing the number of nodes had reduced the computation time.

This work aims at providing to the scientific community a general efficient and scalable tool to carry out a characterization of an underwater soundscape overall several years in a reasonable time with key metrics such as Welch periodogram, SPL, TOL. Moreover, all the codes are available on Github (). We encourage people that is interested in these big data issues to contribute to this repository.

Future directions will be to use this scalable tool to study the variability of the set of parameters to compute metrics in long-time series. In addition, other acoustic indices should be implemented in the workflow to provide more options to the user for the study of a soundscape.
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