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SMARTeBuses

Storing Data in a Hadoop Cluster

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HDFS Hadoop Distributed File System
JRE Java Runtime Environment
Yarn Yet Another Resource Negotiator
DSL Domain Specific Language
RDD Resilient Distributed Datasets

1 Introduction

Big Data is the ability of society to harness information in novel ways to produce useful insights or goods and services of significant value [1]. In this work package we focus on the use of Big Data technology to store, analyse and collect online public data related to the bus network (e.g., routes, timetables, delays) and wind power available from wind farms in the country. Furthermore, we focus on developing a realistic reference road network with essential information for a strategic planning and design of an electric bus network in Ireland. In line with the goals of the work package, we introduce the Big Data ecosystem of tools we are going to use for storing and analysis bus and wind power-related large-datasets.

The document is structured as follows:

Chapter 2 presents our ecosystem of tools to store and analyse large-scale datasets. First, Section 2.1 presents Apache Hadoop [2], specifically its components Hadoop Distributed File System (HDFS) [3, 4], Hadoop Yarn [5, 6] and Hadoop MapReduce [7, 8] for storing and analysing datasets. Then, Section 2.2 presents Apache Spark [9] as our primary data analytics tool (relying on HDFS and Yarn for data storage and job management, resp). In particular, it presents its components Spark Core [10, 11] and Spark SQL [12, 13]. While Python is selected as the programming language of choice (with both MapReduce and Spark providing an API for it), the data analytics applications will run on top of the Java Runtime Environment (JRE) [14].

Chapter 3 serves as a tutorial for installing and configuring such ecosystem of tools, as well as presenting some introductory data analysis examples. First, Section 3.1 presents the specs of the local server. Then, sections 3.2, 3.3, 3.4 and 3.5 present the setup of Java, Python, Hadoop and Spark, resp., including some introductory data analysis examples running on the local cluster.

2 Big Data Ecosystem

This chapter presents our ecosystem of tools to store and analyse large-scale datasets.

2.1 Hadoop

Apache Hadoop is a data framework for store and process big data distributed on clusters of commodity machines. Using the definition of its own website: *"The Apache Hadoop software library is a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is designed to scale up from single servers to thousands of machines, each offering local computation and storage. Rather than rely on hardware to deliver high-availability, the library itself is designed to detect and handle failures at the application layer, so delivering a highly-available service on top of a cluster of computers, each of which may be prone to failures"* [2].

The main idea of the framework is for data to be distributed among the nodes of the cluster for both its storage and processing. This way, each individual node works as much as possible on the data it hosts, minimising the need to talk to other nodes of the cluster (and thus minimising the data transferred over the network). Data is replicated among different nodes of the cluster for redundancy, availability and fault tolerant-free computations. If a node is unexpectedly shut down, the system is still ready to store and process the entire dataset without suffering a noticeable penalisation in the performance to achieve it. At failure, the workload of the node is assumed by any other alive node of the cluster, without any loss of data. Thus, the outcome of the computation does not become affected. When the node recovers, it just joins again the set of operative nodes, becoming available again for storing and processing data. Likewise, the addition of new nodes to the cluster is easy, and provides extra storage and processing capacity under demand. As the nodes cooperate on the tasks, the system is capable of dealing with peak workloads, which result only in slightly penalisation for the overall performance.

There are 3 components of Hadoop that we are going to use:

- HDFS: A distributed file system designed to efficiently allocate data across the multiple commodity machines (nodes) of the cluster.
- Yet Another Resource Negotiator (Yarn): A resource manager, responsible for schedule and monitor the execution of our data analysis applications.
- MapReduce: A framework for easily writing applications processing large-scale datasets across a cluster in a reliable, fault-tolerant manner.

2.1.1 Hadoop Distributed File System

We use HDFS as a distributed file system to store our datasets across a cluster. The master/slave architecture of HDFS consists of two types of daemons:

- A single NameNode. This is a master daemon managing the file system namespace and regulating access to files. In brief, the NameNode acts as the table of contents: it contains no single file itself, but it knows all files in the filesystem, as well as their distribution among the nodes.

- A number of DataNodes, usually one per node in the cluster. This is a slave daemon managing the storage of the node it runs on. That is, the DataNode controls all the files stored in the node, but it lacks any knowledge about the data stored in other nodes.

Figure 2.1 presents a cluster with 4 nodes, where 1 node contains the NameNode and the other 3 a DataNode each. As we can see, the memory storage of each node contains its own local file system and its fraction/slice of the HDFS.

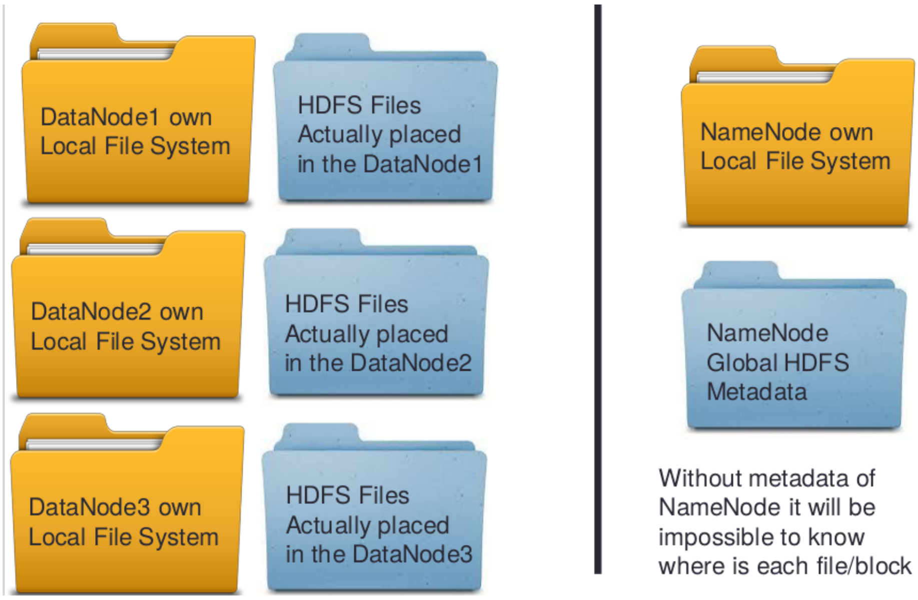


Figure 2.1: HDFS and Local File System

HDFS is designed to reliably store very large files. Its approach consists on splitting each file into manageable blocks and replicate each blocks among multiple nodes (typically 3, although this is configurable). Figure 2.2 shows a file split into 3 blocks when being written to HDFS and the replication of each block among the DataNodes.

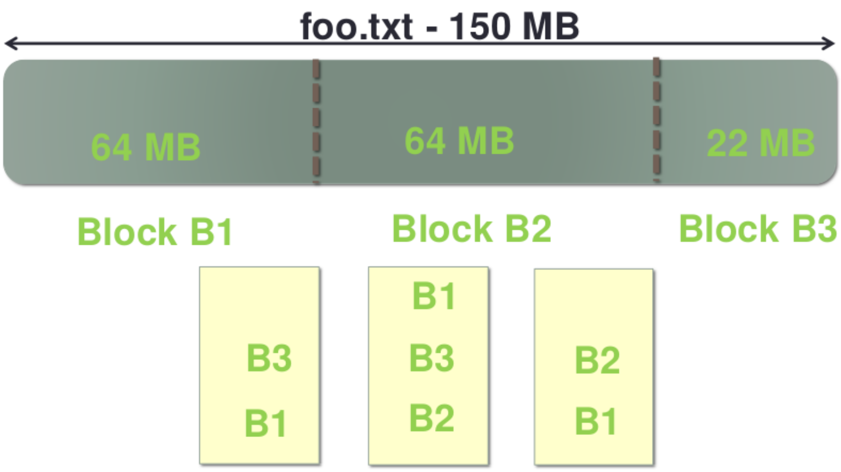


Figure 2.2: File to Block and Block Replication

We envision our data analysis applications to follow a very simple flow:

- Read the dataset from a logic folder of HDFS (e.g., `my_dataset`).

- Write the data analysis result to a new logic folder of HDFS (e.g., `my_result`).

The above requires us to:

- Create a new logic folder `my_dataset` into HDFS.
- Bring `my_dataset` from the local file system to the HDFS folder.
- Bring `my_result` from HDFS to the local file system.

HDFS provide the specific commands `mkdir`, `put` and `get` to accomplish the aforementioned tasks, resp. In brief, any read/write operation is coordinated by the NameNode, who refers to the associated DataNode of the node hosting the block for managing it.

2.1.2 Hadoop Yarn

We use the Yarn system as a resource manager, responsible for schedule and monitor the execution of our data analysis applications.

The key idea of Yarn is to split up the functionalities of resource management and job scheduling/monitoring into separate daemons:

- A single ResourceManager. This is a master daemon distributing the resources of the cluster among all the applications. In an analogy with HDFS, it will play the role of the NameNode, in the sense it executes nothing by itself, but it knows all the resources and tasks to be executed among the nodes of the cluster.
- A NodeManager per node in the cluster. This is a slave daemon monitoring the resource usage (cpu, memory, disk, network) of the node it runs on. In an analogy with HDFS, it will play the role of the DataNode, in the sense it controls the resources of the node and monitors the execution of the tasks assigned to it, but it lacks any knowledge about the resources and execution in other nodes of the cluster.

In brief, given a MapReduce or Spark application, the ResourceManager will provide the application with resources from 1 or more nodes of the cluster. Then, each NodeManager involved in the execution of the application will accomplish its assigned tasks with the resources provided.

2.1.3 Hadoop MapReduce

We use MapReduce as our first framework for easily writing applications processing large-scale datasets across a cluster in a reliable, fault-tolerant manner. A MapReduce application can be seen as a pipeline process operating on files that uses streaming for communication and high-level programming features to isolate the data processing from both the cluster and the pipeline complexities.

As previously stated, we envision a MapReduce application to read the dataset from a HDFS folder (e.g., `my_dataset`) and produce its results to a novel HDFS folder (e.g., `my_result`). In doing so, the application is to follow 3 phases: `map`, `sort` and `reduce`. Figure 2.3 presents an introductory word count MapReduce application, viewing its different phases from a logic and a physical point of views, resp.

As we can see, the *Map Phase* processes the entire dataset of `my_dataset` in a completely parallel manner. On doing so, each data block is processed on its own node as much as possible, with typically a `Map` process allocated to each block. The `Map` functionality is to be programmed just once, with all the processes applying it to their respective data slice (cf. middle picture of Figure 2.3). While the right level of parallelism for `Map` processes seems to be around 10-100 per node, in general the framework figures out the number of processes to be applied, as well as the block allocation for them.

This abstracts the cluster complexity from the user, who just has to focus on the programming of the `Map` functionality.

To specify the `Map` functionality we make use of Hadoop Streaming [15], which abstracts the `Map` process from its underlying programming language by only requiring it to be in the form of an executable command. In our case, we choose to program the `Map` functionality in the form of a Python script (e.g., `my_mapper.py`). Figure 2.4 shows `my_mapper.py` as a black-box. As we can see, it must receive its input from the standard input, and produce a bunch of key-value pairs by writing them to the standard output.

Coming back to Figure 2.3, we see that the *Sort Phase* sorts the outputs of the `Map` processes, which are then input to the `Reduce` processes. Again, while the right level of parallelism for `Reduce` processes seems to be around 1-2 per node, this is abstracted to the user who just has to focus on the programming of the `Reduce` functionality. What it is ensured is that all sorted entries having the same key are to be assigned to the same `Reduce` process.

As we did with the `Map` functionality, we use Hadoop Streaming to program the `Reduce` functionality in the form of a Python script (e.g., `my_reducer.py`). Figure 2.5 shows `my_reducer.py` as a black-box. As we can see, it must receive the key-value pairs produced by `Map` as input from the standard input, and produce a bunch of key-value pairs by writing them to the standard output.

Finally, the bulk of results from the *Reduce Phase* produce the new HDFS folder `my_result`. In particular, the output of each `Reduce` process turns into one or more new blocks in the folder.

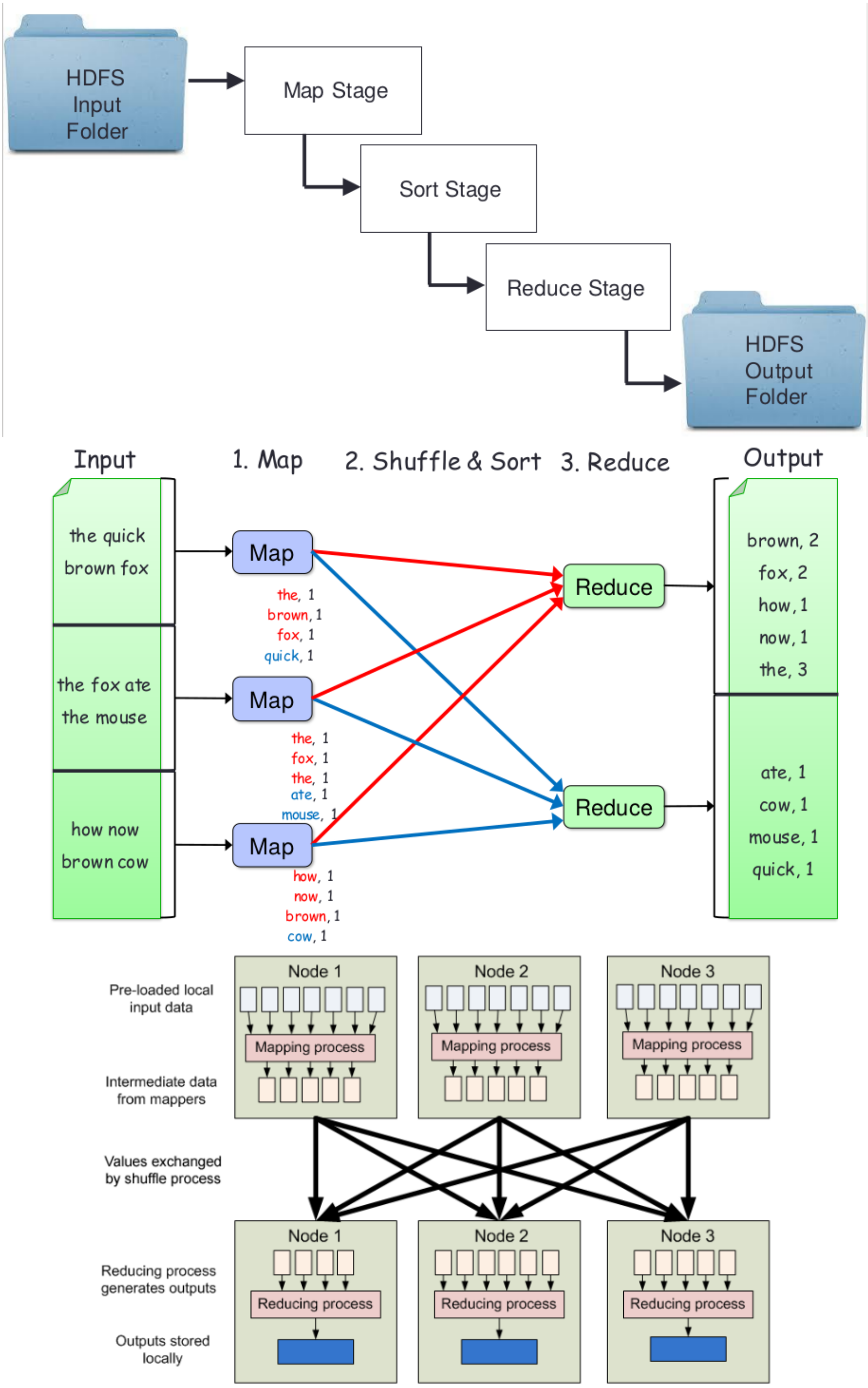


Figure 2.3: MapReduce Application Phases

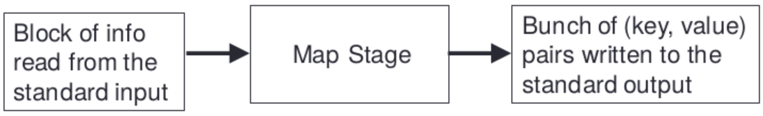


Figure 2.4: Map Phase

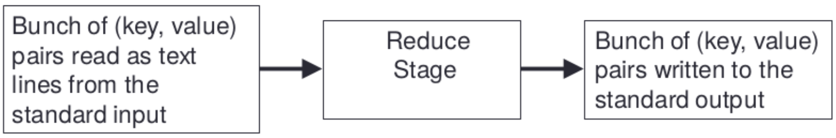


Figure 2.5: Reduce Phase

2.2 Spark

We use Apache Spark as our second framework for easily writing applications processing large-scale datasets across a cluster in a reliable, fault-tolerant manner. Using the definition of its own website: *Apache Spark is a unified analytics engine for large-scale data processing* [9]. It is an an open-source, distributed, general-purpose, cluster-computing framework designed for 3 purposes:

- Be easy to use, allowing us to develop applications locally, using a high-level API.
- Be fast, enabling interactive use and complex algorithms.
- Be general, allowing us to combine multiple types of computations, including text, SQL, graph and machine learning processing (both offline and online) that might previously have required different engines.

Spark itself is written in Scala [16], and runs on the Java Virtual Machine (JVM). However, it offers simple APIs in Scala, Java, Python and R. In our case, we choose Python to program our data analysis applications.

Figure 2.6 presents the different components of Spark. We are going to rely on HDFS for data storage and on Yarn for resource management and job scheduling. For developing our data analytics applications we are going to use Spark Core and Spark SQL.

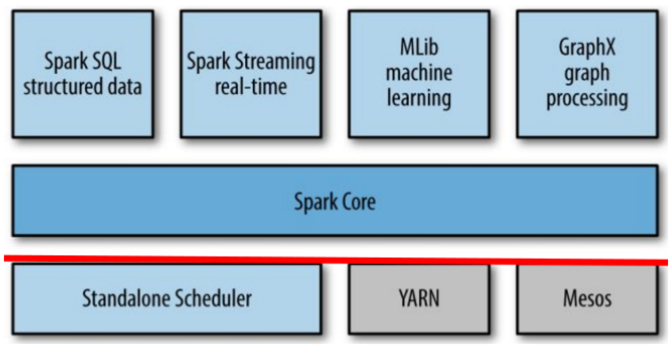


Figure 2.6: Spark Components

2.2.1 Data Storage and Resource Manager

On its own, Spark is not a data storage solution; it performs computations on Java Virtual Machines (JVMs) that last only for the duration of a Spark application. While Spark can be run locally on a single machine with a single JVM (called local mode), this mode is only useful for debugging and testing purposes. Once the application is tested, Spark is designed to efficiently scale up from one to many thousands of compute nodes, so we will use it in distributed mode across a cluster.

When used in a cluster, Spark is used in tandem with a distributed storage system (in our case HDFS) and with a cluster manager (in our case Yarn).

- HDFS is used to provide the input dataset used by Spark application (e.g., the HDFS folder `my_dataset`), as well as to stable store the results such application produces (e.g., the HDFS folder `my_result`).
- Yarn is used to schedule the execution of a Spark application, and for assigning and monitoring the resources of each node executing it.

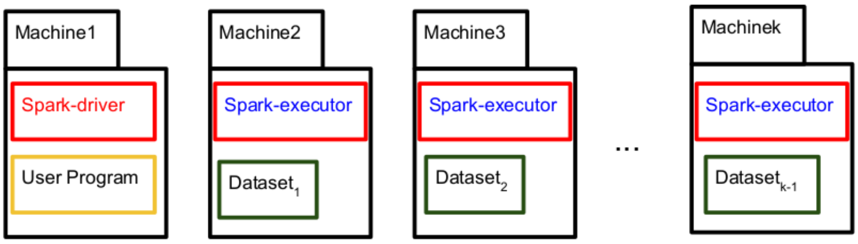


Figure 2.7: Spark Components

Figure 2.7 presents a general view of the execution of a Spark application in a cluster. The master/slave architecture of Spark consists of two types of daemons:

- A single SparkDriver. This is a master daemon coordinating the execution of the User program. In an analogy to HDFS, it plays the role of the NameNode, in the sense that it does not compute anything by itself, but controls who is executing each task and how is this execution going.
- A number of SparkExecutors. This is a slave daemon managing the execution of a single given task. A number of SparkExecutors are distributed among the cluster. While the number of cores per executor can be configured at the user program, typically they correspond to the physical cores on a node, and an executor cannot span cores of different nodes. In an analogy to HDFS, a SparkExecutor plays the role of the DataNode, in the sense that it carries out the computation of the task being given (and reports its status to the SparkDriver), but lacks any knowledge about the tasks executed by other SparkExecutors.

2.2.2 Spark Core

Spark Core contains the basic functionality of Spark, including:

- The main data abstraction being offered to users to express their programs: The Resilient Distributed Datasets (RDD)
- The implementation of the SparkDriver and SparkExecutor daemons needed to execute a Spark application. This includes the Spark driver functionality to generate a logical plan (Direct Acyclic Graph per job, with concrete stages and tasks) and a physical plan (schedule and tracking of the tasks execution).
- Other functionality such as memory management, fault recovery and the interaction with storage systems.

An RDD simply defines a collection of items. It is:

- Indivisible (logically presented as an atomic variable).
- Generic, but statycally-typed (available for any data type T as long as the type T sticks for all its elements).
- Lazily-evaluated (only computed if required, and as much as required).
- Non-mutable (cannot change type nor value).

In this context, we can think of an RDD as a list (in the sense that its elements can be repeated) or a set (in the sense that its elements have no particular default order).

The API of Spark Core offers Creation, Transformation, Persistent and Observer operations. Figure 2.8 presents the life-cycle of a Spark Core user program, based on these operations.

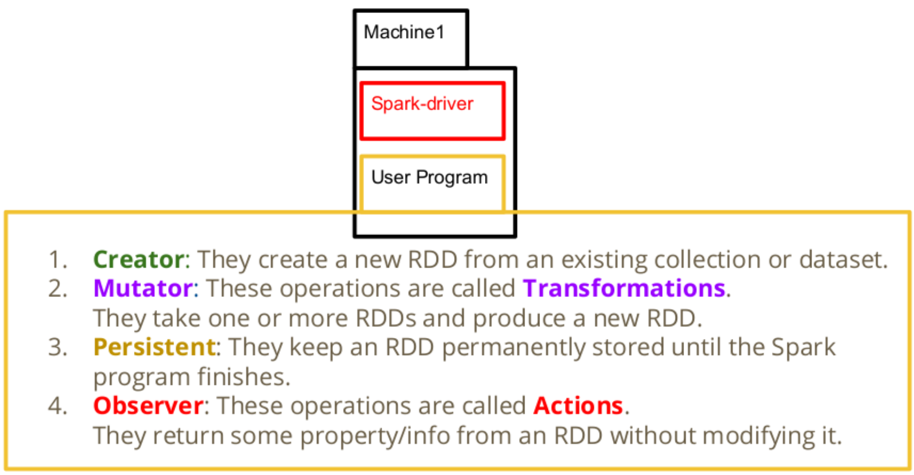


Figure 2.8: Spark Core: User Program

Figure 2.9 presents the execution of a Spark Core application. The application is defined as a set of Jobs triggered by the action operations of the user program. Each Job consists on a sequential execution of stages. Each new stage is caused by a shuffle of information among nodes executing different tasks. While no external communication is needed, each SparkExecutor works locally, performing a pipeline of tasks.

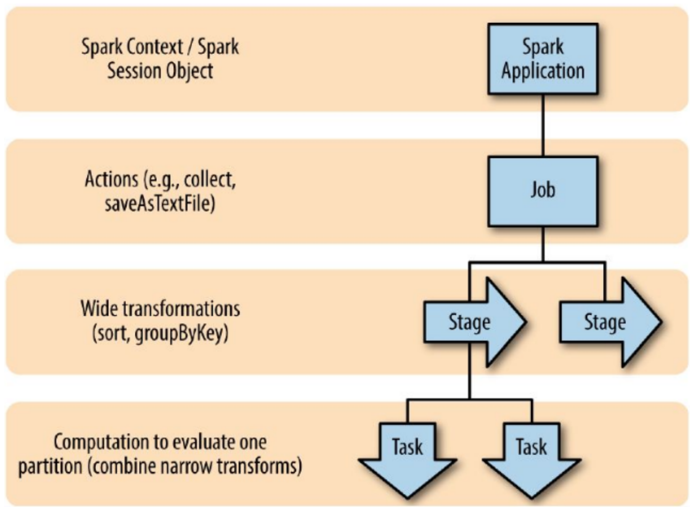


Figure 2.9: Spark Core: Program Execution

2.2.3 Spark SQL

Spark SQL is the module integrating relational processing with the functional programming API of Spark. By using it, we can benefit of a higher-level data abstraction (DataFrames) for ingesting, querying and persisting (semi)structured data using relational queries via a Domain Specific Language (DSL). Under the hood, Spark SQL translates a DataFrame-based program into an equivalent RDD-based one via a catalyst optimiser (which semantically analyse the query expressed by the user) and a Tungsten encoder optimiser (which translates the query to an equivalent binary RDD-based format).

An DataFrame simply defines a collection of items. It is:

- Indivisible (logically presented as an atomic variable).
- Structured, in the sense of having a fixed number of fields, each of them of a concrete data type T.
- Lazily-evaluated (only computed if required, and as much as required).
- Non-mutable (cannot change type nor value).

In this context, we can think of a DataFrame as a table in a relational database (in the sense that each Row follows the schema) or a collection in a NoSQL document oriented database (in the sense that the content of the collection is distributed).

Similarly to Spark Core, the API of Spark SQL offers Creation, Transformation, Persistent and Observer operations. Spark SQL provides them via a catalog of DSL operators. This DSL is being updated on each new release of Spark, making Spark SQL more and more expressive, and thus making it easier for the user to develop its data analysis applications.

3 Configuration and Code Examples

This chapter serves as a tutorial for installing and configuring the ecosystem of tools, as well as presenting some introductory data analysis examples.

3.1 Local Cluster

The local cluster used in this project consist on a server with the following specs:

- **Processor:** Intel Xeon W-2175 2.5GHz, 4.3GHz Turbo, 14C, 19.25M Cache, HT, (140W) DDR4-2666.
- **RAM:** 64GB 4x16GB DDR4 2666MHz RDIMM ECC Memory.
- **Hard Drive:** M.2 2TB PCIe NVMe Class 40 Solid State Drive.
- **Operating System:** Ubuntu 20.04 LTS [17].

The server has been purchased with the funding for equipment assigned to the project.

3.2 Java

In this section we discuss how to install and configure Java OpenJDK 8 [18]. While there is a more recent version available (Java OpenJDK 11 [19]), Java OpenJDK 8 is the most recent version supported by the latest stable release of Spark, thus making it our JRE of choice.

Figure 3.1 presents the script to install and configure Java OpenJDK 8. It can be run from a terminal in our local server.

```
(01) #!/bin/bash
(02) sudo apt-get update
(03) sudo apt-get install openjdk-8-jdk
(04) sudo update-alternatives --config java
(05) sudo update-alternatives --config javac
(06) sudo gedit ~/.bashrc
```

Figure 3.1: Script openJDK_8.sh

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`
  We indicate bin bash as the interpreter being used.
- `(02) sudo apt-get update`
  We update apt-get, the tool to handle packages in Linux.

- `(03) sudo apt-get install openjdk-8-jdk`
  We install Java OpenJDK 8.
- `(04) sudo update-alternatives --config java`
  We ensure that Java OpenJDK 8 is the default JRE. The command shows the different JREs installed in the system, highlighting with a symbol ⋆ the default one. For example, in the case below both Java OpenJDK 8 and Java OpenJDK 11 are installed in the system, with Java OpenJDK 8 being the default one being used.

```
  Selection    Path
------------------------------------------------------------
  0            /usr/lib/jvm/java-11-openjdk-amd64/bin/java
  1            /usr/lib/jvm/java-11-openjdk-amd64/bin/java
* 2            /usr/lib/jvm/java-8-openjdk-amd64/jre/bin/java
```

- `(05) sudo update-alternatives --config javac`
  We ensure that Java OpenJDK 8 is the default Java compiler. The command shows the different Java compilers installed in the system, highlighting with a symbol ⋆ the default one. For example, in the case below both Java OpenJDK 8 and Java OpenJDK 11 are installed in the system, with Java OpenJDK 8 being the default one being used.

```
  Selection    Path
------------------------------------------------------------
  0            /usr/lib/jvm/java-11-openjdk-amd64/bin/javac
  1            /usr/lib/jvm/java-11-openjdk-amd64/bin/javac
* 2            /usr/lib/jvm/java-8-openjdk-amd64/bin/javac
```

- `(06) sudo gedit ~/.bashrc`
  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `bashrc`. In our case we add:

```
export JAVA_HOME="/usr/lib/jvm/java-1.8.0-openjdk-amd64"
export PATH=$PATH:/usr/lib/jvm/java-1.8.0-openjdk-amd64/bin
```

3.3 Python

In this section we discuss how to install and configure Python 3.7.7 [20]. While there is a more recent version available (Python 3.8.2 [21]), Python 3.7.7 is the most recent version supported by the latest stable release of Spark, thus making it our programming language of choice.

Figure 3.2 presents the script to install and configure Python 3.7.7. It can be run from a terminal in our local server.

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`
  We indicate bin bash as the interpreter being used.
- `(02) sudo apt update`
  We update apt, the tool for managing deb packages in Ubuntu.
- `(03) sudo apt install build-essential zlib1g-dev libncurses5-dev \`
  `libgdbm-dev libnss3-dev \`

```
(01) #!/bin/bash
(02) sudo apt update
(03) sudo apt install build-essential zlib1g-dev \
              libncurses5-dev libgdbm-dev libnss3-dev \
              libssl-dev libreadline-dev \
              libffi-dev libsqlite3-dev \
          wget libbz2-dev
(04) wget https://www.python.org/ftp/python/3.7.7/Python-3.7.7.tgz
(05) tar -xf Python-3.7.7.tgz
(06) cd Python-3.7.7
(07) ./configure --enable-optimizations
(08) make -j $(nproc)
(09) sudo make altinstall
(10) sudo python3.7 -m pip install -U pip
(11) which python3.7
(12) python3.7
```

Figure 3.2: Script python_3_7_7.sh

```
                        libssl-dev libreadline-dev \
                        libffi-dev libsqlite3-dev \
      wget libbz2-dev
```

We use apt to install the required dependency packages.

- `(04) wget https://www.python.org/ftp/python/3.7.7/Python-3.7.7.tgz`

  We download Python 3.7.7 as a Gzipped source tarball.
- `(05) tar -xf Python-3.7.7.tgz`

  We extract it.
- `(06) cd Python-3.7.7`

  We move to the extracted Python 3.7.7 folder.
- `(07) ./configure --enable-optimizations`

  We run the `configure` script, which looks for dependencies.
- `(08) make -j $(nproc)`

  We run the `make` accross the number of processors we have in the server.
- `(09) sudo make altinstall`

  We use `altinstall` instead of `install` so as to allow Python 3.7.7 to co-exist with other potential versions installed in the server.
- `(10) sudo python3.7 -m pip install -U pip`

  We upgrade pip, the package installer for Python, to its most recent version 20.1 [22].
- `(11) which python3.7`

  We get the location of Python3.7.7 in our server. In this case it is:

  `/usr/local/bin/python3.7`

- `(12) python3.7`

  We launch Python3.7.7 to ensure it has been installed. In this case we should get the following:

  ```
  Python 3.7.7 (default, May  6 2020, 16:41:07)
  [GCC 7.5.0] on linux
  Type "help", "copyright", "credits" or "license"
  for more information.
  >>>
  ```

3.4 Hadoop

In this section we discuss how to install, configure and manage a Hadoop cluster. We also present a MapReduce application running on the cluster.

3.4.1 Installing Hadoop

We install and configure Hadoop 2.7.1 [23]. While there is a more recent version available (Hadoop 3.2.1 [24]), Hadoop 2.7.x is the most recent version supported by the latest stable release of Spark, thus making it our version of choice.

Figure 3.3 presents the script to install and configure Hadoop 2.7.1 as a Single Node Cluster with Pseudo-Distributed Operation. We choose this mode as our cluster contains just 1 node. Thus, all the HDFS, Yarn, MapReduce and Spark daemons presented in Chapter 2 still take place, each of them running as an independent process. The script can be run from a terminal in our local server.

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`

  We indicate bin bash as the interpreter being used.

- `(02) sudo apt-get install openssh-server openssh-client`

  We need to be able to access localhost by ssh without a passphrase. Thus, first we use apt-get to install OpenSSH, which is the premier connectivity tool for remote login with the ssh protocol [25].

- `(03) ssh-keygen -t rsa -P ""`

  We use ssh-keygen to generate a public/private rsa key pair. If run successfully, it saves the identification and public key in `$HOME\.ssh/`.

- `(04) cat $HOME/.ssh/id_rsa.pub >> $HOME/.ssh/authorized_keys`

  We use the command cat to append the public keys (generated by ssh-keygen) to our file of listed authorised keys.

- `(05) ssh localhost`

  We ensure we can connect now by ssh to the localhost without a passphrase.

- ```
  (06) wget https://archive.apache.org/dist/hadoop/
                    common/hadoop-2.7.1/hadoop-2.7.1.tar.gz
  ```

  We download Hadoop 2.7.1 as a Gzipped source tarball.

- `(07) tar -xzvf hadoop-2.7.1.tar.gz`

  We extract it.
  ```

```
(01) #!/bin/bash
(02) sudo apt-get install openssh-server openssh-client
(03) ssh-keygen -t rsa -P ""
(04) cat $HOME/.ssh/id_rsa.pub >> $HOME/.ssh/authorized_keys
(05) ssh localhost
(06) wget https://archive.apache.org/dist/hadoop/
                 common/hadoop-2.7.1/hadoop-2.7.1.tar.gz
(07) tar -xzvf hadoop-2.7.1.tar.gz
(08) sudo mv hadoop-2.7.1 /usr/local/hadoop/
(09) sudo gedit ~/.bashrc
(10) sudo gedit /usr/local/hadoop/etc/hadoop/hadoop-env.sh
(11) sudo gedit /usr/local/hadoop/etc/hadoop/core-site.xml
(12) sudo gedit /usr/local/hadoop/etc/hadoop/hdfs-site.xml
(13) sudo gedit
          /usr/local/hadoop/etc/hadoop/mapred-site.xml.template
(14) sudo cp
          /usr/local/hadoop/etc/hadoop/mapred-site.xml.template
          /usr/local/hadoop/etc/hadoop/mapred-site.xml
(15) sudo gedit /usr/local/hadoop/etc/hadoop/yarn-site.xml
(16) hadoop
```

Figure 3.3: Script Hadoop_2_7_1.sh

- `(08) sudo mv hadoop-2.7.1 /usr/local/hadoop/`

  We move the extracted folder to /usr/local/hadoop.

- `(09) sudo gedit ~/.bashrc`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `bashrc`. In our case we add:

```
export PATH=$PATH:/usr/local/hadoop/bin/:/usr/local/hadoop/sbin/
export HADOOP_HOME=/usr/local/hadoop/
export HADOOP_CONF_DIR=/usr/local/hadoop/etc/hadoop
export HADOOP_MAPRED_HOME=/usr/local/hadoop/
export HADOOP_COMMON_HOME=/usr/local/hadoop/
export HADOOP_HDFS_HOME=/usr/local/hadoop/
export YARN_HOME=/usr/local/hadoop/
export HADOOP_COMMON_LIB_NATIVE_DIR=/usr/local/hadoop/lib/native
export HADOOP_OPTS="-Djava.library.path=/usr/local/hadoop/lib"
export JAVA_LIBRARY_PATH=$HADOOP_HOME/lib/native:$JAVA_LIBRARY_PATH
```

- `(10) sudo gedit /usr/local/hadoop/etc/hadoop/hadoop-env.sh`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `hadoop-env.sh`. In our case we add:

```
export JAVA_HOME=/usr/lib/jvm/java-1.8.0-openjdk-amd64
```

- `(11) sudo gedit /usr/local/hadoop/etc/hadoop/core-site.xml`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `core-site.xml`. In our case we fill the (originally empty `<configuration></configuration>`) configuration section with:

```
<configuration>
<property>
<name>fs.defaultFS</name>
<value>hdfs://localhost:9000</value>
</property>
</configuration>
```

- `(12) sudo gedit /usr/local/hadoop/etc/hadoop/hdfs-site.xml`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `hdfs-site.xml`. In our case we fill the (originally empty `<configuration></configuration>`) configuration section with:

```
<configuration>
<property>
<name>dfs.replication</name>
<value>1</value>
</property>
</configuration>
```

- `(13) sudo gedit /usr/local/hadoop/etc/hadoop/mapred-site.xml.template`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `mapred-site.xml.template`. In our case we fill the (originally empty `<configuration></configuration>`) configuration section with:

```
<configuration>
<property>
<name>mapreduce.framework.name</name>
<value>yarn</value>
</property>
</configuration>
```

- `(14) sudo cp /usr/local/hadoop/etc/hadoop/mapred-site.xml.template /usr/local/hadoop/etc/hadoop/mapred-site.xml`

  We use super user privileges to copy the file `mapred-site.xml.template` to the new file `mapred-site.xml`.

- `(15) sudo gedit /usr/local/hadoop/etc/hadoop/yarn-site.xml`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `yarn-site.xml`. In our case we fill the (originally empty `<configuration></configuration>`) configuration section with:

```
<configuration>
    <property>
        <name>yarn.nodemanager.aux-services</name>
        <value>mapreduce_shuffle</value>
```

```
    </property>
</configuration>
```

- (16) hadoop

  We launch Hadoop 2.7.1 to ensure it has been installed. In this case we should get the following:

```
Usage: hadoop [--config confdir] [COMMAND | CLASSNAME]
  CLASSNAME            run the class named CLASSNAME
 or
  where COMMAND is one of:
  fs                   run a generic filesystem user client
  version              print the version
  jar <jar>            run a jar file
                       note: please use "yarn jar" to launch
                             YARN applications, not this command.
  checknative [-a|-h]  check native hadoop and compression
  libraries availability
  distcp <srcurl> <desturl> copy file or directories recursively
  archive -archiveName NAME -p <parent path> <src>* <dest>
  create a hadoop archive
  classpath            prints the class path needed to get the
  credential           interact with credential providers
                       Hadoop jar and the required libraries
  daemonlog            get/set the log level for each daemon
  trace                view and modify Hadoop tracing settings

Most commands print help when invoked w/o parameters.
```

3.4.2 Start a Hadoop Cluster

We start the Hadoop Single Node Cluster with Pseudo-Distributed Operation.
Figure 3.4 presents the script to start the cluster. It can be run from a terminal in our local server.

```
(01) #!/bin/bash
(02) ssh localhost
(03) hdfs namenode -format
(04) start-dfs.sh
(05) start-yarn.sh
(06) hdfs dfs -mkdir /user/
(07) hdfs dfs -mkdir /user/my_HDFS/
```

Figure 3.4: Script Start_Hadoop_Cluster.sh

Next, we present more detailed instructions about the steps followed in the script:

- (01) #!/bin/bash

  We indicate bin bash as the interpreter being used.

- `(02) ssh localhost`

  We connect by ssh to the localhost without a passphrase.

- `(03) hdfs namenode -format`

  We ensure HDFS has some format. If the command is successfully executed, then we should get the following, where ***MACHINE_NAME*** represents the name of the server:

```
STARTUP_MSG: Starting NameNode
STARTUP_MSG:   host = ***MACHINE_NAME***/127.0.1.1
STARTUP_MSG:   args = [-format]
STARTUP_MSG:   version = 2.7.1
STARTUP_MSG:   classpath =
STARTUP_MSG:   java = 1.8.0_252
SHUTDOWN_MSG: Shutting down NameNode
              at ***MACHINE_NAME***/127.0.1.1
```

- `(04) start-dfs.sh`

  We start the HDFS daemons NameNode and DataNode. If the command is successfully executed, then we should get the following, where ***USER_NAME*** represents the name of the user:

```
Starting namenodes on [localhost]
localhost: starting namenode, logging to /usr/local/hadoop/
logs/hadoop-***USER_NAME***-namenode-***MACHINE_NAME***.out
localhost: starting datanode, logging to /usr/local/hadoop/
logs/hadoop-***USER_NAME***-***MACHINE_NAME***.out
Starting secondary namenodes [0.0.0.0]
0.0.0.0: starting secondarynamenode, logging to /usr/local/
hadoop/logs/hadoop-***USER_NAME***-secondarynamenode-***MACHINE_NAME***
```

- `(05) start-yarn.sh`

  We start the YARN Job Scheduler, specifically its daemons ResourceManager and NodeManager. If the command is successfully executed, then we should get the following:

```
starting yarn daemons
starting resourcemanager, logging to /usr/local/hadoop/logs/
yarn-***USER_NAME***-resourcemanager-***MACHINE_NAME***.out
localhost: starting nodemanager, logging to /usr/local/hadoop/
logs/yarn-***USER_NAME***-nodemanager-***MACHINE_NAME***.out
```

- `(06) hdfs dfs -mkdir /user/`

  We create the HDFS folder /user.

- `(06) hdfs dfs -mkdir /user/my_HDFS/`

  We create the HDFS subfolder /user/my_HDFS/, where we can place the dataset to be analysed.

3.4.3 Dataset

We use the website Lipsum [26] to generate 4 paragraphs of *Lorem Ipsum* text. We create a dataset `my_dataset` with 4 small text files, each of them containing one of the generated paragraphs. Figure 3.8 presents the content of `my_dataset` in the local file system of our server.

3.4.4 HDFS

Once the cluster is started, we can check the status of the HDFS NameNode at and DataNode at http://localhost:50070/
Figures 3.6 and 3.7 show it. As we can see, the folder my_HDFS is empty.

Figure 3.5 presents the script to run a MapReduce or Spark data analysis application on top of HDFS. It can be run from a terminal in our local server.

```
(01) #!/bin/bash
(02) ssh localhost
(03) hdfs dfs -put ./my_dataset/ /user/my_HDFS/my_dataset
(04) # MapReduce or Spark Job Command
(05) hdfs dfs -get /user/my_HDFS/my_result ./
(06) hdfs dfs -rm -r /user/my_HDFS/my_dataset/
(07) hdfs dfs -rm -r /user/my_HDFS/my_result/
```

Figure 3.5: Script data_analysis.sh

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`
  We indicate bin bash as the interpreter being used.
- `(02) ssh localhost`
  We connect by ssh to the localhost without a passphrase.
- `(03) hdfs dfs -put ./my_dataset/ /user/my_HDFS/my_dataset`
  We use the HDFS command `put` to copy `my_dataset` from the local file system to HDFS. Figure 3.9 shows it.
- `(04) # MapReduce or Spark Job Command`
  We leave out the details of running a MapReduce/Spark Job to the next section. By the moment we assume the MapReduce/Spark Job succeeds, producing the results in the new HDFS folder `my_result`. Figure 3.10 shows it.
- `(05) hdfs dfs -get /user/my_HDFS/my_result ./`
  We use the HDFS command `get` to copy `my_result` from HDFS to our local file system. Figure 3.11 shows it.
- `(06) hdfs dfs -rm -r /user/my_HDFS/my_dataset/`
- `(07) hdfs dfs -rm -r /user/my_HDFS/my_result/`
  We use the the HDFS command `rm` to remove the folders `my_dataset` and `my_result` from HDFS. By doing so, we restore the content of HDFS to the one presented in Figure 3.7, i.e., ready to run the script again with a new data analysis application.

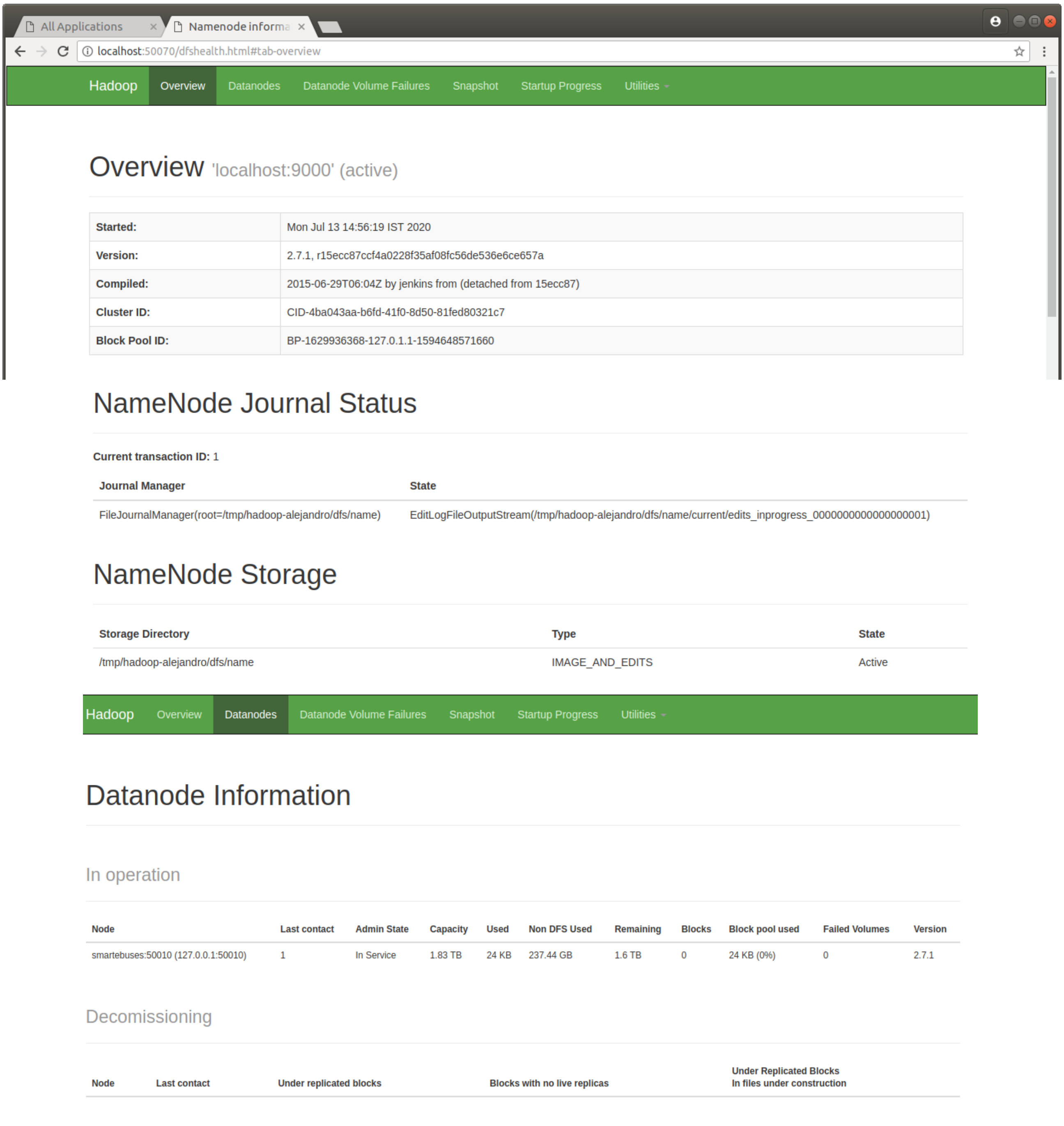


Figure 3.6: Cluster Overview

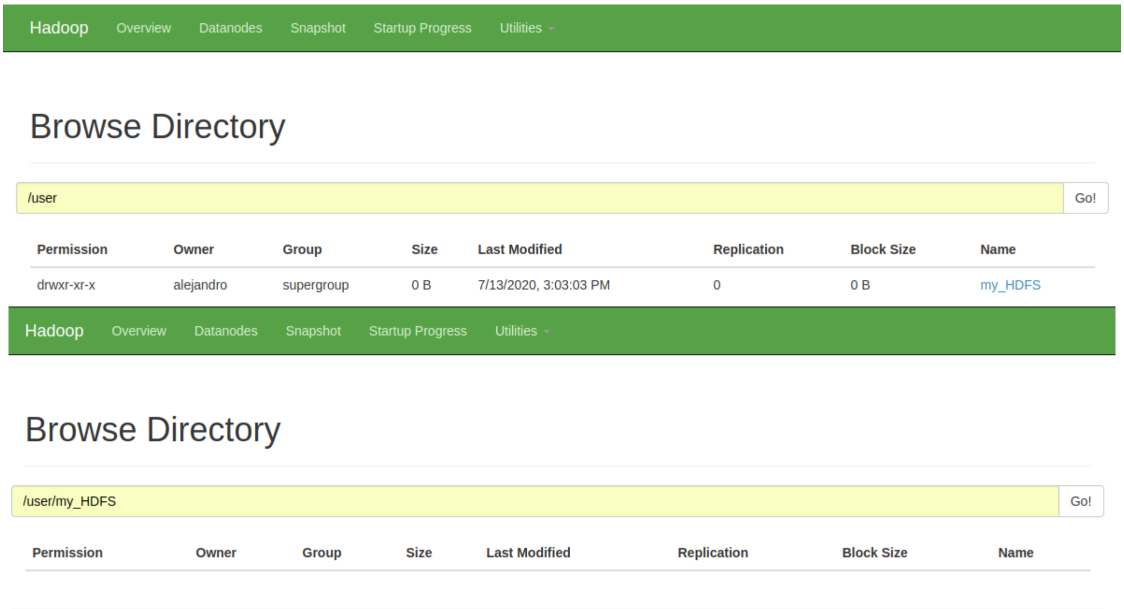


Figure 3.7: HDFS

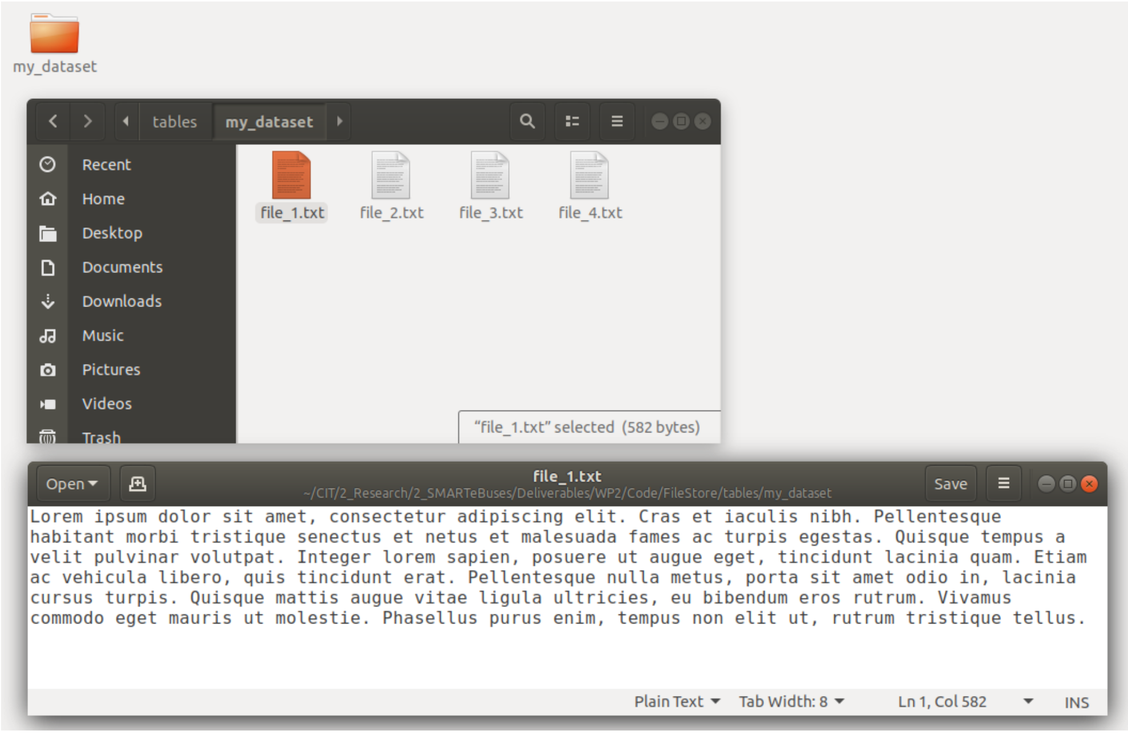


Figure 3.8: Dataset Folder: my_dataset

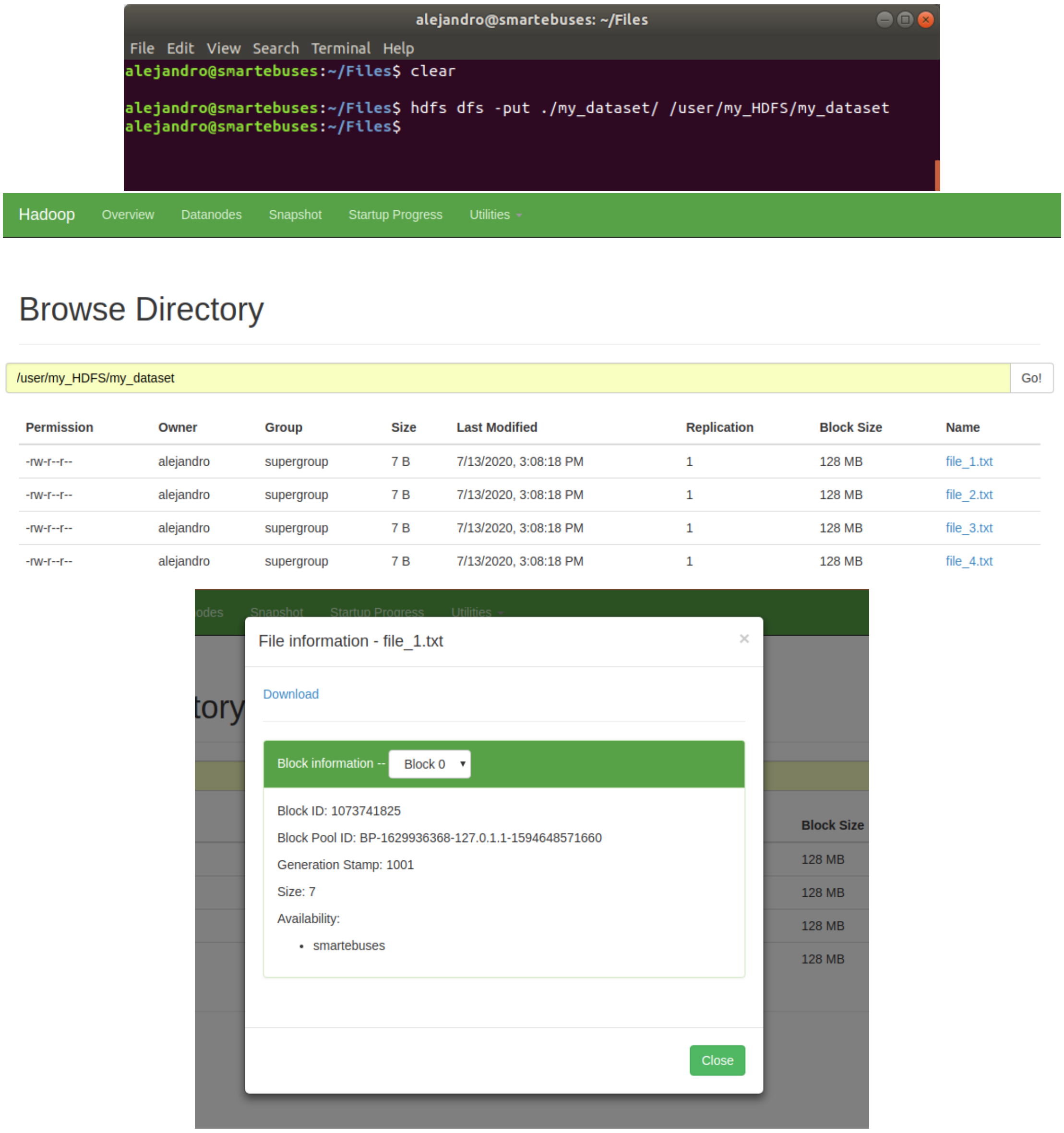


Figure 3.9: Command put: my_dataset from local file system to HDFS

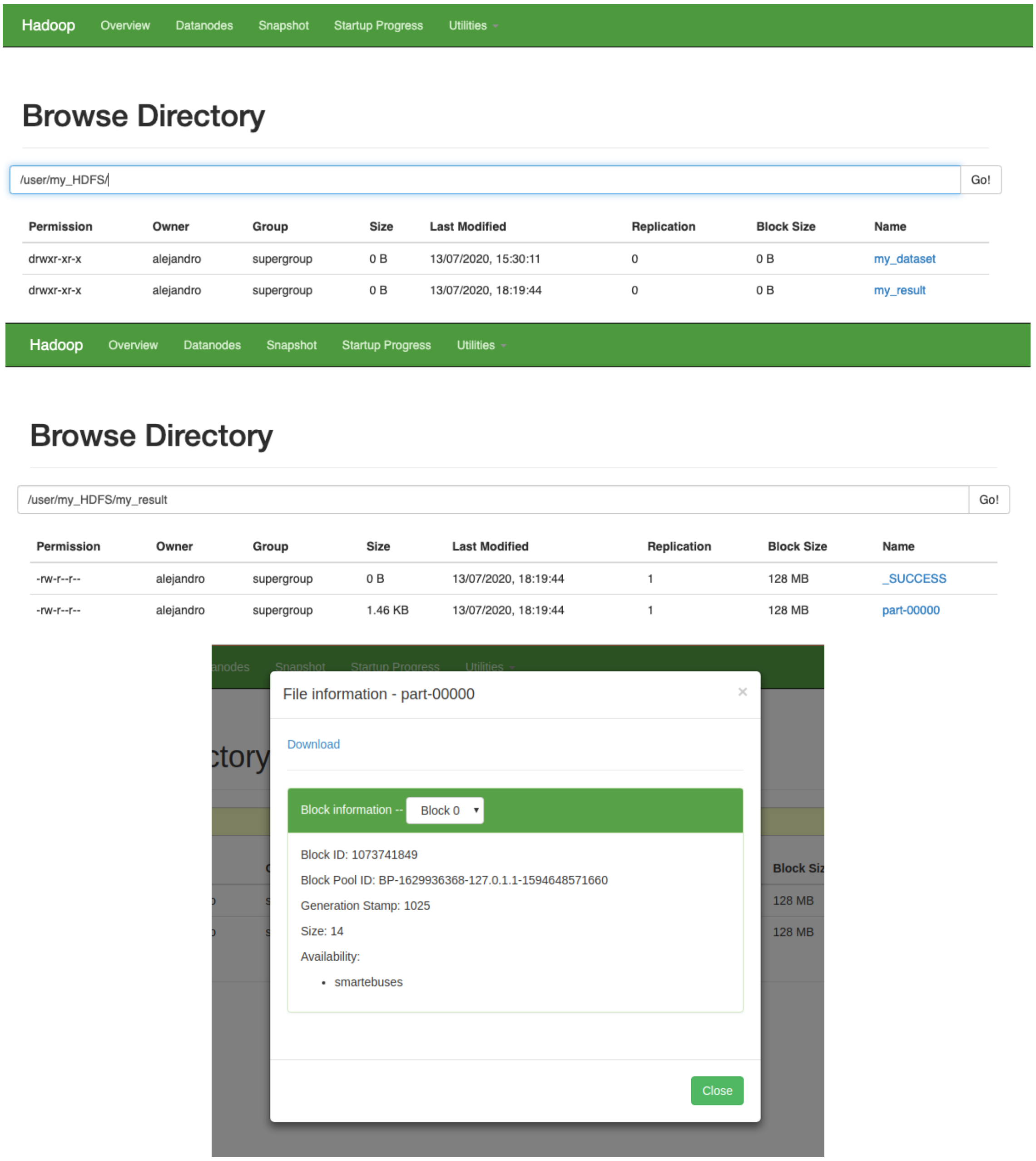


Figure 3.10: HDFS With New Folder my_result

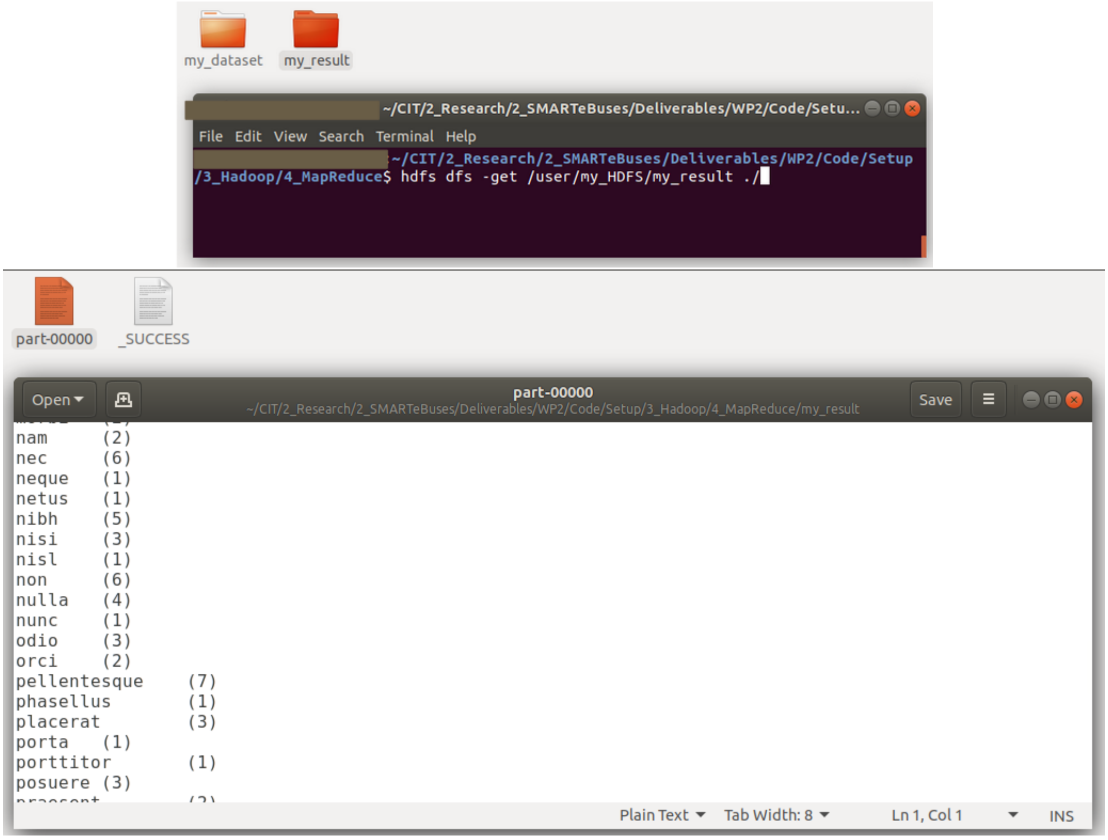


Figure 3.11: Command get: my_result from HDFS to local file system

3.4.5 MapReduce

Once the cluster is started, we can check the status of the Yarn ResourceManager and NodeManager at `http://localhost:8088/`
Figure 3.12 shows it. As we can see, there is no application being run so far.

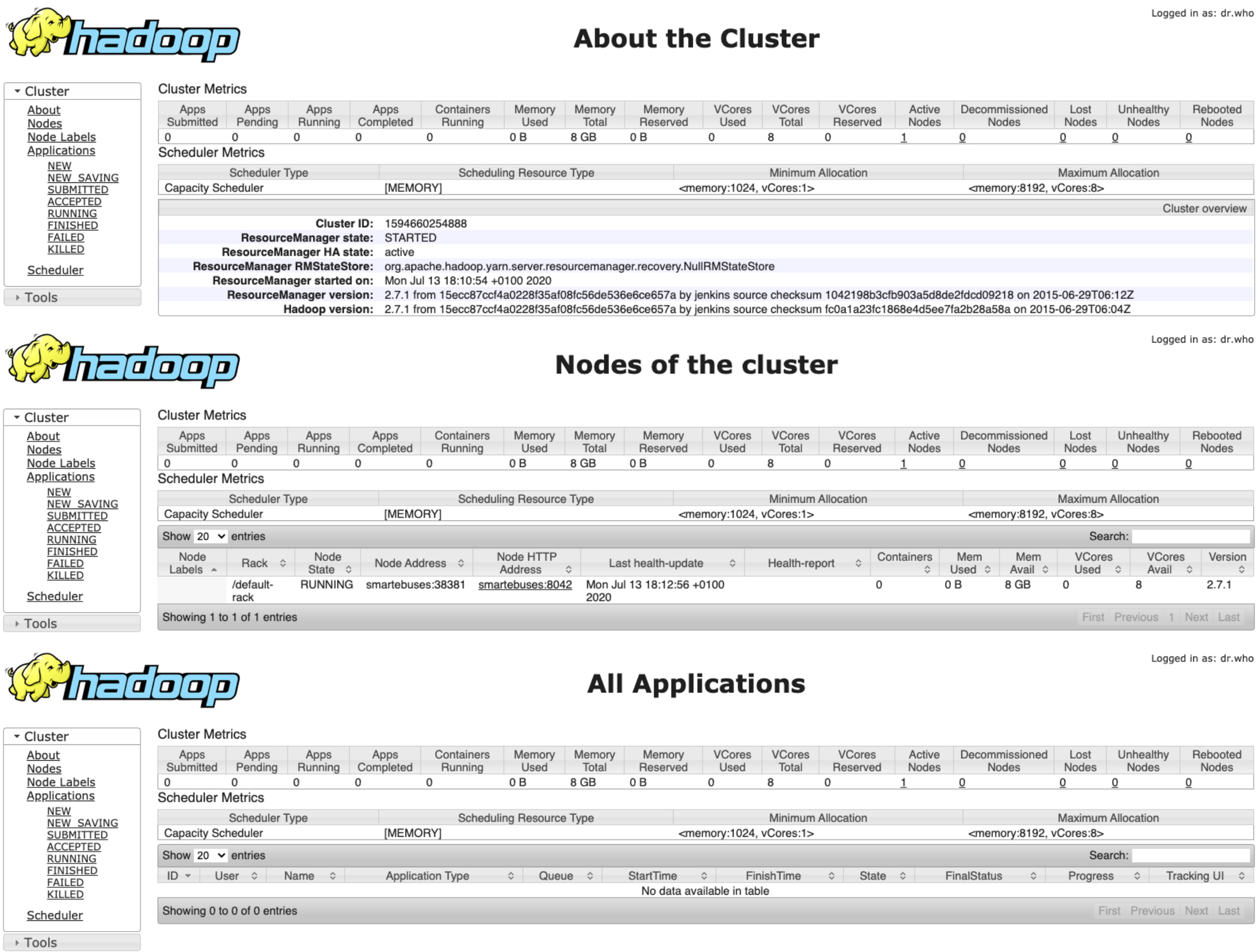


Figure 3.12: ResourceManager Overview

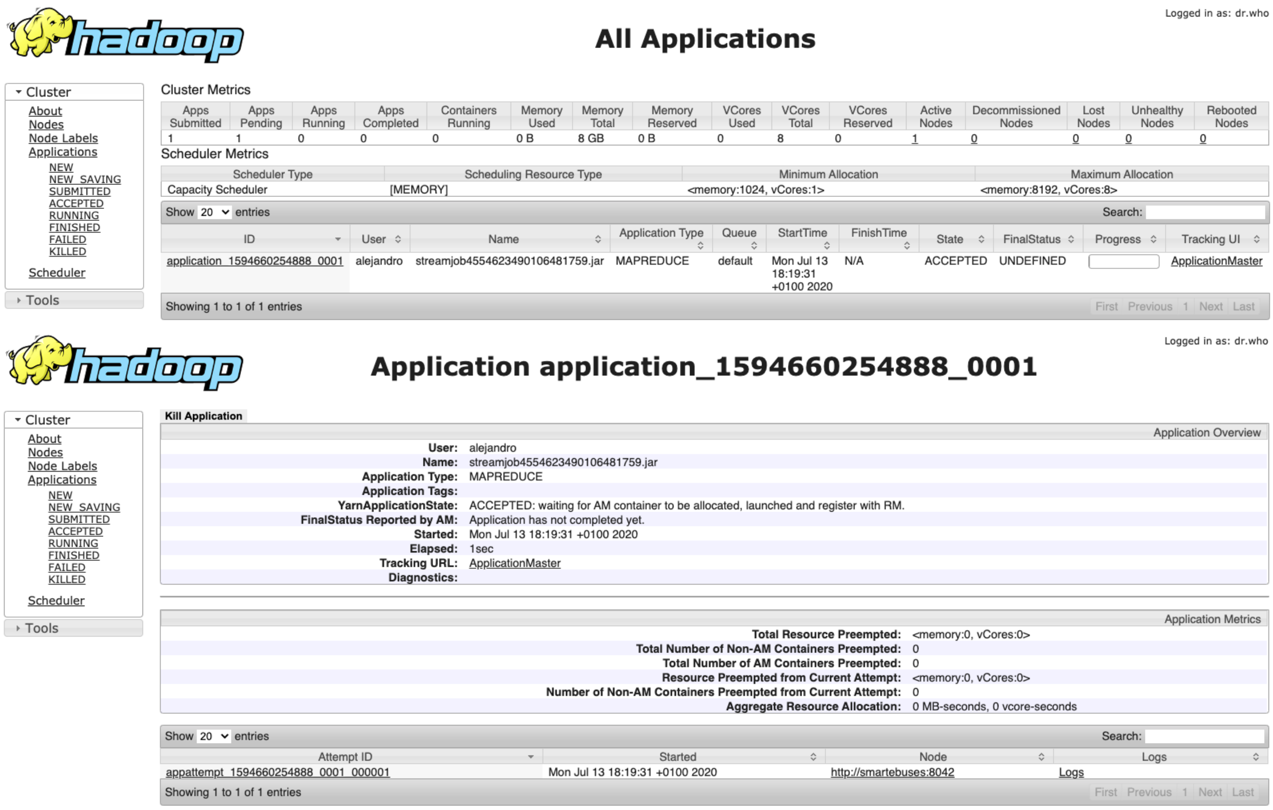


Figure 3.13: ResourceManager: MapReduce Application in Progress

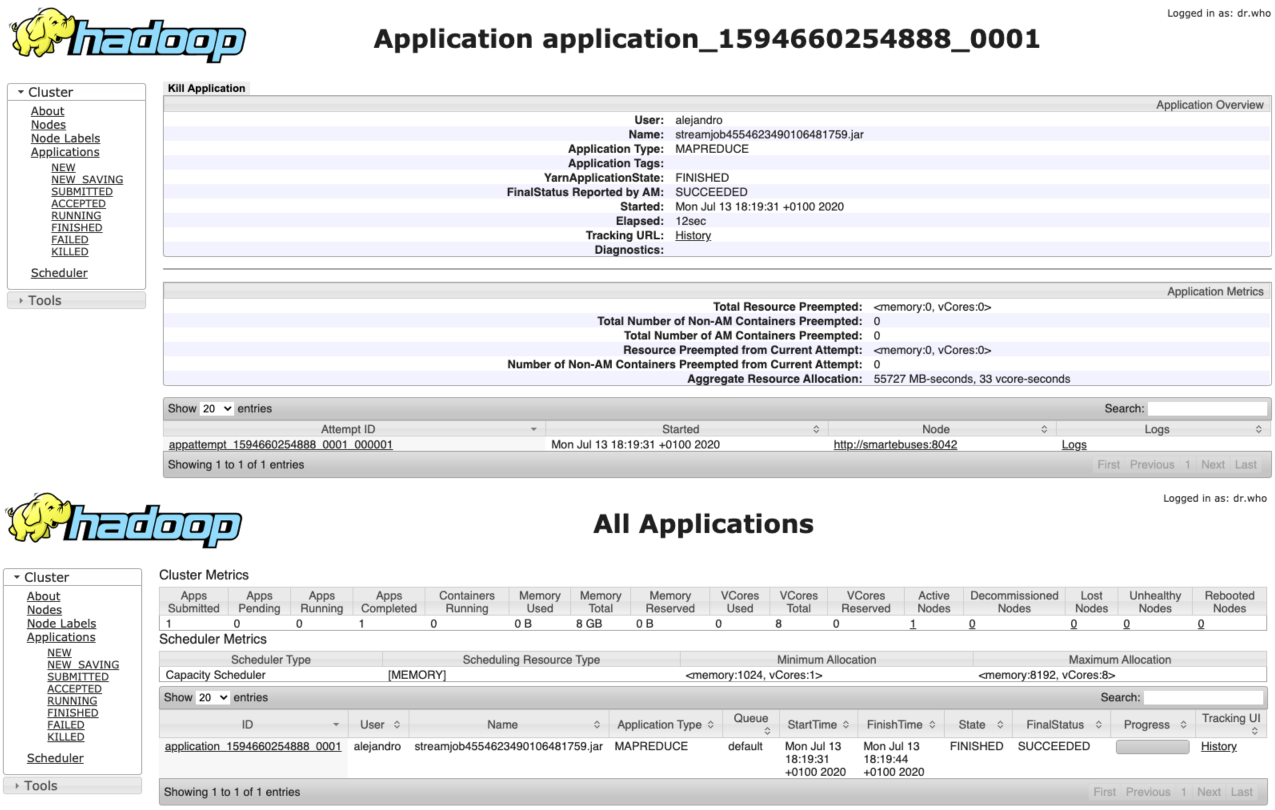


Figure 3.14: ResourceManager: MapReduce Application Finished

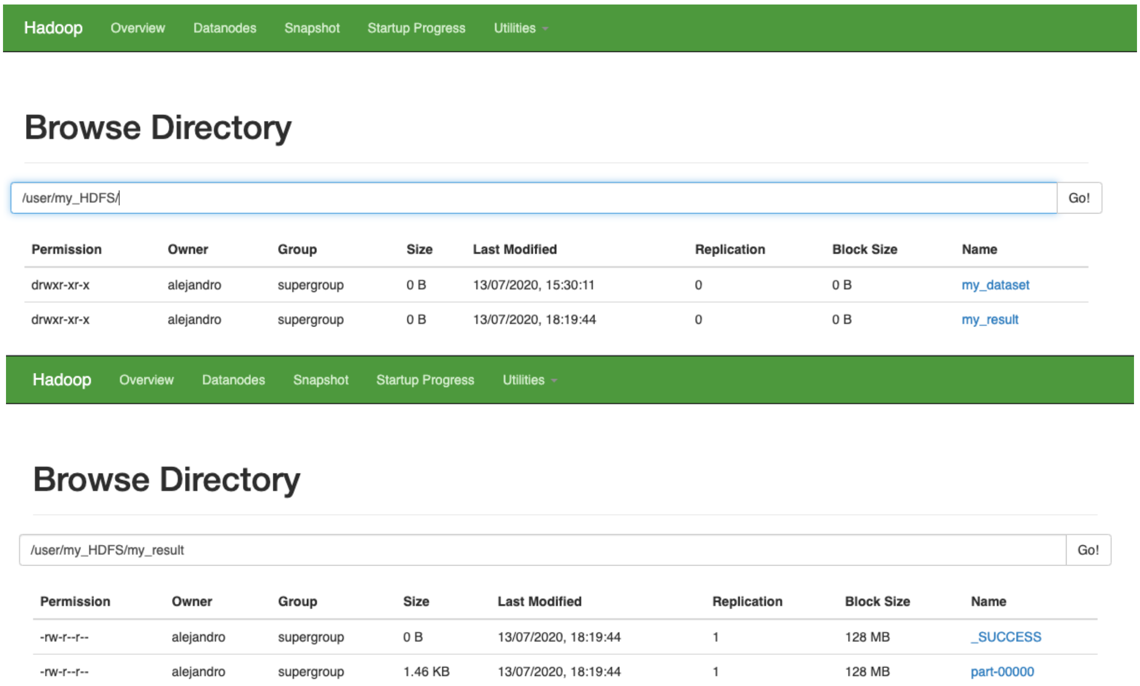


Figure 3.15: HDFS: MapReduce Result in my_result

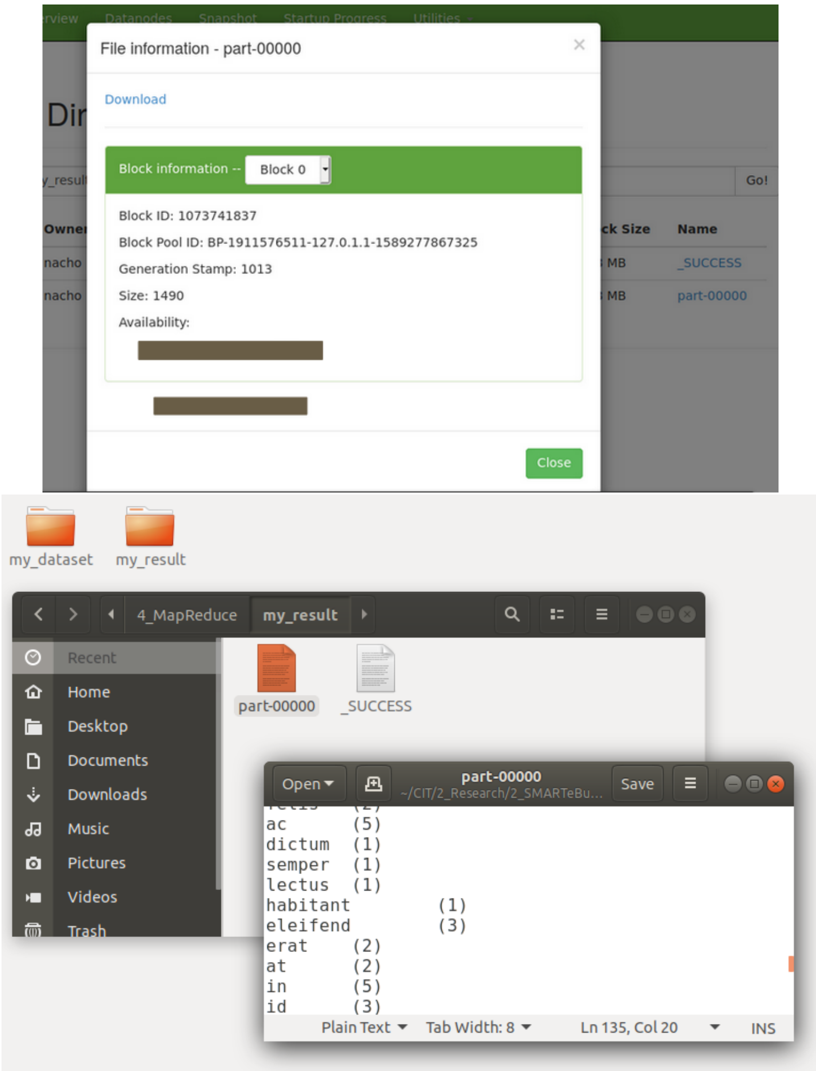


Figure 3.16: HDFS: MapReduce Result Brought Back to Local File System

We edit the command `(04) # MapReduce or Spark Job Command` from the script `data_analysis.sh` (cf. Figure 3.5) to run our introductory MapReduce application. The MapReduce command is presented below:

```
(04) hadoop jar /usr/local/hadoop/share/hadoop/tools/lib/
                 hadoop-streaming-2.7.1.jar \
     -input /user/my_HDFS/my_dataset \
     -output /user/my_HDFS/my_result \
     -mapper ./my_mapper.py \
     -reducer ./my_reducer.py \
     -file ./my_mapper.py \
     -file ./my_reducer.py
```

On it, we use the library Hadoop Streaming [15] to program a MapReduce application where the Map and Reduce stages are specified in the Python files `my_mapper.py` and `my_reducer.py`, resp. Both `my_mapper.py` and `my_reducer.py` are executable scripts, configured to read from the standard input and write to the standard output. The MapReduce application itself is quite simple: it produces as output the new folder `my_result`, containing the word count for the dataset provided in the input folder `my_dataset`.
Figures 3.17, 3.18 and 3.19 present the file `my_mapper.py`.

```
(01) # ------------------------------------------
(02) # IMPORTS
(03) # ------------------------------------------
(04) import sys
(05) import re
```

Figure 3.17: my_mapper.py: Import Section

We present more detailed instructions about the steps followed in the script:

- Lines (01)–(05) import the libraries `sys` and `re`. The former is used to redirect the input and output streams to `stdin` and `stdout`, resp. The latter is used to compile regular expressions for processing the content being read.
- Lines (06)–(27) define the function `my_map`. It receives as parameters an input and an output stream. The function reads the whole content provided by the input stream, producing as result a number of text lines to be written to the output stream. In concrete, for each different `word` being read by the standard input, the function produces a key-value line with the format `word\t(num_appearances)\n`, where `num_appearances` is the amount of times the word `word` has been read.

  The function uses a dictionary `my_dict` to collect as keys all words being read, with each word having as its associated key the number of appearances. `my_dict` is initialised in line (11) and it is populated in the for loop of lines (13)–(23). Line (14) ensures we read one line from the standard input at a time. Line (16) splits the text line to the list of words it contains. The loop of lines (18)–(23) processes each word separately. On line (19) we use `re.sub` and `lower` to remove any non-alphabetic character and to lower any upper case letter appearing in the word,

```
(06) # ------------------------------------------
(07) # FUNCTION my_map
(08) # ------------------------------------------
(09) def my_map(my_input_stream,
               my_output_stream
              ):
(10)     # 1. We create a dictionary with all
              the different words in the file
(11)     my_dict = {}
(12)     num_appearances = 1

(13)     # 2. We traverse the file content, to populate my_dict
(14)     for line in my_input_stream:
(15)         # 2.1. We process the line
(16)         word_list = line.split(" ")

(17)         # 2.2. We populate the dictionary
                    with the words of the sentence
(18)         for w in word_list:
(19)             my_word = re.sub(r"[^a-zA-Z]", "", w).lower()

(20)             if (my_word in my_dict):
(21)                 my_dict[my_word] =
                      my_dict[my_word] + num_appearances
(22)             else:
(23)                my_dict[my_word] = num_appearances

(24)     # 3. We write the content of the dict
(25)     for key in my_dict:
(26)         my_str = key + "\t(" + str(my_dict[key]) + ")\n"
(27)         my_output_stream.write(my_str)
```

Figure 3.18: my_mapper.py: my_map Function

resp. Finally, lines (20)–(23) check if the word has already been registered previously. If so, it increments its number of appearances by one. Otherwise, it enters the word in the dictionary with a single appearance.

Once the entire content of the standard input has been read and processed, lines (24)–(27) produce the lines to be written by the output stream. Line (25) traverses the words stored in the dictionary. Line (26) produces the String with the key-value pair associated to the word. Finally, line (27) writes this String to the standard output.

- Lines (31)–(38) define the main entry point for the program. Lines (35)–(36) redirect the input and output streams to `stdin` and `stdout`, resp. Line (38) calls to the aforementioned function `my_map`.

```
(28) # -------------------------------------------
(29) # MAIN
(30) # ------------------------------------------------
(31) if __name__ == '__main__':
(32)     # 1. We use as many input arguments as needed
(33)     pass

(34)     # 2. We set the input and output streams
(35)     my_input_stream = sys.stdin
(36)     my_output_stream = sys.stdout

(37)     # 3. We launch the Map program
(38)     my_map(my_input_stream,
             my_output_stream
            )
```

Figure 3.19: my_mapper.py: Main Entry Point

A copy of the file `my_mapper.py` is to be placed on each DataNode of the cluster involved in the Map stage, so as to process the subset of `my_dataset` associated to it.

Figures 3.20, 3.21 and 3.22 present the file `my_reducer.py`.

```
(01) # ------------------------------------------
(02) # IMPORTS
(03) # ------------------------------------------
(04) import sys
```

Figure 3.20: my_mapper.py: Import Section

The program is very similar to `my_mapper.py`, so we only higlight the differences:

- Lines (01)–(04) do no longer need to import the library `re`.
- Lines (05)–(26) define the function `my_reduce`. The function has the same responsability as `my_map`. However, instead of reading from `my_dataset`, the function reads the sorted key-value pairs `word\t(num_appearances)\n` produced by the stage `my_map`. Lines (14)–(17) parse each entry to get its associated word and number of appearances.
- Lines (31)–(38) define the main entry point for the program, calling to the aforementioned function `my_reduce`.

  A copy of the file `my_reducer.py` is to be placed on each node of the cluster involved in the Reduce stage, so as to process the subset of the sorted key-value entries associated to it.

Figure 3.13 presents the status of the ResourceManager once the command (04) of the script `data_analysis.sh` is launched. As we can see, the MapReduce application is considered to

```
# ----------------------------------------
# FUNCTION my_reduce
# ----------------------------------------
def my_reduce(my_input_stream,
              my_output_stream
             ):
    # 1. We create a dictionary with all
         the different words in the file
    my_dict = {}

    # 2. We traverse the file content, to populate my_dict
    for line in my_input_stream:
        # 2.1. We get the info from the line
        line = line.replace("\n", "")
        info = line.split("\t")

        my_word = info[0]
        num_appearances = int(info[1][1:-1])

        # 2.2. We populate the dictionary
               with the words of the sentence
        if (my_word in my_dict):
           my_dict[my_word] =
             my_dict[my_word] + num_appearances
        else:
           my_dict[my_word] = num_appearances

    # 3. We write the content of the dict
    for key in my_dict:
        my_str = key + "\t(" + str(my_dict[key]) + ")\n"
        my_output_stream.write(my_str)
```

Figure 3.21: my_mapper.py: my_map Function

be in progress. Figure 3.14 presents the status once the application finishes. As the execution is successful, the new folder `my_result` is available now in HDFS, with Figure 3.15 showing it. While the content of the files is not directly accessible in HDFS, we can execute the command `get` to bring the folder back to our local file system, so as to explore it (Figure 3.16 shows it). All in all, the MapReduce application finds 135 different words with their associated number of appearances in `my_dataset`.

```
# ---------------------------------------------
# MAIN
# --------------------------------------------------
if __name__ == '__main__':
    # 1. We use as many input arguments as needed
    pass

    # 2. We set the input and output streams
    my_input_stream = sys.stdin
    my_output_stream = sys.stdout

    # 3. We launch the Map program
    my_map(my_input_stream,
        my_output_stream
       )
```

Figure 3.22: my_mapper.py: Main Entry Point

3.4.6 Stop a Hadoop Cluster

Once we have run our data analysis application, we stop the Hadoop Single Node Cluster with Pseudo-Distributed Operation.

Figure 3.23 presents the script to stop the cluster. It can be run from a terminal in our local server.

```
(01) #!/bin/bash
(02) ssh localhost
(03) hdfs dfs -rm -r /user
(04) stop-yarn.sh
(05) stop-dfs.sh
```

Figure 3.23: Script Stop_Hadoop_Cluster.sh

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`
  We indicate bin bash as the interpreter being used.
- `(02) ssh localhost`
  We connect by ssh to the localhost without a passphrase.
- `(03) hdfs dfs -rm -r /user`
  We delete our HDFS folder.
- `(04) stop-yarn.sh`

We stop the YARN Job Scheduler, specifically its daemons ResourceManager and NodeManager. If the command is successfully executed, then we should get the following:

```
stopping yarn daemons
stopping resourcemanager
localhost: stopping nodemanager
localhost: nodemanager did not stop gracefully after 5 seconds: killing
no proxyserver to stop
```

- `(05) stop-dfs.sh`

  We stop the HDFS daemons NameNode and DataNode. If the command is successfully executed, then we should get the following:

```
Stopping namenodes on [localhost]
localhost: stopping namenode
localhost: stopping datanode
Stopping secondary namenodes [0.0.0.0]
0.0.0.0: stopping secondarynamenode
```

3.5 Spark

In this section we discuss how to install and configure Spark. We also present a Spark Core and a Spark SQL application running on top of the Hadoop cluster described in Section 3.4.

3.5.1 Installing Spark

We install and configure Spark 2.4.5 [27]. While there is a more recent version available (Spark 3.0.0 [28]), this version is still in preview mode and thus it is not stable.

Figure 3.24 presents the script to install and configure Spark 2.4.5. It can be run from a terminal in our local server.

```
(01) #!/bin/bash
(02) wget https://downloads.apache.org/spark/spark-2.4.5/
                    spark-2.4.5-bin-hadoop2.7.tgz
(03) tar -xzvf spark-2.4.5-bin-hadoop2.7.tgz
(04) sudo mv spark-2.4.5-bin-hadoop2.7 /usr/local/spark
(05) python3.7 -m pip install pyspark
(06) sudo gedit ~/.bashrc
(07) spark-submit --version
```

Figure 3.24: Script Spark_2_4_5.sh

Next, we present more detailed instructions about the steps followed in the script:

- `(01) #!/bin/bash`

  We indicate bin bash as the interpreter being used.

- `(02) wget https://downloads.apache.org/spark/spark-2.4.5/`
  `spark-2.4.5-bin-hadoop2.7.tgz`

  We download Spark 2.4.5 as a Gzipped source tarball. Among the different versions, we choose the one that is pre-built for Hadoop 2.7.
- `(03) tar -xzvf spark-2.4.5-bin-hadoop2.7.tgz`

  We extract it.
- `(04) sudo mv spark-2.4.5-bin-hadoop2.7 /usr/local/spark`

  We move the extracted folder to /usr/local/spark.
- `(05) python3.7 -m pip install pyspark`

  We use pip, the package installer for Python, to download `pyspark 2.4.5` [29]. This package is useful as it allows us to develop, debug and run a Spark application locally, using the Python 3.7.7 interpreter and the Python IDE PyCharm [30]. Once the application has been tested, it can be submitted for running in the Hadoop Single Node Cluster with Pseudo-Distributed Operation described in Section 3.4.
- `(06) sudo gedit ~/.bashrc`

  We use super user privileges with the text editor `gedit` so as to modify the content of the configuration file `bashrc`. In our case we add:

  ```
  export PATH=$PATH:/usr/local/spark/bin/
  export PYSPARK_PYTHON=python3.7
  ```
- `(07) spark-submit --version`

  We launch Spark 2.4.5 to ensure it has been installed. In this case we should get the following:

  ```
  Welcome to
        ____              __
       / __/__  ___ _____/ /__
      _\ \/ _ \/ _ `/ __/  '_/
     /___/ .__/\_,_/_/ /_/\_\   version 2.4.5
        /_/

  Using Scala version 2.11.12, OpenJDK 64-Bit Server VM, 1.8.0_252
  Branch HEAD
  Compiled by user centos on 2020-02-02T19:38:06Z
  Revision cee4ecbb16917fa85f02c635925e2687400aa56b
  Url https://gitbox.apache.org/repos/asf/spark.git
  Type --help for more information.
  ```

3.5.2 Spark Core

In Section 3.4 we started the cluster and run a MapReduce application on it. Figure 3.14 showed the status of the Yarn ResourceManager and NodeManager (available at `http://localhost:8088/`) including such MapReduce application.

We edit now the command `(04) # MapReduce or Spark Job Command` from the script `data_analysis.sh` (cf. Figure 3.5) to run our introductory Spark Core application. The Spark Core command is presented below:

```
(04) spark-submit \
```

```
--master yarn --deploy-mode cluster \
./my_Spark_Core_example.py \
/user/my_HDFS/my_dataset \
/user/my_HDFS/my_result
```

On it, we use `spark-submit` to launch the Spark Core application in the Hadoop Single Node Cluster with Pseudo-Distributed Operation. The line `--master yarn --deploy-mode cluster` specifies Yarn to be the ResourceManager handling the application. The line `./my_Spark_Core_example.py` specifies the Python file containing the Spark Core application. Finally, the lines `/user/my_HDFS/my_dataset` and `/user/my_HDFS/my_result` are the first and second parameter of the Python program, resp.

The functionality of the Spark Core application is equivalent to the one of the MapReduce application presented in Section 3.4: it produces as output the new folder `my_result`, containing the word count for the dataset provided in the input folder `my_dataset`.

Figures 3.25, 3.26 and 3.27 present the file `my_Spark_Core_example.py`.

```
(01) # ------------------------------------------
(02) # IMPORTS
(03) # ------------------------------------------
(04) import pyspark
(05) import sys
(06) import re
```

Figure 3.25: my_Spark_Core_example.py: Import Section

We present more detailed instructions about the steps followed in the script:

- Lines (01)–(06) import the libraries `pyspark`, `sys` and `re`. The library `pyspark` allows us to use the Spark Core API. The library `sys` is used to pass the input and output directories to the program. The library `re` is used to compile regular expressions for processing the content being read.
- Lines (07)–(20) define the function `my_spark_core_job`. It receives as parameters the SparkContext (`sc`) and the aforementioned input and output directories (`my_dataset_dir` and `my_result_dir`, resp). The function processes the dataset in `my_dataset_dir` to produce the new folder `my_result_dir` with its word count.

  Line (12) applies the creator operation `textFile` (with the folder `my_dataset_dir` as parameter) to load the dataset into `inputRDD`, an RDD of String items. In particular, each line of text of the dataset file turns into one item of such RDD. Figure 3.8 showed the content of `file_1.txt` of `my_dataset`. Figure 3.28 presents how the first 2 lines of the file translate into 2 items of `inputRDD`.

  Line (14) applies the transformation operation `flatMap` (with the lambda function `lambda line: line.split(" ")` as parameter) on `inputRDD` to produce the new RDD `all_wordsRDD` of String items. In particular, each item (text line) of `inputRDD` is to be split into a list with the words it contains, and then this word list is exploded, producing

```
(07) # ------------------------------------------
(08) # FUNCTION my_spark_core_job
(09) # ------------------------------------------
(10) def my_spark_core_job(sc, my_dataset_dir, my_result_dir):
(11)     # 1. Operation C1: textFile
(12)     inputRDD = sc.textFile(my_dataset_dir)

(13)     # 2. Operation T1: flatMap
(14)     all_wordsRDD =
                  inputRDD.flatMap(lambda line: line.split(" "))

(15)     # 3. Operation T2: map
(16)     clean_wordsRDD =
             all_wordsRDD.map(lambda w:
                   (re.sub(r"[ˆa-zA-Z]", "", w).lower(),
                    1
                   )
                             )

(17)    # 4. Operation T3: reduceByKey
(18)    solutionRDD =
                   clean_wordsRDD.reduceByKey(lambda x, y: x + y)

(19)    # 5. Operation A1: saveAsTextFile
(20)    solutionRDD.saveAsTextFile(my_result_dir)
```

Figure 3.26: my_Spark_Core_example.py: my_spark_core_job Function

one item per word. Figure 3.29 presents the items produced in `all_wordsRDD` for the first item of `inputRDD` showed in Figure 3.28.

Line (16) applies the transformation operation `map` (with the lambda function `lambda w: (re.sub(r"[ˆa-zA-Z]", "", w).lower(), 1)` as parameter) on `all_wordsRDD` to produce the new RDD `clean_wordsRDD` of tuple (String, int) items. In particular, each item (word) of `all_wordsRDD` is to see removed any non-alphanumeric character; besides that, any upper-case letter is turned into its equivalent lower-case letter. The function returns the tuple (word, 1), registering one appearance of the word. Figure 3.30 presents the items produced in `clean_wordsRDD` for the subset of items of `all_wordsRDD` showed in Figure 3.29.

Line (18) applies the transformation operation `reduceByKey` (with the lambda function `lambda x, y: x + y` as parameter) on `clean_wordsRDD` to produce the new RDD `solutionRDD` of tuple (String, int) items. In particular, all items containing the same key (word) are aggregated (adding the number of appearances). Figure 3.31 presents the content of `solutionRDD` for the words showed in Figure 3.30.

Line (20) applies the action operation `saveAsTextFile` (with the folder `my_result_dir`

```
(21) # ------------------------------------------------
(22) # MAIN
(23) # ------------------------------------------------
(24)     # 1. We use as many input arguments as needed
(25)     my_dataset_dir = "/FileStore/tables/my_dataset/"
(26)     my_result_dir = "/FileStore/tables/my_result/"

(27)     if (len(sys.argv) > 1):
(28)        my_dataset_dir = sys.argv[1]
(29)        my_result_dir = sys.argv[2]

(30)     # 2. We configure the Spark Context
(31)     sc = pyspark.SparkContext.getOrCreate()
(32)     sc.setLogLevel('WARN')
(33)     print("\n\n\n")

(34)     # 3. We call to our main function
(35)     my_spark_core_job(sc, my_dataset_dir, my_result_dir)
```

Figure 3.27: my_Spark_Core_example.py: Main Entry Point

as parameter) to store the content of `solutionRDD` into it. The result folder `my_result_dir` contains as many files as partitions are in `solutionRDD`. In particular, each item of the RDD is stored as a text line. Figures 3.34 and 3.35 present the files and content produced by `solutionRDD` when the program is executed in the Hadoop cluster.

- Lines (21)–(35) define the main entry point for the program. Lines (25)–(26) specify the input and output directories. When testing the program locally, we run the program in PyCharm and assign the dataset folder `my_dataset` of the local file system. When running the program in the Hadoop cluster we use lines (27)–(29) to set the input and output directories to the HDFS folders `/user/my_HDFS/my_dataset` and `/user/my_HDFS/my_result` (as described in the command `(04) spark submit` of the script `data_analysis.sh` for launching the program). Lines (31)–(33) create the SparkContext, configuring how verbose it should be on reporting the status when running the application. Finally, line (35) calls to the aforementioned function `my_spark_core_job`.

A copy of the file `my_Spark_Core_example.py` is to be placed on the DataNode the cluster running the Spark Driver process.

Figure 3.32 presents the status of the ResourceManager once the command (04) of the script `data_analysis.sh` is launched. As we can see, the Spark Core application is considered to be in progress. Figure 3.33 presents the status once the application finishes. As the execution is successful, the new folder `my_result` is available now in HDFS, with Figure 3.34 showing it. While the content of the files is not directly accessible in HDFS, we can execute the command `get` to bring the folder back to our local file system, so as to explore it (Figure 3.35 shows it). All in all, the Spark Core application finds 135 different words with their associated number of appearances in `my_dataset`.

```
Lorem ipsum dolor sit amet, elit. Cras et nibh. Pellentesque\n
habitant morbi tristique senectus et netus et malesuada fames ac
 turpis egestas. Quisque tempus a\n
...
```

Figure 3.28: inputRDD Content

```
Lorem
ipsum
dolor
sit
amet,
elit.
Cras
et
nibh.
Pellentesque\n
...
```

Figure 3.29: all_wordsRDD Content

```
('lorem, 1)
('ipsum, 1)
('dolor, 1)
('sit, 1)
('amet, 1)
('elit, 1)
('cras, 1)
('et, 1)
('nibh, 1)
('pellentesque, 1)
...
```

Figure 3.30: clean_wordsRDD Content

```
('lorem', 4)
('ipsum', 2)
('dolor', 4)
('sit', 6)
('amet', 6)
('elit', 2)
('cras', 3)
('et', 4)
('nibh', 5)
('pellentesque', 7)
...
```

Figure 3.31: RDDs Content

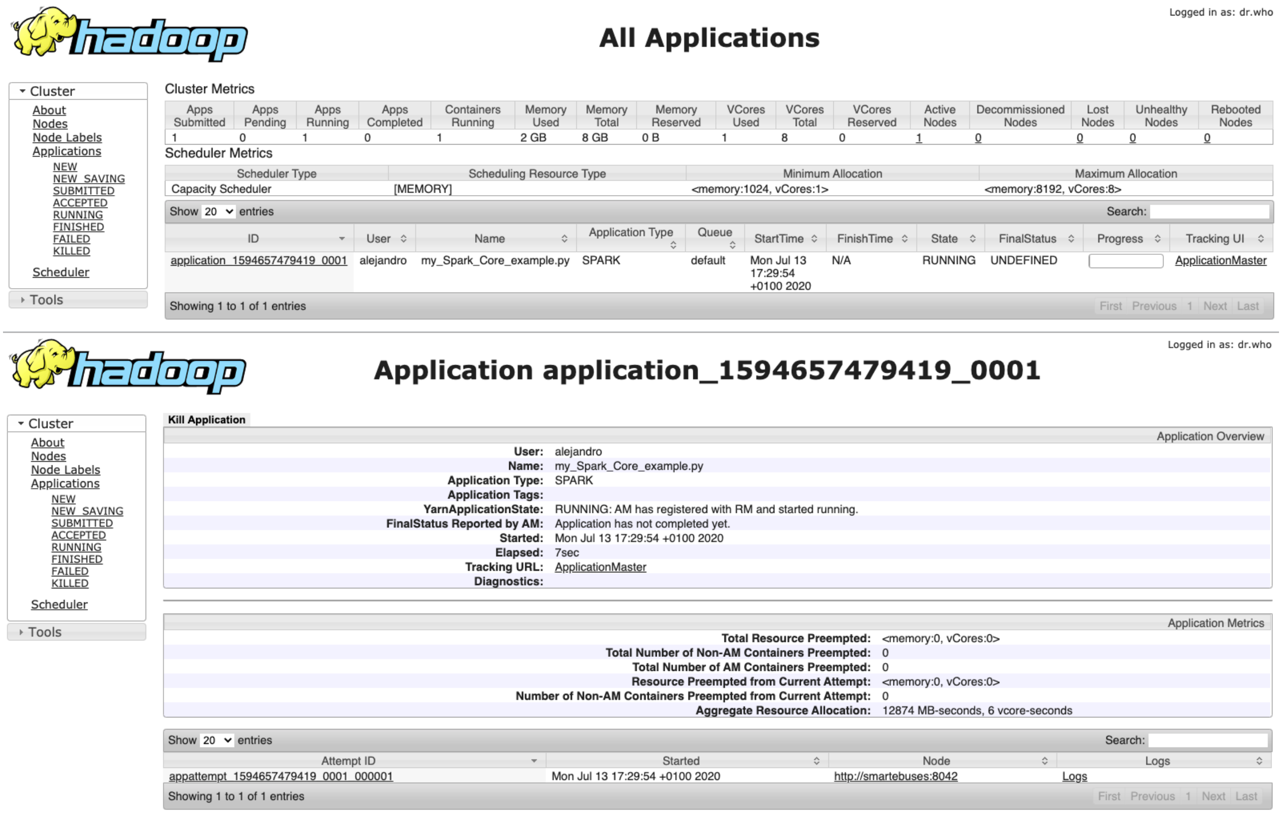


Figure 3.32: ResourceManager: Spark Core Application in Progress

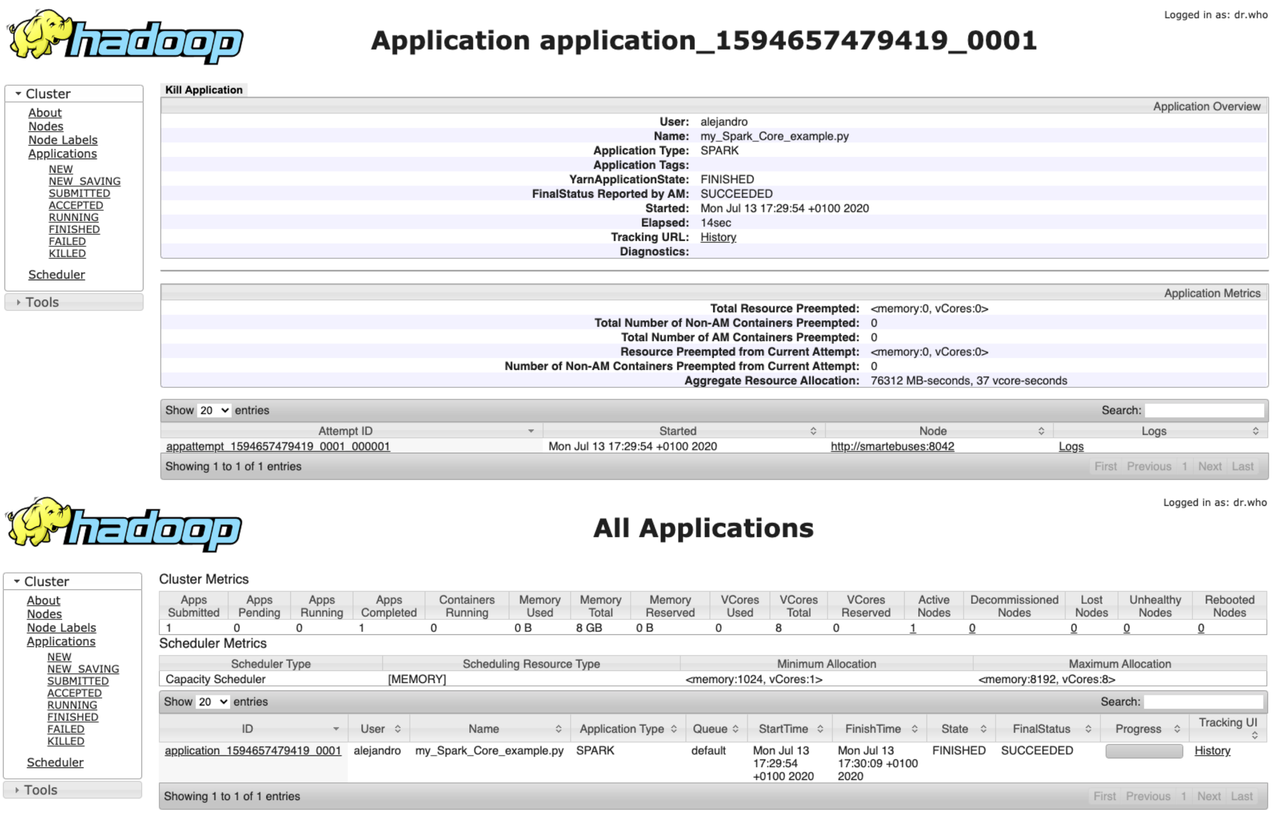


Figure 3.33: ResourceManager: Spark Core Application Finished

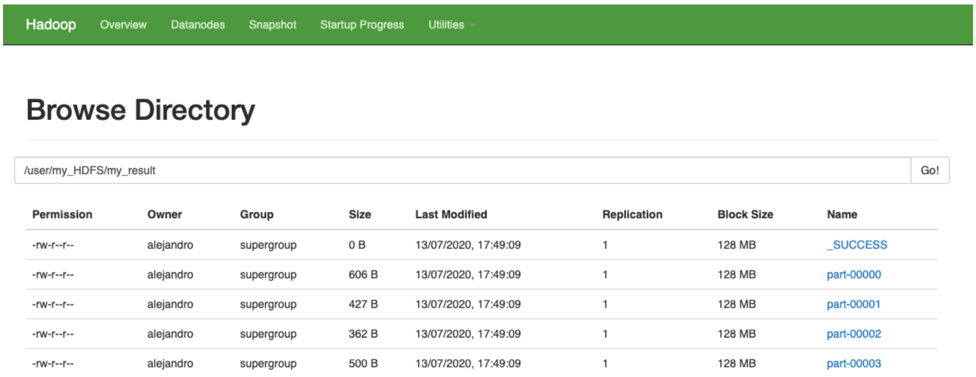


Figure 3.34: HDFS: Spark Core Result in my_result

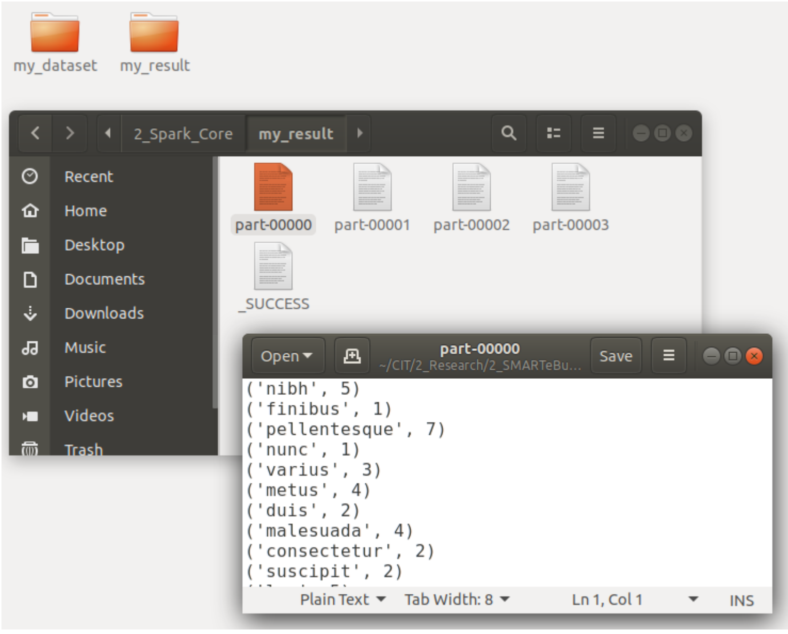


Figure 3.35: HDFS: Spark Core Result Brought Back to Local File System

3.5.3 Spark SQL

We edit now the command `(04) # MapReduce or Spark Job Command` from the script `data_analysis.sh` (cf. Figure 3.5) to run our introductory Spark SQL application. The Spark SQL command is presented below:

```
(04) spark-submit \
     --master yarn --deploy-mode cluster \
     ./my_Spark_SQL_example.py \
     /user/my_HDFS/my_dataset \
     /user/my_HDFS/my_result
```

As we can see, the command is the same as for the Spark Core application, it only changes the name of the Python program. And so it is the functionality of the Spark SQL application equivalent to the ones of the MapReduce and the Spark Core applications: it produces as output the new folder `my_result`, containing the word count for the dataset provided in the input folder `my_dataset`.

Figures 3.36, 3.37, 3.38 and 3.39 present the file `my_Spark_SQL_example.py`.

```
(01) # ------------------------------------------
(02) # IMPORTS
(03) # ------------------------------------------
(04) import pyspark
(05) import pyspark.sql.functions
(06) import pyspark.sql.types
(07) import sys
```

Figure 3.36: my_Spark_SQL_example.py: Import Section

The program is very similar to `my_spark_core_example.py`, so we only higlight the differences:

- Lines (01)–(07) import the additional libraries `pyspark.sql.functions` and `pyspark.sql.types` to use the Spark SQL API.
- Lines (08)–(36) define the function `my_spark_sql_job`. It receives as parameters the SparkSession (`spark`) and the input and output directories (`my_dataset_dir` and `my_result_dir`, resp). The function processes the dataset in `my_dataset_dir` to produce the new folder `my_result_dir` with its word count.

  Line (12) defines the schema `my_schema` for the dataset, matching each line of text of the dataset to a Row object with a single column `line`, of type String.

  Line (14) applies the creator operation `read` (with the folder `my_dataset_dir` and `my_schema` as parameters) to load the dataset into `inputDF`, a DataFrame of Row objects with one column `line` of type String. Figure 3.8 showed the content of `file_1.txt` of `my_dataset`. Figure 3.40 presents how the first 2 lines of the file translate into 2 Row items of `inputDF`.

  Lines (16)–(18) apply the transformation operations `withColumn` and `drop` on `inputDF` to produce the new DF `sentenceDF` of Row objects with one column `words_list` of type list of String. In particular, in line (17) the operation `withColumn` creates the new column `words_list` by splitting the String of `line` into its words. Then, in line (18) the operation `drop` removes the column `line`, for it to not appear in the generated `sentenceDF`. Figure 3.41 presents the Row produced in `sentenceDF` for the first item of `inputDF` showed in Figure 3.40.

Lines (20)–(30) repeat the application of `withColumn` and `drop` over 3 consecutive DataFrames, to shape the content of its unique column to the desired format by: exploding the list of words into a single Row per word (line 21), removing any non-alphanumerical character (line 25) and turning any upper-case character into its equivalent lower-case one (line 29). Likewise, lines (22), (26) and (30) remove any intermediate column being produced. Figures 3.42, 3.43 and 3.44 show the content of these 3 DataFrames, which end up producing the new DataFrame `lowerDF`.

Lines (32)–(33) apply the transformation operation `groupBy` on `lowerDF` to produce the new DF `solutionDF` of Row objects with two column: `word` (of type String) and `count(word)` (of type Integer). In particular, in line (33) the operation `groupBy` specifies the aggregation of Column `word`, counting the appearances for each group. Figure 3.45 shows the content of `solutionDF` for the Rows showed in Figure 3.44.

Lines (35)–(36) apply the action operation `write` (with the folder `my_result_dir` as parameter) to store the content of `solutionDF` into it. Figures 3.48 and 3.49 present the files and content produced by `solutionDF` when the program is executed in the Hadoop cluster.

- Lines (37)–(51) define the main entry point for the program. In particular, line (47) creates the SparkSession. Finally, line (51) calls to the aforementioned function `my_spark_sql_job`.

A copy of the file `my_Spark_SQL_example.py` is to be placed on the DataNode the cluster running the Spark Driver process.

Figure 3.46 presents the status of the ResourceManager once the command (04) of the script `data_analysis.sh` is launched. As we can see, the Spark SQL application is considered to be in progress. Figure 3.47 presents the status once the application finishes. As the execution is successful, the new folder `my_result` is available now in HDFS, with Figure 3.48 showing it. While the content of the files is not directly accessible in HDFS, we can execute the command `get` to bring the folder back to our local file system, so as to explore it (Figure 3.49 shows it). All in all, the Spark SQL application finds 135 different words with their associated number of appearances in `my_dataset`.

```
(08) # -------------------------------------------
(09) # FUNCTION my_spark_sql_job
(10) # -------------------------------------------
(11) def my_spark_sql_job(spark, my_dataset_dir, my_result_dir):
(11) # 1. We define the Schema of our DF.
(12)     my_schema = pyspark.sql.types.StructType(
                   [pyspark.sql.types.StructField("line",
                    pyspark.sql.types.StringType(), True)
                   ]
                                                         )

(13)     # 2. Operation C1: Load DataFrame
(14)     inputDF = spark.read.format("csv") \
                         .option("delimiter", ";") \
                         .option("quote", "") \
                         .option("header", "false") \
                         .schema(my_schema) \
                         .load(my_dataset_dir)

(15)     # 3. Operation T1: split
(16)     sentenceDF = inputDF \
(17)              .withColumn("words_list",
                        pyspark.sql.functions.split(
                          pyspark.sql.functions.col("line"),
                          " "
                                                            )
                        ) \
(18)              .drop("line")

(19)     # 4. Operation T2: explode
(20)     wordsDF = sentenceDF \
(21)              .withColumn("draft_word",
                             pyspark.sql.functions.explode(
                       pyspark.sql.functions.col("words_list")
                                                                   )
                             ) \
(22)              .drop("words_list")
```

Figure 3.37: my_Spark_SQL_example.py: my_spark_sql_job Function

```
    # 5. Operation T3: regexp_replace
    cleanDF = wordsDF \
         .withColumn("clean_word",
                     pyspark.sql.functions.regexp_replace(
                         "draft_word",
r"[^a-zA-Z]",
                         ""
                                                                   )
                    ) \
         .drop("draft_word")

    # 6. Operation T4: lower
    lowerDF = cleanDF \
         .withColumn("word",
                     pyspark.sql.functions.lower(
                pyspark.sql.functions.col("clean_word")
                                                          )
                    ) \
         .drop("clean_word")

    # 7. Operation T5: GroupBy
    solutionDF = lowerDF \
          .groupBy(["word"]).agg({"word": "count"})

    # 8. Operation A1: We save the results
    solutionDF.write.format("csv") \
                    .save(my_result_dir)
```

Figure 3.38: my_Spark_SQL_example.py: my_spark_sql_job Function

```
# ------------------------------------------------
# MAIN
# ------------------------------------------------
    # 1. We use as many input arguments as needed
    my_dataset_dir = "/FileStore/tables/my_dataset/"
    my_result_dir = "/FileStore/tables/my_result/"

    if (len(sys.argv) > 1):
       my_dataset_dir = sys.argv[1]
       my_result_dir = sys.argv[2]

    # 2. We configure the Spark Session
    spark = pyspark.sql.SparkSession.builder.getOrCreate()
    spark.sparkContext.setLogLevel('WARN')
    print("\n\n\n")

    # 3. We call to our main function
    my_spark_sql_job(spark, my_dataset_dir, my_result_dir)
```

Figure 3.39: my_Spark_SQL_example.py: Main Entry Point

```
+--------------------+
|                line|
+--------------------+
|Lorem ipsum dolor...|
|habitant morbi tr...|
|...                 |
+--------------------+
```

Figure 3.40: inputDF Content

```
+--------------------+
|          words_list|
+--------------------+
|[Lorem, ipsum., d...|
|...                 |
+--------------------+
```

Figure 3.41: sentenceDF Content

```
+--------------------+
|          draft_word|
+--------------------+
|Lorem               |
|ipsum.              |
|dolor               |
|...                 |
+--------------------+
```

Figure 3.42: wordsDF Content

```
+--------------------+
|          clean_word|
+--------------------+
|Lorem               |
|ipsum               |
|dolor               |
|...                 |
+--------------------+
```

Figure 3.43: cleanDF Content

```
+--------------------+
|                word|
+--------------------+
|lorem               |
|ipsum               |
|dolor               |
|...                 |
+--------------------+
```

Figure 3.44: lowerDF Content

```
+--------------------+-----------+
|                word|count(word)|
+--------------------+-----------+
|lorem               |          4|
|ipsum               |          2|
|dolor               |          4|
|...                 |        ...|
+--------------------+-----------+
```

Figure 3.45: solutionDF Content

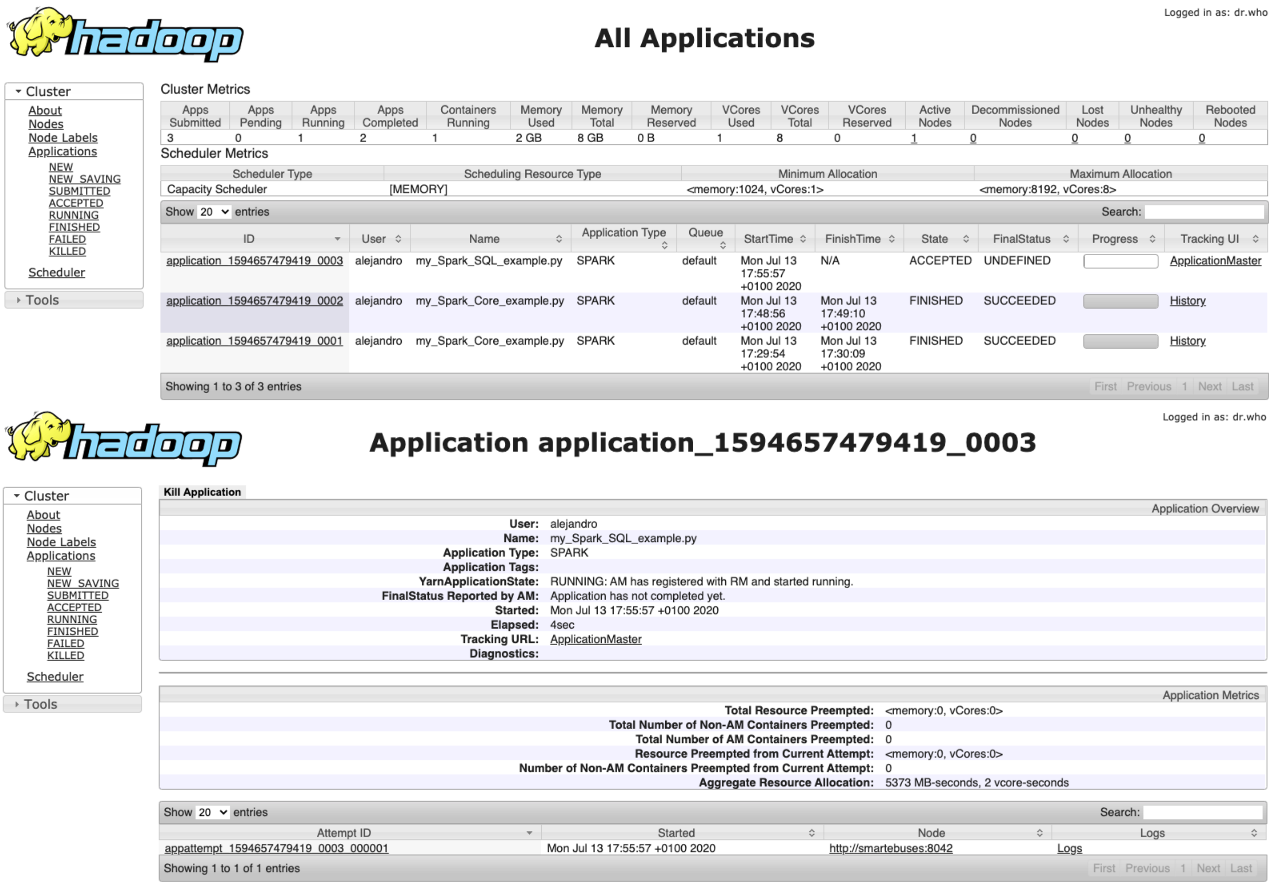


Figure 3.46: ResourceManager: Spark SQL Application in Progress

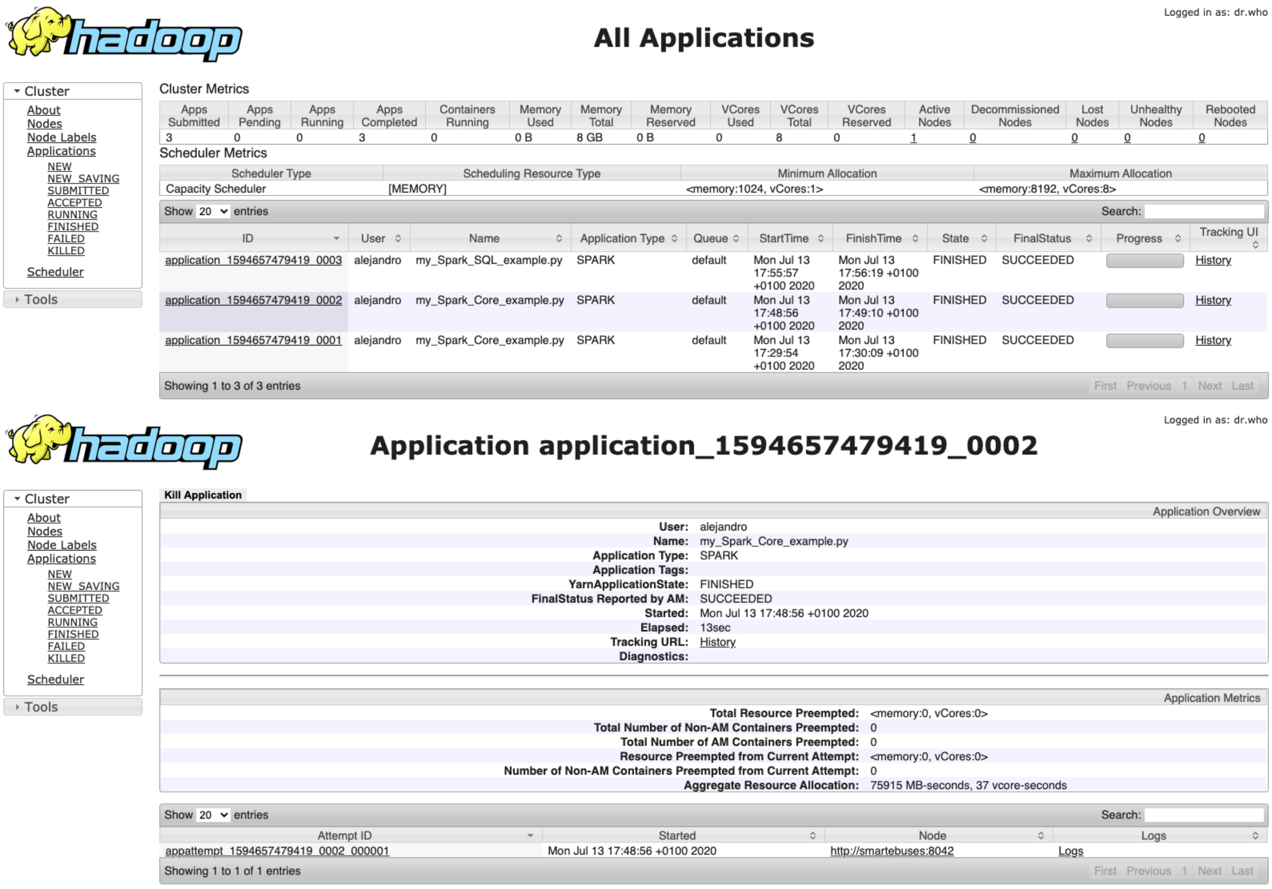
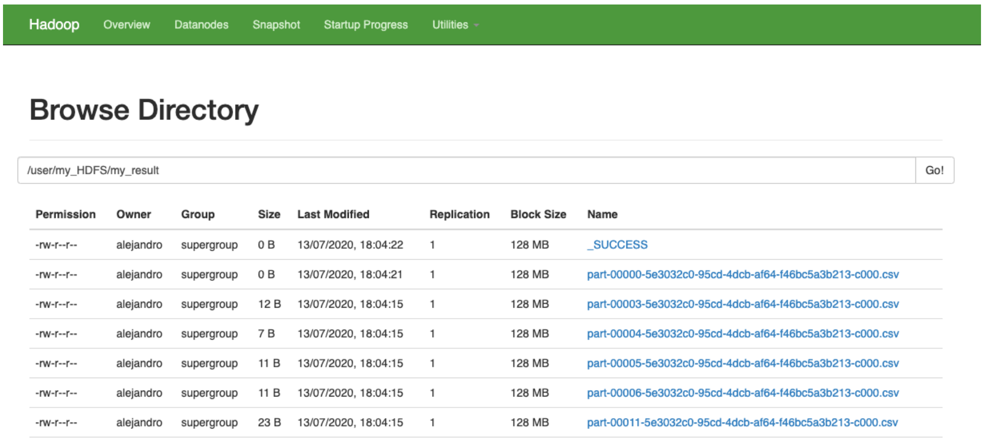


Figure 3.47: ResourceManager: Spark SQL Application Finished



Hadoop Overview Datanodes Snapshot Startup Progress Utilities

Browse Directory

/user/my_HDFS/my_result Go!

Permission	Owner	Group	Size	Last Modified	Replication	Block Size	Name
-rw-r--r--	alejandro	supergroup	0 B	13/07/2020, 18:04:22	1	128 MB	_SUCCESS
-rw-r--r--	alejandro	supergroup	0 B	13/07/2020, 18:04:21	1	128 MB	part-00000-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv
-rw-r--r--	alejandro	supergroup	12 B	13/07/2020, 18:04:15	1	128 MB	part-00003-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv
-rw-r--r--	alejandro	supergroup	7 B	13/07/2020, 18:04:15	1	128 MB	part-00004-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv
-rw-r--r--	alejandro	supergroup	11 B	13/07/2020, 18:04:15	1	128 MB	part-00005-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv
-rw-r--r--	alejandro	supergroup	11 B	13/07/2020, 18:04:15	1	128 MB	part-00006-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv
-rw-r--r--	alejandro	supergroup	23 B	13/07/2020, 18:04:15	1	128 MB	part-00011-5e3032c0-95cd-4dcb-af64-f46bc5a3b213-c000.csv

Figure 3.48: HDFS: Spark SQL Result in my_result

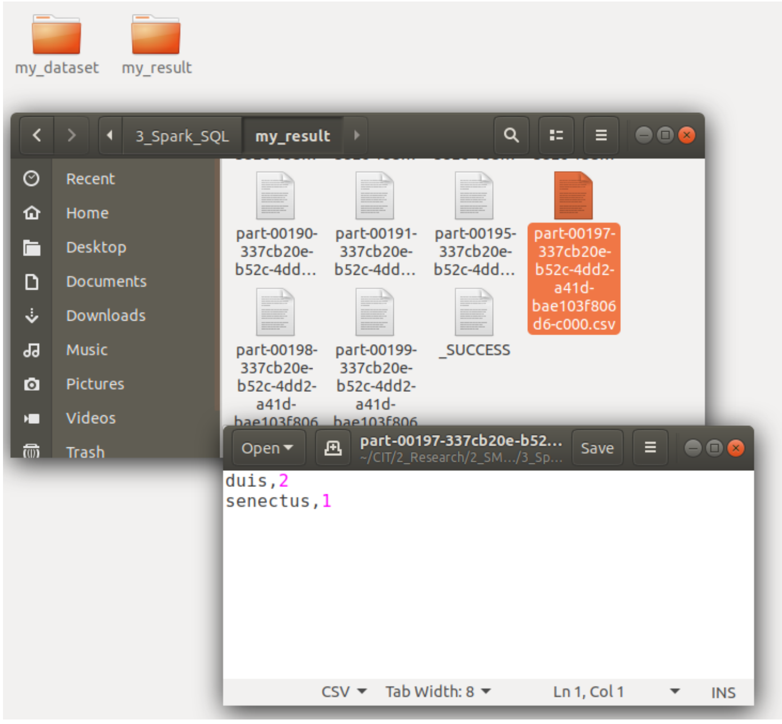


Figure 3.49: HDFS: Spark SQL Result Brought Back to Local File System

4 Conclusions and Future Work

In this deliverable we have introduced the Big Data ecosystem of tools we are going to use for storing and analysis bus and wind power-related large-datasets.

This ecosystem includes HDFS as a distributed file system (designed to efficiently allocate data across the multiple nodes of the cluster), Yarn as a resource manager (responsible for schedule and monitor the execution of our data analysis applications) and MapReduce, Spark Core and Spark SQL as frameworks for easily writing applications processing large-scale datasets across a cluster in a reliable, fault-tolerant manner. While Python is selected as the programming language of choice (with MapReduce, Spark Core and Spark SQL providing an API for it), the data analytics applications run on top of the Java Runtime Environment.

We have presented detailed scripts for installing, configuring and applying Java OpenJDK 8, Python 3.7.7, Hadoop 2.7.1 and Spark 2.4.5. In the case of Hadoop, the scripts include how to start and stop a Single Node Cluster with Pseudo-Distributed Operation. In the case of MapReduce, Spark Core and Spark SQL, a detailed explanation of an introductory example has been presented, together with a detailed explanation of its execution in the aforementioned cluster.

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