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EXCELENCIA SEVERO OCHOA

Data Analytics Using Spark

PATC 2023

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Data Centric Computing – BSC

Computational Resources Orchestration for AI – UPC

February/2023

Introduction

- What is Apache Spark
  - Cluster Computing Framework
  - Programming clusters with data parallelism and fault tolerance
  - Programmable in Java, Scala, Python and R

Motivation for Using Spark

- Spark schedules data parallelism implicitly
  - User defines the set of operations to be performed
  - <u>Spark performs an orchestrated execution</u>
- It works with Hadoop and HDFS
  - Bring <u>execution to where data</u> is distributed
  - Taking advantage Distributed File Systems
- It provides libraries for distributed algorithms
  - Data Queries
  - Machine Learning
  - Streaming

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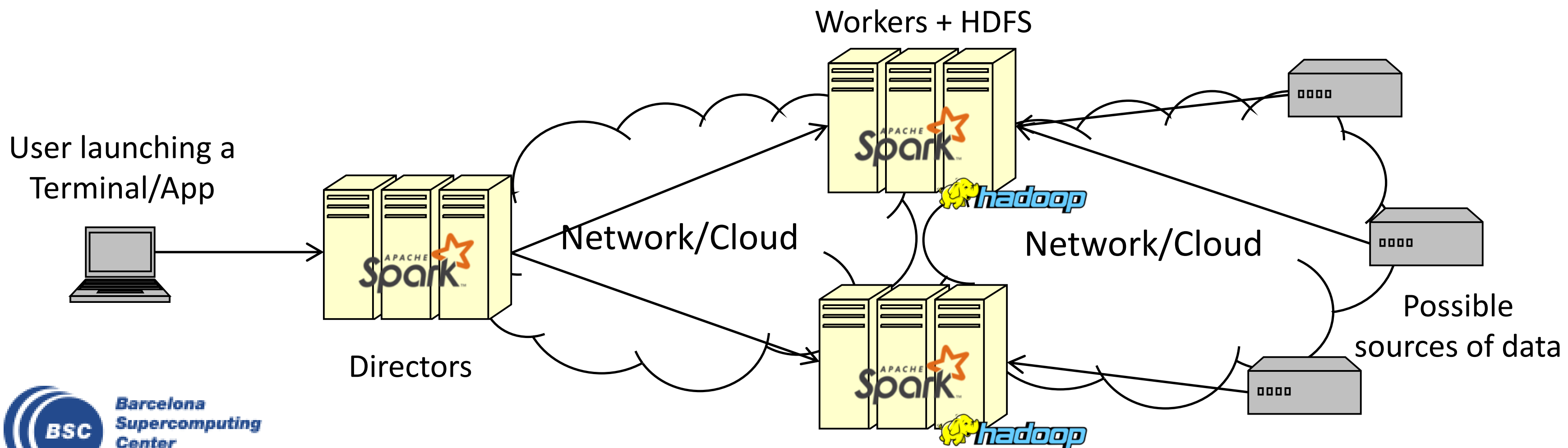
1. Introduction to Spark
2. Treating data as relational with SparkSQL
3. Machine Learning using SparkML
4. Dealing with data streams using SparkStream

Introduction to Apache Spark

- Cluster Computing Framework
  - Implemented in Java
  - Programmable in Java, Scala, Python and R
  - Paradigm of Map-Reduce

- Deployment:
  - Define your cluster (directors and workers)
  - Link to your distributed File System
  - Start a session / Create an app
  - Let Spark to plan and execute the workflow and dataflow



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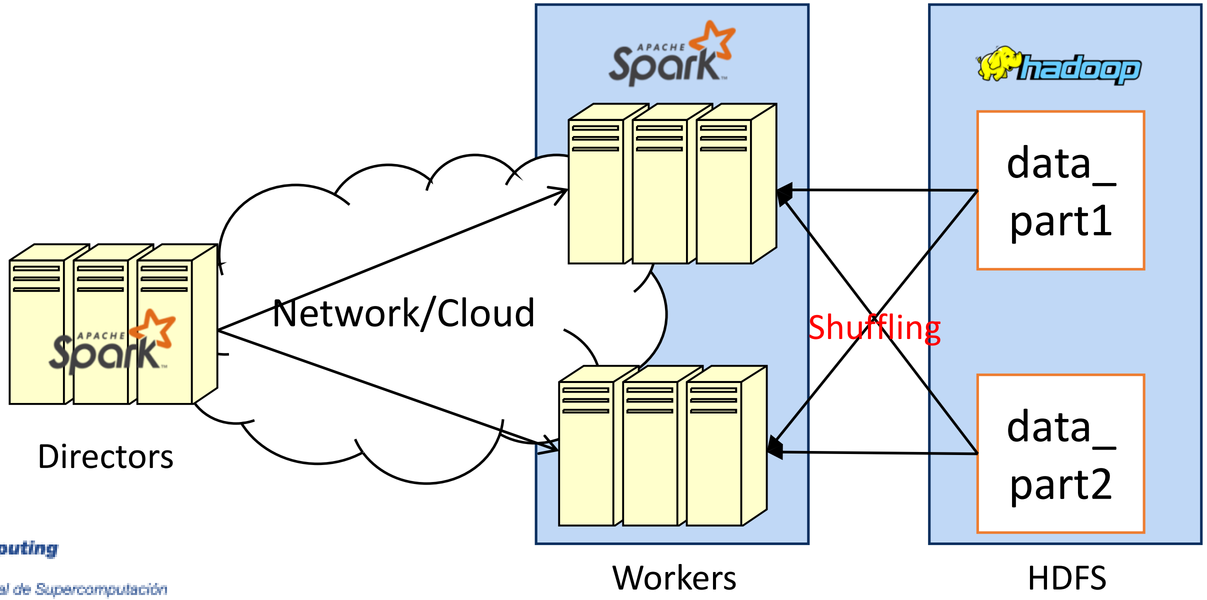
Introduction to Apache Spark

- Computing and Shuffling
  - Spark attempts to compute data "where it sits"
  - When using a DFS, Spark takes advantage of distribution
  - If operations require to cross data from different places
    - Shuffling: Data needs to be crossed among workers
    - We must think of it when preparing operations
    - … also when distributing data on the DFS
    - … also when manually partitioning data for distributed processing



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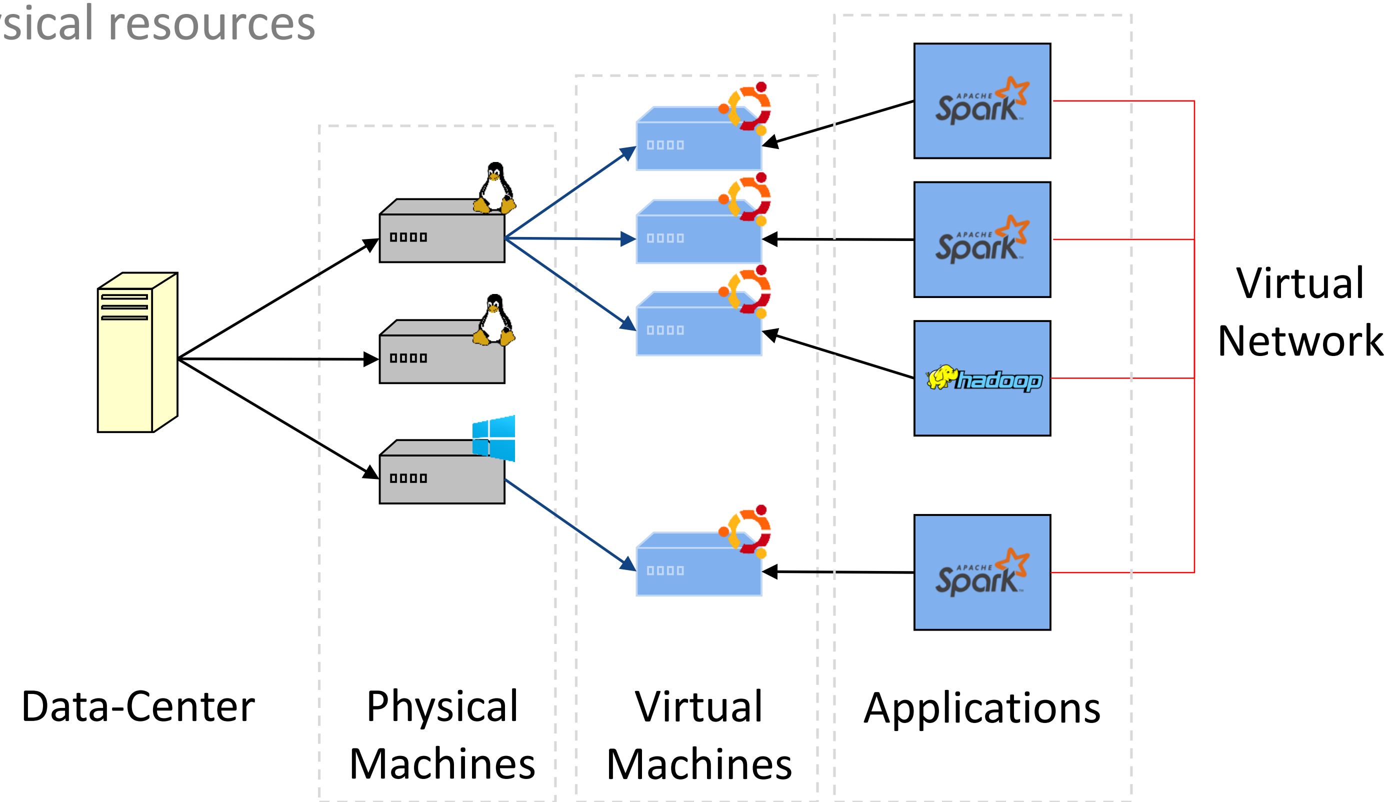
Virtualized Environments

- Data-Center environments
  - Virtualization: Allows running systems isolated, move systems, resize systems… independently from the base system
  - The Cloud and DC-farms use Virtual Machines to allocate clients into physical resources



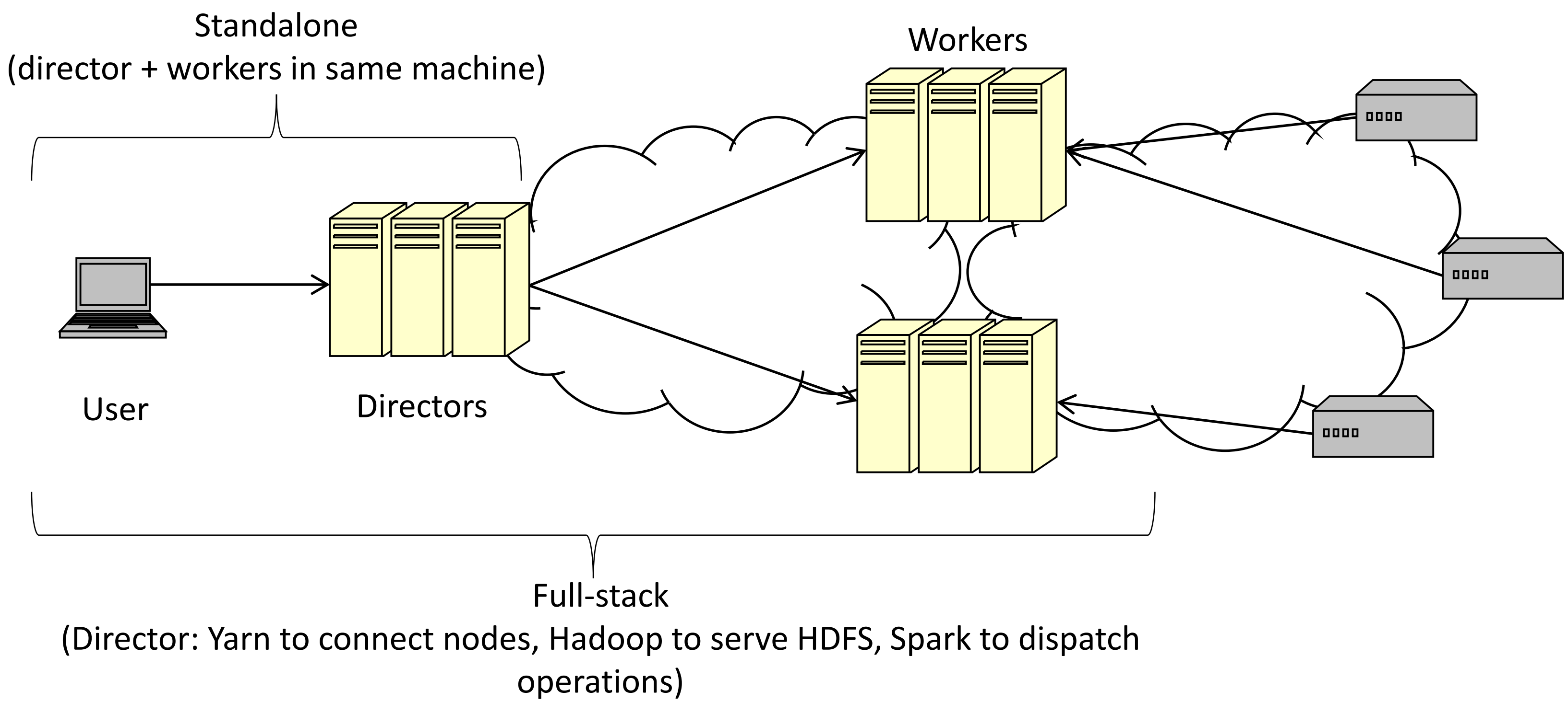
Step 0: Installing the Environment

- Environment:
  - We're working on a Unix Terminal
  - ... Inside the Virtual Machine

  - So execute from the `vm_test` directory:
    - `vagrant up`
    - `vagrant ssh`

- You should have already installed [from the Set-Up Document]:
  - Apache Hadoop 3.3.1
  - Apache Spark 3.2.1
  - OpenSSH
  - Java +1.8

Step 0: Setting up the Environment



- What we will do now:
  - We will use spark in "**standalone mode**", using our computing as single node

- What we could do now:
  - Set up HDFS in a cluster
  - Set up YARN to connect all SPARK nodes
  - Set up all SPARK nodes to find YARN and synchronize

Step 0: Starting the Environment

- Let’s run SPARK!
  - Options:
    - `spark-shell` → We open a Scala session to Spark
    - `sparkR` → We open a R-cran session to Spark
    - `spark-submit` → We send our Spark application to Spark
  - For now, we’re using Scala

```
Spark context Web UI available at http://10.0.2.15:4040
Spark context available as 'sc' (master = local[*], app id = local-1643906908274).
Spark session available as 'spark'.
Welcome to
      ____              __
     / __/__  ___ _____/ /__
    _\ \/ _ \/ _ `/ __/  '_/
   /___/ .__/\_,_/_/ /_/\_\   version 3.2.1
      /_/

Using Scala version 2.12.15 (OpenJDK 64-Bit Server VM, Java 1.8.0_312)
Type in expressions to have them evaluated.
Type :help for more information.

scala>
```

Spark and Scala

- Scala is oriented towards functional programming
  - We use **val** for static values and **var** for variable values
    - `val a = "hello"`
    - `var b = "bye"`
    - `b = "good bye"`
  - We can check the content of variables, values and references
    - `b`

    ```
    res0: String = good bye
    ```
  - We use RDDs as “Resilient Distributed Datasets”
    - Operations on RDDs will be distributed by SPARK over the available nodes
    - Also RDD distributed operations will happen over the HDFS partitioning of data
  - Note: Exit Scala
    - `:q` (two dots + q)

* Some examples here are addapted from: Sandy Ryza et al. “Advanced Analytics with Spark”

Spark and Scala

- Prepare a dataset (from CLI):
  - Retrieve the downloaded “linkage” dataset, done in the set-up document: `donation.zip`

  - Create a working directory:
    - `mkdir linkage`
    - `mv donation.zip linkage/`
    - `cd linkage/`
    - `unzip donation.zip`
    - `unzip 'block_*.zip'`

- Uploading data to HDFS:
  - Start the HDFS
    - `$HADOOP_HOME/sbin/start-dfs.sh`

  - This dataset is already partitioned, and it can be uploaded to HDFS
    - `hdfs dfs -mkdir /linkage`
    - `hdfs dfs -put block_*.csv /linkage`

  - ...or we can access all in local
    - Fuse all blocks in one
      - `cat block_*.csv > block_all.csv`

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* Some examples here are addapted from: Sandy Ryza et al. “Advanced Analytics with Spark”

Spark and Scala

- Dimensioning the VM and the Environment:
  - If you followed the “set-up document”, you already told the VM to use 4GB.
- Opening Session:
  - `spark-shell --master local[*] --driver-memory 2G --executor-memory 768M --executor-cores 2`
- Load blocks:
  - If using the HDFS:
    - `val rawblocks = sc.textFile("hdfs://localhost:54310/linkage")`
  - If using the local FS:
    - `val rawblocks = sc.textFile("file:///home/vagrant/linkage/block_all.csv")`
  - Check that data is loaded, by printing the 1st element:
    - `rawblocks.first()`

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Spark and Scala

- Let's examine the data:
  - `val head = rawblocks.take(10)`
    ```
    head: Array[String] = Array("id_1","id_2",…,1,TRUE)
    ```
  - `head.length`
    ```
    res7: Int = 10
    ```
  - `head.foreach(println)`
    ```
    "id_1","id_2","cmp_fname_c1","cmp_fname_c2",...,"is_match"
    31641,62703,1,?,1,?,1,1,1,1,1,TRUE
    27816,46246,1,?,1,?,1,1,1,1,1,TRUE
    980,2651,1,?,1,?,1,1,1,1,1,TRUE
    6514,8780,1,?,1,?,1,1,1,1,1,TRUE
    5532,14374,1,?,1,?,1,1,1,1,1,TRUE
    25763,61342,1,?,1,?,1,1,1,1,1,TRUE
    59655,59657,1,?,1,?,1,1,1,1,1,TRUE
    23800,32179,1,?,1,?,1,1,1,1,1,TRUE
    33568,38196,1,?,1,?,1,1,1,1,1,TRUE
    ```

Spark and Scala

- Define a function:
  - `def isHeader(line: String) = line.contains("id_1")`

```
isHeader: (line: String)Boolean
```

- Use our function:
  - `head.filter(isHeader).foreach(println)`

```
"id_1","id_2","cmp_fname_c1",...,"is_match"
```

- Notice how we treat data:
  1. We have our value “head”
  2. We apply a filter (select rows based on a Boolean vector/condition)
  3. We introduce our function, that given a String returns a Boolean
  4. The result is the selected rows satisfying the condition
  5. We apply the “println” for each element of such rows

Spark and Scala

- Keep using our function over data:
  - `head.filter(isHeader).length`
    ```
    res10: Int = 1
    ```
  - `head.filterNot(isHeader).length`
    ```
    res11: Int = 9
    ```

- Here we are simplifying a lambda function
  - `head.filterNot(isHeader).length`

  is equivalent to
  - `head.filterNot(x => isHeader(x)).length`

  also is equivalent to
  - `head.filterNot(isHeader(_)).length`

  also is equivalent to
  - `head.filter(!isHeader(_)).length`

  et cetera…

Spark and Scala

- Now, lets process the data a little bit:

  - `val noheader = rawblocks.filter(!isHeader(_))`
  - `noheader.first`

    ```
    res15: String = 31641,62703,1,?,1,?,1,1,1,1,1,TRUE
    ```

  - `val line = head(5)`
  - `val pieces = line.split(',')`
  - `val id1 = pieces(0).toInt`
  - `val id2 = pieces(1).toInt`
  - `val matched = pieces(11).toBoolean`

  - `def toDouble(s: String) = { if ("?".equals(s)) Double.NaN else s.toDouble }`

  Beware ↓: counting starts at 0 so 2 is "3rd pos.", and here "11" is not fetched

  - `val rawscores = pieces.slice(2,11)`
  - `val scores = rawscores.map(x => toDouble(x))`

Spark and Scala

- We can put it all together in a function

  - ```
    def parse(line: String) = {
      val pieces = line.split(',')
      val id1 = pieces(0).toInt
      val id2 = pieces(1).toInt
      val scores = pieces.slice(2, 11).map(toDouble)
      val matched = pieces(11).toBoolean
      (id1, id2, scores, matched)
    }
    ```
    ```
    parse: (line: String)(Int, Int, Array[Double],
      Boolean)
    ```

  - ```
    val tup = parse(line)
    ```
    ```
    tup: (Int, Int, Array[Double], Boolean) = (5532,14374,
      Array(1.0, NaN, 1.0, NaN, 1.0, 1.0, 1.0, 1.0, 1.0),
      true)
    ```

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Spark and Scala

- Accessing our processed values

  like this, it starts at 1

  - `tup._1`

    ```
    res17: Int = 5532
    ```

  like this, it starts at 0, and see the return type

  - `tup.productElement(0)`

    ```
    res18: Any = 5532
    ```

  we can see the number of elements direct into the value

  - `tup.productArity`

    ```
    res19: Int = 4
    ```

  also we can access to the elements of the array inside the value

  - `tup._3.foreach(println)`

    ```
    1.0
    NaN
    ...
    ```

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Spark and Scala

- We can create objects

  - `case class MatchData(id1: Int, id2: Int, scores: Array[Double], matched: Boolean)`

  and use them as types

```
def parse(line: String) = {
    val pieces = line.split(',')
    val id1 = pieces(0).toInt
    val id2 = pieces(1).toInt
    val scores = pieces.slice(2, 11).map(toDouble)
    val matched = pieces(11).toBoolean
    MatchData(id1, id2, scores, matched)
}
```

  Then use as values

  - `val md = parse(line)`
  - `md.matched`
  - `md.scores`

Spark and Scala

- Map operations to elements
  - `val mds = head.filter(s => !isHeader(s)).map(l => parse(l))`
    ```
    mds: Array[MatchData] =
      Array(MatchData(31641,62703,...)
    ```
  - `mds.foreach(println)`
    ```
    MatchData(31641,62703,[D@3a5b429,true)
    …
    ```

- Grouping data, then operate by groups
  - `val grouped = mds.groupBy(md => md.matched)`
    ```
    grouped: scala....Map[Boolean,Array[MatchData]] =
      Map(true -> Array(MatchData(31641,62703,
      [D@63cdd551,true), ...),false->Array(...))
    ```
  - `grouped.mapValues(x => x.size).foreach(println)`
    ```
    (true,9)
    ```

Spark and Scala

- Let's keep data parsed, and enabled in cache
  - `val parsed = noheader.map(line => parse(line))`
  - `parsed.cache()`

- Let's do an operation that requires to be distributed
  - `val mapMatch = parsed.map(entry => entry.matched)`
  - `val matchCounts = mapMatch.countByValue()`

```
res17: scala.collection.Map[Boolean,Long] = Map(false ->
  5728201, true -> 20931)
```

  - Here, due to "count", Spark requires to check all the data and give results, so it starts distributing computation

  - You can see in console how the different "executors" process data, and how the stages on the scheduled plan are passed

  - This is different from before because when playing with "head", it was in the Director machine/process, while now we are querying to all distributed (if it is) data.

Map/Reducing Operations

- The classical example: WordCount

We open a file to count

- `val textFile = sc.textFile("/home/vagrant/spark/README.md")`

we check that we could read the file

- `textFile.first`

```
res21: String = # Apache Spark
```

now we map/reduce

- `val textFlatMap = textFile.flatMap(line =>  line.split(" "))`
- `val words = textFlatMap.map(word => (word,1))`
- `val counts = words.reduceByKey(_ + _)`

then retrieve some results (triggering the scheduler)

- `counts.take(5).foreach(println)`

```
(package,1)
(this,1)
(integration,1)
(Python,2)
(page](http://spark.apache.org/documentation.html).,1)
```

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Map/Reducing Operations

- We can order the results:

Counts is still a distributed operation, and we can keep operating

- `val ranking = counts.sortBy(_._2,false)`

But now, if we want to see the ranking, we need to collect all data, triggering the scheduler

- `val local_result = ranking.collect()`

Then get the top 5

- `ranking.take(5)`

```
res31: Array[(String, Int)] = Array(("",72), (the,24), ...
```

- `ranking.take(5).foreach(println)`

```
(,73)
(the,23)
(to,16)
(Spark,14)
(for,12)
```

Map/Reducing Operations

- We can process the results

Also we can include data process, e.g. to remove the “” word

```
• val cleancount = counts.filter(x => {!"".equals(x._1)})
• val cleanrank = cleancount.sortBy(_._2,false)
• val local_cleanrank = cleanrank.collect()
• local_cleanrank.take(5).foreach(println)
    (the,23)
    (to,16)
    (Spark,14)
    (for,12)
    (##,9)
```

Or filter it before counting, by modifying the previous instruction

```
• val words2 = textFlatMap.filter(word => {!"".equals(word)} )
• val filteredwords = words2.map(word => (word,1))
• val counts2 = filteredwords.reduceByKey(_ + _)
• val ranking2 = counts2.sortBy(_._2,false)
• val local_result2 = ranking2.collect()
• local_result2.take(5).foreach(println)
```

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Part 1 – Recap

- What is Spark
- Where/when are things computed in Spark
- Installing the Spark environment
- Spark and Scala:
  - Creation of values
  - Reading files from local/HDFS as RDDs
  - Show and filter data
  - Creating functions and objects/classes
- Map/Reduce operations

SparkSQL

- With Spark we can
  - Access our data as it was a Relational DB
  - Using a syntax really close to SQL
  - ...great news for people used to DB systems

- Now we are using DataFrames!
  - ...Distributed DataFrames
  - This means that we can also open a SparkR session, and do most of the R usual stuff into those data.frames

Prepare the Data-Sets

- Let’s get some Big Data, (compared to previous examples)
  - Retrieve the downloaded “HUS” dataset, done in the set-up document: `csv_hus.zip`
  - Un-compress the data:
    - `mkdir hus`
    - `mv csv_hus.zip hus/`
    - `cd hus`
    - `unzip csv_hus.zip`
  - Put data into the HDFS
    - `hdfs dfs -mkdir /hus`
    - `hdfs dfs -put ss13husa.csv /hus/`
  - We should see it in
    - `hdfs dfs -ls /hus`

Loading HDFS data

- The file we downloaded contains some CSV files
  - We are going to open one, directly as a Data.Frame

- Let's open it:
  - ```
    val df = spark.read.format("csv")
            .option("inferSchema", true)
            .option("header","true")
            .load("hdfs://localhost:54310/hus
            /ss13husa.csv")
    ```

- First look (as RDD):
  - `df.take(5)`

```
res0: Array[org.apache.spark.sql.Row] =
Array([H,84,6,2600,3,1,1000000,1007549,0,1,3,null,nul
l,null,null,null,null,null,null,null,null,null,null,n
ull,null,2,null,null,null,null,null,null,null,null,nu
ll,null,null,null,null,null,null,null,null,null,null.
..
```

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```

Relational DataFrames

- Let's print the Data.Frame schema:
  - `df.printSchema()`

```
root
 |-- RT: string (nullable = true)
 |-- SERIALNO: integer (nullable = true)
 |-- DIVISION: integer (nullable = true)
 |-- PUMA: integer (nullable = true)
 |-- REGION: integer (nullable = true)
 |-- ST: integer (nullable = true)
 |-- ADJHSG: integer (nullable = true)
 |-- ADJINC: integer (nullable = true)
 |-- WGTP: integer (nullable = true)
 | . . .
```

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Relational DataFrames

- Examining the Data.Frame
  - `df.count()`

    ```
    res4: Long = 756065
    ```

- Selecting a subset of rows
  - `val df1 = df.limit(10)`
  - `df1.show()`

    ```
    [HERE GOES A SQL-like TABLE!]
    ```

  - Now we can operate with “df” as tables in a SQL server

Relational DataFrames

- Selecting Data (column selection)
  - `df.select("SERIALNO","RT","DIVISION","REGION").show()`

```
+--------+---+--------+------+
|SERIALNO| RT|DIVISION|REGION|
+--------+---+--------+------+
|      84|  H|       6|     3|
|     154|  H|       6|     3|
|     156|  H|       6|     3|
|     160|  H|       6|     3|
|     231|  H|       6|     3|
|    ... |...|   ...  |  ... |
|     776|  H|       6|     3|
|     891|  H|       6|     3|
|     944|  H|       6|     3|
|    1088|  H|       6|     3|
|    1117|  H|       6|     3|
|    1242|  H|       6|     3|
+--------+---+--------+------+
only showing top 20 rows
```

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Relational DataFrames

- Filtering Data (row selection)
  - `df.select("SERIALNO","RT","DIVISION","REGION").filter("PUMA > 2600").show()`

```
+--------+---+--------+------+
|SERIALNO| RT|DIVISION|REGION|
+--------+---+--------+------+
|     154|  H|       6|     3|
|     156|  H|       6|     3|
|     160|  H|       6|     3|
|    ... |...|   ...  |  ... |
|     944|  H|       6|     3|
|    1117|  H|       6|     3|
|    1242|  H|       6|     3|
|    1369|  H|       6|     3|
|    1779|  H|       6|     3|
|    1782|  H|       6|     3|
|    1791|  H|       6|     3|
+--------+---+--------+------+
only showing top 20 rows
```

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Relational DataFrames

- Grouping Data

  - `df.groupBy("DIVISION").count().show()`

```
+--------+------+
|DIVISION| count|
+--------+------+
|       1| 58103|
|       6| 60389|
|       3|139008|
|       5|179043|
|       9|163137|
|       4| 55641|
|       8| 63823|
|       7| 36921|
+--------+------+
```

SQL DataFrames

- To use SQL, creating a temporal View (preserved across sessions):
  - `df.createGlobalTempView("husa")`

- Select using SQL:
  - `spark.sql("SELECT SERIALNO, RT, DIVISION, REGION FROM global_temp.husa").show()`

```
+--------+---+--------+------+
|SERIALNO| RT|DIVISION|REGION|
+--------+---+--------+------+
|      84|  H|       6|     3|
|     154|  H|       6|     3|
|     156|  H|       6|     3|
|     ...|...|   ...  |  ... |
|     944|  H|       6|     3|
|    1088|  H|       6|     3|
|    1117|  H|       6|     3|
|    1242|  H|       6|     3|
+--------+---+--------+------+
only showing top 20 rows
```

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SQL DataFrames

- Filtering using SQL:

  - ```
    spark.sql("SELECT SERIALNO, RT, DIVISION, REGION
               FROM global_temp.husa
               WHERE PUMA < 2100").show()
    ```

```
+--------+---+--------+------+
|SERIALNO| RT|DIVISION|REGION|
+--------+---+--------+------+
|     154|  H|       6|     3|
|     156|  H|       6|     3|
|     160|  H|       6|     3|
|   ...  |...|   ...  |  ... |
|     944|  H|       6|     3|
|    1117|  H|       6|     3|
|    1242|  H|       6|     3|
|    1369|  H|       6|     3|
|    1779|  H|       6|     3|
|    1782|  H|       6|     3|
|    1791|  H|       6|     3|
+--------+---+--------+------+
only showing top 20 rows
```
```

SQL DataFrames

- Grouping using SQL:
  - ```
    spark.sql("SELECT DIVISION, COUNT(*)
               FROM global_temp.husa
               GROUP BY DIVISION").show()
    ```

```
+--------+--------+
|DIVISION|count(1)|
+--------+--------+
|       1|   58103|
|       6|   60389|
|       3|  139008|
|       5|  179043|
|       9|  163137|
|       4|   55641|
|       8|   63823|
|       7|   36921|
+--------+--------+
```

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```

Relational side-by-side SQL DataFrames

- Selecting
  1. `df.select("SERIALNO","RT","DIVISION","REGION").show()`
  2. `spark.sql("SELECT SERIALNO, RT, DIVISION, REGION FROM global_temp.husa").show()`

- Filtering
  1. `df.select("SERIALNO","RT","DIVISION","REGION").filter("PUMA > 2600").show()`
  2. `spark.sql("SELECT SERIALNO, RT, DIVISION, REGION FROM global_temp.husa WHERE PUMA < 2100").show()`

- Grouping
  1. `df.groupBy("DIVISION").count().show()`
  2. `spark.sql("SELECT DIVISION, COUNT(*) FROM global_temp.husa GROUP BY DIVISION").show()`

DDF Transformations and Storage

- SparkSQL results can be stored
  - CSV and TXT formats: the ones we already know
  - Parquet: a columnar format widely supported

Save our DDF into Parquet, then load again

- Write:
  - `df.write.parquet("hdfs://localhost:54310/husa.parquet")`
- Read:
  - `val pqFileDF = spark.read.parquet("hdfs://localhost:54310/husa.parquet")`

Also, Parquet DFs can be used directly like regular DFs

- `pqFileDF.createOrReplaceTempView("parquetFile")`
- `val namesDF = spark.sql("SELECT SERIALNO FROM parquetFile WHERE PUMA < 2100")`
- `namesDF.map(attributes => "SerialNo: " + attributes(0)).show()`

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Part 2 - Recap

- Operations Using SparkSQL
  - Relational Algebra functions
    - Selecting
    - Filtering
    - Grouping
  - SQL usual functions
    - Same as above
  - Comparison between two styles

- Storage formats like Parquet

SparkML

- SparkML
  - This is the Machine Learning library for Spark (spark.ml)
  - Before versions 2.3, library MLlib was used (spark.mllib)

- Distributed ML Algorithms
  - Basic Statistics
    - Summaries, Correlations, Hypothesis Tests...
  - Classification and Prediction
    - We'll see the Linear Regression, also the Support Vector Machines
  - Clustering
    - We'll see the k-means
  - Dimension Reduction
    - We'll see Principal Component Analysis
  - Collaborative Filtering
  - Frequent Pattern Mining

* Some examples here are addapted from the Apache Spark introduction tutorials

Distributed Algorithms with SparkML

- Spark takes advantage of splitting data in subsets
  - Subsets are distributedly processed for models
  - Partial Models are aggregated into a general model
  - Such methodology is not as fitted as centralized approaches...
  - ... But at least can be processed
  - ... Also, we could discuss how huge datasets could bring to statistically significant sampled subsets
- ML process relies on a Map/Reduce strategy

SparkML Types of Data

- Vectors (Local)
  - `import org.apache.spark.ml.linalg.{Vector, Vectors}`

  DenseVectors (all values)
  - `val dv: Vector = Vectors.dense(1.0, 0.0, 3.0)`

  SparseVectors (length, indexes, values)
  - `val sv: Vector = Vectors.sparse(3, Array(0, 2), Array(1.0, 3.0))`

- Labeled Points
  - `import org.apache.spark.ml.feature.LabeledPoint`

  Example of Two points, one labeled “1”, the other “0”
  - `val pos = LabeledPoint(1.0, Vectors.dense(1.0,0.0,3.0))`
  - `val neg = LabeledPoint(0.0, Vectors.sparse(3, Array(0,2), Array(1.0,3.0)))`

  - `pos.label`
  - `pos.features`

SparkML Types of Data

- Matrices
  - `import org.apache.spark.ml.linalg.{Matrix, Matrices}`

  Dense Matrices
  - `val dm: Matrix = Matrices.dense(3, 2, Array(1.0, 3.0, 5.0, 2.0, 4.0, 6.0))`

  Sparse Matrices
  - `val sm: Matrix = Matrices.sparse(3, 2, Array(0,1,3), Array(0,2,1), Array(9,6,8))`

- Visit values on matrices
  - `dm(0,0)`
  - `dm(0,1)`
  - `...`

  We can iterate rows and columns
  - `dm.colIter.foreach(println)`
  - `dm.rowIter.foreach(println)`

Basic Statistics with SparkML

- Summaries (I)

  - `import org.apache.spark.ml.linalg.{Vector, Vectors}`
  - `import org.apache.spark.ml.stat.Summarizer`

  We create a DataFrame

  - ```
    val data = Seq(
        (Vectors.dense(2.0, 3.0, 5.0), 1.0),
        (Vectors.dense(4.0, 6.0, 7.0), 2.0)
      )
    ```
  - `val df = data.toDF("features", "weight")`
  - `df.show()`

```
+-------------+------+
|     features|weight|
+-------------+------+
|[2.0,3.0,5.0]|   1.0|
|[4.0,6.0,7.0]|   2.0|
+-------------+------+
```
```

Basic Statistics with SparkML

- Summaries

  Then we create a Summary (example with and without weights)

  - ```
    val (meanVal, varianceVal) = df
      .select(
              Summarizer.metrics("mean", "variance")
              .summary($"features", $"weight").as("summary")
      )
      .select("summary.mean", "summary.variance")
      .as[(Vector, Vector)]
      .first()
      meanVal: …Vector = [3.333333333333333,5.0,6.333333333333333]
      varianceVal: …Vector = [2.0,4.5,2.0]
    ```

  - ```
    val (meanVal2, varianceVal2) = df
      .select(
              Summarizer.mean($"features"),
              Summarizer.variance($"features")
      )
      .as[(Vector, Vector)]
      .first()
      meanVal2: org.apache.spark.ml.linalg.Vector = [3.0,4.5,6.0]
      varianceVal2: org.apache.spark.ml.linalg.Vector = [2.0,4.5,2.0]
    ```

Basic Statistics with SparkML

- Correlations
  - `import org.apache.spark.ml.linalg.{Matrix, Vectors}`
  - `import org.apache.spark.ml.stat.Correlation`
  - `import org.apache.spark.sql.Row`

  We create four series to check for correlation

  - ```
    val data = Seq(
      Vectors.sparse(4, Seq((0, 1.0), (3, -2.0))),
      Vectors.dense(4.0, 5.0, 0.0, 3.0),
      Vectors.dense(6.0, 7.0, 0.0, 8.0),
      Vectors.sparse(4, Seq((0, 9.0), (3, 1.0)))
      )
    ```
  - `val df = data.map(Tuple1.apply).toDF("features")`
    ```

Basic Statistics with SparkML

- Correlations

We compute the Pearson Correlation

```
• val Row(coeff1: Matrix) = Correlation.corr(df, "features").head
• println(s"Pearson Correlation matrix:\n $coeff1")
```

```
1.0                   0.055641488407465814  NaN  0.400471420316813
0.055641488407465814  1.0                   NaN  0.9135958615342522
NaN                   NaN                   1.0  NaN
0.400471420316813     0.9135958615342522    NaN  1.0
```

Also we can compute the Spearman Correlation

```
• val Row(coeff2: Matrix) = Correlation.corr(df, "features",
  "spearman").head
• println(s"Spearman correlation matrix:\n $coeff2")
```

```
1.0                  0.105409255338946532  NaN  0.40000000000000174
0.105409255338946532 1.0                   NaN  0.9486832980505141
NaN                  NaN                   1.0  NaN
0.40000000000000174  0.9486832980505141    NaN  1.0
```

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Regression

- Linear Regression

  - `import org.apache.spark.ml.regression.LinearRegression`

  Load the Data

  - `var datafile = "/home/vagrant/spark/data/mllib/sample_linear_regression_data.txt"`
  - `val dataset = spark.read.format("libsvm").load(datafile)`

  We do some splitting for Training vs. Test data (60% vs. 40%)

  - `val splits = dataset.randomSplit(Array(0.6, 0.4), seed = 11L)`
  - `val training = splits(0).cache()`
  - `val test = splits(1)`

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Regression

- Linear Regression

Then we train our model

```
• val lr = new LinearRegression().setMaxIter(10).setRegParam(0.3).setElasticNetParam(0.8)
• val model = lr.fit(training)

• println(s"Coefficients: ${model.coefficients} Intercept: ${model.intercept}")

    Coefficients: [0.0,0.322925166774,-0.343854803456,1.915601702345,
    0.052880586803,0.765962720459,0.0,-0.151053926691,-0.215879303609,
    0.220253691888] Intercept: 0.159893684423
```

We can pass the Test set

```
• val predictions = model.transform(test)
• predictions.show()

    +-------------------+--------------------+--------------------+
    |              label|            features|          prediction|
    +-------------------+--------------------+--------------------+
    |-26.805483428483072|(10,[0,1,2,3,4,5,...|  0.7396609342028824|
    |-26.736207182601724|(10,[0,1,2,3,4,5,...| -1.9523217339135148|
    | ...               | ...                | ...                |
    |-12.467656381032860|(10,[0,1,2,3,4,5,...| -3.2321660582830720|
    +-------------------+--------------------+--------------------+
```

Regression

- Linear Regression

  - `import org.apache.spark.ml.regression.LinearRegressionModel`
  - `import org.apache.spark.ml.evaluation.RegressionEvaluator`

  Then we evaluate the predictor

  - `val predictionAndLabels = predictions.select("prediction", "label")`
  - `val evaluator = new RegressionEvaluator().setMetricName("mse")`
  - `val lm_eval = evaluator.evaluate(predictionAndLabels)`

  - `println(s"Test set accuracy = ${lm_eval}")`
    `Test set accuracy = 121.31149228612746`

  Finally, we can save the model

  - `model.write.overwrite().save("LR_Model")`
  - `val sameModel = LinearRegressionModel.load("LR_Model")`

Classification

- Support Vector Machines

  - `import org.apache.spark.ml.classification.LinearSVC`
  - `import org.apache.spark.ml.classification.LinearSVCModel`

  Load the data

  - `var datafile = "/home/vagrant/spark/data/mllib/sample_libsvm_data.txt"`
  - `val dataset = spark.read.format("libsvm").load(datafile)`

  We do some splitting for Training vs. Test data (60% vs. 40%)

  - `val splits = dataset.randomSplit(Array(0.6,0.4), seed=11L)`
  - `val training = splits(0).cache()`
  - `val test = splits(1)`

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Classification

- Support Vector Machines

Train the model with the Training Set

- `val lsvc = new LinearSVC().setMaxIter(10).setRegParam(0.1)`
- `val model = lsvc.fit(training)`

Apply the model to predict the Test Set

- `val predictions = model.transform(test)`
- `predictions.show()`

```
+-----+--------------------+--------------------+----------+
|label|            features|       rawPrediction|prediction|
+-----+--------------------+--------------------+----------+
|  0.0|(692,[100,101,102...|[0.71776148799584...|       0.0|
|  0.0|(692,[121,122,123...|[1.44573581464122...|       0.0|
|  0.0|(692,[124,125,126...|[2.38450174138818...|       0.0|
|  ...|        ...         |         ...        |       ...|
|  0.0|(692,[234,235,237...|[0.34669005075936...|       0.0|
|  1.0|(692,[123,124,125...|[-1.5386041465622...|       1.0|
|  1.0|(692,[123,124,125...|[-1.4171162883335...|       1.0|
|  1.0|(692,[123,124,125...|[-1.2079081220678...|       1.0|
|  1.0|(692,[125,126,127...|[-1.1320358784535...|       1.0|
+-----+--------------------+--------------------+----------+
```

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Classification

- Support Vector Machines
  - `import org.apache.spark.ml.evaluation.MulticlassClassificationEvaluator`

  We create an “accuracy” evaluator
  - `val evaluator = new MulticlassClassificationEvaluator().setMetricName("accuracy")`

  Then evaluate the predictions
  - `val predictionAndLabels = predictions.select("prediction", "label")`
  - `predictionAndLabels.show()`

```
+----------+-----+
|prediction|label|
+----------+-----+
|       0.0|  0.0|
|       0.0|  0.0|
|   ...    | ... |
|       1.0|  1.0|
|       1.0|  1.0|
+----------+-----+
```

  - `val svc_eval = evaluator.evaluate(predictionAndLabels)`
  - `println(s"Test set accuracy = ${svc_eval}")`

```
Test set accuracy = 1.0
```

  And we save the model
  - `model.write.overwrite().save("SVM_SGD_Model")`
  - `val sameModel = LinearSVCModel.load("SVM_SGD_Model")`

Clustering

- Our beloved classical k-means

    - `import org.apache.spark.ml.clustering.KMeans`
    - `import org.apache.spark.ml.clustering.KMeansModel`
    - `import org.apache.spark.ml.evaluation.ClusteringEvaluator`

    First of all, load and parse the data

    - `var datafile = "/home/vagrant/spark/data/mllib/sample_kmeans_data.txt"`
    - `val dataset = spark.read.format("libsvm").load(datafile)`

    Then train a model

    - `val kmeans = new KMeans().setK(2).setSeed(1L)`
    - `val model = kmeans.fit(dataset)`

    - `model.clusterCenters.foreach(println)`

    Use for prediction

    - `val predictions = model.transform(dataset)`
    - `predictions.show()`

Clustering

- k-Means

We can evaluate our model using Silhouette score

- `val evaluator = new ClusteringEvaluator()`
- `val silhouette = evaluator.evaluate(predictions)`

```
silhouette: Double = 0.9997530305375207
```

- `println(s"Silhouette with sq.euclidean distance = $silhouette")`

```
Silhouette with squared euclidean distance = 0.999753030…
```

Finally, we save the model

- `model.write.overwrite().save("KMeansModel")`
- `val sameModel = KMeansModel.load("KMeansModel")`

Dimensionality Reduction

- Principal Component Analysis
  - `import org.apache.spark.ml.feature.PCA`
  - `import org.apache.spark.ml.linalg.Vectors`
  - `import org.apache.spark.sql.SparkSession`

  Create some sample data, and parallelize

```
• val data = Array(
      Vectors.sparse(5, Seq((1, 1.0), (3, 7.0))),
      Vectors.dense(2.0, 0.0, 3.0, 4.0, 5.0),
      Vectors.dense(4.0, 0.0, 0.0, 6.0, 7.0)
  )
• val dataframe =
    spark.createDataFrame(data.map(Tuple1.apply)).toDF("features")
• dataframe.show()
```

```
+--------------------+
|            features|
+--------------------+
| (5,[1,3],[1.0,7.0])|
|[2.0,0.0,3.0,4.0,...|
|[4.0,0.0,0.0,6.0,...|
+--------------------+
```

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Dimensionality Reduction

- ...

Compute the Principal Components

- ```
  val pca = new PCA()
    .setInputCol("features").setOutputCol("psi_features").setK(4)
    .fit(dataframe)
  ```
- ```
  pca.explainedVariance
    res28: org.apache.spark.ml.linalg.DenseVector =
    [0.79439325322,0.205606746776,1.25729185411E-16,5.38535301254E-17]
  ```

Project Points into the new space

- `val result = pca.transform(dataframe).select("psi_features")`
- `result.show(truncate = false)`

```
+---------------------------------------- - - - --+
|psi_features                                     |
+---------------------------------------- - - - --+
|[1.6485728230883807,-4.0132827005162960, . . . ] |
|[-4.645104331781534,-1.1167972663619026, . . . ] |
|[-6.428880535676489,-5.3379514277753550, . . . ] |
+---------------------------------------- - - - --+
```

Vectors → DataFrames

- Transform Vectors to Dataframes
  - `result.show(truncate = false)`

```
+-----------------------------------------------------------------------------+
|psi_features                                                                 |
+-----------------------------------------------------------------------------+
|[1.6485728230883807,-4.0132827005162960,-5.524543751369388,0.17258344691630860]|
|[-4.645104331781534,-1.1167972663619026,-5.524543751369387,0.17258344691630922]|
|[-6.428880535676489,-5.3379514277753550,-5.524543751369389,0.17258344691630967]|
+-----------------------------------------------------------------------------+
```

We need to read the Columns as Vectors, the convert to Arrays (we create a SQL User Defined Functions)

- `val vecToArray = udf((xs: Vector) => xs.toArray)`
- `val aux = result.withColumn("sep_features", vecToArray($"psi_features"))`

We create a SQL expression

- `val header = Array("psi_1", "psi_2", "psi_3", "psi_4")`
- ```
  val sqlExpr = header.zipWithIndex.map{
     case (alias, idx) => col("sep_features").getItem(idx).as(alias)
  }
  ```
- `val result_fix = aux.select(sqlExpr : _*)`
- `result_fix.show()`

```
+------------------+-------------------+------------------+-------------------+
|             psi_1|              psi_2|             psi_3|              psi_4|
+------------------+-------------------+------------------+-------------------+
|1.6485728230883807| -4.013282700516296|-5.524543751369388| 0.1725834469163086|
|-4.645104331781534|-1.1167972663619026|-5.524543751369387|0.17258344691630922|
|-6.428880535676489| -5.337951427775355|-5.524543751369389|0.17258344691630967|
+------------------+-------------------+------------------+-------------------+
```

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```

Vectors ← DataFrames

- From DataFrames to Vectors
  - We can use an “Assmbler”
    - `import org.apache.spark.ml.feature.VectorAssembler`
    - `import org.apache.spark.ml.linalg.Vectors`
    - ```
      val dataset = spark.createDataFrame(
            Seq((0, 18, 1.0, Vectors.dense(0.0, 10.0, 0.5), 1.0))
            )
            .toDF("id","hour","mobile","userFeatures","clicked")
      ```
    - ```
      val assembler = new VectorAssembler()
            .setInputCols(Array("hour", "mobile", "userFeatures"))
            .setOutputCol("features")
      ```
    - `val output = assembler.transform(dataset)`
    - `output.select("features", "clicked").show(truncate = false)`

Part 3 – Recap

- What is SparkML

- Some examples of :
  - Basic Types of Data
    - Then DataFrames
  - Basic Statistics that can be performed
    - Summary
    - Correlation
  - Modeling and prediction
    - Least Squares
    - Support Vector Machines
  - Clustering
    - K-Means
  - Dimensionality Reduction
    - PCA

SparkStream

- Spark Stream is the library for dealing with Streams of data
  - Spark has a context for running operations
  - SparkStream has a context that updates each time
- RDDs in the streaming context change each time the stream is updated
  - In Scala, as we indicate *how things are* but not *what to do*, each streaming context will state that "things are" how we defined
  - ...this is, we will have no loops for each update, but an updated dynamic context always running

SparkStream

- In Spark versions prior to v2.2, streams required us to create a thread per stream, then create a function to update the "steady" thread
  - We created a StreamContext to periodically read
  - We defined the functions to be applied in the stream context
  - We created a function to update the steady context for each stream update

- From Spark v2.2 on we have "structured streaming"
  - We define which query will be executed, and the periodicity
  - We define where to dump the results
    - This can be a variable in the "steady" thread
    - Or can be another stream opened for writing

Structured Streaming

- For the following exercise, we'll need to open another terminal
  - **If you are using the VM with vagrant, just open another terminal/cmd and create a new connection "vagrant ssh"**
  - If you are using the VM with the VirtualBox GUI, open a terminal/cmd and connect using a SSH client (check the "set-up document" for more details)
  - If you are running Spark on a bare machine, just open a new terminal/cmd!
- Now we have two terminals:
  - A first terminal will have Spark running
  - A second terminal will have the "nc" command sending data to Spark, via TPC sockets.

Structured Streaming

- On the Spark session…

- Load the required libraries
  - `import org.apache.spark.sql.functions._`
  - `import org.apache.spark.sql.SparkSessionval`
  - `import spark.implicits._`

- Streams for reading (wordcount example)

  Create the stream of input lines from connection to localhost:9999
  - ```
    val lines = spark.readStream.format("socket").option("host",
      "localhost").option("port", 9999).load()
    ```

  Write the wordcount example
  - `val words = lines.as[String].flatMap(_.split(" "))`
  - `val wordCounts = words.groupBy("value").count()`

- Streams for writting

  Start running the query that prints the running counts to the console
  - ```
    val query =
      wordCounts.writeStream.outputMode("complete").format("console")
    ```

Structured Streaming

- On the second terminal…

  Let’s use “nc” to send words to our Spark streaming context. In a bash terminal, run:
  - `nc -lk 9999`

  We opened the streaming context in host: localhost and port: 9999

- Back to the Spark terminal

  We start the thread for streaming and tell the thread to wait until input stream associated to query stops
  - `query.start()`

  IMPORTANT! If “nc” (or the data-source program) is not started, query.start() will return an exception

- In the Bash Terminal

  Just start introducing words, separated by space (as we indicated in the “map” operation). E.g.:
  - `hola adeu`
  - `hola que tal`
  - `adeu siau`
  - `hola hola hola`

Structured Streaming

- Back to the Spark terminal

Our streaming context is performing wordcount continuously

```
-------------------------------------------
Batch: 0
-------------------------------------------
+-----+-----+
|value|count|
+-----+-----+
| hola|    1|
| adeu|    1|
+-----+-----+

-------------------------------------------
Batch: 1
-------------------------------------------
+-----+-----+
|value|count|
+-----+-----+
|  que|    1|
| hola|    5|
| siau|    1|
| adeu|    2|
|  tal|    1|
+-----+-----+
```

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Structured Streaming

- Stream sources (readers)
  - sockets: TCP sockets, options are host, port, etc...
  - applications: kafka, flume, kinesis... (have their own options, like “server”, “topic”, “user”, etc...)
  - files: files in a directory, e.g. as CSV
  - memory: a table in SparkSQL

- Stream sinks (writters)
  - console: direct to terminal
  - sockets: dump into TCP sockets
  - applications: dump into application listeners
  - files: dump results into a file (in the FS, HDFS, etc...)
  - memory: a table in SparkSQL

- The Spark application can build a pipeline for processing data
  - Receive from multiple sources
  - Process inputs
  - Dump results into multiple sinks

Structured Streaming

- Stream Periodicity and updates

  - `import org.apache.spark.sql.functions._`
  - `import org.apache.spark.sql.SparkSession`
  - `import spark.implicits._`
  - `import org.apache.spark.sql.streaming.Trigger`

  First we create the input as a “stream”, then set the wordcount:

  - ```
    val lines = spark.readStream.format("socket")
      .option("host", "localhost")
      .option("port", 9999).load()
    ```

  - `val words = lines.as[String].flatMap(_.split(" "))`
  - `val wordCounts = words.groupBy("value").count()`

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    ```

Structured Streaming

- (Stream Periodicity and updates)

We can set the interval for processing with a “trigger”

```
• var query = wordCounts
    .writeStream
    .outputMode("complete")
    .trigger(Trigger.ProcessingTime("5 seconds"))
    .format("console")
• query.start()
```

We can decide that we don’t want to keep full memory, just the updates

```
• var query = wordCounts
    .writeStream
    .outputMode("update")
    .trigger(ProcessingTime("5 seconds"))
    .format("console")
• query.start()
```

Structured Streaming

- Stream Queries
  - Objects from Structured Streaming are SparkSQL DataFrames
  - Operations are from SparkSQL, and inputs and results be treated as tables
  - Also input streams can be joined and aggregated in time windows

- Stream Management

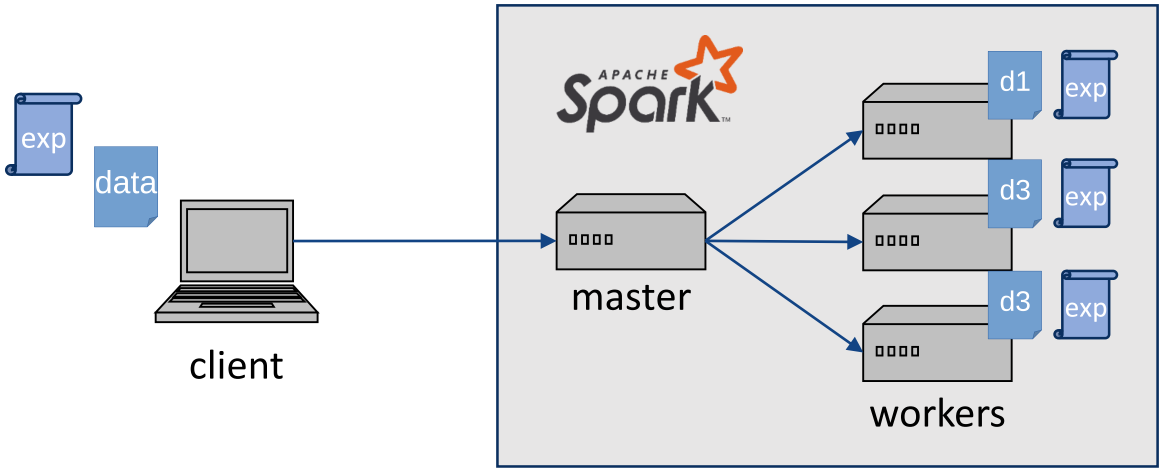
  Streams can be treated as Threads
  - They have Ids
  - Can be started ans stopped
  - Can wait other streams
  - Can be monitored

Part 4 – Recap

- What is SparkStream
- Structured Streams
  - Spark streaming
  - Data sources and sinks
  - Stream properties
- Stream Contexts
  - Stateful Streaming
- Some examples:
  - Streaming WordCount

Demo in MareNostrum

- Let's run it on a MN cluster!
- Basic Spark cluster structure:



- Problem:
  - MN doesn't allow access to Internet, install anything, any permissions, run things directly (queue system), or run VMs nor containers...
  - ... except Singularuity Containers (limited kind of containers)
  - ... and automated scripts

Work with this!

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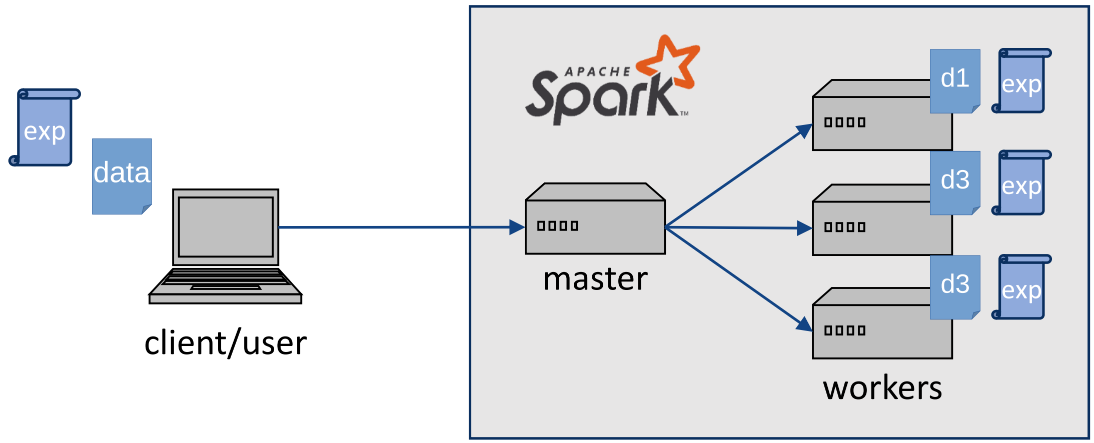
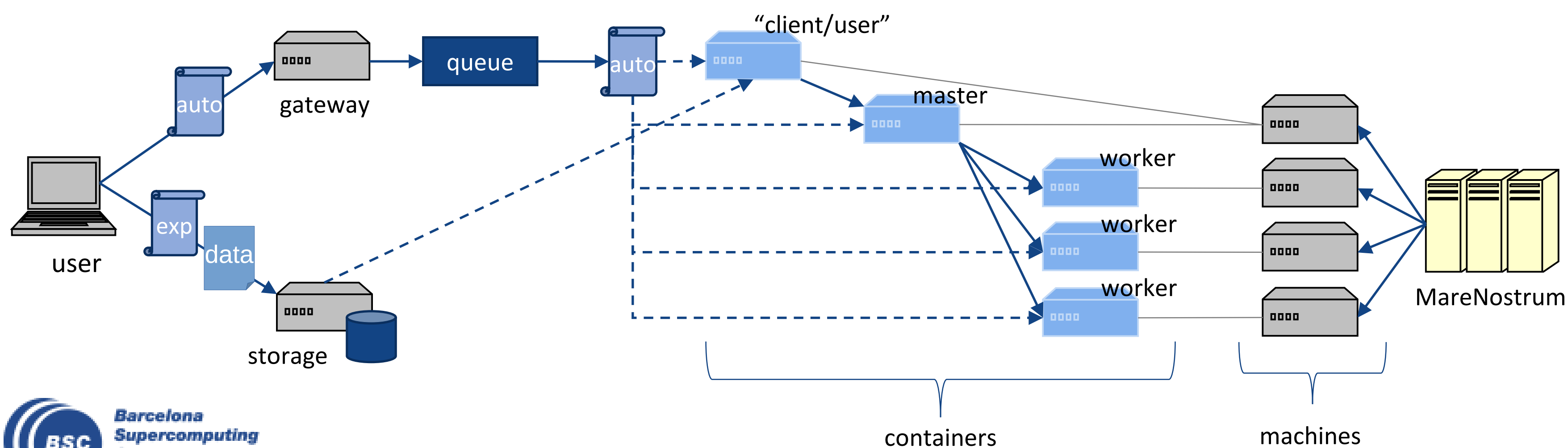
Demo in MareNostrum

- Basic Spark cluster structure → MN/cluster structure





Demo in MareNostrum

- Automation script:

1. Set up environment
   - Retrieve list of provided machines
   - Copy files to work disk
2. In master machine
   - Start a container as “Master node”
3. For each worker machine
   - Start a container as “Worker node”
4. In master machine
   - Start a container as “client” that submits “experiment” to “Master”
5. Wait for results
6. Retrieve results
   - Get results from work disk
   - Stop workers/master from machines
7. Execution ends

Connection to MN-IV

- Let's connect to MN-IV
  - `ssh [USER]@mn1.bsc.es`
- Copy the container image with Spark
  - `cp /gpfs/scratch/nct00/nct00002/spark-mn4.tar.gz ./`
  - `tar xzvf spark-mn4.tar.gz`
- Check the script "start-mniv.sh" (you can use "nano" or "vim")
  - Observe the actions, directories, and data movement before and after executing
  - Put the correct USERS and GROUPS in the DIRectories
    - `HOME_DIR=/gpfs/home/nctXX/nctXXXXX/spark`
    - `WORK_DIR=/gpfs/scratch/nctXX/nctXXXXX/spark`
- Set the script to run!
  - `sbatch start-mniv.sh`
  - `squeue`
  - `scancel`
- When the execution ends:
  - Go to "`experiments_XXXXXXX/wc-result.data`" → We have the "blocks" of the result

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EXCELENCIA SEVERO OCHOA

Thanks for your Attention

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