Big Data processing: a framework suitable for Economists and Statisticians

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The views expressed in the presentation are the authors’ only and do not imply those of the Bank of Italy.
Motivation

Hardware Architecture
- Client Server framework.

Software Architecture
- Apache Spark Framework.

Econometric Benchmarks
- Three Econometric Applications
  - SparkR vs R
  - PySpark vs Python

Concluding Remarks
The need of processing Big Data in short amount of time requires specialized computing platforms.

- Big Data applications are flooding all branches of scientific knowledge.
- Economic and statistical research needs to apply Big Data methodologies to improve on timeliness and accuracy.
- To pursue these goals it is of paramount importance the selection of a suitable computing framework.
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Parallel computing framework is the avenue

The most relevant parallel computing frameworks:

- **openMP** which aims at multicore, single image architecture,

- Message Passing Interface (MPI), suitable for loosely coupled networks,

- **Apache Hadoop** which provides a parallel batch processing environment employing the Map Reduce paradigm,

- **Apache Spark** offers a very fast and general engine for large-scale iterative data processing.
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Hardware Architecture

For the worker nodes we employ a High Performance Computing Platform based on standard blade server HP-BL460c based on INTEL XEON 2630 with 40 cores in Hyperthreading.
Hardware Architecture

Mesos Master
Virt. Machine
16 GB

Mesos slave #1
Physical 256 GB

Mesos slave #2
Physical 256 GB

Mesos slave #5
Physical 256 GB

Mesos slave #6
Physical 256 GB

Apache infrastructure.
Apache Spark Architecture

Driver Program

SparkContext

Cluster Manager (Mesos)

Worker
Executor

Worker
Executor

Worker
Executor

Worker
Executor

Apache infrastructure.
How does Spark execute a job

Apache Spark Architecture

Apache infrastructure.

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Big Data processing framework
Sharing Computing resources

A software platform for efficient distribution of a set of limited resources:

- fair sharing of the resources amongst users;
- Providing resource guarantees to users (e.g. quota, priorities, etc.);
- Providing accurate resource accounting.

The platform shows the user a unified view of the state of services throughout the cluster.

Our choice is fallen on Mesos v. 1.6
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Here we see the general features of a Mesos cluster:
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Apache Spark provides the whole software stack for cluster computing. The main Spark features are:

- designed to efficiently deal with iterative computation,
- distributed and fault tolerant data abstraction (Resilient Distributed Dataset),
- Lazy Evaluation for reducing computation and preventing unnecessary I/O and memory usage.
- open source
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Apache Spark has a layered architecture where all the layers are loosely coupled and integrated with various libraries. The Spark architecture relies on two main concepts:

1. Resilient Distributed Datasets (RDD);
2. Directed Acyclic Graph (DAG);

- A RDD is a collection of data that are split into partitions and can be stored in-memory on workers nodes of the cluster.
- A DAG represents a sequence of computations performed on an RDD partition.
Apache Spark breakdown

Here are shown the Spark main software components:
Apache Spark supplies an ample set of Application Programming Interfaces (API). Among them we have:

- Java,
- Python,
- R,
- Scala (which is the language used for Spark).
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Software for Data Science

Some of the software frameworks employed for data science:

Python, R, Both, or Other platforms for Analytics, Data Science, Machine Learning

- Python: 34% in 2016, 41% in 2017
- R: 42% in 2016, 36% in 2017
- Both: 8.5% in 2016, 12% in 2017
- Other: 16% in 2016, 11% in 2017

Poll 2017

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The Econometric Applications.

Our benchmarks are based on the following three examples:

1. Generalised Linear Models (GLM) with gaussian family;
2. GLM with binomial family;
The Econometric Applications.

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1. Generalised Linear Models (GLM) with gaussian family;
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Generalised Linear Model.

The main elements of a GLM are:

1. a linear predictor:

   \[ y_i = \beta_0 + \beta_1 x_{1i} + \cdots + \beta_p x_{pi} \]  

2. a link function describing how the mean \( E(y_i) \) depends on the linear predictor

   \[ E(y_i) = \mu_i = g^{-1}(X_i \cdot \beta) \]
In case of a dependent variable binomially distributed we use

\[ g(\mu_i) = \text{logit}(\mu_i) = \log \left( \frac{\mu_i}{1 - \mu_i} \right) \]  \hspace{1cm} (3)
A Random Forest is:

1) an ensemble classifier built with many decision trees;
2) a device suitable for classification and regression;
3) it generates accuracy and variable importance information.
Random Forest.

A simple decision tree is shown here:

A binary classification decision tree.
The three used algorithms have been applied to a dataset with growing size.

<table>
<thead>
<tr>
<th>file name</th>
<th># obs.</th>
<th>size</th>
<th>seconds wc</th>
<th>-l</th>
</tr>
</thead>
<tbody>
<tr>
<td>data_1e+03.csv</td>
<td>1,000</td>
<td>90KB</td>
<td>≈ 0</td>
<td></td>
</tr>
<tr>
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<tr>
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you can’t use interactive editor with the largest files. 😞
Empirical Application.

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SparkR code

```r
sparkR.session(
  master = "mesos://osi2-virt-516.utenze.bankit.it:5050",
  appName = "test_GLM_RF_SparkR",
  sparkConfig = list(
    "spark.local.dir = ": "/tmp/work/wisi089",
    "spark.serializer = ": "org.apache.spark.serializer.KryoSerializer",
    "spark.eventLog.enabled = ": "true",
    "spark.eventLog.dir = ":="/tmp/work/wisi089",
    "spark.executor.heartbeatInterval = ": "20s",
    "spark.driver.memory = ": "10g",
    "spark.executor.memory = ": "220g",
    "spark.driver.extraJavaOptions = ": ":-Djava.io.tmpdir=/tmp/work/wisi089",
    "spark.executor.extraJavaOptions = ": ":-Djava.io.tmpdir=/tmp/work/wisi089",
    "spark.cores.max = ": as.character(spark_cores)
    "spark.executor.cores = ": as.character(spark_executor_cores) 
  )
)
modelSparkLinearGLM <- spark.glm(main_data_spark, y ~ x1 + x2 + x3 + x4 + x5,
  family = "gaussian");
fitted_modelSparkLinearGLM <- predict(modelSparkLinearGLM, main_data_spark);
```
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Scalar Python results

Time in sec.

file size (bytes)

Scalar R example

GLM
Logistic
Rand Forest
SparkR 10 GB file.

SparkR with dataset size $10^8$

- GLM
- Logistic
- Rand Forest
SparkR with dataset size $10^9$. 

**Graph:**
- **Y-axis:** Time in sec.
- **X-axis:** Cores
- **Legend:**
  - GLM
  - Logistic
  - Rand Forest

**SparkR vs R vs PySpark vs Python**
from pyspark.sql import SparkSession
from pyspark.sql import Row
from pyspark.sql.types import StructType, StructField
from pyspark.sql.types import DoubleType, IntegerType, StringType
from pyspark.ml.linalg import Vectors
from pyspark.ml import Pipeline
from pyspark.ml.regression import GeneralizedLinearRegression
from pyspark.ml.classification import RandomForestClassifier as RF
from pyspark.ml.feature import StringIndexer, VectorIndexer, VectorAssembler, SQLTransformer

data = spark.read.csv(inputfile, schema=schema, header=True)
data.rdd.getNumPartitions()
cols_now = ['x1','x2','x3','x4','x5']
assembler_features = VectorAssembler(inputCols=cols_now, outputCol='features')
labelIndexer = StringIndexer(inputCol='y', outputCol="label")
tmp = [assembler_features, labelIndexer]
pipeline = Pipeline(stages=tmp)
allData = pipeline.fit(data).transform(data),['label','features']
allData.cache()
glm = GeneralizedLinearRegression(family="gaussian", maxIter=1000)
model = glm.fit(allData)
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Scalar Python results

![Graph showing time vs. file size for different models: GLM, Logistic, and Random Forest. The graph is on a log-log scale, with time in seconds on the y-axis and file size in bytes on the x-axis.](image)

Scalar python example
PySpark 10 GByte file

![Graph showing performance comparison between GLM, Logistic, and Random Forest with varying cores for PySpark with a dataset size of 10^8]
PySpark 100 GByte file

**Motivation**

**Hardware Architecture**

**Software Architecture**

**Econometric Benchmarks**

**Concluding Remarks**

**Three Econometric Applications**

*SparkR vs R*

*PySpark vs Python*

PySpark with dataset size $10^9$
PySpark 1 TByte file

![Graph showing performance of PySpark with dataset size 10^{10}](image)

PySpark with dataset size 10^{10}

- GLM
- Logistic
- Rand Forest

Time in sec.

cores

PySpark with dataset size 10^{10}
Concluding Remarks

- We have presented an easy to deploy computational platform for Big Data applications;
- we have shown the extensibility towards cluster programming for two popular software framework such as $R$ and $Python$;
- we have pinned down a threshold above which it is convenient to shift towards cluster computing;
- In some instances $R$ failed to solve the problem with dataset size around one billion.
For Further Reading


Thank you for your attention.

Any questions?