# Big Data con Apache Spark 3 y Python: Zero to Expert





# Introduction to Apache Spark

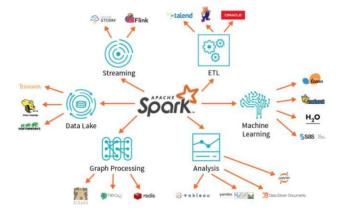


#### **Apache Spark**

Spark is an open source **Big Data** solution . Developed by the **UC Berkeley** RAD Lab (2009).

It has become a tool

of reference in the field of Big Data.





## **Apache Spark vs MapReduce**

Easier and faster than Hadoop MapReduce.

Differences:

- Spark much faster by caching data in memory vs MapReduce in the hard drive (plus read and write)
- Spark optimized for better **parallelism**, **CPU** utilization , and faster startup Spark has a richer **functional programming** model
- Spark is especially useful for iterative algorithms.

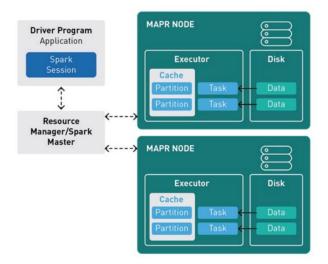






4

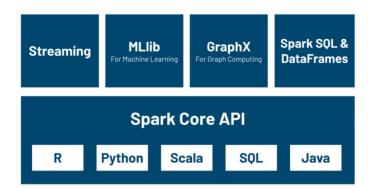
# How to Spark in a Cluster





# **Spark Components**

Spark contains a very complete ecosystem of tools .





6

5

### **PySpark**

**PySpark** is a Spark library **written in Python** to run the Python application using the **Apache Spark capabilities.** 

Advantages of PySpark:

- Easy to learn
- Extensive set of libraries for ML and DS
- Great community support

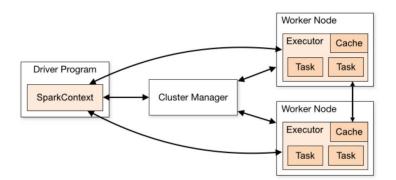






# **PySpark architecture**

Apache Spark works on a **master-slave architecture**. The **operations** are executed in the **workers**, and the **Cluster Manager** manages the resources.





8

## Types of cluster administrators

Spark supports the following cluster managers:

- Standalone : simple cluster manager
- Apache Mesos is a cluster manager that can also run Hadoop MapReduce y PySpark.
- Hadoop YARN : the resource manager in Hadoop 2
- **Kubernetes:** to automate the deployment and management of applications in containers.



Installing Apache Spark



#### Steps to install Spark (1)

- 1. Download Spark from https://spark.apache.org/downloads.html
- 2. Modify the log4j.properties.template to put log4j.rootCategory=ERROR instead of INFO.
- 3. Install Anaconda from https://www.anaconda.com/
- 4. Download winutils.exe. It's a Hadoop binary for Windows from the GitHub repository of <a href="https://github.com/steveloughran/winutils/">https://github.com/steveloughran/winutils/</a>. Navigate to the corresponding Hadoop version with the Spark distribution and look for winutils.exe in /bin.







Steps to install Spark (2)

- 2. Unzip Spark to C:\spark
- 3. Add the downloaded winutils.exe to a winutils folder in C:. It should look like this:

#### C:\winutils\bin\winutils.exe.

- 4. From cmd run: "cd C:\winutils\bin" and then: winutils.exe chmod 777 \tmp\hive
- 5. Add the environment variables:
  - HADOOP\_HOME -> C:\winutils
  - SPARK\_HOME -> C:\spark
  - JAVA\_HOME -> C:\jdk
  - Path -> %SPARK\_HOME%\bin
  - Path -> %JAVA\_HOME%\bin





11

# **Spark Installation Validation**

- 1. From the Anaconda **prompt** run: "cd C:\spark" and then "pyspark". You should see something like that of image 1.
- 2. From jupyter notebook install findspark with "pip install findspark" and run the following code.

import findspark findspark.init() import pyspark sc = pyspark.SparkContext(appName="myAppName") sc







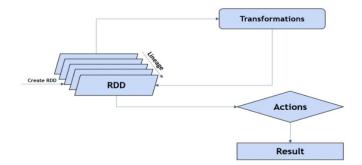
# Apache Spark's RDDs



#### **Apache Spark RDDs**

RDDs are the building blocks of any Spark application. RDD means:

- Resilient: It is fault tolerant and is capable of rebuilding data in case of failure.
- Distributed Data is distributed among multiple nodes in a cluster.
- Dataset: A collection of value-partitioned data.





15

#### **Operations in RDDs**

With RDDs, you can perform two types of operations:

- Transformations: These operations are applied to create a new RDD.
- Actions These operations are applied in an RDD to tell Apache Spark to apply the calculation and return the result to the controller.

```
num = [1,2,3,4,5]
num_rdd = sc.parallelize(num)
num_rdd.collect()
```

[1, 2, 3, 4, 5]



# DataFrames en Apache Spark



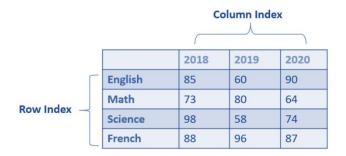
17

#### **Introduction to Data Frames**

DataFrames are tabular in nature . They allow several formats within the same table

(heterogeneous), while each variable usually has values with a single format (homogeneous).

Similar to SQL tables or spreadsheets.

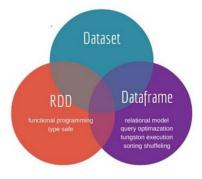




### **Advantages of Data Frames**

Some of the advantages of working with Dataframes in Spark are:

- Ability to process a large amount of structured or semi-structured data
- Easy data handling and imputation of missing values
- Multiple formats as data sources
- Support for multiple languages





19

#### **DataFrames Characteristics**

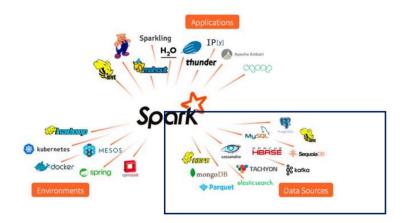
Spark DataFrames **are characterized** by: **being** distributed, lazy evaluation, immutability and Fault tolerance.





### **DataFrames data sources**

Data frames in Pyspark can be created in several ways: via files, using RDDs or through databases.





Spark Advanced Features



#### advanced features

Spark contains many **advanced features** to optimize its performance and perform complex transformations on the data. Some of them are: the expressions of selectExpr(), UDF, cache(), etc.

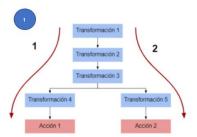


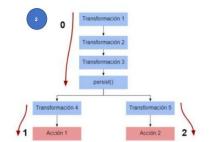


23

# **Performance optimization**

One of the **optimization techniques** are the **cache()** and persist() methods. These methods are used to **store an intermediate computation** of an RDD, DataFrame and Dataset so that they can be reused in subsequent actions.







# Advanced Analytics with Spark



25

# Functions for data analytics

In order to **train a model** or carry out **statistical analyzes** with our data, it is necessary to following functions and tasks:

- Generate a Spark session
- Import the data and generate a correct schema
- Methods to inspect data
- Data and column transformation
- Deal with missing values
- Run queries
- Data visualization





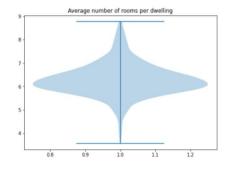
# data visualization

PySpark is compatible with numerous libraries of python data visualization as seaborn, matplotlib, bokehn, etc

```
#Violoin Plot
df5 = aglContext.sql("SELECT RM from BostonTable").toPandas()
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
bp = ax.violinplot(df5['RM'])
plt.tile('Average number of rooms per dwelling')
plt.show()
```









27

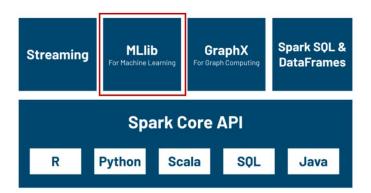
# Machine Learning con Spark



#### **Spark Machine Learning**

**Machine Learning:** is the construction of **algorithms** that can learn from the data and make predictions about them.

**Spark MLlib** is used to perform machine learning on Apache Spark. MLlib consists of algorithms and usual functions



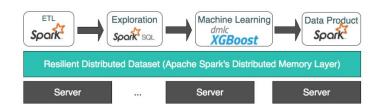


29

# **Herramientas Spark Machine Learning**

#### MLlib tools:

- spark.mllib contains the original API built on top of RDD
- spark.ml provides a higher level API built on top of DataFrames for construction of ML pipelines. The main ML API.



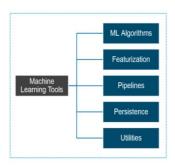
Source: https://www.r-bloggers.com/



#### **Componentes Spark Machine Learning**

#### Spark MLlib provides the following tools:

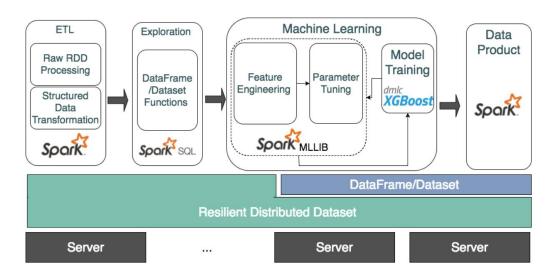
- ML Algorithms: These include common learning algorithms such as classification, regression, grouping and collaborative filtering.
- Characterization: Includes: extraction, transformation, dimensionality reduction and feature selection.
- Pipelines: are tools to build ML models in stages.
- Persistence: allows saving and loading algorithms, models y pipelines.
- Utilities: for linear algebra, statistics and data management.





31

# Proceso de Machine Learning



Source: https://www.r-bloggers.com/



#### Feature Engineering with Spark

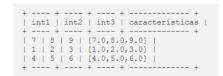
The most commonly used data preprocessing techniques in Spark approaches are as follows

- VectorAssembler
- Grouping
- Scaling and normalization
- · Work with categorical features
- Text data transformers
- Manipulation of functions
- PCA



## Feature Engineering with Spark

- Vector Assembler: It is basically used to concatenate all the features in a single vector that is can pass to estimator or ML algorithm
- **Grouping:** it is the simplest method to convert continuous variables into categorical variables. HE can be done with the Bucketizer class.
- Scaling and normalization: it is another common task in continuous variables. Allows data to have a normal distribution.
- MinMaxScaler and StandardScaler
   Standardize features with zero mean and standard deviation
  of 1.
- **StringIndexer**: to convert categorical features to numeric.

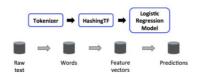




## Pipelines a PySpark

In the **Pipelines** (pipes) the different **stages of the** machine learning work can be grouped together as a single entity and can be thought of as a seamless workflow.

**Each stage** is a **Transformer**. They are executed in **sequence** and the input data is transformed as they go through each stage.



```
tokenizer = Tokenizer(inputCol="SystemInfo", outputCol="words")
hashingTF = HashingTF(inputCol=tokenizer.getOutputCol(), outputCol="features")
lr = LogisticRegression(maxIter=10, regParam=0.01)

# Build the pipeline with our tokenizer, hashingTF, and logistic regression stag
pipeline = Pipeline(stages=[tokenizer, hashingTF, lr])

model = pipeline.fit(training)
```



35

# Apache Spark Koalas

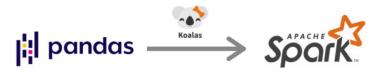


#### Introduction to Koalas

Koalas provide a **drop-in replacement for Pandas**, allowing for efficient scaling to hundreds of nodes for data science and machine learning.

Pandas does not scale to big data.

PySpark DataFrame is more SQL compatible and Koalas DataFrame is closer to Python





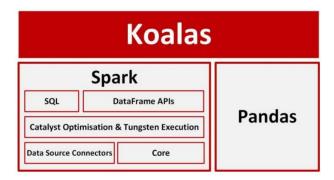
37

#### Koalas y PySpark DataFrames

Koalas and PySpark DataFrames are different. **Koalas** DataFrames follows the **structure of Pandas** and implements an **index**. The **PySpark DataFrame** is more compatible with tables in **databases relational** and has no indexes.

Koalas translates pandas APIs to plan

Spark SQL logic .





#### **Example: Feature Engineering with Koalas**

In data science you often need the **pandas get\_dummies()** function to code categorical variables as (numeric) dummy variables.

Thanks to Koalas you can do this in Spark with just a few tweaks.

```
Pandas
import pandas as pd
data = pd.read_csv("fire_department_calls_sf_clean.csv", header=0)
display(pd.get_dummies(data))

Koalas
import databricks.koalas as ks
data = ks.read_csv("fire_department_calls_sf_clean.csv", header=0)
```

display(ks.get\_dummies(data))

	Call_Me?	Money	Target			Money	Call_Me?_Maybe	Call_Me?_No	Call_Me?_Yes
0	Yes	5	10		0	5	0	0	1
1	No	3	4	_	1	3	0	1	0
2	Maybe	5	5	7	2	5	1	0	0
3	Yes	10	7		3	10	0	0	1
4	Yes	9	9		4	9	0	0	1



39

## **Example: Feature Engineering with Koalas**

In data science you often need to work with **time data.** Pandas allows you to work with this type of data easily, in PySpark it is more complicated.

```
End_date
                           Start date
     0 2013-03-17 21:45:00 2012-01-31 12:00:00
     1 2013-03-24 21:45:00 2012-02-29 12:00:00 2 2013-03-31 21:45:00 2012-03-31 12:00:00
     3 2013-04-07 21:45:00 2012-04-30 12:00:00
     4 2013-04-14 21:45:00 2012-05-31 12:00:00
     5 2013-04-21 21:45:00 2012-06-30 12:00:00
    6 2013-04-28 21:45:00 2012-07-31 12:00:00
  End_date
                       Start_date
0 2013-03-17 21:45:00 2012-01-31 12:00:00 35545500.0
1 2013-03-24 21:45:00 2012-02-29 12:00:00 33644700.0
2 2013-03-31 21:45:00 2012-03-31 12:00:00 31571100.0
3 2013-04-07 21:45:00 2012-04-30 12:00:00 29583900.0
4 2013-04-14 21:45:00 2012-05-31 12:00:00 27510300.0
5 2013-04-21 21:45:00 2012-06-30 12:00:00 25523100.0
6 2013-04-28 21:45:00 2012-07-31 12:00:00 23449500.0
```

```
Pandas

df['diff_seconds'] = df['End_date'] - df['Start_date']

df['diff_seconds'] = df['diff_seconds']/np.timedelta64(1,'s')
print(df)
```

# import databricks.koalas as ks df = ks.from\_pandas(pandas\_df) df['diff\_seconds'] = df['End\_date'] - df['Start\_date'] df['diff\_seconds'] = df['diff\_seconds'] / np.timedelta64(1,'s') print(df)



# **Spark Streaming**



41

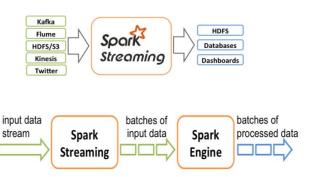
# **Spark Streaming Fundamentals**

PySpark Streaming is a scalable, fault-tolerant system that follows the RDD batch paradigm.

It operates in batch intervals, receiving a continuous stream of input data from sources such as

Apache Flume , Kinesis, Kafka, sockets TCP, etc.

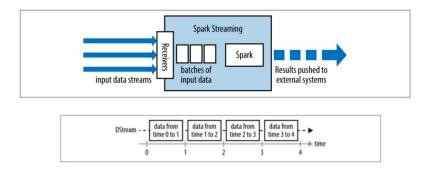
Spark Engine takes care of processing them.





# **How Spark Streaming works**

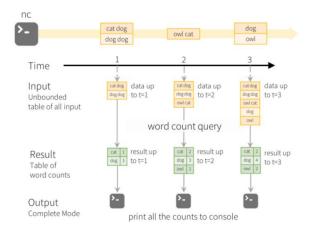
**Spark Streaming** receives data from various sources and groups it into small batches **(Dstreams)** in a time interval. The user can define the **interval**. Each input batch forms an RDD and is processed by Spark jobs to create other RDDs.





#### 43

# **Example: count words**





#### output modes

Spark uses several output modes to store the data:

- Complete mode (Complete): the entire table will be stored
- Addition mode (Append): only the new rows of the last process will be stored. Only for
  queries in which existing rows are not expected to change.
- **Update mode** (*Update*): Only the rows that have been updated since the last process will be stored. This mode only outputs the rows that have changed since the last process. If the query contains no aggregations, it is equivalent to append mode.



45

#### Types of transformations

For **fault tolerance** the received data is copied to two nodes and there is also a mechanism called **checkpointing**.

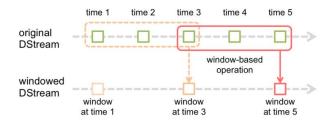
The transformations can be grouped into:

• stateless: does not depend on the data

from previous batches.

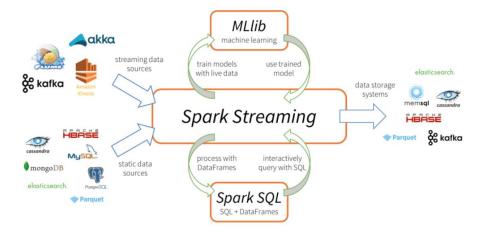
• stateful: use data

from previous batches





# **Spark Streaming Capabilities**





47

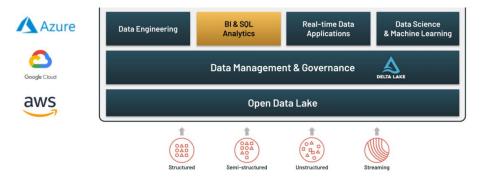
# Databricks



#### **Introduction to Databricks**

Databricks is the Apache **Spark-** based **data analytics platform** developed by the forerunners of Spark. It allows advanced analytics, Big Data and ML in a **simple** and **collaborative way**.

Available as a cloud service on Azure, AWS, and GCP.





49

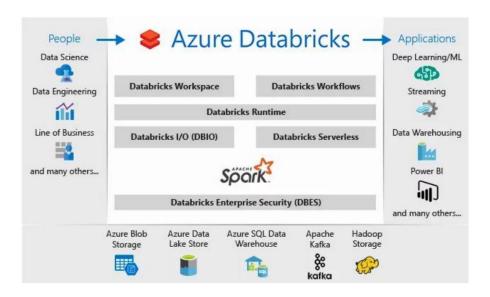
#### **Databricks features**

It allows easy **auto-scaling** and sizing **of Spark environments**. Facilitates deployments and speeds up installation and configuration of the environments.





## **Databricks Architecture**

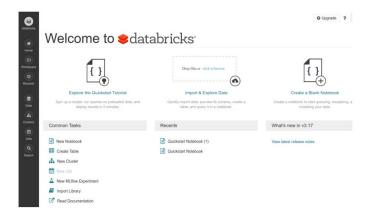




51

### **Databricks Community**

Databricks community is the **free version**. Allows you to use a **small cluster** with limited resources and **non-collaborative notebooks**. The paid version increases the capabilities.

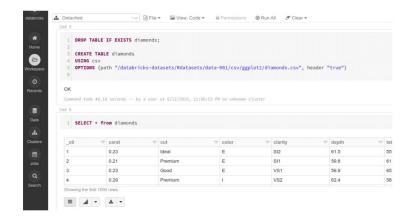




### **Terminology**

Important terms to know:

- 1. Workspaces
- 2. Notebooks
- 3. Bookstores
- 4. Tables
- 5. Clusters
- 6. Jobs





53

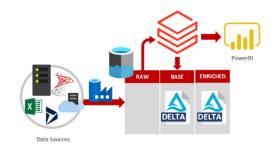
#### **Delta Lake**

Delta Lake is the open source storage layer developed for Spark and Databricks.

It provides ACID transactions and advanced metadata management.

It includes a Spark-compatible query engine that **speeds up operations** and improves the performance. Data stored in **Parquet format**.







# Resources



55

#### Resources:

- https://spark.apache.org/docs/2.2.0/index.html Official Spark Documentation
- https://colab.research.google.com/ Google Colab to have computing capacity additional

