Big Data Analytics and Stream Processing on Apache Spark

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Defining Big Data

- *“Big Data - **the massive amounts of data collected over time that are difficult to analyze and handle using common database management tools**. The data are analyzed for marketing trends in business as well as in the fields of manufacturing, medicine and science. The types of data include **business transactions**, **e-mail messages**, **photos**, **surveillance videos**, **activity logs** and **unstructured text from blogs** and **social media**, as well as **the huge amounts of data** that can be collected **from sensors** of all varieties.”*

pcmag.com-Encyclopedia

- *„Big data analytics is the process of **examining large amounts of data** of a variety of types **to uncover hidden patterns, unknown correlations and other useful information**.”*

Vignesh Prajapati: „Big Data Analytics with R and Hadoop”, Packt Publishing, 2013.

Four Dimensions of Big Data (four V's)

- Volume – scale of data
- Variety – different forms of data
- Velocity – speed of data generation
- Veracity – uncertainty of data

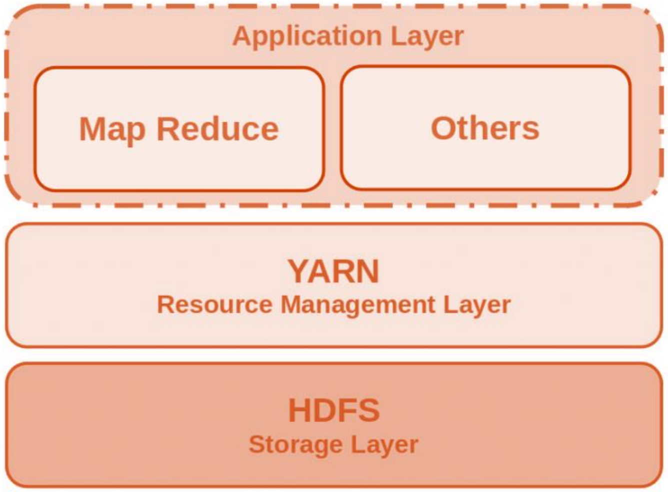
Source: http://www.slideshare.net/findwise/ibm-big-dataanalytics

Apache Hadoop

- A framework that allows a **distributed processing of large data sets** across clusters of computers
- Uses simple programming models
- Written in **Java**
- Scale up from single servers to thousands of machines
- Detects and handles failures at the application layer
- Deliverers **a highly-available service on top of a cluster of computers**, each of which may be prone to failures
- Many other FLOSS (Free/Libre and Open-Source Software) projects depend on it: https://hadoopecosystemtable.github.io/

Apache Hadoop Modules

- **Hadoop Common:** The common utilities that support the other Hadoop modules
- **Hadoop Distributed File System (HDFS):** A distributed file system that provides high-throughput access to application data
- **Hadoop YARN:** A framework for job scheduling and cluster resource management
- **Hadoop MapReduce:** A YARN-based system for parallel processing of large data sets



Source: https://starship-knowledge.com/category/framework

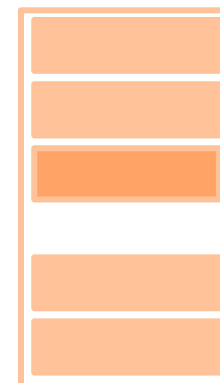
Essential HDFS Commands

- **mkdir** – Creates a directory
  hdfs dfs -mkdir /user/alice/new_dir
- **ls** – Displays the contents of a directory
  hdfs dfs -ls /user/alice/dir_to_list
- **put** – Copies a file from the local filesystem to the DFS
  hdfs dfs -put /home/alice/file_to_put.txt /user/alice/file_to_put.txt
- **get** – Copies a file from the DFS to the local filesystem
  hdfs dfs -get /user/alice/file_to_get.txt /home/alice/file_to_get.txt
- **cat** – Displays the contents of a file
  hdfs dfs -cat /user/alice/file_to_show.txt
- **mv** – Moves a file in the DFS
  hdfs dfs -mv /user/alice/file_to_move.txt /user/alice/moved_file.txt
- **cp** – Copies a file in the DFS
  hdfs dfs -cp /user/alice/file_to_copy.txt /user/alice/copied_file.txt
- **rm** – Deletes a file or directory in the DFS
  hdfs dfs -rm /user/alice/file_to_delete.txt
  hdfs dfs -rm –R /user/alice/folder_to_delete.txt

Running a Hadoop Cluster

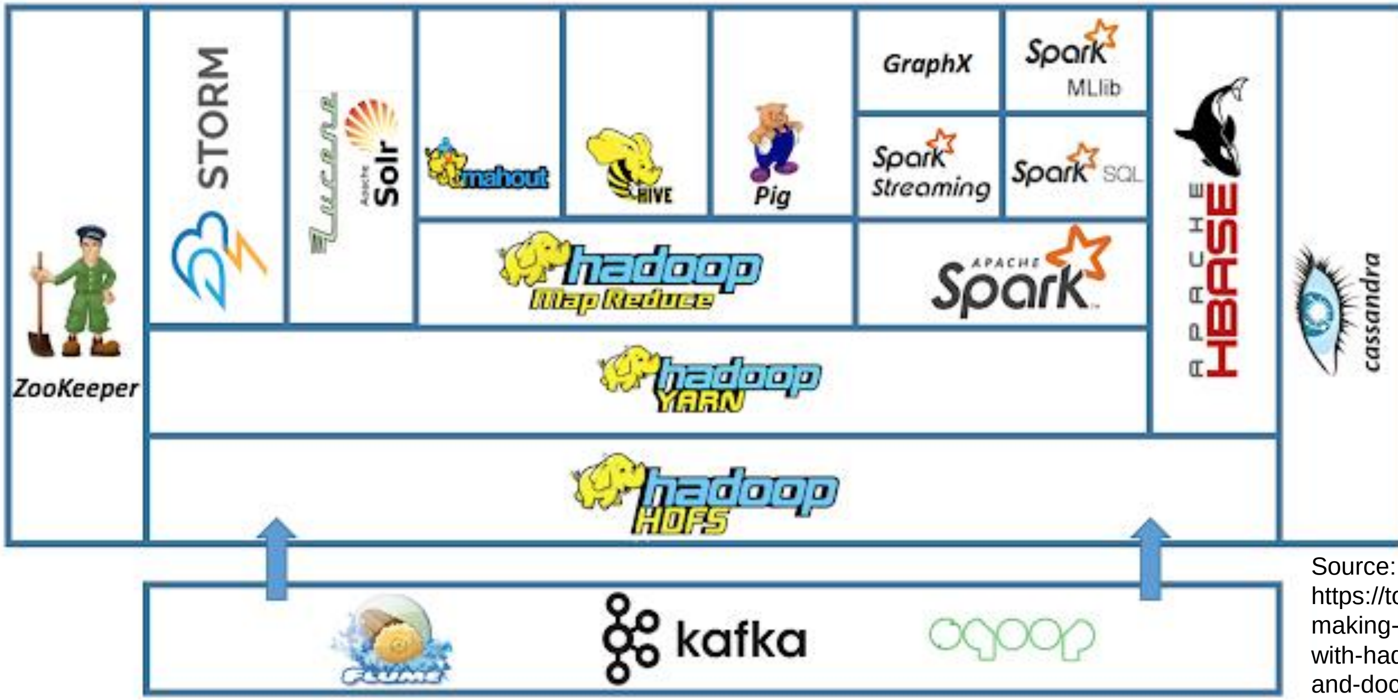
- **Standalone Operation**
  - The default running mode
  - Hadoop runs as a single Java process
  - Useful for debugging purposes
  - HDFS and YARN do not run in this mode

- **Pseudo-Distributed Operation**
  - Hadoop is run on a single-node
  - Each Hadoop daemon runs in a separate Java process
  - Useful for simulating the actual Hadoop cluster
  - Represents a fully-fledged test environment



- **Fully-Distributed Operation**
  - Hadoop daemons run on different nodes

Apache Hadoop Stack



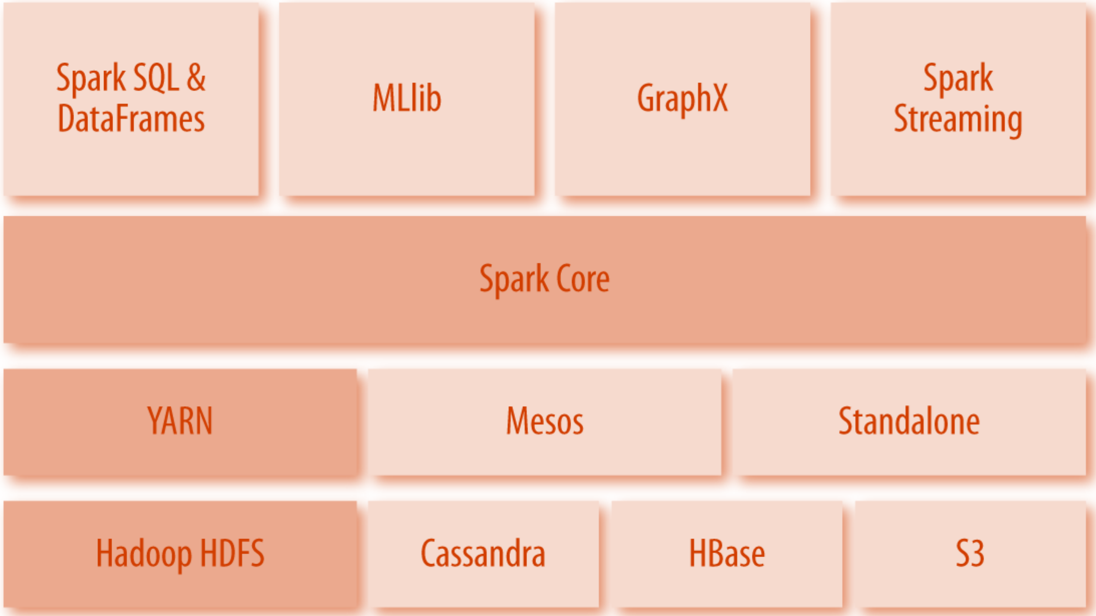
Source: https://towardsdatascience.com/making-big-moves-in-big-data-with-hadoop-hive-parquet-hue-and-docker-320a52ca175

- **HBase**: A scalable, distributed database that supports structured data storage for large tables.
- **Mahout**: A Scalable machine learning and data mining library.
- **Spark:** A fast and general compute engine for Hadoop data. Spark provides a simple and expressive programming model that supports a wide range of applications, including ETL, machine learning, stream processing, and graph computation.
- **Solr**: A popular, blazing-fast, open-source enterprise search platform built on Apache Lucene.
- **ZooKeeper**: A high-performance coordination service for distributed applications.

Apache Spark

- Apache Spark is a **unified analytics engine for large-scale data processing**
- Spark **runs on** a cluster manger (e.g. **Hadoop YARN**, Apache Mesos, Kubernetes), standalone (pseudo or fully-distributed), locally (in a single JVM) or in the cloud (with a pay-as-you-go model)
- Apache Spark runs applications **up to 100x faster in memory and 10x faster on disk than Hadoop**
- Spark offers over 80 high-level operators that make it **easy to build parallel apps**
- Written in **Scala**, but supports writing of applications in Java, Scala, **Python**, R, and SQL
- Access data in **Apache HDFS**, Alluxio, Apache Cassandra, Apache HBase, Apache Hive, and hundreds of other data sources

Apache Spark Components



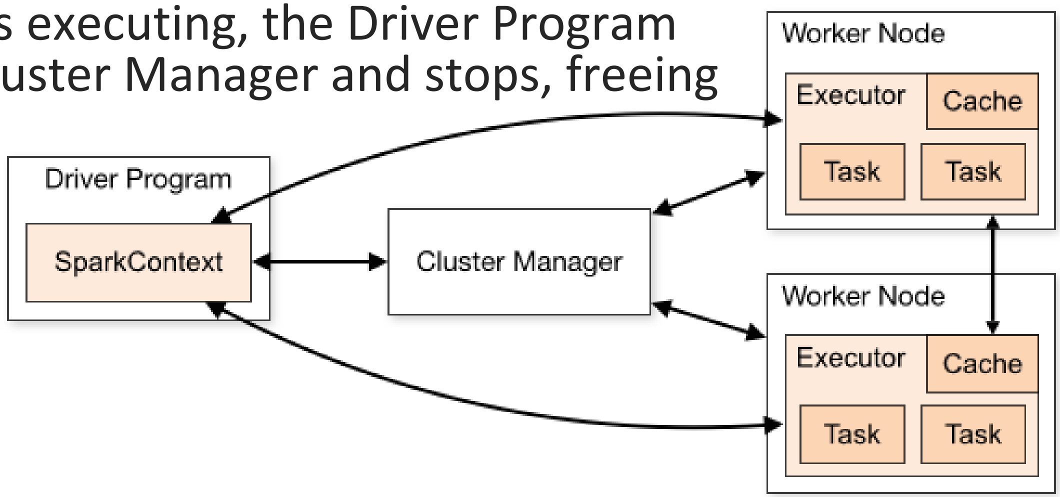
Source: https://devopedia.org/apache-spark

- **Spark Core:** a component for task scheduling, memory management, fault recovery, interacting with storage systems, and more
- **Spark SQL:** a component for working with structured data
- **Spark Streaming:** a component that enables processing of live streams of data
- **Spark MLlib:** a component containing common machine learning (ML) functionality
- **Spark GraphX:** a component for manipulating graphs

(Simplified) Execution of a Spark Application

Source: https://luminousmen.com/post/spark-anatomy-of-spark-application

1. An Spark application is copied to the gateway node and started.
2. The Driver Program starts and implicitly converts user code containing transformations and actions into a **logical execution plan** called a DAG (Directed Acyclic Graph).
3. The Driver Program then converts the DAG into a **physical execution plan** which contain stages. After conversion to a physical execution plan, the driver creates physical execution units called tasks at each stage.
4. The Driver Program now communicates with the Cluster Manager and negotiates resources. Cluster Manager asks worker nodes to run the executors.
5. When the application finishes executing, the Driver Program disconnects itself from the Cluster Manager and stops, freeing up its resources.



Source: https://spark.apache.org/docs/latest/cluster-overview.html

Spark Glossary

Term	Meaning
Application	User program built on Spark. Consists of a driver program and executors on the cluster.
Driver Program	The process running the main() function of the application and creating the SparkContext.
Cluster Manager	An external service for acquiring resources on the cluster (e.g. standalone manager, Mesos, YARN)
Deploy mode	Distinguishes where the driver process runs. In "cluster" mode, the framework launches the driver inside of the cluster. In "client" mode, the submitter launches the driver outside of the cluster.
Worker Node	Any node that can run application code in the cluster
Executor	A process launched for an application on a worker node, that runs tasks and keeps data in memory or disk storage across them. Each application has its own executors.
Job	A parallel computation that gets spawned in response to a Spark action.
Stage	Each job gets divided into smaller sets of tasks called stages that depend on each other.
Task	A unit of work that will be sent to one executor

Spark Data (Programming) Abstractions

All are immutable and read-only!!!

	RDD	DataFrame	Dataset
Release version	Spark 1.0	Spark 1.3	Spark 1.6
Data Representation	Distributed collection of elements.	Distributed collection of data organized into columns.	Combination of RDD and DataFrame.
Data Formats	Structured and unstructured are accepted.	Structured and semi-structured are accepted.	Structured and unstructured are accepted.
Compile-time type safety	Available compile-time type safety.	No compile-time type safety. Errors detect on runtime.	Available compile-time type safety.
Optimization	No built-in optimization engine. Each RDD is optimized individually.	Query optimization through the Catalyst optimizer.	Query optimization through the Catalyst optimizer, like DataFrames.
Serialization	Uses serialization for sending both the data and structure between nodes.	Serialization happens in memory in binary format.	Encoder handles conversions between objects and tables, which is faster than serialization.
Programming Language Support	Java, Scala, Python and R.	Java, Scala, Python and R.	Only Java and Scala.
Schema Projection	Schemas need to be defined manually.	Auto-discovery of file schemas.	Auto-discovery of file schemas.

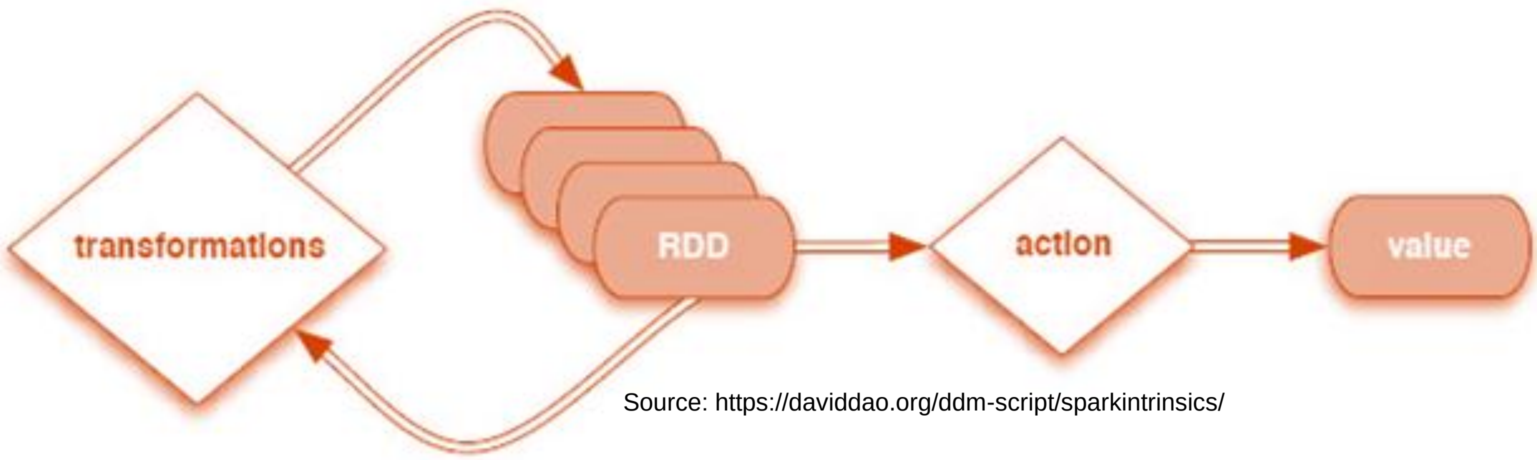
Source: https://phoenixnap.com/kb/rdd-vs-dataframe-vs-dataset

PySpark

- Aa Python API for Spark
- Based on Py4J library that allows Python to dynamically interface with JVM objects
- Supports RDD and DataFrame abstractions
- Detailed API Reference
  - Spark SQL (DataFrame)
  - Structured Streaming (DataFrame-based)
  - MLlib (DataFrame-based)
  - Spark Streaming (RDD-based)
  - MLlib (RDD-based)
  - Spark Core (RDD)

RDD (*Resilient Distributed Dataset*)

- Supports two types of operations
  - *Transformations* transform an RDD to another RDD
    - Lazy execution (i.e. they are not executed immediately)
  - *Actions* consume an RDD
    - An action triggers the execution of transformations



Source: https://daviddao.org/ddm-script/sparkintrinsics/

Essential RDD Transformations 1/2

Transformations	
map(f[, preservesPartitioning])	Return a new RDD by applying a function to each element of this RDD.
filter(f)	Return a new RDD containing only the elements that satisfy a predicate.
flatMap(f[, preservesPartitioning])	Return a new RDD by first applying a function to all elements of this RDD, and then flattening the results.
sample(withReplacement, fraction[, seed])	Return a sampled subset of this RDD.
union(other)	Return the union of this RDD and another one.
distinct([numPartitions])	Return a new RDD containing the distinct elements in this RDD.

Essential RDD Transformations 2/2

Transformations	
groupByKey([numPartitions, partitionFunc])	Group the values for each key in the RDD into a single sequence.
reduceByKey(func[, numPartitions, …])	Merge the values for each key using an associative and commutative reduce function.
sortByKey([ascending, numPartitions, …])	Sorts this RDD, which is assumed to consist of (key, value) pairs.
join(other[, numPartitions])	Return an RDD containing all pairs of elements with matching keys in self and other.
cogroup(other[, numPartitions])	For each key k in self or other, return a resulting RDD that contains a tuple with the list of values for that key in self as well as other.
cartesian(other)	Return the Cartesian product of this RDD and another one.

Essential RDD Actions

Actions	
reduce(f)	Reduces the elements of this RDD using the specified commutative and associative binary operator.
collect()	Return a list that contains all of the elements in this RDD.
count()	Return the number of elements in this RDD.
take(num)	Take the first num elements of the RDD.
saveAsTextFile(path[, compressionCodecClass])	Save this RDD as a text file, using string representations of elements.
foreach(f)	Applies a function to all elements of this RDD.
min([key]) max([key])	Find the minimum/maximum item in this RDD.

Example 1: Counting Words Using PySpark

```
# Imports are excluded

ss = SparkSession.builder.getOrCreate()
sc = ss.sparkContext

result = sc.textFile("1661-0.txt") \
    .flatMap(lambda line: line.strip().split()) \
    .map(lambda word: re.sub("[^a-zA-Z]+", "", word).lower().strip()) \
    .filter(lambda word: len(word) > 0) \
    .map(lambda word: (word, 1)) \
    .reduceByKey(lambda a, b: a + b)

result.saveAsTextFile("word_counts.txt")
```

```
Pseudo-distributed - Time elapsed in seconds:  2.814466714859009

 Fully Distributed - Time elapsed in seconds:  6.459198474884033
```

Example 2: Counting Words in Java using Spark

```java
//imports are excluded

SparkSession ss = SparkSession.builder().getOrCreate();
SparkContext sc = ss.sparkContext();

JavaPairRDD<String, Long> result = sc.textFile("1661-0.txt").
  flatMap(line -> Arrays.asList(line.trim().split("\\s")).iterator()).
  map(word -> word.replaceAll("[^a-zA-Z]", "").toLowerCase().trim()).
  filter(word -> word.length() > 0).
  mapToPair(word -> new Tuple2<>(word, 1L)).
  reduceByKey((x, y) -> x + y);

result.saveAsTextFile("word_counts.txt");
```

Example 3: Counting Words in Java

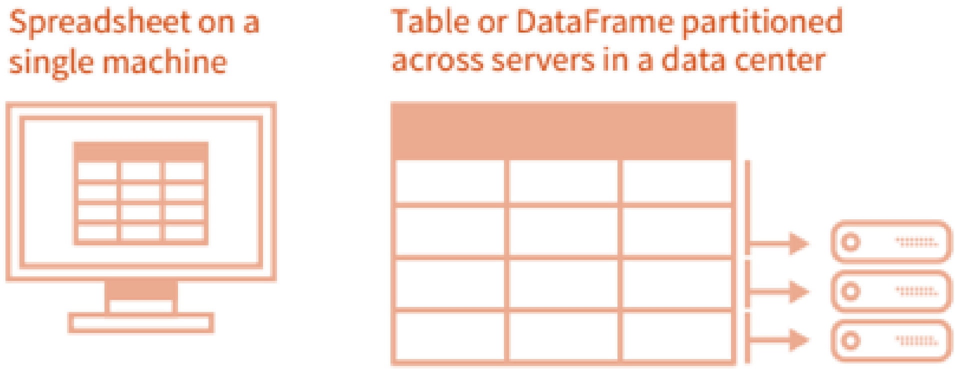
```java
//imports are excluded

Map<String, Long> result = Files.lines(Paths.get(args[0])).
  flatMap(line -> Arrays.stream(line.trim().split("\\s"))).
  map(word -> word.replaceAll("[^a-zA-Z]", "").toLowerCase().trim()).
  filter(word -> word.length() > 0).
  map(word -> new SimpleEntry<>(word, 1L)).
  collect(groupingBy(SimpleEntry::getKey, reducing(0L,
SimpleEntry::getValue, (v1,v2) -> v1 + v2)));

//write results to a file
try (FileWriter fw = new FileWriter(args[1])) {
  result.forEach((k, v) -> writeToFile(fw, k + "," + v + "\n"));
}
```

(Java-like) Streams in Python

- pyxtension is a pure Python GNU-licensed library that includes Scala-like streams (using Fluent Interface pattern), Json with attribute access syntax, and other common-use stuff.
- There are other Python libraries that support Fluent Interface streams as alternatives to pyxtension, but being much poorer in features:
  - https://pypi.org/project/lazy-streams/
  - https://pypi.org/project/pystreams/
  - https://pypi.org/project/fluentpy/
  - https://github.com/matthagy/scalaps
  - https://pypi.org/project/infixpy/
  - https://github.com/sspipe/sspipe

Spark DataFrame

- A DataFrame simply represents a table of data with rows and columns
- A simple analogy would be a spreadsheet with named columns
- The list of columns and the types in those columns represent the schema
- Similar concepts exist in R and Python (Pandas)
- While an R/Python DataFrame or spreadsheet sits on a single computer, a Spark DataFrame is distributed across (possibly) thousands of computers



https://databricks.com/glossary/what-are-dataframes

Essential DataFrame Operations 1/2

Data Manipulation Operations	
toPandas()	Returns the contents of this DataFrame as Pandas DataFrame.
createDataFrame(data[, schema, …])	Creates a DataFrame from an RDD, a list or a pandas.DataFrame.
drop(*cols)	Returns a new DataFrame that drops the specified column.
select(*cols)	Projects a set of expressions and returns a new DataFrame.
filter(condition)	Filters rows using the given condition.
withColumn(colName, col)	Returns a new DataFrame by adding a column or replacing the existing column that has the same name.
SparkSession.read	Returns a DataFrameReader that can be used to read data in as a DataFrame.
write	Interface for saving the content into external storage.

Essential DataFrame Operations 2/2

Essential Operations	
printSchema()	Prints out the schema in the tree format.
show([n, truncate, vertical])	Prints the first n rows to the console
sort(*cols, **kwargs)	Returns a new DataFrame sorted by the specified column(s).
count()	Returns the number of rows in this DataFrame.
crossJoin(other)	Returns the cartesian product with another DataFrame.
foreach(f)	Applies the f function to all Row of this DataFrame.
groupBy(*cols)	Groups the DataFrame using the specified columns, so we can run aggregation on them.
join(other[, on, how])	Joins with another DataFrame, using the given join expression.
corr(col1, col2[, method])	Calculates the correlation of two columns of a DataFrame as a double value.
describe(*cols)	Computes basic statistics.

Example 4: Processing Data using Pandas DataFrame

```
import pandas as pd
import matplotlib.pyplot as plt


df = pd.read_csv("trip_data_small.csv", header="infer")
df.dtypes

df_sel = df[["medallion", "passenger_count", "trip_distance", "trip_time_in_secs"]]
df_sel[["trip_distance", "trip_time_in_secs"]].corr(method='pearson')
df_sel[["trip_time_in_secs", "passenger_count"]].corr(method='pearson')

plt.scatter(x='trip_distance', y='trip_time_in_secs', data=df_sel)
plt.show()
df_sel.describe()

df_sum = df_sel.groupby("medallion").sum()
df_spd = df_sum
df_spd["average_speeed"] = df_sum["trip_distance"] / df_sum["trip_time_in_secs"]

df_sort = df_spd.sort_values("average_speeed", ascending=False)
df_sort.to_csv("sorted_by_avg_speed.csv")
```

Example 5: Processing Data using Spark DataFrame

```
from pyspark.sql import SparkSession
import matplotlib.pyplot as plt

session = SparkSession.builder.getOrCreate()
context = session.sparkContext
df = session.read.csv("trip_data_small.csv", header=True, inferSchema=True)
df.printSchema()
df_sel = df.select("medallion", "passenger_count", "trip_distance", "trip_time_in_secs
")
df_sel.stat.corr('trip_distance', 'trip_time_in_secs', method='pearson')
df_sel.stat.corr('trip_time_in_secs', 'passenger_count', method='pearson’)

plt.scatter(x='trip_distance', y='trip_time_in_secs', data=df_sel.toPandas())
plt.show()
df_sel.describe().show()

df_sum = df_sel.groupBy("medallion").sum()
df_spd = df_sum.withColumn("average_speeed", df_sum["sum(trip_distance)"] / df_sum["su
m(trip_time_in_secs)"])

df_sort = df_spd.sort("average_speeed", ascending=False)
df_spd.write.csv("sorted_by_avg_speed.csv")
session.stop()
```

Spark MLlib

- MLlib is Spark MLlib is a distributed and scalable machine-learning framework
- Usable in Java, Scala, Python, and R
- MLlib fits into Spark's APIs and interoperates with NumPy in Python and R libraries
- You can use any Hadoop data source (e.g. HDFS, HBase, or local files), making it easy to plug into Hadoop workflows
- There are DataFrame-based and RDD-based APIs for MLlib
- At a high level, it provides tools such as:
  - ML Algorithms: common learning algorithms such as classification, regression, clustering, and collaborative filtering
  - Featurization: feature extraction, transformation, dimensionality reduction, and selection
  - Pipelines: tools for constructing, evaluating, and tuning ML Pipelines
  - Persistence: saving and load algorithms, models, and Pipelines
  - Utilities: linear algebra, statistics, data handling, etc.

Example 6 - 1/3: Preparing Data for ML

```
from pyspark.sql import SparkSession
session = SparkSession.builder.getOrCreate()
context = session.sparkContext

df = session.read.csv("trip_data_small.csv", header=True, inferSchema=True)
df_sel = df.select("medallion", "passenger_count", "trip_distance", "trip_time_in_secs
")
df_sel.stat.corr('trip_distance', 'trip_time_in_secs', method='pearson')
df_sel.stat.corr('trip_distance', 'passenger_count', method='pearson’)

from pyspark.ml.feature import VectorAssembler
vectorAssembler = VectorAssembler(inputCols = ["passenger_count", "trip_time_in_secs"]
, outputCol = "features")
df_vec = vectorAssembler.transform(df_sel)
df_prep = df_vec.select(['features', 'trip_distance'])
splits = df_prep.randomSplit([0.7, 0.3])
df_train = splits[0]
df_test = splits[1]
```

Example 6 - 2/3: Linear Regression

```
from pyspark.ml.regression import LinearRegression
lr = LinearRegression(featuresCol = 'features', labelCol='trip_distance', maxIter=10,
regParam=0.3, elasticNetParam=0.8)
lr_model = lr.fit(df_train)
print("Coefficients: " + str(lr_model.coefficients))
print("Intercept: " + str(lr_model.intercept))

lr_model_summ = lr_model.summary
print("RMSE: %f" % lr_model_summ.rootMeanSquaredError)
print("R2: %f" % lr_model_summ.r2)
print("numIterations: %d" % lr_model_summ.totalIterations)
print("objectiveHistory: %s" % str(lr_model_summ.objectiveHistory))
lr_model_summ.residuals.show(5)
df_train.describe().show()

from pyspark.ml.evaluation import RegressionEvaluator
evaluator_rmse = RegressionEvaluator(labelCol="trip_distance", predictionCol="predicti
on", metricName="rmse")
evaluator_r2 = RegressionEvaluator(labelCol="trip_distance", predictionCol="prediction
", metricName="r2")
lr_predictions = lr_model.transform(df_test)
print("RMSE on test data = %g" % evaluator_rmse.evaluate(lr_predictions))
print("R2 on test data = %g" % evaluator_r2.evaluate(lr_predictions))
```

Example 6 - 3/3: DT and GBR Regression

```
# Decision tree learning algorithm for regression
from pyspark.ml.regression import DecisionTreeRegressor
dt = DecisionTreeRegressor(featuresCol ='features', labelCol = 'trip_distance')
dt_model = dt.fit(df_train)
dt_predictions = dt_model.transform(df_test)
print("RMSE on test data = %g" % evaluator_rmse.evaluate(dt_predictions))
print("R2 on test data = %g" % evaluator_r2.evaluate(dt_predictions))

# Gradient-Boosted Trees learning algorithm for regression
from pyspark.ml.regression import GBTRegressor
gbt = GBTRegressor(featuresCol = 'features', labelCol = 'trip_distance', maxIter=10)
gbt_model = gbt.fit(df_train)
gbt_predictions = gbt_model.transform(df_test)
print("RMSE on test data = %g" % evaluator_rmse.evaluate(gbt_predictions))
print("R2 on test data = %g" % evaluator_r2.evaluate(gbt_predictions))
```

Summary