



Laboratory of Advanced Programming

Spark/Scala Tutorial

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Course Outline

- **Spark:** Introduction
 - Spark Framework
 - Spark Resource management
- **Scala:** Introduction
 - Examples (Interactive Shell)
 - Examples (IDE)
- **Processing Data**
 - Working flow
 - Dstreams
 - Transformations
 - RDD Introduction
 - Programming Examples
 - Dataframes Introduction
 - Programming Examples





Spark Framework

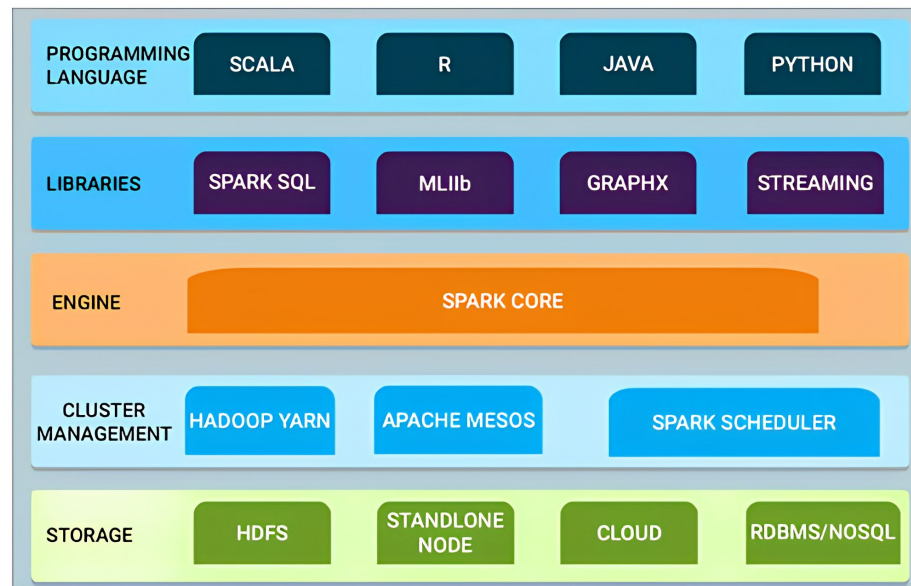




What is SPARK?

- **Analytics Engine, Big Data Engine** for large-scale data processing.
- *Advantages:*
 - faster than Hadoop;
 - write Spark applications in several programming languages: Java, Python, **Scala** and others;
 - Platform Independent;
 - does not need any STORAGE. “Give me data, I will process it.”

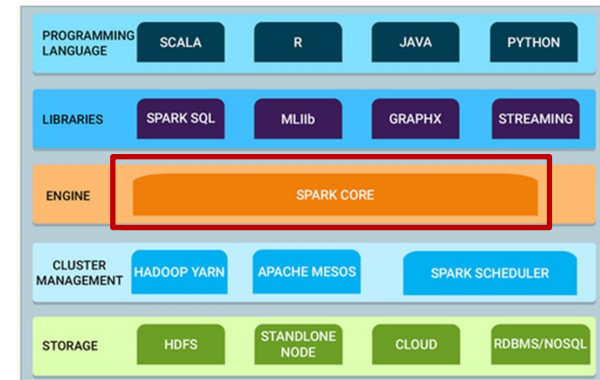
Spark framework (Overview)



Spark framework (Spark Core)



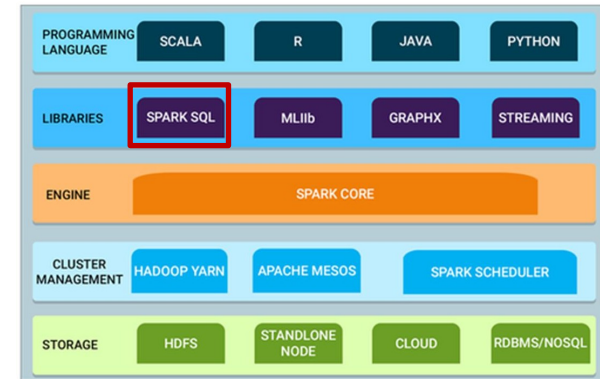
- **Spark Core** is a general-purpose, distributed data processing engine.
- On top of it sit libraries for **SQL, stream processing, machine learning, and graph computation**
- Is the base of a whole project, providing distributed task dispatching, scheduling, and basic I/O functionalities.



Spark framework (Spark SQL)



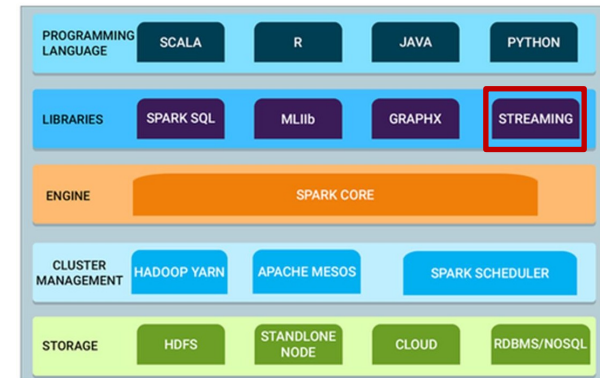
- **Spark SQL** is the Spark module for working with structured data that supports a common way to access a variety of data sources.
- It lets you query structured data inside Spark programs, using either **SQL** or a familiar **DataFrame API**.
- A server mode provides standard connectivity through **Java database connectivity** or **open database connectivity**.



Spark framework (Spark Streaming)



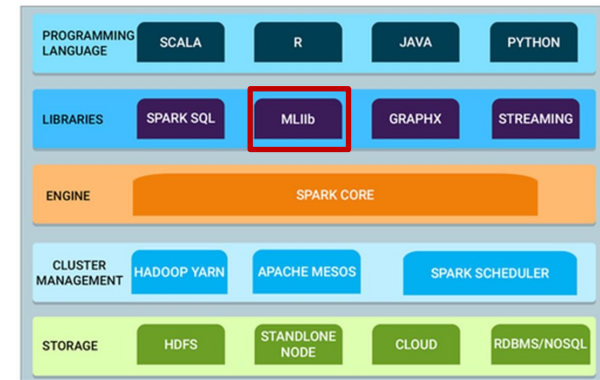
- **Spark Streaming** makes it easy to build scalable, fault-tolerant streaming solutions.
- It brings the Spark language-integrated API to **stream processing**, so you can write streaming jobs in the same way as batch jobs.



Spark framework (Spark MLlib)

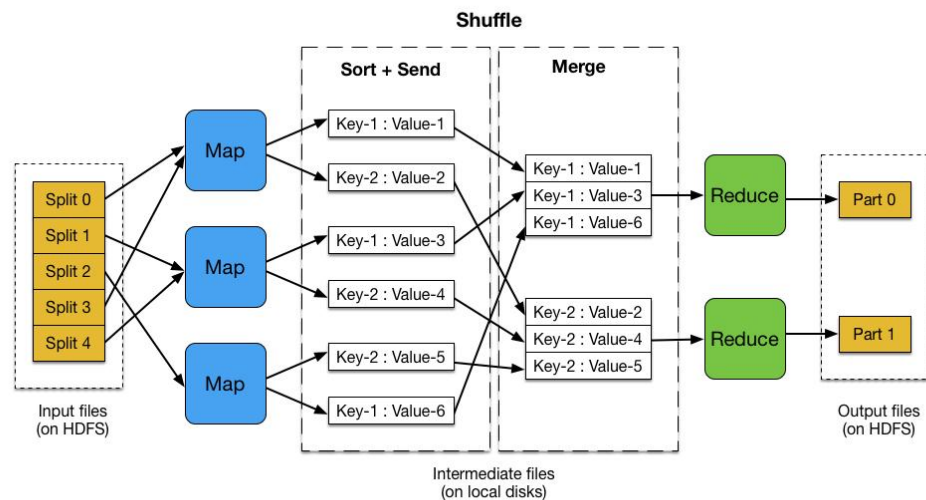


- **MLlib** is the Spark scalable machine learning library with tools that make practical ML scalable and easy.
- It contains many common learning algorithms, such as **classification, regression, recommendation, and clustering**.
- It also contains workflow and other utilities, including feature **transformations, ML pipeline construction, model evaluation, distributed linear algebra, and statistics**.





MapReduce Paradigm





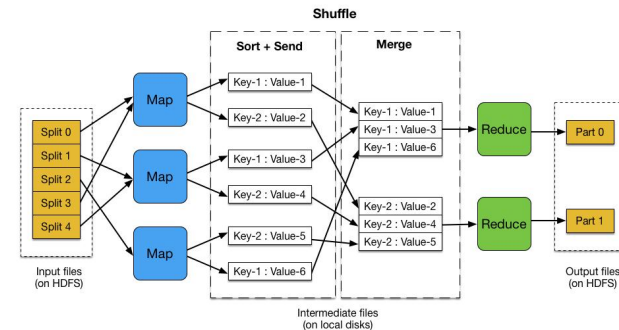
MapReduce Paradigm

Map

The map function, also referred to as the map task, processes a single key/value input pair and produces a set of intermediate key/value pairs.

Reduce

The reduce function, also referred to as the reduce task, consists of taking all key/value pairs produced in the map phase that share the same intermediate key and producing zero, one, or more data items.





Resource Management

- Resources are taken from the cluster manager (e.g. yarn)
 - **Executor:** a combination of CPU and RAM.
- How much RAM do you need? How much CPU?
- You can set these information up.
- **Which is the correct way to setup them?**

Resource Management (Example)



50 Gigabyte
File

We want to analyze this big data file.

How much resources we need?

How many executors? We have several options.

- **A. Single Executor.**
 - All the workload on a single executor. This is not a good idea...

Resource Management (Example)



- **50 Gigabyte File** We want to analyze this big data file.
How much resources we need?
How many executors? We have several options.
- **B. 5 Executors:** ex-1, ex-2, ex-3, ex-4 and ex-5.
 - Each executor: 10 GB (RAM) and 10 CPU Cores.
- Then you can partition the file: 50 GB File -> 50 partitions
- Then you can distribute the workload as:
 - ex-1 partitions from 1 to 10
 - ex-2 partitions from 11 to 20
 - ex-3 partitions from 21 to 30
 - ex-4 partitions from 31 to 40
 - ex-5 partitions from 41 to 50
- Each CPU core has its partition!

Resource Management (Example)



- **50 Gigabyte File**
We want to analyze this big data file.
How much resources we need?
How many executors? We have several options.
- **C. 50 Executors!**
- Data can move between executors. Having too many executors could be a problem.
- **The idea is not to have too less or too more executors.**
There is no magical number, it depends on your design choices!

Setup Executors via command line



(Three major releases. For this course I will use version 2.3.1)

- `> spark-shell` -> launch interactive shell using Scala on top of Spark

And then add these options:

- `--num-executors NUM` -> set how many executors
- `--executor-memory MEM` -> set RAM for each executor
- `--executor-cores NUM` -> set CPU cores for each executor

E.g.: 5 executors, 2GB (RAM) and 2 CPU cores for each one of them.

- `> spark-shell --num-executors 5 --executor-memory 2G --executor-cores 2`



Dynamic Resource Allocation (DRA)

- **DRA** automatically and dynamically adjusts resources for your Spark application. It frees up resources when they are no longer needed.
- Disabled by default.
- Available on all cluster managers (yarn, mesos, standalone...).

In order to enable it, add this option at launch:

```
--conf spark.dynamicAllocation.enabled=true
```



Scala Programming language





What is Scala?

- **Java** -> works on (almost) every platform, complex, difficult to learn.
- **Python** -> scripting language, easy to learn, it suffers of some optimization problems.
- **Scala** pick the best of both languages. It combines object-oriented and functional programming in one concise, high-level language.
- It uses the same **Java Virtual Machine (JVM)** used by Java to run their programs. JVM can be installed on almost every SW/HW combination.
- Where you can run JVM, you are able to run a Scala program!



Scala

- Scala provides an interactive shell.
- Once installed run scala on your terminal.
- It also supports IDE like Eclipse or IntelliJ.
- *For this course we will use **Visual Studio Code***



Dynamic Type Inference

- Scala can automatically figures out data types.
- It automatically “guess” the data type. Similar to Python, you don’t have to declare data types.
- Launch your interactive shell and try this command lines:
 - `scala> 2`
`val res0: Int = 2`
- ***“Did you just type 2? Ok, 2 for me is an Integer”***



Dynamic Type Inference

Other examples:

- `scala> 10.3`
`val res1: Double = 10.3`
- `scala> 'a'`
`val res2: Char = a`
- `scala> "test"`
`val res3: String = test`



Dynamic Type Inference

- You can also directly declare the datatype. Then Scala does not infer it by itself.
 - `scala > val z: Int = 100`
- This is a better practice. You are sure of the data type!
- Scala requires some time to infer the data type. By declaring them you save extra time (microseconds...)



Variables in Scala

- Two types of variables:
 - **Immutable Variables** -> declare them as `'val'`
 - Intuitively, “something you can’t change”. You can see `val` as a constant.
 - **Mutable Variables** -> declare them as `'var'`
 - They can change over time.
- Similar to Java *final* and *not final* variables.



Variables in Scala

- ```
scala> val a = "test"
```

```
val a: String = test
```

```
scala> a = "anotherTest" //ERROR! reassignment to val ERROR!
```

- ```
scala> var b = "Hadoop"
```

```
var b: String = Hadoop
```

```
scala> b = "spark is better" // OK! mutated b
```



Static Typing

- Mutable variables can change BUT they do not allow **type mismatch**:
 - `scala> b = 100 //error: type mismatch;`
`found : Int(100)`
`required: String`
- You can change mutable variables BUT only accordingly to their original data type.



Using Scala with an IDE

- We suggest to use **Visual Studio Code** as default editor with Scala Extension installed

Run Scala applications

- Scala Objects are the basic container of everything. They are similar to Java Static Classes.
- Create the Main method (or extend App trait)
- Compile the file using *scalac*
- Run the Bytecode with *scala*



Scala: If-else

- ```
object example1 {
 def main(args: Array[String]) {
 var fruit = "apple" //you don't need
 semicolons as python
 if (fruit == "pear") println("red")
 else println("not an apple")
 }
}
```



# Scala: While loop

- ```
object example2 {  
  def main(args: Array[String]){  
    var i = 10  
    while(i>0){  
      println("Number " + i)  
      i = i-1  
    }  
  }  
}
```



Scala: For loop

- ```
object example3 {
 def main(args: Array[String]) {
 for (i <- 1 to 10)
 println(i)
 }
}
```
- “x to y” is called **range**. You can also specify the **step**.  
**e.g.:**

```
for (i <- 1 to 10 by 2) // what is the output? Try it!
```



# Scala: block expressions

Try this piece of code:

- ```
var add = {  
    var a = 10  
    var b = 20  
    a - b  
    a + b  
}  
println(add)
```

What will be printed out?



Scala: block expressions

The code will print:

- `add: Int = 30`

In block expressions. The variable will be taking **the value of the last expression**. Be aware of that!



Scala: block expressions

Another example:

- ```
val x = { println("foo"); 10}
println("bar")
println(x)
```

What these 3 lines of code will print out?



# Scala: lazy variables

It prints out:

- ```
foo    //block expression or not, if you have an explicit print statement, then it will print!  
bar  
10     //val x will be the last part of the block expression
```

Rewrite the program in this way:

- ```
lazy val x = { println("foo"); 10}
println("bar")
println(x)
```



# Scala: lazy variables

New output:

- bar
- foo
- 10

**Lazy variable:** With lazy declarations you can delay the initialization of a variable.

*“Ehi Scala this variable is lazy. Don’t run this line, execute the next line.”*

In the example above, Scala:

1. skip the lazy val (first line),
2. prints “bar” (second line)
3. and finally when you call the print statement on the lazy variable (third line), it initializes it.

# Why Scala? (Functional Programming)



- **Functional programming** is a programming paradigm where programs are constructed by applying and composing functions.
- It is a **declarative programming paradigm** in which function definitions are trees of expressions that each return a value, rather than a sequence of imperative statements which change the state of the program.



# Functional Programming

Functional Programming relies on **three key concepts**:

- Immutable Values
- Pure Functions
- Functions are values



# Functional Programming

Functional Programming relies on **three key concepts**:

- Immutable Values
- Pure Functions
- Functions are values



# Scala Exercises





# Exercise 1

Write a method *scalarProd* that, given two vectors represented as a *Seq* of *Double*, evaluates their scalar product.

If the lengths of vectors are different, limit the dot product to the range of valid common indexes.

Example: `scalarProd(Seq(3,4), Seq(2,9,1)) == 3*2 + 4*9 == 42`.

Hint: use *math.min(...)*





# Exercise 2

Write a method *isMappedFrom*, applicable for a Vector  $v$  that verify if another Vector  $m$  is obtainable from  $v$  applying the function  $f$  to each element of  $v$ .

So we want to have this:

$v:\text{Vector}[T].\text{isMappedFrom}(m:\text{Vector}[U], f: T \Rightarrow U): \text{Boolean}$

Hint: You need to create an object with an *implicit class*



# Exercise 3

Write a method *noobSort* that, given a *Vector v* of *n generic* elements, returns the ordered version of *v*.

Hint: Generate all the permutation of indexes from 0 *until* *n* and for each permutation generate the permuted vector, check if is ordered and eventually return it.

Core Hint: using `implicitly[Ordering[U]]` allow you to compare (*lt*, *gt*, *lteq*, *gteq*) *generic* elements (to use it you must define *U* as *Ordering* -> *noobSort[U: Ordering]*).



# Exercise 4

Create a Scala construct named *repeat* that, given an *integer n* and a *body*, executes *body* for *n* times as in the following example:

```
repeat(5) {
 println("test")
}
```

Why is this interesting? Do you ever heard about **call-by-name** parameters?



# Processing Data

**Spark**  Streaming



# WordCount Example

```
import org.apache.spark.SparkContext
import org.apache.spark.SparkConf
object wordCount{

 def main(args: Array[String]) {
 /* configure spark application */
 val conf = new SparkConf().setAppName("Spark Scala WordCount
 Example")

 .setMaster("local[1]")//local : Run Spark locally with one worker
 thread (i.e. 1 == no parallelism at all)

 /* spark context*/
 val sc = new SparkContext(conf)

 /* map */
 var map = sc.textFile("data/input.txt").flatMap(line => line.split("
")).map(word => (word,1))
 }
```

```
//map.collect().foreach(println)
/* reduce */
var counts = map.reduceByKey(_ + _)
/* print */
counts.collect().foreach(println)

/* or save the output to file */
//counts.saveAsTextFile("out.txt")
sc.stop()
}
```



# What is Spark Streaming?

**Spark Streaming** is an extension of the core Spark API that enables scalable, high-throughput, fault-tolerant stream processing of live data streams.

- **Batch Processing:** You have some data collected and stored somewhere (in a dataset, in a database...) and you want to perform some operations on that data.
- **Real Time Processing (Streaming):** You process data as soon as the data arrives. E.g.: In a banking system you want to detect data frauds in real time.



# Processing Data

On the official website:

- **Spark Streaming** -> the original one. Queries over **RDD** data structures.
- **Structured Streaming** -> New Approach, still not so popular. Uses SQL queries over structures called **Dataframes**.

We will see both approaches starting from the first “classic” one.

# Spark Streaming - Overview



- Spark Streaming receives live input data streams and **divides the data into batches**, which are then processed by the Spark engine to generate the final stream of results in batches.







# Data Ingestion

- Data Ingestion is an **optional** step to efficiently store data.
  1. Suppose you have to process **100 entries/min** -> Ok, you can avoid data ingestion and you can directly connect Spark to the data source/s.
  2. Now suppose you have **1M entries/min** -> Probably you need some Data Ingestion mechanism.

E.g. “Analyze tweets on Twitter to discover the trending actor of the week”
- You can use services like **Kafka** or **Flume**. These are services that store data for you.
- Data Ingestion is useful to **avoid missing data**. If Spark crashes for some reason, you can lose part of the data. By using an Ingestion mechanism (e.g. Kafka), it never fails!



# Dstreams and Batch Interval



- **Discretized Streams (Dstreams)** is the basic abstraction provided by Spark Streaming. It represents a continuous stream of data, either the input data stream received from source, or the processed data stream generated by transforming the input stream.
- Each Dstream is divided into batches, i.e. it represents **a sequence of data/RDDs** from a certain interval. A RDD is the Spark's abstraction of an immutable, distributed dataset.
- **Streaming Context Object**: It is used to configure the streaming. With this object you can configure the **Batch Interval**.
  - E.g.: Batch Interval = 1 second. Meaning that you process data collected every second from the data source.



# Configure the Streaming Context



- *E.g.: “I want to discover how many people are searching on Twitter for a new released game”.*
- In this case, I don't need to collect the users' activity from Twitter every second, it's useless. Maybe every 30 minutes.
- Configure the streaming object **depending on your needs** (Scala):

```
import org.apache.spark._
import org.apache.spark.streaming._
import org.apache.spark.streaming.StreamingContext._ // not necessary since Spark 1.3

// Create a local StreamingContext with two working thread and batch interval of 1 second.
// The master requires 2 cores to prevent a starvation scenario.

val conf = new SparkConf().setMaster("local[2]").setAppName("NetworkWordCount")
val ssc = new StreamingContext(conf, Seconds(1))
```

# About the Streaming Context



## Points to remember:

- Once a context has been started, no new streaming computations can be set up or added to it.
- Once a context has been stopped, it cannot be restarted.
- Only one StreamingContext can be active in a JVM at the same time.
- `stop()` on StreamingContext also stops the SparkContext. To stop only the StreamingContext, set the optional parameter of `stop()` called `stopSparkContext` to false.
- A SparkContext can be re-used to create multiple StreamingContexts, as long as the previous StreamingContext is stopped (without stopping the SparkContext) before the next StreamingContext is created.

*For other tips, see the official docs here ->*

<https://spark.apache.org/docs/latest/streaming-programming-guide.html#discretized-streams-dstreams>



# Dynamic Resource Allocation (DRA)

- In streaming, processing data may change over time. Then, you may need to adjust the allocated resources of the program.
- DRA automatically adjusts and scales resources (executors, RAM, CPU...).

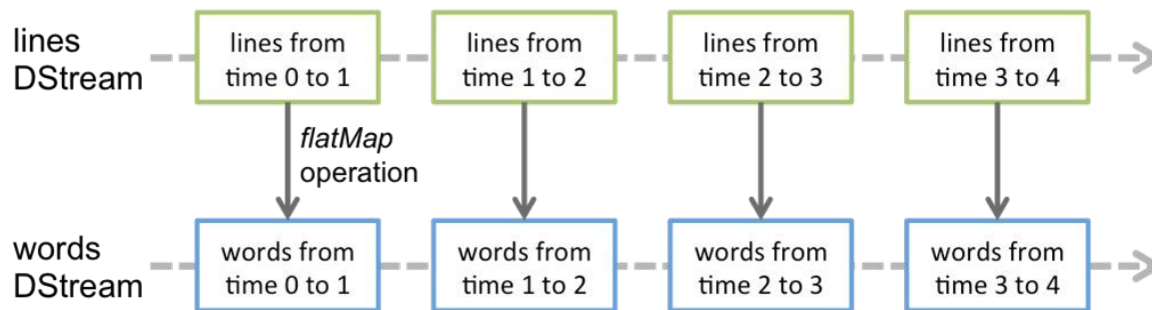
- **// enable DRA via Scala code**

```
val conf = new SparkConf().setAppName("Spark dynamic
allocation demo")
.set("spark.dynamicAllocation.enabled", "true")
```

- If you are interested, you can see how DRA works in this video -> [\[VIDEO\]](#)



# Transformations



- Any operation applied on a DStream translates these operations on the underlying RDDs. E.g., in the figure above the flatMap operation is applied on each RDD in the lines.
- These underlying RDD transformations are computed by the Spark engine. The DStream operations hide most of these details and provide the developer with a higher-level API for convenience.
- List of Transformations from official docs:  
<https://spark.apache.org/docs/latest/streaming-programming-guide.html#transformations-on-dstreams>

# Resilient Distributed Datasets (RDDs)



Spark revolves around the concept of a resilient distributed dataset (RDD), which is a fault-tolerant collection of elements that can be operated on in parallel. There are two ways to create RDDs: parallelizing an existing collection in your driver program, or referencing a dataset in an external storage system, such as a shared filesystem, HDFS, HBase, or any data source offering a Hadoop InputFormat.

- Parallelized collections are created by calling SparkContext's `parallelize` method on an existing collection.

E.g.: Create a parallelized collection holding the numbers 1 to 5 in Scala:

```
val data = Array(1, 2, 3, 4, 5)
val distData = sc.parallelize(data)
```

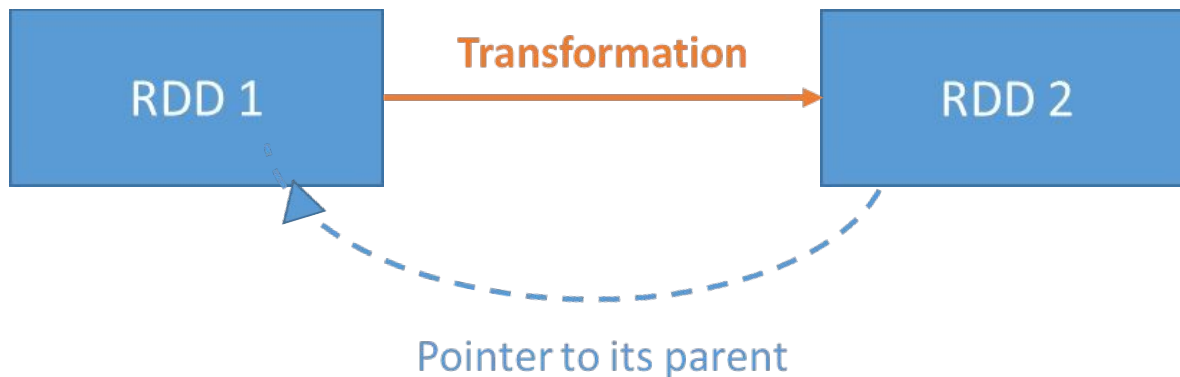
- External Datasets. Spark can create distributed datasets from any storage source. For example, Text file RDDs can be created using SparkContext's `textFile` method.

```
scala> val distFile = sc.textFile("data.txt")
distFile: org.apache.spark.rdd.RDD[String] = data.txt MapPartitionsRDD[10] at textFile at <console>:26
```

# Resilient Distributed Datasets (RDDs)



- Immutable collections of objects. They don't change.
- A Transformation returns a new RDD, one or many.







# 1. map()

- Let's see some examples via interactive shell.

```
spark-shell //launch the interactive shell
val x = sc.parallelize(List("Spark", "rdd", "sample"))
// create an RDD
val y = x.map(x => (x,1)) //maps every entry of x to 1
y.collect //to look the result
```

- **OUTPUT:**

```
res0: Array[(String, Int)] = Array((spark,1), (rdd,1),
(sample,1)) // new RDD y
```



## 2. flatMap()

- `var z = sc.parallelize(List(1,2,3)).flatMap(x=>List(x,x,x))`  
`z.collect`

### OUTPUT:

```
res1: Array[Int] = Array(1, 1, 1, 2, 2, 2, 3, 3, 3)
```

What is the difference with map()? Let's see it:

- `var z2 = sc.parallelize(List(1,2,3)).map(x=>List(x,x,x))`  
`z2.collect`

### OUTPUT:

```
res3: Array[List[Int]] = Array(List(1, 1, 1), List(2, 2, 2),
List(3, 3, 3))
```

FlatMap creates one-dimensional RDDs.



## 3. filter()

- Returns odds and evens from a list of integers:

```
val numbers = sc.parallelize(List(1,2,3,4,5,6,7,8,9,10))
val evens = numbers.filter(_%2==0)
evens.collect
```

### OUTPUT:

```
res4: Array[Int] = Array(2, 4, 6, 8, 10)
```

```
val odds = numbers.filter(_%2!=0)
odds.collect
```

### OUTPUT:

```
res5: Array[Int] = Array(1, 3, 5, 7, 9)
```



## 4. union() and distinct()

- ```
val num1 = sc.parallelize(List(1,2,3,4,5,6,7,8,9,10))  
val num2 = sc.parallelize(List(4,5,6,7,13,14,15))  
num1.union(num2).collect
```

OUTPUT:

```
res6: Array[Int] = Array(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 4, 5, 6, 7,  
13, 14, 15)
```

- ```
num1.union(num2).distinct.collect
```

### OUTPUT:

```
res7: Array[Int] = Array(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15)
//no duplicates
```



## 5. zip()

- ```
val zip1 = sc.parallelize(List(1,2,3,4,5,6,7,8,9,10))  
val zip2 = sc.parallelize(List(11,12,13,14,15,16,17,18,19,20))
```

```
val zipfinal = zip1 zip zip2  
zipfinal.collect
```

OUTPUT:

```
res10: Array[(Int, Int)] = Array((1,11), (2,12), (3,13), (4,14),  
(5,15), (6,16), (7,17), (8,18), (9,19), (10,20))
```



DATAFRAMES in Spark

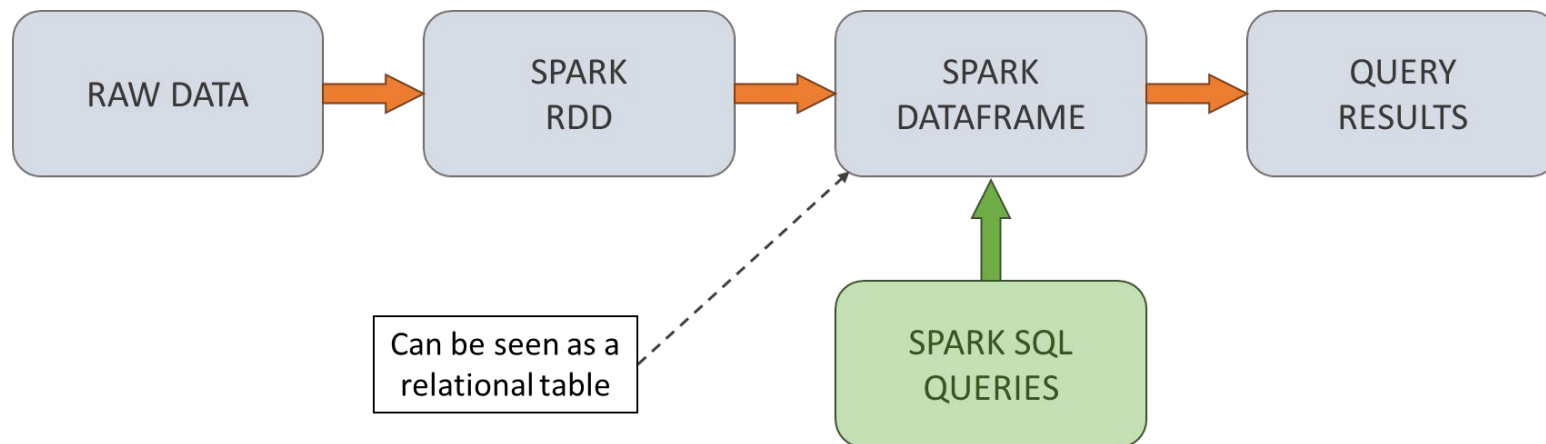
- A DataFrame is a *Dataset* organized into named columns. It is conceptually equivalent to a table in a relational database.
- DataFrames can be constructed from a wide array of sources such as: structured data files, tables in Hive, external databases, or existing RDDs.

- E.g.: create a DataFrame from a CSV file:

```
val df = spark.read.json("PATH_TO_CSV_FILE")
```



SQL Queries on data files



Example: Query data from a text file



E.g.: Search for word occurrences in a text file and then query over the results.

//read text file

```
val rdd = sc.textFile("PATH_TO_TEXTFILE") -> returns a new RDD object
```

//perform transformations on RDD

```
val counts = rdd.flatMap(line => line.split("\\W+"))  
                  .map(word => (word,1))  
                  .reduceByKey(_+_)
```

-> returns a new RDD object (child)

Pointer
to its
parent

//convert the RDD to a DataFrame

```
val df = counts.toDF()
```

//show it as table

```
df.show()
```


Example: Query data from a text file



E.g.: Word occurrences in a text file

The table has `_1` and `_2` as column names. To change df's column names we have to create a new Dataframe (because they are immutable objects):

```
val df2 = df.toDF(Seq("Word", "Count") : _*) //replace each column name with  
format _*
```

```
df2.show() -> now we have Word and Count as column names
```

Now we can perform queries on df2:

//order results by asc and show only top 5 elements

```
df2.orderBy(asc("Count")).show(5)
```

//show only words with more than 1 occurrence in the file

```
df2.filter("Count>1").show()
```



Example: Taxi Dataset

The **yellow taxi trip records** include fields capturing pick-up and drop-off dates/times, pick-up and drop-off locations, trip distances, itemized fares, rate types, payment types, and driver-reported passenger counts. The data used in the attached datasets were collected and provided to the NYC Taxi and Limousine Commission.

What's in this Dataset?

- Rows = 112M
- Columns = 17
- Each row represents a Yellow Taxi Trip

You can download the dataset here -> [\[yellow.csv\]](#)



Example: Taxi Dataset

// read the csv file containing the dataset

```
val df = spark.read.format("csv").  
    .option("header", true)  
    .option("inferSchema", true)  
    .load("PATH_TO_CSV_FILE")
```

configure
one or more
reading options

// create view on that file to refer to it as "taxidata"

```
df.createOrReplaceTempView("taxidata")
```



Example: Taxi Dataset

// count #rows in the dataset

```
spark.sql("select count(*) from taxidata") .show()
```

// get total revenue generated

```
spark.sql("select sum(total_amount) from taxidata").show()
```

// get average revenue in US Dollars:

```
spark.sql("select avg(total_amount) from taxidata").show()
```



Training a language classifier

Suppose we want to build a Spark's application for training a language classifier over tweets from Twitter.



1. **Collect a Dataset of Tweets** - **Spark Streaming** is used to collect a dataset of tweets and write them out to files.
 2. **Examine the Tweets** - **Spark SQL** is used to examine the dataset of Tweets.
 3. **Train a Model** - Then Spark **MLlib** is used to apply the K-Means algorithm to train a model on the data.
- If you are interested [here](#) you can find an example.

