4 Delivery: Spark

OBJECTIVE

We are introducing the use of Spark console and the basic operations with the Scala API to process datasets stored in a HDFS repository.

This tutorial is based on the public Apache Spark documentation. More details on operations and Spark usage is available on spark.apache.org website.

4.1 Working with the Spark interpreter

To work with Scala we need to open a console and open the Spark interactive shell:

```
spark-shell
```

We should get the following welcome message:

Alternatively, we can use PySpark if we are more familiar with Python's syntax:

4.2 Counting words with Spark

We will test two implementations of a Word Count using (a) Scala, and (b) PySpark. The implementations can be seen, respectively, in snippets 1 and 2 below.

Snippet 1: Word count implementation using Scala

```
val f = sc.textFile("/hduser/input/pg2000.txt")
val wc = f.flatMap(l => l.split("")).
map(word => (word, 1)).
reduceByKey(_ + _)
wc.saveAsTextFile("/hduser/spark/wc_scala_out")
```

Now let's check the output:

```
1 hdfs dfs -cat /hduser/spark/wc_scala_out/part-00000 | head -n5
```

```
(agradable,,1)
(derecho.,1)
(vecindad,1)
(invierno,6)
(deshonrar,3)
```

Snippet 2: Word count implementation using PySpark

```
from operator import add
from operator im
```

Now let's check the output:

```
1 hdfs dfs -cat /hduser/spark/wc_pyspark_out/part-00000 | tail -n5
```

```
(u'-Voy', 1)
(u'cupo,', 1)
(u'quit\xe1rselos', 2)
(u'arrojarlos', 1)
(u'embotan', 1)
```

Comparing the outputs of snippets 1 and 2, it's clear that both implementation works, but the format of the outputs is completely different.

Scala seems to be a tad more intuitive and seems to ease the eventual process of post-processing the results.

4.3 Working with Resilient Distributed Datasets

Resilient Distributed Datasets (RDD) are the primary abstraction in Spark, a fault-tolerant collection of elements that can be operated on in parallel. There are currently two types:

(i) Parallelized collections: take an existing Scala collection and run functions on it in parallel:

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

(ii) Hadoop datasets: run functions on each record of a file in Hadoop distributed file system or any other storage system supported by Hadoop:

```
val distFile =
sc.textFile("/hduser/input-weather/weather-data1901.txt")
```

```
distFile.map(1 => 1.split("")).collect()
```

```
res0: Array[Array[String]] = Array(
Array(0029029070999991901010106004+64333+023450...),
Array(0029029070999991901010113004+64333+023450...),
Array(0029029070999991901010120004+64333+023450...),
Array(0029029070999991901010206004+64333+023450...),
Array(0029029070999991901010213004+64333+023450...),
Array(0029029070999991901010220004+64333+023450...)
```

```
3 distFile.flatMap(l => 1.split("")).collect()
```

```
res1: Array[String] = Array(
0029029070999991901010106004+64333+023450...,
0029029070999991901010113004+64333+023450...,
0029029070999991901010120004+64333+023450...,
0029029070999991901010206004+64333+023450...,
0029029070999991901010213004+64333+023450...,
0029029070999991901010220004+64333+023450...
```

The difference between the behaviour between map() and flatMap() is that map() passes each element of the source through our mapper function (we get an Array of Arrays), whilst flatMap() passes them all at once (we get a single Array).

Type and understand the following source code in your Spark console. You must upload reg.tsv and clk.tsv at your own HDFS data input folder.

```
hdfs dfs -mkdir /hduser/input-spark
hdfs dfs -put ~/data/clk.tsv /hduser/input-spark/clk.tsv
hdfs dfs -put ~/data/reg.tsv /hduser/input-spark/reg.tsv

val format = new java.text.SimpleDateFormat("yyyy-MM-dd")

format: java.text.SimpleDateFormat =
    java.text.SimpleDateFormat@f67a0200
```

Now we define our Register and Click classes:

Now we read the reg.tsv from our HDFS and split the lines using the tabulator as a separator; then we give format to each line as an array with the different fields we are interested into using a map job and the Register class:

Then we read the clk.tsv from our HDFS and split the lines using the tabulator as a separator; then we give format to each line as an array with the different fields we are interested into using a map job and the Click class:

We can use the join() transformation to join reg with clk and then return all the elements of the dataset as an array using collect():

5 reg.join(clk).collect()

```
res0: Array[(String, (Register, Click))] = Array(
(81da510acc4111e387f3600308919594,(Register(Tue Mar 04 00:00:00 PST 2014,81da510acc4111e387f3600308919594,2,33.85701,-117.85574),
Click(Thu Mar 06 00:00:00 PST 2014,81da510acc4111e387f3600308919594,61))),
(15dfb8e6cc4111e3a5bb600308919594,(Register(Sun Mar 02 00:00:00 PST 2014,15dfb8e6cc4111e3a5bb600308919594,1,33.659943,-117.95812),
Click(Tue Mar 04 00:00:00 PST 2014,15dfb8e6cc4111e3a5bb600308919594,11))))
```

This final order prints the RDD Lineage Graph as a DAG (Directed Acyclic Graph) to get the dataset reg.join(clk). The indentations indicate a shuffle boundary.

6 reg.join(clk).toDebugString

```
res1: String =
(1) MapPartitionsRDD[30] at join at <console >: 38 []
 | MapPartitionsRDD[29] at join at <console >: 38 []
   CoGroupedRDD[28] at join at <console >: 38 []
+-(1) MapPartitionsRDD[20] at map at <console>:33 []
   | MapPartitionsRDD[19] at map at <console>:32 []
   | /hduser/input-spark/reg.tsv MapPartitionsRDD[18] at textFile
    at <console >: 31 []
    | /hduser/input-spark/reg.tsv HadoopRDD[17] at textFile at
    <console>:31 []
+-(1) MapPartitionsRDD[24] at map at <console>:33 []
    | MapPartitionsRDD[23] at map at <console>:32 []
      /hduser/input-spark/clk.tsv MapPartitionsRDD[22] at textFile
       at <console >: 31 []
      /hduser/input-spark/clk.tsv HadoopRDD[21] at textFile at
       <console>:31 []
```

4.4 Processing weather data with Spark

The implementation of the mapreduce job to find the Minimum Temperature of each year is quite straightforward; it is very similar to what we did in Hadoop, but with a much simpler syntax. This implementation can be seen in snippet 3 below.

It is of crucial importance to apply the filter(line => line.length >= 93) transformation, otherwise Java will complain about some lines that are shorter than expected (a problem one would not have using PySpark, for instance, as it would automatically discard those lines).

Snippet 3: Minimum Temperature implementation using Scala

```
val inputRDD = sc.textFile("/hduser/input-weather/*")
 val minTemp = inputRDD.filter(line => line.length >= 93).
      map{ case line =>
4
             val quality: String = line.substring(92, 93)
5
             val sign: Int = if(line.charAt(87) == '+') 1 else -1
6
             val temp: Int = line.substring(88, 92).toInt
             val year: Int = line.substring(15, 19).toInt
8
             (quality, year, sign, temp) }.
9
      filter { case (q, _, _, t ) => q.matches("[01459]") && t !=
10
         9999}.
      map { case (, y, s, t) => (y, s*t) }.
11
      reduceByKey({ case (prev, curr) => Math.min(prev, curr) })
12
14 minTemp.saveAsTextFile("/hduser/spark/output-min-temp")
```

Now we only need to check the output of our Scala mapreduce job. The results are exactly the same that those obtained using Java classes or Python in Hadoop.

```
1 hdfs dfs -cat /hduser/spark/output-min-temp/part*
```

```
(1920, -344)
(1901, -333)
(1902, -328)
(1903, -306)
(1904, -294)
(1905, -328)
(1906, -250)
(1907, -350)
(1908, -378)
(1909, -378)
(1910, -372)
(1911, -378)
(1912, -411)
(1913, -372)
(1914, -378)
(1915, -411)
(1916, -289)
(1917,-478)
(1918, -450)
(1919, -428)
```