# Cloud Computing Project – Task 1

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#### I. INTRODUCTION

The goal of the Capstone Project is to apply the knowledge acquired through the Cloud computing courses, in order to solve real-world Cloud computing challenges. In particular, the aim of task 1 is to:

- Extract and clean the transportation dataset from the US BTS (Bureau of Transportation Statistics) that is hosted as an Amazon EBS volume snapshot. The dataset contains data and statistics from the US Department of Transportation on aviation, maritime, highway, transit, rail, pipeline, bike/pedestrian and more in CSV format, but only the aviation part of the dataset is useful for this task. Finally, resulting data must be stored in HDFS (Hadoop Distributed File System).
- Answer a set of questions by using Apache Hadoop and/or Spark Streaming, which are two batch processing systems. The results related to questions from Group 2 and question 3.2 are stored in Cassandra.

#### II. VIRTUALIZATION ENVIRONMENT

In order to quickly deploy a complete Apache Hadoop stack, Apache Ambari has been used. Ambari is a completely open source management platform for provisioning, managing and monitoring Apache Hadoop clusters by using a graphical user interface. The Apache Hadoop cluster has been deployed on the EC2 Cloud service offered by Amazon Web Services (AWS), and consists of 1 NameNode (Master) and 3 DataNodes (Slaves – Node1, Node2 and Node3). The NameNode is a master server that manages the filesystem namespace and regulates access to files by clients; it executes namespace operations such as opening, closing, and renaming files and directories. The NameNode also determines the mapping of blocks to DataNodes. The DataNodes manage storage attached to the nodes that they run on, and they are responsible for serving read and write requests from the filesystem clients. The DataNodes also perform block creation, deletion, and replication upon instruction from the NameNode. Finally, the Ambari server runs on a fifth EC2 instance.

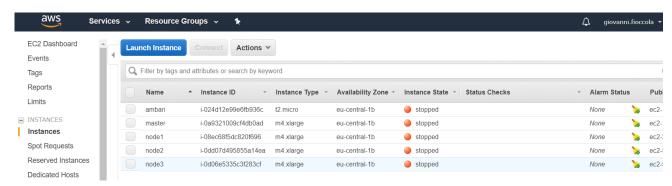


Figure 1 - Virtualization environment

# III. DATA ACQUISITION AND FILTERING

A new EBS volume from the existing EBS snapshot (ID snap-e1608d88 for Linux/Unix in the us-east-1 region) of the transportation dataset has been created and attached to the Master EC2 instance. By using the Isblk command, it is possible to view the available disk devices and their mount points. A new folder has been created (/mnt/data) and the EBS volume has been attached to the filesystem:

\$ sudo mkdir /mnt/data/

#### \$ sudo mount /dev/xvdf /mnt/data

The attached EBS data volume includes data and statistics from the US Department of Transportation on aviation, maritime, highway, transit, rail, pipeline, bike/pedestrian and more, but only the aviation part of the dataset is useful for this task. Therefore, after mounting and attaching the volume, only the aviation directory has been considered, and more specifically the "airline ontime" data that contains on-time performance for each flight. A python script processes all subdirectories of "airline ontime" and the zip archives included in the subdirectories, ignores the "readme" files and searches for CSV extensions.

```
for archived file in archived files:
121
              logger.debug("Dealing with %s" %(archived file))
122
123
              #determine file type
124
              file_type = os.path.splitext(archived file)[-1]
125
126
              #if file is a readme, ignore it
              if file_type == ".html":
127
128
                  logger.debug("ignoring %s" %(archived file))
129
130
              elif file type == ".csv":
                  logger.debug("extract %s to %s" %(archived file, workdir))
131
                  archive.extract(archived file, workdir)
```

Finally, the script divides input files in chunks and compresses CSV files in ".gz" format by using Pigz, performing a compression through concurrent threads, in order to use multiple processors and cores. Data is sent to HDFS by using put command.

```
143
                  #Try to split input files in chunks
144
                  cmd = "split --lines=%s %s %s." % (MAX LINES, archived file, basename)
145
                  cmds = shlex.split(cmd)
146
                  helper.launch (cmds)
147
148
                  #now, remove original file
149
                  os.remove(os.path.join(workdir, data file))
150
151
                  #scan directory for csv, load them in HDFS
152
                  for chunk in os.listdir(workdir):
153
                      chunk = os.path.join(workdir, chunk)
154
                      *pack csv in gzip format
                      cmd = "pigz --best %s" % (chunk)
156
157
                      cmds = shlex.split(cmd)
                      helper.launch (cmds)
159
160
                      chunk += ".gz"
161
162
                       #Load data into HDFS:
                      helper.launch(shlex.split("hadoop fs -put %s %s" %(chunk, raw_data_path)))
163
```

Using mkdir in Apache Hadoop needs the "hadoop file permissions"; hdfs is a user that has permissions to create folders, so the new user is added to hdfs group. Then the folder is created and finally the owner of the folder is changed:

```
$ sudo usermod -aG hdfs $(whoami)
```

\$ sudo -u hdfs hadoop fs -mkdir -p /user/giovanni/capstone/airline\_ontime/raw\_data/

\$ sudo -u hdfs hadoop fs -chown -R \$(whoami) /user/giovanni/

Then the python script is executed:

```
$ python AirlineToHDFS.py --input_path=/mnt/data/aviation/airline_ontime/ \
```

```
--output_path=/user/giovanni/capstone/airline_ontime/raw_data/
```

A pig script allows to load data from HDFS, and the loaded data includes the header (the first row). The script gets rid of the header and only the following fields are considered:

FlightDate, AirlineID, FlightNum, Origin, OriginCityName, OriginStateName, Dest, DestCityName, DestStateName, CRSDepTime, DepDelay, CRSArrTime, ArrDelay, Cancelled, CancellationCode, Diverted, CRSElapsedTime, ActualElapsedTime, AirTime, Distance

Finally, filtered data are put into a new folder in HDFS:

\$ pig -x mapreduce -p input=/user/giovanni/capstone/airline\_ontime/raw\_data/\

-p filtered=/user/giovanni/capstone/airline\_ontime/filtered\_data/ load\_ontime.pig

#### IV. SYSTEM INTEGRATION

In order to install Cassandra, the following steps were performed:

- Add the DataStax Community repository to the /etc/apt/sources.list.d/cassandra.sources.list:
  - \$ echo "deb http://debian.datastax.com/community stable main" | sudo tee -a /etc/apt/sources.list.d/cassandra.sources.list
- Add the DataStax repository key to the aptitude trusted keys:

\$ curl -L http://debian.datastax.com/debian/repo key | sudo apt-key add -

Install the package:

\$ sudo apt-get update

\$ sudo apt-get install dsc20 cassandra=2.0.17

Edit /etc/cassandra/cassandra.yaml:

\$ sudo nano /etc/cassandra/cassandra.yaml

o The default cassandra.yaml uses the local, loopback address as its listen and Thrift addresses:

listen\_address: locahost rpc address: localhost

o listen\_address and rpc\_address must be set to the IP address of the master:

listen\_address: 172.31.44.199 rpc\_address: 172.31.44.199

Similarly for the the seed information:

seeds: "node1,node2,node3"

The developers of Apache Spark have given thoughtful consideration to Python as a language of choice for data analysis. They have developed the PySpark API for working with RDDs in Python. Furthermore, it supports use of powerful IPythonshell instead of the builtin Python REPL. RDD (Resilient Distributed Dataset) is the basic abstraction in Spark and represents an immutable, partitioned collection of elements that can be operated on in parallel.

The developers of IPython have invested considerable effort in building the IPython Notebook, a system inspired by Mathematica that allows to create "executable documents." IPython Notebooks can integrate formatted text (Markdown), executable code (Python), mathematical formulae (LaTeX), and graphics/visualizations (matplotlib) into a single document that captures the flow of an exploration and can be exported as a formatted report or an executable script.

The steps followed in order to use iPython with Spark are the following:

• First an IPython profile for use with PySpark has been created: ipython profile create pyspark

• The file ~/.ipython/profile\_pyspark/startup/00-pyspark-setup.py with the following contents has been created:

```
import os
import sys

# Configure the environment
if 'SPARK_HOME' not in os.environ:
    os.environ['SPARK_HOME'] = '/usr/hdp/current/spark-client'

# Create a variable for our root path
SPARK_HOME = os.environ['SPARK_HOME']

# Add the PySpark/py4j to the Python Path
sys.path.insert(0, os.path.join(SPARK_HOME, "python", "lib"))
sys.path.insert(0, os.path.join(SPARK_HOME, "python"))

# Described here: http://blog.cloudera.com/blog/2014/08/how-to-use-ipython-notebook-with-apache-spark/
sys.path.insert(0, os.path.join(SPARK_HOME, "python/lib/py4j-0.8.2.1-src.zip"))
execfile(os.path.join(SPARK_HOME, 'python/pyspark/shell.py'))
```

An IPython shell with the profile we just created is started:
 \$ ipython --profile spark

Finally, pyspark-cassandra is installed. This module provides python support for Apache Spark's Resillient Distributed Datasets from Apache Cassandra CQL rows using Cassandra Spark Connector within PySpark, both in the interactive shell and in python programmes submitted with spark-submit.

All MapReduce jobs are submitted to YARN, in order to prepare a dataset that can be processed by Spark. Finally, the Spark Cassandra Connector package allows to move loaded DataFrames from Spark to Apache Cassandra.

# V. QUESTION 1.1

A pig script allows to load data from the filtered transportation dataset. Then, tuples that have the same Origin key are grouped together, and tuples that have the same Dest key are grouped together too. The number of elements that have the same Origin key are counted, the number of elements that have the same Dest key are counted too, and results are put in the same table. These results are grouped by airport code and the occurrences are summed up:

Total\_counts = FOREACH United\_group GENERATE FLATTEN(\$0), SUM(United\_counts.count) AS count;

Finally, airports are ordered by occurrences thanks to multiple concurrent reduce tasks:

\$ Popular = ORDER Total\_counts BY count DESC PARALLEL 4;

This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline\_ontime/filtered\_data/ get\_top10.pig

#### VI. QUESTION 1.2

A pig script allows to load data from the filtered transportation dataset. Then, cancelled and diverted flights are excluded. The tuples that have the same AirlineID key are grouped together, and for each airline the average arrival delay is computed:

airline\_delays = FOREACH airlines GENERATE FLATTEN(\$0), AVG(flights.ArrDelay) AS avg\_delay;

Finally, airlines are ordered by arrival delays thanks to multiple concurrent reduce tasks.

This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline ontime/filtered data/ top10 airlines.pig

## VII. QUESTION 2.1

A pig script allows to load data from the filtered transportation dataset. The airlines lookup dictionary, previously downloaded (http://www.transtats.bts.gov/Download\_Lookup.asp?Lookup=L\_AIRLINE\_ID) and put in hadoop filesystem, is loaded. A replicated join is performed:

lookup = LOAD '\$lookup' USING org.apache.pig.piggybank.storage.CSVExcelStorage(',', 'NO\_MULTILINE', 'NOCHANGE', 'SKIP\_INPUT\_HEADER') AS (AirlineIDsec:chararray,Airline:chararray);

joined = JOIN filtered BY AirlineID, lookup BY AirlineIDsec USING 'replicated';

Then, cancelled and diverted flights are excluded. Only the following fields are considered: Origin, AirlineID, Airline, DepDelay:

flights = FOREACH arrived flights GENERATE Origin, AirlineID, Airline, DepDelay;

The tuples that have the same Origin, AirlineID and Airline keys are grouped together, and then the average departure delay for each carrier is computed:

carrier\_delays = FOREACH carrier GENERATE group.Origin, group.AirlineID, group.Airline,
AVG(flights.DepDelay) AS avg\_delay;

The carrier\_delays tuples that have the same Origin key are grouped together. Finally, for each origin, carriers are ordered by their average departure delays by means of concurrent multiple reduce tasks. Data are then stored into Cassandra.

This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline\_ontime/filtered\_data/ -p lookup=/user/giovanni/capstone/lookup/Lookup\_AirlineID.csv -p results=/user/giovanni/capstone/airline\_ontime/top10\_carriersByAirport/ top10\_carriersByAirport.pig

Cassandra table definition is the following:

CREATE KEYSPACE capstone WITH REPLICATION = {'class': 'SimpleStrategy', 'replication\_factor': 1};

USE capstone;

CREATE TABLE carriers by airport (origin TEXT, airlineid INT, airline TEXT, depdelay FLOAT, PRIMARY KEY(origin, depdelay));

To show the results, the following script is used:

\$ cqlsh -f top10 carriersByAirport.cql 172.31.44.199

It includes for example:

SELECT origin, airlineid, depdelay, airline FROM carriersbyairport WHERE origin = 'CMI';)

# VIII. QUESTION 2.2

A pig script allows to load data from the filtered transportation dataset. Then, cancelled and diverted flights are excluded. Only the following fields are considered: Origin, Dest, DepDelay:

flights = FOREACH arrived flights GENERATE Origin, Dest, DepDelay;

The tuples that have the same Origin and Dest keys are grouped together, and then the average departure delay for each path is computed:

path delays = FOREACH path GENERATE group.Origin, group.Dest, AVG(flights.DepDelay) AS avg delay;

The path\_delays tuples that have the same Origin key are grouped together. Finally, for each origin, path\_delays are ordered by their average delays by means of concurrent multiple reduce tasks. Data are then stored into Cassandra.

This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline ontime/filtered data/\

-p results=/user/giovanni/capstone/airline\_ontime/top10\_airportsByAirport/ top10\_airportsByAirport.pig

Cassandra table definition is the following:

CREATE KEYSPACE capstone WITH REPLICATION = {'class': 'SimpleStrategy', 'replication factor': 1};

USE capstone;

CREATE TABLE airportsbyairport (origin TEXT, destination TEXT, depdelay FLOAT, PRIMARY KEY(origin, depdelay));

To show the results, the following script is used:

\$ cqlsh -f top10\_ airportsByAirport.cql 172.31.44.199

It includes for example:

SELECT origin, destination, depdelay FROM airportsbyairport WHERE origin = 'CMI';

#### IX. QUESTION 2.3

A pig script allows to load data from the filtered transportation dataset. The airlines lookup dictionary, previously downloaded (http://www.transtats.bts.gov/Download\_Lookup.asp?Lookup=L\_AIRLINE\_ID) and put in hadoop filesystem, is loaded. A replicated join is performed:

lookup = LOAD '\$lookup' USING org.apache.pig.piggybank.storage.CSVExcelStorage(',', 'NO\_MULTILINE', 'NOCHANGE', 'SKIP INPUT HEADER') AS (AirlineIDsec:chararray, Airline:chararray);

joined = JOIN filtered BY AirlineID, lookup BY AirlineIDsec USING 'replicated';

Then, cancelled and diverted flights are excluded. Only the following fields are considered: Origin, Dest, AirlineID, Airline, ArrDelay:

flights = FOREACH arrived\_flights GENERATE Origin, Dest, AirlineID, Airline, ArrDelay;

The tuples that have the same Origin, Dest, AirlineID and Airline keys are grouped together, and then the average arrival delay for each carrier is computed:

carrier\_delays = FOREACH carrier GENERATE group.Origin, group.Dest, group.AirlineID, group.Airline, AVG(flights.ArrDelay) AS avg\_delay;

The carrier\_delays tuples that have the same Origin and Dest keys are grouped together. Finally, for each origin, carriers are ordered by their average arrival delays by means of concurrent multiple reduce tasks. Data are then stored into Cassandra.

This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline\_ontime/filtered\_data/ -p lookup=/user/giovanni/capstone/lookup/Lookup\_AirlineID.csv -p results=/user/giovanni/capstone/airline\_ontime/top10\_carriersByPath/top10\_carriersByPath.pig

Cassandra table definition is the following:

CREATE KEYSPACE capstone WITH REPLICATION = {'class': 'SimpleStrategy', 'replication\_factor': 1};

USE capstone;

CREATE TABLE carriers by path (origin TEXT, destination TEXT, airlineid INT, airline TEXT, arrdelay FLOAT, PRIMARY KEY(origin, destination, arrdelay));

To show the results, the following script is used:

\$ cqlsh -f top10 carriersByPath.cql 172.31.44.199

It includes for example:

SELECT origin, destination, airlineid, arrdelay, airline FROM carriersbypath WHERE origin = 'CMI' AND destination = 'ORD';

# X. QUESTION 3.1

A pig script allows to load data from the filtered transportation dataset. Then, tuples that have the same Origin key are grouped together, and tuples that have the same Dest key are grouped together too. The number of elements that have the same Origin key are counted, the number of elements that have the same Dest key are counted too, and results are put in the same table. These results are grouped by airport code and the occurrences are summed up. Finally, airports are ordered by occurrences thanks to multiple concurrent reduce tasks:

\$ Popular = ORDER Total\_counts BY count DESC PARALLEL 4;

The RANK operator works with the count field. It sorts the relation on this field and prepends the rank value to each tuple. The rank of a tuple is one plus the number of different rank values preceding it. DESC sorts in descending order.

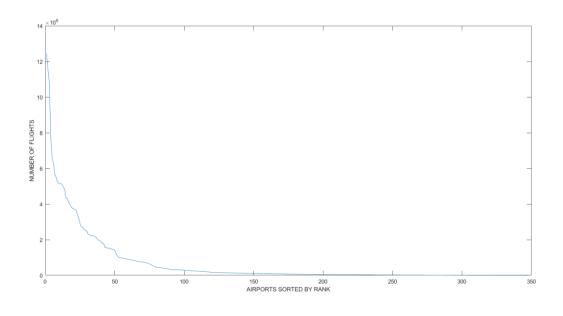
Ranked = RANK Popular BY count DESC;

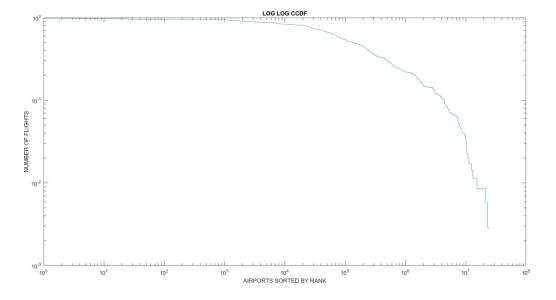
This is the pig script:

\$ pig -x mapreduce -p filtered=/user/giovanni/capstone/airline\_ontime/filtered\_data/ -p popular=/user/giovanni/capstone/airline\_ontime/popular/ get\_popular.pig

Zipf's law is an empirical law formulated by using mathematical statistics, and it refers to the fact that many types of data, studied in the physical and social sciences, can be approximated with a Zipfian distribution, one of a family of related discrete power law probability distributions. Zipf's law states that, given some corpus of natural language utterances, the frequency of any word is inversely proportional to its rank in the

frequency table. Therefore, the airport with a higher rank should have a double number of flights with respect to the next airport with lower rank. The CCDF of the popularity for airports should be a straight line if it had been a Zipf distribution. Instead, the popularity of the airports follows a lognormal distribution.





# XI. QUESTION 3.2

A python script allows to read the CSV Data of filtered transportation dataset into an RDD:

ontime\_data = sc.textFile(DATA\_DIR).map(split).map(parse)

Then, cancelled and diverted flights are excluded:

arrived\_data = ontime\_data.filter(lambda x: x.Cancelled is False and x.Diverted is False and x.FlightDate.year == 2008 and x.CRSDepTime is not None and x.CRSArrTime is not None and x.ArrDelay is not None)

In order to extract date, departure/arrival time scheduled, and the delay, only the following fields are considered:

FlightData = arrived\_data.map(lambda m: (m.FlightDate, m.Origin, m.Dest, m.FlightNum, m.CRSDepTime, m.CRSArrTime, m.ArrDelay))

Data are filtered because Tom wants his flights scheduled to depart airport X before 12:00 PM local time and to depart airport Y after 12:00 PM local time:

path1 = FlightData.filter(lambda (flightdate, origin, dest, flightnum, crsdeptime, crsarrtime, arrdelay): crsdeptime < time(hour=12, minute=00))</pre>

path2 = FlightData.filter(lambda (flightdate, origin, dest, flightnum, crsdeptime, crsarrtime, arrdelay): crsdeptime > time(hour=12, minute=00))

It is possible to transform path by Origin and Dest keys, in order to join path1 destination with path2 origin. Since the second leg of the journey (flight Y-Z) must depart two days after the first leg (flight X-Y), it is possible to subtract two days from the second dataset, then join by two keys:

destPath1 = path1.keyBy(lambda (flightdate, origin, dest, flightnum, crsdeptime, crsarrtime, arrdelay): (dest, flightdate))

originPath2 = path2.keyBy(lambda (flightdate, origin, dest, flightnum, crsdeptime, crsarrtime, arrdelay): (origin, flightdate-timedelta(2)))

It is possible to do a join between the two paths. The airport Y (path1 dest, path2 origin) is the key. When a join is performed, RDD with the same keys are located on the same nodes. Calling a map to transform values could be inefficient since the new keys will invalidate partitioning by keys. So, dates are filtered out before calling a new key map phase:

```
joinedPath = destPath1.join(originPath2).values()
```

Tom wants to arrive at each destination with as little delay as possible, so it is possible to sum delays for each of the two paths, then it is possible to order by such values:

twoDaysPathFlat = joinedPath.map(lambda ((flightdate1, origin1, dest1, flightnum1, crsdeptime1, crsarrtime1, arrdelay1), (flightdate2, origin2, dest2, flightnum2, crsdeptime2, crsarrtime2, arrdelay2)): ((flightdate1, flightdate2, origin1, dest1, dest2), [(flightdate1, origin1, dest1, flightnum1, crsdeptime1, crsarrtime1, arrdelay1, flightdate2, origin2, dest2, flightnum2, crsdeptime2, crsarrtime2, arrdelay2, arrdelay1+arrdelay2)]))

First, flights from the same dataset with the same path are summed up. aggregatebykey first sums partitions on the same node, then intra-nodes:

twoDaysPathSorted = twoDaysPathFlat.aggregateByKey([], getBest, getBest)

Finally, data are stored into Cassandra.

The PYSPARK\_CASSANDRA variable has been set to the pyspark directory:

PYSPARK\_CASSANDRA=/home/giovanni/capstone/pyspark-cassandra/target

Then jar files are added:

```
export PYSPARK_SUBMIT_ARGS="--jars ${PYSPARK_CASSANDRA}/pyspark_cassandra-0.1.5.jar \
```

```
--driver-class-path ${PYSPARK_CASSANDRA}/pyspark_cassandra-0.1.5.jar \
```

```
--py-files ${PYSPARK_CASSANDRA}/pyspark_cassandra-0.1.5-py2.7.egg \
```

--conf spark.cassandra.connection.host=172.31.44.199"

The pyspark\_cassandra library has been imported in order to use Cassandra:

```
import pyspark cassandra
```

The application is launched by using the spark-submit command:

```
spark-submit $PYSPARK_SUBMIT_ARGS --master yarn --executor-cores=3 --num-executors 3 --driver-memory=3G --executor-memory=4G best2pathsnokafka.py
```

Cassandra table definition is the following:

```
CREATE KEYSPACE capstone WITH REPLICATION = {'class': 'SimpleStrategy', 'replication_factor': 1};
```

USE capstone;

CREATE TABLE best2path (startdate TEXT, flightnum1 INT, origin1 TEXT, dest1 TEXT, departure1 TIMESTAMP, arrival1 TIMESTAMP, arrival2 TIMESTAMP, arrival3 TIMESTAMP, ar

To show the results, the following script is used:

\$ cqlsh -f best2paths.cql 172.31.44.199

It includes for example:

```
18 /* CMI → ORD → LAX, 04/03/2008 */
19
     SELECT startdate,
21
            flightnum1,
            origin1.
23
            dest1,
24
            departure1,
25
            arrival1,
26
            arrdelay1
27
            flightnum2,
28
            origin2,
29
            dest2,
            departure2,
31
            arrival2,
            arrdelav2
33
       FROM best2path
      WHERE origin1 = 'CMI' AND
34
35
            dest1 = 'ORD' AND
            dest2 = 'LAX' AND
36
            startdate = '04/03/2008';
37
```

#### XII. OPTIMIZATIONS

The MapReduce algorithm has two important tasks: Map and Reduce. Map takes a set of data and converts it into another set of data, where individual elements are broken down into tuples (key/value pairs). On the other hand, Reduce takes the output from a map as an input and combines the data tuples into smaller set of tuples. In MapReduce, the data is distributed over the cluster and processed. The difference in Spark is that it performs in-memory processing of data. This in-memory processing is a faster process as there is no time spent in moving the data/processes in and out of the disk, whereas MapReduce requires a lot of time to perform these input/output operations, thereby increasing latency. So Spark is used when a large set of files needs to be processed.

In HDFS, the zip files are converted into plain-text CSV files because zip files cannot be split, while CSV files are split into blocks and multiple concurrent map tasks can read the same file that is distributed among different nodes.

# **RESULTS**

#### RESULTS 1.1

```
ubuntu@ip-172-31-44-199: /svn/repos
                                                                                                           2017-10-27 19:49:06,050 [main] INFO org.apache.hadoop.yarn.client.AHSProxy
                                                                                        Connecting to Applicatio
n History server at ip-172-31-44-199.eu-central-1.compute.internal/172.31.44.199:10200
2017-10-27 19:49:06,051 [main] INFO org.apache.hadoop.mapred.ClientServiceDelegate - Application stat
e is completed. FinalApplicationStatus=SUCCEEDED. Redirecting to job history server
2017-10-27 19:49:06,073 [main] INFO org.apache.pig.backend.hadoop.executionengine.mapReduceLayer.MapR
educeLauncher - Success!
2017-10-27 19:49:06,075 [main] INFO org.apache.pig.data.SchemaTupleBackend - Key [pig.schematuple] wa
s not set... will not generate code.
2017-10-27 19:49:06,077 [main] INFO org.apache.hadoop.mapreduce.lib.input.FileInputFormat - Total inp
ut paths to process : 1
2017-10-27 19:49:06,077 [main] INFO org.apache.pig.backend.hadoop.executionengine.util.MapRedUtil -
otal input paths to process: 1
(ORD, 12449354)
(ATL, 11540422)
(DFW, 10799303)
(LAX,7723596)
(PHX, 6585534)
(DEN, 6273787)
(DTW, 5636622)
(IAH,5480734)
(MSP, 5199213)
(SFO, 5171023)
2017-10-27 19:49:06,132 [main] INFO org.apache.pig.Main - Pig script completed in 11 minutes, 40 seco
nds and 754 milliseconds (700754 ms)
ubuntu@ip-172-31-44-199:/home/giovanni/ccc-capstone/ontime$
```

#### **RESULTS 1.2**

```
ubuntu@ip-172-31-44-199: /svn/repos
2017-10-27 20:02:46,541 [main] INFO org.apache.hadoop.yarn.client.AHSE
n History server at ip-172-31-44-199.eu-central-1.compute.internal/172.31.44.199:10200
2017-10-27 20:02:46,543 [main] INFO org.apache.hadoop.mapred.ClientServiceDelegate - Application stat
e is completed. FinalApplicationStatus=SUCCEEDED. Redirecting to job history server
2017-10-27 20:02:46,565 [main] INFO org.apache.pig.backend.hadoop.executionengine.mapReduceLayer.MapR
2017-10-27 20:02:46,570 [main] INFO org.apache.pig.data.SchemaTupleBackend - Key [pig.schematuple] wa
s not set... will not generate code.
2017-10-27 20:02:46,573 [main] INFO
                                     org.apache.hadoop.mapreduce.lib.input.FileInputFormat - Total inp
ut paths to process: 1
2017-10-27 20:02:46,573 [main] INFO org.apache.pig.backend.hadoop.executionengine.util.MapRedUtil - T
otal input paths to process : 1
(19690, -1.01180434574519)
(19678,1.1569234424812056)
(19391,1.4506385127822803)
(20295, 4.747609195734892)
(20384,5.3224309999287875)
(20436, 5.465881148819851)
(19393,5.5607742598815735)
(20363,5.8671846616957595)
017-10-27 20:02:46,651 [main] INFO org.apache.pig.Main - Pig script completed in 7 minutes, 29 secon
ds and 994 milliseconds (449994 ms)
ubuntu@ip-172-31-44-199:/home/giovanni/ccc-capstone/ontime$
```

### RESULTS 2.1

#### ubuntu@ip-172-31-44-199: /home/giovanni/ccc-capstone/ontime

origin	airlineid	depdelay	airline
LAX	20398	1 2.4	Envoy Air: MO
LAX	20304		
LAX	20437		
LAX	20312		
LAX	19391		
LAX	19386		
LAX	20436		
LAX	19690	5.8176	Hawaiian Airlines Inc.: HA
LAX	20378	6.0363	Mesa Airlines Inc.: YV
LAX		6.7294	US Airways Inc.: US (Merged with America West 9/05. Reporting for both starting 10/07.)
(10 rows)			
origin	airlineid 	depdelay	airline
IAH	19386	3.5156	Northwest Airlines Inc.: NW
IAH	20384	3.9016	Pan American World Airways (1): PA (1)
IAH	19822	3.9522	Piedmont Aviation Inc.: PI
IAH	20355	5.0298	US Airways Inc.: US (Merged with America West 9/05. Reporting for both starting 10/07.)
IAH	20436	5.5495	Frontier Airlines Inc.: F9
IAH	19805	5.6169	American Airlines Inc.: AA
IAH	20211		
IAH	19393		
IAH	20304		
IAH	20398	6.7098	Envoy Air: MQ
(10 rows)			
origin	airlineid 	depdelay	airline
SFO			ATA Airlines d/b/a ATA: T2
SFO			
SFO	20436		
SFO	20384		
SFO	19386		
SFO	19391		
SFO	19790		
SFO	19704		
SFO	20355		US Airways Inc.: US (Merged with America West 9/05. Reporting for both starting 10/07.)
SFO	20211	7.7631	Trans World Airways LLC: TW
(10 rows)			

# RESULTS 2.2

abunta@	ip 172 31 11 13317	nome, grovanin, eee caps
origin	destination	depdelay
		-+
LAX	SDF	-16
LAX		
LAX		-0.72727
LAX	MAF	0
LAX		1.1775
LAX	IYK	1.2698
LAX	MEM	1.868
LAX	PIE	
LAX	SNA	
LAX	SBA	2.2744
(10 rows	)	
(10 10 10	,	
origin	destination +	depdelay -+
IAH	MSN	-2
	MLI	
IAH		-0.6173
	EFD	1 1.8877
	HOU	
	JAC	2.4226
IAH		
	RNO	
IAH		
IAH		
27111	J. 1	1 3.3333
(10 rows	)	
origin	destination	depdelay
		+
SFO		
SFO		
SFO		-1.7576
SFO		
SFO	OAK	-0.81371
SFO	FAR	
SFO	BNA	
SFO		
SFO		
SFO	MKE	3.988
(10 rows	)	

```
RESULTS 2.3

₫ ubuntu@ip-172-31-44-199: /home/giovanni/ccc-capstone/ontime

 ubuntu@ip-172-31-44-199:/home/giovanni/ccc-capstone/ontime$ cqlsh -f top10_carriersByPath.cql 172.31.44.199
19384 rows imported in 5.607 seconds.
       CMI |
 (1 rows)
                                                                      -2.349 | Continental Air Lines Inc.: CO

5.5 | American Airlines Inc.: AA

5.6973 | American West Airlines Inc.: HP (Merged with US Airways 9/05.Stopped reporting 10/07.)

5.7615 | Northwest Airlines Inc.: NW

6.8785 | US Airways Inc.: US (Merged with America West 9/05. Reporting for both starting 10/07.)

10.688 | Delta Air Lines Inc.: DL

10.813 | Eastern Air Lines Inc.: EA
                                 CMH
CMH
       IND |
                                 CMH |
                                                    19386 |
20355 |
                                 CMH |
  7 rows)
                                                                    20384 |
20366 |
19977 |
19704 |
20304 |
20374 |
19805 |
       DFW
DFW
                                  IAH
IAH
       DFW
DFW
                                  HAI
HAI
       DFW
DFW
                                 HAI
HAI
                                  HAI
HAI
                                                    19790 |
20398 |
                                                                                                                  Delta Air Lines Inc.: DL
Envoy Air: MQ
       DFW
```

LAX   LAX   LAX   LAX   LAX   LAX   LAX   LAX   LAX	SFO SFO SFO SFO SFO SFO SFO SFO SFO	19391   20436   20366   19805   20398   20355   19393	-2.1463   -2.0287   6.9646   7.3868   7.8078   7.9647   8.7921   9.3548	Southwest Airlines Co.: WN Continental Air Lines Inc.: CO		
(10 rows)						
origin	destination	airlineid	arrdelay	airline		
JFK	LAX	+ I 19977	+   3.3139	United Air Lines Inc.: UA		
JFK	LAX			America West Airlines Inc.: HP (Merged with US Airways 9/05.Stopped reporting 10/07.)		
JFK	LAX	19805		American Airlines Inc.: AA		
JFK	LAX	19790	7.9345	Delta Air Lines Inc.: DL		
JFK	LAX	20384	11.019	Pan American World Airways (1): PA (1)		
JFK	LAX	20211	11.702	Trans World Airways LLC: TW		
(6 rows)	destination	airlineid +	arrdelay	airline		
ATL	PHX	20437	4.5526	AirTran Airways Corporation: FL		
ATL	PHX			US Airways Inc.: US (Merged with America West 9/05. Reporting for both starting 10/07.)		
ATL	PHX			America West Airlines Inc.: HP (Merged with US Airways 9/05.Stopped reporting 10/07.)		
ATL	PHX					
ATL	PHX	19790	9.8083	Delta Air Lines Inc.: DL		
(5 rows) ubuntu@ip-172-31-44-199:/home/giovanni/ccc-capstone/ontime\$						

#### GIOVANNI BATTISTA FIOCCOLA

#### RESULTS 3.1



#### **RESULTS 3.2**

