CLOUD COMPUTING CAPSTONE PROJECT PART 1

INTRODUCTION

The goal of the Capstone project in this Cloud Computing specialization was to apply in practice the knowledge and skills gained throughout the different courses by analyzing a public transportation dataset of the US Bureau of Transportation Statistics.

This report covers the first part of the Capstone project, which focusses on using batch processing systems to solve the presented questions. It contains an overview of the data cleaning process, how the system was constructed, the different optimizations used to improve the performance of the system and queries, the actual results and a conclusion to complete the report.

DATA EXTRACTION AND CLEANING

The RAW data set contained far more data than what was necessary for this project. Analysis of the data directory provided by the EBS volume, indicated that only the 'airline_ontime' directory was of use for this project. The tables in this dataset contained about 80 fields, of which only the following were useful and retained during the cleaning process: FlightDate, Year, Month, Quarter, DayofMonth, DayOfWeek, Origin, Dest, UniqueCarrier, FlightNum, CRSArrTime, ArrTime, ArrDelayMinutes, ArrDelay, CRSDepTime, DepTime, DepDelayMinutes, DepDelay, Cancelled.

To process these files and extract the data. I created a temporary EC2 instance which copy the contents from EBS volume to S3 in the zip format. I used the new serverless paradigm called AWS Lambda to process zip and extract relevant data parallelly. In this managed service, AWS handles the operational challenges like scaling at a very low cost. I implemented 2 functions to process the data:

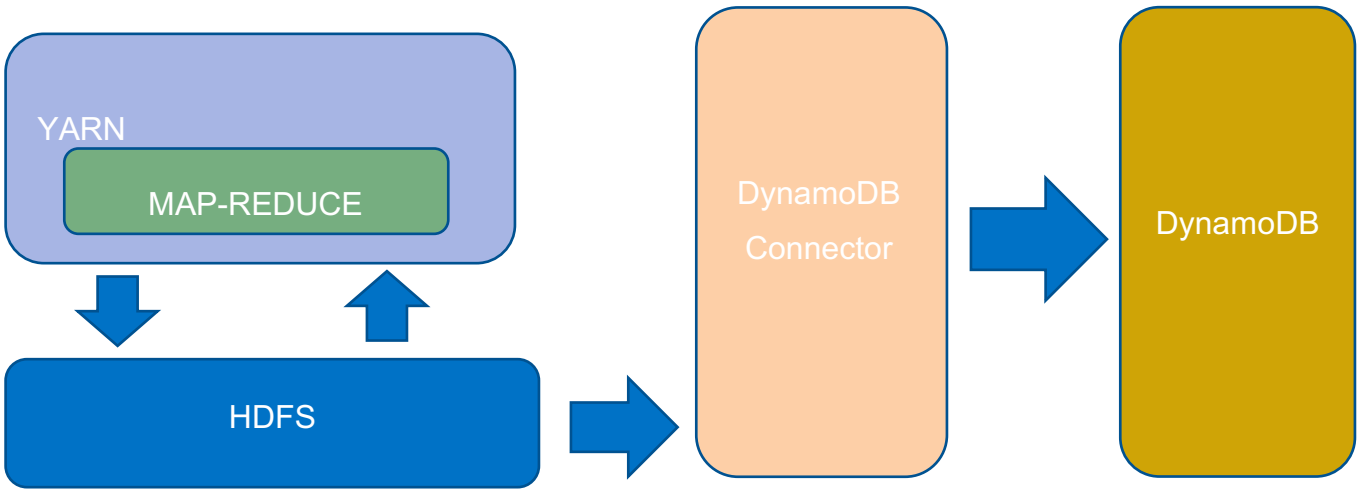
1. The function '*clean_zipfile*' performed the ETL task for a single zip file. From a high-level perspective the function (i) read the RAW zip file from S3 storage, (ii) decompressed it in memory, (iii) extracted the useful fields and (iv) wrote new CSV files onto S3 (uncompressed).

2. The function ‘process_zipfiles ’ (i) queried S3 and (ii) triggered an asynchronous execution of the first function for each zip file on S3.

The advantage is the automatic scaling this approach offered and scale it with larger set of data too. *Note: The processing of the files, revealed there were some invalid files included in the data set.*

SYSTEM

To answer the questions in this project, I decided to use Map-Reduce Hadoop program which processed file from HDFS and eventually stored the final result to DynamoDB using help of HDFS to DynamoDB connector.



I created EMR cluster on AWS to run this Map-Reduce program. EMR cluster provided s3-dist-cp which help me to move clean data from S3 to HDFS as part of initial sets of the setup.

SOLUTIONS

Group 1 (Question 1.1 and 1.2)

A similar approved is being used to solve both questions. I have used two phases of Map Reduce for both questions. First phase differ a bit but second stage is more less common to get top 10 items.

Question 1.1 – Rank the top 10 most popular airports by number of flights to/from the airport

First phase calculate total numbers of flight from and to the airport. Second phase calculate Top 10 items.

Map-Reduce Flow: <.. line> -> **map1()** -> <airport, 1> (for both from and to) -> **reduce1() -> <**airport_id, total_count> -> **map2() ->** < NULL, Top_10_airport_based_on_count> -> **reduce2() ->** <Top10 airport>

Map Reduce Command: *bin/hadoop jar hsc4_capstone_jar.jar com.cloudcomputing.PopularAirportsPlaintext ontime_data top_10_ airports*

Question 1.2 Rank the top 10 airlines by on-time arrival performance

First phase calculate average arrival delay and second phase get top 10 least arrival time carriers.

Map Reduce Flow: <.. line> -> **map1()** -> <carrier_id, arrival_delay> -> **reduce1() -> <** carrier_id, avg_arrival_delay> -> **map2() ->** < NULL, Top_10_carrier_based_on_least_arrival_time> -> **reduce2() ->** <Top10 carriers>

Map Reduce command: *bin/hadoop jar hsc4_capstone_jar.jar com.cloudcomputing.AverageDelays ontime_data top_10_carriers*

Group 2 (Question 2.1, 2.2 and 2.4)

All solutions has two parts of solution. First part summarized the result by processing raw input and second part allow user to query the results on first part summarized result. This way we can response to the query really fast. Final solution is stored to DynamoDB using custom scripts which reads HDFS file and send to DynamoDB. I could use Hive for this but I am not expert of it so I stick to HDFS processing only.

Question 2.1 For each airport X, rank the top-10 carriers in decreasing order of on-time departure performance from X

Part 1, calculate average departure delay for composite key (airport_id, carrier_id).

*<..., line> -> **map()** -> <(airport_id, carrier_id departure_delay> -> **reduce()** -> <(airport_id, carrier_id average_departure_delay>*

Part 2, accepts query input airport X, and process output of part 1, and get top-10 carriers with decreasing order of on-time departure.

*<…, **Part 1** output line> -> **map()** -> For airport X Top-10 <(X, carrier_id), avg_departure_delay> -> **reduce()** -> Top-10 <(X, carrier_id), avg_departure_delay>*

Question 2.2 For each source airport X, rank the top-10 destination airports in decreasing order of on-time departure performance from X.

This is very similar to solution to Question 2.1. Here the compound key consists origin and destination airport.

Part 1:

*<..., line> -> **map()** -> <(airport_from, airport_to departure_delay> -> **reduce()** -> <(airport_from, airport_to average_departure_delay>*

Part 2:

*<…, **Part 1** output line> -> **map()** -> For airport X Top-10 <(X, airport_to), avg_departure_delay> ->*

***reduce()** -> Top 10 < (X, airport_to), avg_departure_delay)>*

Question 2.4 For each source-destination pair X-Y, determine the mean arrival delay (in minutes) for a flight from X to Y.

This is very similar to solution to Question 2.2. Here the compound value consists arrival delay instead of departure delay.

Part 1:

*<..., line> -> **map()** -> <(airport_from, airport_to arrival_delay> -> **reduce()** -> <(airport_from, airport_to average_arrival_delay >*

Part 2:

*<…, **Part 1** output line> -> **map()** -> For airport X Top-10 <(X, airport_to), avg_ arrival_delay > -> **reduce()** -> Top 10 < (X, airport_to), avg_ arrival_delay)>*

Finally all solutions is stored to DynamoDB by calling custom python adapter which accepts hdfs file and DynamoDB table.

Command to run "*python dynanodb_adapter.py <table_name> <hdfs file>*"

Group 3 (Question 3.1 and 3.2)

Question 3.2 Tom wants to travel from airport X to airport Z. However, Tom also wants to stop at airport Y for some sightseeing on the way. More concretely, Tom has the following requirements

We use the same approach except, that key-value pairs will be both custom Writable extensions in this case. Keys will be constructed from (airport_from, airport_to, flight_date, am_or_pm). Values will be created from (carrier_id, flight_num, departure_time, arrival_delay). Reduce jobs will get all arrival delays from all the keys. The main goal here is to be able to tell average delay for all the origin-destination pair at a given date. Distinguishing morning and afternoon flights. Because the problem can be split into two independent events (getting from X to Y and from Y to Z we can answer each questions by two queries.

*<..., line> -> **map()**-> <(airport_from, airport_to, flight_date, am_or_pm (carrier_id, flight_num, departure_time, arrival_delay)> -> **reduce()** -> <(airport_from, airport_to, flight_date, am_or_pm (carrier_id, flight_num, departure_time, average_arrival_delay)>*

Finally, we can run the query as separate map reduce step on output of above map reduce, and get best arrival time. We are going to run below map reduce for two input (X -> Y Date 1, Time 1) and (Y->Z, Date 2, Time 2)

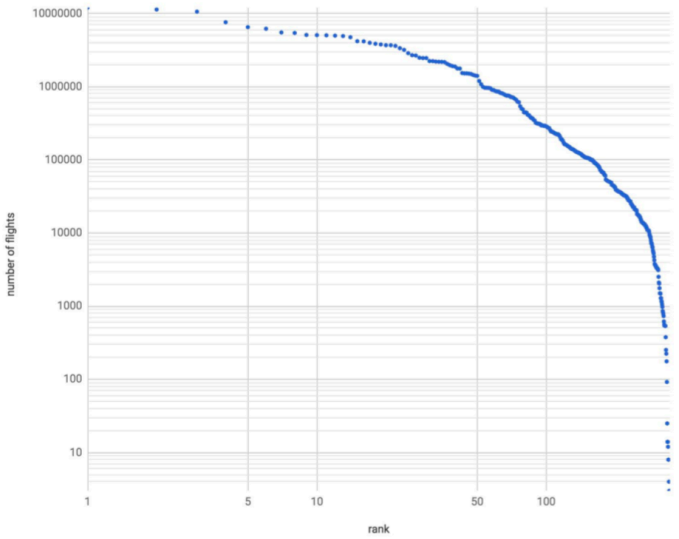
*<…, **Part 1** output line> -> **map()** -> <(X, Y, D1, T1, (carrier_id, flight_num, departure_time, arrival_delay)> -> **reduce()** -> < Best(X, Y, D1, T1 (carrier_id, flight_num, departure_time, average_arrival_delay)>*

Final output is stored the results to DynamoDB table using custom python adapter.

Question 3.1 Does the popularity distribution of airports follow a Zipf distribution? If not, what distribution does it follow?

In a Zipf distribution there is an inverse relation between the rank of an event and the frequency of its occurrence. In context of the aviation dataset, this would mean that the most popular airport should have twice as many flights as the 2nd most popular airport and 3 times as many flights as, the 3rd most popular airport, and so on.

Airport	Rank	Number of flights	Expected
ORD	1	12.051.796	12.051.796
ATL	2	11.323.515	6.025.898
DFW	3	10.591.818	4.017.265
LAX	4	7.586.304	3.012.949
PHX	5	6.505.078	2.410.359
DEN	6	6.183.518	2.008.633
DTW	7	5.504.120	1.721.685
IAH	8	5.416.653	1.506.475
MSP	9	5.087.036	1.339.088
SFO	10	5.062.339	1.205.180
STL	11	5.031.131	1.095.618
EWR	12	4.979.913	1.004.316
LAS	13	4.917.971	927.061
CLT	14	4.735.669	860.843
LGA	15	4.179.969	803.453



The table on the left presents the rank-frequency table for our dataset. The 4th column contains the expected value if the popularity distribution would be a Zipf distribution. Clearly the actual values (3rd column) don't match with the expected values. A Zipf distribution can also easily be recognized as a straight downward line on a log-log graph. The graph on the right above displays this type of graph for the given dataset. Again this is clearly not a straight line. Both support the conclusion that the popularity **distribution is not a Zipf distribution**.

OPTIMIZATIONS

Cleaning Optimization

While cleaning data, I trim down number of columns which help me to process data faster than normal. Also, I used to server less technology (AWS Lambda) to unzip and clean data within 100 seconds.

EMR Cluster Optimization

I experimented with modifying various EMR settings. AWS already did an excellent job in providing an optimized configuration of EMR. Most of the frequently suggested recommendations 3 were already applied out-of-the-box. Not all of the remaining recommended settings resulted in shorter run times. The baseline performance (out-of-the-box EMR cluster) for question 1.1 is improved 30% when I increased cluster size to 5. I also configured to compressing intermediate output, and combiners in map-reduce jobs where cluster do best effort to run reduce job on same node where map was run. This avoid too much data movement.

Query Optimization

For group 2, and group 3 problem, I ran map-reduce in two phases. First phase process all raw data and output summarized data which helps to run query on phase 2 really fast.

RESULTS

Question 1.1
12446097, ORD
11537401, ATL
10795494, DFW
7721141, LAX
6582467, PHX
6270420, DEN
5635421, DTW
5478257, IAH
5197649, MSP
5168898, SFO

Question 1.2
-1.01, HA
1.16, AQ
1.45, PS

4.75, ML
5.35, PA
5.47, F9
5.56, NW
5.56, WN
5.74, OO
5.87, 9E

Question 2.1
CMI
```
[(0.61, u'OH', u'CMI'),
(2.03, u'US', u'CMI'),
(4.12, u'TW', u'CMI'),
(4.46, u'PI', u'CMI'),
(6.03, u'DH', u'CMI'),
(6.67, u'EV', u'CMI'),
(8.02, u'MQ', u'CMI')]
```

BWI
```
[(0.76, u'F9', u'BWI'),
(4.76, u'PA', u'BWI'),
(5.18, u'CO', u'BWI'),
(5.5, u'YV', u'BWI'),
(5.71, u'NW', u'BWI'),
(5.75, u'AL', u'BWI'),
(6.0, u'AA', u'BWI'),
(7.24, u'9E', u'BWI'),
(7.5, u'US', u'BWI'),
(7.68, u'DL', u'BWI')]
```

MIA
```
[(-3.0, u'9E', u'MIA'),
(1.2, u'EV', u'MIA'),
(1.3, u'RU', u'MIA'),
(1.78, u'TZ', u'MIA'),
(2.75, u'XE', u'MIA'),
(4.2, u'PA', u'MIA'),
(4.5, u'NW', u'MIA'),
(6.06, u'US', u'MIA'),
(6.87, u'UA', u'MIA'),
(7.5, u'ML', u'MIA')]
```

LAX
```
[(1.95, u'RU', u'LAX'),
 (2.41, u'MQ', u'LAX'),
 (4.22, u'OO', u'LAX'),
 (4.73, u'FL', u'LAX'),
 (4.76, u'TZ', u'LAX'),
 (4.86, u'PS', u'LAX'),
 (5.12, u'NW', u'LAX'),
 (5.73, u'F9', u'LAX'),
 (5.81, u'HA', u'LAX'),
 (6.02, u'YV', u'LAX')]
```

IAH
```
[(3.56, u'NW', u'IAH'),
 (3.98, u'PA', u'IAH'),
 (3.99, u'PI', u'IAH'),
```

(4.8, u'RU', u'IAH'),
(5.06, u'US', u'IAH'),
(5.1, u'AL', u'IAH'),
(5.55, u'F9', u'IAH'),
(5.71, u'AA', u'IAH'),
(6.05, u'TW', u'IAH'),
(6.23, u'WN', u'IAH')]
```

SFO
```
[(3.95, u'TZ', u'SFO'),
(4.85, u'MQ', u'SFO'),
(5.16, u'F9', u'SFO'),
(5.29, u'PA', u'SFO'),
(5.76, u'NW', u'SFO'),
(6.3, u'PS', u'SFO'),
(6.56, u'DL', u'SFO'),
(7.08, u'CO', u'SFO'),
(7.4, u'US', u'SFO'),
(7.79, u'TW', u'SFO')]
```

*# Question 2.2*
CMI
```
[(-7.0, u'ABI', u'CMI'),
(1.1, u'PIT', u'CMI'),
(1.89, u'CVG', u'CMI'),
(3.12, u'DAY', u'CMI'),
(3.98, u'STL', u'CMI'),
(4.59, u'PIA', u'CMI'),
(5.94, u'DFW', u'CMI'),
(6.67, u'ATL', u'CMI'),
```
```

(8.19, u'ORD', u'CMI')]
```

BWI
```
[(-7.0, u'SAV', u'BWI'),
 (1.16, u'MLB', u'BWI'),
 (1.47, u'DAB', u'BWI'),
 (1.59, u'SRQ', u'BWI'),
 (1.79, u'IAD', u'BWI'),
 (3.65, u'UCA', u'BWI'),
 (3.74, u'CHO', u'BWI'),
 (4.2, u'GSP', u'BWI'),
 (4.45, u'SJU', u'BWI'),
 (4.47, u'OAJ', u'BWI')]
```

MIA
```
[(0.0, u'SHV', u'MIA'),
 (1.0, u'BUF', u'MIA'),
 (1.71, u'SAN', u'MIA'),
 (2.54, u'SLC', u'MIA'),
 (2.91, u'HOU', u'MIA'),
 (3.65, u'ISP', u'MIA'),
 (3.75, u'MEM', u'MIA'),
 (3.98, u'PSE', u'MIA'),
 (4.26, u'TLH', u'MIA'),
 (4.61, u'MCI', u'MIA')]
```

LAX
```
[(-16.0, u'SDF', u'LAX'),
```
```

```
 (-7.0, u'IDA', u'LAX'),
 (-6.0, u'DRO', u'LAX'),
 (-3.0, u'RSW', u'LAX'),
 (-2.0, u'LAX', u'LAX'),
 (-0.73, u'BZN', u'LAX'),
 (0.0, u'MAF', u'LAX'),
 (0.0, u'PIH', u'LAX'),
 (1.27, u'IYK', u'LAX'),
 (1.38, u'MFE', u'LAX')]
```

IAH

```
[(-2.0, u'MSN', u'IAH'),
 (-0.62, u'AGS', u'IAH'),
 (-0.5, u'MLI', u'IAH'),
 (1.89, u'EFD', u'IAH'),
 (2.17, u'HOU', u'IAH'),
 (2.57, u'JAC', u'IAH'),
 (2.95, u'MTJ', u'IAH'),
 (3.22, u'RNO', u'IAH'),
 (3.6, u'BPT', u'IAH'),
 (3.61, u'VCT', u'IAH')]
```

SFO

```
[(-10.0, u'SDF', u'SFO'),
 (-4.0, u'MSO', u'SFO'),
 (-3.0, u'PIH', u'SFO'),
 (-1.76, u'LGA', u'SFO'),
 (-1.34, u'PIE', u'SFO'),
 (-0.81, u'OAK', u'SFO'),
 (0.0, u'FAR', u'SFO'),
```

(2.43, u'BNA', u'SFO'),
(3.3, u'MEM', u'SFO'),
(4.0, u'SCK', u'SFO')]
```

*## Question 2.4*

CMI - ORD

```
[[u'CMI', u'ORD', u'10.14']]
```

IND - CMH

```
[[u'IND', u'CMH', u'2.89']]
```

DFW - IAH

```
[[u'DFW', u'IAH', u'7.62']]
```

LAX - SFO

```
[[u'LAX', u'SFO', u'9.59']]
```

JFK - LAX

```
[[u'JFK', u'LAX', u'6.64']]
```

ATL - PHX

```
[[u'ATL', u'PHX', u'9.02']]
```

Question 3.2

CMI → ORD → LAX, 04/03/2008

```

MQ 4278 at 07:10, delay: -14.00

AA 607 at 19:50, delay: -24.00

```

JAX → DFW → CRP, 09/09/2008

```

AA 845 at 07:25, delay: 1.00

MQ 3627 at 16:45, delay: -7.00

```

SLC → BFL → LAX, 01/04/2008

```

OO 3755 at 11:00, delay: 12.00

OO 5429 at 14:55, delay: 6.00

```

LAX → SFO → PHX, 12/07/2008

```

WN 3534 at 06:50, delay: -13.00

US 412 at 19:25, delay: -19.00

```

DFW → ORD → DFW, 10/06/2008

```

UA 1104 at 07:00, delay: -21.00

AA 2341 at 16:45, delay: -10.00

```

LAX → ORD → JFK, 01/01/2008

```

UA 944 at 07:05, delay: 1.00

B6 918 at 19:00, delay: -7.00

```
```