Analysis of Airport Data using Hadoop-Hive: A Case Study

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ABSTRACT
In the contemporary world, Data analysis is a challenge in the era of varied inters- disciplines though there is a specialization in the respective disciplines. In other words, effective data analytics helps in analyzing the data of any business system. But it is the big data which helps and axialrates the process of analysis of data paving way for a success of any business intelligence system. With the expansion of the industry, the data of the industry also expands. Then, it is increasingly difficult to handle huge amount of data that gets generated no matter what's the business is like, range of fields from social media to finance, flight data, environment and health. Big Data can be used to assess risk in the insurance industry and to track reactions to products in real time. Big Data is also used to monitor things as diverse as wave movements, flight data, traffic data, financial transactions, health and crime. The challenge of Big Data is how to use it to create something that is value to the user. How can it be gathered, stored, processed and analyzed it to turn the raw data information to support decision making. In this paper Big Data is depicted in a form of case study for Airline data based on hive tools.

General Terms
Big data, Hive Tools, Data Analytics, Hadoop, Distributed File System

Keywords
Airline data set, Hive Tools.

1. INTRODUCTION
Big Data is not only a Broad term but also a latest approach to analyze a complex and huge amount of data; there is no single accepted definition for Big Data. But many researchers working on Big Data have defined Big Data in different ways. One such approach is that it is characterized by the widely used 4 V's approach [1]. The first "V" is Volume, from which the Big Data comes from. This is the data which is difficult to handle in conventional data analytics. For example, Volume of data created by the BESCOM (Bengaluru Electricity Supply Company) in the process of the power supply and its consumption for Bangalore city or for the entire Karnataka State generates a huge volume of data. To analyze such data, it is the Big data that comes to aid of data analytics; the second "V" is velocity, the high speed at which the data is created, processed and analyzed; the third "V" is variety which helps to analyze the data like face book data which contains all types of variety, like text messages, attachments, images, photos and so on; the forth "V" is Veracity, that is cleanliness and accuracy of the data with the available huge amount of data which is being used for processing.

Researchers working in the structured data face many challenges [1] in analyzing the data. For instance the data created through social media, in blogs, in Facebook posts or Snap chat. These types of data have different structures and formats and are more difficult to store in a traditional business data base. The data in big data comes in all shapes and formats including structured. Working with big data means handling a variety of data formats and structures. Big data can be a data created from sensors which track the movement of objects or changes in the environment such as temperature fluctuations or astronomy data. In the world of the internet of things, where devices are connected and these wearable create huge volume of data. Thus big data approaches are used to manage and analyze this kind of data. Big Data include data from a whole range of fields such as flight data, population data, financial and health data such data brings as to another V, value which has been proposed by a number of researcher [3, 4 and 5] i.e, Veracity.

Most of the time social media is analyzed by advertisers and used to promote produces and events but big data has many other uses. It can also been used to assess risk in the insurance industry and to track reaction to products in real time. Big Data is also used to monitor things as diverse as wave movements, flight data, traffic data, financial transactions, health and crime. The challenge of Big Data is how to use it to create something that is value to the user. How to gather it, store it, process it and analyze it to turn the raw data information to support decision making.

Hadoop allows to store and process Big Data in a distributed environment across group of computers using simple programming models. It is intended to scale up starting with solitary machines and will be scaled to many machines. In this paper Hive tool is used. The primary goal of Hive [8] is to provide answers about business functions, system performance, and user activity. To meet these needs strongly dumping the data into MYSQL data set, but now since huge amount of data in Terabytes which is injected into Hadoop Distributed File System files and processed by Hive Tool.

2. RELATED WORK
As far as data storage model considered by B-trees or distributed hash tables using key-value pair is too limited to handle large data sets. Many projects have attempted to provide solutions for distributed storage at higher-level services over wide area networks, often at Internet scale. This incorporates take a shot at disseminated hash tables that started with ventures, for example, CAN [14], Chord [16], Tapestry [18], and Pastry [15]. These frameworks address worries that don't emerge for Bigtable, for example, profoundly variable data transfer capacity, untrusted members, decentralized control and Byzantine adaptation to internal failure are not Bigtable objectives.

Several database developers have created parallel databases that can store huge volumes of information. Oracle's Real Application Cluster database [13] utilizes shared disks to store information (Bigtable uses GFS) and an appropriated lock director (Bigtable uses Chubby). IBM's DB2 Parallel Edition

[12] depends on a shared-nothing [17] design like Bigtable. Each DB2 server is accountable for a subset of the columns in a table which it stores in a relational database. Both databases afford a complete relational model with transactions. The limitation is that it is not scalable for huge amount of data as data increases to a very larger extent. Hence apache hive supports for huge amount of data

In this paper Apache Hive is considered for analysing large datasets stored in Hadoop's HDFS and compatible file systems such as Amazon S3 filesystem. It provides an SQL-like language called HiveQL[9] with schema on read and transparently converts queries to MapReduce, Apache Tez[10] and Spark jobs. All three execution engines can run in Hadoop YARN. To accelerate queries, it provides indexes, including bitmap indexes [11].

3. CHALLENGES IN BIG DATA

The uses of Big Data in various fields of knowledge are immense in the sense its potentiality of micro and macro levels of analysis of the data. For instance, the tools in Big Data help the Institutions to study the quantitative and qualitative learning abilities of students from different strata of the society. Even the behavioral learning and the psychological attitudes of the student may also be estimated through the tools of Big Data. Big Data can also be used in analyzing the cognitive abilities and the impact of health in acquiring the knowledge since health condition of the students usually affects on learning process.

Further, the scope of big data is so vast that it has been used in globalized urban societies in planning the locality, intelligence transportation, air ambulance monitoring system, road mapping, environment and natural disaster prediction.

Big Data is supported by range of technologies such as Hadoop [4]. Traditional relational data base skill are still in high demand but increasingly, so are the skills needed to work with the generation of non-relational data bases known as NoSQL. These NoSQL data bases which are often open source are built to handle the processing of large volumes of data and use different design strategies, architectures and query languages. One of the biggest challenges in Big Data is Big Data analytics, where analyze examining and interpret Big Data.

In this paper first tables were created for the below mentioned Data Set [6]. The Data set was loaded into the created tables on an HDFS system. The Hive queries were applied and the results were analyzed.

4. ANALYSIS OF AIRPORT DATA

The proposed method is made by considering following scenario under consideration

An Airport has huge amount of data related to number of flights, data and time of arrival and dispatch, flight routes, No. of airports operating in each country, list of active airlines in each country. The problem they faced till now it's, they have ability to analyze limited data from databases. The Proposed model intension is to develop a model for the airline data to provide platform for new analytics based on the following queries.

The data description is as shown in Table 1 to Table 3

Table 1: Airport Data Set [6]

Attribute	Description
Airport ID	Unique OpenFlights identifier for this airport
Name	Name of airport. May or may not contain the City name.
City	Main city served by airport. May be spelled differently from Name.
Country	Country or territory where airport is located.
IATA/FAA	3-letter FAA code, for airports located in Country "United States of America"
ICAO	4-letter ICAO code.
Latitude	Decimal degrees, usually to six significant digits. Negative is South, positive is North.
Longitude	Decimal degrees, usually to six significant digits. Negative is West, positive is East.
Altitude	In feet.
Timezone	Hours offset from UTC. Fractional hours are expressed as decimals, eg. India is 5.5.
DST	Daylight savings time. One of E (Europe), A (US/Canada), S (South America), O (Australia), Z (New Zealand), N (None) or U (Unknown). See also: Help: Time
Tz database time	Timezone in "tz" (Olson) format, eg. "America/Los_Angeles". zone

Table 2: Airline Data Set [6]

Attribute	Description
Airline	Unique OpenFlights identifier for this airline. ID
Name	Name of the airline
Alias	Alias of the airline. For example, All Nippon Airways is commonly known as "ANA".
IATA	2-letter IATA code, if available.
ICAO	3-letter ICAO code, if available
Callsign	Airline callsign.
Country	Country or territory where airline is incorporated
Active	"Y" if the airline is or has until recently been operational, "N" if it is defunct. This field is not reliable: in particular, major airlines that stopped flying long ago, but have not had their IATA code reassigned (eg. Ansett/AN), will incorrectly show as "Y".

Table 3: Route Data Set [6]

Attribute	Description
Airline	2-letter (IATA) or 3-letter(ICAO) code of the airline.
Airline ID	Unique OpenFlights identifier for airline
Source airport	3-letter (IATA) or 4-letter (ICAO) code of the source airport
Source airport ID	Unique OpenFlights identifier for source airport
Destination airport	3-letter (IATA) or 4-letter (ICAO) code of the destination airport.
Destination airport ID	Unique OpenFlights identifier for destination airport.
Codeshare	"Y" if this flight is a codeshare (that is, not operated by Airline, but another carrier), empty otherwise.
Stops	Number of stops on this flight ("0" for direct)
Equipment	3-letter codes for plane type(s) generally used on this flight, separated by spaces

This paper proposes a method to analyze few aspects which are related to airline data such as

a) list of airports operating in the country India,

b) list of airlines having zero stops

c) list of airlines operating with code share

d) list highest airports in each country

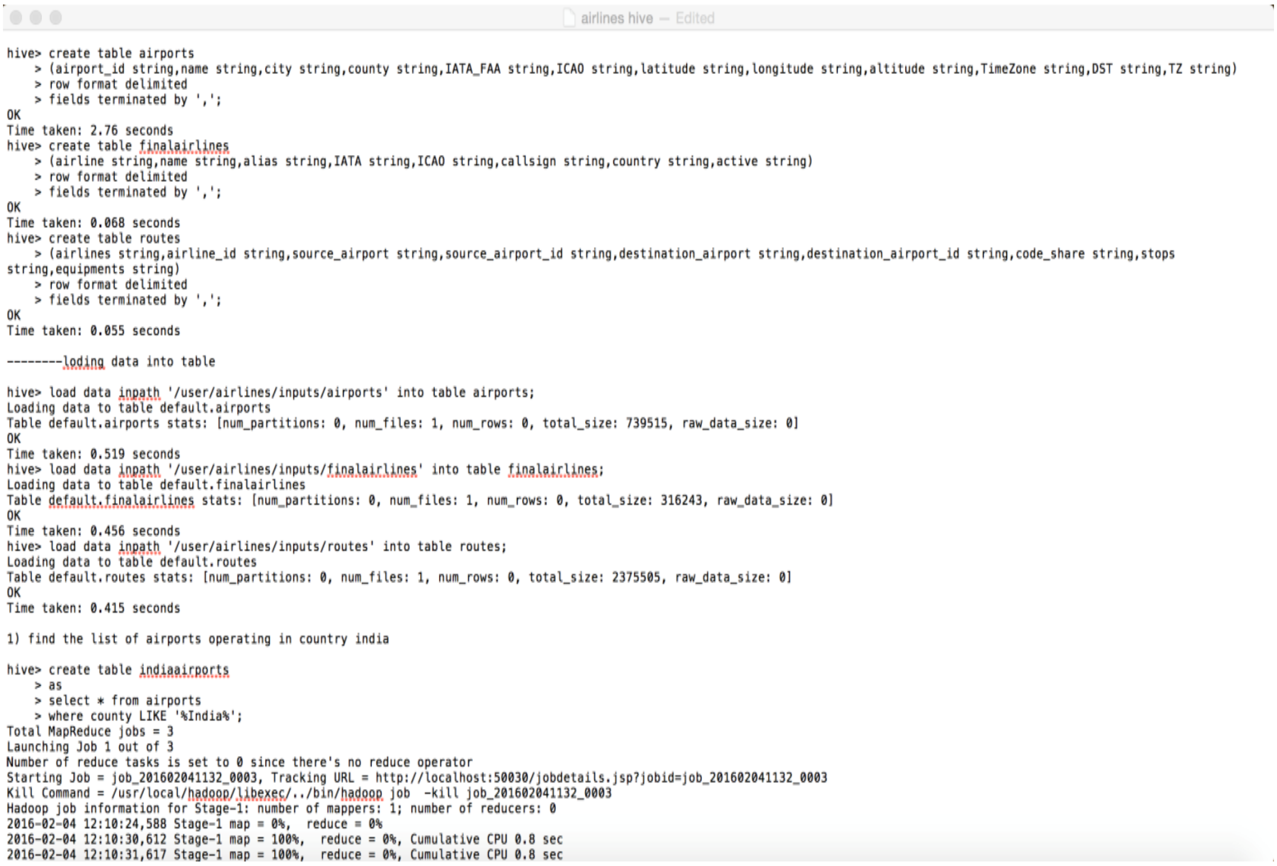
e) list of active airlines in United State

5. METHODOLOGY

In this paper the tools used for the proposed method is Hadoop , Hive and Sqoop which is mainly used for structured data. Assuming all the Hadoop tools have been installed and having semi structured information on airport data [7, 8]. The above mentioned queries have to be addressed

Methodology used is as follows:

1. Create tables with required attributes
2. Extract semi structured data into table using the load a command
3. Analyze data for the following queries
    a) list of airports operating in the country India
    b) list of airlines having zero stops
    c) list of airlines operating with code share
    d) which country has highest airports
    e) list of active airlines in United State



```
airlines hive — Edited

hive> create table airports
    > (airport_id string,name string,city string,county string,IATA_FAA string,ICAO string,latitude string,longitude string,altitude string,TimeZone string,DST string,TZ string)
    > row format delimited
    > fields terminated by ',';
OK
Time taken: 2.76 seconds
hive> create table finalairlines
    > (airline string,name string,alias string,IATA string,ICAO string,callsign string,country string,active string)
    > row format delimited
    > fields terminated by ',';
OK
Time taken: 0.068 seconds
hive> create table routes
    > (airlines string,airline_id string,source_airport string,source_airport_id string,destination_airport string,destination_airport_id string,code_share string,stops
string,equipments string)
    > row format delimited
    > fields terminated by ',';
OK
Time taken: 0.055 seconds

--------loding data into table

hive> load data inpath '/user/airlines/inputs/airports' into table airports;
Loading data to table default.airports
Table default.airports stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 739515, raw_data_size: 0]
OK
Time taken: 0.519 seconds
hive> load data inpath '/user/airlines/inputs/finalairlines' into table finalairlines;
Loading data to table default.finalairlines
Table default.finalairlines stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 316243, raw_data_size: 0]
OK
Time taken: 0.456 seconds
hive> load data inpath '/user/airlines/inputs/routes' into table routes;
Loading data to table default.routes
Table default.routes stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 2375505, raw_data_size: 0]
OK
Time taken: 0.415 seconds

1) find the list of airports operating in country india

hive> create table indiaairports
    > as
    > select * from airports
    > where county LIKE '%India%';
Total MapReduce jobs = 3
Launching Job 1 out of 3
Number of reduce tasks is set to 0 since there's no reduce operator
Starting Job = job_201602041132_0003, Tracking URL = http://localhost:50030/jobdetails.jsp?jobid=job_201602041132_0003
Kill Command = /usr/local/hadoop/libexec/../bin/hadoop job  -kill job_201602041132_0003
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 0
2016-02-04 12:10:24,588 Stage-1 map = 0%,  reduce = 0%
2016-02-04 12:10:30,612 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:31,617 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
```

Fig 1 Create and Load data set into HDFS

```
airlines hive — Edited
Time taken: 0.555 seconds

hive> create table act
    > as
    > select active,count(*) as status
    > from activec
    > group by active;
Total MapReduce jobs = 1
Launching Job 1 out of 1
Number of reduce tasks not specified. Estimated from input data size: 1
In order to change the average load for a reducer (in bytes):
  set hive.exec.reducers.bytes.per.reducer=<number>
In order to limit the maximum number of reducers:
  set hive.exec.reducers.max=<number>
In order to set a constant number of reducers:
  set mapred.reduce.tasks=<number>
Starting Job = job_201602041132_0016, Tracking URL = http://localhost:50030/jobdetails.jsp?jobid=job_201602041132_0016
Kill Command = /usr/local/hadoop/libexec/../bin/hadoop job  -kill job_201602041132_0016
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 1
2016-02-04 13:36:31,549 Stage-1 map = 0%,  reduce = 0%
2016-02-04 13:36:37,575 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:38,579 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:39,583 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:40,586 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:41,590 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:42,594 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:43,598 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:44,601 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:45,606 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.74 sec
2016-02-04 13:36:46,609 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 0.74 sec
2016-02-04 13:36:47,613 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 0.74 sec
2016-02-04 13:36:48,617 Stage-1 map = 100%,  reduce = 33%, Cumulative CPU 0.74 sec
2016-02-04 13:36:49,621 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:50,625 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:51,628 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:52,632 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:53,637 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:54,670 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
2016-02-04 13:36:55,674 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.8 sec
MapReduce Total cumulative CPU time: 1 seconds 800 msec
Ended Job = job_201602041132_0016
Moving data to: hdfs://localhost:54310/user/hive/warehouse/act
Table default.act stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 12, raw_data_size: 0]
2 Rows loaded to hdfs://localhost:54310/tmp/hive-training/hive_2016-02-04_13-36-21_953_93347702611895010/-ext-10000
MapReduce Jobs Launched:
Job 0: Map: 1  Reduce: 1   Cumulative CPU: 1.8 sec   HDFS Read: 62375 HDFS Write: 12 SUCCESS
Total MapReduce CPU Time Spent: 1 seconds 800 msec
OK
Time taken: 34.112 seconds
hive> select * from act;
OK
N       939
Y       141
Time taken: 0.149 seconds
```

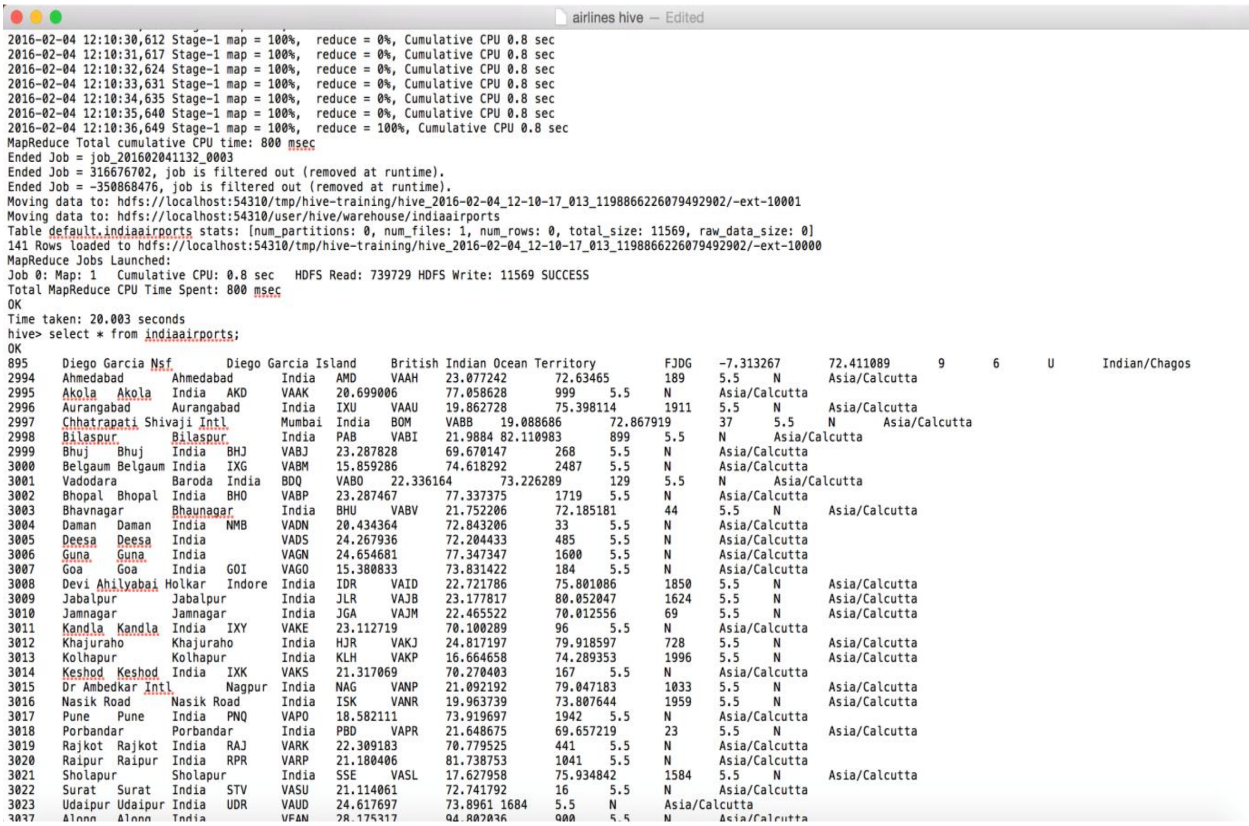
Fig 2 List of airlines operating with code share

```
airlines hive — Edited
Time taken: 0.162 seconds
hive> select * from indiaairports limit 10;
OK
895     Diego Garcia Nsf        Diego Garcia Island     British Indian Ocean Territory          FJDG    -7.313267       72.411089       9       6       U       Indian/Chagos
2994    Ahmedabad       Ahmedabad       India   AMD     VAAH    23.077242       72.63465        189     5.5     N       Asia/Calcutta
2995    Akola   Akola   India   AKD     VAAK    20.699006       77.058628       999     5.5     N       Asia/Calcutta
2996    Aurangabad      Aurangabad      India   IXU     VAAU    19.862728       75.398114       1911    5.5     N       Asia/Calcutta
2997    Chhatrapati Shivaji Intl        Mumbai  India   BOM     VABB    19.088686       72.867919       37      5.5     N       Asia/Calcutta
2998    Bilaspur        Bilaspur        India   PAB     VABI    21.9884 82.110983       899     5.5     N       Asia/Calcutta
2999    Bhuj    Bhuj    India   BHJ     VABJ    23.287828       69.670147       268     5.5     N       Asia/Calcutta
3000    Belgaum Belgaum India   IXG     VABM    15.859286       74.618292       2487    5.5     N       Asia/Calcutta
3001    Vadodara        Baroda  India   BDQ     VABO    22.336164       73.226289       129     5.5     N       Asia/Calcutta
3002    Bhopal  Bhopal  India   BHO     VABP    23.287467       77.337375       1719    5.5     N       Asia/Calcutta
Time taken: 0.155 seconds

----2)find the list of airlines having zero stops

hive> create table stops
    > as
    > select * from routes
    > where stops LIKE '%0%';
Total MapReduce jobs = 3
Launching Job 1 out of 3
Number of reduce tasks is set to 0 since there's no reduce operator
Starting Job = job_201602041132_0004, Tracking URL = http://localhost:50030/jobdetails.jsp?jobid=job_201602041132_0004
Kill Command = /usr/local/hadoop/libexec/../bin/hadoop job  -kill job_201602041132_0004
Hadoop job information for Stage-1: number of mappers: 1; number of reducers: 0
2016-02-04 12:21:57,952 Stage-1 map = 0%,  reduce = 0%
2016-02-04 12:22:03,971 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:04,976 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:05,981 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:06,986 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:07,994 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:08,998 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 1.38 sec
2016-02-04 12:22:10,007 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 1.38 sec
MapReduce Total cumulative CPU time: 1 seconds 380 msec
Ended Job = job_201602041132_0004
Ended Job = 922720114, job is filtered out (removed at runtime).
Ended Job = 791142581, job is filtered out (removed at runtime).
Moving data to: hdfs://localhost:54310/tmp/hive-training/hive_2016-02-04_12-21-48_363_8665527539085313959/-ext-10001
Moving data to: hdfs://localhost:54310/user/hive/warehouse/stops
Table default.stops stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 2307487, raw_data_size: 0]
67652 Rows loaded to hdfs://localhost:54310/tmp/hive-training/hive_2016-02-04_12-21-48_363_8665527539085313959/-ext-10000
MapReduce Jobs Launched:
Job 0: Map: 1   Cumulative CPU: 1.38 sec   HDFS Read: 2375715 HDFS Write: 2307487 SUCCESS
Total MapReduce CPU Time Spent: 1 seconds 380 msec
OK
Time taken: 21.992 seconds
```

Fig 3: List of airlines having zero stops



```
airlines hive — Edited
2016-02-04 12:10:30,612 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:31,617 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:32,624 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:33,631 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:34,635 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:35,640 Stage-1 map = 100%,  reduce = 0%, Cumulative CPU 0.8 sec
2016-02-04 12:10:36,649 Stage-1 map = 100%,  reduce = 100%, Cumulative CPU 0.8 sec
MapReduce Total cumulative CPU time: 800 msec
Ended Job = job_201602041132_0003
Ended Job = 316676702, job is filtered out (removed at runtime).
Ended Job = -350868476, job is filtered out (removed at runtime).
Moving data to: hdfs://localhost:54310/tmp/hive-training/hive_2016-02-04_12-10-17_013_1198866226079492902/-ext-10001
Moving data to: hdfs://localhost:54310/user/hive/warehouse/indiaairports
Table default.indiaairports stats: [num_partitions: 0, num_files: 1, num_rows: 0, total_size: 11569, raw_data_size: 0]
141 Rows loaded to hdfs://localhost:54310/tmp/hive-training/hive_2016-02-04_12-10-17_013_1198866226079492902/-ext-10000
MapReduce Jobs Launched:
Job 0: Map: 1   Cumulative CPU: 0.8 sec   HDFS Read: 739729 HDFS Write: 11569 SUCCESS
Total MapReduce CPU Time Spent: 800 msec
OK
Time taken: 20.003 seconds
hive> select * from indiaairports;
OK
895     Diego Garcia Nsf        Diego Garcia Island     British Indian Ocean Territory        FJDG    -7.313267       72.411089       9       6       U       Indian/Chagos
2994    Ahmedabad       Ahmedabad       India   AMD     VAAH    23.077242       72.63465        189     5.5     N       Asia/Calcutta
2995    Akola   Akola   India   AKD     VAAK    20.699006       77.058628       999     5.5     N       Asia/Calcutta
2996    Aurangabad      Aurangabad      India   IXU     VAAU    19.862728       75.398114       1911    5.5     N       Asia/Calcutta
2997    Chhatrapati Shivaji Intl        Mumbai  India   BOM     VABB    19.088686       72.867919       37      5.5     N       Asia/Calcutta
2998    Bilaspur        Bilaspur        India   PAB     VABI    21.9884 82.110983       899     5.5     N       Asia/Calcutta
2999    Bhuj    Bhuj    India   BHJ     VABJ    23.287828       69.670147       268     5.5     N       Asia/Calcutta
3000    Belgaum Belgaum India   IXG     VABM    15.859286       74.618292       2487    5.5     N       Asia/Calcutta
3001    Vadodara        Baroda  India   BDQ     VABO    22.336164       73.226289       129     5.5     N       Asia/Calcutta
3002    Bhopal  Bhopal  India   BHO     VABP    23.287467       77.337375       1719    5.5     N       Asia/Calcutta
3003    Bhavnagar       Bhaunagar       India   BHU     VABV    21.752206       72.185181       44      5.5     N       Asia/Calcutta
3004    Daman   Daman   India   NMB     VADN    20.434364       72.843206       33      5.5     N       Asia/Calcutta
3005    Deesa   Deesa   India           VADS    24.267936       72.204433       485     5.5     N       Asia/Calcutta
3006    Guna    Guna    India           VAGN    24.654681       77.347347       1600    5.5     N       Asia/Calcutta
3007    Goa     Goa     India   GOI     VAGO    15.380833       73.831422       184     5.5     N       Asia/Calcutta
3008    Devi Ahilyabai Holkar   Indore  India   IDR     VAID    22.721786       75.801086       1850    5.5     N       Asia/Calcutta
3009    Jabalpur        Jabalpur        India   JLR     VAJB    23.177817       80.052047       1624    5.5     N       Asia/Calcutta
3010    Jamnagar        Jamnagar        India   JGA     VAJM    22.465522       70.012556       69      5.5     N       Asia/Calcutta
3011    Kandla  Kandla  India   IXY     VAKE    23.112719       70.100289       96      5.5     N       Asia/Calcutta
3012    Khajuraho       Khajuraho       India   HJR     VAKJ    24.817197       79.918597       728     5.5     N       Asia/Calcutta
3013    Kolhapur        Kolhapur        India   KLH     VAKP    16.664658       74.289353       1996    5.5     N       Asia/Calcutta
3014    Keshod  Keshod  India   IXK     VAKS    21.317069       70.270403       167     5.5     N       Asia/Calcutta
3015    Dr Ambedkar Intl        Nagpur  India   NAG     VANP    21.092192       79.047183       1033    5.5     N       Asia/Calcutta
3016    Nasik Road      Nasik Road      India   ISK     VANR    19.963739       73.807644       1959    5.5     N       Asia/Calcutta
3017    Pune    Pune    India   PNQ     VAPO    18.582111       73.919697       1942    5.5     N       Asia/Calcutta
3018    Porbandar       Porbandar       India   PBD     VAPR    21.648675       69.657219       23      5.5     N       Asia/Calcutta
3019    Rajkot  Rajkot  India   RAJ     VARK    22.309183       70.779525       441     5.5     N       Asia/Calcutta
3020    Raipur  Raipur  India   RPR     VARP    21.180406       81.738753       1041    5.5     N       Asia/Calcutta
3021    Sholapur        Sholapur        India   SSE     VASL    17.627958       75.934842       1584    5.5     N       Asia/Calcutta
3022    Surat   Surat   India   STV     VASU    21.114061       72.741792       16      5.5     N       Asia/Calcutta
3023    Udaipur Udaipur India   UDR     VAUD    24.617697       73.8961 1684    5.5     N       Asia/Calcutta
3037    Along   Along   India           VEAN    28.175317       94.802036       900     5.5     N       Asia/Calcutta
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Fig 4: List of airports operating in country India

6. RESULTS AND DISCUSSION

This paper emphasize on data analysis on airline data set. The paper address the usage of modern analytical tool Hive on Big Data set which focus on common requirements of any airport. Some of the instances are highlighted below with the sample snapshots shown in Figure 1 to 4. Figure 1 shows the create table and load data commands for HDFS system. It also gives number of Map and Reduce that are internally taken care by the underlying tools of Hadoop System. Figure 2, 3 and 4 shows sample queries that have been executed with Hive on Hadoop. It is found that Hive is effective in-terms of processing huge data sets when compared to traditional data bases with respect to time and data volume.

7. CONCLUSION

This paper addresses the related work of distributed data bases that were found in literature, challenges ahead with big data, and a case study on airline data analysis using Hive. Author attempted to explore detailed analysis on airline data sets such as listing airports operating in the India, list of airlines having zero stops, list of airlines operating with code share which country has highest airports and list of active airlines in united state. Here author focused on the processing the big data sets using hive component of hadoop ecosystem in distributed environment. This work will benefit the developers and business analysts in accessing and processing their user queries.

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