



## 1. What happened to OAK in 1994?

In 1994 Southwest opened a crew base at Oakland. Since then the majority of flights to and from OAK are with Southwest. SFO's largest airline is United. SkyWest is probably operating as United Express. Flights to and from SFO exhibit some seasonality, with more flights during the summer, whereas flights at OAK do not.

Photo credit: **Aman Mundra**

# US flight data analysis using hive

🕒 10 minute read

*This post is about analysing 20 million rows of flight on-time/delay performance using hadoop and hive.*

Knowledge required: SQL and basic hadoop(hdfs, hive) concepts

Tools required: Any host system(I'm using windows7), cloudera's CDH 5.4.0 quickstart virtual instance

## Introduction

The Airline On-Time Performance Data, "contains on-time arrival data for non-stop domestic flights by major air carriers, and provides such additional items as departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance."

This dataset can be used to work on cool travel ideas like:

1. When is the best time of day/day of week/time of year to fly to minimise delays?
2. Do older planes suffer more delays?
3. How does the number of people flying between different locations change over time?
4. How well does weather predict plane delays?
5. Can you detect cascading failures as delays in one airport create delays in others? Are there critical links in the system?

# Get the flight data

we can easily get the data from [here](http://stat-computing.org/dataexpo/2009/) (<http://stat-computing.org/dataexpo/2009/>). The data is provided in the form of .csv files from year 1987 to 2008. It's a huge dataset(2 decades old) which contains around 120 million rows of flight details and sums up to about 12GB when uncompressed. Following is the detailed description of all the variables used in the dataset.

## Variable descriptions

	Name	Description
1	Year	: 1987-2008
2	Month	: 1-12
3	DayofMonth	: 1-31
4	DayOfWeek	: 1 (Monday) - 7 (Sunday)
5	DepTime	: actual departure time (local, hhmm)
6	CRSDepTime	: scheduled departure time (local, hhmm)
7	ArrTime	: actual arrival time (local, hhmm)
8	CRSArrTime	: scheduled arrival time (local, hhmm)
9	UniqueCarrier	: unique carrier code
10	FlightNum	: flight number
11	TailNum	plane : tail number
12	ActualElapsedTime	: in minutes
13	CRSElapsedTime	: in minutes
14	AirTime	: in minutes
15	ArrDelay	: arrival delay, in minutes
16	DepDelay	: departure delay, in minutes
17	Origin	: origin IATA airport code
18	Dest	: destination IATA airport code
19	Distance	: in miles
20	TaxiIn	: taxi in time, in minutes
21	TaxiOut	: taxi out time in minutes
22	Cancelled	: was the flight cancelled? 0 or 1
23	CancellationCode	: reason for cancellation (A = carrier, B = weather, C = NAS, D = security)
24	Diverted	: 1 = yes, 0 = no
25	CarrierDelay	: in minutes
26	WeatherDelay	: in minutes
27	NASDelay	: in minutes
28	SecurityDelay	: in minutes
29	LateAircraftDelay	: in minutes

Some important variables:

## Time Related

```
month  
quarter  
day of month
```

## Geography

```
origin  
destination
```

## Operations

```
delays  
arrival  
departure
```

## Flight Data

```
carrier code  
tail number  
flight number
```

## THE DATA

Twenty years of data (120 million observations) on commercial domestic flights in the United States.

### Variables

- *Dates*: day of week, date, month, year
- *Arrival and departure times*: actual and scheduled
- *Flight times*: actual and scheduled
- *Origin and destination*: airport code, latitude, longitude
- *Carrier*: American, Aloha Air, ..., United, US Air

Data are from the Research and Innovative Technology Administration (RITA) which coordinates the U.S. Department of Transportation research programs

## GOALS

- **Summarize data by time periods, airport, and carrier**
- **Temporal effects**
  - Are some time periods more prone to delays than others?
  - Relationships between delays and
    - Seasonal factors*: winter, summer, holidays
    - Weather factors*: blizzards and severe weather
    - Daily factors*: time of day, day of week
- **Spatial effects**
  - Are some airports more prone to delays than others?
  - Are there differences between flying into an airport and flying out?
- **Carrier effects**
  - Are some carriers more prone to delays than others?

# Load data in HDFS

Once we get the data, our next task is to load it in HDFS for further analysis. Currently the data is in the host OS's file system. In order to load the data in HDFS we have to move the data from host OS to guest OS first and then from guest OS's file-system to HDFS. To transfer data from host to guest OS, we can simply create a shared folder in host OS and access it from guest OS. Now transfer the data files from guest OS to HDFS using command line and hadoop fs commands.

```
// put in HDFS
$~ hadoop fs -put /local_path/file_pattern* /path/to/your/directory
// check files
$~ hadoop fs -ls /path/to/your/directory
```

Another easier way is upload it using HUE web GUI(from host OS).

## Create table structure in hive

Now we will create a schema for the dataset and then load all the .csv files in this newly created table. In the background we are simply creating a logical table structure over the HDFS dataset using Hive. Note that at this point, only the logical structure is defined, data is still not loaded in the table. This property is called Schema on read.

"*Schema-on-read*" means you do not need to know how you will use your data when you are storing it. This allows you to innovate quickly by asking different and more powerful questions after storing the data.

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**Schema-on-Read vs Schema-on-Write** from **Amr Awadallah**

## Create External Table

Here we're creating an external hive table, so that the same dataset can be used for other operations(pig, Hbase) as well.

```
CREATE EXTERNAL TABLE if not exists airlines (  
Year int,  
Month int,  
DayOfMonth int,  
DayOfWeek int,  
DepTime int,  
CRSDepTime int,  
ArrTime int,  
CRSArrTime int,  
UniqueCarrier string,  
FlightNum int,  
TailNum string,  
ActualElapsedTime int,  
CRSElapsedTime int,  
AirTime int,  
ArrDelay int,  
DepDelay int,  
Origin string,  
Dest string,  
Distance int,  
TaxiIn int,  
TaxiOut int,  
Cancelled int,  
CancellationCode string,  
Diverted string,  
CarrierDelay int,  
WeatherDelay int,  
NASDelay int,  
SecurityDelay int,  
LateAircraftDelay int  
)  
row format delimited  
fields terminated by ','  
lines terminated by '\n'  
stored as TEXTFILE;
```

## Describe table

Once the table structure is created we can easily view it using Hive describe clause.

```
1 | describe airlines;
```

# Load data in Table

Next step is to load the data in the hive table that we created.

```
Load data local INPATH '/user/aman/airlines_data'
OVERWRITE into TABLE airlines;
```

## Check if data is loaded

Run a simple select/count query to check if the data is loaded correctly in the table.

```
// simple hive statement to fetch top 10 records
select * from airlines limit 10;
```

```
// you can notice from the result how huge the dataset is
select count(*) from airlines;
```

# Bucketing and data sampling

We can also bucket the data using the following query or can further use these buckets to create sample data for test analysis.

```
create table airlines_bucketed (
  Year int, Month int, DayOfMonth int, DayOfWeek int, DepTime int, CRSDepTime int, ArrTime int,
  CRSArrTime int,
  UniqueCarrier string, FlightNum int, TailNum string, ActualElapsedTime int, CRSElapsedTime int,
  AirTime int,
  ArrDelay int, DepDelay int, Origin string, Dest string, Distance int, TaxiIn int, TaxiOut int,
  Cancelled int,
  CancellationCode string, Diverted string, CarrierDelay int, WeatherDelay int, NASDelay int,
  SecurityDelay int, LateAircraftDelay int
)
clustered by (year) into 22 buckets
row format delimited
fields terminated by ','
TBLPROPERTIES('serialization.null.format'='', 'skip.header.line.count'='1')
from airlines
insert overwrite table airlines_bucketed
select * ;
```

```
1 // get count of each bucket
2 select count(*) from airlines_bucketed tablesample(bucket 1 out of 22 on year);
3 select count(*) from airlines_bucketed tablesample(bucket 2 out of 22 on year);
4 select count(*) from airlines_bucketed tablesample(bucket 3 out of 22 on year);
5 select count(*) from airlines_bucketed tablesample(bucket 5 out of 11 on year);
```



```
1 // fetching data from different buckets
2 select distinct Year from airlines_bucketed tablesample(bucket 1 out of 22 on year);
3 select distinct year from airlines_bucketed tablesample(bucket 2 out of 22 on year);
4 select distinct year from airlines_bucketed tablesample(bucket 5 out of 10 on year);
```

```
1 SELECT distinct origin
2 FROM airlines_bucketed tablesample(bucket 1 out of 22 on year)
3 WHERE dest='sfo'
4 ORDER BY day;
```

```
1 // block sampling
2 select count(*) from airlines_bucketed tablesample(10 percent);
3 (output count based on the number of blocks)
```

```
1 select
2     min(year), max(year), uniqueCarrier, count(*) as cnt,
3     sum(if(ArrDelay>30, 1, 0)) as flights_delayed,
4     round(sum(if(ArrDelay>30, 1, 0))/count(*),2) as rate
5 FROM airlines
6 WHERE
7     DayOfWeek not in (6,7) and Origin not in ('AK', 'HI', 'PR', 'VI')
8     and Dest not in ('AK', 'HI', 'PR', 'VI')
9     and year < 2010
10 GROUP by uniquecarrier
11 HAVING cnt > 100000 and max(year) > 1990
12 ORDER by rate DESC
13 LIMIT 1000;
```

# Running ad-hoc queries using Hive

We can use Hive to answer “ad-hoc” queries at the same cost as that for generating aggregate reports. For instance: What was the worst year due to delays caused by weather in the state of Oregon? Answer is 2004, with 383 delayed flights due to weather causes

We can use this hive query to get the result: // todo

Some simple Ad-hoc queries





```
// aggregating all flights on the basis of year
select year,count(*) as count from airlines group by year order by year ;
// getting origin/departure wise flight count
select origin, count(*) as TotalFlights from airlines group by origin order by year;
select dest, count(*) as TotalFlights from airlines group by dest, order by dest;
```

Calculating average departure delay for all flights in minutes: 9.58

```
1
2 select avg(DepDelay) from airlines;
3 query result: 8.17
```

Calculating departure delay standard deviation for all flights in minutes: 27.98

*SD is a measure that is used to quantify the amount of variation or dispersion of a set of data values from its mean.*

```
1
2 select stddev_pop(DepDelay) from airlines;
3 query result: 28.50
```

Count of flights with 'SFO' as source

```
1
2 select sum(f.flights) flightsfrom flight_performance f
3   join origin o on (f.origin = o.origin)
4  where o.origin = 'SFO';
```

```
1
2 select year,sum(*) as TotalFlights from airlines where origin = 'SFO' group by year order by
year;
```

```
1
2 // counts the flights and max delay at each airport
3 select airport_cd, count(*), max(delay) from airlines group by airport_cd;
```

average arrival delay in minutes for each U.S. certified carrier

**Delayed flights performance by state:** Which states have had more relative delayed flights during this time? (For convenience, we will consider a delay each flight whose departure delay in minutes is greater than two times the average: 19.16 minutes).

```

1 select OriginState, count(if(DepDelay > 19.16, "", NULL)), count(*), count(if(DepDelayMinutes >
2 19.16, "", NULL)) / count(*) as pcent_retraso
3 from airlines group by OriginState order by pcent_retraso desc;

```

ResultSet : State A: Delayed flights B: Flights A / B IL 1271765 7446363 0.17 NJ 413214 2567503  
0.16 GA 934228 6012156 0.15

**Delayed flights annual performance by carrier:** Which flight carriers have had more relative delayed flights during this time, by year? This query shows us a "negative annual ranking" of carriers.

```

1 create table year_carrier_stats(year string, carrier string, delayed int, total int, percent
2 double) row format delimited fields terminated by '\t' stored as textfile;

```

```

1 insert overwrite table year_carrier_stats
2 select
3     Year,
4     Carrier,
5     count(if(DepDelayMinutes > 19.16, "", NULL)),
6     count(*),
7     count(if(DepDelayMinutes > 19.16, "", NULL)) / count(*) as pcent_retraso
8 from
9     my_table
10 group by
11     Year,
12     Carrier
13 order by
14     Year asc,
15     pcent_retraso desc;

```

```

1 select year, count(*) as TotalFlights from airlines where origin = 'SFO' group by year order by
year;

```

ResultSet: Year | Carrier| A: Delayed flights | B: Flights | A / B —|——|—————|———|  
2007 | EV | 78482 | 286234 | 0.27 2007 | AA | 134338| 633857| 0.21 2007 | MQ |110457 | 540494 |  
0.20 2007 | B6 | 38695 | 191450 | 0.20 2007 | UA | 97736 | 490002 | 0.19

```
1  select
2      Year,
3      count(if(WeatherDelay > 0, "", NULL)) as foo
4  from
5      my_table
6  where
7      OriginState like '%OR%'
8  group by
9      Year
10 order by
11     foo desc
12 limit 1;
```

Variable correlation:

Let's take the following hypothesis: The later in the day, the more likely it is that a flight will be delayed. Is there any relationship between arrival time and delay time of a flight?

A simple way of proving this hypothesis is through a simple query that extracts and creates groupings by arrival time, measuring the average delay time in each of the time intervals.

```
1  select
2      substr(DepTime, 0, 2) as foo,
3      avg(ArrDelayMinutes)
4  from
5      my_table
6  group by
7      substr(DepTime, 0, 2)
8  order by
9      foo asc;
```

Indeed, the later in the day, the more delays there are, because flight delays are usually accumulative. Because flights that arrive late in the night still arrive after midnight, the early hours of the day are the ones that accumulate the most delay time.

## Creating visualizations and graphs

Other questions that could be asked the same way and at the same cost: What days in the week accumulated the majority of delayed flights? Which flights are delayed the most, by company?

## ToDo

- delays by year
- delay by month or week
- delay on hourly basis of a day
- busiest airports
- top cities
- When is the best time of day/day of week/time of year to fly to minimise delays?
- Do older planes suffer more delays?
- How does the number of people flying between different locations change over time?
- How well does weather predict plane delays?
- Can you detect cascading failures as delays in one airport create delays in others? Are there critical links in the system?

 Tags:

analysis

hadoop

hive

