Analysis on Flight Delay and Cancellation

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Ask 1: Search for a dataset

Identify and describe your dataset

For the project, our group would like to look into the Flight delays and cancellations in the United States . More specifically, the dataset presents flight data from all the domestic airlines inthe year 2015. Some of the data includes flight performance(time delays or aheads), flight origins and destinations, flight identifications.

You can download the dataset by unzipping the folder which can be downloded here: (https://www.kaggle.com/datasets/usdot/flight-delays?select=flights.csv).

The dataset's size is 592.41 MB and is last updated on 2015. The dataset contains data fromover 5800k domestic flight trips completed.

Identify datasetsource

The flight delay and cancellation data was collected and published by the DOT's Bureau of Transportation Statistics. The U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics tracks the on-time performance of domestic flights operated by largeair carriers. Summary information on the number of on-time, delayed, canceled, and diverted flights is published in DOT's monthly Air Travel Consumer Report and in this dataset of 2015 flight delays and cancellations.

Why is important and what appeals to you about it

While we are in the middle of the holiday season, finding a flight or airline that won't do you bad can be tricky. What airlines are prone to delays? What airlines have the best overall performance? What airport seems to be the busiest? We hope by analyzing the performance ofairlines and flights, we can probably find some insights to help you save time and money.

As we dive deeper into the reasons for causing the delays, we can also find some insights regarding the reasons and provide recommendations for the airport and area management tobetter manage delays.

Another reason for choosing this dataset is because this dataset comes in quite a good shape. There are fewer missing values and we have quite a lot factors to choose from when it comes todata analysis.

Acquire data and perform initial exploration to make sure it is suitable for dimensional modeling and analytical analysis

Yes, this dataset has 40 columns of both numerical and categorical data representing informations regarding flight origins, destinations, time, and location. Those attributes includesairtime, distance, arrival time, cancellation reason, etc. I think with all that information, we can generate a lot of interesting questions for analysis.

Describe the analytical questions you want to answer with thedata. Minimum of 3 major questions are required

Business Question 1:

In order to improve the operating efficiency at major airports, the FAA would like to develop a system of reward and punishment based on the performance of major airline carriers. What aresome measurements that they could use? And based on the result from the busiest route in USA in 2015, which airline performs the best and which airline performs the worst?

Business Question 2:

During what time period, does the air route from Washington D.C. to New York sees the mostdelays? What are the reason for delays? Advices that we can give to airlines to better improvetheir service.

Business Question 3:

Is there a relationship between customer's attitude on social media with performance of airlines ? Should people rely on social media platforms to choose airlines or should the airline companies use social media to monitor their brands?

Describe any concerns with the data and changes you expect to overcome

While taking an initial look at the data, we found that there are a lot of missing data in the cancellation reason column, in order to make sure we still have a reasonably large dataset to analyze, we might have to delete this column.

Some other areas that we might have to make efforts on are providing supporting information so that they can be understood by the public. The names of airlines and airports are often timeswritten in its assigned spells or initials, which makes it difficult for us to report.

Limitations in analyzing due to lack of data in the cancellation reasons provided. For example, aflight cancellation might be due to 2 or 3 reasons combined.

Ask 2: Data Wrangling and Dimensional Modeling

Dataset of "flights"

In [1]:
```
!pwd
```

```
/home/ubuntu/notebooks
```

In [2]:
```
!xsv headers flights.csv
```

```
1   YEAR
2   MONTH
3   DAY
4   DAY_OF_WEEK
5   AIRLINE
6   FLIGHT_NUMBER
7   TAIL_NUMBER
8   ORIGIN_AIRPORT
9   DESTINATION_AIRPORT
10  SCHEDULED_DEPARTURE
11  DEPARTURE_TIME
12  DEPARTURE_DELAY
13  TAXI_OUT
14  WHEELS_OFF
15  SCHEDULED_TIME
16  ELAPSED_TIME
17  AIR_TIME
18  DISTANCE
19  WHEELS_ON
20  TAXI_IN
21  SCHEDULED_ARRIVAL
22  ARRIVAL_TIME
23  ARRIVAL_DELAY
24  DIVERTED
25  CANCELLED
26  CANCELLATION_REASON
27  AIR_SYSTEM_DELAY
28  SECURITY_DELAY
29  AIRLINE_DELAY
30  LATE_AIRCRAFT_DELAY
31  WEATHER_DELAY
```

There are 31 columns totally in the original dataset.

Here are the Data definition of “flights”:

WHEELS_OFF Time - The time point that the aircraft's wheels leave the ground.
WHEELS_ON Time - The time point that the aircraft's wheels touch on the ground.
TAXI_OUT Time - The time duration elapsed between departure from the origin airport gate andwheels off.

TAXI_IN Time - The time duration elapsed between wheels-on and gate arrival at the destinationairport.
AIR_TIME - The time duration between wheels_off and wheels_on time.
Data Relationship
arrival_time = wheels_on + taxi_in arrival_delay =
arrival_time - scheduled_arrivaldarture_time =
wheels_off - taxi_outep
departure_delay = departure_time - scheduled_departure
elapsed_time =air_time + taxi_in + taxi_out
air_time = wheels_on - wheels_off

Because some columns we will not used in the analysis, so we want to remove 14 columns from the dataset and keep 17 columns, we can just select the columns which we want to reverve and create a new dataset called 'flights2'.

1 YEAR
2 MONTH
3 DAY
4 DAY_OF_WEEK
5 AIRLINE
6 FLIGHT_NUMBER
7 TAIL_NUMBER
8 ORIGIN_AIRPORT
9 DESTINATION_AIRPORT
10 SCHEDULED_DEPARTURE
11 DEPARTURE_TIME
12 DEPARTURE_DELAY
21 SCHEDULED_ARRIVAL
22 ARRIVAL_TIME
23 ARRIVAL_DELAY
24 DIVERTED
25 CANCELLED

In [3]:
```
!csvcut -c 1,2,3,4,5,6,7,8,9,10,11,12,21,22,23,24,25 flights.csv > flights2.csv
```

check the number of lines in the flights2 file.

In [4]:
```
!wc -l flights2.csv
```

```
5819080 flights2.csv
```

use csvcut -n to find the heading (attribute labels) of the flights2 file

In [5]:
```
!csvcut -n flights2.csv
```

```
 1: YEAR
 2: MONTH
 3: DAY
 4: DAY_OF_WEEK
 5: AIRLINE
 6: FLIGHT_NUMBER
 7: TAIL_NUMBER
 8: ORIGIN_AIRPORT
 9: DESTINATION_AIRPORT
10: SCHEDULED_DEPARTURE
11: DEPARTURE_TIME
12: DEPARTURE_DELAY
13: SCHEDULED_ARRIVAL
14: ARRIVAL_TIME
15: ARRIVAL_DELAY
16: DIVERTED
17: CANCELLED
```

Now there are 17 columns totally in the new dataset, flights2.

Check the first few rows of the dataset in the 17 fields.

In [6]:
```
!head -n 10 flights2.csv
```

```
YEAR,MONTH,DAY,DAY_OF_WEEK,AIRLINE,FLIGHT_NUMBER,TAIL_NUMBER,ORIGIN_AIRPORT,DESTINATI
ON_AIRPORT,SCHEDULED_DEPARTURE,DEPARTURE_TIME,DEPARTURE_DELAY,SCHEDULED_ARRIVAL,ARRIV
AL_TIME,ARRIVAL_DELAY,DIVERTED,CANCELLED
2015,1,1,4,AS,98,N407AS,ANC,SEA,0005,2354,-11,0430,0408,-22,0,0
2015,1,1,4,AA,2336,N3KUAA,LAX,PBI,0010,0002,-8,0750,0741,-9,0,0
2015,1,1,4,US,840,N171US,SFO,CLT,0020,0018,-2,0806,0811,5,0,0
2015,1,1,4,AA,258,N3HYAA,LAX,MIA,0020,0015,-5,0805,0756,-9,0,0
2015,1,1,4,AS,135,N527AS,SEA,ANC,0025,0024,-1,0320,0259,-21,0,0
2015,1,1,4,DL,806,N3730B,SFO,MSP,0025,0020,-5,0602,0610,8,0,0
2015,1,1,4,NK,612,N635NK,LAS,MSP,0025,0019,-6,0526,0509,-17,0,0
2015,1,1,4,US,2013,N584UW,LAX,CLT,0030,0044,14,0803,0753,-10,0,0
2015,1,1,4,AA,1112,N3LAAA,SFO,DFW,0030,0019,-11,0545,0532,-13,0,0
```

Then we can use xsv stat to summarize the statistical information of each column.

In [7]:
```
!xsv select 1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17 flights2.csv | xsv stats | xsv t
```

```
field                type     sum          min    max     min_length  max_length  mea
n                    stddev
YEAR                 Integer  11725444185  2015   2015    4           4           201
5                    0
MONTH                Integer  37964167     1      12      1           2           6.5
240851688037305      3.4051365354718484
DAY                  Integer  91386273     1      31      1           2           15.
704593974407977      8.783424315098282
DAY_OF_WEEK          Integer  22851181     1      7       1           1           3.9
269411877722624      1.9888448425430394
AIRLINE              Unicode                AA     WN      2           2
FLIGHT_NUMBER        Integer  12645398342  1      9855    1           4           217
3.092742339536       1757.0638478123092
TAIL_NUMBER          Unicode                7819A  N9EAMQ  0           6
ORIGIN_AIRPORT       Unicode                10135  YUM     3           5
DESTINATION_AIRPORT  Unicode                10135  YUM     3           5
SCHEDULED_DEPARTURE  Integer  7737061812   1      2359    4           4           132
9.6024700815033      483.75177930708827
DEPARTURE_TIME       Integer  7654628244   1      2400    0           4           133
5.2044390594685      496.4232168236126
DEPARTURE_DELAY      Integer  53718424     -82    1988    0           4           9.3
70158275199213       37.08093926275547
SCHEDULED_ARRIVAL    Integer  8692588209   1      2400    4           4           149
3.8082485218195      507.16465201594326
ARRIVAL_TIME         Integer  8455224236   1      2400    0           4           147
6.4911879127544      526.3196912579521
ARRIVAL_DELAY        Integer  25181961     -87    1971    0           4           4.4
07057357987326       39.27129365748114
DIVERTED             Integer  15187        0      1       1           1           0.0
026098631759425435   0.05102011162419795
CANCELLED            Integer  89884        0      1       1           1           0.0
15446430612128189    0.12332006484540309
```

we use csvstat to examine first 10% of the records.

In [8]:
```
!head -n 505051 flights2.csv | csvstat
```

1. "YEAR"

```
Type of data:          Number
Contains null values: False
Unique values:         1
Smallest value:        2015
Largest value:         2015
Sum:                   1017675750
Mean:                  2015
Median:                2015
StDev:                 0
Most common values:    2015 (505050x)
```

2. "MONTH"

```
Type of data:          Number
Contains null values: False
Unique values:         2
Smallest value:        1
Largest value:         2
Sum:                   540132
Mean:                  1.069
Median:                1
StDev:                 0.254
Most common values:    1 (469968x)
                       2 (35082x)
```

3. "DAY"

```
Type of data:          Number
Contains null values: False
Unique values:         31
Smallest value:        1
Largest value:         31
Sum:                   7512862
Mean:                  14.875
Median:                15
StDev:                 9.35
Most common values:    2 (32716x)
                       1 (27356x)
                       3 (21135x)
                       5 (16548x)
                       4 (16352x)
```

4. "DAY_OF_WEEK"

```
Type of data:          Number
Contains null values: False
Unique values:         7
Smallest value:        1
Largest value:         7
Sum:                   2013103
Mean:                  3.986
Median:                4
StDev:                 2.012
Most common values:    5 (80955x)
                       1 (80142x)
```

```
                                4 (78022x)
                                7 (73087x)
                                2 (66538x)
```

5. "AIRLINE"

```
      Type of data:          Text
      Contains null values:  False
      Unique values:         14
      Longest value:         2 characters
      Most common values:    WN (107403x)
                             DL (69260x)
                             EV (53465x)
                             OO (51674x)
                             AA (47404x)
```

6. "FLIGHT_NUMBER"

```
      Type of data:          Number
      Contains null values:  False
      Unique values:         6345
      Smallest value:        1
      Largest value:         9793
      Sum:                   1142680330
      Mean:                  2262.509
      Median:                1732
      StDev:                 1803.429
      Most common values:    469 (401x)
                             345 (388x)
                             711 (357x)
                             61 (354x)
                             745 (342x)
```

7. "TAIL_NUMBER"

```
      Type of data:          Text
      Contains null values:  True (excluded from calculations)
      Unique values:         4414
      Longest value:         6 characters
      Most common values:    None (3802x)
                             N475HA (409x)
                             N484HA (394x)
                             N476HA (392x)
                             N491HA (391x)
```

8. "ORIGIN_AIRPORT"

```
      Type of data:          Text
      Contains null values:  False
      Unique values:         313
      Longest value:         3 characters
      Most common values:    ATL (31629x)
                             ORD (25202x)
                             DFW (24866x)
                             LAX (18642x)
                             DEN (18310x)
```

9. "DESTINATION_AIRPORT"

Type of data:	Text
Contains null values:	False
Unique values:	313
Longest value:	3 characters
Most common values:	ATL (31730x)
	ORD (25313x)
	DFW (24971x)
	LAX (18622x)
	DEN (18328x)

10. "SCHEDULED_DEPARTURE"

Type of data:	Number
Contains null values:	False
Unique values:	1177
Smallest value:	5
Largest value:	2359
Sum:	665800988
Mean:	1318.287
Median:	1315
StDev:	468.503
Most common values:	600 (10478x)
	700 (7388x)
	800 (5478x)
	900 (3843x)
	1000 (3540x)

11. "DEPARTURE_TIME"

Type of data:	Number
Contains null values:	True (excluded from calculations)
Unique values:	1407
Smallest value:	1
Largest value:	2400
Sum:	648746602
Mean:	1328.318
Median:	1324
StDev:	480.026
Most common values:	None (16653x)
	555 (1328x)
	556 (1290x)
	557 (1167x)
	558 (1095x)

12. "DEPARTURE_DELAY"

Type of data:	Number
Contains null values:	True (excluded from calculations)
Unique values:	684
Smallest value:	-48
Largest value:	1988
Sum:	4937138
Mean:	10.109
Median:	-1
StDev:	37.685

```
       Most common values:    -5 (36470x)
                              -4 (36097x)
                              -3 (35851x)
                              -2 (34034x)
                              -1 (30115x)
```

13. "SCHEDULED_ARRIVAL"

```
       Type of data:          Number
       Contains null values:  False
       Unique values:         1303
       Smallest value:        1
       Largest value:         2359
       Sum:                   758744526
       Mean:                  1502.316
       Median:                1520
       StDev:                 483.286
       Most common values:    1030 (2011x)
                              2100 (1866x)
                              1905 (1727x)
                              1535 (1716x)
                              1210 (1703x)
```

14. "ARRIVAL_TIME"

```
       Type of data:          Number
       Contains null values:  True (excluded from calculations)
       Unique values:         1439
       Smallest value:        1
       Largest value:         2400
       Sum:                   726355084
       Mean:                  1489.492
       Median:                1518
       StDev:                 502.565
       Most common values:    None (17397x)
                              1652 (606x)
                              1645 (602x)
                              1640 (598x)
                              1633 (591x)
```

15. "ARRIVAL_DELAY"

```
       Type of data:          Number
       Contains null values:  True (excluded from calculations)
       Unique values:         710
       Smallest value:        -82
       Largest value:         1971
       Sum:                   3027783
       Mean:                  6.219
       Median:                -4
       StDev:                 40.461
       Most common values:    None (18195x)
                              -9 (14053x)
                              -8 (14045x)
                              -10 (13945x)
                              -7 (13939x)
```


MQ,American Eagle Airlines Inc.
VX,Virgin America

IATA_CODE can be considered as the primary key of the dataset, we use csvstat to check thedata.

In [12]:
```
!head -n 15 airlines.csv | csvstat
```

```
1. "IATA_CODE"

      Type of data:          Text
      Contains null values:  False
      Unique values:         14
      Longest value:         2 characters
      Most common values:    UA (1x)
                             AA (1x)
                             US (1x)
                             F9 (1x)
                             B6 (1x)

2. "AIRLINE"

      Type of data:          Text
      Contains null values:  False
      Unique values:         14
      Longest value:         28 characters
      Most common values:    United Air Lines Inc. (1x)
                             American Airlines Inc. (1x)
                             US Airways Inc. (1x)
                             Frontier Airlines Inc. (1x)
                             JetBlue Airways (1x)

Row count: 14
```

Reference table of Airlines:

IATA_code: The International Air Transport Association's (IATA) Location Identifier is a unique 3-letter code (also commonly known as IATA code) used in aviation and also in logistics to identifyan airport.
AIRPORT: Full name of the airport for that IATA_code, ex: Waterloo Regional AirportCITY:
name of the city where the airport is located
STATE: name of the state where the airport is located
COUNTRY: country where the airport is located
LATITUDE: the latitude of the airport location
LONGITUDE: the longitude of airport location

Dataset of "airports"

In [13]:
```
!xsv headers airports.csv
```

```
1   IATA_CODE
2   AIRPORT
3   CITY
4   STATE
5   COUNTRY
6   LATITUDE
7   LONGITUDE
```

In [14]:
```
!wc -l airports.csv
```

```
323 airports.csv
```

In [15]:
```
!head -n 10 airports.csv
```

```
IATA_CODE,AIRPORT,CITY,STATE,COUNTRY,LATITUDE,LONGITUDE
ABE,Lehigh Valley International Airport,Allentown,PA,USA,40.65236,-75.44040
ABI,Abilene Regional Airport,Abilene,TX,USA,32.41132,-99.68190
ABQ,Albuquerque International Sunport,Albuquerque,NM,USA,35.04022,-106.60919
ABR,Aberdeen Regional Airport,Aberdeen,SD,USA,45.44906,-98.42183
ABY,Southwest Georgia Regional Airport,Albany,GA,USA,31.53552,-84.19447
ACK,Nantucket Memorial Airport,Nantucket,MA,USA,41.25305,-70.06018
ACT,Waco Regional Airport,Waco,TX,USA,31.61129,-97.23052
ACV,Arcata Airport,Arcata/Eureka,CA,USA,40.97812,-124.10862
ACY,Atlantic City International Airport,Atlantic City,NJ,USA,39.45758,-74.57717
```

IATA_CODE can be considered as the primary key of the dataset, we use csvstat to check thedata.

In [16]:
```
!head -n 323 airports.csv | csvstat
```

1. "IATA_CODE"

```
Type of data:          Text
Contains null values:  False
Unique values:         322
Longest value:         3 characters
Most common values:    ABE (1x)
                       ABI (1x)
                       ABQ (1x)
                       ABR (1x)
                       ABY (1x)
```

2. "AIRPORT"

```
Type of data:          Text
Contains null values:  False
Unique values:         322
Longest value:         77 characters
Most common values:    Lehigh Valley International Airport (1x)
                       Abilene Regional Airport (1x)
                       Albuquerque International Sunport (1x)
                       Aberdeen Regional Airport (1x)
                       Southwest Georgia Regional Airport (1x)
```

3. "CITY"

```
Type of data:          Text
Contains null values:  False
Unique values:         308
Longest value:         30 characters
Most common values:    Albany (2x)
                       Columbia (2x)
                       Charleston (2x)
                       San Diego (2x)
                       Columbus (2x)
```

4. "STATE"

```
Type of data:          Text
Contains null values:  False
Unique values:         54
Longest value:         2 characters
Most common values:    TX (24x)
                       CA (22x)
                       AK (19x)
                       FL (17x)
                       MI (15x)
```

5. "COUNTRY"

```
Type of data:          Text
Contains null values:  False
Unique values:         1
Longest value:         3 characters
Most common values:    USA (322x)
```

6. "LATITUDE"

```
Type of data:          Number
Contains null values:  True (excluded from calculations)
Unique values:         320
Smallest value:        13.483
Largest value:         71.285
Sum:                   12435.017
Mean:                  38.981
Median:                39.298
StDev:                 8.617
Most common values:    None (3x)
                       40.652 (1x)
                       32.411 (1x)
                       35.04 (1x)
                       45.449 (1x)
```

7. "LONGITUDE"

```
Type of data:          Number
Contains null values:  True (excluded from calculations)
Unique values:         320
Smallest value:        -176.646
Largest value:         -64.799
Sum:                   -31382.89
Mean:                  -98.379
Median:                -93.403
StDev:                 21.523
Most common values:    None (3x)
                       -75.44 (1x)
                       -99.682 (1x)
                       -106.609 (1x)
                       -98.422 (1x)
```

```
Row count: 322
```

IATA_code: IATA airline designators, sometimes called IATA reservation codes, are two-charactercodes assigned by the International Air Transport Association (IATA) to the world's airlines.
Airline: name of the airline for that IATA_code.

Setup database

In [17]:
```
! pip freeze | grep -E 'ipython-sql|psycopg2'
```

```
ipython-sql==0.4.1
psycopg2==2.9.5
psycopg2-binary==2.9.5
```

First, use PostgreSQL's dropdb command to drop the database named group1, if it exists.

In [18]:
```
! dropdb -U student group1
```

The output said that database Project does not exist, so we can just create it. Now use PostgreSQL's createdb command to create the database named group1.

In [19]:
```
! createdb -U student group1
```

createdb: error: database creation failed: ERROR: database "group1" already exists

In [20]:
```
%load_ext sql
```

Use sql magic to connect to the database we just created

In [21]:
```
%sql  postgresql://student@/group1
```

In [22]:
```
!psql --version
```

```
psql (PostgreSQL) 12.12 (Ubuntu 12.12-0ubuntu0.20.04.1)
```

Create tables

Use the CREATE TABLE command. It is a good practice to DROP the table first then create it in case the table exists. Creating table F_flights as the fact table.

(1) Create F_flights Table

In [23]:
```
%%sql
DROP TABLE IF EXISTS F_flights;

CREATE TABLE F_flights (
  YEAR INTEGER NOT NULL,
  MONTH INTEGER NOT NULL,
  DAY INTEGER NOT NULL,
  DAY_OF_WEEK INTEGER NOT NULL,
  AIRLINE CHAR(2) NOT NULL,
  FLIGHT_NUMBER INTEGER NOT NULL,
  TAIL_NUMBER CHAR(10),
  ORIGIN_AIRPORT CHAR(20) NOT NULL,
  DESTINATION_AIRPORT CHAR(20) NOT NULL,
  SCHEDULED_DEPARTURE INTEGER NOT NULL,
  DEPARTURE_TIME INTEGER,
  DEPARTURE_DELAY INTEGER,
  SCHEDULED_ARRIVAL INTEGER,
  ARRIVAL_TIME INTEGER,
  ARRIVAL_DELAY INTEGER,
  DIVERTED INTEGER,
  CANCELLED INTEGER
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[23]:
```
[]
```

In [24]:
```
%%sql
select * from F_flights
```

```
 *  postgresql://student@/group1
0 rows affected.
```

Out[24]:

year	month	day	day_of_week	airline	flight_number	tail_number	origin_airport	destination_airpor

In [25]:
```
%%sql
COPY F_flights FROM '/home/ubuntu/notebooks/flights2.csv'
CSV
HEADER;
```

```
 *  postgresql://student@/group1
5819079 rows affected.
```

Out[25]: []

In [26]:
```
%%sql
select COUNT(*) from F_flights;
```

```
 *  postgresql://student@/group1
1 rows affected.
```

Out[26]:

count
5819079

In [27]:
```
! wc -l flights2.csv
```

```
5819080 flights2.csv
```

The difference of 1 row is the head of the original files. Therefore, we have uploaded all rows ofthe tables, which is same for following tables.

There are approximately 2% of null data in DEPARTURE_TIME, DEPARTURE_DELAY, ARRIVAL_TIME, ARRIVAL_DELAY columns. We then choose to use the value 0 to replace the nullvalue. The reason for that is we think flight cancellations and diverts are usually non- controllable factors for airlines, besides, it doesn't carry a lot of percentage in the whole dataset,so we are supposing the condition for all those flights that they arrived on time to make it fair for all airline companies.

In [28]:
```
%%sql
UPDATE F_flights
SET DEPARTURE_TIME=0
WHERE DEPARTURE_TIME IS NULL;
```

```
 *  postgresql://student@/group1
86153 rows affected.
```

Out[28]: []

In [29]:
```
%%sql
UPDATE F_flights
SET DEPARTURE_DELAY=0
WHERE DEPARTURE_DELAY IS NULL;
```

```
 *  postgresql://student@/group1
86153 rows affected.
```

Out[29]: []

In [30]:
```
%%sql
UPDATE F_flights
SET  ARRIVAL_TIME=0
WHERE ARRIVAL_TIME IS NULL;
```

```
 * postgresql://student@/group1
92513 rows affected.
```

Out[30]: []

In [31]:
```
%%sql
UPDATE F_flights
SET  ARRIVAL_DELAY=0
WHERE ARRIVAL_DELAY IS NULL;
```

```
 * postgresql://student@/group1
105071 rows affected.
```

Out[31]: []

(2) Create Airports Table

In [32]:
```
%%sql
DROP TABLE IF EXISTS Airports;

CREATE TABLE Airports (
 IATA_CODE CHAR(3) ,
 AIRPORT varchar(100) ,
 CITY CHAR(30) ,
 STATE CHAR(3) ,
 COUNTRY CHAR(3) ,
 LATITUDE FLOAT ,
 LONGITUDE FLOAT
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[32]: []

In [33]:
```
%%sql
COPY  Airports  FROM  '/home/ubuntu/notebooks/airports.csv'
CSV
HEADER;
```

```
 * postgresql://student@/group1
322 rows affected.
```

Out[33]: []

In [34]:
```
%%sql
select COUNT(*) from Airports;
```

```
 * postgresql://student@/group1
1 rows affected.
```

Out[34]:

count
322

In [35]:
```
! wc -l airports.csv
```

```
323 airports.csv
```

(3) Create Airlines Table

In [36]:
```
%%sql
DROP TABLE IF EXISTS Airlines;

CREATE TABLE Airlines (
 IATA_CODE CHAR(3) ,
 AIRLINE  varchar(100)
);
```

```
 *  postgresql://student@/group1
Done.
Done.
```

Out[36]: []

In [37]:
```
%%sql
COPY  Airlines  FROM  '/home/ubuntu/notebooks/airlines.csv'
CSV
HEADER;
```

```
 *  postgresql://student@/group1
14 rows affected.
```

Out[37]: []

In [38]:
```
%%sql
select COUNT(*) from Airlines;
```

```
 *  postgresql://student@/group1
1 rows affected.
```

Out[38]:

count
14

In [39]:
```
! wc -l airlines.csv
```

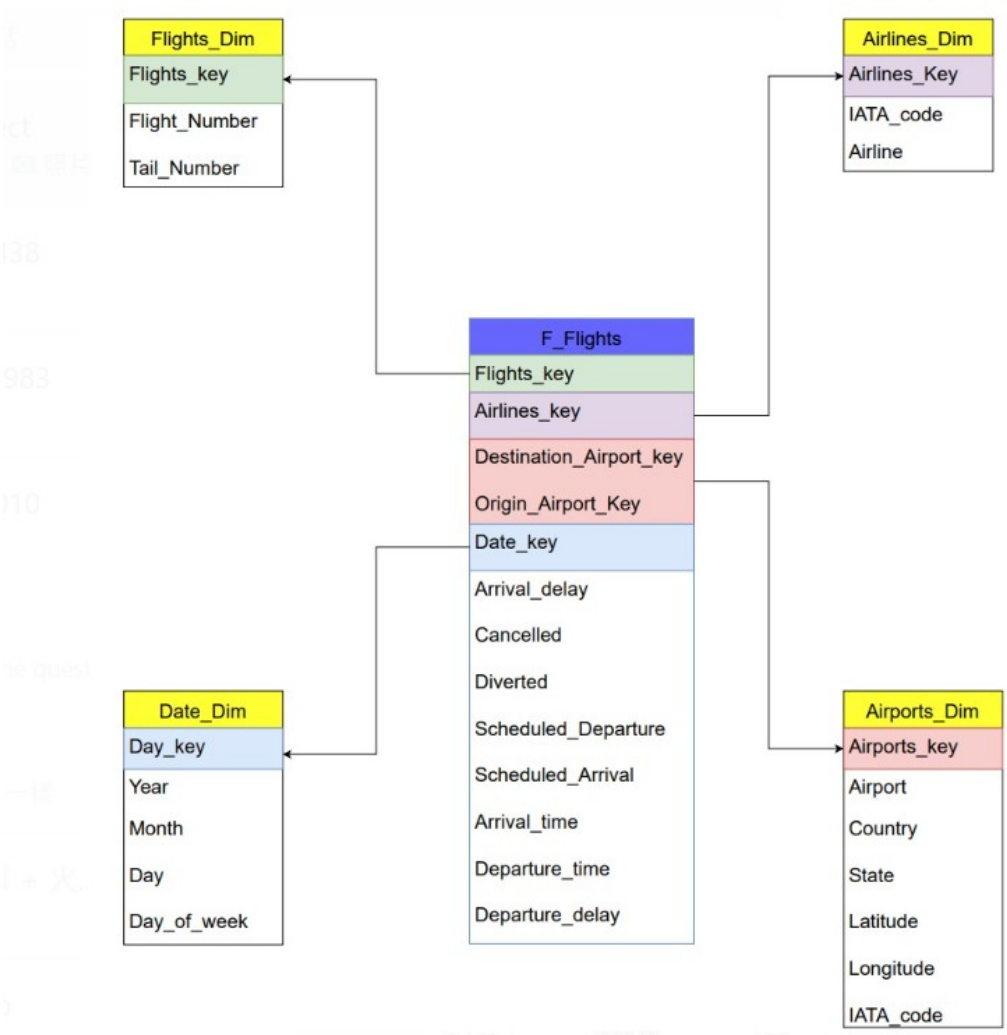
```
15 airlines.csv
```

Dimensional Modeling

For our dimension table we have 8 facts, we focus more on departure delay and arrival delay. Airlines,Flights,Date and airports are the four dimension we created.

In [40]:
```
from IPython import display
display.  Image("dim  table.png")
```

Out[40]:



In [41]:
```
%%sql
DROP TABLE IF EXISTS Date_Dim;

CREATE TABLE Date_Dim (
    Date_Key SERIAL PRIMARY KEY,
    YEAR INTEGER NOT NULL,
    MONTH INTEGER NOT NULL,
    DAY INTEGER NOT NULL,
    DAY_OF_WEEK INTEGER NOT NULL,
    DATE DATE NOT NULL
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[41]: []

Populate the Date_Dim table with data from table F_flights

In [42]:
```
%%sql
INSERT INTO Date_Dim(year,month,day,day_of_week,date)
SELECT distinct year,month,day,day_of_week,
cast(year::char(4)||'-'||month::char(2)||'-'||day::char(2) as date)::date
```

```
FROM F_flights
ORDER BY date;
```

```
 *  postgresql://student@/group1
365 rows affected.
```

Out[42]: []

In [43]:
```
%%sql
select * from Date_Dim
limit 10
```

```
 *  postgresql://student@/group1
10 rows affected.
```

Out[43]:

date_key	year	month	day	day_of_week	date
1	2015	1	1	4	2015-01-01
2	2015	1	2	5	2015-01-02
3	2015	1	3	6	2015-01-03
4	2015	1	4	7	2015-01-04
5	2015	1	5	1	2015-01-05
6	2015	1	6	2	2015-01-06
7	2015	1	7	3	2015-01-07
8	2015	1	8	4	2015-01-08
9	2015	1	9	5	2015-01-09
10	2015	1	10	6	2015-01-10

Next, we add FK Date_key to the F_flights table.

In [44]:
```
%%sql
ALTER TABLE F_flights
ADD COLUMN Date_Key INTEGER NULL ,
ADD CONSTRAINT fk_Date
    FOREIGN KEY (Date_Key)
    REFERENCES  Date_Dim(Date_Key);
```

```
 *  postgresql://student@/group1
Done.
```

Out[44]: []

Populate the Date_key by linking the attributes from Date_Dim table and F_flights table

In [45]:
```
%%sql
UPDATE F_flights AS f
SET Date_Key = t.Date_Key
FROM Date_Dim AS t
WHERE f.year = t.year
and f.month = t.month
and f.day = t.day
and  f.day_of_week=t.day_of_week;
```

```
 * postgresql://student@/group1
5819079 rows affected.
```

Out[45]: []

We can check the F_flights table we just modified by examining the first 10 rows.

In [46]:
```
%%sql
select * from F_flights
limit 10
```

```
 * postgresql://student@/group1
10 rows affected.
```

Out[46]:

year	month	day	day_of_week	airline	flight_number	tail_number	origin_airport	destination_airpor
2015	1	1	4	AS	98	N407AS	ANC	SE
2015	1	1	4	AA	2336	N3KUAA	LAX	P
2015	1	1	4	HA	102	N492HA	HNL	IT
2015	1	1	4	OO	5467	N701BR	ONT	SF
2015	1	1	4	HA	108	N476HA	HNL	KO
2015	1	1	4	UA	1119	N69810	GEG	DE
2015	1	1	4	UA	1237	N65832	SEA	IA
2015	1	1	4	UA	1540	N78509	DCA	IA
2015	1	1	4	AA	1433	N4YNAA	SAT	DF
2015	1	1	4	UA	247	N462UA	PHX	IA

The Date_key attribute has been successfully added to the F_flights table from the output.

Create the Airports_Dim table as a dimension table

In [47]:
```
%%sql
CREATE TABLE Airports_Dim (
 Airports_Key SERIAL PRIMARY KEY,
 IATA_CODE CHAR(3) ,
 AIRPORT varchar(100) ,
 CITY CHAR(30) ,
 STATE CHAR(3) ,
 COUNTRY CHAR(3) ,
 LATITUDE FLOAT ,
 LONGITUDE FLOAT
);
```

```
 * postgresql://student@/group1
Done.
```

Out[47]: []

Populate the Airports_Dim table with data from the F_flights table

In [48]:
```
%%sql
INSERT INTO Airports_Dim (IATA_CODE,AIRPORT,CITY,STATE,COUNTRY,LATITUDE,LONGITUDE)
SELECT DISTINCT IATA_CODE,AIRPORT,CITY,STATE,COUNTRY,LATITUDE,LONGITUDE
FROM Airports;
```

```
 * postgresql://student@/group1
322 rows affected.
```

Out[48]: []

Check the Airports_Dim table we just created by examining the first 10 rows

In [49]:
```
%%sql
SELECT * FROM Airports_Dim
Limit 10
```

```
 * postgresql://student@/group1
10 rows affected.
```

Out[49]:

airports_key	iata_code	airport	city	state	country	latitude	longitude
1	ORH	Worcester Regional Airport	Worcester	MA	USA	42.26734	-71.87571
2	SAN	San Diego International Airport (Lindbergh Field)	San Diego	CA	USA	32.73356	-117.18966
3	RST	Rochester International Airport	Rochester	MN	USA	43.90883	-92.49799
4	BUR	Bob Hope Airport (Hollywood Burbank Airport)	Burbank	CA	USA	34.20062	-118.3585
5	FAY	Fayetteville Regional Airport	Fayetteville	NC	USA	34.99147	-78.88
6	AGS	Augusta Regional Airport (Bush Field)	Augusta	GA	USA	33.36996	-81.9645
7	ICT	Wichita Dwight D. Eisenhower National Airport (Wichita Mid-Continent Airport)	Wichita	KS	USA	37.64996	-97.43305
8	DRO	Durango-La Plata County Airport	Durango	CO	USA	37.15152	-107.75377
9	SUX	Sioux Gateway Airport	Sioux City	IA	USA	42.4026	-96.38437
10	RIC	Richmond International Airport	Richmond	VA	USA	37.50517	-77.31967

Next, we add FK origin_airport_key and destination_airport_key to the F_flights table.

In [50]:
```
%%sql
ALTER TABLE f_flights
ADD COLUMN origin_airport_key INTEGER  NULL,
ADD COLUMN destination_airport_key INTEGER  NULL,
ADD FOREIGN KEY (origin_airport_key) REFERENCES Airports_DIM (Airports_Key) ON DELETE
```

```
ADD FOREIGN KEY (destination_airport_key) REFERENCES Airports_DIM (Airports_Key) ON DE
;
```

```
 * postgresql://student@/group1
Done.
```

Out[50]: []

Populate the origin_airport_key and destination_airport_key

In [51]:
```
%%sql
UPDATE F_flights AS f
SET origin_airport_key = t.Airports_Key
FROM Airports_Dim AS t
WHERE f.origin_airport = t.IATA_CODE;
```

```
 * postgresql://student@/group1
5332914 rows affected.
```

Out[51]: []

In [52]:
```
%%sql
UPDATE F_flights AS f
SET destination_airport_key = t.Airports_Key
FROM Airports_Dim AS t
WHERE f.destination_airport = t.IATA_CODE;
```

```
 * postgresql://student@/group1
5332914 rows affected.
```

Out[52]: []

In [53]:
```
%%sql
select * from F_flights
limit 10
```

```
 * postgresql://student@/group1
10 rows affected.
```

Out[53]:

year	month	day	day_of_week	airline	flight_number	tail_number	origin_airport	destination_airpo
2015	1	1	4	AS	98	N407AS	ANC	SE
2015	1	1	4	AA	2336	N3KUAA	LAX	P
2015	1	1	4	HA	102	N492HA	HNL	IT
2015	1	1	4	OO	5467	N701BR	ONT	SF
2015	1	1	4	HA	108	N476HA	HNL	KO
2015	1	1	4	UA	1119	N69810	GEG	DE
2015	1	1	4	UA	1237	N65832	SEA	IA
2015	1	1	4	UA	1540	N78509	DCA	IA
2015	1	1	4	AA	1433	N4YNAA	SAT	DF
2015	1	1	4	UA	247	N462UA	PHX	IA

The origin_airport_key and destination_airport_keyha have been successfully added to the Exempt_Organization table from the output.

Create the Airlines_Dim table as a dimension table

In [54]:
```
%%sql
DROP TABLE IF EXISTS Airlines_Dim;
CREATE TABLE Airlines_Dim (
 Airlines_Key SERIAL PRIMARY KEY,
 IATA_CODE CHAR(3) ,
 AIRLINE  varchar(100)
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[54]: []

Populate the Airlines_Dim with data from table F_Flights

In [55]:
```
%%sql
INSERT INTO Airlines_Dim (IATA_CODE,AIRLINE)
SELECT DISTINCT
IATA_CODE, AIRLINE
FROM Airlines;
```

```
 * postgresql://student@/group1
14 rows affected.
```

Out[55]: []

Next, we add FK Airlines_key to the F_flights table:

In [56]:
```
%%sql
ALTER TABLE F_flights
ADD COLUMN Airlines_Key INTEGER NULL,
ADD FOREIGN KEY (Airlines_Key)
REFERENCES Airlines_Dim (Airlines_Key) ON DELETE SET NULL;
```

```
 * postgresql://student@/group1
Done.
```

Out[56]: []

Populate the Airlines_key by linking the attributes from airlines table and F_flights table

In [57]:
```
%%sql
UPDATE F_flights AS f
SET Airlines_Key = t.Airlines_Key
FROM Airlines_Dim AS t
WHERE f.airline = t.IATA_CODE;
```

```
 * postgresql://student@/group1
5819079 rows affected.
```

Out[57]: []

Check the F_flights table we just created by examining the first 10 rows

In [58]:
```
%%sql
select * from F_flights
limit 10;
```

```
 * postgresql://student@/group1
10 rows affected.
```

Out[58]:

year	month	day	day_of_week	airline	flight_number	tail_number	origin_airport	destination_airpor
2015	1	1	4	AS	98	N407AS	ANC	SE
2015	1	1	4	AA	2336	N3KUAA	LAX	P
2015	10	6	2	MQ	3241	N662MQ	13930	1336
2015	10	6	2	OO	4671	N685BR	11823	1039
2015	10	6	2	DL	581	N3753	14869	1474
2015	10	6	2	DL	2567	N950DL	12278	1039
2015	10	6	2	DL	1690	N938DL	10529	1039
2015	10	6	2	EV	4175	N11194	10431	1161
2015	10	6	2	DL	1532	N904DL	11423	1039
2015	10	6	2	UA	1749	N78509	14771	1383

The Airlines_KEY attribute has been successfully added to the F_flights table from the output.

Create the Flights_Dim table as a dimension table

In [59]:
```
%%sql
DROP TABLE IF EXISTS Flights_Dim;
CREATE TABLE Flights_Dim (
 Flights_Key SERIAL PRIMARY KEY,
 flight_number INTEGER ,
 tail_number CHAR(10)
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[59]: []

Populate the Flights_Dim table with data from the F_filghts table

In [60]:
```
%%sql
INSERT INTO Flights_Dim (flight_number,tail_number)
SELECT DISTINCT
flight_number,tail_number
FROM F_flights;
```

```
 * postgresql://student@/group1
2098568 rows affected.
```

Out[60]: []

Add FK Flights_KEY to the F_flights table:

In [61]:
```
%%sql
ALTER TABLE F_flights
ADD COLUMN Flights_Key INTEGER NULL,
ADD FOREIGN KEY (Flights_Key)
    REFERENCES Flights_Dim (Flights_Key) ON DELETE SET NULL;
```

```
 * postgresql://student@/group1
Done.
```

Out[61]: []

Populate the Flights_KEY by linking the attributes from Flights table and F_flights table

In [62]:
```
%%sql
UPDATE F_flights AS f
SET Flights_Key = t.Flights_Key
FROM Flights_Dim AS t
WHERE f.flight_number = t.flight_number AND f.tail_number = t.tail_number;
```

```
 * postgresql://student@/group1
5804358 rows affected.
```

Out[62]: []

The Flights_KEY attribute has been successfully added to the F_flights table from the output.

We can drop all the unnecessary columns from the rides table and only reserve the facts and surrogate keys.

In [63]:
```
%%sql
ALTER TABLE F_flights
DROP COLUMN year,
DROP COLUMN month,
DROP COLUMN day,
DROP COLUMN day_of_week,
DROP COLUMN airline,
DROP COLUMN flight_number,
DROP COLUMN tail_number,
DROP COLUMN origin_airport,
DROP  COLUMN  destination_airport;
```

```
 * postgresql://student@/group1
Done.
```

Out[63]: []

Check the F_flights table we just modified by examining the first 10 rows.

In [64]:
```
%%sql
select * from F_flights
```

```
limit 20;
```

```
 * postgresql://student@/group1
20 rows affected.
```

Out[64]:

scheduled_departure	departure_time	departure_delay	scheduled_arrival	arrival_time	arrival_delay	di
1659	1636	-23	1744	1725	-19	
1659	1704	5	2001	1951	-10	
5	2354	-11	430	408	-22	
1659	1656	-3	1957	1928	-29	
1659	1659	0	1941	1917	-24	
1700	1710	10	1805	1808	3	
1700	1700	0	1800	1753	-7	
1700	1652	-8	1945	1920	-25	
500	452	-8	549	543	-6	
502	501	-1	544	549	5	
1700	1655	-5	1930	1901	-29	
1700	1657	-3	1900	1849	-11	
1700	1656	-4	1808	1816	8	
1700	1659	-1	2013	1955	-18	
1700	1651	-9	1848	1817	-31	
1700	1710	10	2010	1953	-17	
1700	1655	-5	1852	1839	-13	
1700	1715	15	1804	1811	7	
1700	1652	-8	1810	1754	-16	
1700	1659	-1	2005	1940	-25	

Check the number of records in our fact table. If it shows 5819079 , which is the original numberof records in our dataset, then we have succeeded in the wrangling steps.

In [65]:
```
%%sql
select count(*) from F_flights
```

```
 * postgresql://student@/group1
1 rows affected.
```

Out[65]:

count
5819079

In [66]:
```
!wc -l flights2.csv
```

```
5819080 flights2.csv
```

Ask 3: Data analysis and visualization

Business Question 1:

In order to improve the operating efficiency at major airports, the FAA would like to develop a system of reward and punishment based on the performance of major airline carriers. What aresome measurements that they could use? And based on the result from the busiest route in USA in 2015, which airline performs the best and which airline performs the worst?

The average method

First, our data scientist thinks that its always good to take a look at the avearges. So we aregoing to find what that number is for our dataset.

Avg departure delay of airlines

We start with departure delay because this type of delay would mean that the flights are using resources such as runway space, air space, operating capacity, etc. This will generate a higher operating cost for the airpots, and for FAA, running at capacity or exceeding it may raise safty concerns as well. By calculating the average, we hope we can provide some insights for regulorsso that they can probably using a price ladder to encourage airline carriers to operate more efficiently.

In [67]:
```
%%sql
SELECT f.airlines_key , air.iata_code,air.airline, AVG(f.departure_delay) as total_avg
FROM F_flights as f
join Airlines_Dim as air
    on f.airlines_key=air.airlines_key
GROUP BY f.airlines_key, air.iata_code, air.airline
ORDER BY total_avg_delay Desc
```

```
 * postgresql://student@/group1
14 rows affected.
```

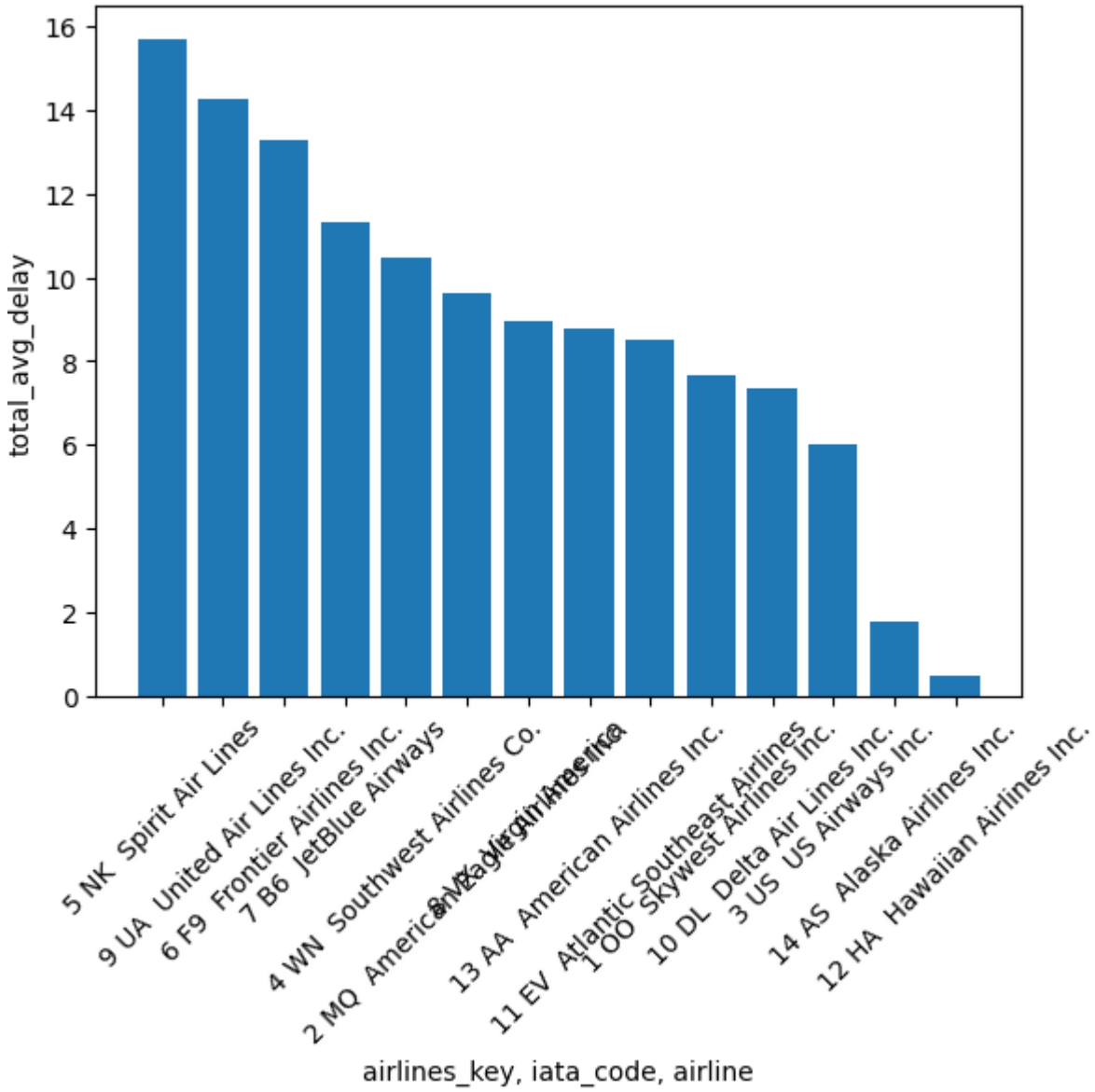
Out[67]:

airlines_key	iata_code	airline	total_avg_delay
5	NK	Spirit Air Lines	15.6832738394431713
9	UA	United Air Lines Inc.	14.2622066496937309
6	F9	Frontier Airlines Inc.	13.2706085692897089
7	B6	JetBlue Airways	11.3330449956562116
4	WN	Southwest Airlines Co.	10.4501071834719520
2	MQ	American Eagle Airlines Inc.	9.6320426837546499
8	VX	Virgin America	8.9470946480784453
13	AA	American Airlines Inc.	8.7735198020893022
11	EV	Atlantic Southeast Airlines	8.4921911195729898
1	OO	Skywest Airlines Inc.	7.6782305860597294
10	DL	Delta Air Lines Inc.	7.3380904483599941
3	US	US Airways Inc.	6.0209194071912035
14	AS	Alaska Airlines Inc.	1.7794761217474974
12	HA	Hawaiian Airlines Inc.	0.48473882945248584015

In [68]:
```
%matplotlib inline
```

In [69]:
```
_.bar()
```

Out[69]:
```
<BarContainer object of 14 artists>
```



As per the above graph, Spirit Air Lines has a maximum delay of 15.68 mins. The best- performance airline is Hawaiian Airlines, with 0.48 mins of delay. We recommend our customersprefer Hawaiian AirlinesSpirit Air Lines for stressfree travel.Other airlines can use the use Alaska airlines practices to better their performance.

Avg arrival delay of airlines

We also want to count arrival delay as a factor, because the delay of arrival would also meanthat this airline is prone to use more reasources mentioned above.

In [70]:
```
%%sql
SELECT f.airlines_key , air.iata_code,air.airline, AVG(f.arrival_delay) as avg_arrival
FROM F_flights as f
join Airlines_Dim as air
    on  f.airlines_key=air.airlines_key
GROUP BY f.airlines_key, air.iata_code, air.airline
ORDER BY avg_arrival_delay Desc
```

```
 * postgresql://student@/group1
14 rows affected.
```

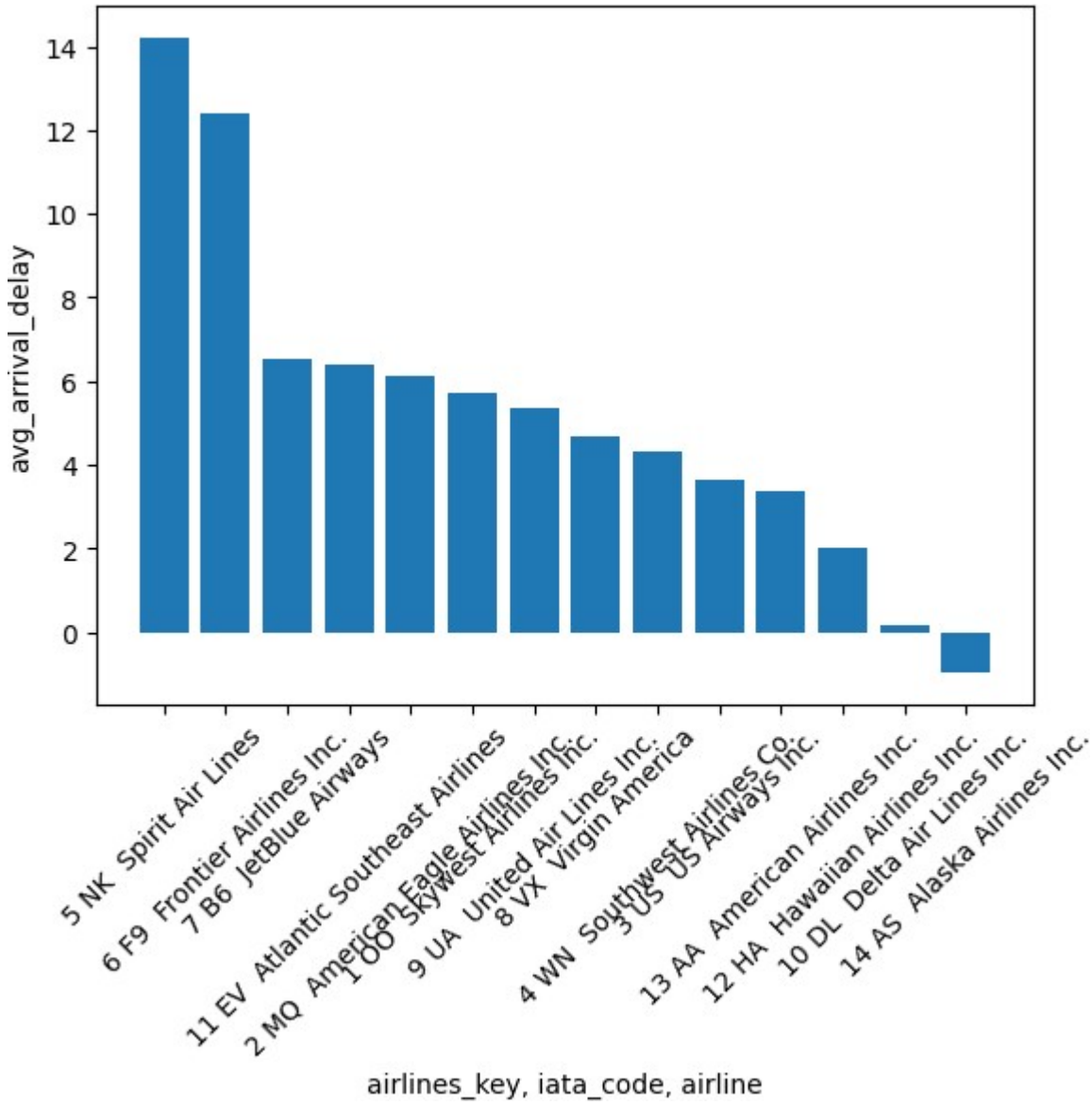
Out[70]:

airlines_key	iata_code	airline	avg_arrival_delay
5	NK	Spirit Air Lines	14.2022849061586826
6	F9	Frontier Airlines Inc.	12.4020102162138359
7	B6	JetBlue Airways	6.5526796680746532
11	EV	Atlantic Southeast Airlines	6.3870610181877943
2	MQ	American Eagle Airlines Inc.	6.1106634717206549
1	OO	Skywest Airlines Inc.	5.7310050258943185
9	UA	United Air Lines Inc.	5.3477486945511447
8	VX	Virgin America	4.6875757233090480
4	WN	Southwest Airlines Co.	4.3075218626545839
3	US	US Airways Inc.	3.6224291070125557
13	AA	American Airlines Inc.	3.3893364041080795
12	HA	Hawaiian Airlines Inc.	2.0169655968114118
10	DL	Delta Air Lines Inc.	0.18555831214514300459
14	AS	Alaska Airlines Inc.	-0.97043838141443650338

In [71]:
```
%matplotlib inline
```

In [72]:
```
_.bar()
```

Out[72]:
```
<BarContainer object of 14 artists>
```



From the above graph we guys can see that even after having departure delay Alaska Airlines manages to reach on time, along with Delta airlines, these two are the best for arrival performance. spirit air lines and frontier airline has the wrost arrival delay.

The Percentage of delay Method

Afterwards, we are going to set up another performance measurement criteria that seems to bemore . The Federal Aviation Administration (FAA) considers a flight to be delayed when it is 15 minutes later than its scheduled time. As a result, we will use a 15 minutes delay as threshold tomeasure the percentage of flight delays that is less than or equal to 15 minutes. But Why 15 minutes? Interestingly, few airlines strive to be 100 percent on time. In fact, reaching 100 percent OTP is all but impossible, and if achieved, it would have a negative effect on profits andfinancial performance. External factors ranging from weather, poorly located airport gates, industrial disputes or long immigration queues all can result in delays. Airlines plan with 15- minute criteria and typically aim to achieve around 85 percent to-90 percent OTP throughout the year. Planning for a shorter time period of 10 minutes and striving to achieve a higher OTP

level of 95 percent would require additional resources and lead to higher airfares for some travelers. A requirement for additional resources in terms of aircraft, crew and supporting operations woulbdn't make sense. For the best economic value for both airlines and customers,we choose 15 minutes as a threshold as the definition of delay.

Finding the busiest Air route.

In order to put this criteria into use, we think it would make more sense to specify this performance criteria by route than calculating the universal statistics like above. As a result, weare using the busiest airline route to demostrate, it would be connecting the 2 airports, which obviously, has the most count of departure flights and arrival flights.

In [73]:
```
%%sql
select  origin_airport_key,destination_airport_key,count(*)  as  total_flight
from F_flights
group  by  origin_airport_key,destination_airport_key
order by total_flight desc
limit 6
```

```
 *  postgresql://student@/group1
6 rows affected.
```

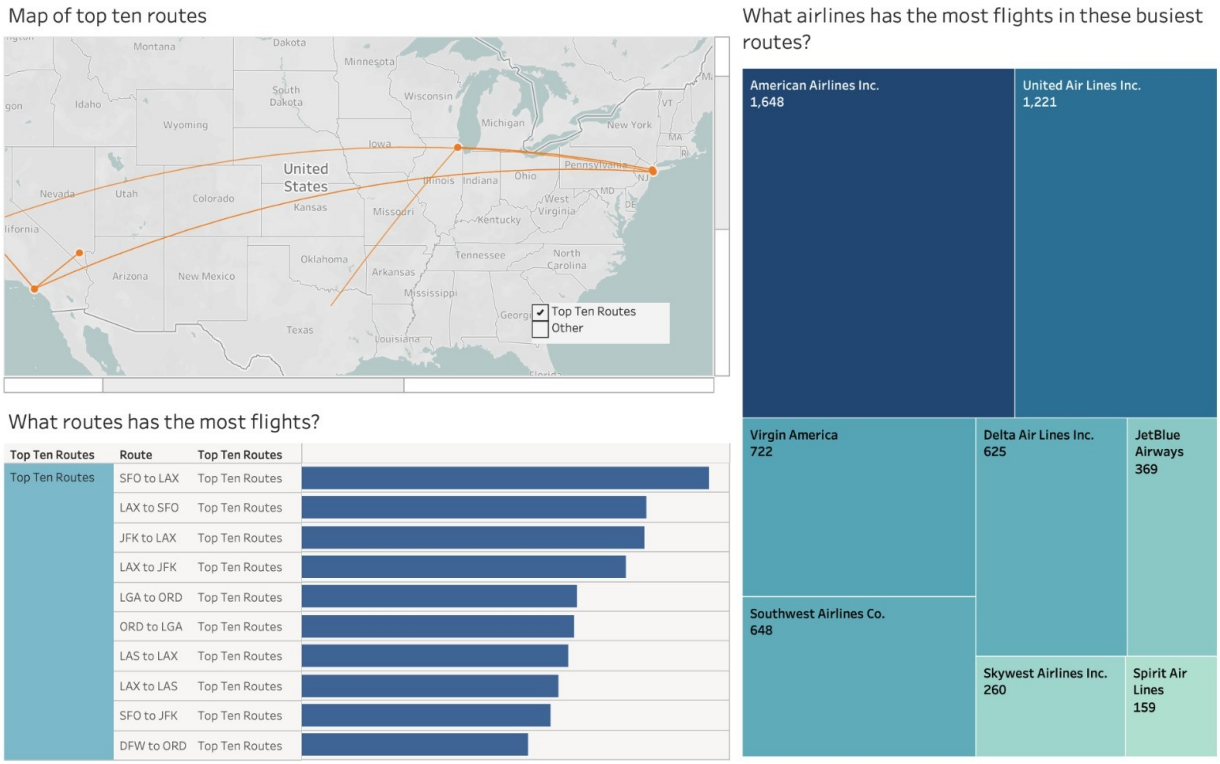
Out[73]:

origin_airport_key	destination_airport_key	total_flight
None	None	486165
302	78	13744
78	302	13457
65	78	12016
78	65	12015
73	78	9715

After reffering to the airport key table, we found that the busiest route is SFO to LAX. So, we are combining the flgiht route LAX to SFO along with the flight route SFO to LAX, so that it counts both incoming flights and outgoing flights of those two airports.

In [74]:
```
from IPython import display
display.  Image("abba.jpg")
```

Out[74]:



In [75]:

```
%%sql
with t1 as (
select case when cast(origin_airport_key as integer) > cast(destination_airport_key as
origin_airport_key,destination_airport_key
from F_flights)
select route , count(*) as total_flights
from t1
group by route
order by total_flights desc
limit 10
```

```
 *  postgresql://student@/group1
10 rows affected.
```

Out[75]:

route	total_flights
,	486165
302,78	27201
78,65	24031
78,73	19309
290,100	19214
302,65	16877
252,174	16595
290,146	16449
293,146	16404
100,78	16197

Calculating the percentage of arrival delay.

Here we put the 15 minute thershhold into use.

In [76]:
```
%%sql
with t1 as (
select case when cast(origin_airport_key as integer) > cast(destination_airport_key as
origin_airport_key,destination_airport_key,airlines_key, case when arrival_delay > 15
from F_flights),
t2 as (select airlines_key,count(*) as total_flights,sum(delay) as total_delay_flights
from t1
where route = '302,78'
group by airlines_key)
select * ,(total_delay_flights*100)/total_flights as delay_percent
from t2
```

```
 * postgresql://student@/group1
6 rows affected.
```

Out[76]:

airlines_key	total_flights	total_delay_flights	delay_percent
1	1235	313	25
4	6143	1539	25
8	6155	1491	24
9	7043	1571	22
10	2727	1078	39
13	3898	825	21

airline key 1 = skywest airlines

airline key 4 = southwest airlines

airline key 8 = virgin america airline

key 9 = united airlines airline key

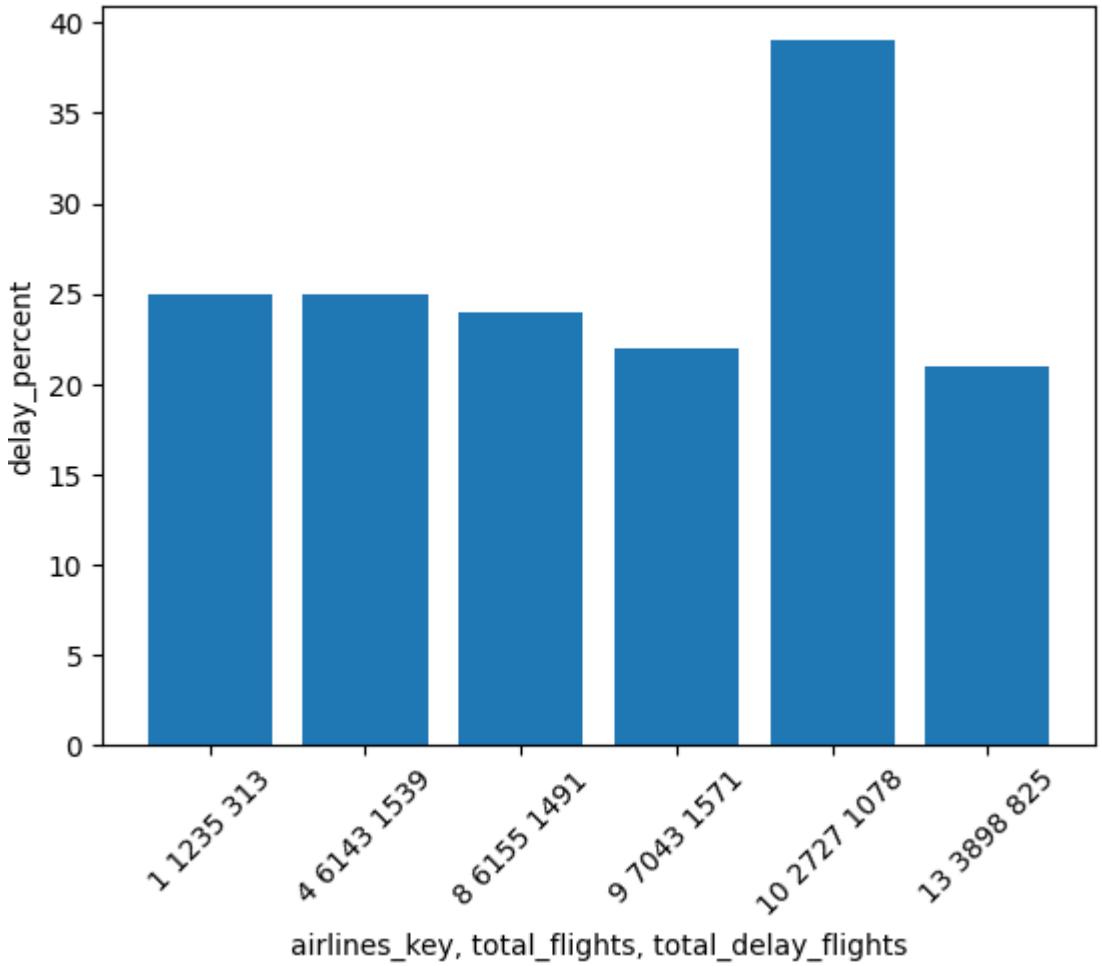
10 = delta airlines airline key 13 =

american airlines

In [77]:
```
%matplotlib inline
```

In [78]:
```
_.bar()
```

Out[78]:
```
<BarContainer object of 6 artists>
```



While travelling from Manchester-Boston Regional Airport to Los Angeles International Airport, the Southwest Airline with key number 4 has highest arrival delay percentage of 20 followed by Virgin America airlines of key number 8 with 17 percent, United airlines of key number 9 with 19percent and American airlines of key number 13 with 19 percent. We can suggest customers that the virgin America airline has minimal arrival delay

airlinekey 1 represent

In [79]:
```
%%sql
SELECT
a.airline,
CASE
    WHEN (f.arrival_delay)  < 15 THEN 'On Time'
    ELSE 'Late'
END as delay,
COUNT(*) AS cnt,
SUM(COUNT(*))OVER(PARTITION BY a.airline) AS total_cnt,
COUNT(*)/SUM(COUNT(*))OVER(PARTITION BY a.airline )::float   AS Percentage_Rate
FROM F_flights f
INNER JOIN date_dim d  ON  f.date_key=d.date_key
INNER JOIN airlines_dim a ON f.airlines_key=a.airlines_key
GROUP BY 1,2;
```

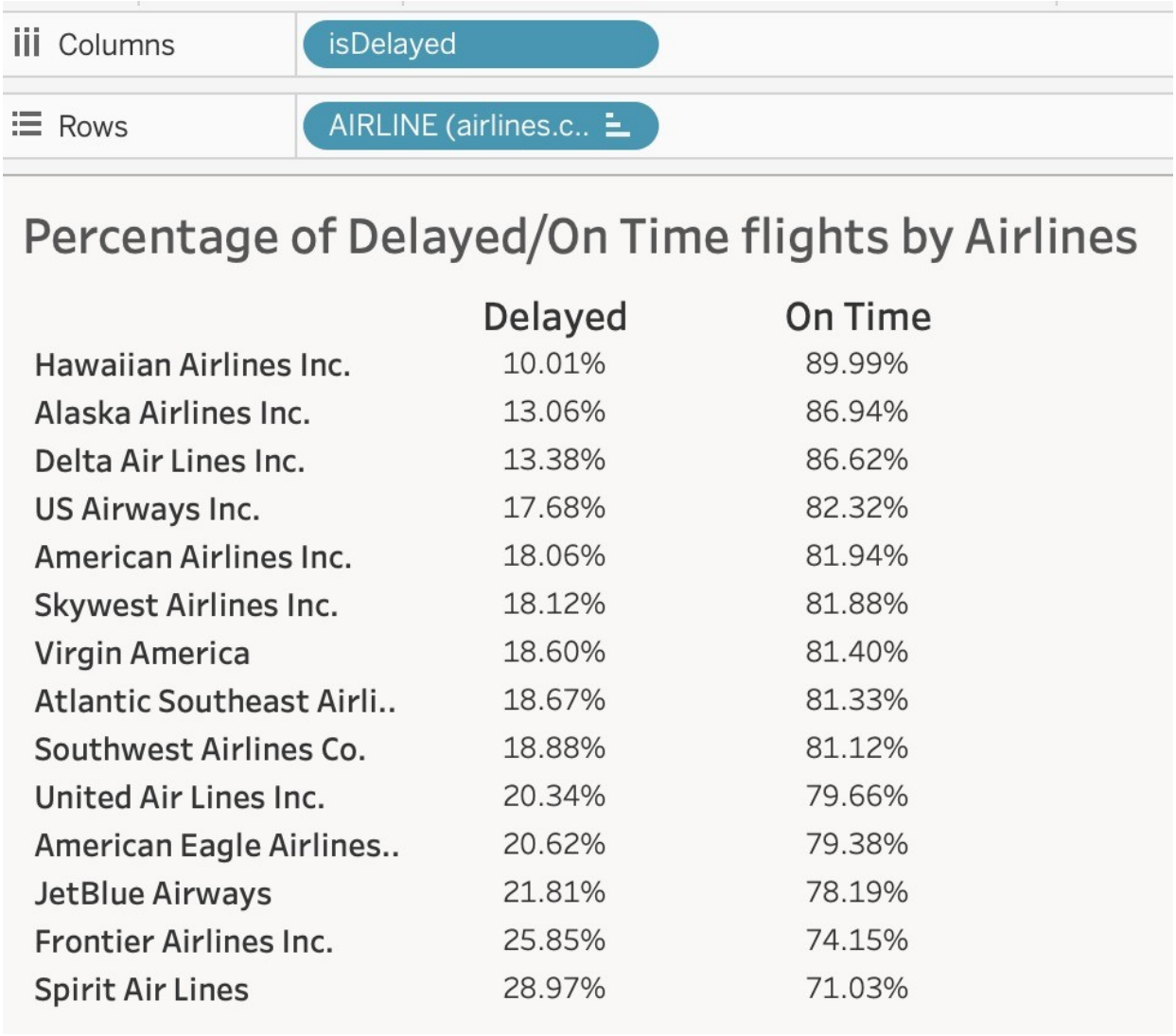
```
 * postgresql://student@/group1
28 rows affected.
```

Out[79]:

airline	delay	cnt	total_cnt	percentage_rate
Alaska Airlines Inc.	Late	22352	172521	0.1295610389459834
Alaska Airlines Inc.	On Time	150169	172521	0.8704389610540166
American Airlines Inc.	Late	130279	725984	0.1794516132586944
American Airlines Inc.	On Time	595705	725984	0.8205483867413056
American Eagle Airlines Inc.	Late	60547	294632	0.20550042086399306
American Eagle Airlines Inc.	On Time	234085	294632	0.794499579136007
Atlantic Southeast Airlines	Late	109184	571977	0.1908887944794983
Atlantic Southeast Airlines	On Time	462793	571977	0.8091112055205018
Delta Air Lines Inc.	Late	118023	875881	0.13474775682998033
Delta Air Lines Inc.	On Time	757858	875881	0.8652522431700197
Frontier Airlines Inc.	Late	23570	90836	0.25947862081113215
Frontier Airlines Inc.	On Time	67266	90836	0.7405213791888678
Hawaiian Airlines Inc.	Late	8618	76272	0.11299035032515209
Hawaiian Airlines Inc.	On Time	67654	76272	0.887009649674848
JetBlue Airways	Late	59175	267048	0.22158937719061741
JetBlue Airways	On Time	207873	267048	0.7784106228093826
Skywest Airlines Inc.	Late	107795	588353	0.183214838710774
Skywest Airlines Inc.	On Time	480558	588353	0.8167851612892261
Southwest Airlines Co.	Late	236626	1261855	0.18752233814503252
Southwest Airlines Co.	On Time	1025229	1261855	0.8124776618549675
Spirit Air Lines	Late	34221	117379	0.29154278022474206
Spirit Air Lines	On Time	83158	117379	0.7084572197752579
US Airways Inc.	Late	36549	198715	0.18392672923533704
US Airways Inc.	On Time	162166	198715	0.816073270764663
United Air Lines Inc.	Late	104722	515723	0.20305861867708053
United Air Lines Inc.	On Time	411001	515723	0.7969413813229195
Virgin America	Late	11778	61903	0.19026541524643395
Virgin America	On Time	50125	61903	0.8097345847535661

In [80]:
```
from IPython import display
display.  Image("image5.jpeg")
```

Out[80]:



Calculating the percentage of Departure delay

In [81]:

```
%%sql
with t1 as (
select case when cast(origin_airport_key as integer) > cast(destination_airport_key as
origin_airport_key,destination_airport_key,airlines_key,  case  when  departure_delay  > 1
from F_flights),
t2  as  (select  airlines_key,count(*)  as  total_flights,sum(delay)  as  total_delay_flights
from t1
where route = '302,78'
group  by  airlines_key)
select  *  ,(total_delay_flights*100)/total_flights  as  delay_percent
from t2
```

```
 *  postgresql://student@/group1
6 rows affected.
```

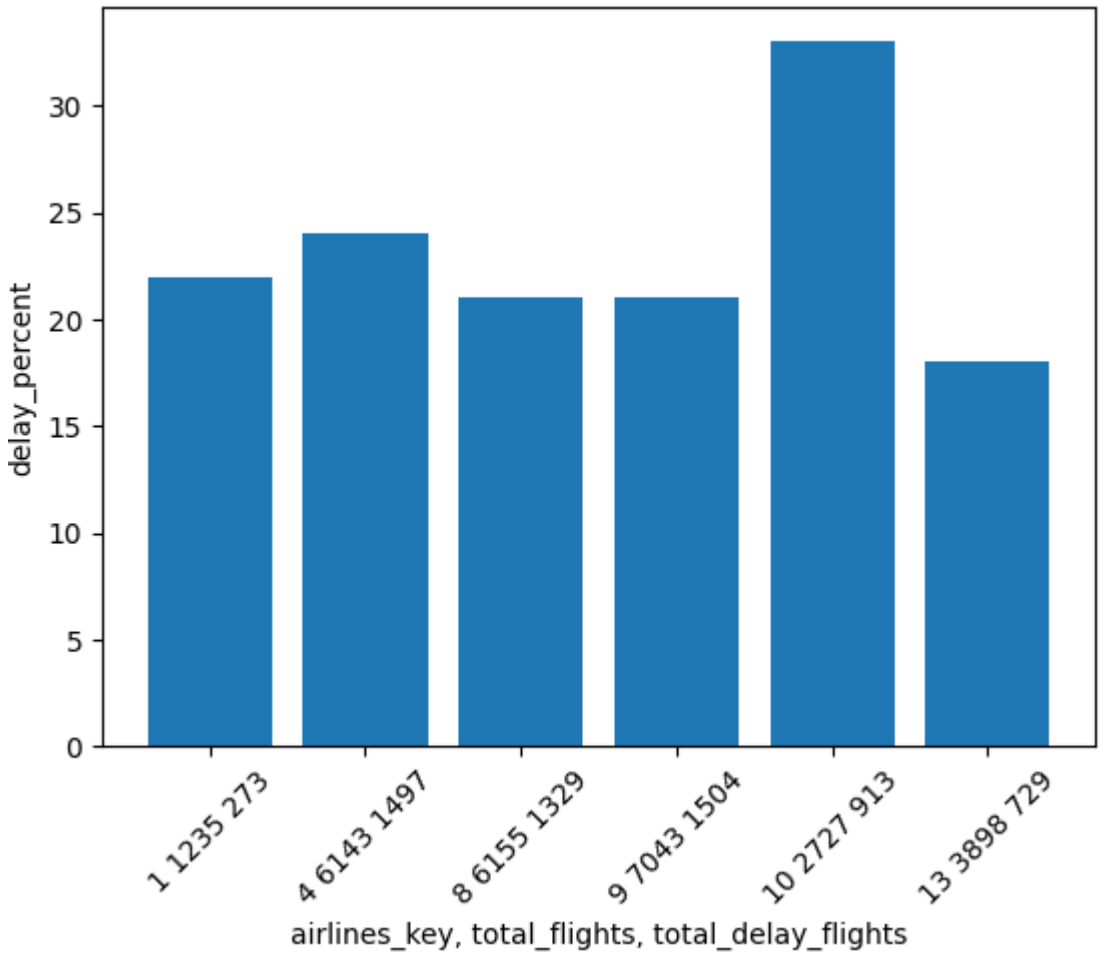
Out[81]:

airlines_key	total_flights	total_delay_flights	delay_percent
1	1235	273	22
4	6143	1497	24
8	6155	1329	21
9	7043	1504	21
10	2727	913	33
13	3898	729	18

In [82]:
```
%matplotlib inline
```

In [83]:
```
_.bar()
```

Out[83]: <BarContainer object of 6 artists>



The Virgin America airlines has minimal departure delay among the other airlines- Southwest airline, United airlines and American airlines while travelling from Manchester-Boston Regional Airport to Los Angeles International Airport. Only 16 percent of the flights have departure delays. We can suggest customers that the Virgin America airlines have minimal departure delay

Question 2 : DC airports(DCA,IAD) to NYU(JFK)

In the second question, we are shifting our focus from regulaors to cusotmers.

During what time period, does the air route from Washington D.C. to New York sees the most delays? What are the reason for delays? Advices that we can give to airlines to better improve their service.

For customers: calculating arrival delay

In [84]:
```
%%sql
SELECT
a.airline,d.year,  d.month,
CASE
    WHEN (f.arrival_delay)  < 15 THEN 'On Time'
    ELSE 'Late'
END as delay,
COUNT(*) AS cnt,
SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  ) AS total_cnt,
COUNT(*)/SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  )::float AS rate
FROM F_flights f
INNER JOIN date_dim d  ON  f.date_key=d.date_key
INNER JOIN airlines_dim a ON f.airlines_key=a.airlines_key
GROUP BY 1,2,3,4
Limit 15;
```

```
 *  postgresql://student@/group1
15 rows affected.
```

Out[84]:

airline	year	month	delay	cnt	total_cnt	rate
Alaska Airlines Inc.	2015	1	Late	1939	13257	0.14626235196499962
Alaska Airlines Inc.	2015	1	On Time	11318	13257	0.8537376480350004
Alaska Airlines Inc.	2015	2	Late	1652	12194	0.1354764638346728
Alaska Airlines Inc.	2015	2	On Time	10542	12194	0.8645235361653272
Alaska Airlines Inc.	2015	3	Late	1970	14276	0.13799383580834967
Alaska Airlines Inc.	2015	3	On Time	12306	14276	0.8620061641916503
Alaska Airlines Inc.	2015	4	Late	1407	13974	0.10068699012451696
Alaska Airlines Inc.	2015	4	On Time	12567	13974	0.899313009875483
Alaska Airlines Inc.	2015	5	Late	1682	14682	0.11456204876719793
Alaska Airlines Inc.	2015	5	On Time	13000	14682	0.8854379512328021
Alaska Airlines Inc.	2015	6	Late	1803	15075	0.11960199004975125
Alaska Airlines Inc.	2015	6	On Time	13272	15075	0.8803980099502487
Alaska Airlines Inc.	2015	7	Late	2067	15821	0.1306491372226787
Alaska Airlines Inc.	2015	7	On Time	13754	15821	0.8693508627773213
Alaska Airlines Inc.	2015	8	Late	2685	16095	0.1668219944082013

DC local, calculate on time percentage base on month.

In [85]:
```
%%sql
SELECT * FROM (
SELECT
a.airline,d.year,  d.month,
CASE
    WHEN (f.arrival_delay)  < 15 THEN 'On Time'
    ELSE 'Late'
END as delay,
COUNT(*) AS cnt,
SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  ) AS total_cnt,
COUNT(*)/SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  )::float   AS rate
FROM F_flights f
INNER JOIN date_dim d  ON  f.date_key=d.date_key
INNER JOIN airlines_dim a ON f.airlines_key=a.airlines_key
WHERE  origin_airport_key in (select airports_key from airports_dim WHERE iata_code in
and destination_airport_key in (select airports_key from airports_dim WHERE iata_code
GROUP BY 1,2,3,4
) AS T
WHERE delay='On Time';
```

```
 *  postgresql://student@/group1
35 rows affected.
```

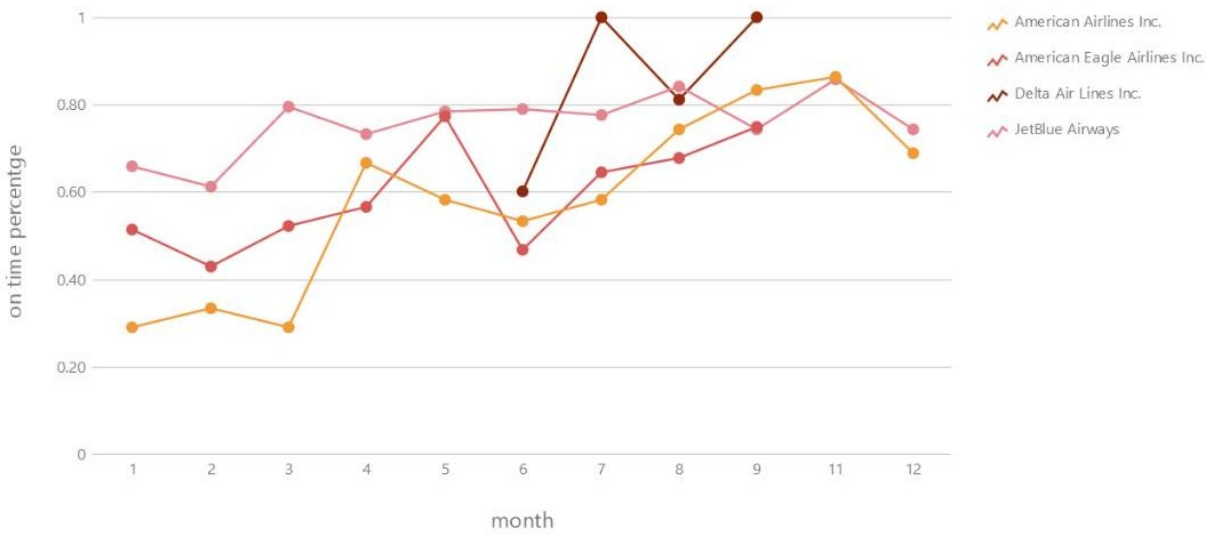
Out[85]:

airline	year	month	delay	cnt	total_cnt	rate
American Airlines Inc.	2015	1	On Time	11	31	0.3548387096774194
American Airlines Inc.	2015	2	On Time	12	27	0.4444444444444444
American Airlines Inc.	2015	3	On Time	12	31	0.3870967741935484
American Airlines Inc.	2015	4	On Time	20	30	0.6666666666666666
American Airlines Inc.	2015	5	On Time	18	31	0.5806451612903226
American Airlines Inc.	2015	6	On Time	18	30	0.6
American Airlines Inc.	2015	7	On Time	18	31	0.5806451612903226
American Airlines Inc.	2015	8	On Time	23	31	0.7419354838709677
American Airlines Inc.	2015	9	On Time	25	30	0.8333333333333334
American Airlines Inc.	2015	11	On Time	25	29	0.8620689655172413
American Airlines Inc.	2015	12	On Time	20	29	0.6896551724137931
American Eagle Airlines Inc.	2015	1	On Time	103	154	0.6688311688311688
American Eagle Airlines Inc.	2015	2	On Time	93	140	0.6642857142857143
American Eagle Airlines Inc.	2015	3	On Time	105	144	0.7291666666666666
American Eagle Airlines Inc.	2015	4	On Time	23	30	0.7666666666666667
American Eagle Airlines Inc.	2015	5	On Time	26	31	0.8387096774193549
American Eagle Airlines Inc.	2015	6	On Time	19	30	0.6333333333333333
American Eagle Airlines Inc.	2015	7	On Time	20	31	0.6451612903225806
American Eagle Airlines Inc.	2015	8	On Time	24	31	0.7741935483870968
American Eagle Airlines Inc.	2015	9	On Time	7	8	0.875
Delta Air Lines Inc.	2015	6	On Time	3	5	0.6
Delta Air Lines Inc.	2015	7	On Time	29	29	1.0
Delta Air Lines Inc.	2015	8	On Time	26	32	0.8125
Delta Air Lines Inc.	2015	9	On Time	1	1	1.0
JetBlue Airways	2015	1	On Time	64	88	0.7272727272727273
JetBlue Airways	2015	2	On Time	58	80	0.725
JetBlue Airways	2015	3	On Time	77	88	0.875
JetBlue Airways	2015	4	On Time	67	86	0.7790697674418605
JetBlue Airways	2015	5	On Time	72	88	0.8181818181818182
JetBlue Airways	2015	6	On Time	70	86	0.813953488372093
JetBlue Airways	2015	7	On Time	72	89	0.8089887640449438
JetBlue Airways	2015	8	On Time	75	88	0.8522727272727273
JetBlue Airways	2015	9	On Time	66	86	0.7674418604651163

	airline	year	month	delay	cnt	total_cnt	rate
	JetBlue Airways	2015	11	On Time	74	85	0.8705882352941177
	JetBlue Airways	2015	12	On Time	65	86	0.7558139534883721

In [86]:
```
from IPython import display
display.  Image("Image2.jpeg")
```

Out[86]:



Four airways travel from IAD to NYU - American Airlines Inc, American Eagle Airlines Inc, DeltaAir Lines Inc and JetBlue Airways.

For JetBlue Airways, the On-time percentage is consistent for the months 3 to 12.

For American Egale Airlines, the on time percentage vaires a lot, but keeps rising until winterseason.

For Delta Airlines, they only offer flights during the summer seasons, but it has the highest ontime percentage during that time.

For American airlines, it has the worst on time percentage during winter season, but it keepsgetting better as the weather gets warm.

Overall, the on-time percentage is less in the month of January and February. However, JetBlueairways outperformed it's competitors a lot. It looks like they are the best choice during the winter seasons if you don't want delays.

Advice for airline companies:

Because American airlines and American Eagle airlines has the worst on time perforamce duringthe winter, they could probably ask consulting comapnies to help them take a look into the practices that JetBlueis using.

For Delta airlines, if they can successfully manage on-time percentage during the winter time,there might be a chance for them to further the competition by adding flights from Dec to

March. espcially if they could keep up with the good job during summer time.

In [87]:
```
%%sql
SELECT * FROM (
SELECT
a.airline,d.year,  d.month,
CASE
    WHEN (f.departure_delay)  < 15 THEN 'On Time'
    ELSE 'Late'
END as delay,
COUNT(*) AS cnt,
SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  ) AS total_cnt,
COUNT(*)/SUM(COUNT(*))OVER(PARTITION BY a.airline,d.year,  d.month  )::float   AS On_time
FROM F_flights f
INNER JOIN date_dim d  ON  f.date_key=d.date_key
INNER JOIN airlines_dim a ON f.airlines_key=a.airlines_key
WHERE  origin_airport_key in (select airports_key from airports_dim WHERE iata_code in
and destination_airport_key in (select airports_key from airports_dim WHERE iata_code
GROUP BY 1,2,3,4
) AS T
WHERE delay='On Time';
```

```
 *  postgresql://student@/group1
35 rows affected.
```

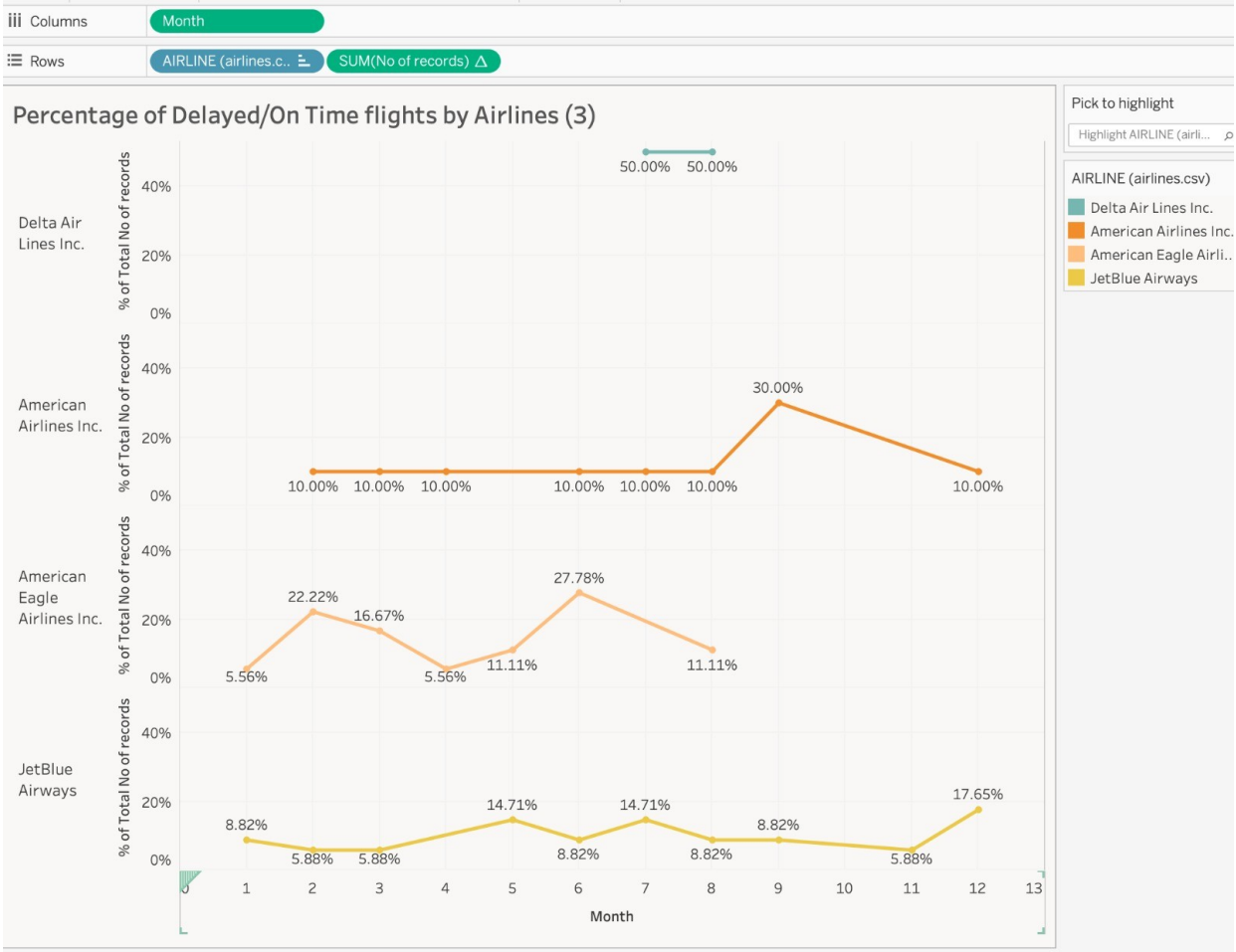
Out[87]:

airline	year	month	delay	cnt	total_cnt	on_time_rate
American Airlines Inc.	2015	1	On Time	17	31	0.5483870967741935
American Airlines Inc.	2015	2	On Time	14	27	0.5185185185185185
American Airlines Inc.	2015	3	On Time	14	31	0.45161290322580644
American Airlines Inc.	2015	4	On Time	19	30	0.6333333333333333
American Airlines Inc.	2015	5	On Time	20	31	0.6451612903225806
American Airlines Inc.	2015	6	On Time	19	30	0.6333333333333333
American Airlines Inc.	2015	7	On Time	18	31	0.5806451612903226
American Airlines Inc.	2015	8	On Time	21	31	0.6774193548387096
American Airlines Inc.	2015	9	On Time	21	30	0.7
American Airlines Inc.	2015	11	On Time	25	29	0.8620689655172413
American Airlines Inc.	2015	12	On Time	15	29	0.5172413793103449
American Eagle Airlines Inc.	2015	1	On Time	112	154	0.7272727272727273
American Eagle Airlines Inc.	2015	2	On Time	103	140	0.7357142857142858
American Eagle Airlines Inc.	2015	3	On Time	112	144	0.7777777777777778
American Eagle Airlines Inc.	2015	4	On Time	25	30	0.8333333333333334
American Eagle Airlines Inc.	2015	5	On Time	23	31	0.7419354838709677
American Eagle Airlines Inc.	2015	6	On Time	22	30	0.7333333333333333
American Eagle Airlines Inc.	2015	7	On Time	21	31	0.6774193548387096
American Eagle Airlines Inc.	2015	8	On Time	22	31	0.7096774193548387
American Eagle Airlines Inc.	2015	9	On Time	6	8	0.75
Delta Air Lines Inc.	2015	6	On Time	4	5	0.8
Delta Air Lines Inc.	2015	7	On Time	29	29	1.0
Delta Air Lines Inc.	2015	8	On Time	29	32	0.90625
Delta Air Lines Inc.	2015	9	On Time	1	1	1.0
JetBlue Airways	2015	1	On Time	75	88	0.8522727272727273
JetBlue Airways	2015	2	On Time	65	80	0.8125
JetBlue Airways	2015	3	On Time	77	88	0.875
JetBlue Airways	2015	4	On Time	66	86	0.7674418604651163
JetBlue Airways	2015	5	On Time	68	88	0.7727272727272727
JetBlue Airways	2015	6	On Time	68	86	0.7906976744186046
JetBlue Airways	2015	7	On Time	71	89	0.797752808988764
JetBlue Airways	2015	8	On Time	74	88	0.8409090909090909
JetBlue Airways	2015	9	On Time	66	86	0.7674418604651163

	airline	year	month	delay	cnt	total_cnt	on_time_rate
	JetBlue Airways	2015	11	On Time	78	85	0.9176470588235294
	JetBlue Airways	2015	12	On Time	72	86	0.8372093023255814

In [88]:
```
from IPython import display
display.  Image("image11.jpeg")
```

Out[88]:



Here, we used Tableau to create a graph that compares the performance of each airlines.

Question 3

Is there a relationship between customer's attitude on social media with performance of airlines ? Should people rely on social media platforms to choose airlines or should the airline companies use social media to monitor their brands?

We found an extra dataset, twitter_2015.csv that represents customers' interactions with airline comapnies that alreday has twitter account.

Situation Analysis:

Social media platforms, in nature, in an excellent place where companies can collect important business information such as customer attitude, product experience, as well as managing and

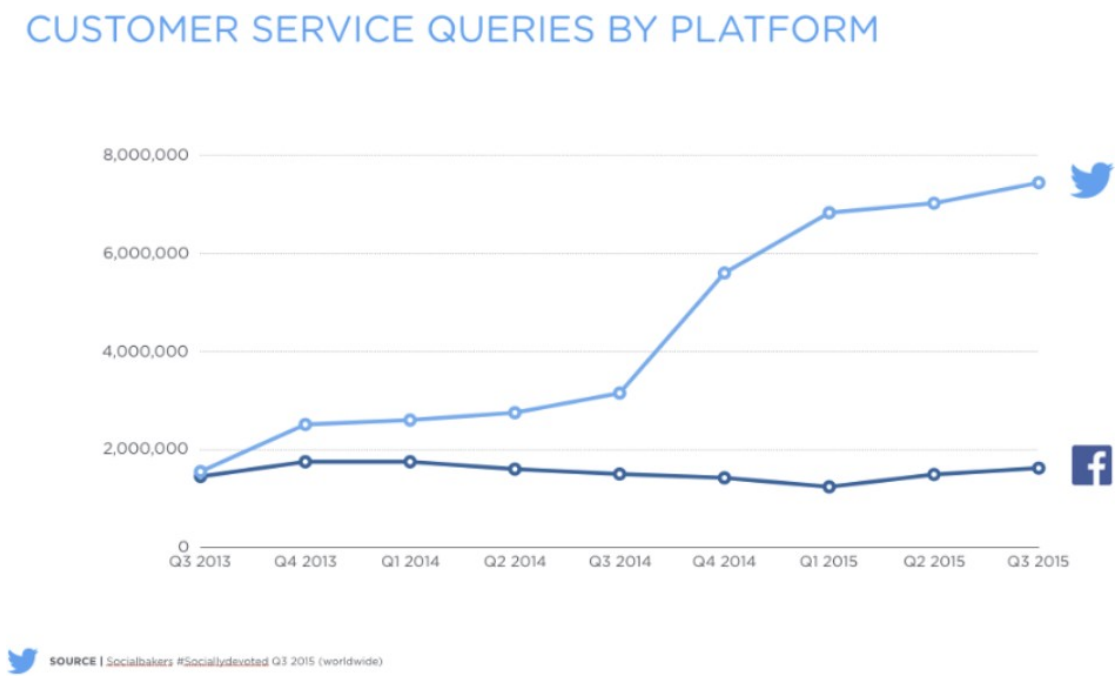
processing customer questions. The twitter platform, stands out among all the other platformsas it provides a more focused, simple environment for both users and companies to interact with each other. As we can see in the graph, from 2013 to 2015, more and more customers choose to express their attitude on the twitter platform than the others.

To testify that, we are trying to see if twitter is a good source of information for airline companies to help explain insights provided by our previous analysis, such as whether the performance of airlines would have a positive effect on brand attitude. Thus, an airline shouldinvest resources in managing and creating social media presence. We can also use this information to see whether or not consumers can rely on informations on social media to determine what airline they should trust for a better experience.

As a result, we are choosing Twitter data from 6 major airlines that has a twitter account in 2015.We also have data for all 6 of the airlines in our previous dataset. So let's start comparing.

In [89]:
```
from IPython import display
display.  Image("image202.png")
```

Out[89]:



In [101…
```
!xsv headers Tweets.csv
```

```
1   tweet_id
2   airline_sentiment
3   airline_sentiment_confidence
4   negativereason
5   negativereason_confidence
6   airline
7   airline_sentiment_gold
8   name
9   negativereason_gold
10  retweet_count
11  text
12  tweet_coord
13  tweet_created
14  tweet_location
15  user_timezone
```

In [112…
```
!csvcut -c 2,6 Tweets.csv > Tweets2.csv
```

In [113…
```
!xsv headers Tweets2.csv
```

```
1   airline_sentiment
2   airline
```

First, we create a new table that combines twitter sentiment data with the names of airline

In [114…
```
%%sql
DROP TABLE IF EXISTS T_tweets;
CREATE TABLE T_tweets (
 Airline_sentiment  varchar(100),
 airline char(100)
);
```

```
 * postgresql://student@/group1
Done.
Done.
```

Out[114]: []

In [115…
```
%%sql
select *
from T_tweets
limit 10
```

```
 * postgresql://student@/group1
0 rows affected.
```

Out[115]:

airline_sentiment	airline

In [116…
```
%%sql
COPY T_tweets FROM '/home/ubuntu/notebooks/Tweets2.csv'
CSV
HEADER;
```

```
 * postgresql://student@/group1
14640 rows affected.
```

Out[116]: []

We are changing the airline names on the twitter data, so that the names match our data in theairline dimension atable

In [117…
```
%%sql
update T_tweets set airline = (
case  when airline='Southwest' then 'WN'
      when airline='Virgin America' then 'VX'
   when airline='Delta' then 'DL'
   when airline='American' then 'AA'
   when airline='US Airways' then 'US'
   when airline='United' then 'UA'  end
);
```

```
 * postgresql://student@/group1
14640 rows affected.
```

Out[117]: []

Here we count the oveall number of customers' attitutes in the format of percentage of total interactions.

In [118…
```
%%sql
SELECT
airline ,
ROUND(SUM(CASE WHEN airline_sentiment='neutral' THEN 1 ELSE 0.0 END)/COUNT(*),2) AS
ROUND(SUM(CASE WHEN airline_sentiment='positive' THEN 1 ELSE 0.0 END)/COUNT(*),2)  AS
ROUND(SUM(CASE WHEN airline_sentiment='negative' THEN 1 ELSE 0.0 END)/COUNT(*),2)  AS
FROM T_tweets
GROUP BY airline ;
```

```
 * postgresql://student@/group1
6 rows affected.
```

Out[118]:

airline	neutral	positive	negative
AA	0.17	0.12	0.71
VX	0.34	0.30	0.36
UA	0.18	0.13	0.69
US	0.13	0.09	0.78
WN	0.27	0.24	0.49
DL	0.33	0.24	0.43

add the columns into airline dimension table

In [119…
```
%%sql
ALTER TABLE airlines_dim
  ADD COLUMN neutral float,
  ADD COLUMN positive float,
  ADD COLUMN negative float;
```

```
 * postgresql://student@/group1
(psycopg2.errors.DuplicateColumn) column "neutral" of relation "airlines_dim" already
exists

[SQL: ALTER TABLE airlines_dim
  ADD COLUMN neutral float,
  ADD COLUMN positive float,
  ADD COLUMN negative float;]
(Background on this error at: https://sqlalche.me/e/14/f405)
```

In [120…

```
%%sql
UPDATE airlines_dim AS f
SET neutral = t.neutral,positive = t.positive,negative = t.negative
FROM (
 SELECT
 airline ,
 ROUND(SUM(CASE WHEN airline_sentiment='neutral' THEN 1 ELSE 0.0 END)/COUNT(*),2) AS
 ROUND(SUM(CASE WHEN airline_sentiment='positive' THEN 1 ELSE 0.0 END)/COUNT(*),2)  AS
 ROUND(SUM(CASE WHEN airline_sentiment='negative' THEN 1 ELSE 0.0 END)/COUNT(*),2)  AS
 FROM T_tweets
 GROUP BY airline
) AS t
WHERE f.iata_code = t.airline;
```

```
 * postgresql://student@/group1
6 rows affected.
```

Out[120]: []

In [121…

```
%%sql
select  * from  airlines_dim  where  neutral is not null;
```

```
 * postgresql://student@/group1
6 rows affected.
```

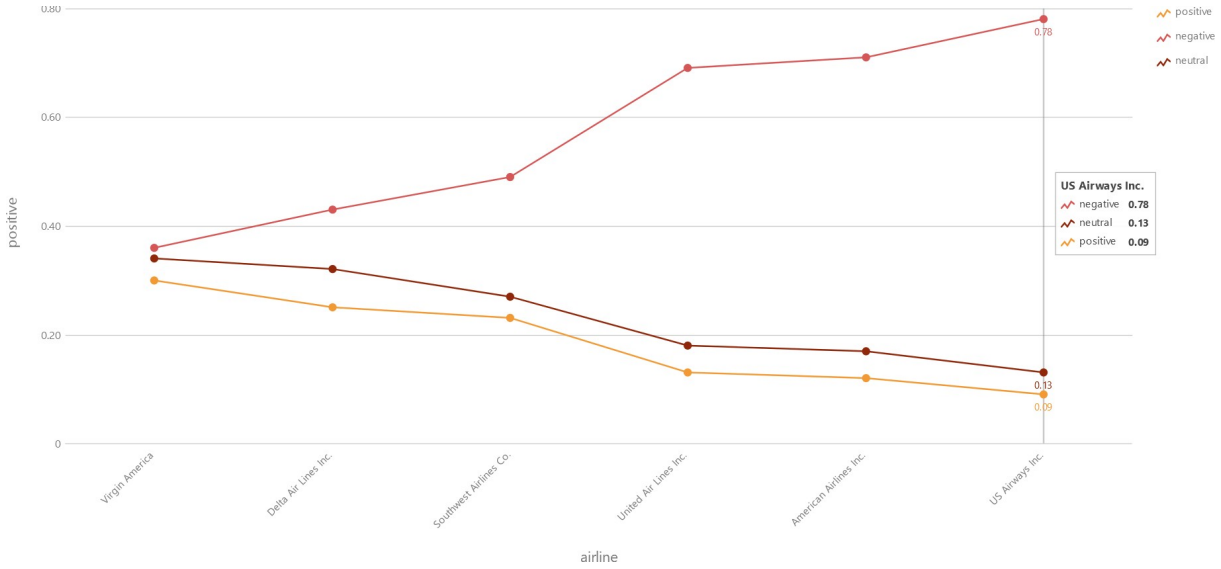
Out[121]:

airlines_key	iata_code	airline	neutral	positive	negative
3	US	US Airways Inc.	0.13	0.09	0.78
4	WN	Southwest Airlines Co.	0.27	0.24	0.49
8	VX	Virgin America	0.34	0.3	0.36
9	UA	United Air Lines Inc.	0.18	0.13	0.69
10	DL	Delta Air Lines Inc.	0.33	0.24	0.43
13	AA	American Airlines Inc.	0.17	0.12	0.71

In [122…

```
from IPython import display
display.  Image("image302.png")
```

Out[122]:



The 6 Airlines are all received mostly negative feedback.

In [127…

```
%%sql
SELECT
a.airline,
CASE
WHEN (f.arrival_delay) < 15 THEN 'On Time'
ELSE 'Late'
END as delay,
COUNT(*) AS cnt,
SUM(COUNT(*))OVER(PARTITION BY a.airline) AS total_cnt,
COUNT(*)/SUM(COUNT(*))OVER(PARTITION BY a.airline )::float AS Rate
FROM F_flights f
INNER JOIN date_dim d ON f.date_key=d.date_key
INNER JOIN airlines_dim a ON f.airlines_key=a.airlines_key
WHERE f.airlines_key in (select airlines_key from airlines_dim where neutral is not nu
GROUP BY 1,2;
```

```
 *  postgresql://student@/group1
12 rows affected.
```

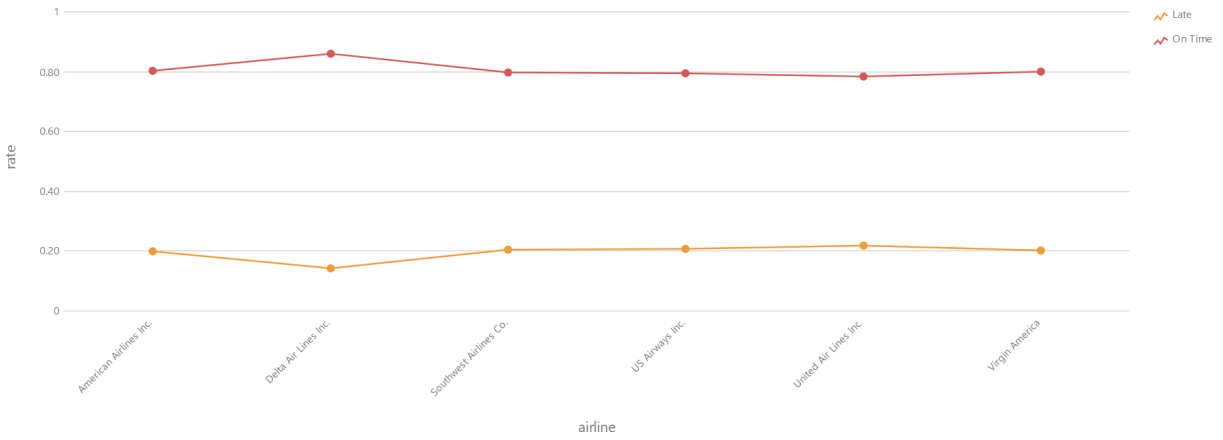
Out[127]:

airline	delay	cnt	total_cnt	rate
American Airlines Inc.	Late	130279	725984	0.1794516132586944
American Airlines Inc.	On Time	595705	725984	0.8205483867413056
Delta Air Lines Inc.	Late	118023	875881	0.13474775682998033
Delta Air Lines Inc.	On Time	757858	875881	0.8652522431700197
Southwest Airlines Co.	Late	236626	1261855	0.18752233814503252
Southwest Airlines Co.	On Time	1025229	1261855	0.8124776618549675
US Airways Inc.	Late	36549	198715	0.18392672923533704
US Airways Inc.	On Time	162166	198715	0.816073270764663
United Air Lines Inc.	Late	104722	515723	0.20305861867708053
United Air Lines Inc.	On Time	411001	515723	0.7969413813229195
Virgin America	Late	11778	61903	0.19026541524643395
Virgin America	On Time	50125	61903	0.8097345847535661

In [128…

```
from IPython import display
display.  Image("image303.png")
```

Out[128]:



There are not directly relationship between on time percentage rate and sentiment on Twitter.Result

showcase:

For passengers flight delays is a problem that cause inconveniences. This not only irritate passengers and disrupt their schedules but also cause a decrease in efficiency and brand damage for the airline. We are expecting that there will be a positive relationship between thesentiment of airline and delay time. (Higher delay will have a higher negative sentiment rate)

About the data

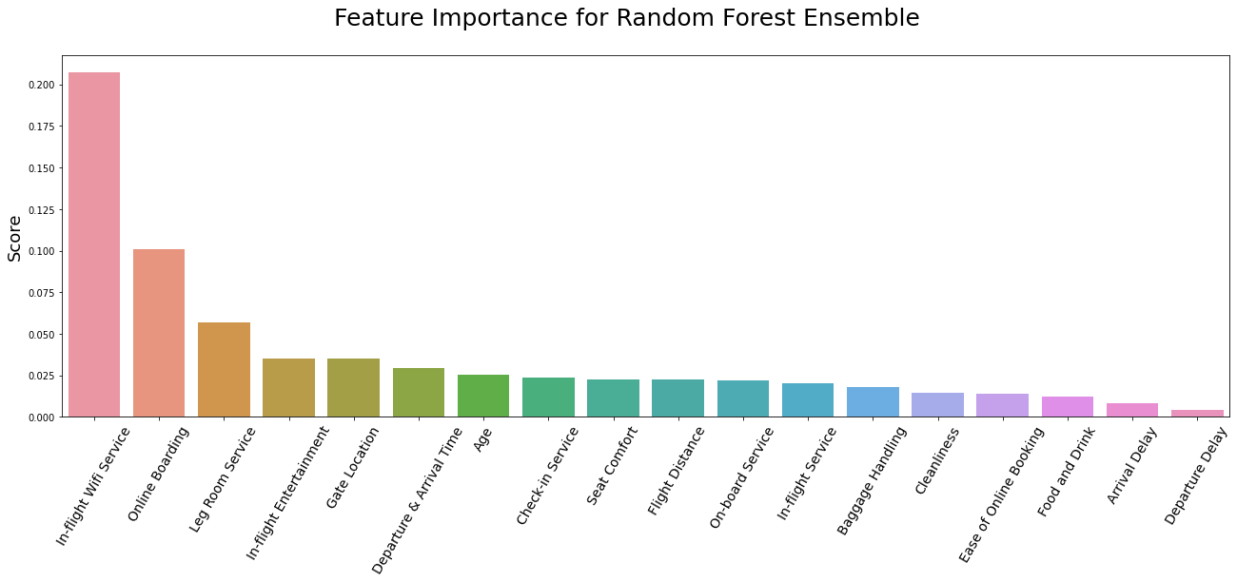
Virgin America and delta airlines have the highest positive review on twitter, but we do not observe any relationship between delay time and reviews on twitter.Below are the reasons whythis approach of analysis does not work out

Most airline companies from the data set have a lot of negative reviews on twitter. The reasonfor this can be that anyone can share their incomplete opinions freely. That also includes the potential widespread of false information. And when false news is spread, it creates a lot of emotional responses from people, which drives more toxicity onto the platform.

On kaggle we found an Airline Customer Satisfaction Analysis that shows all other variables thatcan also affect customers satisfaction. Surprisingly for customers there are a lot of things that come before punctuality.

In [98]:
```
from IPython import display
display.  Image("image301.png")
```

Out[98]:



In [ ]:

In [ ]:

In [ ]: