2015 US Domestic Flights Analysis: Delays and Cancellations (Capstone 2)

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General note

> The goal of this Capstone2 project is multifold: **1)** to incorporate all the learnings (technical & analytical skills) acquired throughout the Data Analytics Career Track course offered by Springboard, **2)** to demonstrate & strengthen technical skills and computer literacy related to Python, Tableau, statistics, predictive analytics and modeling, **3)** generate a basic tutorial for people who are new to Python and Exploratory Data Analysis

Acknowledgments

> I would like to offer my thanks to my Springboard advisor Akshay Jhawar and all other mentors that gave me support throughout this project (Wayne Ang, Chris Hui, Chris Young)

Python libraries used

> - **Data manipulation**: numpy, pandas, geopandas
> - **Visualization**: matplotlib, seaborn
> - **Statistics**: statsmodel,scipy
> - **Modeling**:statsmodel, sklearn
>
> ---

OUTLINE

III. Exploratory data analysis (EDA): visualization, statistics (descriptive & inferential), trends & relationships

A. EDA approach
B. Analysis of cancellation, delayed flights, and frequency of flights

1. 2015 Cancelled and Diverted flights overview
2. Flights frequency - Temporal analysis
3. Flight frequency - Spatial analysis
4. Flight frequency - Airlines (carrier) analysis

C. Analysis of flight delays: frequency, magnitude, reasons, temporal, spatial and carrier - based analysis

1. Understand the relationship between variables
2. Delays at departure vs. delays at arrival
3. Delays @ Departure (DD): frequency vs. magnitude
4. Flight delays distribution by reason
5. Flight delays carrier-based analysis
6. Flight delays temporal analysis

IV. Predictive Analytics: Modeling & Prediction for Delays at Departure

1. Multivariate linear regression model_1: all Departure Delay data for 2015
2. Multivariate linear regression model_2: Departure Delays <= p99
3. Multivariate linear regression model_3: Departure Delays > p99

I. Introduction

Why this data set

I chose this data set based on these characteristics:

- Richness in dimensions such as categorical, numerical data, geographic data, and time series
- Prediction potential
- High potential business impact
- Interesting subject

Context

- The U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics tracks the on-time performance and the causes of delays and cancellation of domestic flights operated by large air carriers since 2003. Summary information on the number of on-time, delayed, canceled, and diverted flights is published in DOT's monthly Air Travel Consumer Report. It covers nonstop scheduled-service flights between points within the United States (including territories) by the fourteen (14) U.S. air carriers that have at least one percent of total domestic scheduled-service passenger revenues.

- The current analysis focuses on the 2015 historical daily data of domestic flights operated by large air carriers, which includes specs on airlines, flights, airports, dates, time, and causes of delays and cancellations

Goals

- Identify major drivers for delays and cancellations
- Build a model to predict overall flight delays

Sources

- Kaggle: https://www.kaggle.com/usdot/flight-delays?select=flights.csv

- US Department of Transportation: https://www.transportation.gov/airconsumer

- Bureau of Transportation Statistics: https://www.transtats.bts.gov

II. Exploratory Data Analysis (EDA): data examination & cleaning

A. Import python libraries & raw data

B. Data overview & description: understanding the variables & dimensions

1. The *flights* dataset
2. The *airports* dataset
3. The *airlines* dataset
4. Renaming columns

C. Data cleaning (add link to section): unique identifiers, missing values, duplicates, data inconsistencies, transforming data

1. The *flights* dataset
2. The *airports* dataset
3. Merging datasets

A. Import python libraries & raw data

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
import scipy as sp
import statsmodels.api as sm
import datetime
import time
import os

sns.set_style("darkgrid")
mpl.rcParams['figure.figsize'] = (20, 5)
```

```
#magic panda line that renders the figure in a notebook
%matplotlib inline
```

In [2]:

```
# import 4 files part of the data set
# 1. flights:  the main file
flights_raw=pd.read_csv("/Users/iulialaptop/Documents/0. Career/Python_Projects_

# 2. airports file includes airport geographic coordinates
airports_raw=pd.read_csv("/Users/iulialaptop/Documents/0. Career/Python_Projects

# 3. airlines file includes the airlines 2-letter code
airlines=pd.read_csv("/Users/iulialaptop/Documents/0. Career/Python_Projects_Spr

# 4. the Ocotber file includes data for the month of October 2015 only to correc
October_2015_Flights=pd.read_csv("/Users/iulialaptop/Documents/0. Career/Python_
```

In [52]:

```
# summary table
pd.concat([
    flights_raw.dtypes,
    flights_raw.count(),
    flights_raw.nunique(),
    flights_raw.duplicated().value_counts(),
    flights_raw.isnull().sum(),
    round(100 * flights_raw.isnull().sum() / len(flights_raw), 1)
],
          axis=1).rename(
              columns={
                  0: 'Dtype',
                  1: 'Non-null counts',
                  2: 'Unique values',
                  3: 'Duplicates',
                  4: 'Missing Nulls',
                  5: 'Missing (%)'
              })
```

Out[52]:

	Dtype	Non-null counts	Unique values	Duplicates	Missing Nulls	Missing (%)
YEAR	int16	5819079.0	1.0	NaN	0.0	0.0
MONTH	int8	5819079.0	12.0	NaN	0.0	0.0
DAY	int8	5819079.0	31.0	NaN	0.0	0.0
DAY_OF_WEEK	int8	5819079.0	7.0	NaN	0.0	0.0
AIRLINE	category	5819079.0	14.0	NaN	0.0	0.0
ORIGIN_AIRPORT	object	5819079.0	628.0	NaN	0.0	0.0
DESTINATION_AIRPORT	object	5819079.0	629.0	NaN	0.0	0.0
SCHEDULED_DEPARTURE	float32	5819079.0	1321.0	NaN	0.0	0.0
DEPARTURE_TIME	float32	5732926.0	1440.0	NaN	86153.0	1.5
DEPARTURE_DELAY	float32	5732926.0	1217.0	NaN	86153.0	1.5
TAXI_OUT	float32	5730032.0	184.0	NaN	89047.0	1.5
WHEELS_OFF	float32	5730032.0	1440.0	NaN	89047.0	1.5
SCHEDULED_TIME	float32	5819073.0	550.0	NaN	6.0	0.0

	Dtype	Non-null counts	Unique values	Duplicates	Missing Nulls	Missing (%)
ELAPSED_TIME	float32	5714008.0	712.0	NaN	105071.0	1.8
AIR_TIME	float32	5714008.0	675.0	NaN	105071.0	1.8
DISTANCE	int16	5819079.0	1363.0	NaN	0.0	0.0
WHEELS_ON	float32	5726566.0	1440.0	NaN	92513.0	1.6
TAXI_IN	float32	5726566.0	185.0	NaN	92513.0	1.6
SCHEDULED_ARRIVAL	float32	5819079.0	1435.0	NaN	0.0	0.0
ARRIVAL_TIME	float32	5726566.0	1440.0	NaN	92513.0	1.6
ARRIVAL_DELAY	float32	5714008.0	1240.0	NaN	105071.0	1.8
DIVERTED	int8	5819079.0	2.0	NaN	0.0	0.0
CANCELLED	int8	5819079.0	2.0	NaN	0.0	0.0
CANCELLATION_REASON	category	89884.0	4.0	NaN	5729195.0	98.5
AIR_SYSTEM_DELAY	float32	1063439.0	570.0	NaN	4755640.0	81.7
SECURITY_DELAY	float32	1063439.0	154.0	NaN	4755640.0	81.7
AIRLINE_DELAY	float32	1063439.0	1067.0	NaN	4755640.0	81.7
LATE_AIRCRAFT_DELAY	float32	1063439.0	695.0	NaN	4755640.0	81.7
WEATHER_DELAY	float32	1063439.0	632.0	NaN	4755640.0	81.7
False	NaN	NaN	NaN	5819079.0	NaN	NaN

Optimize files for memory usage

In [4]:

```
flights_size = os.stat(
    "/Users/iulialaptop/Documents/0. Career/Python_Projects_Springboard/2015 Fli
)
airports_size = os.stat(
    "/Users/iulialaptop/Documents/0. Career/Python_Projects_Springboard/2015 Fli
)
airlines_size = os.stat(
    "/Users/iulialaptop/Documents/0. Career/Python_Projects_Springboard/2015 Fli
)
october_size = os.stat(
    "/Users/iulialaptop/Documents/0. Career/Python_Projects_Springboard/2015 Fli
)

print('The size of "flights_raw" is:', round(flights_size.st_size / 1000000,
                                             2), "MB")
print('The size of "airports" is:', round(airports_size.st_size / 1000000, 2),
      "MB")
print('The size of "airlines" is:', round(airlines_size.st_size / 1000000, 2),
      "MB")
print('The size of "october" is:', round(october_size.st_size / 1000000, 2),
      "MB")
```

```
The size of "flights_raw" is: 592.41 MB
The size of "airports" is: 0.02 MB
```

```
The size of "airlines" is: 0.0 MB
The size of "october" is: 177.3 MB
```

In [5]:
```
# reducing the file memory usage by changind the dtypes
dtype = {'YEAR':'int16', 'MONTH':'int8', 'DAY':'int8', 'DAY_OF_WEEK':'int8', 'AI
flights_raw = pd.read_csv("/Users/iulialaptop/Documents/0. Career/Python_Project

#drop 2 columns
flights_raw=flights_raw.drop(columns=['FLIGHT_NUMBER', 'TAIL_NUMBER'])
```

B. Data overview & description: understanding the variables & dimensions

In [6]:
```
#raw data summary
print("1. flights_df_dimensions:", flights_raw.shape)
print("2. airports_df_dimensions:",airports_raw.shape)
print("3. airlines_df_dimensions:",airlines.shape)
print("4. October_2015_df_dimensions:",October_2015_Flights.shape)
```

```
1. flights_df_dimensions: (5819079, 29)
2. airports_df_dimensions: (322, 7)
3. airlines_df_dimensions: (14, 2)
4. October_2015_df_dimensions: (486165, 65)
```

#	File Name	Description	No. of columns
1.	**flights_raw**	• the main data set to be used in analysis	29
2.	**airports_raw**	• reference file for the airports; • includes details for all airports such as name, city, state, & geographic coordinates; • to be merged with flights	7
3.	**airlines**	• reference file for the airlines; • includes the full names for all the airlines	2
4.	**October_2015_Flights**	• details of all flights for the month of October 2015 (see below why); • to be merged with flights	65

1. The "flights" dataset

In [7]:
```
#main table
flights_raw.head()
```

Out[7]:

	YEAR	MONTH	DAY	DAY_OF_WEEK	AIRLINE	ORIGIN_AIRPORT	DESTINATION_AIRPORT	SCH
0	2015	1	1	4	AS	ANC	SEA	
1	2015	1	1	4	AA	LAX	PBI	
2	2015	1	1	4	US	SFO	CLT	
3	2015	1	1	4	AA	LAX	MIA	
4	2015	1	1	4	AS	SEA	ANC	

5 rows × 29 columns

General comments

- the date columns (YEAR, MONTH, DAY) need to be transformed into a single-column date format;
- the total number of airlines is 14;
- the total number of airports is 628 (origin) & 629 (destination);
- AIRLINE column represents a 2-letter unique identifier for the airlines (aka IATA_CODE);
- ORIGIN_AIRPORT & DESTINATION_AIRPORT list 3-letter unique identifiers for airports (aka IATA_CODE);
- the time is either integer or float; they will need to be transformed into integers & converted to time stamps;
- the completeness of the data is good for the time value columns of interest;the rows with null values will be dropped;
- only 1.5% of flights were cancelled during 2015;
- 18.3% of flights recorded delays during 2015.

Major data dimensions

- **CARRIER-BASED (Airlines):** an identification number assigned by US DOT to identify a unique domestic airline, represented by a 2-letter code and corresponding name; Total = 14 airlines designated by the 2-letter code ;
- **SPATIAL (Airports):** ORIGIN_AIRPORT & DESTINATION_AIRPORT corresponding to each flight; a 3-letter code attributed by IATA to uniquely identify the airports; Total = 322 airports designated by the 3-letter code; -**TEMPORAL / Date:** Year, Month, Day, Day of week; dates corresponding to the flights; -**TEMPORAL / Time:**
  - real time expressed as **xx:yy (hour:minute)** format: schedule *vs.* actuals
    - scheduled_departure
    - departure_time
    - scheduled_arrival
    - arrival_time
    - wheels_off
    - wheels_on
  - calculated time metrics **in minutes**: departure_delays, arrival delays, taxi_out, taxi_in, air time, elapsed time
    - arrival_delay
    - departure_delay
    - taxi_in
    - taxi_out
    - scheduled_time
    - elapsed_time
    - air_time -**On-time schedule performance metrics:** on-time *vs.* delayed *vs.* cancelled
- **Cancellation reasons:** 4 main causes (A, B, C, D) as defined by the U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics

  - A = Carrier caused
  - B = Weather

- C = National Aviation System
- D = Security

- **Delay reasons:** 5 reasons (E, F, G, H, I) as defined by the U.S. Department of Transportation's (DOT) Bureau of Transportation Statistics; **delays are defined for flights with >=15 minutes**

    - E = Carrier caused
    - F = Weather
    - G = National Aviation System
    - H = Security
    - I = Late arriving aircraft

Definitions:

- **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 and wheels off.
- **TAXI_IN** time = the time duration elapsed between wheels-on and gate arrival at the destination airport.
- **AIR_TIME** = the time duration between wheels_off and wheels_on time
- **SCHEDULED_TIME** = the time duration between scheduled arrival and scheduled departure

Calculated metrics (minutes):

- **DEPARTURE_DELAY** = DEPARTURE_TIME - SCHEDULED_DEPARTURE
- **TAXI_OUT** = WHEELS_OFF - DEPARTURE_TIME
- **SCHEDULED_TIME** = SCHEDULED_ARRIVAL - SCHEDULED_DEPARTURE
- **AIR_TIME** = WHEELS_ON - WHEELS_OFF
- **ELAPSED_TIME** = AIR_TIME + TAXI_IN + TAXI_OUT
- **TAXI_IN** = ARRIVAL_TIME - WHEEL_ON
- **ARRIVAL_DELAY** = ARRIVAL_TIME - SCHEDULED_ARRIVAL

---

2. The "*airports*" dataset

In [8]:
```
airports_raw.head()
```

Out[8]:

	IATA_CODE	AIRPORT	CITY	STATE	COUNTRY	LATITUDE	LONGITUDE
0	ABE	Lehigh Valley International Airport	Allentown	PA	USA	40.65236	-75.44040
1	ABI	Abilene Regional Airport	Abilene	TX	USA	32.41132	-99.68190
2	ABQ	Albuquerque International Sunport	Albuquerque	NM	USA	35.04022	-106.60919
3	ABR	Aberdeen Regional Airport	Aberdeen	SD	USA	45.44906	-98.42183

	IATA_CODE	AIRPORT	CITY	STATE	COUNTRY	LATITUDE	LONGITUDE
4	ABY	Southwest Georgia Regional Airport	Albany	GA	USA	31.53552	-84.19447

In [9]:
```
# summary table
pd.concat([airports_raw.dtypes,
           airports_raw.count(),
           airports_raw.nunique(),
           airports_raw.isnull().sum(),
           round(100 * airports_raw.isnull().sum()/len(airports_raw),1)],
             axis=1).rename(columns={0:'Dtype',1:'Non-null counts',2:'Unique va
                                    3:'Missing Nulls',4:'Missing (%)'})
```

Out[9]:

	Dtype	Non-null counts	Unique values	Missing Nulls	Missing (%)
IATA_CODE	object	322	322	0	0.0
AIRPORT	object	322	322	0	0.0
CITY	object	322	308	0	0.0
STATE	object	322	54	0	0.0
COUNTRY	object	322	1	0	0.0
LATITUDE	float64	319	319	3	0.9
LONGITUDE	float64	319	319	3	0.9

General comments

- the total number of unique airports is 322 which is very different from the number of airports in the flights file; this needs to be investigated;
- 3 airports don't have lat and long coordinates;
- IATA_CODE represents the unique identifier for airports which corresponds to the ORIGIN_AIRPORT & DESTINATION_AIRPORT in the *flights* file;
- IATA_CODE for airports (3-letter unique identifier) not to be confused with IATA_CODE for airlines (2-letter unique identifier);
- for clarity I will rename the columns in the *flights* and *airports* files;
- the *flights* & *airport files* will be merged using IATA_CODE for airports

---

3. The "*airlines*" dataset

In [10]:
```
airlines
```

Out[10]:

	IATA_CODE	AIRLINE
0	UA	United Air Lines Inc.
1	AA	American Airlines Inc.
2	US	US Airways Inc.
3	F9	Frontier Airlines Inc.
4	B6	JetBlue Airways

	IATA_CODE	AIRLINE
5	OO	Skywest Airlines Inc.
6	AS	Alaska Airlines Inc.
7	NK	Spirit Air Lines
8	WN	Southwest Airlines Co.
9	DL	Delta Air Lines Inc.
10	EV	Atlantic Southeast Airlines
11	HA	Hawaiian Airlines Inc.
12	MQ	American Eagle Airlines Inc.
13	VX	Virgin America

In [11]:
```
pd.concat([airlines.dtypes,
           airlines.count(),
           airlines.nunique(),
           airlines.isnull().sum(),
           round(100 * airlines.isnull().sum()/len(airlines),1)],
              axis=1).rename(columns={0:'Dtype',1:'Non-null counts',2:'Unique va
                                      3:'Missing Nulls',4:'Missing (%)'})
```

Out[11]:

	Dtype	Non-null counts	Unique values	Missing Nulls	Missing (%)
IATA_CODE	object	14	14	0	0.0
AIRLINE	object	14	14	0	0.0

General comments

- the total number of unique airlines is 14;
- IATA_CODE is for airlines (a 2-letter unique identifier);
- AIRLINE columns represents the name of the airline; not to be confused with AIRLINE column in the flights file which is actually is the IATA_CODE for the airlines.

---

4. Renaming columns for consistency

In [12]:
```
# Renaming columns in the flights file
flights_new=flights_raw.rename(columns={"AIRLINE": "ARL_CODE", "ORIGIN_AIRPORT":
                                        "DESTINATION_AIRPORT": "DST_ARP_CODE"})

# Renaming columns in the airports file
airports_new=airports_raw.rename(columns={"IATA_CODE": "ARP_CODE", "AIRPORT": "A

# Renaming columns in the airline file
airlines_new=airlines.rename(columns={"IATA_CODE": "ARL_CODE", "AIRLINE": "ARL_N
```

C. Data cleaning

1. The "flights" dataset

1.1. Converting the date variables (YEAR, MONTH, DAY) into a datetime format

In [13]:
```
# Convert Date to Datetime format
flights_new['Date'] = pd.to_datetime(flights_new[['YEAR','MONTH','DAY']])
flights_new.Date.head()

#adding the day & month name columns
flights_new['Day_name'] = flights_new['Date'].dt.day_name()
flights_new['Month_name']=flights_new['Date'].dt.month_name()
```

In [14]:
```
flights_new[['Date','Day_name','Month_name']].head()
```

Out[14]:

	Date	Day_name	Month_name
0	2015-01-01	Thursday	January
1	2015-01-01	Thursday	January
2	2015-01-01	Thursday	January
3	2015-01-01	Thursday	January
4	2015-01-01	Thursday	January

1.2. Converting the time variables to time stamps

In [15]:
```
# the columns to be converted
flights_new[['Date','SCHEDULED_DEPARTURE','DEPARTURE_TIME', 'WHEELS_OFF','WHEELS
```

Out[15]:

	Date	SCHEDULED_DEPARTURE	DEPARTURE_TIME	WHEELS_OFF	WHEELS_ON	SCHEDULED_/
0	2015-01-01	5.0	2354.0	15.0	404.0	
1	2015-01-01	10.0	2.0	14.0	737.0	
2	2015-01-01	20.0	18.0	34.0	800.0	
3	2015-01-01	20.0	15.0	30.0	748.0	
4	2015-01-01	25.0	24.0	35.0	254.0	

In [16]:
```
# Define function that convert the 'HHMM' values to time
def Format_Hoursmin(hours):
    if pd.isnull(hours):
        return np.nan
    else:
        if hours == 2400: hours = 0
        hours = "{0:04d}".format(int(hours))
        Hoursmin = datetime.time(int(hours[0:2]), int(hours[2:4]))
        return Hoursmin
```

In [17]:
```
flights_new['SCHEDULED_DEPARTURE'] = flights_new['SCHEDULED_DEPARTURE'].apply(Fo
flights_new['DEPARTURE_TIME'] = flights_new['DEPARTURE_TIME'].apply(Format_Hours
flights_new['SCHEDULED_ARRIVAL'] = flights_new['SCHEDULED_ARRIVAL'].apply(Format
flights_new['ARRIVAL_TIME'] = flights_new['ARRIVAL_TIME'].apply(Format_Hoursmin)
```

```
flights_new['WHEELS_OFF'] = flights_new['WHEELS_OFF'].apply(Format_Hoursmin)
flights_new['WHEELS_ON'] = flights_new['WHEELS_ON'].apply(Format_Hoursmin)
```

In [18]:
```
flights_new[['Date','SCHEDULED_DEPARTURE','DEPARTURE_TIME', 'WHEELS_OFF','WHEELS
```

Out[18]:

	Date	SCHEDULED_DEPARTURE	DEPARTURE_TIME	WHEELS_OFF	WHEELS_ON	SCHEDULED_/
0	2015-01-01	00:05:00	23:54:00	00:15:00	04:04:00	(
1	2015-01-01	00:10:00	00:02:00	00:14:00	07:37:00	(
2	2015-01-01	00:20:00	00:18:00	00:34:00	08:00:00	(
3	2015-01-01	00:20:00	00:15:00	00:30:00	07:48:00	(
4	2015-01-01	00:25:00	00:24:00	00:35:00	02:54:00	(

In [19]:
```
# summary table
pd.concat([flights_new.dtypes,
           flights_new.count(),
           flights_new.nunique(),
           flights_new.isnull().sum(),
           round(100 * flights_new.isnull().sum()/len(flights_new),1)],
              axis=1).rename(columns={0:'Dtype',1:'Non-null counts',2:'Unique va
```

Out[19]:

	Dtype	Non-null counts	Unique values	# Nulls	Missing (%)
YEAR	int16	5819079	1	0	0.0
MONTH	int8	5819079	12	0	0.0
DAY	int8	5819079	31	0	0.0
DAY_OF_WEEK	int8	5819079	7	0	0.0
ARL_CODE	category	5819079	14	0	0.0
ORG_ARP_CODE	object	5819079	628	0	0.0
DST_ARP_CODE	object	5819079	629	0	0.0
SCHEDULED_DEPARTURE	object	5819079	1321	0	0.0
DEPARTURE_TIME	object	5732926	1440	86153	1.5
DEPARTURE_DELAY	float32	5732926	1217	86153	1.5
TAXI_OUT	float32	5730032	184	89047	1.5
WHEELS_OFF	object	5730032	1440	89047	1.5
SCHEDULED_TIME	float32	5819073	550	6	0.0
ELAPSED_TIME	float32	5714008	712	105071	1.8
AIR_TIME	float32	5714008	675	105071	1.8
DISTANCE	int16	5819079	1363	0	0.0
WHEELS_ON	object	5726566	1440	92513	1.6

	Dtype	Non-null counts	Unique values	# Nulls	Missing (%)
TAXI_IN	float32	5726566	185	92513	1.6
SCHEDULED_ARRIVAL	object	5819079	1435	0	0.0
ARRIVAL_TIME	object	5726566	1440	92513	1.6
ARRIVAL_DELAY	float32	5714008	1240	105071	1.8
DIVERTED	int8	5819079	2	0	0.0
CANCELLED	int8	5819079	2	0	0.0
CANCELLATION_REASON	category	89884	4	5729195	98.5
AIR_SYSTEM_DELAY	float32	1063439	570	4755640	81.7
SECURITY_DELAY	float32	1063439	154	4755640	81.7
AIRLINE_DELAY	float32	1063439	1067	4755640	81.7
LATE_AIRCRAFT_DELAY	float32	1063439	695	4755640	81.7
WEATHER_DELAY	float32	1063439	632	4755640	81.7
Date	datetime64[ns]	5819079	365	0	0.0
Day_name	object	5819079	7	0	0.0
Month_name	object	5819079	12	0	0.0

1.3. Investigating airport codes

In [20]:
```
# no. of airport codes in the flights file for the origin airports
flights_new["ORG_ARP_CODE"].nunique()
```

Out[20]: 628

In [21]:
```
# no. of airport codes in the flights file for the destination airports
flights_new["DST_ARP_CODE"].nunique()
```

Out[21]: 629

In [22]:
```
#a list with all airport codes
flights_new["ORG_ARP_CODE"].unique()
```

Out[22]:
```
array(['ANC', 'LAX', 'SFO', 'SEA', 'LAS', 'DEN', 'SLC', 'PDX', 'FAI',
       'MSP', 'PHX', 'SJU', 'PBG', 'IAG', 'PSE', 'BQN', 'ORD', 'GEG',
       'HNL', 'ONT', 'MCO', 'BOS', 'HIB', 'ABR', 'MAF', 'DFW', 'MKE',
       'IAH', 'BNA', 'BRO', 'VPS', 'BOI', 'BJI', 'SGF', 'PHL', 'SBN',
       'RDD', 'EUG', 'IAD', 'BUF', 'PWM', 'JFK', 'CRP', 'PIA', 'FAT',
       'SMF', 'AUS', 'MCI', 'ATL', 'JAX', 'MFR', 'IDA', 'MSN', 'DCA',
       'SAT', 'CHS', 'SBA', 'SMX', 'IND', 'CLE', 'GSP', 'BDL', 'ABI',
       'RIC', 'BFL', 'OMA', 'RDM', 'FLL', 'CID', 'TPA', 'SYR', 'ROC',
       'TYR', 'LAN', 'XNA', 'GSO', 'EWR', 'PBI', 'RSW', 'OAK', 'PVD',
       'RNO', 'PIT', 'ABQ', 'MIA', 'BWI', 'LGA', 'TUL', 'LIT', 'MSY',
       'OKC', 'ATW', 'PNS', 'MEM', 'TYS', 'MHT', 'SAV', 'CLT', 'GRB',
       'ABE', 'JAN', 'OAJ', 'FAR', 'ERI', 'LEX', 'CWA', 'MSO', 'TTN',
       'AMA', 'CLL', 'HOU', 'JLN', 'MLI', 'RDU', 'CVG', 'MHK', 'MOB',
       'TLH', 'BHM', 'CAE', 'TXK', 'ACY', 'DTW', 'RAP', 'TUS', 'EAU',
       'DLH', 'FSD', 'INL', 'CMX', 'SPI', 'CLD', 'COD', 'CMH', 'LRD',
       'PSC', 'CPR', 'ACV', 'DAL', 'PAH', 'MRY', 'ESC', 'ISN', 'PSP',
       'MFE', 'STL', 'BTV', 'FSM', 'AEX', 'SPS', 'ACT', 'SJT', 'MTJ',
```

```
'GCC', 'OGG', 'SJC', 'GUC', 'ORF', 'MOT', 'MLU', 'KOA', 'SAN',
'LAW', 'PIB', 'MGM', 'SBP', 'COS', 'LAR', 'DRO', 'BIS', 'ITO',
'BTR', 'GRI', 'HLN', 'BZN', 'MDW', 'MDT', 'SCE', 'LIH', 'TWF',
'BPT', 'GPT', 'STC', 'HPN', 'MLB', 'PLN', 'CIU', 'CAK', 'DSM',
'BLI', 'SHV', 'ROW', 'FWA', 'SNA', 'ALB', 'HOB', 'LNK', 'CMI',
'COU', 'GTF', 'EKO', 'LGB', 'AVL', 'HSV', 'SAF', 'GRR', 'SUX',
'LFT', 'HYS', 'ELP', 'DVL', 'ISP', 'BUR', 'DAB', 'DAY', 'GRK',
'GJT', 'BMI', 'LBE', 'ASE', 'RKS', 'GUM', 'TVC', 'ALO', 'IMT',
'LCH', 'JNU', 'JAC', 'MEI', 'DBQ', 'GCK', 'GNV', 'BRD', 'DIK',
'SDF', 'LBB', 'AVP', 'BTM', 'ELM', 'PIH', 'ICT', 'SUN', 'LWS',
'VEL', 'STT', 'YUM', 'FLG', 'FCA', 'HDN', 'JMS', 'ROA', 'CHA',
'EYW', 'MYR', 'CRW', 'MQT', 'CHO', 'ECP', 'EVV', 'EGE', 'MBS',
'GFK', 'TOL', 'BIL', 'OTZ', 'KTN', 'STX', 'ILM', 'PUB', 'RHI',
'CDC', 'HRL', 'SCC', 'FNT', 'LSE', 'MMH', 'APN', 'AGS', 'CEC',
'DHN', 'WRG', 'PHF', 'CNY', 'BRW', 'GGG', 'AZO', 'SRQ', 'ORH',
'TRI', 'VLD', 'SIT', 'BQK', 'PSG', 'FAY', 'MKG', 'CSG', 'EWN',
'OME', 'SGU', 'RST', 'GTR', 'BET', 'ABY', 'SWF', 'ILG', 'ADK',
'UST', 'YAK', 'CDV', 'OTH', 'ADQ', 'PPG', 'BGM', 'BGR', 'ITH',
'ACK', 'MVY', 'WYS', 'DLG', 'AKN', 'GST', 'HYA', '14747', '14771',
'12889', '12892', '14869', '10299', '11292', '14107', '11630',
'10732', '14254', '10141', '10627', '11982', '12173', '13930',
'14683', '12266', '11618', '10721', '13487', '11884', '15919',
'13851', '11111', '10693', '12191', '14783', '15016', '14487',
'10423', '15370', '11953', '13891', '15376', '11778', '11278',
'14100', '13204', '15304', '11637', '14842', '10155', '11775',
'11298', '11057', '13931', '10821', '14122', '11049', '10990',
'10631', '13158', '14108', '13198', '11447', '12206', '13495',
'14057', '15624', '10747', '15411', '12891', '10994', '13256',
'10792', '14492', '12451', '13127', '10781', '14960', '12278',
'14685', '11995', '13485', '11977', '10257', '13796', '13232',
'13296', '14570', '14893', '14524', '12217', '10713', '10208',
'10136', '11603', '14689', '11471', '11315', '13264', '12478',
'14814', '11308', '11066', '12896', '10397', '14307', '11721',
'11140', '10185', '13277', '11203', '13342', '11433', '11697',
'12953', '10599', '12156', '14952', '10620', '11042', '15096',
'10408', '15249', '11423', '12915', '12264', '12339', '10140',
'13871', '14027', '13244', '11267', '11540', '14576', '10868',
'13486', '13476', '14489', '12945', '15607', '10529', '11986',
'14635', '13303', '10785', '15380', '11996', '10561', '10874',
'13367', '10146', '10431', '11973', '10980', '12197', '14098',
'12323', '10577', '11150', '10135', '11617', '13795', '13029',
'11003', '11146', '11577', '15356', '11259', '10279', '14321',
'14843', '11638', '14828', '11481', '12951', '10434', '12448',
'14730', '15323', '14252', '11193', '10849', '14193', '14986',
'11641', '12992', '13422', '11612', '11823', '11980', '13290',
'10158', '10685', '13377', '11109', '11076', '11122', '11865',
'14543', '14905', '11587', '14457', '12335', '12343', '12003',
'10157', '12884', '14633', '15048', '10268', '15295', '12389',
'11525', '14262', '12888', '12391', '11648', '14696', '12758',
'13830', '10469', '15412', '10731', '14679', '14831', '11413',
'13433', '12982', '11867', '14698', '11537', '15389', '12402',
'11337', '13360', '13076', '14006', '10728', '15401', '13230',
'12016', '11067', '11274', '11921', '12519', '11013', '10779',
'14150', '14794', '12511', '12177', '12523', '14908', '12007',
'14588', '13577', '13061', '15041', '14109', '10800', '12954',
'12441', '12898', '11695', '16218', '14113', '11624', '11503',
'10739', '14574', '14711', '12129', '15070', '14520', '13184',
'11252', '12280', '13241', '11898', '15024', '14674', '10551',
'12819', '13459', '10581', '13970', '10372', '10918', '14709',
'12255', '11905', '10333', '15841', '13344', '13933', '15991',
'10754', '14256', '12094', '13873', '11097', '10154', '10926',
'13964', '13541', '15027', '10170', '10165', '15497', '12265',
'14222', '14025', '13502'], dtype=object)
```

> 💡 **The airport codes are either a 3-letter or 5-digit code**

In [23]:
```
# create 2 new columns based on the length of data for the airport codes
flights_new["Len_ORG_ARP"]=flights_new["ORG_ARP_CODE"].str.len()
flights_new["Len_DST_ARP"]=flights_new["DST_ARP_CODE"].str.len()
```

In [24]:
```
flights_new["Len_ORG_ARP"].unique()
```

Out[24]:
```
array([3, 5])
```

In [25]:
```
flights_new["Len_DST_ARP"].unique()
```

Out[25]:
```
array([3, 5])
```

> 💡 **Both columns have two unique values, 3 or 5; 3 corresponds to the 3-letter code and 5 corresponds to the 5-digit code**

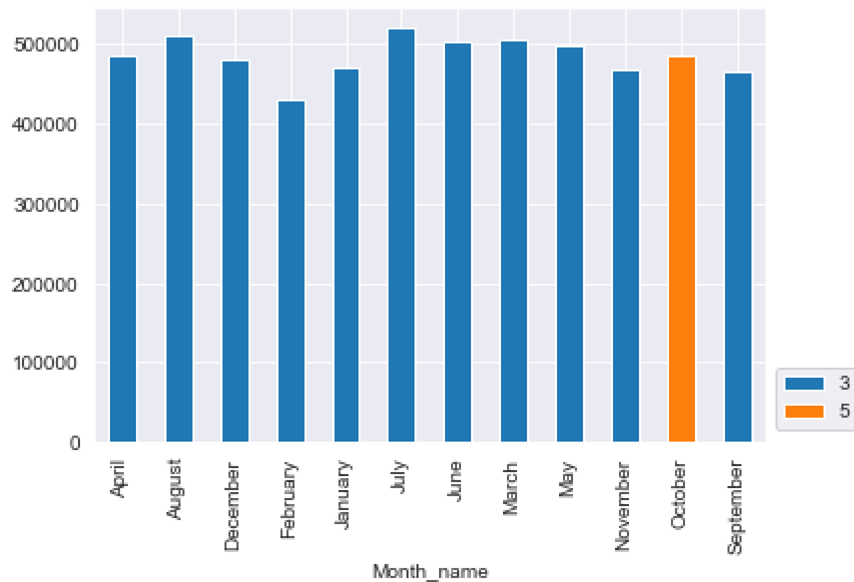
In [26]:
```
# create a crosstab to investigate the occurrence patterns of the 2 string lengt
pd.crosstab(flights_new['Month_name'],flights_new['Len_ORG_ARP'])
```

Out[26]:

Len_ORG_ARP	3	5
Month_name		
April	485151	0
August	510536	0
December	479230	0
February	429191	0
January	469968	0
July	520718	0
June	503897	0
March	504312	0
May	496993	0
November	467972	0
October	0	486165
September	464946	0

In [27]:
```
# when the 5-digit flights occur?
pd.crosstab(flights_new['Month_name'],flights_new['Len_ORG_ARP']).plot(kind='bar
plt.legend(loc='center left', bbox_to_anchor=(1,0.1))
```

Out[27]:
```
<matplotlib.legend.Legend at 0x7f8fc5bab9d0>
```



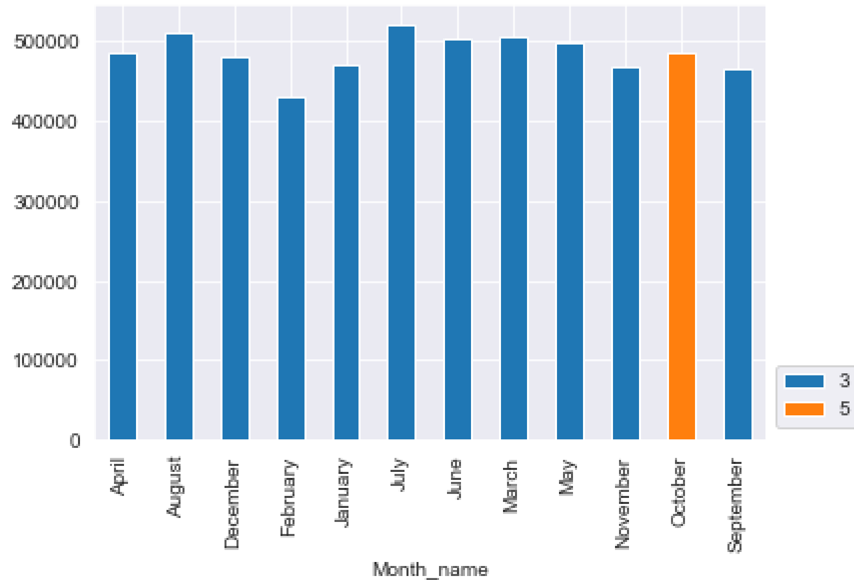
In [28]:
```
# create a crosstab to investigate the occurrence patterns of the 2 string lengt
pd.crosstab(flights_new['Month_name'],flights_new['Len_DST_ARP'])
```

Out[28]:

Len_DST_ARP	3	5
Month_name		
April	485151	0
August	510536	0
December	479230	0
February	429191	0
January	469968	0
July	520718	0
June	503897	0
March	504312	0
May	496993	0
November	467972	0
October	0	486165
September	464946	0

In [29]:
```
pd.crosstab(flights_new['Month_name'],flights_new['Len_DST_ARP']).plot(kind='bar
plt.legend(loc='center left', bbox_to_anchor=(1,0.1))
```

Out[29]:
```
<matplotlib.legend.Legend at 0x7f8dbb1e87f0>
```



> 💡 **We can see that the 5-digit airport codes, for both Origin and Destination airports, occur for the month of October only; all other months have a 3-letter code**

In [30]:
```
# subsetting the rows wiht 5-digit airport code
flights_5digit=flights_new[flights_new['Len_DST_ARP']==5]

# subsetting the rows wiht 3-digit airport code
flights_3digit=flights_new[flights_new['Len_DST_ARP']==3]
```

In [31]:
```
flights_new['ORG_ARP_CODE'].nunique(), flights_new['DST_ARP_CODE'].nunique()
```

Out[31]:
```
(628, 629)
```

In [32]:
```
flights_5digit['ORG_ARP_CODE'].nunique()
```

Out[32]:
```
306
```

In [33]:
```
flights_3digit['ORG_ARP_CODE'].nunique()
```

Out[33]:
```
322
```

In [34]:
```
flights_5digit['DST_ARP_CODE'].nunique()
```

Out[34]:
```
307
```

In [35]:
```
flights_3digit['DST_ARP_CODE'].nunique()
```

Out[35]:
```
322
```

---

2. The "airports" dataset

2.1. Investigating the codes for the airports

In [36]:
```
airports_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 322 entries, 0 to 321
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   ARP_CODE   322 non-null    object 
 1   ARP_Name   322 non-null    object 
 2   CITY       322 non-null    object 
 3   STATE      322 non-null    object 
 4   COUNTRY    322 non-null    object 
 5   LATITUDE   319 non-null    float64
 6   LONGITUDE  319 non-null    float64
dtypes: float64(2), object(5)
memory usage: 17.7+ KB
```

In [37]:
```
airports_new["ARP_CODE"].str.len().unique()
```

Out[37]:
```
array([3])
```

> 💡 **the code for the airports is a 3-letter unique code and thus this dataset can be merged with the flights dataset based on this unique identifier**

2.2. Investigating the null values for the Lat & Long

In [38]:
```
# Lat & Long missing values
# method_1: display the airports that have NO coordinates (3 counts)
is_NaN = airports_new.isnull()
row_has_NaN = is_NaN.any(axis=1)
rows_with_NaN = airports_new[row_has_NaN]
print(rows_with_NaN)
```

```
    ARP_CODE                                       ARP_Name  \
96       ECP    Northwest Florida Beaches International Airport   
234      PBG                 Plattsburgh International Airport   
313      UST  Northeast Florida Regional Airport (St. August...   

            CITY STATE COUNTRY  LATITUDE  LONGITUDE  
96   Panama City    FL     USA       NaN        NaN  
234  Plattsburgh    NY     USA       NaN        NaN  
313 St. Augustine    FL     USA       NaN        NaN  
```

2.3. Replacing the null values

In [39]:
```
# replacing null values for coordinates that are missing
airports_new.iloc[[96],[5,6]] = [30.354673,-85.8000081697587]
airports_new.iloc[[234],[5,6]] = [44.6519299287931,-73.467855928325]
airports_new.iloc[[313],[5,6]] = [29.9545573,-81.34298816]
airports_new.iloc[[96,234,313]]
```

Out[39]:

	ARP_CODE	ARP_Name	CITY	STATE	COUNTRY	LATITUDE	LONGITUDE
96	ECP	Northwest Florida Beaches International Airport	Panama City	FL	USA	30.354673	-85.800008
234	PBG	Plattsburgh International Airport	Plattsburgh	NY	USA	44.651930	-73.467856
313	UST	Northeast Florida Regional Airport (St. August...	St. Augustine	FL	USA	29.954557	-81.342988

3. Merging datasets

3.1. Merging "flights" with "2015 October"

Investigate the "October flights" dataset

In [40]:
```
October_2015_Flights.shape
```

Out[40]:
```
(486165, 65)
```

In [41]:
```
# display columns names
October_2015_Flights.columns
```

Out[41]:
```
Index(['YEAR', 'QUARTER', 'MONTH', 'DAY_OF_MONTH', 'DAY_OF_WEEK', 'FL_DATE',
       'OP_UNIQUE_CARRIER', 'OP_CARRIER_AIRLINE_ID', 'OP_CARRIER', 'TAIL_NUM',
       'OP_CARRIER_FL_NUM', 'ORIGIN_AIRPORT_ID', 'ORIGIN_AIRPORT_SEQ_ID',
       'ORIGIN_CITY_MARKET_ID', 'ORIGIN', 'ORIGIN_CITY_NAME',
       'ORIGIN_STATE_ABR', 'ORIGIN_STATE_FIPS', 'ORIGIN_STATE_NM',
       'ORIGIN_WAC', 'DEST_AIRPORT_ID', 'DEST_AIRPORT_SEQ_ID',
       'DEST_CITY_MARKET_ID', 'DEST', 'DEST_CITY_NAME', 'DEST_STATE_ABR',
       'DEST_STATE_FIPS', 'DEST_STATE_NM', 'DEST_WAC', 'CRS_DEP_TIME',
       'DEP_TIME', 'DEP_DELAY', 'DEP_DELAY_NEW', 'DEP_DEL15',
       'DEP_DELAY_GROUP', 'DEP_TIME_BLK', 'TAXI_OUT', 'WHEELS_OFF',
       'WHEELS_ON', 'TAXI_IN', 'CRS_ARR_TIME', 'ARR_TIME', 'ARR_DELAY',
       'ARR_DELAY_NEW', 'ARR_DEL15', 'ARR_DELAY_GROUP', 'ARR_TIME_BLK',
       'CANCELLED', 'CANCELLATION_CODE', 'DIVERTED', 'CRS_ELAPSED_TIME',
       'ACTUAL_ELAPSED_TIME', 'AIR_TIME', 'FLIGHTS', 'DISTANCE',
       'DISTANCE_GROUP', 'CARRIER_DELAY', 'WEATHER_DELAY', 'NAS_DELAY',
       'SECURITY_DELAY', 'LATE_AIRCRAFT_DELAY', 'FIRST_DEP_TIME',
       'TOTAL_ADD_GTIME', 'LONGEST_ADD_GTIME', 'Unnamed: 64'],
      dtype='object')
```

> 💡 **we need 4 columns to correct the airport codes in the flights file: 1) ORIGIN_AIRPORT_ID, 2) ORIGIN, 3) DEST_AIRPORT_ID, 4) DEST**

Correct the codes for the ORIGIN airport

In [42]:
```
# create a df by extracting the codes for the Origin aiports from the October fi
Oct_ORG = October_2015_Flights[['ORIGIN_AIRPORT_ID','ORIGIN']]

#dropping the duplicates
Oct_ORG = Oct_ORG.drop_duplicates()

# renaming the columns to match the columns in flights file
Oct_ORG.columns  = ['ORG_ARP_CODE', 'ORIGIN']

# converting the datatype to string to be able to join
Oct_ORG['ORG_ARP_CODE'] = Oct_ORG['ORG_ARP_CODE'].astype(str)

# converting the datatype to string to be able to join
flights_new['ORG_ARP_CODE']  = flights_new['ORG_ARP_CODE'].astype(str)

# merge files to correct the airports codes at Origin
flights_OCT = pd.merge(flights_new, Oct_ORG, on ='ORG_ARP_CODE', how='left')

# create a column with final 3-letter code for airports at Origin
flights_OCT['ORG_ARP_FINAL']   = np.where(flights_OCT['ORIGIN'].isnull(),flights
```

Correct the codes for the DESTINATION airport

In [43]:
```
# create a df by extracting the codes for the Destination aiports from the Octob
Oct_DST = October_2015_Flights[['DEST_AIRPORT_ID','DEST']]

#dropping the duplicates
Oct_DST = Oct_DST.drop_duplicates()

# renaming the columns to match the columns in flights file
Oct_DST.columns  = ['DST_ARP_CODE', 'DEST']

# converting the datatype to string to be able to join
Oct_DST['DST_ARP_CODE'] = Oct_DST['DST_ARP_CODE'].astype(str)

# converting the datatype to string to be able to join
flights_OCT['DST_ARP_CODE']  = flights_OCT['DST_ARP_CODE'].astype(str)

# merge files to correct the airports codes at Destination
flights_OCT_2 = pd.merge(flights_OCT, Oct_DST, on ='DST_ARP_CODE', how='left')

# create a column with final 3-letter code for airports at Destination
flights_OCT_2['DST_ARP_FINAL']   = np.where(flights_OCT_2['DEST'].isnull(),fligh
```

In [44]:
```
#drop unneccessary columns
flights_OCT_2=flights_OCT_2.drop(columns=['ORG_ARP_CODE','DST_ARP_CODE','Len_ORG
```

In [45]:
```
flights_OCT_2.shape
```

Out[45]:
```
(5819079, 32)
```

In [46]:
```
#summary table
pd.concat([flights_OCT_2.dtypes,
           flights_OCT_2.count(),
           flights_OCT_2.nunique(),
           flights_OCT_2.isnull().sum(),
           round(100 * flights_OCT_2.isnull().sum()/len(flights_OCT_2),1)],
              axis=1).rename(columns={0:'Dtype',1:'Non-null counts',2:'Unique va
```

Out[46]:

	Dtype	Non-null counts	Unique values	Missing Nulls	Missing (%)
YEAR	int16	5819079	1	0	0.0
MONTH	int8	5819079	12	0	0.0
DAY	int8	5819079	31	0	0.0
DAY_OF_WEEK	int8	5819079	7	0	0.0
ARL_CODE	category	5819079	14	0	0.0
SCHEDULED_DEPARTURE	object	5819079	1321	0	0.0
DEPARTURE_TIME	object	5732926	1440	86153	1.5
DEPARTURE_DELAY	float32	5732926	1217	86153	1.5
TAXI_OUT	float32	5730032	184	89047	1.5
WHEELS_OFF	object	5730032	1440	89047	1.5
SCHEDULED_TIME	float32	5819073	550	6	0.0

	Dtype	Non-null counts	Unique values	Missing Nulls	Missing (%)
ELAPSED_TIME	float32	5714008	712	105071	1.8
AIR_TIME	float32	5714008	675	105071	1.8
DISTANCE	int16	5819079	1363	0	0.0
WHEELS_ON	object	5726566	1440	92513	1.6
TAXI_IN	float32	5726566	185	92513	1.6
SCHEDULED_ARRIVAL	object	5819079	1435	0	0.0
ARRIVAL_TIME	object	5726566	1440	92513	1.6
ARRIVAL_DELAY	float32	5714008	1240	105071	1.8
DIVERTED	int8	5819079	2	0	0.0
CANCELLED	int8	5819079	2	0	0.0
CANCELLATION_REASON	category	89884	4	5729195	98.5
AIR_SYSTEM_DELAY	float32	1063439	570	4755640	81.7
SECURITY_DELAY	float32	1063439	154	4755640	81.7
AIRLINE_DELAY	float32	1063439	1067	4755640	81.7
LATE_AIRCRAFT_DELAY	float32	1063439	695	4755640	81.7
WEATHER_DELAY	float32	1063439	632	4755640	81.7
Date	datetime64[ns]	5819079	365	0	0.0
Day_name	object	5819079	7	0	0.0
Month_name	object	5819079	12	0	0.0
ORG_ARP_FINAL	object	5819079	322	0	0.0
DST_ARP_FINAL	object	5819079	322	0	0.0

3.2. Merging "flights_OCT_2" with "airlines"

In [47]:
```
# merging with "airlines" to get the full name of the airlines
flights_OCT_airlines=flights_OCT_2.merge(airlines_new, on="ARL_CODE", how="left"
flights_OCT_airlines.shape
```

Out[47]:
```
(5819079, 33)
```

3.3. Merging "flights_OCT_airlines" with "airports"

In [48]:
```
# merging with airports to get details on the ORIGIN airports
flights_OCT_ARL_ARP = flights_OCT_airlines.merge(airports_new, how = "left",
                                                  left_on = "ORG_ARP_FINAL", righ

# merging with airports to get details on the DESTINATION airports
flights_FINAL= flights_OCT_ARL_ARP.merge(airports_new, how = "left",
                                          left_on = "DST_ARP_FINAL", right_on = "
```

In [49]:
```
# summary table of the FINAL file
pd.concat([flights_FINAL.dtypes,
           flights_FINAL.count(),
```

```
            flights_FINAL.nunique(),
            flights_FINAL.isnull().sum(),
            round(100 * flights_FINAL.isnull().sum()/len(flights_FINAL),1)],
               axis=1).rename(columns={0:'Dtype',1:'Non-null counts',2:'Unique va
```

Out[49]:

	Dtype	Non-null counts	Unique values	# Nulls	Missing (%)
YEAR	int16	5819079	1	0	0.0
MONTH	int8	5819079	12	0	0.0
DAY	int8	5819079	31	0	0.0
DAY_OF_WEEK	int8	5819079	7	0	0.0
ARL_CODE	object	5819079	14	0	0.0
SCHEDULED_DEPARTURE	object	5819079	1321	0	0.0
DEPARTURE_TIME	object	5732926	1440	86153	1.5
DEPARTURE_DELAY	float32	5732926	1217	86153	1.5
TAXI_OUT	float32	5730032	184	89047	1.5
WHEELS_OFF	object	5730032	1440	89047	1.5
SCHEDULED_TIME	float32	5819073	550	6	0.0
ELAPSED_TIME	float32	5714008	712	105071	1.8
AIR_TIME	float32	5714008	675	105071	1.8
DISTANCE	int16	5819079	1363	0	0.0
WHEELS_ON	object	5726566	1440	92513	1.6
TAXI_IN	float32	5726566	185	92513	1.6
SCHEDULED_ARRIVAL	object	5819079	1435	0	0.0
ARRIVAL_TIME	object	5726566	1440	92513	1.6
ARRIVAL_DELAY	float32	5714008	1240	105071	1.8
DIVERTED	int8	5819079	2	0	0.0
CANCELLED	int8	5819079	2	0	0.0
CANCELLATION_REASON	category	89884	4	5729195	98.5
AIR_SYSTEM_DELAY	float32	1063439	570	4755640	81.7
SECURITY_DELAY	float32	1063439	154	4755640	81.7
AIRLINE_DELAY	float32	1063439	1067	4755640	81.7
LATE_AIRCRAFT_DELAY	float32	1063439	695	4755640	81.7
WEATHER_DELAY	float32	1063439	632	4755640	81.7
Date	datetime64[ns]	5819079	365	0	0.0
Day_name	object	5819079	7	0	0.0
Month_name	object	5819079	12	0	0.0
ORG_ARP_FINAL	object	5819079	322	0	0.0

	Dtype	Non-null counts	Unique values	# Nulls	Missing (%)
DST_ARP_FINAL	object	5819079	322	0	0.0
ARL_Name	object	5819079	14	0	0.0
ARP_CODE_org	object	5819079	322	0	0.0
ARP_Name_org	object	5819079	322	0	0.0
CITY_org	object	5819079	308	0	0.0
STATE_org	object	5819079	54	0	0.0
COUNTRY_org	object	5819079	1	0	0.0
LATITUDE_org	float64	5819079	322	0	0.0
LONGITUDE_org	float64	5819079	322	0	0.0
ARP_CODE_dst	object	5819079	322	0	0.0
ARP_Name_dst	object	5819079	322	0	0.0
CITY_dst	object	5819079	308	0	0.0
STATE_dst	object	5819079	54	0	0.0
COUNTRY_dst	object	5819079	1	0	0.0
LATITUDE_dst	float64	5819079	322	0	0.0
LONGITUDE_dst	float64	5819079	322	0	0.0

3.4. Export final file to a csv file

In [50]:
```
# export final file to a csv file
flights_FINAL.to_csv("/Users/iulialaptop/Documents/0. Career/Python_Projects_Spr
```