```python
import requests
from bs4 import BeautifulSoup
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import mean_absolute_percentage_error
import statsmodels.api as sm
import scipy.stats as stats
from sklearn.linear_model import SGDClassifier
from sklearn.model_selection import StratifiedKFold,
RandomizedSearchCV, train_test_split
from statsmodels.formula.api import glm
import statsmodels.api as sm
from sklearn.preprocessing import OrdinalEncoder, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import classification_report, accuracy_score
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
```

Data import and aggregation steps:

I.   Collate the information specific to flights, airports (like type of airport, elevation etc) and runway(length_ft, width_ft, surface etc.). Get all those fields in single dataset which you believe may impact the delay.

```python
address = '/home/labsuser/Capstone_3'

airlines = pd.read_excel(address + '/Airlines.xlsx')
airports = pd.read_excel(address + '/airports.xlsx')
runways = pd.read_excel(address + '/runways.xlsx')

airlines.head()
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay
0   1      CO     269         SFO       IAH          3    15     205
1
1   2      US    1558         PHX       CLT          3    15     222
1
2   3      AA    2400         LAX       DFW          3    20     165
1
3   4      AA    2466         SFO       DFW          3    20     195
1
4   5      AS     108         ANC       SEA          3    30     202
0
```

```python
airports.head(2)
```

```
       id ident           type                  name  latitude_deg  \
0    6523   00A       heliport     Total Rf Heliport     40.070801
1  323361  00AA  small_airport  Aero B Ranch Airport     38.704022

   longitude_deg  elevation_ft continent iso_country iso_region
municipality  \
0     -74.933601          11.0       NaN          US      US-PA
Bensalem
1    -101.473911        3435.0       NaN          US      US-KS
Leoti

  scheduled_service gps_code iata_code local_code home_link
wikipedia_link  \
0                no      00A       NaN        00A       NaN
NaN
1                no     00AA       NaN       00AA       NaN
NaN

  keywords
0      NaN
1      NaN
```

```
runways.head()
```

```
       id  airport_ref airport_ident  length_ft  width_ft surface
lighted  \
0  269408         6523           00A       80.0      80.0  ASPH-G
1
1  255155         6524          00AK     2500.0      70.0    GRVL
0
2  254165         6525          00AL     2300.0     200.0    TURF
0
3  270932         6526          00AR       40.0      40.0   GRASS
0
4  322128       322127          00AS     1450.0      60.0    Turf
0

   closed le_ident  le_latitude_deg  le_longitude_deg  le_elevation_ft
\
0       0       H1              NaN               NaN              NaN

1       0        N              NaN               NaN              NaN

2       0        1              NaN               NaN              NaN

3       0       H1              NaN               NaN              NaN

4       0        1              NaN               NaN              NaN
```

```
   le_heading_degT  le_displaced_threshold_ft he_ident
he_latitude_deg  \
0              NaN                        NaN      NaN
NaN
1              NaN                        NaN        S
NaN
2              NaN                        NaN       19
NaN
3              NaN                        NaN       H1
NaN
4              NaN                        NaN       19
NaN

   he_longitude_deg  he_elevation_ft  he_heading_degT  \
0               NaN              NaN              NaN
1               NaN              NaN              NaN
2               NaN              NaN              NaN
3               NaN              NaN              NaN
4               NaN              NaN              NaN

   he_displaced_threshold_ft
0                        NaN
1                        NaN
2                        NaN
3                        NaN
4                        NaN
```

```
airports.head(2)
```

```
       id ident           type                  name  latitude_deg  \
0    6523   00A       heliport     Total Rf Heliport     40.070801
1  323361  00AA  small_airport  Aero B Ranch Airport     38.704022

   longitude_deg  elevation_ft continent iso_country iso_region
municipality  \
0     -74.933601          11.0       NaN          US      US-PA
Bensalem
1    -101.473911        3435.0       NaN          US      US-KS
Leoti

  scheduled_service gps_code iata_code local_code home_link
wikipedia_link  \
0                no      00A       NaN        00A       NaN
NaN
1                no     00AA       NaN       00AA       NaN
NaN

  keywords
0      NaN
1      NaN
```

```
airport_run = pd.merge(airports, runways, left_on = 'ident', right_on
= 'airport_ident', how = "left")
airport_run.head(2)
```

```
     id_x ident           type                 name  latitude_deg  \
0    6523   00A       heliport    Total Rf Heliport     40.070801   
1  323361  00AA  small_airport  Aero B Ranch Airport     38.704022   

   longitude_deg  elevation_ft continent iso_country
iso_region  ...  \
0     -74.933601          11.0       NaN          US      US-PA  ...

1    -101.473911        3435.0       NaN          US      US-KS  ...


  le_longitude_deg le_elevation_ft le_heading_degT
le_displaced_threshold_ft  \
0              NaN             NaN             NaN
NaN
1              NaN             NaN             NaN
NaN

  he_ident he_latitude_deg he_longitude_deg he_elevation_ft
he_heading_degT  \
0      NaN             NaN              NaN             NaN
NaN
1      NaN             NaN              NaN             NaN
NaN

   he_displaced_threshold_ft
0                        NaN
1                        NaN

[2 rows x 38 columns]
```

```
count_runway = airport_run.groupby('airport_ident')
[['id_y']].count().sort_values(by = 'id_y', ascending =
False).reset_index()
count_runway.head(2)
```

```
  airport_ident  id_y
0          KORD    11
1          KNHU    10
```

```
air_run = pd.merge(airports, count_runway, how = 'left', left_on =
'ident', right_on = 'airport_ident')[['iata_code', 'type',
'elevation_ft','id_y']]
air_run.rename(columns = {'id_y': 'runway_count'}, inplace = True)
air_run.head(2)
```

```
  iata_code           type  elevation_ft  runway_count
0       NaN       heliport          11.0           1.0
1       NaN  small_airport        3435.0           NaN
```

```
air_run.dropna().to_csv('run_2.csv', index = False)
```

```
airlines.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length  
Delay
0   1      CO     269         SFO       IAH          3    15     205  
1
1   2      US    1558         PHX       CLT          3    15     222  
1
```

```
combined_data = pd.merge(airlines, air_run, how = 'left', left_on = 
'AirportFrom', right_on = 'iata_code')

new_names = list(combined_data[air_run.columns].columns + 
'_source_airport')
old_names = list(combined_data[air_run.columns].columns)

combined_data.rename(columns = {old:new for old,new in zip(old_names, 
new_names)}, inplace = True)
combined_data.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length  
Delay  \
0   1      CO     269         SFO       IAH          3    15     205  
1
1   2      US    1558         PHX       CLT          3    15     222  
1

  iata_code_source_airport type_source_airport 
elevation_ft_source_airport  \
0                      SFO       large_airport 
13.0
1                      PHX       large_airport 
1135.0

   runway_count_source_airport
0                          4.0
1                          3.0
```

```
combined_data.columns
```

```
Index(['id', 'Airline', 'Flight', 'AirportFrom', 'AirportTo', 
'DayOfWeek',
       'Time', 'Length', 'Delay', 'iata_code_source_airport',
       'type_source_airport', 'elevation_ft_source_airport',
```

```
       'runway_count_source_airport'],
      dtype='object')
```

```
combined_data = pd.merge(combined_data, air_run, how = 'left', left_on
= 'AirportTo', right_on = 'iata_code')

new_names = list(combined_data[air_run.columns].columns +
'_dest_airport')
old_names = list(combined_data[air_run.columns].columns)
combined_data.rename(columns = {old:new for old,new in zip(old_names,
new_names)}, inplace = True)
combined_data.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   2      US    1558         PHX       CLT          3    15     222
1

  iata_code_source_airport type_source_airport
elevation_ft_source_airport  \
0                      SFO       large_airport
13.0
1                      PHX       large_airport
1135.0

   runway_count_source_airport iata_code_dest_airport
type_dest_airport  \
0                          4.0                    IAH
large_airport
1                          3.0                    CLT
large_airport

   elevation_ft_dest_airport  runway_count_dest_airport
0                       97.0                        5.0
1                      748.0                        4.0
```

```
# drop iata_code columns
combined_data.drop(columns =
list(combined_data.columns[combined_data.columns.str.startswith('iata_
code')]), inplace = True)
```

II. Different airline companies may perform differently in terms of on time arrival. The performance may depend on the experience of the airline company. Pull the information specific to different airlines from the Wikipedia page https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States. Use web scaping to fetch the information about how long the airlines has been in the business.

```
website_url = 
requests.get('https://en.wikipedia.org/wiki/List_of_airlines_of_the_Un
ited_States').text
soup = BeautifulSoup(website_url,'lxml')
My_table = soup.findAll("table",{"class":"wikitable"})

len(My_table)

7

airlines_wiki_list = []
for tab in My_table:
    temp = pd.read_html(str(tab))
    temp = pd.DataFrame(temp[0])
    airlines_wiki_list.append(temp)

airlines_wiki = pd.concat(airlines_wiki_list)
```

III. Get all the information pulled so far in one table.

```
combined_data.head(2)

   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length  
Delay  \
0   1      CO     269         SFO       IAH          3    15     205      
1  
1   2      US    1558         PHX       CLT          3    15     222      
1  

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0   
1       large_airport                       1135.0   

   runway_count_source_airport type_dest_airport  
elevation_ft_dest_airport  \
0                          4.0     large_airport                       
97.0   
1                          3.0     large_airport                      
748.0   

   runway_count_dest_airport  
0                        5.0  
1                        4.0  
```

finding the year founded of airlines

```
airlines_founded = 
pd.merge(combined_data[['Airline']].drop_duplicates(),airlines_wiki[['
IATA', 'Founded']].drop_duplicates(),
         how = 'left', left_on = 'Airline', right_on = 'IATA')

airlines_founded
```

```
   Airline IATA  Founded
0       CO  NaN      NaN
1       US  NaN      NaN
2       AA   AA   1926.0
3       AS   AS   1932.0
4       DL   DL   1924.0
5       B6   B6   1998.0
6       HA   HA   1929.0
7       OO   OO   1972.0
8       9E   9E   1985.0
9       OH   OH   1979.0
10      EV  NaN      NaN
11      XE   XE   2016.0
12      YV   YV   1980.0
13      UA   UA   1926.0
14      MQ   MQ   1984.0
15      F9   F9   1994.0
16      WN   WN   1967.0
```

```
# will fill in missing values later
```

IV. Look into Wikipedia page: https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States Total passenger traffic may also contribute to the delay of flights. The term hub is used to identify busy commercial airports. Large hubs are the airports that each account for at least one percent of total U.S. passenger enplanements. Medium hubs are defined as airports that each account for between 0.25 percent and 1 percent of the total passenger enplanements.

Pull passenger traffic data using web scraping and collate in a table.

```
website_url = 
requests.get('https://en.wikipedia.org/wiki/List_of_the_busiest_airpor
ts_in_the_United_States').text
soup = BeautifulSoup(website_url,'lxml')
My_table = soup.findAll("table",{"class":"wikitable"})

hub_data = {}
i = 0
for tab in My_table:
    hub_data[i] = pd.read_html(str(tab))
    hub_data[i] = pd.DataFrame(hub_data[i][0])
    i +=1
```

We need only hub data hence first two table

```
large_hub = hub_data[0].copy()
med_hub = hub_data[1].copy()

large_hub.insert(loc =1, column= 'Hub_type', value = 'large')
med_hub.insert(loc =1, column= 'Hub_type', value = 'medium')

# before combinig lets work with column names

# remove any special characters or things in bracket

# remove refrences from brackets
column_temp =
large_hub.columns.str.split('[([]').str[0].str.strip().str.lower().str
.replace(' ','_').values
column_temp[list(map( lambda x : x.isnumeric(), column_temp))]  =
'data_' + column_temp[list(map( lambda x : x.isnumeric(),
column_temp))]
large_hub.columns = column_temp
large_hub.columns

Index(['rank', 'hub_type', 'airports', 'iatacode',
'major_cities_served',
       'state', 'data_2021', 'data_2020', 'data_2019', 'data_2018',
       'data_2017', 'data_2016', 'data_2015', 'data_2014',
'data_2013',
       'data_2012', 'data_2011'],
      dtype='object')

# remove refrences from brackets
column_temp =
med_hub.columns.str.split('[([]').str[0].str.strip().str.lower().str.r
eplace(' ','_').values
column_temp[list(map( lambda x : x.isnumeric(), column_temp))]  =
'data_' + column_temp[list(map( lambda x : x.isnumeric(),
column_temp))]
med_hub.columns = column_temp
med_hub.columns

Index(['rank', 'hub_type', 'airports', 'iatacode', 'city_served',
'state',
       'data_2020', 'data_2019', 'data_2018', 'data_2017',
'data_2016',
       'data_2015', 'data_2014'],
      dtype='object')

large_hub.rename(columns = {'major_cities_served':'city_served'},
inplace = True)

final_hub_data = pd.concat([large_hub, med_hub])

final_hub_data.head(2)
```

```
   rank hub_type                                         airports
iatacode  \
0     1    large  Hartsfield–Jackson Atlanta International Airport
ATL
1     2    large           Dallas/Fort Worth International Airport
DFW

          city_served state   data_2021  data_2020  data_2019
data_2018  \
0             Atlanta    GA  36676010.0   20559866   53505795
51865797.0
1  Dallas & Ft. Worth    TX  30005266.0   18593421   35778573
32821799.0

    data_2017   data_2016   data_2015   data_2014   data_2013
data_2012  \
0  50251964.0  50501858.0  49340732.0  46604273.0  45308407.0
45798928.0
1  31816933.0  31283579.0  31589839.0  30804567.0  29038128.0
28022904.0

    data_2011
0  44414121.0
1  27518358.0
```

```
final_hub_data.data_2019.isnull().sum()
```

```
0
```

```
combined_data_pax = pd.merge(combined_data,
final_hub_data[['iatacode', 'data_2019']],how = 'left' , left_on =
'AirportFrom', right_on = 'iatacode')

combined_data_pax.rename(columns = {'iatacode':
'iatacode_source' ,'data_2019': 'data_2019_source_airport'}, inplace =
True)

combined_data_pax = pd.merge(combined_data_pax,
final_hub_data[['iatacode', 'data_2019']],how = 'left' , left_on =
'AirportTo', right_on = 'iatacode')

combined_data_pax.rename(columns = {'iatacode':
'iatacode_dest' ,'data_2019': 'data_2019_dest_airport'}, inplace =
True)

combined_data_pax =
combined_data_pax.loc[:,~combined_data_pax.columns.str.startswith('iat
acode')].copy()

combined_data_pax
```

```
             id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  
Length  \
0             1      CO     269         SFO       IAH          3    15   
205   
1             2      US    1558         PHX       CLT          3    15   
222   
2             3      AA    2400         LAX       DFW          3    20   
165   
3             4      AA    2466         SFO       DFW          3    20   
195   
4             5      AS     108         ANC       SEA          3    30   
202   
...         ...     ...     ...         ...       ...        ...   ...   
...   
518551  539377      B6     717         JFK       SJU          5  1439   
220   
518552  539378      B6     739         JFK       PSE          5  1439   
223   
518553  539379      CO     178         OGG       SNA          5  1439   
326   
518554  539382      UA      78         HNL       SFO          5  1439   
313   
518555  539383      US    1442         LAX       PHL          5  1439   
301   

        Delay type_source_airport  elevation_ft_source_airport  \
0           1       large_airport                         13.0   
1           1       large_airport                       1135.0   
2           1       large_airport                        125.0   
3           1       large_airport                         13.0   
4           0       large_airport                        152.0   
...       ...                 ...                          ...   
518551      1       large_airport                         13.0   
518552      1       large_airport                         13.0   
518553      0      medium_airport                         54.0   
518554      1       large_airport                         13.0   
518555      1       large_airport                        125.0   

        runway_count_source_airport type_dest_airport  \
0                               4.0     large_airport   
1                               3.0     large_airport   
2                               4.0     large_airport   
3                               4.0     large_airport   
4                               3.0     large_airport   
...                             ...               ...   
518551                          4.0     large_airport   
518552                          4.0    medium_airport   
518553                          2.0     large_airport   
518554                          6.0     large_airport   
518555                          4.0     large_airport   
```

```
        elevation_ft_dest_airport  runway_count_dest_airport  \
0                            97.0                        5.0
1                           748.0                        4.0
2                           607.0                        7.0
3                           607.0                        7.0
4                           433.0                        4.0
...                           ...                        ...
518551                        9.0                        2.0
518552                       29.0                        1.0
518553                       56.0                        2.0
518554                       13.0                        4.0
518555                       36.0                        4.0

        data_2019_source_airport  data_2019_dest_airport
0                     27779230.0              21905309.0
1                     22433552.0              24199688.0
2                     42939104.0              35778573.0
3                     27779230.0              35778573.0
4                      2713843.0              25001762.0
...                          ...                     ...
518551                31036655.0               4590117.0
518552                31036655.0                     NaN
518553                 3791807.0               5153276.0
518554                 9988678.0              27779230.0
518555                42939104.0              16006389.0

[518556 rows x 17 columns]
```

addd founded column

```
airlines_founded
```

```
   Airline IATA  Founded
0       CO  NaN      NaN
1       US  NaN      NaN
2       AA   AA   1926.0
3       AS   AS   1932.0
4       DL   DL   1924.0
5       B6   B6   1998.0
6       HA   HA   1929.0
7       OO   OO   1972.0
8       9E   9E   1985.0
9       OH   OH   1979.0
10      EV  NaN      NaN
11      XE   XE   2016.0
12      YV   YV   1980.0
13      UA   UA   1926.0
14      MQ   MQ   1984.0
15      F9   F9   1994.0
16      WN   WN   1967.0
```

```
combined_data_pax = pd.merge(combined_data_pax,
airlines_founded[['Airline', 'Founded']], on = 'Airline')

combined_data_pax.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0

   data_2019_dest_airport  Founded
0              21905309.0      NaN
1              21905309.0      NaN
```

1. Check the missing values in each field. Perform missing value treatment. Justify your actions

combined pax

```
combined_data_pax.isna().sum().sort_values(ascending = False)
```

```
data_2019_source_airport       85894
data_2019_dest_airport         85841
Founded                        83601
runway_count_dest_airport         31
elevation_ft_dest_airport         31
type_dest_airport                 31
runway_count_source_airport       31
elevation_ft_source_airport       31
type_source_airport               31
AirportTo                          0
Airline                            0
Flight                             0
AirportFrom                        0
```

```
Delay                              0
DayOfWeek                          0
Time                               0
Length                             0
id                                 0
dtype: int64
```

for type runway count and elevation lets get the airports for which information is missing

```
combined_data_pax[combined_data_pax.type_source_airport.isna()].AirportFrom.unique()
```

```
array(['CYS'], dtype=object)
```

```
combined_data_pax[combined_data_pax.type_dest_airport.isna()].AirportTo.unique()
```

```
array(['CYS'], dtype=object)
```

As we see information for only CYS is missing Lets check for this information using data dictionary and match the description and name of the airport to fetch information

```
airport_dict = pd.read_excel(address + '/Data Dictionary.xlsx',
sheet_name = 'airlines',header = 29, usecols = [0,1])
airport_dict.head(2)
```

```
  Aiport ID    Description
0       ABE   RAF Calveley
1       ABE  Bisho Airport
```

```
name = airport_dict[airport_dict['Aiport ID'] ==
'CYS'].Description.values[0]
name.lower()
```

```
'cheyenne regional jerry olson field'
```

```
air_miss = airports.loc[name.lower() == airports.name.str.lower(),
['ident', 'name', 'iata_code', 'type', 'elevation_ft']]
```

```
air_miss_comb = pd.merge(air_miss, runways[['airport_ident', 'id']],
how = 'left', left_on = 'ident', right_on = 'airport_ident')
runway_count_miss = air_miss_comb.groupby('ident')
[['id']].count().sort_values(by = 'id', ascending =
False).reset_index()
runway_count_miss
```

```
  ident  id
0  KCYS   2
```

```
air_miss_data = pd.merge(air_miss,runway_count_miss ).rename(columns =
{'id' : 'runway_count'})[['iata_code', 'type', 'elevation_ft',
'runway_count']]
```

```
combined_data_pax.loc[combined_data_pax.AirportFrom == 'CYS',
'type_source_airport'] = air_miss_data.type.values[0]
combined_data_pax.loc[combined_data_pax.AirportFrom == 'CYS',
'elevation_ft_source_airport'] = air_miss_data.elevation_ft.values[0]
combined_data_pax.loc[combined_data_pax.AirportFrom == 'CYS',
'runway_count_source_airport'] = air_miss_data.runway_count.values[0]

combined_data_pax.loc[combined_data_pax.AirportTo == 'CYS',
'type_dest_airport'] = air_miss_data.type.values[0]
combined_data_pax.loc[combined_data_pax.AirportTo == 'CYS',
'elevation_ft_dest_airport'] = air_miss_data.elevation_ft.values[0]
combined_data_pax.loc[combined_data_pax.AirportTo == 'CYS',
'runway_count_dest_airport'] = air_miss_data.runway_count.values[0]

combined_data_pax.isna().sum().sort_values(ascending = False)
```

```
data_2019_source_airport       85894
data_2019_dest_airport         85841
Founded                        83601
Length                             0
Airline                            0
Flight                             0
AirportFrom                        0
AirportTo                          0
DayOfWeek                          0
Time                               0
Delay                              0
type_source_airport                0
elevation_ft_source_airport        0
runway_count_source_airport        0
type_dest_airport                  0
elevation_ft_dest_airport          0
runway_count_dest_airport          0
id                                 0
dtype: int64
```

```
airline_dict = pd.read_excel(address + '/Data Dictionary.xlsx',
sheet_name = 'airlines',header = 10, usecols = [0,1])
airline_dict.head(2)
```

	Airlines ID	Description
0	WN	Southwest
1	DL	Delta

```
miss_founded =
combined_data_pax[combined_data_pax.Founded.isna()].Airline.unique()
print(airline_dict[airline_dict['Airlines ID'].isin( ['EV', 'CO',
'US'])])
```

```
  Airlines ID                        Description
5          US  PSA (initially US Airway Express)
```

```
7          EV                         ExpressJet
9          CO     United Airlines (initially CO)
```

```
miss_val = {'US' : 1967, 'CO' : 1934, 'EV' : 1986}
for aline in miss_founded:
    combined_data_pax.loc[(combined_data_pax.Founded.isna()) &
                      (combined_data_pax.Airline == aline), 'Founded']
= miss_val[aline]
```

```
(combined_data_pax.isna().sum().sort_values(ascending =
False)/combined_data_pax.shape[0])*100
```

```
data_2019_source_airport       16.564074
data_2019_dest_airport         16.553853
Founded                         0.000000
Length                          0.000000
Airline                         0.000000
Flight                          0.000000
AirportFrom                     0.000000
AirportTo                       0.000000
DayOfWeek                       0.000000
Time                            0.000000
Delay                           0.000000
type_source_airport             0.000000
elevation_ft_source_airport     0.000000
runway_count_source_airport     0.000000
type_dest_airport               0.000000
elevation_ft_dest_airport       0.000000
runway_count_dest_airport       0.000000
id                              0.000000
dtype: float64
```

For missing pax data use median value based on 'type' of airport

```
combined_data_pax.groupby('type_source_airport')
[['data_2019_source_airport']].median()
```

```
                     data_2019_source_airport
type_source_airport
large_airport                      21905309.0
medium_airport                      3323614.0
small_airport                             NaN
```

```
med_val = combined_data_pax.groupby('type_source_airport')
[['data_2019_source_airport']].median()
med_val
```

```
                     data_2019_source_airport
type_source_airport
large_airport                      21905309.0
medium_airport                      3323614.0
small_airport                             NaN
```

```
for typ in combined_data_pax.type_source_airport.unique():
      combined_data_pax.loc[(combined_data_pax.type_source_airport ==
typ)& (combined_data_pax.data_2019_source_airport.isna()),
                      'data_2019_source_airport'] =
med_val.loc[typ].values[0]

med_val_dest = combined_data_pax.groupby('type_dest_airport')
[['data_2019_dest_airport']].median()
med_val_dest
```

```
                   data_2019_dest_airport
type_dest_airport
large_airport                  21905309.0
medium_airport                  3323614.0
small_airport                         NaN
```

```
for typ in combined_data_pax.type_source_airport.unique():
      combined_data_pax.loc[(combined_data_pax.type_dest_airport ==
typ)& (combined_data_pax.data_2019_dest_airport.isna()),
                      'data_2019_dest_airport'] =
med_val.loc[typ].values[0]

combined_data_pax.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0

   data_2019_dest_airport  Founded
0              21905309.0   1934.0
1              21905309.0   1934.0
```

```
(combined_data_pax.isna().sum().sort_values(ascending = False)/combined_data_pax.shape[0])*100
```

```
data_2019_source_airport       0.226205
data_2019_dest_airport         0.224855
Founded                        0.000000
Length                         0.000000
Airline                        0.000000
Flight                         0.000000
AirportFrom                    0.000000
AirportTo                      0.000000
DayOfWeek                      0.000000
Time                           0.000000
Delay                          0.000000
type_source_airport            0.000000
elevation_ft_source_airport    0.000000
runway_count_source_airport    0.000000
type_dest_airport              0.000000
elevation_ft_dest_airport      0.000000
runway_count_dest_airport      0.000000
id                             0.000000
dtype: float64
```

Since % of values missing is 0.2% we can simply eliminate these rows

2. Perform data visualization and share your insights related to following aspects:

I. According to the data provided, around 70% of the flights are delayed for Southwest airlines. Visualize to compare the same for other airlines.
II. No delayed flights on different weekdays. Which days of the week are safest to travel.
III. Which airlines to recommend for short, medium and long length of travel.

Do you observe any pattern in the time of departure of flights of long duration

```
# get id for "southwest Airlines"
id_airline = airline_dict.loc[airline_dict['Description'].str.strip().str.lower() == 'southwest', 'Airlines ID'].values[0]
```

```
round(combined_data_pax[combined_data_pax.Airline == id_airline].Delay.sum()/
      combined_data_pax[combined_data_pax.Airline == id_airline].Delay.size*100)
```

```
70
```

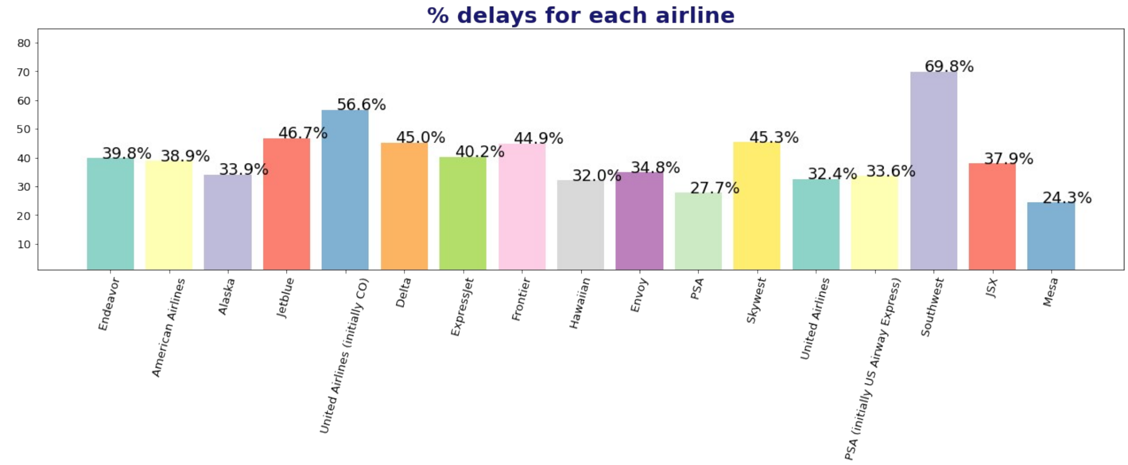
```
def percent_Delay(x):
    return round(x.sum()/x.size * 100,2)
```

```
delay_perc = combined_data_pax.groupby('Airline')
['Delay'].agg(percent_Delay)
delay_perc = delay_perc.reset_index()

plot_data = pd.merge(delay_perc, airline_dict, left_on = 'Airline',
                     right_on = 'Airlines ID', how = 'left')
[['Airline', 'Description', 'Delay']]
plot_data
```

```
   Airline                         Description  Delay
0       9E                            Endeavor  39.77
1       AA                   American Airlines  38.85
2       AS                              Alaska  33.93
3       B6                            Jetblue  46.70
4       CO      United Airlines (initially CO)  56.62
5       DL                               Delta  45.05
6       EV                          ExpressJet  40.22
7       F9                            Frontier  44.90
8       HA                            Hawaiian  32.02
9       MQ                               Envoy  34.81
10      OH                                 PSA  27.73
11      OO                             Skywest  45.29
12      UA                     United Airlines  32.39
13      US  PSA (initially US Airway Express)  33.60
14      WN                           Southwest  69.78
15      XE                                 JSX  37.89
16      YV                                Mesa  24.29
```

```
plt.figure(figsize = (22,5))
plt.bar(plot_data.Description, height =  plot_data.Delay, color =
plt.get_cmap('Set3').colors)
for v, idx in zip(plot_data.Delay.values,plot_data.index ):
    plt.annotate('{:.1f}%'.format(v), xy = (idx-0.15, v), size = 18,
family = 'times')
plt.ylim(1,85)
plt.xticks(size = 13, rotation = 75)
plt.yticks(size = 13)
plt.title('% delays for each airline', size = 25, color =
'midnightblue', weight = 'heavy', family = 'times')
plt.show()
```

```
findfont: Font family ['times'] not found. Falling back to DejaVu
Sans.
findfont: Font family ['times'] not found. Falling back to DejaVu
Sans.
```



II. No delayed flights on different weekdays. Which days of the week are safest to travel.

```
combined_data_pax.head()
```

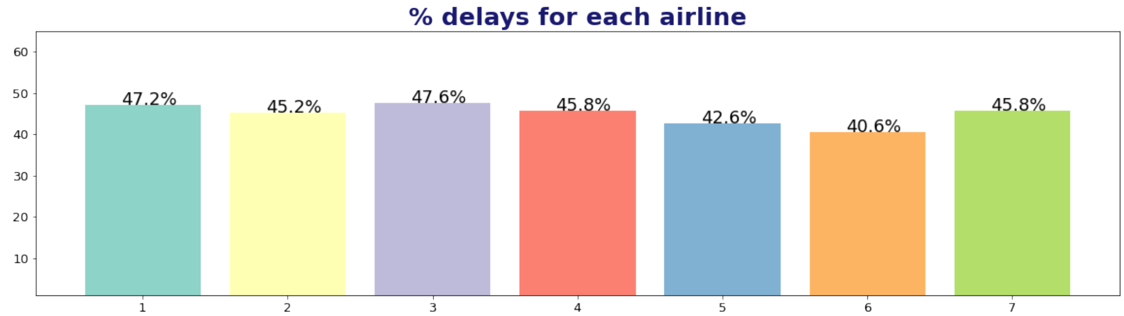
```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1
2  11      CO     223         ANC       SEA          3    49     201
1
3  18      CO    1496         LAS       IAH          3    60     162
0
4  20      CO     507         ONT       IAH          3    75     167
0

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0
2       large_airport                        152.0
3       large_airport                       2181.0
4       large_airport                        944.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0
2                          3.0     large_airport
433.0
3                          4.0     large_airport
97.0
```

```
4                           2.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0
2                        4.0                 2713843.0
3                        5.0                24728361.0
4                        5.0                 2723002.0

   data_2019_dest_airport  Founded
0              21905309.0   1934.0
1              21905309.0   1934.0
2              25001762.0   1934.0
3              21905309.0   1934.0
4              21905309.0   1934.0
```

```
delay_perc_weekday = combined_data_pax.groupby('DayOfWeek')
['Delay'].agg(percent_Delay)
delay_perc_weekday
```

```
DayOfWeek
1    47.22
2    45.21
3    47.58
4    45.78
5    42.56
6    40.56
7    45.77
Name: Delay, dtype: float64
```

```
plt.figure(figsize = (20,5))
plt.bar(delay_perc_weekday.index, height =  delay_perc_weekday.values,
color = plt.get_cmap('Set3').colors)
for v, idx in zip(delay_perc_weekday.values, range(1,
len(delay_perc_weekday.index)+1)):
    # print(v, idx)
    plt.annotate('{:.1f}%'.format(v), xy = (idx-0.15, v), size = 18,
family = 'times')
plt.ylim(1,65)
plt.xticks(size = 13)
plt.yticks(size = 13)
plt.title('% delays for each airline', size = 25, color =
'midnightblue', weight = 'heavy', family = 'times')
plt.show()
```



III. Which airlines to recommend for short, medium and long length of travel.

```
duration_data = combined_data_pax[['Airline', 'Length',
'Delay']].copy()

duration_data['duration'] = pd.cut(duration_data.Length, 3, labels =
['short', 'medium', 'long'])
duration_data_grp = duration_data.groupby(['Airline','duration'])
['Delay'].agg(
    percent_Delay).reset_index().pivot(index = 'Airline',
                                        columns = 'duration').fillna(0)
['Delay']
duration_data_grp.columns = duration_data_grp.columns.astype(str)
duration_data_grp.reset_index()
```

```
duration Airline  short  medium   long
0             9E  39.77    0.00   0.00
1             AA  37.62   43.25  60.40
2             AS  32.58   38.17   0.00
3             B6  45.70   51.05   0.00
4             CO  52.88   64.96  66.87
5             DL  43.88   50.24  48.62
6             EV  40.22   50.00   0.00
7             F9  45.03   43.56   0.00
8             HA  30.16   40.48   0.00
9             MQ  34.82   27.42   0.00
10            OH  27.61   39.20   0.00
11            OO  45.25   53.03   0.00
12            UA  29.92   37.10  39.26
13            US  31.96   40.72   0.00
14            WN  69.12   77.61   0.00
15            XE  37.87   53.70   0.00
16            YV  24.28   25.86   0.00
```

```
duration_data.index
```

```
Int64Index([     0,      1,      2,      3,      4,      5,      6,
7,
                 8,      9,
```

```
            ...
            518546, 518547, 518548, 518549, 518550, 518551, 518552,
518553,
            518554, 518555],
           dtype='int64', length=518556)
```

```
# get names of airlines also

airline_dict
```

```
    Airlines ID              Description
0            WN                Southwest
1            DL                    Delta
2            OO                  Skywest
3            AA        American Airlines
4            MQ                    Envoy
..          ...                      ...
683         XNA  Nambour Hospital Helipad
684         YAK        Aussenkehr Airport
685         YAK        Congo Town Airport
686         YAK          Yalkulka Airport
687         YUM          Yuinmery Airport

[688 rows x 2 columns]
```

```
airline_dict.Description = airline_dict.Description.str.strip()
duration_data_grp = pd.merge(duration_data_grp,airline_dict[['Airlines
ID', 'Description']],
         left_on = 'Airline', right_on = 'Airlines ID',
         how = 'left')
duration_data_grp
```

```
    short  medium   long Airlines ID
Description
0   39.77    0.00   0.00          9E
Endeavor
1   37.62   43.25  60.40          AA                  American
Airlines
2   32.58   38.17   0.00          AS
Alaska
3   45.70   51.05   0.00          B6
Jetblue
4   52.88   64.96  66.87          CO     United Airlines (initially
CO)
5   43.88   50.24  48.62          DL
Delta
6   40.22   50.00   0.00          EV
ExpressJet
7   45.03   43.56   0.00          F9
Frontier
8   30.16   40.48   0.00          HA
```

```
Hawaiian
9   34.82   27.42   0.00          MQ
Envoy
10  27.61   39.20   0.00          OH
PSA
11  45.25   53.03   0.00          OO
Skywest
12  29.92   37.10  39.26          UA                   United
Airlines
13  31.96   40.72   0.00          US  PSA (initially US Airway
Express)
14  69.12   77.61   0.00          WN
Southwest
15  37.87   53.70   0.00          XE
JSX
16  24.28   25.86   0.00          YV
Mesa
```

```
combined_data_pax.Airline.nunique()
```

```
17
```

```
long = duration_data_grp[duration_data_grp.long ==
duration_data_grp.long.min()].Description.values.tolist()
print('Airlines with no delays for long flights :\n',', '.join(long))
medium = duration_data_grp[duration_data_grp.medium ==
duration_data_grp.medium.min()].Description.values.tolist()
print('\nAirlines with no delays for medium flights :\n', ',
'.join(medium))
short = duration_data_grp[duration_data_grp.short ==
duration_data_grp.short.min()].Description.values.tolist()
print('\nAirlines with no delays for short flights :\n',  ',
'.join(short)     )
```

```
Airlines with no delays for long flights :
 Endeavor, Alaska, Jetblue, ExpressJet, Frontier, Hawaiian, Envoy,
PSA, Skywest, PSA (initially US Airway Express), Southwest, JSX, Mesa

Airlines with no delays for medium flights :
 Endeavor

Airlines with no delays for short flights :
 Mesa
```

IV.   Do you observe any pattern in the time of departure of flights of long duration

```
combined_data_pax['duration'] = pd.cut(combined_data_pax.Length, 3,
labels = ['short', 'medium', 'long'])
```

```
combined_data_pax.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0

   data_2019_dest_airport  Founded duration
0              21905309.0   1934.0    short
1              21905309.0   1934.0    short
```

```
pd.crosstab(combined_data_pax.Time, combined_data_pax.duration)
['long']
```

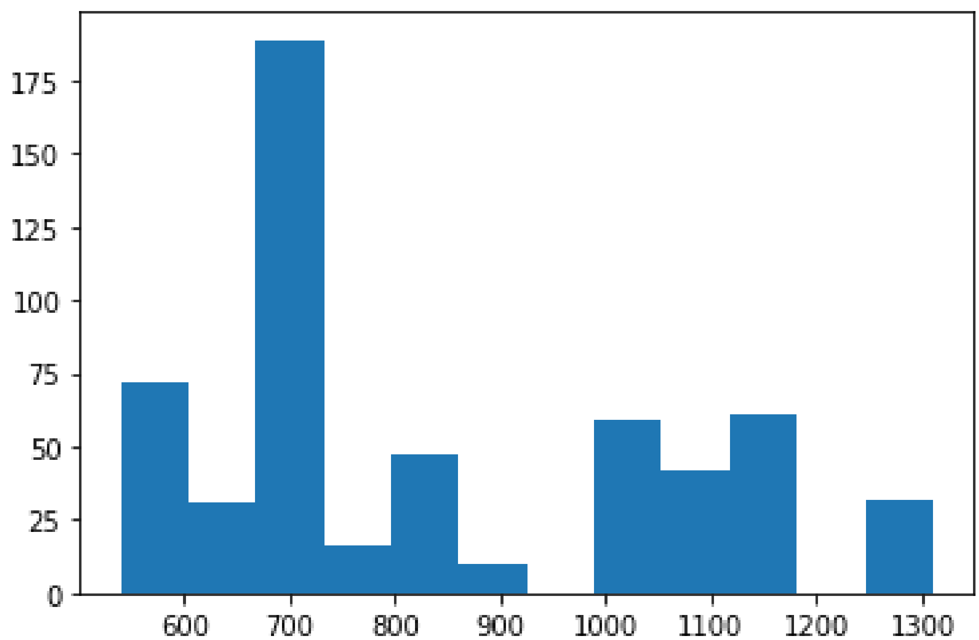
```
Time
10      0
15      0
20      0
21      0
25      0
       ..
1428    0
1430    0
1431    0
1435    0
1439    0
Name: long, Length: 1131, dtype: int64
```

```
y = pd.crosstab(combined_data_pax.Time, combined_data_pax.duration)
['long'].index
x = pd.crosstab(combined_data_pax.Time, combined_data_pax.duration)
['long'].values
```

```
filter_data = combined_data_pax.loc[combined_data_pax.duration ==
'long', ['Time', 'duration']]

filter_data.Time.describe()
```

```
count     559.000000
mean      840.635063
std       221.020092
min       540.000000
25%       670.000000
50%       717.000000
75%      1045.000000
max      1310.000000
Name: Time, dtype: float64
```

```
plt.hist(filter_data.Time, bins = 12)
plt.show()
```



3. How Large Hubs compare to Medium hubs in terms of count of delayed flights. Use appropriate visualization to represent your findings.

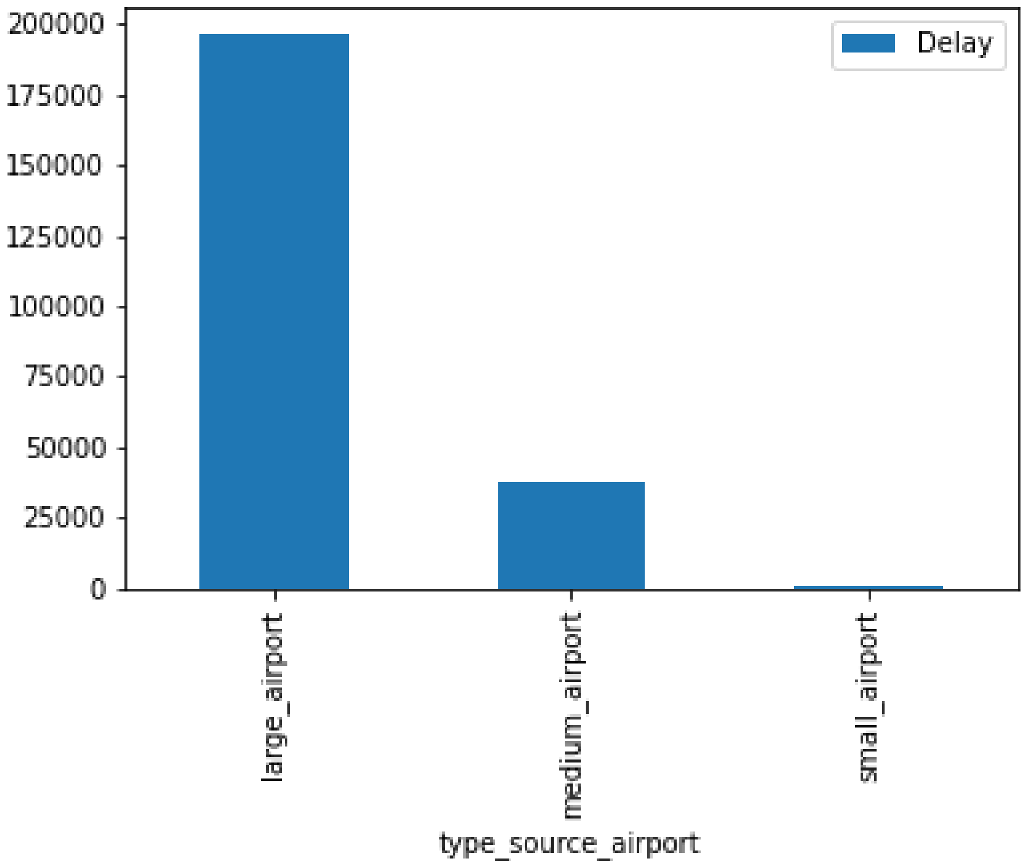
```
combined_data_pax.head()
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1
2  11      CO     223         ANC       SEA          3    49     201
1
```

```
3  18      CO    1496         LAS       IAH          3    60     162
0
4  20      CO     507         ONT       IAH          3    75     167
0

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0
2       large_airport                        152.0
3       large_airport                       2181.0
4       large_airport                        944.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0
2                          3.0     large_airport
433.0
3                          4.0     large_airport
97.0
4                          2.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0
2                        4.0                 2713843.0
3                        5.0                24728361.0
4                        5.0                 2723002.0

   data_2019_dest_airport  Founded duration
0              21905309.0   1934.0    short
1              21905309.0   1934.0    short
2              25001762.0   1934.0    short
3              21905309.0   1934.0    short
4              21905309.0   1934.0    short
```

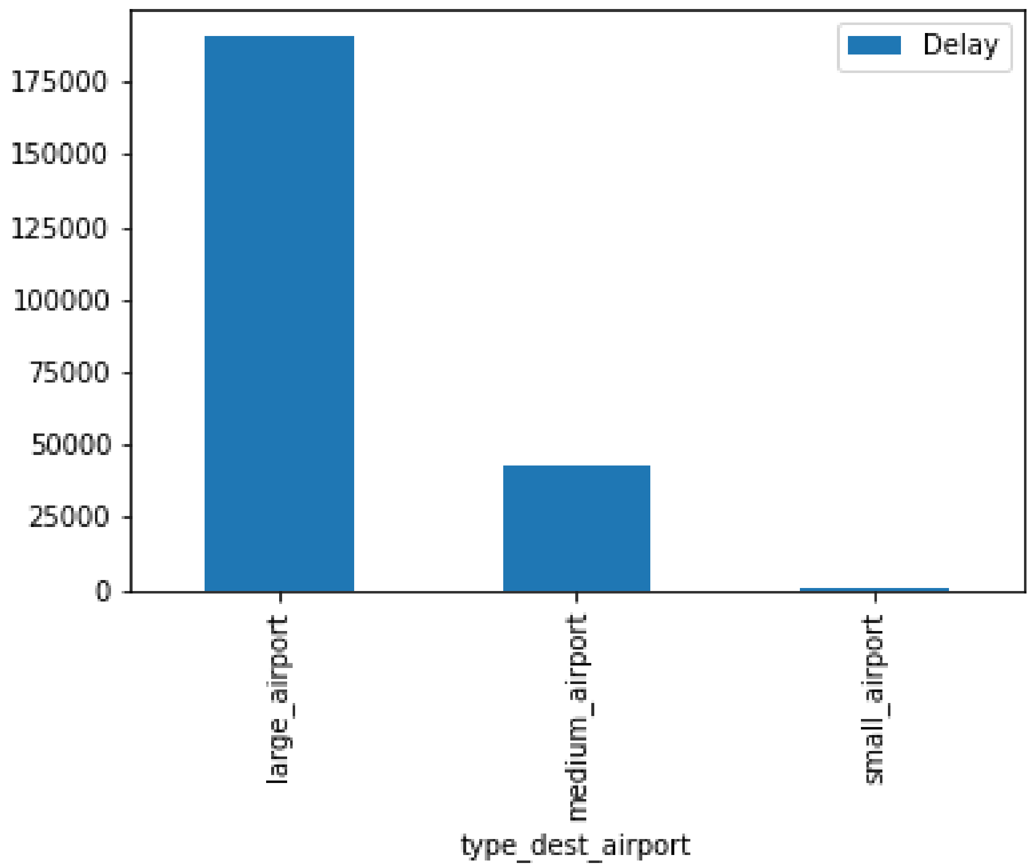
```
combined_data_pax.groupby('type_source_airport')
[['Delay']].agg('sum').plot.bar()
```

```
<AxesSubplot:xlabel='type_source_airport'>
```




```
combined_data_pax.groupby('type_dest_airport')
[['Delay']].agg('sum').plot.bar()
```

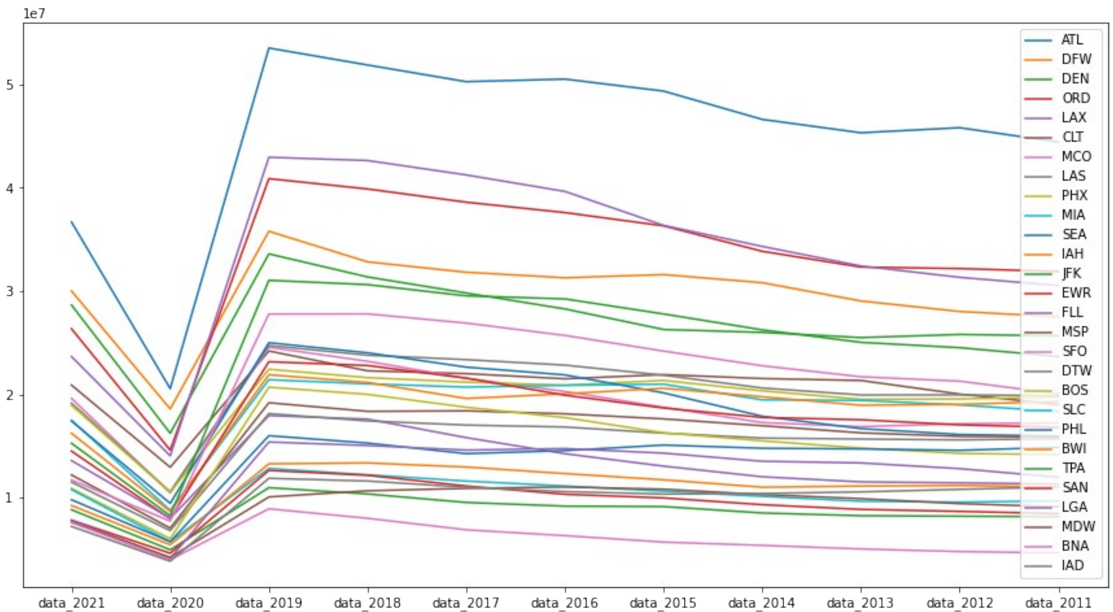
```
<AxesSubplot:xlabel='type_dest_airport'>
```



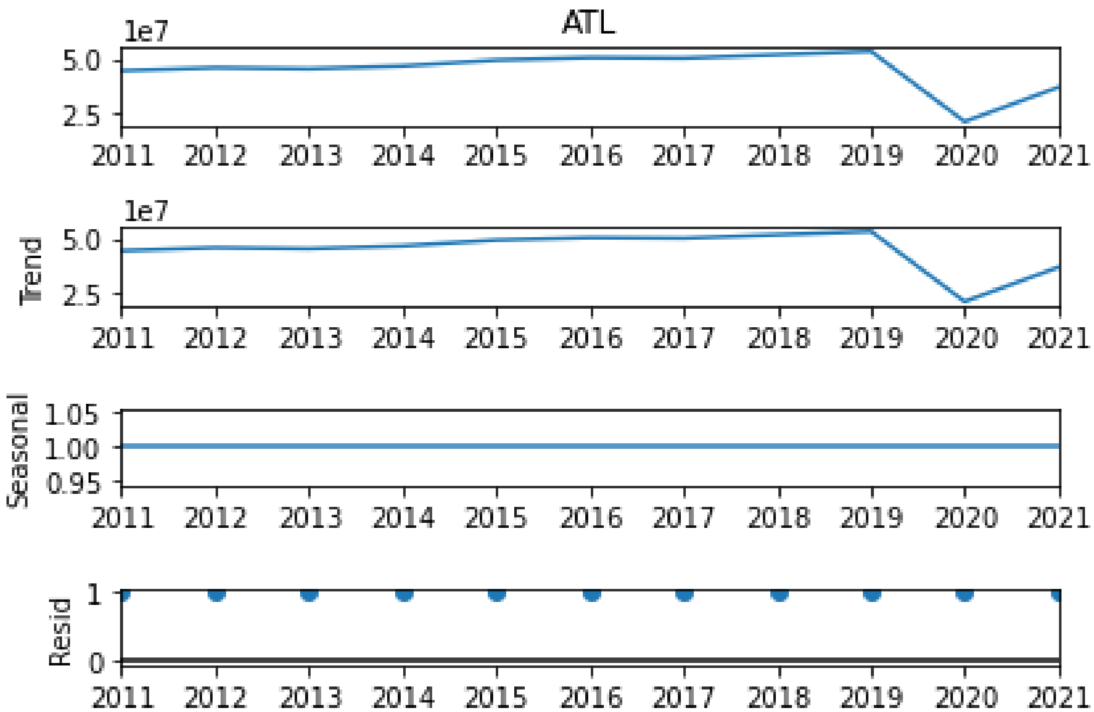
4. For Large hubs, forecast the number of passengers for 2022 using simple moving average method.

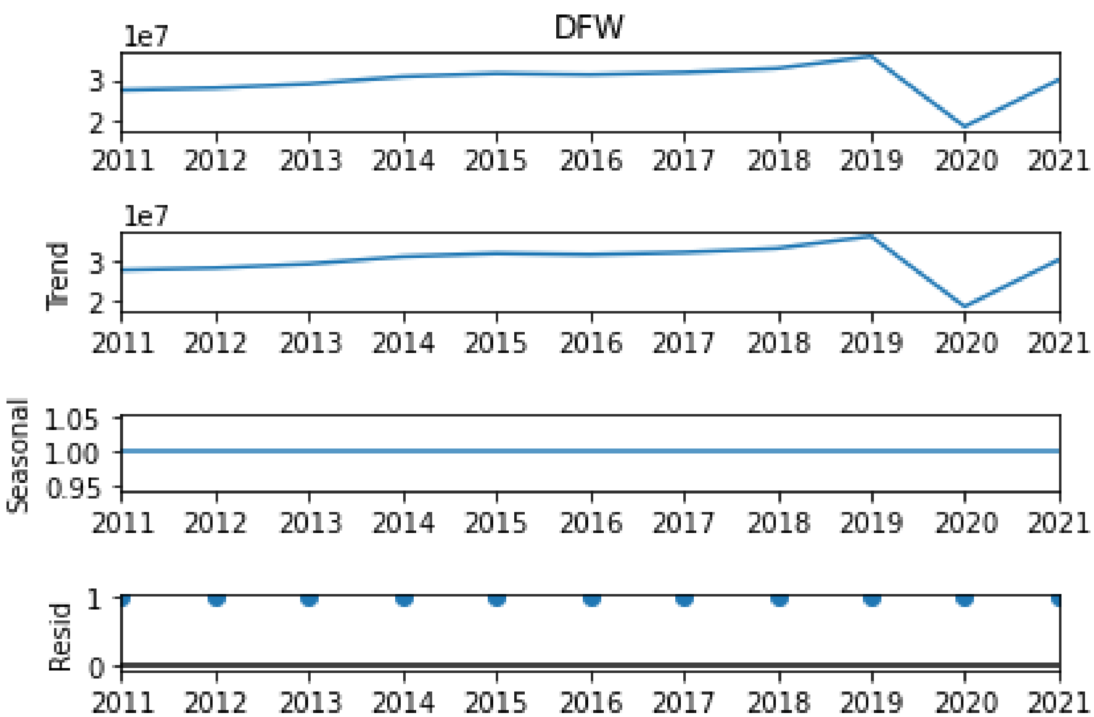
```
# develop the series

cols = ['iatacode'] +
final_hub_data.columns[ final_hub_data.columns.str.startswith('data_')
].tolist()

time_series = final_hub_data.loc[final_hub_data.hub_type == 'large',
cols].set_index('iatacode').T

time_series['ATL']

data_2021    36676010.0
data_2020    20559866.0
data_2019    53505795.0
data_2018    51865797.0
data_2017    50251964.0
data_2016    50501858.0
data_2015    49340732.0
data_2014    46604273.0
data_2013    45308407.0
```

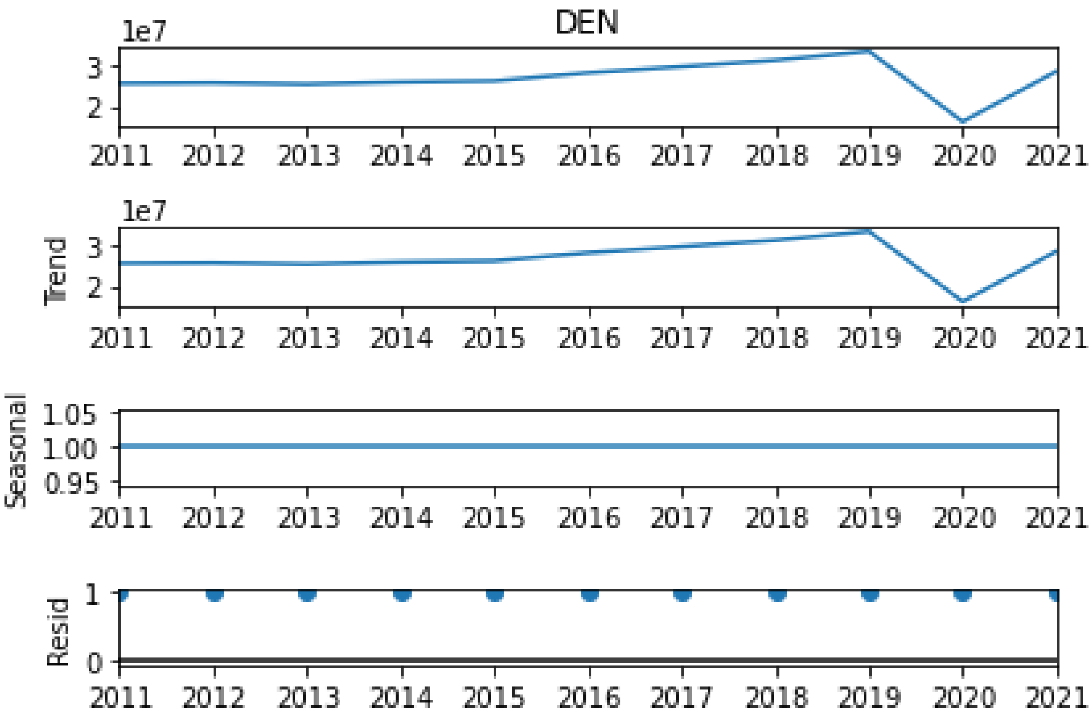
```
data_2012    45798928.0
data_2011    44414121.0
Name: ATL, dtype: float64

# there are 28 series with 11 values each

plt.figure(figsize = (15,8))
for ser in time_series.columns:
    plt.plot(time_series[ser], label = ser)
    plt.legend()
plt.show(block = True)
```

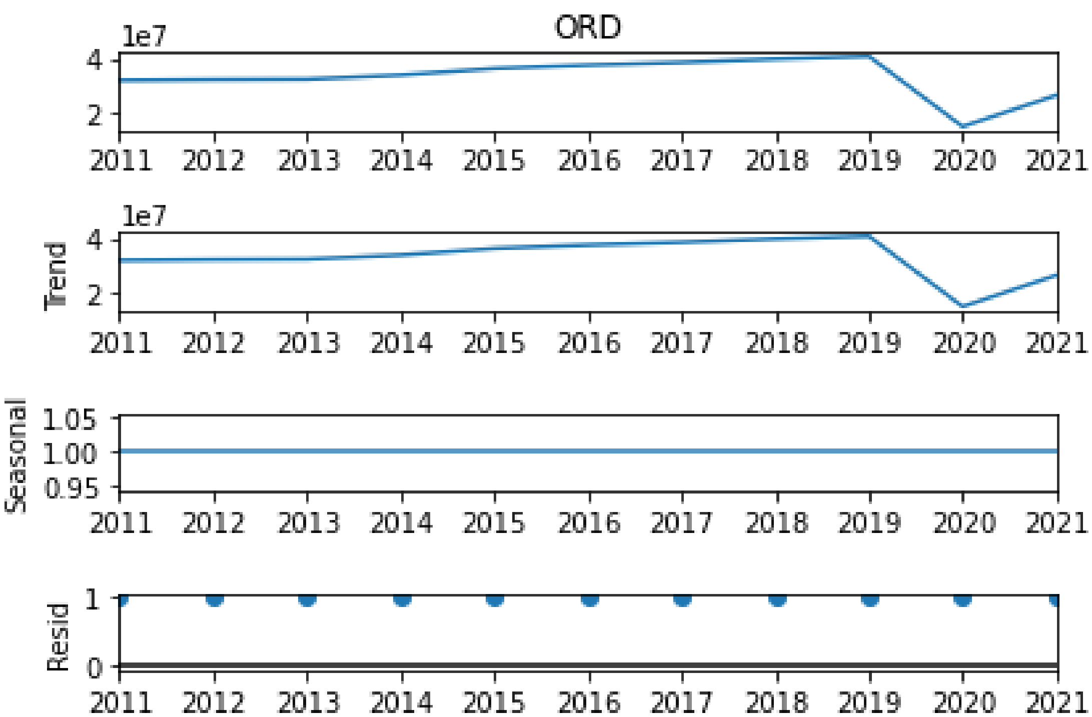



```
for ser in time_series.columns[:4]:
    series = time_series[ser].copy()
    series.index = 
pd.to_datetime(series.index.str.replace('data_',''))
    series.sort_index(inplace = True)
    decomposition = sm.tsa.seasonal_decompose(series, 
model='multiplicative')
    decomposition.plot()
plt.show()
```


ATL
1e7
5.0
2.5
Trend
Seasonal
1.05
1.00
0.95
Resid
1
0
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021


DFW
1e7
3
2
Trend
Seasonal
1.05
1.00
0.95
Resid
1
0
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021






```
error = {}
forecast_2022 = {}
f = {}
wind_min = {}
win_min_mape = {}
```

```python
for ser in time_series.columns:
    series = time_series[ser].copy()
    series.index =
pd.to_datetime(series.index.str.replace('data_',''))
    series.sort_index(inplace = True)
    test = series[-1:]
    train = series[:-1]
    err_temp = {}
    fore_2022 = {}
    for window in range(2,10):
        forecast = series.rolling(window).mean()
        # accuracy
        mape = round(mean_absolute_percentage_error(test, forecast[-
1:]),4)
        err_temp.update({window : mape})
        # forecast for 2022
        fore_2022.update({window : series[-window:].mean()})
    err_ser = pd.Series(err_temp)
    min_wind = err_ser[(err_ser == err_ser.min())].index.values[0]
    forecast_2022.update({ser : round(series[-min_wind:].mean(),2)})
    wind_min.update({ser : min_wind})
    win_min_mape.update({ser :err_temp[min_wind] })
    f.update({ser :pd.Series(fore_2022).round(2) })
    error.update({ser : err_ser})

    # forecast for 2022
```

```python
win_min_mape
```

```
{'ATL': 0.0065,
 'DFW': 0.0015,
 'DEN': 0.023,
 'ORD': 0.0351,
 'LAX': 0.1362,
 'CLT': 0.0006,
 'MCO': 0.0077,
 'LAS': 0.0212,
 'PHX': 0.0001,
 'MIA': 0.0182,
 'SEA': 0.0076,
 'IAH': 0.0389,
 'JFK': 0.1912,
 'EWR': 0.0486,
 'FLL': 0.0122,
 'MSP': 0.0502,
 'SFO': 0.1697,
 'DTW': 0.0559,
 'BOS': 0.1502,
 'SLC': 0.0062,
 'PHL': 0.0727,
 'BWI': 0.0082,
```

```
 'TPA': 0.0029,
 'SAN': 0.0686,
 'LGA': 0.1655,
 'MDW': 0.0453,
 'BNA': 0.0598,
 'IAD': 0.0595}
```

```python
sma_forecast = pd.DataFrame(f)
sma_error = pd.DataFrame(error)

sma_prediction = pd.DataFrame(forecast_2022.values(), index =
forecast_2022.keys(), columns = ['forecast_2022'] )
sma_prediction['window_used'] = wind_min.values()
sma_prediction['mape_at_window'] = win_min_mape.values()

sma_prediction
```

	forecast_2022	window_used	mape_at_window
ATL	36913890.33	3	0.0065
DFW	30049928.50	6	0.0015
DEN	27986853.33	6	0.0230
ORD	27276077.67	3	0.0351
LAX	26886097.00	3	0.1362
CLT	20913675.38	8	0.0006
MCO	19467356.50	8	0.0077
LAS	19566943.50	4	0.0212
PHX	18942662.60	5	0.0001
MIA	17182193.50	4	0.0182
SEA	17298122.67	3	0.0076
IAH	15610229.33	3	0.0389
JFK	18193272.00	3	0.1912
EWR	15220095.33	3	0.0486
FLL	13765555.89	9	0.0122
MSP	12824682.00	3	0.0502
SFO	9735202.00	2	0.1697
DTW	12161020.00	3	0.0559
BOS	12548215.33	3	0.1502
SLC	10729401.33	6	0.0062
PHL	10523198.67	3	0.0727
BWI	9329867.67	3	0.0082
TPA	8872731.89	9	0.0029
SAN	8374302.67	3	0.0686
LGA	9122674.67	3	0.1655
MDW	7333000.33	3	0.0453
BNA	7140261.25	4	0.0598
IAD	7658216.67	3	0.0595

1. Perform hypothesis testing techniques to learn:

   I. Has the altitude of the airport anything to do with flight delays. Check for incoming and outgoing flights

II. Has surface-type of runways of airports anything to do with flight delays

III. Has length, duration of flight, anything to do with flight delays

I. Has the altitude of the airport anything to do with flight delays. Check for incoming and outgoing flights

2 sample t test

for outgoing

```
sample1 = combined_data_pax[combined_data_pax.Delay ==
1].elevation_ft_source_airport
sample2 = combined_data_pax[combined_data_pax.Delay ==
0].elevation_ft_source_airport

t, p = stats.ttest_ind(sample1, sample2)

if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'

result
```

```
'reject null'
```

for incoming flights

```
sample1 = combined_data_pax[combined_data_pax.Delay ==
1].elevation_ft_dest_airport
sample2 = combined_data_pax[combined_data_pax.Delay ==
0].elevation_ft_dest_airport

t, p = stats.ttest_ind(sample1, sample2)

if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'

result
```

```
'reject null'
```

Conclusion : Significant difference in avg elevation wrt flight delay for both incoming and outgoing flights

is no. of runway at airport for delayed < for non delayed

```
combined_data_pax

            id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  
Length  \
0            1      CO     269         SFO       IAH          3    15  
205   
1            6      CO    1094         LAX       IAH          3    30  
181   
2           11      CO     223         ANC       SEA          3    49  
201   
3           18      CO    1496         LAS       IAH          3    60  
162   
4           20      CO     507         ONT       IAH          3    75  
167   
...        ...     ...     ...         ...       ...        ...   ...  
...   
518551  538750      WN    2601         LAS       SMF          5  1230  
85   
518552  538783      WN    1936         SMF       SAN          5  1235  
85   
518553  538810      WN    2629         LAS       RNO          5  1240  
75   
518554  538833      WN    1226         SFO       LAX          5  1245  
75   
518555  538834      WN    2370         LAX       SFO          5  1245  
75   

        Delay type_source_airport  elevation_ft_source_airport  \
0           1       large_airport                         13.0   
1           1       large_airport                        125.0   
2           1       large_airport                        152.0   
3           0       large_airport                       2181.0   
4           0       large_airport                        944.0   
...       ...                 ...                          ...   
518551      1       large_airport                       2181.0   
518552      1       large_airport                         27.0   
518553      1       large_airport                       2181.0   
518554      1       large_airport                         13.0   
518555      1       large_airport                        125.0   

        runway_count_source_airport type_dest_airport  \
0                               4.0     large_airport   
1                               4.0     large_airport   
2                               3.0     large_airport   
3                               4.0     large_airport   
```

```
4                                2.0     large_airport
...                              ...               ...
518551                           4.0     large_airport
518552                           2.0     large_airport
518553                           4.0     large_airport
518554                           4.0     large_airport
518555                           4.0     large_airport

        elevation_ft_dest_airport  runway_count_dest_airport  \
0                            97.0                        5.0
1                            97.0                        5.0
2                           433.0                        4.0
3                            97.0                        5.0
4                            97.0                        5.0
...                           ...                        ...
518551                       27.0                        2.0
518552                       17.0                        1.0
518553                     4415.0                        3.0
518554                      125.0                        4.0
518555                       13.0                        4.0

        data_2019_source_airport  data_2019_dest_airport  Founded
duration
0                     27779230.0              21905309.0   1934.0
short
1                     42939104.0              21905309.0   1934.0
short
2                      2713843.0              25001762.0   1934.0
short
3                     24728361.0              21905309.0   1934.0
short
4                      2723002.0              21905309.0   1934.0
short
...                          ...                     ...      ...
...
518551                24728361.0               6454413.0   1967.0
short
518552                 6454413.0              12648692.0   1967.0
short
518553                24728361.0               2162250.0   1967.0
short
518554                27779230.0              42939104.0   1967.0
short
518555                42939104.0              27779230.0   1967.0
short

[518556 rows x 19 columns]
```

```
s1 = combined_data_pax[combined_data_pax.Delay ==
1].runway_count_source_airport
```

```
s2 = combined_data_pax[combined_data_pax.Delay ==
0].runway_count_source_airport

t, p = stats.ttest_ind(s1, s2)
if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'
print(result)
```

```
reject null
```

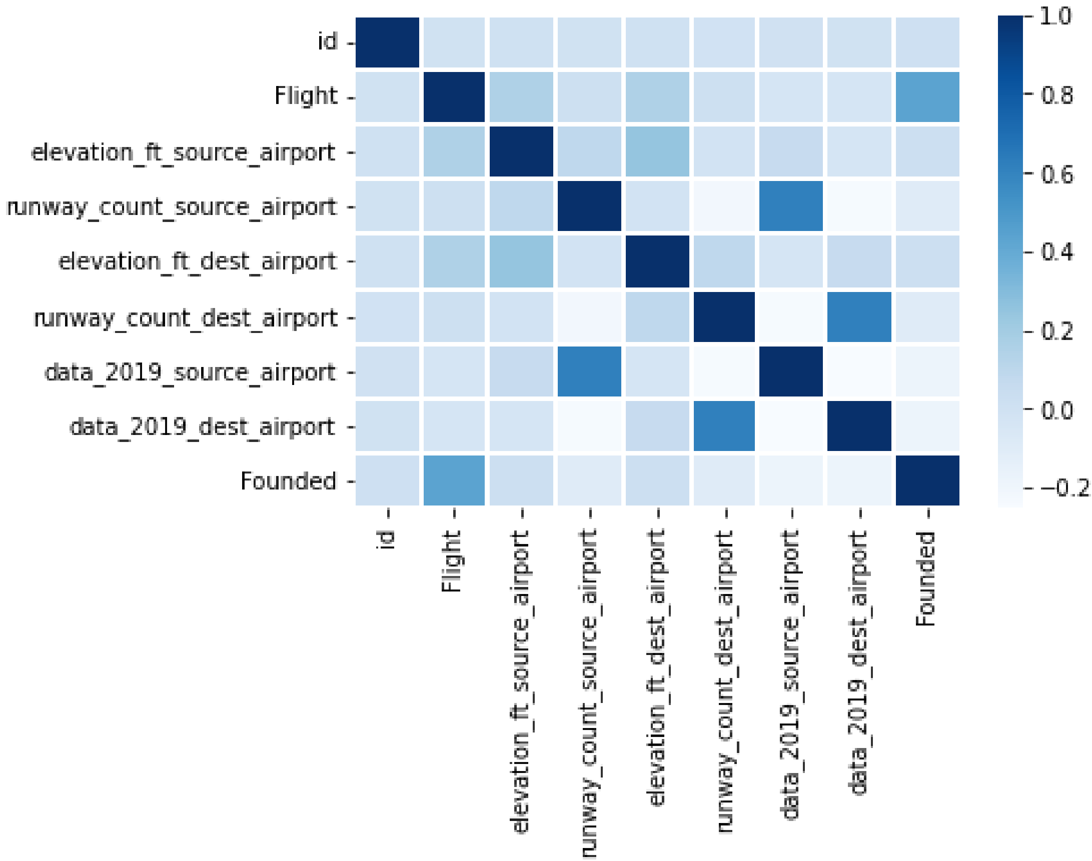
```
s1 = combined_data_pax[combined_data_pax.Delay ==
1].runway_count_dest_airport
s2 = combined_data_pax[combined_data_pax.Delay ==
0].runway_count_dest_airport

t, p = stats.ttest_ind(s1, s2)
if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'
print(result)
```

```
reject null
```

```
combined_data_pax.columns
```

```
Index(['id', 'Airline', 'Flight', 'AirportFrom', 'AirportTo',
'DayOfWeek',
       'Time', 'Length', 'Delay', 'type_source_airport',
       'elevation_ft_source_airport', 'runway_count_source_airport',
       'type_dest_airport', 'elevation_ft_dest_airport',
       'runway_count_dest_airport', 'data_2019_source_airport',
       'data_2019_dest_airport', 'Founded', 'duration'],
      dtype='object')
```

```
# Find correlation matrix amongst predictors of flight delay. Create a
heatmap to visualize. Share your findings.

correlation_matix = combined_data_pax.drop(columns = ['DayOfWeek',
'Time', 'Length',
'Delay','type_source_airport','type_dest_airport']).corr()

sns.heatmap(correlation_matix, cmap='Blues',linecolor='white',
linewidths=2)
plt.show()
```



Conclusion : avg runway count at destination airport for delayed filghts < avg runway count at destination airport for delayed filghts for Incoming flights

Has length, duration of flight, anything to do with flight delays!

```
s1 = combined_data_pax[combined_data_pax.Delay == 1].Length
s2 = combined_data_pax[combined_data_pax.Delay == 0].Length

t, p = stats.ttest_ind(s1, s2)

if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'
print(result)
```

```
reject null
```

```
# there is isgnificant difference
```

```
cs = pd.crosstab(combined_data_pax.duration, combined_data_pax.Delay)
cs
```

```
Delay          0       1
duration
```

```
short     255324  204474
medium     28991   29208
long         252     307
```

```
chi, p, df, ex = stats.chi2_contingency(cs)
if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'
print(result)
```

```
reject null
```

```
t, p = stats.ttest_ind(s1, s2)
if p < 0.05:
    result = 'reject null'
else :
    result = 'fail to reject null'
print(result)
```

```
reject null
```

Conclusion : avg duration for delayed filghts and non Delayed flights are significantly different.

```
    - avg duration of flights is less for non delayed flights
    - short duration flights get delayed less.
```

check info of dat

```
combined_data_pax.head(2)
```

```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length
Delay  \
0   1      CO     269         SFO       IAH          3    15     205
1
1   6      CO    1094         LAX       IAH          3    30     181
1

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0
```

```
   data_2019_dest_airport  Founded duration
0              21905309.0   1934.0    short
1              21905309.0   1934.0    short
```

```
combined_data_pax.columns
```

```
Index(['id', 'Airline', 'Flight', 'AirportFrom', 'AirportTo',
'DayOfWeek',
       'Time', 'Length', 'Delay', 'type_source_airport',
       'elevation_ft_source_airport', 'runway_count_source_airport',
       'type_dest_airport', 'elevation_ft_dest_airport',
       'runway_count_dest_airport', 'data_2019_source_airport',
       'data_2019_dest_airport', 'Founded', 'duration'],
      dtype='object')
```

```
combined_data_pax.to_csv('combined_data_pax.csv', index=False)
```

7. Use Onehotencoder and Ordinalencoder to deal with categorical variables.

```
combined_data_pax.isna().sum()
```

```
id                               0
Airline                          0
Flight                           0
AirportFrom                      0
AirportTo                        0
DayOfWeek                        0
Time                             0
Length                           0
Delay                            0
type_source_airport              0
elevation_ft_source_airport      0
runway_count_source_airport      0
type_dest_airport                0
elevation_ft_dest_airport        0
runway_count_dest_airport        0
data_2019_source_airport      1173
data_2019_dest_airport        1166
Founded                          0
duration                         0
dtype: int64
```

```
combined_data_pax.dropna(inplace = True)
```

```
combined_data_pax.drop(columns = ['id', 'Flight',  'duration'],
inplace = True)
```

```
combined_data_pax.head(2)
```

```
  Airline AirportFrom AirportTo  DayOfWeek  Time  Length  Delay  \
0      CO         SFO       IAH          3    15     205      1
1      CO         LAX       IAH          3    30     181      1

  type_source_airport  elevation_ft_source_airport  \
0       large_airport                         13.0
1       large_airport                        125.0

   runway_count_source_airport type_dest_airport
elevation_ft_dest_airport  \
0                          4.0     large_airport
97.0
1                          4.0     large_airport
97.0

   runway_count_dest_airport  data_2019_source_airport  \
0                        5.0                27779230.0
1                        5.0                42939104.0

   data_2019_dest_airport  Founded
0              21905309.0   1934.0
1              21905309.0   1934.0
```

```
combined_data_pax.type_dest_airport.unique()
```

```
array(['large_airport', 'medium_airport'], dtype=object)
```

```
ordinal = OrdinalEncoder(categories=[['medium_airport',
'large_airport'],['medium_airport', 'large_airport']])
ordinal.fit(combined_data_pax[['type_source_airport',
'type_dest_airport']])
```

```
OrdinalEncoder(categories=[['medium_airport', 'large_airport'],
                           ['medium_airport', 'large_airport']])
```

```
combined_data_pax[['type_source_airport', 'type_dest_airport']] =
ordinal.transform(combined_data_pax[['type_source_airport',
'type_dest_airport']])
```

```
model_data = combined_data_pax.drop(columns = ['Airline',
'AirportFrom', 'AirportTo'])
```

```
model_data.shape
```

```
(516217, 13)
```

```
dummy = pd.get_dummies(model_data)
dummy.shape
```

```
(516217, 13)
```

```
airlines.shape
```

```
(518556, 9)

dummy.Founded = 2022 - dummy.Founded

dummy.head(2)

   DayOfWeek  Time  Length  Delay  type_source_airport  \
0          3    15     205      1                  1.0
1          3    30     181      1                  1.0

   elevation_ft_source_airport  runway_count_source_airport  \
0                         13.0                          4.0
1                        125.0                          4.0

   type_dest_airport  elevation_ft_dest_airport
runway_count_dest_airport  \
0                1.0                       97.0
5.0
1                1.0                       97.0
5.0

   data_2019_source_airport  data_2019_dest_airport  Founded
0                27779230.0              21905309.0     88.0
1                42939104.0              21905309.0     88.0

model_data.reset_index(drop = True, inplace = True)

np.random.seed(12)
deploy_idx = np.random.choice(model_data.index, replace = False, size
= 5000)

deploy = model_data.loc[deploy_idx]

X_deploy = deploy.drop(columns = 'Delay')

model_dev = model_data.loc[~model_data.index.isin(deploy.index)]

deploy.reset_index(drop = True, inplace = True)
model_dev.reset_index(drop = True, inplace = True)

X = model_dev.drop(columns = 'Delay')
y = model_dev.Delay

folds = StratifiedKFold(n_splits=5, shuffle = True, random_state=12)
accuracy_train = {}
accuracy_test = {}
final_predictions_sgd = {}
i = 1
for train_index, test_index in folds.split(X,y):
    print('iter ', i)
    train, test = model_dev.loc[train_index,],
model_dev.loc[test_index,]
```

```
    sc = StandardScaler()
    sgd = SGDClassifier()

    # define search space

    space = dict()
    space['sgd__penalty'] = ['l1', 'l2', 'elasticnet']
    space['sgd__l1_ratio'] = [0,.1,.2,.8,1]
    space['sgd__alpha'] = [1e-5, 1e-4, 1e-3, 1e-2, 1e-1, 1, 10, 100,
1000,10000]
    space['sgd__learning_rate'] = ['constant', 'adaptive']
    space['sgd__eta0']=[1e-5, 1e-4, 1e-3, 1e-2, 1e-1 , 2e-1, 3e-1, 5e-
1, 8e-1, 4e-1, 8e-1, 1, 10, 100]

    pipe = Pipeline([('sc',sc), ('sgd', sgd)])

    # define search
    search = RandomizedSearchCV( pipe, space, scoring='accuracy',
                                cv=5, refit=True, return_train_score =
True,
                                random_state = 12, n_jobs = -1, n_iter
= 2
                           )

    # execute search
    X_train = train.drop(columns = 'Delay')
    y_train = train.Delay

    result = search.fit(X_train, y_train)

    train_pred = result.predict(X_train)

    X_test = test.drop(columns = 'Delay')
    y_test = test.Delay
    test_pred = result.predict(X_test)

final_predictions_sgd.update({'Fold{}'.format(i):result.predict(X_depl
oy)})

    # get rmse for each fold for train data
    accuracy_train.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_train, y_pred = train_pred)*100,3)})
    accuracy_test.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_test, y_pred = test_pred) * 100,3)})
    i += 1

iter  1
iter  2
iter  3
```

```
iter  4
iter  5

folds = StratifiedKFold(n_splits=5, shuffle = True, random_state=12)
dt_accuracy_train = {}
dt_accuracy_test = {}
final_predictions_dt = {}
i = 1
for train_index, test_index in folds.split(X,y):
    print('iter ', i)

    train, test = model_dev.loc[train_index,],
model_dev.loc[test_index,]

    sc = StandardScaler()
    dt = DecisionTreeClassifier()


    # define search space
    space = dict()
    space['dt__min_samples_split'] = [25000, 30000, 35000, 40000,
45000, 50000, 60000 ]
    space['dt__min_samples_leaf'] = [10000, 15000, 20000]

    pipe = Pipeline([('sc',sc), ('dt', dt)])

    # define search
    search = RandomizedSearchCV( pipe, space, scoring='accuracy',
                                cv=5, refit=True, return_train_score =
True,
                                random_state = 12, n_jobs = -1, n_iter
= 2
                           )

    # execute search
    X_train = train.drop(columns = 'Delay')
    y_train = train.Delay

    result = search.fit(X_train, y_train)

    train_pred = result.predict(X_train)

    X_test = test.drop(columns = 'Delay')
    y_test = test.Delay
    test_pred = result.predict(X_test)

final_predictions_dt.update({'Fold{}'.format(i):result.predict(X_deplo
y)})

    # get rmse for each fold for train data
```

```
    dt_accuracy_train.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_train, y_pred = train_pred)*100,3)})
    dt_accuracy_test.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_test, y_pred = test_pred) * 100,3)})
    i += 1
```

```
iter  1
iter  2
iter  3
iter  4
iter  5
```

```
# compare results :
train_results = pd.DataFrame ({'sgd' : accuracy_train.values(), 'dt':
dt_accuracy_train.values() },
                             index = ['Fold {}'.format(i) for i in
range(1,6)])
train_results
```

	sgd	dt
Fold 1	57.103	62.149
Fold 2	57.134	61.945
Fold 3	57.070	62.041
Fold 4	47.679	62.123
Fold 5	57.121	61.940

```
test_results = pd.DataFrame ({'sgd' : accuracy_test.values(), 'dt':
dt_accuracy_test.values() },
                             index = ['Fold {}'.format(i) for i in
range(1,6)])
test_results
```

	sgd	dt
Fold 1	57.074	62.145
Fold 2	57.032	61.773
Fold 3	57.199	62.248
Fold 4	47.829	61.918
Fold 5	57.045	62.019

getting accuracies for final predictions

```
final_predictions_dt
```

```
{'Fold1': array([1, 0, 0, ..., 1, 0, 0]),
 'Fold2': array([0, 0, 0, ..., 0, 0, 0]),
 'Fold3': array([1, 0, 0, ..., 1, 0, 0]),
 'Fold4': array([1, 0, 0, ..., 1, 0, 0]),
 'Fold5': array([0, 0, 0, ..., 0, 0, 0])}
```

```
final_predictions_sgd
```

```
{'Fold1': array([1, 0, 0, ..., 0, 0, 0]),
 'Fold2': array([1, 0, 0, ..., 0, 0, 0]),
 'Fold3': array([0, 0, 0, ..., 0, 0, 0]),
 'Fold4': array([0, 1, 0, ..., 0, 1, 1]),
 'Fold5': array([0, 0, 0, ..., 0, 0, 0])}
```

```
folds = StratifiedKFold(n_splits=5, shuffle = True, random_state=12)
xgb_accuracy_train = {}
xgb_accuracy_test = {}
final_predictions_xgb = []

i = 1
for train_index, test_index in folds.split(X,y):
    print('iter ', i)
    train, test = model_dev.loc[train_index,],
model_dev.loc[test_index,]
    sc = StandardScaler()
    xgb_r = XGBClassifier(random_state = 12, use_label_encoder =
False)

    # define search space
    space = dict()
    space['xgb_r__n_estimators'] = [40,50,60]
    space['xgb_r__max_depth'] = [3,4,5]
    space['xgb_r__colsample_bytree']:[0.4,.5,.6]
    space['xgb_r__lambda'] = [.0001,.002,.0004,.0003]
    space['xgb_r__alpha'] = [.01,.02,.1,.4]

    pipe = Pipeline([('sc',sc), ('xgb_r', xgb_r)])

    # define search
    search = RandomizedSearchCV( pipe, space,
scoring='neg_root_mean_squared_error',
                                cv=5, refit=True, return_train_score =
True,
                                random_state = 12, n_jobs = -1, n_iter
= 2
                           )

    # execute search
    X_train = train.drop(columns = 'Delay')
    y_train = train.Delay

    result = search.fit(X_train, y_train)

    train_pred = result.predict(X_train)

    X_test = test.drop(columns = 'Delay')
    y_test = test.Delay
    test_pred = result.predict(X_test)
```

```
    final_predictions_xgb.append(result.predict(X_deploy))

    # get rmse for each fold for train data
    xgb_accuracy_train.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_train, y_pred = train_pred),3)})
    xgb_accuracy_test.update({'Fold{}'.format(i):
round(accuracy_score(y_true = y_test, y_pred = test_pred),3)})
    i += 1
```

```
iter  1
```

```
/usr/local/lib/python3.7/site-packages/joblib/externals/loky/
process_executor.py:706: UserWarning: A worker stopped while some jobs
were given to the executor. This can be caused by a too short worker
timeout or by a memory leak.
  "timeout or by a memory leak.", UserWarning
```

```
iter  2
iter  3
iter  4
iter  5
```

```
xgb_accuracy_train
```

```
{'Fold1': 0.64, 'Fold2': 0.647, 'Fold3': 0.647, 'Fold4': 0.646,
'Fold5': 0.647}
```

```
xgb_accuracy_train.values()
```

```
dict_values([0.64, 0.647, 0.647, 0.646, 0.647])
```

```
train_results['xgb'] = xgb_accuracy_train.values()
test_results['xgb'] = xgb_accuracy_test.values()
```

```
train_results
```

	sgd	dt	xgb
Fold 1	57.103	62.149	0.640
Fold 2	57.134	61.945	0.647
Fold 3	57.070	62.041	0.647
Fold 4	47.679	62.123	0.646
Fold 5	57.121	61.940	0.647

```
test_results
```

	sgd	dt	xgb
Fold 1	57.074	62.145	0.639
Fold 2	57.032	61.773	0.644
Fold 3	57.199	62.248	0.645
Fold 4	47.829	61.918	0.644
Fold 5	57.045	62.019	0.644