project-us-airlines

April 14, 2023

[1]:
```
# Let's import the necessary library.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[2]:
```
# let's remove the unnecessary warnings.
import warnings
warnings.filterwarnings("ignore")
```

Project Task: Week 1 (Applied data science with Python) 1. Import and aggregate data:

a. Collect information related to flights, airports (e.g., type of airport and elevation), and runways (e.g., length_ft, width_ft, surface, and number of runways). Gather all fields you believe might cause avoidable delays in one dataset.

[3]:
```
# Now let's import the data for the further operation.
airline_df = pd.read_excel("Airlines.xlsx")
```

[4]:
```
airline_df.shape
```

[4]: (518556, 9)

[5]:
```
airline_df.head(2)
```

[5]:

	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

[6]:
```
airport_df = pd.read_excel("airports.xlsx")
```

[7]:
```
airport_df.shape
```

[7]: (73805, 18)

[8]:
```
airport_df.head(2)
```

[8]:
```
       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
```

[9]:
```python
airport_df = airport_df.drop(['continent', 'iso_country',␣
↪'iso_region','municipality', 'gps_code','local_code', 'home_link',
                       'wikipedia_link', 'keywords'], axis=1)
```

[10]:
```python
airport_df.head(2)
```

[10]:
```
       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 scheduled_service iata_code
0     -74.933601          11.0                no       NaN
1    -101.473911        3435.0                no       NaN
```

[11]:
```python
runway_df = pd.read_excel("runways.xlsx")
```

[12]:
```python
runway_df.shape
```

[12]: (43977, 20)

[13]:
```python
runway_df.head(2)
```

[13]:
```
       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

   closed le_ident  le_latitude_deg  le_longitude_deg  le_elevation_ft  \
0       0       H1              NaN               NaN              NaN
1       0        N              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

   he_longitude_deg  he_elevation_ft  he_heading_degT  \
0               NaN              NaN              NaN
1               NaN              NaN              NaN

   he_displaced_threshold_ft
0                        NaN
1                        NaN
```

[14]:
```
runways_df = runway_df.drop(['le_ident', 'le_latitude_deg','le_longitude_deg',␣
↪'le_elevation_ft', 'le_heading_degT',
       'le_displaced_threshold_ft', 'he_ident',␣
↪'he_latitude_deg','he_longitude_deg', 'he_elevation_ft', 'he_heading_degT',
       'he_displaced_threshold_ft'], axis = 1)
```

[15]:
```
runways_df.head(2)
```

[15]:
```
       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

   closed
0       0
1       0
```

[16]:
```
# Now lets merge the runways and airport data.
airport_runway = pd.merge(airport_df, runways_df, left_on = "ident", right_on =␣
↪"airport_ident")
airport_runway.drop(['id_x', 'id_y'], axis=1, inplace=True)
```

[17]:
```
airport_runway.head(2)
```

[17]:
```
  ident           type               name  latitude_deg  longitude_deg  \
0   00A       heliport  Total Rf Heliport     40.070801     -74.933601
1  00AK  small_airport       Lowell Field     59.947733    -151.692524

   elevation_ft scheduled_service iata_code  airport_ref airport_ident  \
0          11.0                no       NaN         6523           00A
1         450.0                no       NaN         6524          00AK

   length_ft  width_ft surface  lighted  closed
0       80.0      80.0  ASPH-G        1       0
1     2500.0      70.0    GRVL        0       0
```

[18]:
```
# Now lets merge the final column airline.
final_data = pd.merge(airline_df,airport_runway,how = "inner", left_on =␣
↪"AirportFrom", right_on = "iata_code" )
```

[19]:
```
final_data.drop_duplicates(subset=['id'], keep='first', inplace=True)
final_data.head(2)
```

[19]:
```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length  Delay  \
0   1      CO     269         SFO       IAH          3    15     205      1
4   4      AA    2466         SFO       DFW          3    20     195      1

  ident  … elevation_ft scheduled_service  iata_code  airport_ref  \
0  KSFO  …         13.0               yes        SFO         3878
4  KSFO  …         13.0               yes        SFO         3878

   airport_ident length_ft width_ft  surface lighted  closed
0           KSFO    7500.0    200.0      ASP       1       0
4           KSFO    7500.0    200.0      ASP       1       0

[2 rows x 24 columns]
```

b. When it comes to on-time arrivals, different airlines perform differently based on the amount of experience they have. The major airlines in this field include US Airways Express (founded in

1967) Continental Airlines (founded in 1934), and Express Jet (founded in 19860. Pull such information specific to various airlines from the Wikipedia page link given below. https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States.

[20]:
```
# Now lets use the web scrapping to import the data frome the wikipedia.
url = "https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States"
airline_tables = pd.read_html(url)
```

[21]:
```
airline_tables[1].head(2)
```

[21]:
```
           Airline  Image IATA ICAO   Callsign  \
0  Alaska Airlines    NaN   AS  ASA     ALASKA
1    Allegiant Air    NaN   G4  AAY  ALLEGIANT

                         Primary hubs, Secondary hubs  Founded  \
0  Seattle/Tacoma Anchorage Portland (OR) San Fra…     1932
1  Las Vegas Cincinnati Fort Walton Beach Indiana…     1997

                                               Notes
0  Founded as McGee Airways and commenced operati…
1  Founded as WestJet Express and commenced opera…
```

[22]:
```
airline_tables[2].head(2)
```

[22]:
```
          Airline  Image IATA ICAO   Callsign  \
0  Air Wisconsin    NaN   ZW  AWI  WISCONSIN
1       Cape Air    NaN   9K  KAP       CAIR

                        Primary Hubs, Secondary Hubs  Founded  \
0  Appleton Chicago-O'Hare Columbia Milwaukee Was…     1965
1  Hyannis Billings Boston Nantucket St. Louis Sa…     1988

                        Notes
0  Operates as United Express
1                         NaN
```

[23]:
```python
# We have different tables, let us combine all the tables together
```

[24]:
```python
# Lets first merge all wikipedia table.
airline_table_final =␣
↪[airline_tables[0],airline_tables[1],airline_tables[2],airline_tables[3],airline_tables[4],
```

[25]:
```python
airline_table_final = pd.concat(airline_table_final, ignore_index=True)
```

[26]:
```python
airline_table_final.head(2)
```

[26]:
```
    0                                                 1         Airline  \
0 NaN  This article does not cite any sources. Please…             NaN
1 NaN                                               NaN  Alaska Airlines

  Image IATA ICAO Callsign  \
0   NaN  NaN  NaN      NaN
1   NaN   AS  ASA   ALASKA

                        Primary hubs, Secondary hubs  Founded  \
0                                                NaN      NaN
1  Seattle/Tacoma Anchorage Portland (OR) San Fra…   1932.0

                                              Notes  \
0                                               NaN
1  Founded as McGee Airways and commenced operati…

  Primary Hubs, Secondary Hubs
0                          NaN
1                          NaN
```

c. You should then get all the information gathered so far in one place.

[27]:
```python
# First we got only that column from wiki pedia table that we need to merge.
airline_table_final_df = airline_table_final[['IATA', "Founded"]]
airline_table_final_df.head(2)
```

[27]:
```
  IATA  Founded
0  NaN      NaN
1   AS   1932.0
```

[28]:
```
# Now we gather all the information that we got from wiki pedia link and the
↪data that we have.
final_df = final_data.merge(airline_table_final_df, left_on ='Airline',
↪right_on = "IATA")
```

d. The total passenger traffic may also contribute to flight delays. The term hub refers to busy commercial airports. Large hubs are airports that account for at least 1 percent of the total passenger enplanements in the United States. Airports that account for 0.25 percent to 1 percent of total passenger enplanements are considered medium hubs. Pull passenger traffic data from the Wikipedia page given below using web scraping and collate it in a table. https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States

[29]:
```
url2 = "https://en.wikipedia.org/wiki/
↪List_of_the_busiest_airports_in_the_United_States"
busiest_airports_table = pd.read_html(url2)
```

[30]:
```
busiest_airports_table[0].head(2)
```

[30]:
```
   Rank (2021)                              Airports (large hubs) IATA Code  \
0            1  Hartsfield-Jackson Atlanta International Airport       ATL
1            2           Dallas/Fort Worth International Airport       DFW

   Major cities served State   2021[3]   2020[4]   2019[5]   2018[6]  \
0              Atlanta    GA  36676010  20559866  53505795  51865797
1   Dallas & Fort Worth    TX  30005266  18593421  35778573  32821799

    2017[7]   2016[8]   2015[9]  2014[10]  2013[11]  2012[12]
0  50251964  50501858  49340732  46604273  45308407  45798928
1  31816933  31283579  31589839  30804567  29038128  28022904
```

[31]:
```
busiest_airports_table[0]['traffic_change_20_21'] =
↪busiest_airports_table[0]['2021[3]'] - busiest_airports_table[0]['2020[4]']
```

[32]:
```
busiest_airports_table[0]['traffic_change_19_20'] =
↪busiest_airports_table[0]['2020[4]'] - busiest_airports_table[0]['2019[5]']
```

[33]:
```
busiest_airports_table[0]['hubs'] = str('large_hub')
```

[34]:
```
busiest_airports_table[0] = busiest_airports_table[0][['IATA Code',
↪'traffic_change_20_21', 'traffic_change_19_20', 'hubs']]
busiest_airports_table[0].head(2)
```

[34]:
```
  IATA Code  traffic_change_20_21  traffic_change_19_20       hubs
0       ATL              16116144             -32945929  large_hub
1       DFW              11411845             -17185152  large_hub
```

[35]:
```
busiest_airports_table[1]['traffic_change_20_21'] =␣
 ↪busiest_airports_table[1]['2021[3]'] - busiest_airports_table[1]['2020[4]']
busiest_airports_table[1]['traffic_change_19_20'] =␣
 ↪busiest_airports_table[1]['2020[4]'] - busiest_airports_table[1]['2019[5]']
```

[36]:
```
busiest_airports_table[1]['hubs'] = str('Medium_hub')
```

[37]:
```
busiest_airports_table[1] = busiest_airports_table[1][['IATA Code',␣
 ↪'traffic_change_20_21', 'traffic_change_19_20','hubs']]
busiest_airports_table[1].head(2)
```

[37]:
```
  IATA Code  traffic_change_20_21  traffic_change_19_20        hubs
0       DAL               2817633              -4738527  Medium_hub
1       HNL               2704537              -6862287  Medium_hub
```

[38]:
```
busiest_airports = [busiest_airports_table[0],busiest_airports_table[1]]
```

[39]:
```
busiest_airports_df = pd.concat(busiest_airports, ignore_index=True)
```

[40]:
```
final_df = final_data.merge(busiest_airports_df, left_on ='iata_code', right_on␣
 ↪= "IATA Code")
```

[41]:
```
final_df.head(2)
```

[41]:
```
   id Airline  Flight AirportFrom AirportTo  DayOfWeek  Time  Length  Delay  \
0   1      CO     269         SFO       IAH          3    15     205      1
1   4      AA    2466         SFO       DFW          3    20     195      1

  ident  … airport_ident length_ft  width_ft  surface  lighted closed  \
0  KSFO  …          KSFO    7500.0     200.0      ASP        1      0
1  KSFO  …          KSFO    7500.0     200.0      ASP        1      0

  IATA Code  traffic_change_20_21 traffic_change_19_20       hubs
0       SFO               3980290            -20034173  large_hub
1       SFO               3980290            -20034173  large_hub

[2 rows x 28 columns]
```

[42]:
```
final_df = final_df.
 ↪drop(['id','AirportFrom','airport_ident','iata_code','AirportTo','surface',␣
 ↪'ident',
                         'IATA Code','name'], axis=1)
```

2. You should then examine the missing values in each field, perform missing value treatment, and justify your actions.

[43]:
```
# Now lets check the null value and treat them.
final_df.isnull().sum()
```

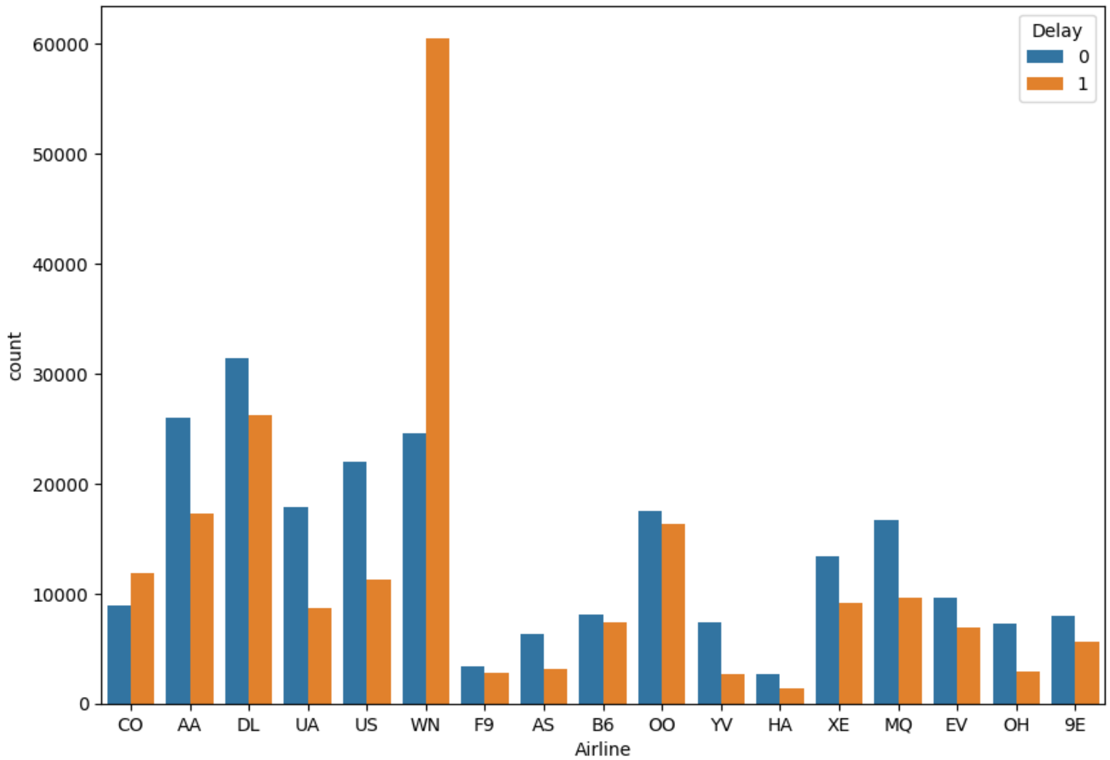
[43]:
```
Airline                 0
Flight                  0
DayOfWeek               0
Time                    0
Length                  0
Delay                   0
type                    0
latitude_deg            0
longitude_deg           0
elevation_ft            0
scheduled_service       0
airport_ref             0
length_ft               0
width_ft                0
lighted                 0
closed                  0
traffic_change_20_21    0
traffic_change_19_20    0
hubs                    0
dtype: int64
```

[44]:
```
# There are no null values in the dataset
```

3. Perform data visualization and share your insights on the following points:

a. According to the data provided, approximately 70% of Southwest Airlines flights are delayed. Visualize it to compare it with the data of other airlines.

[45]:
```
plt.figure(figsize=(10,7))
sns.countplot(x='Airline', hue='Delay', data=final_df)
plt.show()
```



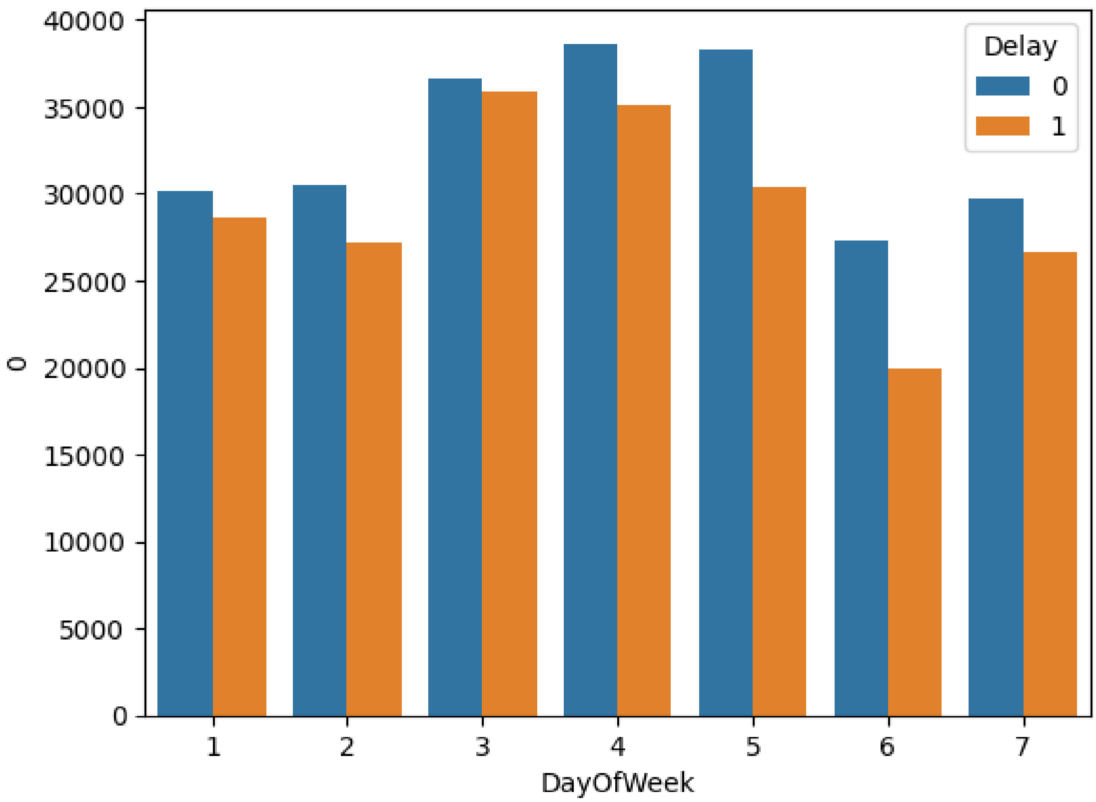

```
[46]: # The graph clear show that 70% of flight of south west airline (code of WN) is
      ↪delayed
```

b. Flights were delayed on various weekdays. Which day of the week is the safest for travel?

```
[47]: weekday_df = final_df[['DayOfWeek','Delay']].value_counts().reset_index()
```

```
[48]: sns.barplot(x='DayOfWeek', y=0, hue='Delay', data=weekday_df)
```

```
[48]: <Axes: xlabel='DayOfWeek', ylabel='0'>
```



[49]:
```
# On the 5th or 6th day of week its clear that there is less no of flight delay.
```

c. Which airlines should be recommended for short-, medium-, and long-distance travel?

[50]:
```
final_df['Airline'][final_df['Length']<200].value_counts()
```

[50]:
```
WN    75941
DL    43872
OO    32965
AA    30246
US    26363
MQ    26076
XE    22114
EV    16553
UA    16388
9E    13573
CO    12261
B6    11628
OH     9963
YV     9884
AS     6350
```

```
F9     5406
HA     3034
Name: Airline, dtype: int64
```

[51]:
```
# The above airlines should be recommended for short distance travel
```

[52]:
```
final_df['Airline'][final_df['Length']>400].value_counts()
```

[52]:
```
UA    549
AA    304
DL    226
CO    177
B6     83
US     79
AS     31
HA     14
Name: Airline, dtype: int64
```

[53]:
```
# The above airlines should be recommended for long distance travel
```

[54]:
```
# All the above airlines should be recommended for medium distance travel
```

d. Do you notice any patterns in the departure times of long-duration flights?

[55]:
```
long = final_df[final_df['Length']>400]
long
```

[55]:
```
       Airline  Flight  DayOfWeek  Time  Length  Delay            type  \
11870       US      20          3   715     403      0   large_airport
12362       US      20          4   715     403      0   large_airport
12841       US     146          5   675     412      1   large_airport
12865       US      20          5   715     403      0   large_airport
13319       US     146          6   675     412      0   large_airport
…          …     …          …    …       …     …                 …
413895      UA      92          3  1416     404      0  medium_airport
413939      AA       6          4  1080     420      0  medium_airport
413955      UA      92          4  1416     404      0  medium_airport
414000      AA       6          5  1080     420      1  medium_airport
414017      UA      92          5  1416     404      0  medium_airport

        latitude_deg  longitude_deg  elevation_ft scheduled_service  \
11870      33.435302    -112.005905        1135.0               yes
12362      33.435302    -112.005905        1135.0               yes
12841      33.435302    -112.005905        1135.0               yes
12865      33.435302    -112.005905        1135.0               yes
13319      33.435302    -112.005905        1135.0               yes
…               …             …             …                 …
```

```
413895     20.898543    -156.431212          54.0               yes
413939     20.898543    -156.431212          54.0               yes
413955     20.898543    -156.431212          54.0               yes
414000     20.898543    -156.431212          54.0               yes
414017     20.898543    -156.431212          54.0               yes

        airport_ref  length_ft  width_ft  lighted  closed  \
11870          3772    10300.0     150.0        1       0
12362          3772    10300.0     150.0        1       0
12841          3772    10300.0     150.0        1       0
12865          3772    10300.0     150.0        1       0
13319          3772    10300.0     150.0        1       0
…                …          …    …      …      …
413895         5455     6995.0     150.0        1       0
413939         5455     6995.0     150.0        1       0
413955         5455     6995.0     150.0        1       0
414000         5455     6995.0     150.0        1       0
414017         5455     6995.0     150.0        1       0

        traffic_change_20_21  traffic_change_19_20        hubs
11870                8408851             -11902116   large_hub
12362                8408851             -11902116   large_hub
12841                8408851             -11902116   large_hub
12865                8408851             -11902116   large_hub
13319                8408851             -11902116   large_hub
…                          …                   …           …
413895               1798174              -2656666  Medium_hub
413939               1798174              -2656666  Medium_hub
413955               1798174              -2656666  Medium_hub
414000               1798174              -2656666  Medium_hub
414017               1798174              -2656666  Medium_hub

[1463 rows x 19 columns]
```

[56]:
```
long['width_ft'].unique()
```

[56]:
```
array([150., 200.])
```

[57]:
```
final_df['width_ft'].unique()
```

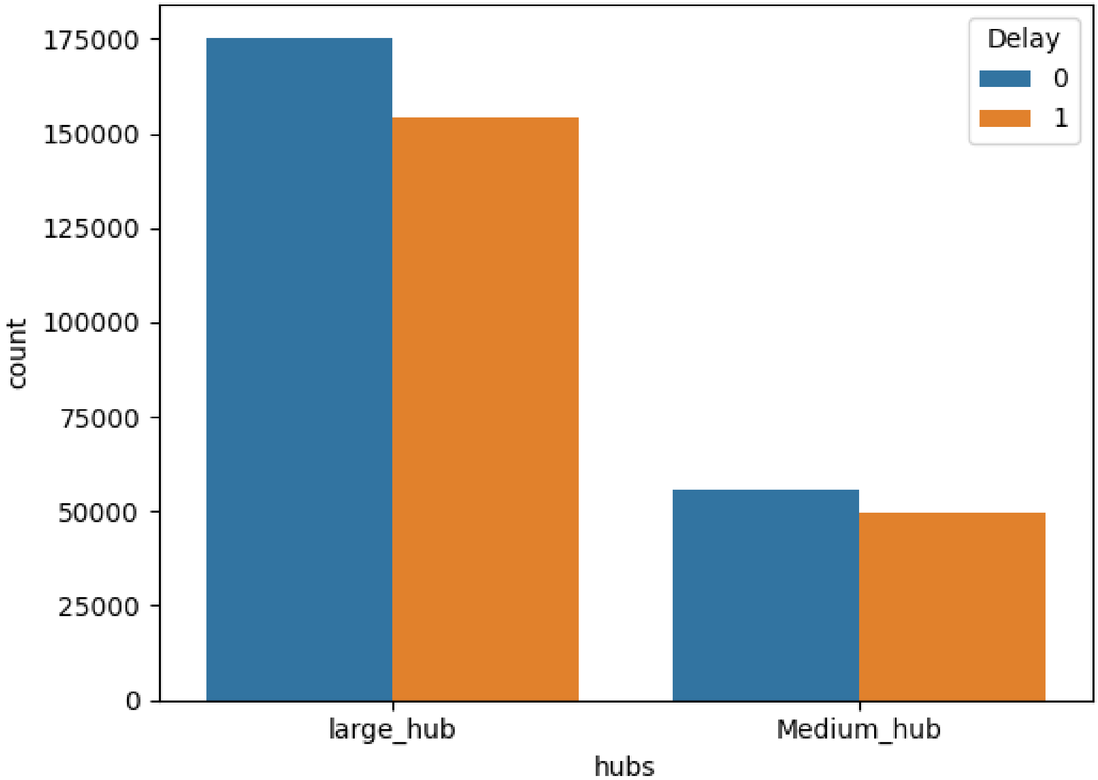
[57]:
```
array([200., 150., 100.,  75.])
```

[58]:
```
# We can see that width of runway for long flights is 150 or 200
```

4. How many flights were delayed at large hubs compared to medium hubs? Use appropriate visualization to represent your findings.

[59]:
```python
sns.countplot(x='hubs', hue='Delay', data=final_df)
```

[59]: <Axes: xlabel='hubs', ylabel='count'>



[60]:
```python
# 150000 flights were delayed at large hubs compared to 50000 at medium hubs
```

5. Use hypothesis testing strategies to discover:

a. If the airport's altitude has anything to do with flight delays for incoming and departing flights

[61]:
```python
from scipy.stats import chi2_contingency
table = [final_df['latitude_deg'],final_df['Delay']]
stat, p, dof, expected = chi2_contingency(table)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Altitude and flight delay are probably independent')
else:
    print('Altitude and flight delay are probably dependent')
```

```
stat=235997.906, p=1.000
Altitude and flight delay are probably independent
```

b. If the number of runways at an airport affects flight delays

[62]:
```
from scipy.stats import chi2_contingency
table = [final_df['airport_ref'],final_df['Delay']]
stat, p, dof, expected = chi2_contingency(table)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Number of runways and delay are probably independent')
else:
    print('Number of runways and delay are probably dependent')
```

```
stat=241372.507, p=1.000
Number of runways and delay are probably independent
```

c. If the duration of a flight (length) affects flight delays

[63]:
```
from scipy.stats import spearmanr
data1 = final_df['Length']
data2 = final_df['Delay']
stat, p = spearmanr(data1, data2)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Duration of flight and delay are probably independent')
else:
    print('Duration of flight and delay are probably dependent')
```

```
stat=0.020, p=0.000
Duration of flight and delay are probably dependent
```

6. Find the correlation matrix between the flight delay predictors, create a heatmap to visualize this, and share your findings

[64]:
```
corr = final_df.corr()
corr
```

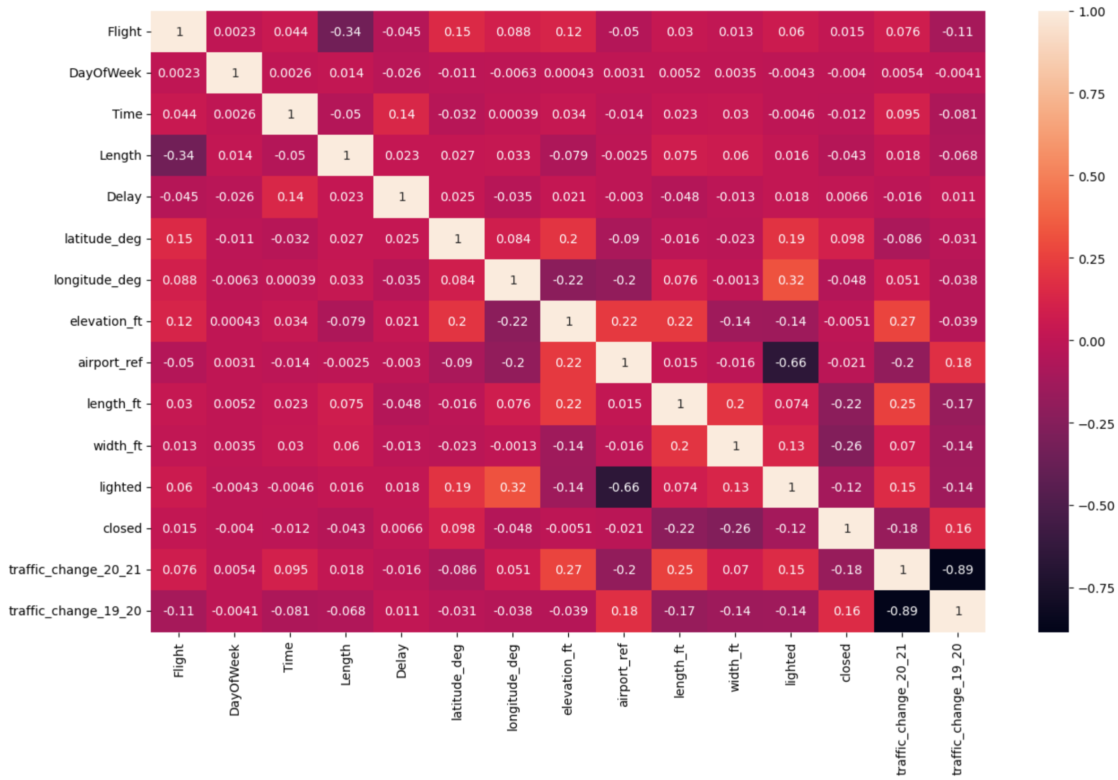
[64]:

	Flight	DayOfWeek	Time	Length	Delay	\
Flight	1.000000	0.002269	0.043689	-0.337794	-0.045179	
DayOfWeek	0.002269	1.000000	0.002635	0.013866	-0.025960	
Time	0.043689	0.002635	1.000000	-0.050408	0.135503	
Length	-0.337794	0.013866	-0.050408	1.000000	0.023412	
Delay	-0.045179	-0.025960	0.135503	0.023412	1.000000	
latitude_deg	0.152883	-0.010634	-0.031631	0.027318	0.024829	
longitude_deg	0.088454	-0.006323	0.000388	0.032629	-0.034535	
elevation_ft	0.120979	0.000425	0.033781	-0.079260	0.020978	
airport_ref	-0.050394	0.003097	-0.014079	-0.002509	-0.003039	
length_ft	0.029879	0.005228	0.023236	0.075392	-0.047662	
width_ft	0.012713	0.003480	0.029868	0.059915	-0.013209	
lighted	0.060445	-0.004319	-0.004570	0.016097	0.018187	
closed	0.015213	-0.004022	-0.012347	-0.042696	0.006584	

```
traffic_change_20_21  0.075725   0.005440  0.094924  0.017518 -0.015961
traffic_change_19_20 -0.109500  -0.004073 -0.081149 -0.067547  0.011029

                      latitude_deg  longitude_deg  elevation_ft  airport_ref  \
Flight                    0.152883       0.088454      0.120979    -0.050394
DayOfWeek                -0.010634      -0.006323      0.000425     0.003097
Time                     -0.031631       0.000388      0.033781    -0.014079
Length                    0.027318       0.032629     -0.079260    -0.002509
Delay                     0.024829      -0.034535      0.020978    -0.003039
latitude_deg              1.000000       0.084202      0.201612    -0.089998
longitude_deg             0.084202       1.000000     -0.222753    -0.196454
elevation_ft              0.201612      -0.222753      1.000000     0.221794
airport_ref              -0.089998      -0.196454      0.221794     1.000000
length_ft                -0.015735       0.076358      0.223794     0.015004
width_ft                 -0.023087      -0.001285     -0.140600    -0.015558
lighted                   0.191397       0.318683     -0.142687    -0.663213
closed                    0.097754      -0.047516     -0.005079    -0.020885
traffic_change_20_21     -0.086251       0.050641      0.270102    -0.195977
traffic_change_19_20     -0.030518      -0.038413     -0.039259     0.178396

                      length_ft  width_ft   lighted    closed  \
Flight                 0.029879  0.012713  0.060445  0.015213
DayOfWeek              0.005228  0.003480 -0.004319 -0.004022
Time                   0.023236  0.029868 -0.004570 -0.012347
Length                 0.075392  0.059915  0.016097 -0.042696
Delay                 -0.047662 -0.013209  0.018187  0.006584
latitude_deg          -0.015735 -0.023087  0.191397  0.097754
longitude_deg          0.076358 -0.001285  0.318683 -0.047516
elevation_ft           0.223794 -0.140600 -0.142687 -0.005079
airport_ref            0.015004 -0.015558 -0.663213 -0.020885
length_ft              1.000000  0.200062  0.074199 -0.219117
width_ft               0.200062  1.000000  0.125793 -0.260123
lighted                0.074199  0.125793  1.000000 -0.117796
closed                -0.219117 -0.260123 -0.117796  1.000000
traffic_change_20_21   0.251813  0.069963  0.153282 -0.175781
traffic_change_19_20  -0.174391 -0.143210 -0.140151  0.159639

                      traffic_change_20_21  traffic_change_19_20
Flight                            0.075725             -0.109500
DayOfWeek                         0.005440             -0.004073
Time                              0.094924             -0.081149
Length                            0.017518             -0.067547
Delay                            -0.015961              0.011029
latitude_deg                     -0.086251             -0.030518
longitude_deg                     0.050641             -0.038413
elevation_ft                      0.270102             -0.039259
airport_ref                      -0.195977              0.178396
```

```
length_ft                          0.251813             -0.174391
width_ft                           0.069963             -0.143210
lighted                            0.153282             -0.140151
closed                            -0.175781              0.159639
traffic_change_20_21               1.000000             -0.885008
traffic_change_19_20              -0.885008              1.000000
```

[65]:
```python
plt.figure(figsize=(15,9))
sns.heatmap(corr, annot=True)
plt.show()
```



[66]:
```python
# Traffic change 20-21 is having a negative correlation of -0.89 with traffic
↪change 19-20
```

Project Task: Week 1 (Machine learning)

1. Use OneHotEncoder and OrdinalEncoder to deal with categorical variables

[67]:
```python
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 434974 entries, 0 to 434973
Data columns (total 19 columns):
```

```
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   Airline               434974 non-null  object
 1   Flight                434974 non-null  int64
 2   DayOfWeek             434974 non-null  int64
 3   Time                  434974 non-null  int64
 4   Length                434974 non-null  int64
 5   Delay                 434974 non-null  int64
 6   type                  434974 non-null  object
 7   latitude_deg          434974 non-null  float64
 8   longitude_deg         434974 non-null  float64
 9   elevation_ft          434974 non-null  float64
 10  scheduled_service     434974 non-null  object
 11  airport_ref           434974 non-null  int64
 12  length_ft             434974 non-null  float64
 13  width_ft              434974 non-null  float64
 14  lighted               434974 non-null  int64
 15  closed                434974 non-null  int64
 16  traffic_change_20_21  434974 non-null  int64
 17  traffic_change_19_20  434974 non-null  int64
 18  hubs                  434974 non-null  object
dtypes: float64(5), int64(10), object(4)
memory usage: 66.4+ MB
```

[68]:
```
# Scheduled service has value "yes" in all rows, let us remove it since it␣
↪doesnt help in prediction
```

[69]:
```
final_df = final_df.drop(['scheduled_service'], axis=1)
```

[70]:
```
final_df.to_csv('airlines_new.csv', index = True)
```

[71]:
```
from sklearn.preprocessing import LabelEncoder
```

[72]:
```
le = LabelEncoder()
```

[73]:
```
final_df['Airline'] = le.fit_transform(final_df['Airline'])
final_df['type'] = le.fit_transform(final_df['type'])
final_df['hubs'] = le.fit_transform(final_df['hubs'])
```

[74]:
```
final_df.head()
```

[74]:

	Airline	Flight	DayOfWeek	Time	Length	Delay	type	latitude_deg	\
0	4	269	3	15	205	1	0	37.618999	
1	1	2466	3	20	195	1	0	37.618999	
2	5	2606	3	35	216	1	0	37.618999	
3	5	1580	3	345	270	0	0	37.618999	
4	12	756	3	348	158	0	0	37.618999	

```
   longitude_deg  elevation_ft  airport_ref  length_ft  width_ft  lighted  \
0       -122.375          13.0         3878     7500.0     200.0        1
1       -122.375          13.0         3878     7500.0     200.0        1
2       -122.375          13.0         3878     7500.0     200.0        1
3       -122.375          13.0         3878     7500.0     200.0        1
4       -122.375          13.0         3878     7500.0     200.0        1

   closed  traffic_change_20_21  traffic_change_19_20  hubs
0       0               3980290             -20034173     1
1       0               3980290             -20034173     1
2       0               3980290             -20034173     1
3       0               3980290             -20034173     1
4       0               3980290             -20034173     1
```

2. Perform the following model building steps:

a. Apply logistic regression (use stochastic gradient descent optimizer) and decision tree models
b. Use the stratified five-fold method to build and validate the models
c. Use RandomizedSearchCV for hyperparameter tuning, and use k-fold for crossvalidation
d. Keep a few data points (10%) for prediction purposes to evaluate how you would make the final prediction, and do not use this data for testing or validation
e. Compare the results of logistic regression and decision tree classifier

[75]:
```
# Seperating the predictors and the output variable
x = final_df.drop(['Delay'], axis= 1)
y = final_df["Delay"]
```

[76]:
```
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
x = scaler.fit_transform(x)
```

[77]:
```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.9,␣
 ↪random_state=10)
```

LogisticRegression

[78]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

[79]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[80]:
```
params = {"penalty": ["l1","l2"],
         'solver': ['newton-cg', 'liblinear']}

# Cross Validation
folds = 5
```

```
rscv = RandomizedSearchCV(estimator = lr,
                          param_distributions = params,
                          scoring = "accuracy",
                          verbose = 1,
                          cv= folds)

rscv.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
```

[80]:
```
RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                   param_distributions={'penalty': ['l1', 'l2'],
                                        'solver': ['newton-cg', 'liblinear']},
                   scoring='accuracy', verbose=1)
```

[81]:
```
print(rscv.best_params_)
print(rscv.best_score_)
```

```
{'solver': 'newton-cg', 'penalty': 'l2'}
0.5808555257836805
```

[82]:
```
lr = LogisticRegression(penalty= 'l2', solver= 'newton-cg')
lr.fit(x_train,y_train).score(x_train,y_train)
```

[82]:
```
0.5810011341691445
```

[83]:
```
lr.score(x_test, y_test)
```

[83]:
```
0.5863947767713458
```

DecisionTreeClassifier

[84]:
```
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()

params = {'criterion': ["gini", "entropy"],
          'min_samples_leaf' : [2,3,4,5,6,7,8,9],
         "max_depth": [2,3,4,5,6,7,8,9]}

rscv = RandomizedSearchCV(estimator = dt,
                              param_distributions= params,
                              scoring = "accuracy",
                              cv= 5,
                              verbose=1)
rscv.fit(x_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
```

[84]:
```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [2, 3, 4, 5, 6, 7, 8, 9],
                                        'min_samples_leaf': [2, 3, 4, 5, 6, 7,
                                                             8, 9]},
                   scoring='accuracy', verbose=1)
```

[85]:
```python
print(rscv.best_params_)
print(rscv.best_score_)
```

```
{'min_samples_leaf': 6, 'max_depth': 9, 'criterion': 'entropy'}
0.6435566921164465
```

[86]:
```python
dtc = DecisionTreeClassifier(max_depth= 9, criterion=␣
↪'entropy',min_samples_leaf= 6)
```

[87]:
```python
dtc.fit(x_train, y_train).score(x_train, y_train)
```

[87]:
```
0.6493143896432987
```

[88]:
```python
dtc.score(x_test, y_test)
```

[88]:
```
0.6431789967354821
```

3. Use the stratified five-fold method to build and validate the models using the XGB classifier, compare all methods, and share your findings

[89]:
```python
from xgboost import XGBClassifier

# Create the parameter grid: gbm_param_grid
gbm_param_grid = {
                'n_estimators': range(8, 20),
                'max_depth': range(6, 10),
                'learning_rate': [.4, .45, .5, .55, .6],
                'colsample_bytree': [.6, .7, .8, .9, 1]
                 }

# Instantiate the regressor: gbm
gbm = XGBClassifier()

# Perform random search: grid_mse
xgb_random = RandomizedSearchCV(param_distributions=gbm_param_grid,
                                    estimator = gbm, scoring = "accuracy",
                                    verbose = 1, n_iter = 50, cv = 3)

# Fit randomized_mse to the data
```

```python
xgb_random.fit(x_train, y_train)

# Print the best parameters and lowest RMSE
print("Best parameters found: ", xgb_random.best_params_)
print("Best accuracy found: ", xgb_random.best_score_)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
Best parameters found:  {'n_estimators': 18, 'max_depth': 9, 'learning_rate':
0.5, 'colsample_bytree': 0.6}
Best accuracy found:  0.6610647906895952
```

[90]:
```python
xgb = XGBClassifier(n_estimators=14, max_depth=9, learning_rate=0.45,␣
 ↪colsample_bytree=0.9)
xgb.fit(x_train,y_train).score(x_train,y_train)
```

[90]: 0.6806802971318804

[91]:
```python
# Now lets compare the all method.
print(lr.score(x_test, y_test))
print(dtc.score(x_test, y_test))
print(xgb.score(x_test, y_test))
```

```
0.5863947767713458
0.6431789967354821
0.6620534277438043
```