```
In [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
```

```
In [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.

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

```
In [4]: airline.shape
Out[4]: (518556, 9)
```

```
In [5]: airline.head()
```

Out[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
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

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

```
In [7]: airpot.shape
Out[7]: (73805, 18)
```

In [8]:
```
airpot.head()
```
Out[8]:

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	continent	iso_country	iso_region
0	6523	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	NaN	US	US-PA
1	323361	00AA	small_airport	Aero B Ranch Airport	38.704022	-101.473911	3435.0	NaN	US	US-KS
2	6524	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	NaN	US	US-AK
3	6525	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	NaN	US	US-AL
4	6526	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	NaN	US	US-AR

In [9]:
```
runway = pd.read_excel("runways.xlsx")
```

In [10]:
```
runway.shape
```
Out[10]:
```
(43977, 20)
```

In [11]:
```
runway.head()
```
Out[11]:

	id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed	le_ident	le_latitude_deg	le_longitu
0	269408	6523	00A	80.0	80.0	ASPH-G	1	0	H1	NaN	
1	255155	6524	00AK	2500.0	70.0	GRVL	0	0	N	NaN	
2	254165	6525	00AL	2300.0	200.0	TURF	0	0	1	NaN	
3	270932	6526	00AR	40.0	40.0	GRASS	0	0	H1	NaN	
4	322128	322127	00AS	1450.0	60.0	Turf	0	0	1	NaN	

In [12]:
```
# Before merging the data lets drop the columns that will not play an important role in the mode
runway.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 43977 entries, 0 to 43976
Data columns (total 20 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   id                         43977 non-null  int64  
 1   airport_ref                43977 non-null  int64  
 2   airport_ident              43977 non-null  object 
 3   length_ft                  43753 non-null  float64
 4   width_ft                   41088 non-null  float64
 5   surface                    43520 non-null  object 
 6   lighted                    43977 non-null  int64  
 7   closed                     43977 non-null  int64  
 8   le_ident                   43793 non-null  object 
 9   le_latitude_deg            15016 non-null  float64
 10  le_longitude_deg           15000 non-null  float64
 11  le_elevation_ft            12781 non-null  float64
 12  le_heading_degT            14624 non-null  float64
 13  le_displaced_threshold_ft  2883 non-null   float64
 14  he_ident                   37332 non-null  object 
 15  he_latitude_deg            14971 non-null  float64
 16  he_longitude_deg           14973 non-null  float64
 17  he_elevation_ft            12620 non-null  float64
 18  he_heading_degT            16428 non-null  float64
 19  he_displaced_threshold_ft  3176 non-null   float64
dtypes: float64(12), int64(4), object(4)
memory usage: 6.7+ MB
```

In [13]:
```
runways = runway.drop(['le_ident', 'le_latitude_deg','le_longitude_deg', 'le_elevation_ft', 'le
       'le_displaced_threshold_ft', 'he_ident', 'he_latitude_deg','he_longitude_deg', 'he_eleva
       'he_displaced_threshold_ft'], axis = 1)
```

In [14]:
```
runways
```

Out[14]:

	id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed
0	269408	6523	00A	80.0	80.0	ASPH-G	1	0
1	255155	6524	00AK	2500.0	70.0	GRVL	0	0
2	254165	6525	00AL	2300.0	200.0	TURF	0	0
3	270932	6526	00AR	40.0	40.0	GRASS	0	0
4	322128	322127	00AS	1450.0	60.0	Turf	0	0
...	...	...	...	...	...	...	...	...
43972	235186	27243	ZYTX	10499.0	148.0	CON	1	0
43973	235169	27244	ZYYJ	8530.0	148.0	CON	1	0
43974	354997	317861	ZYYK	8202.0	NaN	NaN	0	0
43975	346789	346788	ZZ-0003	1800.0	15.0	Turf	0	0
43976	313663	313629	ZZZZ	1713.0	82.0	concrete	0	0

43977 rows × 8 columns

In [15]:
```
# Now lets remove the feature from the airpot data that is not usefull.
airpot.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 73805 entries, 0 to 73804
Data columns (total 18 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 73805 non-null  int64  
 1   ident              73805 non-null  object 
 2   type               73805 non-null  object 
 3   name               73805 non-null  object 
 4   latitude_deg       73805 non-null  float64
 5   longitude_deg      73805 non-null  float64
 6   elevation_ft       59683 non-null  float64
 7   continent          38086 non-null  object 
 8   iso_country        73546 non-null  object 
 9   iso_region         73805 non-null  object 
 10  municipality       68739 non-null  object 
 11  scheduled_service  73805 non-null  object 
 12  gps_code           42996 non-null  object 
 13  iata_code          9160 non-null   object 
 14  local_code         32975 non-null  object 
 15  home_link          3492 non-null   object 
 16  wikipedia_link     10705 non-null  object 
 17  keywords           13951 non-null  object 
dtypes: float64(3), int64(1), object(14)
memory usage: 10.1+ MB
```

In [16]:
```
airpots = airpot.drop(['continent', 'iso_country', 'iso_region','municipality', 'gps_code','loc
                       'wikipedia_link', 'keywords'], axis=1)
```

In [17]:
```
airpots
```

Out[17]:

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	scheduled_service	iata_code
0	6523	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	no	NaN
1	323361	00AA	small_airport	Aero B Ranch Airport	38.704022	-101.473911	3435.0	no	NaN
2	6524	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	no	NaN
3	6525	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	no	NaN
4	6526	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	no	NaN
...	...	...	...	...	...	...	...	...	...
73800	46378	ZZ-0001	heliport	Sealand Helipad	51.894444	1.482500	40.0	no	NaN
73801	307326	ZZ-0002	small_airport	Glorioso Islands Airstrip	-11.584278	47.296389	11.0	no	NaN
73802	346788	ZZ-0003	small_airport	Fainting Goat Airport	32.110587	-97.356312	690.0	no	NaN
73803	342102	ZZZW	closed	Scandium City Heliport	69.355287	-138.939310	4.0	no	ZYW
73804	313629	ZZZZ	small_airport	Satsuma I≈çjima Airport	30.784722	130.270556	338.0	no	NaN

73805 rows × 9 columns

In [18]:
```
# Now lets merge the runways and airport data.
airpot_runway = pd.merge(airpots, runways, left_on = "ident", right_on = "airport_ident")
airpot_runway.drop(['id_x', 'id_y'], axis=1, inplace=True)
```

In [19]:
```
airpot_runway
```

Out[19]:

	ident	type	name	latitude_deg	longitude_deg	elevation_ft	scheduled_service	iata_code
0	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	no	NaN
1	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	no	NaN
2	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	no	NaN
3	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	no	NaN
4	00AS	small_airport	Fulton Airport	34.942803	-97.818019	1100.0	no	NaN
...	...	...	...	...	...	...	...	...
43972	ZYTX	large_airport	Shenyang Taoxian International Airport	41.639801	123.483002	198.0	yes	SHE
43973	ZYYJ	medium_airport	Yanji Chaoyangchuan Airport	42.882801	129.451004	624.0	yes	YNJ
43974	ZYYK	medium_airport	Yingkou Lanqi Airport	40.542524	122.358600	NaN	yes	YKH
43975	ZZ-0003	small_airport	Fainting Goat Airport	32.110587	-97.356312	690.0	no	NaN
43976	ZZZZ	small_airport	Satsuma I≈çjima Airport	30.784722	130.270556	338.0	no	NaN

43977 rows × 15 columns

In [20]:
```
# Now lets merge the final column airline.
final_df = pd.merge(airline,airpot_runway,how = "inner", left_on = "AirportFrom", right_on = "i
```

In [21]:
```
final_df.drop_duplicates(subset=['id'], keep='first', inplace=True)
```

In [22]:
```
final_df
```

Out[22]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	...	elevation_ft	s
0	1	CO	269	SFO	IAH	3	15	205	1	KSFO	...	13.0	
4	4	AA	2466	SFO	DFW	3	20	195	1	KSFO	...	13.0	
8	9	DL	2606	SFO	MSP	3	35	216	1	KSFO	...	13.0	
12	129	DL	1580	SFO	DTW	3	345	270	0	KSFO	...	13.0	
16	150	UA	756	SFO	DEN	3	348	158	0	KSFO	...	13.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	
2160266	451344	CO	2	GUM	HNL	1	400	430	1	PGUM	...	298.0	
2160268	469866	CO	2	GUM	HNL	2	400	430	1	PGUM	...	298.0	
2160270	488365	CO	2	GUM	HNL	3	400	430	0	PGUM	...	298.0	
2160272	506855	CO	2	GUM	HNL	4	400	430	1	PGUM	...	298.0	
2160274	525138	CO	2	GUM	HNL	5	400	430	1	PGUM	...	298.0	

518525 rows × 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)](https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States).

In [23]:
```
# 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"
tables = pd.read_html(url)
```

In [24]:
```
print(tables)
```

```
[                  Airline  Image IATA ICAO         Callsign  \
0       Alaska Airlines    NaN   AS  ASA           ALASKA
1         Allegiant Air    NaN   G4  AAY        ALLEGIANT
2     American Airlines    NaN   AA  AAL         AMERICAN
3        Avelo Airlines    NaN   XP  VXP            AVELO
4        Breeze Airways    NaN   MX  MXY             MOXY
5       Delta Air Lines    NaN   DL  DAL            DELTA
6      Eastern Airlines    NaN   2D  EAL          EASTERN
7     Frontier Airlines    NaN   F9  FFT  FRONTIER FLIGHT
8     Hawaiian Airlines    NaN   HA  HAL         HAWAIIAN
9               JetBlue    NaN   B6  JBU          JETBLUE
10   Southwest Airlines    NaN   WN  SWA        SOUTHWEST
11      Spirit Airlines    NaN   NK  NKS     SPIRIT WINGS
12  Sun Country Airlines    NaN   SY  SCX      SUN COUNTRY
13      United Airlines    NaN   UA  UAL           UNITED

                           Primary hubs, Secondary hubs  Founded  \
0   Seattle/TacomaAnchoragePortland (OR)San Franci...     1932
1   Las VegasCincinnatiFort Walton BeachIndianapol...     1997
```

In [25]:
```
tables[0]
```

Out[25]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	Notes
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932	Founded as McGee Airways and commenced operati...
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997	Founded as WestJet Express and commenced opera...
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926	Founded as American Airways and commenced oper...
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987	First did business as Casino Express Airlines ...
4	Breeze Airways	NaN	MX	MXY	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018	NaN
5	Delta Air Lines	NaN	DL	DAL	DELTA	AtlantaBostonDetroitLos AngelesMinneapolis/St....	1924	Founded as Huff Daland Dusters and commenced o...
6	Eastern Airlines	NaN	2D	EAL	EASTERN	MiamiNew York-JFK	2010	NaN
7	Frontier Airlines	NaN	F9	FFT	FRONTIER FLIGHT	DenverAtlantaChicago-O'HareCincinnatiCleveland...	1994	NaN
8	Hawaiian Airlines	NaN	HA	HAL	HAWAIIAN	HonoluluKahului	1929	Founded as Inter-Island Airways in early 1929 ...
9	JetBlue	NaN	B6	JBU	JETBLUE	New York-JFKBostonLos AngelesFort LauderdaleOr...	1998	Founded as New Air and commenced operations in...
10	Southwest Airlines	NaN	WN	SWA	SOUTHWEST	Dallas-LoveAtlantaBaltimoreChicago-MidwayDenve...	1967	Founded as Air Southwest and commenced operati...
11	Spirit Airlines	NaN	NK	NKS	SPIRIT WINGS	Atlantic CityDetroitLas VegasFort LauderdaleCh...	1980	Founded as Charter One.
12	Sun Country Airlines	NaN	SY	SCX	SUN COUNTRY	Minneapolis/St. PaulDallas/Fort WorthLas Vegas	1982	Commenced operations in 1983.Operates some Ama...
13	United Airlines	NaN	UA	UAL	UNITED	Chicago-O'HareDenverGuamHouston-Intercontinent...	1926	Founded as Varney Air Lines and commenced oper...

In [26]:
```
tables[6]
```

Out[26]:

	Airline	Image	IATA	ICAO	Callsign	Primary Hubs, Secondary Hubs	Founded	Notes
0	Comco	NaN	NaN	NaN	NaN	NaN	2002	NaN
1	Janet	NaN	NaN	WWW	JANET	Las Vegas	1972	NaN
2	Justice Prisoner and Alien Transportation System	NaN	NaN	JUD	JUSTICE	Oklahoma City	1980	Commenced operations in 1995.

In [27]:
```
# Lets first merge all wikipedia table.
wiki_table = [tables[0],tables[1],tables[2],tables[3],tables[4],tables[5],tables[6]]
```

In [28]:
```
wiki_tables = pd.concat(wiki_table, ignore_index=True)
```

In [29]:
```
wiki_tables
```

Out[29]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	Notes	Primar Hub Secondar Hub
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932.0	Founded as McGee Airways and commenced operati...	Na
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997.0	Founded as WestJet Express and commenced opera...	Na
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926.0	Founded as American Airways and commenced oper...	Na
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987.0	First did business as Casino Express Airlines ...	Na
4	Breeze Airways	NaN	MX	MXY	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018.0	NaN	Na
...	...	...	...	...	...	...	...	...	
137	Lifestar	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
138	Life Lion	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
139	Comco	NaN	NaN	NaN	NaN	NaN	2002.0	NaN	Na
140	Janet	NaN	NaN	WWW	JANET	NaN	1972.0	NaN	Las Vega
141	Justice Prisoner and Alien Transportation System	NaN	NaN	JUD	JUSTICE	NaN	1980.0	Commenced operations in 1995.	Oklahom Ci

142 rows × 9 columns

In [30]:
```python
# First we got only that column from wiki pedia table that we need to merge.
wiki_df = wiki_tables[['IATA', "Founded"]]
wiki_df
```

Out[30]:

	IATA	Founded
0	AS	1932.0
1	G4	1997.0
2	AA	1926.0
3	XP	1987.0
4	MX	2018.0
...	...	...
137	NaN	NaN
138	NaN	NaN
139	NaN	2002.0
140	NaN	1972.0
141	NaN	1980.0

142 rows × 2 columns

In [31]:
```python
# Now we gather all the information that we got from wiki pedia link and the data that we have.
df = final_df.merge(wiki_df, left_on ='Airline', right_on = "IATA")
```

In [32]:
```python
df
```

Out[32]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	...	iata_code	airp
0	4	AA	2466	SFO	DFW	3	20	195	1	KSFO	...	SFO	
1	231	AA	526	SFO	DFW	3	360	215	0	KSFO	...	SFO	
2	234	AA	552	SFO	MIA	3	360	315	1	KSFO	...	SFO	
3	905	AA	810	SFO	ORD	3	385	255	0	KSFO	...	SFO	
4	1739	AA	24	SFO	JFK	3	425	325	1	KSFO	...	SFO	
...	...	...	...	...	...	...	...	...	...	...	...	...	
434919	497838	9E	4292	LWB	JFK	3	890	110	1	KLWB	...	LWB	
434920	516333	9E	4292	LWB	JFK	4	890	110	0	KLWB	...	LWB	
434921	534123	9E	4292	LWB	JFK	5	890	110	0	KLWB	...	LWB	
434922	69058	9E	3752	ABR	MSP	7	410	76	1	KABR	...	ABR	
434923	189396	9E	3752	ABR	MSP	7	410	76	0	KABR	...	ABR	

434924 rows × 26 columns

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)

In [33]:
```python
# Now lets use the web scrapping to import the data frome the wikipedia.
url2 = "https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States"
table = pd.read_html(url2)
```

In [34]:
```python
table
```

Out[34]:
```
[     Rank(2021)                           Airports (large hubs) IATACode  \
 0             1  Hartsfield–Jackson Atlanta International Airport      ATL
 1             2               Los Angeles International Airport      LAX
 2             3             Chicago O'Hare International Airport      ORD
 3             4         Dallas/Fort Worth International Airport      DFW
 4             5                    Denver International Airport      DEN
 5             6           John F. Kennedy International Airport      JFK
 6             7             San Francisco International Airport      SFO
 7             8            Seattle–Tacoma International Airport      SEA
 8             9                   Orlando International Airport      MCO
 9            10                Harry Reid International Airport      LAS
 10           11         Charlotte–Douglas International Airport      CLT
 11           12            Newark Liberty International Airport      EWR
 12           13        Phoenix Sky Harbor International Airport      PHX
 13           14            George Bush Intercontinental Airport      IAH
 14           15                     Miami International Airport      MIA
 15           16              Boston Logan International Airport      BOS
 16           17      Minneapolis–Saint Paul International Airport      MSP
 17           18                   Detroit Metropolitan Airport      DTW
```

In [35]:
```python
table[0] = table[0].drop(['2021', '2013[10]', '2012[11]', '2011[12]'], axis=1)
```

In [36]:
```python
table[0].head()
```

Out[36]:

	Rank(2021)	Airports (large hubs)	IATACode	Major cities served	State	2020[3]	2019[4]	2018[5]	2017[6]	2016[7]	2015
0	1	Hartsfield–Jackson Atlanta International Airport	ATL	Atlanta	GA	20559866	53505795	51865797	50251964	50501858	493407
1	2	Los Angeles International Airport	LAX	Los Angeles	CA	18593421	35778573	32821799	31816933	31283579	315898
2	3	Chicago O'Hare International Airport	ORD	Chicago	IL	16243216	33592945	31362941	29809097	28267394	262800
3	4	Dallas/Fort Worth International Airport	DFW	Dallas/Fort Worth	TX	14606034	40871223	39873927	38593028	37589899	363056
4	5	Denver International Airport	DEN	Denver	CO	14055777	42939104	42624050	41232432	39636042	363512

In [37]:
```python
table[0]['traffic_Chg19_20'] = table[0]['2020[3]'] - table[0]['2019[4]']
```

In [38]:
```python
table[0]['traffic_Chg18_19'] = table[0]['2019[4]'] - table[0]['2018[5]']
table[0]['hubs'] = str('large_hub')
```

In [39]:
```
table[0] = table[0][['IATACode', 'traffic_Chg19_20', 'traffic_Chg18_19', 'hubs']]
table[0]
```

Out[39]:

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	ATL	-32945929	1639998	large_hub
1	LAX	-17185152	2956774	large_hub
2	ORD	-17349729	2230004	large_hub
3	DFW	-26265189	997296	large_hub
4	DEN	-28883327	315054	large_hub
5	JFK	-11246819	1917739	large_hub
6	SFO	-14094543	1359791	large_hub
7	SEA	-14144302	933349	large_hub
8	MCO	-11902116	810972	large_hub
9	LAS	-12635024	399391	large_hub
10	CLT	-15539351	976854	large_hub
11	EWR	-13222751	747911	large_hub
12	PHX	-22766836	415886	large_hub
13	IAH	-15175289	363161	large_hub
14	MIA	-9935245	338658	large_hub
15	BOS	-12123197	830975	large_hub
16	MSP	-20034173	-11487	large_hub
17	DTW	-11320716	706203	large_hub
18	FLL	-14663925	692856	large_hub
19	PHL	-7087602	614111	large_hub
20	LGA	-10253150	713719	large_hub
21	BWI	-7833332	-87129	large_hub
22	SLC	-6011981	610242	large_hub
23	SAN	-8010836	474468	large_hub
24	IAD	-11246485	335100	large_hub
25	DCA	-5845178	-596237	large_hub
26	TPA	-4921659	918307	large_hub
27	MDW	-8021459	262494	large_hub

In [40]:
```python
table[1].head()
```

Out[40]:

	Rank(2020)	Airports (medium hubs)	IATACode	City served	State	2020	2019	2018	2017	2016	20
0	29	Daniel K. Inouye International Airport	HNL	Honolulu	HI	9893930	8408457	8134848.0	7876769.0	7554596.0	7040
1	30	Portland International Airport	PDX	Portland	OR	9790489	11595454	11367176.0	11506310.0	11470854.0	11242
2	31	Nashville International Airport	BNA	Nashville	TN	8498877	9797408	9940866.0	9435473.0	9071154.0	8340
3	32	Austin–Bergstrom International Airport	AUS	Austin	TX	3141505	8683711	7921797.0	6973115.0	6095545.0	5797
4	33	Dallas Love Field	DAL	Dallas	TX	8069178	7069614	6937061.0	6741870.0	6285181.0	5937

In [41]:
```python
table[1]['traffic_Chg19_20'] = table[1]['2020'] - table[1]['2019']
table[1]['traffic_Chg18_19'] = table[1]['2019'] - table[1]['2018']
table[1]['hubs'] = str('Medium_hub')
```

In [42]:
```
table[1] = table[1][['IATACode', 'traffic_Chg19_20', 'traffic_Chg18_19','hubs']]
table[1]
```

Out[42]:

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	HNL	1485473	273609.0	Medium_hub
1	PDX	-1804965	228278.0	Medium_hub
2	BNA	-1298531	-143458.0	Medium_hub
3	AUS	-5542206	761914.0	Medium_hub
4	DAL	999564	132553.0	Medium_hub
5	STL	-2238287	410173.0	Medium_hub
6	SJC	-270221	124712.0	Medium_hub
7	HOU	1912672	424899.0	Medium_hub
8	RDU	452929	422783.0	Medium_hub
9	MSY	141501	151623.0	Medium_hub
10	OAK	1950734	556705.0	Medium_hub
11	SMF	-470933	502607.0	Medium_hub
12	MCI	-2080699	688269.0	Medium_hub
13	SNA	-1409936	-238091.0	Medium_hub
14	RSW	-719803	-175712.0	Medium_hub
15	SAT	126615	57961.0	Medium_hub
16	CLE	174943	14143.0	Medium_hub
17	IND	-338022	178553.0	Medium_hub
18	PIT	-477440	-163873.0	Medium_hub
19	SJU	-172541	45914.0	Medium_hub
20	CVG	-17062	144199.0	Medium_hub
21	CMH	-16471	117495.0	Medium_hub
22	OGG	316303	197387.0	Medium_hub
23	JAX	-7422	361383.0	Medium_hub
24	PBI	79312	-174744.0	Medium_hub
25	MKE	635944	223831.0	Medium_hub
26	BDL	604458	70942.0	Medium_hub
27	BUR	-338581	-7120.0	Medium_hub
28	ONT	-1074666	219674.0	Medium_hub
29	ANC	334018	NaN	Medium_hub
30	ABQ	182971	-1813.0	Medium_hub
31	OMA	132539	NaN	Medium_hub
32	BUF	390491	NaN	Medium_hub
33	CHS	284	NaN	Medium_hub
34	MEM	-67924	NaN	Medium_hub
35	RIC	44986	NaN	Medium_hub

In [43]:
```
# Lets first merge all wikipedia table.
wiki_data = [table[0],table[1]]
```

In [44]:
```
wiki_data = pd.concat(wiki_data, ignore_index=True)
```

In [45]:
```
wiki_data
```

Out[45]:

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	ATL	-32945929	1639998.0	large_hub
1	LAX	-17185152	2956774.0	large_hub
2	ORD	-17349729	2230004.0	large_hub
3	DFW	-26265189	997296.0	large_hub
4	DEN	-28883327	315054.0	large_hub
...	...	...	...	...
59	OMA	132539	NaN	Medium_hub
60	BUF	390491	NaN	Medium_hub
61	CHS	284	NaN	Medium_hub
62	MEM	-67924	NaN	Medium_hub
63	RIC	44986	NaN	Medium_hub

64 rows × 4 columns

In [46]:
```
# Now we gather all the information that we got from wiki pedia link and the data that we have.
final_df = df.merge(wiki_data, left_on ='iata_code', right_on = "IATACode")
```

In [47]:
```
final_df
```

Out[47]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	...	width_ft	surfac
0	4	AA	2466	SFO	DFW	3	20	195	1	KSFO	...	200.0	ASI
1	231	AA	526	SFO	DFW	3	360	215	0	KSFO	...	200.0	ASI
2	234	AA	552	SFO	MIA	3	360	315	1	KSFO	...	200.0	ASI
3	905	AA	810	SFO	ORD	3	385	255	0	KSFO	...	200.0	ASI
4	1739	AA	24	SFO	JFK	3	425	325	1	KSFO	...	200.0	ASI
...	...	...	...	...	...	...	...	...	...	...	...	...	.
363125	506267	9E	4052	DAL	MEM	4	370	90	0	KDAL	...	150.0	COI
363126	512858	9E	3704	DAL	MEM	4	705	92	1	KDAL	...	150.0	COI
363127	518247	9E	4060	DAL	MEM	4	990	90	0	KDAL	...	150.0	COI
363128	524678	9E	4052	DAL	MEM	5	370	90	1	KDAL	...	150.0	COI
363129	530841	9E	3704	DAL	MEM	5	705	92	0	KDAL	...	150.0	COI

363130 rows × 30 columns

In [48]:
```
# Now we have the final data first we remove some column that is not useable.
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 363130 entries, 0 to 363129
Data columns (total 30 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   id                 363130 non-null  int64  
 1   Airline            363130 non-null  object 
 2   Flight             363130 non-null  int64  
 3   AirportFrom        363130 non-null  object 
 4   AirportTo          363130 non-null  object 
 5   DayOfWeek          363130 non-null  int64  
 6   Time               363130 non-null  int64  
 7   Length             363130 non-null  int64  
 8   Delay              363130 non-null  int64  
 9   ident              363130 non-null  object 
 10  type               363130 non-null  object 
 11  name               363130 non-null  object 
 12  latitude_deg       363130 non-null  float64
 13  longitude_deg      363130 non-null  float64
 14  elevation_ft       363130 non-null  float64
 15  scheduled_service  363130 non-null  object 
 16  iata_code          363130 non-null  object 
 17  airport_ref        363130 non-null  int64  
 18  airport_ident      363130 non-null  object 
 19  length_ft          363130 non-null  float64
 20  width_ft           363130 non-null  float64
 21  surface            363130 non-null  object 
 22  lighted            363130 non-null  int64  
 23  closed             363130 non-null  int64  
 24  IATA               363130 non-null  object 
 25  Founded            363130 non-null  float64
 26  IATACode           363130 non-null  object 
 27  traffic_Chg19_20   363130 non-null  int64  
 28  traffic_Chg18_19   351555 non-null  float64
 29  hubs               363130 non-null  object 
dtypes: float64(7), int64(10), object(13)
memory usage: 85.9+ MB
```

In [49]:
```
final_df = final_df.drop(['id','AirportFrom','airport_ident','iata_code','AirportTo','surface',
                          'IATA', 'IATACode','name'], axis=1)
```

In [50]:
```
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 363130 entries, 0 to 363129
Data columns (total 20 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Airline            363130 non-null  object 
 1   Flight             363130 non-null  int64  
 2   DayOfWeek          363130 non-null  int64  
 3   Time               363130 non-null  int64  
 4   Length             363130 non-null  int64  
 5   Delay              363130 non-null  int64  
 6   type               363130 non-null  object 
 7   latitude_deg       363130 non-null  float64
 8   longitude_deg      363130 non-null  float64
 9   elevation_ft       363130 non-null  float64
 10  scheduled_service  363130 non-null  object 
 11  airport_ref        363130 non-null  int64  
 12  length_ft          363130 non-null  float64
 13  width_ft           363130 non-null  float64
 14  lighted            363130 non-null  int64  
 15  closed             363130 non-null  int64  
 16  Founded            363130 non-null  float64
 17  traffic_Chg19_20   363130 non-null  int64  
 18  traffic_Chg18_19   351555 non-null  float64
 19  hubs               363130 non-null  object 
dtypes: float64(7), int64(9), object(4)
memory usage: 58.2+ MB
```

In [51]:
```
# Now lets check the null value and treat them.
final_df.isnull().sum()
```

Out[51]:
```
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
Founded                  0
traffic_Chg19_20         0
traffic_Chg18_19     11575
hubs                     0
dtype: int64
```

Only one column contain the null value so simply ww will drop that rows of null value because we have plenty of data.

In [52]:
```
final_df = final_df.dropna(axis=0)
```

In [53]:
```
final_df.head()
```

Out[53]:

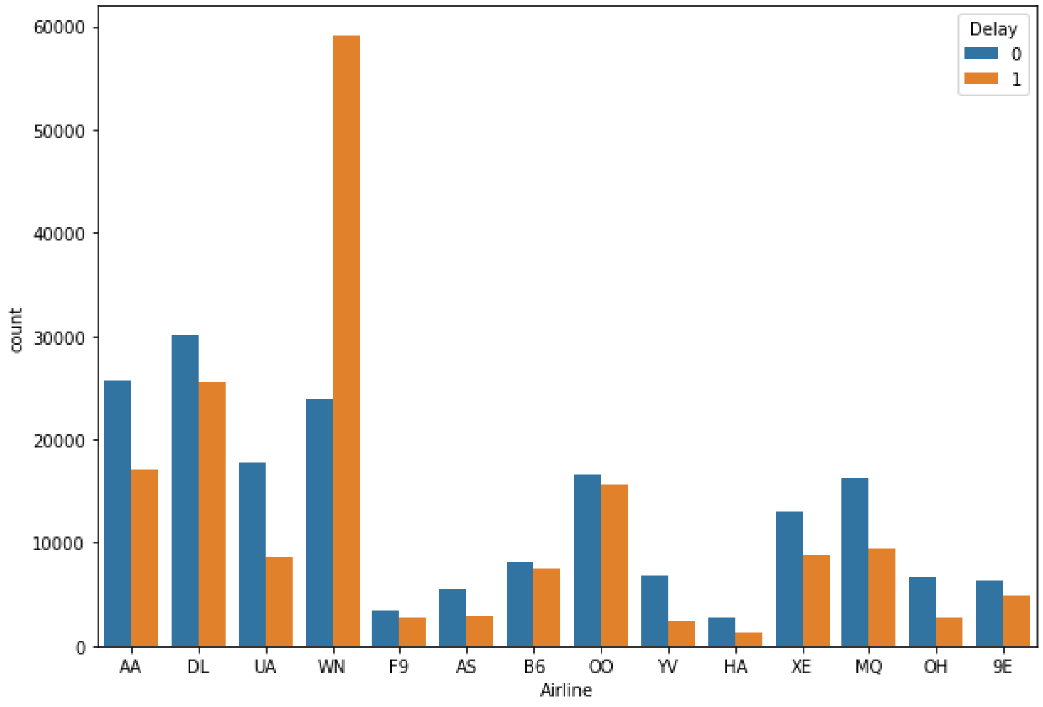
	Airline	Flight	DayOfWeek	Time	Length	Delay	type	latitude_deg	longitude_deg	elevation_ft	scheduled_
0	AA	2466	3	20	195	1	large_airport	37.618999	-122.375	13.0	
1	AA	526	3	360	215	0	large_airport	37.618999	-122.375	13.0	
2	AA	552	3	360	315	1	large_airport	37.618999	-122.375	13.0	
3	AA	810	3	385	255	0	large_airport	37.618999	-122.375	13.0	
4	AA	24	3	425	325	1	large_airport	37.618999	-122.375	13.0	

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.

Airline code WN represent the southwest airlines.

In [133]:
```
plt.figure(figsize=(10,7))
sns.countplot(final_df['Airline'], hue= final_df['Delay'])
plt.show()
```



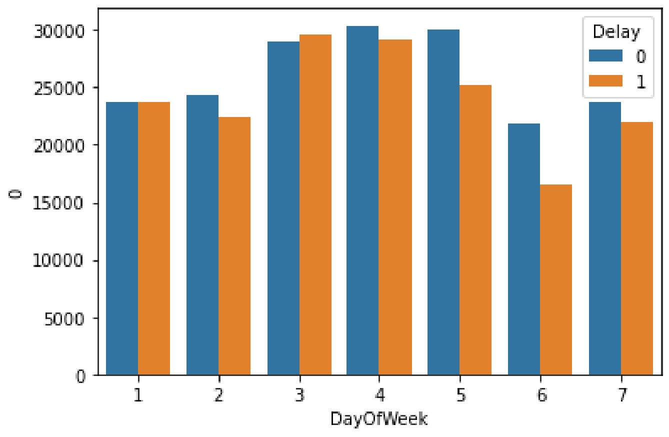
The graph clear show that 70% of flight of south west airline is delayed

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

In [115]:
```
weekday_df = final_df[['DayOfWeek','Delay']].value_counts().reset_index()
```

```
In [117]: sns.barplot(weekday_df['DayOfWeek'], weekday_df[0], hue= weekday_df['Delay'])
```

```
Out[117]: <AxesSubplot:xlabel='DayOfWeek', ylabel='0'>
```

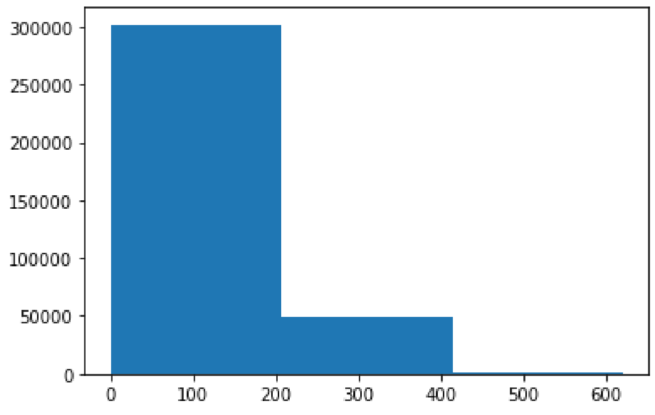


On the 5th day of week its clear that there is less no of flight delay.

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

We divided the length parameter in three range and from that basis we findout airline acc to the distance

```
In [121]: plt.hist(final_df['Length'], bins = 3)
          plt.show()
```



airlines should be recommended for short distance Travel.

In [123]:
```
final_df['Airline'][final_df['Length']<200].value_counts()
```

Out[123]:
```
WN    73809
DL    42200
OO    31468
AA    29948
MQ    25466
XE    21341
UA    16157
B6    11628
9E    11192
YV     9280
OH     9192
AS     5731
F9     5406
HA     3034
Name: Airline, dtype: int64
```

In [128]:
```
final_df['Airline'][final_df['Length']>400].value_counts()
```

Out[128]:
```
UA    549
AA    304
DL    226
B6     83
AS     31
HA     14
Name: Airline, dtype: int64
```

Airlines should be recommended for long distance Travel and remaining for the medium distance.

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

In [129]:
```
final_df['Time'][final_df['Length']>400]
```

Out[129]:

	Airline	Flight	DayOfWeek	Time	Length	Delay	type	latitude_deg	longitude_deg	elevation_ft	sc
46345	HA	5	4	1045	405	1	large_airport	36.083361	-115.151817	2181.0	
46348	HA	5	5	1045	405	0	large_airport	36.083361	-115.151817	2181.0	
46356	HA	5	1	1045	405	1	large_airport	36.083361	-115.151817	2181.0	
46364	HA	5	4	1045	405	1	large_airport	36.083361	-115.151817	2181.0	
46367	HA	5	5	1045	405	1	large_airport	36.083361	-115.151817	2181.0	
...	...	...	...	...	...	...	...	...	...	...	
315043	UA	92	1	1416	404	0	medium_airport	20.898543	-156.431212	54.0	
315049	UA	92	2	1416	404	0	medium_airport	20.898543	-156.431212	54.0	
315055	UA	92	3	1416	404	0	medium_airport	20.898543	-156.431212	54.0	
315061	UA	92	4	1416	404	0	medium_airport	20.898543	-156.431212	54.0	
315067	UA	92	5	1416	404	0	medium_airport	20.898543	-156.431212	54.0	

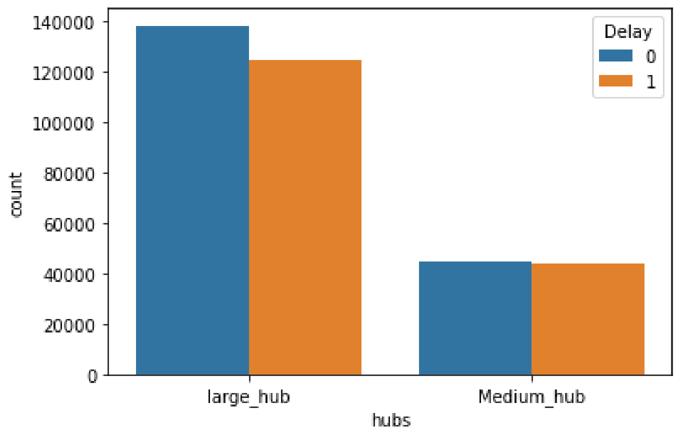
1207 rows × 20 columns

It is clear from the above table that is only of that flight which travel a long distance and comman thing in the departure time is all long distance flight leave the airport above 1045 time.

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

```
In [132]: sns.countplot(final_df['hubs'], hue = final_df['Delay'])
```

```
Out[132]: <AxesSubplot:xlabel='hubs', ylabel='count'>
```



From the large hubs its clear approx 120000 filght is delayed but from the small hubs aprrox 40000 is delayed.

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

```
In [134]: 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('Probably independent')
else:
    print('Probably dependent')
```

```
stat=186602.569, p=1.000
Probably independent
```

So its clear from the above hypothesis testing that altitude is nothing to do with the flight delay

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

```
In [135]: 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('Probably independent')
else:
    print('Probably dependent')
```

```
stat=192200.911, p=1.000
Probably independent
```

So its clear from the above hypothesis testing that no of runway is nothing to do with the flight delay

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

In [150]:

```
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('Probably independent')
else:
    print('Probably dependent')
```

```
stat=-0.002, p=0.179
Probably independent
```

Both the variable are independent so that length of the flight is not affecting directly the delay.

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

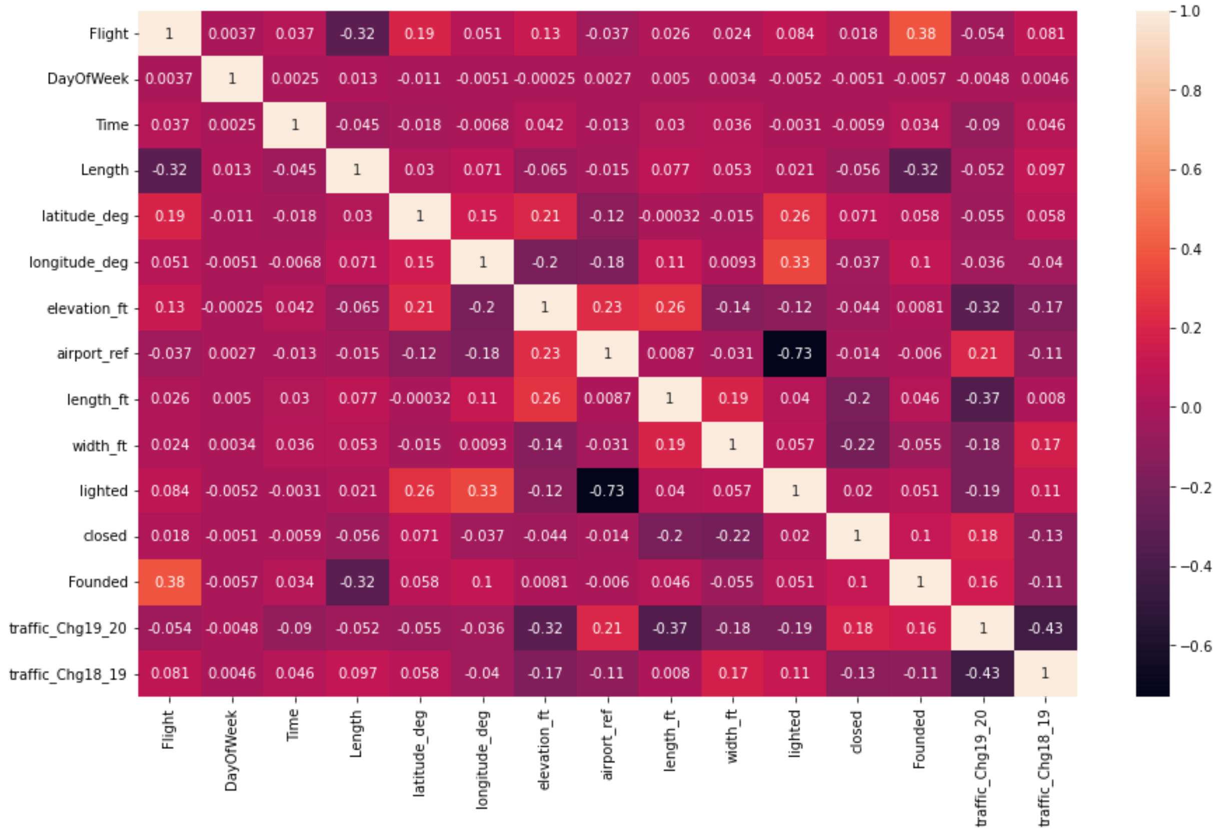
In [148]:

```
predictor = final_df.drop(['Delay'], axis=1)
corr = predictor.corr()
corr
```

Out[148]:

	Flight	DayOfWeek	Time	Length	latitude_deg	longitude_deg	elevation_ft	airport_ref
Flight	1.000000	0.003732	0.037147	-0.315231	0.194294	0.050626	0.127833	-0.036501
DayOfWeek	0.003732	1.000000	0.002477	0.013215	-0.010733	-0.005069	-0.000254	0.002677
Time	0.037147	0.002477	1.000000	-0.045410	-0.017776	-0.006839	0.041580	-0.012562
Length	-0.315231	0.013215	-0.045410	1.000000	0.029843	0.070918	-0.065413	-0.015262
latitude_deg	0.194294	-0.010733	-0.017776	0.029843	1.000000	0.149229	0.214040	-0.120146
longitude_deg	0.050626	-0.005069	-0.006839	0.070918	0.149229	1.000000	-0.196951	-0.181168
elevation_ft	0.127833	-0.000254	0.041580	-0.065413	0.214040	-0.196951	1.000000	0.232130
airport_ref	-0.036501	0.002677	-0.012562	-0.015262	-0.120146	-0.181168	0.232130	1.000000
length_ft	0.025819	0.004980	0.030107	0.077367	-0.000323	0.114557	0.259572	0.008687
width_ft	0.024280	0.003404	0.036335	0.053432	-0.014539	0.009334	-0.144024	-0.031283
lighted	0.084263	-0.005173	-0.003140	0.020547	0.255750	0.334031	-0.123519	-0.730141
closed	0.018225	-0.005079	-0.005892	-0.055789	0.070942	-0.036947	-0.043553	-0.014319
Founded	0.384262	-0.005709	0.033724	-0.321202	0.058121	0.099585	0.008079	-0.006035
traffic_Chg19_20	-0.054194	-0.004771	-0.089522	-0.052246	-0.054513	-0.036013	-0.322286	0.210036
traffic_Chg18_19	0.081196	0.004565	0.046173	0.096530	0.058426	-0.039925	-0.172352	-0.108319

```
In [149]: plt.figure(figsize=(15,9))
          sns.heatmap(corr, annot=True)
          plt.show()
```



Project Task: Week 1 (Machine learning)

1. Use OneHotEncoder and OrdinalEncoder to deal with categorical variables

In [153]:
```
# Before applying the one hot encodding or the label encoding first we check all feature data ty
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 351555 entries, 0 to 363129
Data columns (total 20 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   Airline            351555 non-null  object 
 1   Flight             351555 non-null  int64  
 2   DayOfWeek          351555 non-null  int64  
 3   Time               351555 non-null  int64  
 4   Length             351555 non-null  int64  
 5   Delay              351555 non-null  int64  
 6   type               351555 non-null  object 
 7   latitude_deg       351555 non-null  float64
 8   longitude_deg      351555 non-null  float64
 9   elevation_ft       351555 non-null  float64
 10  scheduled_service  351555 non-null  object 
 11  airport_ref        351555 non-null  int64  
 12  length_ft          351555 non-null  float64
 13  width_ft           351555 non-null  float64
 14  lighted            351555 non-null  int64  
 15  closed             351555 non-null  int64  
 16  Founded            351555 non-null  float64
 17  traffic_Chg19_20   351555 non-null  int64  
 18  traffic_Chg18_19   351555 non-null  float64
 19  hubs               351555 non-null  object 
dtypes: float64(7), int64(9), object(4)
memory usage: 56.3+ MB
```

In [155]:
```
final_df['Airline'].value_counts()
```

Out[155]:
```
WN    82903
DL    55724
AA    42841
OO    32315
UA    26303
MQ    25698
XE    21733
B6    15497
9E    11192
OH     9440
YV     9337
AS     8355
F9     6180
HA     4037
Name: Airline, dtype: int64
```

In [156]:
```
final_df['type'].value_counts()
```

Out[156]:
```
large_airport     334982
medium_airport     16573
Name: type, dtype: int64
```

In [157]:
```
final_df['scheduled_service'].value_counts()
```

Out[157]:
```
yes    351555
Name: scheduled_service, dtype: int64
```

In [158]:
```
final_df['hubs'].value_counts()
```

Out[158]:
```
large_hub     262540
Medium_hub     89015
Name: hubs, dtype: int64
```

The scheduled_service column throught has same value so it will not help in prediction so lets remove it and other three object column we will change through label encoder.

In [160]:
```
final_df = final_df.drop(['scheduled_service'], axis=1)
```

In [163]:
```
# Now using the ordinal encoder.
from sklearn.preprocessing import LabelEncoder
```

In [164]:
```
le = LabelEncoder()
```

In [165]:
```
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'])
```

In [166]:
```
final_df.head()
```

Out[166]:

	Airline	Flight	DayOfWeek	Time	Length	Delay	type	latitude_deg	longitude_deg	elevation_ft	airport_ref	lengtl
0	1	2466	3	20	195	1	0	37.618999	-122.375	13.0	3878	75(
1	1	526	3	360	215	0	0	37.618999	-122.375	13.0	3878	75(
2	1	552	3	360	315	1	0	37.618999	-122.375	13.0	3878	75(
3	1	810	3	385	255	0	0	37.618999	-122.375	13.0	3878	75(
4	1	24	3	425	325	1	0	37.618999	-122.375	13.0	3878	75(

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

Note: Make sure you use standardization effectively, ensuring no data leakage and leverage pipelines to have a cleaner code

c. Use RandomizedSearchCV for hyperparameter tuning, and use k-fold for cross validation

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

Note: The final prediction will be based on the voting (majority class by 5 models created using the stratified 5-fold method)

g. Compare the results of logistic regression and decision tree classifier

In [205]:
```
# Lets first seperate the predictors and the output Variable.
x = final_df.drop(['Delay'], axis= 1)
y = final_df["Delay"]
```

In [206]:
```
from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
x = scaler.fit_transform(x)
```

In [207]:
```
# First Split the data into the training and testing set before performing the further operatio
from sklearn.model_selection import train_test_split
```

In [208]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.9, random_state=10)
```

LogisticRegression

In [209]:
```
# lets apply the logistic regression with the randomsearchcv hypermeter tunning.
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

In [210]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [211]:
```
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 3 folds for each of 4 candidates, totalling 12 fits
```

Out[211]:
```
RandomizedSearchCV(cv=3, estimator=LogisticRegression(),
                   param_distributions={'penalty': ['l1', 'l2'],
                                        'solver': ['newton-cg', 'liblinear']},
                   scoring='accuracy', verbose=1)
```

In [212]:
```
print(rscv.best_params_)
print(rscv.best_score_)
```

```
{'solver': 'newton-cg', 'penalty': 'l2'}
0.592195292796719
```

In [213]:
```
lr = LogisticRegression(penalty= 'l2', solver= 'newton-cg')
lr.fit(x_train,y_train).score(x_train,y_train)
```

Out[213]:
```
0.5923280414919136
```

In [214]:
```
lr.score(x_test, y_test)
```

Out[214]:
```
0.593013994766185
```

DecisionTreeClassifier

In [215]:
```
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
```

Out[215]:
```
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)
```

In [216]:
```
print(rscv.best_params_)
print(rscv.best_score_)
```

```
{'min_samples_leaf': 6, 'max_depth': 9, 'criterion': 'entropy'}
0.6469110137916109
```

In [220]:
```
dtc = DecisionTreeClassifier(max_depth= 9, criterion= 'entropy',min_samples_leaf= 6)
```

In [221]:
```
dtc.fit(x_train, y_train).score(x_train, y_train)
```

Out[221]:
```
0.6539464410443775
```

In [222]:
```
dtc.score(x_test, y_test)
```

Out[222]:
```
0.649049948799636
```

After seeing the result its clear decision tree has good accuracy.

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

In [224]:
```
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
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': 14, 'max_depth': 9, 'learning_rate': 0.45, 'colsample
_bytree': 0.9}
Best accuracy found:  0.6612157449541393
```

In [225]:
```
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)
```

Out[225]:
```
0.6860830786443699
```

In [226]:
```
# 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))
```

```
0.593013994766185
0.649049948799636
0.6630447149846399
```

After comparing the accuracy of the diffrent model the best result we getting from the XGBclassifier.