

# United States Airlines Analysis

```
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.

Hint: In this case, you would have to determine the keys to join the tables. A data description will be useful.

```
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]: airport = pd.read_excel("airports.xlsx")
```

```
In [7]: airport.shape
```

```
Out[7]: (73805, 18)
```

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

Out[8]:

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

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_lati
0	269408	6523	00A	80.0	80.0	ASPH-G	1	0	H1	
1	255155	6524	00AK	2500.0	70.0	GRVL	0	0	N	
2	254165	6525	00AL	2300.0	200.0	TURF	0	0	1	
3	270932	6526	00AR	40.0	40.0	GRASS	0	0	H1	
4	322128	322127	00AS	1450.0	60.0	Turf	0	0	1	

In [12]: `# Before merging the data Lets drop the columns that will not play an important role  
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_displaced_threshold_ft', 'he_ident', 'he_latitude_deg', 'he_longitude_deg',
                                '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 airport data that is not usefull.
airport.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',
                               'wikipedia_link', 'keywords'], axis=1)

```

```

In [17]: airpots

```

Out[17]:

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	schedule
0	6523	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	
1	323361	00AA	small_airport	Aero B Ranch Airport	38.704022	-101.473911	3435.0	
2	6524	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	
3	6525	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	
4	6526	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	
...	...	...	...	...	...	...	...	...
73800	46378	ZZ-0001	heliport	Sealand Helipad	51.894444	1.482500	40.0	
73801	307326	ZZ-0002	small_airport	Glorioso Islands Airstrip	-11.584278	47.296389	11.0	
73802	346788	ZZ-0003	small_airport	Fainting Goat Airport	32.110587	-97.356312	690.0	
73803	342102	ZZZW	closed	Scandium City Heliport	69.355287	-138.939310	4.0	
73804	313629	ZZZZ	small_airport	Satsuma Ijima Airport	30.784722	130.270556	338.0	

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_id")
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
--	-------	------	------	--------------	---------------	--------------	-----------

0	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	
1	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	
2	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	
3	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	
4	00AS	small_airport	Fulton Airport	34.942803	-97.818019	1100.0	
...	...	...	...	...	...	...	...
43972	ZYTX	large_airport	Shenyang Taoxian International Airport	41.639801	123.483002	198.0	
43973	ZYYJ	medium_airport	Yanji Chaoyangchuan Airport	42.882801	129.451004	624.0	
43974	ZYYK	medium_airport	Yingkou Lanqi Airport	40.542524	122.358600	NaN	
43975	ZZ-0003	small_airport	Fainting Goat Airport	32.110587	-97.356312	690.0	
43976	ZZZZ	small_airport	Satsuma Iqjima Airport	30.784722	130.270556	338.0	

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", 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	ide
0	1	CO	269	SFO	IAH	3	15	205	1	KSF
4	4	AA	2466	SFO	DFW	3	20	195	1	KSF
8	9	DL	2606	SFO	MSP	3	35	216	1	KSF
12	129	DL	1580	SFO	DTW	3	345	270	0	KSF
16	150	UA	756	SFO	DEN	3	348	158	0	KSF
...	...	...	...	...	...	...	...	...	...	...
2160266	451344	CO	2	GUM	HNL	1	400	430	1	PGU
2160268	469866	CO	2	GUM	HNL	2	400	430	1	PGU
2160270	488365	CO	2	GUM	HNL	3	400	430	0	PGU
2160272	506855	CO	2	GUM	HNL	4	400	430	1	PGU
2160274	525138	CO	2	GUM	HNL	5	400	430	1	PGU

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 1986). 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)

Hint: Here, you should use web scraping to learn how long an airline has been operating.

```
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	MXV	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
2	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926
3	BurbankNew HavenOrlando	1987
4	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018
5	AtlantaBostonDetroitLos AngelesMinneapolis/St....	1924
6	MiamiNew York-JFK	2010
7	DenverAtlantaChicago-O'HareCincinnatiCleveland...	1994
8	HonoluluKahului	1929
9	New York-JFKBostonLos AngelesFort LauderdaleOr...	1998
10	Dallas-LoveAtlantaBaltimoreChicago-MidwayDenve...	1967
11	Atlantic CityDetroitLas VegasFort LauderdaleCh...	1980
12	Minneapolis/St. PaulDallas/Fort WorthLas Vegas	1982
13	Chicago-O'HareDenverGuamHouston-Intercontinent...	1926

	Notes
0	Founded as McGee Airways and commenced operati...
1	Founded as WestJet Express and commenced opera...
2	Founded as American Airways and commenced oper...
3	First did business as Casino Express Airlines ...
4	NaN
5	Founded as Huff Daland Dusters and commenced o...
6	NaN
7	NaN
8	Founded as Inter-Island Airways in early 1929 ...
9	Founded as New Air and commenced operations in...
10	Founded as Air Southwest and commenced operati...
11	Founded as Charter One.
12	Commenced operations in 1983.Operates some Ama...
13	Founded as Varney Air Lines and commenced oper...

age	IATA	ICAO	Callsign	\	
0		Air Wisconsin	NaN	ZW AWI	WISCONSIN
1		Cape Air	NaN	9K KAP	CAIR
2		CommutAir	NaN	C5 UCA	COMMUTAIR
3		Contour Airlines	NaN	LF VTE	VOLUNTEER
4		Elite Airways	NaN	7Q MNU	MAINER
5		Endeavor Air	NaN	9E EDV	ENDEAVOR
6		Envoy Air	NaN	MQ ENY	ENVOY
7		GoJet Airlines	NaN	G7 GJS	LINDBERGH
8		Horizon Air	NaN	QX QXE	HORIZON
9		Mesa Airlines	NaN	YV ASH	AIR SHUTTLE
10		Piedmont Airlines	NaN	PT PDT	PIEDMONT
11		PSA Airlines	NaN	OH JIA	BLUE STREAK
12		Republic Airways	NaN	YX RPA	BRICKYARD
13		Silver Airways	NaN	3M SIL	SILVER WINGS
14		SkyWest Airlines	NaN	OO SKW	SKYWEST



	Primary Hubs, Secondary Hubs	Founded \
0	AppletonChicago-O'HareColumbiaMilwaukeeWashing...	1965
1	HyannisBillingsBostonNantucketSt. LouisSan Jua...	1988
2	DenverNewarkWashington-Dulles	1989
3	Smyrna (TN)	1982
4	Melbourne/OrlandoNewarkPortland (Maine)	2006
5	Minneapolis/St. PaulAtlanta CincinnatiDetroitN...	1985
6	Dallas/Fort WorthChicago-O'Hare Miami	1984
7	Chicago-O'HareDenver	2004
8	Seattle/TacomaPortland (OR)	1981
9	As American Eagle:Phoenix-Sky HarborDallas/For...	1980
10	CharlottePhiladelphiaWashington-National	1961
11	CharlottePhiladelphiaWashington-National	1979
12	As American Eagle:IndianapolisColumbus (OH)Kan...	1998
13	Fort LauderdaleOrlandoTampa	2011
14	As Delta Connection:AtlantaBoiseColorado Sprin...	1972

	Notes
0	Operates as United Express
1	NaN
2	Operates as United Express.
3	NaN
4	Commenced operations in 2014.
5	Founded as Express Airlines I. Operates as Del...
6	Founded as American Eagle Airlines. Operates a...
7	Commenced operations in 2005. Operates as Unit...
8	Operates as Alaska Airlines.
9	Founded as Mesa Air Shuttle. All but one aircr...
10	Founded as Henson Aviation and commenced opera...
11	Founded as Vee Neal Airlines. Operates as Amer...
12	Commenced operations in 2005. Operates as Amer...
13	NaN
14	Operates as Delta Connection, United Express, ... ,

Airline	Image	IATA	ICAO	Callsign \
0		Advanced Air	NaN	AN WSN WINGSPAN
1		Air Sunshine	NaN	YI RSI AIR SUNSHINE
2		Bering Air	NaN	8E BRG BERING AIR
3		Boutique Air	NaN	4B BTQ BOUTIQUE
4		Everts Air	NaN	5V VTS EVERTS
5		Gem Air	NaN	NaN NaN NaN
6		Grand Canyon Airlines	NaN	YR CVU CANYON VIEW
7		Grand Canyon Scenic Airlines	NaN	YR SCE SCENIC
8		Grant Aviation	NaN	GV GUN HOOT
9		Griffing Flying Service	NaN	NaN NaN NaN
10		Island Airways	NaN	NaN NaN NaN
11		JSX	NaN	XE JSX BIGSTRIPE
12		Kenmore Air	NaN	M5 KEN KENMORE
13		Key Lime Air	NaN	KG LYM KEY LIME
14		Mokulele Airlines	NaN	MW MHO MAHALO
15		New England Airlines	NaN	EJ NEA NEW ENGLAND
16		Penobscot Island Air	NaN	NaN NaN NaN
17		Reliant Air	NaN	NaN NaN RLI RELIANT
18		San Juan Airlines	NaN	NaN NaN NaN SKYFERRY
19		Servant Air	NaN	8D NaN NaN
20		Southern Airways Express	NaN	9X FDY FRIENDLY
21		Surf Air	NaN	NaN NaN UF SURFAIR
22		Taquan Air	NaN	K3 TQN TAQUAN
23		Tradewind Aviation	NaN	TJ GPD GOODSPEED
24		Ultimate Air Shuttle	NaN	UE UJC ULTIMATE
25		Utah Airways	NaN	NaN NaN NaN
26		Warbelow's Air Ventures	NaN	4W WAV WARBELOW
27		Wright Air Service	NaN	8V WRF WRIGHT FLYER

Primary Hubs, Secondary Hubs Founded \

0		Hawthorne	2005
1		San Juan	1982
2		NomeKotzebueUnalakleet	1979
3	Dallas/Fort Worth	DenverPhoenix-Sky Harbor	2007
4		FairbanksAnchorage	1978
5		Salmon	2014
6		Boulder CityGrand CanyonPage	1927
7		Grand Canyon	1967
8	AnchorageBethelCold BayDillinghamEmmonakKenaiK...		1971
9		Port Clinton	1937
10		Charlevoix	1945
11	BurbankOaklandLas VegasSanta AnaPhoenixConcord		2016
12		KenmoreSeattle-Lake UnionSeattle-Boeing	1946
13	Denver-CentennialDenverDenver-Rocky MountainGr...		1997
14		Kailua-KonaKahului	1994
15		Westerly	1970
16		Rockland	2004
17		Danbury	1988
18		Bellingham	2002
19		Kodiak	2003
20	MemphisDestinPittsburghWashington-Dulles		2013
21	HawthorneOaklandSan CarlosSanta BarbaraTruckee		2012
22		Ketchikan Harbor	1977
23	Oxford (CT)San Juan White Plains		2001
24		Cincinnati-Lunken	2009
25		Ogden	2015
26		Fairbanks	1958
27		Fairbanks	1966

## Notes

0	Has the EAS contract to serve Grant County Air...					
1		NaN				
2		NaN				
3		NaN				
4	Founded as Tatonduk Flying Service.					
5		NaN				
6	Founded as Scenic Airways.					
7	Founded as Scenic Airlines.					
8	Founded as Delta Air Services.					
9		NaN				
10	Founded as McPhillips Flying Service.					
11	Operator of Taos Air flights from 2022.					
12	Founded as Mines Collins Munro.					
13	Operates as Denver Air Connection.					
14	Founded as Mokulele Flight Service.					
15		NaN				
16		NaN				
17		NaN				
18		NaN				
19		NaN				
20		NaN				
21		NaN				
22		NaN				
23		NaN				
24		NaN				
25		NaN				
26		NaN				
27		NaN				
Airline Image IATA ICAO Callsign \						
0		Air Charter Bahamas	NaN	NaN	NaN	NaN
1		Air Flight Charters	NaN	NaN	FLL	NaN
2		Airshare	NaN	NaN	XSR	AIRSHARE
3		Berry Aviation	NaN	NaN	BYA	BERRY
4		Bighorn Airways	NaN	NaN	BHR	BIGHORN AIR

5	Charter Air Transport	NaN	VC	SRY	STINGRAY
6	Choice Airways	NaN	NaN	CSX	CHOICE AIR
7	ExcelAire	NaN	NaN	XLS	EXCELAIRE
8	Global Crossing Airlines	NaN	G6	GXA	GEMINI
9	Great Lakes Air	NaN	NaN	NaN	NaN
10	Gryphon Airlines	NaN	Y3	VOS	NaN
11	IAero Airways	NaN	WQ	SWQ	SWIFTFLIGHT
12	IBC Airways	NaN	II	CSQ	CHASQUI
13	L-3 Flight International Aviation	NaN	NaN	RTD	RIPTIDE
14	Liberty Jet Management	NaN	NaN	LRT	LIBERTY JET
15	NetJets	NaN	1I	EJA	EXECJET
16	Omni Air International	NaN	X9	OAE	OMNI-EXPRESS
17	Omni Air Transport	NaN	NaN	DRL	DRILLER
18	Pacific Coast Jet	NaN	NaN	PXT	PACK COAST
19	Pentastar Aviation	NaN	NaN	DCX	TANGO
20	Phoenix Air	NaN	NaN	PHA	GRAY BIRD
21	PlaneSense	NaN	NaN	CNS	CHRONOS
22	Presidential Airways	NaN	NaN	PRD	PRESIDENTIAL
23	Sierra Pacific Airlines	NaN	SI	SPA	SIERRA PACIFIC
24	Skymax	NaN	NaN	SMX	SKYMAX
25	Songbird Airways	NaN	SK	SGB	SONGBIRD
26	Stampede Aviation	NaN	NaN	NaN	NaN
27	Superior Air Charter	NaN	NaN	RSP	REDSTRIPE
28	Superior Aviation	NaN	SO	HKA	SPEND AIR
29	Talkeetna Air Taxi	NaN	NaN	NaN	NaN
30	Tropic Ocean Airways	NaN	NaN	NaN	NaN
31	World Atlantic Airlines	NaN	K8	WAL	WORLD ATLANTIC
32	XOJET Aviation LLC	NaN	NaN	XOJ	XOJET

	Primary Hubs, Secondary Hubs	Founded \
0	NaN	NaN
1	Fort Lauderdale	1987.0
2	NaN	2000.0
3	San Marcos	1983.0
4	Sheridan	1947.0
5	Cleveland-Lakefront	1997.0
6	Fort Lauderdale-Executive	2009.0
7	Long Island/Islip	1993.0
8	Atlantic CityLas VegasMiami	2019.0
9	St. Ignace	NaN
10	NaN	NaN
11	Miami	1997.0
12	Fort Lauderdale	1991.0
13	Newport News	1972.0
14	Long Island/Islip	2006.0
15	Columbus	1964.0
16	Tulsa	1993.0
17	Tulsa	NaN
18	NaN	2006.0
19	Waterford	1964.0
20	Cartersville	1978.0
21	Portsmouth (NH)	1992.0
22	Melbourne/Orlando	NaN
23	Tucson	1970.0
24	Fort Lauderdale	1997.0
25	Miami	1990.0
26	Healy/Denali NP	2011.0
27	NaN	2006.0
28	Lansing	1979.0
29	Talkeetna	1947.0
30	Fort Lauderdale	2009.0
31	Miami	2002.0
32	Sacramento-McClellan	2006.0

	Notes
0	NaN
1	NaN
2	Founded as Executive Flight Services
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	NaN
9	NaN
10	NaN
11	Founded as Swift Air
12	NaN
13	NaN
14	NaN
15	Founded as Executive Jets Aviation.
16	NaN
17	NaN
18	NaN
19	Founded as Chrysler Air Transportation.
20	NaN
21	NaN
22	NaN
23	Commenced operations in 1971.
24	Commenced operations in 2013.
25	NaN
26	NaN
27	NaN
28	NaN
29	Founded as Talkeetna Flying Service.
30	NaN
31	Founded as Caribbean Sun Airlines and commence...
32	NaN ,

A

airline	Image	IATA	ICAO	Callsign	\
0			21 Air	NaN	2I CSB CARGO SOUTH
1			ABX Air	NaN	GB ABX ABEX
2			Air Cargo Carriers	NaN	2Q SNC NIGHT CARGO
3			AirNet Express	NaN	NaN USC STAR CHECK
4			Air Transport International	NaN	8C ATN AIR TRANSPORT
5			Alaska Central Express	NaN	KO AER ACE AIR
6			Aloha Air Cargo	NaN	KH AAH ALOHA
7			Alpine Air Express	NaN	5A AIP ALPINE AIR
8			Amazon Air	NaN	AFW KAFW AMAZON AIR
9			Ameriflight	NaN	A8 AMF AMFLIGHT
10			Amerijet International	NaN	M6 AJT AMERIJET
11			Ameristar Jet Charter	NaN	7Z AJI AMERISTAR
12			Asia Pacific Airlines	NaN	P9 MGE MAGELLAN
13			Atlas Air	NaN	5Y GTI GIANT
14			Bemidji Airlines	NaN	CH BMJ BEMIDJI
15			Castle Aviation	NaN	NaN CSJ CASTLE
16			Corporate Air	NaN	NaN CPT AIRSPUR
17			CSA Air	NaN	NaN IRO IRON AIR
18			Empire Airlines	NaN	EM CFS EMPIRE
19			Everts Air Cargo	NaN	5V VTS EVERTS
20			FedEx Express	NaN	FX FDX FEDEX
21			Freight Runners Express	NaN	NaN FRG FREIGHT RUNNERS
22			IFL Group	NaN	IF IFL EIFFEL
23			Kalitta Air	NaN	K4 CKS CONNIE
24			Kalitta Charters	NaN	CB KFS KALITTA
25			Lynden Air Cargo	NaN	L2 LYC LYNDEN
26			Martinaire	NaN	NaN MRA MARTEX
27			Merlin Airways	NaN	NaN MEI AVALON
28			Mountain Air Cargo	NaN	C2 MTN MOUNTAIN

29	National Airlines	NaN	N8	NCR	NATIONAL CARGO
30	Northern Air Cargo	NaN	NC	NAC	YUKON
31	Polar Air Cargo	NaN	PO	PAC	POLAR
32	Royal Air Freight	NaN	NaN	RAX	AIR ROYAL
33	Ryan Air Services	NaN	7S	RYA	RYAN AIR
34	Sky Lease Cargo	NaN	GG	KYE	SKY CUBE
35	Skyway Enterprises	NaN	KI	SKZ	SKYWAY-INC
36	Strat Air	NaN	NaN	NaN	NaN
37	Trans Executive Airlines	NaN	KH	MUI	RHOADES EXPRESS
38	UPS Airlines	NaN	5X	UPS	UPS
39	USA Jet Airlines	NaN	UJ	JUS	JET USA
40	West Air	NaN	NaN	PCM	PAC VALLEY
41	Western Global Airlines	NaN	KD	WGN	WESTERN GLOBAL
42	Wiggins Airways	NaN	WG	WIG	WIGGINS AIRWAYS

	Primary Hubs,	Secondary Hubs	Founded	\
0		Miami	2014.0	
1	Wilmington (OH)	Cincinnati	1980.0	
2		Milwaukee	1986.0	
3		Columbus-Rickenbacker	1974.0	
4		Wilmington (OH)	1978.0	
5		Anchorage	1996.0	
6		Honolulu	1946.0	
7		Provo	1971.0	
8	Fort Worth/Alliance	Cincinnati	2015.0	
9		Dallas/Fort Worth	1968.0	
10		Miami	1974.0	
11		Dallas-Addison	2000.0	
12		Guam	1998.0	
13	New York-JFK	Anchorage	1992.0	
14		Bemidji	1946.0	
15		Akron/Canton	1986.0	
16		Billings	1981.0	
17		Iron Mountain	1998.0	
18		Coeur d' Alene	1977.0	
19		Fairbanks	1995.0	
20	Memphis	Anchorage	1971.0	
21		Milwaukee	1985.0	
22		Waterford	1983.0	
23	Ypsilanti	Anchorage	1967.0	
24		Ypsilanti	NaN	
25		Anchorage	1995.0	
26		Addison	1978.0	
27		Billings	1983.0	
28		Kinston	1974.0	
29		Orlando/Sanford	1985.0	
30		Anchorage	1956.0	
31	Anchorage	Cincinnati	1993.0	
32		Waterford	1961.0	
33	Anchorage	Aniak	1953.0	
34		Miami	1969.0	
35		NaN	1981.0	
36		Miami	2018.0	
37		Honolulu	1982.0	
38	Louisville	Chicago/Rockford	1988.0	
39		Ypsilanti	1994.0	
40		Las Vegas	1988.0	
41		Miami	2013.0	
42		Manchester	1929.0	

	Notes
0	NaN
1	Founded as Airborne Express. Operates some Ama...
2	Commenced operations in 1980.

```

3           Founded as Financial Air Express.
4   Founded as US Airways and commenced operations...
5                                           NaN
6   Founded as Trans-Pacific Airlines and separate...
7                                           NaN
8           Formerly Amazon Prime Air
9           Founded as California Air Charter.
10                                          NaN
11                                          NaN
12                                          NaN
13   Commenced operations in 1993. Operates some Am...
14           Commenced operations in 1947.
15                                          NaN
16                                          NaN
17                                          NaN
18                                          NaN
19                                          NaN
20   Founded as Federal Express and commenced opera...
21                                          NaN
22           Founded as Air Contract Cargo.
23   Founded as American International Airways.
24                                          NaN
25                                          NaN
26                                          NaN
27                                          NaN
28                                          NaN
29           Commenced operations in 1986.
30                                          NaN
31                                          NaN
32                                          NaN
33           Founded as Unalakleet Air Taxi.
34   Founded as Wrangler Aviation and commenced ope...
35           Commenced operations in 1983.
36                                          NaN
37                                          NaN
38                                          NaN
39                                          NaN
40                                          NaN
41                                          NaN
42                                          NaN ,           Airline

```

```

Image IATA ICAO Callsign \
0   AirMed International   NaN   NaN   NaN   NaN
1           Air Methods   NaN   NaN   NaN   NaN
2   Critical Air Medicine   NaN   NaN   NaN   NaN
3           Lifestar      NaN   NaN   NaN   NaN
4           Life Lion      NaN   NaN   NaN   NaN

```

```

Primary Hubs, Secondary Hubs   Founded   Notes
0   Birmingham-Shuttlesworth   1987.0   Founded as MEDjet International.
1           Denver-Centennial   1980.0           NaN
2           NaN   1984.0           NaN
3           NaN   NaN           NaN
4           NaN   NaN           NaN ,

```

```

Airline Image IATA ICAO \
0           Comco   NaN   NaN   NaN
1           Janet   NaN   NaN   WWW
2   Justice Prisoner and Alien Transportation System   NaN   NaN   JUD

```

```

Callsign Primary Hubs, Secondary Hubs   Founded \
0   NaN   NaN   2002
1   JANET   Las Vegas   1972
2   JUSTICE   Oklahoma City   1980

```

Notes

```

0           NaN
1           NaN
2 Commenced operations in 1995. ,           vteLists of a
irlines \
0           By airline codes
1           By continent
2           By country
3           vteExpand for full list
4 A Abkhazia Afghanistan Akrotiri and Dhekelia Å...
5           A
6           B
7           C
8           D
9           E
10          F
11          G
12          H
13          I
14          J
15          K
16          L
17          M
18          N
19          O
20          P
21          Q
22          R
23          S
24          T
25 U Uganda Ukraine United Arab Emirates United K...
26          U
27          V
28          W
29          Y
30          Z
31          See also

```

```

           vtelists of airlines.1
0 All 0-9 A B C D E F G H I J K L M N O P Q R S ...
1           Africa Americas Asia Europe Oceania
2 vteExpand for full listA Abkhazia Afghanistan ...
3           vteExpand for full list
4 A Abkhazia Afghanistan Akrotiri and Dhekelia Å...
5 Abkhazia Afghanistan Akrotiri and Dhekelia Åla...
6 The Bahamas Bahrain Bangladesh Barbados Belaru...
7 Cambodia Cameroon Canada Cape Verde Cayman Isl...
8 Denmark Dhekelia Djibouti Dominica Dominican R...
9 East Timor Ecuador Egypt El Salvador Equatoria...
10 Falkland Islands Faroe Islands Fiji Finland Fr...
11 Gabon The Gambia Georgia Germany Ghana Gibralt...
12           Haiti Honduras Hong Kong Hungary
13 Iceland India Indonesia Iran Iraq Ireland Isra...
14           Jamaica Japan Jersey Jordan
15 Kazakhstan Kenya Kiribati North Korea South Ko...
16 Laos Latvia Lebanon Lesotho Liberia Libya Liec...
17 Macau Macedonia, Republic of Madagascar Malawi...
18 Namibia Nauru Nepal Netherlands Netherlands An...
19           Oman
20 Pakistan Palau Palestine Panama Papua New Guin...
21           Qatar
22           Romania Russia Rwanda
23 Sahrawi Arab Democratic Republic Saint Barthél...
24 Taiwan Tajikistan Tanzania Thailand Togo Tokel...
25 U Uganda Ukraine United Arab Emirates United K...

```

```

26 Uganda Ukraine United Arab Emirates United Kin...
27 Vanuatu Vatican City Venezuela Vietnam British...
28 Wallis and Futuna
29 Yemen
30 Zambia Zimbabwe
31 List of airline holding companies List of airl... ,
vteExpand for full list \
0 A Abkhazia Afghanistan Akrotiri and Dhekelia Å...
1 A
2 B
3 C
4 D
5 E
6 F
7 G
8 H
9 I
10 J
11 K
12 L
13 M
14 N
15 O
16 P
17 Q
18 R
19 S
20 T
21 U Uganda Ukraine United Arab Emirates United K...
22 U
23 V
24 W
25 Y
26 Z

```

```

vteExpand for full list.1
0 A Abkhazia Afghanistan Akrotiri and Dhekelia Å...
1 Abkhazia Afghanistan Akrotiri and Dhekelia Åla...
2 The Bahamas Bahrain Bangladesh Barbados Belaru...
3 Cambodia Cameroon Canada Cape Verde Cayman Isl...
4 Denmark Dhekelia Djibouti Dominica Dominican R...
5 East Timor Ecuador Egypt El Salvador Equatoria...
6 Falkland Islands Faroe Islands Fiji Finland Fr...
7 Gabon The Gambia Georgia Germany Ghana Gibralt...
8 Haiti Honduras Hong Kong Hungary
9 Iceland India Indonesia Iran Iraq Ireland Isra...
10 Jamaica Japan Jersey Jordan
11 Kazakhstan Kenya Kiribati North Korea South Ko...
12 Laos Latvia Lebanon Lesotho Liberia Libya Liec...
13 Macau Macedonia, Republic of Madagascar Malawi...
14 Namibia Nauru Nepal Netherlands Netherlands An...
15 Oman
16 Pakistan Palau Palestine Panama Papua New Guin...
17 Qatar
18 Romania Russia Rwanda
19 Sahrawi Arab Democratic Republic Saint Barthél...
20 Taiwan Tajikistan Tanzania Thailand Togo Tokel...
21 U Uganda Ukraine United Arab Emirates United K...
22 Uganda Ukraine United Arab Emirates United Kin...
23 Vanuatu Vatican City Venezuela Vietnam British...
24 Wallis and Futuna
25 Yemen
26 Zambia Zimbabwe , 0
1

```



```

0 A Abkhazia Afghanistan Akrotiri and Dhekelia Åla...
1 B The Bahamas Bahrain Bangladesh Barbados Belaru...
2 C Cambodia Cameroon Canada Cape Verde Cayman Isl...
3 D Denmark Dhekelia Djibouti Dominica Dominican R...
4 E East Timor Ecuador Egypt El Salvador Equatoria...
5 F Falkland Islands Faroe Islands Fiji Finland Fr...
6 G Gabon The Gambia Georgia Germany Ghana Gibralt...
7 H Haiti Honduras Hong Kong Hungary
8 I Iceland India Indonesia Iran Iraq Ireland Isra...
9 J Jamaica Japan Jersey Jordan
10 K Kazakhstan Kenya Kiribati North Korea South Ko...
11 L Laos Latvia Lebanon Lesotho Liberia Libya Liec...
12 M Macau Macedonia, Republic of Madagascar Malawi...
13 N Namibia Nauru Nepal Netherlands Netherlands An...
14 O Oman
15 P Pakistan Palau Palestine Panama Papua New Guin...
16 Q Qatar
17 R Romania Russia Rwanda
18 S Sahrawi Arab Democratic Republic Saint Barthél...
19 T Taiwan Tajikistan Tanzania Thailand Togo Tokel..., 0
1
0 U Uganda Ukraine United Arab Emirates United Kin...
1 V Vanuatu Vatican City Venezuela Vietnam British...
2 W Wallis and Futuna
3 Y Yemen
4 Z Zambia Zimbabwe, vteAi
rlines of the United States \
0 Mainline
1 Regional
2 Affiliated
3 Independent
4 Cargo
5 Charter
6 Air taxi and tours
7 Air ambulance
8 Government
9 List of airline holding companies List of airl...

vteAirlines of the United States.1
0 Alaska Airlines Allegiant Air American Airline...
1 Affiliated Air Wisconsin CommutAir Endeavor Ai...
2 Air Wisconsin CommutAir Endeavor Air Envoy Air...
3 Advanced Air Air Flamenco Air Sunshine Bering ...
4 ABX Air Air Cargo Carriers Air Transport Inter...
5 Air Charter Bahamas Airstream Jets Alerion Avi...
6 Gem Air Grand Canyon Scenic Airlines Griffing ...
7 Air Evac Lifeteam AirMed International Air Met...
8 Comco Janet JPATS Patriot Express
9 List of airline holding companies List of airl... , 0
1
0 Affiliated Air Wisconsin CommutAir Endeavor Air Envoy Air...
1 Independent Advanced Air Air Flamenco Air Sunshine Bering ...,
vteList of airlines of the Americas \
0 United States and Canada Latin America and the...
1 Latin America Hispanic North America Northern ...
2 Sovereign states
3 Dependencies and other territories

vteList of airlines of the Americas.1 \
0 United States and Canada Latin America and the...
1 Latin America Hispanic North America Northern ...
2 Antigua and Barbuda Argentina Bahamas Barbados...
3 Anguilla Aruba Bermuda Bonaire British Virgin ...

```

```

      vteList of airlines of the Americas.2
0  United States and Canada Latin America and the...
1                                     NaN
2                                     NaN
3                                     NaN ,
0                                     1
0  Authority control: National libraries  Israel United States]
```

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

Out[25]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932	Fou Airw com (
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997	Fou Exp com
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926	Fou A Airw com
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987	bus A
4	Breeze Airways	NaN	MX	MXY	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018	
5	Delta Air Lines	NaN	DL	DAL	DELTA	AtlantaBostonDetroitLos AngelesMinneapolis/St....	1924	Fou Hufi Dus com
6	Eastern Airlines	NaN	2D	EAL	EASTERN	MiamiNew York-JFK	2010	
7	Frontier Airlines	NaN	F9	FFT	FRONTIER FLIGHT	DenverAtlantaChicago-O'HareCincinnatiCleveland...	1994	
8	Hawaiian Airlines	NaN	HA	HAL	HAWAIIAN	HonoluluKahului	1929	Fou Inte Ai early
9	JetBlue	NaN	B6	JBU	JETBLUE	New York-JFKBostonLos AngelesFort LauderdaleOr...	1998	Fou New com op
10	Southwest Airlines	NaN	WN	SWA	SOUTHWEST	LoveAtlantaBaltimoreChicago-MidwayDenve...	1967	Fou Air So com (
11	Spirit Airlines	NaN	NK	NKS	SPIRIT WINGS	Atlantic CityDetroitLas VegasFort LauderdaleCh...	1980	Fou Char
12	Sun Country Airlines	NaN	SY	SCX	SUN COUNTRY	Minneapolis/St. PaulDallas/Fort WorthLas Vegas	1982	Com opera 1983.C som
13	United Airlines	NaN	UA	UAL	UNITED	Chicago-O'HareDenverGuamHouston-	1926	Fou Va

Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded
					Intercontinent...	Li com

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

Out[26]:

	Airline	Image	IATA	ICAO	Callsign	Primary Hubs, Secondary Hubs	Founded	Notes
0	Comco		NaN	NaN	NaN	NaN	2002	NaN
1	Janet		NaN	NaN	WWW	JANET	Las Vegas	1972
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	
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932.0	A
1	Allegiant Air	NaN	G4	AAY	ALLEGiant	Las VegasCincinnatiFort Walton BeachIndianapol...	1997.0	E
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926.0	A
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987.0	I
4	Breeze Airways	NaN	MX	MXV	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018.0	
...	...	...	...	...	...	...	...	...
136	Lifestar	NaN	NaN	NaN	NaN	NaN	NaN	
137	Life Lion	NaN	NaN	NaN	NaN	NaN	NaN	
138	Comco	NaN	NaN	NaN	NaN	NaN	2002.0	
139	Janet	NaN	NaN	WWW	JANET	NaN	1972.0	
140	Justice Prisoner and Alien Transportation System	NaN	NaN	JUD	JUSTICE	NaN	1980.0	C

141 rows × 9 columns



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

```
In [30]: # 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
...	...	...
136	NaN	NaN
137	NaN	NaN
138	NaN	2002.0
139	NaN	1972.0
140	NaN	1980.0

141 rows × 2 columns

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

In [32]: df

Out[32]:

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

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](https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States)

```
In [33]: # 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]: print(table)
```

	Rank(2021)	Airports (large hubs)	IATACode	\
0	1	Hartsfield-Jackson Atlanta International Airport	ATL	
1	2	Dallas/Fort Worth International Airport	DFW	
2	3	Denver International Airport	DEN	
3	4	O'Hare International Airport	ORD	
4	5	Los Angeles International Airport	LAX	
5	6	Charlotte Douglas International Airport	CLT	
6	7	Orlando International Airport	MCO	
7	8	Harry Reid International Airport	LAS	
8	9	Phoenix Sky Harbor International Airport	PHX	
9	10	Miami International Airport	MIA	
10	11	Seattle-Tacoma International Airport	SEA	
11	12	George Bush Intercontinental Airport	IAH	
12	13	John F. Kennedy International Airport	JFK	
13	14	Newark Liberty International Airport	EWR	
14	15	Fort Lauderdale-Hollywood International Airport	FLL	
15	16	Minneapolis-Saint Paul International Airport	MSP	
16	17	San Francisco International Airport	SFO	
17	18	Detroit Metropolitan Airport	DTW	
18	19	Logan International Airport	BOS	
19	20	Salt Lake City International Airport	SLC	
20	21	Philadelphia International Airport	PHL	
21	22	Baltimore/Washington International Airport	BWI	
22	23	Tampa International Airport	TPA	
23	24	San Diego International Airport	SAN	
24	25	LaGuardia Airport	LGA	
25	26	Midway International Airport	MDW	
26	27	Nashville International Airport	BNA	
27	28	Washington Dulles International Airport	IAD	
28	29	Ronald Reagan Washington National Airport	DCA	
29	30	Austin-Bergstrom International Airport	AUS	

	Major cities served	State	2021[3]	2020[4]	2019[5]	\
0	Atlanta	GA	36676010	20559866	53505795	
1	Dallas & Fort Worth	TX	30005266	18593421	35778573	
2	Denver	CO	28645527	16243216	33592945	
3	Chicago	IL	26350976	14606034	40871223	
4	Los Angeles	CA	23663410	14055777	42939104	
5	Charlotte	NC	20900875	12952869	24199688	
6	Orlando	FL	19618838	10467728	24562271	
7	Las Vegas	NV	19160342	10584059	24728361	
8	Phoenix	AZ	18940287	10531436	22433552	
9	Miami	FL	17500096	8786007	21421031	
10	Seattle	WA	17430195	9462411	25001762	
11	Houston	TX	16242821	8682558	21905309	
12	New York City	NY	15273342	8269819	31036655	
13	Newark & New York City	NJ	14514049	7985474	23160763	
14	Fort Lauderdale & Hollywood	FL	13598994	8015744	17950989	
15	Minneapolis & Saint Paul	MN	12211409	7069720	19192917	
16	San Francisco	CA	11725347	7745057	27779230	
17	Detroit	MI	11517696	6822324	18143040	
18	Boston	MA	10909817	6035452	20699377	
19	Salt Lake City	UT	10795906	5753239	12840841	
20	Philadelphia	PA	9820222	5753239	16006389	
21	Baltimore & Washington, D.C.	MD	9253561	5451355	13284687	
22	Tampa	FL	8847197	4966775	10978756	
23	San Diego	CA	7836360	4637856	12648692	
24	New York City	NY	7827307	4147116	15393601	
25	Chicago	IL	7680617	4236603	10081781	
26	Nashville	TN	7594049	4013995	8935654	
27	Washington, D.C.	VA	7227875	3862658	11884117	
28	Washington, D.C.	VA	6731737	3573489	11595454	
29	Austin	TX	6666215	3141505	8683711	



	2018[6]	2017[7]	2016[8]	2015[9]	2014[10]	2013[11]	2012[12]	
0	51865797	50251964	50501858	49340732	46604273	45308407	45798928	
1	32821799	31816933	31283579	31589839	30804567	29038128	28022904	
2	31362941	29809097	28267394	26280043	26000591	25496885	25799841	
3	39873927	38593028	37589899	36305668	33843426	32317835	32171795	
4	42624050	41232432	39636042	36351272	34314197	32425892	31326268	
5	22281949	22011251	21511880	21913166	21537725	21346601	20033816	
6	23202480	21565448	20283541	18759938	17278608	16884524	17159427	
7	23795012	23364393	22833267	21857693	20620248	19946179	19959651	
8	21622580	21185458	20896265	21351504	20344867	19525109	19560870	
9	21021640	20709225	20875813	20986349	19471466	19420089	18987488	
10	24024908	22639124	21887110	20148980	17888080	16690295	16121123	
11	21157398	19603731	20062072	20595881	19772087	18952840	19039000	
12	30620769	29533154	29239151	27782369	26244928	25036358	24520981	
13	22797602	21571198	19923009	18684818	17773405	17546506	17055993	
14	17612331	15817043	14263270	13061632	12031860	11538140	11445103	
15	18361942	18409704	18123844	17634273	16972678	16280835	15943878	
16	27790717	26900048	25707101	24190560	22770783	21704626	21284236	
17	17436837	17036092	16847135	16255520	15775941	15683523	15599879	
18	20006521	18759742	17759044	16290362	15507561	14810153	14293695	
19	12226730	11615954	11143738	10634538	10139065	9668048	9579840	
20	15292670	14271243	14564419	15101349	14792339	14727945	14589337	
21	13371816	12976554	12340972	11738845	11022200	11132731	11186444	
22	10368514	9548580	9194994	9150458	8531561	8267752	8218487	
23	12174224	11139933	10340164	9985763	9333152	8878772	8686621	
24	15058501	14614802	14762593	14319924	13535372	13372269	12818717	
25	10678018	10912074	11044387	10830850	10311996	9915646	9436387	
26	8017347	6902771	6338517	5715205	5396958	5050989	4797102	
27	11621623	11024306	10596942	10363974	10415948	10570993	10816216	
28	11367176	11506310	11470854	11242375	10057794	9838034	9462231	
29	7921797	6973115	6095545	5797547	5219982	4900959	4606252	Ra
nk(2021)								
Airports (medium hubs) IATACode \								
0	31					Dallas Love Field	DAL	
1	32		Daniel K. Inouye International Airport			HNL		
2	33		Portland International Airport			PDX		
3	34		William P. Hobby Airport			HOU		
4	35		Southwest Florida International Airport			RSW		
5	36		St. Louis Lambert International Airport			STL		
6	37		Sacramento International Airport			SMF		
7	38		Luis Muñoz Marín International Airport			SJU		
8	39		Raleigh-Durham International Airport			RDU		
9	40	Louis Armstrong New Orleans International Airport				MSY		
10	41		Oakland International Airport			OAK		
11	42		John Wayne Airport			SNA		
12	43		Kansas City International Airport			MCI		
13	44		San Antonio International Airport			SAT		
14	45	Norman Y. Mineta San José International Airport				SJC		
15	46		Cleveland Hopkins International Airport			CLE		
16	47		Indianapolis International Airport			IND		
17	48		Pittsburgh International Airport			PIT		
18	49	Cincinnati/Northern Kentucky International Air...				CVG		
19	50		Kahului Airport			OGG		
20	51		John Glenn Columbus International Airport			CMH		
21	52		Palm Beach International Airport			PBI		
22	53		Jacksonville International Airport			JAX		
23	54		Bradley International Airport			BDL		
24	55		Milwaukee Mitchell International Airport			MKE		
25	56		Ontario International Airport			ONT		
26	57		Ted Stevens Anchorage International Airport			ANC		
27	58		Charleston International Airport			CHS		
28	59		Hollywood Burbank Airport			BUR		
29	60		Eppeley Airfield			OMA		
30	61		Boise Airport			BOI		
31	62		Memphis International Airport			MEM		

32	63	Reno-Tahoe International Airport	RNO
33	64	Albuquerque International Sunport	ABQ
34	65	Norfolk International Airport	ORF

	City served	State	2021[3]	2020[4]	2019[5]	2018[6]	\
0	Dallas	TX	6487563	3669930	8408457	8134848	
1	Honolulu	HI	5830928	3126391	9988678	9578505	
2	Portland	OR	5759879	3455877	9797408	9940866	
3	Houston	TX	5560780	3127178	7069614	6937061	
4	Fort Myers	FL	5080805	2947139	5144467	4719568	
5	St. Louis	MO	5070471	3041765	7946986	7822274	
6	Sacramento	CA	4760275	2710342	6454413	6031630	
7	San Juan	PR	4738725	2362851	4590117	4033412	
8	Raleigh	NC	4311049	2337496	6919429	6416822	
9	New Orleans	LA	4017147	2632606	6717105	6565482	
10	Oakland	CA	4011953	2271294	6560230	6798321	
11	Orange County	CA	3807205	1824836	5153276	5317149	
12	Kansas City	MO	3795290	2167616	5759419	5935131	
13	San Antonio	TX	3677643	1919958	5022980	4844427	
14	San Jose	CA	3619690	2283186	7828885	7140616	
15	Cleveland	OH	3552402	1990156	4894541	4836580	
16	Indianapolis	IN	3487100	1989126	4709183	4695040	
17	Pittsburgh	PA	3069259	1742406	4715947	4670033	
18	Cincinnati & Covington	OH/KY	3050597	1729395	4413457	4269258	
19	Kahului	HI	2933315	1135141	3791807	3572133	
20	Columbus	OH	2825259	1577596	4172067	4054572	
21	West Palm Beach	FL	2567897	1518732	3460429	3263042	
22	Jacksonville	FL	2425685	1367501	3479923	3118540	
23	Hartford	CT	2273259	1150033	3323614	3330734	
24	Milwaukee	WI	2231010	1263385	3374073	3548817	
25	Ontario	CA	2201528	1237946	2723002	2499171	
26	Anchorage	AK	2184959	1157301	2713843	2642901	
27	Charleston	SC	2015277	944660	2375868	2192893	
28	Burbank	CA	1942417	1056838	2988720	2680240	
29	Omaha	NE	1829912	1036245	2455274	2457087	
30	Boise	ID	1809000	991241	2057750	1943181	
31	Memphis	TN	1793073	1015981	2318442	2213083	
32	Reno	NV	1781785	976937	2162250	2048916	
33	Albuquerque	NM	1688646	868922	2641450	2647269	
34	Norfolk	VA	1658024	884882	1990864	1846031	

	2017[7]	2016[8]	2015[9]	2014[10]	2013[11]	2012[12]
0	7876769	7554596	7040921	4522341	4023779	3902628
1	9743989	9656340	9656340	9463000	9466995	9225848
2	9435473	9071154	8340234	7878760	7452603	7142620
3	6741870	6285181	5937944	5800726	5377050	5043737
4	4461304	4350650	4231134	4025959	3788870	3634152
5	7372805	6793076	6239231	6108758	6216104	6208750
6	5460526	4969366	4816440	4384616	4255145	4357899
7	4163587	4343354	4218785	4150828	4103197	4204478
8	5851004	5401714	4954717	4673869	4482016	4490374
9	6005527	5569705	5329696	4870569	4576539	4293624
10	6530308	5934639	5506672	5069257	4770716	4926683
11	5195047	5217242	4945175	4584147	4540628	4381172
12	5744918	5391557	5135127	4982722	4836221	4866850
13	4521611	4179994	4091389	4046856	4005874	4036625
14	6225148	5321603	4885690	4621003	4315839	4077654
15	4562740	4205739	4083476	3686315	4375448	4346941
16	4376432	4216766	3889567	3605908	3535015	3586422
17	4327431	3986114	3890677	3827860	3812460	3892338
18	3926158	3269979	3036697	2874684	2776377	2937850
19	3442189	3352813	3220753	3019338	2955304	2861278
20	3765007	3567864	3312496	3115501	3063822	3095575
21	3166532	3100624	3113485	2926242	2844507	2796359

22	2759067	2799587	2716465	2589198	2549070	2579023	
23	3214976	2982194	2926047	2913380	2681181	2647610	
24	3452544	3383271	3229876	3228607	3214811	3710384	
25	2247645	2127387	2089801	2037346	1970538	2142393	
26	2556188	2563524	2525876	2381826	2325030	2249717	
27	1945699	1811695	1669988	1539326	1441415	1283970	
28	2402106	2077892	1973897	1928491	1918011	2027203	
29	2303223	2127387	2046155	2020354	1975339	2018738	
30	1777642	1633507	1487777	1378352	1313741	1307505	
31	2102739	2016089	1873716	1800268	2301003	3359668	
32	1953028	1771864	1669876	1611572	1671926	1685333	
33	2412328	2341719	2323883	2354184	2477783	2630574	
34	1694329	1602631	1515200	1488114	1560754	1651440	, Rank Rank change

Airport name \				Airport name		
	Rank	Rank	change			
0	1		NaN	Hartsfield-Jackson Atlanta International Airport		
1	2		2.0	Dallas/Fort Worth International Airport		
2	3		2.0	Denver International Airport		
3	4		1.0	O'Hare International Airport		
4	5		3.0	Los Angeles International Airport		
5	6		5.0	Charlotte Douglas International Airport		
6	7		2.0	Harry Reid International Airport		
7	8		5.0	Phoenix Sky Harbor International Airport		
8	9		1.0	Orlando International Airport		
9	10		2.0	Seattle-Tacoma International Airport		
10	11		3.0	Miami International Airport		
11	12		3.0	George Bush Intercontinental Airport		
12	13		7.0	John F. Kennedy International Airport		
13	14		5.0	Fort Lauderdale-Hollywood International Airport		
14	15		8.0	San Francisco International Airport		
15	16		4.0	Newark Liberty International Airport		
16	17		NaN	Minneapolis-Saint Paul International Airport		
17	18		NaN	Detroit Metropolitan Airport		
18	19		3.0	General Edward Lawrence Logan International Ai...		
19	20		3.0	Salt Lake City International Airport		
20	21		1.0	Philadelphia International Airport		
21	22		NaN	Baltimore/Washington International Airport		
22	23		4.0	Tampa International Airport		
23	24		NaN	San Diego International Airport		
24	25		4.0	Chicago Midway International Airport		
25	26		1.0	Washington Dulles International Airport		
26	27		4.0	Nashville International Airport		
27	28		7.0	LaGuardia Airport		
28	29		4.0	Dallas Love Field		
29	30		4.0	Ronald Reagan Washington National Airport		
30	31		1.0	Portland International Airport		
31	32		4.0	Daniel K. Inouye International Airport		
32	33		NaN	William P. Hobby Airport		
33	34		2.0	Austin-Bergstrom International Airport		
34	35		1.0	St. Louis Lambert International Airport		

	Location	IATA Code	Traffic	Aircraft	
	Location	IATA Code	Passengers % chg.2019/20	Movements	
0	College Park, Georgia	ATL	42918685	61.2	NaN
1	Irving, Texas	DFW	39364990	47.6	NaN
2	Denver, Colorado	DEN	33741129	51.1	NaN
3	Chicago, Illinois	ORD	30860251	63.5	NaN
4	Los Angeles, California	LAX	28779527	67.3	NaN
5	Charlotte, North Carolina	CLT	27205082	45.8	NaN
6	Paradise, Nevada	LAS	22201479	56.9	NaN
7	Phoenix, Arizona	PHX	21978708	52.5	NaN
8	Orlando, Florida	MCO	21617803	57.3	NaN
9	SeaTac, Washington	SEA	20061507	61.3	NaN
10	Miami, Florida	MIA	18663858	59.4	NaN

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		Harikrishnan_K			
11	Houston, Texas	IAH	18213571	59.8	NaN
12	Queens, New York	JFK	16630642	73.4	NaN
13	Fort Lauderdale, Florida	FLL	16484132	55.1	NaN
14	San Mateo County, California	SFO	16409625	71.5	NaN
15	Newark, New Jersey	EWB	15892892	65.7	NaN
16	Minneapolis, Minnesota	MSP	14851289	59.8	NaN
17	Romulus, Michigan	DTW	14105007	61.6	NaN
18	Boston, Massachusetts	BOS	12618128	70.3	NaN
19	Salt Lake City, Utah	SLC	12559026	53.2	NaN
20	Philadelphia, Pennsylvania	PHL	11865006	64.1	NaN
21	Linthicum Heights, Maryland	BWI	11204511	58.5	NaN
22	Tampa, Florida	TPA	10238151	54.5	NaN
23	San Diego, California	SAN	8991533	64.3	NaN
24	Chicago, Illinois	MDW	8853948	57.5	NaN
25	Dulles, Virginia	IAD	8333460	66.4	NaN
26	Nashville, Tennessee	BNA	8284570	54.7	NaN
27	Queens, New York	LGA	8245192	73.5	NaN
28	Dallas, Texas	DAL	7684653	54.2	NaN
29	Arlington, Virginia	DCA	7574966	68.4	NaN
30	Portland, Oregon	PDX	7084543	64.4	NaN
31	Honolulu, Hawaii	HNL	6656825	69.6	NaN
32	Houston, Texas	HOU	6476309	55.2	NaN
33	Austin, Texas	AUS	6472579	62.7	NaN
34	St Louis, Missouri	STL	6302402	60.3	NaN

% chg.2019/20	
0	0.0
1	NaN
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	NaN
9	NaN
10	NaN
11	NaN
12	NaN
13	NaN
14	NaN
15	NaN
16	NaN
17	NaN
18	NaN
19	NaN
20	NaN
21	NaN
22	NaN
23	NaN
24	NaN
25	NaN
26	NaN
27	NaN
28	NaN
29	NaN
30	NaN
31	NaN
32	NaN
33	NaN
34	NaN , Location of 35 busiest airports in the United States
0 .mw-parser-output .locmap .od{position:absolut... , Rank Rank change	
Airport name \	

	Rank	Rank change	Airport name
0	1	NaN	Hartsfield-Jackson Atlanta International Airport
1	2	NaN	Los Angeles International Airport[13]
2	3	NaN	O'Hare International Airport
3	4	NaN	Dallas/Fort Worth International Airport
4	5	NaN	Denver International Airport
5	6	NaN	John F. Kennedy International Airport[14]
6	7	NaN	San Francisco International Airport
7	8	NaN	Seattle-Tacoma International Airport[15]
8	9	NaN	Harry Reid International Airport[16]
9	10	NaN	Orlando International Airport
10	11	NaN	Charlotte Douglas International Airport
11	12	NaN	Newark Liberty International Airport[17]
12	13	1.0	Phoenix Sky Harbor International Airport[18]
13	14	1.0	Miami International Airport
14	15	NaN	George Bush Intercontinental Airport[19]
15	16	NaN	General Edward Lawrence Logan International Ai...
16	17	NaN	Minneapolis-Saint Paul International Airport[21]
17	18	1.0	Detroit Metropolitan Airport[22]
18	19	1.0	Fort Lauderdale-Hollywood International Airpor...
19	20	NaN	Philadelphia International Airport
20	21	NaN	LaGuardia Airport[24]
21	22	NaN	Baltimore/Washington International Airport
22	23	NaN	Salt Lake City International Airport[25]
23	24	NaN	San Diego International Airport[26]
24	25	NaN	Washington Dulles International Airport
25	26	NaN	Ronald Reagan Washington National Airport
26	27	1.0	Tampa International Airport[27]
27	28	1.0	Daniel K. Inouye International Airport[28]
28	29	2.0	Chicago Midway International Airport
29	30	NaN	Portland International Airport[29]
30	31	1.0	Nashville International Airport[30]
31	32	1.0	Austin-Bergstrom International Airport
32	33	2.0	Dallas Love Field[31]
33	34	NaN	St. Louis Lambert International Airport[32]
34	35	NaN	Norman Y. Mineta San Jose International Airpor...

	Location	IATA Code	Traffic	Aircraft \
	Location	IATA Code	Passengers % chg.2018/19	Movements
0	College Park, Georgia	ATL	110531300	2.3 904301.0
1	Los Angeles, California	LAX	88068013	0.6 691257.0
2	Chicago, Illinois	ORD	84649115	1.7 919704.0
3	Irving, Texas	DFW	75066956	8.6 720007.0
4	Denver, Colorado	DEN	69015703	7.0 640098.0
5	Queens, New York	JFK	62551072	1.5 456060.0
6	San Mateo County, California	SFO	57488023	0.5 458496.0
7	SeaTac, Washington	SEA	51829239	4.0 450487.0
8	Paradise, Nevada	LAS	51537638	3.7 552962.0
9	Orlando, Florida	MCO	50613072	6.1 357689.0
10	Charlotte, North Carolina	CLT	50168783	8.0 578263.0
11	Newark, New Jersey	EWK	46336452	1.0 446320.0
12	Phoenix, Arizona	PHX	46288337	3.0 438891.0
13	Miami, Florida	MIA	45924466	2.0 416773.0
14	Houston, Texas	IAH	45264059	3.3 478070.0
15	Boston, Massachusetts	BOS	42522411	3.9 427176.0
16	Minneapolis, Minnesota	MSP	39555035	4.0 406076.0
17	Romulus, Michigan	DTW	36769279	4.3 396909.0
18	Fort Lauderdale, Florida	FLL	36747622	2.2 331447.0
19	Philadelphia, Pennsylvania	PHL	33018886	4.2 390321.0
20	Queens, New York	LGA	31084894	3.3 373356.0
21	Linthicum Heights, Maryland	BWI	26993896	0.6 262597.0
22	Salt Lake City, Utah	SLC	26808014	4.9 344715.0
23	San Diego, California	SAN	25216947	4.0 231354.0
24	Dulles, Virginia	IAD	24817677	3.1 285042.0

25	Arlington, Virginia	DCA	23945527	1.8	292682.0
26	Tampa, Florida	TPA	22497953	5.7	217360.0
27	Honolulu, Hawaii	HNL	21870691	4.2	326832.0
28	Chicago, Illinois	MDW	20844860	5.4	232084.0
29	Portland, Oregon	PDX	19891365	0.0	238384.0
30	Nashville, Tennessee	BNA	18273434	14.2	NaN
31	Austin, Texas	AUS	17343729	9.6	209726.0
32	Dallas, Texas	DAL	16780158	3.4	231879.0
33	St Louis, Missouri	STL	15878527	1.6	193925.0
34	San Jose, California	SJC	15650444	9.3	207111.0

% chg.2018/19					
0	1.0				
1	2.3				
2	1.8				
3	7.9				
4	6.1				
5	0.1				
6	2.5				
7	2.8				
8	2.4				
9	2.9				
10	5.1				
11	1.6				
12	1.1				
13	0.2				
14	2.4				
15	0.7				
16	0.3				
17	0.8				
18	0.6				
19	2.8				
20	0.4				
21	1.5				
22	2.2				
23	2.8				
24	3.9				
25	0.4				
26	5.0				
27	10.7				
28	4.6				
29	1.9				
30	NaN				
31	0.2				
32	0.3				
33	0.2				
34	19.4	,	Rank Rank change	Airp	

ort name \				Airport name	
Rank	Rank change				
0	1	NaN	Hartsfield-Jackson Atlanta International Airpo...		
1	2	NaN	Los Angeles International Airport[35]		
2	3	NaN	O'Hare International Airport[36]		
3	4	NaN	Dallas/Fort Worth International Airport[37]		
4	5	NaN	Denver International Airport[38]		
5	6	NaN	John F. Kennedy International Airport[39]		
6	7	NaN	San Francisco International Airport[40]		
7	8	1.0	Seattle-Tacoma International Airport[41]		
8	9	1.0	Harry Reid International Airport[42]		
9	10	2.0	Orlando International Airport[43]		
10	11	1.0	Charlotte Douglas International Airport[44]		
11	12	1.0	Newark Liberty International Airport[45]		
12	13	1.0	Miami International Airport[46]		
13	14	1.0	Phoenix Sky Harbor International Airport[47]		

14	15	NaN	George Bush Intercontinental Airport[48]
15	16	NaN	General Edward Lawrence Logan International Ai...
16	17	NaN	Minneapolis-Saint Paul International Airport[50]
17	18	1.0	Fort Lauderdale-Hollywood International Airpor...
18	19	1.0	Detroit Metropolitan Airport[52]
19	20	NaN	Philadelphia International Airport[53]
20	21	NaN	LaGuardia Airport[54]
21	22	NaN	Baltimore/Washington International Airport[55]
22	23	NaN	Salt Lake City International Airport[56]
23	24	2.0	San Diego International Airport[57]
24	25	NaN	Washington Dulles International Airport[58]
25	26	2.0	Ronald Reagan Washington National Airport[59]
26	27	NaN	Chicago Midway International Airport[60]
27	28	NaN	Tampa International Airport[61]
28	29	NaN	Daniel K. Inouye International Airport
29	30	NaN	Portland International Airport[62]
30	31	NaN	Dallas Love Field[63]
31	32	1.0	Nashville International Airport[64]
32	33	1.0	Austin-Bergstrom International Airport[65]
33	34	2.0	St. Louis Lambert International Airport[66]
34	35	NaN	Norman Y. Mineta San Jose International Airpor...

	Location	IATA Code	Traffic	
	Location	IATA Code	Passengers	% chg.2017/18
0	College Park, Georgia	ATL	107394029	3.3
1	Los Angeles, California	LAX	87534384	3.5
2	Chicago, Illinois	ORD	83245472	4.3
3	Irving, Texas	DFW	69112607	3.0
4	Denver, Colorado	DEN	64494613	5.1
5	Queens, New York	JFK	61909148	3.9
6	South San Francisco, California	SFO	57793313	3.5
7	SeaTac, Washington	SEA	49849520	6.2
8	Las Vegas, Nevada	LAS	49716584	2.5
9	Orlando, Florida	MCO	47696627	6.9
10	Charlotte, North Carolina	CLT	46444380	1.2
11	Newark, New Jersey	EWB	46065175	6.6
12	Miami, Florida	MIA	45044312	2.2
13	Phoenix, Arizona	PHX	44943686	2.3
14	Houston, Texas	IAH	43807539	7.6
15	Boston, Massachusetts	BOS	40941925	6.6
16	Minneapolis, Minnesota	MSP	38037381	0.0
17	Fort Lauderdale, Florida	FLL	35963370	10.6
18	Romulus, Michigan	DTW	35236676	1.5
19	Philadelphia, Pennsylvania	PHL	31691956	7.1
20	Queens, New York	LGA	30094074	1.8
21	Linthicum Heights, Maryland	BWI	27145831	2.9
22	Salt Lake City, Utah	SLC	25554244	5.6
23	San Diego, California	SAN	24238300	9.3
24	Dulles, Virginia	IAD	24060709	5.1
25	Arlington, Virginia	DCA	23464618	1.8
26	Chicago, Illinois	MDW	22027737	1.9
27	Tampa, Florida	TPA	21289390	8.5
28	Honolulu, Hawaii	HNL	20990932	1.1
29	Portland, Oregon	PDX	19882788	4.2
30	Dallas, Texas	DAL	16229151	3.2
31	Nashville, Tennessee	BNA	15996194	13.2
32	Austin, Texas	AUS	15819912	13.9
33	St Louis, Missouri	STL	15632586	5.9
34	San Jose, California	SJC	14319292	14.7

Aircraft		
Movements % chg.2017/18		
0	895682	01.7
1	707833	01.1

2	903747	04.2	
3	667213	02.0	
4	603403	03.6	
5	455529	01.6	
6	470164	02.1	
7	438391	05.4	
8	539857	00.6	
9	347672	05.1	
10	550013	00.4	
11	458674	04.6	
12	416032	00.7	
13	434252	00.8	
14	466738	03.6	
15	424024	05.6	
16	407476	02.1	
17	329662	05.4	
18	393681	00.4	
19	379665	02.6	
20	372025	00.8	
21	266569	01.9	
22	337276	03.1	
23	225058	07.5	
24	274281	03.6	
25	293827	00.2	
26	243322	03.2	
27	206938	05.9	
28	295233	5.30	
29	233993	02.2	
30	231110	01.6	
31	216966	05.2	
32	210080	05.2	
33	-	-	
34	173389	011.3	Rank

Airpor

t name \		Rank		Airport name	
0	1	Hartsfield-Jackson Atlanta International Airport			
1	2	Los Angeles International Airport			
2	3	O'Hare International Airport			
3	4	Dallas/Fort Worth International Airport			
4	5	John F. Kennedy International Airport			
5	6	Denver International Airport			
6	7	San Francisco International Airport			
7	8	Harry Reid International Airport			
8	9	Seattle-Tacoma International Airport			
9	10	Miami International Airport			
10	11	Charlotte Douglas International Airport			
11	12	Phoenix Sky Harbor International Airport			
12	13	Orlando International Airport			
13	14	George Bush Intercontinental Airport			
14	15	Newark Liberty International Airport			
15	16	Minneapolis-Saint Paul International Airport			
16	17	General Edward Lawrence Logan International Ai...			
17	18	Detroit Metropolitan Airport			
18	19	Philadelphia International Airport			
19	20	LaGuardia Airport			
20	21	Fort Lauderdale-Hollywood International Airport			
21	22	Baltimore/Washington International Airport			
22	23	Ronald Reagan Washington National Airport			
23	24	Salt Lake City International Airport			
24	25	Chicago Midway International Airport			
25	26	Washington Dulles International Airport			
26	27	San Diego International Airport			
27	28	Honolulu International Airport			
28	29	Tampa International Airport			



29	30	Portland International Airport
30	31	Dallas Love Field
31	32	St. Louis Lambert International Airport
32	33	Nashville International Airport
33	34	William P. Hobby Airport
34	35	Austin-Bergstrom International Airport
35	36	Oakland International Airport

	Location	IATA Code	Traffic	
	Location	IATA Code	Passengers	% chg.2015/16
0	College Park, Georgia	ATL	104171935	02.6
1	Los Angeles, California	LAX	80921527	08.0
2	Chicago, Illinois	ORD	77960588	01.3
3	Irving, Texas	DFW	65670697	00.2
4	Queens, New York	JFK	59105513	03.9
5	Denver, Colorado	DEN	58266515	07.9
6	South San Francisco, California	SFO	53099282	06.1
7	Las Vegas, Nevada	LAS	47496614	04.5
8	SeaTac, Washington	SEA	45736700	08.0
9	Miami, Florida	MIA	44584603	00.5
10	Charlotte, North Carolina	CLT	44422022	01.0
11	Phoenix, Arizona	PHX	43302381	01.6
12	Orlando, Florida	MCO	41923399	08.0
13	Houston, Texas	IAH	41622594	03.3
14	Newark, New Jersey	EWR	40563285	08.2
15	Minneapolis, Minnesota	MSP	37413728	02.3
16	Boston, Massachusetts	BOS	36356917	08.5
17	Romulus, Michigan	DTW	34401254	02.9
18	Philadelphia, Pennsylvania	PHL	30155090	04.1
19	Queens, New York	LGA	29786769	04.7
20	Fort Lauderdale, Florida	FLL	29205002	08.4
21	Linthicum Heights, Maryland	BWI	25122651	05.4
22	Arlington, Virginia	DCA	23568586	02.4
23	Salt Lake City, Utah	SLC	23157445	04.5
24	Chicago, Illinois	MDW	22677859	02.1
25	Dulles, Virginia	IAD	21817340	01.5
26	San Diego, California	SAN	20725801	03.2
27	Honolulu, Hawaii	HNL	19878659	- 00.0
28	Tampa, Florida	TPA	18931922	00.6
29	Portland, Oregon	PDX	18352767	08.9
30	Dallas, Texas	DAL	15562738	07.3
31	St Louis, Missouri	STL	13959126	09.5
32	Nashville, Tennessee	BNA	12979803	011.2
33	Houston, Texas	HOU	12909075	06.1
34	Austin, Texas	AUS	12436849	04.5
35	Oakland, California	OAK	12070967	07.7

	Aircraft	
	Movements	% chg.2015/16
0	898356	01.8
1	697138	06.3
2	867635	00.9
3	672748	01.3
4	452415	03.0
5	565503	04.5
6	450388	04.8
7	541428	02.1
8	412170	08.1
9	414234	00.3
10	545742	00.3
11	440643	00.1
12	316981	02.9
13	470780	06.4
14	435907	05.3

15	412872	02.0	
16	372930	02.5	
17	393427	03.7	
18	394022	04.2	
19	369987	02.7	
20	290239	04.4	
21	248585	00.9	
22	295038	00.8	
23	320137	02.7	
24	253046	00.2	
25	265743	01.5	
26	197132	01.5	
27	316154	01.1	
28	—	—	
29	227709	04.4	
30	224193	03.7	
31	190560	02.5	
32	194758	05.6	
33	200741	00.1	
34	192032	00.4	
35	222771	03.3	Rank

Airpo

rt	name \	
0	1	John F. Kennedy International Airport
1	2	Miami International Airport
2	3	Los Angeles International Airport
3	4	George Bush Intercontinental Airport
4	5	Newark Liberty International Airport
5	6	Dallas/Fort Worth International Airport
6	7	Hartsfield-Jackson Atlanta International Airport
7	8	O'Hare International Airport
8	9	Fort Lauderdale-Hollywood International Airport
9	10	Washington Dulles International Airport
10	11	San Francisco International Airport
11	12	General Edward Lawrence Logan International Ai...
12	13	Charlotte Douglas International Airport
13	14	Denver International Airport
14	15	Orlando International Airport
15	16	Seattle-Tacoma International Airport
16	17	Phoenix Sky Harbor International Airport
17	18	Philadelphia International Airport
18	19	Detroit Metropolitan Wayne County Airport
19	20	Harry Reid International Airport

	Location	IATA Code	2021[68]	2020[69]	2019[70]
0	Queens, New York	JFK	12466165	8219317	33432159
1	Miami, Florida	MIA	11592445	6565834	20735658
2	Los Angeles, California	LAX	7862532	6246602	25210140
3	Houston, Texas	IAH	6458473	3491935	10764589
4	Newark, New Jersey	EWB	6250880	3688541	14087622
5	Irving, Texas	DFW	5852397	3268822	9103438
6	College Park, Georgia	ATL	5474264	3347184	12268779
7	Chicago, Illinois	ORD	5148494	3481860	13412885
8	Fort Lauderdale, Florida	FLL	4016553	2839383	8524251
9	Dulles, Virginia	IAD	3230027	1917510	7990292
10	South San Francisco, California	SFO	3139041	3210024	14357960
11	Boston, Massachusetts	BOS	2046561	1574712	7534504
12	Charlotte, North Carolina	CLT	1989704	1069001	3405907
13	Denver, Colorado	DEN	1856124	934563	3037012
14	Orlando, Florida	MCO	1837706	1525177	6957048
15	SeaTac, Washington	SEA	1393603	1273179	5392147
16	Phoenix, Arizona	PHX	1223856	750138	1958468
17	Philadelphia, Pennsylvania	PHL	988733	682030	3847253
18	Romulus, Michigan	DTW	966375	873744	3717775
19	Paradise, Nevada	LAS	738257	711614	3462627

, R

ank		Airport name \		
Rank		Airport name		
0	1	Memphis International Airport		
1	2	Ted Stevens Anchorage International Airport		
2	3	Louisville Muhammad Ali International Airport		
3	4	O'Hare International Airport		
4	5	Miami International Airport		
5	6	Los Angeles International Airport		
6	7	Cincinnati/Northern Kentucky International Air...		
7	8	Indianapolis International Airport		
8	9	Dallas/Fort Worth International Airport		
9	10	Ontario International Airport		

		Location	IATA code	Cargo	
		Location	IATA code	Ibs.	% chg.2017/16
0		Memphis, Tennessee	MEM	23949525780	00.35%
1		Anchorage, Alaska	ANC	17337337377	02.79%
2		Louisville, Kentucky	SDF	13403682652	04.68%
3		Chicago, Illinois	ORD	10373559593	010.84%
4		Miami, Florida	MIA	7963988407	00.82%
5		Los Angeles, California	LAX	7197930264	03.85%
6		Hebron, Kentucky	CVG	5700282994	033.32%
7		Indianapolis, Indiana	IND	5138500318	0-3.58%
8		Irving, Texas	DFW	4155362297	07.65%
9		Ontario, California	ONT	3522510318	015.81%

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height:inherit}.mw-parser-output .navbar-brackets::before{margin-right:-0.125em;co  
ntent:"[ "}.mw-parser-output .navbar-brackets::after{margin-left:-0.125em;conten  
t:" ]"}.mw-parser-output .navbar li{word-spacing:-0.125em}.mw-parser-output .navba  
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e;cursor:inherit}.mw-parser-output .navbar-ct-full{font-size:114%;margin:0 7em}.mw  
-parser-output .navbar-ct-mini{font-size:114%;margin:0 4em}vteMajor airports in th  
e United States \

0 Atlanta (Hartsfield-Jackson - ATL) Austin (Aus...  
1 Statistics

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ce:nowrap;line-height:inherit}.mw-parser-output .navbar-brackets::before{margin-ri  
ght:-0.125em;content:"[ "}.mw-parser-output .navbar-brackets::after{margin-left:-  
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decoration:none;cursor:inherit}.mw-parser-output .navbar-ct-full{font-size:114%;ma  
rgin:0 7em}.mw-parser-output .navbar-ct-mini{font-size:114%;margin:0 4em}vteMajor  
airports in the United States.1

0 Atlanta (Hartsfield-Jackson - ATL) Austin (Aus...  
1 Statistics

, vteList of the busiest airports in North America \

0 Sovereign states

1 Dependencies andother territories

vteList of the busiest airports in North America.1

0 Antigua and Barbuda Bahamas Barbados Belize Ca...  
1 Anguilla Aruba Bermuda Bonaire British Virgin ... , vteLists of the bus  
iest airports by continent \

0 Africa Asia Europe North America Oceania South...

vteLists of the busiest airports by continent.1

0 Africa Asia Europe North America Oceania South... , vte

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Aviation statistics \
0 Airports worldwide
1 Busiest airports by continent and country
2 Africa
3 Asia
4 Europe
5 North America
6 Oceania
7 South America
8 By region
9 Airlines
10 Routes

vteAviation statistics.1
0 Busiest airports by continent By aircraft move...
1 Africa Morocco South Africa Asia China (exclud...
2 Morocco South Africa
3 China (excluding Hong Kong and Macau) India In...
4 Austria Belgium Bulgaria Croatia France German...
5 Canada Dominican Republic Mexico United States...
6 Australia New Zealand
7 Argentina Brazil Chile Colombia Ecuador Paragu...
8 Baltic Caribbean Central America Latin America...
9 World's largest airlines Airline holding compa...
10 Busiest passenger air routes General aviation ... , 0

1
0 Africa Morocco South Africa
1 Asia China (excluding Hong Kong and Macau) India In...
2 Europe Austria Belgium Bulgaria Croatia France German...
3 North America Canada Dominican Republic Mexico United States...
4 Oceania Australia New Zealand
5 South America Argentina Brazil Chile Colombia Ecuador Paragu...
6 By region Baltic Caribbean Central America Latin America...]
```

```
In [35]: table[0].head()
```

Out[35]:

	Rank(2021)	Airports (large hubs)	IATACode	Major cities served	State	2021[3]	2020[4]	2019[5]	2018[6]
0	1	Hartsfield– Jackson Atlanta International Airport	ATL	Atlanta	GA	36676010	20559866	53505795	51865797
1	2	Dallas/Fort Worth International Airport	DFW	Dallas & Fort Worth	TX	30005266	18593421	35778573	32821799
2	3	Denver International Airport	DEN	Denver	CO	28645527	16243216	33592945	31362941
3	4	O'Hare International Airport	ORD	Chicago	IL	26350976	14606034	40871223	39873927
4	5	Los Angeles International Airport	LAX	Los Angeles	CA	23663410	14055777	42939104	42624050

```
In [36]: table[0]['hubs'] = str('large_hub')
         table[0] = table[0][['IATACode', 'hubs']]
```

```
In [37]: table[0]
```

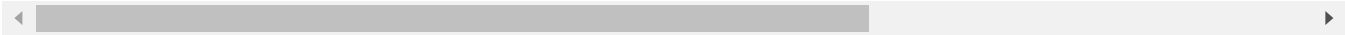
Out[37]:

	IATACode	hubs
0	ATL	large_hub
1	DFW	large_hub
2	DEN	large_hub
3	ORD	large_hub
4	LAX	large_hub
5	CLT	large_hub
6	MCO	large_hub
7	LAS	large_hub
8	PHX	large_hub
9	MIA	large_hub
10	SEA	large_hub
11	IAH	large_hub
12	JFK	large_hub
13	EWR	large_hub
14	FLL	large_hub
15	MSP	large_hub
16	SFO	large_hub
17	DTW	large_hub
18	BOS	large_hub
19	SLC	large_hub
20	PHL	large_hub
21	BWI	large_hub
22	TPA	large_hub
23	SAN	large_hub
24	LGA	large_hub
25	MDW	large_hub
26	BNA	large_hub
27	IAD	large_hub
28	DCA	large_hub
29	AUS	large_hub

```
In [38]: table[1].head()
```

Out[38]:

	Rank(2021)	Airports (medium hubs)	IATACode	City served	State	2021[3]	2020[4]	2019[5]	2018[6]	2017[7]
0	31	Dallas Love Field	DAL	Dallas	TX	6487563	3669930	8408457	8134848	787
1	32	Daniel K. Inouye International Airport	HNL	Honolulu	HI	5830928	3126391	9988678	9578505	974
2	33	Portland International Airport	PDX	Portland	OR	5759879	3455877	9797408	9940866	943
3	34	William P. Hobby Airport	HOU	Houston	TX	5560780	3127178	7069614	6937061	674
4	35	Southwest Florida International Airport	RSW	Fort Myers	FL	5080805	2947139	5144467	4719568	446



```
In [39]: table[1]['hubs'] = str('Medium_hub')
```

```
In [40]: table[1] = table[1][['IATACode', 'hubs']]
table[1]
```

Out[40]:

	IATACode	hubs
0	DAL	Medium_hub
1	HNL	Medium_hub
2	PDX	Medium_hub
3	HOU	Medium_hub
4	RSW	Medium_hub
5	STL	Medium_hub
6	SMF	Medium_hub
7	SJU	Medium_hub
8	RDU	Medium_hub
9	MSY	Medium_hub
10	OAK	Medium_hub
11	SNA	Medium_hub
12	MCI	Medium_hub
13	SAT	Medium_hub
14	SJC	Medium_hub
15	CLE	Medium_hub
16	IND	Medium_hub
17	PIT	Medium_hub
18	CVG	Medium_hub
19	OGG	Medium_hub
20	CMH	Medium_hub
21	PBI	Medium_hub
22	JAX	Medium_hub
23	BDL	Medium_hub
24	MKE	Medium_hub
25	ONT	Medium_hub
26	ANC	Medium_hub
27	CHS	Medium_hub
28	BUR	Medium_hub
29	OMA	Medium_hub
30	BOI	Medium_hub
31	MEM	Medium_hub
32	RNO	Medium_hub
33	ABQ	Medium_hub
34	ORF	Medium_hub

```
In [41]: # Lets first merge all wikipedia table.  
wiki_data = [table[0],table[1]]
```

```
In [42]: wiki_data = pd.concat(wiki_data, ignore_index=True)
```

```
In [43]: wiki_data
```

Out[43]:

	IATACode	hubs
0	ATL	large_hub
1	DFW	large_hub
2	DEN	large_hub
3	ORD	large_hub
4	LAX	large_hub
...	...	...
60	BOI	Medium_hub
61	MEM	Medium_hub
62	RNO	Medium_hub
63	ABQ	Medium_hub
64	ORF	Medium_hub

65 rows × 2 columns

```
In [44]: # Now we gather all the information that we got from wiki pedia link and the data  
final_df = df.merge(wiki_data, left_on ='iata_code', right_on = "IATACode")
```

```
In [45]: final_df
```

Out[45]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident
0	4	AA	2466	SFO	DFW	3	20	195	1	KSFO
1	231	AA	526	SFO	DFW	3	360	215	0	KSFO
2	234	AA	552	SFO	MIA	3	360	315	1	KSFO
3	905	AA	810	SFO	ORD	3	385	255	0	KSFO
4	1739	AA	24	SFO	JFK	3	425	325	1	KSFO
...	...	...	...	...	...	...	...	...	...	...
364272	506267	9E	4052	DAL	MEM	4	370	90	0	KDAL
364273	512858	9E	3704	DAL	MEM	4	705	92	1	KDAL
364274	518247	9E	4060	DAL	MEM	4	990	90	0	KDAL
364275	524678	9E	4052	DAL	MEM	5	370	90	1	KDAL
364276	530841	9E	3704	DAL	MEM	5	705	92	0	KDAL

364277 rows × 28 columns



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

In [46]: *# Now we have the final data first we remove some column that is not useable.*  
final\_df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364277 entries, 0 to 364276
Data columns (total 28 columns):
#   Column                Non-Null Count  Dtype
---  -
0   id                     364277 non-null  int64
1   Airline                364277 non-null  object
2   Flight                 364277 non-null  int64
3   AirportFrom            364277 non-null  object
4   AirportTo              364277 non-null  object
5   DayOfWeek              364277 non-null  int64
6   Time                   364277 non-null  int64
7   Length                 364277 non-null  int64
8   Delay                  364277 non-null  int64
9   ident                  364277 non-null  object
10  type                   364277 non-null  object
11  name                   364277 non-null  object
12  latitude_deg           364277 non-null  float64
13  longitude_deg          364277 non-null  float64
14  elevation_ft           364277 non-null  float64
15  scheduled_service      364277 non-null  object
16  iata_code              364277 non-null  object
17  airport_ref            364277 non-null  int64
18  airport_ident          364277 non-null  object
19  length_ft              364277 non-null  float64
20  width_ft               364277 non-null  float64
21  surface                 364277 non-null  object
22  lighted                364277 non-null  int64
23  closed                 364277 non-null  int64
24  IATA                   364277 non-null  object
25  Founded                364277 non-null  float64
26  IATACode               364277 non-null  object
27  hubs                   364277 non-null  object
dtypes: float64(6), int64(9), object(13)
memory usage: 80.6+ MB
```

In [47]: final\_df = final\_df.drop(['id', 'AirportFrom', 'airport\_ident', 'iata\_code', 'AirportTo', 'IATA', 'IATACode', 'name'], axis=1)

In [48]: final\_df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364277 entries, 0 to 364276
Data columns (total 18 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Airline                364277 non-null object
1   Flight                 364277 non-null int64
2   DayOfWeek              364277 non-null int64
3   Time                   364277 non-null int64
4   Length                 364277 non-null int64
5   Delay                  364277 non-null int64
6   type                   364277 non-null object
7   latitude_deg           364277 non-null float64
8   longitude_deg           364277 non-null float64
9   elevation_ft           364277 non-null float64
10  scheduled_service       364277 non-null object
11  airport_ref             364277 non-null int64
12  length_ft               364277 non-null float64
13  width_ft                364277 non-null float64
14  lighted                 364277 non-null int64
15  closed                  364277 non-null int64
16  Founded                 364277 non-null float64
17  hubs                    364277 non-null object
dtypes: float64(6), int64(8), object(4)
memory usage: 52.8+ MB
```

```
In [49]: # Now Lets check the null value and treat them.
final_df.isnull().sum()
```

```
Out[49]: 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
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 [50]: final_df = final_df.dropna(axis=0)
```

```
In [51]: final_df.head()
```

Out[51]:

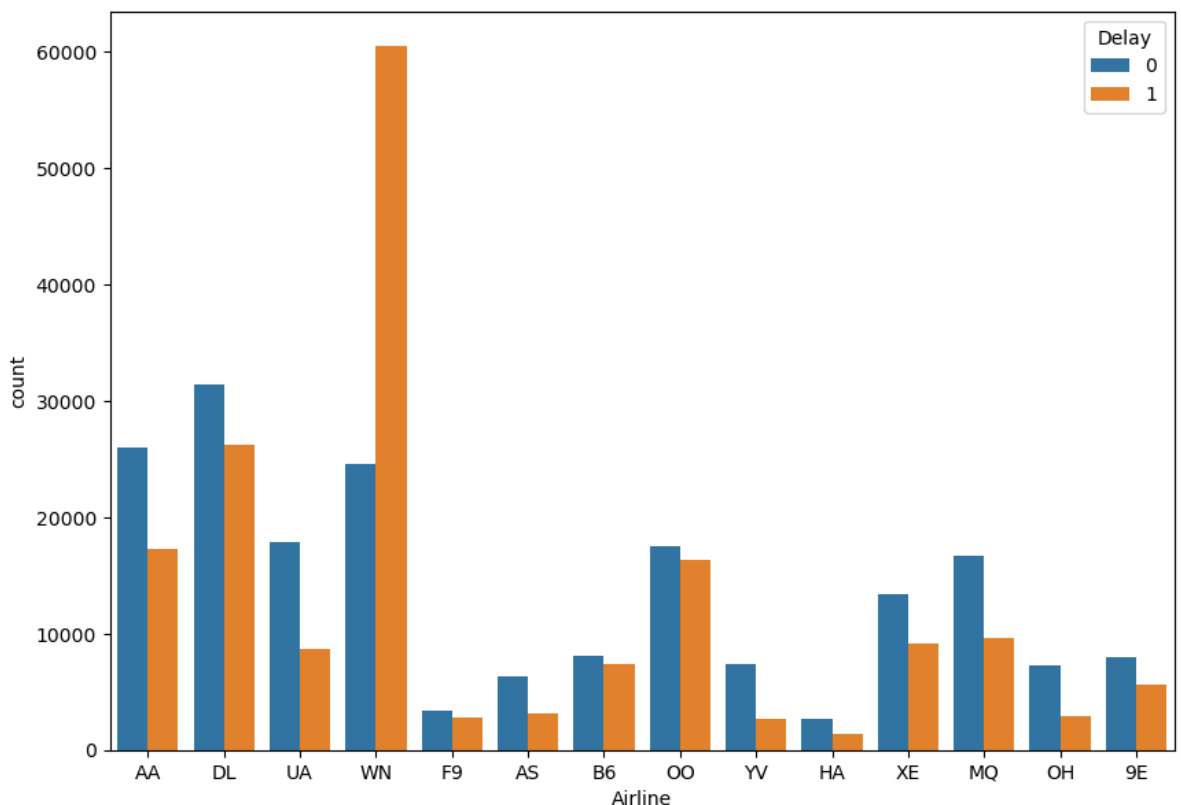
	Airline	Flight	DayOfWeek	Time	Length	Delay	type	latitude_deg	longitude_deg	el
0	AA	2466	3	20	195	1	large_airport	37.618999	-122.375	
1	AA	526	3	360	215	0	large_airport	37.618999	-122.375	
2	AA	552	3	360	315	1	large_airport	37.618999	-122.375	
3	AA	810	3	385	255	0	large_airport	37.618999	-122.375	
4	AA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

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



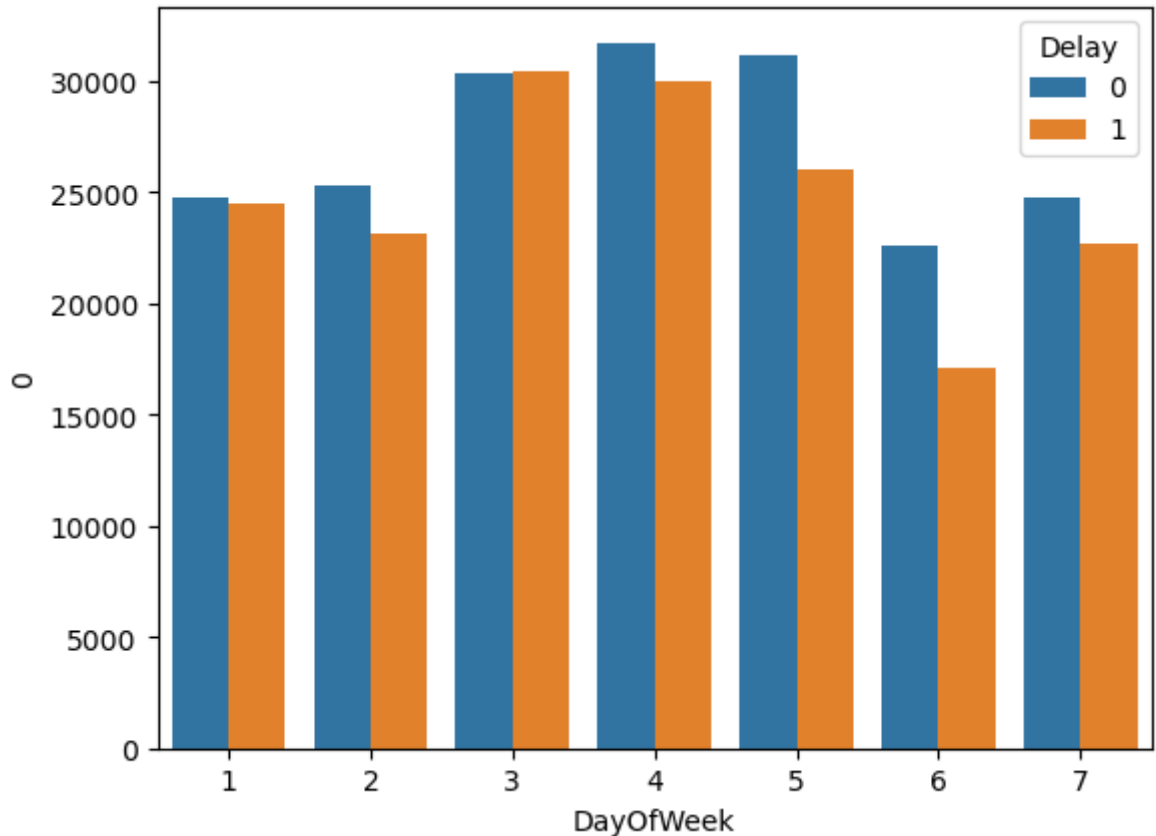
The graph clearly shows that 70% of flight of south west airline is delayed

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

```
In [53]: weekday_df = final_df[['DayOfWeek', 'Delay']].value_counts().reset_index()
```

```
In [54]: sns.barplot(weekday_df['DayOfWeek'], weekday_df[0], hue= weekday_df['Delay'])
```

```
Out[54]: <AxesSubplot:xlabel='DayOfWeek', ylabel='0'>
```

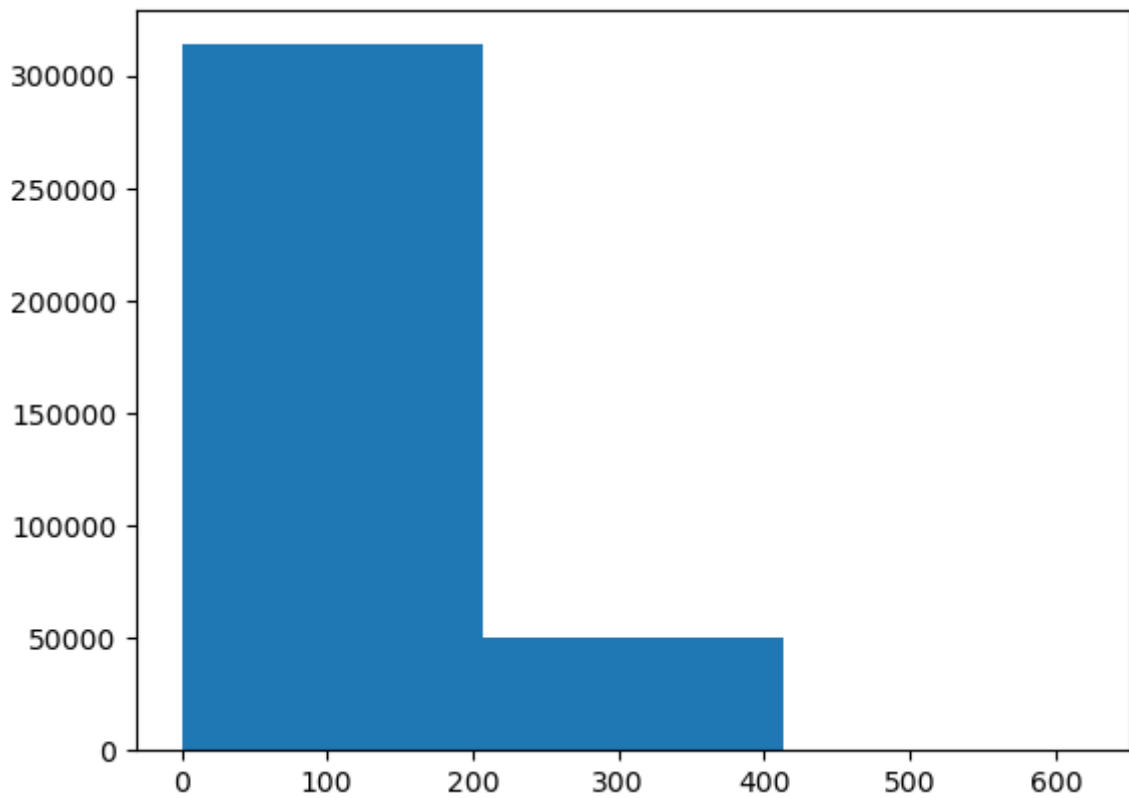


On the 5th day of week its clear that there is less no of flight delay.

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



airlines should be recommended for short distance Travel.

```
In [56]: final_df['Airline'][final_df['Length']<200].value_counts()
```

```
Out[56]: WN    75941
DL     43872
OO     32965
AA     30246
MQ     26076
XE     22114
UA     16388
9E     13573
B6     11628
OH      9963
YV      9884
AS      6350
F9      5406
HA      3034
Name: Airline, dtype: int64
```

```
In [57]: final_df['Airline'][final_df['Length']>400].value_counts()
```

```
Out[57]: 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 [58]: final_df['Time'][final_df['Length']>400]
```

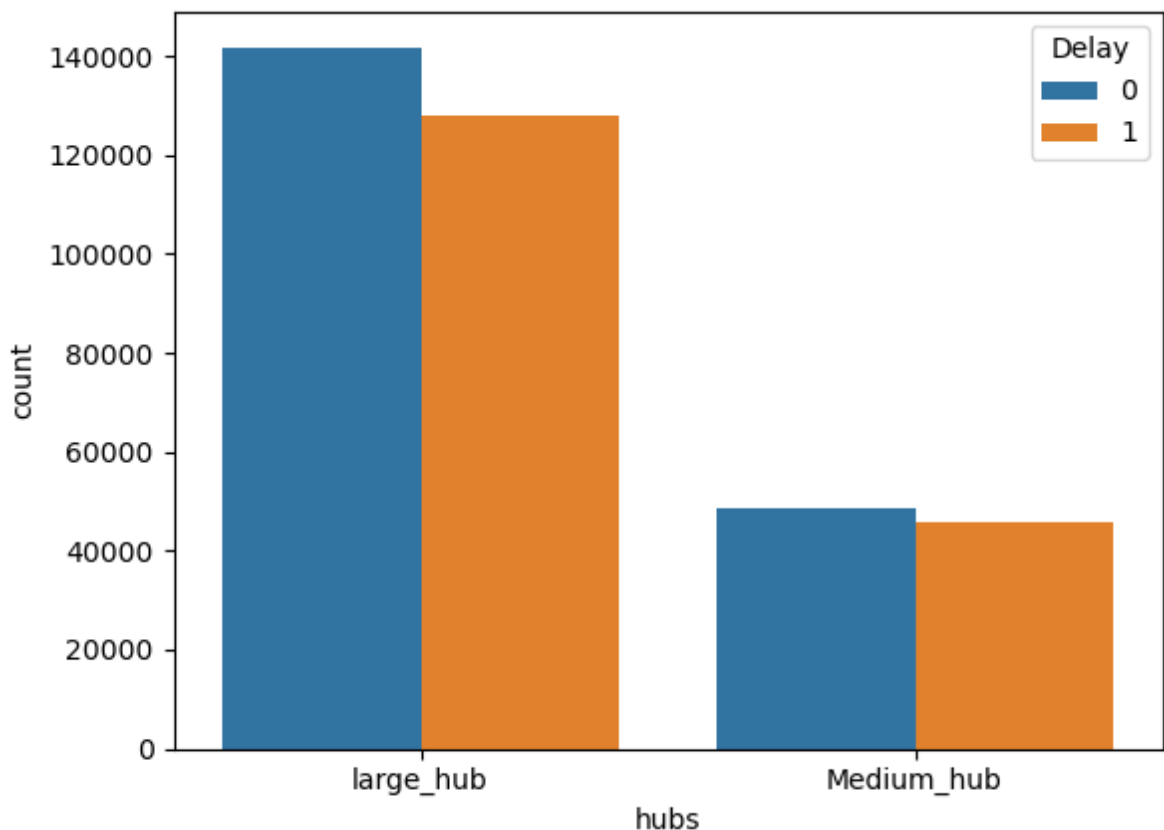
```
Out[58]: 46345      1045
         46348      1045
         46356      1045
         46364      1045
         46367      1045
         ...
         315043     1416
         315049     1416
         315055     1416
         315061     1416
         315067     1416
         Name: Time, Length: 1207, dtype: int64
```

It is clear from the above table that is only of that flight which travel a long distance and common 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 [59]: sns.countplot(final_df['hubs'], hue = final_df['Delay'])
```

```
Out[59]: <AxesSubplot:xlabel='hubs', ylabel='count'>
```



From the large hubs its clear approx 120000 flight is delayed but from the small hubs approx 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 [60]: 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=194730.438, 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 [61]: 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=200241.469, 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 [62]: 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=0.203  
Probably independent

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

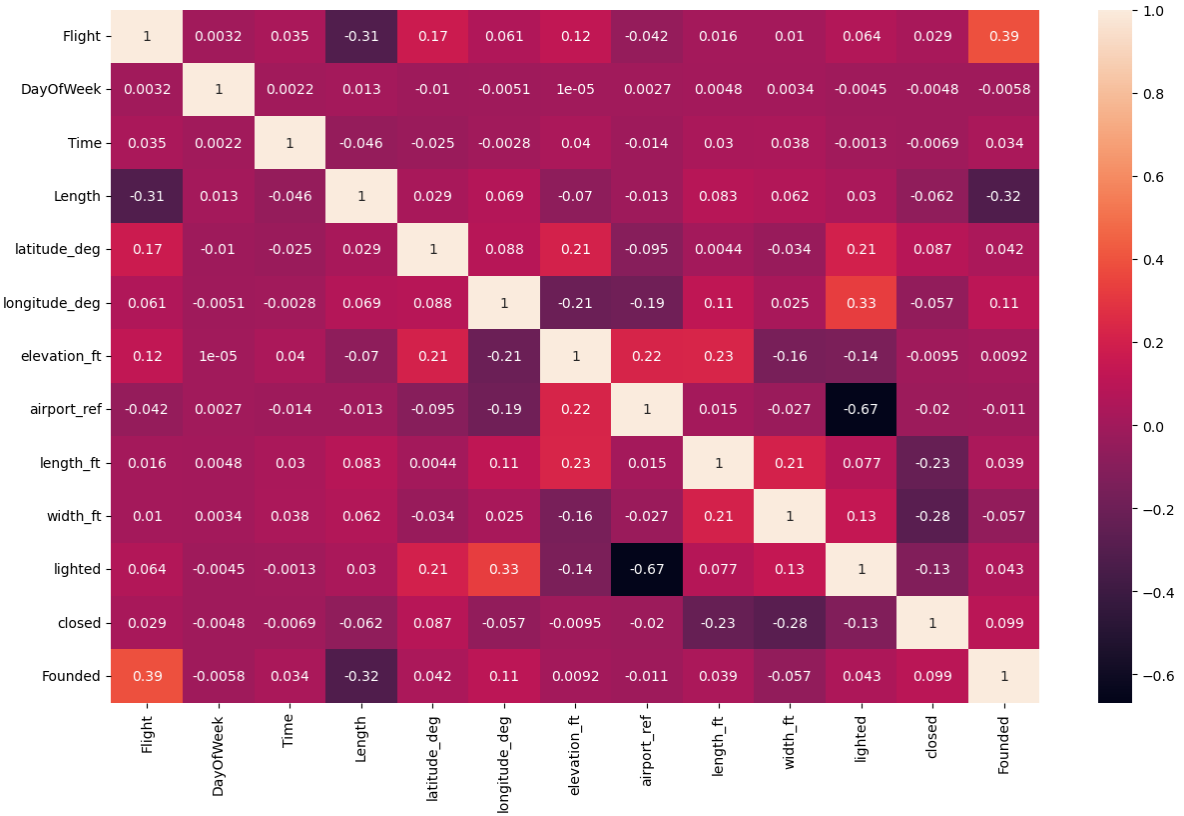
## 6. Find the correlation matrix between the flight delay predictors, create a heatmap to visualize this, and share your findings

```
In [63]: predictor = final_df.drop(['Delay'], axis=1)
corr = predictor.corr()
corr
```

Out[63]:

	Flight	DayOfWeek	Time	Length	latitude_deg	longitude_deg	elevation
Flight	1.000000	0.003249	0.034959	-0.311840	0.168127	0.061268	0.124437
DayOfWeek	0.003249	1.000000	0.002218	0.013059	-0.010100	-0.005075	0.000010
Time	0.034959	0.002218	1.000000	-0.045729	-0.024743	-0.002804	0.039522
Length	-0.311840	0.013059	-0.045729	1.000000	0.028905	0.068559	-0.070187
latitude_deg	0.168127	-0.010100	-0.024743	0.028905	1.000000	0.087885	0.208233
longitude_deg	0.061268	-0.005075	-0.002804	0.068559	0.087885	1.000000	-0.208175
elevation_ft	0.124437	0.000010	0.039522	-0.070187	0.208233	-0.208175	1.000000
airport_ref	-0.042421	0.002675	-0.014048	-0.012986	-0.095324	-0.190519	0.224940
length_ft	0.016064	0.004768	0.029940	0.083335	0.004430	0.114385	0.225000
width_ft	0.010186	0.003414	0.038049	0.062138	-0.034404	0.024904	-0.155000
lighted	0.064012	-0.004520	-0.001339	0.029629	0.205215	0.325019	-0.141000
closed	0.029169	-0.004811	-0.006927	-0.062091	0.087013	-0.056677	-0.009000
Founded	0.389930	-0.005840	0.033776	-0.318902	0.042304	0.107272	0.009000

```
In [64]: 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 [65]: *# Before applying the one hot encoding or the Label encoding first we check all for*  
final\_df.info()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364277 entries, 0 to 364276
Data columns (total 18 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   Airline                364277 non-null object
 1   Flight                364277 non-null int64
 2   DayOfWeek              364277 non-null int64
 3   Time                  364277 non-null int64
 4   Length                364277 non-null int64
 5   Delay                 364277 non-null int64
 6   type                  364277 non-null object
 7   latitude_deg           364277 non-null float64
 8   longitude_deg           364277 non-null float64
 9   elevation_ft           364277 non-null float64
10   scheduled_service      364277 non-null object
11   airport_ref            364277 non-null int64
12   length_ft              364277 non-null float64
13   width_ft              364277 non-null float64
14   lighted                364277 non-null int64
15   closed                 364277 non-null int64
16   Founded                364277 non-null float64
17   hubs                   364277 non-null object
dtypes: float64(6), int64(8), object(4)
memory usage: 52.8+ MB
```

In [66]: final\_df['Airline'].value\_counts()

```
Out[66]: WN      85067
DL       57720
AA       43261
OO       33843
UA       26535
MQ       26308
XE       22566
B6       15497
9E       13573
OH       10211
YV       10002
AS        9477
F9        6180
HA        4037
Name: Airline, dtype: int64
```

In [67]: final\_df['type'].value\_counts()

```
Out[67]: large_airport    342705
medium_airport    21572
Name: type, dtype: int64
```

In [68]: final\_df['scheduled\_service'].value\_counts()

```
Out[68]: yes      364277
Name: scheduled_service, dtype: int64
```

```
In [69]: final_df['hubs'].value_counts()
```

```
Out[69]: large_hub      269953
Medium_hub      94324
Name: hubs, dtype: int64
```

The scheduled\_service column thought 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 [70]: final_df = final_df.drop(['scheduled_service'], axis=1)
```

```
In [71]: # Now using the ordinal encoder.
from sklearn.preprocessing import LabelEncoder
```

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

```
In [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'])
```

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

```
Out[74]:
```

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

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

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

```
In [77]: # First Split the data into the training and testing set before performing the fur
from sklearn.model_selection import train_test_split
```

```
In [78]: x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.9, random_s
```

## LogisticRegression

```
In [79]: # Lets apply the Logistic regression with the randomsearchcv hypermeter tunning.
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

```
In [80]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [81]: 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)
```

```
Out[81]: Fitting 5 folds for each of 4 candidates, totalling 20 fits
RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                  param_distributions={'penalty': ['l1', 'l2'],
                                      'solver': ['newton-cg', 'liblinear']}},
                  scoring='accuracy', verbose=1)
```

```
In [82]: print(rscv.best_params_)
print(rscv.best_score_)

{'solver': 'newton-cg', 'penalty': 'l2'}
0.5929315093558369
```

```
In [83]: lr = LogisticRegression(penalty= 'l2', solver= 'newton-cg')
lr.fit(x_train,y_train).score(x_train,y_train)
```

```
Out[83]: 0.5929193012636915
```

```
In [84]: lr.score(x_test, y_test)
```

```
Out[84]: 0.5937191171626222
```

## DecisionTreeClassifier

```
In [85]: 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[85]: 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 [86]: print(rscv.best_params_)
         print(rscv.best_score_)
```

```
{'min_samples_leaf': 9, 'max_depth': 7, 'criterion': 'entropy'}
0.6430124896771539
```

```
In [87]: dtc = DecisionTreeClassifier(max_depth= 9, criterion= 'entropy', min_samples_leaf= 1)
```

```
In [88]: dtc.fit(x_train, y_train).score(x_train, y_train)
```

```
Out[88]: 0.653956547068925
```

```
In [89]: dtc.score(x_test, y_test)
```

```
Out[89]: 0.6493356758537389
```

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 [ ]:
```

```
In [90]: 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': 19, 'max\_depth': 9, 'learning\_rate': 0.4, 'colsample\_bytree': 1}  
 Best accuracy found: 0.6621798449896141

In [91]: `xgb = XGBClassifier(n_estimators=14, max_depth=9, learning_rate=0.45, colsample_bytree=0.6)`  
`xgb.fit(x_train,y_train).score(x_train,y_train)`

Out[91]: 0.6860200885163596

In [92]: `# 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))`

0.5937191171626222  
 0.6493356758537389  
 0.6633358954650269

After comparing the accuracy of the different model the best result we getting from the XGBClassifier.

In [ ]:

In [ ]: