

United States Airlines Analysis

```
In [1]: # Let's import the necessary Dependencies.  
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
import seaborn as sns  
import warnings  
warnings.filterwarnings("ignore")
```

1. Import and aggregate data:

```
In [2]: airline = pd.read_excel("Airlines.xlsx")
```

```
In [3]: airline.head()
```

```
Out[3]:
```

	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 [4]: airline.shape
```

```
Out[4]: (518556, 9)
```

```
In [5]: airport= pd.read_excel("airports.xlsx")
```

```
In [6]: airport.head()
```

Out[6]:

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	continent	iso_cou
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 [7]: `airport.shape`

Out[7]: (73805, 18)

In [8]: `runway = pd.read_excel("runways.xlsx")`

In [9]: `runway.head()`

Out[9]:

	id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed	le_ident	le_latitude
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 [10]: `runway.shape`

Out[10]: (43977, 20)

- ### Before Aggregating The Data Lets Drop The Columns Which Are Not Important In Anaylsis

In [11]: `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 [12]: # 'le_ident', 'le_latitude_deg', 'le_longitude_deg', 'le_elevation_ft', 'le_heading_deg'
#         'le_displaced_threshold_ft', 'he_ident', 'he_latitude_deg', 'he_longitude_deg'
#         'he_displaced_threshold_ft'

# These are the feautres are irrelevant in our anaylsis
```

```
In [13]: 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_displaced_threshold_ft'], axis=1, inplace=True)
```

```
In [14]: runway.head()
```

```
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

```
In [15]: 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]: airport.drop(['continent', 'iso_country', 'iso_region', 'municipality', 'gps_code', 'local_code',
                    'wikipedia_link', 'keywords'], axis=1, inplace=True)
```

```
In [17]: airport.head()
```

```
Out[17]:
```

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	scheduled_service
0	6523	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	no
1	323361	00AA	small_airport	Aero B Ranch Airport	38.704022	-101.473911	3435.0	no
2	6524	00AK	small_airport	Lowell Field	59.947733	-151.692524	450.0	no
3	6525	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820.0	no
4	6526	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237.0	no

- ### Now Lets Merge The Runway And Airport Data.

```
In [18]: # As The "Ident" IN Airport Is Same As The "Airport_ident" In The Runway
```

```
In [19]: airport_runway = pd.merge(airport, runway, left_on="ident", right_on="airport_ident")
airport_runway.drop(['id_x', 'id_y'], axis=1, inplace=True)
```

In [20]:

airport_runway

Out[20]:

	ident	type	name	latitude_deg	longitude_deg	elevation_ft	scheduled_ser
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 Iriomote Airport	30.784722	130.270556	338.0	

43977 rows × 15 columns



In [21]:

Now Lets The Final Column Airline.
final_df= pd.merge(airline,airport_runway, how="inner",left_on="AirportFrom",right_on=

In [22]:

final_df.drop_duplicates(subset=['id'], keep='first',inplace=True)
final_df.head()

Out[22]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	...	elevati
0	1	CO	269	SFO	IAH	3	15	205	1	KSFO	...	
4	4	AA	2466	SFO	DFW	3	20	195	1	KSFO	...	
8	9	DL	2606	SFO	MSP	3	35	216	1	KSFO	...	
12	129	DL	1580	SFO	DTW	3	345	270	0	KSFO	...	
16	150	UA	756	SFO	DEN	3	348	158	0	KSFO	...	

5 rows × 24 columns

B. Web Scrapping

- 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.

```
In [23]: # Now Lets use the web scrapping to import the data from 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	AAV	ALLEGIAN
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...

	IATA	ICAO	Callsign \	Airline	Image
0				Air Wisconsin	NaN
1				Cape Air	NaN
2				CommutAir	NaN
3				Contour Airlines	NaN
4				Elite Airways	NaN
5				Endeavor Air	NaN
6				Envoy Air	NaN
7				GoJet Airlines	NaN
8				Horizon Air	NaN
9				Mesa Airlines	NaN
10				Piedmont Airlines	NaN
11				PSA Airlines	NaN

12	Republic Airways	NaN	YX	RPA	BRICKYARD
13	Silver Airways	NaN	3M	SIL	SILVER WINGS
14	SkyWest Airlines	NaN	00	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, ... ,

Air

line	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 RLI RELIANT
18				San Juan Airlines	NaN NaN NaN SKYFERRY
19				Servant Air	NaN 8D NaN NaN
20				Southern Airways Express	NaN 9X FDY FRIENDLY
21				Surf Air	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 WorthDenverPhoenix-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	NaN
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 ,

Airl

ine	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	VTG	EVERTS
20	FedEx Express	NaN	FX	FDX	FEDEX
21	Freight Runners Express	NaN	NaN	FRG	FREIGHT RUNNERS
22	IFL Group	NaN	IF	IFL	IEIFFEL
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	Tepper Aviation	NaN	NaN	NaN	NaN
38	Trans Executive Airlines	NaN	KH	MUI	RHOADES EXPRESS
39	UPS Airlines	NaN	5X	UPS	UPS
40	USA Jet Airlines	NaN	UJ	JUS	JET USA
41	West Air	NaN	NaN	PCM	PAC VALLEY
42	Western Global Airlines	NaN	KD	WGN	WESTERN GLOBAL
43	Wiggins Airways	NaN	WG	WIG	WIGGINS AIRWAYS

	Primary Hubs, Secondary Hubs	Founded \
0	Miami	2014.0
1	Wilmington (OH)Cincinnati	1980.0
2	MilwaukeeCincinnati	1986.0
3	Columbus-Rickenbacker	1974.0
4	Wilmington (OH)Cincinnati	1978.0
5	Anchorage	1996.0
6	Honolulu	1946.0
7	ProvoBillingsSioux Falls	1971.0
8	Fort Worth/AllianceCincinnatiLeipzig/HalleSan ...	2015.0
9	Dallas/Fort Worth	1968.0
10	MiamiPort of Spain	1974.0
11	Dallas-AddisonEl PasoWillow Run	2000.0
12	GuamHonolulu	1998.0
13	New York-JFKAnchorageCincinnatiHoustonHuntsvil...	1992.0
14	BemidjiMinneapolis/St. Paul	1946.0
15	Akron/Canton	1986.0
16	Billings	1981.0
17	Iron Mountain	1998.0
18	Coeur d' AleneSpokane	1977.0
19	FairbanksAnchorage	1995.0
20	MemphisAnchorageCologne/BonnDubaiFort WorthGre...	1971.0
21	Milwaukee	1985.0
22	WaterfordMiami	1983.0

23	Ypsilanti	Anchorage	Bahrain	Cincinnati	Hong Kong	Ne...	1967.0
24					Ypsilanti		NaN
25					Anchorage		1995.0
26					Addison		1978.0
27				Billings	Miami	San Juan	1983.0
28					Kinston		1974.0
29					Orlando/Sanford		1985.0
30					Anchorage	Miami	1956.0
31	Anchorage	Cincinnati	Hong Kong	Honolulu	Los Angeles...		1993.0
32					Waterford		1961.0
33	Anchorage	Aniak	Bethel	Emmonak	Kotzebue	Nome	St. Mar...
34					Miami		1969.0
35					NaN		1981.0
36					Miami		2018.0
37					Crestview		1987.0
38					Honolulu		1982.0
39	Louisville	Chicago/Rockford	Cologne/Bonn	Columbia...			1988.0
40					Ypsilanti	Laredo	1994.0
41		Las Vegas	Oakland	Ontario	Sacramento	San Diego	1988.0
42		Miami	Liege, Belgium;	Anchorage	Fort Myers, FL		2013.0
43					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
43							NaN ,
age	IATA	ICAO	Callsign	\			Airline Im
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 airl
ines	\	

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 Gibral...
 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
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 14 N
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 22 U
 23 V
 24 W
 25 Y
 26 Z

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0 A Abkhazia Afghanistan Akrotiri and Dhekelia Å...
 1 Abkhazia Afghanistan Akrotiri and Dhekelia Åla...
 2 The Bahamas Bahrain Bangladesh Barbados Belaru...
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 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
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```

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, vteAirli
nes 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
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1 Independent Advanced Air Air Flamenco Air Sunshine Bering ..., v
telist of airlines of the Americas \
0 North America Caribbean Central America Northe...
1 Sovereign states
2 Dependencies andother territories

vteList of airlines of the Americas.1 \
0 North America Caribbean Central America Northe...
1 Antigua and Barbuda Argentina Bahamas Barbados...
2 Anguilla Aruba Bermuda Bonaire British Virgin ...

vteList of airlines of the Americas.2
0 North America Caribbean Central America Northe...
1 NaN
2 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	Notes
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932	Founder: McCarren Airways; common operation
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997	Founder: Westwood Express; common operation
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926	Founder: American Airlines; common operation
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987	First business case; Express Airline
4	Breeze Airways	NaN	MX	MXY	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018	
5	Delta Air Lines	NaN	DL	DAL	DELTA	AtlantaBostonDetroitLos AngelesMinneapolis/St...	1924	Founder: Huff Dusters; common operation
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	Founder: Inter-Island Airways; early 1920s
9	JetBlue	NaN	B6	JBU	JETBLUE	New York-JFKBostonLos AngelesFort LauderdaleOr...	1998	Founder: New Air; common operation
10	Southwest Airlines	NaN	WN	SWA	SOUTHWEST	LoveAtlantaBaltimoreChicago-MidwayDenve...	1967	Founder: Air South; common operation
11	Spirit Airlines	NaN	NK	NKS	SPIRIT WINGS	Atlantic CityDetroitLas VegasFort LauderdaleCh...	1980	Founder: Charter C
12	Sun Country Airlines	NaN	SY	SCX	SUN COUNTRY	Minneapolis/St. PaulDallas/Fort WorthLas Vegas	1982	Common operation

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	Notes
								1983.Oper some Ar
13	United Airlines	NaN	UA	UAL	UNITED	O'HareDenverGuamHouston-Intercontinent...	1926	Founder Varney Lines commen

```
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.head()
```

Out[29]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	Notes
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932.0	Founded as McGee Airways and commenced operati...
1	Allegiant Air	NaN	G4	AAY	ALLEGiant	Las VegasCincinnatiFort Walton BeachIndianapol...	1997.0	Founded as WestJet Express and commenced opera...
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926.0	Founded as American Airways and commenced oper...
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987.0	First did business as Casino Express Airlines ...
4	Breeze Airways	NaN	MX	MXV	MOXY	CharlestonHartfordNew OrleansNorfolkProvoTampa	2018.0	NaN

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
...
137	NaN	NaN
138	NaN	NaN
139	NaN	2002.0
140	NaN	1972.0
141	NaN	1980.0

142 rows × 2 columns

In [31]:

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

Out[31]:

	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

```
In [32]: # 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 [33]: table[0]
```

Out[33]:

	Rank(2021)	Airports (large hubs)	IATACode	Major cities served	State	2021[3]	2020[4]	2019[5]	
0	1	Hartsfield–Jackson Atlanta International Airport	ATL	Atlanta	GA	36676010	20559866	53505795	1
1	2	Dallas/Fort Worth International Airport	DFW	Dallas & Ft. Worth	TX	30005266	18593421	35778573	3
2	3	Denver International Airport	DEN	Denver	CO	28645527	16243216	33592945	3
3	4	O'Hare International Airport	ORD	Chicago	IL	26350976	14606034	40871223	3
4	5	Los Angeles International Airport	LAX	Los Angeles	CA	23663410	14055777	42939104	4
5	6	Charlotte Douglas International Airport	CLT	Charlotte	NC	20900875	12952869	24199688	2
6	7	Orlando International Airport	MCO	Orlando	FL	19618838	10467728	24562271	2
7	8	Harry Reid International Airport	LAS	Las Vegas	NV	19160342	10584059	24728361	2
8	9	Phoenix Sky Harbor International Airport	PHX	Phoenix	AZ	18940287	10531436	22433552	2
9	10	Miami International Airport	MIA	Miami	FL	17500096	8786007	21421031	2
10	11	Seattle–Tacoma International Airport	SEA	Seattle	WA	17430195	9462411	25001762	2
11	12	George Bush Intercontinental Airport	IAH	Houston	TX	16242821	8682558	21905309	2
12	13	John F. Kennedy International Airport	JFK	New York City	NY	15273342	8269819	31036655	3
13	14	Newark Liberty International Airport	EWK	Newark & New York City	NJ	14514049	7985474	23160763	2
14	15	Fort Lauderdale–Hollywood International Airport	FLL	Fort Lauderdale	FL	13598994	8015744	17950989	1
15	16	Minneapolis–Saint Paul International Airport	MSP	Minneapolis & Saint Paul	MN	12211409	7069720	19192917	1
16	17	San Francisco International Airport	SFO	San Francisco	CA	11725347	7745057	27779230	2
17	18	Detroit Metropolitan Airport	DTW	Detroit	MI	11517696	6822324	18143040	1
18	19	Logan International Airport	BOS	Boston	MA	10909817	6035452	20699377	2

	Rank(2021)	Airports (large hubs)	IATACode	Major cities served	State	2021[3]	2020[4]	2019[5]
19	20	Salt Lake City International Airport	SLC	Salt Lake City	UT	10795906	5753239	12840841
20	21	Philadelphia International Airport	PHL	Philadelphia	PA	9820222	5753239	16006389
21	22	Baltimore/Washington International Airport	BWI	Baltimore & Washington, D.C.	MD	9253561	5451355	13284687
22	23	Tampa International Airport	TPA	Tampa	FL	8847197	4966775	10978756
23	24	San Diego International Airport	SAN	San Diego	CA	7836360	4637856	12648692
24	25	LaGuardia Airport	LGA	New York City	NY	7827307	4147116	15393601
25	26	Midway International Airport	MDW	Chicago	IL	7680617	4236603	10081781
26	27	Nashville International Airport	BNA	Nashville	TN	7594049	4013995	8935654
27	28	Washington Dulles International Airport	IAD	Washington, D.C.	VA	7227875	3862658	11884117
28	29	Ronald Reagan Washington National Airport	DCA	Washington, D.C.	VA	6731737	3573489	11595454
29	30	Austin–Bergstrom International Airport	AUS	Austin	TX	6666215	3141505	8683711

```
In [34]: table[0] = table[0].drop(['2021[3]', '2013[11]', '2012[12]'], axis=1)
```

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


Out[35]:

	Rank(2021)	Airports (large hubs)	IATACode	Major cities served	State	2020[4]	2019[5]	2018[6]	2017[7]	20
0	1	Hartsfield– Jackson Atlanta International Airport	ATL	Atlanta	GA	20559866	53505795	51865797	50251964	505
1	2	Dallas/Fort Worth International Airport	DFW	Dallas & Ft. Worth	TX	18593421	35778573	32821799	31816933	312
2	3	Denver International Airport	DEN	Denver	CO	16243216	33592945	31362941	29809097	282
3	4	O'Hare International Airport	ORD	Chicago	IL	14606034	40871223	39873927	38593028	375
4	5	Los Angeles International Airport	LAX	Los Angeles	CA	14055777	42939104	42624050	41232432	396

```
In [36]: table[0]['traffic_Chg19_20'] = table[0]['2020[4]'] - table[0]['2019[5]']
```

```
In [37]: table[0]['traffic_Chg18_19'] = table[0]['2019[5]'] - table[0]['2018[6]']
table[0]['hubs']=str('large_hub')
```

```
In [38]: table[0]=table[0][['IATACode','traffic_Chg19_20','traffic_Chg18_19','hubs']]
table[0].head()
```

```
Out[38]:
```

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	ATL	-32945929	1639998	large_hub
1	DFW	-17185152	2956774	large_hub
2	DEN	-17349729	2230004	large_hub
3	ORD	-26265189	997296	large_hub
4	LAX	-28883327	315054	large_hub

```
In [39]: table[1].head()
```

Out[39]:

	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	7876761
1	32	Daniel K. Inouye International Airport	HNL	Honolulu	HI	5830928	3126391	9988678	9578505	9743981
2	33	Portland International Airport	PDX	Portland	OR	5759879	3455877	9797408	9940866	9435471
3	34	William P. Hobby Airport	HOU	Houston	TX	5560780	3127178	7069614	6937061	6741871
4	35	Southwest Florida International Airport	RSW	Fort Myers	FL	5080805	2947139	5144467	4719568	4461301

```
In [40]: table[1]['traffic_Chg19_20'] = table[1]['2020[4]'] - table[1]['2019[5]']
table[1]['traffic_Chg18_19'] = table[1]['2019[5]'] - table[1]['2018[6]']
table[1]['hubs'] = str('Medium_hub')
```

```
In [41]: table[1]=table[1][['IATACode','traffic_Chg19_20','traffic_Chg18_19','hubs']]
table[1].head()
```

```
Out[41]:
```

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	DAL	-4738527	273609	Medium_hub
1	HNL	-6862287	410173	Medium_hub
2	PDX	-6341531	-143458	Medium_hub
3	HOU	-3942436	132553	Medium_hub
4	RSW	-2197328	424899	Medium_hub

```
In [42]: # Lets Merge All Wikipedia Table.
wiki_data=[table[0],table[1]]
```

```
In [43]: wiki_data=pd.concat(wiki_data,ignore_index= True)
```

```
In [44]: wiki_data
```

Out[44]:

	IATACode	traffic_Chg19_20	traffic_Chg18_19	hubs
0	ATL	-32945929	1639998	large_hub
1	DFW	-17185152	2956774	large_hub
2	DEN	-17349729	2230004	large_hub
3	ORD	-26265189	997296	large_hub
4	LAX	-28883327	315054	large_hub
...
60	BOI	-1066509	114569	Medium_hub
61	MEM	-1302461	105359	Medium_hub
62	RNO	-1185313	113334	Medium_hub
63	ABQ	-1772528	-5819	Medium_hub
64	ORF	-1105982	144833	Medium_hub

65 rows × 4 columns

In [45]: *# Now We Gather The Information That we Got From Wikipedia Link And The Data That We Have*
`final_df = df.merge(wiki_data, left_on='iata_code', right_on='IATACode')`
`final_df.head()`

Out[45]:

	id	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	...	width_
0	4	AA	2466	SFO	DFW	3	20	195	1	KSFO	...	200
1	231	AA	526	SFO	DFW	3	360	215	0	KSFO	...	200
2	234	AA	552	SFO	MIA	3	360	315	1	KSFO	...	200
3	905	AA	810	SFO	ORD	3	385	255	0	KSFO	...	200
4	1739	AA	24	SFO	JFK	3	425	325	1	KSFO	...	200

5 rows × 30 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 So Lets Examine The Data And Remove The Unnecessary Data*
`final_df.info()`

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364277 entries, 0 to 364276
Data columns (total 30 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  traffic_Chg19_20       364277 non-null  int64
28  traffic_Chg18_19       364277 non-null  int64
29  hubs                   364277 non-null  object
dtypes: float64(6), int64(11), object(13)
memory usage: 86.2+ MB
```

```
In [47]: final_df = final_df.drop(['id', 'AirportFrom', 'airport_ident', 'iata_code', 'AirportTo', 'IATA', 'IATACode', 'name'], axis=1)
```

```
In [48]: # Lets Check The Missing Values Of The Final Dataset
final_df.isnull().sum()
```

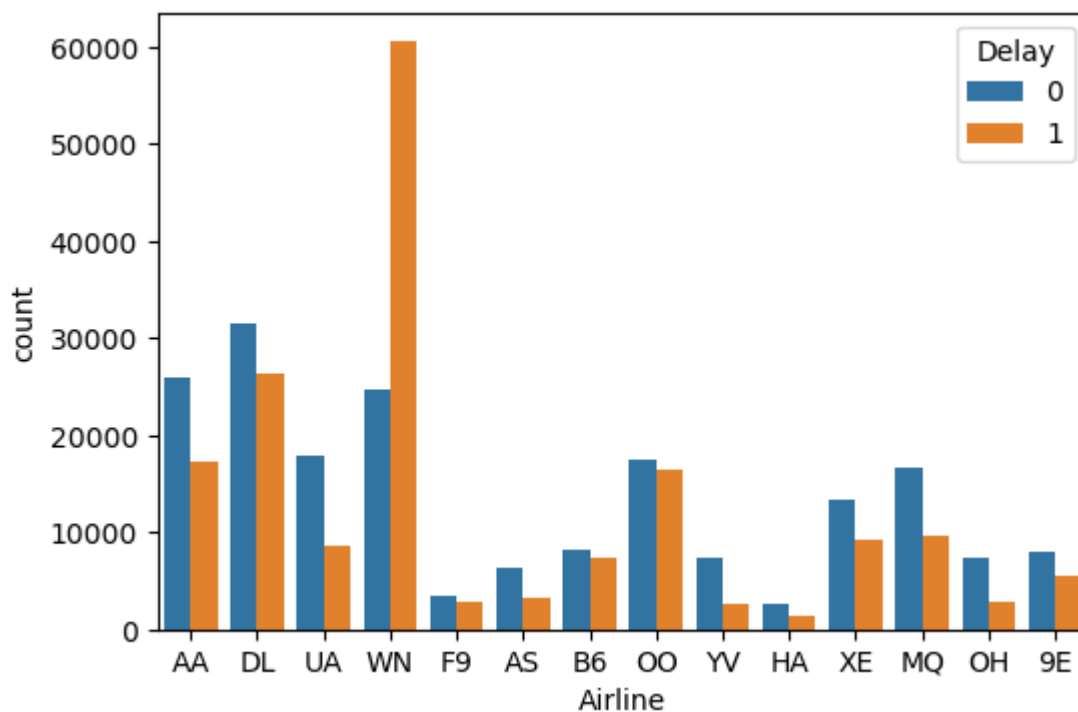
```
Out[48]: Airline      0
         Flight      0
         DayOfWeek   0
         Time        0
         Length      0
         Delay       0
         type        0
         latitude_deg 0
         longitude_deg 0
         elevation_ft 0
         scheduled_service 0
         airport_ref 0
         length_ft    0
         width_ft     0
         lighted      0
         closed       0
         Founded      0
         traffic_Chg19_20 0
         traffic_Chg18_19 0
         hubs         0
         dtype: int64
```

- No Null Data

3. Data Visualization

- ### 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.

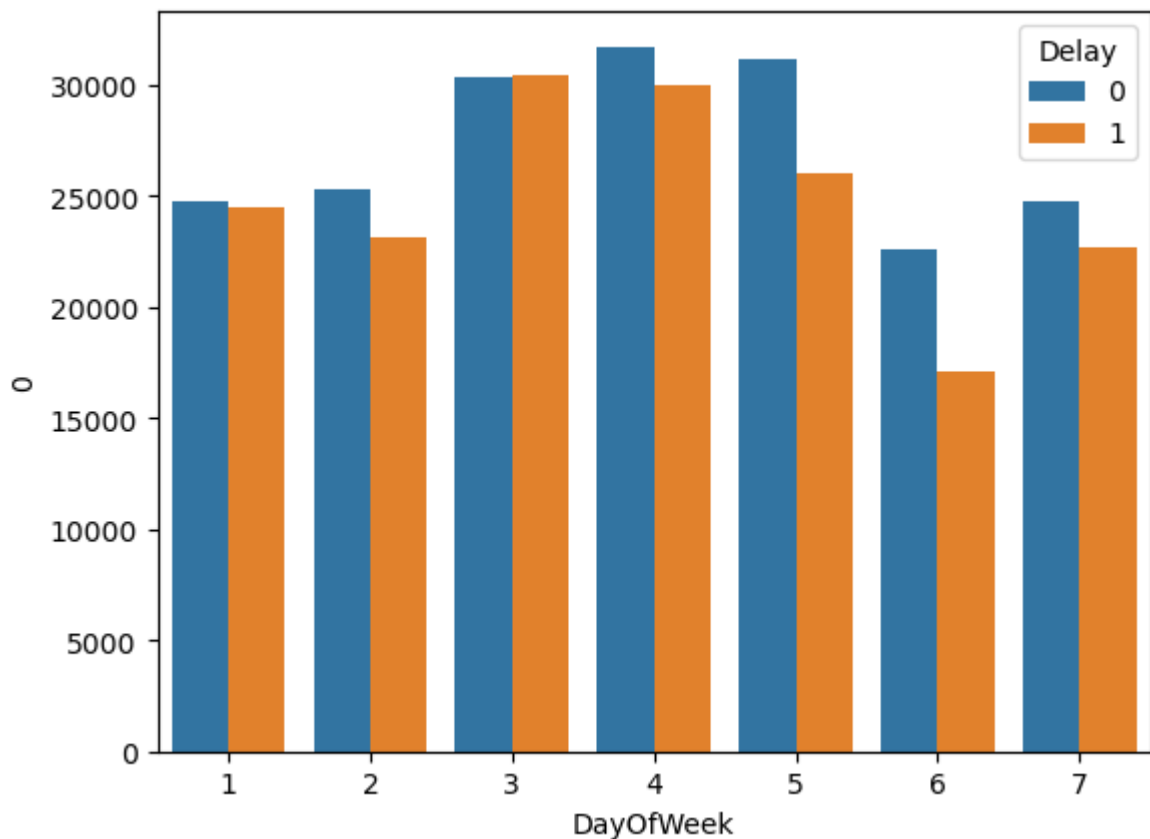
```
In [49]: plt.figure(figsize=(6,4))
         sns.countplot(final_df['Airline'], hue= final_df['Delay'])
         plt.show()
```



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

```
In [50]: weekday_df = final_df[['DayOfWeek', 'Delay']].value_counts().reset_index()
```

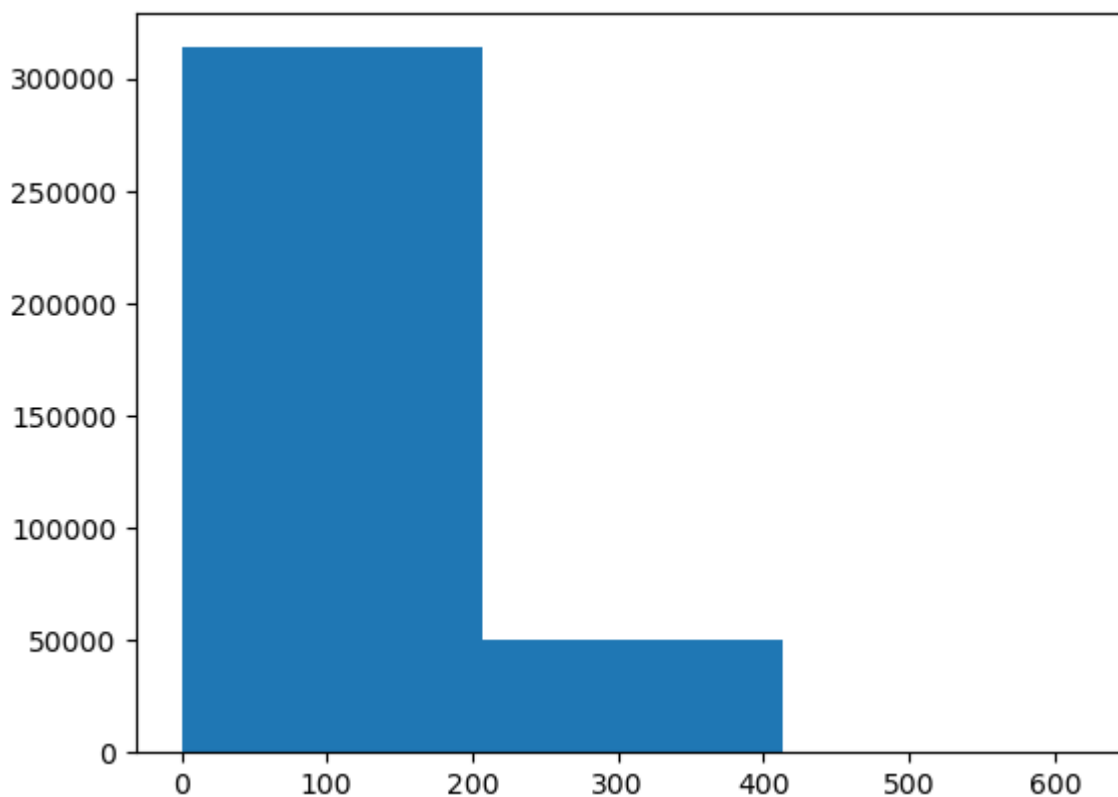
```
In [51]: sns.barplot(weekday_df['DayOfWeek'], weekday_df[0], hue=weekday_df['Delay'])  
plt.show()
```



- On The 5th And 6th Day Of The Week There Are Less No. Of Delay.

C. Airlines That Should Be Recommended For Short-, Medium-, And Long-Distance Travel

```
In [52]: plt.hist(final_df['Length'], bins=3)
plt.show()
```



```
In [53]: final_df['Airline'][final_df['Length']<200].value_counts()
```

```
Out[53]: 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
```

- Airline For Short Distance Travel.

```
In [54]: final_df['Airline'][final_df['Length']>400].value_counts()
```

```
Out[54]: UA      549
AA      304
DL      226
B6       83
AS       31
HA       14
Name: Airline, dtype: int64
```

- Airline For Long Distance Travel

- And Remaining Are For Medium Distance Travel

D. Patterns in the departure times of long-duration flights

```
In [55]: final_df['Time'] [final_df['Length']>400]
```

```
Out[55]: 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
```

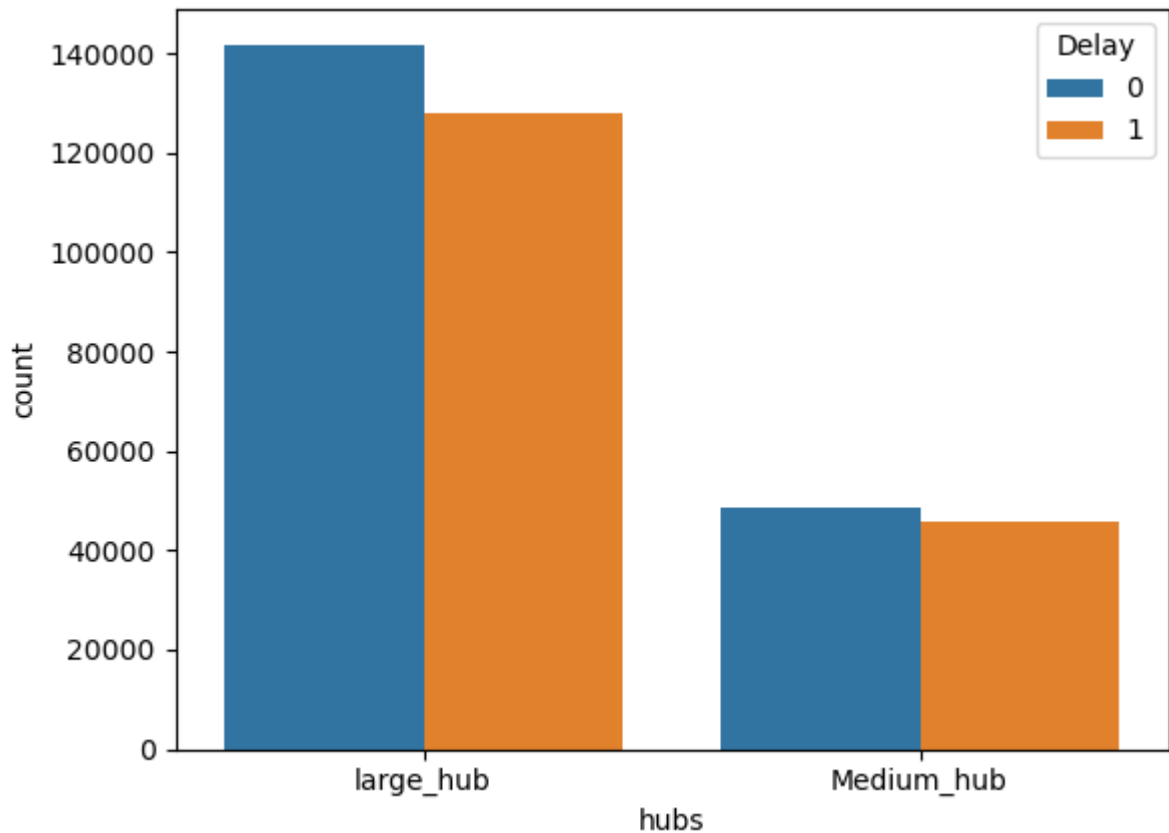
```
In [56]: final_df['Length']>400
```

```
Out[56]: 0      False
         1      False
         2      False
         3      False
         4      False
         ...
         364272   False
         364273   False
         364274   False
         364275   False
         364276   False
         Name: Length, Length: 364277, dtype: bool
```

- 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. visualization to represent of flights were delayed at large hubs compared to medium hubs

```
In [57]: sns.countplot(final_df['hubs'], hue= final_df['Delay'])
         plt.show()
```



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 [58]: 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

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

```
In [59]: 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

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

```
In [60]: 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

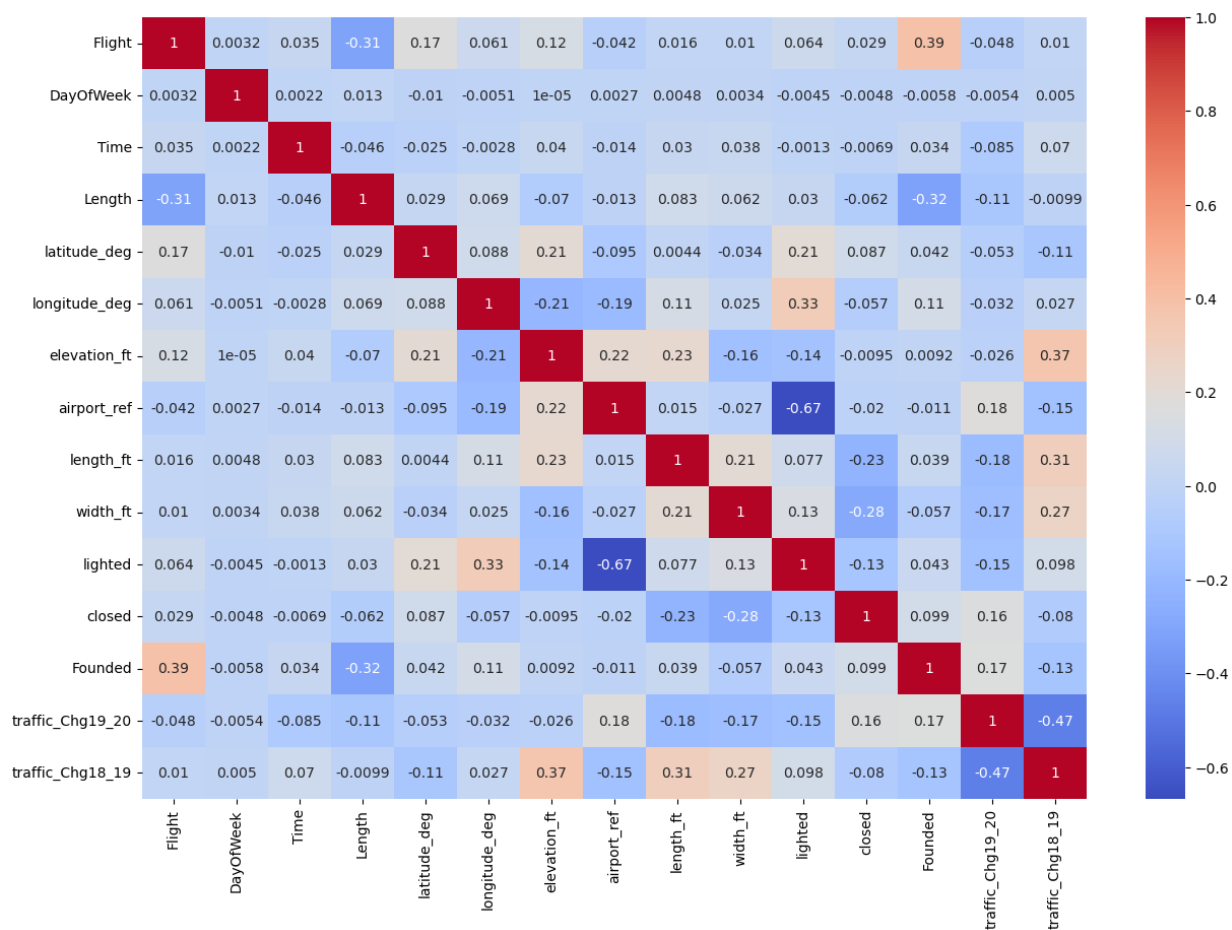
6. Correlation Matrix

```
In [61]: predictor = final_df.drop(['Delay'], axis=1)
corr= predictor.corr()
corr
```

```
Out[61]:
```

	Flight	DayOfWeek	Time	Length	latitude_deg	longitude_deg	elevation_ft
Flight	1.000000	0.003249	0.034959	-0.311840	0.168127	0.061268	0.12443
DayOfWeek	0.003249	1.000000	0.002218	0.013059	-0.010100	-0.005075	0.00001
Time	0.034959	0.002218	1.000000	-0.045729	-0.024743	-0.002804	0.03952
Length	-0.311840	0.013059	-0.045729	1.000000	0.028905	0.068559	-0.07018
latitude_deg	0.168127	-0.010100	-0.024743	0.028905	1.000000	0.087885	0.20823
longitude_deg	0.061268	-0.005075	-0.002804	0.068559	0.087885	1.000000	-0.20817
elevation_ft	0.124437	0.000010	0.039522	-0.070187	0.208233	-0.208175	1.00000
airport_ref	-0.042421	0.002675	-0.014048	-0.012986	-0.095324	-0.190519	0.22456
length_ft	0.016064	0.004768	0.029940	0.083335	0.004430	0.114385	0.22592
width_ft	0.010186	0.003414	0.038049	0.062138	-0.034404	0.024904	-0.15523
lighted	0.064012	-0.004520	-0.001339	0.029629	0.205215	0.325019	-0.14175
closed	0.029169	-0.004811	-0.006927	-0.062091	0.087013	-0.056677	-0.00950
Founded	0.389930	-0.005840	0.033776	-0.318902	0.042304	0.107272	0.00917
traffic_Chg19_20	-0.048014	-0.005420	-0.084557	-0.112389	-0.053065	-0.031525	-0.02618
traffic_Chg18_19	0.010379	0.005002	0.070448	-0.009942	-0.114517	0.027168	0.36667

```
In [62]: plt.figure(figsize=(15,10))
sns.heatmap(corr, annot=True, cmap='coolwarm')
plt.show()
```



Machine Learning

- ### 1. Use OneHotEncoder and OrdinalEncoder to deal with categorical variables

```
In [63]: # Before applying the one hot encoding or the label encoding first we check all features
final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 364277 entries, 0 to 364276
Data columns (total 20 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  traffic_Chg19_20        364277 non-null int64
18  traffic_Chg18_19        364277 non-null int64
19  hubs                    364277 non-null object
dtypes: float64(6), int64(10), object(4)
memory usage: 58.4+ MB
```

```
In [64]: final_df['Airline'].value_counts()
```

```
Out[64]: 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 [65]: final_df['type'].value_counts()
```

```
Out[65]: large_airport    342705
medium_airport    21572
Name: type, dtype: int64
```

```
In [66]: final_df['scheduled_service'].value_counts()
```

```
Out[66]: yes      364277
Name: scheduled_service, dtype: int64
```

```
In [67]: final_df['hubs'].value_counts()
```

```
Out[67]: large_hub      269953
Medium_hub    94324
Name: hubs, dtype: int64
```

```
In [68]: final_df = final_df.drop(['scheduled_service'], axis=1)
```

```
In [69]: # Now using the ordinal encoder.
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

```
In [70]: 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 [71]: final_df.head()
```

```
Out[71]:
```

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

- ### 2. Perform the following model building steps:

Logistic Regression

```
In [72]: # Lets first separate the predictors and the output Variable.
x = final_df.drop(['Delay'], axis=1)
y = final_df["Delay"]
```

```
In [73]: from sklearn import preprocessing
scaler = preprocessing.MinMaxScaler()
x = scaler.fit_transform(x)
```

```
In [74]: # First Split the data into the training and testing set before performing the further
from sklearn.model_selection import train_test_split
```

```
In [75]: x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.9, random_state=42)
```

```
In [76]: # Lets apply the logistic regression with the randomsearchcv hypermeter tuning.
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

```
In [77]: from sklearn.model_selection import RandomizedSearchCV
```

```
In [78]: params = {"penalty": ["l1", "l2"],
                  'solver': ['newton-cg', 'liblinear']}
```

```
# Cross Validation
folds = 5

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

rscv.fit(x_train, y_train)
```

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

```
Out[78]: RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                          param_distributions={'penalty': ['l1', 'l2'],
                                              'solver': ['newton-cg', 'liblinear']},
                          scoring='accuracy', verbose=1)
```

```
In [79]: print(rscv.best_params_)
         print(rscv.best_score_)

{'solver': 'newton-cg', 'penalty': 'l2'}
0.5950940921237212
```

```
In [80]: lr = LogisticRegression(penalty= 'l2', solver= 'newton-cg')
         lr.fit(x_train,y_train).score(x_train,y_train)
```

```
Out[80]: 0.5951215346089206
```

DecisionTreeClassifier

```
In [81]: 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[81]: 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 [82]: print(rscv.best_params_)
         print(rscv.best_score_)

{'min_samples_leaf': 9, 'max_depth': 9, 'criterion': 'entropy'}
0.649521580649087
```

```
In [83]: dtc = DecisionTreeClassifier(max_depth= 9, criterion= 'entropy',min_samples_leaf= 6)
dtc.fit(x_train, y_train).score(x_train, y_train)
```

```
Out[83]: 0.6552772770391248
```

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

```
Out[84]: 0.6503788294718349
```

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 [87]: 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_)
```


[illegible]

[illegible]

[illegible]

```
[14:37:55] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:56] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:56] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:57] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:57] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:58] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:58] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:58] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:37:59] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:00] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:00] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:01] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:01] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:02] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:02] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:03] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:03] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:04] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
[14:38:04] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
```

[illegible]

[illegible]

```
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:27] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:28] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:29] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:29] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:30] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:31] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:31] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:32] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:33] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:34] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
[14:38:34] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
Best parameters found: {'n_estimators': 19, 'max_depth': 9, 'learning_rate': 0.4, 'c
olsample_bytree': 1}
Best accuracy found: 0.6623872575484445
```

- Best parameters found: {'n_estimators': 16, 'max_depth': 9, 'learning_rate': 0.4, 'colsample_bytree': 0.8}
- Best accuracy found: 0.6623964081025107

```
In [86]: xgb = XGBClassifier(n_estimators=14, max_depth=9, learning_rate=0.45, colsample_bytree=0.8)
xgb.fit(x_train,y_train).score(x_train,y_train)
```

```
[14:36:57] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default ev
aluation metric used with the objective 'binary:logistic' was changed from 'error' to
'logloss'. Explicitly set eval_metric if you'd like to restore the old behavior.
0.6857333711556235
```

Out[86]:

```
In [88]: # 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))
```


0.595640715932799
 0.6503788294718349
 0.664955528714176

- As We Can See After Comparing The Accuracy Of the Different Model The Best Result We Getting From The XGBClassifier.

Tableau_Dashboard Link:-

- https://public.tableau.com/app/profile/akshaydeep.chauhan/viz/UnitedStatesAirlinesAnalysis_10/publish=yes



SQL

/ Question No1:- Determine the number of flights that are delayed on various days of the week /

-- First calling the database to import the data. use job_readiness; -- Import the data set to perform further operation. select from airline; select from airports; select * from runways;

select DayOfWeek, count(Flight), Delay from airline where Delay=1 group by DayOfWeek;

/ Question No2:- Determine the number of delayed flights for various airlines /

select Airline, count(Flight) from airline where Delay=1 group by Airline;

/ Question No3:- Determine how many delayed flights land at airports with at least 10 runways /

select AirportTo, Flight, Delay from airline where Delay=1 group by AirportTo;

/ Question No4:- Compare the number of delayed flights at airports higher than average elevation and those that are lower than average elevation for both source and destination airports /

-- Lets first compare for the source airport select l.AirportFrom, count(l.Flight), avg(p.elevation_ft) as avg_elevation, p.elevation_ft from airline as l inner join airports as p on p.iata_code = l.AirportFrom where p.elevation_ft > 1037.25 and l.Delay=1 group by l.AirportFrom;

select l.AirportFrom, count(l.Flight), avg(p.elevation_ft) as avg_elevation, p.elevation_ft from airline as l inner join airports as p on p.iata_code = l.AirportFrom where p.elevation_ft < 1037.25 and l.Delay=1 group by l.AirportFrom;

-- Lets now compare for the destination airport select l.AirportTo, count(l.Flight), avg(p.elevation_ft) as avg_elevation, p.elevation_ft from airline as l inner join airports as p on p.iata_code = l.AirportTo where p.elevation_ft > 1037.25 and l.Delay=1 group by l.AirportTo;

```
select l.AirportTo, count(l.Flight), avg(p.elevation_ft) as avg_elevation, p.elevation_ft from airline
as l inner join airports as p on p.iata_code = l.AirportFrom where p.elevation_ft < 1037.25 and
l.Delay=1 group by l.AirportTo;
```