

Delay Analysis for USA Aviation

Business Scenario

Problem statement:

According to air travel consumer reports, a large proportion of consumer complaints are about frequent flight delays.

Out of all the complaints received from consumers about airline services, 32% were related to cancellations, delays, or other deviations from the airlines' schedules.

There are unavoidable delays that can be caused by air traffic, no passengers at the airport, weather conditions, mechanical issues, passengers coming from delayed connecting flights, security clearance, and aircraft preparation.

Objective:

The objective of this project is to identify the factors that contribute to avoidable flight delays. You are also required to build a model to predict if the flight will be delayed.

Dataset Snapshot

Airlines.xlsx

ID	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay
1	CO	269	SFO	IAH	3	15	205	1
2	US	1558	PHX	CLT	3	15	222	1
3	AA	2400	LAX	DFW	3	20	165	1
4	AA	2466	SFO	DFW	3	20	195	1
5	AS	108	ANC	SEA	3	30	202	0
6	CO	1094	LAX	IAH	3	30	181	1
7	DL	1768	LAX	MSP	3	30	220	0
8	DL	2722	PHX	DTW	3	30	228	0
9	DL	2606	SFO	MSP	3	35	216	1
10	AA	2538	LAS	ORD	3	40	200	1
11	CO	223	ANC	SEA	3	49	201	1
12	DL	1646	PHX	ATL	3	50	212	1
13	DL	2055	SLC	ATL	3	50	210	0
14	AA	2408	LAX	DFW	3	55	170	0
15	AS	132	ANC	PDX	3	55	215	0
16	US	498	DEN	CLT	3	55	179	0
17	B6	98	DEN	JFK	3	59	213	0
18	CO	1496	LAS	IAH	3	60	162	0
19	DL	1450	LAS	MSP	3	60	181	0
20	CO	507	ONT	IAH	3	75	167	0

Dataset Description

Airlines.xlsx

Variables	Description
id	Flight number
Airline	Type of commercial airlines
Flight	Type of aircraft
AirportFrom	Source airport
AirportTo	Destination airport
DayOfWeek	Day of the week
Time	Departure time measured in minutes from midnight (range is from 10 to 1439)
Length	Duration of the flight in minutes
Delay	If the flight is delayed

Dataset Snapshot

airports.xlsx

id	ident	type	name	latitude_deg	longitude_deg	elevation	continent	iso_country	iso_region	municipality	scheduled	gps_code
6523 00A		heliport	Total Rf Helip	40.0708008	-74.933601	11	NA	US	US-PA	Bensalem	no	00A
32361 00AA		small_airport	Aero B Ranch	38.704022	-101.47391	3435	NA	US	US-KS	Leoti	no	00AA
6524 00AK		small_airport	Lowell Field	59.947733	-151.69252	450	NA	US	US-AK	Anchor Point	no	00AK
6525 00AL		small_airport	Epps Airpark	34.8647995	-86.770302	820	NA	US	US-AL	Harvest	no	00AL
6526 00AR		closed	Newport Hos	35.6087	-91.254898	237	NA	US	US-AR	Newport	no	
322127 00AS		small_airport	Fulton Airport	34.9428028	-97.818019	1100	NA	US	US-OK	Alex	no	00AS
6527 00AZ		small_airport	Cordes Airpor	34.3055992	-112.165	3810	NA	US	US-AZ	Cordes	no	00AZ
6528 00CA		small_airport	Goldstone (G	35.35474	-116.88533	3038	NA	US	US-CA	Barstow	no	00CA
324424 00CL		small_airport	Williams Ag /	39.427188	-121.76343	87	NA	US	US-CA	Biggs	no	00CL
322658 00CN		heliport	Kitcher Creel	32.7273736	-116.45974	3350	NA	US	US-CA	Pine Valley	no	00CN
6529 00CO		closed	Cass Field	40.622202	-104.344	4830	NA	US	US-CO	Briggsdale	no	
6531 00FA		small_airport	Grass Patch /	28.6455002	-82.219002	53	NA	US	US-FL	Bushnell	no	00FA
6532 00FD		closed	Ringhaver He	28.8466	-82.345398	25	NA	US	US-FL	Riverview	no	
6533 00FL		small_airport	River Oak Air	27.2308998	-80.9692	35	NA	US	US-FL	Okeechobee	no	00FL
6534 00GA		small_airport	Lt World Airp	33.7675018	-84.068298	700	NA	US	US-GA	Lithonia	no	00GA
6535 00GE		heliport	Caffrey Helip	33.887982	-84.736983	957	NA	US	US-GA	Hiram	no	00GE
6536 00HI		heliport	Kaupulehu Hr	19.832881	-155.97835	43	OC	US	US-HI	Kailua-Kona	no	00HI
6537 00ID		small_airport	Delta Shores	48.1453018	-116.214	2064	NA	US	US-ID	Clark Fork	no	00ID
322581 00IG		small_airport	Golti Airport	39.724028	-101.39599	3359	NA	US	US-KS	McDonald	no	00IG
6538 00II		closed	Bailey Gener	41.644501	-87.122803	600	NA	US	US-IN	Chesterton	no	

Dataset Description

airports.xlsx

Variables	Description
id	This is an identifier for the airport. It will stay persistent even if the airport code changes.
ident	This is the text identifier used in the <i>OurAirports</i> URL. This will be the International Civil Aviation Organization (ICAO) code if available. Otherwise, it will be a local airport code (if there is no conflict) or will be an internally-generated code starting with the ISO2 country code followed by a dash and a four-digit number.
type	This shows the type of the airport. The values allowed here are <i>closed_airport</i> , <i>heliport</i> , <i>large_airport</i> , <i>medium_airport</i> , <i>seaplane_base</i> , and <i>small_airport</i> .
name	This shows the official name of the airport, including <i>Airport</i> and <i>Airstrip</i>
latitude_deg	This shows the latitude of the airport in decimal degrees (north is positive).
longitude_deg	This shows the longitude of the airport in decimal degrees (east is positive).

Dataset Description

airports.xlsx

Variables	Description
elevation_ft	This shows the elevation MSL of the airport in feet (not meters).
continent	This shows the code for the continent where the airport is (primarily) located. The allowed values include <i>AF</i> (Africa), <i>AN</i> (Antarctica), <i>AS</i> (Asia), <i>EU</i> (Europe), <i>NA</i> (North America), <i>OC</i> (Oceania), or <i>SA</i> (South America).
iso_country	This shows the two-character ISO 3166-1-alpha2 code for the country where the airport is (primarily) located. A handful of unofficial, non-ISO codes are also in use, such as <i>XK</i> for Kosovo.
iso_region	This is an alphanumeric code for the high-level administrative subdivision of a country where the airport is primarily located (e.g., province and governorate) prefixed by the ISO2 country code and a hyphen. <i>OurAirports</i> uses ISO 3166-2 codes whenever possible, preferring higher administrative levels, but also includes some custom codes.
municipality	This shows the primary municipality that the airport serves (when available). Note that this is not necessarily the municipality where the airport is physically located.

Dataset Description

airports.xlsx

Variables	Description
scheduled_service	This shows <i>yes</i> if the airport currently has scheduled airline service and <i>no</i> if otherwise.
gps_code	This shows the code that an aviation GPS database (such as, Jeppesen's or Garmin's) would normally use for the airport. This will always be the ICAO code if one exists. Note that, unlike the <i>ident</i> column, this is not guaranteed to be globally unique.
iata_code	This shows the three-letter IATA code for the airport (if it has one).
local_code	This shows the local country code for the airport if it's different from the <i>gps_code</i> and <i>iata_code</i> fields (used mainly for US airports).
home_link	This shows the URL of the airport's official home page on the web if one exists.
wikipedia_link	This shows the URL of the airport's page on Wikipedia if one exists.
Keywords	This field contains other keywords or phrases to assist with the search. These are separated by a comma. It may also include former names for the airport, alternate codes, names in other languages, and nearby tourist destinations.

Dataset Snapshot

runways.xlsx

id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed	le_ident	le_latitude_d	le_longitude_d	le_elevation	le_heading_c
269408	6523	00A	80	80	ASP-H-G	1	0	0 H1				
255155	6524	00AK	2500	70	GRVL	0	0	0 N				
254165	6525	00AL	2300	200	TURF	0	0	0				
270932	6526	00AR	40	40	GRASS	0	0	0 H1				
322128	322127	00AS	1450	60	Turf	0	0	0				
257681	6527	00AZ	1700	60	GRAVEL	0	0	0			15	
245528	6528	00CA	6000	80	ASP-H	0	0	4	35.3493004	-116.893		50
250597	6529	00CO	3900	20	TURF-G	0	0	0				
247972	6531	00FA	3200	100	TURF	0	0	0				
265037	6532	00FD	74	74	TURF	0	0	0 H1				
250414	6533	00FL	4090	100	TURF	0	0	0				12
253429	6534	00GA	2600	80	TURF	0	0	0				9
265038	6535	00GE	125	95	ASP-H	1	0	0 H1				
265039	6536	00HI	1155	45	ASP-H-G	0	0	0 H1				
246648	6537	00ID	3300	40	TURF	0	0	0				8
246649	6537	00ID	2700	40	TURF	0	0	0				11
252182	6539	00IL	2500	75	TURF-F	0	0	0				18
265040	6540	00IN	40	40	MATS	1	0	0 H1				
254597	6541	00IS	1600	70	TURF	0	0	0				9
256603	6542	00KS	2600	85	TURF	0	0	0				17

Dataset Description

runways.xlsx

Variables	Description
id	This shows the internal <i>OurAirports</i> integer identifier for the runway. This will stay persistent even if the runway numbering changes.
airport_ref	This shows the internal integer foreign key matching the <i>id</i> column for the associated airport in airports.csv . Here, <i>airport_ident</i> is a better alternative.
airport_ident	This shows the externally-visible string foreign key matching the <i>ident</i> column for the associated airport in airports.csv .
length_ft	This shows the length of the full runway surface (including displaced thresholds and overrun areas) in feet.
width_ft	This shows the width of the runway surface in feet.
surface	This shows the code for the runway surface type. This is not a controlled vocabulary yet but probably will be soon. Some common values include <i>ASP</i> (asphalt), <i>TURF</i> (turf), <i>CON</i> (concrete), <i>GRS</i> (grass), <i>GRE</i> (gravel), <i>WATER</i> (water), and <i>UNK</i> (unknown).

Dataset Description

runways.xlsx

Variables	Description
lighted	This shows 1 if the surface is lit at night and 0 if not. Note that this is inconsistent with airports.csv which uses yes and no instead.)
closed	This shows 1 if the runway surface is currently closed and 0 if not.
le_ident	This shows the identifier for the low-numbered end of the runway.
le_latitude_deg	This shows the latitude of the center of the low-numbered end of the runway in decimal degrees (north is positive) if available.
le_longitude_deg	This shows the longitude of the centre of the low-numbered end of the runway in decimal degrees (east is positive) if available.
le_elevation_ft	This shows the elevation above MSL of the low-numbered end of the runway in feet.
le_heading_degT	This shows the heading of the low-numbered end of the runway in degrees true (not magnetic).

Dataset Description

runways.xlsx

Variables	Description
le_displaced_threshold_ft	This shows the length of the displaced threshold (if any) for the low-numbered end of the runway in feet.
he_ident	This shows the identifier for the high-numbered end of the runway.
he_latitude_deg	This shows the latitude of the centre of the high-numbered end of the runway in decimal degrees (north is positive) if available.
he_longitude_deg	This shows the longitude of the centre of the high-numbered end of the runway in decimal degrees (east is positive) if available.
he_elevation_ft	This shows the elevation above MSL of the high-numbered end of the runway in feet.
he_heading_degT	This shows the heading of the high-numbered end of the runway in degrees true (not magnetic).
he_displaced_threshold_ft	This shows the length of the displaced threshold (if any) for the high-numbered end of the runway in feet.

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.

- 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.

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

Project Task: Week 1

Applied data science with Python

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

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

Project Task: Week 1

Applied data science with Python

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.
 - b. Flights were delayed on various weekdays. Which day of the week is the safest for travel?
 - c. Which airlines should be recommended for short-, medium-, and long-distance travel?
 - d. Do you notice any patterns in the departure times of long-duration flights?
4. How many flights were delayed at large hubs compared to medium hubs? Use appropriate visualization to represent your findings.

Project Task: Week 1

Applied data science with Python

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
 - b. If the number of runways at an airport affects flight delays
 - c. If the duration of a flight (length) affects flight delays

Hint: Test this from the perspective of both the source and destination airports

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

Project Task: Week 1

Machine learning

1. Use OneHotEncoder and OrdinalEncoder to deal with categorical variables
 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

Project Task: Week 1

Machine learning

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

Project Task: Week 2

Tableau

1. Create a dashboard in Tableau by selecting appropriate chart types and metrics for the business

Note: Put more emphasis on data storytelling

Project Task: Week 2

Excel

1. Create an Excel dashboard showcasing the following (use form controls to make a dynamic chart):
 - a. Compare different airlines based on their on-time performance
 - b. Compare the percentage of delayed flights for different days of the week
 - c. Create a trend chart for the number of passengers at large and medium hubs
 - d. Visualize the count of delayed and on-time flights for different pairs of source and destination airports
 - Create a dynamic chart that allows users to select a source and destination airport.

Project Task: Week 2

SQL

1. Determine the number of flights that are delayed on various days of the week
2. Determine the number of delayed flights for various airlines
3. Determine how many delayed flights land at airports with at least 10 runways
4. 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

Delay Analysis for USA Aviation

```
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()
```

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

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

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

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

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

	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()`

	id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed	le_ident	le_lat
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_eleva
'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 airpot data that is not usefull.
airpot.info()`

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

```
In [16]: airpots = airpot.drop(['continent', 'iso_country', 'iso_region','municipality', 'gi  
'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 Iojima 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 Iejima 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",`

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

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	MXY		MOXY
5	Delta Air Lines	NaN	DL	DAL		DELTA
6	Eastern Airlines	NaN	2D	EAL		EASTERN
7	Frontier Airlines	NaN	F9	FFT	FRONTIER	FLIGHT
8	Hawaiian Airlines	NaN	HA	HAL		HAWAIIAN
9	JetBlue	NaN	B6	JBU		JETBLUE
10	Southwest Airlines	NaN	WN	SWA		SOUTHWEST
11	Spirit Airlines	NaN	NK	NKS		SPIRIT WINGS
12	Sun Country Airlines	NaN	SY	SCX		SUN COUNTRY
13	United Airlines	NaN	UA	UAL		UNITED

	Primary hubs, Secondary hubs	Founded	\
0	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932	
1	Las VegasCincinnatiFort Walton BeachIndianapol...	1997	
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-MidwayDenne...	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	AIRLINE	IATA	ICAO	Callsign	\	AIRLINE	IM
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 LauderdaleOrlandoOrlandoTampa	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	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	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
1		Air Flight Charters		NaN	NaN	FLL
2		Airshare		NaN	NaN	XSR
3		Berry Aviation		NaN	NaN	BYA
4		Bighorn Airways		NaN	NaN	BHR

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		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	
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		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		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

					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		Wilmingtton (OH)	Cincinnati	Miami	1980.0		
2			Milwaukee	Cincinnati	1986.0		
3			Columbus-Rickenbacker		1974.0		
4			Wilmington (OH)	Cincinnati	1978.0		
5				Anchorage	1996.0		
6				Honolulu	1946.0		
7		Provo	Billings	Sioux Falls	1971.0		
8	Fort Worth/Alliance	Cincinnati	Leipzig/Halle	San ...	2015.0		
9			Dallas/Fort Worth		1968.0		
10			Miami	Port of Spain	1974.0		
11		Dallas-Addison	El Paso	Willow Run	2000.0		
12				Guam	Honolulu	1998.0	
13	New York-JFK	Anchorage	Cincinnati	Houston	Huntsvil...	1992.0	
14			Bemidji	Minneapolis/St. Paul		1946.0	
15				Akron/Canton		1986.0	
16				Billings		1981.0	
17				Iron Mountain		1998.0	
18			Coeur d' Alene	Spokane		1977.0	
19			Fairbanks	Anchorage		1995.0	
20	Memphis	Anchorage	Cologne/Bonn	Dubai	Fort Worth	Gre...	1971.0
21					Milwaukee		1985.0
22				Waterford	Miami		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	AniakBethel	Emmonak	Kotzebue	Nome	St. Mar...	1953.0
34					Miami		1969.0
35					NaN		1981.0
36					Miami		2018.0
37					Honolulu		1982.0
38	Louisville	Chicago/Rockford	Cologne/Bonn	Columbia...			1988.0
39					Ypsilanti	Laredo	1994.0
40		Las Vegas	Oakland	Ontario	Sacramento	San Diego	1988.0
41		Miami Liege, Belgium;	Belgium; Anchorage	Fort Myers, FL			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	NaN
1		Air Methods	NaN	NaN	NaN	NaN	NaN
2	Critical Air Medicine		NaN	NaN	NaN	NaN	NaN
3		Lifestar	NaN	NaN	NaN	NaN	NaN
4		Life Lion	NaN	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
3		NaN	NaN
4		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
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21	U Uganda Ukraine United Arab Emirates United K...
22	U
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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,
 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 Hufl 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	Dallas-LoveAtlantaBaltimoreChicago-MidwayDenne...	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 oper: 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	Notes	
						Hubs, Secondary		
0	Comco	NaN	NaN	NaN	NaN	NaN	2002	NaN
1	Janet	NaN	NaN	WWW	JANET	Las Vegas	1972	NaN
2	Justice Prisoner and Alien Transportation System	NaN	NaN	JUD	JUSTICE	Oklahoma City	1980	Commenced operations in 1995.

In [27]: `# Lets first merge all wikipedia table.``wiki_table = [tables[0],tables[1],tables[2],tables[3],tables[4],tables[5],tables[6]]`In [28]: `wiki_tables = pd.concat(wiki_table, ignore_index=True)`In [29]: `wiki_tables`

Out[29]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, Secondary hubs	Founded	
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932.0	A cc
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997.0	E cc
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926.0	A cc
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlando	1987.0	I
4	Breeze Airways	NaN	MX	MXY	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

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 wikipedia link and the data
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

```
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		Eppley 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

Airport name \ Rank Rank change , 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	Aircraft \		
			Location	IATA Code	Traffic 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

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	EWR	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
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21	NaN
22	NaN
23	NaN
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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 \ Movements
			Location	IATA	Code	
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	EWR	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 \	Rank	Rank	change	Airport name	
				Rank	Rank
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	EWR	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		
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	
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
rt name \		Airpo
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	EWR	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	

Rank	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% , .mw-parser-output .navbar{display:inline;font-size:88%;font-weight:normal}.mw-parser-output .navbar-collapse{float:left;text-align:left}.mw-parser-output .navbar-boxtext{word-spacing:0}.mw-parser-output .navbar ul{display:inline-block;white-space:nowrap;line-height:inherit}.mw-parser-output .navbar-brackets::before{margin-right:-0.125em;content:"[".mw-parser-output .navbar-brackets::after{margin-left:-0.125em;content:"]".mw-parser-output .navbar li{word-spacing:-0.125em}.mw-parser-output .navbar a>span,.mw-parser-output .navbar a>abbr{text-decoration:inherit}.mw-parser-output .navbar-mini abbr{font-variant:small-caps;border-bottom:none;text-decoration:none;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 the United States \
0 Atlanta (Hartsfield-Jackson - ATL) Austin (Aus... 1 Statistics	
0 Atlanta (Hartsfield-Jackson - ATL) Austin (Aus... 1 Statistics	
, vteList of the busiest airports in North America \	
0 Sovereign states	
1 Dependencies and other 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 busiest airports by continent \	
0 Africa Asia Europe North America Oceania South... 1 vteLists of the busiest airports by continent.1 0 Africa Asia Europe North America Oceania South... , vte	

```

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()`

	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 wikipedia link and the data 1
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 we 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()`

	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	

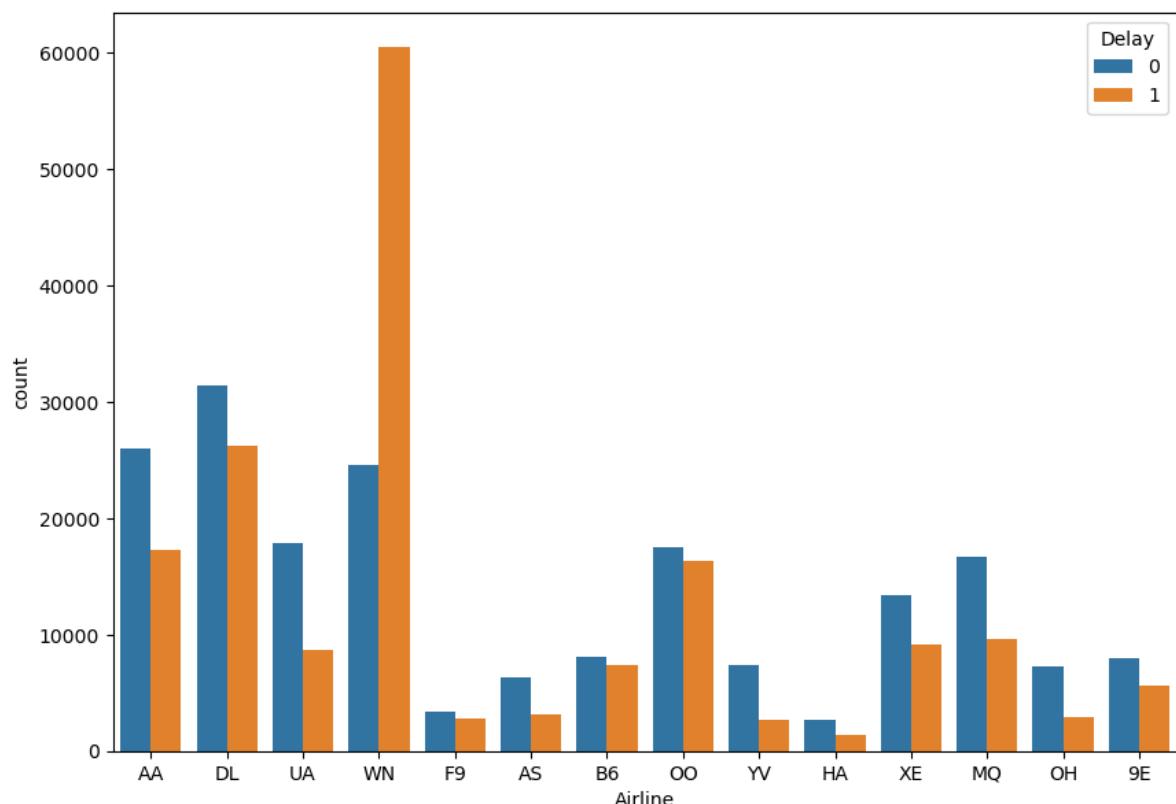
3. Perform data visualization and share your insights on the following points:

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 flights of Southwest Airlines are delayed.

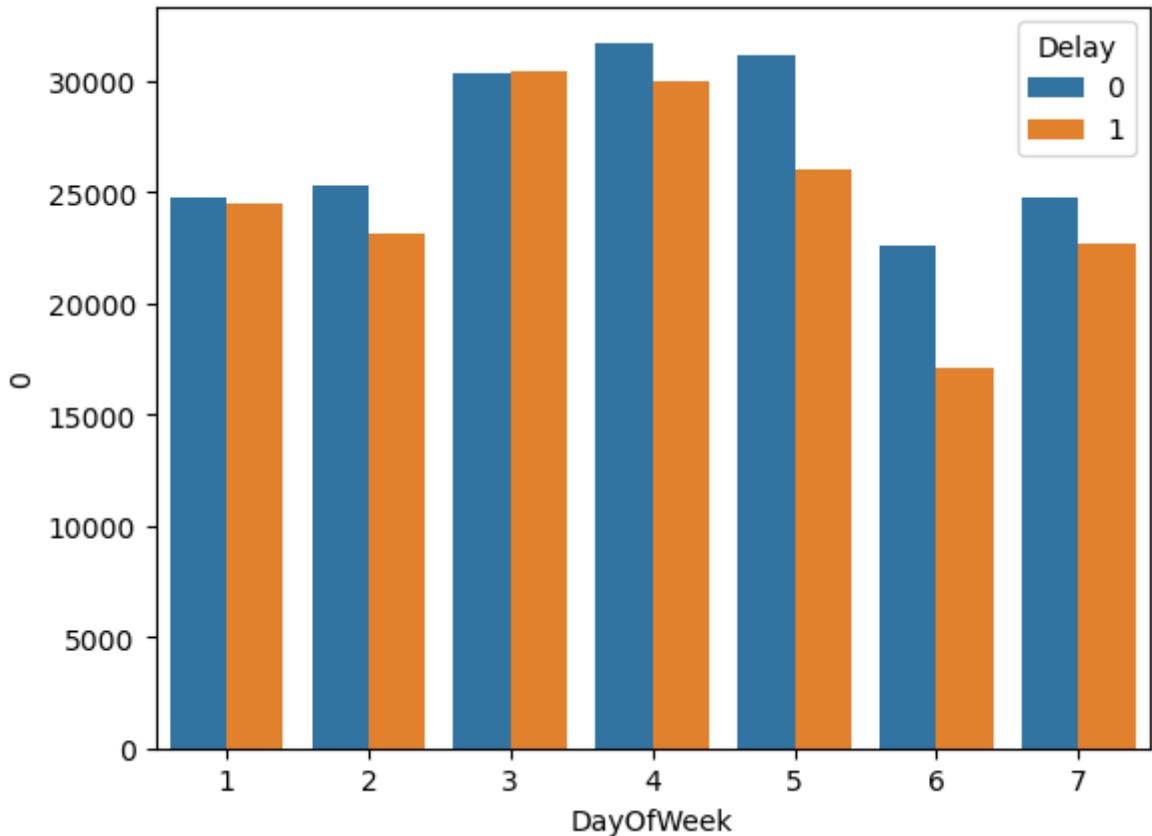
b. Flights were delayed on various weekdays. Which day of the week is the safest for travel?

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'>
```

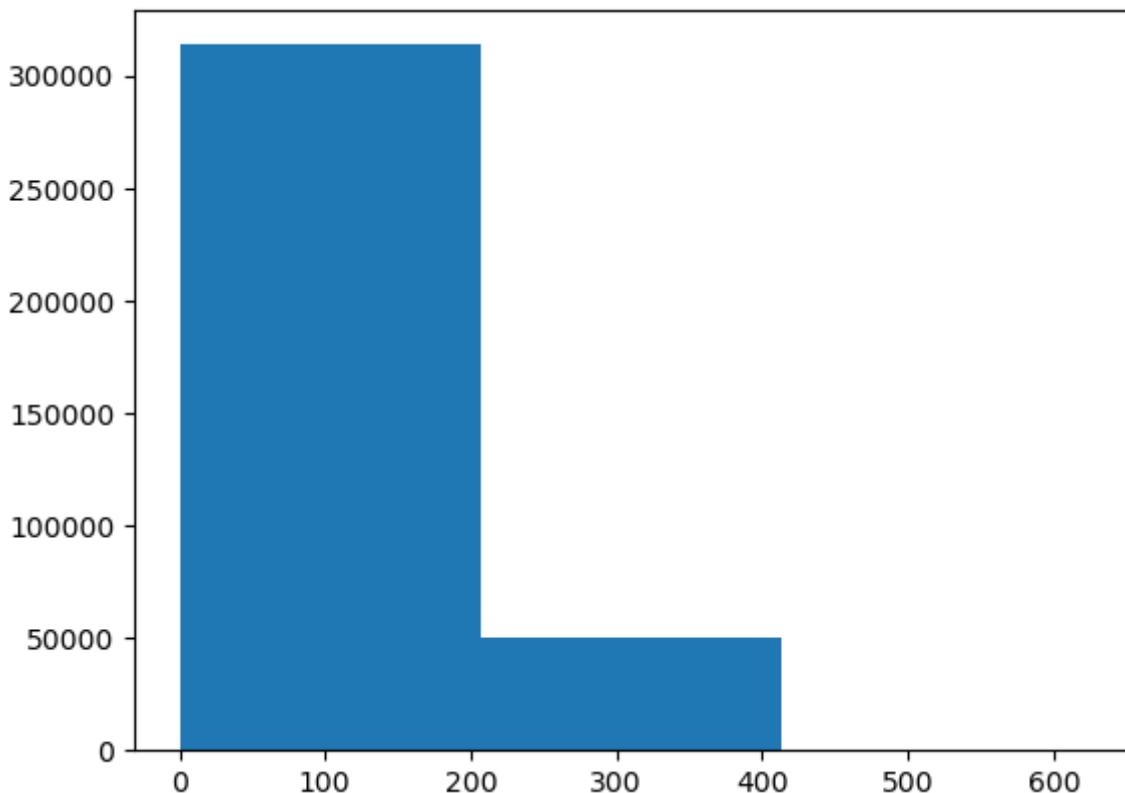


On the 5th day of week its clear that there is less no of flight delay.

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]
```

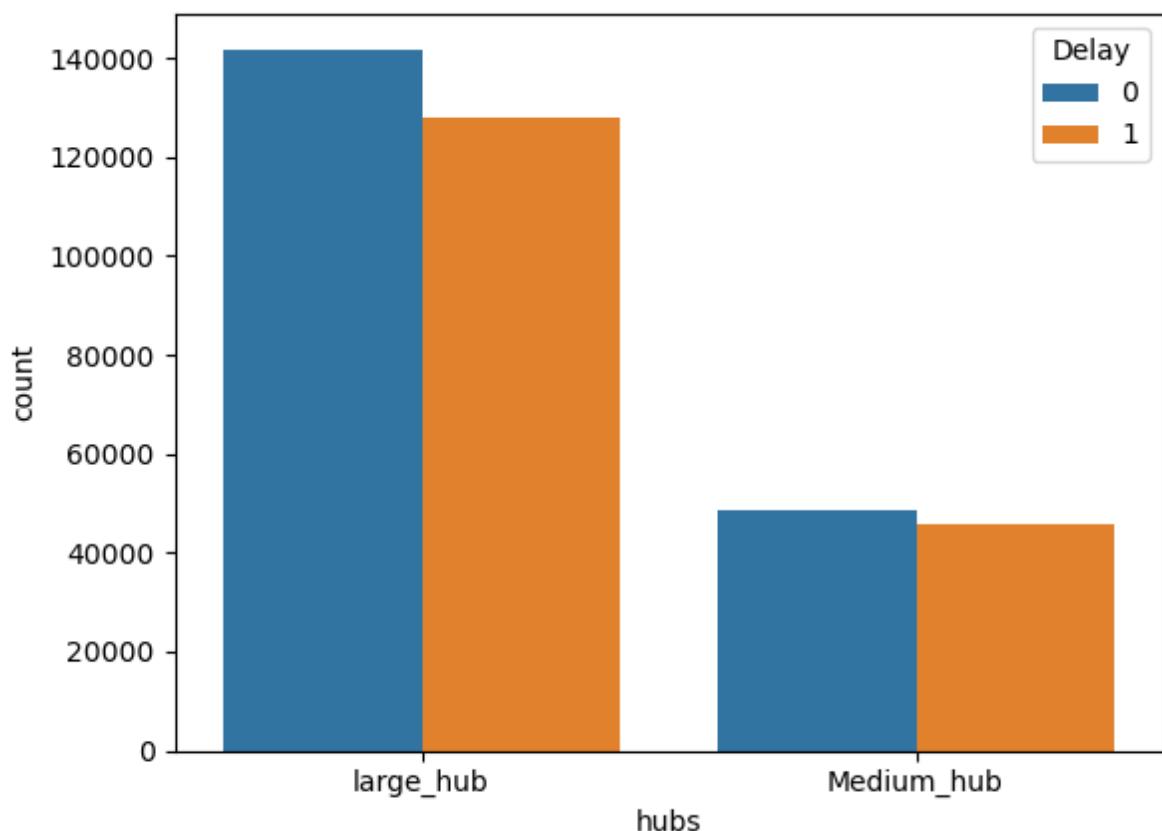
```
Out[58]: 46345    1045
46348    1045
46356    1045
46364    1045
46367    1045
...
315043   1416
315049   1416
315055   1416
315061   1416
315067   1416
Name: Time, Length: 1207, dtype: int64
```

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 filght is delayed but from the small hubs aprrox 40000 is delayed.

5. Use hypothesis testing strategies to discover:

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

```
In [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.

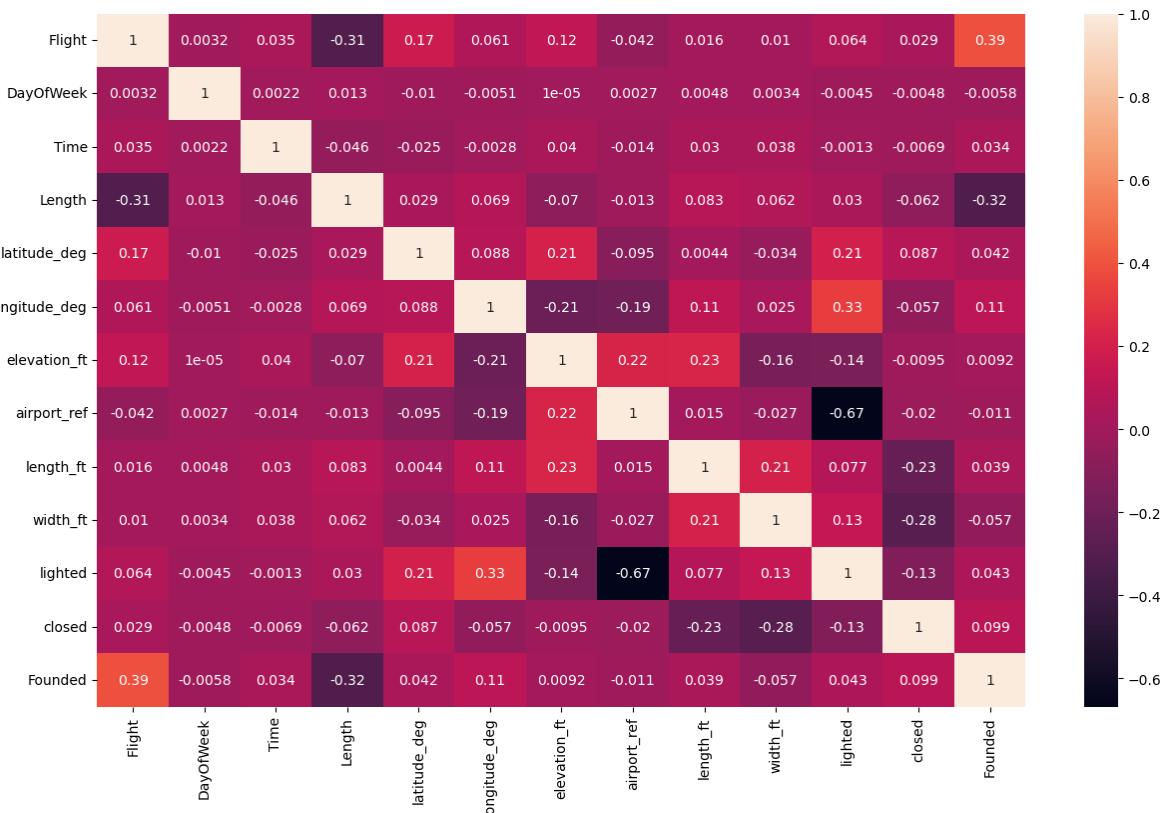
6. Find the correlation matrix between the flight delay predictors, create a heatmap to visualize this, and share your findings

```
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	0.124
DayOfWeek	0.003249	1.000000	0.002218	0.013059	-0.010100	-0.005075	0.000
Time	0.034959	0.002218	1.000000	-0.045729	-0.024743	-0.002804	0.039
Length	-0.311840	0.013059	-0.045729	1.000000	0.028905	0.068559	-0.070
latitude_deg	0.168127	-0.010100	-0.024743	0.028905	1.000000	0.087885	0.208
longitude_deg	0.061268	-0.005075	-0.002804	0.068559	0.087885	1.000000	-0.208
elevation_ft	0.124437	0.000010	0.039522	-0.070187	0.208233	-0.208175	1.000
airport_ref	-0.042421	0.002675	-0.014048	-0.012986	-0.095324	-0.190519	0.224
length_ft	0.016064	0.004768	0.029940	0.083335	0.004430	0.114385	0.225
width_ft	0.010186	0.003414	0.038049	0.062138	-0.034404	0.024904	-0.155
lighted	0.064012	-0.004520	-0.001339	0.029629	0.205215	0.325019	-0.141
closed	0.029169	-0.004811	-0.006927	-0.062091	0.087013	-0.056677	-0.009
Founded	0.389930	-0.005840	0.033776	-0.318902	0.042304	0.107272	0.009

```
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 fe
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 through 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()
```

	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 further analysis
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_state=42)
```

LogisticRegression

```
In [79]: # Lets apply the Logistic regression with the randomsearchcv hypermeter tuning.
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)
```

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

```
Out[81]: 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= 9)`

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_by
 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 diffrent model the best result we getting from the XGBclassifier.

In []:

In []:

SQL PART

```
/* Question No1:- Determine the number of flights that are delayed on various days of the week */
-- First calling the database to import the data.
CREATE DATABASE job_readiness;
USE job_readiness;
-- Import the data set to perform further operation.
SELECT * FROM airline;
SELECT * FROM airports;
SELECT * FROM runways;

SELECT
    DayOfWeek,
    COUNT(Flight) AS delayed_flights_count,
    Delay
FROM
    airline
WHERE
    Delay = 1
GROUP BY
    DayOfWeek, Delay;

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

SELECT
    Airline,
    COUNT(Flight) AS delayed_flights_count
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, Flight, Delay;
```

```

/* 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) AS delayed_flights_count,
    AVG(p.elevation_ft) AS average_departure_elevation
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, p.elevation_ft;

SELECT
    l.AirportFrom,
    COUNT(l.Flight) AS delayed_flights_count,
    AVG(p.elevation_ft) AS average_departure_elevation
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, p.elevation_ft;

-- Lets now compare for the destination airport

SELECT
    l.AirportTo,
    COUNT(l.Flight) AS delayed_flights_count,
    AVG(p.elevation_ft) AS average_destination_elevation,
    p.elevation_ft AS destination_elevation
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, p.elevation_ft;

```

```

SELECT
    l.AirportTo,
    COUNT(l.Flight) AS delayed_flights_count,
    AVG(p.elevation_ft) AS average_destination_elevation,
    p.elevation_ft AS destination_elevation
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, p.elevation_ft;

```

MySQL Workbench

File Edit View Query Database Server Tools Scripting Help

Navigator: Schemas Filter objects

Tables: job_readiness (airline, airports, runways)

Views, Stored Procedures, Functions

Administration Schemas

Information Connection Details: Nroot, Hd27.0.0.1, Pd306, Lo, User root, User root@localhost, SSL TLS_AES_256_GCM_SHA256, Ciphers, Server MySQL Community Server - GPL, Version 8.0.32, Connector VeC++ 8.0.32

Object Info Session

United States Airlines Analysis... ×

SQL Additions: Automatic context help is disabled. Use the toolbar to manually get help for the current caret position or to toggle automatic help.

10
11 • SELECT
12 DayOfWeek,
13 COUNT(Flight) AS delayed_flights_count,
14 Delay
15 FROM
16 airline
17 WHERE
18 Delay = 1
19 GROUP BY
20 DayOfWeek, Delay;

Result Grid: Filter Rows: Export: Wrap Cell Content:

DayOfWeek	delayed_flights_count	Delay
3	41144	1
4	40280	1
5	34813	1
6	22860	1
7	30761	1
1	33059	1
2	31072	1

Result 4 × Result 5 Result 6 Result 7 Result 8 Result 9 Result 10

Action Output: # Time Action Message Duration / Fetch

10 01:00:49 SELECT l.AirportTo, COUNT(l.Flight) AS delayed_flights_count, AVG(p.elevation_ft... 79 row(s) returned 0.843 sec / 0.000 sec

MySQL Workbench

File Edit View Query Database Server Tools Scripting Help

Navigator: United States Airlines Analysis_...

SCHEMAS: job_readiness

Tables: airline, airports, runways

Views, Stored Procedures, Functions

Administration Schemas

Information: Connection Details, Server, Connector, Object Info, Session

SQL:

```
10
11 • SELECT
12     DayOfWeek,
13     COUNT(Flight) AS delayed_flights_count,
14     Delay
```

Result Grid:

Airline	delayed_flights_count
CO	11957
US	11591
AA	17736
DL	27452
HA	1786
OH	3502
9E	8226
OO	22760
EV	11255
XE	11795
MQ	12742
B6	8459
F9	2899
UA	8946
WN	65657
YV	3334
AC	2002

airline 1 airports 2 runways 3 Result 4 Result 5 Result 6 Result 7 Result 8 Result 9 Result 10

Output:

Action Output:

#	Time	Action	Message	Duration / Fetch
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft...)	79 row(s) returned	0.843 sec / 0.000 sec

Result Grid, Form Editor, Field Types, Query Stats, Read Only, Context Help, Snippets

Automatic context help is disabled. Use the toolbar to manually get help for the current caret position or to toggle automatic help.

MySQL Workbench

File Edit View Query Database Server Tools Scripting Help

Navigator: United States Airlines Analysis_...

SCHEMAS: job_readiness

Tables: airline, airports, runways

Views, Stored Procedures, Functions

Administration Schemas

Information: Connection Details, Server, Connector, Object Info, Session

SQL:

```
10
11 • SELECT
12     DayOfWeek,
13     COUNT(Flight) AS delayed_flights_count,
14     Delay
```

Result Grid:

AirportTo	Flight	Delay
IAH	269	1
CLT	1558	1
DFW	2400	1
DFW	2466	1
IAH	1094	1
MSP	2606	1
ORD	2538	1
SEA	223	1
ATL	1646	1
HNL	17	1
PHX	122	1
OGG	206	1
ATL	6338	1
PHX	149	1
MSP	3854	1
MSP	4651	1
CLT	4710	1

airline 1 airports 2 runways 3 Result 4 Result 5 Result 6 Result 7 Result 8 Result 9 Result 10

Output:

Action Output:

#	Time	Action	Message	Duration / Fetch
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft...)	79 row(s) returned	0.843 sec / 0.000 sec

Result Grid, Form Editor, Field Types, Query Stats, Read Only, Context Help, Snippets

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MySQL Workbench

File Edit View Query Database Server Tools Scripting Help

Navigator Schemas

SCHEMAS

- job_readiness
 - Tables
 - airline
 - airports
 - runways
 - Views
 - Stored Procedures
 - Functions

Administration Schemas

Information

Connection Details

- Nroot
- Hd27.0.0.1
- Pd306
- Lo_root
- User root
- C_root@localhost
- User root@localhost
- SSL TLS_AES_256_GCM_SHA256
- Server MySQL Community Server - GPL
- V8.0.32

Connector Vc++ 8.0.32

Object Info Session

United States Airlines Analysis _

```

10
11 • SELECT
12     DayOfWeek,
13     COUNT(Flight) AS delayed_flights_count,
14     Delay
  
```

Result Grid | Filter Rows: Export: Wrap Cell Content:

AirportFrom	delayed_flights_count	average_departure_elevation
PHX	6816	1135.0000
LAS	6642	2181.0000
DLH	84	1428.0000
LWS	33	1442.0000
PIT	1387	1203.0000
ITH	36	1099.0000
CAK	175	1228.0000
COS	370	6187.0000
MFR	140	1335.0000
BOI	621	2871.0000
GEG	479	2376.0000
SGU	76	2941.0000
ICT	267	1333.0000
XNA	317	1287.0000
DEN	9399	5431.0000
TUS	617	2643.0000
airline 1	airports 2	runways 3
Result 4	Result 5	Result 6
Result 7	Result 8	Result 9
Result 10		

SQLAdditions | Read Only | Context Help | Snippets

Action Output

#	Time	Action	Message	Duration / Fetch
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft... 79 row(s) returned		0.843 sec / 0.000 sec

MySQL Workbench

File Edit View Query Database Server Tools Scripting Help

Navigator Schemas

SCHEMAS

- job_readiness
 - Tables
 - airline
 - airports
 - runways
 - Views
 - Stored Procedures
 - Functions

Administration Schemas

Information

Connection Details

- Nroot
- Hd27.0.0.1
- Pd306
- Lo_root
- User root
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- V8.0.32

Connector Vc++ 8.0.32

Object Info Session

United States Airlines Analysis _

```

10
11 • SELECT
12     DayOfWeek,
13     COUNT(Flight) AS delayed_flights_count,
14     Delay
  
```

Result Grid | Filter Rows: Export: Wrap Cell Content:

AirportFrom	delayed_flights_count	average_departure_elevation
BTR	199	70.0000
ORD	11906	672.0000
CLE	1995	791.0000
MHT	427	266.0000
CVG	1824	896.0000
LSE	40	655.0000
CHS	315	46.0000
SRQ	99	30.0000
SPI	47	598.0000
SCC	15	65.0000
HSV	204	629.0000
BRO	49	22.0000
EAU	34	913.0000
LTH	243	153.0000
AVP	86	962.0000
OME	44	37.0000
MDW	55	97.0000
airline 1	airports 2	runways 3
Result 4	Result 5	Result 6
Result 7	Result 8	Result 9
Result 10		

SQLAdditions | Read Only | Context Help | Snippets

Action Output

#	Time	Action	Message	Duration / Fetch
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft... 79 row(s) returned		0.843 sec / 0.000 sec

MySQL Workbench

root

File Edit View Query Database Server Tools Scripting Help

Navigator: United States Airlines Analysis

SCHEMAS job_readiness

Tables: airline, airports, runways

Views, Stored Procedures, Functions

Administration Schemas

Information

Connection Details

- Nroot
- Hd27.0.0.1
- Pd306
- Lo root
- User C root@localhost
- User SSL TLS_AES_256_GCM_SHA256

Server

- MySQL Community Server - GPL
- V8.0.32
- Connector
- Vc++ 8.0.32

Object Info Session

United States Airlines Analysis

10 • SELECT DayOfWeek, COUNT(Flight) AS delayed_flights_count, Delay

Result Grid

AirportTo	delayed_flights_count	average_destination_elevation	destination_elevation									
PHX	7073	1135.0000	1135									
SLC	5146	4227.0000	4227									
DEN	8605	5431.0000	5431									
LAS	6824	2181.0000	2181									
ELP	1032	3959.0000	3959									
ABQ	1643	5355.0000	5355									
BOI	740	2871.0000	2871									
RNO	978	4415.0000	4415									
OKC	1002	1295.0000	1295									
PIT	1375	1203.0000	1203									
SJT	8	1919.0000	1919									
TUS	948	2643.0000	2643									
EKO	57	5140.0000	5140									
SUN	106	5318.0000	5318									
MAF	316	2871.0000	2871									
PIH	58	4452.0000	4452									
YIA	105	1227.0000	1227									
airline	1	airports	2	runways	3	Result 4	Result 5	Result 6	Result 7	Result 8	Result 9	Result 10

Action Output

#	Time	Action	Message
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft... 79 row(s) returned	79 row(s) returned

SQLAdditions

Automatic context help is disabled. Use the toolbar to manually get help for the current caret position or to toggle automatic help.

MySQL Workbench

root

File Edit View Query Database Server Tools Scripting Help

Navigator: United States Airlines Analysis

SCHEMAS job_readiness

Tables: airline, airports, runways

Views, Stored Procedures, Functions

Administration Schemas

Information

Connection Details

- Nroot
- Hd27.0.0.1
- Pd306
- Lo root
- User C root@localhost
- User SSL TLS_AES_256_GCM_SHA256

Server

- MySQL Community Server - GPL
- V8.0.32
- Connector
- Vc++ 8.0.32

Object Info Session

United States Airlines Analysis

10 • SELECT DayOfWeek, COUNT(Flight) AS delayed_flights_count, Delay

Result Grid

AirportTo	delayed_flights_count	average_destination_elevation	destination_elevation									
ORD	9295	672.0000	672									
CVG	1658	896.0000	896									
CLE	2058	791.0000	791									
SCC	10	65.0000	65									
SPI	78	598.0000	598									
CHS	420	46.0000	46									
BTR	265	70.0000	70									
MHT	592	266.0000	266									
OME	51	37.0000	37									
HSV	273	629.0000	629									
SRQ	130	30.0000	30									
LIH	296	153.0000	153									
BRO	89	22.0000	22									
AVP	102	962.0000	962									
EAU	35	913.0000	913									
LSE	39	655.0000	655									
airline	1	airports	2	runways	3	Result 4	Result 5	Result 6	Result 7	Result 8	Result 9	Result 10

Action Output

#	Time	Action	Message
10	01:00:49	SELECT I.AirportTo, COUNT(I.Flight) AS delayed_flights_count, AVG(p.elevation_ft... 79 row(s) returned	79 row(s) returned

SQLAdditions

Automatic context help is disabled. Use the toolbar to manually get help for the current caret position or to toggle automatic help.

Project Task: Week 2

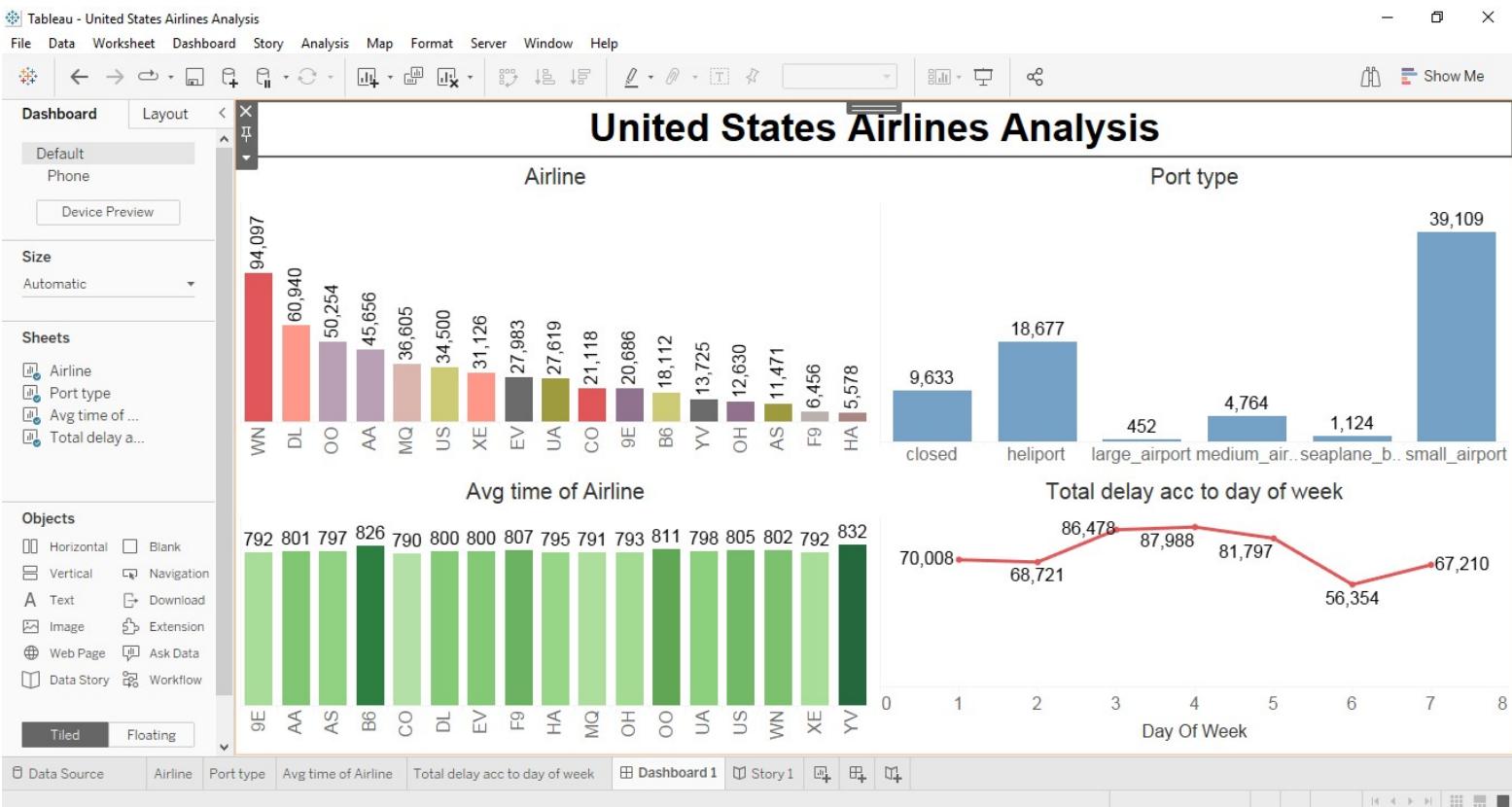
1. Create a dashboard in Tableau by selecting appropriate chart types and metrics for the business

Note: Put more emphasis on data storytelling

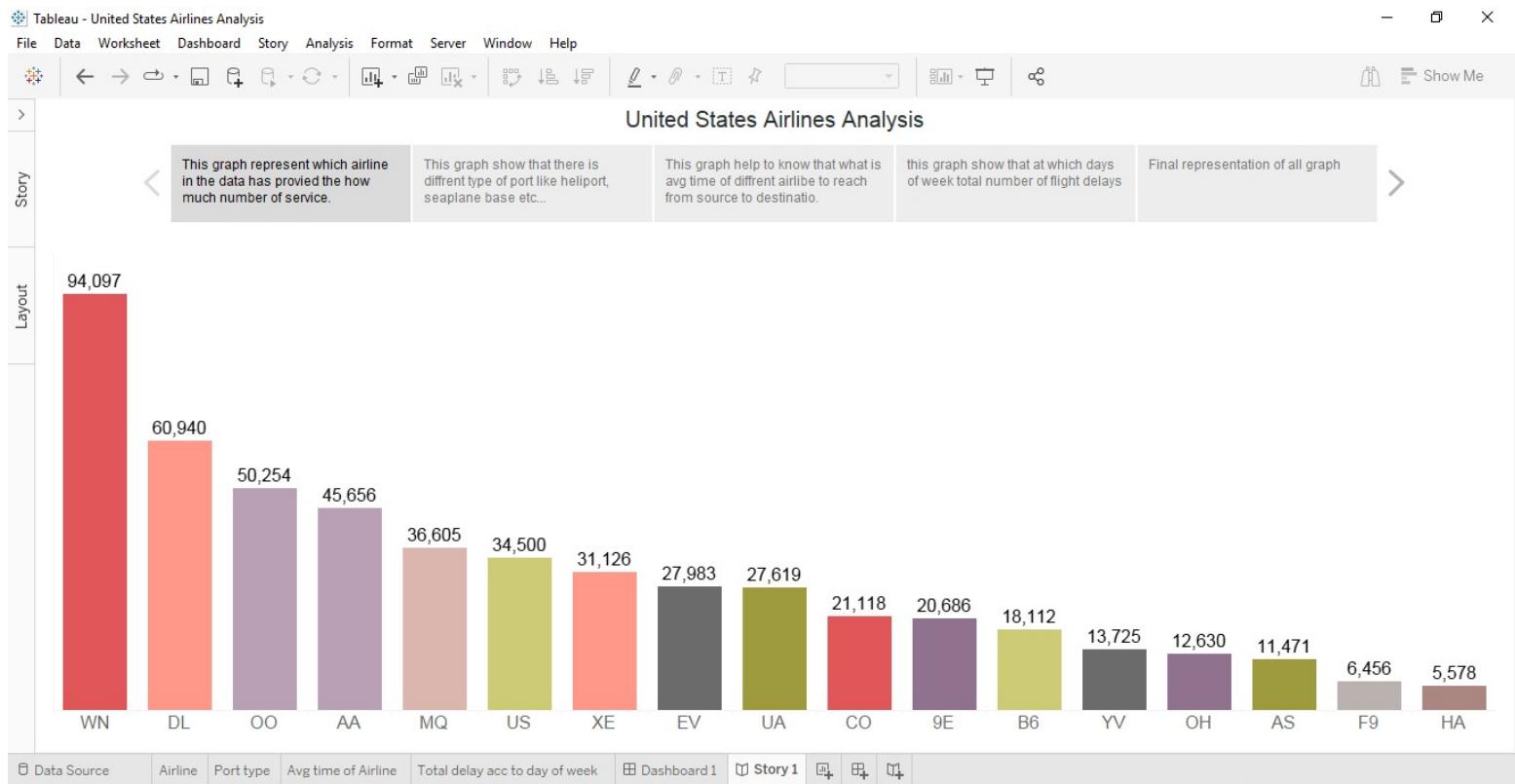
Dashboard

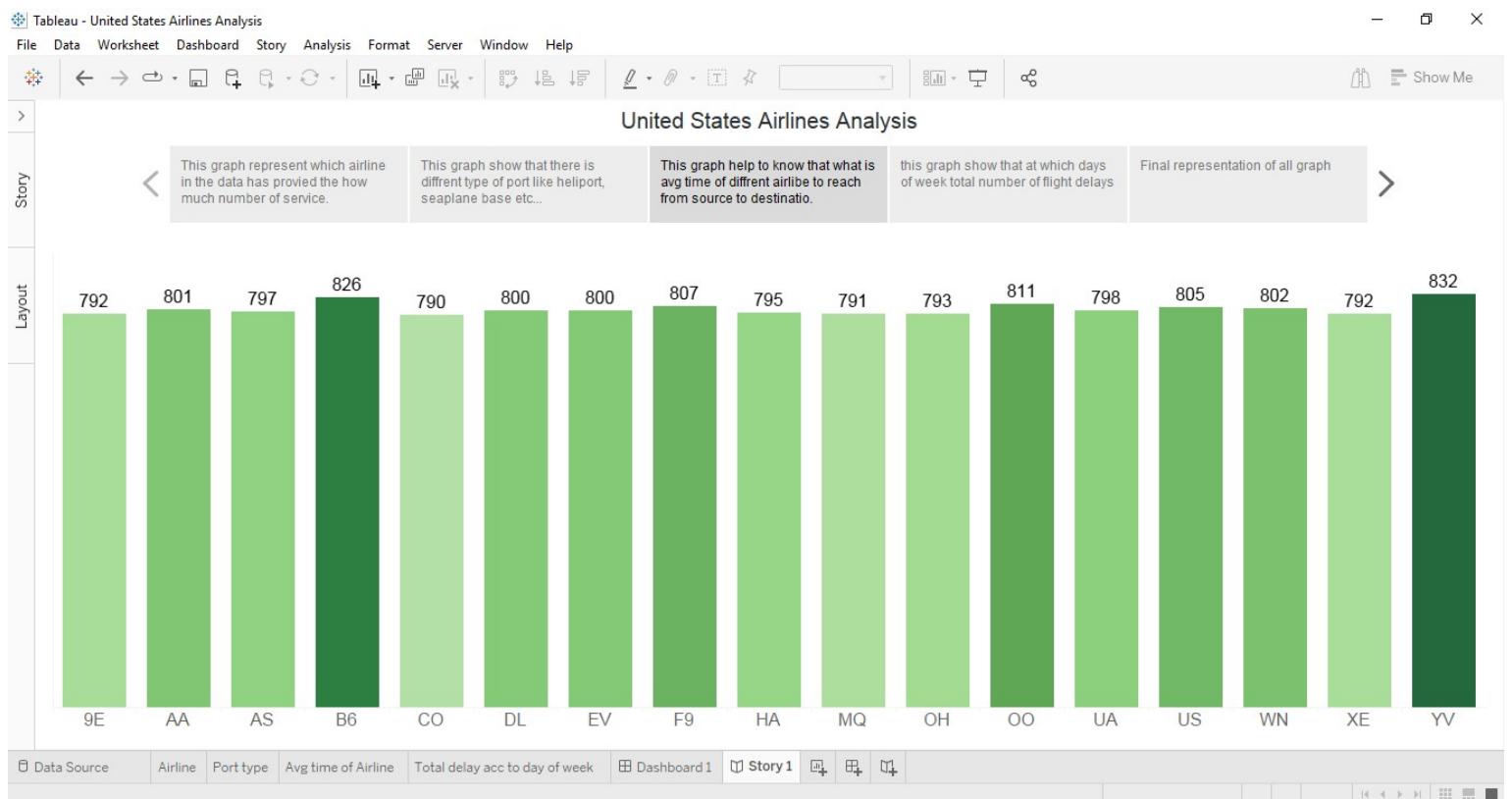
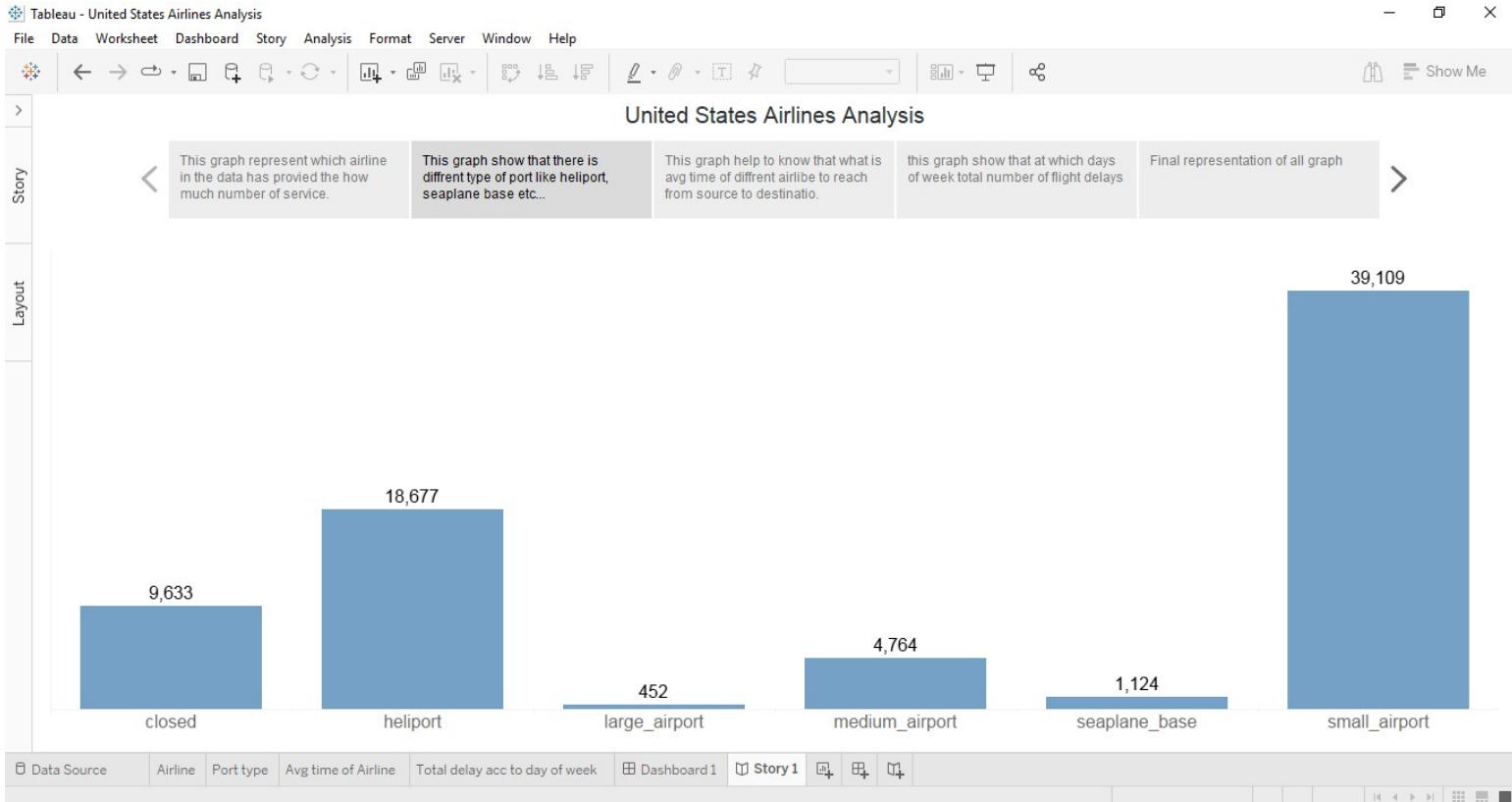
Storytelling

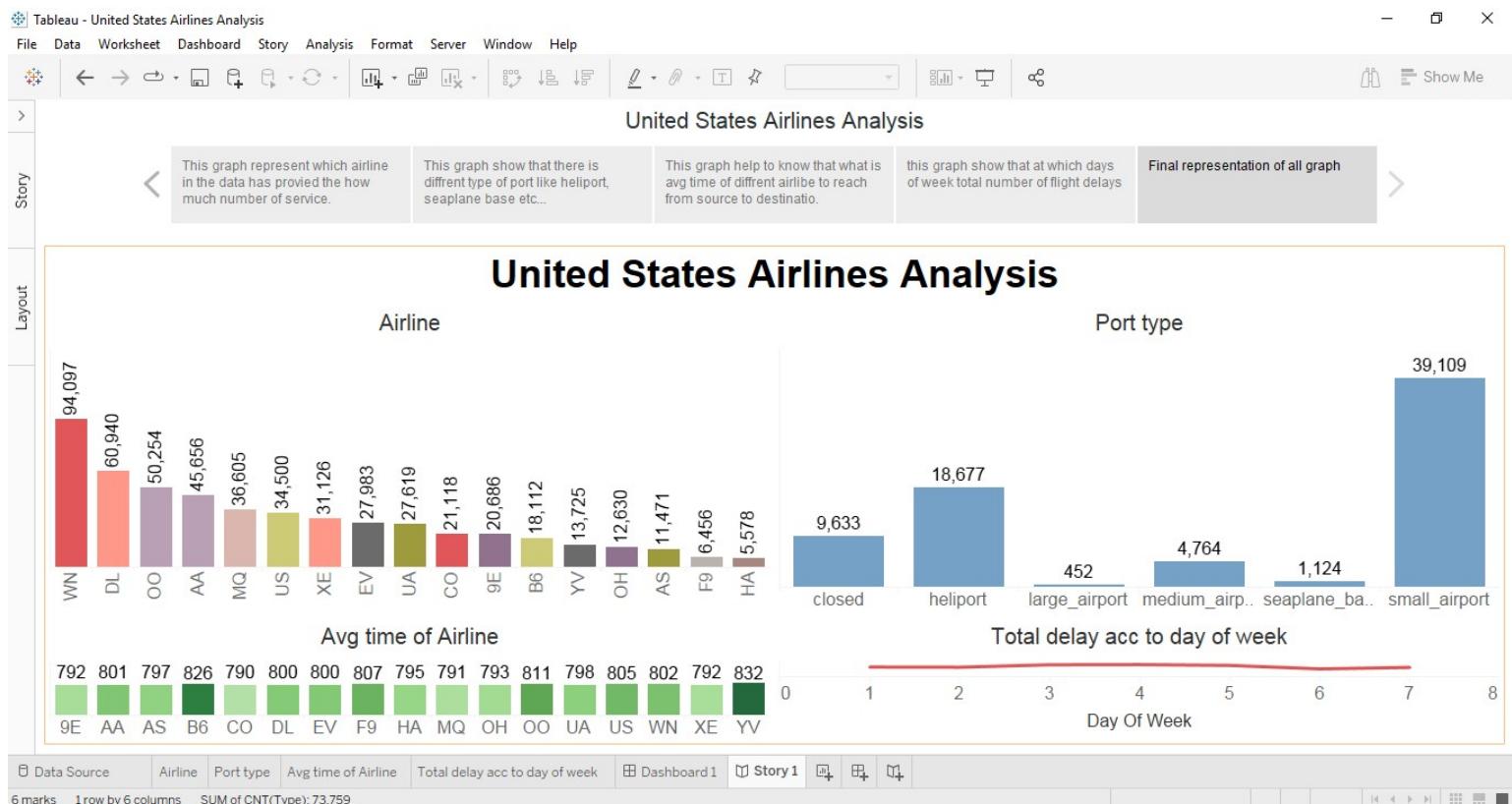
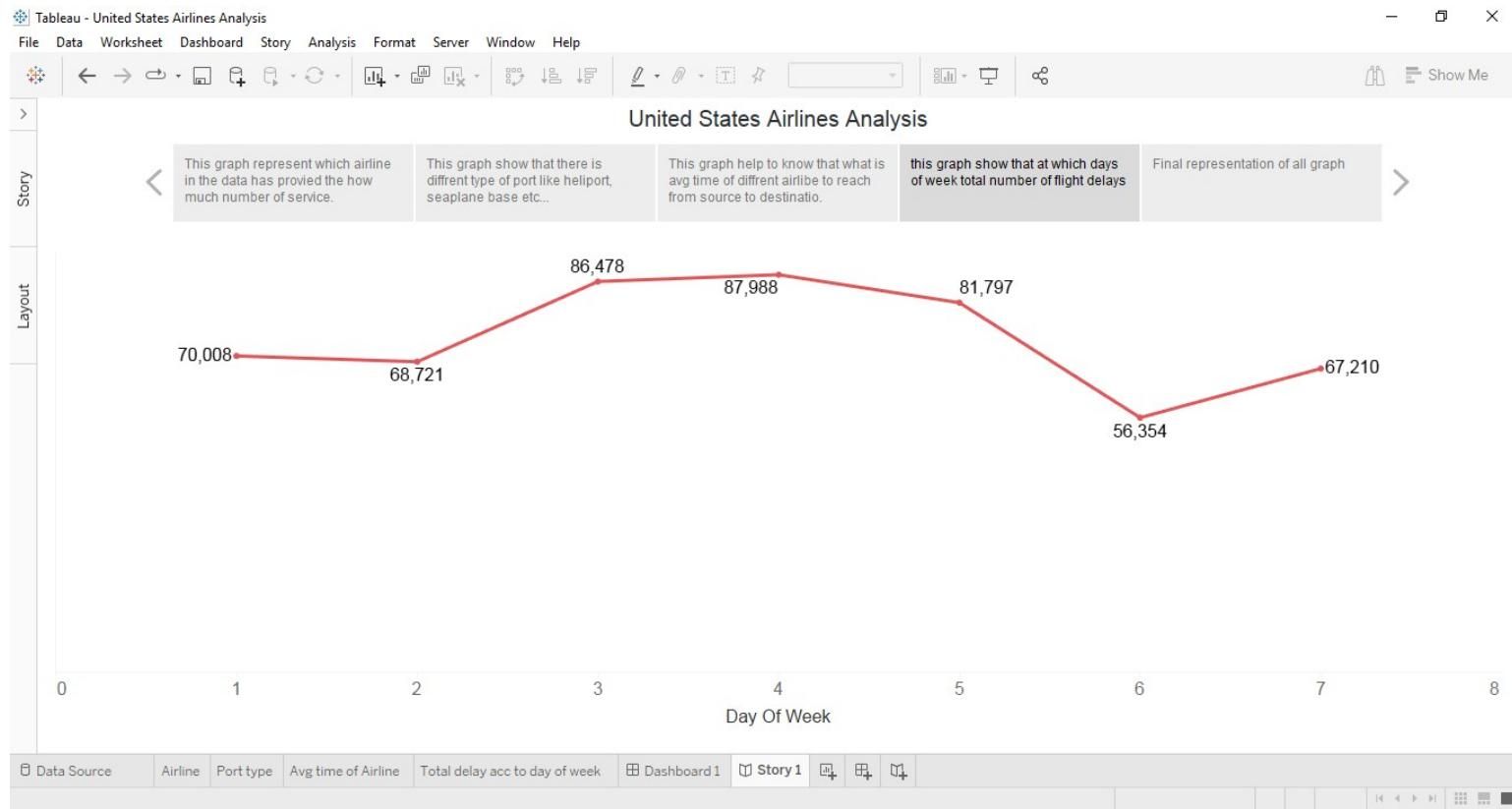
Dashboard



story







Excel

1. Create an Excel dashboard showcasing the following (use form controls to make a dynamic chart):
 - a. Compare different airlines based on their on-time performance
 - b. Compare the percentage of delayed flights for different days of the week
 - c. Create a trend chart for the number of passenger's at large and medium hubs
 - d. Visualize the count of delayed and on-time flights for different pairs of source and destination airports
- Create a dynamic chart that allows users to select a source and destination airport.

