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, and also required to build a model to predict if the flight will be delayed.

Importing necessary Libraries

In [1]:
```
# Data manipulation
import numpy as np
import pandas as pd

# Data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# warnings
import warnings
warnings.simplefilter('ignore')
```

-- Reading data from all the datasets

In [2]:
```
df1=pd.read_excel('Downloads/Datasets (1)/Capstone_3/Airlines.xlsx')
df1.head(2)
```

Out[2]:

	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

In [3]:
```
df2=pd.read_excel('Downloads/Datasets (1)/Capstone_3/airports.xlsx')
df2.head(2)
```

Out[3]:

	id	ident	type	name	latitude_deg	longitude_deg	elevation_ft	continent	iso_country	iso_region	municipality	scheduled_service	gps_code
0	6523	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11.0	NaN	US	US-PA	Bensalem	no	00A
1	323361	00AA	small_airport	Aero B Ranch Airport	38.704022	-101.473911	3435.0	NaN	US	US-KS	Leoti	no	00AA

In [4]:
```
df3=pd.read_excel('Downloads/Datasets (1)/Capstone_3/runways.xlsx')
df3.head(2)
```

Out[4]:

	id	airport_ref	airport_ident	length_ft	width_ft	surface	lighted	closed	le_ident	le_latitude_deg	le_longitude_deg	le_elevation_ft	le_heading_degT	le
0	269408	6523	00A	80.0	80.0	ASPH-G	1	0	H1	NaN	NaN	NaN	NaN	
1	255155	6524	00AK	2500.0	70.0	GRVL	0	0	N	NaN	NaN	NaN	NaN	

In [5]:
```
print(df1.shape)
print(df2.shape)
print(df3.shape)
```

```
(518556, 9)
(73805, 18)
(43977, 20)
```

**checking for null values in all 3 dataframes

In [6]:
```
df3.isnull().sum()
```

Out[6]:
```
id                            0
airport_ref                   0
airport_ident                 0
length_ft                   224
width_ft                   2889
surface                     457
lighted                       0
closed                        0
le_ident                    184
le_latitude_deg           28961
le_longitude_deg          28977
le_elevation_ft           31196
le_heading_degT           29353
le_displaced_threshold_ft 41094
he_ident                   6645
he_latitude_deg           29006
he_longitude_deg          29004
he_elevation_ft           31357
he_heading_degT           27549
he_displaced_threshold_ft 40801
dtype: int64
```

In [7]:
```
df2.isnull().sum()
```

Out[7]:
```
id                     0
ident                  0
type                   0
name                   0
latitude_deg           0
longitude_deg          0
elevation_ft       14122
continent          35719
iso_country          259
iso_region             0
municipality        5066
scheduled_service      0
gps_code           30809
iata_code          64645
local_code         40830
home_link          70313
wikipedia_link     63100
keywords           59854
dtype: int64
```

In [8]:
```
df1.isnull().sum()
```

Out[8]:
```
id             0
Airline        0
Flight         0
AirportFrom    0
AirportTo      0
DayOfWeek      0
Time           0
Length         0
Delay          0
dtype: int64
```

** Renaming column airport_ident into ident to have the columns with the same name in df2 and df3 dataframes

In [9]:
```
df3.rename(columns={'airport_ident':'ident'},inplace=True)
df3.columns
```

Out[9]:
```
Index(['id', 'airport_ref', 'ident', 'length_ft', 'width_ft', 'surface',
       'lighted', 'closed', 'le_ident', 'le_latitude_deg', 'le_longitude_deg',
       'le_elevation_ft', 'le_heading_degT', 'le_displaced_threshold_ft',
       'he_ident', 'he_latitude_deg', 'he_longitude_deg', 'he_elevation_ft',
       'he_heading_degT', 'he_displaced_threshold_ft'],
      dtype='object')
```

** below command is used for displaying all the columns(if it has more columns)

In [10]:
```
pd.set_option('display.max_columns',None)
```

--Gathering all fields in one dataframe

**for df1 and df2 using concatenating to combine dataframes

**ofter that using merge for concat_df and df3 dataframes, ident column is key to combine the dataframes

In [11]:
```
concat_df=pd.concat([df1,df2],axis=1)
merged_df=pd.merge(concat_df,df3,how='outer',on='ident')
merged_df.head()
```

Out[11]:

	id_x	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	id_x	ident	type	name	latitude_deg	longitude_deg	elevation_
0	1	CO	269	SFO	IAH	3	15	205	1	6523.0	00A	heliport	Total Rf Heliport	40.070801	-74.933601	11
1	2	US	1558	PHX	CLT	3	15	222	1	323361.0	00AA	small_airport	Aero B Ranch	38.704022	-101.473911	3435

3	4	AA	2466	SFO	DFW	3	20	195	1	6525.0	00AL	small_airport	Epps Airpark	34.864799	-86.770302	820
4	5	AS	108	ANC	SEA	3	30	202	0	6526.0	00AR	closed	Newport Hospital & Clinic Heliport	35.608700	-91.254898	237

In [12]:
```
merged_df.shape
```

Out[12]:
```
(525268, 46)
```

In [13]:
```
merged_df.isnull().sum().sum()
```

Out[13]:
```
17887502
```

In [14]:
```
merged_df.columns
```

Out[14]:
```
Index(['id_x', 'Airline', 'Flight', 'AirportFrom', 'AirportTo', 'DayOfWeek',
       'Time', 'Length', 'Delay', 'id_x', 'ident', 'type', 'name',
       'latitude_deg', 'longitude_deg', 'elevation_ft', 'continent',
       'iso_country', 'iso_region', 'municipality', 'scheduled_service',
       'gps_code', 'iata_code', 'local_code', 'home_link', 'wikipedia_link',
       'keywords', 'id_y', 'airport_ref', 'length_ft', 'width_ft', 'surface',
       'lighted', 'closed', 'le_ident', 'le_latitude_deg', 'le_longitude_deg',
       'le_elevation_ft', 'le_heading_degT', 'le_displaced_threshold_ft',
       'he_ident', 'he_latitude_deg', 'he_longitude_deg', 'he_elevation_ft',
       'he_heading_degT', 'he_displaced_threshold_ft'],
      dtype='object')
```

**** Deleting unwanted columns from the merged dataframe**

In [15]:
```
merged_df.drop(columns=['id_x','name','latitude_deg','longitude_deg','continent','iso_country', 'iso_region', 'municipality',
        'scheduled_service','gps_code','local_code', 'home_link', 'wikipedia_link','keywords', 'id_y','lighted',
        'closed','le_ident', 'le_latitude_deg', 'le_longitude_deg',
       'le_elevation_ft', 'le_heading_degT', 'le_displaced_threshold_ft',
```

```
        'he_ident', 'he_latitude_deg', 'he_longitude_deg', 'he_elevation_ft',
        'he_heading_degT', 'he_displaced_threshold_ft'],inplace=True)
```

In [16]:
```
merged_df.head(2)
```

Out[16]:

	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	type	elevation_ft	iata_code	airport_ref	length_ft	width_ft	surface
0	CO	269	SFO	IAH	3	15	205	1	00A	heliport	11.0	NaN	6523.0	80.0	80.0	ASPH-G
1	US	1558	PHX	CLT	3	15	222	1	00AA	small_airport	3435.0	NaN	NaN	NaN	NaN	NaN

In [17]:
```
merged_df.shape
```

Out[17]:
```
(525268, 16)
```

In [18]:
```
merged_df.dtypes
```

Out[18]:
```
Airline          object
Flight            int64
AirportFrom      object
AirportTo        object
DayOfWeek         int64
Time              int64
Length            int64
Delay             int64
ident            object
type             object
elevation_ft    float64
iata_code        object
airport_ref     float64
length_ft       float64
width_ft        float64
surface          object
dtype: object
```

In [19]:
```
merged_df.isnull().sum()
```

Out[19]:
```
Airline             0
Flight              0
AirportFrom         0
AirportTo           0
DayOfWeek           0
Time                0
Length              0
Delay               0
ident          444751
type           444751
elevation_ft   459138
iata_code      513068
airport_ref    481291
length_ft      481515
width_ft       484180
surface        481748
dtype: int64
```

--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). Pull such information specific to various airlines from the Wikipedia page link given below.

https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States.

In [21]:
```
test_df=pd.read_html('https://en.wikipedia.org/wiki/List_of_airlines_of_the_United_States')
```

In [22]:
```
len(test_df)
```

Out[22]:
```
21
```

** Extracting List of airlines of the United States from above test_df

In [23]:
```
us_air_lines=test_df[0]
us_air_lines.head()
```

Out[23]:

	Airline	Image	IATA	ICAO	Callsign	Primary hubs, secondary hubs	Founded	Notes
0	Alaska Airlines	NaN	AS	ASA	ALASKA	Seattle/TacomaAnchoragePortland (OR)San Franci...	1932	Founded as McGee Airways and commenced operati...
1	Allegiant Air	NaN	G4	AAY	ALLEGIANT	Las VegasCincinnatiFort Walton BeachIndianapol...	1997	Founded as WestJet Express and began operation...
2	American Airlines	NaN	AA	AAL	AMERICAN	Dallas/Fort WorthCharlotteChicago-O'HareLos An...	1926	Founded as American Airways and commenced oper...
3	Avelo Airlines	NaN	XP	VXP	AVELO	BurbankNew HavenOrlandoRaleigh/DurhamWilmingto...	1987	First did business as Casino Express Airlines ...
4	Breeze Airways	NaN	MX	MXY	MOXY	CharlestonHartfordNew OrleansNorfolkProvidence...	2018	Founded as Moxy Airways but was renamed due to...

In [24]:
```
us_air_lines.shape
```

Out[24]:
```
(15, 8)
```

In [25]:
```
us_air_lines.isnull().sum()
```

Out[25]:
```
Airline                       0
Image                        15
IATA                          0
ICAO                          0
Callsign                      0
Primary hubs, secondary hubs  0
Founded                       0
Notes                         2
dtype: int64
```

--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 percentof 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 .

https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States

In [26]:
```
test_df1=pd.read_html('https://en.wikipedia.org/wiki/List_of_the_busiest_airports_in_the_United_States')
```

In [27]:
```
len(test_df1)
```

Out[27]:
```
20
```

**Extracting Large hubs airports data from the given wikipedia

In [28]:
```
large_hub_df1=test_df1[1]
large_hub_df1.head(2)
```

Out[28]:

	Rank(2022)	Airports (large)	IATACode	Major cities served	Metro Area	State	2022[2]	2021[3]	2020[4]	2019[5]	2018[6]	2017[7]	2016[8]	2015[9]	2014[10]	2
0	1	Hartsfield–Jackson Atlanta International Airport	ATL	Atlanta	Atlanta	GA	45396001	36676010	20559866	53505795	51865797	50251964	50501858	49340732	46604273	45
1	2	Dallas/Fort Worth International Airport	DFW	Dallas & Fort Worth	Dallas–Fort Worth	TX	35345138	30005266	18593421	35778573	32821799	31816933	31283579	31589839	30804567	29

In [29]:
```
large_hub_df1.columns
```

Out[29]:
```
Index(['Rank(2022)', 'Airports (large)', 'IATACode', 'Major cities served',
       'Metro Area', 'State', '2022[2]', '2021[3]', '2020[4]', '2019[5]',
       '2018[6]', '2017[7]', '2016[8]', '2015[9]', '2014[10]', '2013[11]'],
      dtype='object')
```

In [30]:
```
len(large_hub_df1)
```

Out[30]:
```
31
```

In [31]:
```
large_hub_df1.drop(columns=['2022[2]', '2021[3]', '2020[4]', '2019[5]','2018[6]', '2017[7]', '2016[8]', '2015[9]','2014[10]',
                            '2013[11]','Rank(2022)','Major cities served','Metro Area','State'],inplace=True)
```

In [32]:
```
large_hub_df1.isnull().sum()
```

Out[32]:
```
Airports (large)    0
IATACode            0
dtype: int64
```

****Extracting Medium hubs airports data from the given wikipedia**

In [33]:
```
medium_hub_df1=test_df1[2]
medium_hub_df1.head(2)
```

Out[33]:

	Rank(2021)	Airports (medium hubs)	IATACode	City served	Metro Area	State	2022[2]	2021[3]	2020[4]	2019[5]	2018[6]	2017[7]	2016[8]	2015[9]	2014[10]	2013[11]
0	32	Dallas Love Field	DAL	Dallas	Dallas–Fort Worth	TX	7819129	6487563	3669930	8408457	8134848	7876769	7554596	7040921	4522341	4023779
1	33	Portland International Airport	PDX	Portland	Portland	OR	7241882	5759879	3455877	9797408	9940866	9435473	9071154	8340234	7878760	7452603

In [34]:
```
len(medium_hub_df1)
```

Out[34]:
```
33
```

In [35]:
```
medium_hub_df1.drop(columns=['2022[2]', '2021[3]', '2020[4]', '2019[5]','2018[6]', '2017[7]', '2016[8]', '2015[9]','2014[10]',
                             '2013[11]','Rank(2021)','City served','Metro Area','State'],inplace=True)
```

In [36]:
```
medium_hub_df1.isnull().sum()
```

Out[36]:
```
Airports (medium hubs)    0
IATACode                  0
dtype: int64
```

**** And then combining both large hub airports data and medium hub airports data into one Dataframe using merge**

In [37]:
```
large_medium_hubs=pd.merge(large_hub_df1,medium_hub_df1,on='IATACode',how='outer')
large_medium_hubs.head()
```

Out[37]:

	Airports (large)	IATACode	Airports (medium hubs)
0	Hartsfield–Jackson Atlanta International Airport	ATL	NaN
1	Dallas/Fort Worth International Airport	DFW	NaN
2	Denver International Airport	DEN	NaN
3	O'Hare International Airport	ORD	NaN
4	Los Angeles International Airport	LAX	NaN

In [38]:
```
large_medium_hubs.isnull().sum()
```

Out[38]:
```
Airports (large)          33
IATACode                   0
Airports (medium hubs)    31
dtype: int64
```

In [39]:
```
large_medium_hubs.shape
```
Out[39]:
```
(64, 3)
```

**** In large_medium_hubs dataframe, Renaming column IATACode into iata_code to match the column name in merged_df dataframe**

In [40]:
```
large_medium_hubs.rename(columns={'IATACode':'iata_code'},inplace=True)
large_medium_hubs.columns
```
Out[40]:
```
Index(['Airports (large)', 'iata_code', 'Airports (medium hubs)'], dtype='object')
```

****Combining merged_df and large_medium_hubs dataframes into one so that all the information is in one place, key should be iata_code**

In [41]:
```
merged_Df1=pd.merge(merged_df,large_medium_hubs,on='iata_code',how='outer')
merged_Df1.head()
```
Out[41]:

	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	type	elevation_ft	iata_code	airport_ref	length_ft	width_ft	surface
0	CO	269	SFO	IAH	3	15	205	1	00A	heliport	11.0	NaN	6523.0	80.0	80.0	ASPH-G
1	US	1558	PHX	CLT	3	15	222	1	00AA	small_airport	3435.0	NaN	NaN	NaN	NaN	NaN
2	AA	2400	LAX	DFW	3	20	165	1	00AK	small_airport	450.0	NaN	6524.0	2500.0	70.0	GRVL
3	AA	2466	SFO	DFW	3	20	195	1	00AL	small_airport	820.0	NaN	6525.0	2300.0	200.0	TURF
4	AS	108	ANC	SEA	3	30	202	0	00AR	closed	237.0	NaN	6526.0	40.0	40.0	GRASS

In [42]:
```
merged_Df1.shape
```
Out[42]:
```
(525268, 18)
```

In [43]:
```
merged_Df1.isnull().sum()
```

Out[43]:
```
Airline                       0
Flight                        0
AirportFrom                   0
AirportTo                     0
DayOfWeek                     0
Time                          0
Length                        0
Delay                         0
ident                    444751
type                     444751
elevation_ft             459138
iata_code                513068
airport_ref              481291
length_ft                481515
width_ft                 484180
surface                  481748
Airports (large)         525134
Airports (medium hubs)   525170
dtype: int64
```

****There are null values in some columns so replacing them with median,mode and with 'none' for some other columns**

In [44]:
```
merged_Df1['type']=merged_Df1['type'].fillna(merged_Df1['type'].mode()[0])

merged_Df1['elevation_ft']=merged_Df1['elevation_ft'].fillna(merged_Df1['elevation_ft'].median())

merged_Df1['airport_ref']=merged_Df1['airport_ref'].fillna(merged_Df1['airport_ref'].median())

merged_Df1['length_ft']=merged_Df1['length_ft'].fillna(merged_Df1['length_ft'].median())

merged_Df1['width_ft']=merged_Df1['width_ft'].fillna(merged_Df1['width_ft'].median())

merged_Df1['Airports (large)']=merged_Df1['Airports (large)'].fillna('none')
```

```
merged_Df1['Airports (medium hubs)']=merged_Df1['Airports (medium hubs)'].fillna('none')
```

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

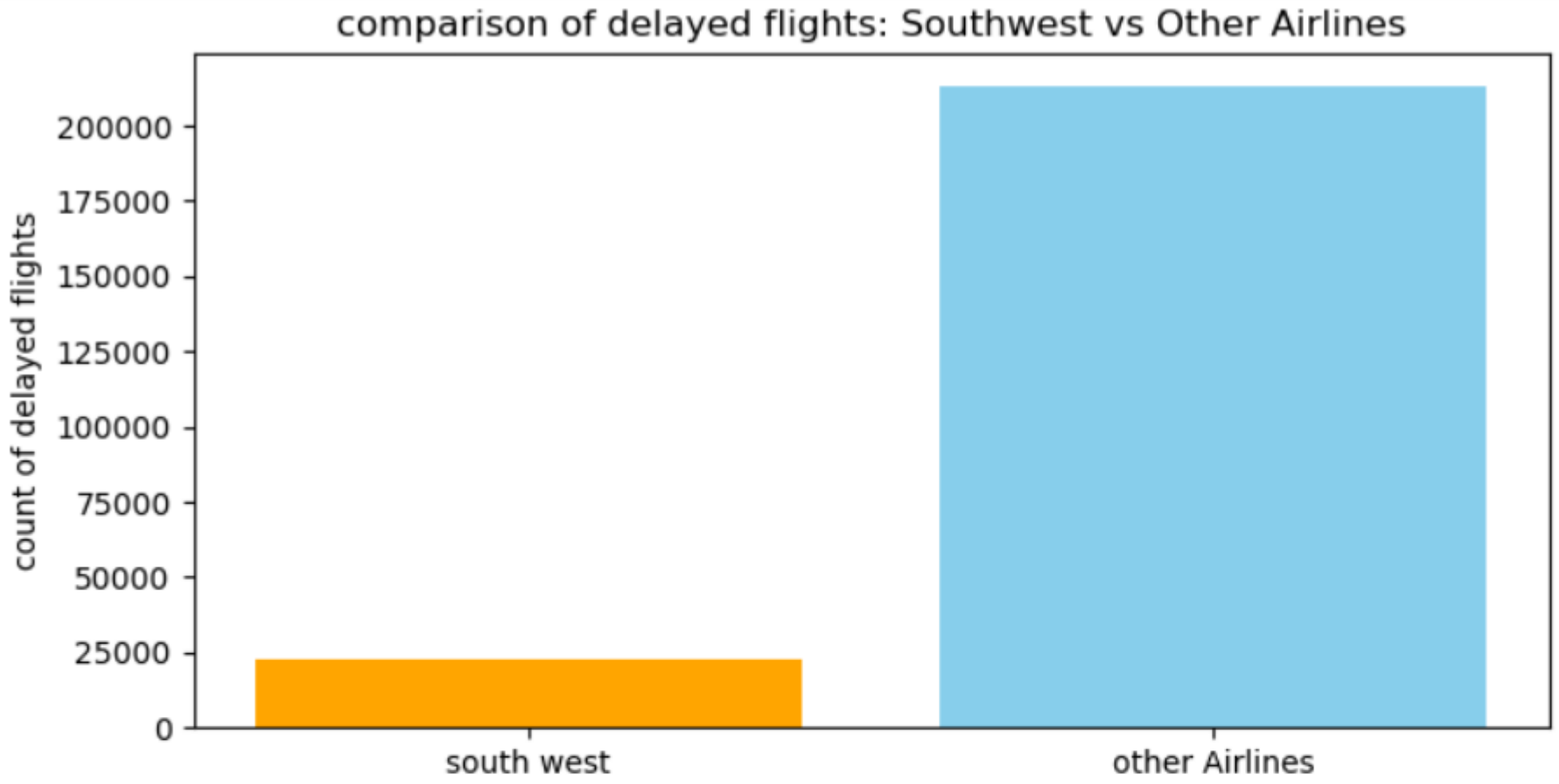
In [45]:
```
merged_Df1.head(1)
```

Out[45]:

	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	type	elevation_ft	iata_code	airport_ref	length_ft	width_ft	surface	Airp (la
0	CO	269	SFO	IAH	3	15	205	1	00A	heliport	11.0	NaN	6523.0	80.0	80.0	ASPH-G	r

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

In [46]:
```
southwest_data=merged_Df1[merged_Df1['Airline']=='OO']    # 'OO'-southwest
other_airlines_data=merged_Df1[merged_df['Airline']!='OO']
plt.figure(figsize=(8,4))
plt.bar('south west',southwest_data['Delay'].sum(),color='orange') # count of delayed flights for southwest
plt.bar('other Airlines',other_airlines_data['Delay'].sum(),color='skyblue') # count of delayed flights for other airlines
plt.title('comparison of delayed flights: Southwest vs Other Airlines')
plt.ylabel('count of delayed flights')
plt.show()
```



** approximately 25000 Southwest Airlines flights were delayed and above 200000 airlines were delayed for other airlines **

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

In [47]:
```
merged_Df1['DayOfWeek'].value_counts()
```

Out[47]:
```
4    89504
3    87587
5    84777
1    70008
2    68721
7    68012
```

```
6    56659
Name: DayOfWeek, dtype: int64
```

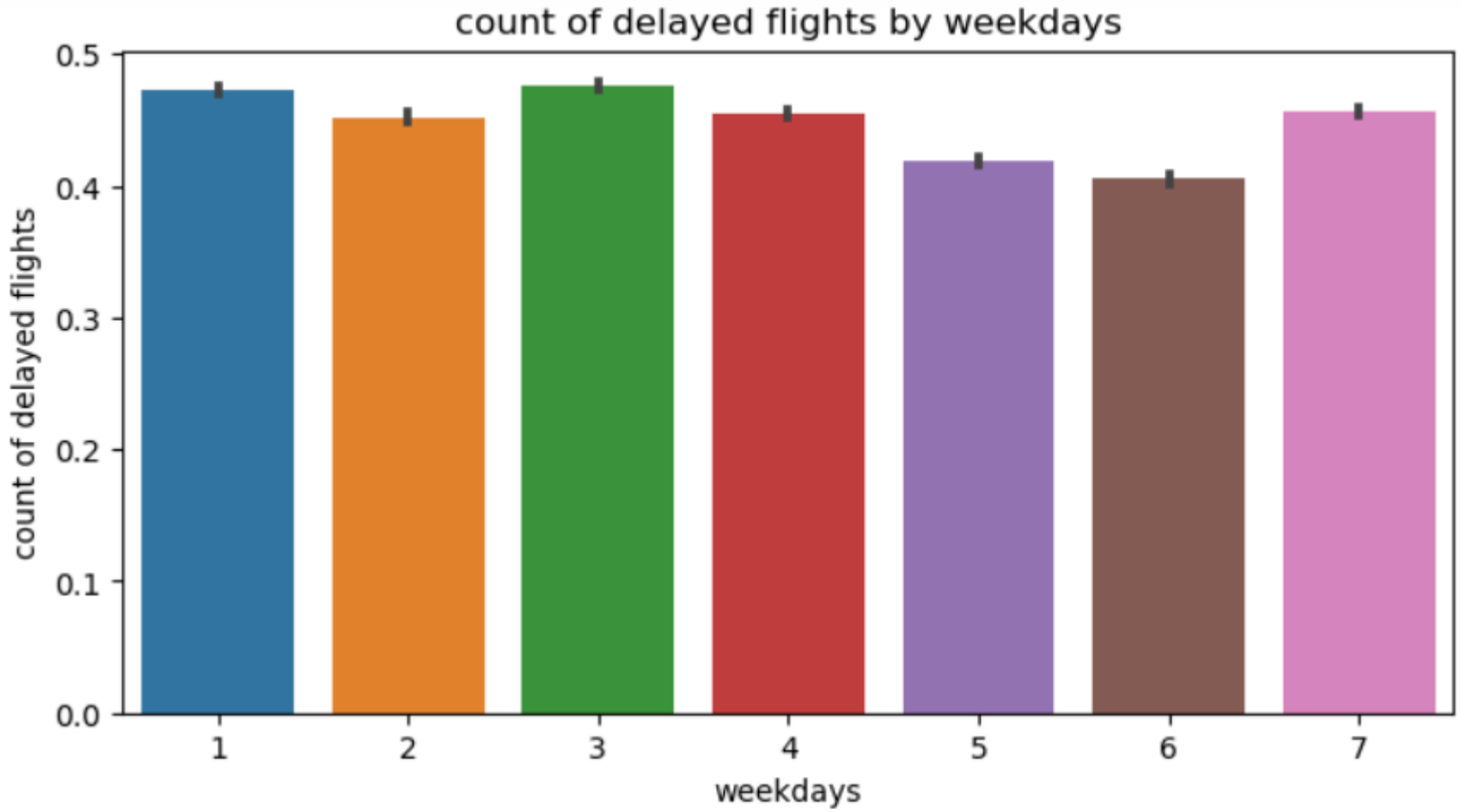
In [48]:
```
week_delays=merged_Df1.groupby('DayOfWeek')['Delay'].sum()
week_delays
```

Out[48]:
```
DayOfWeek
1    33059
2    31072
3    41620
4    40712
5    35519
6    22963
7    31054
Name: Delay, dtype: int64
```

In [49]:
```
safest_weekday=week_delays.idxmin()
print(f'safest weekday for travelling is {safest_weekday}:')
```

```
safest weekday for travelling is 6:
```

In [50]:
```
plt.figure(figsize=(8,4))
sns.barplot(x='DayOfWeek',y='Delay',data=merged_Df1)
plt.title('count of delayed flights by weekdays')
plt.xlabel('weekdays')
plt.ylabel('count of delayed flights')
plt.show()
```



** the safest weekday for travelling is 6th weekday with the count of delays 22963 **

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

In [51]:
```
merged_Df1.describe().Length
```

Out[51]:
```
count    525268.000000
mean        132.207692
std          70.924749
min           0.000000
25%          80.000000
```

```
50%         115.000000
75%         163.000000
max         655.000000
Name: Length, dtype: float64
```

**** column 'Length' has continuous numeric data so for converting into categorical data binning is used**

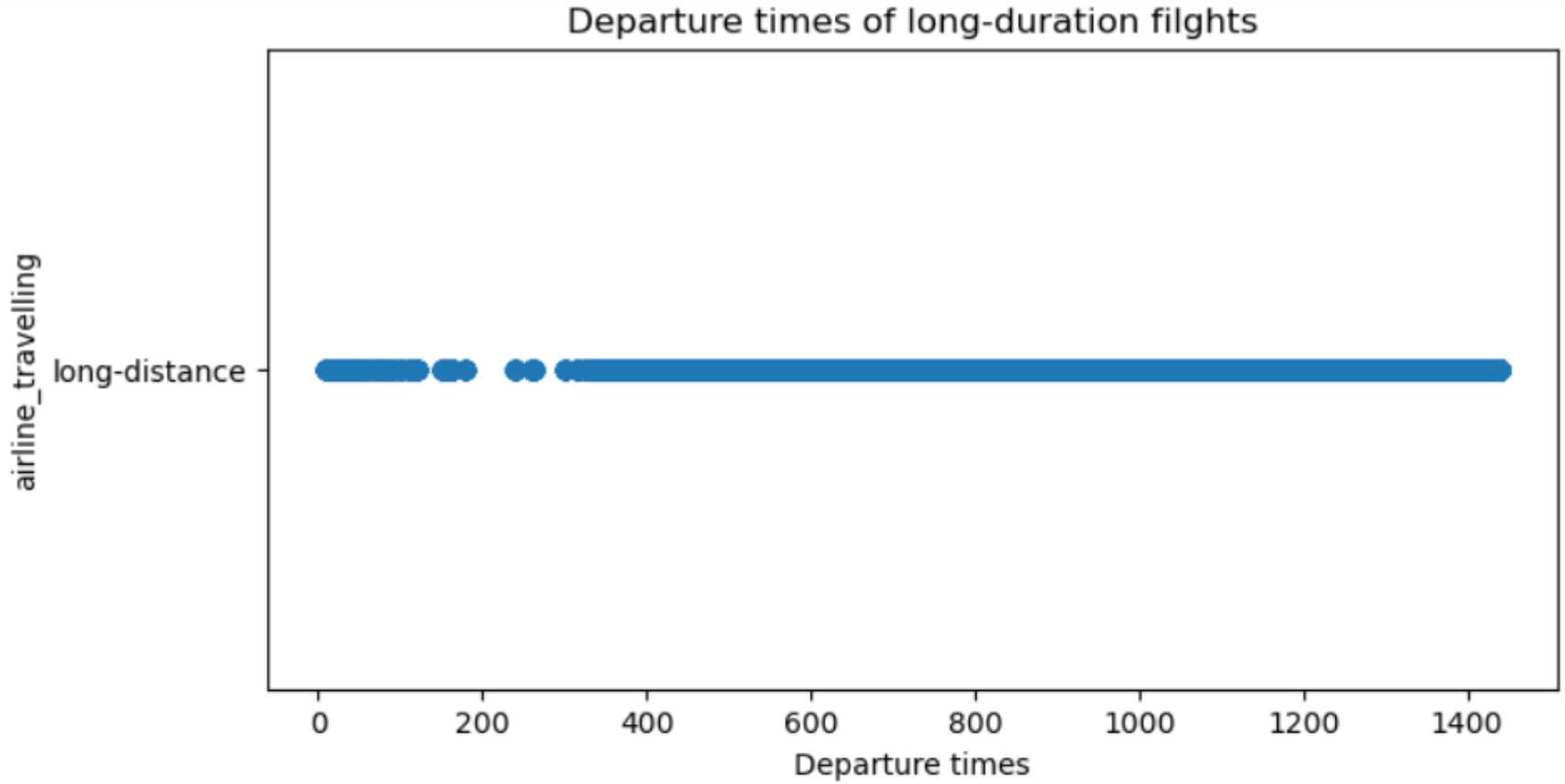
In [52]:
```
bin_edges=[0.000000,80.000000,163.000000,655.000000]
bin_names=['short-distance','medium-distance','long-distance']
merged_Df1['travelling_duration']=pd.cut(merged_Df1['Length'],bin_edges,labels=bin_names)
merged_Df1.head()
```

Out[52]:

	Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	ident	type	elevation_ft	iata_code	airport_ref	length_ft	width_ft	surface
0	CO	269	SFO	IAH	3	15	205	1	00A	heliport	11.0	NaN	6523.0	80.0	80.0	ASPH-G
1	US	1558	PHX	CLT	3	15	222	1	00AA	small_airport	3435.0	NaN	19486.0	2700.0	75.0	NaN
2	AA	2400	LAX	DFW	3	20	165	1	00AK	small_airport	450.0	NaN	6524.0	2500.0	70.0	GRVL
3	AA	2466	SFO	DFW	3	20	195	1	00AL	small_airport	820.0	NaN	6525.0	2300.0	200.0	TURF
4	AS	108	ANC	SEA	3	30	202	0	00AR	closed	237.0	NaN	6526.0	40.0	40.0	GRASS

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

In [55]:
```
long_duration_flights=merged_Df1[merged_Df1['travelling_duration']=='long-distance']
plt.figure(figsize=(8,4))
plt.scatter(long_duration_flights['Time'],long_duration_flights['travelling_duration'])
plt.title('Departure times of long-duration filghts')
plt.xlabel('Departure times')
plt.ylabel('airline_travelling')
plt.show()
```



** the Large hubs and Medium hubs columns are melted into a single column, and then Delay column is used for hue **

** There is no difference between Large and Medium hubs in delayed flights **

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

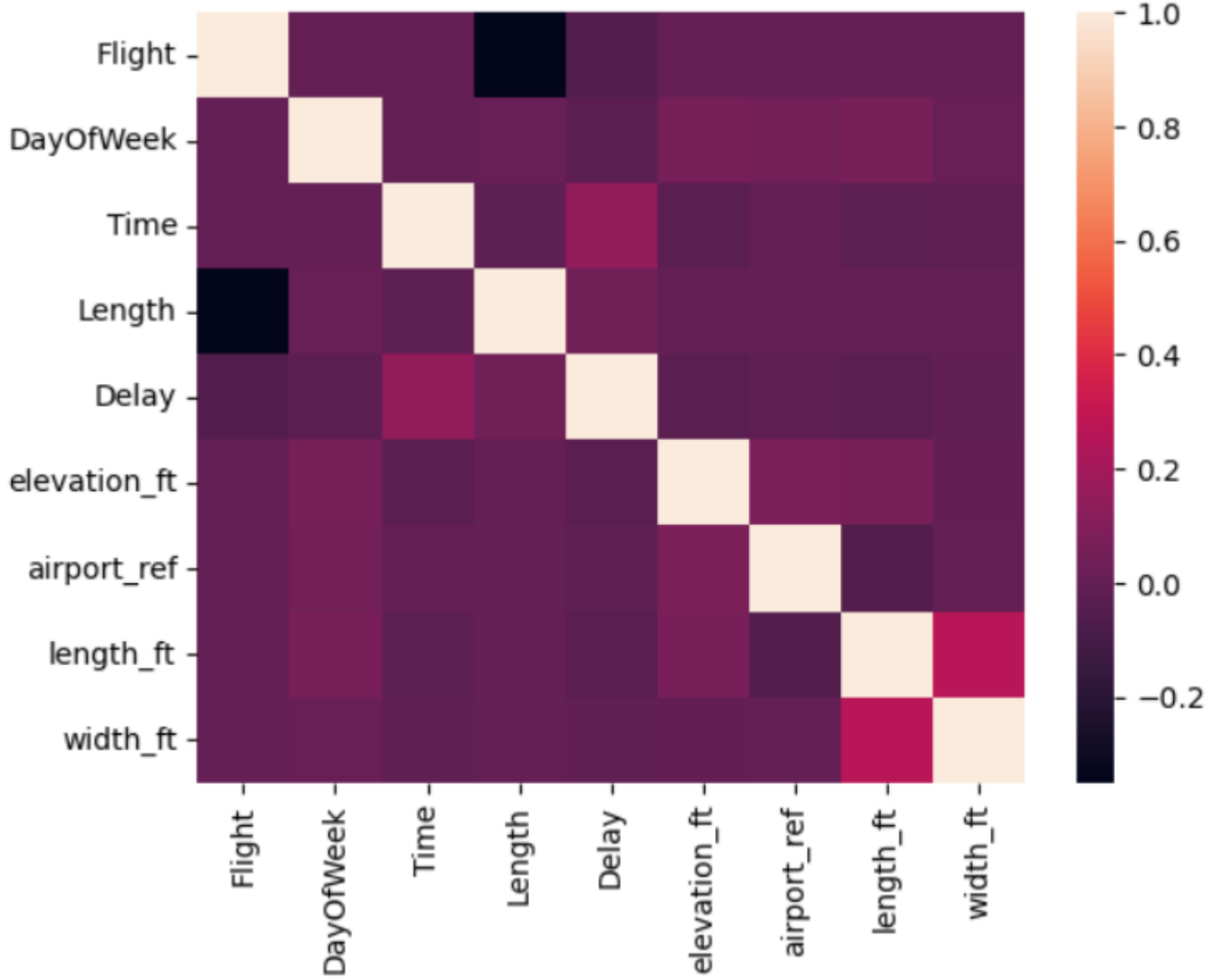
In [56]:
```
merged_Df1.corr()
```

Out[56]:

Out[56]:

	Flight	DayOfWeek	Time	Length	Delay	elevation_ft	airport_ref	length_ft	width_ft
Flight	1.000000	0.001435	-0.001842	-0.350262	-0.057803	-0.001719	-0.000765	0.001721	0.001163
DayOfWeek	0.001435	1.000000	-0.001936	0.012987	-0.027152	0.059487	0.049505	0.066406	0.013380
Time	-0.001842	-0.001936	1.000000	-0.020418	0.150678	-0.028650	-0.001762	-0.021194	-0.014841
Length	-0.350262	0.012987	-0.020418	1.000000	0.040592	0.001805	-0.000223	0.002130	-0.001519
Delay	-0.057803	-0.027152	0.150678	0.040592	1.000000	-0.030692	-0.016027	-0.029028	-0.009960
elevation_ft	-0.001719	0.059487	-0.028650	0.001805	-0.030692	1.000000	0.074755	0.065895	-0.003731
airport_ref	-0.000765	0.049505	-0.001762	-0.000223	-0.016027	0.074755	1.000000	-0.059373	0.000108
length_ft	0.001721	0.066406	-0.021194	0.002130	-0.029028	0.065895	-0.059373	1.000000	0.263711
width_ft	0.001163	0.013380	-0.014841	-0.001519	-0.009960	-0.003731	0.000108	0.263711	1.000000

In [57]:
```
sns.heatmap(merged_Df1.corr());
```



** there is no highly positive correlation among variables **

In [58]:
```
merged_Df1.isnull().sum()
```

Out[58]:
```
Airline                       0
Flight                        0
AirportFrom                   0
AirportTo                     0
DayOfWeek                     0
Time                          0
Length                        0
Delay                         0
ident                    444751
type                          0
elevation_ft                  0
iata_code                513068
airport_ref                   0
length_ft                     0
width_ft                      0
surface                  481748
Airports (large)              0
Airports (medium hubs)        0
travelling_duration           4
dtype: int64
```

In [59]:
```
merged_Df1['travelling_duration']=merged_Df1['travelling_duration'].fillna(merged_Df1['travelling_duration'].mode()[0])
```

In [60]:
```
merged_Df1.columns
```

Out[60]:
```
Index(['Airline', 'Flight', 'AirportFrom', 'AirportTo', 'DayOfWeek', 'Time',
       'Length', 'Delay', 'ident', 'type', 'elevation_ft', 'iata_code',
       'airport_ref', 'length_ft', 'width_ft', 'surface', 'Airports (large)',
       'Airports (medium hubs)', 'travelling_duration'],
      dtype='object')
```

In [61]:
```
merged_Df1.drop(columns=['ident','iata_code','surface'],inplace=True)
```

In [62]:
```
merged_Df1.isnull().sum()
```

Out[62]:
```
Airline                   0
Flight                    0
AirportFrom               0
AirportTo                 0
DayOfWeek                 0
Time                      0
Length                    0
Delay                     0
type                      0
elevation_ft              0
airport_ref               0
length_ft                 0
width_ft                  0
Airports (large)          0
Airports (medium hubs)    0
travelling_duration       0
dtype: int64
```

In [63]:
```
#merged_Df2=merged_Df1.copy()
```

In [64]:
```
#merged_Df2.to_csv('Downloads/Datasets (1)/Capstone_3/Airlines_Airports_runways.csv')
```

**Dropping unwanted columns

In [65]:
```
merged_Df1.drop(columns=['AirportFrom', 'AirportTo','Airports (large)','Airports (medium hubs)'],
                inplace=True)
```

--Use OneHotEncoder and OrdinalEncoder to deal with categorical variables

**Using Encoding to convert categorical data to numeric(binary) data

In [66]:
```
merged_Df1=pd.get_dummies(merged_Df1,columns=['Airline','type','travelling_duration'])
```

In [68]:
```
merged_Df1.head()
```

Out[68]:

	Flight	DayOfWeek	Time	Length	Delay	elevation_ft	airport_ref	length_ft	width_ft	Airline_9E	Airline_AA	Airline_AS	Airline_B6	Airline_CO	Airline_DL
0	269	3	15	205	1	11.0	6523.0	80.0	80.0	0	0	0	0	1	0
1	1558	3	15	222	1	3435.0	19486.0	2700.0	75.0	0	0	0	0	0	0
2	2400	3	20	165	1	450.0	6524.0	2500.0	70.0	0	1	0	0	0	0
3	2466	3	20	195	1	820.0	6525.0	2300.0	200.0	0	1	0	0	0	0
4	108	3	30	202	0	237.0	6526.0	40.0	40.0	0	0	1	0	0	0

*Importing Machine Learning libraries

In [69]:
```
from sklearn.model_selection import train_test_split,StratifiedKFold,RandomizedSearchCV
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.model_selection import cross_val_score,KFold
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score,make_scorer
```

In [70]:
```
merged_Df1.head()
```

Out[70]:

	Flight	DayOfWeek	Time	Length	Delay	elevation_ft	airport_ref	length_ft	width_ft	Airline_9E	Airline_AA	Airline_AS	Airline_B6	Airline_CO	Airline_DL
0	269	3	15	205	1	11.0	6523.0	80.0	80.0	0	0	0	0	1	0
1	1558	3	15	222	1	3435.0	19486.0	2700.0	75.0	0	0	0	0	0	0

2	2400	3	20	165	1	450.0	6524.0	2500.0	70.0	0	1	0	0	0	0
3	2466	3	20	195	1	820.0	6525.0	2300.0	200.0	0	1	0	0	0	0
4	108	3	30	202	0	237.0	6526.0	40.0	40.0	0	0	1	0	0	0

****Performing Standardization on some coloumns to bring values in same range**

In [71]:
```
cols_to_scale=['Flight','Time','Length','elevation_ft','airport_ref','length_ft','width_ft']
```

In [72]:
```
scaler=StandardScaler()
```

In [73]:
```
merged_Df1[cols_to_scale]=scaler.fit_transform(merged_Df1[cols_to_scale])
```

In [74]:
```
merged_Df1.head()
```

Out[74]:

	Flight	DayOfWeek	Time	Length	Delay	elevation_ft	airport_ref	length_ft	width_ft	Airline_9E	Airline_AA	Airline_AS	Airline_B6	Airline_CO	A
0	-1.074536	3	-2.823451	1.026333	1	-1.268408	-0.552417	-3.358642	0.036184	0	0	0	0	1	
1	-0.453383	3	-2.823451	1.266023	1	4.287461	-0.084808	-0.057593	-0.041617	0	0	0	0	0	
2	-0.047633	3	-2.805463	0.462354	1	-0.556075	-0.552381	-0.309582	-0.119418	0	1	0	0	0	
3	-0.015829	3	-2.805463	0.885338	1	0.044296	-0.552345	-0.561570	1.903412	0	1	0	0	0	
4	-1.152120	3	-2.769487	0.984034	0	-0.901695	-0.552309	-3.409040	-0.586225	0	0	1	0	0	

****splitting data into the x and y variables**

In [75]:
```
x=merged_Df1.drop(['Delay'],axis=1)
y=merged_Df1.Delay
```

In [76]:
```
# split data into training and testing
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.1,random_state=42)
```

--Apply logistic regression (use stochastic gradient descent optimizer) and decision tree models

In [77]:
```
# define models
sgd=SGDClassifier(loss='log',random_state=42)  # SGDClassifier with logisticregression(loss='log')
decision=DecisionTreeClassifier(random_state=42)
```

--Use the stratified five-fold method to build and validate the models

In [78]:
```
# define cross-validation
stratified_kfold=StratifiedKFold(n_splits=5,shuffle=True,random_state=42)
```

In [79]:
```
# define scorer
accuracy_scorer=make_scorer(accuracy_score)
```

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

In [85]:
```
# define hyperparameter search space
sgd_param={
    'alpha':[1.0,2.0,3.0,4.0],
    'l1_ratio':[0,0.1,0.5,0.7,0.9,1]
}
tree_param={
    'max_depth':[5,10,15,20,25],
    'min_samples_split':[2,5,10],
    'min_samples_leaf':[1,2,4],
```

```
}
```

In [91]:
```
# hyperparameter tuning with RandomizedSearchCV
sgd_random_search=RandomizedSearchCV(sgd,sgd_param,scoring=accuracy_scorer,cv=stratified_kfold,n_iter=10,random_state=42)
Decision_tree_random_search=RandomizedSearchCV(decision,tree_param,scoring=accuracy_scorer,cv=stratified_kfold,n_iter=10,
                            random_state=42)
```

In [92]:
```
# fit models
sgd_random_search.fit(x_train,y_train)
Decision_tree_random_search.fit(x_train,y_train)
```

Out[92]:
```
RandomizedSearchCV(cv=StratifiedKFold(n_splits=5, random_state=42, shuffle=True),
                   estimator=DecisionTreeClassifier(random_state=42),
                   param_distributions={'max_depth': [None, 5, 10, 15, 20],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10]},
                   random_state=42, scoring=make_scorer(accuracy_score))
```

In [93]:
```
# evaluate models
sgd_accuracy=sgd_random_search.score(x_test,y_test)
tree_accuracy=Decision_tree_random_search.score(x_test,y_test)
```

In [94]:
```
print(f'SGD Classifier Accuracy:{sgd_accuracy}')
print(f'Decision Tree Classifier Accuracy:{tree_accuracy}')
```

```
SGD Classifier Accuracy:0.6340358291926057
Decision Tree Classifier Accuracy:0.6479715194090658
```

** Decision tree classifier Accuracy(0.6479715194090658) is higher than the stochastic gradient descent optimizer(0.6340358291926057)

** So Decision tree classifier predicting more accurately compared to stochastic gradient descent optimizer

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

In [95]:
```
# create xgboostclassifier
xgb=XGBClassifier()
```

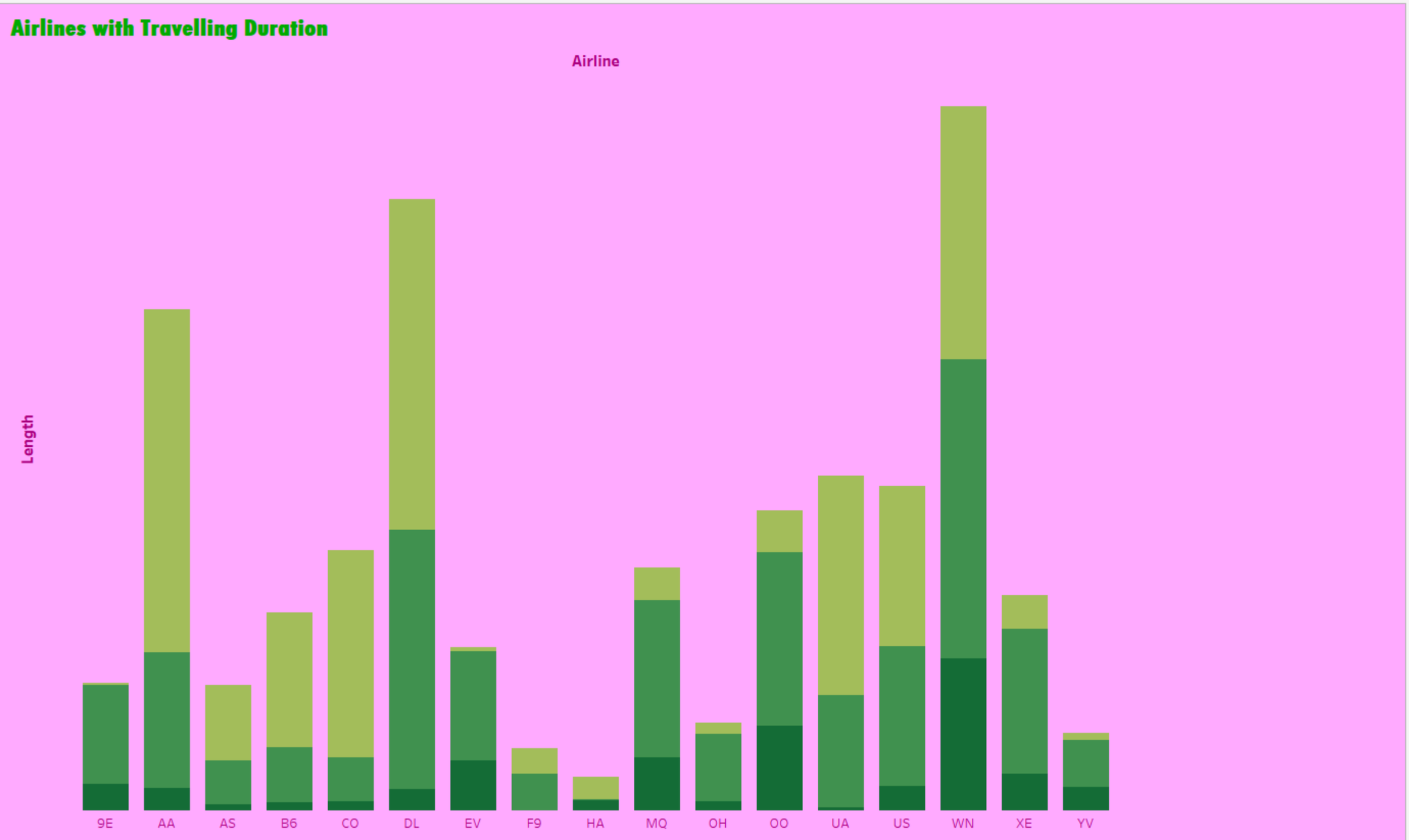
In [96]:
```
# define stratified five-fold cross-validation
stratified_kfold=StratifiedKFold(n_splits=5,shuffle=True,random_state=42)
```

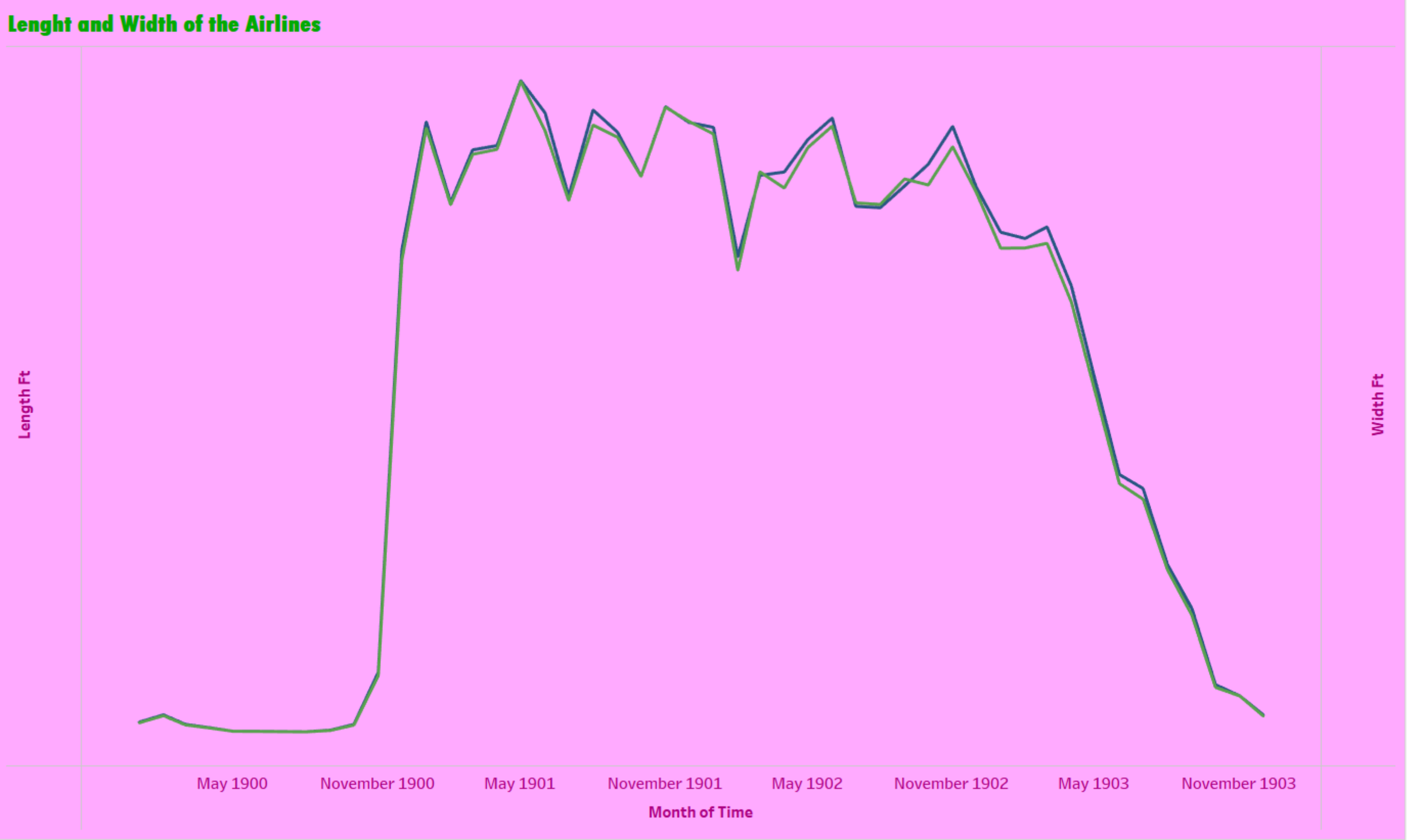
In [97]:
```
# use cross_val_score to perform cross-validation
# Note: xGBoost automatically handles multiclass classification for binary targets
cv_results=cross_val_score(xgb,x,y,cv=stratified_kfold,scoring='accuracy')

# print the cross-validation results
print('cross-validation results:')
print(cv_results)
print(f'Mean accuracy: {np.mean(cv_results)}')
```

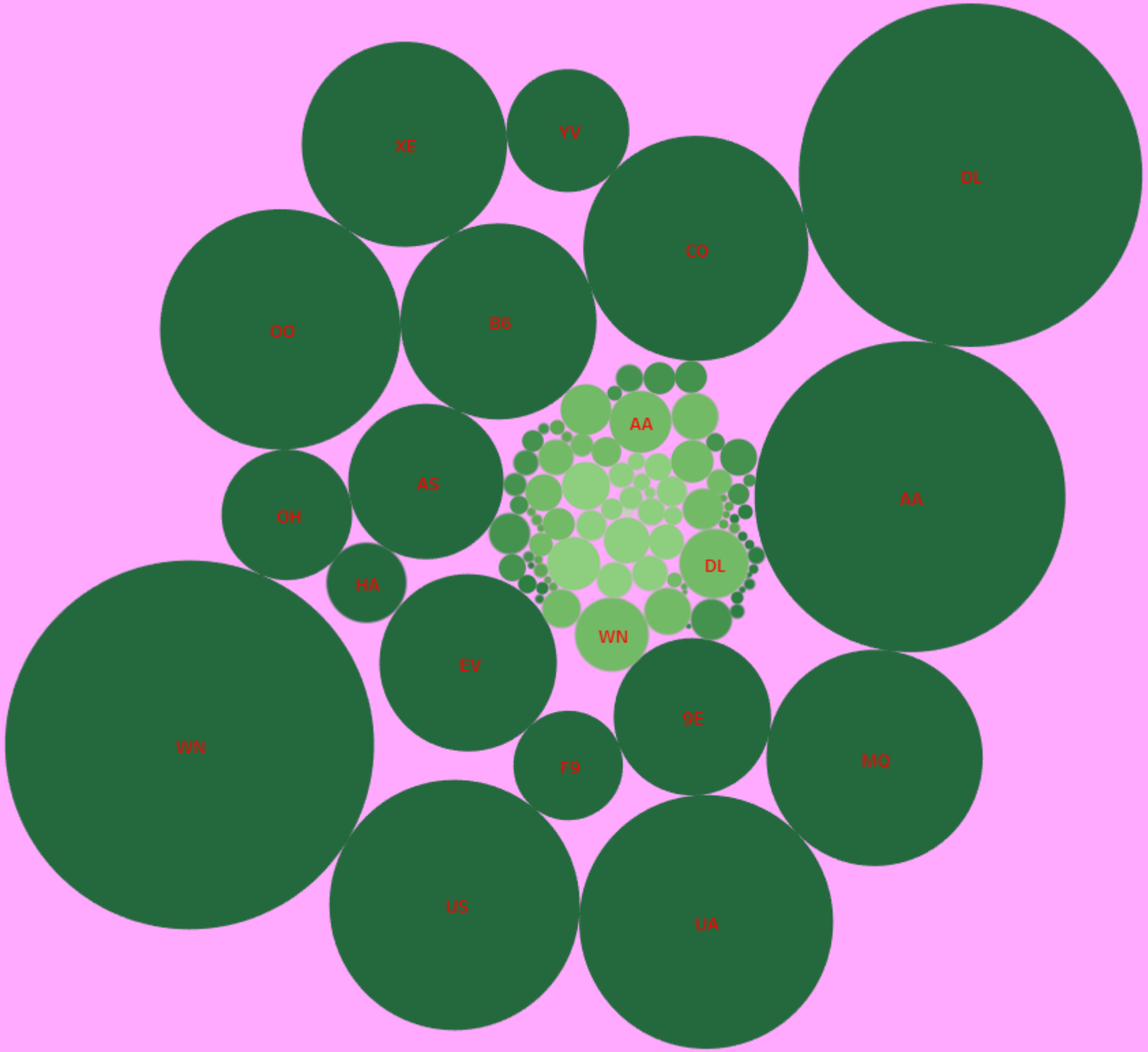
```
cross-validation results:
[0.65447294 0.65622442 0.65837569 0.65670661 0.65774419]
Mean accuracy: 0.6567047698341825
```

XGB classifier predicts more accurately with accuracy 0.6567047698341825 compare with Decision tree classifier and stochastic gradient descent optimizer.


Airlines with Travelling Duration
Airline
Length
9E
AA
AS
B6
CO
DL
EV
F9
HA
MQ
OH
OO
UA
US
WN
XE
YV
Travelling Duration
long-distance
medium-distance
short-distance


Lenght and Width of the Airlines
Length Ft
Width Ft
May 1900
November 1900
May 1901
November 1901
May 1902
November 1902
May 1903
November 1903
Month of Time
Measure Names
Length Ft
Width Ft

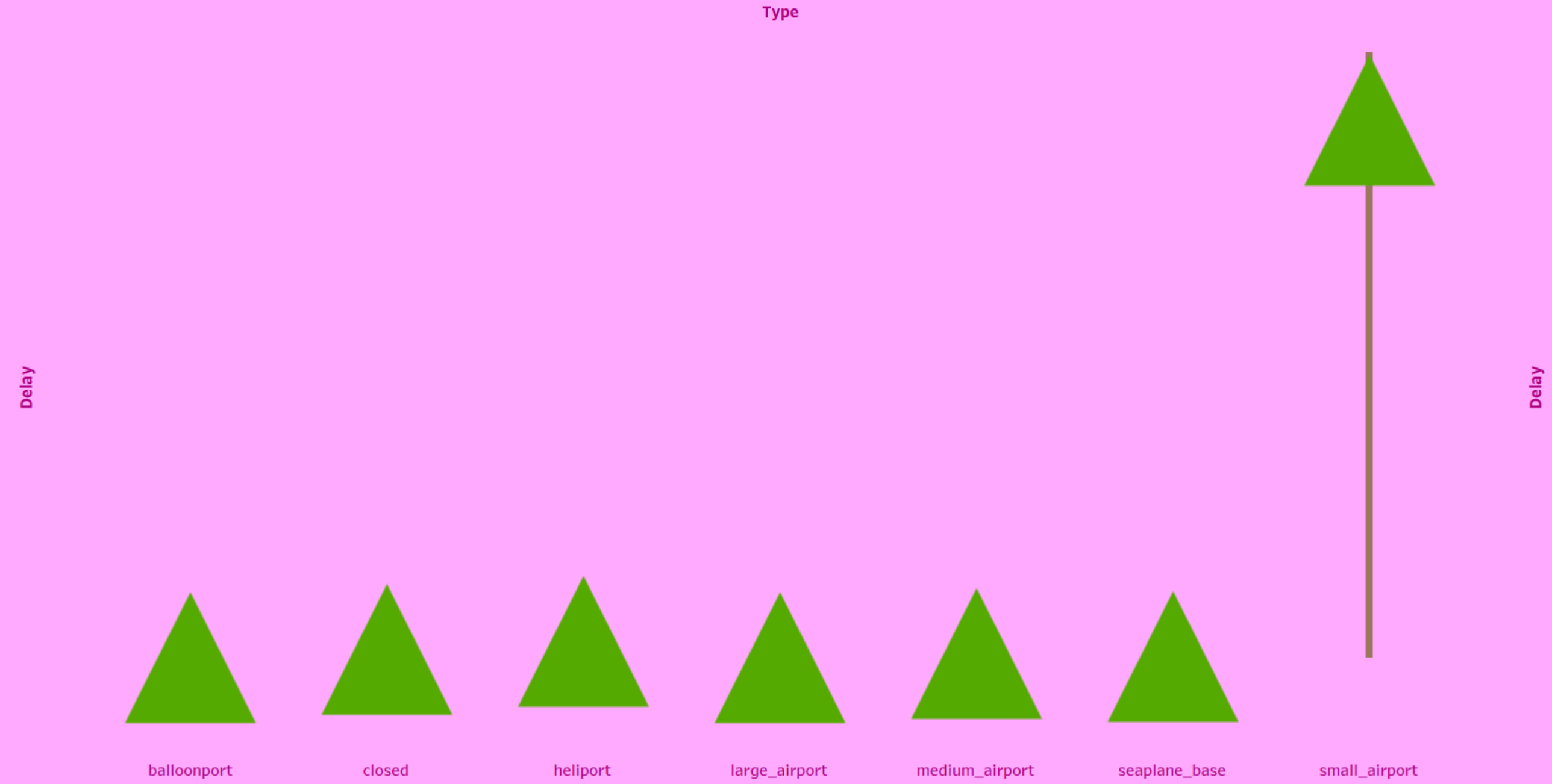
Airlines with Type of Airport and Duration of flights



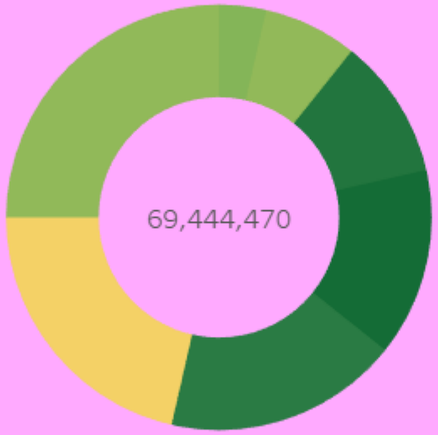
Type

- balloonport
- closed
- heliport
- large_airport
- medium_airport
- seaplane_base
- small_airport

flight delays based on type of Airport



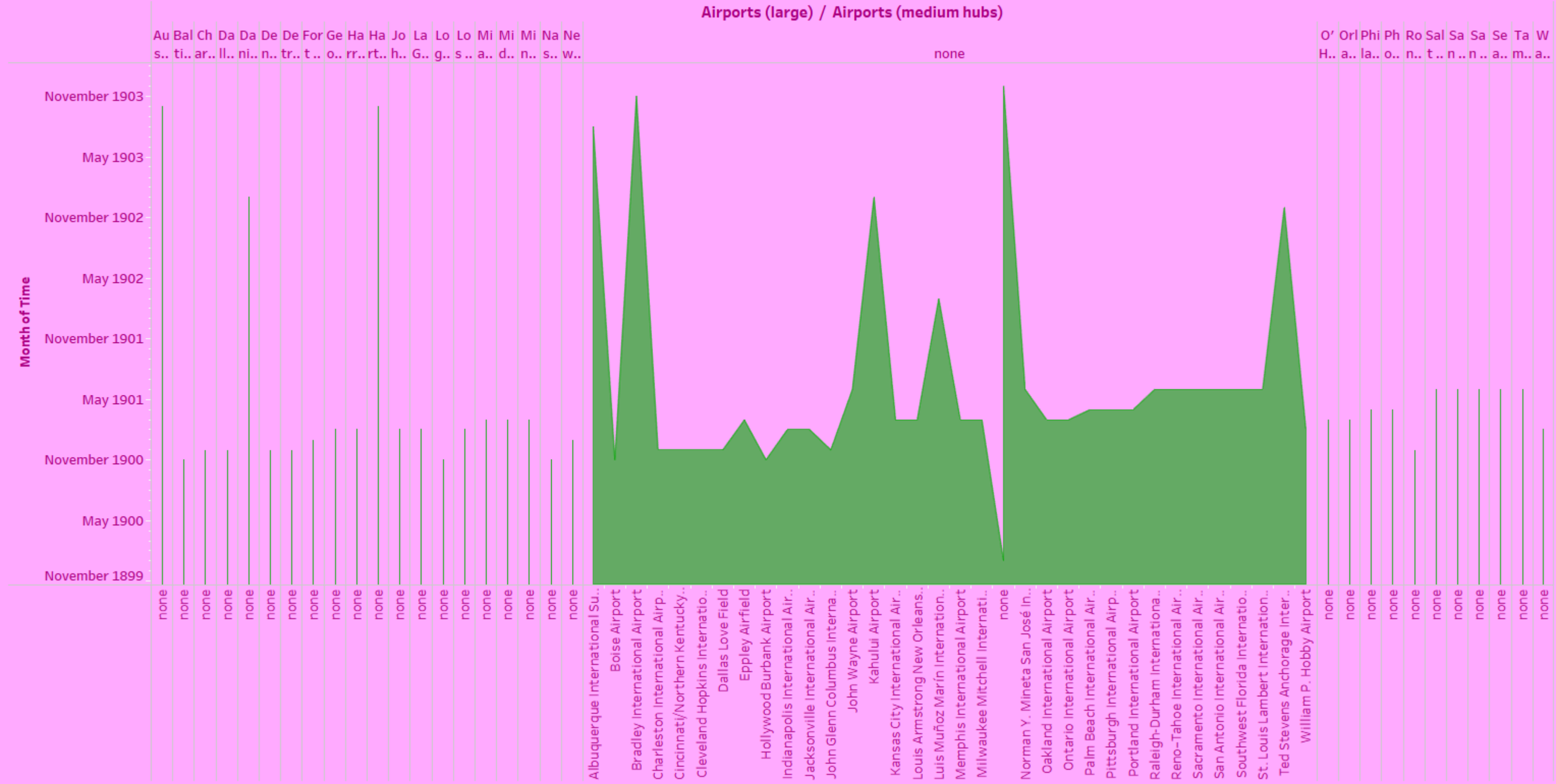
Duration of flight according to Day of the week



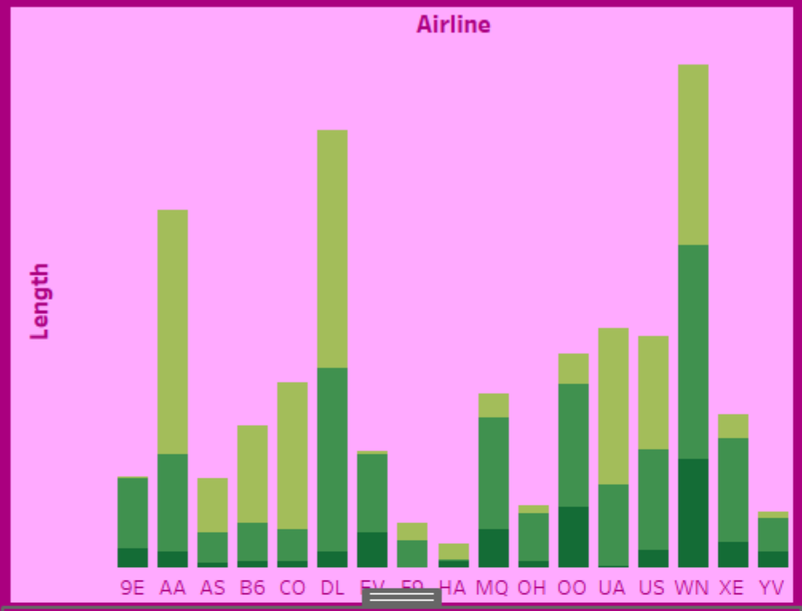
SUM(Length)

8M 12M

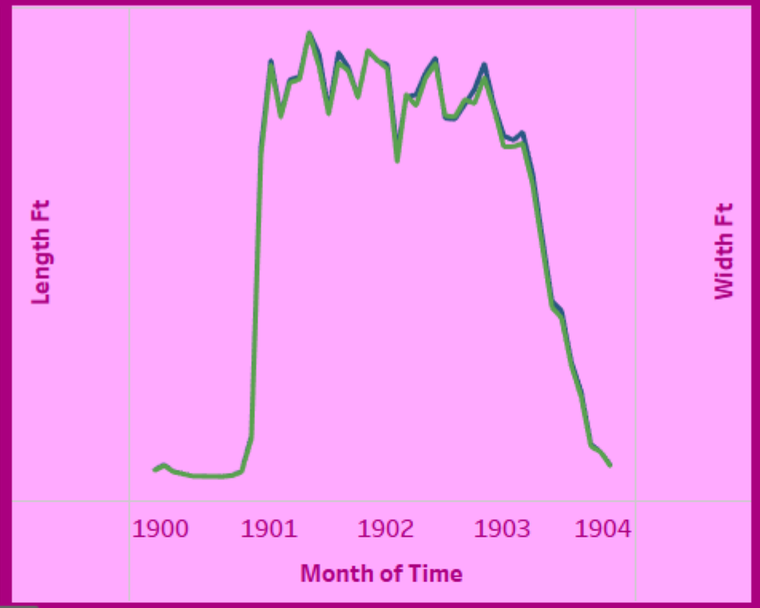
Large and Medium hub Airports according to year and month wise



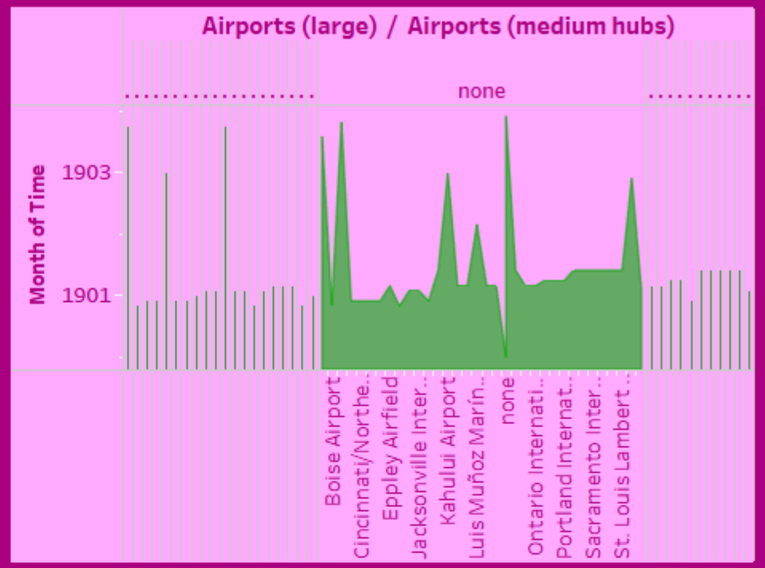
Airlines with Travelling Duration



Lenght and Width of the Airlines



Large and Medium hub Airports according to year and month wise



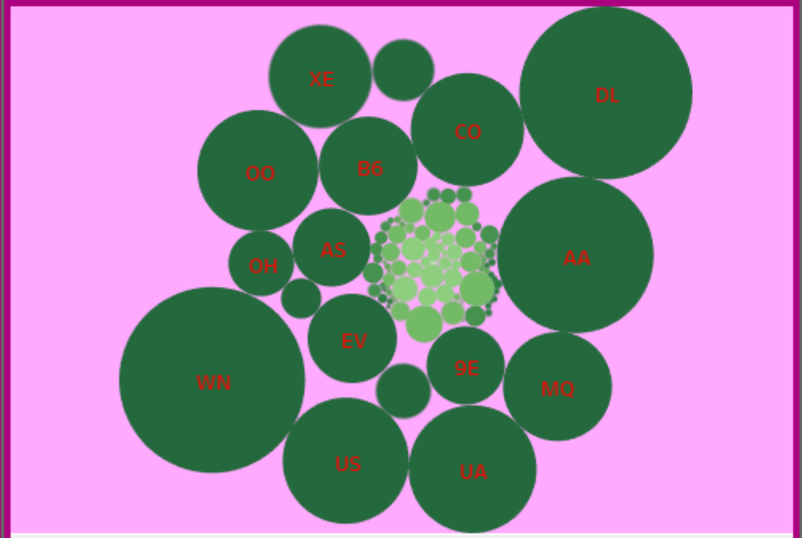
Travelling Duration
- long-distance
- medium-distance
- short-distance

Measure Names
- Length Ft
- Width Ft

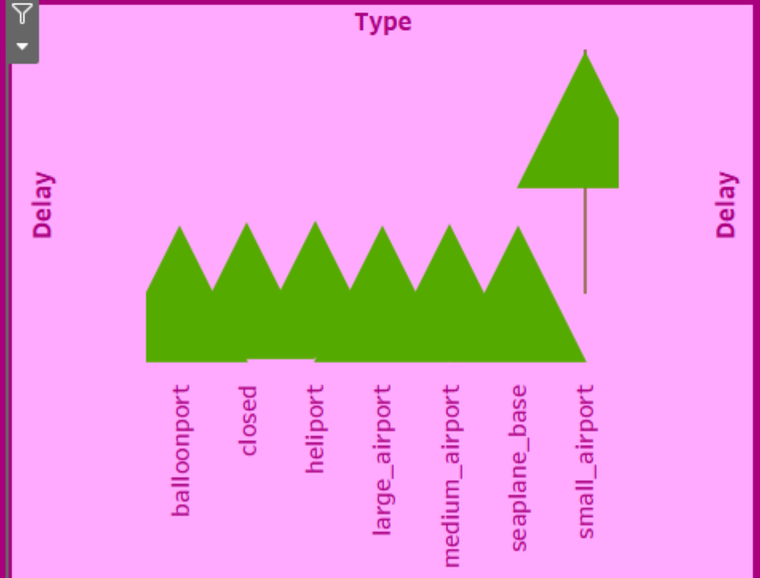
Type
- balloonport
- closed
- heliport
- large_airport
- medium_airport
- seaplane_base
- small_airport

Length
8M 12M

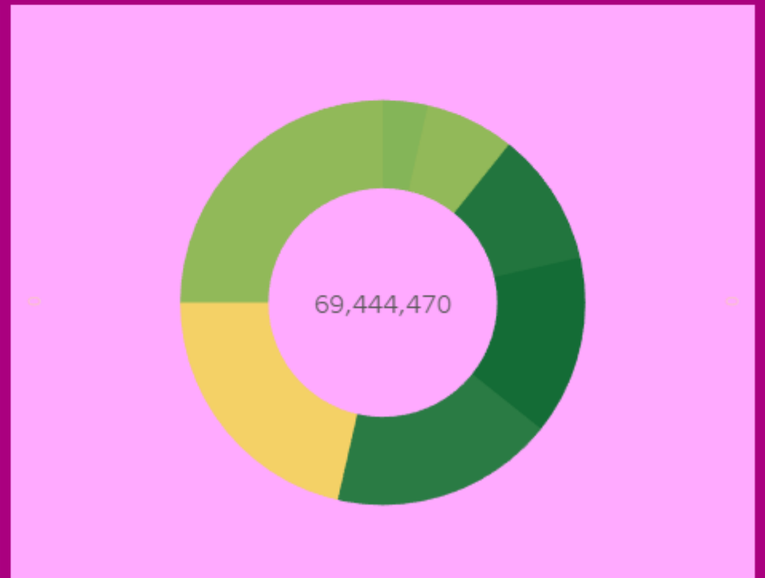
Airlines with Type of Airport and Duration of flights



ight delays based on type of Airport



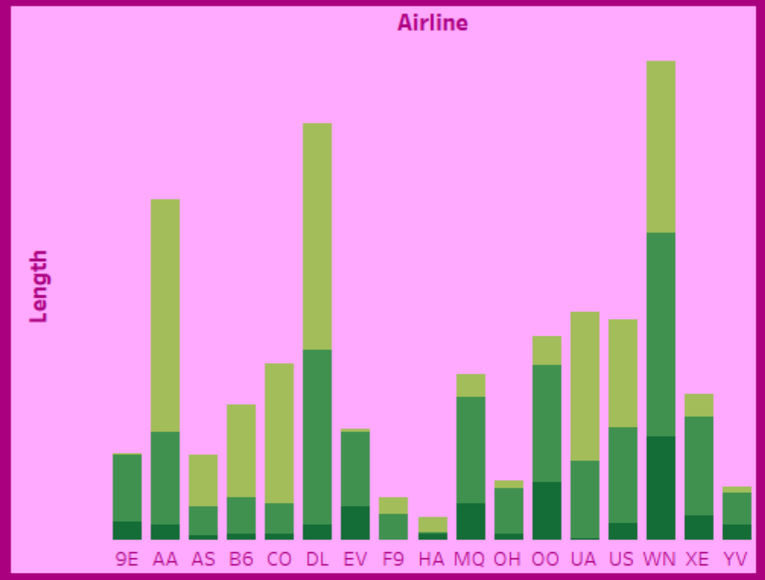
Duration of flight according to Day of the week



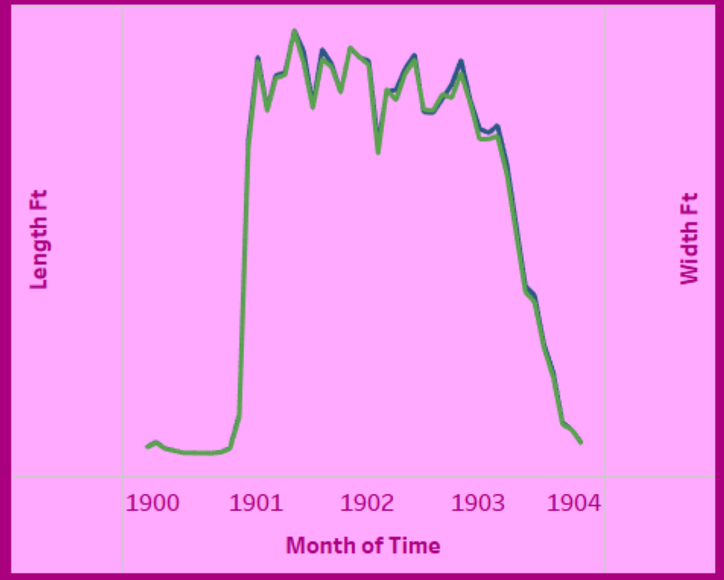
Story telling for Airlines_airways_runways data

I have created multiple visualizations using Airlines_airports_runways.csv file.Firstly created stacked bar chart using Airlines and length variables. then duel line chart with length,width and Time columns. Area chart with large,medium hubs and Time. Bubble chart using Airlines, type of the airport and length columns. fifth visualization would be kind of tree chart using type of the airport ,delay and created duplicate dimensions for this. last one is donut map using Day of week and length

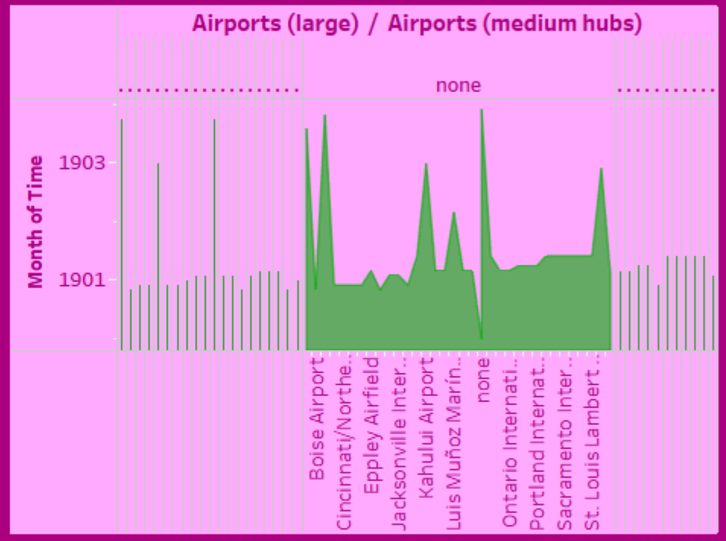
Airlines with Travelling Duration



Lenght and Width of the Airlines



Large and Medium hub Airports according to year and month wise



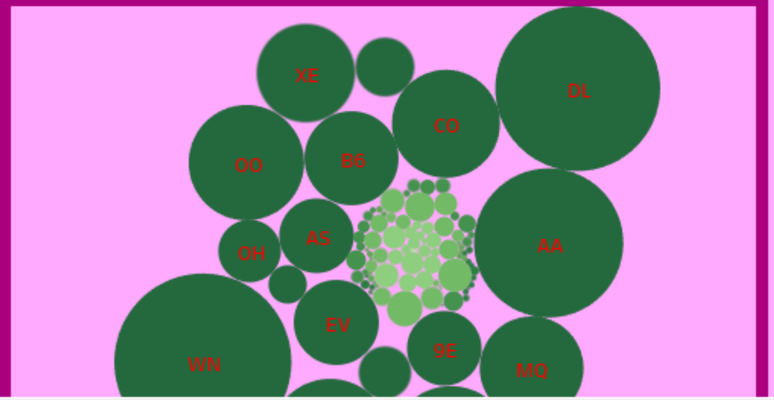
Travelling Duration
- long-distance
- medium-distance
- short-distance

Measure Names
- Length Ft
- Width Ft

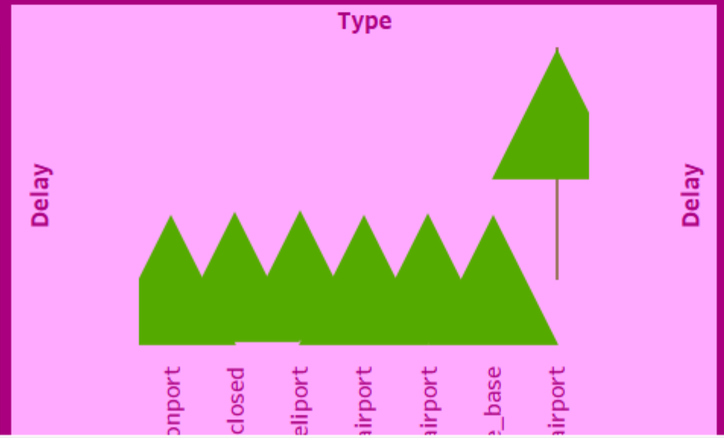
Type
- balloonport
- closed
- heliport
- large_airport
- medium_airport
- seaplane_base
- small_airport

Length
8M 12M

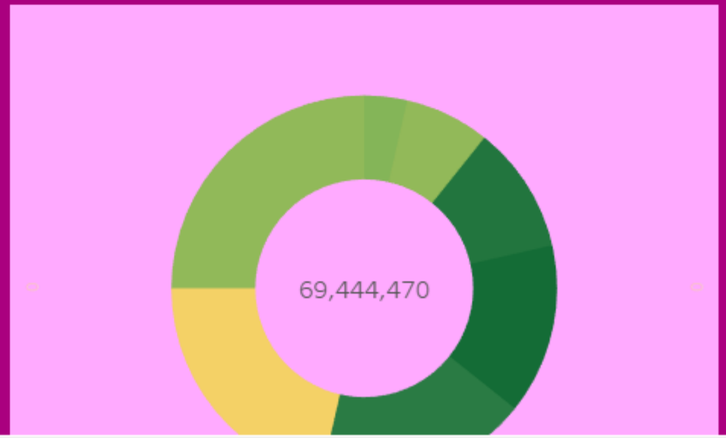
Airlines with Type of Airport and Duration of flights



flight delays based on type of Airport

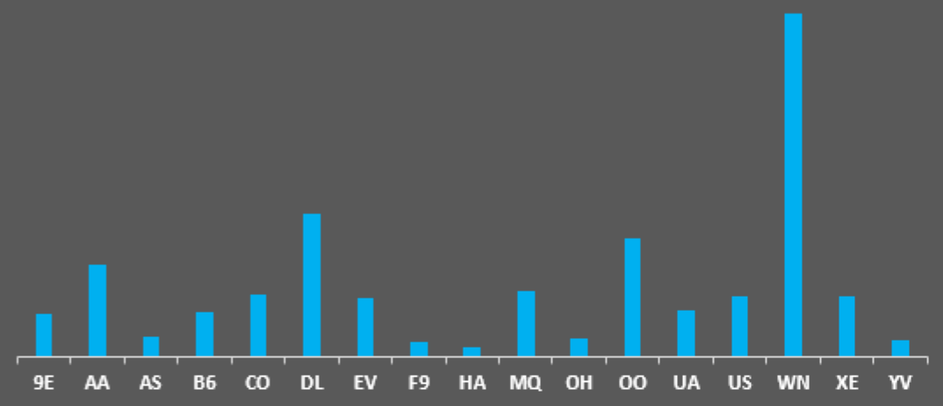


Duration of flight according to Day of the week

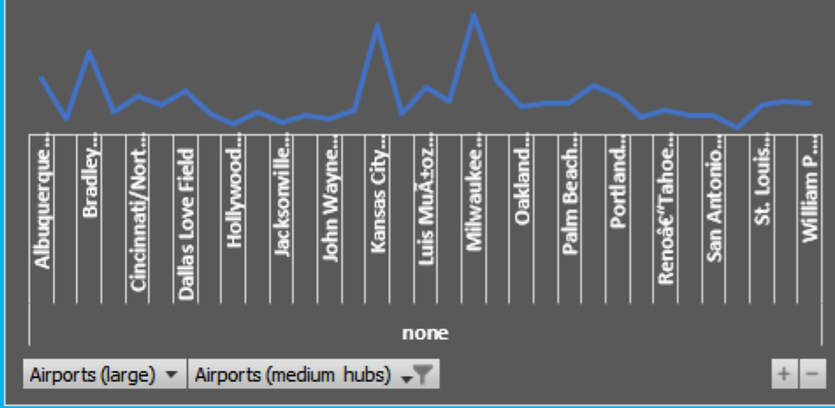


EXCEL DASHBOARD

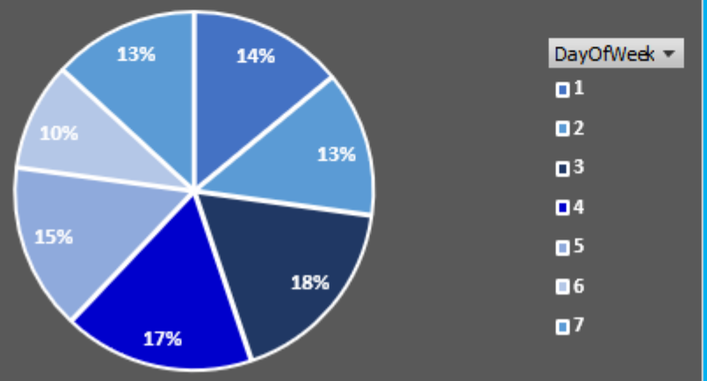
Different airlines based on their on-time performance



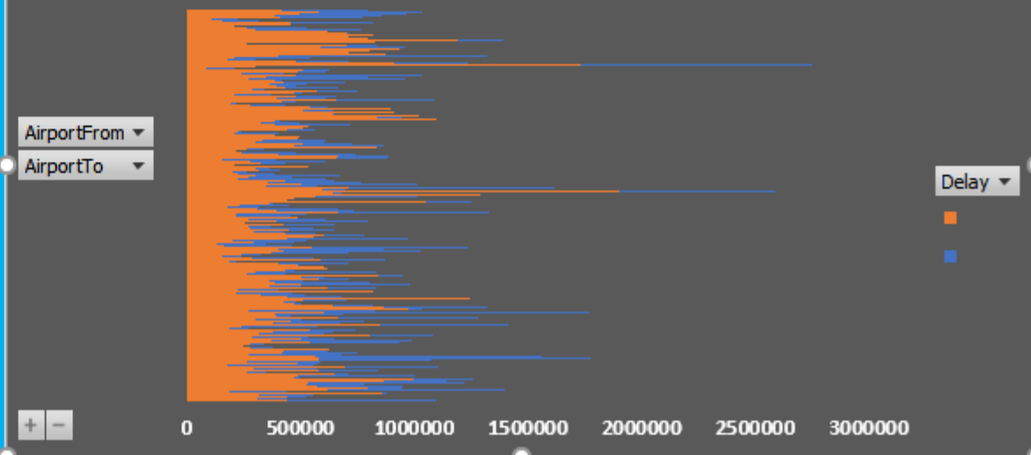
Number of passengers at large and medium hubs



Percentage of delayed flights for different days of the week



Count of delayed and on-time flights for different pairs of source and destination airports



```sql
create table Airlines_Airports_runways
(
Airline varchar(65),
Flight int,
AirportFrom varchar(65),
AirportTo varchar(65),
DayOfWeek int,
Time int,
Length int,
Delay int,
type varchar(65),
elevation_ft float,
airport_ref float,
length_ft float,
width_ft float,
Airports_large varchar(65),
Airports_medium_hubs varchar(65),
travelling_duration varchar(65)
);
load data infile 'Airlines_Airports_runways.csv' into table airlines_airports_runways
fields terminated by ','
ignore 1 lines;
select * from airlines_airports_runways;
```

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

Airline	Flight	AirportFrom	AirportTo	DayOfWeek	Time	Length	Delay	type	elevation_ft	airport_ref	length_ft	width_ft	Airports_large	Airports_medium_hubs	travelling_duration
CO	269	SFO	IAH	3	15	205	1	heliport	11	6523	80	80	none	none	long-distance
US	1558	PHX	CLT	3	15	222	1	small_airport	3435	19486	2700	75	none	none	long-distance
AA	2400	LAX	DFW	3	20	165	1	small_airport	450	6524	2500	70	none	none	long-distance
AA	2466	SFO	DFW	3	20	195	1	small_airport	820	6525	2300	200	none	none	long-distance
AS	108	ANC	SEA	3	30	202	0	closed	237	6526	40	40	none	none	long-distance
CO	1094	LAX	IAH	3	30	181	1	small_airport	1100	322127	1450	60	none	none	long-distance
DL	1768	LAX	MSP	3	30	220	0	small_airport	3810	6527	1700	60	none	none	long-distance
DL	2722	PHX	DTW	3	30	228	0	small_airport	3038	6528	6000	80	none	none	long-distance
DL	2606	SFO	MSP	3	35	216	1	small_airport	87	19486	2700	75	none	none	long-distance
AA	2538	LAS	ORD	3	40	200	1	heliport	3350	19486	2700	75	none	none	long-distance
CO	223	ANC	SEA	3	49	201	1	closed	4830	6529	3900	20	none	none	long-distance
DL	1646	PHX	ATL	3	50	212	1	small_airport	53	6531	3200	100	none	none	long-distance
DL	2055	SLC	ATL	3	50	210	0	closed	25	6532	74	74	none	none	long-distance
AA	2408	LAX	DFW	3	55	170	0	small_airport	35	6533	4090	100	none	none	long-distance
AS	132	ANC	PDX	3	55	215	0	small_airport	700	6534	2600	80	none	none	long-distance

Result Grid | Form Editor | Field Types | Query Stats

```sql
/*Determine the number of flights that are delayed on various days of the week*/
select DayOfWeek,count(Flight) as count_of_delayed_flights
from airlines_airports_runways
where Delay=1
group by DayOfWeek order by DayOfWeek asc ;
```

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

DayOfWeek	count_of_delayed_flights
1	33059
2	31072
3	41620
4	40712
5	35519
6	22963
7	31054

Result Grid
Form Editor
Field Types

```sql
/*Determine the number of delayed flights for various airlines*/
select Airline, count(Flight) as count_of_delayed_flights
from airlines_airports_runways
where Delay = 1
group by Airline;
```

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

Airline	count_of_delayed_flights
CO	12052
US	11711
AA	17895
DL	27684
HA	1794
OH	3529
9E	8320
OO	22946
EV	11354
XE	11855
MQ	12854
B6	8556
F9	2911
UA	9007
WN	66251
YV	3347
AS	3933

Result Grid | Form Editor | Field Types | Query Stats | Execution Plan

Limit to 1000 rows

```sql
/*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*/
select AirportFrom as Location, avg(elevation_ft) as avg_elevation,
count(case when Delay=1 then 1 else 0 end) as delayed_flights     /* delay=1*/
from airlines_airports_runways
where elevation_ft>(select avg(elevation_ft) from airlines_airports_runways)
group by AirportFrom
union all
select AirportTo as Location, avg(elevation_ft) as avg_elevation,
count(case when Delay=1 then 1 else 0 end) as delayed_flights
from airlines_airports_runways
where elevation_ft>(select avg(elevation_ft) from airlines_airports_runways)
group by AirportTo;
```

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

Location	avg_elevation	delayed_flights
PHX	2492.0859465737512	861
SFO	2365.3789329685364	731
LAX	2496.417994376757	1067
LAS	2421.3785310734465	708
ANC	2498.0833333333335	84
DEN	2409.055801594331	1129
FAI	2052.714285714286	21
IYK	2914.1666666666665	6
EWR	2251.82842287695	577
BOS	2335.8084358523724	569
OMA	2410.9469696969695	132
LMT	2808.4285714285716	7
SEA	2681.2611464968154	471
HNL	2632.766666666667	270
DLH	1537.5454545454545	11
MSP	2457.7359454855196	587
MFE	2279.842105263158	19
BWI	2534.2166666666667	420
RST	2147.923076923077	13
DSM	2495.909090909091	66
CHS	2198.1384615384613	65
MSN	2594.1041666666665	48
MCO	2388.008163265306	490
JAX	2297.3048780487807	164
SAT	2407.1943127962086	211
TPA	2208.2327044025155	318
BNA	2328.2392156862743	255
ICT	1987.7142857142858	63

Result Grid
Form Editor
Field Types
Query Stats
Execution Plan