Group9 Data Analysis

February 6, 2024

1 Project 1 Data Analysis

The extent of analysis of a dataset is largely up to the analyst. There is much subjectivity when deciding how to explore a dataset. How much is too much exploration, to a point where you are not getting any information from some charts? What if you do not explore enough, will you miss key patterns and correlations between variables?

For Project 1 exploration, since we are relatively new to analyzing your data, I will give you exactly what I need from your analysis. If you do the minimum exploration I have listed here, then you will get a 87%-90% on this portion of the project. If you add more insightful analysis on your own, you will get an A.

We are utilizing two datasets for our analysis:

1. Air Traffic Passenger Statistics
2. Air Traffic Landing Statistics

1.1 Exploring Air Traffic Passenger Patterns

1.2 Basics of Dataset

[5]:
```
#Find the size of your dataset (number of features and observations)
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv('Air_Traffic_Passenger_Statistics_20240131.csv')
df.head()
```

[5]:
```
   Activity Period Activity Period Start Date  \
0           199907                 1999/07/01
1           199907                 1999/07/01
2           199907                 1999/07/01
3           199907                 1999/07/01
4           199907                 1999/07/01

                     Operating Airline Operating Airline IATA Code  \
0                          ATA Airlines                          TZ
```

```
1                          ATA Airlines                          TZ
2                          ATA Airlines                          TZ
3  Aeroflot Russian International Airlines                      NaN
4  Aeroflot Russian International Airlines                      NaN

                         Published Airline Published Airline IATA Code  \
0                          ATA Airlines                          TZ
1                          ATA Airlines                          TZ
2                          ATA Airlines                          TZ
3  Aeroflot Russian International Airlines                      NaN
4  Aeroflot Russian International Airlines                      NaN

     GEO Summary GEO Region Activity Type Code Price Category Code  \
0       Domestic         US           Deplaned            Low Fare
1       Domestic         US           Enplaned            Low Fare
2       Domestic         US     Thru / Transit            Low Fare
3  International     Europe           Deplaned               Other
4  International     Europe           Enplaned               Other

     Terminal Boarding Area  Passenger Count             data_as_of  \
0  Terminal 1             B            31432  2023/12/21 12:05:27 AM
1  Terminal 1             B            31353  2023/12/21 12:05:27 AM
2  Terminal 1             B             2518  2023/12/21 12:05:27 AM
3  Terminal 2             D             1324  2023/12/21 12:05:27 AM
4  Terminal 2             D             1198  2023/12/21 12:05:27 AM

           data_loaded_at
0  2024/01/20 07:02:35 AM
1  2024/01/20 07:02:35 AM
2  2024/01/20 07:02:35 AM
3  2024/01/20 07:02:35 AM
4  2024/01/20 07:02:35 AM
```

[6]:
```python
# Get the number of rows and columns in the DataFrame
num_rows, num_columns = df.shape

# Display the size of the dataset
print(f"Number of observations (rows): {num_rows}")
print(f"Number of features (columns): {num_columns}")
```

```
Number of observations (rows): 35172
Number of features (columns): 15
```

[7]:
```python
from IPython.display import display

# Summary statistics for numeric columns
numeric_summary = df.describe()
```

```python
# Summary statistics for categorical columns
categorical_summary = df.describe(include='object')

print("Numeric Summary:")
display(numeric_summary)

print("\nCategorical Summary:")
display(categorical_summary)
```

```
Numeric Summary:

       Activity Period  Passenger Count
count     35172.000000     35172.000000
mean     201173.280792     28000.508075
std         706.637527     62772.762446
min      199907.000000         0.000000
25%      200603.000000      4452.000000
50%      201206.000000      8634.000000
75%      201804.000000     19893.750000
max      202311.000000    856501.000000


Categorical Summary:

       Activity Period Start Date                 Operating Airline  \
count                       35172                             35172
unique                        293                               134
top                    2018/06/01  United Airlines - Pre 07/01/2013
freq                          170                              3670

       Operating Airline IATA Code                 Published Airline  \
count                        34856                             35172
unique                         111                               121
top                             UA  United Airlines - Pre 07/01/2013
freq                          7095                              4317

       Published Airline IATA Code    GEO Summary GEO Region  \
count                        34856          35172      35172
unique                         100              2          9
top                             UA  International         US
freq                          8339          22620      12552

       Activity Type Code Price Category Code       Terminal Boarding Area  \
count               35172               35172          35172         35172
unique                  3                   2              5             8
top              Enplaned               Other  International             A
freq                16629               31348          21714         12063

                    data_as_of          data_loaded_at
```

```
count                       35172                   35172
unique                          2                       1
top     2023/12/21 12:05:28 AM  2024/01/20 07:02:35 AM
freq                        33261                   35172
```

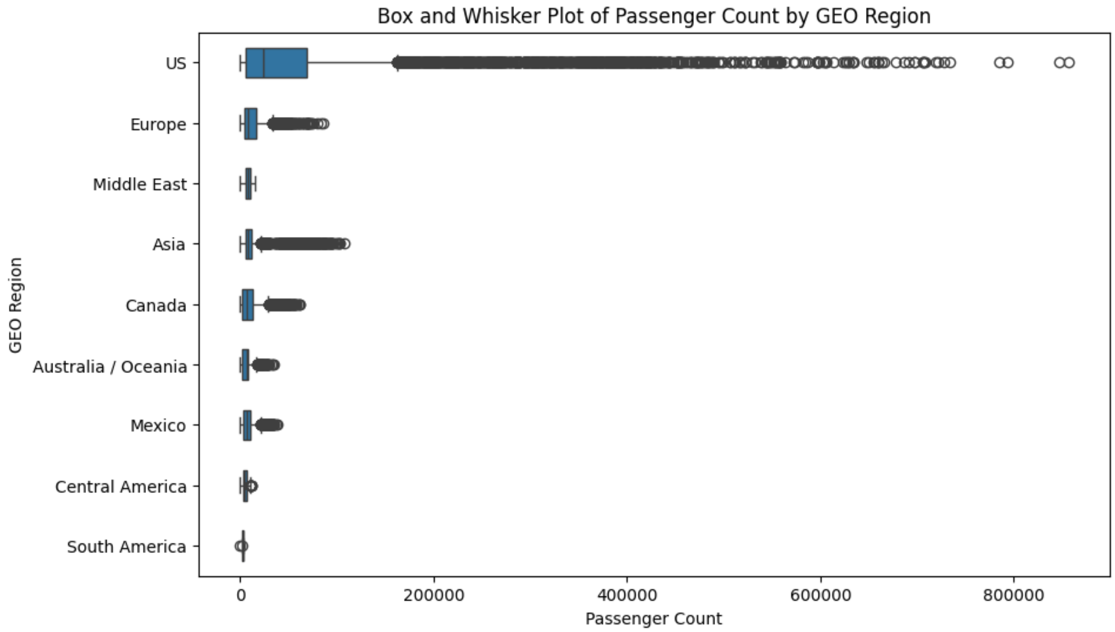
[8]:
```
df.isnull().sum()
```

[8]:
```
Activity Period                   0
Activity Period Start Date        0
Operating Airline                 0
Operating Airline IATA Code     316
Published Airline                 0
Published Airline IATA Code     316
GEO Summary                       0
GEO Region                        0
Activity Type Code                0
Price Category Code               0
Terminal                          0
Boarding Area                     0
Passenger Count                   0
data_as_of                        0
data_loaded_at                    0
dtype: int64
```

The columns "Operating Airline IATA Code" and "Published Airline IATA Code" have missing values, but we won't be using these features in our analysis, hence we can ignore those missing values.

1.3 Distribution of Dataset

[9]:
```
#Add at least one box and whisker plot of an important numerical variable in␣
↪your table

median_order = df.groupby('GEO Region')['Passenger Count'].median().
↪sort_values(ascending=False).index

plt.figure(figsize=(10, 6))
sns.boxplot(x = 'Passenger Count', y='GEO Region', order=median_order, data=df,␣
↪width=0.5)

plt.title('Box and Whisker Plot of Passenger Count by GEO Region')
plt.show()
```

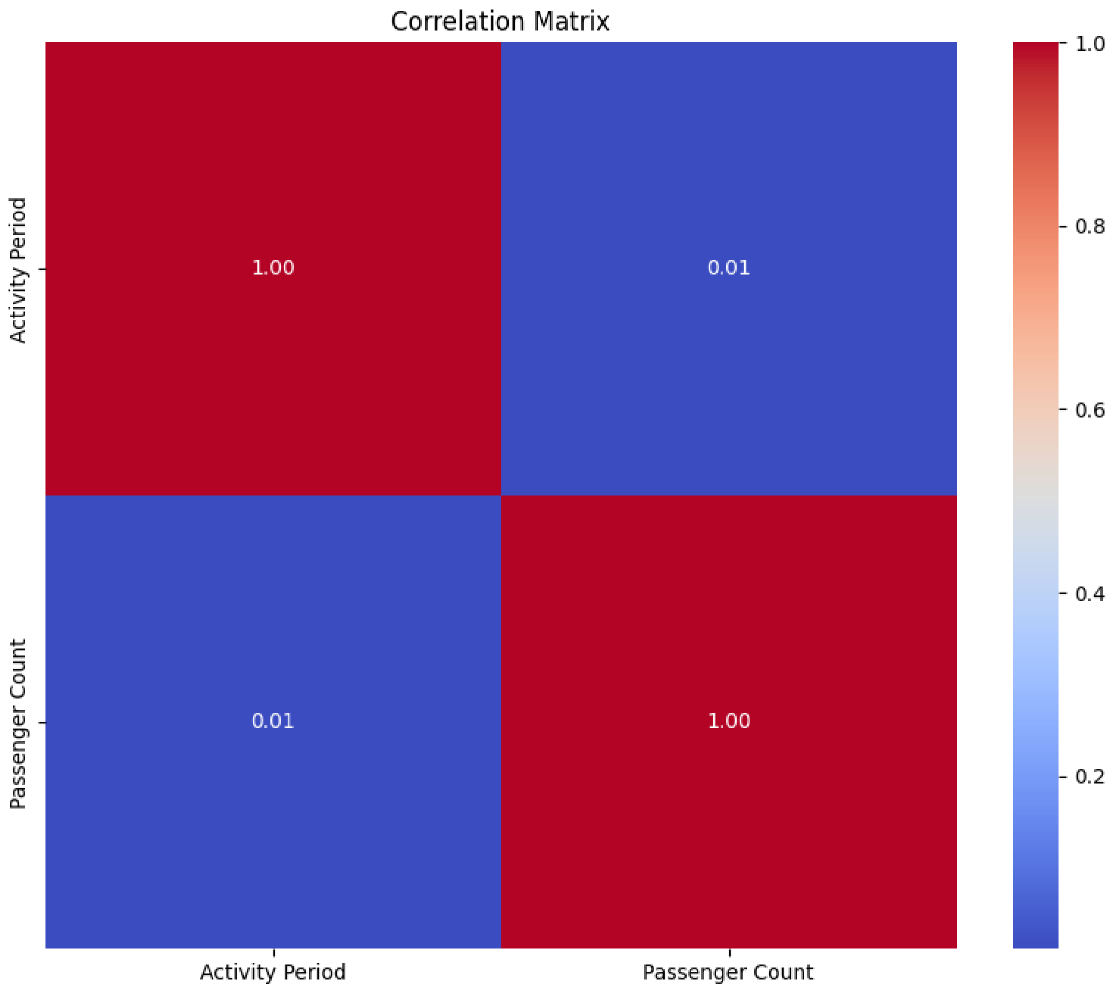


Observations:

1. The number of passengers arriving from or departing to the United States is significantly higher than the number of passengers from any other region.
2. The number of passengers from Europe is the second highest, followed by Asia, Canada, and Mexico.
3. The number of passengers from Central America and South America is the lowest.

[10]:
```python
#Add a correlation matrix of all your numerical variables and give written
#anlaysis of any variables that show strong correlation

# Creating a correlation matrix
correlation_matrix = df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```

```
<ipython-input-10-60df8f04d2bb>:5: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlation_matrix = df.corr()
```



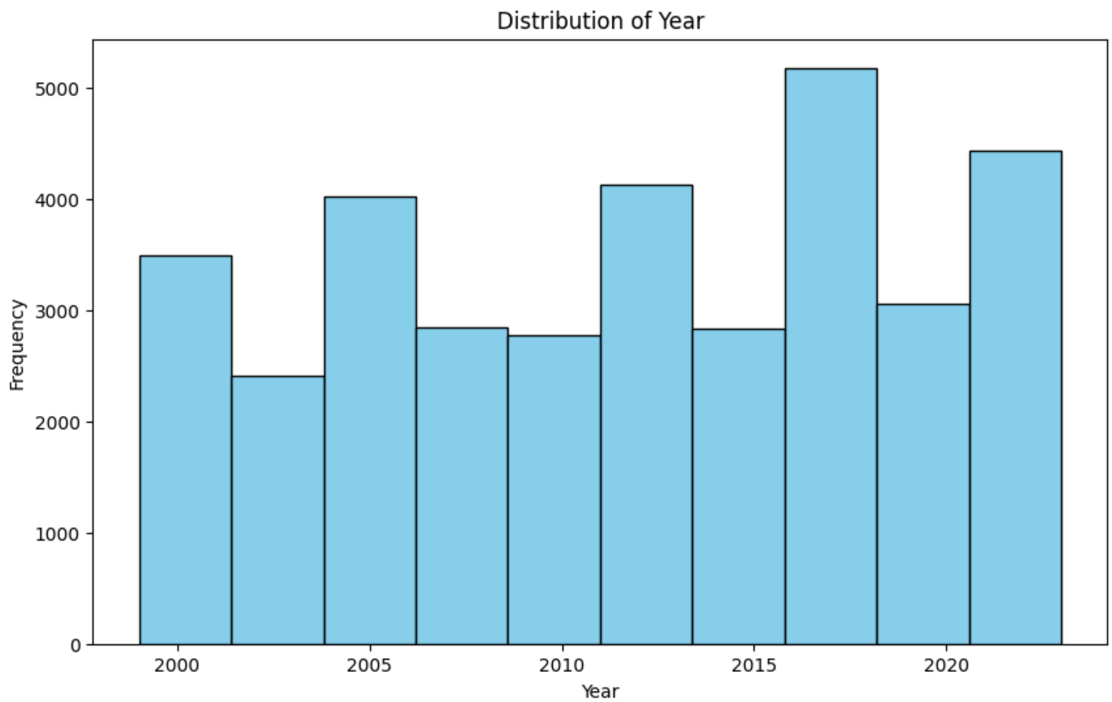
Interpretation:

We can see that correlation coefficient between passenger count and activity period is 0.01, suggesting that there is little to no linear relationship between passenger count and activity period.

[11]:
```
# Converting the 'Activity Period' column to datetime format
df.loc[:,"Activity Period"] = pd.to_datetime(df.loc[:,"Activity Period"].
 ↪astype(str), format="%Y%m")

# Extracting the year from the 'Activity Period'
df.loc[:,"Year"] = df["Activity Period"].dt.year

# Extracting the month from the 'Activity Period'
df.loc[:,"Month"] = df["Activity Period"].dt.month
```

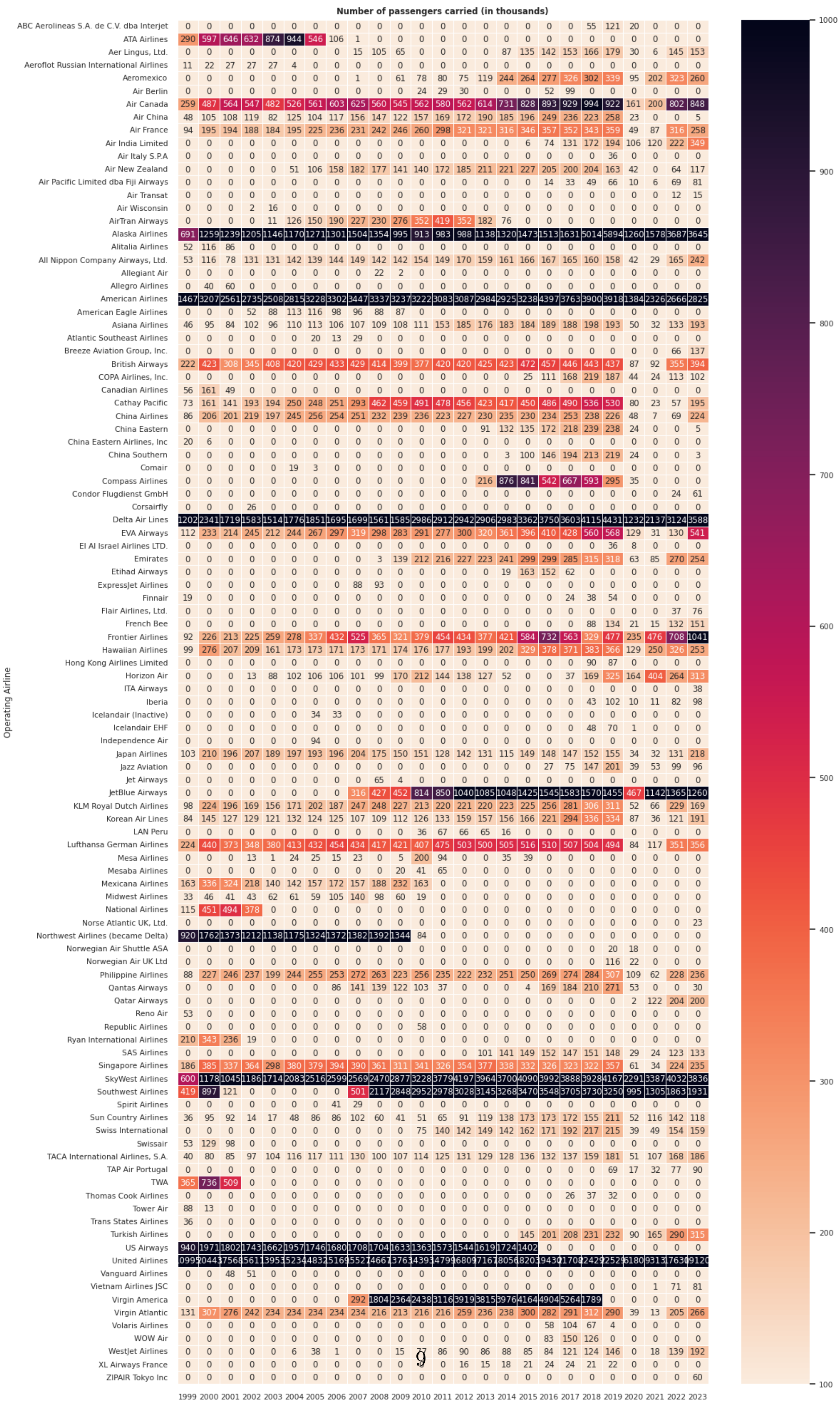
[12]:
```
#BONUS: You can create a histogram to show distribution of a numerical variable
```

```
plt.figure(figsize=(10, 6))
plt.hist(df['Year'], bins=10, color='skyblue', edgecolor='black')

plt.xlabel('Year')
plt.ylabel('Frequency')
plt.title('Distribution of Year')

plt.show()
```



[13]:
```
#BONUS: Include any other charts we learned in class on 01/30



import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Grouping and summing passenger counts
passenger_airline_year = df.groupby(["Year", "Operating Airline"])["Passenger␣
 ↪Count"].sum().divide(1000)
passenger_airline_year = passenger_airline_year.reset_index()

# Creating a pivot table
pivot_table_passenger = passenger_airline_year.pivot_table(values="Passenger␣
 ↪Count", index="Operating Airline", columns="Year", fill_value=0)
```

```
# Combining rows for United Airlines
pivot_table_passenger.loc["United Airlines", :] = pivot_table_passenger.loc["United Airlines", :] + pivot_table_passenger.loc["United Airlines - Pre 07/01/2013", :]
pivot_table_passenger.drop("United Airlines - Pre 07/01/2013", axis=0, inplace=True)

# Dropping the small airlines
smallest_airlines = pivot_table_passenger[pivot_table_passenger.sum(axis=1) < 13]
pivot_table_passenger = pivot_table_passenger.drop(smallest_airlines.index, axis=0)

sns.set(font_scale=0.7)

# Creating a heatmap
fig1 = plt.figure(figsize=(12, 20))
heatmap_passenger = sns.heatmap(pivot_table_passenger, annot=True, linewidths=.5, vmin=100, vmax=1000, fmt='.0f', cmap=sns.cm.rocket_r)
heatmap_passenger.set_title("Number of passengers carried (in thousands)", fontweight="bold")
heatmap_passenger.set_yticklabels(heatmap_passenger.get_yticklabels(), rotation=0)

plt.tight_layout()
plt.show()
```


Number of passengers carried (in thousands)
Operating Airline
Year
ABC Aerolineas S.A. de C.V. dba Interjet
ATA Airlines
Aer Lingus, Ltd.
Aeroflot Russian International Airlines
Aeromexico
Air Berlin
Air Canada
Air China
Air France
Air India Limited
Air Italy S.P.A
Air New Zealand
Air Pacific Limited dba Fiji Airways
Air Transat
Air Wisconsin
AirTran Airways
Alaska Airlines
Alitalia Airlines
All Nippon Company Airways, Ltd.
Allegiant Air
Allegro Airlines
American Airlines
American Eagle Airlines
Asiana Airlines
Atlantic Southeast Airlines
Breeze Aviation Group, Inc.
British Airways
COPA Airlines, Inc.
Canadian Airlines
Cathay Pacific
China Airlines
China Eastern
China Eastern Airlines, Inc
China Southern
Comair
Compass Airlines
Condor Flugdienst GmbH
Corsairfly
Delta Air Lines
EVA Airways
El Al Israel Airlines LTD.
Emirates
Etihad Airways
ExpressJet Airlines
Finnair
Flair Airlines, Ltd.
French Bee
Frontier Airlines
Hawaiian Airlines
Hong Kong Airlines Limited
Horizon Air
ITA Airways
Iberia
Icelandair (Inactive)
Icelandair EHF
Independence Air
Japan Airlines
Jazz Aviation
Jet Airways
JetBlue Airways
KLM Royal Dutch Airlines
Korean Air Lines
LAN Peru
Lufthansa German Airlines
Mesa Airlines
Mesaba Airlines
Mexicana Airlines
Midwest Airlines
National Airlines
Norse Atlantic UK, Ltd.
Northwest Airlines (became Delta)
Norwegian Air Shuttle ASA
Norwegian Air UK Ltd
Philippine Airlines
Qantas Airways
Qatar Airways
Reno Air
Republic Airlines
Ryan International Airlines
SAS Airlines
Singapore Airlines
SkyWest Airlines
Southwest Airlines
Spirit Airlines
Sun Country Airlines
Swiss International
Swissair
TACA International Airlines, S.A.
TAP Air Portugal
TWA
Thomas Cook Airlines
Tower Air
Trans States Airlines
Turkish Airlines
US Airways
United Airlines
Vanguard Airlines
Vietnam Airlines JSC
Virgin America
Virgin Atlantic
Volaris Airlines
WOW Air
WestJet Airlines
XL Airways France
ZIPAIR Tokyo Inc
1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022 2023
1000
900
800
700
600
500
400
300
200
100

The above heatmap shows what amount of traffic various airlines generated through the years (in thousands).

[14]:
```
average_passengers_per_airline = pivot_table_passenger.mean(axis=1)
top_5_airlines = average_passengers_per_airline.nlargest(5).to_frame().
  ↪mul(1000).astype("int64")
top_5_airlines.columns = ["Mean no. of passengers per year"]
total_passengers = top_5_airlines.loc[:, "Mean no. of passengers per year"].
  ↪sum()
top_5_airlines.loc[:, "Share [%]"] = top_5_airlines.loc[:, "Mean no. of␣
  ↪passengers per year"].div(total_passengers).mul(100).round(1)

top_5_airlines
```

[14]:
```
                     Mean no. of passengers per year  Share [%]
Operating Airline
United Airlines                             16221060       61.2
American Airlines                            3022542       11.4
SkyWest Airlines                             2932604       11.1
Delta Air Lines                              2503895        9.4
Southwest Airlines                           1842872        6.9
```

Observations:

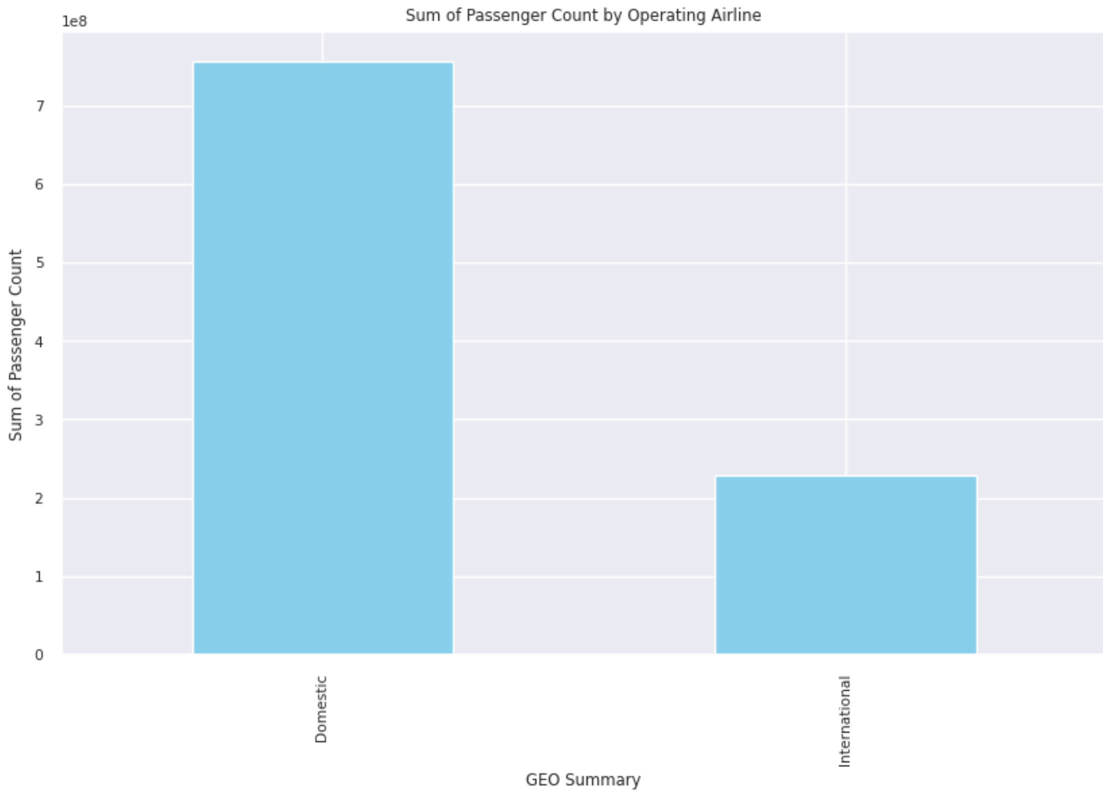
From the above heatmap and table, the top 5 airlines which generated the highest passenger traffic are:

1. United Airlines
2. Amercian Airlines
3. SkyWest Airlines
4. Delta Air Lines
5. Southwest Airlines

1.4 Aggregation of Categorical Data

[15]:
```
#Create either a bar chart or pie chart of the sum of one numerical value in
#relation to one categorical variable (i.e. sum of sales for each category of␣
  ↪product)

grouped_data = df.groupby('GEO Summary')['Passenger Count'].sum()

plt.figure(figsize=(10, 6))
grouped_data.plot(kind='bar', color='skyblue')
plt.title('Sum of Passenger Count by Operating Airline')
plt.xlabel('GEO Summary')
plt.ylabel('Sum of Passenger Count')
```

```
plt.show()
```



[16]:
```
#BONUS: Include any other charts we learned in class on 01/30

PAX_yr = df.groupby(["Activity Period"])["Passenger Count"].sum().divide(1000)

fig, ax = plt.subplots(figsize=(15,7))

#Plotting the main PAX line
sns.lineplot(x=PAX_yr.index, y=PAX_yr.values, markers=True, ax=ax,zorder=0)

# Looking for maximum PAX for each year
PAX_yr_maxs = PAX_yr.groupby(PAX_yr.index.year).max()
PAX_yr_max_complete = PAX_yr[PAX_yr.isin(PAX_yr_maxs.values)].to_frame()

# Marking points of interest
plt.scatter(PAX_yr_max_complete.index, PAX_yr_max_complete.values, color =␣
 ↪"red", zorder=2)

#Annotating each marker
for t,v in PAX_yr_max_complete.reset_index().values:
```

```python
    ax.text(t,v+90,int(v))

# Looking for minimum PAX for each year
PAX_yr_mins = PAX_yr.groupby(PAX_yr.index.year).min()
PAX_yr_min_complete = PAX_yr[PAX_yr.isin(PAX_yr_mins.values)].to_frame()
plt.scatter(PAX_yr_min_complete.index, PAX_yr_min_complete.values, color = "green", zorder=2)
for t,v in PAX_yr_min_complete.reset_index().values:
    ax.text(t,v-150,int(v))

plt.title("SFO passengers over time", size = 20)
plt.xlabel("Date", fontweight="bold", size = 12)
plt.ylabel("Total Number of Passengers (in thousands)", fontweight="bold", size = 12)
plt.show()
```

Observations:

1. Passenger numbers have been steadily increasing over time. From 2000 to 2019, the number of passengers increased from around 2 million to around 5.7 million per month. This is likely due to a number of factors, such as the growing population of the San Francisco Bay Area, the increasing popularity of air travel, and the addition of new routes and airlines at SFO.

2. The COVID-19 pandemic had a significant impact on passenger numbers. In 2020, the number of passengers at SFO dropped to around 138,000 per month. However, passenger numbers have been recovering since then, and they are now at around 4 million per month.

3. Passenger numbers are higher in the summer months and lower in the winter months. This is likely due to a number of factors, such as school holidays, summer vacations, and business travel patterns.

1.5 Analyzing Air Traffic Landings

1.6 Basics of Dataset

[ ]:
```
#Find the size of your dataset (number of features and observations)
```

[20]:
```
import pandas as pd
df=pd.read_csv("Air_Traffic_Landings_Statistics.csv")
df.head()
```

[20]:
```
   Activity Period Activity Period Start Date  \
0           199907                 1999/07/01
1           199907                 1999/07/01
2           199907                 1999/07/01
3           199907                 1999/07/01
4           199907                 1999/07/01

                      Operating Airline Operating Airline IATA Code  \
0                          ATA Airlines                          TZ
1                          ATA Airlines                          TZ
2                          ATA Airlines                          TZ
3                          ATA Airlines                          TZ
4  Aeroflot Russian International Airlines                      NaN

                      Published Airline Published Airline IATA Code  \
0                          ATA Airlines                          TZ
1                          ATA Airlines                          TZ
2                          ATA Airlines                          TZ
3                          ATA Airlines                          TZ
4  Aeroflot Russian International Airlines                      NaN

     GEO Summary GEO Region Landing Aircraft Type Aircraft Body Type  \
0       Domestic         US             Passenger        Narrow Body
1       Domestic         US             Passenger        Narrow Body
2       Domestic         US             Passenger          Wide Body
3       Domestic         US             Passenger          Wide Body
4  International     Europe             Passenger          Wide Body

  Aircraft Manufacturer Aircraft Model Aircraft Version  Landing Count  \
0                Boeing            727              200              4
1                Boeing            757              NaN             78
2              Lockheed          L1011                0             71
3              Lockheed          L1011              100              1
4                Boeing            767                0              9

   Total Landed Weight              data_as_of           data_loaded_at
0               618000  2023/12/21 12:05:26 AM  2024/01/20 07:03:22 AM
1             15444000  2023/12/21 12:05:26 AM  2024/01/20 07:03:22 AM
```

```
2             25418000  2023/12/21 12:05:26 AM  2024/01/20 07:03:22 AM
3               368000  2023/12/21 12:05:26 AM  2024/01/20 07:03:22 AM
4              2879955  2023/12/21 12:05:26 AM  2024/01/20 07:03:22 AM
```

[21]:
```
total=df.size
size=df.shape
print("Total size of the Air traffic Landing statistics dataset:",total)
print("Total no of features:",size[0])
print("Total no of Observations:",size[1])
```

```
Total size of the Air traffic Landing statistics dataset: 698054
Total no of features: 41062
Total no of Observations: 17
```

[22]:
```
#Add summary statistics of your dataset here
```

[23]:
```
import pandas as pd

df['Activity Period Start Date'] = pd.to_datetime(df['Activity Period Start␣
↪Date'])
print(df['Activity Period Start Date'].dtype)
```

```
datetime64[ns]
```

[24]:
```
print("The summary statistics of Air traffic Landing :\n")
df.describe()
```

```
The summary statistics of Air traffic Landing :
```

[24]:

	Activity Period	Landing Count	Total Landed Weight
count	41062.000000	41062.000000	4.106200e+04
mean	201140.001705	105.232088	1.823557e+07
std	716.110101	239.168516	2.874351e+07
min	199907.000000	1.000000	3.600000e+03
25%	200507.000000	13.000000	3.114325e+06
50%	201201.000000	30.000000	9.384952e+06
75%	201801.000000	82.000000	1.953000e+07
max	202311.000000	2979.000000	3.122460e+08

[25]:
```
df.dtypes #check numerical data
```

[25]:
```
Activity Period                          int64
Activity Period Start Date      datetime64[ns]
Operating Airline                       object
Operating Airline IATA Code             object
Published Airline                       object
Published Airline IATA Code             object
GEO Summary                             object
```

```
GEO Region                                 object
Landing Aircraft Type                      object
Aircraft Body Type                         object
Aircraft Manufacturer                      object
Aircraft Model                             object
Aircraft Version                           object
Landing Count                               int64
Total Landed Weight                         int64
data_as_of                                 object
data_loaded_at                             object
dtype: object
```

[26]:
```
df.isnull().sum().reset_index(name = "Null values").set_index("index")
```

[26]:
```
                              Null values
index
Activity Period                         0
Activity Period Start Date              0
Operating Airline                       0
Operating Airline IATA Code           556
Published Airline                       0
Published Airline IATA Code           551
GEO Summary                             0
GEO Region                              0
Landing Aircraft Type                   0
Aircraft Body Type                      0
Aircraft Manufacturer                   0
Aircraft Model                          0
Aircraft Version                     3283
Landing Count                           0
Total Landed Weight                     0
data_as_of                              0
data_loaded_at                          0
```

The columns "Operating Airline IATA Code","Published Airline IATA Code" and "Aircraft Version" have missing values, but we won't be using these features in your analysis, hence we can ignore those missing values.

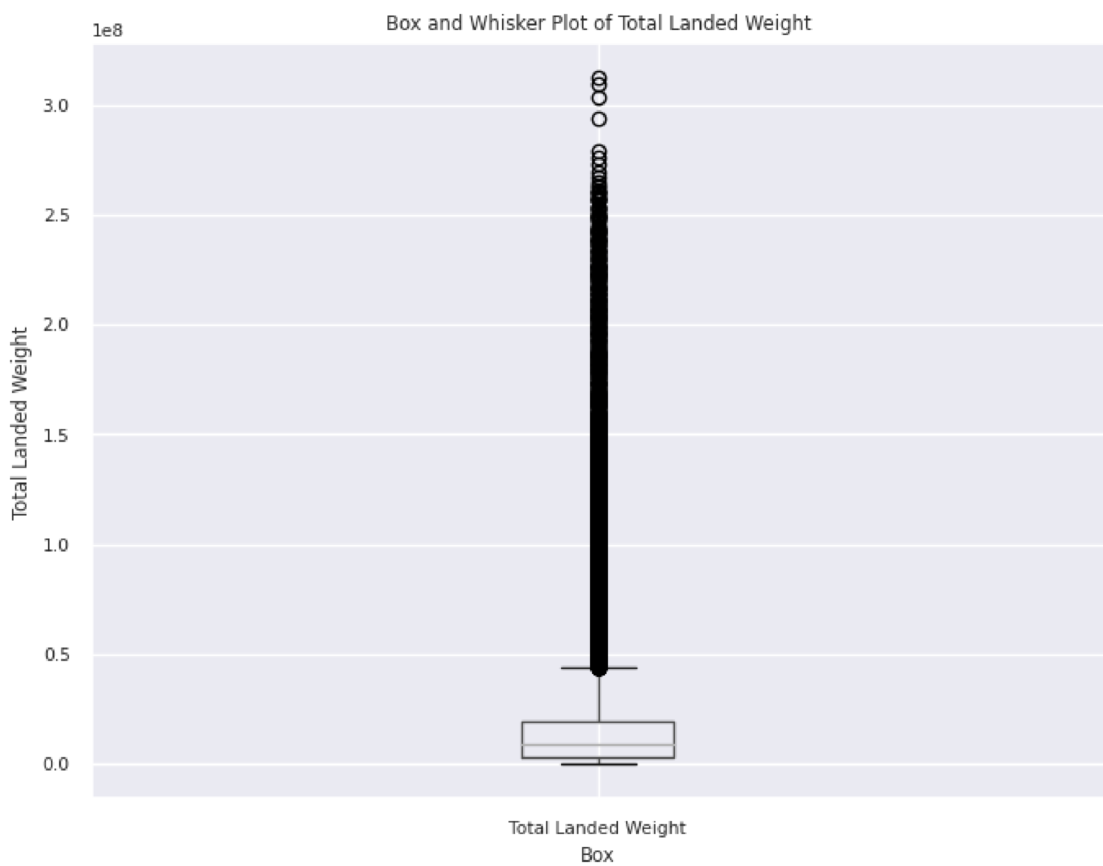
1.7 Distribution of Dataset

[ ]:
```
#Add at least one box and whisker plot of an important numerical variable in␣
 ↪your table
```

BOX PLOT 1:

[27]:
```
#To check box plot for the total landed Weight
import matplotlib.pyplot as plt
```

```
numerical_variable = "Total Landed Weight"

plt.figure(figsize=(8, 6))
df.boxplot(column=numerical_variable)
plt.title('Box and Whisker Plot of {}'.format(numerical_variable))
plt.ylabel('{}'.format(numerical_variable))
plt.xlabel('Box')
plt.show()
```

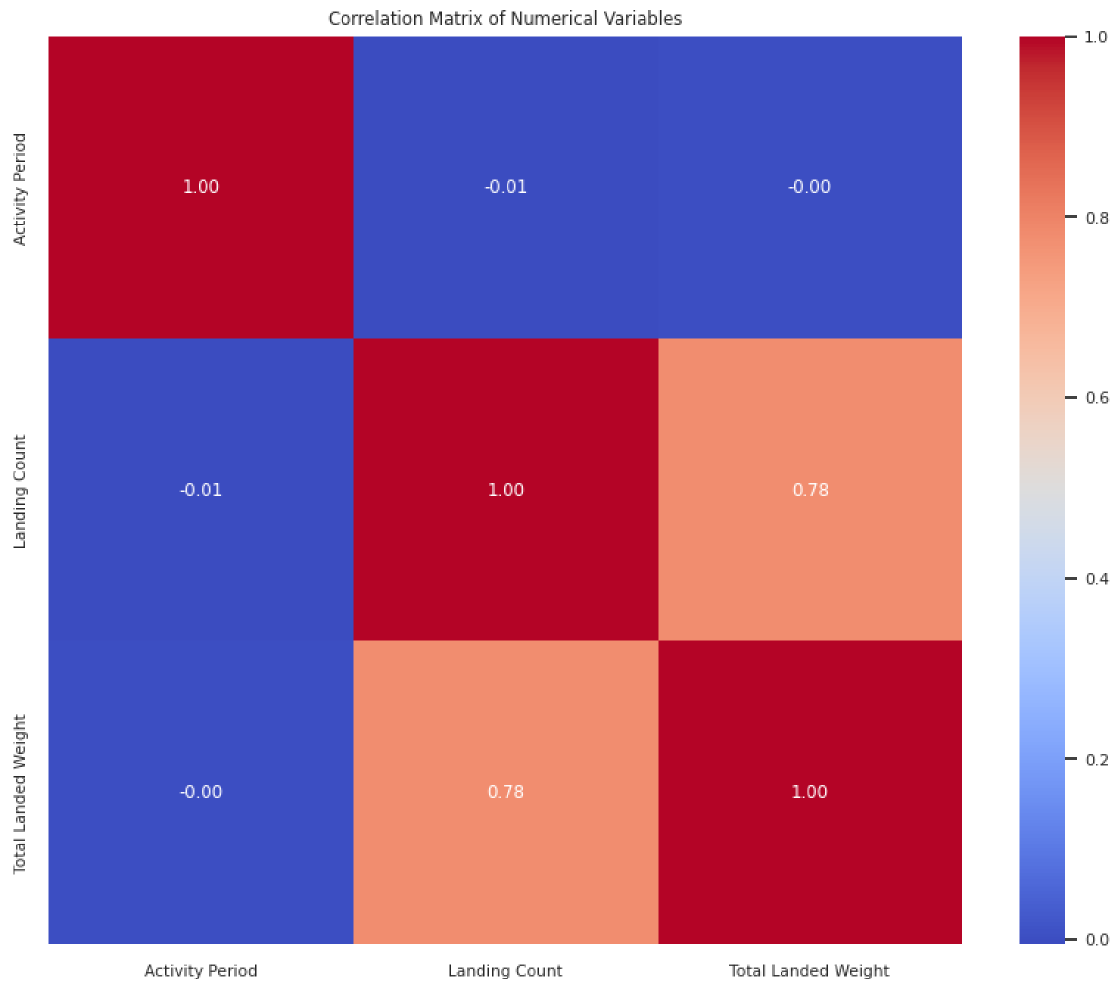


Based on the graph, we can see that the total landed weight of airplanes at SFO is right skewed. This means that there are more airplanes that land with a lower weight than there are airplanes that land with a higher weight. The median landed weight is around 15 million pounds. There are a few outliers, on the high end.

[ ]:
```
#Add a correlation matrix of all your numerical variables and give written
#anlaysis of any variables that show strong correlation
```

[28]:
```
import seaborn as sns

numerical_df = df.select_dtypes(include=['int64', 'float64'])
```

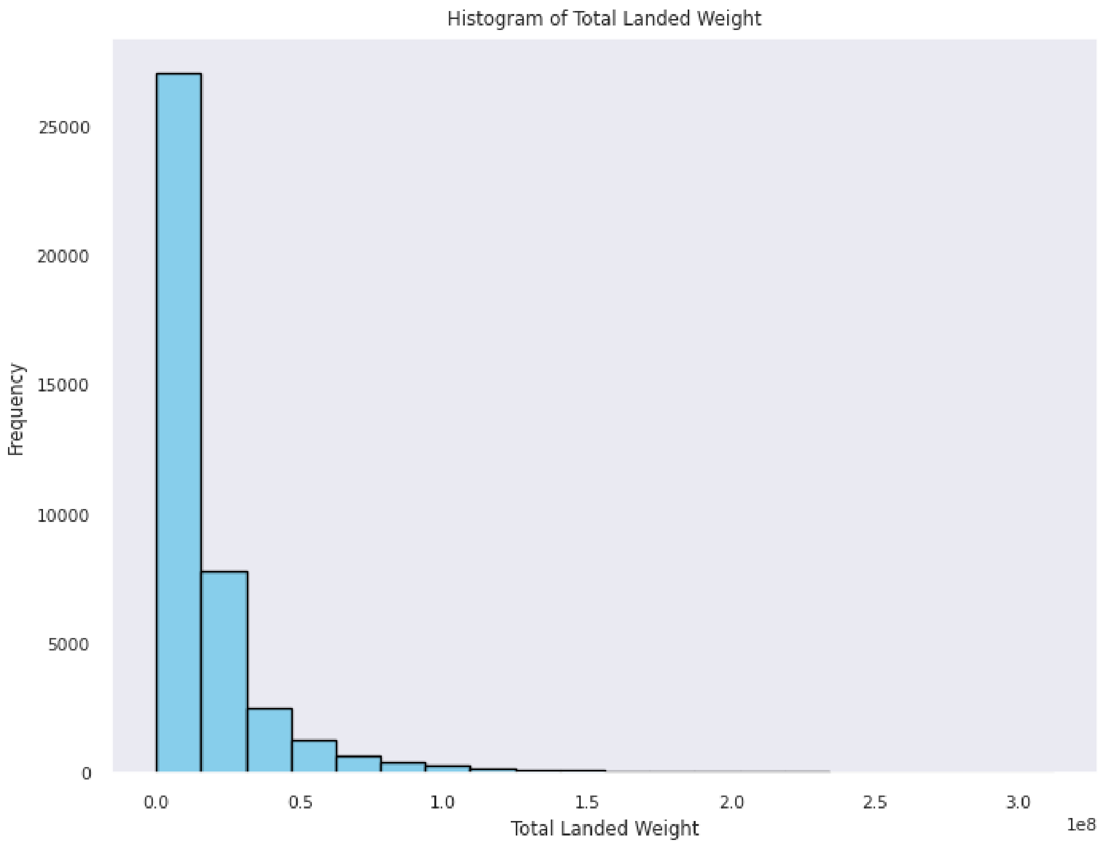
```
# Compute pairwise correlation of numerical columns
correlation_matrix = numerical_df.corr()

# Plotting the correlation matrix as a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix of Numerical Variables')
plt.show()
```



The heat Map computes and visualizes the correlation matrix of numerical variables in the DataFrame, providing insights into the relationships between different variables like Activity Period,Landing count ,Total Landed Weight. We can see high positive correlation between Landing Count and Total Landed Weight.

[ ]:
```
#BONUS: You can create a histogram to show distribution of a numerical variable
```

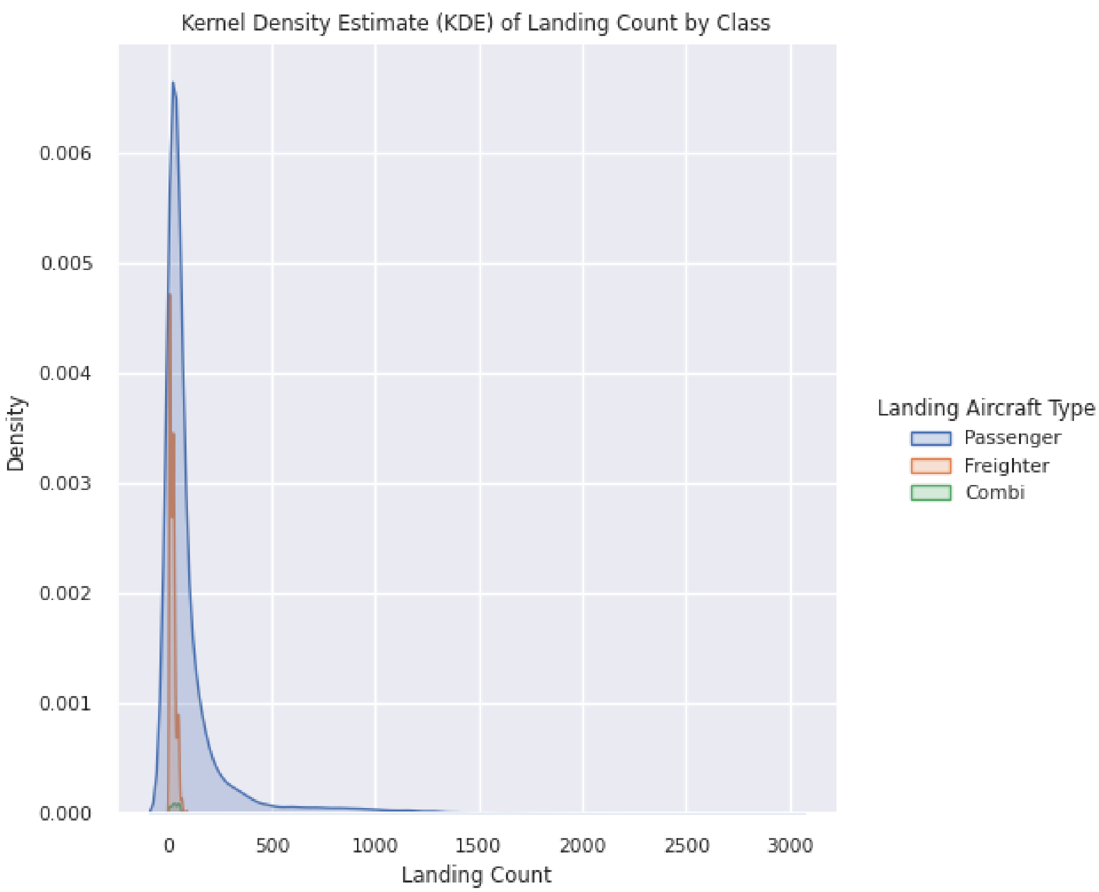
[29]:
```
numerical_variable = "Total Landed Weight"

plt.figure(figsize=(8, 6))
df[numerical_variable].hist(bins=20, color='skyblue', edgecolor='black')
plt.title('Histogram of {}'.format(numerical_variable))
plt.xlabel(numerical_variable)
plt.ylabel('Frequency')
plt.grid(False)
plt.show()
```



The histogram shows that most airplanes landing in the US weigh between 0 and 10 million pounds. There is a secondary peak between 10 and 50 million pounds, and the distribution tails off to the right, with a few airplanes weighing more than 150 million pounds.

[30]:
```
#BONUS: Include any other charts we learned in class on 01/30

import seaborn as sns
import matplotlib.pyplot as plt
```

```python
sns.displot(df, x='Landing Count', kind='kde', hue='Landing Aircraft Type',␣
  ↪fill=True)
plt.title('Kernel Density Estimate (KDE) of Landing Count by Class')
plt.show()
```



The graph uses a KDE plot to visualize the distribution of the "Landing Count" variable, with the KDE curves colored based on the categories of the "Landing Aircraft Type" variable. This allows for the exploration of the distribution of landing counts across different types of aircraft.

1.8 Aggregation of Categorical Data

[31]:
```python
#Create either a bar chart or pie chart of the sum of one numerical value in
#relation to one categorical variable (i.e. sum of sales for each category of␣
  ↪product)
```

[32]:
```python
df["Landing Aircraft Type"].value_counts()
```

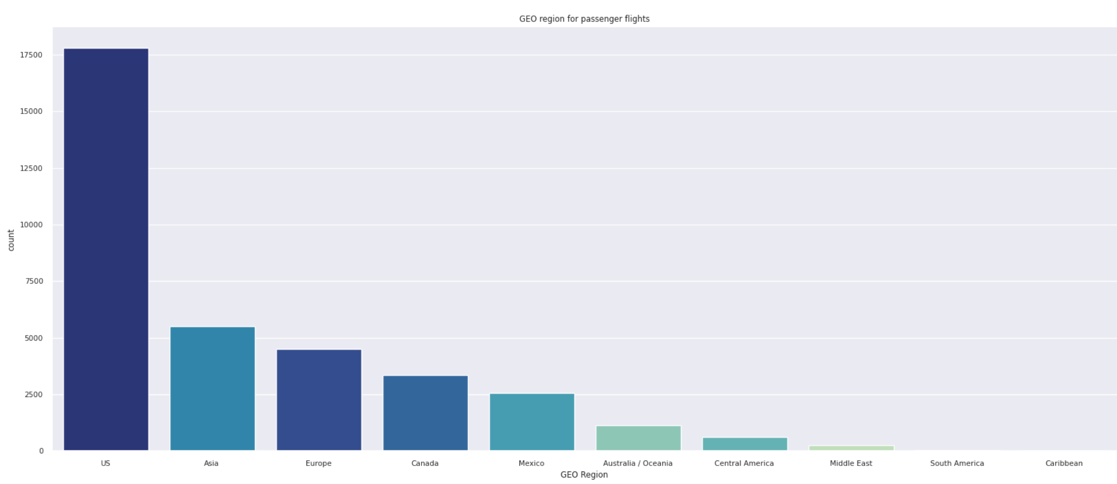
[32]:
```
Passenger     35738
Freighter      5108
```

```
Combi          216
Name: Landing Aircraft Type, dtype: int64
```

[33]:
```
Passenger = df[df["Landing Aircraft Type"]=="Passenger"]

print("There are",Passenger["Published Airline"].nunique(),"published airlines␣
↪operating for passenger flights")
```

```
There are 120 published airlines operating for passenger flights
```

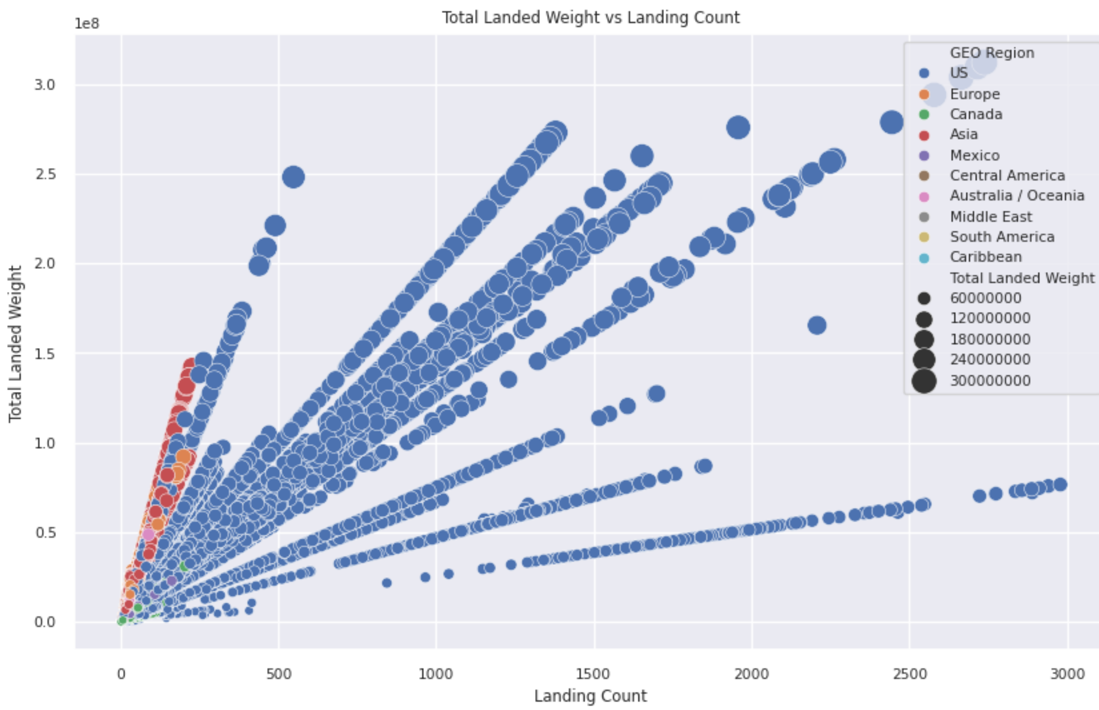
[34]:
```
plt.figure(figsize=(20, 8))

# Plotting the countplot
sns.countplot(x="GEO Region",  hue="GEO Region", data=Passenger,␣
↪order=Passenger["GEO Region"].value_counts().index, palette="YlGnBu_r",␣
↪legend=False)

# Modifying the graph
plt.title("GEO region for passenger flights")
sns.despine(top=True, right=True, left=False, bottom=False)

plt.show()
```



When analyzing passenger flights by GEO region, it's evident that domestic flights are the most frequent, followed by flights to Asia and Europe. Notably, neighboring North American countries, such as the United States, Canada, and Mexico, are also significant destinations. Grouping these countries into a single variable emphasizes the prominence of North American nations, particularly in comparison to regions consisting of multiple countries.

[35]:
```
#BONUS: Create a scatterplot with more than 2 visual encodings
#BONUS: Include any other charts we learned in class on 01/30
```

[36]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a scatterplot with multiple visual encodings
plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='Landing Count', y='Total Landed Weight', hue='GEO␣
↪Region', size='Total Landed Weight', sizes=(20, 200))

plt.title('Total Landed Weight vs Landing Count')
plt.xlabel('Landing Count')
plt.ylabel('Total Landed Weight')

plt.show()
```

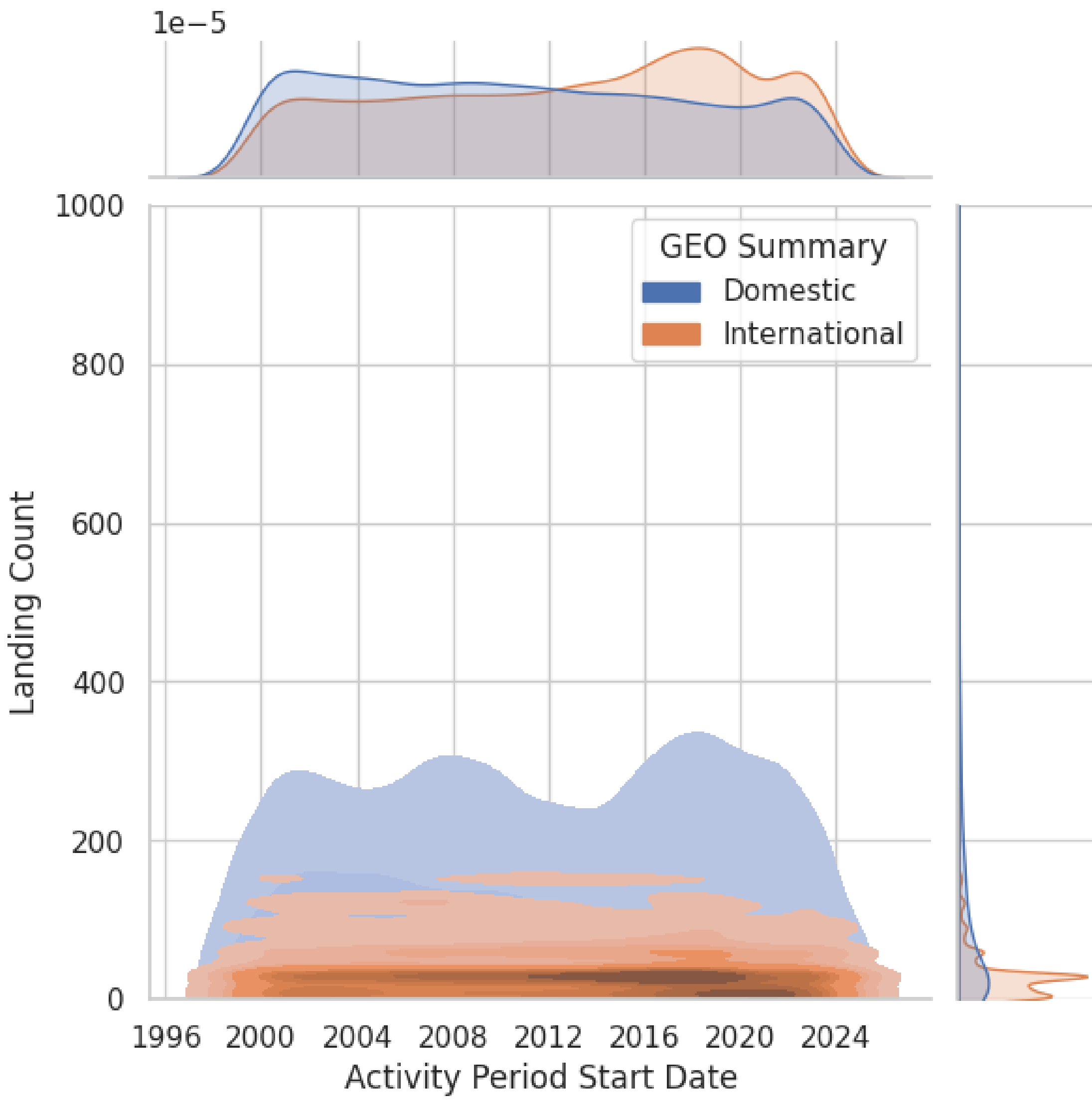


The scatter plot shows the "Landing Count" variable on the x-axis, the "Total Landed Weight" variable on the y-axis, colors the points based on the "GEO Region" variable, and scales the size of the points based on the "Total Landed Weight" variable. We can see most of the Landings airplanes in SFO Airport are by Geo Region "US".

[42]:
```
sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))

filtered_df = df[df['Landing Count'] <= 1000]
```

```
sns.jointplot(data=filtered_df, x='Activity Period Start Date', y='Landing␣
↪Count', kind='kde', hue='GEO Summary', fill=True)

plt.ylim(0, 1000)

plt.show()
```

<Figure size 1000x600 with 0 Axes>



The graph shows a joint plot to visualize the relationship between the “Landing Count” and “Activity Period Start Date” variables. The KDE contours provide insight into the density of observations, and the colors indicate different categories of the “GEO Summary” variable.

The interpretations are as follows:

1. The number of domestic flights is significantly higher than the number of international flights. This is likely due to the fact that there are simply more domestic flights overall, and because the SFO airport is located in a major metropolitan area with a lot of domestic traffic.
2. The number of both domestic and international flights has been increasing steadily over time. This is likely due to a number of factors, including population growth, economic growth, and the increasing affordability of air travel.
3. There is a slight downward trend in the number of landings in the most recent years (2020-2024). This could be due to the impact of the COVID-19 pandemic on air travel.

1.9 Insights & Trends

Here you can include some key conclusions you can make of your dataset based on your analysis above. What visualizations do you hope to create based on what patterns you have observed in your dataset? What trends have you noticed that will help with your investigation into this topic?

1.9.1 Trends from Air Traffic Passenger Statistics

- SFO airport experiences the highest passenger traffic with the United States, followed by Europe, Asia, Canada, and Mexico, while Central America and South America contribute the lowest numbers.
- At SFO Airport, the top five airlines that generate the highest passenger traffic are United Airlines, American Airlines, SkyWest Airlines, Delta Air Lines, and Southwest Airlines.
- The number of passengers generally follows an increasing trend with a clear seasonal pattern, repeating approximately every year. The peak in traffic occurs during summertime, while the lowest point is in wintertime at the beginning of the year.
- We can infer that SFO is a busy airport with a growing number of passengers. However, the COVID-19 pandemic has had a significant impact on passenger numbers, and it is difficult to say what the long-term trend will be.

1.9.2 Trends from Air Traffic Landing Statistics

- The dataset reveals insights into flight activities across diverse geographical regions, offering valuable information on travel patterns and destination preferences.
- Utilizing scatterplots with visual encodings, we can discern relationships between flight characteristics like "Landing Count" and "Total Landed Weight," considering factors such as "GEO Region" and "Landing Aircraft Type." Notably, SFO Airport sees a majority of landings from the "US" GEO Region.
- The joint plot with KDE visualization for "Landing Count" and "Activity Period Start Date" unveils temporal trends, aiding in identifying peak periods, seasonal variations, and scheduling trends.

1.9.3 Visualizations for further insights:

- Stacked bar charts or area plots to compare flight activities by aircraft type and GEO region.
- Violin plots to analyze numerical variables like "Landing Count" and "Total Landed Weight" across different categories.