

Final Project Submission

Please fill out:

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- Student pace: Full Time Hybrid
- Scheduled project review date/time: N/A
- Instructor name: Mr. Antonny Muiko

Naviar Corporation Aircraft Project Analysis

Company Logo

Overview

Naviar Corporation is a company that rents and sells luxury vehicles and offers chauffeuring services. However, the company has decided to venture into the aircraft industry where it would be purchasing and operating airplanes for commercial and private enterprises.

In this project, the public dataset from the National Transportation Safety Board will be used to determine the aircrafts that have the least amount of risks.

Business Understanding

Private Jet

Naviar Corporation requires a risk-free set of commercial and private aircraft in order to avoid casualties and financial losses which might damage the business. I am responsible for analyzing data/findings and developing insights and recommendations that will help the head of the new aviation division decide which aircraft to purchase.

Data Understanding

The aviation accident data (1962-2023) from the National Transportation Safety Board highlights the civil aviation accidents and selected incidents in the United States and international waters. In this case, there would be statistics about the plane descriptions, type of accidents and the number of fatalities/injuries sustained during the accident.

The Event ID is the unique identifier. I need to get the description of the dataset in order to know the data structure and data types in order to clean the data.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

```

df = pd.read_csv('./data/Aviation_Data.csv')

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Event.Id                             88889 non-null  object
1   Investigation.Type                    90348 non-null  object
2   Accident.Number                       88889 non-null  object
3   Event.Date                           88889 non-null  object
4   Location                             88837 non-null  object
5   Country                              88663 non-null  object
6   Latitude                             34382 non-null  object
7   Longitude                            34373 non-null  object
8   Airport.Code                         50132 non-null  object
9   Airport.Name                         52704 non-null  object
10  Injury.Severity                      87889 non-null  object
11  Aircraft.damage                      85695 non-null  object
12  Aircraft.Category                    32287 non-null  object
13  Registration.Number                 87507 non-null  object
14  Make                                88826 non-null  object
15  Model                               88797 non-null  object
16  Amateur.Built                       88787 non-null  object
17  Number.of.Engines                   82805 non-null  float64
18  Engine.Type                         81793 non-null  object
19  FAR.Description                     32023 non-null  object
20  Schedule                            12582 non-null  object
21  Purpose.of.flight                   82697 non-null  object
22  Air.carrier                         16648 non-null  object
23  Total.Fatal.Injuries                 77488 non-null  float64
24  Total.Serious.Injuries               76379 non-null  float64
25  Total.Minor.Injuries                 76956 non-null  float64
26  Total.Uninjured                      82977 non-null  float64
27  Weather.Condition                    84397 non-null  object
28  Broad.phase.of.flight                61724 non-null  object
29  Report.Status                       82505 non-null  object
30  Publication.Date                     73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB

C:\Users\PHIL CONRAD\AppData\Local\Temp\ipykernel_9360\222585957.py:1:
DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option
on import or set low_memory=False.
df = pd.read_csv('./data/Aviation_Data.csv')

```

There seems to be a lot of null values in many of the columns. We then have to figure out the outlook of the 1st 10 rows and the last 10 rows.

```
df.head(10)
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	\
0	20001218X45444	Accident	SEA87LA080	1948-10-24	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	
5	20170710X52551	Accident	NYC79AA106	1979-09-17	
6	20001218X45446	Accident	CHI81LA106	1981-08-01	
7	20020909X01562	Accident	SEA82DA022	1982-01-01	
8	20020909X01561	Accident	NYC82DA015	1982-01-01	
9	20020909X01560	Accident	MIA82DA029	1982-01-01	

	Location	Country	Latitude	Longitude	Airport.Code	\
0	MOOSE CREEK, ID	United States	NaN	NaN	NaN	
1	BRIDGEPORT, CA	United States	NaN	NaN	NaN	
2	Saltville, VA	United States	36.922223	-81.878056	NaN	
3	EUREKA, CA	United States	NaN	NaN	NaN	
4	Canton, OH	United States	NaN	NaN	NaN	
5	BOSTON, MA	United States	42.445277	-70.758333	NaN	
6	COTTON, MN	United States	NaN	NaN	NaN	
7	PULLMAN, WA	United States	NaN	NaN	NaN	
8	EAST HANOVER, NJ	United States	NaN	NaN	N58	
9	JACKSONVILLE, FL	United States	NaN	NaN	JAX	

	Airport.Name	...	Purpose.of.flight	Air.carrier	Total.Fatal.Injuries	\
0	NaN	...	Personal	NaN	2.0	
1	NaN	...	Personal	NaN	4.0	
2	NaN	...	Personal	NaN	3.0	
3	NaN	...	Personal	NaN	2.0	
4	NaN	...	Personal	NaN	1.0	
5	NaN	...	NaN	Air Canada	NaN	

```

6          NaN ... Personal NaN
4.0
7 BLACKBURN AG STRIP ... Personal NaN
0.0
8          HANOVER ... Business NaN
0.0
9 JACKSONVILLE INTL ... Personal NaN
0.0

Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured \
0          0.0          0.0          0.0
1          0.0          0.0          0.0
2          NaN          NaN          NaN
3          0.0          0.0          0.0
4          2.0          NaN          0.0
5          NaN          1.0         44.0
6          0.0          0.0          0.0
7          0.0          0.0          2.0
8          0.0          0.0          2.0
9          0.0          3.0          0.0

Weather.Condition Broad.phase.of.flight Report.Status
Publication.Date
0          UNK          Cruise Probable Cause
NaN
1          UNK          Unknown Probable Cause 19-
09-1996
2          IMC          Cruise Probable Cause 26-
02-2007
3          IMC          Cruise Probable Cause 12-
09-2000
4          VMC          Approach Probable Cause 16-
04-1980
5          VMC          Climb Probable Cause 19-
09-2017
6          IMC          Unknown Probable Cause 06-
11-2001
7          VMC          Takeoff Probable Cause 01-
01-1982
8          IMC          Landing Probable Cause 01-
01-1982
9          IMC          Cruise Probable Cause 01-
01-1982

[10 rows x 31 columns]

df.tail(10)

Event.Id Investigation.Type Accident.Number
Event.Date \

```

90338	20221219106472	Accident	DCA23LA096	2022-12-18	
90339	20221219106477	Accident	WPR23LA071	2022-12-18	
90340	20221221106483	Accident	CEN23LA067	2022-12-21	
90341	20221222106486	Accident	CEN23LA068	2022-12-21	
90342	20221228106502	Accident	GAA23WA046	2022-12-22	
90343	20221227106491	Accident	ERA23LA093	2022-12-26	
90344	20221227106494	Accident	ERA23LA095	2022-12-26	
90345	20221227106497	Accident	WPR23LA075	2022-12-26	
90346	20221227106498	Accident	WPR23LA076	2022-12-26	
90347	20221230106513	Accident	ERA23LA097	2022-12-29	
	Location	Country	Latitude	Longitude	Airport.Code
90338	Kahului, HI	United States	NaN	NaN	NaN
90339	San Manuel, AZ	United States	NaN	NaN	NaN
90340	Auburn Hills, MI	United States	NaN	NaN	NaN
90341	Reserve, LA	United States	NaN	NaN	NaN
90342	Brasnorte,	Brazil	NaN	NaN	NaN
90343	Annapolis, MD	United States	NaN	NaN	NaN
90344	Hampton, NH	United States	NaN	NaN	NaN
90345	Payson, AZ	United States	341525N	1112021W	PAN
90346	Morgan, UT	United States	NaN	NaN	NaN
90347	Athens, GA	United States	NaN	NaN	NaN
	Airport.Name	...	Purpose.of.flight	Air.carrier	\
90338	NaN	...	NaN	HAWAIIAN AIRLINES INC	
90339	NaN	...	Personal	Chandler Air Service	
90340	NaN	...	Personal	Pilot	
90341	NaN	...	Instructional	NaN	
90342	NaN	...	NaN	NaN	
90343	NaN	...	Personal	NaN	

90344	NaN	...	NaN	NaN
90345	PAYSON	...	Personal	NaN
90346	NaN	...	Personal	MC CESSNA 210N LLC
90347	NaN	...	Personal	NaN
Total.Fatal.Injuries Total.Serious.Injuries Total.Minor.Injuries				
\				
90338		0.0	0.0	0.0
90339		0.0	0.0	0.0
90340		0.0	1.0	0.0
90341		0.0	1.0	0.0
90342		1.0	0.0	0.0
90343		0.0	1.0	0.0
90344		0.0	0.0	0.0
90345		0.0	0.0	0.0
90346		0.0	0.0	0.0
90347		0.0	1.0	0.0
Total.Uninjured Weather.Condition Broad.phase.of.flight				
Report.Status \				
90338	NaN	0.0	NaN	NaN
90339	NaN	3.0	NaN	NaN
90340	NaN	0.0	NaN	NaN
90341	NaN	1.0	NaN	NaN
90342	NaN	0.0	NaN	NaN
90343	NaN	0.0	NaN	NaN
90344	NaN	0.0	NaN	NaN
90345	NaN	1.0	VMC	NaN
90346	NaN	0.0	NaN	NaN
90347	NaN	1.0	NaN	NaN

	Publication.Date
90338	NaN
90339	20-12-2022
90340	22-12-2022
90341	27-12-2022
90342	28-12-2022
90343	29-12-2022
90344	NaN
90345	27-12-2022
90346	NaN
90347	30-12-2022

[10 rows x 31 columns]

Data Preparation

Data Cleaning

I will normalize the column names for easier clarity.

```
df.columns = df.columns.str.lower().str.replace('.', '_')
```

```
df.head()
```

	event_id	investigation_type	accident_number	event_date	\
0	20001218X45444	Accident	SEA87LA080	1948-10-24	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	

	location	country	latitude	longitude	
airport_code	\				
0	MOOSE CREEK, ID	United States	NaN	NaN	NaN
1	BRIDGEPORT, CA	United States	NaN	NaN	NaN
2	Saltville, VA	United States	36.922223	-81.878056	NaN
3	EUREKA, CA	United States	NaN	NaN	NaN
4	Canton, OH	United States	NaN	NaN	NaN

	airport_name	...	purpose_of_flight	air_carrier	total_fatal_injuries
\					
0	NaN	...	Personal	NaN	2.0
1	NaN	...	Personal	NaN	4.0

2	NaN	...	Personal	NaN	3.0
3	NaN	...	Personal	NaN	2.0
4	NaN	...	Personal	NaN	1.0

	total_serious_injuries	total_minor_injuries	total_uninjured	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	NaN	NaN	NaN	
3	0.0	0.0	0.0	
4	2.0	NaN	0.0	

	weather_condition	broad_phase_of_flight	report_status	
publication_date				
0	UNK	Cruise	Probable Cause	
NaN				
1	UNK	Unknown	Probable Cause	19-
09-1996				
2	IMC	Cruise	Probable Cause	26-
02-2007				
3	IMC	Cruise	Probable Cause	12-
09-2000				
4	VMC	Approach	Probable Cause	16-
04-1980				

[5 rows x 31 columns]

Checking number of missing values in each column

```
df.isna().sum()
```

event_id	1459
investigation_type	0
accident_number	1459
event_date	1459
location	1511
country	1685
latitude	55966
longitude	55975
airport_code	40216
airport_name	37644
injury_severity	2459
aircraft_damage	4653
aircraft_category	58061
registration_number	2841
make	1522
model	1551

amateur_built	1561
number_of_engines	7543
engine_type	8555
far_description	58325
schedule	77766
purpose_of_flight	7651
air_carrier	73700
total_fatal_injuries	12860
total_serious_injuries	13969
total_minor_injuries	13392
total_uninjured	7371
weather_condition	5951
broad_phase_of_flight	28624
report_status	7843
publication_date	16689
dtype:	int64

I need to delete rows based on NaN values. In this case, the `accident_number` column should not have any missing values because it is a unique identifier.

```
df.dropna(subset=['accident_number'], inplace=True)
df.head()
```

	event_id	investigation_type	accident_number	event_date	\
0	20001218X45444	Accident	SEA87LA080	1948-10-24	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	

	location	country	latitude	longitude	
airport_code \					
0	MOOSE CREEK, ID	United States	NaN	NaN	NaN
1	BRIDGEPORT, CA	United States	NaN	NaN	NaN
2	Saltville, VA	United States	36.922223	-81.878056	NaN
3	EUREKA, CA	United States	NaN	NaN	NaN
4	Canton, OH	United States	NaN	NaN	NaN

	airport_name	...	purpose_of_flight	air_carrier	total_fatal_injuries
\					
0	NaN	...	Personal	NaN	2.0
1	NaN	...	Personal	NaN	4.0
2	NaN	...	Personal	NaN	3.0

3	NaN	...	Personal	NaN	2.0
4	NaN	...	Personal	NaN	1.0

	total_serious_injuries	total_minor_injuries	total_uninjured	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	NaN	NaN	NaN	
3	0.0	0.0	0.0	
4	2.0	NaN	0.0	

	weather_condition	broad_phase_of_flight	report_status	
publication_date				
0	UNK	Cruise	Probable Cause	
NaN				
1	UNK	Unknown	Probable Cause	19-
09-1996				
2	IMC	Cruise	Probable Cause	26-
02-2007				
3	IMC	Cruise	Probable Cause	12-
09-2000				
4	VMC	Approach	Probable Cause	16-
04-1980				

[5 rows x 31 columns]

df.isna().sum()

event_id	0
investigation_type	0
accident_number	0
event_date	0
location	52
country	226
latitude	54507
longitude	54516
airport_code	38757
airport_name	36185
injury_severity	1000
aircraft_damage	3194
aircraft_category	56602
registration_number	1382
make	63
model	92
amateur_built	102
number_of_engines	6084
engine_type	7096
far_description	56866

```

schedule                76307
purpose_of_flight        6192
air_carrier              72241
total_fatal_injuries     11401
total_serious_injuries   12510
total_minor_injuries     11933
total_uninjured          5912
weather_condition        4492
broad_phase_of_flight    27165
report_status            6384
publication_date         15230
dtype: int64

df['aircraft_category'].unique()

array([nan, 'Airplane', 'Helicopter', 'Glider', 'Balloon',
       'Gyrocraft',
       'Ultralight', 'Unknown', 'Blimp', 'Powered-Lift', 'Weight-
       Shift',
       'Powered Parachute', 'Rocket', 'WSFT', 'UNK', 'ULTR'],
      dtype=object)

df['make'].nunique()

8237

```

We also need to get rid of rows with NaN values in the model column because the make and the model are important attributes.

```
df.dropna(subset=['model'], inplace=True)
```

We also need to get rid of the duplicates especially for the make/model columns. So, we need to combine both columns and change the case to uppercase.

```

df['make/model'] = (df['make'] + ' ' + df['model']).str.upper()
df['make/model']

0          STINSON 108-3
1          PIPER PA24-180
2          CESSNA 172M
3          ROCKWELL 112
4          CESSNA 501
...
90343      PIPER PA-28-151
90344      BELLANCA 7ECA
90345      AMERICAN CHAMPION AIRCRAFT 8GCBC
90346      CESSNA 210N
90347      PIPER PA-24-260
Name: make/model, Length: 88797, dtype: object

```

```
df.drop_duplicates()
```

	event_id	investigation_type	accident_number	event_date
0	20001218X45444	Accident	SEA87LA080	1948-10-24
1	20001218X45447	Accident	LAX94LA336	1962-07-19
2	20061025X01555	Accident	NYC07LA005	1974-08-30
3	20001218X45448	Accident	LAX96LA321	1977-06-19
4	20041105X01764	Accident	CHI79FA064	1979-08-02
...
90343	20221227106491	Accident	ERA23LA093	2022-12-26
90344	20221227106494	Accident	ERA23LA095	2022-12-26
90345	20221227106497	Accident	WPR23LA075	2022-12-26
90346	20221227106498	Accident	WPR23LA076	2022-12-26
90347	20221230106513	Accident	ERA23LA097	2022-12-29

	location	country	latitude	longitude
0	MOOSE CREEK, ID	United States	NaN	NaN
1	BRIDGEPORT, CA	United States	NaN	NaN
2	Saltville, VA	United States	36.922223	-81.878056
3	EUREKA, CA	United States	NaN	NaN
4	Canton, OH	United States	NaN	NaN
...
90343	Annapolis, MD	United States	NaN	NaN
90344	Hampton, NH	United States	NaN	NaN
90345	Payson, AZ	United States	341525N	1112021W
90346	Morgan, UT	United States	NaN	NaN
90347	Athens, GA	United States	NaN	NaN

	airport_name	...	air_carrier	total_fatal_injuries	\
0	NaN	...	NaN	2.0	
1	NaN	...	NaN	4.0	
2	NaN	...	NaN	3.0	
3	NaN	...	NaN	2.0	
4	NaN	...	NaN	1.0	
...	
90343	NaN	...	NaN	0.0	
90344	NaN	...	NaN	0.0	
90345	PAYSON	...	NaN	0.0	
90346	NaN	...	MC CESSNA 210N LLC	0.0	
90347	NaN	...	NaN	0.0	

	total_serious_injuries	total_minor_injuries	total_uninjured	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	NaN	NaN	NaN	
3	0.0	0.0	0.0	
4	2.0	NaN	0.0	
...	
90343	1.0	0.0	0.0	
90344	0.0	0.0	0.0	
90345	0.0	0.0	1.0	
90346	0.0	0.0	0.0	
90347	1.0	0.0	1.0	

	weather_condition	broad_phase_of_flight	report_status	\
0	UNK	Cruise	Probable Cause	
1	UNK	Unknown	Probable Cause	
2	IMC	Cruise	Probable Cause	
3	IMC	Cruise	Probable Cause	
4	VMC	Approach	Probable Cause	
...	
90343	NaN	NaN	NaN	
90344	NaN	NaN	NaN	
90345	VMC	NaN	NaN	
90346	NaN	NaN	NaN	
90347	NaN	NaN	NaN	

	publication_date	make/model
0	NaN	STINSON 108-3
1	19-09-1996	PIPER PA24-180
2	26-02-2007	CESSNA 172M
3	12-09-2000	ROCKWELL 112
4	16-04-1980	CESSNA 501
...
90343	29-12-2022	PIPER PA-28-151
90344	NaN	BELLANCA 7ECA
90345	27-12-2022	AMERICAN CHAMPION AIRCRAFT 8GCBC

90346	NaN	CESSNA 210N
90347	30-12-2022	PIPER PA-24-260

[88797 rows x 32 columns]

Save the cleaned dataframe as csv file for later use

```
df.to_csv('aviation_data3.csv', index=False, encoding='utf-8',
na_rep='NA')
```

Data Visualization

We first have to see which make/model has the highest number of total uninjured cases.

```
relevant_columns = ['make/model', 'total_uninjured']
mini_df = df[relevant_columns]

# Replace NaN values with 0 for total_uninjured
mini_df['total_uninjured'] = mini_df['total_uninjured'].fillna(0)

# Group by Make/Model and sum the total uninjured counts
agg_df = mini_df.groupby('make/model')
['total_uninjured'].sum().reset_index()

# Sort the DataFrame by total_uninjured in descending order and choose
the top 10
top_10_makes = agg_df.sort_values(by='total_uninjured',
ascending=False).head(10)

# Filter the original dataset to include only the top 10 make/models
top_10_makes_list = top_10_makes['make/model'].tolist()
filtered_df = mini_df[mini_df['make/model'].isin(top_10_makes_list)]

# Set the figure size for the plot
plt.figure(figsize=(14, 8))

# Create the boxplot
sns.boxplot(x='make/model', y='total_uninjured', data=filtered_df)

# Set plot labels and title
plt.title('Boxplot of Total Uninjured per Make/Model (Top 10)')
plt.xlabel('Make/Model')
plt.ylabel('Total Uninjured')

plt.xticks(rotation=45)

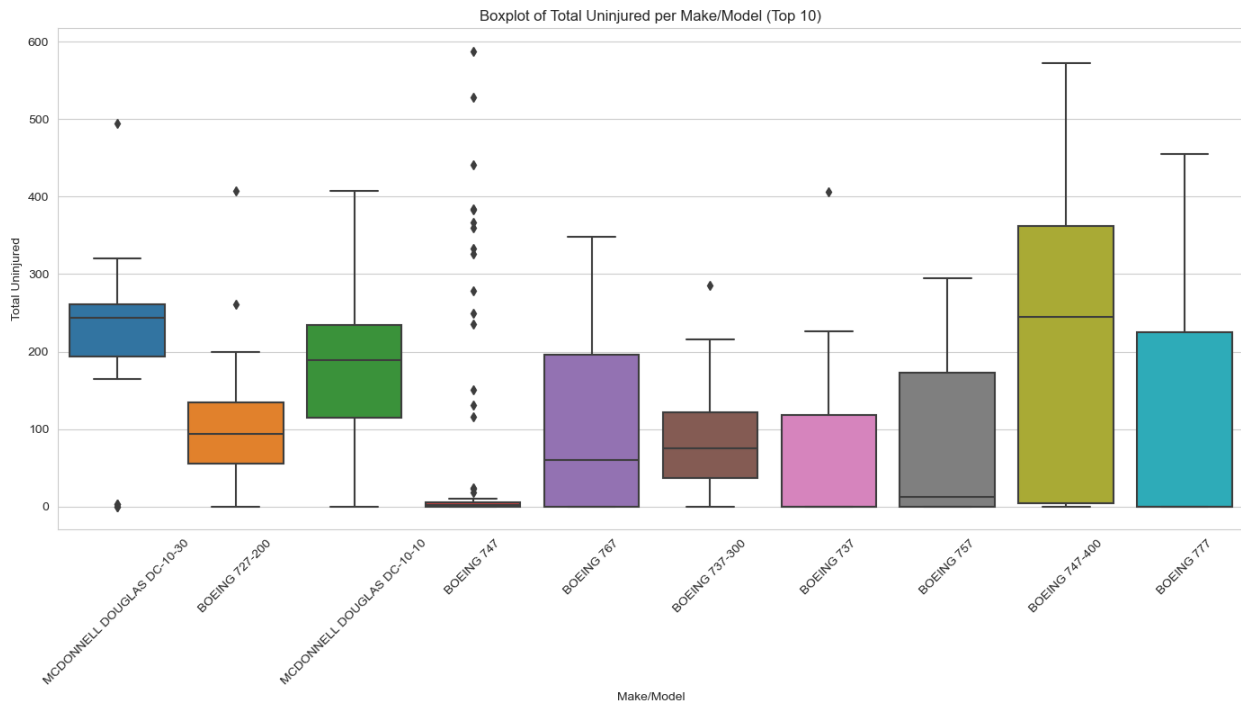
# Display the plot
plt.tight_layout()
plt.show()
```

```
C:\Users\PHIL CONRAD\AppData\Local\Temp\
ipykernel_9360\3334349586.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation:

https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
mini_df['total_uninjured'] = mini_df['total_uninjured'].fillna(0)
```

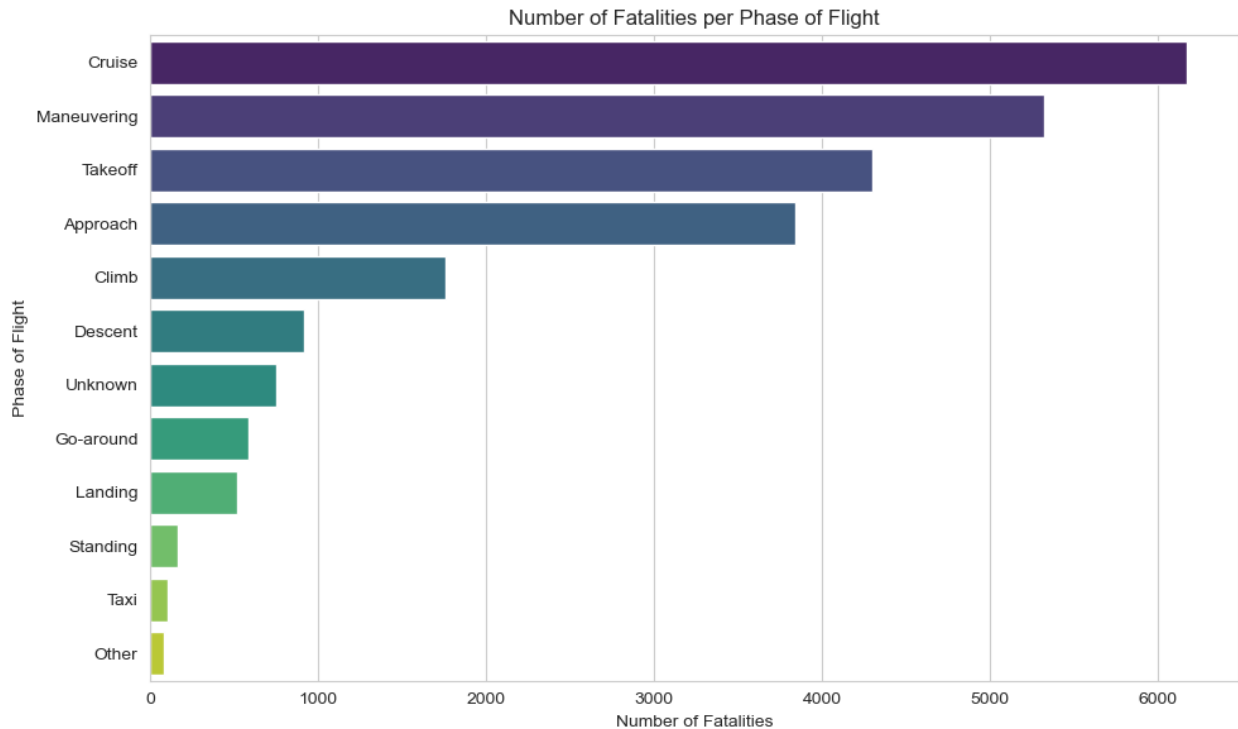


We then visualize the number of fatalities according to the phase of flight.

```
fatalities_by_phase = df.groupby('broad_phase_of_flight')
['total_fatal_injuries'].sum().reset_index()

fatalities_by_phase =
fatalities_by_phase.sort_values(by='total_fatal_injuries',
ascending=False)

# Plotting the data
plt.figure(figsize=(10, 6))
sns.barplot(x='total_fatal_injuries', y='broad_phase_of_flight',
data=fatalities_by_phase, palette='viridis')
plt.xlabel('Number of Fatalities')
plt.ylabel('Phase of Flight')
plt.title('Number of Fatalities per Phase of Flight')
plt.tight_layout()
plt.show()
```



```
print(fatalities_by_phase)
```

	broad_phase_of_flight	total_fatal_injuries
2	Cruise	6171.0
6	Maneuvering	5319.0
9	Takeoff	4302.0
0	Approach	3838.0
1	Climb	1759.0
3	Descent	913.0
11	Unknown	749.0
4	Go-around	587.0
5	Landing	518.0
8	Standing	161.0
10	Taxi	102.0
7	Other	85.0

We then visualize the total injuries and total_uninjured by the purpose of flight. However, there are many NaN values on the purpose_of_flight column. So we need to get rid of the rows with NaN values.

```
df.dropna(subset=['purpose_of_flight'], inplace=True)

required_columns = ['purpose_of_flight', 'total_fatal_injuries',
                    'total_serious_injuries', 'total_minor_injuries', 'total_uninjured']
min2_df = df[required_columns]

# Replace NaN values with 0 for injury counts
```



```

min2_df = min2_df.fillna(0)

# Group by Purpose of Flight and sum the injury counts
agg_df = min2_df.groupby('purpose_of_flight').sum().reset_index()

# Melt the aggregated DataFrame
melted_df = agg_df.melt(id_vars='purpose_of_flight',
                        value_vars=['total_fatal_injuries',
                                    'total_serious_injuries', 'total_minor_injuries', 'total_uninjured'],
                        var_name='injury_type',
                        value_name='Count')

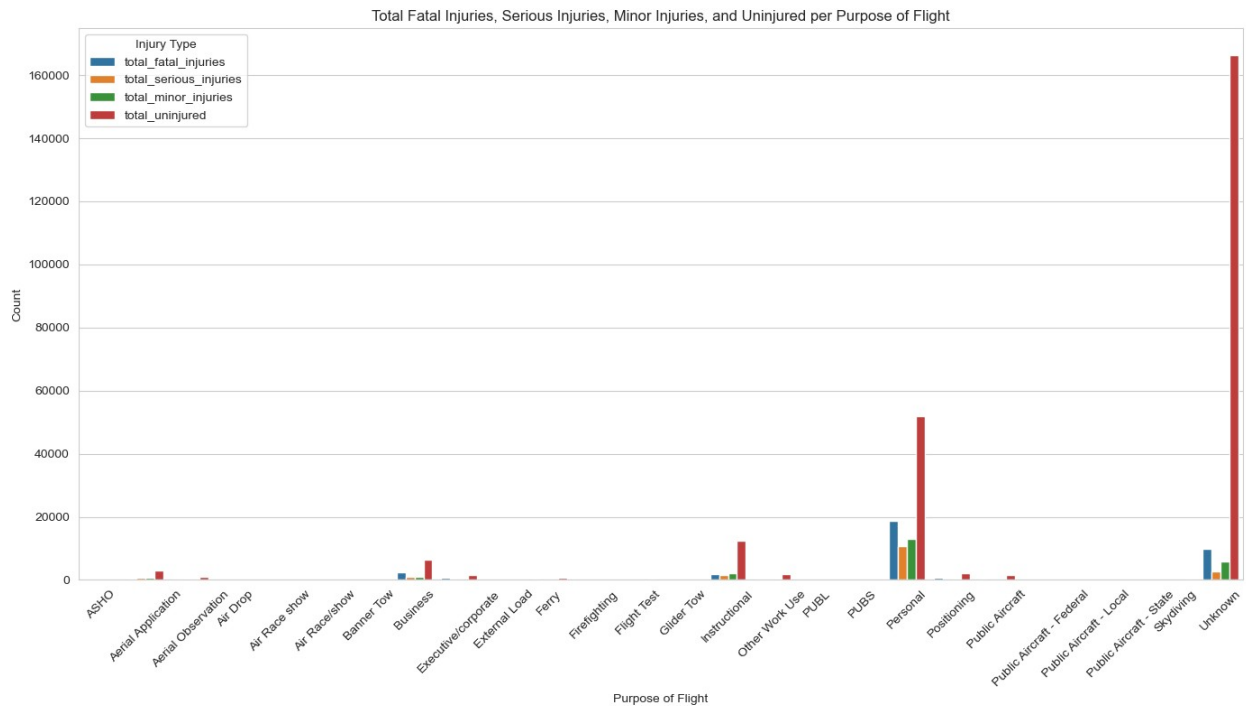
# Setting the figure size for the plot
plt.figure(figsize=(14, 8))

# Creating the bar plot
sns.barplot(x='purpose_of_flight', y='Count', hue='injury_type',
            data=melted_df)

# Setting the title & plot labels
plt.title('Total Fatal Injuries, Serious Injuries, Minor Injuries, and
Uninjured per Purpose of Flight')
plt.xlabel('Purpose of Flight')
plt.ylabel('Count')
plt.xticks(rotation=45)
plt.legend(title='Injury Type')

# Display the plot
plt.tight_layout()
plt.show()

```



```
print(melted_df)
```

	purpose_of_flight	injury_type	Count
0	ASHO	total_fatal_injuries	14.0
1	Aerial Application	total_fatal_injuries	549.0
2	Aerial Observation	total_fatal_injuries	414.0
3	Air Drop	total_fatal_injuries	10.0
4	Air Race show	total_fatal_injuries	42.0
..
99	Public Aircraft - Federal	total_uninjured	267.0
100	Public Aircraft - Local	total_uninjured	96.0
101	Public Aircraft - State	total_uninjured	65.0
102	Skydiving	total_uninjured	555.0
103	Unknown	total_uninjured	166479.0

```
[104 rows x 3 columns]
```

```
df.isna().sum()
```

event_id	0
investigation_type	0
accident_number	0
event_date	0
location	42
country	219
latitude	51585
longitude	51595
airport_code	34737
airport_name	32205

injury_severity	51
aircraft_damage	1569
aircraft_category	54841
registration_number	806
make	17
model	0
amateur_built	35
number_of_engines	3126
engine_type	3737
far_description	54730
schedule	73956
purpose_of_flight	0
air_carrier	69195
total_fatal_injuries	10118
total_serious_injuries	11176
total_minor_injuries	10571
total_uninjured	5358
weather_condition	1139
broad_phase_of_flight	22058
report_status	3208
publication_date	14365
make/model	17
dtype:	int64

Recommendations

1. The BOEING 737 aircraft (airplane category) has the highest number of total_uninjured. That means that in case of an accident, there are more likely to be survivors at the scene. According to the chart, the top 10 aircraft are dominated by the BOEING make, making it the best choice to purchase and operate.
2. Cruise is the most fatal broad phase of flight as it has the most casualties. It is recommended to avoid purchasing aircraft that is associated with cruise as a phase of flight when accidents occur.
3. Personal as a purpose for flight has the highest number of uninjured victims hence the most recommended purpose of flight while operating the aircraft.