

AVIATION ACCIDENTS DATA CLEANSING & ANALYSIS

Introduction

This project aims at cleaning and analyzing data for aviation accidents that occurred in the United States, all its territories as well as international waters. The analysis will derive insights that will help one of my clients to make a decision on the type of aircrafts to purchase.

Objectives

- Cleaning the data
- Analysing the data and getting insights
- Determining which aircrafts has low risk
- Presenting the findings and actionable insights to the client

Data content & Source

The aviation accidents data contains information about aircraft accidents in USA, its territories and international waters. It is contained in 2 CSV files downloaded from Kaggle.com (URL:

[https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses?
select=AviationData.csv](https://www.kaggle.com/datasets/khsamaha/aviation-accident-database-synopses?select=AviationData.csv)

Data Analysis Methods

The data is analyzed using python libraries including:

- Pandas: Data manipulation and analysis
- Matplotlib: Data visualization
- Seaborn: Statistical plotting

```
In [1]: #Importing the necessary python Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

DATA CLEANSING

```
In [2]: #Importing and displaying the first data set
df1=pd.read_csv("AviationData.csv",encoding='cp1252',low_memory=False)
df1.head(2)
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	Nan	

Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN

2 rows × 31 columns

```
In [3]: #Importing and displaying the second data set
df2=pd.read_csv("USState_Codes.csv",encoding='cp1252',low_memory=False)
df2.head(2)
```

```
Out[3]:   US_State  Abbreviation
0    Alabama        AL
1     Alaska        AK
```

```
In [4]: #Checking the dimensions of the first data sets
df1.shape
```

Out[4]: (88889, 31)

```
In [5]: #Checking the dimensions of the second data sets
df2.shape
```

Out[5]: (62, 2)

```
In [6]: #Getting a summary of the first data set
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   Event.Id         88889 non-null   object 
 1   Investigation.Type 88889 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      50249 non-null   object 
 9   Airport.Name      52790 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 87572 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       81812 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          82508 non-null  object
30 Publication.Date       75118 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

```
In [7]: #Getting a summary of the second data set
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 62 entries, 0 to 61
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype  
---  --  
 0   US_State    62 non-null    object  
 1   Abbreviation 62 non-null    object  
dtypes: object(2)
memory usage: 1.1+ KB
```

```
In [8]: # getting the percentage of null values in each column (first data set)
percent_missing = df1.isnull().sum() * 100 / len(df1)
percent_missing
```

```
Out[8]: Event.Id            0.000000
Investigation.Type      0.000000
Accident.Number          0.000000
Event.Date              0.000000
Location                 0.058500
Country                  0.254250
Latitude                 61.320298
Longitude                61.330423
Airport.Code             43.469946
Airport.Name              40.611324
Injury.Severity           1.124999
Aircraft.damage           3.593246
Aircraft.Category         63.677170
Registration.Number       1.481623
Make                      0.070875
Model                     0.103500
Amateur.Built             0.114750
Number.ofEngines          6.844491
Engine.Type               7.961615
FAR.Description           63.974170
Schedule                  85.845268
Purpose.of.flight          6.965991
Air.carrier                81.271023
Total.Fatal.Injuries       12.826109
Total.Serious.Injuries     14.073732
Total.Minor.Injuries        13.424608
Total.Uninjured             6.650992
Weather.Condition           5.053494
Broad.phase.of.flight       30.560587
Report.Status              7.178616
Publication.Date            15.492356
dtype: float64
```

```
In [9]: # getting the percentage of null values in each column (second data set)
percent_missing = df2.isnull().sum() * 100 / len(df2)
percent_missing
```

```
Out[9]: US_State      0.0
Abbreviation    0.0
dtype: float64
```

```
In [10]: #dropping columns with more than 30% of missing data
threshold = 0.3
min_count = int((1 - threshold) * len(df1))
df1 = df1.dropna(axis=1, thresh=min_count)
```

```
In [11]: # getting the percentage of null values in the new data set
percent_missing = df1.isnull().sum() * 100 / len(df1)
percent_missing
```

```
Out[11]: Event.Id          0.000000
Investigation.Type    0.000000
Accident.Number       0.000000
Event.Date           0.000000
Location              0.058500
Country               0.254250
Injury.Severity       1.124999
Aircraft.damage      3.593246
Registration.Number   1.481623
Make                  0.070875
Model                 0.103500
Amateur.Built         0.114750
Number.ofEngines      6.844491
Engine.Type            7.961615
Purpose.of.flight     6.965991
Total.Fatal.Injuries  12.826109
Total.Serious.Injuries 14.073732
Total.Minor.Injuries  13.424608
Total.Uninjured        6.650992
Weather.Condition     5.053494
Report.Status          7.178616
Publication.Date      15.492356
dtype: float64
```

```
In [12]: #checking the dimension of the new data frame 1
df1.shape
```

```
Out[12]: (88889, 22)
```

```
In [13]: #check for duplicate
df1_duplicates=df1.duplicated()
df1_duplicates
```

```
Out[13]: 0      False
1      False
2      False
3      False
4      False
...
88884  False
88885  False
88886  False
88887  False
88888  False
Length: 88889, dtype: bool
```

```
In [14]: #Replace full stop with hivens on column names in df1
df1.columns = df1.columns.str.replace('.', '_')
```

```
In [15]: #displaying columns
print(list(df1.columns))

['Event_Id', 'Investigation_Type', 'Accident_Number', 'Event_Date', 'Location', 'Country', 'Injury_Severity', 'Aircraft_damage', 'Registration_Number', 'Make', 'Model', 'Amateur_Built', 'Number_of_Engines', 'Engine_Type', 'Purpose_of_flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries', 'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition', 'Report_Status', 'Publication_Date']
```

```
In [16]: #dropping other unnecessary columns
df1 = df1.drop(['Event_Id', 'Accident_Number', 'Registration_Number', 'Publication_Date'])
```

```
In [17]: #displaying remaining columns
print(list(df1.columns))

['Investigation_Type', 'Event_Date', 'Location', 'Country', 'Injury_Severity', 'Aircraft_damage', 'Make', 'Model', 'Amateur_Built', 'Number_of_Engines', 'Engine_Type', 'Purpose_of_flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries', 'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition', 'Report_Status']
```

```
In [18]: #convert Event_Date column to datetime
df1['Event_Date'] = pd.to_datetime(df1['Event_Date'])
```

```
In [19]: #dropping rows with missing entries
df1 = df1.dropna()
```

```
In [20]: #confirming there are no rows with misisng numbers
percent_missing = df1.isnull().sum() * 100 / len(df1)
percent_missing
```

```
Out[20]: Investigation_Type      0.0
Event_Date          0.0
Location            0.0
Country             0.0
Injury_Severity     0.0
Aircraft_damage    0.0
Make                0.0
Model               0.0
Amateur_Built      0.0
Number_of_Engines   0.0
Engine_Type         0.0
Purpose_of_flight   0.0
Total_Fatal_Injuries 0.0
Total_Serious_Injuries 0.0
Total_Minor_Injuries 0.0
Total_Uninjured     0.0
Weather_Condition   0.0
Report_Status       0.0
dtype: float64
```

```
In [21]: #confirming number of remaining rows and columns
df1.shape
```

```
Out[21]: (63085, 18)
```

```
In [22]: #Removing white spaces in column 'Location'
df1['Location'] = df1['Location'].str.replace(' ', '')
```

```
In [23]: #Coming up with a column 'location_code' from Location
df1['Location_code']=df1['Location'].str.split(',').str[1].str.strip()

In [24]: #displaying columns
print(list(df1.columns))

['Investigation_Type', 'Event_Date', 'Location', 'Country', 'Injury_Severity', 'Aircraft_damage', 'Make', 'Model', 'Amateur_Built', 'Number_of_Engines', 'Engine_Type', 'Purpose_of_flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries', 'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition', 'Report_Status', 'Location_code']

In [25]: #displaying the first 2 rows
df1.head(1)
```

```
Out[25]: Investigation_Type Event_Date Location Country Injury_Severity Aircraft_damage Make Model Amateur_Built Number_of_Engines Engine_Type Purpose_of_flight Total_Fatal_Injuries Total_Serious_Injuries Total_Minor_Injuries Total_Uninjured Weather_Condition Report_Status Location_code
```

	Investigation_Type	Event_Date	Location	Country	Injury_Severity	Aircraft_damage	Make	Model	Amateur_Built	Number_of_Engines	Engine_Type	Purpose_of_flight	Total_Fatal_Injuries	Total_Serious_Injuries	Total_Minor_Injuries	Total_Uninjured	Weather_Condition	Report_Status	Location_code
0	Accident	1948-10-24	MOOSECREEK, ID	United States	Fatal(2)	Destroyed	Stinson												

```
In [26]: #checking what percentage of data is from United States
Countrycount = df1.groupby('Country').size()
proportion = (Countrycount / Countrycount.sum()) * 100
print(proportion)
```

```
Country
ATLANTIC OCEAN      0.085599
Afghanistan          0.001585
American Samoa      0.004755
Angola               0.003170
Antarctica           0.001585
...
UN                  0.007926
United Kingdom       0.001585
United States         99.131331
Venezuela            0.003170
West Indies          0.006341
Length: 81, dtype: float64
```

```
In [27]: #dropping other countries given that USA represent 99% of the data
df1 = df1[df1['Country'] == 'United States']
```

```
In [28]: #checking what percentage of data is from United States
Countrycount = df1.groupby('Country').size()
proportion = (Countrycount / Countrycount.sum()) * 100
print(proportion)
```

```
Country
United States     100.0
dtype: float64
```

```
In [29]: #changing the name of 'Abbreviation' column to Location_code
df2 = df2.rename(columns={'Abbreviation': 'Location_code'})
```

```
In [30]: # Merge the 2 data sets using the 'Location_code' column
df = pd.merge(df1, df2, on='Location_code')
#displaying columns
print(list(df.columns))
```

```
['Investigation_Type', 'Event_Date', 'Location', 'Country', 'Injury_Severity', 'Aircraft_damage', 'Make', 'Model', 'Amateur_Built', 'Number_of_Engines', 'Engine_Type', 'Purpose_of_flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries', 'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition', 'Report_Status', 'Location_code', 'US_State']
```

```
In [31]: # Displaying the columns and their data types  
print(df.dtypes)
```

```
Investigation_Type          object  
Event_Date                  datetime64[ns]  
Location                     object  
Country                      object  
Injury_Severity              object  
Aircraft_damage              object  
Make                          object  
Model                         object  
Amateur_Built                object  
Number_of_Engines            float64  
Engine_Type                  object  
Purpose_of_flight             object  
Total_Fatal_Injuries         float64  
Total_Serious_Injuries        float64  
Total_Minor_Injuries          float64  
Total_Uninjured               float64  
Weather_Condition             object  
Report_Status                 object  
Location_code                 object  
US_State                      object  
dtype: object
```

```
In [32]: #For data uniformity capitalize data under 'Make' and 'Model'  
df['Make'] = df['Make'].str.upper()  
df['Model'] = df['Model'].str.upper()
```

```
In [33]: #create a column called year from 'Event_Date' column  
df['Event_Date'] = pd.to_datetime(df['Event_Date'], format='%Y-%m-%d')  
df['Year']=df['Event_Date'].dt.strftime('%Y')
```

```
In [34]: # Specify the file path to export df  
file_path = 'C:/Users/jgatonye/Documents/DS_COURSE/PHASE1/PROJECT1/Project-Phase-1/df.csv'  
# Export to CSV  
df.to_csv(file_path, index=False)
```

Data Analysis & Visualization

```
In [35]: #Top 10 most used aircraft makes by percentage-We will assume that aircraft makes with  
top_10_makes = df['Make'].value_counts(normalize=True).head(10) * 100  
print(top_10_makes)
```

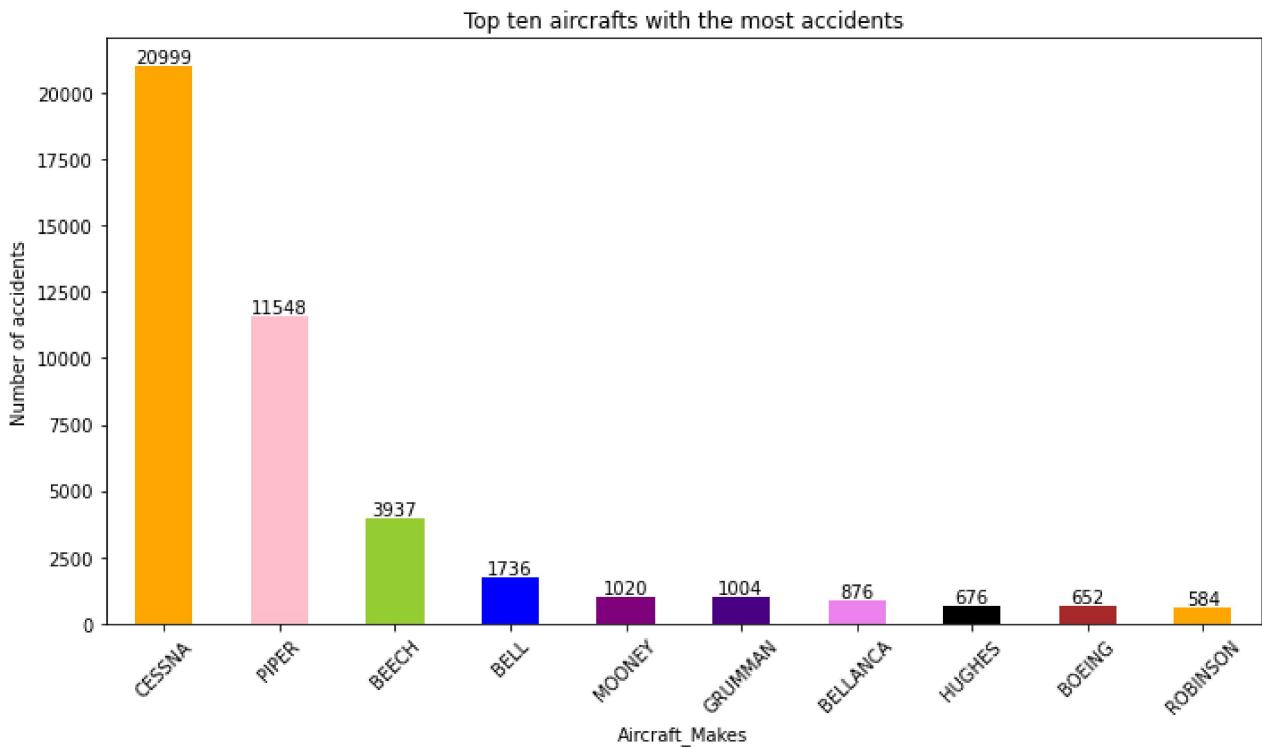
```
CESSNA      33.603239  
PIPER       18.479461  
BEECH        6.300107  
BELL        2.778000  
MOONEY      1.632235  
GRUMMAN     1.606631  
BELLANCA    1.401802  
HUGHES      1.081756  
BOEING      1.043350  
ROBINSON    0.934535  
Name: Make, dtype: float64
```

Bar chart showing top ten aircrafts with the most accidents

In [36]:

```
# getting a count of every aircraft make and sorting top 10
top_ten_aircrafts_makes_accidents = df['Make'].value_counts().head(10)
# getting colours
colors = ['orange', 'pink', 'yellow', 'green', 'blue', 'purple', 'indigo', 'violet', 'black',
# Plotting the a bar graph of to 10 aircrafts
plt.figure(figsize=(10, 6))
bar=top_ten_aircrafts_makes_accidents.plot(kind='bar', color=colors)
#capture number of accidents on top of the bar
for p in bar.patches:
    bar.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2., p.get_y() + p.get_height() / 2., p.get_color(), ha='center', va='center', fontsize=10, color='black', xytext=(0, 0), textcoords='offset points')

plt.title('Top ten aircrafts with the most accidents')
plt.xlabel('Aircraft_Makes')
plt.ylabel('Number of accidents')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Deductions from the above chart:

- Top 10 flown aircrafts in the USA include Cessna, Piper, Beech, Bell, Mooney, Grumman, Bellanca, Hughes, Boeing, Robinson
- Top 3 aircrafts with the most accidents include Cessna, Piper, Beech
- Top 3 aircrafts with the least accidents include Robinson, Boeing, Hughes

A pivot table showing total number of accidents for top 10 aircrafts since 2010

```
In [37]: #Generating new data set showing the total number of accidents for the top 10 aircrafts
df['Year'] = df['Year'].astype(int)
df_3 = df[df['Year'] > 2009]
# List of selected variables to include in the pivot
selected_variables = ['CESSNA', 'BOEING', 'PIPER', 'BEECH', 'BELL', 'MOONEY', 'GRUMMAN', 'BEL
# Filtering the data set
filtered_df = df_3[df_3['Make'].isin(selected_variables)]
# Create a pivot table to count accidents of each aircraft per 'year'
pivot = pd.pivot_table(filtered_df, index='Year', columns='Make', aggfunc='size', fill_
pivot
```

```
Out[37]: Make  BEECH  BELL  BELLANCA  BOEING  CESSNA  GRUMMAN  HUGHES  MOONEY  PIPER  ROBINSON
Year
2010    84     28       6      9    369       6      7     16   223       7
2011    72     32      15     10    373       6      6     18   215       8
2012    79     29      18      7    342       6     12     26   227       4
2013    54     37      13      5    312       3      7     20   184       9
2014    41     27      15      4    269       4      5     13   183       2
2015    64     25       9      4    309       4      8     16   184       3
2016    69     31      17     10    335       4      9     15   171       6
2017    49     19      16      7    322       4      6     20   166       6
2018    62     22       6      3    309       7      9     17   192      18
2019    57     16       4      1    228       4      4     12   159      33
2020    24      9       3      0    177       5      2     11   88        11
2021    12      9       3      3     96       0      3      4    62        1
2022    10      7       3      2    121       0      1      5    65        0
```

A line graph showing top ten aircrafts accidents trends since 2010

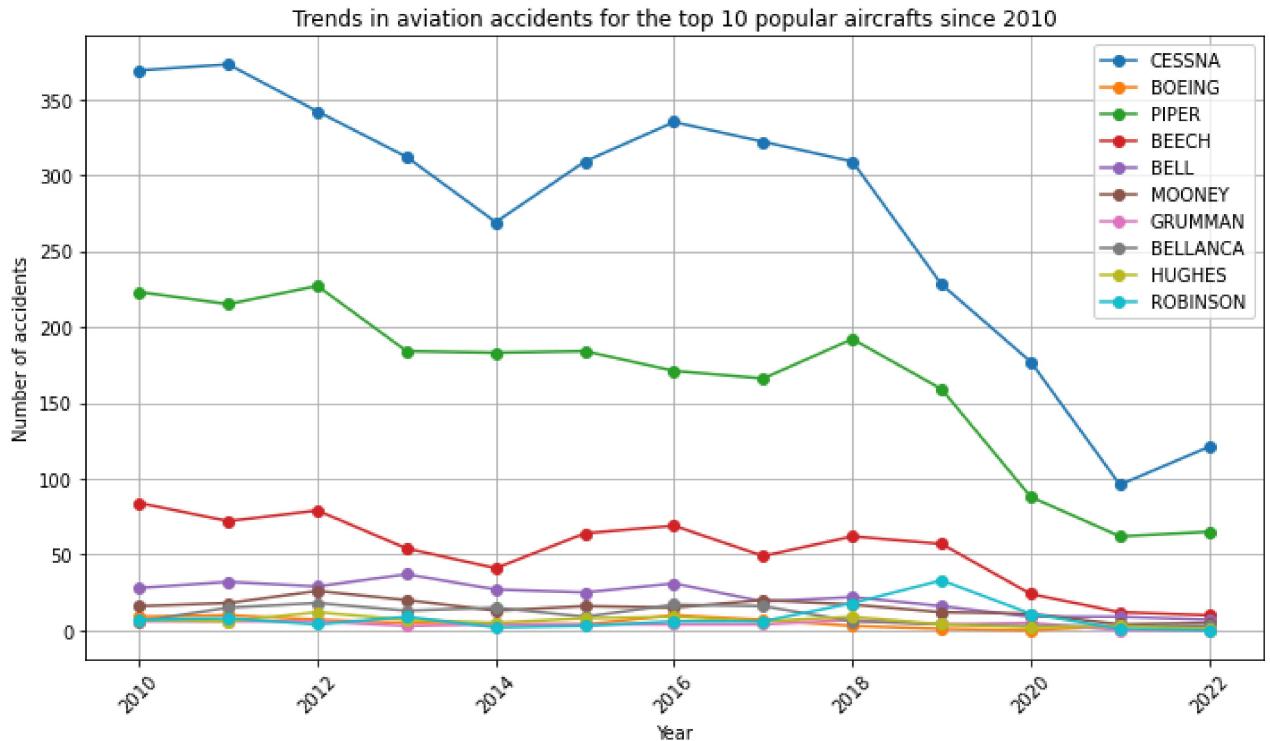
```
In [38]: plt.figure(figsize=(10, 6))
plt.plot(pivot.index, pivot['CESSNA'], label='CESSNA', marker='o')
plt.plot(pivot.index, pivot['BOEING'], label='BOEING', marker='o')
plt.plot(pivot.index, pivot['PIPER'], label='PIPER', marker='o')
plt.plot(pivot.index, pivot['BEECH'], label='BEECH', marker='o')
plt.plot(pivot.index, pivot['BELL'], label='BELL', marker='o')
plt.plot(pivot.index, pivot['MOONEY'], label='MOONEY', marker='o')
plt.plot(pivot.index, pivot['GRUMMAN'], label='GRUMMAN', marker='o')
plt.plot(pivot.index, pivot['BELLANCA'], label='BELLANCA', marker='o')
plt.plot(pivot.index, pivot['HUGHES'], label='HUGHES', marker='o')
plt.plot(pivot.index, pivot['ROBINSON'], label='ROBINSON', marker='o')
```

```

# Adding Labels and title
plt.xlabel('Year')
plt.ylabel('Number of accidents')
plt.title('Trends in aviation accidents for the top 10 popular aircrafts since 2010')
plt.legend()
plt.grid(True)
plt.xticks(rotation=45) # Rotate year Labels for better readability

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

```



Deductions from the above chart:

- Aviation accidents have been reducing over time probably due to improvement in technology, training and regulations
- Cessna, Mooney and Piper aircraft accidents were in a downward trend but went up in 2022 contrary to the downward trend sustained by the other aircrafts

In [39]: `###We exclude top 3 aircrafts with the most accidents from the data for the line graph`

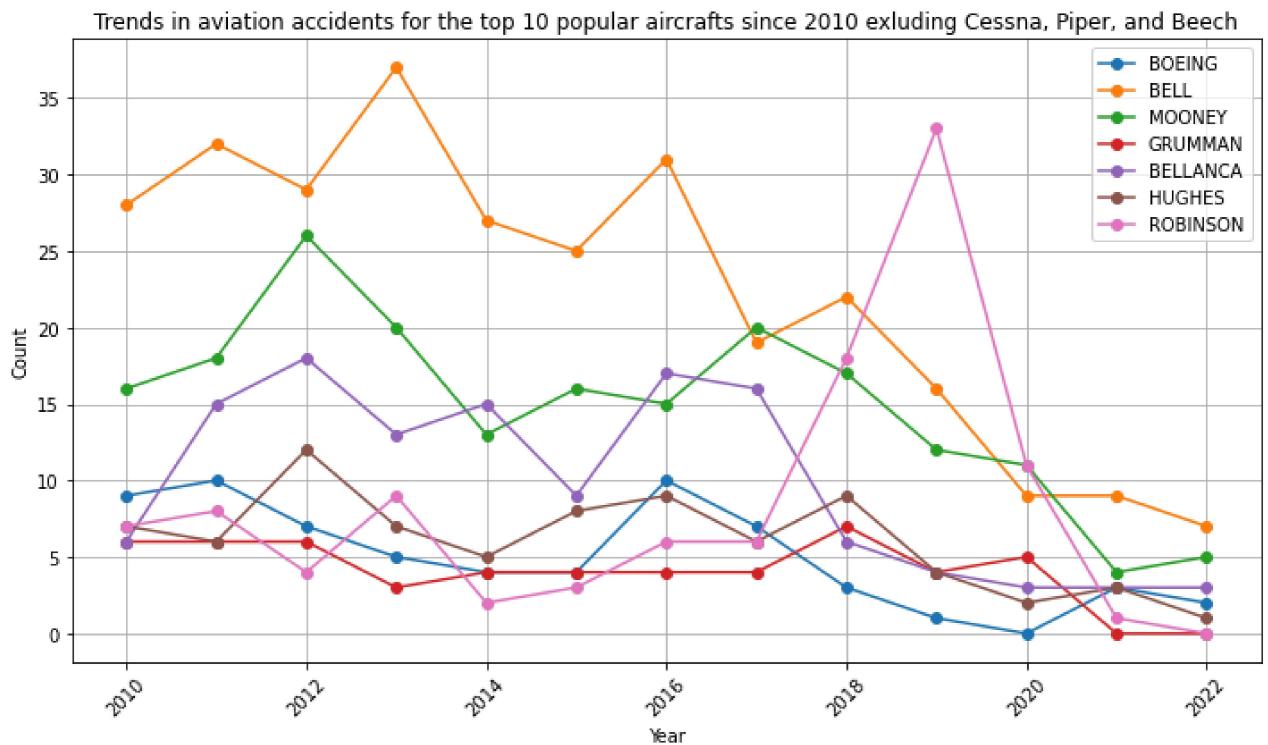
In [40]: `plt.figure(figsize=(10, 6))
plt.plot(pivot.index, pivot['BOEING'], label='BOEING', marker='o')
plt.plot(pivot.index, pivot['BELL'], label='BELL', marker='o')
plt.plot(pivot.index, pivot['MOONEY'], label='MOONEY', marker='o')
plt.plot(pivot.index, pivot['GRUMMAN'], label='GRUMMAN', marker='o')
plt.plot(pivot.index, pivot['BELLANCA'], label='BELLANCA', marker='o')
plt.plot(pivot.index, pivot['HUGHES'], label='HUGHES', marker='o')
plt.plot(pivot.index, pivot['ROBINSON'], label='ROBINSON', marker='o')
Adding Labels and title
plt.xlabel('Year')
plt.ylabel('Count')
plt.title('Trends in aviation accidents for the top 10 popular aircrafts since 2010 exl')`

```

plt.legend()
plt.grid(True)
plt.xticks(rotation=45) # Rotate year Labels for better readability

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

```



Deductions from the above chart:

- Top 5 safest aircrafts with steadily decreasing number of accidents over the last 10 years include
 1. Robinson
 2. Grumman
 3. Hughes
 4. Boeing
 5. Bellanca

A bar graph showing the number of accidents for the 5 safest aircrafts by purpose

```

In [41]: # Generate data for the 5 aircrafts with the least accidents from 2010 henceforth for Bar chart
df4 = df[(df['Year'] >= 2010) & (df['Make'].isin(['ROBINSON', 'BOEING', 'HUGHES', 'BELLANCA']))]

# Group the data by 'Make' and 'Purpose_of_flight' and then count the number of accidents
grouped_data = df4.groupby(['Make', 'Purpose_of_flight']).size().unstack()

# Plotting the bar chart
grouped_data.plot(kind='bar', figsize=(10, 6))

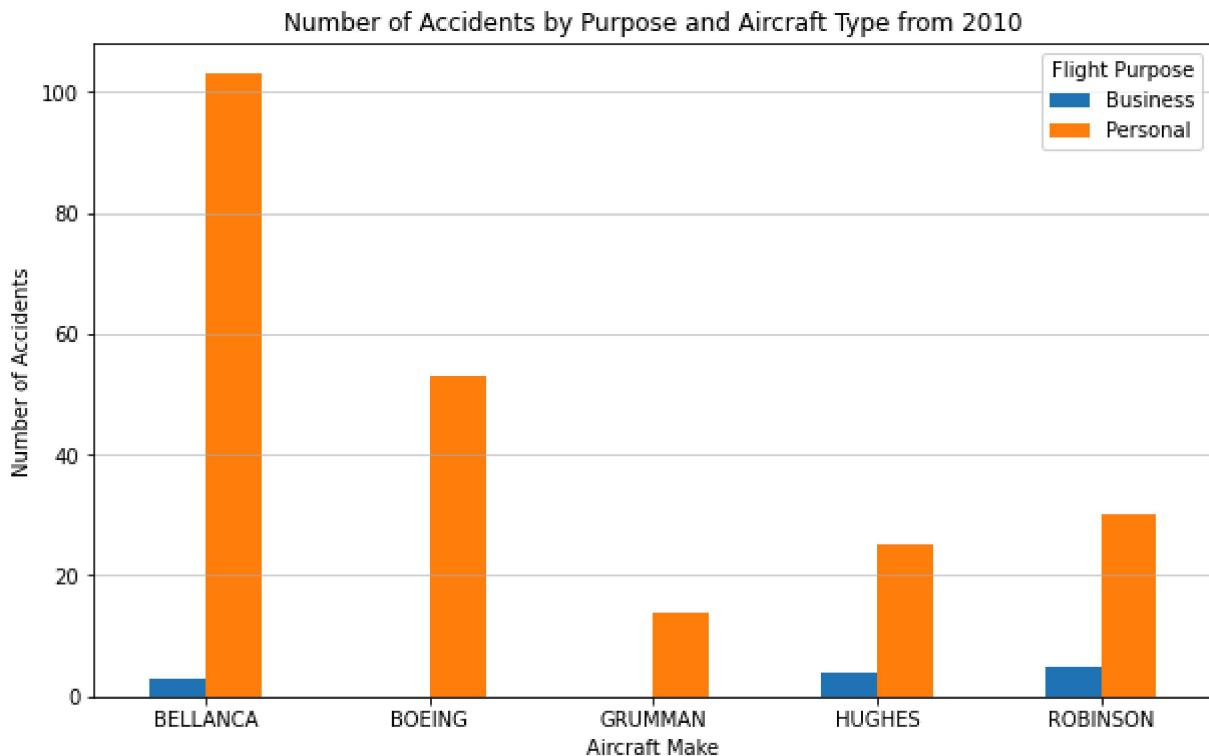
# Labels for the bar chart
plt.title('Number of Accidents by Purpose and Aircraft Type from 2010')

```

```

plt.xlabel('Aircraft Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=0)
plt.legend(title="Flight Purpose")
plt.grid(axis='y', linestyle='-', alpha=0.7)
# Show the plot
plt.show()

```



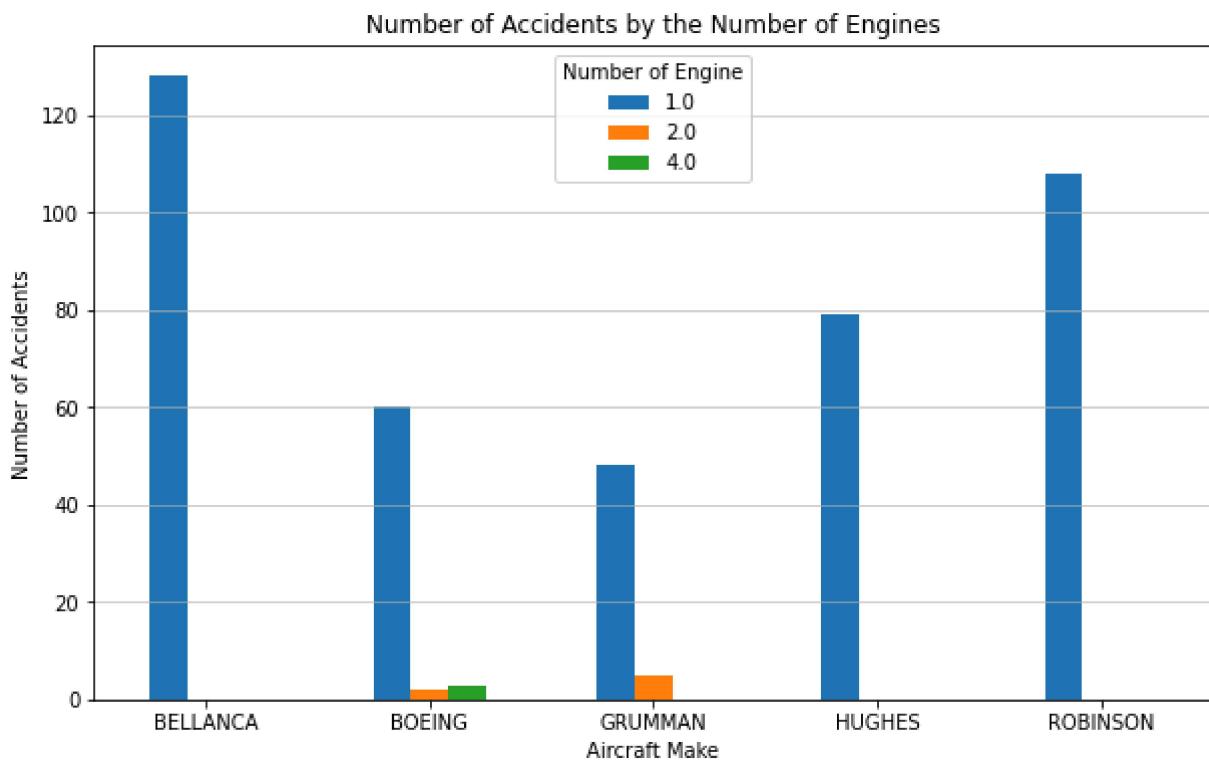
Deductions from the above chart:

1. Boeing and Grumman Aircrafts are the safest for the business flights because they did not have any accidents from 2010
2. Grumman are the safest for the personal flights-

In [42]: *###A bar graph showing the number of accidents for the 5 safest aircrafts by the Number of Engines*

In [43]: *# Generate data for the 5 aircrafts with the Least accidents from 2010 henceforth for Business*
df4 = df[(df['Year'] >= 2010) & (df['Make'].isin(['ROBINSON', 'BOEING', 'HUGHES', 'BELLANCA']))]
Group the data by 'Make' and 'Purpose_of_flight' and then count the number of accidents
grouped_data = df4.groupby(['Make', 'Number_of_Engines']).size().unstack()
Plotting the bar chart
grouped_data.plot(kind='bar', figsize=(10, 6))
Labels for the bar chart
plt.title('Number of Accidents by the Number of Engines')
plt.xlabel('Aircraft Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=0)
plt.legend(title="Number of Engine")
plt.grid(axis='y', linestyle='-', alpha=0.7)

```
# Showing the chart  
plt.show()
```



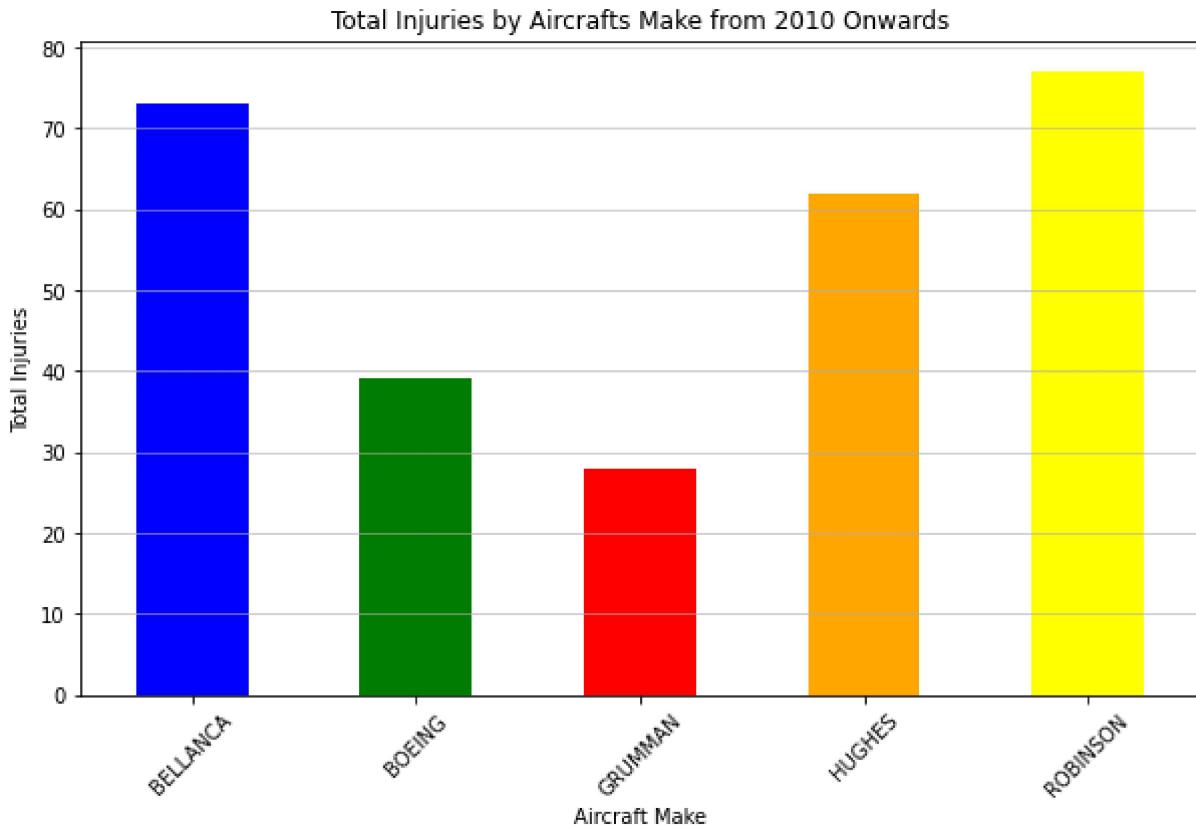
Deductions from the above chart:

1. The number of accidents reduces as the number of engines increases

Plotting a graph that shows the Total Passangers' Injuries for the 5 safest aircrafts from 2010

```
In [44]:  
# Include data from 2010  
df = df[df['Year'] >= 2010]  
  
# Computation of total injuries  
df['Total_Injuries'] = df[['Total_Fatal_Injuries', 'Total_Serious_Injuries', 'Total_Minor_Injuries']].sum(axis=1)  
  
# Group data by 'Make'  
injuries_group = df.groupby('Make')['Total_Injuries'].sum()  
  
# Including Least_Accidents_Aircrafts only  
Least_Accidents_Aircrafts = ['ROBINSON', 'BOEING', 'HUGHES', 'BELLANCA', 'GRUMMAN']  
injuries_group = injuries_group[injuries_group.index.isin(Least_Accidents_Aircrafts)]  
  
# Plot the chart  
plt.figure(figsize=(10, 6))  
bars = injuries_group.plot(kind='bar', color=['blue', 'green', 'red', 'orange', 'yellow'])  
# Labels and title  
plt.xlabel('Aircraft Make')  
plt.ylabel('Total Injuries')  
plt.title('Total Injuries by Aircrafts Make from 2010 Onwards')  
plt.xticks(rotation=45)  
plt.grid(axis='y', linestyle='-', alpha=0.7)
```

```
# Show the chart  
plt.show()
```



Deductions from the above chart:

1. Boeing and Grumman have the lowest number of injuries since 2010 meaning they are the top 2 safest aircrafts.

CONCLUSION

1. Top 3 highest risk aircrafts with the most accidents include Cessna, Piper, Beech
2. Top 3 low risk aircrafts with the least accidents include Robinson, Boeing, Hughes
3. Aviation accidents have been reducing over time probably due to improvement in technology, training and regulations
4. Aircrafts with more than one engine are less likely to be involved in accidents
5. Boeing and Grumman Aircrafts are the safest for the business flights because they did not have any accidents from 2010
6. Grumman are the safest for the personal flights as they had the lowest number of accidents since 2010.
7. Boeing and Grumman have the lowest number of injuries since 2010 meaning they are the top 2 safest aircrafts.

RECOMMENDATION

From the analysis, it would be prudent to acquire the latest models of Boeing for business flights and Grumman for personal flights. Further, acquiring an aircraft with more than one engine significantly reduce the risk of accidents.