Exploring Aircrafts And Their Risks: A Data-Driven Approach

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Overview

Choosing aircrafts for investment purposes is difficult due to the many risks that a particular aircraft encompasses. The aim of this project is to explore various aircrafts and the accompanied risks, in order to make a learned approach of choosing an aircraft with the lowest risk. The dataset is from the National Transportation Safety Board that includes aviation accident data from 1962 to 2023 about civil aviation accidents and selected incidents in the United States and international waters.

Data Understanding

In [1]:
```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [2]:
```
# Create a variable to save the dataset
aviation_data = pd.read_csv('data/Aviation_data.csv')

# View the dataset
aviation_data
```

```
C:\Users\Admin\anaconda3\envs\learn-env\lib\site-packages\IPython\core\interactiveshell.py:3145: DtypeWarning: Columns (6,7,28) have mixed types.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpose.of.flight	Air.carrier	Total.Fatal.Injuries	To
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	2.0	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	4.0	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9222	-81.8781	NaN	NaN	...	Personal	NaN	3.0	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	2.0	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	1.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
90343	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	0.0	
90344	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	NaN	...	NaN	NaN	0.0	
90345	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	PAYSON	...	Personal	NaN	0.0	
90346	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	NaN	...	Personal	MC CESSNA 210N LLC	0.0	
90347	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	0.0	

90348 rows × 31 columns

In [3]:
```
aviation_data.shape
```

Out[3]:
```
(90348, 31)
```

From above, we can see that the dataset has 90348 rows and 31 columns

In [4]:
```
# Enables the viewing of column names, their data types and the number of values in them
aviation_data.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            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        73659 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

In [5]:
```
# Returns the number of null values in each column
aviation_data.isna().sum()
```

Out[5]:
```
Event.Id                   1459
Investigation.Type            0
Accident.Number            1459
Event.Date                 1459
Location                   1511
Country                    1685
Latitude                  55966
Longitude                 55975
Airport.Code              40099
Airport.Name              37558
Injury.Severity            2459
Aircraft.damage            4653
Aircraft.Category         58061
Registration.Number        2776
Make                       1522
Model                      1551
Amateur.Built              1561
Number.of.Engines          7543
Engine.Type                8536
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              7840
Publication.Date          16689
dtype: int64
```

From above, we can see that some columns have a lot of missing values, for example the Schedule column, Air.carrier column and FAR.Description.

In [6]:
```
# Returns the percentage of missing values in each column
percent_missing = aviation_data.isnull().sum() * 100 / len(aviation_data)
percent_missing = percent_missing.sort_values(ascending = False)
percent_missing
```

Out[6]:
```
Schedule                  86.073848
Air.carrier               81.573471
FAR.Description           64.555939
Aircraft.Category         64.263736
Longitude                 61.954886
Latitude                  61.944924
Airport.Code              44.382831
Airport.Name              41.570372
Broad.phase.of.flight     31.681941
Publication.Date          18.471909
Total.Serious.Injuries    15.461327
Total.Minor.Injuries      14.822686
Total.Fatal.Injuries      14.233851
Engine.Type                9.447913
Report.Status              8.677558
Purpose.of.flight          8.468367
Number.of.Engines          8.348829
Total.Uninjured            8.158454
Weather.Condition          6.586753
Aircraft.damage            5.150086
Registration.Number        3.072564
Injury.Severity            2.721698
Country                    1.865011
Amateur.Built              1.727764
Model                      1.716695
Make                       1.684597
Location                   1.672422
Event.Date                 1.614867
Accident.Number            1.614867
Event.Id                   1.614867
Investigation.Type         0.000000
dtype: float64
```

By finding the percentage of missing values in each column, I can choose the best way to deal with the missing values.

In [7]:
```
# Finding out the number of duplicate events based on the Event.Id column
duplicates = aviation_data[aviation_data.duplicated(subset='Event.Id')]
print(len(duplicates))
duplicates
```

```
2396
```

Out[7]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpose.of.flight	Air.carrier	Total.Fatal.Injuri
118	20020917X01908	Accident	DCA82AA012A	1982-01-19	ROCKPORT, TX	United States	NaN	NaN	RKP	ARANSAS COUNTY AIRPORT	...	Executive/corporate	NaN	
159	20020917X02400	Accident	MIA82FA038A	1982-01-23	NEWPORT RICHEY, FL	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	
160	20020917X02259	Accident	LAX82FA049B	1982-01-23	VICTORVILLE, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	
245	20020917X02585	Accident	SEA82DA028B	1982-02-06	MEDFORD, OR	United States	NaN	NaN	MFR	MEDFORD-JACKSON COUNTY	...	Personal	NaN	
248	20020917X02173	Accident	LAX82DA065A	1982-02-06	SAN JOSE, CA	United States	NaN	NaN	RHV	RIED HILLVIEW	...	Personal	NaN	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
90097	NaN	20-12-2022	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	N
90236	20221112106276	Accident	CEN23MA034	2022-11-12	Dallas, TX	United States	324026N	0965146W	RBD	Dallas Executive	...	ASHO	Commemorative Air Force	
90255	20221121106336	Accident	WPR23LA041	2022-11-18	Las Vegas, NV	United States	361239N	1151140W	VGT	NORTH LAS VEGAS	...	Instructional	702 HELICOPTER INC	
90257	20221122106340	Incident	DCA23WA071	2022-11-18	Marrakech,	Morocco	NaN	NaN	NaN	NaN	...	NaN	Valair Private Jets	
90273	20221123106354	Accident	WPR23LA045	2022-11-22	San Diego, CA	United States	323414N	1165825W	SDM	Brown Field Municipal Airport	...	Public Aircraft - Federal	U.S. Navy	

2396 rows × 31 columns

Data Preparation

Dealing with duplicate values

First, I will drop the duplicates values.

In [8]:
```
aviation_data = aviation_data.drop_duplicates(subset = 'Event.Id')
aviation_data
```

Out[8]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpose.of.flight	Air.carrier	Total.Fatal.Injuries	To
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	2.0	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	4.0	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9222	-81.8781	NaN	NaN	...	Personal	NaN	3.0	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	2.0	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	1.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
90343	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	0.0	
90344	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	NaN	...	NaN	NaN	0.0	
90345	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	PAYSON	...	Personal	NaN	0.0	
90346	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	NaN	...	Personal	MC CESSNA 210N LLC	0.0	
90347	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	NaN	...	Personal	NaN	0.0	

87952 rows × 31 columns

Dealing with missing values

Columns

Let's revisit the percentage of missing values in each column

In [9]:
```
percent_missing
```

Out[9]:
```
Schedule                  86.073848
Air.carrier               81.573471
FAR.Description           64.555939
Aircraft.Category         64.263736
Longitude                 61.954886
Latitude                  61.944924
Airport.Code              44.382831
Airport.Name              41.570372
Broad.phase.of.flight     31.681941
Publication.Date          18.471909
Total.Serious.Injuries    15.461327
Total.Minor.Injuries      14.822686
Total.Fatal.Injuries      14.233851
Engine.Type                9.447913
Report.Status              8.677558
Purpose.of.flight          8.468367
Number.of.Engines          8.348829
Total.Uninjured            8.158454
Weather.Condition          6.586753
Aircraft.damage            5.150086
Registration.Number        3.072564
Injury.Severity            2.721698
Country                    1.865011
Amateur.Built              1.727764
Model                      1.716695
Make                       1.684597
Location                   1.672422
Event.Date                 1.614867
Accident.Number            1.614867
Event.Id                   1.614867
Investigation.Type         0.000000
dtype: float64
```

In one line, I will:

1. Drop the Air.carrier and Schedule columns since they have the most missing values: over 80%. I will drop all irrelevant columns.
2. Drop the Aircraft.Category, Airport.Code and Airport.Name columns because they are irrelevant and have a high percentage of missing values(over 40%).
3. Drop the Longitude, FAR.Description and Latitude columns because they have a high percentage of missing values (60%) and is irrelevant.
4. Drop any other irrelevant column

In [10]:
```
aviation_data = aviation_data.drop(['Air.carrier', 'Schedule', 'Aircraft.Category', 'Airport.Code', 'Airport.Name', 'Longitude', 'Latitude', 'FAR.Description',
aviation_data
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 87952 entries, 0 to 90347
Data columns (total 17 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                87951 non-null  object 
 1   Investigation.Type      87952 non-null  object 
 2   Accident.Number         87951 non-null  object 
 3   Event.Date              87951 non-null  object 
 4   Injury.Severity         86961 non-null  object 
 5   Aircraft.damage         84848 non-null  object 
 6   Make                    87888 non-null  object 
 7   Model                   87859 non-null  object 
 8   Amateur.Built           87851 non-null  object 
 9   Number.of.Engines       81924 non-null  float64
 10  Engine.Type             80927 non-null  object 
 11  Purpose.of.flight       81829 non-null  object 
 12  Total.Fatal.Injuries    76684 non-null  float64
 13  Total.Serious.Injuries  75629 non-null  float64
 14  Total.Minor.Injuries    76191 non-null  float64
 15  Total.Uninjured         82088 non-null  float64
 16  Broad.phase.of.flight   60837 non-null  object 
dtypes: float64(5), object(12)
memory usage: 12.1+ MB
```

The Broad.phase.of.flight column has a missing value percentage of 30%. Since this column consists of categorical data and is important in my analysis. I decided to drop the rows that consist of NaN values in the column.

In [11]:
```
aviation_data = aviation_data.dropna(subset=['Broad.phase.of.flight'])
aviation_data
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60837 entries, 0 to 63911
Data columns (total 17 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                60837 non-null  object 
 1   Investigation.Type      60837 non-null  object 
 2   Accident.Number         60837 non-null  object 
 3   Event.Date              60837 non-null  object 
 4   Injury.Severity         60837 non-null  object 
 5   Aircraft.damage         59459 non-null  object 
 6   Make                    60826 non-null  object 
 7   Model                   60807 non-null  object 
 8   Amateur.Built           60819 non-null  object 
 9   Number.of.Engines       59942 non-null  float64
 10  Engine.Type             60456 non-null  object 
 11  Purpose.of.flight       59790 non-null  object 
 12  Total.Fatal.Injuries    50299 non-null  float64
 13  Total.Serious.Injuries  49618 non-null  float64
 14  Total.Minor.Injuries    50248 non-null  float64
 15  Total.Uninjured         55871 non-null  float64
 16  Broad.phase.of.flight   60837 non-null  object 
dtypes: float64(5), object(12)
memory usage: 8.4+ MB
```

The two columns, 'Total.Fatal.Injuries' and 'Injury.Severity' contain similar data, yet 'Injury.Severity' contains no missing values. Therefore, I will create a new column 'Fatality' to show numerical data of the 'Injury.Severity', and drop the 'Total.Fatal.Injuries' and 'Injury.'column.

In [12]:
```
# Extracts the number from each value in the Injury.Severity column. e.g Fatal(2) -> 2 and fills the Fatility column with those numbers
aviation_data['Fatality'] = aviation_data['Injury.Severity'].str.extract(r'\((\d+)\)')

# Fills the NaN values in the Fatility column with categorical values from Injury.Severitiy
aviation_data['Fatality'].fillna(aviation_data['Injury.Severity'], inplace=True)

# Replaces the categorical values with 0
aviation_data['Fatality'].replace({'Non-Fatal': 0, 'Minor': 0, 'Serious': 0, 'Incident': 0}, inplace=True)

#
aviation_data['Fatality'] = aviation_data.apply(lambda row: row['Total.Fatal.Injuries'] if row['Fatality'] == 'Fatal' else row['Fatality'], axis=1)

# Replaces the 'Unavailable' values with NaN
aviation_data['Fatality'].replace('Unavailable', np.nan, inplace=True)

# Changes the values from strings to integers
aviation_data['Fatality'][~aviation_data['Fatality'].isna()] = aviation_data['Fatality'][~aviation_data['Fatality'].isna()].astype(int)

# Changes to float
pd.options.display.float_format = '{:.0f}'.format

aviation_data = aviation_data.drop(['Injury.Severity','Total.Fatal.Injuries'], axis = 1)
aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 60837 entries, 0 to 63911
Data columns (total 16 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                60837 non-null  object 
 1   Investigation.Type      60837 non-null  object 
 2   Accident.Number         60837 non-null  object 
 3   Event.Date              60837 non-null  object 
 4   Aircraft.damage         59459 non-null  object 
 5   Make                    60826 non-null  object 
 6   Model                   60807 non-null  object 
 7   Amateur.Built           60819 non-null  object 
 8   Number.of.Engines       59942 non-null  float64
 9   Engine.Type             60456 non-null  object 
 10  Purpose.of.flight       59790 non-null  object 
 11  Total.Serious.Injuries  49618 non-null  float64
 12  Total.Minor.Injuries    50248 non-null  float64
 13  Total.Uninjured         55871 non-null  float64
 14  Broad.phase.of.flight   60837 non-null  object 
 15  Fatality                60832 non-null  object 
dtypes: float64(4), object(12)
memory usage: 10.4+ MB
<ipython-input-12-edb5534a46bb>:17: SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  aviation_data['Fatality'][~aviation_data['Fatality'].isna()] = aviation_data['Fatality'][~aviation_data['Fatality'].isna()].astype(int)
```

Next, I will create a new column 'Date' and extract the years from the 'Event.Date' column. I will then drop the 'Event.Date' column.

In [13]:
```
# Convert the Event.Date column to date type
aviation_data['Event.Date'] = pd.to_datetime(aviation_data['Event.Date'], format='%Y-%m-%d')

# Create a new column ('Year') that contains extracted years from the 'Event.Date' column
aviation_data['Year'] = aviation_data['Event.Date'].dt.year

aviation_data = aviation_data.drop(['Event.Date'], axis = 1)

aviation_data
```

Out[13]:

	Event.Id	Investigation.Type	Accident.Number	Aircraft.damage	Make	Model	Amateur.Built	Number.of.Engines	Engine.Type	Purpose.of.flight	Total.Serious.Injuries	Total.Minor.Injuries
0	20001218X45444	Accident	SEA87LA080	Destroyed	Stinson	108-3	No	1	Reciprocating	Personal	0	0
1	20001218X45447	Accident	LAX94LA336	Destroyed	Piper	PA24-180	No	1	Reciprocating	Personal	0	0
2	20061025X01555	Accident	NYC07LA005	Destroyed	Cessna	172M	No	1	Reciprocating	Personal	nan	nan
3	20001218X45448	Accident	LAX96LA321	Destroyed	Rockwell	112	No	1	Reciprocating	Personal	0	0
4	20041105X01764	Accident	CHI79FA064	Destroyed	Cessna	501	No	nan	NaN	Personal	2	nan
...	...	...	...	...	...	...	...	...	...	...	...	...
63907	20071231X02014	Accident	DFW08FA053	Destroyed	Bell	206L1	No	1	Turbo Shaft	NaN	1	2
63908	20080109X00032	Accident	NYC08FA071	Substantial	Bell	206L-3	No	1	Turbo Shaft	Other Work Use	0	0
63909	20080114X00045	Accident	LAX08FA043	Substantial	Cirrus Design Corp.	SR22	No	1	Reciprocating	Personal	nan	nan
63910	20080129X00122	Accident	CHI08CA057	Substantial	Lerohl	RV-8	Yes	1	Reciprocating	Personal	nan	nan
63911	20080125X00106	Accident	SEA08CA056	Substantial	Piper	PA-12	No	1	Reciprocating	Instructional	nan	nan

60837 rows × 16 columns

In [14]:
```
# Check the percentage of missing values per column for the updated dataset
tmp = aviation_data
percent_missing = tmp.isnull().sum() * 100 / len(aviation_data)
percent_missing = percent_missing.sort_values(ascending = False)
percent_missing
```

Out[14]:
```
Total.Serious.Injuries   18
Total.Minor.Injuries     17
Total.Uninjured           8
Aircraft.damage           2
Purpose.of.flight         2
Number.of.Engines         1
Engine.Type               1
Model                     0
Amateur.Built             0
Make                      0
Fatality                  0
Year                      0
Broad.phase.of.flight     0
Accident.Number           0
Investigation.Type        0
Event.Id                  0
dtype: float64
```

There are still some missing values, notably in the 'Total.Serious.Injuries' and 'Total.Minor.Injuries' columns but I do not find them significant in my analysis.

Data Modeling

Let's investigate the relationship of make, models and accidents.

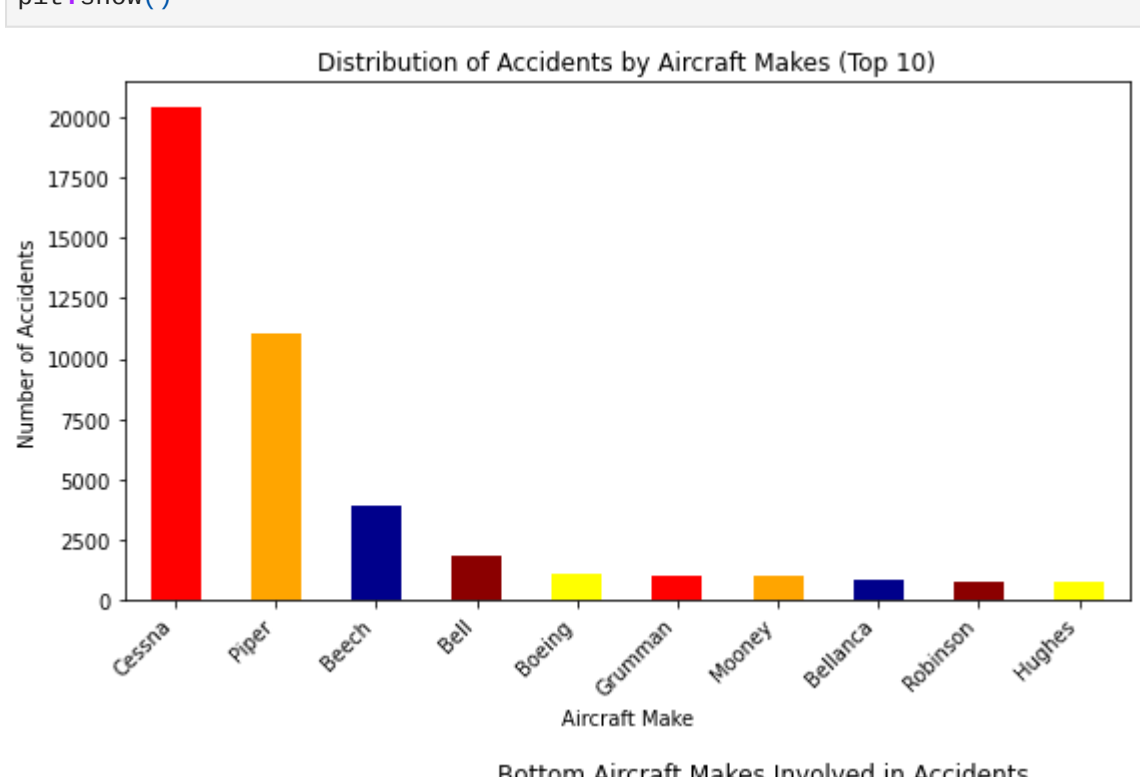
In [15]:
```
# Making a subset of Make, Model and adding an Accident Count of each aircraft
makes_models_accident_counts = aviation_data.groupby(['Make', 'Model']).size().reset_index(name='Accident_count', drop=False)
makes_models_accident_counts = makes_models_accident_counts.sort_values(by='Accident_count', ascending=False)
makes_models_accident_counts
```

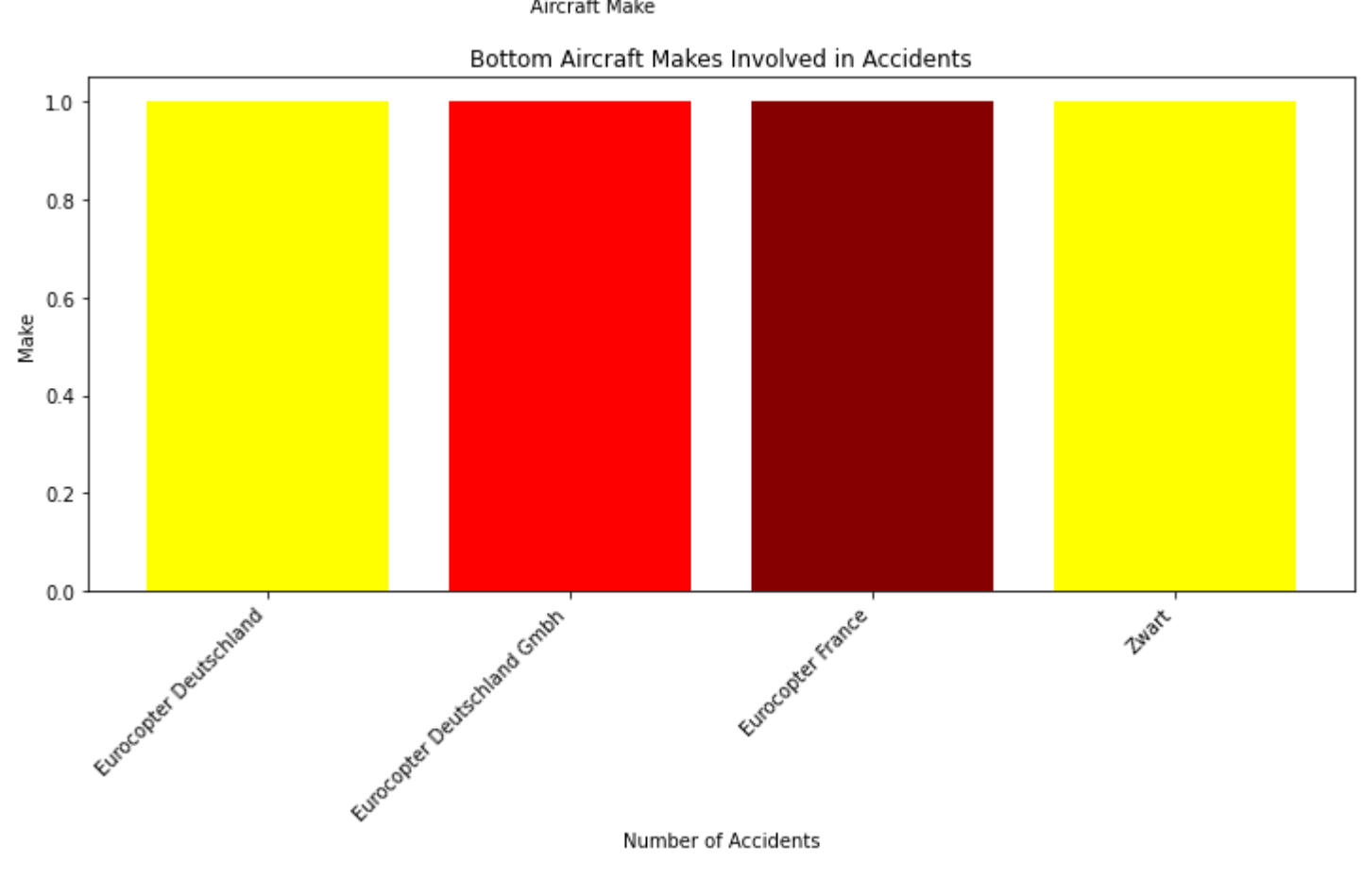
Out[15]:

	Make	Model	Accident_count
2988	Cessna	152	2061
3008	Cessna	172	1003
3051	Cessna	172N	956
8740	Piper	PA-28-140	787
2963	Cessna	150	655
...	...	...	...
4914	Eurocopter Deutschland Gmbh	MBB BK-117 A4	1
4915	Eurocopter France	AS 350 B2	1
4916	Eurocopter France	AS 350 B3	1
4917	Eurocopter France	AS 350 BA	1
11861	Zwart	KIT FOX VIXEN	1

11862 rows × 3 columns

In [16]:
```
# Find the top 10 makes
top_10_makes = aviation_data['Make'].value_counts().nlargest(10).sort_values(ascending = False)

plt.figure(figsize=(8, 5))

# Plot the first visualization
color = ['red', 'orange', 'darkblue', 'darkred', 'yellow']
top_10_makes.plot(kind = 'bar', color=color)
plt.title('Distribution of Accidents by Aircraft Makes (Top 10)')
plt.xlabel('Aircraft Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()

# Plot the second visualization
fig, axes = plt.subplots(figsize=(12, 5))
bottom_10_makes = makes_models_accident_counts.tail(10)
axes.bar(bottom_10_makes['Make'], bottom_10_makes['Accident_count'], color=color)
axes.set_xlabel('Number of Accidents')
axes.set_ylabel('Make')
axes.set_title('Bottom Aircraft Makes Involved in Accidents')
plt.xticks(rotation=45, ha='right')


plt.show()
```

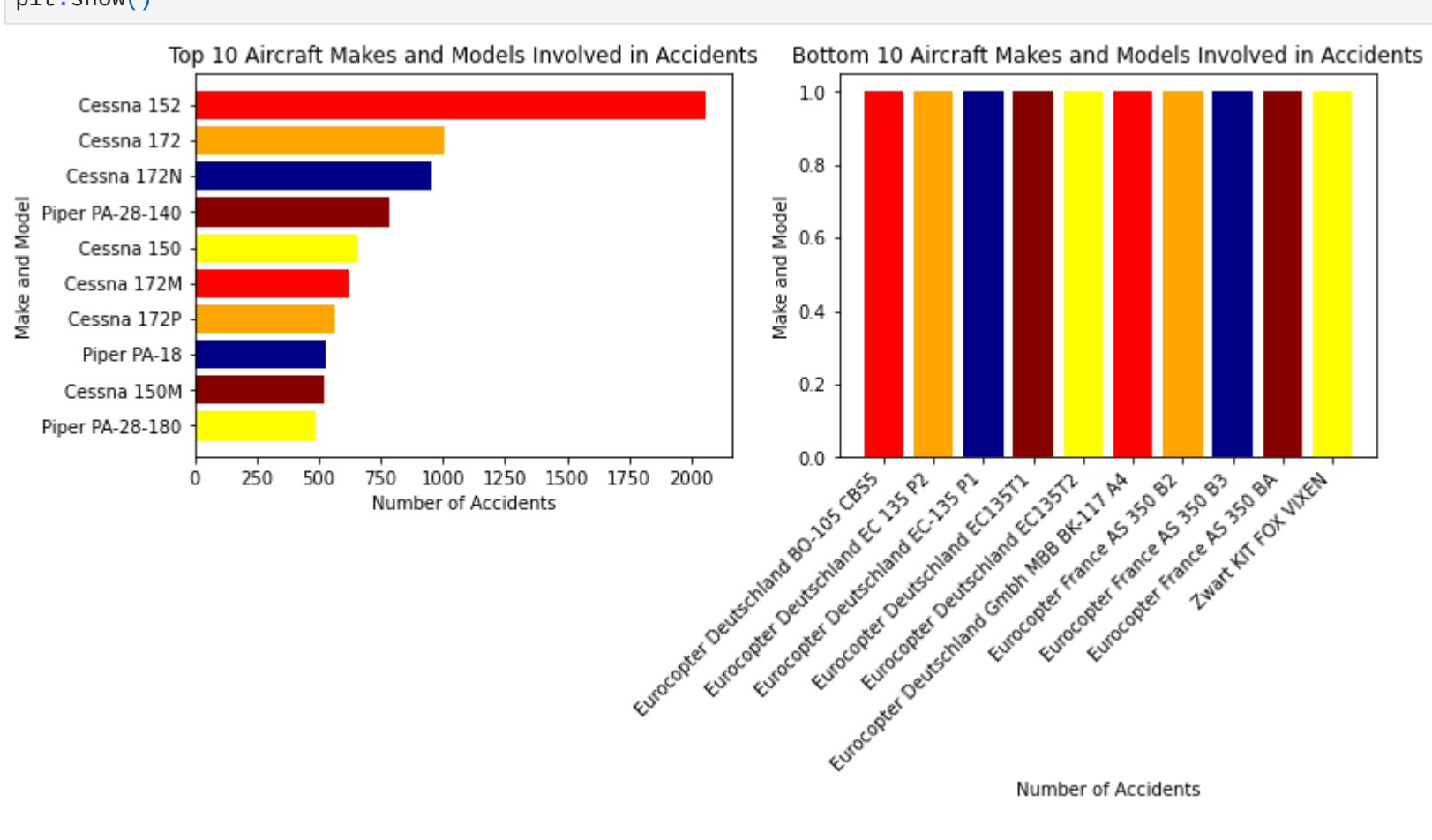




From above, we can see that Cessnas are responsible for a significant number of accidents, and that .

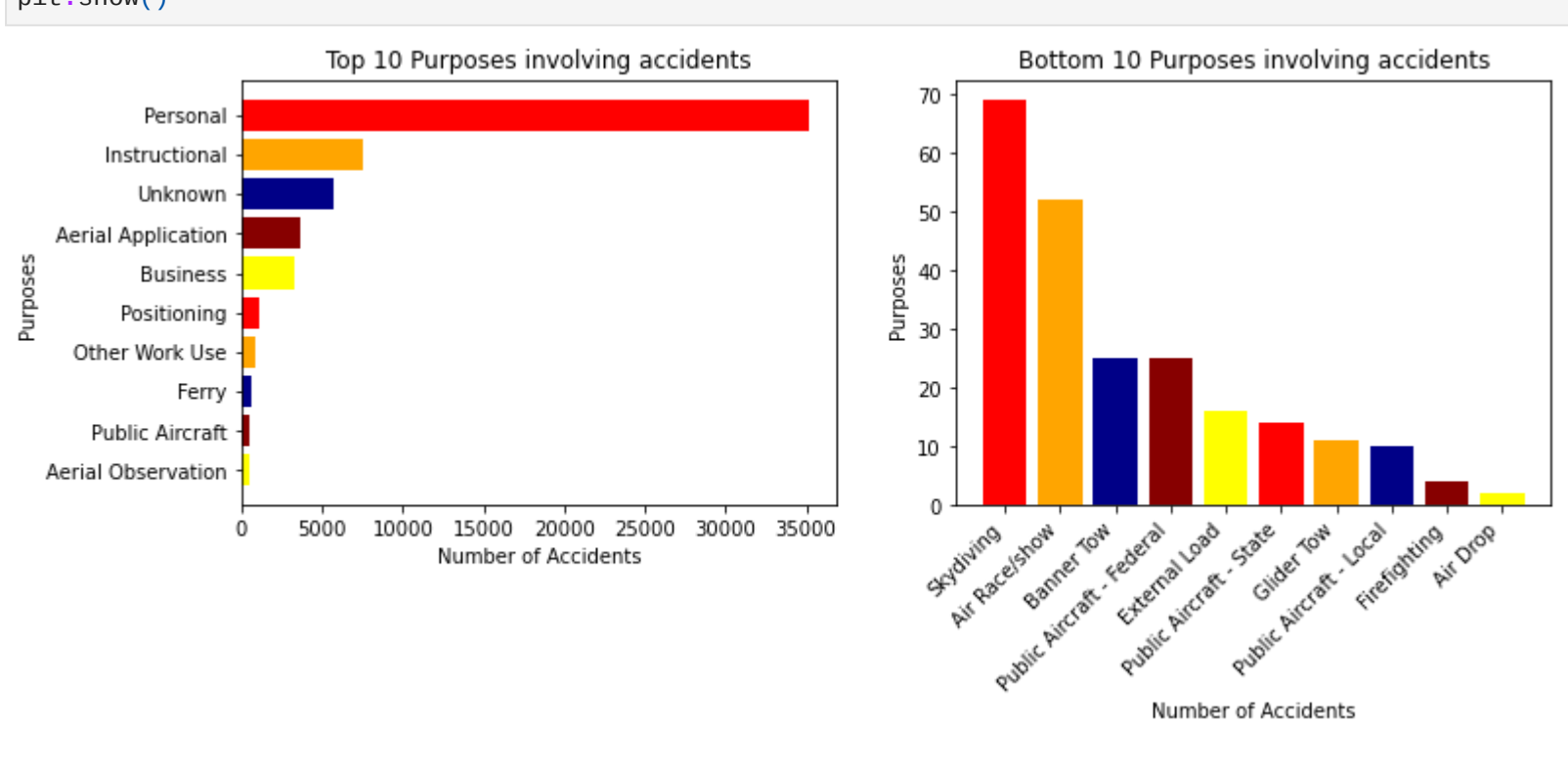
Since Cessnas are most responsible for the accidents, let's see what specific model was most responsible.

In [17]:
```
fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Plot the first visualization
color = ['red', 'orange', 'darkblue', 'darkred', 'yellow']
top_10_make_model = makes_models_accident_counts.head(10)
axes[0].barh(top_10_make_model['Make'] + ' ' + top_10_make_model['Model'], top_10_make_model['Accident_count'], color=color)
axes[0].set_xlabel('Number of Accidents')
axes[0].set_ylabel('Make and Model')
axes[0].set_title('Top 10 Aircraft Makes and Models Involved in Accidents')
axes[0].invert_yaxis()

# Plot the second visualization
bottom_10_make_model = makes_models_accident_counts.tail(10)
axes[1].bar(bottom_10_make_model['Make'] + ' ' + bottom_10_make_model['Model'], bottom_10_make_model['Accident_count'], color=color)
axes[1].set_xlabel('Number of Accidents')
axes[1].set_ylabel('Make and Model')
axes[1].set_title('Bottom 10 Aircraft Makes and Models Involved in Accidents')
plt.xticks(rotation=45, ha='right')

plt.show()
```



From above, we can see that the Cessna 152 had the most acccidents (at over 2000 accidents) while all bottom 10 models had 1 accident each.

In [18]:
```
purposes = aviation_data['Purpose.of.flight'].value_counts()

fig, axes = plt.subplots(1, 2, figsize=(12, 4))

# Plot the first visualization

color = ['red', 'orange', 'darkblue', 'darkred', 'yellow']
top_10_purposes = purposes.head(10)

# Convert the index and values to list type in order to plot the visualization
axes[0].barh(list(top_10_purposes.index), list(top_10_purposes.values), color=color)
axes[0].set_xlabel('Number of Accidents')
axes[0].set_ylabel('Purposes')
axes[0].set_title('Top 10 Purposes involving accidents')
axes[0].invert_yaxis()


# Plot the second visualization

bottom_10_purposes = purposes.tail(10)

# Convert the index and values to list type in order to plot the visualization
axes[1].bar(list(bottom_10_purposes.index), list(bottom_10_purposes.values), color=color)
axes[1].set_xlabel('Number of Accidents')
axes[1].set_ylabel('Purposes')
axes[1].set_title('Bottom 10 Purposes involving accidents')
plt.xticks(rotation=45, ha='right')

plt.show()
```



As a recommendation for the purchase and operation of an aircraft, I would recommend to use either the aircrafts listed below as they have the least number of accidents in the dataset:

In [19]:
```
bottom_10_make_model
```

Out[19]:

	Make	Model	Accident_count
4909	Eurocopter Deutschland	BO-105 CBS5	1
4910	Eurocopter Deutschland	EC 135 P2	1
4911	Eurocopter Deutschland	EC-135 P1	1
4912	Eurocopter Deutschland	EC135T1	1
4913	Eurocopter Deutschland	EC135T2	1
4914	Eurocopter Deutschland Gmbh	MBB BK-117 A4	1
4915	Eurocopter France	AS 350 B2	1
4916	Eurocopter France	AS 350 B3	1
4917	Eurocopter France	AS 350 BA	1
11861	Zwart	KIT FOX VIXEN	1