Airplane_Analysis

February 11, 2025

1 Aviation Accident Database Analysis

2 Business Understanding

Goals for the Project: This project will use data cleaning, analysis, and visualization to generate insights for business stakeholders on to improve the quality and safety of traveling by Airplane.

The Business problem involves; breaking down and analysing the data to find the lowest risk Aircraft. This will help the stakeholders to choose the right aircraft to purchase and invest in.

Data: I am using the Kaggle "Aviation Accident Database & Synopses, up to 2023" for my data.

3 Data Understanding

[1]:
```
# Loading the necessary libraries
import pandas as pd # To manipulate the dataset
import numpy as np # for any statistics/averages
import matplotlib.pyplot as plt # visiaulaisation library
import seaborn as sns # more extensive visualization library
%matplotlib inline
```

[2]:
```
#load the datasets loaded
df1 = pd.read_csv('Data/AviationData.csv',encoding='ISO-8859-1') #The usual␣
 ↪encoding of utf-8 was not working.
df2 = pd.read_csv('Data/USState_Codes.csv',encoding='ISO-8859-1')
```

```
C:\Users\MichelleChekwooti\AppData\Local\Temp\ipykernel_9244\3973064077.py:2:
DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option on import
or set low_memory=False.
  df1 = pd.read_csv('Data/AviationData.csv',encoding='ISO-8859-1') #The usual
encoding of utf-8 was not working.
```

[3]:
```
#This is to get a general overview of the first dataset..
df1.head(5)
```

[3]:

	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]
```

[4]:
```
df2.head(5) #To see the second dataset and see its significance in the analysis.
```

[4]:
```
     US_State Abbreviation
0     Alabama           AL
1      Alaska           AK
2     Arizona           AZ
3    Arkansas           AR
4  California           CA
```

[5]:
```
#Info is to understand the columns and their data types.
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            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        75118 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

[6]:
```
df2.info() # info of the second dataset.
```

```
<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
```

[7]:
```
df1.describe() #To show the descriptive statistics of the integer columns␣
 ↪inside the first dataset.
```

[7]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries
count	82805.000000	77488.000000	76379.000000
mean	1.146585	0.647855	0.279881
std	0.446510	5.485960	1.544084
min	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000
75%	1.000000	0.000000	0.000000
max	8.000000	349.000000	161.000000

	Total.Minor.Injuries	Total.Uninjured
count	76956.000000	82977.000000
mean	0.357061	5.325440
std	2.235625	27.913634
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	0.000000	2.000000
max	380.000000	699.000000

[8]:
```
'''
This brief overview shows that there are 88889 rows of data in the Aviation␣
 ↪dataset and they are 62 rows in,
inside the US city dataset.
Under head you see a number of NaN values, I also note that,
all columns in the first data set are non-null while that of the second data␣
 ↪set,
has many object data columns most likely inconsistent data types.

We also note from the descriptive statistics that the max number of engines is␣
 ↪8, however,
the average is 1.
The max number of Fatal injuries is 349 but on average it is 1.This will help␣
 ↪us,
understand the safety in terms of injuries for the airplanes.


Limitations in data:
There are not many numerical values which will make statistical analysis not as␣
 ↪effective,
The data has many categorical values which may become difficult to fill in data␣
 ↪cleaning.
They is an ID for Event but another column for registration number which is␣
 ↪confusing,
```

```
as to which is the unique ID.
'''
```

[8]:
```
'\nThis brief overview shows that there are 88889 rows of data in the Aviation
dataset and they are 62 rows in,\ninside the US city dataset.\nUnder head you
see a number of NaN values, I also note that,\nall columns in the first data set
are non-null while that of the second data set,\nhas many object data columns
most likely inconsistent data types.\n\nWe also note from the descriptive
statistics that the max number of engines is 8, however,\nthe average is 1.\nThe
max number of Fatal injuries is 349 but on average it is 1.This will help
us,\nunderstand the safety in terms of injuries for the
airplanes.\n\n\nLimitations in data:\nThere are not many numerical values which
will make statistical analysis not as effective,\nThe data has many categorical
values which may become difficult to fill in data cleaning.\nThey is an ID for
Event but another column for registration number which is confusing,\nas to
which is the unique ID.\n'
```

4 Data Cleaning & Preparation

To prepare the data for analysis we will fix the mssing values and handle data types and duplicates.

I will focus on the first dataset as it has significant data for the analysis.

Missing values

[9]:
```
df1.isna().sum() #The isna shows the true or false if null values are found
↪then sum() adds the all.
```

[9]:
```
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          13771
dtype: int64
```

[10]:
```
'''
Multiple null values have been found in the majority of columns they will need␣
 ↪to
be filled or dropped.
They are only dropped if the impact will be small compared to the dataset.
'''
```

[10]:
```
'\nMultiple null values have been found in the majority of columns they will
need to\nbe filled or dropped.\nThey are only dropped if the impact will be
small compared to the dataset.\n'
```

[11]:
```
#FILL
#The number of missing rows is very large compared to actual entries of 88889.
# So for all integer/float columns tye Nulls will be filled with the mean value.
# This will hopefully present less loss of data and not affect the analysis.
Mean_Number_of_Engines = df1['Number.of.Engines'].mean()
Mean_Fatal_Injuries = df1['Total.Fatal.Injuries'].mean()
Mean_Serious_Injuries = df1['Total.Serious.Injuries'].mean()
Mean_Minor_Injuries = df1['Total.Minor.Injuries'].mean()
Mean_Uninjured = df1['Total.Uninjured'].mean()
```

[12]:
```
df1['Number.of.Engines'] = df1['Number.of.Engines'].
 ↪fillna(Mean_Number_of_Engines)
df1['Total.Fatal.Injuries'] = df1['Total.Fatal.Injuries'].
 ↪fillna(Mean_Fatal_Injuries)
df1['Total.Serious.Injuries'] = df1['Total.Serious.Injuries'].
 ↪fillna(Mean_Serious_Injuries)
df1['Total.Minor.Injuries'] = df1['Total.Minor.Injuries'].
 ↪fillna(Mean_Minor_Injuries)
df1['Total.Uninjured'] = df1['Total.Uninjured'].fillna(Mean_Uninjured)
```

[13]:
```
df1.isna().sum()
```

[13]:
```
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           0
Engine.Type              7096
FAR.Description         56866
Schedule                76307
Purpose.of.flight        6192
Air.carrier             72241
Total.Fatal.Injuries        0
Total.Serious.Injuries      0
Total.Minor.Injuries        0
Total.Uninjured             0
Weather.Condition        4492
Broad.phase.of.flight   27165
Report.Status            6384
Publication.Date        13771
dtype: int64
```

[14]:
```
#Drop
#For the smaller null columns ike location, make, model, Amateur.Built, Country␣
 ↪we will drop these.
#It is also difficult to find the average of categorical values, as they can␣
 ↪all be unique and replacing them may affect the analysis.

#Drop smaller values
df1 = df1.dropna(subset= ['Location', 'Country', 'Make', 'Model','Amateur.
 ↪Built', 'Injury.Severity'])
#Drop Missing dates as we want to do a Time series later on and weather␣
 ↪conditions which I believe will be critical.
df1 = df1.dropna(subset= ['Publication.Date','Weather.Condition'])
#I could not drop the other columns as it would significantly reduce the data.
```

[15]:
```
df1.isna().sum() #To check if they are still nulls.
```

[15]:
```
Event.Id                    0
Investigation.Type          0
Accident.Number             0
Event.Date                  0
Location                    0
Country                     0
Latitude                38840
Longitude               38850
Airport.Code            28708
Airport.Name            27008
Injury.Severity             0
Aircraft.damage          1704
Aircraft.Category       43075
Registration.Number       736
Make                        0
Model                       0
Amateur.Built               0
Number.of.Engines           0
Engine.Type              3163
FAR.Description         43073
Schedule                62267
Purpose.of.flight        2656
Air.carrier             57069
Total.Fatal.Injuries        0
Total.Serious.Injuries      0
Total.Minor.Injuries        0
Total.Uninjured             0
Weather.Condition           0
Broad.phase.of.flight   22125
Report.Status            2426
Publication.Date            0
dtype: int64
```

[16]:
```
#Because we still have some many missing values we can fill them with N/A
df1 = df1.fillna('N/A')
```

[17]:
```
df1.isna().sum()
```

[17]:
```
Event.Id                0
Investigation.Type      0
Accident.Number         0
Event.Date              0
Location                0
Country                 0
Latitude                0
```

```
Longitude                0
Airport.Code             0
Airport.Name             0
Injury.Severity          0
Aircraft.damage          0
Aircraft.Category        0
Registration.Number      0
Make                     0
Model                    0
Amateur.Built            0
Number.of.Engines        0
Engine.Type              0
FAR.Description          0
Schedule                 0
Purpose.of.flight        0
Air.carrier              0
Total.Fatal.Injuries     0
Total.Serious.Injuries   0
Total.Minor.Injuries     0
Total.Uninjured          0
Weather.Condition        0
Broad.phase.of.flight    0
Report.Status            0
Publication.Date         0
dtype: int64
```

Handling Duplicates

[18]:
```
#I remove duplicates in the data using the ID as I assume this is unique and
 ↪should be single.
df1[df1['Event.Id'].duplicated()]
```

[18]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	\
118	20020917X01908	Accident	DCA82AA012A	1982-01-19	
159	20020917X02400	Accident	MIA82FA038A	1982-01-23	
160	20020917X02259	Accident	LAX82FA049B	1982-01-23	
245	20020917X02585	Accident	SEA82DA028B	1982-02-06	
248	20020917X02173	Accident	LAX82DA065A	1982-02-06	
…	…	…	…	…	
88387	20220822105776	Accident	ERA22LA379	2022-08-20	
88538	20220918105957	Accident	CEN22FA424	2022-09-17	
88777	20221112106276	Accident	CEN23MA034	2022-11-12	
88796	20221121106336	Accident	WPR23LA041	2022-11-18	
88814	20221123106354	Accident	WPR23LA045	2022-11-22	

	Location	Country	Latitude	Longitude	Airport.Code	\
118	ROCKPORT, TX	United States	N/A	N/A	RKP	
159	NEWPORT RICHEY, FL	United States	N/A	N/A	N/A	

```
160       VICTORVILLE, CA  United States      N/A       N/A          N/A
245           MEDFORD, OR  United States      N/A       N/A          MFR
248          SAN JOSE, CA  United States      N/A       N/A          RHV
…                     …            …      …       …          …
88387        Bealeton, VA  United States  038338N  0774255W         3VA3
88538        Longmont, CO  United States  040619N  0105721W          N/A
88777          Dallas, TX  United States  324026N  0965146W          RBD
88796       Las Vegas, NV  United States  361239N  1151140W          VGT
88814       San Diego, CA  United States  323414N  1165825W          SDM

                      Airport.Name  …          Purpose.of.flight  \
118           ARANSAS COUNTY AIRPORT  …        Executive/corporate
159                             N/A  …                  Personal
160                             N/A  …                  Personal
245           MEDFORD-JACKSON COUNTY  …                  Personal
248                     RIED HILLVIEW  …                  Personal
…                                 …  …                     …
88387        Flying Circus Aerodrome  …                  Business
88538                           N/A  …              Instructional
88777                Dallas Executive  …                      ASHO
88796                 NORTH LAS VEGAS  …              Instructional
88814  Brown Field Municipal Airport  …  Public Aircraft - Federal

                 Air.carrier Total.Fatal.Injuries Total.Serious.Injuries  \
118                      N/A                 3.0                    0.0
159                      N/A                 0.0                    0.0
160                      N/A                 2.0                    0.0
245                      N/A                 0.0                    0.0
248                      N/A                 0.0                    0.0
…                        …                   …                      …
88387                    N/A                 0.0                    2.0
88538           McAir Aviation               3.0                    0.0
88777  Commemorative Air Force               6.0                    0.0
88796       702 HELICOPTER INC               0.0                    0.0
88814                U.S. Navy               0.0                    0.0

      Total.Minor.Injuries Total.Uninjured Weather.Condition  \
118                    0.0             0.0               IMC
159                    0.0             3.0               VMC
160                    4.0             0.0               VMC
245                    0.0             3.0               VMC
248                    0.0             3.0               VMC
…                      …               …                 …
88387                  0.0             2.0               VMC
88538                  0.0             0.0               VMC
88777                  0.0             0.0               VMC
88796                  0.0             3.0               VMC
```

```
88814                  0.0             4.0                VMC

       Broad.phase.of.flight   Report.Status Publication.Date
118                 Approach  Probable Cause       19-01-1983
159                 Approach  Probable Cause       23-01-1983
160                   Cruise  Probable Cause       23-01-1983
245                     Taxi  Probable Cause       06-02-1983
248                     Taxi  Probable Cause       06-02-1983
…                          …               …                …
88387                   N/A             N/A       27-09-2022
88538                   N/A             N/A       07-10-2022
88777                   N/A             N/A       30-11-2022
88796                   N/A             N/A       07-12-2022
88814                   N/A             N/A       22-12-2022

[747 rows x 31 columns]
```

[19]:
```
'''
They are 747 rows of duplicated data , I will drop these to ensure data␣
 ↪entegrity.
'''
```

[19]:
```
'\nThey are 747 rows of duplicated data , I will drop these to ensure data
entegrity.\n'
```

[20]:
```
#to drop I use drop duplicates then specify the event column and I state I only␣
 ↪wmat the first ID to stay.
df1 = df1.drop_duplicates(subset=['Event.Id'],keep= 'first')
```

[21]:
```
df1[df1['Event.Id'].duplicated()] #Just to check that the duplicates are gone.
```

[21]:
```
Empty DataFrame
Columns: [Event.Id, Investigation.Type, Accident.Number, Event.Date, Location,
Country, Latitude, Longitude, Airport.Code, Airport.Name, Injury.Severity,
Aircraft.damage, Aircraft.Category, Registration.Number, Make, Model,
Amateur.Built, Number.of.Engines, Engine.Type, FAR.Description, Schedule,
Purpose.of.flight, Air.carrier, Total.Fatal.Injuries, Total.Serious.Injuries,
Total.Minor.Injuries, Total.Uninjured, Weather.Condition, Broad.phase.of.flight,
Report.Status, Publication.Date]
Index: []

[0 rows x 31 columns]
```

Transforming Data Types.

[22]:
```
# to change the data types as it could cause errors when doing analysis.
#As the totals columns and Number.of.Engines are already float.
String_columns = [
```

```
'Latitude',
'Longitude',
'Location',
'Country',
'Airport.Code',
'Airport.Name',
'Injury.Severity',
'Aircraft.damage',
'Aircraft.Category',
'Registration.Number',
'Make',
'Model',
'Amateur.Built',
'Engine.Type',
'FAR.Description',
'Schedule',
'Purpose.of.flight',
'Air.carrier',
'Weather.Condition',
'Broad.phase.of.flight',
'Report.Status']

df1[String_columns] = df1[String_columns].apply(lambda x: x.astype(str)) # The␣
 ↪lambda function just takes each row and converts this into string
# Apply helps to apply to every row in the dataset.
```

[23]:
```
df1.info() # To check if the change worked.
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 70392 entries, 1 to 88886
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                70392 non-null  object
 1   Investigation.Type      70392 non-null  object
 2   Accident.Number         70392 non-null  object
 3   Event.Date              70392 non-null  object
 4   Location                70392 non-null  object
 5   Country                 70392 non-null  object
 6   Latitude                70392 non-null  object
 7   Longitude               70392 non-null  object
 8   Airport.Code            70392 non-null  object
 9   Airport.Name            70392 non-null  object
 10  Injury.Severity         70392 non-null  object
 11  Aircraft.damage         70392 non-null  object
 12  Aircraft.Category       70392 non-null  object
 13  Registration.Number     70392 non-null  object
 14  Make                    70392 non-null  object
```

```
 15  Model                    70392 non-null  object
 16  Amateur.Built            70392 non-null  object
 17  Number.of.Engines        70392 non-null  float64
 18  Engine.Type              70392 non-null  object
 19  FAR.Description          70392 non-null  object
 20  Schedule                 70392 non-null  object
 21  Purpose.of.flight        70392 non-null  object
 22  Air.carrier              70392 non-null  object
 23  Total.Fatal.Injuries     70392 non-null  float64
 24  Total.Serious.Injuries   70392 non-null  float64
 25  Total.Minor.Injuries     70392 non-null  float64
 26  Total.Uninjured          70392 non-null  float64
 27  Weather.Condition        70392 non-null  object
 28  Broad.phase.of.flight    70392 non-null  object
 29  Report.Status            70392 non-null  object
 30  Publication.Date         70392 non-null  object
dtypes: float64(5), object(26)
memory usage: 17.2+ MB
```

[24]:
```
#Resetting the index. I want to change the index to the unique ID Events.
df1 = df1.set_index(['Event.Id'])
df1
```

[24]:

Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude
20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	N/A	N/A
20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056
20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	N/A	N/A
20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	N/A	N/A
20170710X52551	Accident	NYC79AA106	1979-09-17	BOSTON, MA	United States	42.445277	-70.758333
…	…	…	…	…	…	…	…
20221212106443	Accident	WPR23LA064	2022-12-09	Casa Grande, AZ	United States	325736N	1114536W
20221212106444	Accident	ERA23LA085	2022-12-12	Knoxville, TN	United States	355745N	0835218W
20221215106463	Accident	ERA23LA090	2022-12-14				
20221219106470	Accident	ERA23LA091	2022-12-16				
20221227106497	Accident	WPR23LA075	2022-12-26				

```
20221215106463     San Juan, PR  United States    182724N    0066554W
20221219106470  Brooksville, FL  United States    282825N    0822719W
20221227106497       Payson, AZ  United States    341525N    1112021W

               Airport.Code                    Airport.Name Injury.Severity  \
Event.Id
20001218X45447          N/A                             N/A        Fatal(4)
20061025X01555          N/A                             N/A        Fatal(3)
20001218X45448          N/A                             N/A        Fatal(2)
20041105X01764          N/A                             N/A        Fatal(1)
20170710X52551          N/A                             N/A       Non-Fatal
…                     …                               …              …
20221212106443          CGZ  Casa Grande Municipal Airport       Non-Fatal
20221212106444          DKX      KNOXVILLE DOWNTOWN ISLAND       Non-Fatal
20221215106463          SIG  FERNANDO LUIS RIBAS DOMINICCI       Non-Fatal
20221219106470          BKV     BROOKSVILLE-TAMPA BAY RGNL           Minor
20221227106497          PAN                          PAYSON       Non-Fatal

                … Purpose.of.flight                        Air.carrier  \
Event.Id        …
20001218X45447  …          Personal                               N/A
20061025X01555  …          Personal                               N/A
20001218X45448  …          Personal                               N/A
20041105X01764  …          Personal                               N/A
20170710X52551  …               N/A                        Air Canada
…             …               …                                 …
20221212106443  …          Personal                               N/A
20221212106444  …     Instructional  Knoxville Flight Training Academy
20221215106463  …          Personal      SKY WEST AVIATION INC TRUSTEE
20221219106470  …          Personal                GERBER RICHARD E
20221227106497  …          Personal                               N/A

               Total.Fatal.Injuries Total.Serious.Injuries  \
Event.Id
20001218X45447             4.000000              0.000000
20061025X01555             3.000000              0.279881
20001218X45448             2.000000              0.000000
20041105X01764             1.000000              2.000000
20170710X52551             0.647855              0.279881
…                             …                     …
20221212106443             0.000000              0.000000
20221212106444             0.000000              0.000000
20221215106463             0.000000              0.000000
20221219106470             0.000000              1.000000
20221227106497             0.000000              0.000000

               Total.Minor.Injuries Total.Uninjured  Weather.Condition  \
```

```
Event.Id
20001218X45447             0.000000         0.00000                UNK
20061025X01555             0.357061         5.32544                IMC
20001218X45448             0.000000         0.00000                IMC
20041105X01764             0.357061         0.00000                VMC
20170710X52551             1.000000        44.00000                VMC
…                             …             …                    …
20221212106443             0.000000         1.00000                VMC
20221212106444             0.000000         1.00000                VMC
20221215106463             0.000000         1.00000                VMC
20221219106470             0.000000         0.00000                VMC
20221227106497             0.000000         1.00000                VMC

               Broad.phase.of.flight   Report.Status Publication.Date
Event.Id
20001218X45447               Unknown  Probable Cause       19-09-1996
20061025X01555                Cruise  Probable Cause       26-02-2007
20001218X45448                Cruise  Probable Cause       12-09-2000
20041105X01764              Approach  Probable Cause       16-04-1980
20170710X52551                 Climb  Probable Cause       19-09-2017
…                                 …             …                …
20221212106443                   N/A           N/A       13-12-2022
20221212106444                   N/A           N/A       15-12-2022
20221215106463                   N/A           N/A       27-12-2022
20221219106470                   N/A           N/A       23-12-2022
20221227106497                   N/A           N/A       27-12-2022

[70392 rows x 30 columns]
```

[ ]:

The data is now prepared for analysis with no duplicates, missing values and a new index with the unique ID.

5 Data Analysis

The stakeholders require an analysis of each aircraft and aspects that influence risk. I will look at differences in each variable that influences Risk in an airplains. The type of airplane, its use wether commercuial and private and how it influences its risk.

Questions I would like to look at involve:

Aircraft: Make, model with lowest accidents top 5 Make, model with lowest Incidents top 5 Air.carrier with highest Total.Fatal.Injuries and least. Aircraft.Category with highest Total.Fatal.Injuries and least. Amateur.Built

Accidents: Total number of accidents over time with Total number of Incidents over time country with the most accidents and least accidents. Main causes for accidents- report highest.

Further deep analysis: Engine.Type correlation with number of accidents, also Amateur.Built

[25]:
```
df1['Make'].value_counts()
```

[25]:
```
Make
Cessna           17242
Piper             9340
CESSNA            4259
Beech             3423
PIPER             2493
                 ...
Gavilan              1
Baughman             1
Mcconnell            1
Micket               1
ORLICAN S R O        1
Name: count, Length: 7442, dtype: int64
```

CESSNA seems to be the same make as Cessna it could be an error. I will convert all text to small letter so they are many makes I am I want to catch any other doubles.

[26]:
```
df1['Make'] = df1['Make'].str.lower()
df1
```

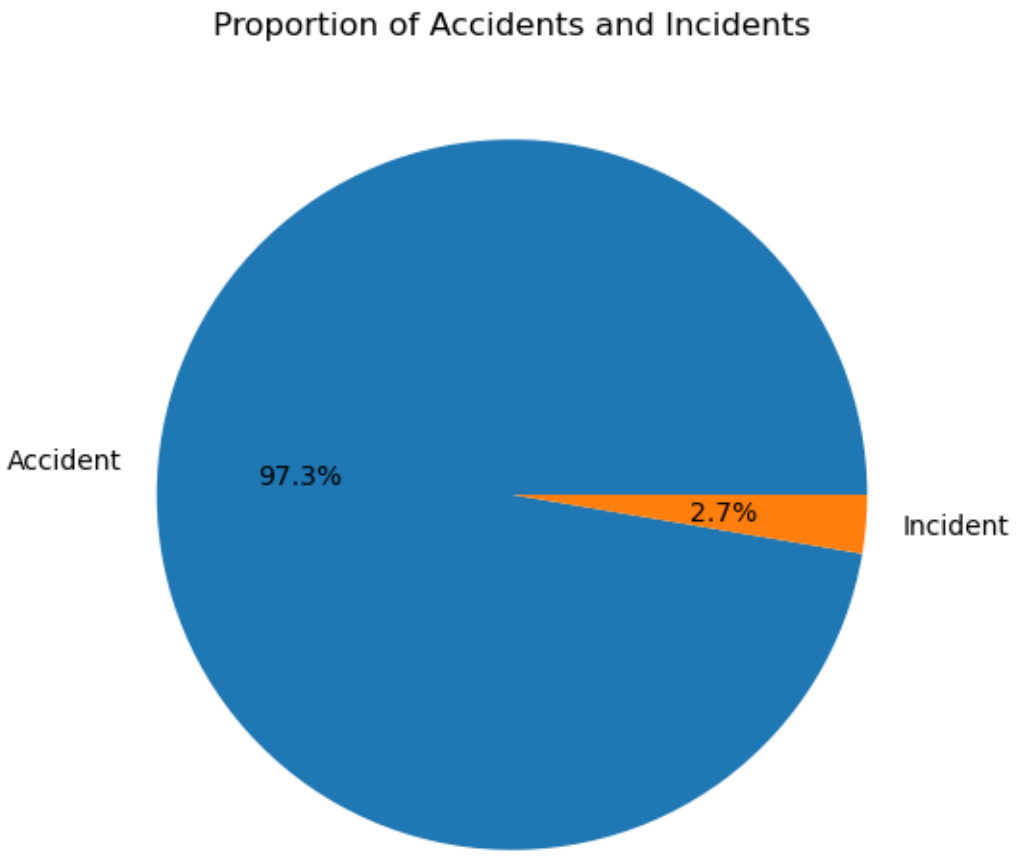
[26]:

Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude
20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	N/A	N/A
20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056
20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	N/A	N/A
20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	N/A	N/A
20170710X52551	Accident	NYC79AA106	1979-09-17	BOSTON, MA	United States	42.445277	-70.758333
...	...	...	...	...	...	...	...
20221212106443	Accident	WPR23LA064	2022-12-09	Casa Grande, AZ	United States	325736N	1114536W
20221212106444	Accident	ERA23LA085	2022-12-12	Knoxville, TN	United States	355745N	0835218W
20221215106463	Accident	ERA23LA090	2022-12-14				
20221219106470	Accident	ERA23LA091	2022-12-16				
20221227106497	Accident	WPR23LA075	2022-12-26				

```
20221215106463     San Juan, PR  United States    182724N    0066554W
20221219106470  Brooksville, FL  United States    282825N    0822719W
20221227106497       Payson, AZ  United States    341525N    1112021W

               Airport.Code                    Airport.Name Injury.Severity  \
Event.Id
20001218X45447          N/A                             N/A        Fatal(4)
20061025X01555          N/A                             N/A        Fatal(3)
20001218X45448          N/A                             N/A        Fatal(2)
20041105X01764          N/A                             N/A        Fatal(1)
20170710X52551          N/A                             N/A       Non-Fatal
…                         …                               …             …
20221212106443          CGZ  Casa Grande Municipal Airport       Non-Fatal
20221212106444          DKX      KNOXVILLE DOWNTOWN ISLAND       Non-Fatal
20221215106463          SIG  FERNANDO LUIS RIBAS DOMINICCI       Non-Fatal
20221219106470          BKV     BROOKSVILLE-TAMPA BAY RGNL           Minor
20221227106497          PAN                          PAYSON       Non-Fatal

                … Purpose.of.flight                       Air.carrier  \
Event.Id        …
20001218X45447  …          Personal                               N/A
20061025X01555  …          Personal                               N/A
20001218X45448  …          Personal                               N/A
20041105X01764  …          Personal                               N/A
20170710X52551  …               N/A                        Air Canada
…             …                 …                                 …
20221212106443  …          Personal                               N/A
20221212106444  …     Instructional  Knoxville Flight Training Academy
20221215106463  …          Personal      SKY WEST AVIATION INC TRUSTEE
20221219106470  …          Personal                GERBER RICHARD E
20221227106497  …          Personal                               N/A

               Total.Fatal.Injuries Total.Serious.Injuries  \
Event.Id
20001218X45447             4.000000              0.000000
20061025X01555             3.000000              0.279881
20001218X45448             2.000000              0.000000
20041105X01764             1.000000              2.000000
20170710X52551             0.647855              0.279881
…                             …                     …
20221212106443             0.000000              0.000000
20221212106444             0.000000              0.000000
20221215106463             0.000000              0.000000
20221219106470             0.000000              1.000000
20221227106497             0.000000              0.000000

               Total.Minor.Injuries Total.Uninjured  Weather.Condition  \
```

```
Event.Id
20001218X45447             0.000000         0.00000                UNK
20061025X01555             0.357061         5.32544                IMC
20001218X45448             0.000000         0.00000                IMC
20041105X01764             0.357061         0.00000                VMC
20170710X52551             1.000000        44.00000                VMC
…                                 …               …                …
20221212106443             0.000000         1.00000                VMC
20221212106444             0.000000         1.00000                VMC
20221215106463             0.000000         1.00000                VMC
20221219106470             0.000000         0.00000                VMC
20221227106497             0.000000         1.00000                VMC

               Broad.phase.of.flight   Report.Status Publication.Date
Event.Id
20001218X45447               Unknown  Probable Cause       19-09-1996
20061025X01555                Cruise  Probable Cause       26-02-2007
20001218X45448                Cruise  Probable Cause       12-09-2000
20041105X01764              Approach  Probable Cause       16-04-1980
20170710X52551                 Climb  Probable Cause       19-09-2017
…                                  …               …                …
20221212106443                   N/A             N/A       13-12-2022
20221212106444                   N/A             N/A       15-12-2022
20221215106463                   N/A             N/A       27-12-2022
20221219106470                   N/A             N/A       23-12-2022
20221227106497                   N/A             N/A       27-12-2022

[70392 rows x 30 columns]
```

[27]:
```
#I will focus on Accidents and Incidents in the column in the Investigation␣
 ↪Type.

#This is because we are looking at risk and the aircraft's safety.
#Percentage of accidents and Incidents.
plt.figure(figsize=(6,6))
Accidents_and_Incidents = df1['Investigation.Type'].value_counts()
plt.pie(Accidents_and_Incidents,labels = Accidents_and_Incidents.index, autopct␣
 ↪= '%1.1f%%' )
plt.title('Proportion of Accidents and Incidents')
plt.ylabel('')
plt.show()
```



[28]:
```
'''
This shows they are alot more accidents concerning aircraft than incidents. An␣
 ↪accident leads to serious injury and death while an incident is,
something that affects safety but not an accident.
'''
```

[28]:
```
'\nThis shows they are alot more accidents concerning aircraft than incidents.
An accident leads to serious injury and death while an incident is,\nsomething
that affects safety but not an accident. \n'
```

[29]:
```
#Now I will break down accidents first, the Make & Model with lowest accidents␣
 ↪(top 5)
#I extract only the data with Accidents.
accidents = df1[df1['Investigation.Type'] == 'Accident']
accidents.head(5)
```

[29]:

Event.Id	Investigation.Type	Accident.Number	Event.Date	Location
20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA
20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA
20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA
20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH
20170710X52551	Accident	NYC79AA106	1979-09-17	BOSTON, MA

Event.Id	Country	Latitude	Longitude	Airport.Code
20001218X45447	United States	N/A	N/A	N/A
20061025X01555	United States	36.922223	-81.878056	N/A
20001218X45448	United States	N/A	N/A	N/A
20041105X01764	United States	N/A	N/A	N/A
20170710X52551	United States	42.445277	-70.758333	N/A

Event.Id	Airport.Name	Injury.Severity	…	Purpose.of.flight
20001218X45447	N/A	Fatal(4)	…	Personal
20061025X01555	N/A	Fatal(3)	…	Personal
20001218X45448	N/A	Fatal(2)	…	Personal
20041105X01764	N/A	Fatal(1)	…	Personal
20170710X52551	N/A	Non-Fatal	…	N/A

Event.Id	Air.carrier	Total.Fatal.Injuries	Total.Serious.Injuries
20001218X45447	N/A	4.000000	0.000000
20061025X01555	N/A	3.000000	0.279881
20001218X45448	N/A	2.000000	0.000000
20041105X01764	N/A	1.000000	2.000000
20170710X52551	Air Canada	0.647855	0.279881

Event.Id	Total.Minor.Injuries	Total.Uninjured	Weather.Condition
20001218X45447	0.000000	0.00000	UNK
20061025X01555	0.357061	5.32544	IMC
20001218X45448	0.000000	0.00000	IMC
20041105X01764	0.357061	0.00000	VMC
20170710X52551	1.000000	44.00000	VMC

Event.Id	Broad.phase.of.flight	Report.Status	Publication.Date
20001218X45447	Unknown	Probable Cause	19-09-1996
20061025X01555	Cruise	Probable Cause	26-02-2007
20001218X45448	Cruise	Probable Cause	12-09-2000
20041105X01764	Approach	Probable Cause	16-04-1980
20170710X52551	Climb	Probable Cause	19-09-2017

```
[5 rows x 30 columns]
```

[30]:
```
# To get the lowest accidents I look for only the Model and count the accidents.
 ↪ I used reset_index to make it into dataset again.
lowest_accidents = accidents.groupby(['Make','Model'])['Investigation.Type'].
 ↪count().reset_index()
lowest_accidents = lowest_accidents.sort_values(by = ['Investigation.Type'],␣
 ↪ascending = True ) # To find the lowest I use ascending order.
lowest_accidents.head(10)#This shows the top 5 lowest accident Makes and Models␣
 ↪in the industry.
```

[30]:

	Make	Model	Investigation.Type
0	107.5 flying corporation	One Design DR 107	1
9681	mcfarland bill	CHALLENGER II	1
9682	mcfarland wm h	RANS S6S	1
9683	mcfaul, daniel d.	Quicksilver GT500	1
9684	mcglashan	T-51 Mustang	1
9685	mcgrath robert f	SONEX	1
9686	mcguire	RAF2000	1
9687	mchargue	BUCKEYE DREAM	1
9688	mchenry george b jr	KR2S	1
9689	mcholland	GLASTAR	1

[31]:
```
#I will now filter for Incidents to get a complete understanding.
incidents = df1[df1['Investigation.Type'] == 'Incident']
incidents.head(5)
```

[31]:

Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	Injury.Severity	…	Purpose.of.flight
20020917X02333	Incident	LAX82IA034	1982-01-03	VAN NUYS, CA	United States	N/A	N/A	VNY	VAN NUYS	Incident	…	Personal
20020917X01764	Incident	ATL82IA029	1982-01-05	PENSACOLA, FL	United States	N/A	N/A	N/A				
20020917X01897	Incident	CHI82IA026	1982-01-12	CHICAGO, IL	United States	N/A	N/A	ORD				
20020917X01765	Incident	ATL82IA034	1982-01-12	CLARKSBURG, WV	United States	N/A	N/A	CKB				
20020917X01766	Incident	ATL82IA038	1982-01-19	WASHINGTON, DC	United States	N/A	N/A	IAD				

```
20020917X01764                    N/A        Incident  …          Business
20020917X01897  CHICAGO O'HARE INTER'L        Incident  …           Unknown
20020917X01765                BENEDUM        Incident  …           Unknown
20020917X01766                    N/A        Incident  …             Ferry

                        Air.carrier Total.Fatal.Injuries  \
Event.Id
20020917X02333                   N/A                 0.0
20020917X01764                   N/A                 0.0
20020917X01897   Trans World Airlines                 0.0
20020917X01765  Aeromech Incorporated                 0.0
20020917X01766                   N/A                 0.0

               Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
Event.Id
20020917X02333                    0.0                 0.0             1.0
20020917X01764                    0.0                 0.0             1.0
20020917X01897                    0.0                 0.0           149.0
20020917X01765                    0.0                 0.0             2.0
20020917X01766                    0.0                 0.0             1.0

                Weather.Condition Broad.phase.of.flight   Report.Status  \
Event.Id
20020917X02333               VMC              Approach  Probable Cause
20020917X01764               VMC                Cruise  Probable Cause
20020917X01897               UNK                Cruise  Probable Cause
20020917X01765               VMC                  Taxi  Probable Cause
20020917X01766               IMC               Descent  Probable Cause

               Publication.Date
Event.Id
20020917X02333       03-01-1983
20020917X01764       05-01-1983
20020917X01897       12-01-1983
20020917X01765       12-01-1983
20020917X01766       19-01-1983

[5 rows x 30 columns]
```

[32]:
```
# To get the lowest Incidents i look for only the Model and count the Incidents␣
 ↪. I use reset_index to make it a dataset again.
lowest_incidents = incidents.groupby(['Make','Model'])['Investigation.Type'].
 ↪count().reset_index()
lowest_incidents= lowest_incidents.sort_values(by = ['Investigation.Type'],␣
 ↪ascending = True ) # To find the lowest I use ascending order.
lowest_incidents.head(10)#This shows the top 5 lowest Incidents Makes and␣
 ↪Models in the industry.
```

[32]:

	Make	Model	Investigation.Type
0	2007 savage air llc	EPIC LT	1
646	embraer	EMB-505	1
648	embraer	ERJ-135	1
649	embraer	ERJ170 200LR	1
650	enstrom	280	1
651	enstrom	F 28F	1
652	enstrom	F-28A	1
653	enstrom	F-28C	1
654	enstrom	F28C	1
656	eurocopter	AS 350 B3	1

Recommendation 1

[33]:
```
'''
An incident is better than an accident in terms of safety, and therefore the␣
 ↪Make and models with top incidents are more recommended for safety, than␣
 ↪that  of the accidents.
You also notice that they are models that repeat for example for accidents it's␣
 ↪mcfarland and for incidents its Embraer.
I recommend that you focus on Models like the 107.5 flying␣
 ↪corporation        One Design DR 107,mcfarland bill        CHALLENGER II,␣
 ↪and mcfarland wm h        RANS S6S
which have few accidents .
Then also look at the 2007 savage air llc        EPIC␣
 ↪LT,embraer        EMB-505, and the embraer        ERJ-135        for␣
 ↪Incidents.
Focus on safe Makes like the Enstorm, embraer, and 2007 savage air ll if the␣
 ↪specific Models are difficult to acquire.
'''
```

[33]:
```
"\nAn incident is better than an accident in terms of safety, and therefore the
Make and models with top incidents are more recommended for safety, than that
of the accidents.\nYou also notice that they are models that repeat for example
for accidents it's mcfarland and for incidents its Embraer. \nI recommend that
you focus on Models like the 107.5 flying corporation\tOne Design DR
107,mcfarland bill\tCHALLENGER II, and mcfarland wm h\tRANS S6S\nwhich have few
accidents .\nThen also look at the 2007 savage air llc\tEPIC
LT,embraer\tEMB-505, and the embraer\tERJ-135\tfor Incidents.\nFocus on safe
Makes like the Enstorm, embraer, and 2007 savage air ll if the specific Models
are difficult to acquire.\n"
```

[34]:
```
# For further analysis I will look at the air carrier and Make with the highest␣
 ↪Total.Fatal.Injuries and the least.
# To get the lowest accidents i look for only the Model and count the accidents␣
 ↪. I use reset index to make it a dataset again.
```

```
Total_Injuries = df1.groupby(['Make'])['Total.Fatal.Injuries'].sum().
 ↪reset_index()
Total_Injuries = Total_Injuries.sort_values(by = ['Total.Fatal.Injuries'],␣
 ↪ascending = False ) # To find the lowest I use ascending order.
Total_Injuries.head(10)#This shows the top 5 lowest accident Makes and Models␣
 ↪in the industry.
```

[34]:

	Make	Total.Fatal.Injuries
1131	cessna	9120.416374
4762	piper	6072.891028
731	boeing	3863.907353
569	beech	3245.855320
583	bell	1104.510027
4048	mcdonnell douglas	1039.137660
164	airbus industrie	882.209916
1775	douglas	853.548524
4287	mooney	637.078941
5193	robinson	517.681615

[35]:
```
#Make with the Lowest Total.Fatal.Injuries
Total_Injuries = Total_Injuries.sort_values(by = ['Total.Fatal.Injuries'],␣
 ↪ascending = True ) # To find the lowest I use ascending order.
Total_Injuries.head(10)#This shows the top 5 lowest accident Makes and Models␣
 ↪in the industry.
```

[35]:

	Make	Total.Fatal.Injuries
6655	william m oprendek	0.0
1548	darney	0.0
1524	dan jelinek	0.0
1520	dale conover	0.0
1490	curtiss moses	0.0
1499	czech sport	0.0
1500	czech sport aircraft	0.0
1501	czech sport aircraft a s	0.0
1502	czech sport aircraft a.s.	0.0
1504	czech sportplanes sro	0.0

Recommendation 2

[36]:
```
'''
The Makes to avoid the most include the cessna, piper, being, beech, bell,␣
 ↪mcdonnell douglas, airbus industries, douglas, money and robinson.
As these have some of the highest Fatal injuries in the industry.
The Makes that you can further focus on which are less prone to fatal injuries␣
 ↪include the campbell john,holmes gary don,holmes william e,holmgren,
holmlund victor p        ,holsclaw francis e, hood john sidney, john murphy,␣
 ↪john roscoe.
```

```
These top Makes have has Zero Fatal injuries which assures maximum safetly and thus less risk.
'''
```

[36]:
```
'\nThe Makes to avoid the most include the cessna, piper, being, beech, bell, mcdonnell douglas, airbus industries, douglas, money and robinson.\nAs these have some of the highest Fatal injuries in the industry. \nThe Makes that you can further focus on which are less prone to fatal injuries include the campbell john,holmes gary don,holmes william e,holmgren,\nholmlund victor p\t,holsclaw francis e, hood john sidney, john murphy, john roscoe.\nThese top Makes have has Zero Fatal injuries which assures maximum safetly and thus less risk.\n'
```

[37]:
```
#Aircraft.Category with highest Total.Fatal.Injuries and least.
Aircraft_Injuries = df1.groupby(['Aircraft.Category'])['Total.Fatal.Injuries'].sum().reset_index()
Aircraft_Injuries = Aircraft_Injuries.sort_values(by = ['Total.Fatal.Injuries'], ascending = True ) # To find the lowest I use ascending order.
Aircraft_Injuries.head(100)#This shows the top 5 lowest Fatal Injuries and aircraft category
```

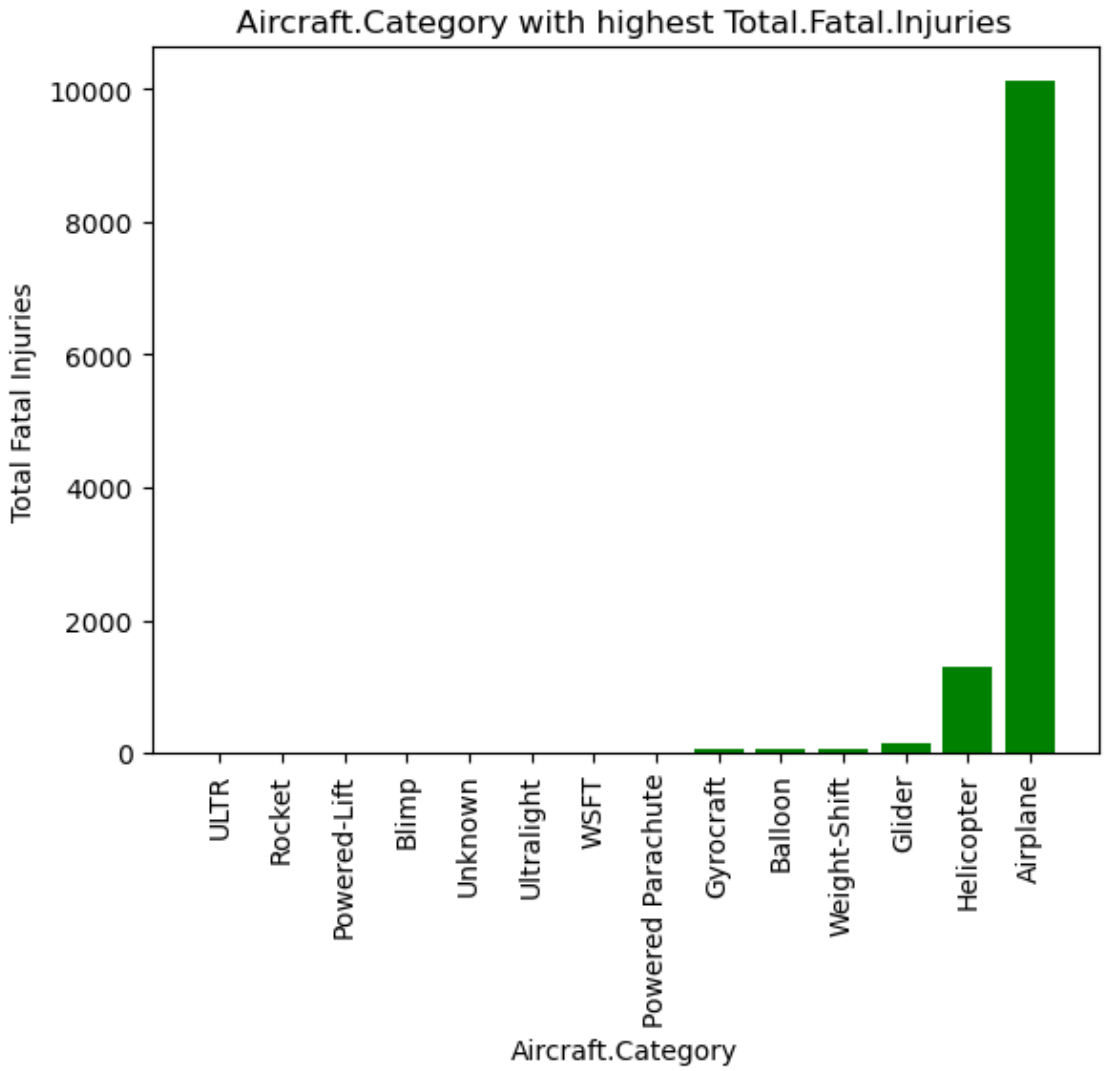
[37]:

	Aircraft.Category	Total.Fatal.Injuries
10	ULTR	0.000000
9	Rocket	1.000000
8	Powered-Lift	1.295710
2	Blimp	1.943565
12	Unknown	2.000000
11	Ultralight	8.887131
13	WSFT	9.000000
7	Powered Parachute	14.000000
4	Gyrocraft	55.957103
1	Balloon	63.266351
14	Weight-Shift	67.000000
3	Glider	147.363398
5	Helicopter	1288.819275
0	Airplane	10123.299104
6	N/A	27863.385505

[38]:
```
Aircraft_Injuries = Aircraft_Injuries[Aircraft_Injuries['Aircraft.Category'] != 'N/A'] #To help filter out the N/A
```

[39]:
```
#This is a bar graph to visually see the lowest and highest.
plt.bar(Aircraft_Injuries['Aircraft.Category'],Aircraft_Injuries['Total.Fatal.Injuries'], color='green') #The columns needed
plt.xlabel('Aircraft.Category')
plt.xticks(rotation=90) # This is to make the categories veritical so that they all fit.
plt.ylabel('Total Fatal Injuries')
```

```
plt.title('Aircraft.Category with highest Total.Fatal.Injuries')

plt.show()
```



Recommendation 3

[40]:
```
'''
As seen in the graph the most injury-prone aircraft is the airplane, compared␣
 ↪to that of the Helicopter and even Rocket.
This shows that the company should consider having aircraft that move away from␣
 ↪purchasing a large amount of Airplanes for safeflights.
However, I also note that Airplanes are practical, and therefore still needed␣
 ↪in a business sense so I will further breakdown Airplanes,
To see which is the most safe.
```

```
'''
```

[40]:
```
'\nAs seen in the graph the most injury-prone aircraft is the airplane, compared
to that of the Helicopter and even Rocket.\nThis shows that the company should
consider having aircraft that move away from purchasing a large amount of
Airplanes for safeflights.\nHowever, I also note that Airplanes are practical,
and therefore still needed in a business sense so I will further breakdown
Airplanes,\nTo see which is the most safe.\n'
```

[41]:
```
#Airplanes with the Lowest total Fatal. Injuries .
'''
In order to focus on airplanes I had to create a group by the can filter for␣
 ↪airplanes with their Make, Model, Later on, I added total unInjuried
Because I realized I have to further filter as the number of non fatalities is␣
 ↪very high so I added into the dataset and summed it also.

I aslo further added the column 'Aircraft.damage' to reduce the list of␣
 ↪aircraft further into what I would consider the strongest.
'''
Airplane_Injuries= df1.groupby(['Aircraft.Category','Make', 'Model','Aircraft.
 ↪damage'])[['Total.Fatal.Injuries','Total.Uninjured','Total.Serious.
 ↪Injuries','Total.Minor.Injuries']].sum().reset_index()
```

[42]:
```
#To filter for both Airplanes and Fatalities that are Zero. then store this␣
 ↪inside a variable
Airplane_Injuries = Airplane_Injuries[(Airplane_Injuries['Aircraft.Category']␣
 ↪== 'Airplane') & (Airplane_Injuries['Total.Fatal.Injuries'] == 0 )]
```

[43]:
```
Airplane_Injuries # just to see if it loads correctly
```

[43]:

	Aircraft.Category	Make	Model	Aircraft.damage	\
0	Airplane	177mf llc	PITTS MODEL 12	Substantial	
1	Airplane	2007 savage air llc	EPIC LT	Minor	
2	Airplane	2021fx3 llc	CCX-2000	Substantial	
3	Airplane	5 rivers llc	SQ-2	Substantial	
4	Airplane	781569 inc	FX 210	Substantial	
…	…	…	…	…	
7892	Airplane	ziermann	RV8	Substantial	
7896	Airplane	zlin	Savage	Substantial	
7897	Airplane	zlin	Z143	Substantial	
7900	Airplane	zlin aviation	Savage Cub-S	Substantial	
7902	Airplane	zwicker murray r	GLASTAR	Substantial	

	Total.Fatal.Injuries	Total.Uninjured	Total.Serious.Injuries	\
0	0.0	0.0	2.0	
1	0.0	4.0	0.0	
2	0.0	4.0	0.0	

```
3                       0.0                 1.0                       0.0
4                       0.0                 0.0                       3.0
…                       …                   …                         …
7892                    0.0                 0.0                       0.0
7896                    0.0                 1.0                       0.0
7897                    0.0                 1.0                       0.0
7900                    0.0                 1.0                       0.0
7902                    0.0                 2.0                       0.0

      Total.Minor.Injuries
0                       0.0
1                       0.0
2                       0.0
3                       1.0
4                       0.0
…                       …
7892                    1.0
7896                    0.0
7897                    0.0
7900                    0.0
7902                    0.0

[4596 rows x 8 columns]
```

[44]:
```
#To further reduce the dataset to safe airplanes
Airplane_Injuries = Airplane_Injuries[(Airplane_Injuries['Total.Serious.
 ↪Injuries'] == 0) & (Airplane_Injuries['Total.Minor.Injuries'] == 0 )]
Airplane_Injuries
```

[44]:
```
     Aircraft.Category                  Make                 Model  \
1              Airplane   2007 savage air llc               EPIC LT
2              Airplane          2021fx3 llc              CCX-2000
5              Airplane   aardema robert john  1 AARDEMA RAG WNG SP
6              Airplane  ab sportine aviacija             Genesis 2
11             Airplane  ackland jeffrey dean                 SH 3R
…                 …                     …                    …
7887           Airplane                zenith         Zodiac 601 XL
7896           Airplane                  zlin               Savage
7897           Airplane                  zlin                 Z143
7900           Airplane         zlin aviation          Savage Cub-S
7902           Airplane     zwicker murray r               GLASTAR

     Aircraft.damage  Total.Fatal.Injuries  Total.Uninjured  \
1              Minor                   0.0              4.0
2        Substantial                   0.0              4.0
5        Substantial                   0.0              1.0
6        Substantial                   0.0              1.0
```

```
11       Substantial                   0.0              2.0
…              …                     …                …
7887     Substantial                   0.0              1.0
7896     Substantial                   0.0              1.0
7897     Substantial                   0.0              1.0
7900     Substantial                   0.0              1.0
7902     Substantial                   0.0              2.0

      Total.Serious.Injuries  Total.Minor.Injuries
1                        0.0                   0.0
2                        0.0                   0.0
5                        0.0                   0.0
6                        0.0                   0.0
11                       0.0                   0.0
…                        …                     …
7887                     0.0                   0.0
7896                     0.0                   0.0
7897                     0.0                   0.0
7900                     0.0                   0.0
7902                     0.0                   0.0

[2747 rows x 8 columns]
```

[45]:
```
#This is still a very large list we can further filter for Total.Uninjured and␣
 ↪see the highest number saved
Airplane_Injuries = Airplane_Injuries[(Airplane_Injuries['Total.Uninjured'] >␣
 ↪100) & (Airplane_Injuries['Aircraft.damage'] == 'Minor' )]
Airplane_Injuries = Airplane_Injuries.sort_values(by = ['Total.Uninjured'],␣
 ↪ascending = False )
Airplane_Injuries
```

[45]:
```
     Aircraft.Category               Make        Model Aircraft.damage  \
1277          Airplane             boeing      737-732           Minor
340           Airplane             airbus         A330           Minor
371           Airplane   airbus industrie     A330-323           Minor
1369          Airplane             boeing      777-2Q8           Minor
346           Airplane             airbus   A340 - 300           Minor
4922          Airplane  mcdonnell douglas    DC-10-30F           Minor
1360          Airplane             boeing      777 222           Minor
1264          Airplane             boeing      737-3H4           Minor
319           Airplane             airbus     A319 115           Minor
1241          Airplane             boeing      737 7H4           Minor
1308          Airplane             boeing      747-422           Minor
1337          Airplane             boeing          767           Minor
1342          Airplane             boeing      767 332           Minor
1278          Airplane             boeing      737-7H4           Minor
1323          Airplane             boeing      757-222           Minor
```

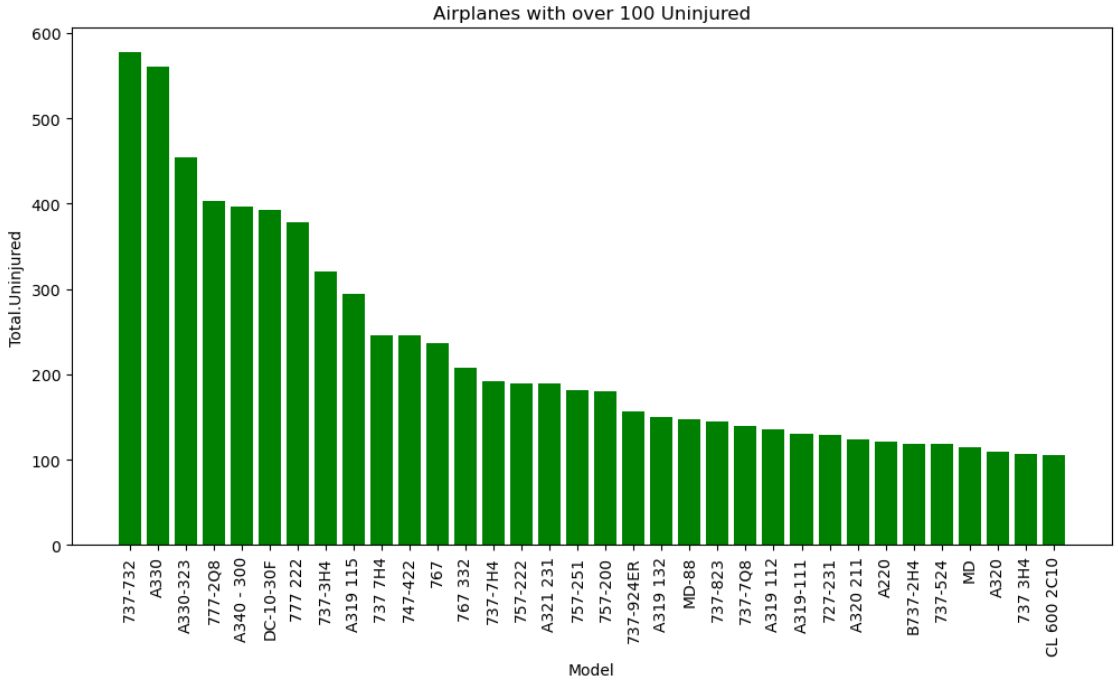
336	Airplane	airbus	A321 231	Minor
1330	Airplane	boeing	757-251	Minor
1321	Airplane	boeing	757-200	Minor
1291	Airplane	boeing	737-924ER	Minor
321	Airplane	airbus	A319 132	Minor
4944	Airplane	mcdonnell douglas	MD-88	Minor
1282	Airplane	boeing	737-823	Minor
1281	Airplane	boeing	737-7Q8	Minor
317	Airplane	airbus	A319 112	Minor
323	Airplane	airbus	A319-111	Minor
1227	Airplane	boeing	727-231	Minor
361	Airplane	airbus industrie	A320 211	Minor
313	Airplane	airbus	A220	Minor
1397	Airplane	boeing	B737-2H4	Minor
1271	Airplane	boeing	737-524	Minor
1411	Airplane	boeing	MD	Minor
325	Airplane	airbus	A320	Minor
1235	Airplane	boeing	737 3H4	Minor
1461	Airplane	bombardier inc	CL 600 2C10	Minor

	Total.Fatal.Injuries	Total.Uninjured	Total.Serious.Injuries	\
1277	0.0	577.0	0.0	
340	0.0	560.0	0.0	
371	0.0	454.0	0.0	
1369	0.0	403.0	0.0	
346	0.0	397.0	0.0	
4922	0.0	393.0	0.0	
1360	0.0	378.0	0.0	
1264	0.0	320.0	0.0	
319	0.0	294.0	0.0	
1241	0.0	246.0	0.0	
1308	0.0	246.0	0.0	
1337	0.0	237.0	0.0	
1342	0.0	208.0	0.0	
1278	0.0	192.0	0.0	
1323	0.0	190.0	0.0	
336	0.0	189.0	0.0	
1330	0.0	182.0	0.0	
1321	0.0	180.0	0.0	
1291	0.0	157.0	0.0	
321	0.0	150.0	0.0	
4944	0.0	148.0	0.0	
1282	0.0	145.0	0.0	
1281	0.0	139.0	0.0	
317	0.0	136.0	0.0	
323	0.0	130.0	0.0	
1227	0.0	129.0	0.0	

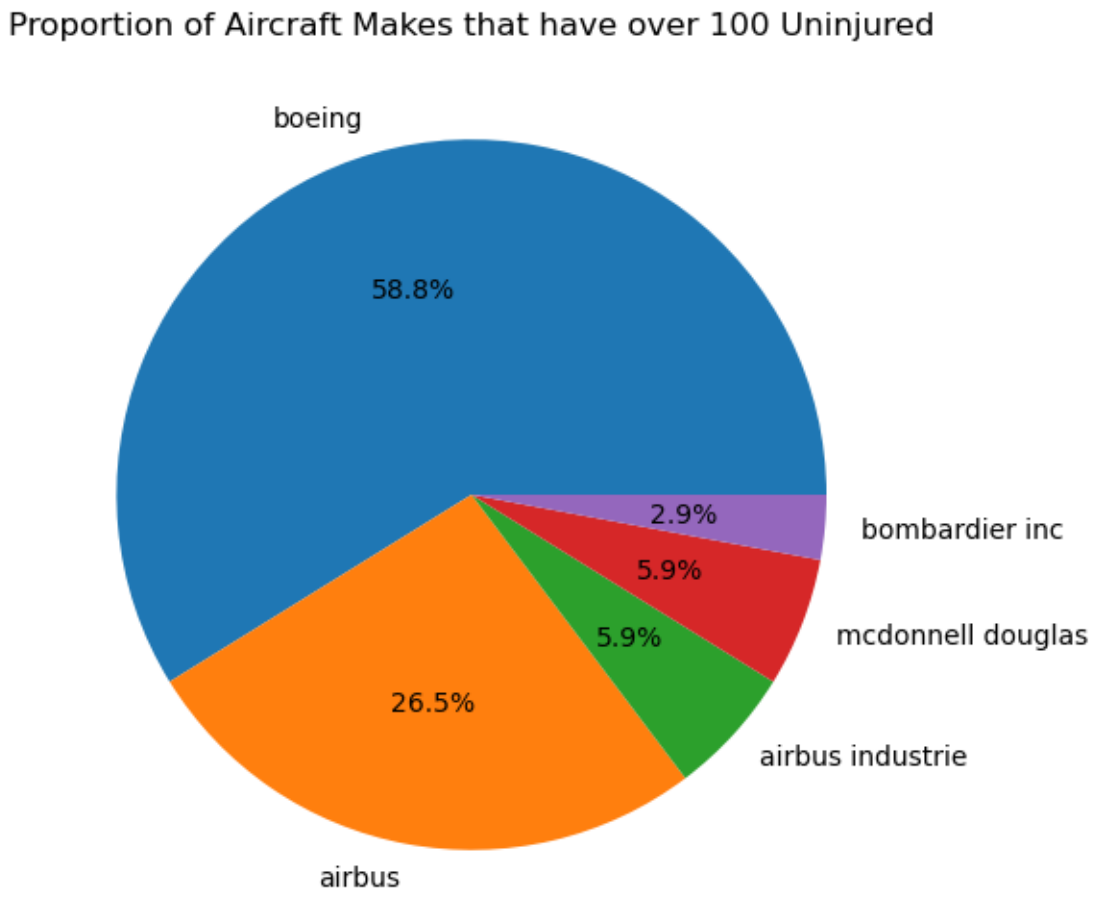
```
361                     0.0             124.0                   0.0
313                     0.0             121.0                   0.0
1397                    0.0             119.0                   0.0
1271                    0.0             118.0                   0.0
1411                    0.0             115.0                   0.0
325                     0.0             109.0                   0.0
1235                    0.0             107.0                   0.0
1461                    0.0             105.0                   0.0

      Total.Minor.Injuries
1277                    0.0
340                     0.0
371                     0.0
1369                    0.0
346                     0.0
4922                    0.0
1360                    0.0
1264                    0.0
319                     0.0
1241                    0.0
1308                    0.0
1337                    0.0
1342                    0.0
1278                    0.0
1323                    0.0
336                     0.0
1330                    0.0
1321                    0.0
1291                    0.0
321                     0.0
4944                    0.0
1282                    0.0
1281                    0.0
317                     0.0
323                     0.0
1227                    0.0
361                     0.0
313                     0.0
1397                    0.0
1271                    0.0
1411                    0.0
325                     0.0
1235                    0.0
1461                    0.0
```

[46]:
```
#I will turn this into a pie chat and bar chart
#Airplanes with over 100 Uninjured.
```

```
plt.figure(figsize=(12, 6))
plt.bar(Airplane_Injuries['Model'],Airplane_Injuries['Total.Uninjured'], color␣
↪='green')
plt.xlabel('Model')
plt.ylabel('Total.Uninjured')
plt.title('Airplanes with over 100 Uninjured')
plt.xticks(rotation=90)
plt.show()
```



[47]:
```
plt.figure(figsize=(6,6))
Aircraft_Makes = Airplane_Injuries['Make'].value_counts()
plt.pie(Aircraft_Makes, labels = Aircraft_Makes.index, autopct = '%1.1f%%' )
plt.title('Proportion of Aircraft Makes that have over 100 Uninjured')
plt.ylabel('')
plt.show()
```



Recommendation 4

[48]:
```
'''
If you have to get an airplane you can focus on the least risky which is the␣
 ↪737-732.
This shows a Data set of all of the least risky airplanes, with the best being␣
 ↪the boeing        737-732        which leads me to assume that,
despite the boeing Make being on the list for some of the highest number of␣
 ↪accidents it is also ranked for having the highest number of
Uninjured. The Make is very strong and the model has the least amount of␣
 ↪Injuries and leaves with minor damage.
'''
```

[48]:
```
'\nIf you have to get an airplane you can focus on the least risky which is the
737-732.\nThis shows a Data set of all of the least risky airplanes, with the
best being the boeing\t737-732\twhich leads me to assume that,\ndespite the
boeing Make being on the list for some of the highest number of accidents it is
```

```
also ranked for having the highest number of\nUninjured. The Make is very strong
and the model has the least amount of Injuries and leaves with minor damage.\n'
```

[49]:
```
df1 = df1.reset_index()
```

[50]:
```
df1.to_csv('Cleaned_AviationData.csv',index = False)#extract the data for␣
↪tableau
```

[ ]:
```

```