Analysis on risk of Aircraft

Overview

This work is a first attemp trying to determine the risks associated with aircrafts using caggle Aviation dataset that includes aviation accident data from 1962 to 2023.

Business Understanding

- A company wants to purchase and operate airplanes for commercial and private enterprises.
- As data scientists, We are charged to find the aircraft with the lowest risk for the company using caggle Aviation dataset that includes aviation accident data from 1962 to 2023.
- We will clean the data and then make analysis to propose potential solutions.

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

Data Understanding

```
# importing the data with a glampse on the top 5 rows.
df = pd.read_csv('Data/Aviation_Data.csv', low_memory=False)
df.head()
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
2  20061025X01555           Accident      NYC07LA005  1974-08-30
3  20001218X45448           Accident      LAX96LA321  1977-06-19
4  20041105X01764           Accident      CHI79FA064  1979-08-02

          Location        Country   Latitude   Longitude Airport.Code
\
0  MOOSE CREEK, ID  United States        NaN         NaN          NaN

1   BRIDGEPORT, CA  United States        NaN         NaN          NaN

2    Saltville, VA  United States  36.922223  -81.878056          NaN

3       EUREKA, CA  United States        NaN         NaN          NaN

4       Canton, OH  United States        NaN         NaN          NaN
```

```
  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0

3          NaN  ...          Personal         NaN                  2.0

4          NaN  ...          Personal         NaN                  1.0


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN
3                    0.0                  0.0             0.0
4                    2.0                  NaN             0.0

  Weather.Condition  Broad.phase.of.flight   Report.Status
Publication.Date
0               UNK                 Cruise  Probable Cause
NaN
1               UNK                Unknown  Probable Cause       19-
09-1996
2               IMC                 Cruise  Probable Cause       26-
02-2007
3               IMC                 Cruise  Probable Cause       12-
09-2000
4               VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

Data Preparation

The first thing we see while looking at the top 5 rows of our dataset is that the columns name are not properly writen, let's fix that.

```
# Replacing "." in the name with a space.
df.columns = df.columns.str.replace("."," ")
df.head()

         Event Id Investigation Type Accident Number  Event Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19
2  20061025X01555           Accident      NYC07LA005  1974-08-30
3  20001218X45448           Accident      LAX96LA321  1977-06-19
```

```
4  20041105X01764         Accident      CHI79FA064  1979-08-02

          Location       Country   Latitude   Longitude Airport Code
\
0  MOOSE CREEK, ID  United States        NaN         NaN          NaN

1   BRIDGEPORT, CA  United States        NaN         NaN          NaN

2    Saltville, VA  United States  36.922223  -81.878056          NaN

3       EUREKA, CA  United States        NaN         NaN          NaN

4       Canton, OH  United States        NaN         NaN          NaN


  Airport Name  ... Purpose of flight Air carrier Total Fatal Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0

3          NaN  ...          Personal         NaN                  2.0

4          NaN  ...          Personal         NaN                  1.0


  Total Serious Injuries Total Minor Injuries Total Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN
3                    0.0                  0.0             0.0
4                    2.0                  NaN             0.0

  Weather Condition  Broad phase of flight   Report Status Publication
Date
0               UNK                 Cruise  Probable Cause
NaN
1               UNK                Unknown  Probable Cause       19-
09-1996
2               IMC                 Cruise  Probable Cause       26-
02-2007
3               IMC                 Cruise  Probable Cause       12-
09-2000
4               VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

Let's see our dataset information, that will allow us to answer to the questions:

- What are all of our columns label?
- What is the size of the dataset?
- Do we have missing values?

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event Id                88889 non-null  object 
 1   Investigation Type      90348 non-null  object 
 2   Accident Number         88889 non-null  object 
 3   Event Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport Code            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
```

Before saying that we have 90348 records in our dataset, let us check for duplicated values.

```
# Checking for duplicated values
df.duplicated().sum()
```

```
1390
```

We have 1390 duplicated values, let us remove them.

```python
# Remove duplicates and validation
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

```
0
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 88958 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event Id                88889 non-null  object 
 1   Investigation Type      88958 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: 21.7+ MB
```

Now we can say that we have 88958 distinct records, 30 columns with several missing values. Let's see them by column name.

```
# missing values by column name
df.isna().sum() #/df.isna().count())*100
```

```
Event Id                      69
Investigation Type             0
Accident Number               69
Event Date                    69
Location                     121
Country                      295
Latitude                   54576
Longitude                  54585
Airport Code               38709
Airport Name               36168
Injury Severity             1069
Aircraft damage             3263
Aircraft Category          56671
Registration Number         1386
Make                         132
Model                        161
Amateur Built                171
Number of Engines           6153
Engine Type                 7146
FAR Description            56935
Schedule                   76376
Purpose of flight           6261
Air carrier                72310
Total Fatal Injuries       11470
Total Serious Injuries     12579
Total Minor Injuries       12002
Total Uninjured             5981
Weather Condition           4561
Broad phase of flight      27234
Report Status               6450
Publication Date           15299
dtype: int64
```

We are already noticing big problems here, we have variable with 60% to 85% of missing values, which is a lot by variable. lets us treat them separately, starting with the leading variable Aircraft Category.

64% of data of Aircraft Category column are missing, as it is a decisive variable, let's us see it's values

```
df['Aircraft Category'].value_counts()
```

```
Airplane              27617
Helicopter             3440
```

```
Glider                  508
Balloon                 231
Gyrocraft               173
Weight-Shift            161
Powered Parachute        91
Ultralight               30
Unknown                  14
WSFT                      9
Powered-Lift              5
Blimp                     4
UNK                       2
Rocket                    1
ULTR                      1
Name: Aircraft Category, dtype: int64
```

As there is an 'Unknown' Category, let's fusion the NaNs with this category, as they are also unknown.

```
# Replacing all NaN values in Aircraft.Category with 'Null Category'
df['Aircraft Category'].fillna('Unknown',inplace=True)
df['Aircraft Category'].value_counts()
```

```
Unknown               56685
Airplane              27617
Helicopter             3440
Glider                  508
Balloon                 231
Gyrocraft               173
Weight-Shift            161
Powered Parachute        91
Ultralight               30
WSFT                      9
Powered-Lift              5
Blimp                     4
UNK                       2
Rocket                    1
ULTR                      1
Name: Aircraft Category, dtype: int64
```

Now, let us drop all the rows with less than 1% of missing data by column, but before let us take a look at the Make column

```
df['Make'].value_counts()[:20]
```

```
Cessna                22227
Piper                 12029
CESSNA                 4922
Beech                  4330
PIPER                  2841
```

```
Bell                      2134
Boeing                    1594
BOEING                    1151
Grumman                   1094
Mooney                    1092
BEECH                     1042
Robinson                   946
Bellanca                   886
Hughes                     795
Schweizer                  629
Air Tractor                595
BELL                       588
Mcdonnell Douglas          526
Aeronca                    487
Maule                      445
Name: Make, dtype: int64
```

We see some incoherences in the formating, Let'us fix it.

```
df['Make'] = df['Make'].str.title()

df.dropna(axis =0, subset= ['Event Id','Location','Country','Accident Number','Event Date','Make','Model','Amateur Built'], inplace=True)

df.isna().sum()  #/df.isna().count())*100
```

```
Event Id                      0
Investigation Type            0
Accident Number               0
Event Date                    0
Location                      0
Country                       0
Latitude                  54094
Longitude                 54103
Airport Code              38271
Airport Name              35751
Injury Severity             979
Aircraft damage            3134
Aircraft Category             0
Registration Number        1185
Make                          0
Model                         0
Amateur Built                 0
Number of Engines          5913
Engine Type                6921
FAR Description           56509
Schedule                  76060
Purpose of flight          6060
Air carrier               71856
Total Fatal Injuries      11299
```

```
Total Serious Injuries    12378
Total Minor Injuries      11797
Total Uninjured            5813
Weather Condition          4375
Broad phase of flight     26970
Report Status              6335
Publication Date          15145
dtype: int64
```

Also, let's us drop the columns with too many NaNs, more than 60%

```
#  Drop the columns with more than 60% NaNs
df.drop(['Schedule','Air carrier','FAR
Description','Latitude','Longitude'],axis =1, inplace =True)
```

Now let's us drop columns that won't serve this analysis as Airport code or Airport Name or Registration Number Columns.

```
df.drop(['Airport Code','Airport Name','Registration
Number','Publication Date'],axis =1, inplace =True)

(df.isna().sum()/df.isna().count())*100

Event Id                   0.000000
Investigation Type         0.000000
Accident Number            0.000000
Event Date                 0.000000
Location                   0.000000
Country                    0.000000
Injury Severity            1.107391
Aircraft damage            3.545008
Aircraft Category          0.000000
Make                       0.000000
Model                      0.000000
Amateur Built              0.000000
Number of Engines          6.688460
Engine Type                7.828654
Purpose of flight          6.854738
Total Fatal Injuries      12.780807
Total Serious Injuries    14.001312
Total Minor Injuries      13.344117
Total Uninjured            6.575346
Weather Condition          4.948759
Broad phase of flight     30.506979
Report Status              7.165803
dtype: float64
```

Things are starting to look great, let us treat the remaining columns with missing values individually. As we don't want to modify in a certain way the data, if one of the column category is 'Unknown' or 'Unavailable', we will merge the NaNs with the value of this column.

```
df['Injury Severity'].unique()
```

```
array(['Fatal(2)', 'Fatal(4)', 'Fatal(3)', 'Fatal(1)', 'Non-Fatal',
       'Incident', 'Fatal(8)', 'Fatal(78)', 'Fatal(7)', 'Fatal(6)',
       'Fatal(5)', 'Fatal(153)', 'Fatal(12)', 'Fatal(14)',
'Fatal(23)',
       'Fatal(10)', 'Fatal(11)', 'Fatal(17)', 'Fatal(13)',
'Fatal(29)',
       'Fatal(70)', 'Fatal(9)', 'Unavailable', 'Fatal(135)',
'Fatal(31)',
       'Fatal(256)', 'Fatal(25)', 'Fatal(82)', 'Fatal(156)',
'Fatal(28)',
       'Fatal(18)', 'Fatal(43)', 'Fatal(270)', 'Fatal(144)',
'Fatal(174)',
       'Fatal(111)', 'Fatal(131)', 'Fatal(20)', 'Fatal(73)',
'Fatal(27)',
       'Fatal(34)', 'Fatal(87)', 'Fatal(30)', 'Fatal(16)',
'Fatal(47)',
       'Fatal(56)', 'Fatal(37)', 'Fatal(132)', 'Fatal(68)',
'Fatal(15)',
       'Fatal(54)', 'Fatal(52)', 'Fatal(65)', 'Fatal(72)',
'Fatal(160)',
       'Fatal(189)', 'Fatal(123)', 'Fatal(33)', 'Fatal(110)',
       'Fatal(230)', 'Fatal(97)', 'Fatal(349)', 'Fatal(125)',
'Fatal(35)',
       'Fatal(228)', 'Fatal(75)', 'Fatal(104)', 'Fatal(229)',
'Fatal(80)',
       'Fatal(217)', 'Fatal(169)', 'Fatal(88)', 'Fatal(19)',
'Fatal(60)',
       'Fatal(113)', 'Fatal(143)', 'Fatal(83)', 'Fatal(24)',
'Fatal(44)',
       'Fatal(64)', 'Fatal(92)', 'Fatal(118)', 'Fatal(265)',
'Fatal(26)',
       'Fatal(138)', 'Fatal(206)', 'Fatal(71)', 'Fatal(21)',
'Fatal(46)',
       'Fatal(102)', 'Fatal(115)', 'Fatal(141)', 'Fatal(55)',
       'Fatal(121)', 'Fatal(45)', 'Fatal(145)', 'Fatal(117)',
       'Fatal(107)', 'Fatal(124)', 'Fatal(49)', 'Fatal(154)',
'Fatal(96)',
       'Fatal(199)', 'Fatal(89)', 'Fatal', nan, 'Minor', 'Serious'],
      dtype=object)
```

As there is an 'Unavailable' label, let's us fill the NaNs with that too as both categories look the same for us in our analysis.

```
df['Injury Severity'].fillna('Unavailable',inplace=True)

# Aircraft Damage values
df['Aircraft damage'].value_counts()

Substantial    63944
Destroyed      18459
Minor           2750
Unknown          119
Name: Aircraft damage, dtype: int64

# Fill Aircraft Damage 3263 null values
df['Aircraft damage'].fillna('Unknown',inplace=True)

df['Number of Engines'].value_counts(normalize = True)

1.0    0.841017
2.0    0.133223
0.0    0.014789
3.0    0.005770
4.0    0.005152
8.0    0.000036
6.0    0.000012
Name: Number of Engines, dtype: float64

df['Number of Engines'].median()

1.0

df['Number of Engines'].fillna(df['Number of Engines'].median(),
inplace=True)

df['Number of Engines'].value_counts()

1.0    75291
2.0    10990
0.0     1220
3.0      476
4.0      425
8.0        3
6.0        1
Name: Number of Engines, dtype: int64

df['Engine Type'].value_counts(normalize = True)

Reciprocating      0.851236
Turbo Shaft        0.043186
Turbo Prop         0.041455
Turbo Fan          0.030214
Unknown            0.024728
Turbo Jet          0.008603
None               0.000233
```

```
Geared Turbofan    0.000147
Electric           0.000123
LR                 0.000025
NONE               0.000025
UNK                0.000012
Hybrid Rocket      0.000012
Name: Engine Type, dtype: float64
```

```
df['Engine Type'].fillna('Unknown',inplace=True)
```

```
df['Purpose of flight'].value_counts(normalize = True)
```

```
Personal                     0.599094
Instructional                0.128507
Unknown                      0.080878
Aerial Application           0.057198
Business                     0.048576
Positioning                  0.019746
Other Work Use               0.015289
Ferry                        0.009764
Aerial Observation           0.009533
Public Aircraft              0.008719
Executive/corporate          0.006631
Flight Test                  0.004894
Skydiving                    0.002210
External Load                0.001494
Public Aircraft - Federal    0.001263
Banner Tow                   0.001227
Air Race show                0.001202
Public Aircraft - Local      0.000899
Public Aircraft - State      0.000765
Air Race/show                0.000716
Glider Tow                   0.000644
Firefighting                 0.000486
Air Drop                     0.000134
ASHO                         0.000073
PUBS                         0.000049
PUBL                         0.000012
Name: Purpose of flight, dtype: float64
```

```
df['Purpose of flight'].fillna('Unknown',inplace=True)
```

```
df['Total Fatal Injuries'].fillna(df['Total Fatal Injuries'].median(),
inplace=True)
```

```
df['Total Minor Injuries'].fillna(df['Total Minor Injuries'].median(),
inplace=True)
```

```
df['Total Serious Injuries'].fillna(df['Total Serious
Injuries'].median(), inplace=True)
```

```
df['Total Uninjured'].fillna(df['Total Uninjured'].median(),
inplace=True)
```

```
df['Weather Condition'].value_counts() #(normalize = True)
#fillna('Unknown',inplace=True)
```

```
VMC    76999
IMC     5947
UNK      823
Unk      262
Name: Weather Condition, dtype: int64
```

```
df['Weather Condition'] = df['Weather Condition'].str.upper()
```

```
df['Weather Condition'].value_counts()
```

```
VMC    76999
IMC     5947
UNK     1085
Name: Weather Condition, dtype: int64
```

```
df['Weather Condition'].mode()
```

```
0    VMC
dtype: object
```

```
df['Weather Condition'].fillna('VMC', inplace=True)
```

```
df['Broad phase of flight'].value_counts(normalize = True) #'Broad
phase of flight'
```

```
Landing        0.250374
Takeoff        0.202406
Cruise         0.166124
Maneuvering    0.132056
Approach       0.106078
Climb          0.032847
Taxi           0.031740
Descent        0.030503
Go-around      0.021990
Standing       0.015203
Unknown        0.008741
Other          0.001937
Name: Broad phase of flight, dtype: float64
```

```
df['Broad phase of flight'].fillna('Unknown',inplace=True)
```

```
df['Report Status'].mode()
```

```
0    Probable Cause
dtype: object
```

```python
df['Report Status'].fillna('Probable Cause', inplace=True)

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

```
Event Id                  0
Investigation Type        0
Accident Number           0
Event Date                0
Location                  0
Country                   0
Injury Severity           0
Aircraft damage           0
Aircraft Category         0
Make                      0
Model                     0
Amateur Built             0
Number of Engines         0
Engine Type               0
Purpose of flight         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
dtype: int64
```

We have handled all of our missing data. let's see how many rows per column we have left

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 88406 entries, 0 to 90347
Data columns (total 22 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event Id                88406 non-null  object
 1   Investigation Type      88406 non-null  object
 2   Accident Number         88406 non-null  object
 3   Event Date              88406 non-null  object
 4   Location                88406 non-null  object
 5   Country                 88406 non-null  object
 6   Injury Severity         88406 non-null  object
 7   Aircraft damage         88406 non-null  object
 8   Aircraft Category       88406 non-null  object
 9   Make                    88406 non-null  object
 10  Model                   88406 non-null  object
 11  Amateur Built           88406 non-null  object
 12  Number of Engines       88406 non-null  float64
```

```
 13  Engine Type             88406 non-null  object
 14  Purpose of flight       88406 non-null  object
 15  Total Fatal Injuries    88406 non-null  float64
 16  Total Serious Injuries  88406 non-null  float64
 17  Total Minor Injuries    88406 non-null  float64
 18  Total Uninjured         88406 non-null  float64
 19  Weather Condition       88406 non-null  object
 20  Broad phase of flight   88406 non-null  object
 21  Report Status           88406 non-null  object
dtypes: float64(5), object(17)
memory usage: 15.5+ MB
```

We had 88958 distinct rows and after cleaning missing data, we have 88406 remaining rows per columns, we only removed 552 rows and 9 irrelevant columns to us to clean our data, which is good. Let's move on.

Exploratory and Analysis

Let's see some indicators for our numerical variables

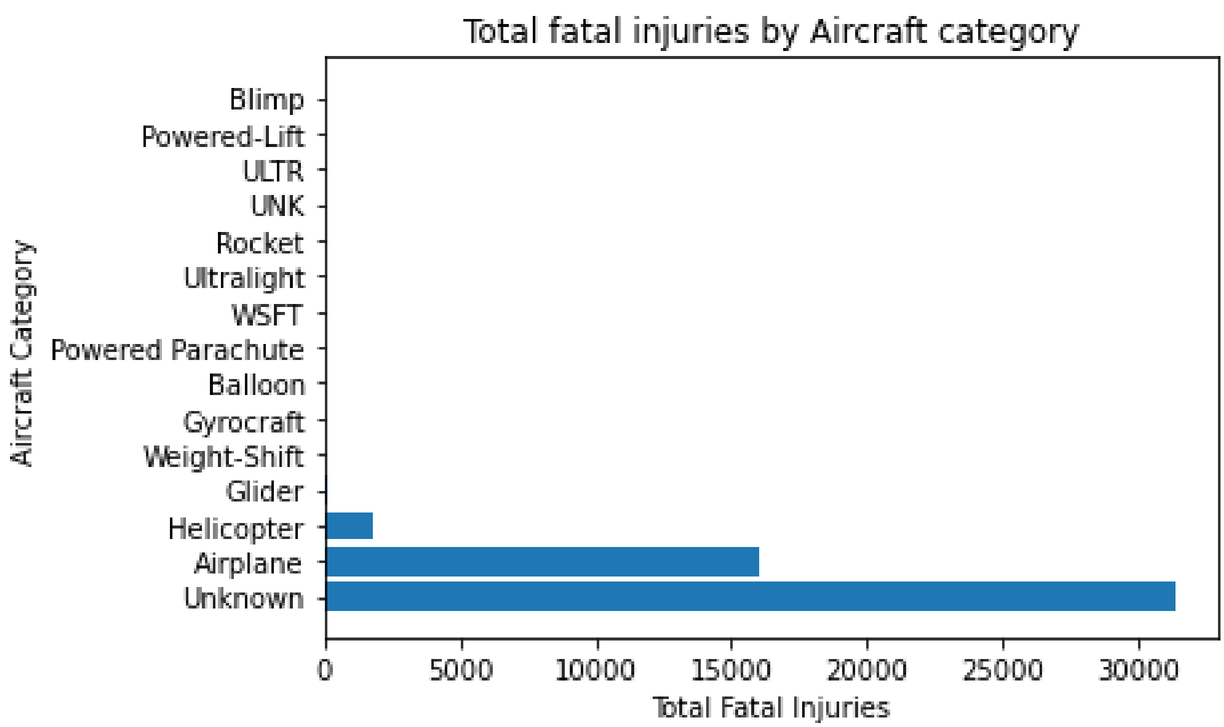
```
df.describe()
```

```
       Number of Engines  Total Fatal Injuries  Total Serious Injuries  \
count       88406.000000          88406.000000            88406.000000

mean            1.135998              0.558152                0.239712

std             0.431704              5.090423                1.429433

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          88406.000000     88406.000000
mean               0.308791         5.011990
std                2.087133        26.913973
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
```

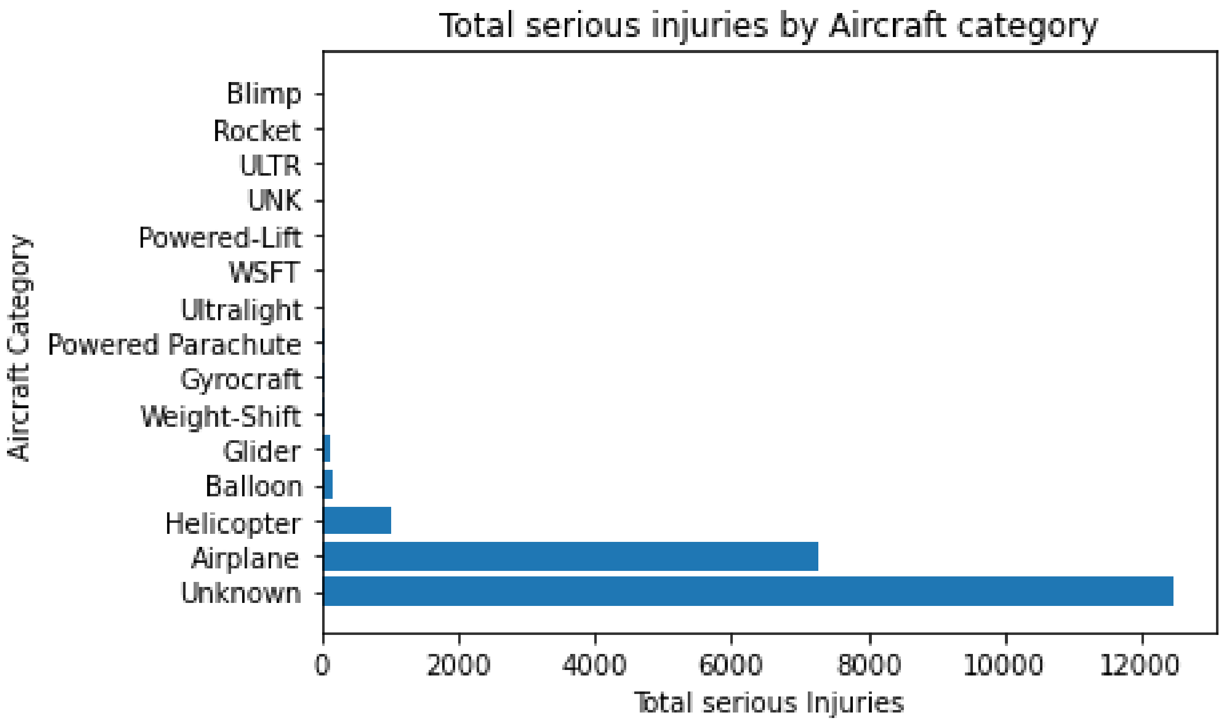
We have 4 numerical variables, lets us see them by different categories

```
ACI_TFI = df.groupby('Aircraft Category',sort=True).sum()['Total Fatal Injuries'].sort_values(ascending = False).index
ACV_TFI = df.groupby('Aircraft Category',sort=True).sum()['Total Fatal Injuries'].sort_values(ascending = False).values

fig, ax = plt.subplots()
ax.barh(ACI_TFI,ACV_TFI)
ax.set_title('Total fatal injuries by Aircraft category')
ax.set_xlabel('Total Fatal Injuries')
ax.set_ylabel('Aircraft Category')

plt.plot()

[]
```

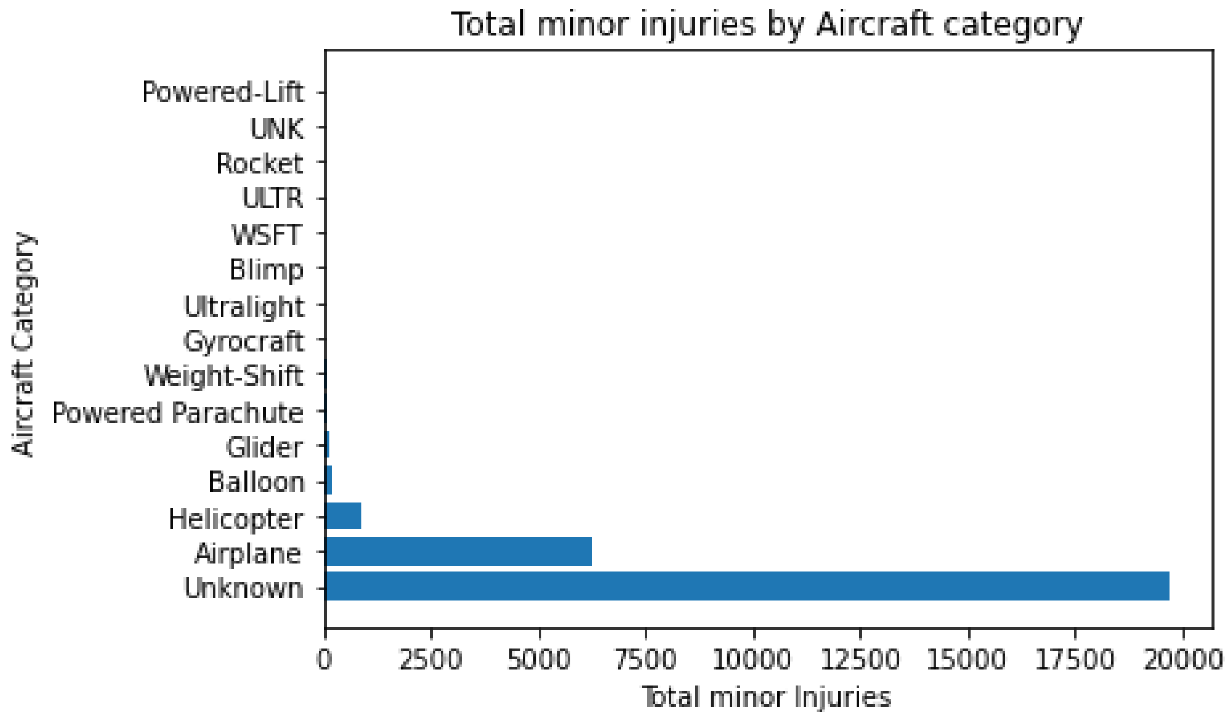



```
ACI_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total Serious Injuries'].sort_values(ascending = False).index
ACV_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total Serious Injuries'].sort_values(ascending = False).values
```

```
fig, ax = plt.subplots()
ax.barh(ACI_TSI,ACV_TSI)
ax.set_title('Total serious injuries by Aircraft category')
ax.set_xlabel('Total serious Injuries')
ax.set_ylabel('Aircraft Category')

plt.plot();
```




```
ACI_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total Minor
Injuries'].sort_values(ascending = False).index
ACV_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total Minor
Injuries'].sort_values(ascending = False).values

fig, ax = plt.subplots()
ax.barh(ACI_TSI,ACV_TSI)
ax.set_title('Total minor injuries by Aircraft category')
ax.set_xlabel('Total minor Injuries')
ax.set_ylabel('Aircraft Category')

plt.plot()

[]
```



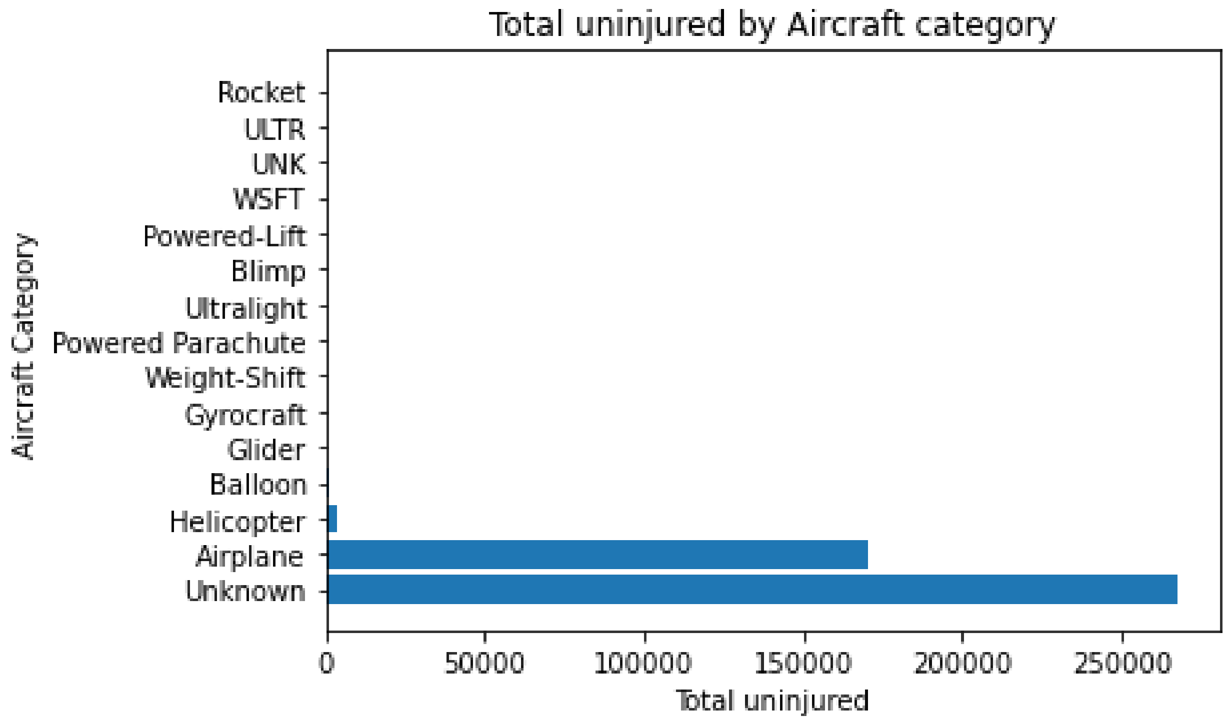

```
ACI_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total
Uninjured'].sort_values(ascending = False).index
ACV_TSI = df.groupby('Aircraft Category',sort=True).sum()['Total
Uninjured'].sort_values(ascending = False).values
df.groupby('Aircraft Category').sum()
```

```
                   Number of Engines  Total Fatal Injuries  \
Aircraft Category
Airplane                     31478.0               15991.0
Balloon                        106.0                  43.0
Blimp                            6.0                   0.0
Glider                         162.0                  99.0
Gyrocraft                      173.0                  44.0
Helicopter                    3662.0                1754.0
Powered Parachute               91.0                  15.0
Powered-Lift                     7.0                   0.0
Rocket                           1.0                   1.0
ULTR                             1.0                   0.0
UNK                              2.0                   0.0
Ultralight                      31.0                  10.0
Unknown                      64540.0               31310.0
WSFT                             9.0                  10.0
Weight-Shift                   160.0                  67.0

                   Total Serious Injuries  Total Minor Injuries  \
Aircraft Category
Airplane                           7253.0                6276.0
```

Balloon	186.0	185.0
Blimp	0.0	3.0
Glider	113.0	112.0
Gyrocraft	55.0	30.0
Helicopter	1034.0	888.0
Powered Parachute	40.0	73.0
Powered-Lift	1.0	0.0
Rocket	0.0	1.0
ULTR	0.0	1.0
UNK	0.0	0.0
Ultralight	11.0	8.0
Unknown	12440.0	19670.0
WSFT	1.0	2.0
Weight-Shift	58.0	50.0

	Total Uninjured
Aircraft Category	
Airplane	170487.0
Balloon	844.0
Blimp	5.0
Glider	367.0
Gyrocraft	90.0
Helicopter	3994.0
Powered Parachute	23.0
Powered-Lift	4.0
Rocket	0.0
ULTR	0.0
UNK	0.0
Ultralight	14.0
Unknown	267214.0
WSFT	1.0
Weight-Shift	47.0

```
fig, ax = plt.subplots()
ax.barh(ACI_TSI,ACV_TSI)
ax.set_title('Total uninjured by Aircraft category')
ax.set_xlabel('Total uninjured')
ax.set_ylabel('Aircraft Category')

plt.plot();
```



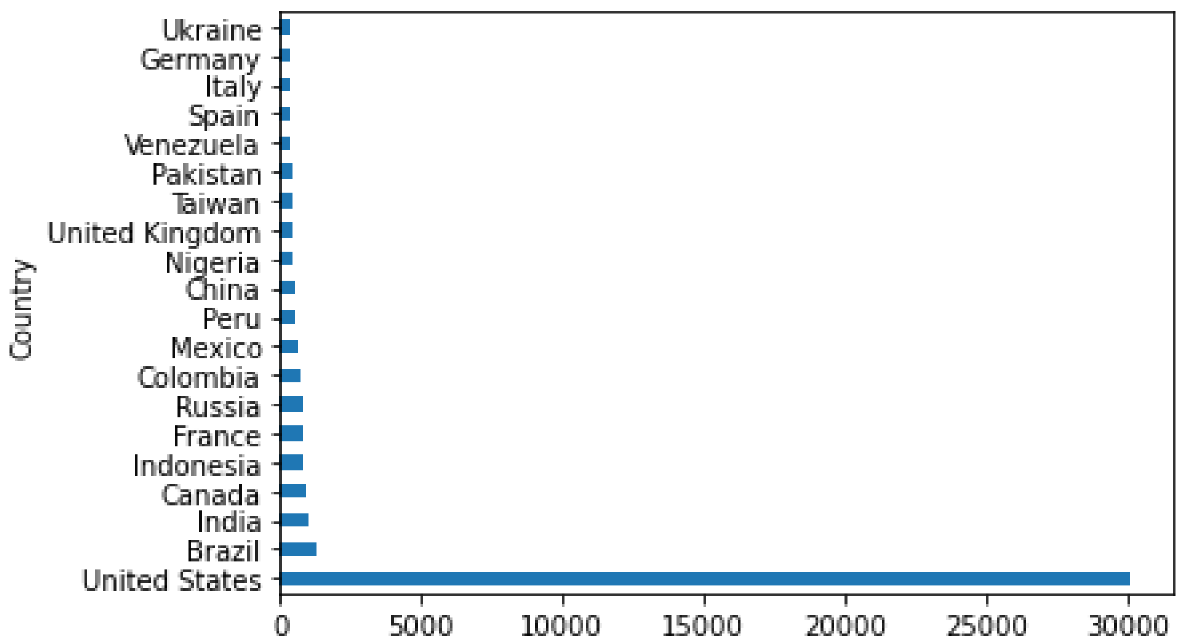

```
df.groupby(['Aircraft Category','Investigation Type']).sum()
```

```
                                        Number of Engines  Total Fatal
Injuries  \
Aircraft Category Investigation Type

Airplane          Accident                        28984.0
15989.0
                  Incident                         2494.0
2.0
Balloon           Accident                          105.0
43.0
                  Incident                            1.0
0.0
Blimp             Accident                            6.0
0.0
Glider            Accident                          162.0
99.0
Gyrocraft         Accident                          173.0
44.0
Helicopter        Accident                         3546.0
1754.0
                  Incident                          116.0
0.0
Powered Parachute Accident                           91.0
15.0
Powered-Lift      Accident                            3.0
```

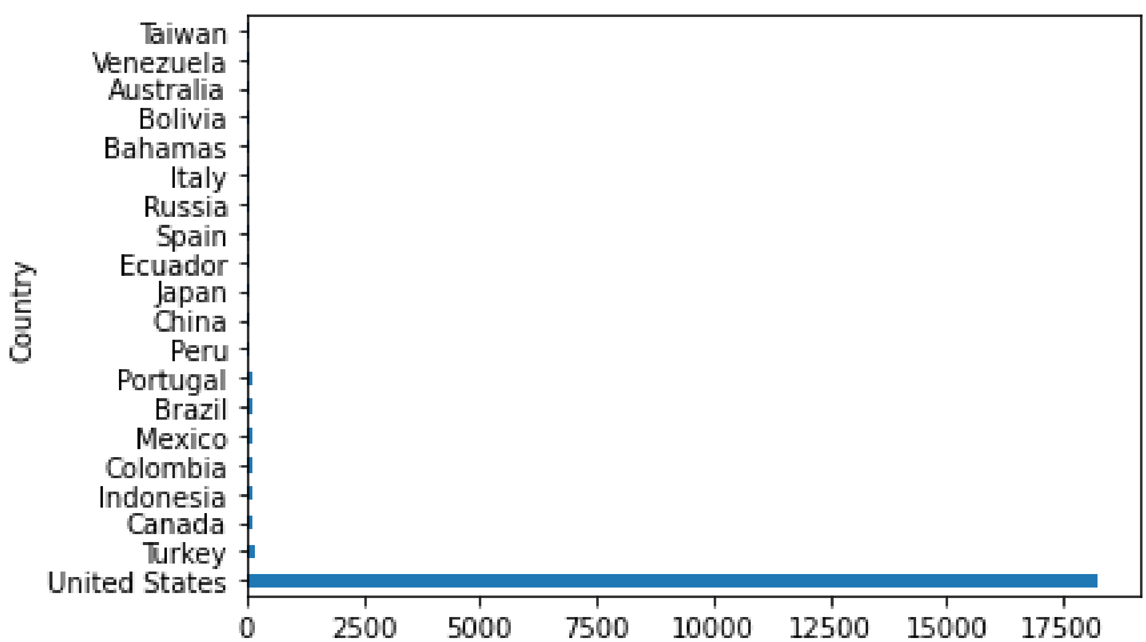
```
0.0
                  Incident                                 4.0
0.0
Rocket            Accident                                 1.0
1.0
ULTR              Accident                                 1.0
0.0
UNK               Accident                                 2.0
0.0
Ultralight        Accident                                31.0
10.0
Unknown           Accident                             60595.0
31290.0
                  Incident                              3945.0
20.0
WSFT              Accident                                 9.0
10.0
Weight-Shift      Accident                               160.0
67.0

                                      Total Serious Injuries  \
Aircraft Category Investigation Type
Airplane          Accident                            6980.0
                  Incident                             273.0
Balloon           Accident                             185.0
                  Incident                               1.0
Blimp             Accident                               0.0
Glider            Accident                             113.0
Gyrocraft         Accident                              55.0
Helicopter        Accident                            1031.0
                  Incident                               3.0
Powered Parachute Accident                              40.0
Powered-Lift      Accident                               1.0
                  Incident                               0.0
Rocket            Accident                               0.0
ULTR              Accident                               0.0
UNK               Accident                               0.0
Ultralight        Accident                              11.0
Unknown           Accident                           12411.0
                  Incident                              29.0
WSFT              Accident                               1.0
Weight-Shift      Accident                              58.0

                                      Total Minor Injuries  Total
Uninjured
Aircraft Category Investigation Type

Airplane          Accident                          5818.0
105675.0
                  Incident                           458.0
```

```
64812.0
Balloon           Accident                                 185.0
836.0
                  Incident                                   0.0
8.0
Blimp             Accident                                   3.0
5.0
Glider            Accident                                 112.0
367.0
Gyrocraft         Accident                                  30.0
90.0
Helicopter        Accident                                 888.0
3672.0
                  Incident                                   0.0
322.0
Powered Parachute Accident                                  73.0
23.0
Powered-Lift      Accident                                   0.0
3.0
                  Incident                                   0.0
1.0
Rocket            Accident                                   1.0
0.0
ULTR              Accident                                   1.0
0.0
UNK               Accident                                   0.0
0.0
Ultralight        Accident                                   8.0
14.0
Unknown           Accident                               18947.0
148413.0
                  Incident                                 723.0
118801.0
WSFT              Accident                                   2.0
1.0
Weight-Shift      Accident                                  50.0
47.0
```

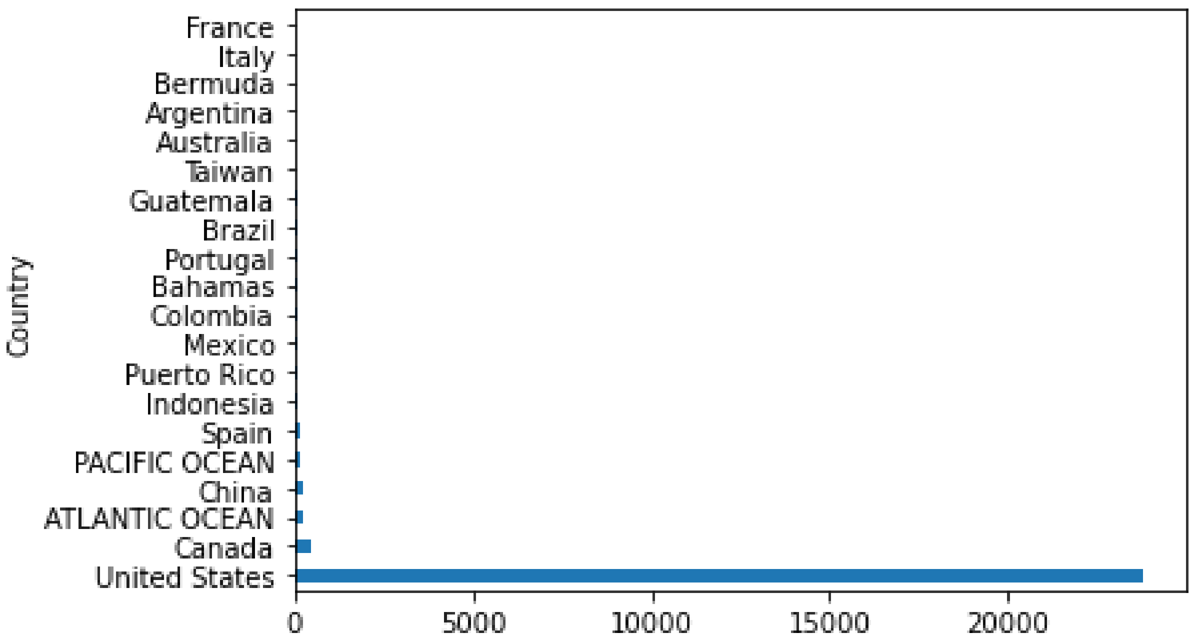
```
df.groupby('Country').sum()['Total Fatal
Injuries'].sort_values(ascending =False)[:20].plot(kind='barh');
```



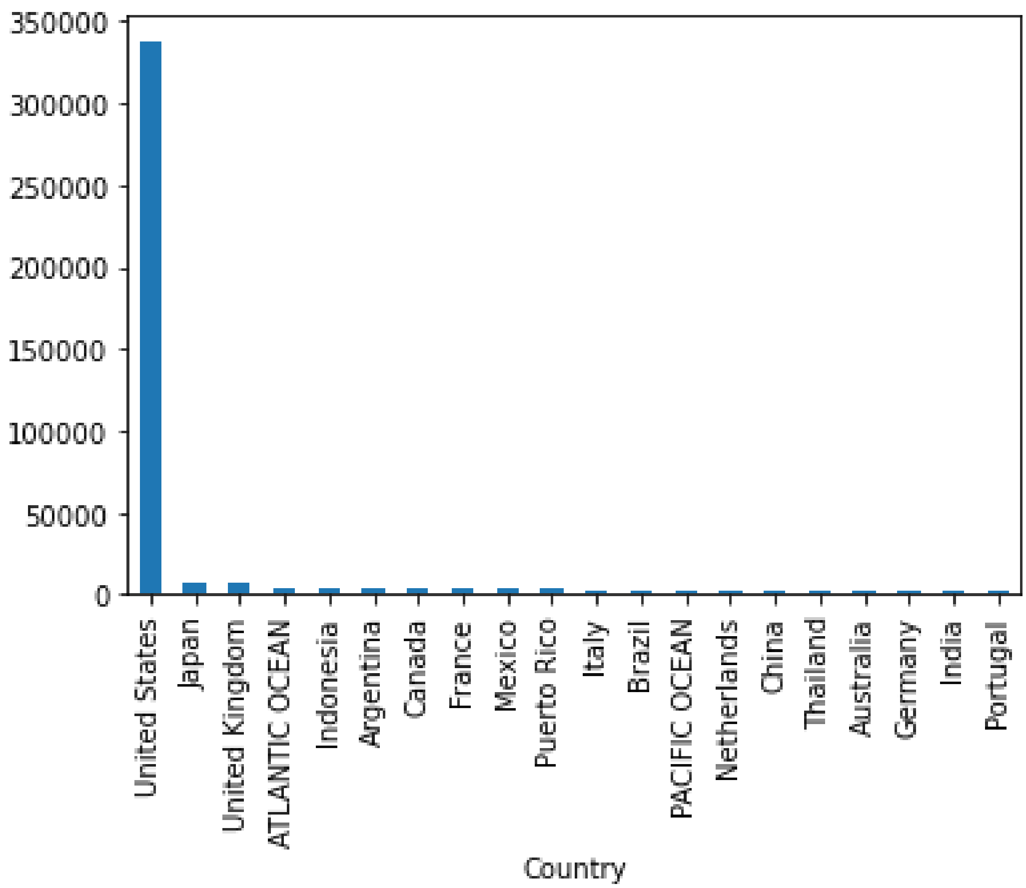

```
df.groupby('Country').sum()['Total Serious
Injuries'].sort_values(ascending =False)[:20].plot(kind = 'barh');
```




```
df.groupby('Country').sum()['Total Minor
Injuries'].sort_values(ascending =False)[:20].plot(kind = 'barh');
```




```
df.groupby('Country').sum()['Total Uninjured'].sort_values(ascending
=False)[:20].plot(kind ='bar');
```



hipnlkl

```
df.groupby(['Aircraft Category','Aircraft damage']).sum()['Total Fatal Injuries'].sort_values(ascending=False)
```

```
Aircraft Category  Aircraft damage
Unknown            Destroyed          27387.0
Airplane           Destroyed          11483.0
                   Substantial         4183.0
Unknown            Substantial         2770.0
                   Unknown             1046.0
Helicopter         Destroyed           1020.0
                   Substantial          697.0
Airplane           Minor                176.0
                   Unknown              149.0
Unknown            Minor                107.0
Glider             Substantial           76.0
Weight-Shift       Substantial           57.0
Helicopter         Unknown               34.0
Balloon            Destroyed             28.0
Gyrocraft          Substantial           23.0
                   Destroyed             21.0
Glider             Destroyed             21.0
Powered Parachute  Substantial           11.0
Weight-Shift       Destroyed             10.0
Balloon            Substantial           10.0
Ultralight         Substantial            8.0
WSFT               Substantial            8.0
Balloon            Unknown                4.0
Helicopter         Minor                  3.0
Powered Parachute  Unknown                3.0
WSFT               Destroyed              2.0
Glider             Minor                  1.0
                   Unknown                1.0
Balloon            Minor                  1.0
Ultralight         Unknown                1.0
                   Destroyed              1.0
Powered Parachute  Destroyed              1.0
Rocket             Destroyed              1.0
Blimp              Destroyed              0.0
                   Substantial            0.0
Weight-Shift       Unknown                0.0
Gyrocraft          Minor                  0.0
Powered-Lift       Destroyed              0.0
                   Minor                  0.0
                   Substantial            0.0
                   Unknown                0.0
ULTR               Substantial            0.0
UNK                Unknown                0.0
Weight-Shift       Minor                  0.0
```

```
Powered Parachute  Minor                  0.0
Name: Total Fatal Injuries, dtype: float64
```

```
df.groupby(['Aircraft Category','Make']).sum()['Total Fatal
Injuries'].sort_values(ascending=False)[:20]
```

```
Aircraft Category  Make
Unknown            Cessna                6532.0
                   Boeing                5155.0
                   Piper                 4766.0
Airplane           Boeing                3278.0
                   Cessna                3049.0
Unknown            Beech                 2574.0
Airplane           Piper                 1882.0
                   Airbus                1316.0
                   Beech                 1192.0
Unknown            Mcdonnell Douglas     1185.0
                   Douglas                917.0
                   Airbus Industrie       822.0
                   Bell                   733.0
Helicopter         Bell                   552.0
Unknown            Mooney                 474.0
                   Tupolev                420.0
Airplane           Airbus Industrie       352.0
Helicopter         Robinson               329.0
Airplane           Embraer                319.0
Unknown            Robinson               286.0
Name: Total Fatal Injuries, dtype: float64
```

```
df.groupby(['Aircraft Category','Amateur Built']).sum()['Total Fatal
Injuries'].sort_values(ascending=False)[:20]
```

```
Aircraft Category  Amateur Built
Unknown            No               29299.0
Airplane           No               14972.0
Unknown            Yes               2011.0
Helicopter         No                1709.0
Airplane           Yes               1019.0
Glider             No                  90.0
Weight-Shift       No                  58.0
Helicopter         Yes                 45.0
Balloon            No                  41.0
Gyrocraft          Yes                 37.0
Powered Parachute  No                  14.0
WSFT               No                  10.0
Glider             Yes                  9.0
Weight-Shift       Yes                  9.0
Ultralight         No                   8.0
Gyrocraft          No                   7.0
Balloon            Yes                  2.0
```

```
Ultralight         Yes                    2.0
Powered Parachute  Yes                    1.0
Rocket             No                     1.0
Name: Total Fatal Injuries, dtype: float64
```

```
df.groupby(['Aircraft Category','Weather Condition']).mean()['Total Fatal Injuries']
```

```
Aircraft Category  Weather Condition
Airplane           IMC                    2.014245
                   UNK                    1.643799
                   VMC                    0.486669
Balloon            IMC                    6.000000
                   UNK                    0.000000
                   VMC                    0.110132
Blimp              VMC                    0.000000
Glider             IMC                    0.500000
                   UNK                    0.666667
                   VMC                    0.190855
Gyrocraft          IMC                    0.000000
                   VMC                    0.257310
Helicopter         IMC                    1.893805
                   UNK                    2.042553
                   VMC                    0.442131
Powered Parachute  VMC                    0.164835
Powered-Lift       VMC                    0.000000
Rocket             VMC                    1.000000
ULTR               VMC                    0.000000
UNK                VMC                    0.000000
Ultralight         IMC                    0.000000
                   VMC                    0.344828
Unknown            IMC                    1.968319
                   UNK                    2.876336
                   VMC                    0.405319
WSFT               VMC                    1.111111
Weight-Shift       IMC                    1.000000
                   VMC                    0.405063
Name: Total Fatal Injuries, dtype: float64
```

In order to analyze our data better, let us export it and continue with Power BI

```
df.to_csv('Aviation_treated2.csv')
```