BUSINESS UNDERSTANDING

The business wishes to venture into a new field, they have choosen the aviation sector as they next venture. The company's main focus is however to operate for commercial and private enterprises. The fact that the company is expanding to now this new field means that they have no prior knowledge of the aircraft sector. This means that they are faced with the problem of determining what type of aircraft to purchase and the potential risks associated with it i.e damage. Due to this shortcomings the business is faced with the problem of making a decision. The goal of my analysis is so that I can Identify the different categories of aircrafts especially the ones that are associated with the lowest risks of accidents. This analysis will help the business to make informed decision as they venture into aviation field.

DATA UNDERSTANDING

The dataset used for the analysis is from National Transportation Safety Board and it was downloaded from kaggle. The data is from the years 1962 to 2023. The key data points from the dataset are for example;

- "Aircraft.damage" - In aircraft damage it describes the extent to which the aircraft in question was damaged. Either completely destroyed , substantial or minor.
- "Aircraft.Category" - Aircraft category describes what type of aircraft it was. Maybe an airplane or a helicopter.
- "Injury.Severity" = This decribes the levels of injuries sustained by the people on board.

DATA PREPARATION

```python
#importing the required libraries
#importing pandas with the standard alias
#numpy for basic computation of numerals
import pandas as  pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

Viewing the first five rows of the Aviation Data

```python
#loading the CSV files into Pandas DataFrames
df = pd.read_csv('AviationData.csv',encoding='latin1')
df.head()
```

```
C:\Users\sam\AppData\Local\Temp\ipykernel_32264\737321279.py:2: 
DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option 
on import or set low_memory=False.
  df = pd.read_csv('AviationData.csv',encoding='latin1')

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

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

1   BRIDGEPORT, CA  United States        NaN        NaN          NaN   

2    Saltville, VA  United States  36.922223 -81.878056          NaN   

3       EUREKA, CA  United States        NaN        NaN          NaN   

4       Canton, OH  United States        NaN        NaN          NaN   


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

1          NaN  ...          Personal         NaN                  4.0   

2          NaN  ...          Personal         NaN                  3.0   

3          NaN  ...          Personal         NaN                  2.0   

4          NaN  ...          Personal         NaN                  1.0   


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

  Weather.Condition  Broad.phase.of.flight   Report.Status 
Publication.Date  
0               UNK                 Cruise  Probable Cause       
NaN  
1               UNK                Unknown  Probable Cause       19-
09-1996  
```

```
2             IMC                 Cruise  Probable Cause       26-
02-2007
3             IMC                 Cruise  Probable Cause       12-
09-2000
4             VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

```
df.tail()
```

```
             Event.Id Investigation.Type Accident.Number
Event.Date  \
88884  20221227106491           Accident      ERA23LA093  2022-12-26

88885  20221227106494           Accident      ERA23LA095  2022-12-26

88886  20221227106497           Accident      WPR23LA075  2022-12-26

88887  20221227106498           Accident      WPR23LA076  2022-12-26

88888  20221230106513           Accident      ERA23LA097  2022-12-29


            Location        Country Latitude Longitude Airport.Code  \
88884  Annapolis, MD  United States      NaN       NaN          NaN
88885    Hampton, NH  United States      NaN       NaN          NaN
88886     Payson, AZ  United States  341525N  1112021W          PAN
88887     Morgan, UT  United States      NaN       NaN          NaN
88888     Athens, GA  United States      NaN       NaN          NaN

      Airport.Name  ... Purpose.of.flight         Air.carrier  \
88884          NaN  ...          Personal                 NaN
88885          NaN  ...               NaN                 NaN
88886       PAYSON  ...          Personal                 NaN
88887          NaN  ...          Personal  MC CESSNA 210N LLC
88888          NaN  ...          Personal                 NaN

      Total.Fatal.Injuries Total.Serious.Injuries Total.Minor.Injuries
\
88884                  0.0                    1.0                  0.0

88885                  0.0                    0.0                  0.0

88886                  0.0                    0.0                  0.0

88887                  0.0                    0.0                  0.0

88888                  0.0                    1.0                  0.0
```

```
      Total.Uninjured Weather.Condition  Broad.phase.of.flight
Report.Status  \
88884             0.0               NaN                   NaN
NaN
88885             0.0               NaN                   NaN
NaN
88886             1.0               VMC                   NaN
NaN
88887             0.0               NaN                   NaN
NaN
88888             1.0               NaN                   NaN
NaN

      Publication.Date
88884       29-12-2022
88885              NaN
88886       27-12-2022
88887              NaN
88888       30-12-2022

[5 rows x 31 columns]
```

```
#Identify the type of data in question and the number of rows and
columns
df.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
```

The dataset consists of 88,889 rows of data pertaining each aircraft that has been involved in any type of accident

```
df.describe()

       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
```

```
#checking for null values
df.isna().sum()
```

```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Latitude                  54507
Longitude                 54516
Airport.Code              38757
Airport.Name              36185
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7096
FAR.Description           56866
Schedule                  76307
Purpose.of.flight          6192
Air.carrier               72241
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
Report.Status              6384
Publication.Date          13771
dtype: int64
```

DATA PREPARATION

DROPPING COLUMNS

In my analysis the dataset contained alot of columns which are very useful, however for my analysis some columns will not be vital for my analysis so I decided to drop them and focus on those which highly influence my findings.

```
df = df[[#'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','Broad.phase.of.flight',
'Purpose.of.flight',
         #'Engine.Type', 'FAR.Description',
       #'Schedule', 'Air.carrier',
         'Total.Fatal.Injuries',
       'Total.Serious.Injuries', 'Total.Minor.Injuries',
'Total.Uninjured',
      # 'Weather.Condition', 'Report.Status',
      # 'Publication.Date'
         ]]
```

DEALING WITH MISSING VALUES

- For the numerical columns null values were filled zero. This is because there are missing maybe because at that particular year there were zero injuries. Filling it with the mean or median could possibly alter our outcome.

```
#replacing null values with zero
df['Total.Fatal.Injuries'] = df['Total.Fatal.Injuries'].fillna(0)
df['Total.Serious.Injuries'] = df['Total.Serious.Injuries'].fillna(0)
df['Total.Minor.Injuries'] = df['Total.Minor.Injuries'].fillna(0)
df['Total.Uninjured'] = df['Total.Uninjured'].fillna(0)

df['Broad.phase.of.flight'] =
df['Broad.phase.of.flight'].fillna(df['Broad.phase.of.flight'].mode()
[0])
```

DROPPING ROWS

In my dataset there are columns with missing values in the row columns, this rows could not affect our outcome hence it is easier to drop them rather than filling them

```
#dropping rows with missing values
df[df[['Make','Model','Injury.Severity','Aircraft.damage','Number.of.Engines','Purpose.of.flight']].isna().any(axis=1)]
df.dropna(subset=['Make','Model','Injury.Severity','Aircraft.damage','Number.of.Engines', 'Purpose.of.flight'],inplace=True)

#format make to uppercase
df['Make'] = df['Make'].str.upper().str.strip()
```

CHECKING TO SEE IF OUR DATA IS CLEAN

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

```
Investigation.Type        0
Event.Date                0
Injury.Severity           0
Aircraft.damage           0
Make                      0
Model                     0
Number.of.Engines         0
Broad.phase.of.flight     0
Purpose.of.flight         0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
dtype: int64
```

CHECKING FOR OUTLIERS

Now that the data is clean it is now time to check for any outliers in our dataset. The reason for looking for outliers after the cleaning is because a column with many missing values can give a misleading IQR.

```
# Selecting numerical columns
cols = df.select_dtypes(include='number')

# Looping through the numerical column
for col in cols.columns:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
```

```
    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]
    print(f"{col} has {outliers.shape[0]} outliers")
```

```
Number.of.Engines has 10142 outliers
Total.Fatal.Injuries has 14977 outliers
Total.Serious.Injuries has 11163 outliers
Total.Minor.Injuries has 13791 outliers
Total.Uninjured has 1595 outliers
```

Our Numerical columns seem to contain many outliers , however my decision was on keeping them because they depict real scenarios. This scenarios are however rare but are extremely important in aircraft selection and also help in safety analysis.

```
#checking for duplicates
df.duplicated().value_counts()
```

```
False    78119
True       104
Name: count, dtype: int64
```

```
#Dropping duplicates
df.drop_duplicates(inplace=True)

# Saving the cleaned data to a new CSV file
df.to_csv('C:\\Users\\sam\\Desktop\\clean_AviationData.csv',
index=False)

df
```

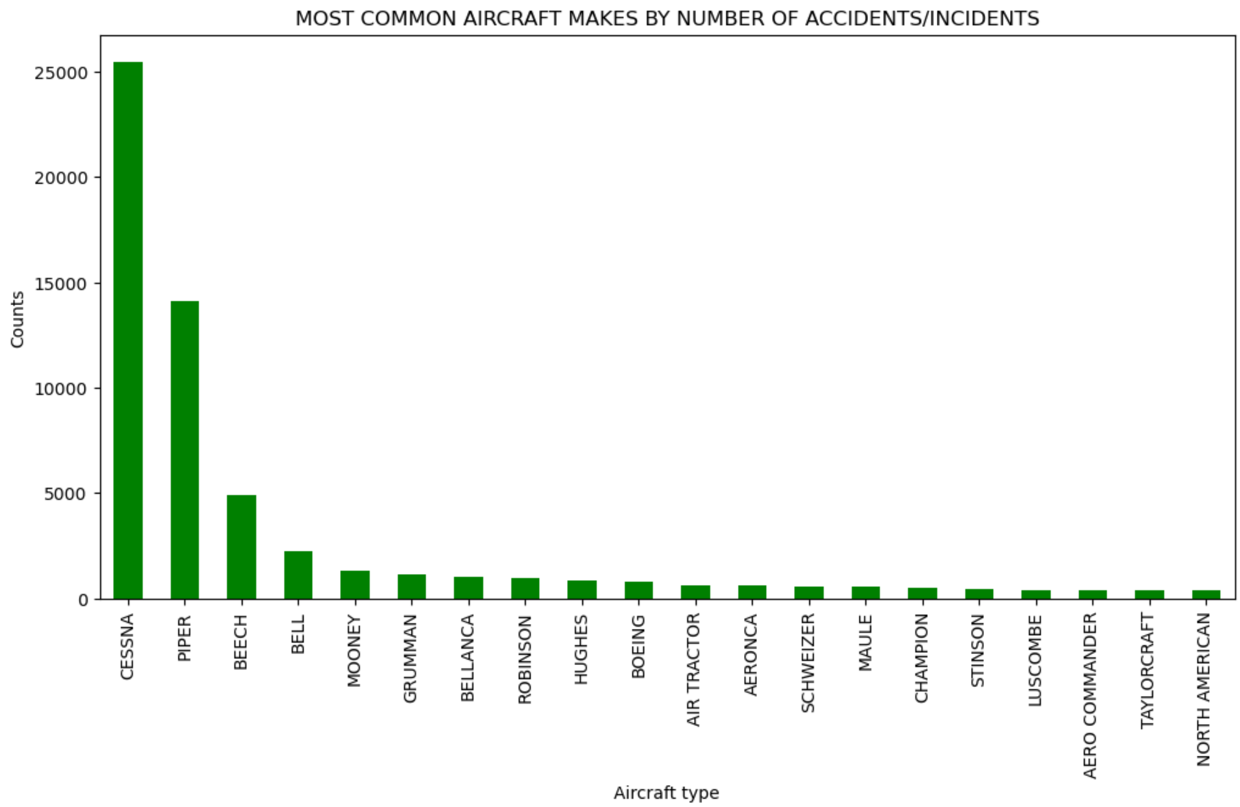
```
      Investigation.Type  Event.Date Injury.Severity
Aircraft.damage  \
0               Accident  1948-10-24        Fatal(2)       Destroyed

1               Accident  1962-07-19        Fatal(4)       Destroyed

2               Accident  1974-08-30        Fatal(3)       Destroyed

3               Accident  1977-06-19        Fatal(2)       Destroyed

6               Accident  1981-08-01        Fatal(4)       Destroyed

...                  ...         ...             ...             ...

88865           Accident  2022-12-12       Non-Fatal     Substantial

88867           Accident  2022-12-12           Minor     Substantial

88873           Accident  2022-12-14       Non-Fatal     Substantial

88877           Accident  2022-12-16           Minor     Substantial
```

```
88886           Accident  2022-12-26       Non-Fatal     Substantial


                            Make       Model  Number.of.Engines  \
0                        STINSON       108-3                1.0
1                          PIPER    PA24-180                1.0
2                         CESSNA        172M                1.0
3                       ROCKWELL         112                1.0
6                         CESSNA         180                1.0
...                          ...         ...                ...
88865                     CESSNA         172                1.0
88867         AIRBUS HELICOPTERS  EC 130 T2                1.0
88873         CIRRUS DESIGN CORP        SR22                1.0
88877                     CESSNA       R172K                1.0
88886  AMERICAN CHAMPION AIRCRAFT      8GCBC                1.0

      Broad.phase.of.flight Purpose.of.flight  Total.Fatal.Injuries  \
0                    Cruise          Personal                   2.0
1                   Unknown          Personal                   4.0
2                    Cruise          Personal                   3.0
3                    Cruise          Personal                   2.0
6                   Unknown          Personal                   4.0
...                     ...               ...                   ...
88865               Landing     Instructional                   0.0
88867               Landing          Business                   0.0
88873               Landing          Personal                   0.0
88877               Landing          Personal                   0.0
88886               Landing          Personal                   0.0

       Total.Serious.Injuries  Total.Minor.Injuries  Total.Uninjured
0                         0.0                   0.0              0.0
1                         0.0                   0.0              0.0
2                         0.0                   0.0              0.0
3                         0.0                   0.0              0.0
6                         0.0                   0.0              0.0
...                       ...                   ...              ...
88865                     0.0                   0.0              1.0
88867                     1.0                   0.0              0.0
88873                     0.0                   0.0              1.0
88877                     1.0                   0.0              0.0
88886                     0.0                   0.0              1.0

[78119 rows x 13 columns]
```

BAR GRAPH

```
#Grouping the most common aircraft makes
Same_Make_Count = df['Make'].value_counts().reset_index()
```

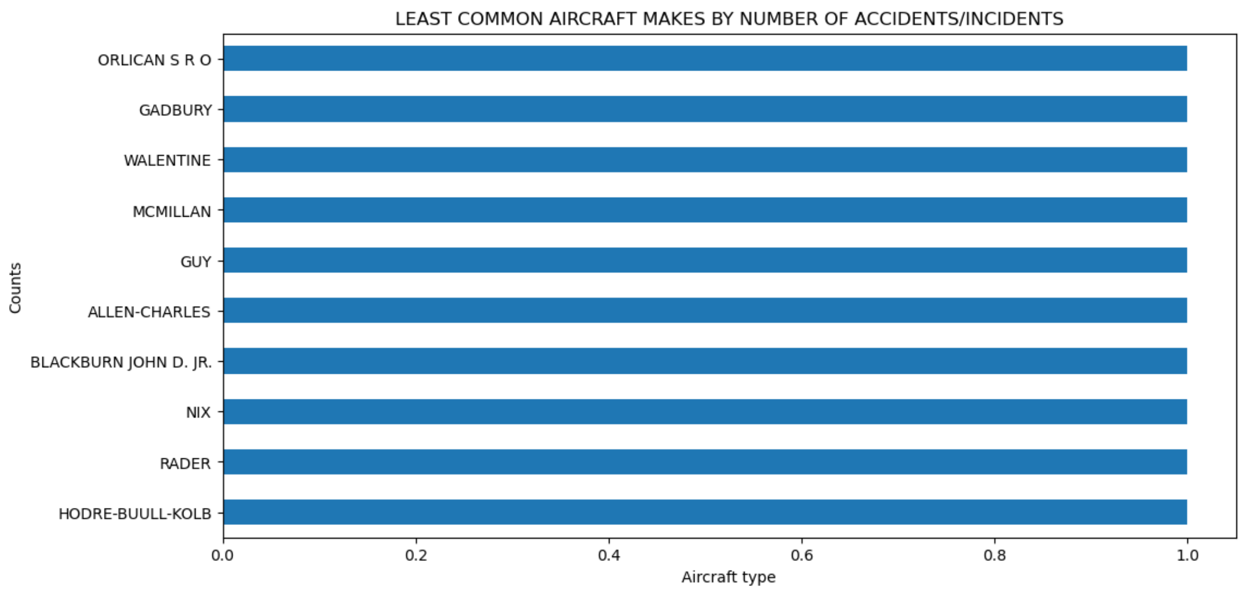
```
Same_Make_Count.columns = ['Make', 'Counts']
#plotting the bar graph
#top 20 most common makes
Same_Make_Count.head(20).plot(kind='bar', x='Make', y='Counts',
figsize=(12, 6), legend=False,color='green')
plt.title('MOST COMMON AIRCRAFT MAKES BY NUMBER OF
ACCIDENTS/INCIDENTS')
plt.xlabel('Aircraft type')
plt.ylabel('Counts')


plt.show()
```



The Bar graph above represents the top 10 most common makes of aircraft used throughout years 1963 to 2023

```
#Grouping aircraft with the lowest  makes
Same_Make_Count = df['Make'].value_counts().reset_index()
Same_Make_Count.columns = ['Make', 'Counts']
#plotting the bar graph
#The least common makes
Same_Make_Count.tail(10).plot(kind='barh', x='Make', y='Counts',
figsize=(12, 6), legend=False)
plt.title('LEAST COMMON AIRCRAFT MAKES BY NUMBER OF
ACCIDENTS/INCIDENTS')
```

```
plt.xlabel('Aircraft type')
plt.ylabel('Counts')


plt.show()
```



CONVERTING TO DATES

The date in which the events took place is important in that it helps in narrowing down on the dates the accidents happened. This helps us to know whether the aircraft accidents are increasing, decreasing or the accident have remained stable. This will be crucial in our decision making process.In my dataset I have alot of years which are impossible to fit in one plot so Binning is the best way whereby I grouped the ages in ranges of 10 years. Initially in our dataset the event date column is of type object and to work with it it needs to be datetime hence the conversion.

```
#converting the Event date column to dates
df['Event_Year'] = pd.to_datetime(df['Event.Date']).dt.year
#Binning
df['Event_by_Year'] =
pd.cut(df['Event_Year'],bins=[1960,1970,1980,1990,2000,2010,2020,2023]
,labels = ['60s','70s','80s','90s','20s','2010s','2020s'])
```

Representing the total number of fatal accidents over the years 1963 to 2023 on a line plot

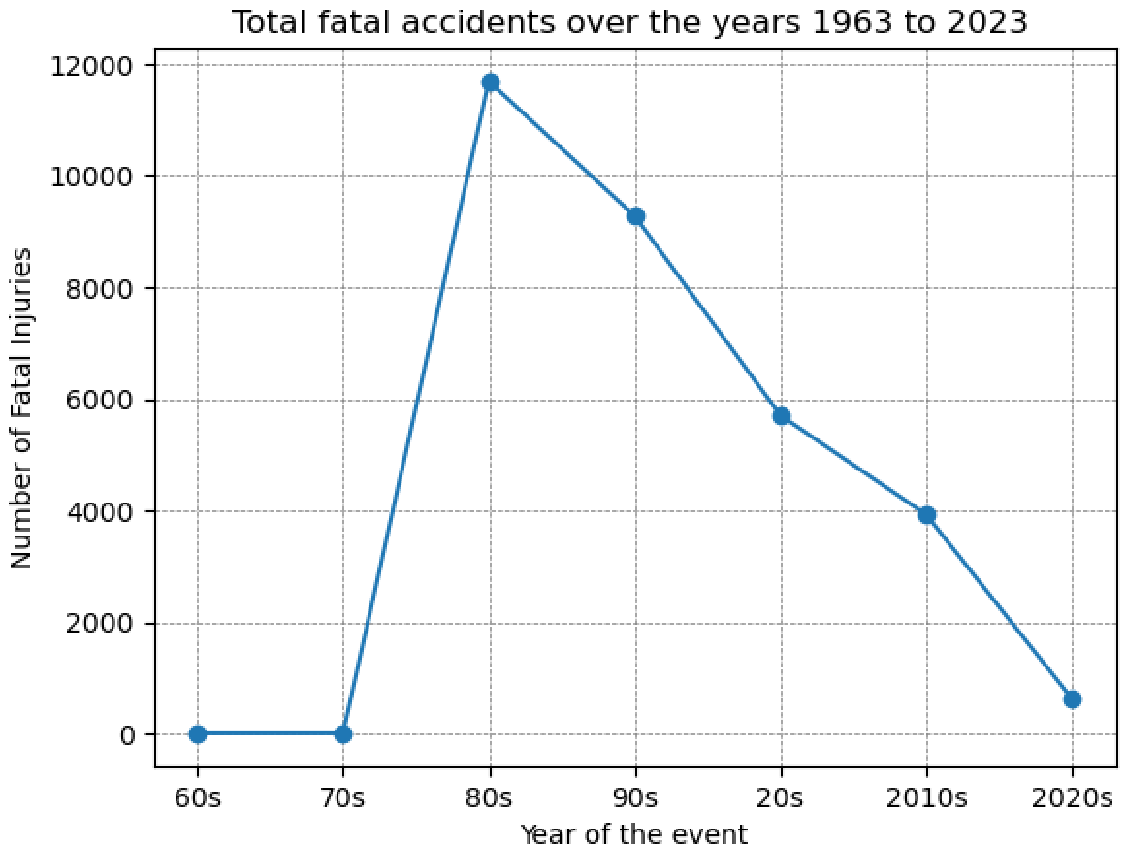
```
# Create the plot for the total fatal injuries throughout the years
plt.figure(figsize=(12, 6))
```

```
fig, ax = plt.subplots()
#groupby function
grouping = df.groupby('Event_by_Year')['Total.Fatal.Injuries'].sum()
ax.plot(grouping.index, grouping.values,marker='o')

# Add labels for x and y axes
ax.set_xlabel('Year of the event')
ax.set_ylabel('Number of Fatal Injuries')
ax.grid(
    True,
    which='both',
    color='gray',
    linestyle='--',
    linewidth=0.5
)
# title
ax.set_title('Total fatal accidents over the years 1963 to 2023 ')
```

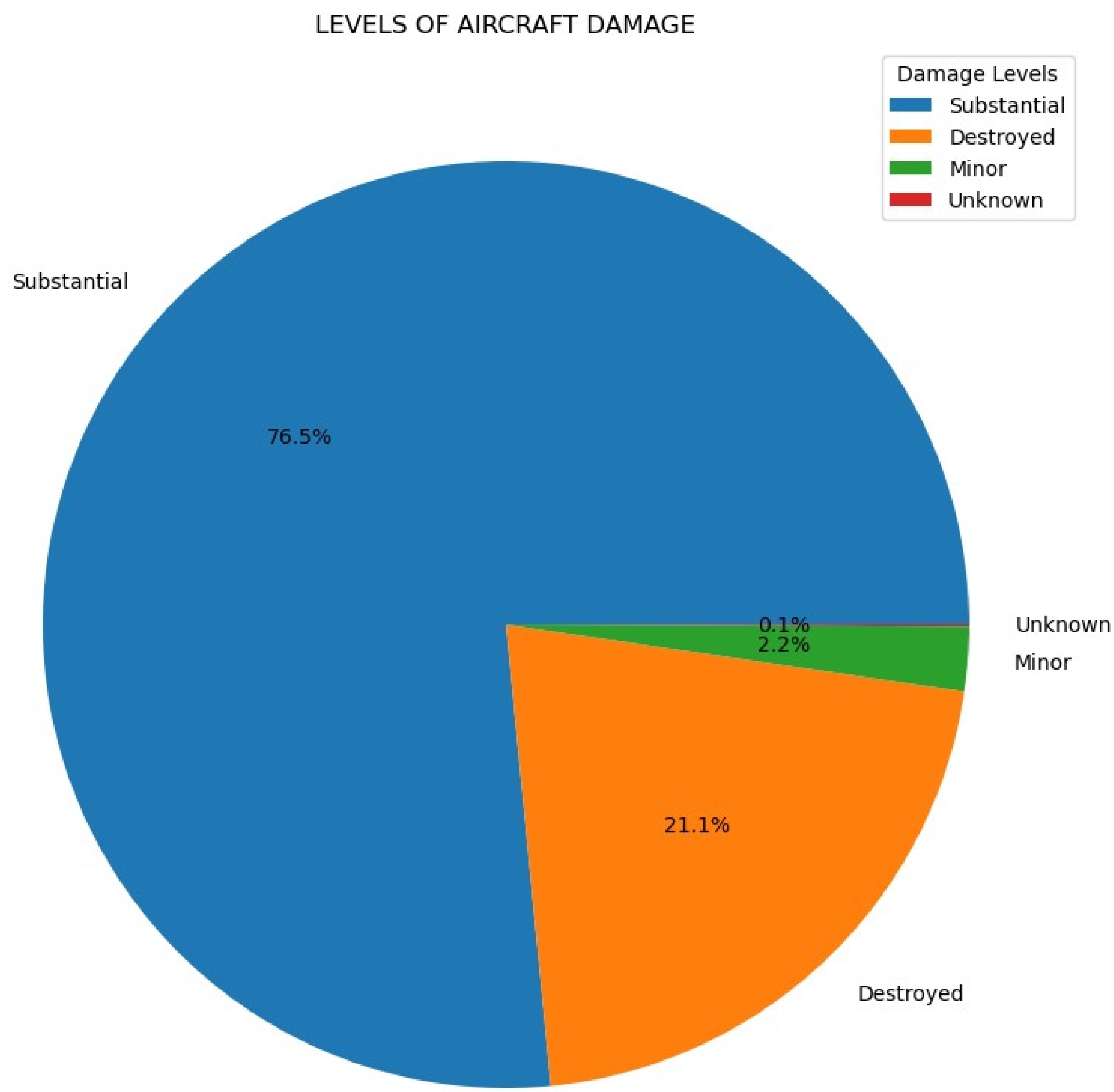
```
C:\Users\sam\AppData\Local\Temp\ipykernel_32264\995120231.py:5:
FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to
retain current behavior or observed=True to adopt the future default
and silence this warning.
  grouping = df.groupby('Event_by_Year')['Total.Fatal.Injuries'].sum()
```

```
Text(0.5, 1.0, 'Total fatal accidents over the years 1963 to 2023 ')
```

```
<Figure size 1200x600 with 0 Axes>
```



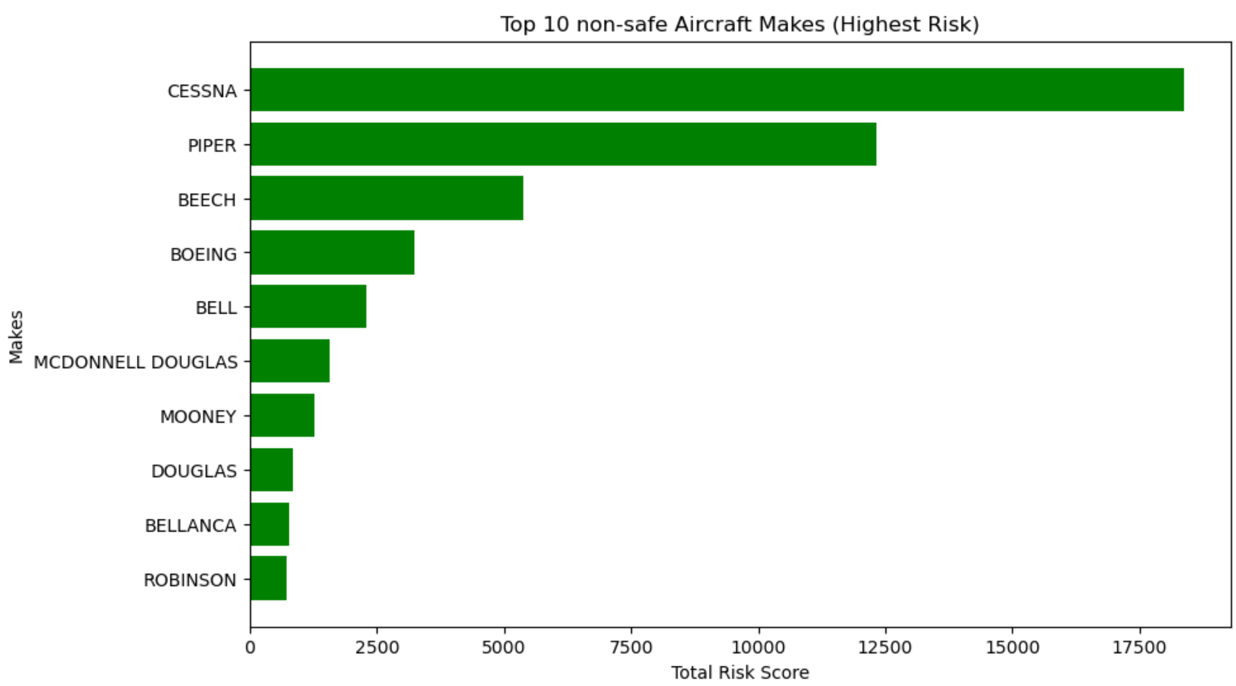

```
#creating a dataset for DAMAGE
Same_Damage = df['Aircraft.damage'].value_counts().reset_index()
Same_Damage.columns = ['Aircraft.damage','No_of_Damages']

plt.figure(figsize=(10,10))
plt.pie(Same_Damage['No_of_Damages'],labels =
Same_Damage['Aircraft.damage'],autopct= '%2.1f%%')
plt.title('LEVELS OF AIRCRAFT DAMAGE')
plt.legend(title='Damage Levels')
plt.show()
```



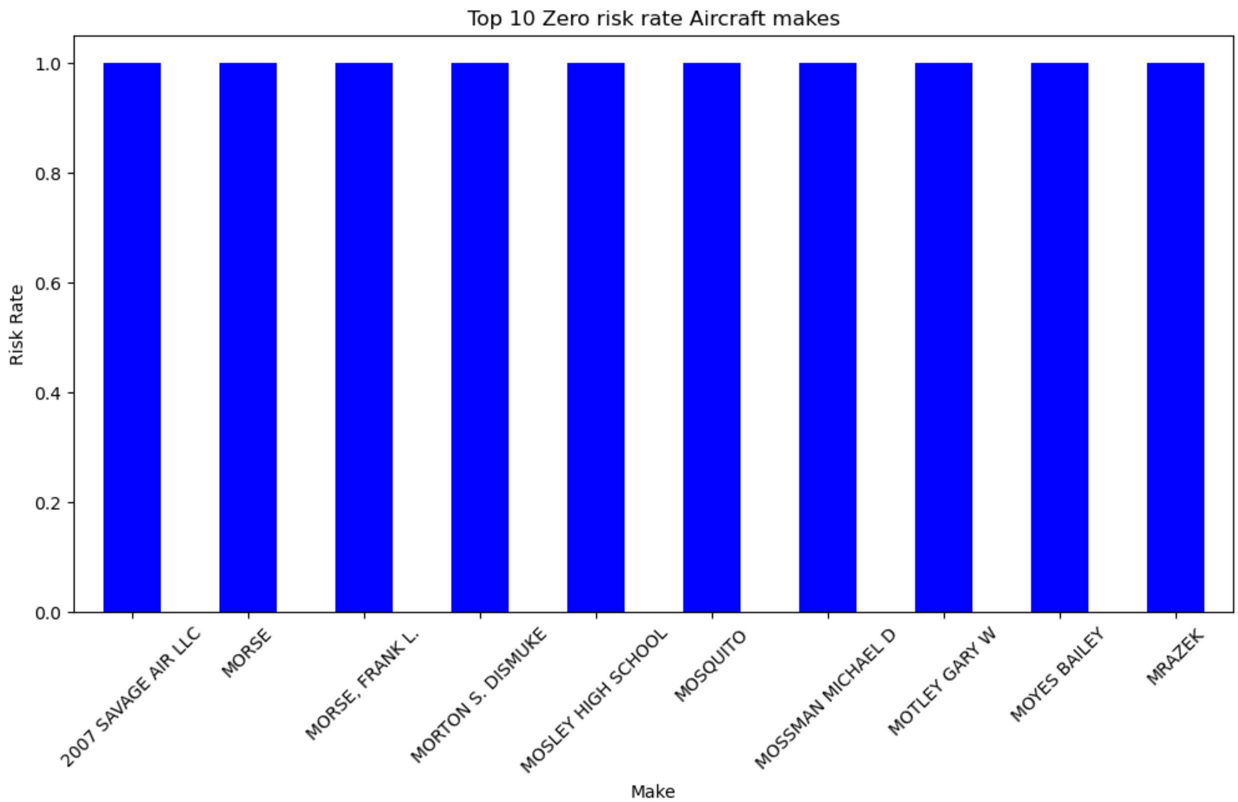

```
#creating a risk rate column based on the totals from the injuries
#some planes had no reported injuries so I decided to add 5,3,1
respectively for plotting purposes
df['Risk_rate'] = (
    (df['Total.Fatal.Injuries']) +
    (df['Total.Serious.Injuries']) +
    (df['Total.Minor.Injuries'])
)
risk = df.groupby(['Make'])['Risk_rate'].sum().reset_index()
risk = risk.sort_values(by='Risk_rate')
risk
```

```
                              Make  Risk_rate
7210          ZWICKER MURRAY R        0.0
2207  FIGHTER ESCORT WINGS LTD        0.0
5202                     QUIST        0.0
5201       QUINN AVIATION INC.        0.0
2210      FINGERHUT REVOLUTION        0.0
...                        ...        ...
597                       BELL     2283.0
759                     BOEING     3232.0
582                      BEECH     5372.0
5019                     PIPER    12318.0
1168                    CESSNA    18382.0

[7211 rows x 2 columns]
```

```
#plotting a bar graph for the top 15 non-safe aircrafts based on the
risk rate
least_15_aircrafts = risk.tail(10)

plt.figure(figsize=(10,6))
plt.barh(least_15_aircrafts['Make'],
least_15_aircrafts['Risk_rate'],color='green')
plt.xlabel('Total Risk Score')
plt.ylabel('Makes')
plt.title('Top 10 non-safe Aircraft Makes (Highest Risk)')
plt.show()
```



```
#plotting the top 10 aircreft makes with the lowest risk
top_15_aircrafts = risk.head(10)
plt.figure(figsize=(10, 6))

#plt.plot(top_15_aircrafts['Make'], top_15_aircrafts['Risk_rate'],
color='skyblue')
# Assuming you have a column 'Total_Accidents'
safe_makes = df[df['Risk_rate'] ==
0].groupby('Make').size().sort_values(ascending=True).head(10)

safe_makes.plot(kind='bar', figsize=(12, 6), color='blue')
plt.title('Top 10 Zero risk rate Aircraft makes')
plt.ylabel('Risk Rate')
plt.xlabel('Make')
plt.xticks(rotation=45)

plt.show()
```



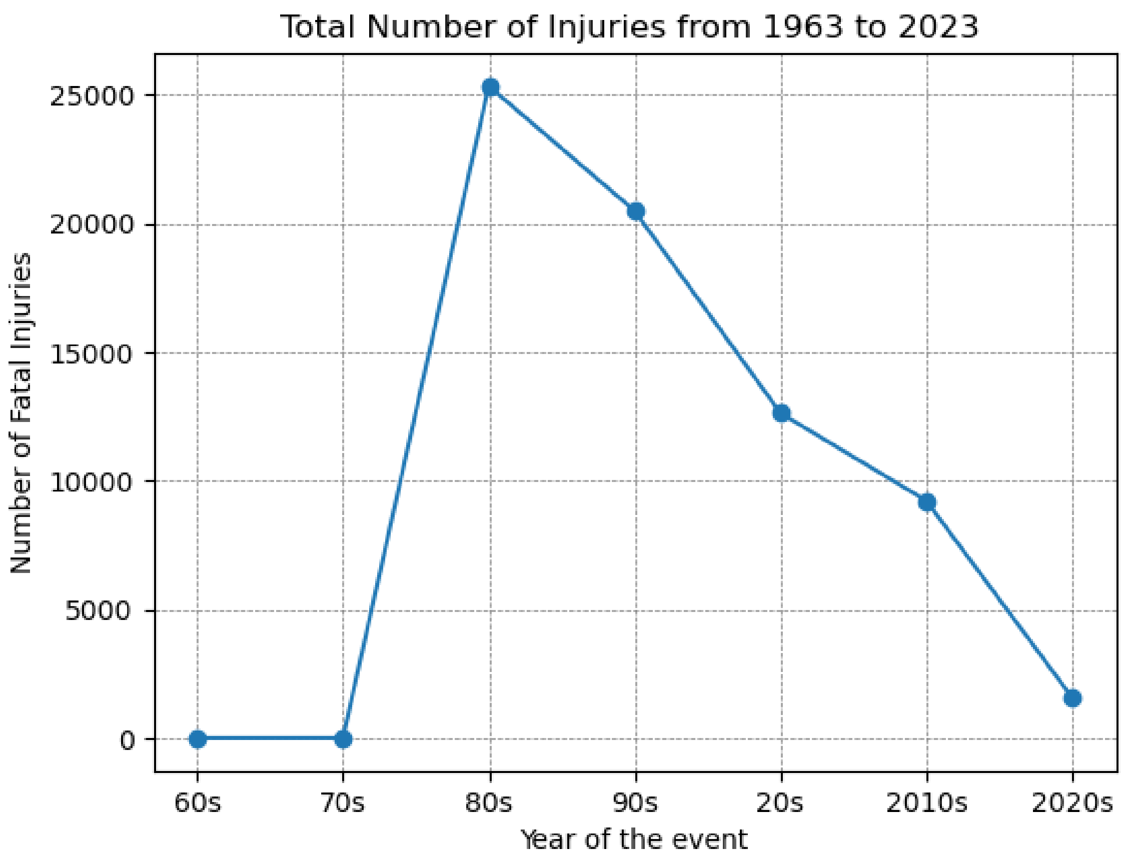

```
#calculating the total number of injuries
df['Total_Injuries'] = (
    (df['Total.Fatal.Injuries']) +
    (df['Total.Serious.Injuries']) +
    (df['Total.Minor.Injuries'])
)
```

```python
# Create the plot
plt.figure(figsize=(12, 6))
fig, ax = plt.subplots()
#groupby function
grouping = df.groupby('Event_by_Year')['Total_Injuries'].sum()
ax.plot(grouping.index, grouping.values,marker='o')

# Add labels for x and y axes
ax.set_xlabel('Year of the event')
ax.set_ylabel('Number of Fatal Injuries')
ax.grid(
    True,
    which='both',
    color='gray',
    linestyle='--',
    linewidth=0.5
)

# title
ax.set_title('Total Number of Injuries from 1963 to 2023 ')
```

```
C:\Users\sam\AppData\Local\Temp\ipykernel_32264\918329361.py:5:
FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to
retain current behavior or observed=True to adopt the future default
and silence this warning.
  grouping = df.groupby('Event_by_Year')['Total_Injuries'].sum()
```

```
Text(0.5, 1.0, 'Total Number of Injuries from 1963 to 2023 ')
```

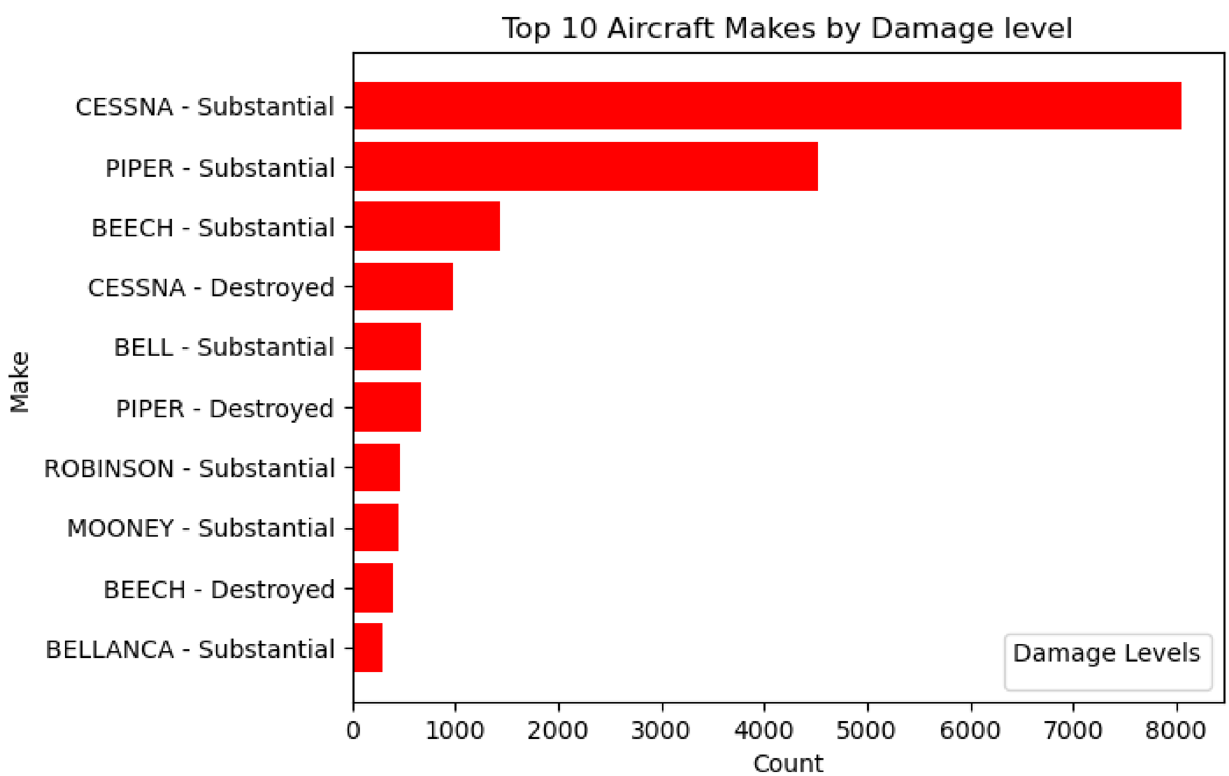
```
<Figure size 1200x600 with 0 Axes>
```




```
#Filtered years
filtered_years = df[df['Event_Year'] >=2000]

D_levels = filtered_years.groupby(['Make',
'Aircraft.damage']).size().reset_index(name='counts')
D_levels = D_levels.sort_values(by='counts', ascending=True).tail(10)


#displays top aircraft makes by their damage levels
D_levels
```

	Make	Aircraft.damage	counts
553	BELLANCA	Substantial	290
515	BEECH	Destroyed	399
3433	MOONEY	Substantial	448
4166	ROBINSON	Substantial	469
3828	PIPER	Destroyed	661
531	BELL	Substantial	674
968	CESSNA	Destroyed	970
517	BEECH	Substantial	1435
3830	PIPER	Substantial	4528
970	CESSNA	Substantial	8054

```
#plotting
#Combining two categorical entries to be on the same axis
plt.barh(D_levels['Make'] + " - " + D_levels['Aircraft.damage'],
D_levels['counts'], color='red')
plt.title('Top 10 Aircraft Makes by Damage level')
plt.xlabel('Count')
plt.ylabel('Make')
plt.legend(title='Damage Levels')

plt.show()

No artists with labels found to put in legend.  Note that artists
whose label start with an underscore are ignored when legend() is
called with no argument.
```

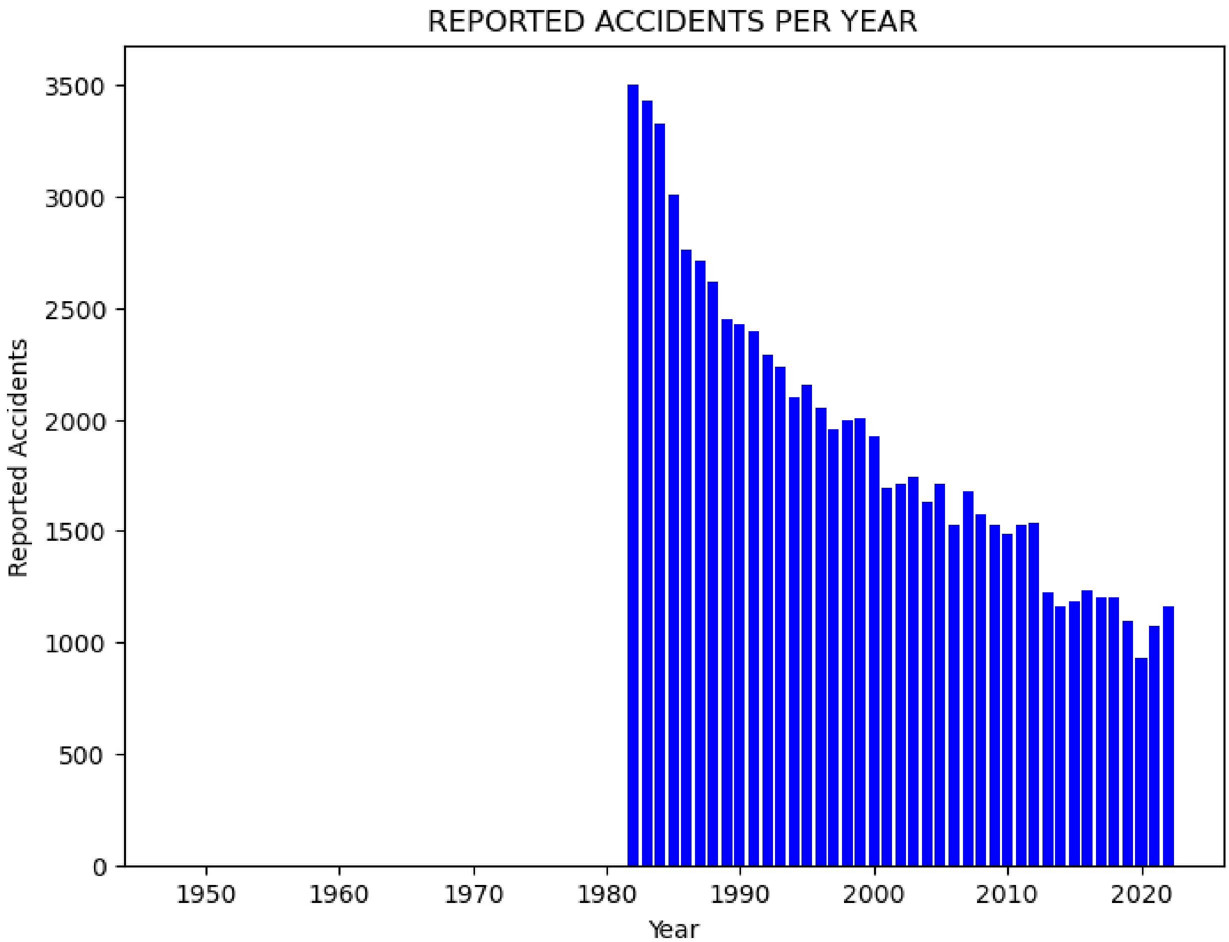



```
accidents_per_year = df['Event_Year'].value_counts().sort_index()

accidents_per_year

Event_Year
1948        1
1962        1
1974        1
1977        1
1981        1
```

```
1982    3503
1983    3428
1984    3326
1985    3008
1986    2758
1987    2712
1988    2614
1989    2452
1990    2428
1991    2395
1992    2294
1993    2233
1994    2098
1995    2155
1996    2049
1997    1953
1998    2000
1999    2002
2000    1921
2001    1693
2002    1706
2003    1742
2004    1627
2005    1713
2006    1529
2007    1675
2008    1574
2009    1527
2010    1484
2011    1524
2012    1533
2013    1220
2014    1162
2015    1187
2016    1232
2017    1196
2018    1203
2019    1094
2020     929
2021    1075
2022    1160
Name: count, dtype: int64
```

```
plt.figure(figsize=(8, 6))
plt.bar(accidents_per_year.index, accidents_per_year.values,
color='blue')
plt.xlabel('Year')
plt.ylabel('Reported Accidents')
plt.title('REPORTED ACCIDENTS PER YEAR')
```

```
plt.show()
```




```
filtered_years2 = df[df['Event_Year'] >=2000]
D_levels2 = filtered_years2.groupby(['Make',
'Event_Year']).size().reset_index(name='counts')
D_levels2 = D_levels2.sort_values(by='counts',
ascending=True).head(15)

D_levels2
```

	Make	Event_Year	counts
0	107.5 FLYING CORPORATION	2006	1
5204	MILLER	2000	1
5203	MILHOLLAND	2016	1
5202	MILESKI	2009	1
5201	MIKOYAN MIG	2004	1
5200	MIKOYAN GUREVICH	2013	1
5199	MIKOYAN GUREVICH	2012	1
5198	MIKOYAN GUREVICH	2002	1

```
5197                  MIKOYAN        2003       1
5196              MIKE SMILEE        2006       1
5195                MIKE REED        2017       1
5194                MIHLEBACH        2000       1
5193                    MIGAS        2010       1
5192                   MIELEC        2003       1
5191           MIDGET MUSTANG        2007       1

#plotting
plt.figure(figsize=(10,6))
plt.barh(D_levels2['Make'], D_levels2['counts'],color='green')
plt.xlabel('Total Report Counts')
plt.ylabel('Makes')
plt.title('Top 15 safe Aircraft Makes from 2000 to Date')
plt.show()
```