phase1_project

June 23, 2024

1 Business Understanding

1.1 Project Prompt

Your company is expanding in to new industries to diversify its portfolio. Specifically, they are interested in purchasing and operating airplanes for commercial and private enterprises, but do not know anything about the potential risks of aircraft. You are charged with determining which aircraft are the lowest risk for the company to start this new business endeavor. You must then translate your findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

1.2 Goal

Find the variables that make an airplane the safest and provide business recommendations based on these findings

2 Data Understanding

2.1 Dataset Overview

Summary: The dataset contains records of aircraft crashes between 1948 - 2022. The data from 1948 -1982 is limited so we drop those data points to focus on the majority of the volume following 1982. Data points include the number of engines, seveirty of passenger injuries, severity of aircraft damage,and more.

Important Data Columns:

1. Aircraft Make and Model: Information about the specific make and model of the aircraft involved in each incident.
2. Aircraft Damage: The severity of the damage to the aircraft
3. Severity of Injuries: A count for each incident on the number of uninjured, minor, serious, and fatal injuries.
4. Engine Type: The type of engine on the aircraft

5. Num of Engines: The number of engines on an airplane. The mean is 1 but can range from 1 - 8.

3 Data Preparation

3.1 Step 1: Load and Explore Dataset

[1]:
```
#Import necessary packages

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

%matplotlib inline
```

[2]:
```
#Load and print head of Aviation Datasets ('AviationData.csv', 'USState_Codes.
↪csv')

df = pd.read_csv('AviationData.csv', encoding='ISO-8859-1', low_memory=False)

df.head()
```

[2]:
```
         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]
```

[3]:
```python
# Explore the shape of the dataset

df.shape
```

[3]: (88889, 31)

[7]:
```python
# Evaluate the column headers

df.columns
```

[7]:
```
Index(['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'],
      dtype='object')
```

[9]:
```python
# understand the data types, counts, and null values

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
```

3.2 Missing Values

There are several columns that have significant missing values: Latitude, Longitude, Airport.Code, Airport.Name, Aircraft.Category, FAR.Description, Schedule, Air.carrier, Broad.phase.of.flight

[14]:
```
# Get descriptive statistics for the dataset

df.describe()
```

[14]:
```
       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
```

3.3 Description output of dataset

General Observations 1. Number of engines - M 1. jority of the time there is one engine in an airplane as this was the value for the 25%, 50% , and 75% qua2. rtile - The max # of engines is 8

2. Injury Columns

- Injuries are broken into 4 distinct columns based on the s everity: Fatal, Serious, Minor, Uninjure1. d2. 3. . - = = - - -
- =- -

---

4 Cleaning Data

[19]:
```
#Identify missing values across dataframe columns

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

[19]:
```
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
```

[20]:
```
#Identify columns with more than 25% of missing data and add them to a list

(df['FAR.Description'].isna().sum()/len(df)) * 100

columns_to_drop=[]
for x in df:
    if (df[x].isna().sum() / len(df[x])) * 100 > 25:
        columns_to_drop.append(x)
print(columns_to_drop)
```

```
['Latitude', 'Longitude', 'Airport.Code', 'Airport.Name', 'Aircraft.Category',
'FAR.Description', 'Schedule', 'Air.carrier', 'Broad.phase.of.flight']
```

Dropping columns missing more than 25% to ensure there is a significant amount of data populated in columns that we analyze

[24]:
```
#Drop columns from dataframe that are missing too much data

df_new = df.drop(columns= columns_to_drop)
df_new.columns
```

[24]:
```
Index(['Event.Id', 'Investigation.Type', 'Accident.Number', 'Event.Date',
       'Location', 'Country', 'Injury.Severity', 'Aircraft.damage',
       'Registration.Number', 'Make', 'Model', 'Amateur.Built',
       'Number.of.Engines', 'Engine.Type', 'Purpose.of.flight',
       'Total.Fatal.Injuries', 'Total.Serious.Injuries',
```

```
 'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
 'Report.Status', 'Publication.Date'],
dtype='object')
```

[25]:
```python
#Exploring unique column values

print('Investigation Type:',df['Investigation.Type'].unique())
print('Aircraft damage:',df['Aircraft.damage'].unique())
print('Engine Type:',df['Engine.Type'].unique())
```

```
Investigation Type: ['Accident' 'Incident']
Aircraft damage: ['Destroyed' 'Substantial' 'Minor' nan 'Unknown']
Engine Type: ['Reciprocating' nan 'Turbo Fan' 'Turbo Shaft' 'Unknown' 'Turbo
Prop'
 'Turbo Jet' 'Electric' 'Hybrid Rocket' 'Geared Turbofan' 'LR' 'NONE'
 'UNK']
```

[27]:
```python
# Explore different airplane makes

df_new['Make'].value_counts()
```

[27]:
```
Make
Cessna             22227
Piper              12029
CESSNA              4922
Beech               4330
PIPER               2841
                   …
Leonard Walters        1
Maule Air Inc.         1
Motley Vans            1
Perlick                1
ROYSE RALPH L          1
Name: count, Length: 8237, dtype: int64
```

[29]:
```python
#Clean data amongst same make but different spelling

df_new['Make'] = df_new['Make'].str.title()
df_new['Make'].value_counts()
```

[29]:
```
Make
Cessna           27149
Piper            14870
Beech             5372
Boeing            2745
Bell              2722
                 …
```

```
Cohen                     1
Kitchens                  1
Lutes                     1
Izatt                     1
Royse Ralph L             1
Name: count, Length: 7587, dtype: int64
```

[31]:
```
#Clean values in Weather Condition column

df_new['Weather.Condition'] = df_new['Weather.Condition'].str.title()
df_new['Weather.Condition'].value_counts()
```

[31]:
```
Weather.Condition
Vmc    77303
Imc     5976
Unk     1118
Name: count, dtype: int64
```

[33]:
```
# Explore different types of airplane models

df_new['Model'].value_counts()
```

[33]:
```
Model
152              2367
172              1756
172N             1164
PA-28-140         932
150               829
                 …
GC-1-A              1
737-3S3             1
MBB-BK117-B2        1
GLASSAIR GL25       1
M-8 EAGLE           1
Name: count, Length: 12318, dtype: int64
```

[35]:
```
# Explore values in the damage count column

damage_count = df_new['Aircraft.damage'].value_counts()
damage_count
```

[35]:
```
Aircraft.damage
Substantial    64148
Destroyed      18623
Minor           2805
Unknown          119
Name: count, dtype: int64
```

[37]:
```
# Explore different types of engines

engine_type = df_new['Engine.Type'].value_counts()
engine_type
```

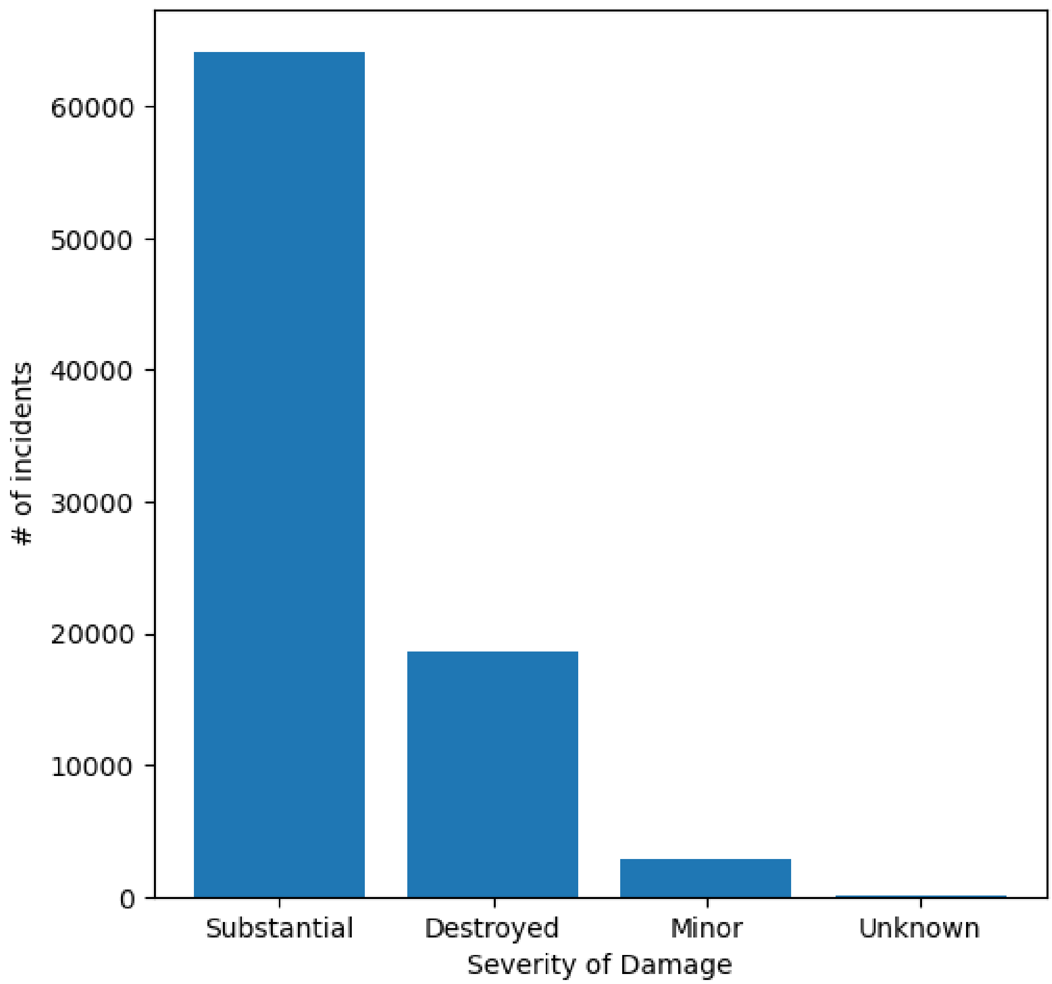
[37]:
```
Engine.Type
Reciprocating      69530
Turbo Shaft         3609
Turbo Prop          3391
Turbo Fan           2481
Unknown             2051
Turbo Jet            703
Geared Turbofan       12
Electric              10
LR                     2
NONE                   2
Hybrid Rocket          1
UNK                    1
Name: count, dtype: int64
```

---

5 Exploratory Data Analysis

[42]:
```
# Visualizing the breakdown of damage across airplane crashes

fig, ax = plt.subplots(figsize= (6,6))

ax.bar(damage_count.index,damage_count.values)
ax.set_ylabel('# of incidents')
ax.set_xlabel('Severity of Damage')
```

[42]:
```
Text(0.5, 0, 'Severity of Damage')
```

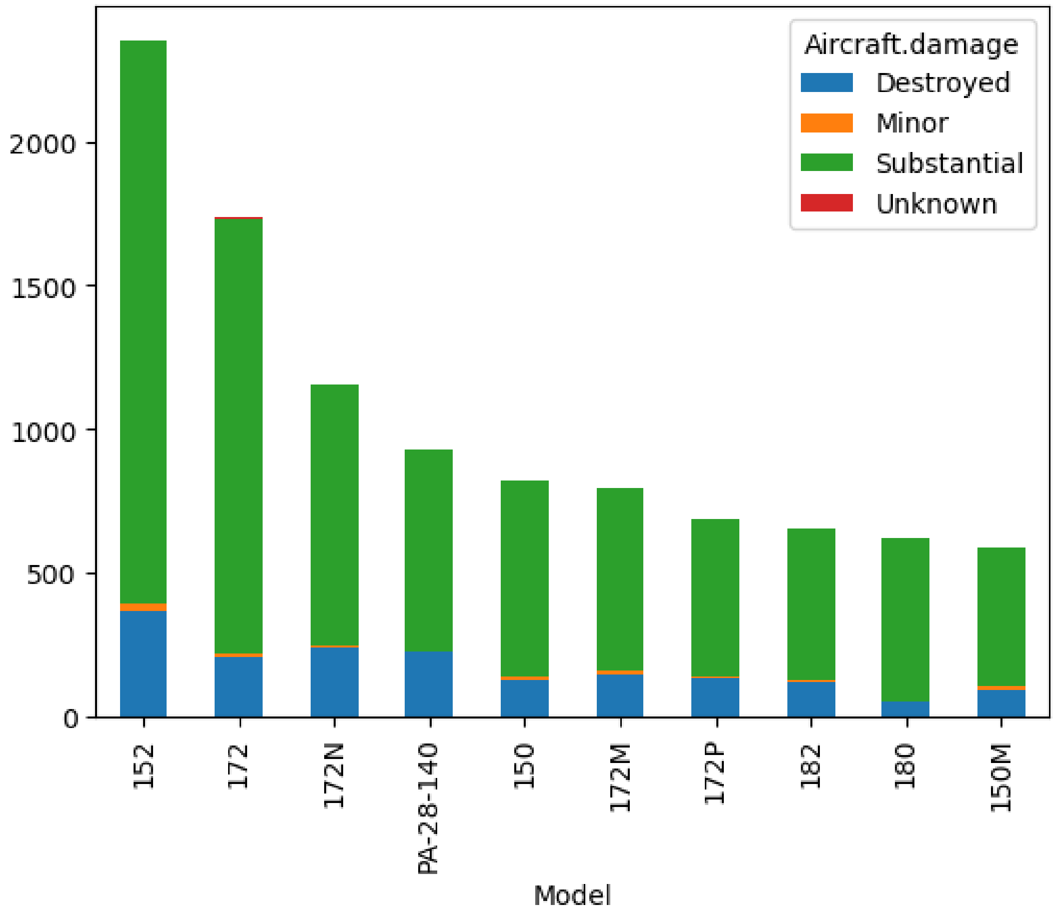


[43]:
```
#Group model and aircraft damage data to create a bar chart of damage across␣
↪models
damage_by_model = df_new.groupby(['Model','Aircraft.damage']).size().
↪unstack(fill_value=0)
damage_by_model['Total']= damage_by_model.sum(axis=1)
damage_by_model_sorted = damage_by_model.sort_values(by='Total',ascending=False)


# Filter for the top 10 models by volume
top_10_damage_by_model=damage_by_model_sorted.head(10)
top_10_damage_by_model=top_10_damage_by_model.drop(columns=['Total'])
top_10_damage_by_model
```

[43]:
```
Aircraft.damage  Destroyed  Minor  Substantial  Unknown
Model
152                    365     29         1958        2
```

```
172                  207     9      1514     4
172N                 236     7       910     0
PA-28-140            223     5       699     1
150                  128    10       682     1
172M                 146    11       638     2
172P                 135     5       547     0
182                  118     8       526     2
180                   51     3       566     1
150M                  94     8       482     0
```

[45]:
```
# Visualizing the damage breakdown across different airplane models

top_10_damage_by_model.plot(kind='bar',stacked=True)
plt.show()
```



[47]:
```
#Group make and aircraft damage data to create a bar chart of damage across␣
↪airplane makes
```

```
damage_by_make = df_new.groupby(['Make','Aircraft.damage']).size().
 ↪unstack(fill_value=0)
damage_by_make['Total']= damage_by_make.sum(axis=1)
damage_by_make_sorted = damage_by_make.sort_values(by='Total',ascending=False)

# Filter to the top 10
top_10_damage_by_make = damage_by_make_sorted.head(10)
top_10_damage_by_make = top_10_damage_by_make.drop(columns=['Total'])
top_10_damage_by_make
```

[47]:

```
Aircraft.damage  Destroyed  Minor  Substantial  Unknown
Make
Cessna                5202    387        21268       38
Piper                 3428    204        11100       15
Beech                 1585    170         3539        5
Bell                   708     47         1900        5
Boeing                 170    711          739       11
Mooney                 373     24          923        3
Robinson               282      8          916        4
Grumman                299     18          845        0
Bellanca               233      7          800        0
Hughes                 190     10          718        0
```

[49]:

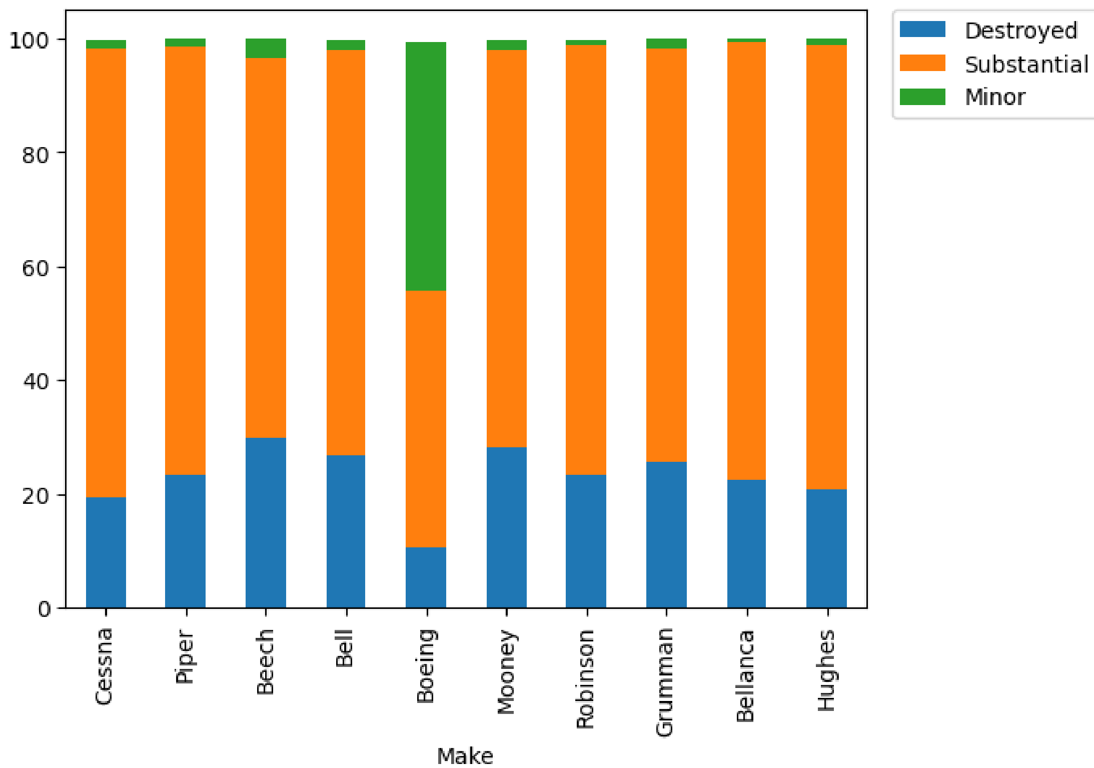
```
# Convert values into percentages so you can compare damage in an apples to␣
 ↪apples comparison

# Find the sum of the row
row_sums = top_10_damage_by_make.sum(axis=1)

# Divide each value by its row sum and multiply by 100
top_10_damage_by_make_percentage = top_10_damage_by_make.div(row_sums, axis=0)␣
 ↪* 100

column_order = ['Destroyed','Substantial','Minor']

top_10_damage_by_make_percentage = top_10_damage_by_make_percentage.loc[:
 ↪,column_order]

# Display the resulting DataFrame
print(top_10_damage_by_make_percentage)
```

```
Aircraft.damage  Destroyed  Substantial     Minor
Make
Cessna           19.341885    79.077896  1.438929
Piper            23.245406    75.269546  1.383332
Beech            29.911304    66.786186  3.208152
Bell             26.616541    71.428571  1.766917
```

```
Boeing          10.423053    45.309626  43.592888
Mooney          28.193500    69.765684   1.814059
Robinson        23.305785    75.702479   0.661157
Grumman         25.731497    72.719449   1.549053
Bellanca        22.403846    76.923077   0.673077
Hughes          20.697168    78.213508   1.089325
```

[52]:

```
#Visulize the top 10 airplane makes by severity of damage

top_10_damage_by_make_percentage.plot(kind='bar',stacked=True)
plt.legend(bbox_to_anchor=(1.29,1),loc='upper right',borderaxespad=0)

plt.show()
```



Takaways from the above graph - Beech has the highest % of destroyed aircrafts - Bell has the highest % of substantially damaged aircrafts - Boeing seems to have the safest planes with the highest % of minor damage

[54]:

```
df_new['Event.Date']
```

[54]:

```
0        1948-10-24
1        1962-07-19
2        1974-08-30
```

```
3        1977-06-19
4        1979-08-02
            …
88884    2022-12-26
88885    2022-12-26
88886    2022-12-26
88887    2022-12-26
88888    2022-12-29
Name: Event.Date, Length: 88889, dtype: object
```

[57]:
```
#Converting the event date column to a date dtype and extracting the year and␣
↪month

df_new['Event.Date'] = pd.to_datetime(df['Event.Date'])
df_new['Year'] = df_new['Event.Date'].dt.year
df_new['Month'] = df_new['Event.Date'].dt.month
```

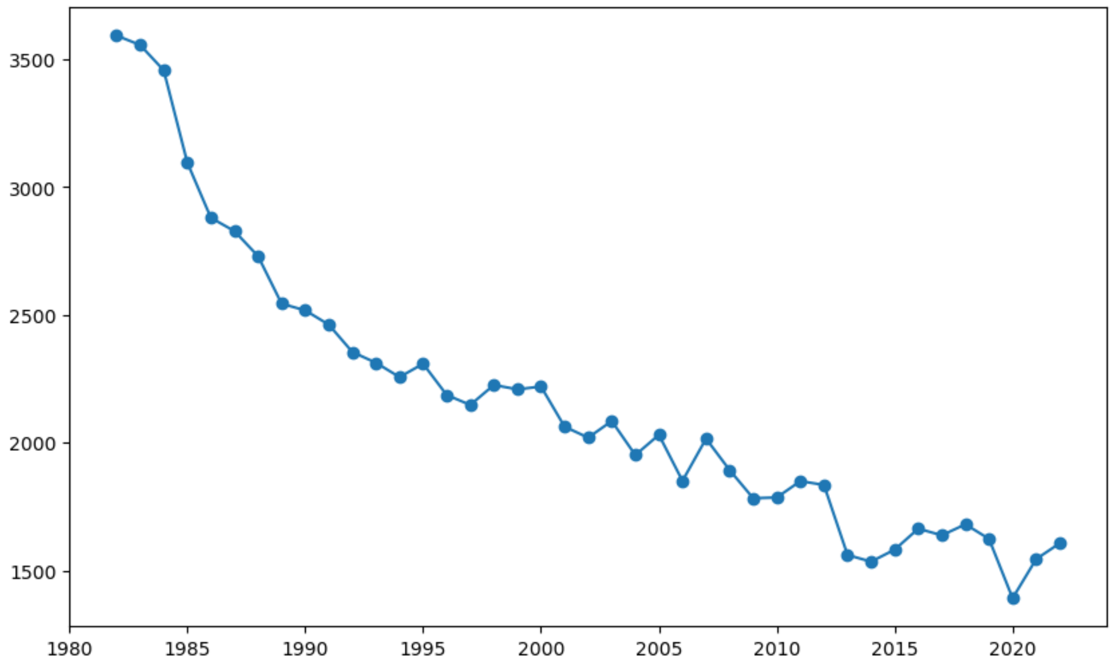
[58]:
```
#drop values before 1982 since there is limited data

df_new = df_new[df_new['Year'] >=1982]
df_new['Year']

#Group by year and sum number of crashes
yearly_crashes = df_new.groupby('Year').size()
yearly_crashes
```

[58]:
```
Year
1982    3593
1983    3556
1984    3457
1985    3096
1986    2880
1987    2828
1988    2730
1989    2544
1990    2518
1991    2462
1992    2355
1993    2313
1994    2257
1995    2309
1996    2187
1997    2148
1998    2226
1999    2209
2000    2220
2001    2063
```

```
2002    2020
2003    2085
2004    1952
2005    2031
2006    1851
2007    2016
2008    1893
2009    1783
2010    1786
2011    1850
2012    1835
2013    1561
2014    1535
2015    1582
2016    1664
2017    1638
2018    1681
2019    1624
2020    1392
2021    1545
2022    1607
dtype: int64
```

[60]:
```
#crashes over the years

plt.figure(figsize=(10, 6))  # You can adjust the size as needed
plt.plot(yearly_crashes.index, yearly_crashes.values, marker='o')  # 'o' adds␣
 ↪circle markers
```

[60]:
```
[<matplotlib.lines.Line2D at 0x7fdf1750dad0>]
```



[62]:
```
df_new.isna().sum()
```

[62]:
```
Event.Id                      0
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Injury.Severity            1000
Aircraft.damage            3194
Registration.Number        1382
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6083
Engine.Type                7095
Purpose.of.flight          6191
Total.Fatal.Injuries      11400
Total.Serious.Injuries    12508
Total.Minor.Injuries      11931
Total.Uninjured            5911
Weather.Condition          4492
Report.Status              6384
Publication.Date          13770
Year                          0
```

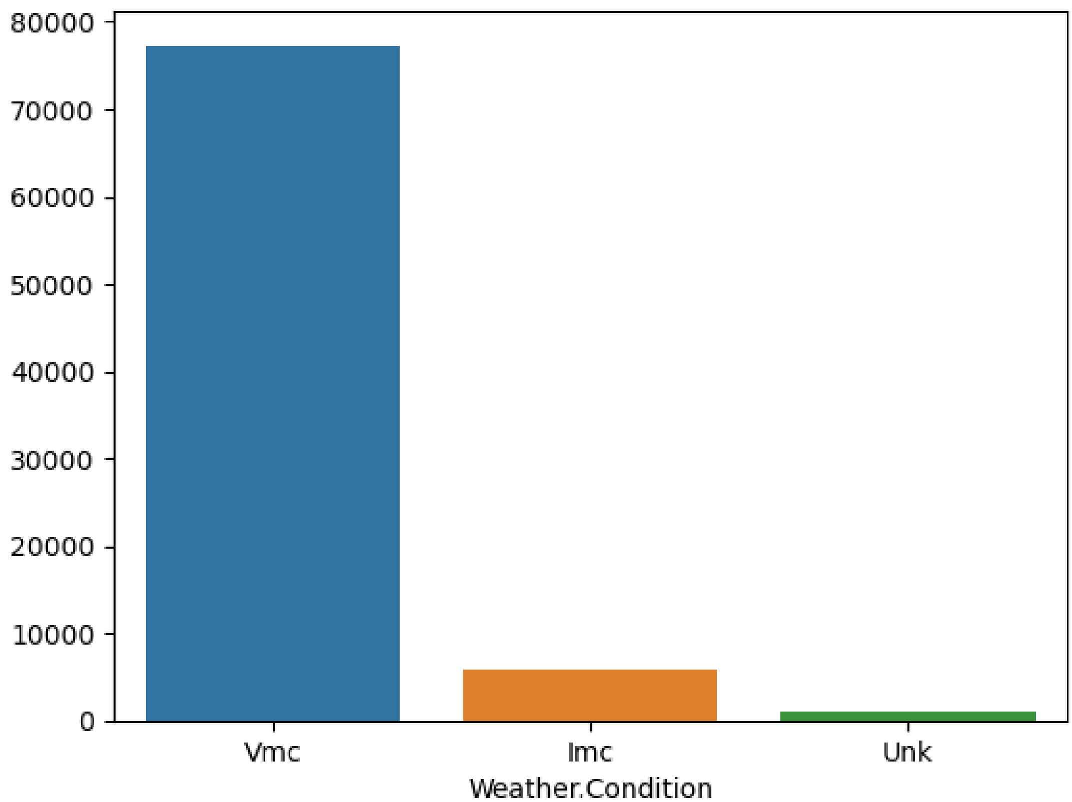
```
Month                              0
dtype: int64
```

[63]:
```
#Exploring Weather Data

weather_group = df_new['Weather.Condition'].value_counts()
print(weather_group.values)
```

```
[77301  5973  1116]
```

[64]:
```
sns.barplot(x=weather_group.index, y=weather_group.values)
```

[64]: <Axes: xlabel='Weather.Condition'>



[66]:
```
# Grouping weather data with damage history

weather_injuries = df_new.groupby('Weather.Condition')[['Total.Fatal.Injuries',
'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured']].count()

weather_injuries
```

[66]:

```
                   Total.Fatal.Injuries  Total.Serious.Injuries  \
Weather.Condition
Imc                                5585                    5115
Unk                                1017                    1000
Vmc                               66699                   66203

                   Total.Minor.Injuries  Total.Uninjured
Weather.Condition
Imc                                5091             5268
Unk                                1001             1045
Vmc                               66826            72498
```

Since there is skewed data with 90%+ of data representing Vmc weather there is not much to explore here

[72]:

```python
# Exploring crashes with serious / fatal injuries vs Total.Fatal.Injuries',
#'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured

injuries = df_new.groupby('Make')[['Total.Fatal.Injuries',
'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured']].count()

#identify top 10 makes by injuries
injuries['Total'] = injuries.sum(axis=1)
injuries_sorted = injuries.sort_values(by=['Total'],ascending=False)
injuries_sorted_top_10 = injuries_sorted.head(10)
injuries_sorted_top_10_final= injuries_sorted_top_10.drop(columns=['Total'])


injuries_sorted_top_10_final
```

[72]:

```
          Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries  \
Make
Cessna                   23809                   23450                 23725
Piper                    13194                   12933                 13004
Beech                     4795                    4609                  4620
Bell                      2352                    2339                  2360
Boeing                    2270                    2313                  2289
Mooney                    1157                    1125                  1147
Grumman                   1077                    1073                  1081
Robinson                   958                     917                   942
Bellanca                   924                     919                   936
Hughes                     788                     798                   809

          Total.Uninjured
Make
Cessna              25698
Piper               14015
```

```
Beech              4933
Bell               2501
Boeing             2581
Mooney             1225
Grumman            1128
Robinson           1083
Bellanca            988
Hughes              870
```

[73]:

```
# Convert values into percentages for an easy comparative visual

Total = injuries_sorted_top_10_final.sum(axis = 1)

injuries_percentage = injuries_sorted_top_10_final.div(Total,axis=0)
injuries_percentage
```

[73]:

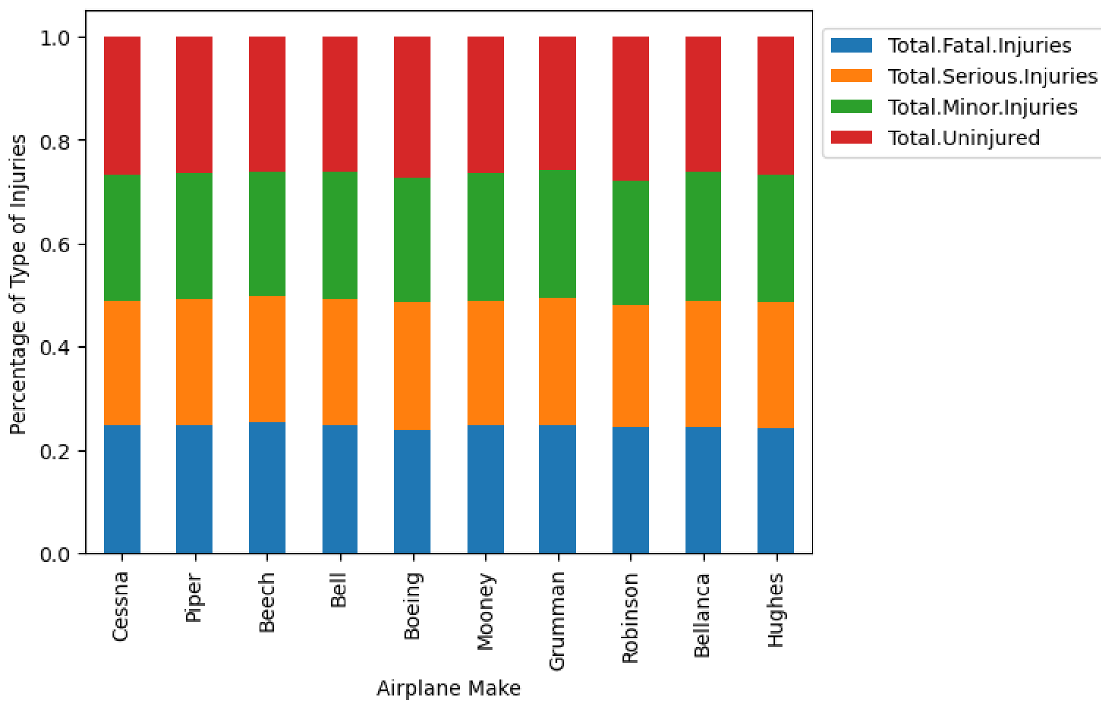
```
          Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries  \
Make
Cessna                0.246261                0.242548              0.245392
Piper                 0.248260                0.243349              0.244684
Beech                 0.252941                0.243129              0.243709
Bell                  0.246231                0.244870              0.247069
Boeing                0.240135                0.244684              0.242145
Mooney                0.248603                0.241728              0.246455
Grumman               0.247075                0.246157              0.247993
Robinson              0.245641                0.235128              0.241538
Bellanca              0.245288                0.243961              0.248474
Hughes                0.241348                0.244410              0.247779

          Total.Uninjured
Make
Cessna           0.265799
Piper            0.263708
Beech            0.260220
Bell             0.261830
Boeing           0.273035
Mooney           0.263214
Grumman          0.258775
Robinson         0.277692
Bellanca         0.262278
Hughes           0.266462
```

[74]:

```
# Visaulize the types of injuries sustained compared to different airplane␣
 ↪manufacturers
ax= injuries_percentage.plot(kind='bar',stacked='True')
ax.legend(loc='center left', bbox_to_anchor=(1, .85), ncol=1)
plt.xlabel('Airplane Make')
```

```
plt.ylabel('Percentage of Type of Injuries')
```

[74]: Text(0, 0.5, 'Percentage of Type of Injuries')



Graph Takeaways - There seems to be little difference in the % of injuries sustained across airplane makes

Let's explore if there are certain models for each make that have a higher % of substanstial injuries

5.1 Exploring Correlation Between Engine Types and Severity of Accidents

[78]:
```
# Grouping engine types and airplane damage to look for a correlation

engine_accidents = df_new.groupby('Engine.Type')[['Total.Fatal.Injuries',
'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured']].count()

engine_accidents
```

[78]:
```
                   Total.Fatal.Injuries  Total.Serious.Injuries  \
Engine.Type
Electric                             10                      10
Geared Turbofan                      12                      12
Hybrid Rocket                         1                       1
LR                                    2                       2
NONE                                  2                       2
```

```
Reciprocating                  60837                 60060
Turbo Fan                       1994                  2062
Turbo Jet                        590                   588
Turbo Prop                      2870                  2753
Turbo Shaft                     3040                  3035
UNK                                1                     1
Unknown                         1901                  1873

                 Total.Minor.Injuries  Total.Uninjured
Engine.Type
Electric                           10               10
Geared Turbofan                    12               12
Hybrid Rocket                       1                1
LR                                  2                2
NONE                                2                2
Reciprocating                   60702            65244
Turbo Fan                        2026             2416
Turbo Jet                         581              668
Turbo Prop                       2790             3121
Turbo Shaft                      3081             3323
UNK                                 1                1
Unknown                          1877             1926
```

[79]:

```python
engine_accidents['Total'] = engine_accidents.sum(axis=1)
engine_accidents = engine_accidents.sort_values(by=['Total'],ascending=False)
engine_accidents_sorted_top_10 = engine_accidents.head(10)
engine_accidents_final= engine_accidents_sorted_top_10.drop(columns=['Total'])

engine_accidents_final
```

[79]:

```
                 Total.Fatal.Injuries  Total.Serious.Injuries  \
Engine.Type
Reciprocating                   60837                   60060
Turbo Shaft                      3040                    3035
Turbo Prop                       2870                    2753
Turbo Fan                        1994                    2062
Unknown                          1901                    1873
Turbo Jet                         590                     588
Geared Turbofan                    12                      12
Electric                           10                      10
LR                                  2                       2
NONE                                2                       2

                 Total.Minor.Injuries  Total.Uninjured
Engine.Type
Reciprocating                   60702            65244
Turbo Shaft                      3081             3323
```

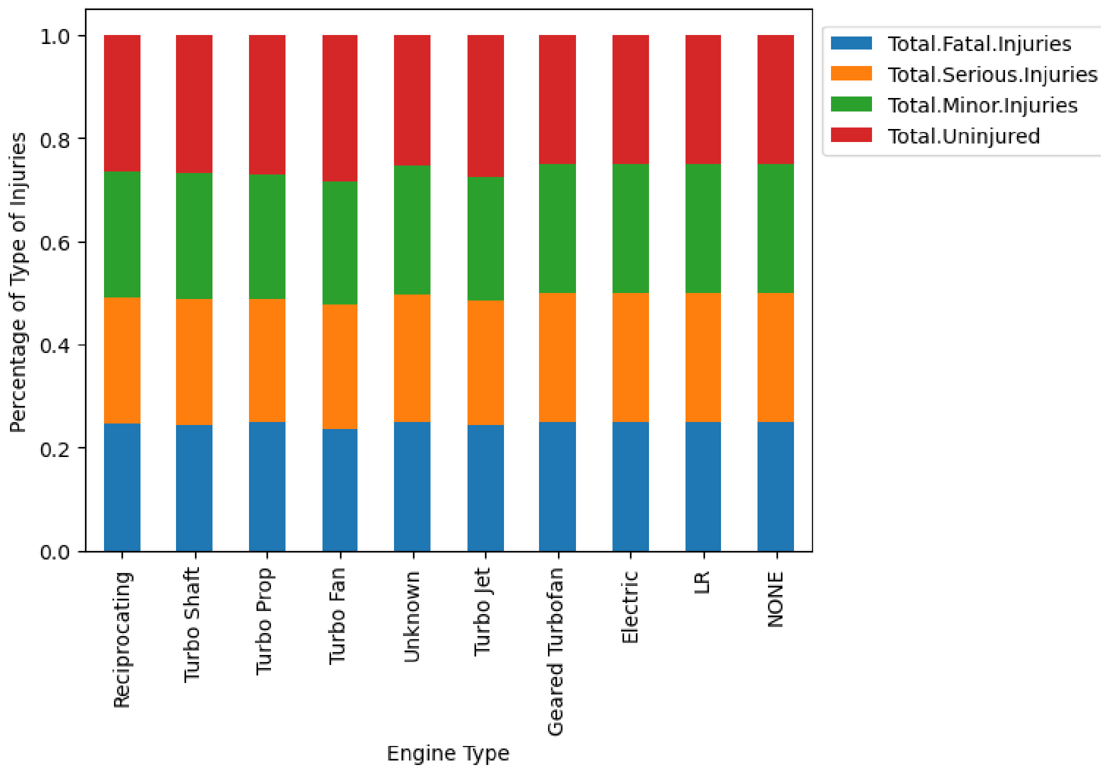
```
Turbo Prop                      2790             3121
Turbo Fan                       2026             2416
Unknown                         1877             1926
Turbo Jet                        581              668
Geared Turbofan                   12               12
Electric                          10               10
LR                                 2                2
NONE                               2                2
```

[80]:
```
Total = engine_accidents_final.sum(axis = 1)

engine_percentage = engine_accidents_final.div(Total,axis=0)
engine_percentage
```

[80]:
```
                 Total.Fatal.Injuries  Total.Serious.Injuries  \
Engine.Type
Reciprocating                0.246460                0.243313
Turbo Shaft                  0.243609                0.243209
Turbo Prop                   0.248830                0.238686
Turbo Fan                    0.234643                0.242645
Unknown                      0.250891                0.247195
Turbo Jet                    0.243098                0.242274
Geared Turbofan              0.250000                0.250000
Electric                     0.250000                0.250000
LR                           0.250000                0.250000
NONE                         0.250000                0.250000

                 Total.Minor.Injuries  Total.Uninjured
Engine.Type
Reciprocating                0.245913         0.264314
Turbo Shaft                  0.246895         0.266287
Turbo Prop                   0.241894         0.270591
Turbo Fan                    0.238409         0.284302
Unknown                      0.247723         0.254190
Turbo Jet                    0.239390         0.275237
Geared Turbofan              0.250000         0.250000
Electric                     0.250000         0.250000
LR                           0.250000         0.250000
NONE                         0.250000         0.250000
```

[81]:
```
# Visaulize the types of injuries sustained compared to different engine types
ax= engine_percentage.plot(kind='bar',stacked='True')
ax.legend(loc='center left', bbox_to_anchor=(1, .85), ncol=1)
plt.xlabel('Engine Type')
plt.ylabel('Percentage of Type of Injuries')
```

[81]: Text(0, 0.5, 'Percentage of Type of Injuries')



5.2 Exploring Correlation Between Engine Type and Aircraft Damage

[84]:

```
# Grouping engine types and airplane damage to look for a correlation

engine_damage = df_new.groupby('Engine.Type')['Aircraft.damage'].value_counts().
 ↪unstack(fill_value=0)
engine_damage['Total'] = engine_damage.sum(axis=1)
engine_damage_sort = engine_damage.sort_values(by='Total', ascending = False)
engine_damage_sorted = engine_damage_sort[engine_damage_sort['Total'] >= 10]
engine_damage_drop=engine_damage_sorted.drop(columns=['Total'])
engine_damage_drop
```

[84]:

Aircraft.damage	Destroyed	Minor	Substantial	Unknown
Engine.Type				
Reciprocating	14524	853	53805	6
Turbo Shaft	879	91	2549	0
Turbo Prop	807	306	2035	0
Unknown	544	132	1133	0
Turbo Fan	196	670	729	0
Turbo Jet	140	162	234	0

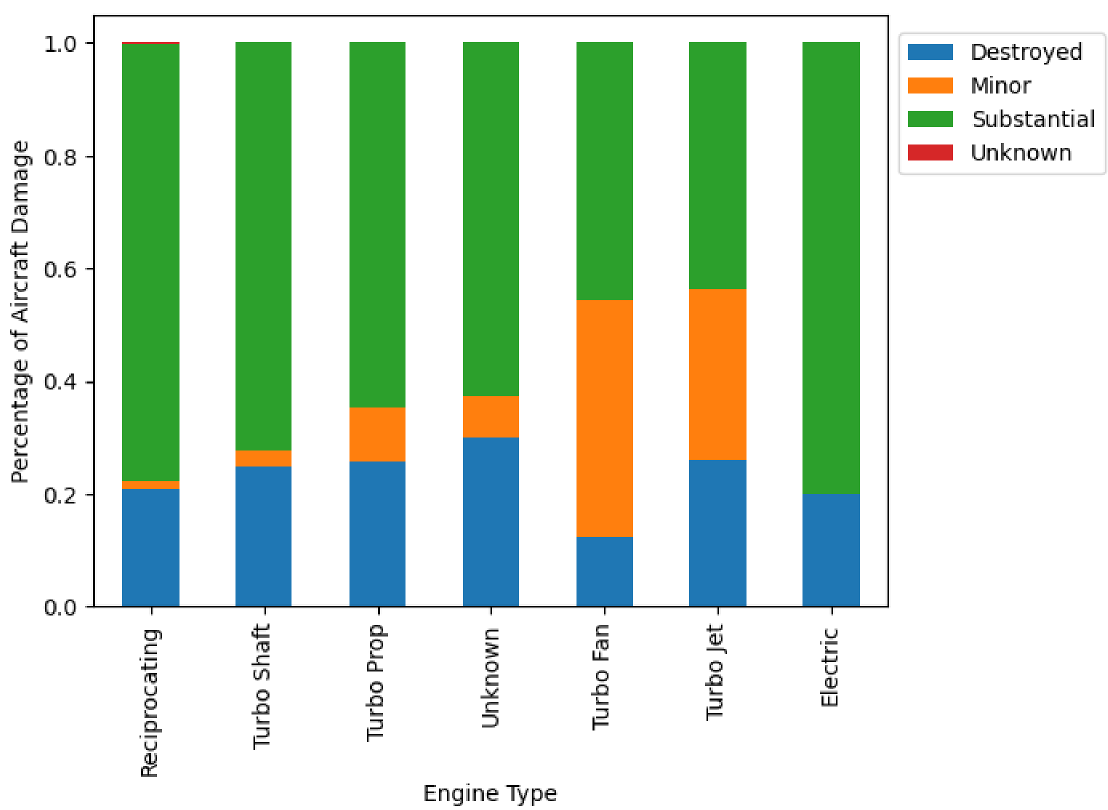
```
Electric                     2       0             8         0
```

[86]:
```
Total_engine = engine_damage_drop.sum(axis = 1)
engine_damage_updated = engine_damage_drop.div(Total_engine,axis=0)
engine_damage_updated
```

[86]:
```
Aircraft.damage  Destroyed     Minor  Substantial   Unknown
Engine.Type
Reciprocating     0.209921  0.012329     0.777664  0.000087
Turbo Shaft       0.249787  0.025860     0.724354  0.000000
Turbo Prop        0.256353  0.097205     0.646442  0.000000
Unknown           0.300719  0.072968     0.626313  0.000000
Turbo Fan         0.122884  0.420063     0.457053  0.000000
Turbo Jet         0.261194  0.302239     0.436567  0.000000
Electric          0.200000  0.000000     0.800000  0.000000
```

[87]:
```
# Visaulize the types of injuries sustained compared to different engine types
ax= engine_damage_updated.plot(kind='bar',stacked='True')
ax.legend(loc='center left', bbox_to_anchor=(1, .85), ncol=1)
plt.xlabel('Engine Type')
plt.ylabel('Percentage of Aircraft Damage')
```

[87]:
```
Text(0, 0.5, 'Percentage of Aircraft Damage')
```



Engine Type and Aircraft Damage Graph Takeaways 1. The Turbo Fan and Turbo Jet have by far the highest percentage of minor aircraft damage across engine types 2. Electric engines seem the most dangerous with the highest percentage of substantial damage

5.3 Exploring Correlation Between # of Engines and Aircraft Damage

[91]:
```
# Grouping number of engines and airplane damage to look for a correlation

# Assuming df_new is already defined and contains the necessary data
num_engine_damage = df_new.groupby('Number.of.Engines')['Aircraft.damage'].
 ↪value_counts().unstack(fill_value=0)
num_engine_damage['Total'] = num_engine_damage.sum(axis=1)
num_engine_damage_sort = num_engine_damage.sort_values(by='Total',␣
 ↪ascending=False)

# Check if 'Unknown' column exists before dropping it
columns_to_drop = ['Total']
if 'Unknown' in num_engine_damage_sort.columns:
    columns_to_drop.append('Unknown')

num_engine_damage_updated = num_engine_damage_sort.drop(columns=columns_to_drop)
num_engine_damage_updated
```

[91]:

Aircraft.damage Number.of.Engines	Destroyed	Minor	Substantial
1.0	13857	726	54565
2.0	2871	1095	5867
0.0	173	74	842
3.0	25	197	104
4.0	58	145	114
8.0	0	0	2
6.0	0	0	1

[92]:
```
# Changing table results to percentage for better interpratation

Total_num = num_engine_damage_updated.sum(axis=1)
num_engine_total_updated = num_engine_damage_updated.div(Total_num,axis=0)
num_engine_total_updated
```

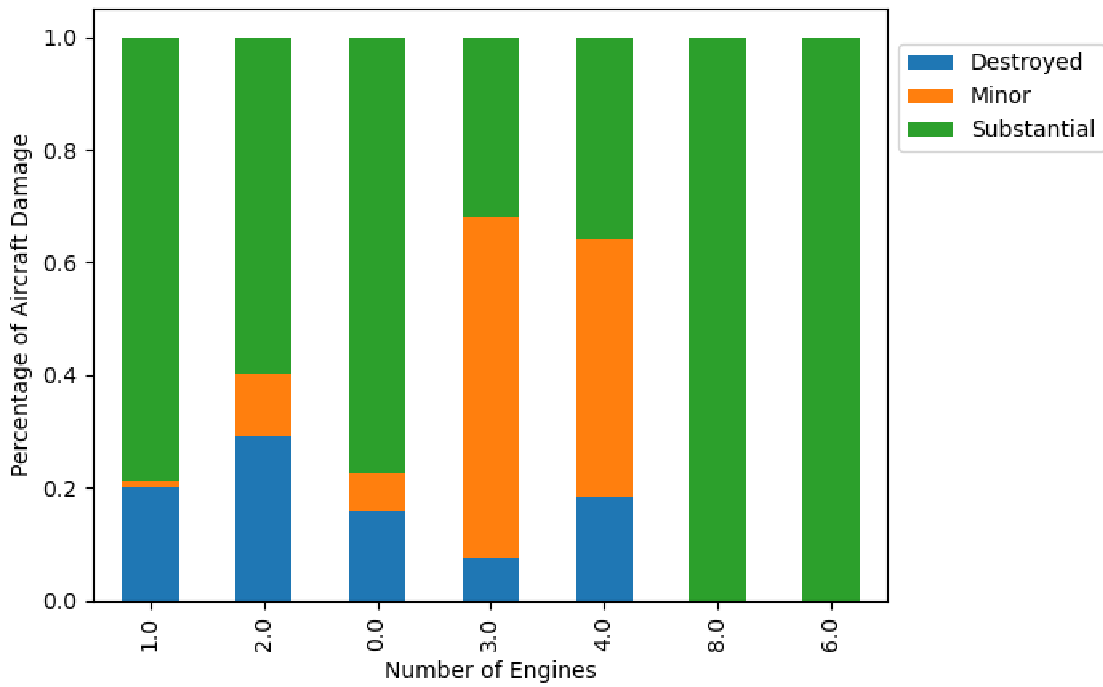
[92]:

Aircraft.damage Number.of.Engines	Destroyed	Minor	Substantial
1.0	0.200396	0.010499	0.789105
2.0	0.291976	0.111360	0.596664
0.0	0.158861	0.067952	0.773186
3.0	0.076687	0.604294	0.319018

```
4.0                    0.182965  0.457413     0.359621
8.0                    0.000000  0.000000     1.000000
6.0                    0.000000  0.000000     1.000000
```

[93]:
```
# Visaulize the types of injuries sustained compared to different engine types
ax= num_engine_total_updated.plot(kind='bar',stacked='True')
ax.legend(loc='center left', bbox_to_anchor=(1, .85), ncol=1)
plt.xlabel('Number of Engines')
plt.ylabel('Percentage of Aircraft Damage')
```

[93]:
```
Text(0, 0.5, 'Percentage of Aircraft Damage')
```



---

6 Diving Deeper Into Boeing

We have identified Boeing as the safest aircraft manufacturer. Now, let's analyze the severity of damage for each model within the Boeing lineup to determine which model is the safest.

[97]:
```
#Creating a df for Boeing to dive deeper into safety of each model
boeing = df_new['Make'] == "Boeing"
boeing_df = df_new[boeing]
boeing_df
```

[97]:
```
                 Event.Id Investigation.Type Accident.Number Event.Date  \
50       20020917X02242           Accident      LAX82DVA10 1982-01-06
84       20020917X01907           Accident      DCA82AA011 1982-01-13
242      20020917X02585           Accident     SEA82DA028A 1982-02-06
320      20020917X02336           Incident      LAX82IA075 1982-02-15
344      20020917X02404           Accident      MIA82FA051 1982-02-17
…                   …                …               …          …
88821    20221125106357           Incident      DCA23WA075 2022-11-25
88826    20221222106484           Incident      DCA23WA099 2022-11-26
88849    20221208106433           Accident      DCA23WA091 2022-12-05
88851    20221222106485           Incident      DCA23WA100 2022-12-05
88855    20221212106439           Accident      DCA23LA093 2022-12-08

                  Location        Country Injury.Severity Aircraft.damage  \
50     NEAR BAKERSFIEL, CA  United States       Non-Fatal     Substantial
84          WASHINGTON, DC  United States       Fatal(78)       Destroyed
242            MEDFORD, OR  United States       Non-Fatal           Minor
320            ONTARIO, CA  United States        Incident           Minor
344              MIAMI, FL  United States       Non-Fatal     Substantial
…                      …              …               …               …
88821             Breslau,         Canada       Non-Fatal             NaN
88826             Bangkok,       Thailand       Non-Fatal             NaN
88849            Dortmund,        Georgia             NaN             NaN
88851             Bangkok,       Thailand       Non-Fatal             NaN
88855           Newark, NJ  United States         Serious             NaN

      Registration.Number    Make  …     Purpose.of.flight  \
50                 N59737  Boeing  …               Unknown
84                  N62AF  Boeing  …               Unknown
242                N56270  Boeing  …    Aerial Application
320                N73717  Boeing  …               Unknown
344                 N4734  Boeing  …               Unknown
…                     …       …  …                   …
88821              C-FFLC  Boeing  …                   NaN
88826              HS-DBO  Boeing  …                   NaN
88849              EI-DLV  Boeing  …                   NaN
88851              HS-LUZ  Boeing  …                   NaN
88855              N649UA  Boeing  …                   NaN

      Total.Fatal.Injuries  Total.Serious.Injuries Total.Minor.Injuries  \
50                     0.0                     1.0                  0.0
84                    78.0                     6.0                  3.0
242                    0.0                     0.0                  0.0
320                    0.0                     0.0                  0.0
344                    0.0                     1.0                  1.0
…                      …                      …                    …
88821                  0.0                     0.0                  0.0
```

```
88826                 0.0                     0.0                     0.0
88849                 0.0                     0.0                     0.0
88851                 0.0                     0.0                     0.0
88855                 0.0                     3.0                     1.0

      Total.Uninjured  Weather.Condition   Report.Status  Publication.Date  \
50                1.0                Imc  Probable Cause        06-01-1983
84                0.0                Imc  Probable Cause        13-01-1983
242               3.0                Vmc  Probable Cause        06-02-1983
320             119.0                Imc  Probable Cause        15-02-1983
344              51.0                Vmc  Probable Cause        17-02-1983
…                 …                …             …                …
88821           140.0                NaN             NaN        25-11-2022
88826           186.0                NaN             NaN        22-12-2022
88849             0.0                NaN             NaN               NaN
88851           102.0                NaN             NaN        22-12-2022
88855           175.0                NaN             NaN        12-12-2022

       Year Month
50     1982     1
84     1982     1
242    1982     2
320    1982     2
344    1982     2
…       …    …
88821  2022    11
88826  2022    11
88849  2022    12
88851  2022    12
88855  2022    12

[2745 rows x 24 columns]
```

[98]:

```
# Viewing the most frequently used Boeing aircrafts

boeing_df['Model'].value_counts

boeing_sorted = boeing_df['Model'].value_counts().sort_values(ascending=False)

print(boeing_sorted)
```

```
Model
737              489
A75N1            107
777               95
747               85
767               68
```

```
               …
727 - 221F       1
757 2B7          1
747-47UF         1
747-8F           1
737-8            1
Name: count, Length: 563, dtype: int64
```

[99]:

```
# Calculate the counts of each model
model_counts = boeing_df['Model'].value_counts()

# Sort the models by counts and select the top 10 models
top_10_models = model_counts.head(10).index

# Filter the DataFrame to include only the top 10 models
boeing_top_10_df = boeing_df[boeing_df['Model'].isin(top_10_models)]

# Now boeing_top_10_df contains only the rows where the Model is one of the top␣
↪10 models.
boeing_top_10_df.value_counts(['Model'])
```

[99]:

```
Model
737         489
A75N1       107
777          95
747          85
767          68
757          59
737-200      53
737-300      51
B75N1        45
727-200      43
Name: count, dtype: int64
```

[103]:

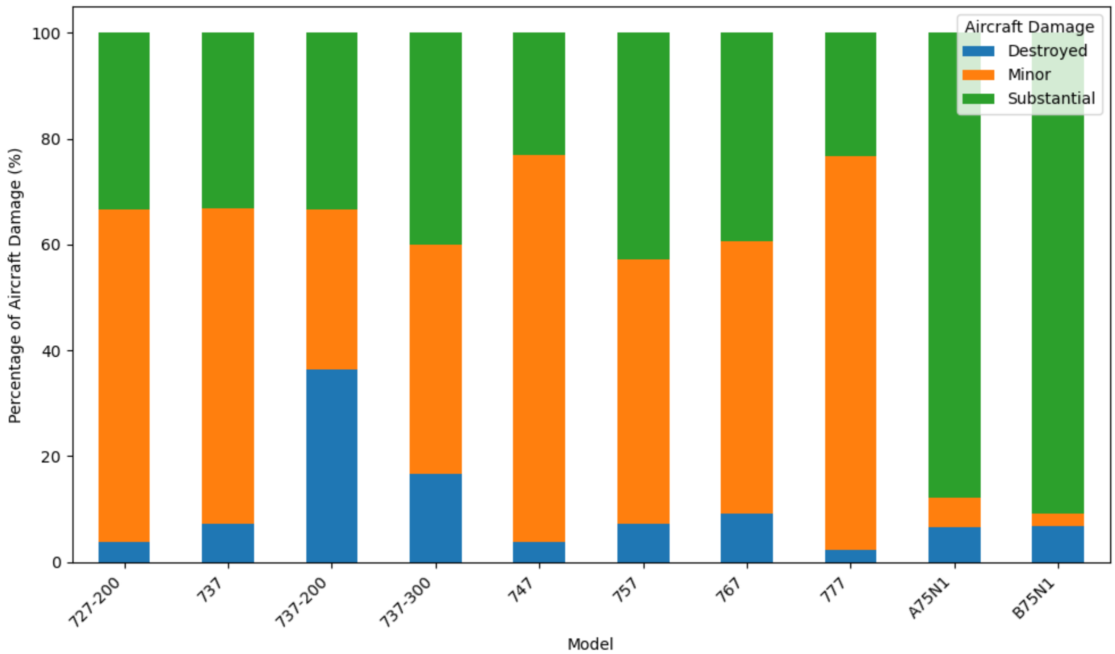
```
# Grouping the Boeing dataframe by the type of aircraft damage
boeing_grouped = boeing_top_10_df.groupby(['Model', 'Aircraft.damage']).size().
↪unstack(fill_value=0)

# Check if 'Unknown' column exists before dropping it
if 'Unknown' in boeing_grouped.columns:
    boeing_grouped_2 = boeing_grouped.drop(columns='Unknown')
else:
    boeing_grouped_2 = boeing_grouped

# Now boeing_grouped_2 contains the count of each type of aircraft damage for␣
↪each model.
boeing_grouped_2
```

[103]:
```
Aircraft.damage  Destroyed  Minor  Substantial
Model
727-200                  1     17            9
737                     15    124           69
737-200                 12     10           11
737-300                  5     13           12
747                      2     38           12
757                      2     14           12
767                      3     17           13
777                      1     32           10
A75N1                    7      6           94
B75N1                    3      1           40
```

[106]:
```python
# Calculate the sum of each row
row_sum = boeing_grouped_2.sum(axis=1)

# Divide each value in the DataFrame by the sum of the row and multiply by 100
boeing_grouped_percentage = boeing_grouped_2.div(row_sum, axis=0) * 100

print(boeing_grouped_percentage)
```

```
Aircraft.damage  Destroyed      Minor  Substantial
Model
727-200           3.703704  62.962963    33.333333
737               7.211538  59.615385    33.173077
737-200          36.363636  30.303030    33.333333
737-300          16.666667  43.333333    40.000000
747               3.846154  73.076923    23.076923
757               7.142857  50.000000    42.857143
767               9.090909  51.515152    39.393939
777               2.325581  74.418605    23.255814
A75N1             6.542056   5.607477    87.850467
B75N1             6.818182   2.272727    90.909091
```

[113]:
```python
# Plotting the stacked bar chart
boeing_grouped_percentage.plot(kind='bar', stacked=True, figsize=(10, 6))
plt.xlabel('Model')
plt.ylabel('Percentage of Aircraft Damage (%)')
plt.xticks(rotation=45, ha='right')
plt.legend(title='Aircraft Damage')
plt.tight_layout()
plt.show()
```



---

7 Conclusions

7.0.1

1. Boeing is recognized as the safest aircraft manufacturer.2. Among Boeing models, the 777 stands out as the safest based on the severity of damage in accidents.
2. Overall, the number of aircraft accidents has been decreasing for many year

---

7.1 Limitations

1. We have limited data for certain Boeing models making inferences hard to validate