student

April 12, 2024

1 Phase 1 Project Submission

- Student name: Connor Anastasio
- Student pace: self paced (part time)
- Scheduled project review date/time: TBD
- Instructor name: Morgan Jones
- Blog post URL: https://dev.to/connoranastasio/a-history-of-computing-what-led-up-to-ai-4ond

2 Aircraft Analysis: Low-risk Aviation Investments

2.1 Overview

This project focuses on finding low-risk Aviation aircraft. Investment companies can use this information to determine which aircraft makes and models would be the safest (ie, most profitable) to invest in.

The main approach here will be cleaning our dataset to remove irrelevant information, then manipulate it to uncover relational trends that we can use to gain insight into what factors contribute to accidents.

2.2 Business Problem

Descriptive analysis of this dataset shows that certain makes, models, and types of aircraft appear to be significantly less likely to be involved in an accident than others. Choosing aircraft with one or two engines or those from overall safer companies such as Cessna, Piper, and Beech will allow investors to face significantly reduced risk.

2.3 Data Understanding

We will be using the publicly available Aviation Accident Data from the United States National Transport Safety Board. It contains very detailed information about each occurence, including flight information, weather, purpose of flight, and time of day. We will be focusing on eliminating the 'human element' and less predicatable information from the dataset wherever possible. This approach will enable investors to make informed decisions about what they are investing in. We cannot predict the weather next month or if a flight will need to be made at night or in low visibilty, so this information will be less helpful when considering long-term profitability.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
#load our dataset
#Columns 6, 7, and 28 have mixed data types so we will treat them as strings
columns_to_object = [6, 7, 28]
df = pd.read_csv('data/Aviation_Data.csv', dtype={col: 'str' for col in␣
 ↪columns_to_object})

#set max columns to none to see information on each column
pd.set_option('display.max_columns', None)
df
```

[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
…                  …                …               …           …
90343   20221227106491           Accident      ERA23LA093  2022-12-26
90344   20221227106494           Accident      ERA23LA095  2022-12-26
90345   20221227106497           Accident      WPR23LA075  2022-12-26
90346   20221227106498           Accident      WPR23LA076  2022-12-26
90347   20221230106513           Accident      ERA23LA097  2022-12-29

               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
…                   …              …          …           …          …
90343     Annapolis, MD  United States        NaN         NaN          NaN
90344       Hampton, NH  United States        NaN         NaN          NaN
90345        Payson, AZ  United States    341525N    1112021W          PAN
```

```
90346       Morgan, UT  United States        NaN         NaN          NaN
90347       Athens, GA  United States        NaN         NaN          NaN

      Airport.Name Injury.Severity Aircraft.damage Aircraft.Category  \
0              NaN        Fatal(2)       Destroyed               NaN
1              NaN        Fatal(4)       Destroyed               NaN
2              NaN        Fatal(3)       Destroyed               NaN
3              NaN        Fatal(2)       Destroyed               NaN
4              NaN        Fatal(1)       Destroyed               NaN
…              …             …             …              …
90343          NaN           Minor             NaN               NaN
90344          NaN             NaN             NaN               NaN
90345       PAYSON       Non-Fatal     Substantial          Airplane
90346          NaN             NaN             NaN               NaN
90347          NaN           Minor             NaN               NaN

      Registration.Number                       Make      Model  \
0                  NC6404                    Stinson      108-3
1                  N5069P                      Piper   PA24-180
2                  N5142R                     Cessna       172M
3                  N1168J                   Rockwell        112
4                   N15NY                     Cessna        501
…                   …                         …          …
90343              N1867H                      PIPER  PA-28-151
90344              N2895Z                   BELLANCA       7ECA
90345              N749PJ  AMERICAN CHAMPION AIRCRAFT      8GCBC
90346              N210CU                     CESSNA       210N
90347              N9026P                      PIPER  PA-24-260

      Amateur.Built  Number.of.Engines    Engine.Type FAR.Description  \
0                No                1.0  Reciprocating             NaN
1                No                1.0  Reciprocating             NaN
2                No                1.0  Reciprocating             NaN
3                No                1.0  Reciprocating             NaN
4                No                NaN            NaN             NaN
…              …                 …              …            …
90343            No                NaN            NaN             091
90344            No                NaN            NaN             NaN
90345            No                1.0            NaN             091
90346            No                NaN            NaN             091
90347            No                NaN            NaN             091

      Schedule 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
…         …            …                 …                   …
90343       NaN         Personal                NaN                   0.0
90344       NaN              NaN                NaN                   0.0
90345       NaN         Personal                NaN                   0.0
90346       NaN         Personal  MC CESSNA 210N LLC                  0.0
90347       NaN         Personal                NaN                   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                         NaN                   NaN              NaN
3                         0.0                   0.0              0.0
4                         2.0                   NaN              0.0
…                        …                     …                …
90343                     1.0                   0.0              0.0
90344                     0.0                   0.0              0.0
90345                     0.0                   0.0              1.0
90346                     0.0                   0.0              0.0
90347                     1.0                   0.0              1.0

      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
…                  …                     …               …                …
90343               NaN                   NaN             NaN       29-12-2022
90344               NaN                   NaN             NaN              NaN
90345               VMC                   NaN             NaN       27-12-2022
90346               NaN                   NaN             NaN              NaN
90347               NaN                   NaN             NaN       30-12-2022

[90348 rows x 31 columns]
```

[3]:
```
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            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        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

Our dataset contains an impressive amount of individual entries and information on flights dating back to 1948.

As we are primarily concerned with the objective safety of each make and model, we can begin data cleaning and investigation as to which aspects will not be useful for this.

2.4 Data Preparation

2.4.1 Data Cleaning

[4]:
```
#normalize column names for ease of use
df.columns = df.columns.str.lower().str.replace('.', '_')
df['make'].replace('Air Tractor', 'Air Tractor Inc', inplace=True)
```

At a glance, certain columns will not be useful for our analysis and we can drop them now. Others will need to be looked at further before we make our judgment.

[5]:
```
#drop obvious unnecessary columns
df.drop(columns = ['latitude', 'longitude', 'event_id'], inplace=True)
```

[6]:
```python
#Examine Broad Phase of Flight
print(df['broad_phase_of_flight'].value_counts())
print('broad phase null counts:', df['broad_phase_of_flight'].isnull().sum())
```

```
broad_phase_of_flight
Landing        15428
Takeoff        12493
Cruise         10269
Maneuvering     8144
Approach        6546
Climb           2034
Taxi            1958
Descent         1887
Go-around       1353
Standing         945
Unknown          548
Other            119
Name: count, dtype: int64
broad phase null counts: 28624
```

[7]:
```python
df.drop(columns = ['broad_phase_of_flight'], inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 27 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   investigation_type     90348 non-null  object
 1   accident_number        88889 non-null  object
 2   event_date             88889 non-null  object
 3   location               88837 non-null  object
 4   country                88663 non-null  object
 5   airport_code           50132 non-null  object
 6   airport_name           52704 non-null  object
 7   injury_severity        87889 non-null  object
 8   aircraft_damage        85695 non-null  object
 9   aircraft_category      32287 non-null  object
 10  registration_number    87507 non-null  object
 11  make                   88826 non-null  object
 12  model                  88797 non-null  object
 13  amateur_built          88787 non-null  object
 14  number_of_engines      82805 non-null  float64
 15  engine_type            81793 non-null  object
 16  far_description        32023 non-null  object
 17  schedule               12582 non-null  object
 18  purpose_of_flight      82697 non-null  object
 19  air_carrier            16648 non-null  object
```

```
 20  total_fatal_injuries    77488 non-null  float64
 21  total_serious_injuries  76379 non-null  float64
 22  total_minor_injuries    76956 non-null  float64
 23  total_uninjured         82977 non-null  float64
 24  weather_condition       84397 non-null  object
 25  report_status           82505 non-null  object
 26  publication_date        73659 non-null  object
dtypes: float64(5), object(22)
memory usage: 18.6+ MB
```

Broad Phase of Flight could be interesting to consider further but unfortunately it is missing far too many values to be useful in our analysis.

Additionally, investing in a non-professionally made aircraft is undoubtedly a risky and unpredicatable investment. We should only consider accident data for professionally made aircraft. We will have to also drop the rows where it is unknown as we cannot confirm it was not amateur built:

[8]:
```
#Remove All Non-Accident Investigation Type Rows, and all amateur built aircraft
df = df[df['investigation_type'] == 'Accident']
df = df[df['amateur_built'] == 'No']
df.drop(columns = ['investigation_type', 'accident_number', 'airport_code',␣
↪'airport_name', 'aircraft_category','registration_number',
                    'amateur_built', 'far_description', 'schedule',␣
↪'purpose_of_flight', 'air_carrier', 'publication_date'], inplace=True)
```

2.4.2 Data Engineering

It will be helpful to create a few of our own columns for analysis.

[9]:
```
df['total_injuries'] = df['total_fatal_injuries'] +␣
↪df['total_serious_injuries'] + df['total_minor_injuries']
df['total_non_fatal_injuries'] = df['total_serious_injuries'] +␣
↪df['total_minor_injuries']
df
```

[9]:
```
       event_date         location        country injury_severity  \
0      1948-10-24  MOOSE CREEK, ID  United States        Fatal(2)
1      1962-07-19   BRIDGEPORT, CA  United States        Fatal(4)
2      1974-08-30    Saltville, VA  United States        Fatal(3)
3      1977-06-19       EUREKA, CA  United States        Fatal(2)
4      1979-08-02       Canton, OH  United States        Fatal(1)
…             …              …              …               …
90343  2022-12-26    Annapolis, MD  United States           Minor
90344  2022-12-26      Hampton, NH  United States             NaN
90345  2022-12-26       Payson, AZ  United States       Non-Fatal
90346  2022-12-26       Morgan, UT  United States             NaN
90347  2022-12-29       Athens, GA  United States           Minor

      aircraft_damage                        make      model  \
```

```
0          Destroyed                     Stinson      108-3
1          Destroyed                       Piper   PA24-180
2          Destroyed                      Cessna       172M
3          Destroyed                    Rockwell        112
4          Destroyed                      Cessna        501
…                …                          …         …
90343            NaN                       PIPER  PA-28-151
90344            NaN                    BELLANCA       7ECA
90345    Substantial  AMERICAN CHAMPION AIRCRAFT      8GCBC
90346            NaN                      CESSNA       210N
90347            NaN                       PIPER  PA-24-260

       number_of_engines   engine_type  total_fatal_injuries  \
0                    1.0  Reciprocating                   2.0
1                    1.0  Reciprocating                   4.0
2                    1.0  Reciprocating                   3.0
3                    1.0  Reciprocating                   2.0
4                    NaN            NaN                   1.0
…                  …             …                    …
90343                NaN            NaN                   0.0
90344                NaN            NaN                   0.0
90345                1.0            NaN                   0.0
90346                NaN            NaN                   0.0
90347                NaN            NaN                   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                         NaN                   NaN              NaN
3                         0.0                   0.0              0.0
4                         2.0                   NaN              0.0
…                       …                     …               …
90343                     1.0                   0.0              0.0
90344                     0.0                   0.0              0.0
90345                     0.0                   0.0              1.0
90346                     0.0                   0.0              0.0
90347                     1.0                   0.0              1.0

      weather_condition   report_status  total_injuries  \
0                   UNK  Probable Cause             2.0
1                   UNK  Probable Cause             4.0
2                   IMC  Probable Cause             NaN
3                   IMC  Probable Cause             2.0
4                   VMC  Probable Cause             NaN
…                 …             …             …
90343               NaN             NaN             1.0
90344               NaN             NaN             0.0
```

```
90345                VMC              NaN              0.0
90346                NaN              NaN              0.0
90347                NaN              NaN              1.0

       total_non_fatal_injuries
0                           0.0
1                           0.0
2                           NaN
3                           0.0
4                           NaN
…                         …
90343                       1.0
90344                       0.0
90345                       0.0
90346                       0.0
90347                       1.0

[76520 rows x 17 columns]
```

We need to ensure the date column is properly formatted for all 76,520 remaining rows. We can do this by writing a simple for loop to ensure all of the values can be converted to standard Pandas datetime. If this code does not return an error, we won't have to worry.

[10]:
```
def check_date_format(date):
    try:
        pd.to_datetime(date)
        return True
    except ValueError:
        return False

# Check if all dates in the column are properly formatted
all_dates_valid = df['event_date'].map(check_date_format).all()

if all_dates_valid:
    print("All dates are properly formatted.")
else:
    print("Some dates have formatting issues.")
```

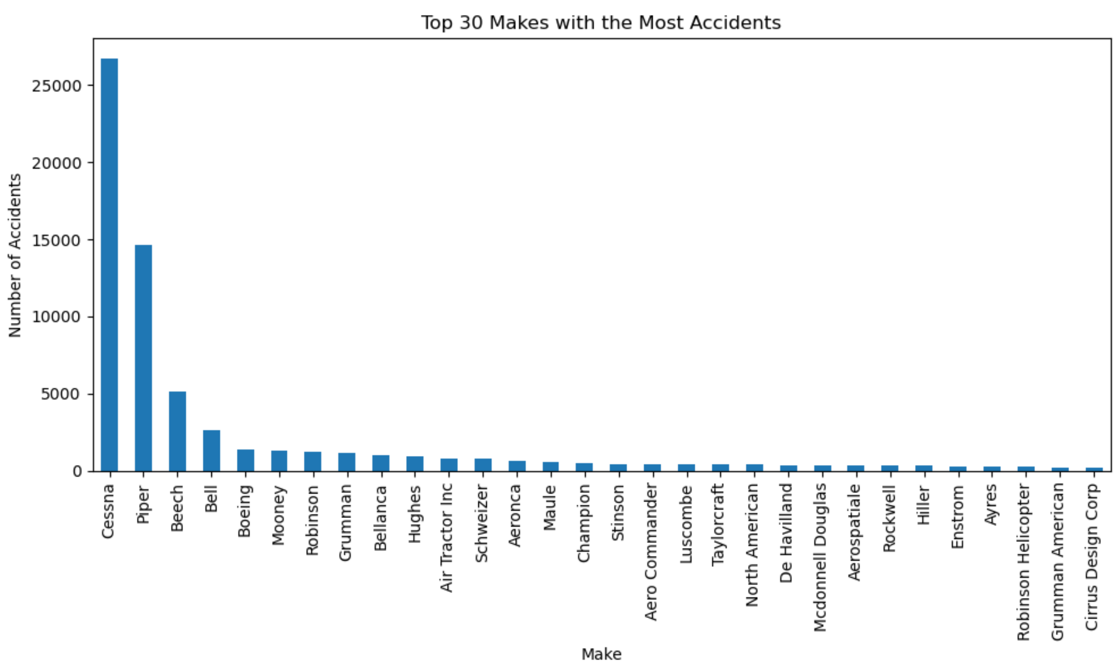
```
All dates are properly formatted.
```

[11]:
```
#create a new column of make + model
df['make_model'] = df['make'] + '_' + df['model']

#Format 'make' column and describe its properties
df['make'] = df['make'].str.title()
df['make'].describe()
```

[11]:
```
count       76500
unique       1880
top        Cessna
freq        26695
Name: make, dtype: object
```

As we can see, there are 1880 different Makes, and many appear only once. This isn't very helpful in looking for data trends, so let's create a histogram with the top 30 most frequently occurring makes in our dataset:

[12]:
```python
#Create a variable to store the top 30 most frequently occurring makes:
top_30_makes = df['make'].value_counts().nlargest(30)

# Plotting the histogram for top 30 makes
plt.figure(figsize=(10, 6))
top_30_makes.plot(kind='bar')
plt.title('Top 30 Makes with the Most Accidents')
plt.xlabel('Make')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



Cessna has the most accidents by a wide margin, but we will need additional and deeper analysis in order to make assessments on this.

[13]:
```python
#analyze frequency
df['year'] = pd.to_datetime(df['event_date']).dt.year
accidents_since_2000 = df[df['year'] >= 2000]
accidents_since_2000
```

[13]:
```
      event_date         location        country injury_severity  \
47675 2000-01-01    HOMESTEAD, FL  United States       Non-Fatal
47676 2000-01-01    MONTEAGLE, TN  United States        Fatal(2)
47677 2000-01-02  VICTORVILLE, CA  United States       Non-Fatal
47678 2000-01-02    DOS PALOS, CA  United States       Non-Fatal
47679 2000-01-02      CORNING, AR  United States       Non-Fatal
…            …                …              …             …
90343 2022-12-26    Annapolis, MD  United States           Minor
90344 2022-12-26      Hampton, NH  United States             NaN
90345 2022-12-26       Payson, AZ  United States       Non-Fatal
90346 2022-12-26       Morgan, UT  United States             NaN
90347 2022-12-29       Athens, GA  United States           Minor

     aircraft_damage                       make       model  \
47675    Substantial                     Cessna         550
47676      Destroyed                   Bellanca   BL-17-30A
47677    Substantial                     Cessna        172G
47678    Substantial                     Cessna        172A
47679    Substantial                      Piper   PA-46-310P
…              …                          …          …
90343            NaN                      Piper   PA-28-151
90344            NaN                   Bellanca        7ECA
90345    Substantial  American Champion Aircraft       8GCBC
90346            NaN                     Cessna        210N
90347            NaN                      Piper   PA-24-260

      number_of_engines   engine_type  total_fatal_injuries  \
47675               2.0     Turbo Fan                   0.0
47676               1.0  Reciprocating                   2.0
47677               1.0  Reciprocating                   0.0
47678               1.0  Reciprocating                   0.0
47679               1.0     Turbo Prop                   0.0
…                   …            …                     …
90343               NaN           NaN                   0.0
90344               NaN           NaN                   0.0
90345               1.0           NaN                   0.0
90346               NaN           NaN                   0.0
90347               NaN           NaN                   0.0

      total_serious_injuries  total_minor_injuries  total_uninjured  \
47675                    0.0                   0.0              3.0
47676                    0.0                   0.0              0.0
```

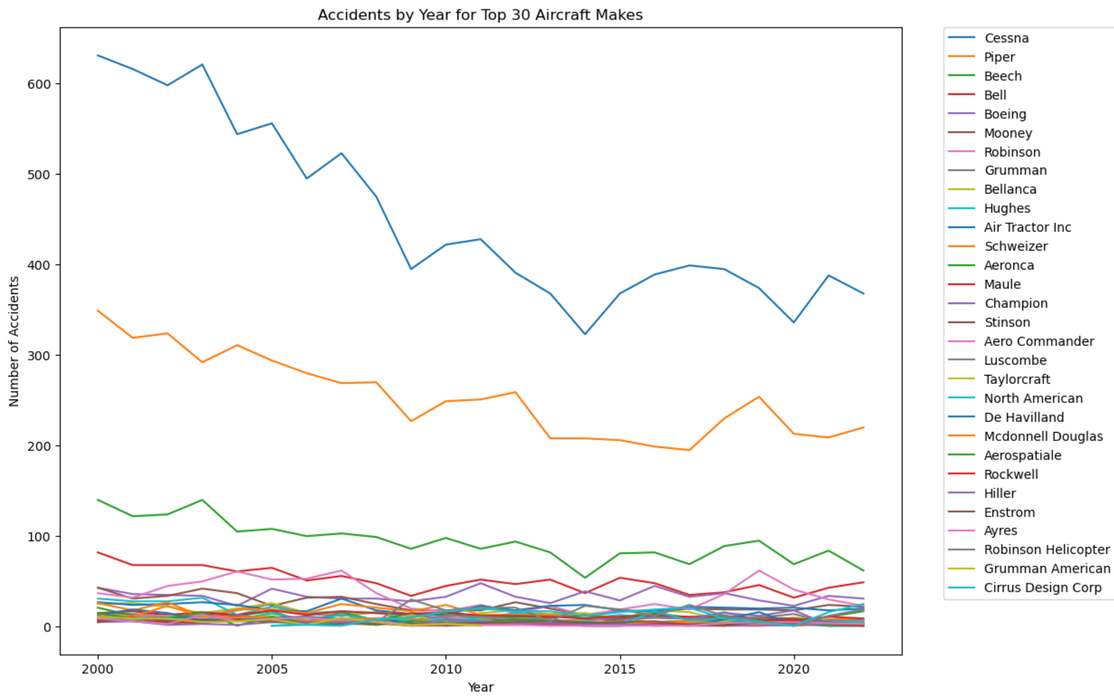
```
47677                0.0              0.0             2.0
47678                0.0              1.0             0.0
47679                0.0              0.0             5.0
…                  …                …               …
90343                1.0              0.0             0.0
90344                0.0              0.0             0.0
90345                0.0              0.0             1.0
90346                0.0              0.0             0.0
90347                1.0              0.0             1.0

      weather_condition   report_status  total_injuries  \
47675               VMC  Probable Cause             0.0
47676               IMC  Probable Cause             2.0
47677               VMC  Probable Cause             0.0
47678               VMC  Probable Cause             1.0
47679               VMC  Probable Cause             0.0
…                 …              …              …
90343               NaN             NaN             1.0
90344               NaN             NaN             0.0
90345               VMC             NaN             0.0
90346               NaN             NaN             0.0
90347               NaN             NaN             1.0

       total_non_fatal_injuries                        make_model  year
47675                       0.0                        Cessna_550  2000
47676                       0.0                 Bellanca_BL-17-30A  2000
47677                       0.0                       Cessna_172G  2000
47678                       1.0                       Cessna_172A  2000
47679                       0.0                   Piper_PA-46-310P  2000
…                         …                                 …    …
90343                       1.0                   PIPER_PA-28-151  2022
90344                       0.0                     BELLANCA_7ECA  2022
90345                       0.0  AMERICAN CHAMPION AIRCRAFT_8GCBC  2022
90346                       0.0                       CESSNA_210N  2022
90347                       1.0                   PIPER_PA-24-260  2022

[34210 rows x 19 columns]
```

We will focus on the 30 most common aircraft makes for our analysis; these are the companies with enough instances to be statistically relevant.

While older planes are still in service, flight safety and security has improved drastically in our post-9/11 world. For this reason it is worth looking into whether there has been a noticeable decrease in accidents since:

[14]:
```
top_30_aircraft = df['make'].value_counts().nlargest(30).index.tolist()

# Filtering DataFrame for 30 most prevalent aircraft makes
```

```python
df_top_30 = df[df['make'].isin(top_30_aircraft)]

# Grouping data by make and year, and counting occurrences
df_top_30_since_2000 = df[(df['make'].isin(top_30_aircraft)) & (df['year'] >=
 ↪2000)]
grouped = df_top_30_since_2000.groupby(['make', 'year']).size().
 ↪reset_index(name='accidents')

# Creating a line chart for each aircraft make
plt.figure(figsize=(12, 9))

for make in top_30_aircraft:
    make_data = grouped[grouped['make'] == make]
    plt.plot(make_data['year'], make_data['accidents'], label=make)

plt.title('Accidents by Year for Top 30 Aircraft Makes')
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.show()
```

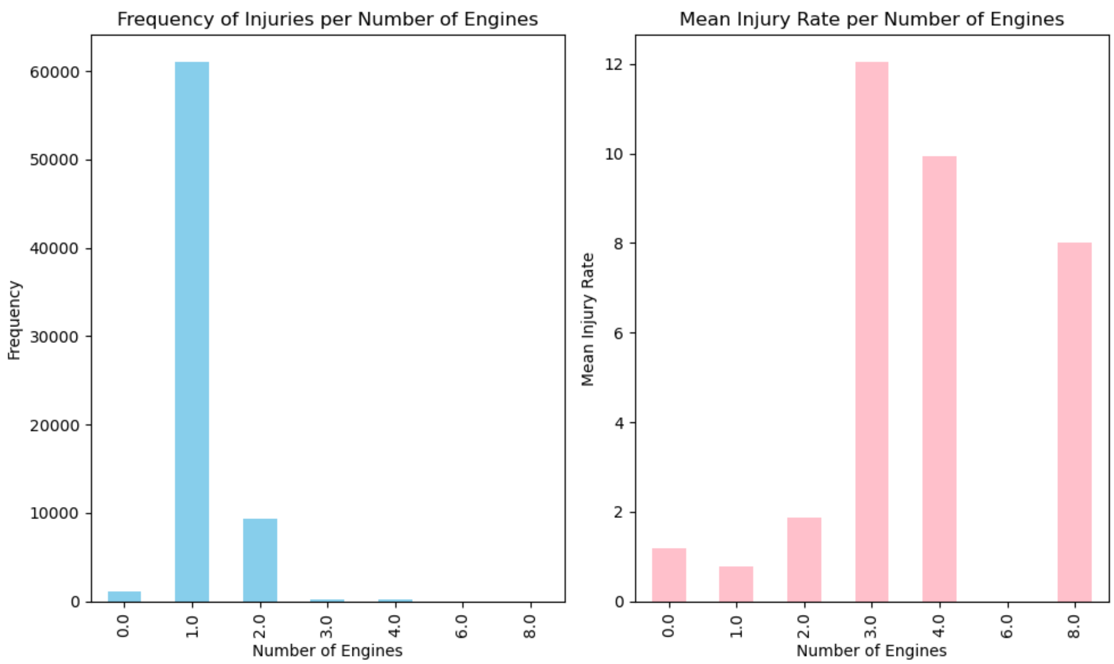


While this provides us with interesting information, it is not the full picture of what is happening. The dataset does not include the amount of planes in service for each company by year, so we don't know the percentage of each company's models that are involved in accidents. Still, it is noteworthy that every aircraft maker is on a downard trend in number of accidents. This implies it is a safer and potentially more profitable to invest in essentially any aircraft company than it was even 15 years ago.

Although we do not have the ability to create an "in-use" aircraft ratio by company, we thankfully have plenty of other useful information in our dataset, and approaches we can take.

The relationship between the number of engines and the total injuries will be instrumental in our analysis. To analyze this, we will create two bar plots:

[15]:
```
# Calculate frequency of instances for each number of engines
instance_counts = df['number_of_engines'].value_counts().sort_index()

# Calculate mean injury rate for each number of engines
injury_rates = df.groupby('number_of_engines')['total_injuries'].mean().
 ↪sort_index()

plt.figure(figsize=(10, 6))

# Plot the bar plots side-by-side
plt.subplot(1, 2, 1)
instance_counts.plot(kind='bar', color='skyblue')
plt.title('Frequency of Injuries per Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
injury_rates.plot(kind='bar', color='pink')
plt.title('Mean Injury Rate per Number of Engines')
plt.xlabel('Number of Engines')
plt.ylabel('Mean Injury Rate')

plt.tight_layout()
plt.show()
```



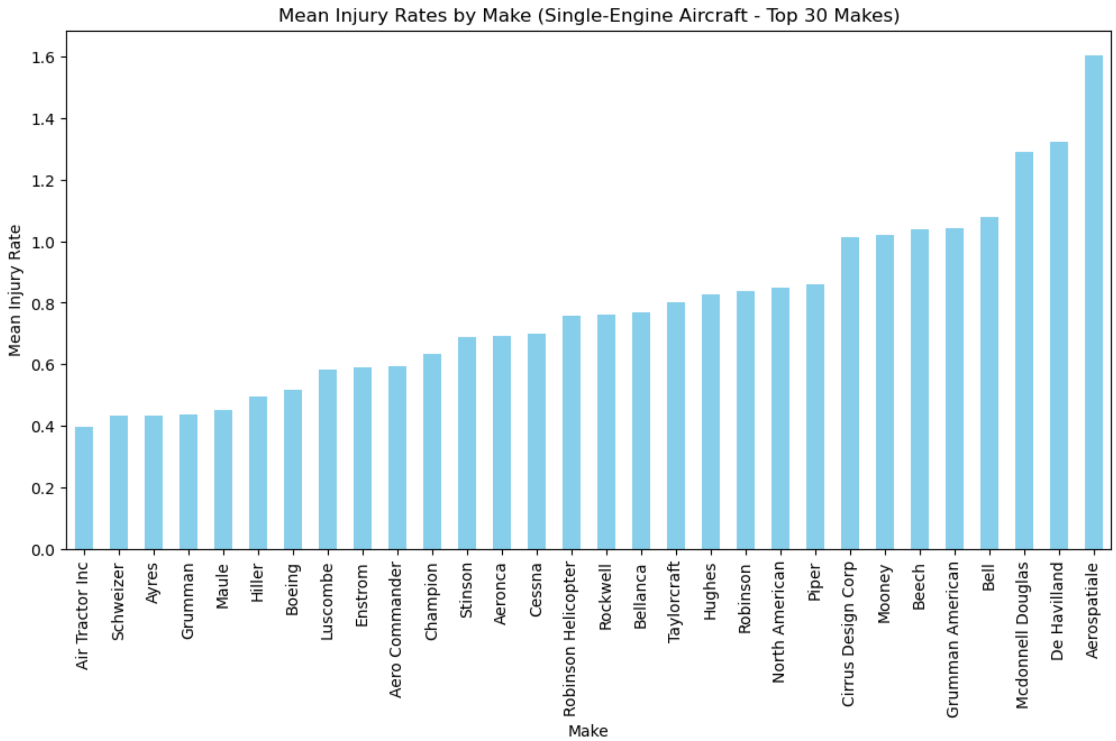
The left subplot displays a bar plot showing the frequency of instances for each number of engines, and the right shows a bar plot representing the mean injury rates for the corresponding number of engines.

Using these plots, it is easy to see that injury rates tend to increase as the number of engines does. In other words, aircraft with 1 or 2 engines appear to be the safest.

Notably, single engine aircraft have the second lowest mean injury rate while making up nearly all of the instances in our dataset. We will focus our analysis on these, and determine the safest make/model with one engine:

[16]:
```
# Filtering df_top_30 for entries where the number of engines is one
df_top_30_single_engine = df_top_30[df_top_30['number_of_engines'] == 1]

# Grouping data by 'make' for single-engine aircraft (top 30 makes) and␣
↪calculating mean injury rates
make_injury_rates_single_engine = df_top_30_single_engine.
↪groupby('make')['total_injuries'].mean().sort_values()

# Plotting bar plot
make_injury_rates_single_engine.plot(kind='bar', figsize=(12, 6),␣
↪color='skyblue')
plt.title('Mean Injury Rates by Make (Single-Engine Aircraft - Top 30 Makes)')
plt.xlabel('Make')
plt.ylabel('Mean Injury Rate')
plt.xticks(rotation=90)
```

```
plt.show()
```

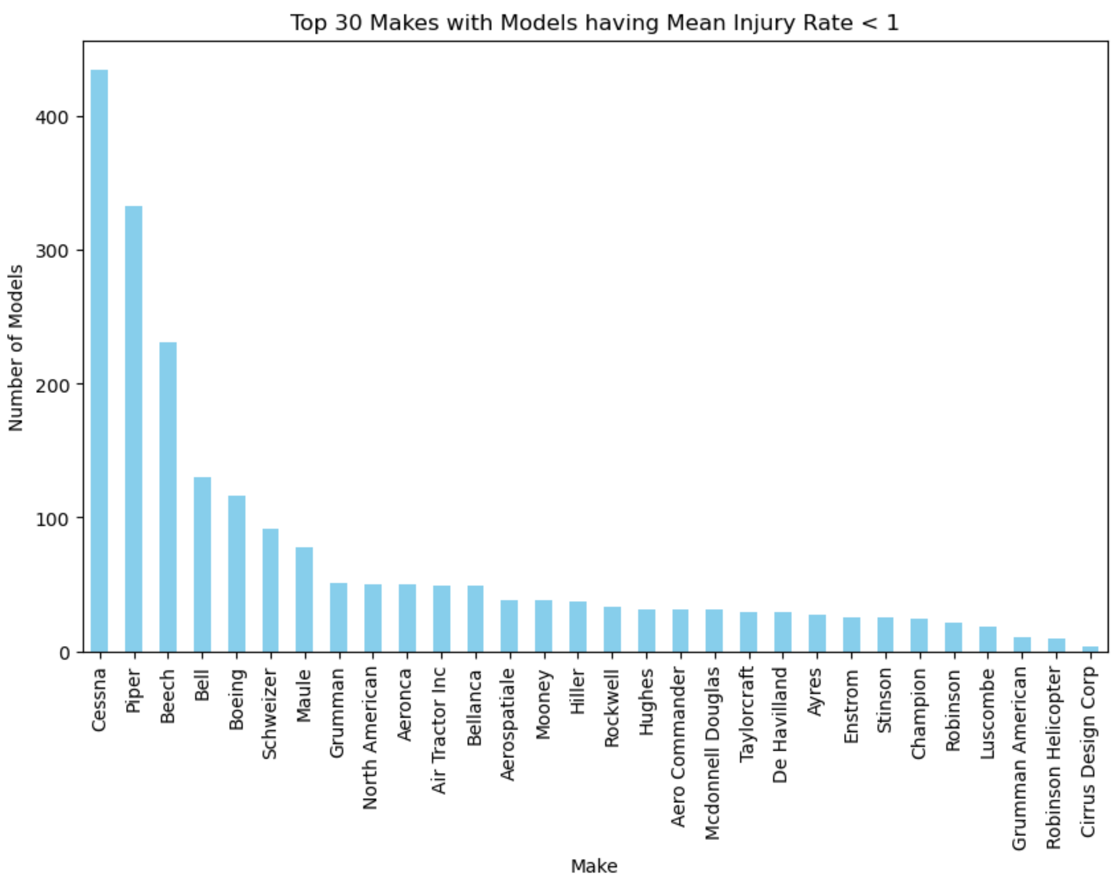


There are 22 makes with an injury rate below 1.0. This is excellent, as further restricting to these will still give us plenty of options to invest in.

In order to see if there is a single company with the overall best safety rating, we will examine the models in a similar fashion (using the top 30 most common again). In order to do this, we will find each model with an average injury rate less than 1, add each by make, and then plot them:

[17]:
```
# Create a variable with the top 30 most common makes
top_30_makes = df['make'].value_counts().nlargest(30).index.tolist()

# Filter the DataFrame for the top 30 makes
df_top_30_makes = df[df['make'].isin(top_30_makes)]

# Calculate the mean injury rate per model for the top 30 makes
mean_injury_rate_per_model_top_30 = df_top_30_makes.groupby(['make', 'model'])['total_injuries'].mean()

# Filter models with a mean injury rate < 1 for the top 30 makes
models_with_mean_injury_lt_1_top_30 = mean_injury_rate_per_model_top_30[mean_injury_rate_per_model_top_30 < 1].reset_index()
```

```python
# Count the number of models with mean injury rate < 1 for each make among the top 30 makes
models_lt_1_count_per_make_top_30 = models_with_mean_injury_lt_1_top_30.groupby('make')['model'].count().sort_values(ascending=False)

# Plotting the top 30 makes with the count of models having mean injury rate < 1
plt.figure(figsize=(10, 6))
models_lt_1_count_per_make_top_30.plot(kind='bar', color='skyblue')
plt.title('Top 30 Makes with Models having Mean Injury Rate < 1')
plt.xlabel('Make')
plt.ylabel('Number of Models')
plt.xticks(rotation=90)
plt.show()
```



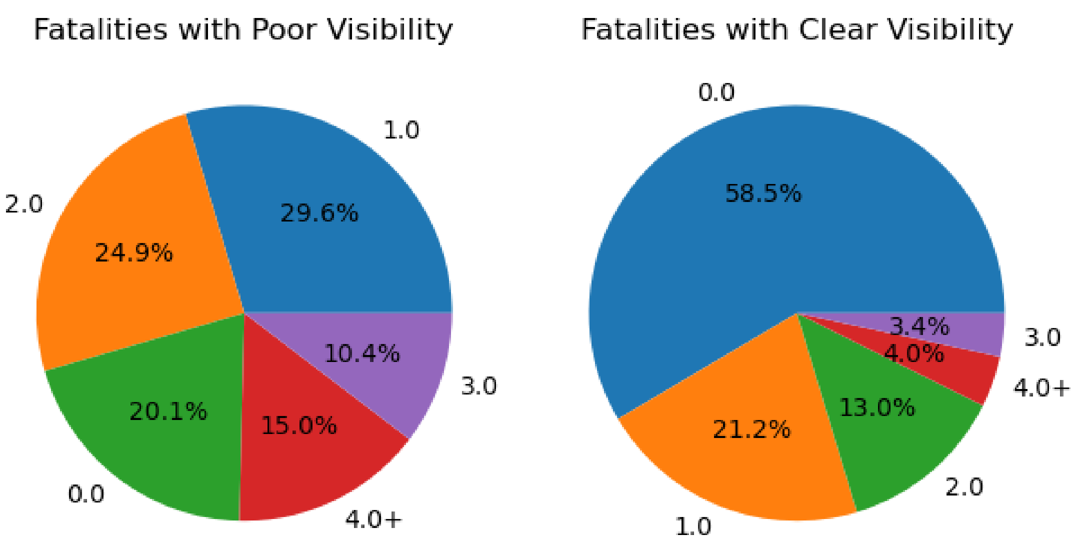
Cessna has the most models with the the lowest injury rates. Hooray!

2.4.3 Weather Influence

It will be useful to see if there is a noticeable relationship between poor visibility and accident statistics.

[18]:

```python
# Filter data for 'IMC' and 'VMC' while dropping null values in 'total_injuries'
imc_data = df[(df['weather_condition'] == 'IMC') & (df['total_injuries'].
 ↪notnull())].copy()
vmc_data = df[(df['weather_condition'] == 'VMC') & (df['total_injuries'].
 ↪notnull())].copy()

# Group counts of 4.0 injuries or more as '4+'
imc_data.loc[:, 'total_injuries_grouped'] = imc_data['total_injuries'].
 ↪apply(lambda x: '4.0+' if x >= 4.0 else str(x))
vmc_data.loc[:, 'total_injuries_grouped'] = vmc_data['total_injuries'].
 ↪apply(lambda x: '4.0+' if x >= 4.0 else str(x))

# Calculate value counts for 'IMC' and 'VMC' with grouping
imc_counts = imc_data['total_injuries_grouped'].value_counts()
vmc_counts = vmc_data['total_injuries_grouped'].value_counts()

# Convert counts to dictionary for pie chart plotting
imc_counts_dict = imc_counts.to_dict()
vmc_counts_dict = vmc_counts.to_dict()

# Replace count of '4+' if it doesn't exist in 'IMC' or 'VMC' counts
if '4.0+' not in imc_counts_dict:
    imc_counts_dict['4.0+'] = 0
if '4.0+' not in vmc_counts_dict:
    vmc_counts_dict['4.0+'] = 0

# Plot pie chart for 'IMC'
plt.subplot(1, 2, 1)
plt.pie(imc_counts_dict.values(), labels=imc_counts_dict.keys(), autopct='%1.
 ↪1f%%')
plt.title('Fatalities with Poor Visibility')

# Plot pie chart for 'VMC'
plt.subplot(1, 2, 2)
plt.pie(vmc_counts_dict.values(), labels=vmc_counts_dict.keys(), autopct='%1.
 ↪1f%%')
plt.title('Fatalities with Clear Visibility')

plt.tight_layout()
plt.show()
```



It is apparent from these pie charts that aircraft flying in poor visibilty conditions (requiring pilots to rely solely on instruments) leads to a significant increase in casualties. It is highly advised to avoid investing in planes that fly routes that have poor visibilty.

2.5 Conclusion:

- In terms of overall safety ratings for investing, single engine planes should make up the majority of investments.
- Investing in a single well-known company may be a safe approach to start with. Cessna is a great choice, as our dataset has provided ample information for model choices.
- Avoiding routes with poor visibility and providing further training pilots to deal with adverse conditions would likely aid in reducing accidents and increase profit.

2.6 Future:

- Compare cost of the safest aircraft models to determine which can bring the largest return on investment
- Gathering data on Aircraft sales and in-use data for individual aircraft would allow us to make more informative individual model recommendations