Final Project Submission

Please fill out:

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- Student pace: part time
- Scheduled project review date/time: 9/9/2024 2359hrs
- Instructor name: William Okomba
- Blog post URL:https://github.com/vnelima/Phase-1_Project_Aviation_

Project Overview

For this project I will collect, explore and prepare relevant data and use models that will help me understand and give feedback to the company so as to make informed, low-risk decisions when purchasing aircrafts for the new division.

Business Problem

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

Objectives

- To identify which aircrafts or make have the lowest risk.
- To identify locations or environments where incidents or accidents are most prone
- To determine whether to invest in amateur built aircrafts
- To determine the make with least number of accidents
- To determine factors that contribute to aviation risk, that is, make/model, weather condition, Location
- To determine purpose of the flight

In [178…

```
# Importing Libraries
# numpy is a python library that helps us work with large arrays
import numpy as np
# pandas is used for manipulating spreadsheets
import pandas as pd
# matplotlib enbles us to plot a line plot with x and y axis
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [179…

```
# Reading dataset from CSV file and creating the dataset
df = pd.read_csv("AviationData.csv", encoding='latin-1')
df
```

```
c:\Users\ADMIN\anaconda3\envs\learn-env\lib\site-packages\IPython\core\interactivesh
ell.py:3145: DtypeWarning: Columns (6,7,28) have mixed types.Specify dtype option on
import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
```

Out[179…

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Co
0	20001218X45444	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	U
1	20001218X45447	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	U
2	20061025X01555	Accident	NYC07LA005	8/30/1974	Saltville, VA	U
3	20001218X45448	Accident	LAX96LA321	6/19/1977	EUREKA, CA	U
4	20041105X01764	Accident	CHI79FA064	8/2/1979	Canton, OH	U
...	...	...	...	...	...	
88884	2.02212E+13	Accident	ERA23LA093	12/26/2022	Annapolis, MD	U
88885	2.02212E+13	Accident	ERA23LA095	12/26/2022	Hampton, NH	U
88886	2.02212E+13	Accident	WPR23LA075	12/26/2022	Payson, AZ	U
88887	2.02212E+13	Accident	WPR23LA076	12/26/2022	Morgan, UT	U
88888	2.02212E+13	Accident	ERA23LA097	12/29/2022	Athens, GA	U

88889 rows × 31 columns

In [180…

```
# Reviewing the first 5 rows of the dataset
df.head()
```

Out[180…

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
0	20001218X45444	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United State
1	20001218X45447	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United State
2	20061025X01555	Accident	NYC07LA005	8/30/1974	Saltville, VA	United State
3	20001218X45448	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United State
4	20041105X01764	Accident	CHI79FA064	8/2/1979	Canton, OH	United State

In [181…

```
# column check
df.columns
```

Out[181…

```
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')
```

In [182…

```
# checking the number of columns
len(df.columns)
```

Out[182…

```
31
```

In [183…

```
# Reviewing the last 5 rows of the dataset
df.tail()
```

Out[183…

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country
88884	2.02212E+13	Accident	ERA23LA093	12/26/2022	Annapolis, MD	United States
88885	2.02212E+13	Accident	ERA23LA095	12/26/2022	Hampton, NH	United States
88886	2.02212E+13	Accident	WPR23LA075	12/26/2022	Payson, AZ	United States
88887	2.02212E+13	Accident	WPR23LA076	12/26/2022	Morgan, UT	United States
88888	2.02212E+13	Accident	ERA23LA097	12/29/2022	Athens, GA	United States

Data Cleaning

In [184…

```
# Assessing Dataset information
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            50249 non-null  object 
 9   Airport.Name            52790 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87572 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81812 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82508 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [185…

```
# To calculate statistical data, mean, median, mode, percentile
df.describe()
```

Out[185...

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Tot
count	82805.000000	77488.000000	76379.000000	76956.000000	8
mean	1.146585	0.647855	0.279881	0.357061	
std	0.446510	5.485960	1.544084	2.235625	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	
75%	1.000000	0.000000	0.000000	0.000000	
max	8.000000	349.000000	161.000000	380.000000	

In [186...

```
# Dropping columns that we will not need during analysis and that do not feed into
# For credibility of the dataset
df.drop(columns=['Event.Id', 'Latitude', 'Longitude', 'Airport.Code', 'Schedule', '
df
```

Out[186...

	Investigation.Type	Accident.Number	Event.Date	Location	Country	Airport.Na
0	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United States	N
1	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United States	N
2	Accident	NYC07LA005	8/30/1974	Saltville, VA	United States	N
3	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United States	N
4	Accident	CHI79FA064	8/2/1979	Canton, OH	United States	N
...	...	...	...	...	...	
88884	Accident	ERA23LA093	12/26/2022	Annapolis, MD	United States	N
88885	Accident	ERA23LA095	12/26/2022	Hampton, NH	United States	N
88886	Accident	WPR23LA075	12/26/2022	Payson, AZ	United States	PAYS
88887	Accident	WPR23LA076	12/26/2022	Morgan, UT	United States	N
88888	Accident	ERA23LA097	12/29/2022	Athens, GA	United States	N

88889 rows × 23 columns

In [187...

```
# To change all letters to be uppercase in the Make column
# This is for uniformity and to enable me identify the unique characters in the col
df['Make'] = df['Make'].str.upper()
df['Make']
```

Out[187...

```
0                          STINSON
1                            PIPER
2                           CESSNA
3                         ROCKWELL
4                           CESSNA
                   ...
88884                        PIPER
88885                     BELLANCA
88886    AMERICAN CHAMPION AIRCRAFT
88887                       CESSNA
88888                        PIPER
Name: Make, Length: 88889, dtype: object
```

In [188…
```
 # # To change all letters to be uppercase in the Make column combined with the uni
# df['combined Make'] = df['Make'] + df['unique_code'].astype(str)
pd.set_option("display.max_columns", None)
Make_counts = df['Make'].unique()

Make_counts
```

Out[188…
```
array(['STINSON', 'PIPER', 'CESSNA', ..., 'JAMES R DERNOVSEK',
       'ORLICAN S R O', 'ROYSE RALPH L'], dtype=object)
```

In [189…
```
# For uniformity in 'Make' column replacing CESNA with CESSNA and Airbus Industrie
# Define replacements
replacements = {'CESNA': 'CESSNA','Airbus Industrie': 'Airbus'}
# Apply replacements
df['Make'] = df['Make'].replace(replacements, regex=True)
```

In [190…
```
# Checking for missing values in the data set so as to ensure dataset is complete
df.isnull().sum()
```

Out[190…
```
Investigation.Type            0
Accident.Number               0
Event.Date                    0
Location                     52
Country                     226
Airport.Name              36099
Injury.Severity            1000
Aircraft.damage            3194
Aircraft.Category         56602
Registration.Number        1317
Make                         63
Model                        92
Amateur.Built               102
Number.of.Engines          6084
Engine.Type                7077
FAR.Description           56866
Purpose.of.flight          6192
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
Total.Uninjured            5912
Weather.Condition          4492
Broad.phase.of.flight     27165
dtype: int64
```

In [191…
```
# replacing the null values in the columns with 'unknown'
columns_to_replace = ['Location', 'Country', 'Airport.Name', 'Injury.Severity', 'Ai
df[columns_to_replace] = df[columns_to_replace].fillna('Unknown')



df
```

Out[191…

	Investigation.Type	Accident.Number	Event.Date	Location	Country	Airport.Na
0	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United States	Unkno
1	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United States	Unkno
2	Accident	NYC07LA005	8/30/1974	Saltville, VA	United States	Unkno
3	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United States	Unkno
4	Accident	CHI79FA064	8/2/1979	Canton, OH	United States	Unkno
...	...	...	...	...	...	
88884	Accident	ERA23LA093	12/26/2022	Annapolis, MD	United States	Unkno
88885	Accident	ERA23LA095	12/26/2022	Hampton, NH	United States	Unkno
88886	Accident	WPR23LA075	12/26/2022	Payson, AZ	United States	PAYS
88887	Accident	WPR23LA076	12/26/2022	Morgan, UT	United States	Unkno
88888	Accident	ERA23LA097	12/29/2022	Athens, GA	United States	Unkno

88889 rows × 23 columns

In [192…

```
# Convert the entire 'Weather.Condition' column to uppercase
df['Weather.Condition'].str.upper()
df
```

Out[192...

	Investigation.Type	Accident.Number	Event.Date	Location	Country	Airport.Na
0	Accident	SEA87LA080	10/24/1948	MOOSE CREEK, ID	United States	Unkno
1	Accident	LAX94LA336	7/19/1962	BRIDGEPORT, CA	United States	Unkno
2	Accident	NYC07LA005	8/30/1974	Saltville, VA	United States	Unkno
3	Accident	LAX96LA321	6/19/1977	EUREKA, CA	United States	Unkno
4	Accident	CHI79FA064	8/2/1979	Canton, OH	United States	Unkno
...	...	...	...	...	...	
88884	Accident	ERA23LA093	12/26/2022	Annapolis, MD	United States	Unkno
88885	Accident	ERA23LA095	12/26/2022	Hampton, NH	United States	Unkno
88886	Accident	WPR23LA075	12/26/2022	Payson, AZ	United States	PAYS
88887	Accident	WPR23LA076	12/26/2022	Morgan, UT	United States	Unkno
88888	Accident	ERA23LA097	12/29/2022	Athens, GA	United States	Unkno

88889 rows × 23 columns

In [193...

```
# Replace "Unk" with "UNK" in the 'Weather.Condition' column
df['Weather.Condition'].replace('Unk', 'UNK', inplace=True)
df['Weather.Condition']
```

Out[193...

```
0        UNK
1        UNK
2        IMC
3        IMC
4        VMC
        ...
88884    NaN
88885    NaN
88886    VMC
88887    NaN
88888    NaN
Name: Weather.Condition, Length: 88889, dtype: object
```

In [194…
```
# Replace NaN values in 'Weather.Condition' with 'UNK'
df['Weather.Condition'].fillna('UNK', inplace=True)
df['Weather.Condition']
```

Out[194…
```
0        UNK
1        UNK
2        IMC
3        IMC
4        VMC
        ...
88884    UNK
88885    UNK
88886    VMC
88887    UNK
88888    UNK
Name: Weather.Condition, Length: 88889, dtype: object
```

In [195…
```
# To get a list of all column names in the dataset
column_names = df.columns.tolist()
column_names
```

Out[195…
```
['Investigation.Type',
 'Accident.Number',
 'Event.Date',
 'Location',
 'Country',
 'Airport.Name',
 'Injury.Severity',
 'Aircraft.damage',
 'Aircraft.Category',
 'Registration.Number',
 'Make',
 'Model',
 'Amateur.Built',
 'Number.of.Engines',
 'Engine.Type',
 'FAR.Description',
 'Purpose.of.flight',
 'Total.Fatal.Injuries',
 'Total.Serious.Injuries',
 'Total.Minor.Injuries',
 'Total.Uninjured',
 'Weather.Condition',
 'Broad.phase.of.flight']
```

In [196…
```
df.isnull().sum()
```

Out[196…

```
Investigation.Type        0
Accident.Number           0
Event.Date                0
Location                  0
Country                   0
Airport.Name              0
Injury.Severity           0
Aircraft.damage           0
Aircraft.Category         0
Registration.Number       0
Make                      0
Model                     0
Amateur.Built             0
Number.of.Engines         0
Engine.Type               0
FAR.Description           0
Purpose.of.flight         0
Total.Fatal.Injuries      0
Total.Serious.Injuries    0
Total.Minor.Injuries      0
Total.Uninjured           0
Weather.Condition         0
Broad.phase.of.flight     0
dtype: int64
```

In [197…

```
# Saving the cleaned DataFrame to a CSV file
df.to_csv('cleaned_aviation_data.csv', index=False)
```

In [198…

```
# To determine the aircraft with the lowest risk for the company i want to check th


# Group by 'Make' and 'Model', count the number of incidents (rows)
accident_frequency = df.groupby(['Make', 'Model']).size().reset_index(name='Acciden

# Sort the results by 'Accident_Frequency' to find models with the highest incident
accident_frequency_sorted = accident_frequency.sort_values(by='Accident_Frequency',

# Display the top 10 aircraft models with the highest accident frequency
print(accident_frequency_sorted.head(10))
```

```
         Make      Model  Accident_Frequency
4670   CESSNA        152                2366
4694   CESSNA        172                1753
4745   CESSNA       172N                1163
13569   PIPER  PA-28-140                 932
4643   CESSNA        150                 829
4743   CESSNA       172M                 798
4748   CESSNA       172P                 689
4802   CESSNA        182                 659
4778   CESSNA        180                 621
4669   CESSNA       150M                 585
```

In [199…

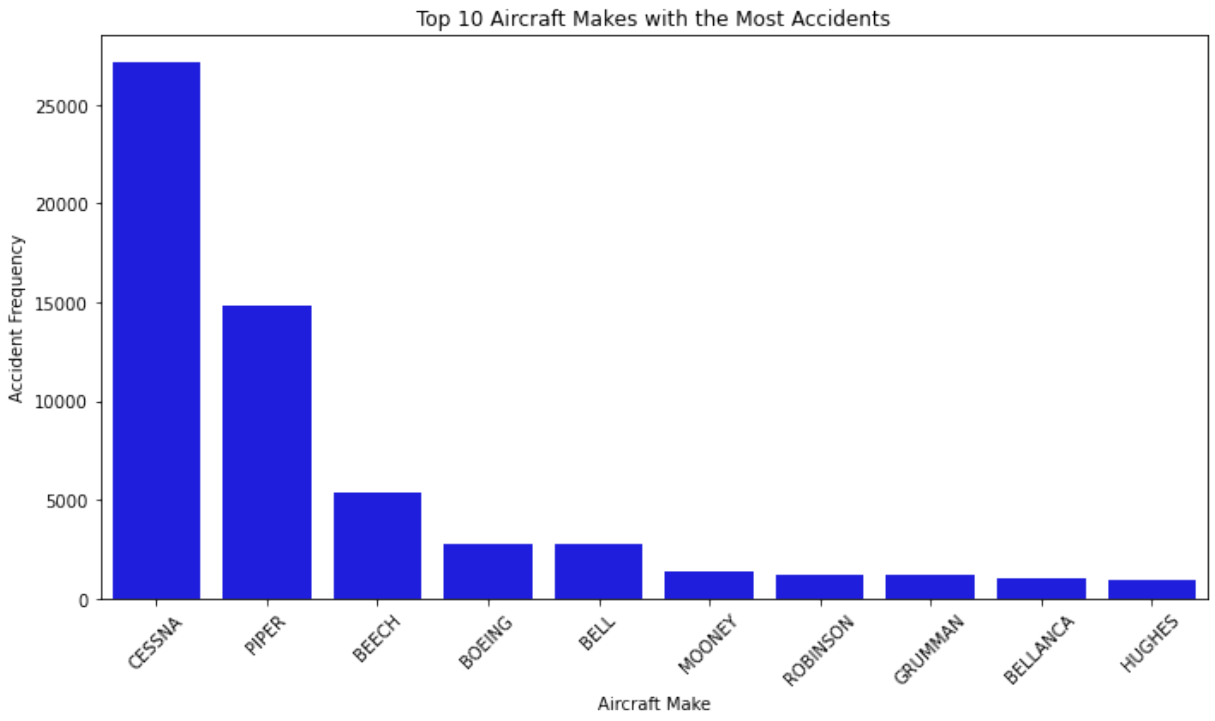
```
# Group by 'Aircraft.Category' to count the number of incidents
accidents_by_category = df.groupby('Aircraft.Category').size().reset_index(name='In

# Sort the data to see which category has the highest number of incidents
```

```
accidents_by_category_sorted = accidents_by_category.sort_values(by='Incident_Count

# Display the result
print(accidents_by_category_sorted)
```

```
    Aircraft.Category  Incident_Count
12            Unknown           56616
0            Airplane           27617
5          Helicopter            3440
3              Glider             508
1             Balloon             231
4           Gyrocraft             173
14      Weight-Shift             161
6   Powered Parachute              91
11         Ultralight              30
13               WSFT               9
7        Powered-Lift               5
2               Blimp               4
10                UNK               2
8              Rocket               1
9                ULTR               1
```

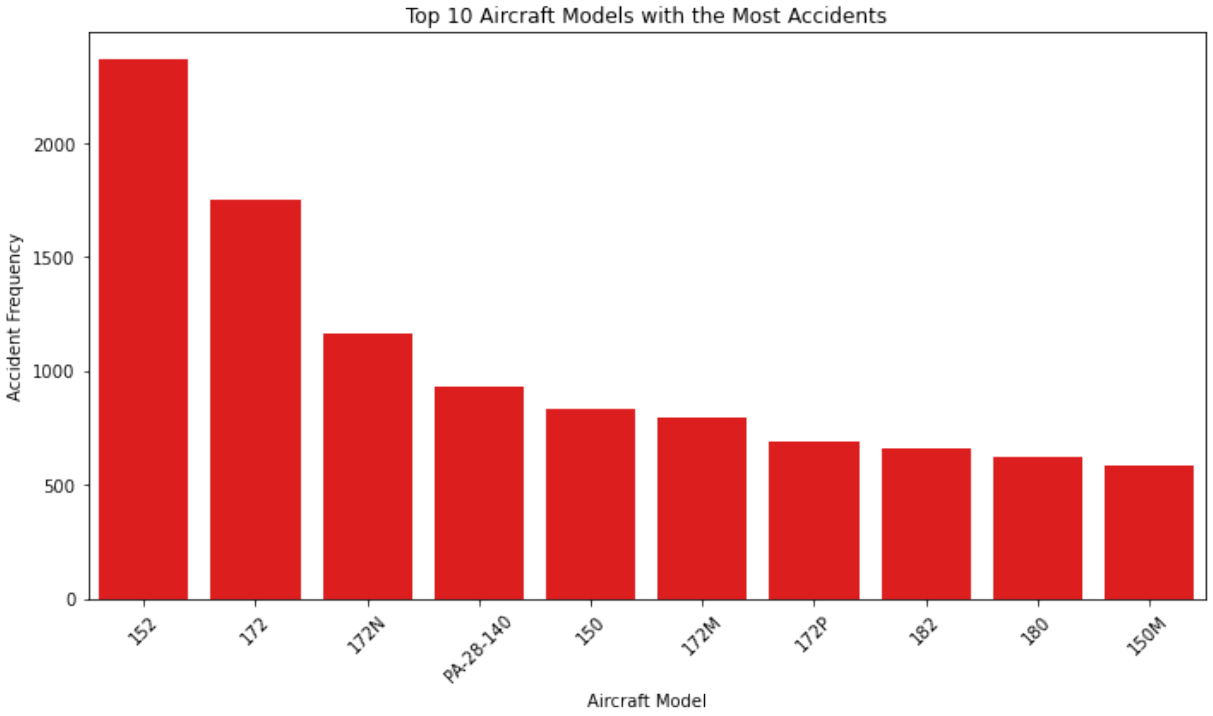
In [200…

```
# To identify the Top 10 Makes with the highest accident frequency
top_10_makes = accident_frequency.groupby('Make').sum().sort_values(by='Accident_Fr

# Plot the data
plt.figure(figsize=(10, 6))
sns.barplot(x=top_10_makes.index, y=top_10_makes['Accident_Frequency'], color='Blue
plt.title('Top 10 Aircraft Makes with the Most Accidents')
plt.xlabel('Aircraft Make')
plt.ylabel('Accident Frequency')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [201…

```
# To determine the model that is frequently involved in accidents
# Top 10 Models with the highest accident frequency
top_10_models = accident_frequency_sorted.head(10)

# Plot the data
plt.figure(figsize=(10, 6))
sns.barplot(x='Model', y='Accident_Frequency', data=top_10_models, color='Red')
plt.title('Top 10 Aircraft Models with the Most Accidents')
plt.xlabel('Aircraft Model')
plt.ylabel('Accident Frequency')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [202…

```
# Identifying the Risk on the aircraft associated with factors such as Make, Model,
# Group by 'Make', 'Model', and 'Aircraft.Category' to calculate accident frequency
accident_frequency = df.groupby(['Make', 'Model', 'Aircraft.Category']).size().rese

# Sort the results by 'Accident_Frequency' to get the most frequent accidents
accident_frequency_sorted = accident_frequency.sort_values(by='Accident_Frequency',

# Display the top 10
print(accident_frequency_sorted.head(10))
```

	Make	Model	Aircraft.Category	Accident_Frequency
5387	CESSNA	152	Unknown	1916
5419	CESSNA	172	Unknown	886
5418	CESSNA	172	Airplane	867
5490	CESSNA	172N	Unknown	848
15285	PIPER	PA-28-140	Unknown	700
5487	CESSNA	172M	Unknown	581
5346	CESSNA	150	Unknown	573
5494	CESSNA	172P	Unknown	522
5385	CESSNA	150M	Unknown	485
15126	PIPER	PA-18	Unknown	470

In [203…

```
# Check data types of the injury columns
print(df[['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Injuries']

# Check for non-numeric values in these columns
print(df[['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Injuries']
```

```
Total.Fatal.Injuries      object
Total.Serious.Injuries    object
Total.Minor.Injuries      object
dtype: object
Total.Fatal.Injuries      11401
Total.Serious.Injuries    12510
Total.Minor.Injuries      11933
dtype: int64
```

In [204…

```
# Select injury-related columns
injury_columns = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.In

# Ensure the injury columns are numeric
df[injury_columns] = df[injury_columns].apply(pd.to_numeric, errors='coerce')

# Recalculate the Severity Index
df['Severity_Index'] = (df['Total.Fatal.Injuries'] * 3 +
                        df['Total.Serious.Injuries'] * 2 +
                        df['Total.Minor.Injuries'] * 1) / (df['Total.Fatal.Injuries

# Display the top 10 severity index results
severity_index_sorted = df.groupby(['Make', 'Model', 'Aircraft.Category'])['Severit
severity_index_sorted = severity_index_sorted.sort_values(by='Severity_Index', asce
print(severity_index_sorted.head(10))
```

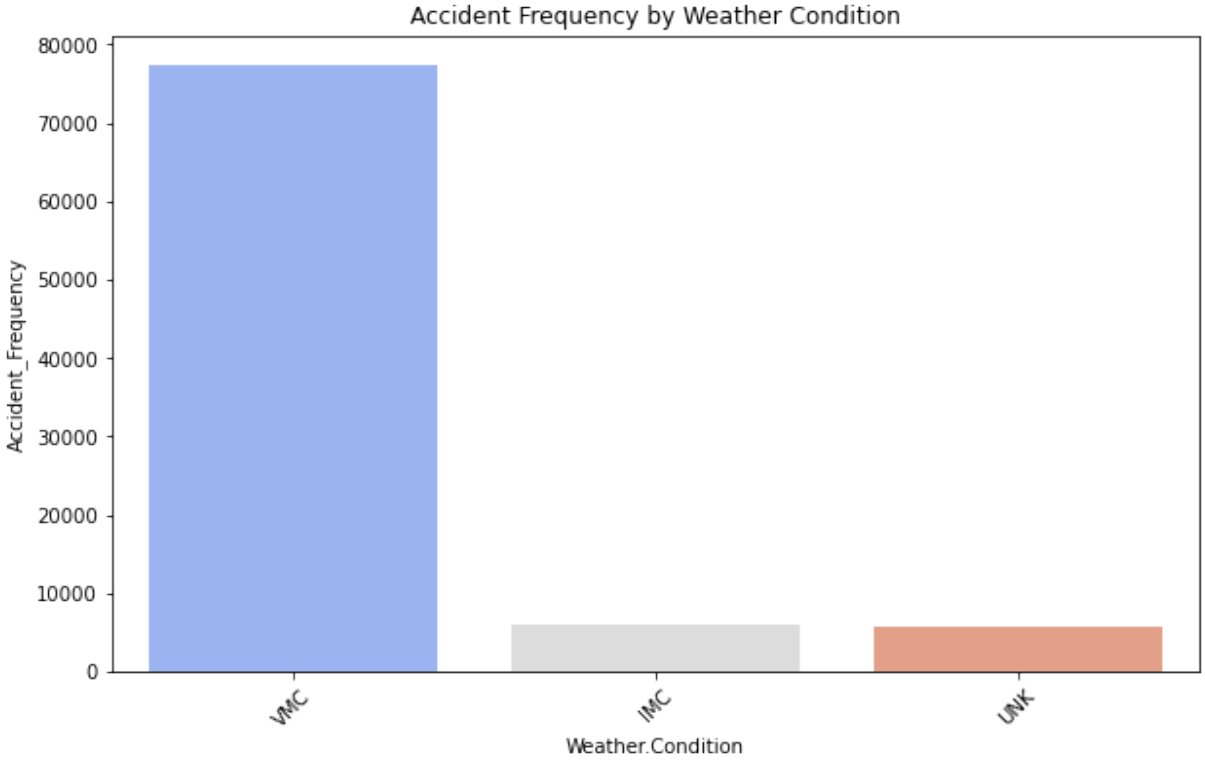
	Make	Model	Aircraft.Category	Severity_Index
13191	MCDONNELL DOUGLAS	DC-8-62	Unknown	2.982857
992	AIRBUS	A320 - 216	Airplane	2.981595
4288	BOEING	MD-83	Unknown	2.980519
3641	BOEING	707	Unknown	2.979310
3633	BOEING	-959	Unknown	2.975806
971	AIRBUS	A310	Airplane	2.967532
19546	TUPOLEV	TU154	Airplane	2.966667
8085	DOUGLAS	MD-83	Unknown	2.966292
1501	ANTONOV	AN148	Airplane	2.958333
4192	BOEING	B-757-23A	Unknown	2.957746

In [205…

```
# Group by 'Weather.Condition' to calculate the accident frequency under different
weather_impact = df.groupby('Weather.Condition').size().reset_index(name='Accident_
```

```
# Sort the results by frequency
weather_impact_sorted = weather_impact.sort_values(by='Accident_Frequency', ascendi

# Display the weather conditions with the highest accident frequency
print(weather_impact_sorted.head(10))

# To visualize accident frequency by weather conditions

plt.figure(figsize=(10, 6))
sns.barplot(x='Weather.Condition', y='Accident_Frequency', data=weather_impact_sort
plt.xticks(rotation=45)
plt.title('Accident Frequency by Weather Condition')
plt.show()
```

```
  Weather.Condition  Accident_Frequency
2               VMC               77303
0               IMC                5976
1               UNK                5610
```



In [206…
```
df.columns
```

Out[206…
```
Index(['Investigation.Type', 'Accident.Number', 'Event.Date', 'Location',
       'Country', 'Airport.Name', 'Injury.Severity', 'Aircraft.damage',
       'Aircraft.Category', 'Registration.Number', 'Make', 'Model',
       'Amateur.Built', 'Number.of.Engines', 'Engine.Type', 'FAR.Description',
       'Purpose.of.flight', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Broad.phase.of.flight', 'Severity_Index'],
      dtype='object')
```

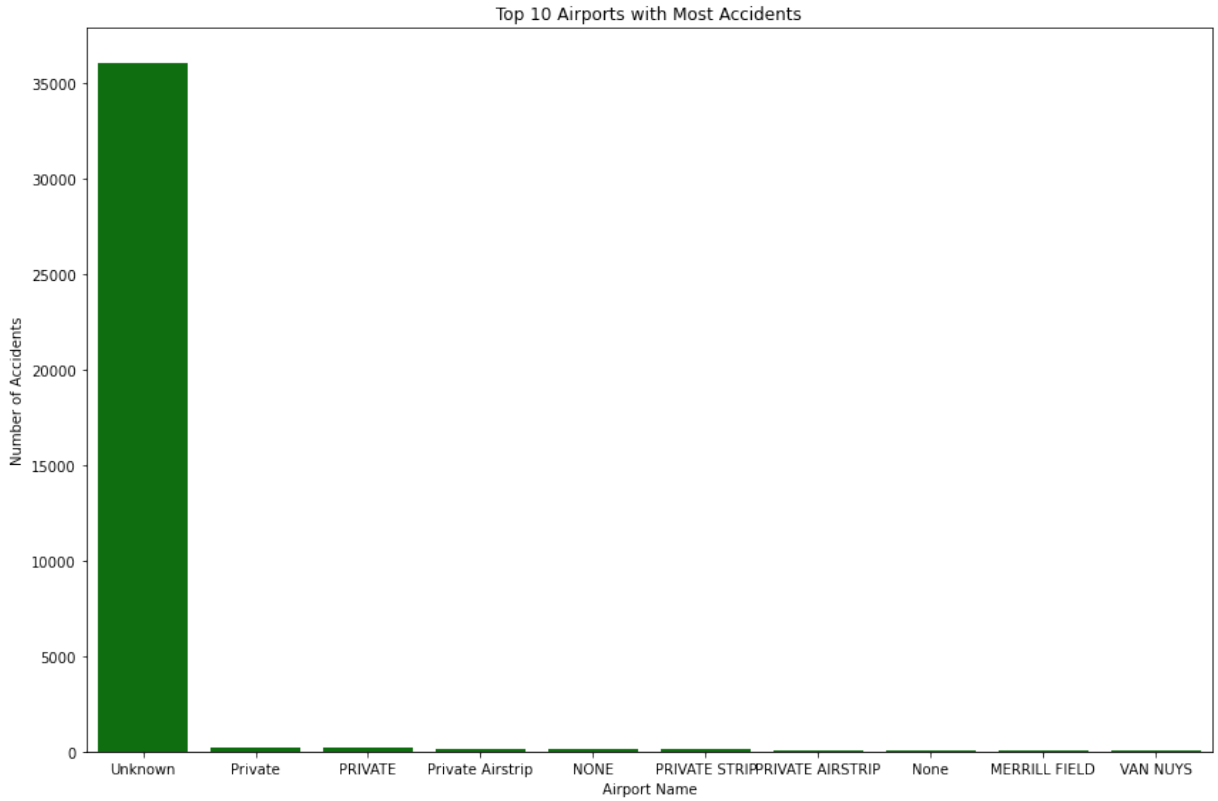
In [207…
```
# Further breaking down frequency of accidents by specific airports to check if the
# Group by airport name to get the frequency of accidents
```

```
airport_accidents = df.groupby('Airport.Name').size().reset_index(name='Accident_Co
airport_accidents_sorted = airport_accidents.sort_values(by='Accident_Count', ascen

# Display top 10 airports with the most accidents
print(airport_accidents_sorted.head(10))
```

```
          Airport.Name  Accident_Count
23107          Unknown           36106
18126          Private             240
17494          PRIVATE             224
18135  Private Airstrip             153
15729             NONE             146
17518     PRIVATE STRIP             111
17503  PRIVATE AIRSTRIP              92
16051             None              86
14006     MERRILL FIELD              83
23150          VAN NUYS              81
```

In [208…

```
plt.figure(figsize=(12, 8))
sns.barplot(x='Airport.Name', y='Accident_Count', data=airport_accidents_sorted.hea
plt.title('Top 10 Airports with Most Accidents')
plt.xlabel('Airport Name')
plt.ylabel('Number of Accidents')
plt.tight_layout()
plt.show()
```



In [209…

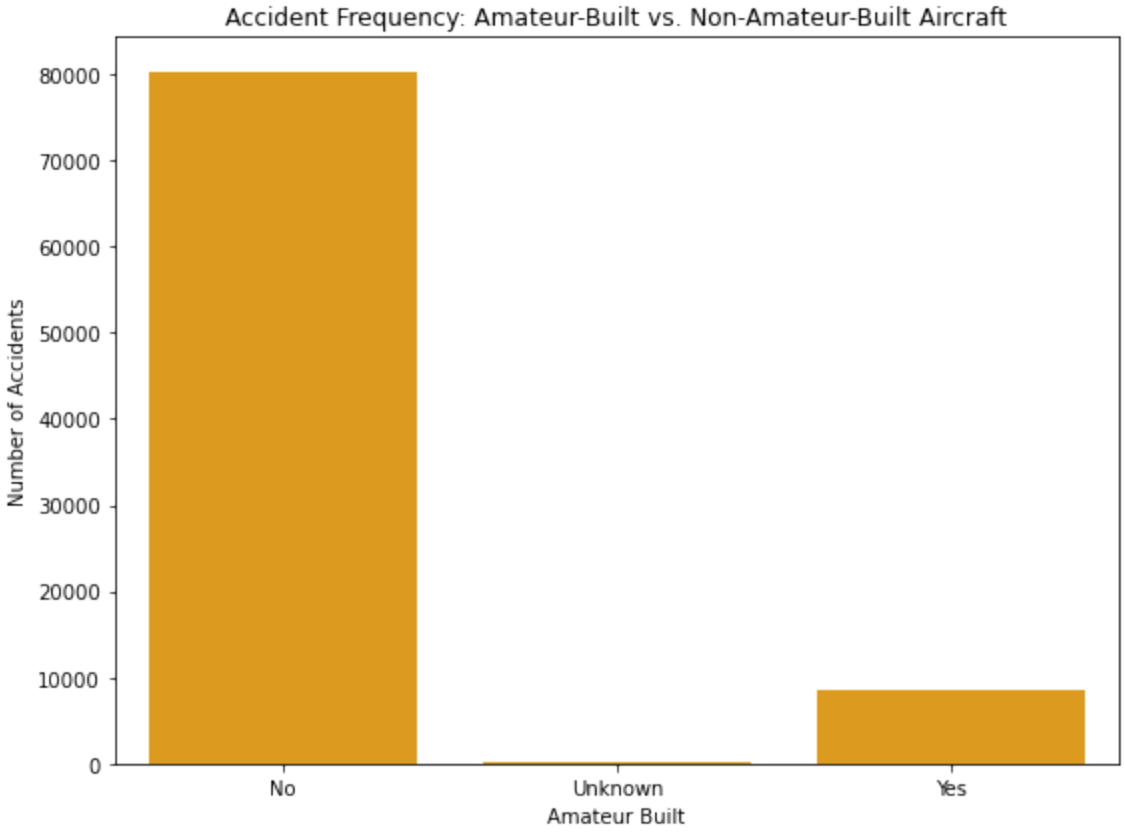
```
# To compare accident rates and weather conditions for amateur-built vs. non-amateu
# Group by 'Amateur.Built' to compare accident frequencies
amateur_vs_non_amateur = df.groupby('Amateur.Built').size().reset_index(name='Accid

# Calculate percentage of accidents for each category
total_accidents = df['Amateur.Built'].count()
```

```
amateur_vs_non_amateur['Percentage'] = (amateur_vs_non_amateur['Accident_Frequency'

print(amateur_vs_non_amateur)
```

```
  Amateur.Built  Accident_Frequency  Percentage
0            No               80312   90.350887
1       Unknown                 102    0.114750
2           Yes                8475    9.534363
```

In [210…

```
# Bar plot for accident frequency comparison
plt.figure(figsize=(8, 6))
sns.barplot(x='Amateur.Built', y='Accident_Frequency', data=amateur_vs_non_amateur,
plt.title('Accident Frequency: Amateur-Built vs. Non-Amateur-Built Aircraft')
plt.xlabel('Amateur Built')
plt.ylabel('Number of Accidents')
plt.tight_layout()
plt.show()
```



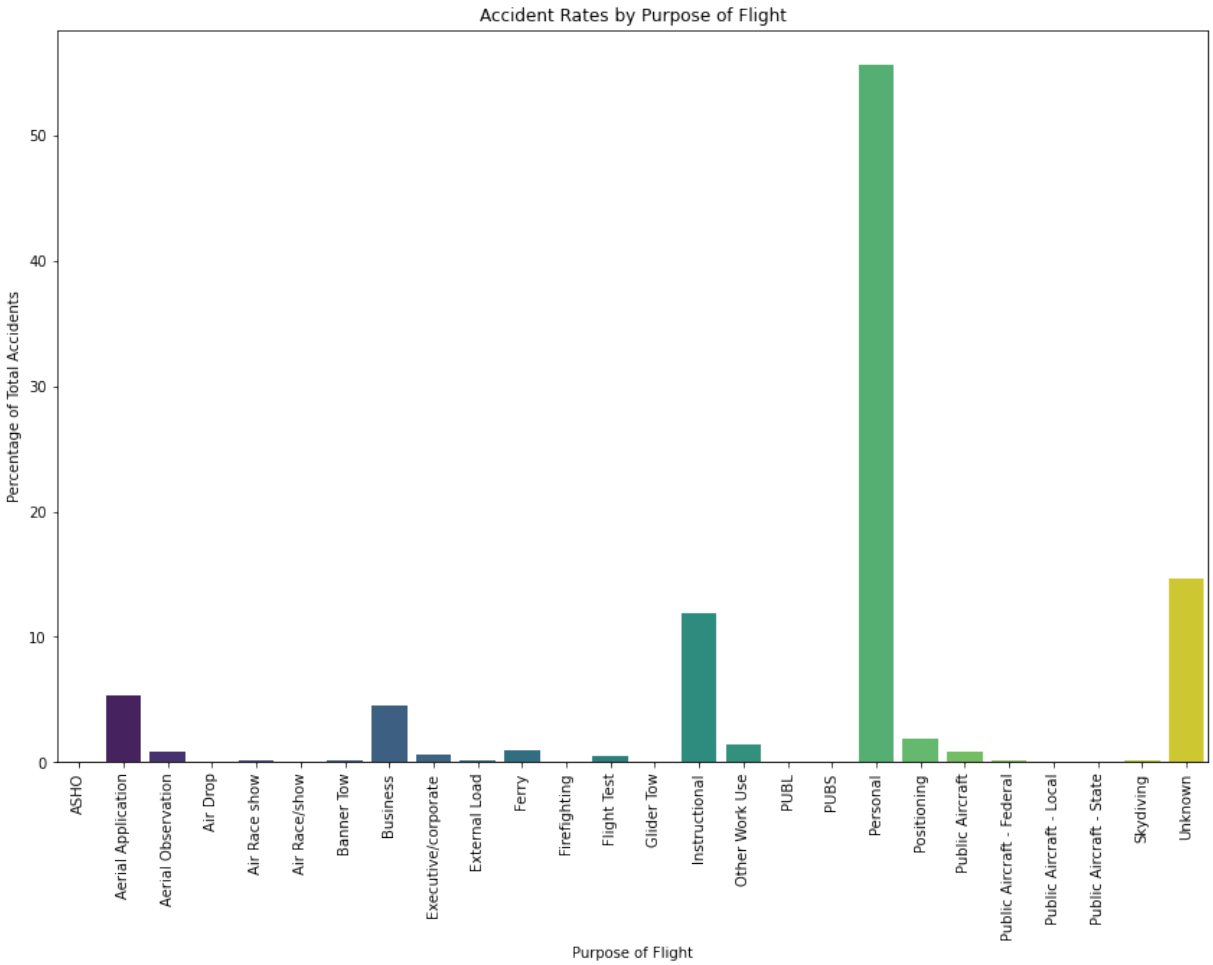
In [211…

```
# Identify if certain flight purposes (e.g., training, commercial, private) are mor
# Group by 'Purpose.of.flight' and calculate accident frequency
accident_rates_by_purpose = df.groupby('Purpose.of.flight').size().reset_index(name

# Calculate the total number of accidents for normalization
total_accidents = df.shape[0]

# Calculate the percentage of accidents for each purpose
accident_rates_by_purpose['Accident_Percentage'] = (accident_rates_by_purpose['Acci

print(accident_rates_by_purpose)
```

	Purpose.of.flight	Accident_Count	Accident_Percentage
0	ASHO	6	0.006750
1	Aerial Application	4712	5.300993
2	Aerial Observation	794	0.893249
3	Air Drop	11	0.012375
4	Air Race show	99	0.111375
5	Air Race/show	59	0.066375
6	Banner Tow	101	0.113625
7	Business	4018	4.520244
8	Executive/corporate	553	0.622124
9	External Load	123	0.138375
10	Ferry	812	0.913499
11	Firefighting	40	0.045000
12	Flight Test	405	0.455624
13	Glider Tow	53	0.059625
14	Instructional	10601	11.926110
15	Other Work Use	1264	1.421998
16	PUBL	1	0.001125
17	PUBS	4	0.004500
18	Personal	49448	55.628930
19	Positioning	1646	1.851748
20	Public Aircraft	720	0.809999
21	Public Aircraft - Federal	105	0.118125
22	Public Aircraft - Local	74	0.083250
23	Public Aircraft - State	64	0.072000
24	Skydiving	182	0.204750
25	Unknown	12994	14.618232

In [212…

```
# Bar plot for accident rates by flight purpose
plt.figure(figsize=(12, 8))
sns.barplot(x='Purpose.of.flight', y='Accident_Percentage', data=accident_rates_by_
plt.title('Accident Rates by Purpose of Flight')
plt.xlabel('Purpose of Flight')
plt.ylabel('Percentage of Total Accidents')
plt.tight_layout()
plt.xticks(rotation=90)
plt.show()
```


Accident Rates by Purpose of Flight
Percentage of Total Accidents
0
10
20
30
40
50
ASHO
Aerial Application
Aerial Observation
Air Drop
Air Race show
Air Race/show
Banner Tow
Business
Executive/corporate
External Load
Ferry
Firefighting
Flight Test
Glider Tow
Instructional
Other Work Use
PUBL
PUBS
Personal
Positioning
Public Aircraft
Public Aircraft - Federal
Public Aircraft - Local
Public Aircraft - State
Skydiving
Unknown
Purpose of Flight

In [141…