Business Diversification

Phase 1 project, November 2024

DSF-PT09 CLASS

Overview

The company in concern, intends to diversify its business portfolio to purchasing and operating airplanes for commercial and private enterprises.

Due to the high capital investment required this project intends to determine the lowest risk aircraft, the company can purchase to start this new business endeavor.

The project, intends to translate the findings into actionable insights that the head of the new aviation division can use to help decide which aircraft to purchase.

Business Undestanding

Objectives

1. Develop an accident risk frequency for the different aircraft makes and models from historical accident records
2. Develop an acquisition strategy based on potential risk portfolio for different make of aircraft
3. Evaluate and determine lowest risk aircraft for purchase for private and commercial enterprises

```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

```
#importing the dataset
df=pd.read_csv('/content/AviationData.csv', encoding='latin-1', low_memory=False )
```

```
df.head()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	A
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	NaN	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN	

5 rows × 31 columns

```
df.tail()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	A
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	

5 rows × 31 columns

Data Understanding

1. Extract the few first and last rows in the dataset to View content
2. View the % of missing values per column and datatypes in the dataset
3. Do a statistical analysis for the numerical columns
4. View the size of the dataset
5. Visualize raw data

df.shape

```
(88889, 31)
```

df.columns

```
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')
```

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
```

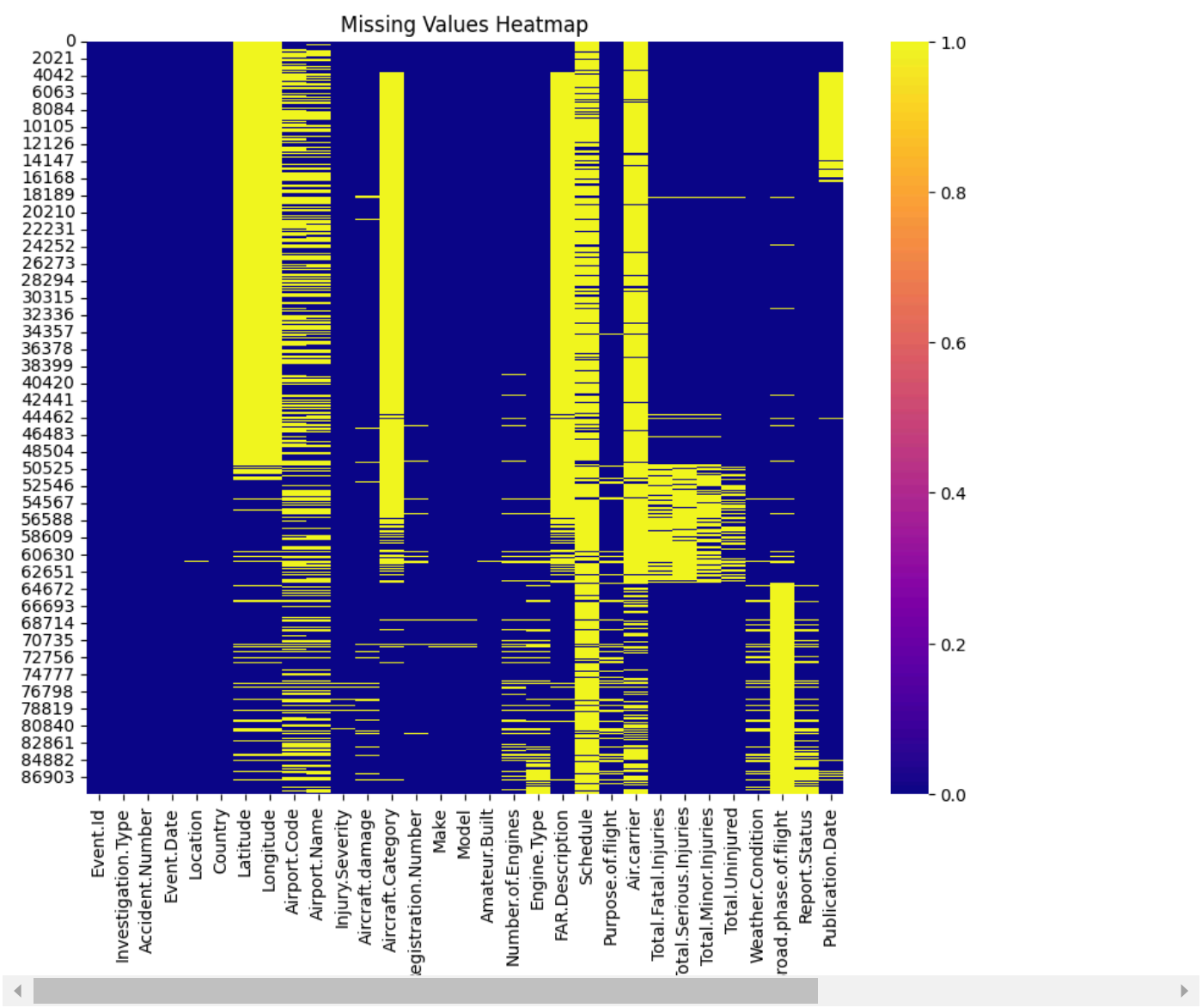
```
df.describe()
```

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.000000
mean	1.146585	0.647855	0.279881	0.357061	5.325440
std	0.446510	5.485960	1.544084	2.235625	27.913634
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000	1.000000
75%	1.000000	0.000000	0.000000	0.000000	2.000000
max	8.000000	349.000000	161.000000	380.000000	699.000000

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

	0
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

```
# Visualize the missing values
plt.figure(figsize=(10, 8))
sns.heatmap(df.isnull(), cbar=True, cmap="plasma")
plt.title("Missing Values Heatmap")
plt.show()
```



Data Preparation

The data cleaning process will be as follows;

1. Drop columns with more than 70% missing values
2. Drop of all columns that are not of immediate concern to the objective of low risk airplanes. For example

    * `Investigation.Type`
    * `Registration.Number`
    * `Publication.Date`
    * `Airport.Code`
    * `Airport.Name`

3. Substitute the object type column with mode and float64 columns with mean
4. Remove fuzzy duplicates and aliases in Make, Model and Weather conditions column
5. Define the target market by country with the greatest % of available data
6. Import changes to CSV for onward processing in Tableau and visualization
7. As per the business problem a risk matrix best answers the hypothesis. In this case therefore;

- Develop risk metrics
- Assign severity as per the string values provided in the dataset
- Aggregate the risk metrics
- Assign risk scores
- Develop a risk matrix

```
# Drop columns with more than 70% of missing data
df = df.dropna(axis=1, thresh=0.7 * df.shape[0])
print(df.columns)
```

```
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')
```

```
# Drop more columns
df = df.drop(columns=['Investigation.Type', 'Publication.Date', 'Registration.Number'])
```

```
#Dropping data before Year 1982. Too few details available in prior years
df= df[df['Event.Date'] >= '1982-01-01']
```

```
# As stated in the business problem, the only the area of interest is in airplanes for Business and Private purposes
# Therefore relevant rows = Business, Corporate, Charter, Air Taxi and  Commercial
df = df[df['Purpose.of.flight'].isin(['Business', 'Corporate', 'Charter', 'Air Taxi', 'Commercial'])]
print(df['Purpose.of.flight'].value_counts())
```

```
Purpose.of.flight
Business    4018
Name: count, dtype: int64
```

```
# create a new column called total incidents
# Which is sum of Total.Fatal.Injuries, Total.Serious.Injuries, Total.Minor.Injuries and Total.Uninjured
df['Total.Incidents'] = df['Total.Fatal.Injuries'] + df['Total.Serious.Injuries'] + df['Total.Minor.Injuries'] + df['Total.Uninjured']
```

```
# view if new column has been added
df.head()
```

	Event.Id	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage	Make	Model	Amateu
8	20020909X01561	NYC82DA015	1982-01-01	EAST HANOVER, NJ	United States	Non-Fatal	Substantial	Cessna	401B	
25	20020917X01905	DCA82AA008	1982-01-03	ASHLAND, VA	United States	Fatal(8)	Destroyed	Cessna	414A	
36	20020917X02410	MIA82FKA05	1982-01-04	SAINT CROIX	NaN	Fatal(1)	Destroyed	Cessna	206	
37	20020917X02304	LAX82FUM06	1982-01-05	RAMONA, CA	United States	Fatal(3)	Destroyed	Navion	A	
40	20020917X01764	ATL82IA029	1982-01-05	PENSACOLA, FL	United States	Incident	Minor	Rockwell	114	

```
# drop missing values in Aircraft.Damage column
df = df.dropna(subset=['Aircraft.damage'])
```

```
# View the data types and available entries
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3926 entries, 8 to 88867
Data columns (total 20 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Event.Id               3926 non-null   object
```

```
 1   Accident.Number         3926 non-null   object
 2   Event.Date              3926 non-null   object
 3   Location                3925 non-null   object
 4   Country                 3913 non-null   object
 5   Injury.Severity         3925 non-null   object
 6   Aircraft.damage         3926 non-null   object
 7   Make                    3926 non-null   object
 8   Model                   3924 non-null   object
 9   Amateur.Built           3924 non-null   object
 10  Number.of.Engines       3794 non-null   float64
 11  Engine.Type             3792 non-null   object
 12  Purpose.of.flight       3926 non-null   object
 13  Total.Fatal.Injuries    3598 non-null   float64
 14  Total.Serious.Injuries  3506 non-null   float64
 15  Total.Minor.Injuries    3530 non-null   float64
 16  Total.Uninjured         3734 non-null   float64
 17  Weather.Condition       3880 non-null   object
 18  Report.Status           3815 non-null   object
 19  Total.Incidents         3457 non-null   float64
dtypes: float64(6), object(14)
memory usage: 644.1+ KB
```

```
# View missing values again
df.isna().sum()
```

	0
Event.Id	0
Accident.Number	0
Event.Date	0
Location	1
Country	13
Injury.Severity	1
Aircraft.damage	0
Make	0
Model	2
Amateur.Built	2
Number.of.Engines	132
Engine.Type	134
Purpose.of.flight	0
Total.Fatal.Injuries	328
Total.Serious.Injuries	420
Total.Minor.Injuries	396
Total.Uninjured	192
Weather.Condition	46
Report.Status	111
Total.Incidents	469

```
# Fill the missing values float64 columns(numeric) with their respective columns mean value
df.fillna(df.select_dtypes(include=['float64']).mean(), inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3757 entries, 8 to 88867
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                3757 non-null   object
```

```
 1   Accident.Number         3757 non-null   object
 2   Event.Date              3757 non-null   object
 3   Location                3757 non-null   object
 4   Country                 3757 non-null   object
 5   Injury.Severity         3757 non-null   object
 6   Aircraft.damage         3757 non-null   object
 7   Make                    3757 non-null   object
 8   Model                   3756 non-null   object
 9   Amateur.Built           3757 non-null   object
 10  Number.of.Engines       3757 non-null   float64
 11  Engine.Type             3678 non-null   object
 12  Purpose.of.flight       3757 non-null   object
 13  Total.Fatal.Injuries    3757 non-null   float64
 14  Total.Serious.Injuries  3757 non-null   float64
 15  Total.Minor.Injuries    3757 non-null   float64
 16  Total.Uninjured         3757 non-null   float64
 17  Weather.Condition       3739 non-null   object
 18  Report.Status           3682 non-null   object
 19  Total.Incidents         3757 non-null   float64
dtypes: float64(6), object(14)
memory usage: 616.4+ KB
```

```
df = df.drop('Engine.Type', axis=1)
```

```
# Check duplicates
df.duplicated().sum()
# View duplicated data
df[df.duplicated()]
# Remove the duplicated data
df = df.drop_duplicates()
```

```
# Apply uniform casing to the dataset
df = df.apply(lambda col: col.str.upper() if col.dtype == 'object' else col)
```

```
# check the country with the more data to allow substansive analysis
df['Country'].value_counts()
```

Country	count
UNITED STATES	3756

```
# For analysis of the business problem, our target market will be the US because of the amount of available data
# Extract the US dataset
df = df[df['Country'].str.strip().eq('UNITED STATES')]
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 3756 entries, 8 to 88867
Data columns (total 19 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                3756 non-null   object
 1   Accident.Number         3756 non-null   object
 2   Event.Date              3756 non-null   object
 3   Location                3756 non-null   object
 4   Country                 3756 non-null   object
 5   Injury.Severity         3756 non-null   object
 6   Aircraft.damage         3756 non-null   object
 7   Make                    3756 non-null   object
 8   Model                   3755 non-null   object
 9   Amateur.Built           3756 non-null   object
 10  Number.of.Engines       3756 non-null   float64
 11  Purpose.of.flight       3756 non-null   object
 12  Total.Fatal.Injuries    3756 non-null   float64
 13  Total.Serious.Injuries  3756 non-null   float64
 14  Total.Minor.Injuries    3756 non-null   float64
 15  Total.Uninjured         3756 non-null   float64
 16  Weather.Condition       3738 non-null   object
 17  Report.Status           3681 non-null   object
 18  Total.Incidents         3756 non-null   float64
```

```
dtypes: float64(6), object(13)
memory usage: 586.9+ KB
```

```
# save the copy of the target market for analysis and visualization in tableau
df.to_csv('target_market.csv', index=False)
from google.colab import files
files.download('target_market.csv')
```

```
#  A risk Matrix best answers the business problem in question for the phase 1 project
# Group the make and Model columns and specify  the function to apply to each risk column and regularize new column

risk_metrics = df.groupby(['Make', 'Model']).agg({
    'Aircraft.damage': lambda x: x[x.isin(['Substantial', 'Destroyed'])].value_counts().to_dict(),  # Frequency of damage categories
    'Total.Fatal.Injuries': 'mean',  # Average fatal injuries
    'Total.Serious.Injuries': 'mean',  # Average serious injuries
    'Total.Minor.Injuries': 'mean',  # Average minor injuries
    'Total.Uninjured': 'mean',  # Average uninjured
    'Total.Incidents': 'sum'  # Total incidents
}).reset_index()

print(risk_metrics)

# Reset index for readability
risk_metrics.reset_index(inplace=True)
```

```
                          Make         Model Aircraft.damage  \
0         AAA AIRCRAFT LEASING           192              {}
1                        ADAMS          A60S              {}
2          ADVANCED TECHNOLOGY  PREDATOR 480              {}
3               AERO COMMANDER           100              {}
4               AERO COMMANDER       100-180              {}
...                        ...           ...             ...
1288         WHEELER ACFT. CO.   EXPRESS 100              {}
1289  WHEELER TECHNOLOGY, INC.        FT-210              {}
1290                       WSK       PZL-104              {}
1291           WSK PZL MIELEC          M-26              {}
1292                   YUNEEC        YUNEEC              {}

      Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries  \
0                      2.0                0.232459              0.304249
1                      0.0                1.000000              0.000000
2                      0.0                0.000000              1.000000
3                      0.0                0.333333              0.666667
4                      3.0                0.000000              0.000000
...                    ...                     ...                   ...
1288                   0.0                0.000000              2.000000
1289                   3.0                0.000000              0.000000
1290                   0.0                0.000000              0.000000
1291                   1.0                1.000000              0.000000
1292                   0.0                0.000000              0.000000

      Total.Uninjured  Total.Incidents
0            1.447509         2.412496
1            4.000000         5.000000
2            0.000000         1.000000
3            0.333333         4.000000
4            0.000000         3.000000
...               ...              ...
1288         0.000000         2.000000
1289         0.000000         3.000000
1290         2.000000         2.000000
1291         0.000000         2.000000
1292         2.000000         2.000000

[1293 rows x 8 columns]
```

```
# Map severity scores to 'Aircraft.damage'
severity_map = {'Substantial': 1, 'Destroyed': 2}
df['Damage.Score'] = df['Aircraft.damage'].map(severity_map)

# Calculate the severity frequency for each row
df['Severe.Damage.Frequency'] = df.groupby(['Make', 'Model'])['Damage.Score'].transform('sum')

# Convert damage scores to string format (optional, for clarity)
df['Damage.Score.String'] = df['Damage.Score'].astype(str)

print(df[['Make', 'Model', 'Aircraft.damage', 'Damage.Score', 'Severe.Damage.Frequency']])
```

```
                    Make       Model Aircraft.damage  Damage.Score  \
8                 CESSNA        401B     SUBSTANTIAL           NaN
25                CESSNA        414A       DESTROYED           NaN
37                NAVION           A       DESTROYED           NaN
40              ROCKWELL         114           MINOR           NaN
41                 PIPER   PA-24-250     SUBSTANTIAL           NaN
...                  ...         ...             ...           ...
88765              PIPER  PA46-500TP       DESTROYED           NaN
88786           FAIRCHILD    SA227-AT     SUBSTANTIAL           NaN
88804              CESSNA         207     SUBSTANTIAL           NaN
88834         LEARJET INC          45     SUBSTANTIAL           NaN
88867  AIRBUS HELICOPTERS   EC 130 T2     SUBSTANTIAL           NaN

       Severe.Damage.Frequency
8                          0.0
25                         0.0
37                         0.0
40                         0.0
41                         0.0
...                        ...
88765                      0.0
88786                      0.0
88804                      0.0
88834                      0.0
88867                      0.0

[3756 rows x 5 columns]
```

```
df.head()
```

	Event.Id	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage	Make	Model	Ama
8	20020909X01561	NYC82DA015	1982-01-01	EAST HANOVER, NJ	UNITED STATES	NON-FATAL	SUBSTANTIAL	CESSNA	401B	
25	20020917X01905	DCA82AA008	1982-01-03	ASHLAND, VA	UNITED STATES	FATAL(8)	DESTROYED	CESSNA	414A	
37	20020917X02304	LAX82FUM06	1982-01-05	RAMONA, CA	UNITED STATES	FATAL(3)	DESTROYED	NAVION	A	
40	20020917X01764	ATL82IA029	1982-01-05	PENSACOLA, FL	UNITED STATES	INCIDENT	MINOR	ROCKWELL	114	
41	20020917X01993	FTW82DA037	1982-01-05	LONOKE, AR	UNITED STATES	NON-FATAL	SUBSTANTIAL	PIPER	PA-24-250	

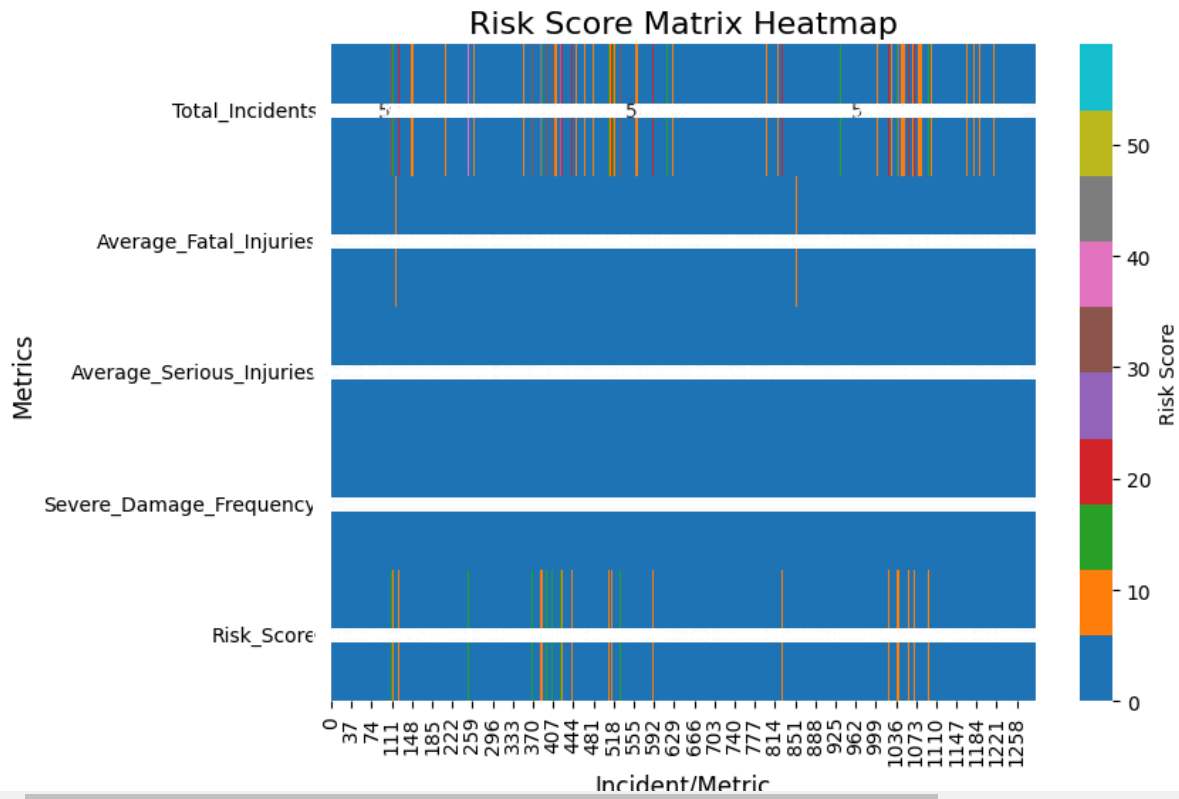
5 rows × 22 columns

```
# Function to calculate the severity of damage (sum of 'Destroyed' and 'Substantial' values)
def calculate_damage_severity(damage):
    if isinstance(damage, str):  # Ensure it's a string
        return damage.count('Destroyed') + damage.count('Substantial')
    return 0

# Apply the filter and calculation
df['Severe.Damage.Frequency'] = df['Aircraft.damage'].apply(calculate_damage_severity)


# Function to calculate the severity of damage
def calculate_damage_severity(damage):
    if isinstance(damage, str):  # Ensure it's a string
        return damage.count('Destroyed') + damage.count('Substantial')
    return 0

# Apply the calculation to create a new column for 'Severe.Damage.Frequency'
df['Severe.Damage.Frequency'] = df['Aircraft.damage'].apply(calculate_damage_severity)


df.head()
```

	Event.Id	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage	Make	Model	Ama
8	20020909X01561	NYC82DA015	1982-01-01	EAST HANOVER, NJ	UNITED STATES	NON-FATAL	SUBSTANTIAL	CESSNA	401B	
25	20020917X01905	DCA82AA008	1982-01-03	ASHLAND, VA	UNITED STATES	FATAL(8)	DESTROYED	CESSNA	414A	
37	20020917X02304	LAX82FUM06	1982-01-05	RAMONA, CA	UNITED STATES	FATAL(3)	DESTROYED	NAVION	A	
40	20020917X01764	ATL82IA029	1982-01-05	PENSACOLA, FL	UNITED STATES	INCIDENT	MINOR	ROCKWELL	114	
41	20020917X01993	FTW82DA037	1982-01-05	LONOKE, AR	UNITED STATES	NON-FATAL	SUBSTANTIAL	PIPER	PA-24-250	

5 rows × 22 columns

```
# Aggregate risk metrics by Make and Model
aggregated_metrics = df.groupby(['Make', 'Model']).agg(
    Total_Incidents=('Event.Id', 'count'),
    Average_Fatal_Injuries=('Total.Fatal.Injuries', 'mean'),
    Average_Serious_Injuries=('Total.Serious.Injuries', 'mean'),
    Average_Minor_Injuries=('Total.Minor.Injuries', 'mean'),
    Severe_Damage_Frequency=('Severe.Damage.Frequency', 'sum')
).reset_index()


# Define weights for the risk score components
weights = {
    'Total_Incidents': 0.4,
    'Average_Fatal_Injuries': 0.3,
    'Average_Serious_Injuries': 0.2,
    'Severe_Damage_Frequency': 0.1
}

# Calculate Risk Score
aggregated_metrics['Risk_Score'] = (
    weights['Total_Incidents'] * aggregated_metrics['Total_Incidents'] +
    weights['Average_Fatal_Injuries'] * aggregated_metrics['Average_Fatal_Injuries'].fillna(0) +
    weights['Average_Serious_Injuries'] * aggregated_metrics['Average_Serious_Injuries'].fillna(0) +
    weights['Severe_Damage_Frequency'] * aggregated_metrics['Severe_Damage_Frequency']
)

# Classifying the risk based on the calculated Risk Score
def classify_risk(score):
    if score <= 1:
        return 'Low Risk'
    elif score <= 2:
        return 'Medium Risk'
    else:
        return 'High Risk'

aggregated_metrics['Risk_Category'] = aggregated_metrics['Risk_Score'].apply(classify_risk)

# Plotting the Risk Matrix Heatmap
plt.figure(figsize=(8, 6))

# Creating the heatmap for metrics and Risk Score
sns.heatmap(aggregated_metrics[['Total_Incidents', 'Average_Fatal_Injuries',
                                'Average_Serious_Injuries', 'Severe_Damage_Frequency', 'Risk_Score']].T,
            annot=True, cmap='tab10', fmt='.2f', cbar_kws={'label': 'Risk Score'})

# Adding titles and labels
plt.title("Risk Score Matrix Heatmap", fontsize=16)
plt.xlabel("Incident/Metric", fontsize=12)
plt.ylabel("Metrics", fontsize=12)

plt.show()
```




```
# Sort by Risk Score in ascending order to identify low-risk aircraft
low_risk_aircraft = aggregated_metrics.sort_values(by='Risk_Score', ascending=True)

# Display the top 10 low-risk aircraft
low_risk_aircraft.head()

# create a new dataframe fro aggregated numerics
df_metrics = aggregated_metrics.copy()


df_metrics.head()
```

	Make	Model	Total_Incidents	Average_Fatal_Injuries	Average_Serious_Injuries	Average_Minor_Injuries	Severe_
0	AAA AIRCRAFT LEASING	192	1	2.0	0.232459	0.304249	
1	ADAMS	A60S	1	0.0	1.000000	0.000000	
2	ADVANCED TECHNOLOGY	PREDATOR 480	1	0.0	0.000000	1.000000	
3	AERO COMMANDER	100	3	0.0	0.333333	0.666667	
4	AERO COMMANDER	100-180	1	3.0	0.000000	0.000000	

Next steps: Generate code with df_metrics | View recommended plots | New interactive sheet

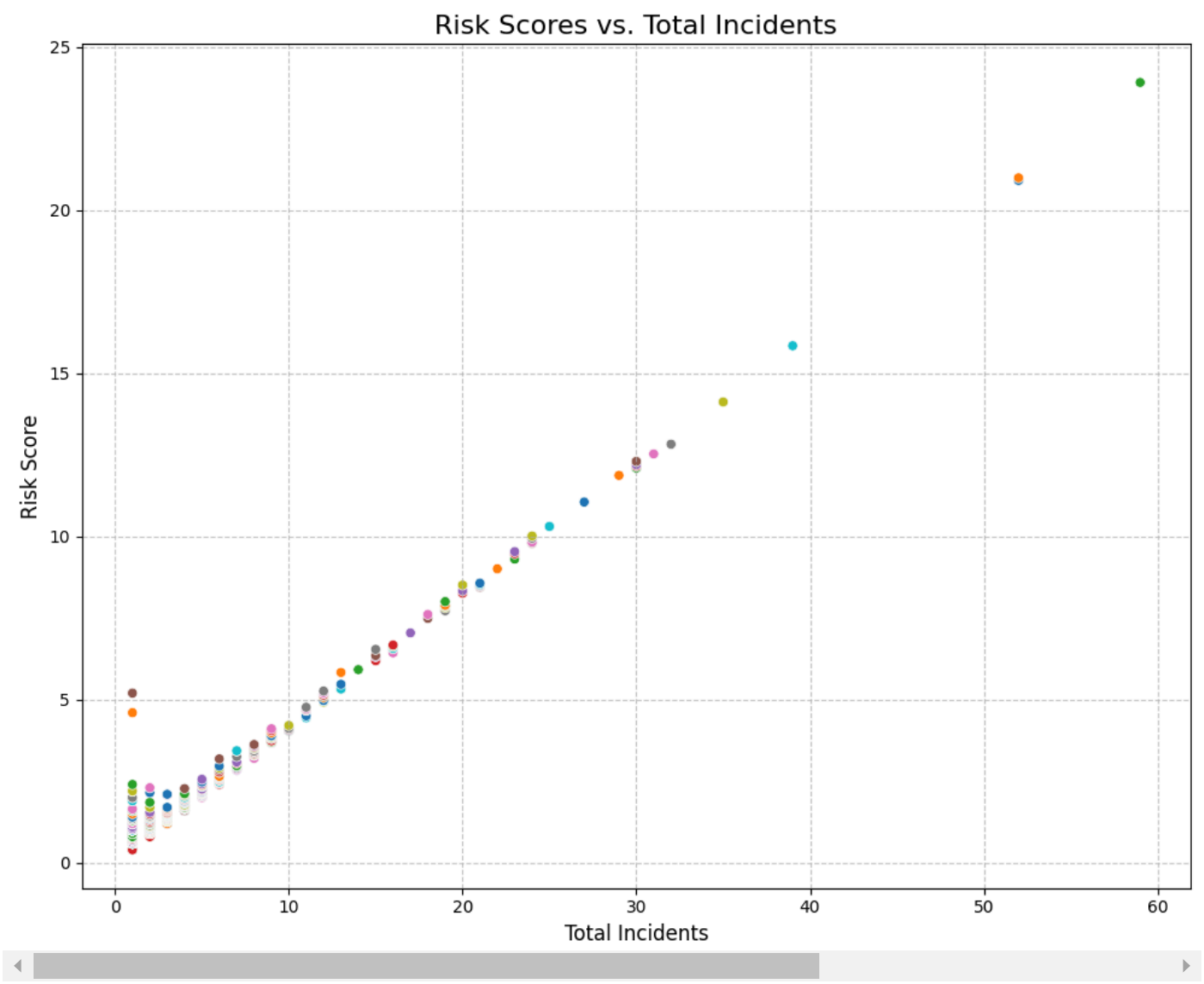
Data Visualization

```
df_metrics.info()
```

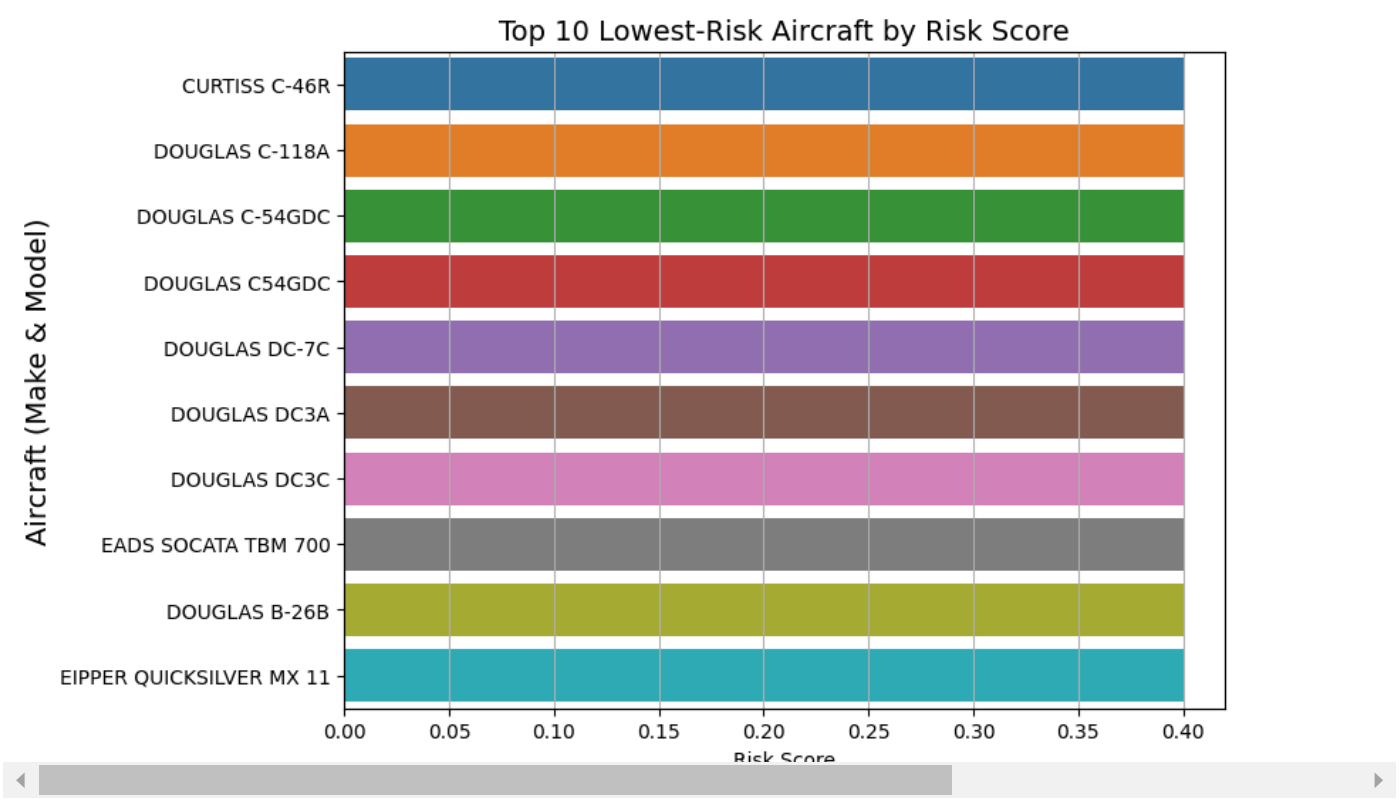
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1293 entries, 0 to 1292
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
```

```
 ---  ------                     --------------  -----
  0   Make                       1293 non-null   object
  1   Model                      1293 non-null   object
  2   Total_Incidents            1293 non-null   int64
  3   Average_Fatal_Injuries     1293 non-null   float64
  4   Average_Serious_Injuries   1293 non-null   float64
  5   Average_Minor_Injuries     1293 non-null   float64
  6   Severe_Damage_Frequency    1293 non-null   int64
  7   Risk_Score                 1293 non-null   float64
  8   Risk_Category              1293 non-null   object
dtypes: float64(4), int64(2), object(3)
memory usage: 91.0+ KB
```

```
# Defining the weights
weights = {
    'Total_Incidents': 0.4,
    'Average_Fatal_Injuries': 0.3,
    'Average_Serious_Injuries': 0.2,
    'Severe_Damage_Frequency': 0.1
}

# Calculating the Risk Score
aggregated_metrics['Risk_Score'] = (
    weights['Total_Incidents'] * aggregated_metrics['Total_Incidents'] +
    weights['Average_Fatal_Injuries'] * aggregated_metrics['Average_Fatal_Injuries'].fillna(0) +
    weights['Average_Serious_Injuries'] * aggregated_metrics['Average_Serious_Injuries'].fillna(0) +
    weights['Severe_Damage_Frequency'] * aggregated_metrics['Severe_Damage_Frequency']
)



#
low_risk_aircraft['Make_Model'] = low_risk_aircraft['Make'] + " " + low_risk_aircraft['Model']

# Create a figure with specific size
plt.figure(figsize=(10, 8))

# Create the scatter plot using seaborn
sns.scatterplot(
    data=low_risk_aircraft,
    x='Total_Incidents',
    y='Risk_Score',
    hue='Make_Model',
    palette='tab10',
    legend=False
)

# Title and labels with customized font sizes
plt.title('Risk Scores vs. Total Incidents', fontsize=16)
plt.xlabel('Total Incidents', fontsize=12)
plt.ylabel('Risk Score', fontsize=12)

# Add gridlines for better readability
plt.grid(linestyle='--', alpha=0.7)

# Ensure everything fits within the plot
plt.tight_layout()

# Show the plot
plt.show()
```




```
# combine the make and aircraft model data in to one column
low_risk_aircraft['Make_Model'] = low_risk_aircraft['Make'] + " " + low_risk_aircraft['Model']

# View the top 10 lowest risk aircraft
top_low_risk = low_risk_aircraft.head(10)

plt.figure(figsize=(8, 6))
sns.barplot(
    data=top_low_risk,
    x='Risk_Score',
    y='Make_Model',
    hue='Make_Model',
    palette='tab10',
    order=top_low_risk.sort_values('Risk_Score')['Make_Model']
)
plt.title('Top 10 Lowest-Risk Aircraft by Risk Score', fontsize=14)
plt.xlabel('Risk Score', fontsize=10)
plt.ylabel('Aircraft (Make & Model)', fontsize=14)
plt.grid(axis='x', linestyle='-')
plt.show()
```




```
# Sort aircraft by Risk Score in ascending order
lowest_risk_aircraft = aggregated_metrics[['Make', 'Risk_Score']].sort_values(by='Risk_Score', ascending=True)

# Select top 5 lowest-risk models
top_low_risk_aircraft = lowest_risk_aircraft.head(10)

# Plot the Risk Score for the top 5 lowest-risk aircraft
plt.figure(figsize=(10, 6))
plt.bar(
    top_low_risk_aircraft['Make'],
    top_low_risk_aircraft['Risk_Score'],
    color='olive'
)
plt.xlabel('Aircraft (Make)', fontsize=12)
plt.ylabel('Risk Score', fontsize=12)
plt.title('Top 10 Lowest-Risk Aircraft (Make)', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()

# Show plot
plt.show()

# Display acquisition strategy
print("Acquisition Strategy:")
for index, row in top_low_risk_aircraft.iterrows():
    print(f"Make: {row['Make']}, Risk Score: {row['Risk_Score']:.2f}")
```


```
# Sort aircraft by Risk Score in ascending order
lowest_risk_aircraft = aggregated_metrics[['Make','Model', 'Risk_Score']].sort_values(by='Risk_Score', ascending=True)

# Select top 5 lowest-risk models
top_low_risk_aircraft = lowest_risk_aircraft.head(10)

# Plot the Risk Score for the top 5 lowest-risk aircraft
plt.figure(figsize=(10, 6))
plt.bar(
    top_low_risk_aircraft['Model'] + ' ' + top_low_risk_aircraft['Make'],
    top_low_risk_aircraft['Risk_Score'],
    color='olive'
)
plt.xlabel('Aircraft (Make & Model)', fontsize=12)
plt.ylabel('Risk Score', fontsize=12)
plt.title('Top 10 Lowest-Risk Aircraft (Make & Model)', fontsize=14)
plt.xticks(rotation=45, ha='right')
plt.tight_layout()

# Show plot
plt.show()

# Display acquisition strategy
print("Acquisition Strategy:")
for index, row in top_low_risk_aircraft.iterrows():
    print(f"Make: {row['Make']},'Model': {row['Model']}, Risk Score: {row['Risk_Score']:.2f}")
```