Phase 1 Project

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- Student pace: **part time**
- Scheduled project review date/time: **November 24th 2024**
- Instructor name: **Bonface Manyara**
- Blog post URL:

Business Understanding

The primary objective is to analyze and predict the risk involved in purchasing and operating airplanes for commercial and private entreprises as part of a my company's new diversification plan.

Problem statement

I am aiming to analyze the AviationData dataset to identify key factors that would affect the viability of the project by analysing the risk of airplane accidents and the survival rates from such accidents.

Objectives

1) Analyze the the relationship between engine type and number of accidents.

2) Analyze the the corelation between the number of engines per aircraft and number of accidents recorded.

3) Identify and analyze key factors that contribute to aircraft accidents e.g weather conditions, amateur built.

4) Develop visualizations to effectively communicate the insights and findings derived from the analysis

Research Questions

1) What are the key airplane features that influence the likelihood of an aircraft accident?

2) Does the countries of operation matter when evaluating the likelihood of an airplane accident?

3) How does the phase of the flight affect the survival rate of passengers incase of an accident

Data Understanding

```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
Aviation_Data = pd.read_csv('Aviation_Data.csv', low_memory=False)
```

```
csv_file_path = "./Aviation_Data.csv"
```

```
with open(csv_file_path) as csvfile:
    print(csvfile.readline())
```

```
Event.Id,Investigation.Type,Accident.Number,Event.Date,Location,Country,Latitude,Longitude,Airport.Code,Airport.Name,Injury.Severity,Air
```

```
Aviation_Data.head()
```

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

5 rows × 31 columns

```
Aviation_Data.tail()
```

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Na
90343	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	N
90344	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	N
90345	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	PAYS(
90346	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	N
90347	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	N

5 rows × 31 columns

```
# To get the summary information about the dataset
Aviation_Data.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            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        73659 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

```
#Statistical aspects of the data
Aviation_Data.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

Identifying Missing Data

```
#missing values
Aviation_Data.isna().sum()
```

```
Event.Id                   1459
Investigation.Type            0
Accident.Number            1459
Event.Date                 1459
Location                   1511
Country                    1685
Latitude                  55966
Longitude                 55975
Airport.Code              40099
Airport.Name              37558
Injury.Severity            2459
Aircraft.damage            4653
Aircraft.Category         58061
Registration.Number        2776
Make                       1522
Model                      1551
Amateur.Built              1561
Number.of.Engines          7543
Engine.Type                8536
FAR.Description           58325
Schedule                  77766
Purpose.of.flight          7651
Air.carrier               73700
Total.Fatal.Injuries      12860
Total.Serious.Injuries    13969
Total.Minor.Injuries      13392
Total.Uninjured            7371
Weather.Condition          5951
Broad.phase.of.flight     28624
Report.Status              7840
Publication.Date          16689
dtype: int64
```

Handling Missing Data

```
# Fill missing values (NaN) in specific columns of the 'Aviation_data' DataFrame
# Set missing values to 0
Aviation_Data = Aviation_Data.fillna({'Total.Fatal.Injuries': 0, 'Total.Serious.Injuries':0, 'Total.Minor.Injuries':0, 'Total.Uninjured':0,
```

```
#Replacing missing values in the Aircraft damage/Phase of flight column
Aviation_Data = Aviation_Data.fillna({'Aircraft.damage': 'Unknown', 'Broad.phase.of.flight': 'Unknown'})
```

```
#Additional replacement of missing values
Aviation_Data = Aviation_Data.fillna({'Amateur.Built': 'Undefined', 'Engine.Type': 'Unknown', 'Weather.Condition': 'Unknown'})
```

```
#Additional replacement of missing values
Aviation_Data = Aviation_Data.fillna({'Accident.Number': 'Undefined', 'Event.Date': 'Unknown'})
```

```
#Additional replacement of missing values
Aviation_Data = Aviation_Data.fillna({'Country': 'Undefined', 'Location': 'Unknown', 'Injury.Severity': 'Unknown', 'Model': 0, 'Make': 'Unkr
```

```
#Dropping unneccesary columns with huge missing data
Aviation_Data = Aviation_Data.drop(['Aircraft.Category', 'Latitude', 'Longitude' ,'Airport.Code', 'FAR.Description', 'Air.carrier', 'Schedul
```

```
#Dropping additional unneccesary columns with huge missing data
Aviation_Data = Aviation_Data.drop(['Event.Id', 'Airport.Name', 'Registration.Number' ,'Report.Status'], axis=1)
```

```
#Forward filing of missing data in publicattion date
Aviation_Data['Publication.Date'] = Aviation_Data['Publication.Date'].fillna(method='bfill')
```

```
#updated columns
Aviation_Data.isna().sum()
```

```
Investigation.Type        0
Accident.Number           0
Event.Date                0
Location                  0
Country                   0
Injury.Severity           0
Aircraft.damage           0
Make                      0
Model                     0
Amateur.Built             0
Number.of.Engines         0
Engine.Type               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
Publication.Date          0
Year                      0
dtype: int64
```

```
#Check if we have duplicated data
Aviation_Data.duplicated().sum()
```

```
1002
```

```
Aviation_Data.drop_duplicates(keep='last')
```

	Investigation.Type	Accident.Number	Event.Date	Location	Country	Injury.Severity	Aircraft.damage	Make	Model	Ama
0	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	Fatal(2)	Destroyed	Stinson	108-3	
1	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	Fatal(4)	Destroyed	Piper	PA24-180	
2	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	Fatal(3)	Destroyed	Cessna	172M	
3	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	Fatal(2)	Destroyed	Rockwell	112	
4	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	Fatal(1)	Destroyed	Cessna	501	
...	...	...	...	...	...	...	...	...	...	
90343	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	Minor	Unknown	PIPER	PA-28-151	
90344	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	Unknown	Unknown	BELLANCA	7ECA	
90345	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	Non-Fatal	Substantial	AMERICAN CHAMPION AIRCRAFT	8GCBC	
90346	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	Unknown	Unknown	CESSNA	210N	
90347	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	Minor	Unknown	PIPER	PA-24-260	

89346 rows × 20 columns

```
#Check the shape of the data
Aviation_Data.shape
```

```
(90348, 20)
```

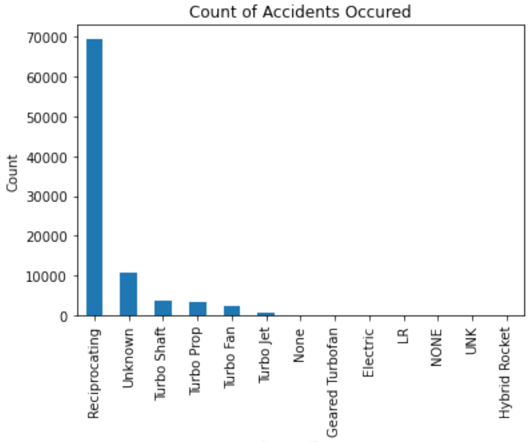
Data Analysis

1) Bar Graph- Number of accidents vs Engine type

```
#Creating a summary of number of accidents by engine type
Summary_data1 = Aviation_Data.pivot_table(aggfunc='size', index='Engine.Type', fill_value=0)
print(Summary_data1)
```

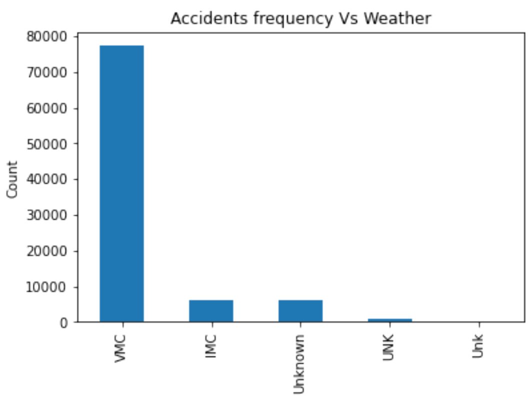
```
Engine.Type
Electric              10
Geared Turbofan       12
Hybrid Rocket          1
LR                     2
NONE                   2
None                  19
Reciprocating      69530
Turbo Fan           2481
Turbo Jet            703
Turbo Prop          3391
Turbo Shaft         3609
UNK                    1
Unknown            10587
dtype: int64
```

```
Aviation_Data['Engine.Type'].value_counts().plot(kind='bar')
plt.title('Count of Accidents Occured')
plt.xlabel('Engine.Type')
plt.ylabel('Count')
plt.show()
```



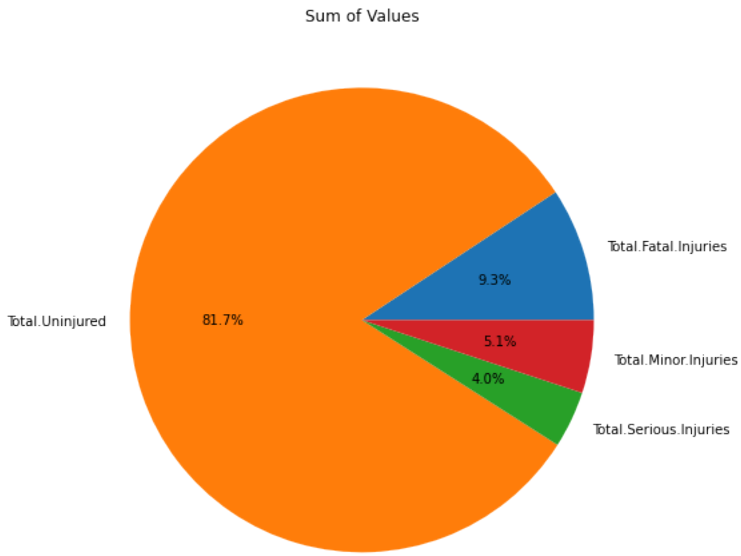
2.Bar Graph - Accidents Frequency vs Weather

```
Aviation_Data['Weather.Condition'].value_counts().plot(kind='bar')
plt.title('Accidents frequency Vs Weather')
plt.xlabel('weather.Type')
plt.ylabel('Count')
plt.show()
```



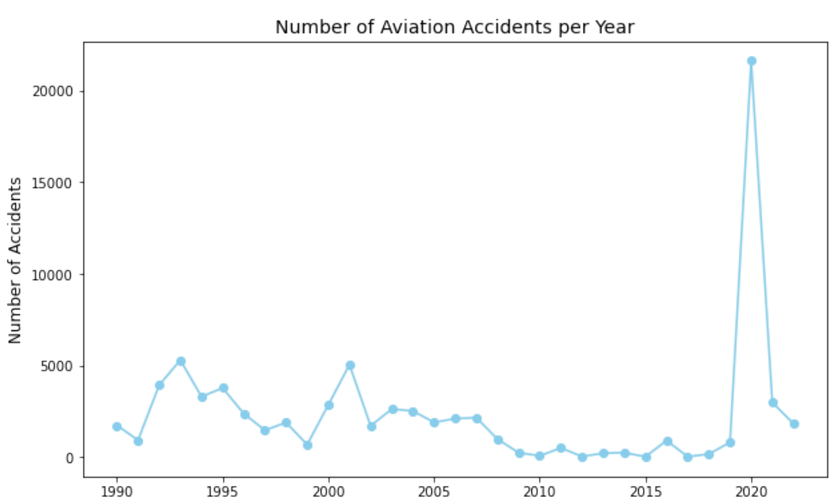
3) Pie Chart- Accidents Impact on Passengers

```
Aviation_data_selected = Aviation_Data[['Total.Fatal.Injuries', 'Total.Uninjured', 'Total.Serious.Injuries', 'Total.Minor.Injuries']].sum()


Aviation_data_selected.plot(kind='pie', autopct='%1.1f%%', figsize=(8, 8), title="Sum of Values")
plt.ylabel('')  # Hide the y label
plt.show()
```



3) Line Graphs- Accidents Trend by Year

```
# Compare the incidents Year to year from 1990 to 2022 in a bar chart

Aviation_Data['Publication.Date'] = pd.to_datetime(Aviation_Data['Publication.Date'], errors='coerce')

# Extract the year from the 'Event.Date' column
Aviation_Data['Year'] = Aviation_Data['Publication.Date'].dt.year

# Filter the data to only include incidents from 1980 to 2022
Aviation_data_filtered = Aviation_Data[(Aviation_Data['Year'] >= 1990) & (Aviation_Data['Year'] <= 2022)]

# Group the data by year and count the number of incidents per year
Grouped_by_Year = Aviation_data_filtered.groupby('Year').size()

# Plot the incidents per year as a line chart
Grouped_by_Year.plot(kind='line', color='skyblue', marker='o', figsize=(10, 6))

# Generating Visuals
plt.title('Number of Aviation Accidents per Year', fontsize=14)
plt.xlabel('Year', fontsize=12)
plt.ylabel('Number of Accidents', fontsize=12)

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



Data Limitations

Reporting StandardS Variations

1) Countries like the United States have a high likelihood of better/consistent accident reporting mechanisms and by extension shall report relatively more accidents

2) Unavailability of the volumes of air traffic data Countries like the united states shall have more incidents compared to countries like kenya because of the volumes they have. The high incidents does not reflect risks level