Aviation Data Analysis

Overview

As technology has advanced, today's aircraft market has become saturated with countless options for different kinds of aircraft. With all these options it is hard to immediately know which variants are safer, and which variants are more prone to accidents. This project analyzes problematic flights in an attempt to understand what factors may lead to undesired occurrences. Descriptive analysis of this data shows that certain factors such as the type of engine or aircraft size may point to which types are aircraft are more prone to fatal incidents. My company can use this analysis to help understand the risks of investing in different types of airplane operations.

Business Problem

My company would like to invest in new industries to diversify its portfolio. Specifically, they are interested in purchasing and operating airplanes for commercial and private enterprises, but first need to learn more about the potential risks of different kinds of aircraft. Shedding light on these risks could help guide my company to make aircraft operation selections that are less problematic. By analyzing the NTSB Aviation Accident Dataset I describe patterns in engine types, aircraft passenger capacities, and operation regional locations to help anticipate which aircraft operations will have the lowest risks for the investors.

Data Understanding

The NTSB aviation accident database includes information on civil aviation accidents and certain incidents from 1962 onward, covering the United States, its territories/possessions, and international waters. Due to this Dataset not including the total instances of all flights, and only showing the problematic flights, we cannot gauge a true estimation of which aircraft are more incident-prone. Because of this, we can only use this dataset to highlight what attributes were present in the flights that experienced the least amount of fatalities and navigation difficulties. The analyses to follow are presented given this contextual clarification.

```
#Import the relevant libraries to help us view and manipulate the
data.

import numpy as np
import pandas as pd

#Convert the CSV file into a dataframe.

#low_memory= False ells Pandas to read the entire file into memory at
once,
#instead of processing it in sections.

Aviation_Data= pd.read_csv('data2/Aviation_Data.csv',
low_memory=False)
```

Aircraft Data

This dataset has 90,348 records of problematic flights from 1962 to 2023 with 93% of these data points coming from the USA. Each record refers to the date, location, and severity of each event, along with information about the type of aircraft involved in the incident (i.e. make, model, engine type...).

```
#A preview of what the dataframe looks like.

Aviation_Data.head(3)
```

```
         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

          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
```

```
  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0


  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

  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 rows x 31 columns]
```

```python
#A description of the Dataframe and the types of data in it.

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            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
```

Data Preperation

Data Cleaning and Trimming

To make the Dataframe easier to manipulate for analysis, I will drop irrelevant columns, normalize column names/values and filter out irrelevant data points. In addition to this, where needed, instead of estimating and imputing new values, I will drop all rows that are missing relevant data. This is done to avoid creating an over-representation bias in the dataset.

This analysis will specifically focus on which Jet operations pose the lowest risks in America. Due to this, I will be filtering out the following, to get rid of any data that is outside of the scope of the investment project, and any data that could add unnecessary additional risk.

All instances where the aircraft is not an "Airplane" will be removed because my company is only interested in investing in airplane operations. All instances where the country is not "United States" will be removed, because my company would like to keep their investment operation local to the USA. All aircraft that was not professionally built will be removed in an attempt to remove bias from incidents that could have been caused by improper aircraft assembly. Finally, all aircraft that do not use a type of Jet engine will be removed, because my company is specifically interested in investing in a Jet operation.

After the above filters have been applied, we will specifically keep the following columns due to their ability to highlight attributes of flights that are less problematic. The Injury Severity columns can tell us crucial information about the severity of the aircraft instances, as well as aircraft general carrying capacity. The 'Event.Date' column can help us understand the how often these events occurred, and if the frequency decreased over time. The 'Engine.Type' column can show us which engines experienced the least amount of fatal incidents over this time period. The 'Location' and 'Weather.Condition' columns can help us understand if certain areas are more prone to experiencing problematic flight conditions.

After these measures have been taken, our Dataframe will be ready for feature engineering.

```
#Narrow the Dataframe down to only relevant columns.

Rel_Aviation_Data=
Aviation_Data[['Event.Id','Aircraft.Category','Amateur.Built',
                                  'Engine.Type',
'Total.Fatal.Injuries',
                                  'Total.Serious.Injuries',
'Total.Minor.Injuries',

'Total.Uninjured','Event.Date','Location',

'Country','Weather.Condition']].copy()

#Normalize the data in the Weather.Condition column.

Rel_Aviation_Data['Weather.Condition']=
Rel_Aviation_Data['Weather.Condition'].str.title()


#Drop all data instances where the type of aircraft is not an
Airplane.
Rel_Aviation_Data=
Rel_Aviation_Data[Rel_Aviation_Data['Aircraft.Category']== 'Airplane']

#Drop all data instances where the Country of incident is not United
States.
Rel_Aviation_Data= Rel_Aviation_Data[Rel_Aviation_Data['Country']==
'United States']

#Drop all data instances where the aircraft is not professionally
built. This is
#done to avoid any bias from incidents that may be due to faulty
assembly.
Rel_Aviation_Data=
Rel_Aviation_Data[Rel_Aviation_Data['Amateur.Built']== 'No']

#Drop all data instances where the aircraft does not use a type of Jet
engine.
Rel_Aviation_Data=
Rel_Aviation_Data[Rel_Aviation_Data['Engine.Type'].isin(['Turbo Fan',

'Turbo Jet',

'Turbo Prop'])]

#Drop all data instances where the weather condition is unknown.
Rel_Aviation_Data=
Rel_Aviation_Data[Rel_Aviation_Data['Weather.Condition'].isin(['Vmc',
```

```
'Imc'])]
```

After reviewing the injury and fatality counts rows I discovered that the NaN values in these columns are used in place of 0. These NaN values can be problematic for numeric feature engineering so I will create a function to convert them to 0.

```
#A function that replaces all the NaN values in a column to the number
0.
def Nan_Stripper(cols):
    for x in cols:
        Rel_Aviation_Data[x]= Rel_Aviation_Data[x].fillna(0)

#Applying the NaN convertor function to the relevant columns.
Nan_Stripper(['Total.Fatal.Injuries', 'Total.Serious.Injuries',
'Total.Minor.Injuries',
              'Total.Uninjured'])

#Drop all duplicates to help avoid over-representation bias.
Jet_Data= Rel_Aviation_Data.drop_duplicates()

#Preview of the cleaned and filtered Dataset
Jet_Data.head(3)
```

```
          Event.Id Aircraft.Category Amateur.Built Engine.Type  \
5   20170710X52551          Airplane            No   Turbo Fan
80  20020917X01765          Airplane            No  Turbo Prop
93  20020917X02538          Airplane            No  Turbo Prop

    Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries
\
5                    0.0                     0.0                   1.0

80                   0.0                     0.0                   0.0

93                   0.0                     1.0                   2.0


    Total.Uninjured  Event.Date        Location        Country  \
5              44.0  1979-09-17      BOSTON, MA  United States
80              2.0  1982-01-12  CLARKSBURG, WV  United States
93             12.0  1982-01-15     JAMAICA, NY  United States

   Weather.Condition
5                Vmc
80               Vmc
93               Vmc
```

```
#Description of the data in the filtered and cleaned Dataset
Jet_Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1941 entries, 5 to 89851
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                1941 non-null   object 
 1   Aircraft.Category       1941 non-null   object 
 2   Amateur.Built           1941 non-null   object 
 3   Engine.Type             1941 non-null   object 
 4   Total.Fatal.Injuries    1941 non-null   float64
 5   Total.Serious.Injuries  1941 non-null   float64
 6   Total.Minor.Injuries    1941 non-null   float64
 7   Total.Uninjured         1941 non-null   float64
 8   Event.Date              1941 non-null   object 
 9   Location                1941 non-null   object 
 10  Country                 1941 non-null   object 
 11  Weather.Condition       1941 non-null   object 
dtypes: float64(4), object(8)
memory usage: 197.1+ KB
```

Feature Engineering

Feature engineer new columns to help assist analyze what Jet operations have the lowest risks in operating.

```
#Create column Incident.Severity that shows 1 if an incident has fatalities and 0 if not.
Jet_Data.loc[:,'Incident.Severity']=Jet_Data.loc[:,'Total.Fatal.Injuries'].map(lambda x:1 if x >= 1 \

else 0)

#Create a column "State" that extracts the state from the location column.
Jet_Data.loc[:,'State']= Jet_Data['Location'].str[-2:]

#Create a column "Year" that extracts the year from the Event.Date column.
Jet_Data.loc[:,'Year']= Jet_Data['Event.Date'].str[:4]

#Creation of lists that sort states into regions of the USA.
West=
['WA','OR','CA','HI','AK','ID','NV','MT','WY','UT','CO','AZ','NM']
Midwest= ['ND','SD','NE','KS','MN','IA','MO','WI','IL','MI','IN','OH']
Northeast= ['PA','NY','NJ','CT','RI','MA','VT','NH','ME']
South=
['TX','OK','AR','LA','KY','TN','MS','AL','WV','DE','MD','DC','VA','NC','SC','GA','FL']
```

```
#Creation of function that sorts states into regions.
def where_am_i(x):
    if x in West:
        return 'West'
    elif x in Midwest:
        return 'Midwest'
    elif x in Northeast:
        return 'Northeast'
    elif x in South:
        return 'South'

#Create a column "Region" that displays what region of the USA the
incident took place in.
Jet_Data.loc[:,'Region']= Jet_Data['State'].apply( lambda x :
where_am_i(x))

#Create a column "Number.of.Passengers" that shows the number of
passengers on an
#aircraft. This will help show the passenger capacity (size) of each
aircraft. This
#is done by adding up all the passengers from the injury level
columns.
Jet_Data.loc[:,'Number.of.Passengers']=Jet_Data['Total.Fatal.Injuries'
]\

+Jet_Data['Total.Serious.Injuries']\

+Jet_Data['Total.Minor.Injuries']\

+Jet_Data['Total.Uninjured']

#Create a function that sorts the aircrafts into a size based on the
number of
#passengers they can hold.
def size_selector(x):
    if x <= 10:
        return 'Personal'
    elif 11 <= x <= 50:
        return 'Small'
    elif 51 <= x <= 100:
        return 'Medium'
    elif 101 <= x <= 200:
        return 'Large'
    else:
        return 'Jumbo'

#Create a column "Aircraft.Size" that shows what size the aircraft in
the incident is.
Jet_Data.loc[:,'Aircraft.Size']=
Jet_Data['Number.of.Passengers'].apply( lambda x : \
```

```
size_selector(x))

#Preview of the Dataset with the new feature engineered columns.
Jet_Data.head(3)

          Event.Id Aircraft.Category Amateur.Built Engine.Type  \
5   20170710X52551          Airplane            No   Turbo Fan
80  20020917X01765          Airplane            No  Turbo Prop
93  20020917X02538          Airplane            No  Turbo Prop

    Total.Fatal.Injuries  Total.Serious.Injuries  Total.Minor.Injuries
\
5                    0.0                     0.0                   1.0

80                   0.0                     0.0                   0.0

93                   0.0                     1.0                   2.0


    Total.Uninjured  Event.Date        Location        Country  \
5              44.0  1979-09-17      BOSTON, MA  United States
80              2.0  1982-01-12  CLARKSBURG, WV  United States
93             12.0  1982-01-15     JAMAICA, NY  United States

   Weather.Condition  Incident.Severity State  Year     Region  \
5                Vmc                  0    MA  1979  Northeast
80               Vmc                  0    WV  1982      South
93               Vmc                  0    NY  1982  Northeast

    Number.of.Passengers Aircraft.Size
5                   45.0         Small
80                   2.0      Personal
93                  15.0         Small

#Save is cleaned and feature engineered dataset as a .CSV file for use
elsewhere.
Jet_Data.to_csv('./data2/Jet_Data.csv')
```

Analysis

```
#Import library to help display data analysis
import matplotlib.pyplot as plt
%matplotlib inline
```

Region of Operation

The Dataset places the weather conditions experienced during each incident into one of two categories. The first option is VMC (Visual Meteorological Conditions) which often is considered the safer of the two options due to the pilot's ability to navigate the aircraft based on visual references. The second option is IMC (Instrument Meteorological Conditions) which is the more problematic and usually the more accident-prone of the two options due to the pilot needing to rely on flight instruments due to the lack of visibility and rough weather.

In an effort to analyze which area of the USA is the safest to operate these Jets in, I will run an analysis to see which region of the USA experienced the least amount of incidents with IMC flight conditions.

Prep the Dataframe for this specific analysis

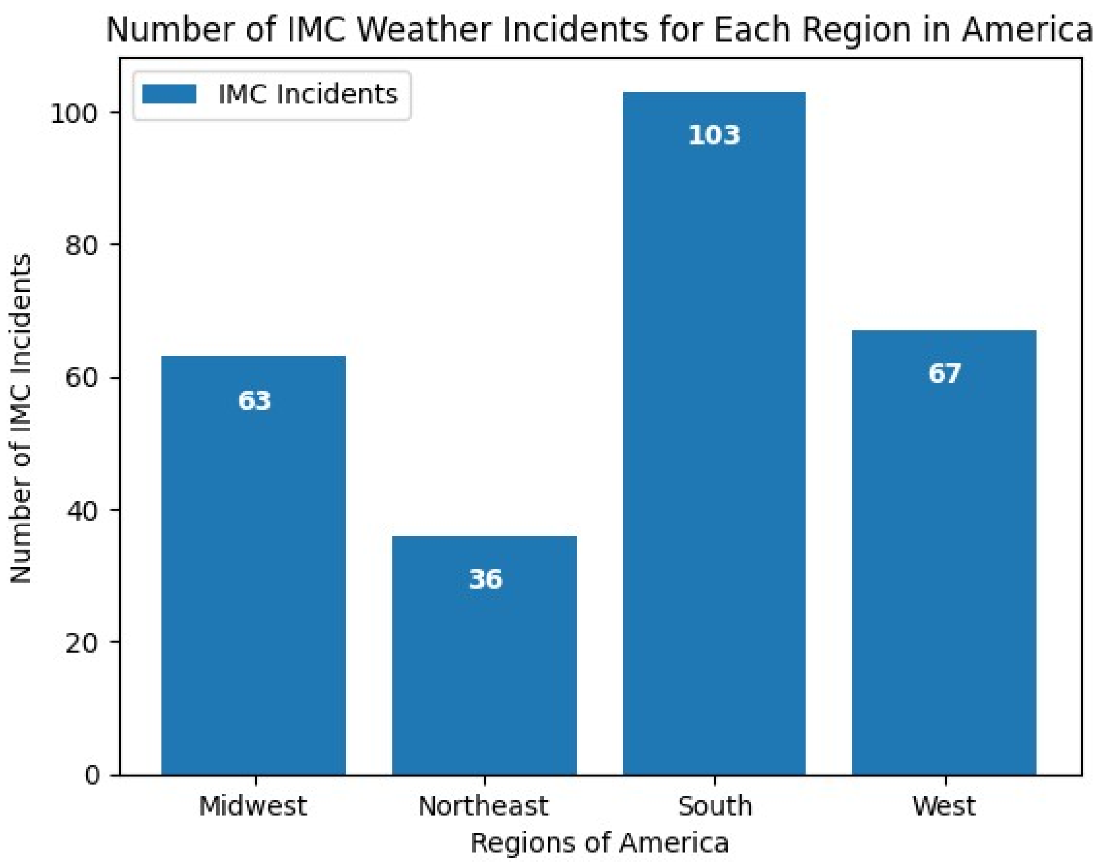
```
#Create a new focused dataframe from the relevant columns of Jet_Data
Regional_Weather=Jet_Data[['Weather.Condition', 'Region']]

#Filter out all data instances that aren't taking place during 'IMC'
Regional_IMC_Weather=Regional_Weather[Regional_Weather['Weather.Condit
ion']=='Imc']

#Group the data instances by 'Region' to sum up the number of 'IMC'
events in each
#'Region'
Regional_IMC_Weather_Series= Regional_IMC_Weather.groupby(['Region'])\
['Weather.Condition'].count()

#The previous line of code returns a series. This changes that series
back to a
#Data Frame
Regional_IMC_DF=Regional_IMC_Weather_Series.to_frame()

#Rename the 'Weather.Condition' column
Regional_IMC_DF.rename(columns={'Weather.Condition':\
    'Imc.Weather.Events'},inplace=True)

#Change the index from "Region" to a new numbered column
Regional_IMC_DF.reset_index(inplace=True)

#Show the Dataframe
Regional_IMC_DF
```

	Region	Imc.Weather.Events
0	Midwest	63
1	Northeast	36
2	South	103
3	West	67

Regional Weather Analysis

```
#Assign Dataframe columns to variables for plotting
x= Regional_IMC_DF['Region']
y= Regional_IMC_DF['Imc.Weather.Events']
```

```
#Create a bar plot based on the 'x' and 'y' variables
Imc_Weather_Fig, Imc_Weather_Axes= plt.subplots()
Imc_Weather_plt=Imc_Weather_Axes.bar(x,y)

#Annontate the bars in the plot with their respective heights
for event in Imc_Weather_plt:
    height= event.get_height()
    Imc_Weather_Axes.annotate(f'{height}', xy=(event.get_x() +
event.get_width() / 2,\
                            height-10), xytext=(0,3), textcoords=
'offset points',\
                               ha= 'center', va= 'bottom', color=
'white',\
                               fontweight= 'bold')

#Set the labels for the plot
Imc_Weather_Axes.set_title(\
    'Number of IMC Weather Incidents for Each Region in America')
Imc_Weather_Axes.set_ylabel('Number of IMC Incidents')
Imc_Weather_Axes.set_xlabel('Regions of America')

#Set the legend for the plot
Imc_Weather_Axes.legend([Imc_Weather_plt], \
                              ['IMC Incidents'], \
                              loc = 'upper left')

#Save the plot as a PNG file
plt.savefig("./images2/Regional_Weather_Analysis_Distribution.png",
dpi=150)

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



From the above graph, we can see that during the 1962-2023 period, the Northeast Region of the USA has experienced the least amount of Airplane incidents during Instrument Meteorological Conditions.

Size of Jet (Number of Passengers)

This dataset displays fatal incident information on Jets of all different shapes, sizes, and capacities. This analysis breaks these events down into different passenger carrying capacities categories in an attempt to guide our investors to the type of jet plane with the lowest fatality rates. The results of this analysis are displayed below.

Prep the Dataframe for this specific analysis

```
#Create a new focused dataframe from the relevant columns of Jet_Data
Jet_Size=Jet_Data[['Aircraft.Size', 'Incident.Severity']]

#Group the data instances by 'Aircraft.Size' to sum up the number of
Fatal events in
#'Incident.Severity'
Jet_Size_Series= Jet_Size.groupby(['Aircraft.Size'])\
['Incident.Severity'].count()

#The previous line of code returns a series. This changes that series
```

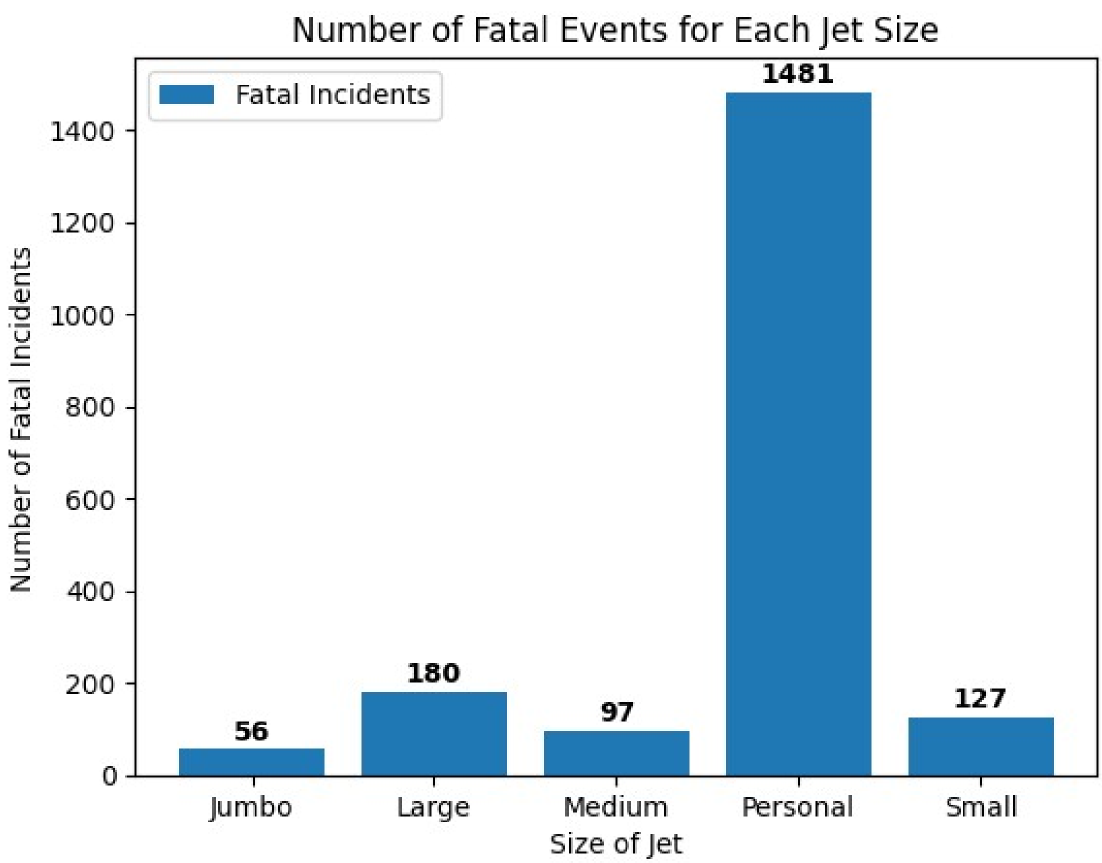
```
back to a
#Data Frame
Jet_Size_DF=Jet_Size_Series.to_frame()

#Rename the 'Incident.Severity' column as 'Fatal.Events'
Jet_Size_DF.rename(columns={'Incident.Severity':\
    'Fatal.Events'},inplace=True)

#Change the index from "Aircraft.Size" to a new numbered column
Jet_Size_DF.reset_index(inplace=True)

#Show the Dataframe
Jet_Size_DF
```

	Aircraft.Size	Fatal.Events
0	Jumbo	56
1	Large	180
2	Medium	97
3	Personal	1481
4	Small	127

Jet Size Analysis

```
#Assign Dataframe columns to variables for plotting
x= Jet_Size_DF['Aircraft.Size']
y= Jet_Size_DF['Fatal.Events']

#Create a bar plot based on the 'x' and 'y' variables
Aircraft_Size_Fig, Aircraft_Size_Axes= plt.subplots()
Aircraft_Size_plt=Aircraft_Size_Axes.bar(x,y)

#Annontate the bars in the plot with their respective heights
for size in Aircraft_Size_plt:
    height= size.get_height()
    Aircraft_Size_Axes.annotate(f'{height}', xy=(size.get_x() +
size.get_width() / 2,\
                            height-10), xytext=(0,3), textcoords=
'offset points',\
                               ha= 'center', va= 'bottom', color=
'black',\
                               fontweight= 'bold')
#Set the labels for the plot
Aircraft_Size_Axes.set_title(\
    'Number of Fatal Events for Each Jet Size')
Aircraft_Size_Axes.set_ylabel('Number of Fatal Incidents')
Aircraft_Size_Axes.set_xlabel('Size of Jet')

#Set the legend for the plot
Aircraft_Size_Axes.legend([Aircraft_Size_plt], \
                              ['Fatal Incidents'], \
```

```
                                    loc = 'upper left')

#Save the plot as a PNG file
plt.savefig("./images2/Aircraft_Size_Analysis_Distribution_2.png",
dpi=150)

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



From the above graph, we can see that during the 1962-2023 period, Personal Aircrafts (aricrafts that have a carrying capacity of 10 or fewer people) have experienced more than three times the amount of Fatal incidents than all of the other plane capacity categories combined.

Type of Jet Engine

While jet planes may be one of the most common types of commercial and private aircraft, not all jets utilize the same type of engine for propulsion. Due to this variance, I will run an analysis to see if certain jet engine types tend to experience fewer fatal incidents than the other models. This will help the ivestors narrow down which type of jet operation they would have the lowest risk investing in.

Prep the Dataframe for this specific analysis

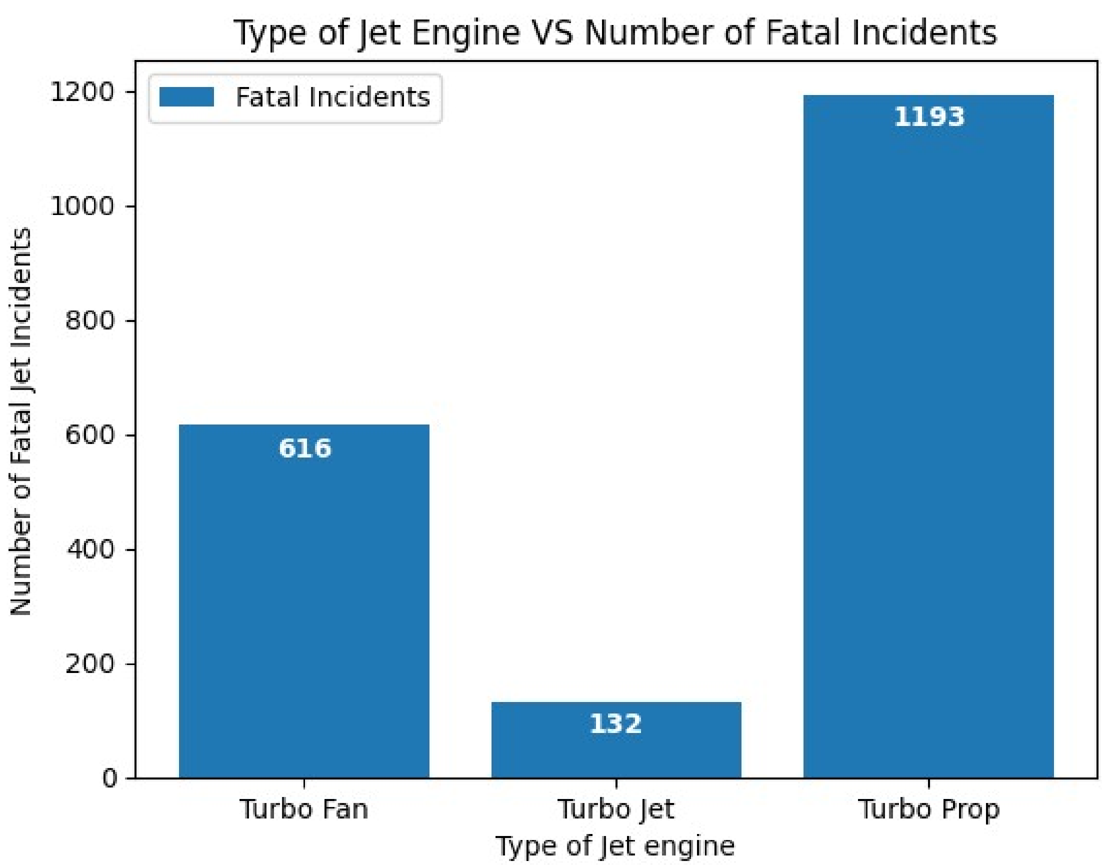
```
#Create a new focused dataframe from the relevant columns of Jet_Data
Jet_Engine_Type=Jet_Data[['Engine.Type', 'Incident.Severity']]

#Group the data instances by 'Engine.Type' to sum up the number of
Fatal events in
#'Incident.Severity'
Jet_Engine_Type_Series= Jet_Engine_Type.groupby(['Engine.Type'])\
['Incident.Severity'].count()

#The previous line of code returns a series. This changes that series
back to a
#Data Frame
Jet_Engine_Type_DF=Jet_Engine_Type_Series.to_frame()

#Rename the 'Incident.Severity' column as 'Fatal.Events'
Jet_Engine_Type_DF.rename(columns={'Incident.Severity':\
    'Fatal.Events'},inplace=True)

#Change the index from "Engine.Type" to a new numbered column
Jet_Engine_Type_DF.reset_index(inplace=True)

#Show the Dataframe
Jet_Engine_Type_DF
```

	Engine.Type	Fatal.Events
0	Turbo Fan	616
1	Turbo Jet	132
2	Turbo Prop	1193

Jet Engine Type Analysis

```
#Assign Dataframe columns to variables for plotting
x= Jet_Engine_Type_DF['Engine.Type']
y= Jet_Engine_Type_DF['Fatal.Events']

#Create a bar plot based on the 'x' and 'y' variables
Jet_Engine_Fig, Jet_Engine_Axes= plt.subplots()
Fatal_Jet_Incidents_plt=Jet_Engine_Axes.bar(x,y)

#Annontate the bars in the plot with their respective heights
for FEng in Fatal_Jet_Incidents_plt:
    height= FEng.get_height()
    Jet_Engine_Axes.annotate(f'{height}', xy=(FEng.get_x() +
FEng.get_width() / 2,\
                            height-80), xytext=(0,3), textcoords=
'offset points',\
                               ha= 'center', va= 'bottom', color=
'white',\
                               fontweight= 'bold')
```

```
#Set the labels for the plot
Jet_Engine_Axes.set_title(\
    'Type of Jet Engine VS Number of Fatal Incidents')
Jet_Engine_Axes.set_ylabel('Number of Fatal Jet Incidents')
Jet_Engine_Axes.set_xlabel('Type of Jet engine')

#Set the legend for the plot
Jet_Engine_Axes.legend([Fatal_Jet_Incidents_plt], \
                              ['Fatal Incidents'], \
                              loc = 'upper left')

#Save the plot as a PNG file
plt.savefig("./images2/Jet_Engine_Fatal_Incident_Distrobution.png",
dpi=150)

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



From the above graph, we can see that during the 1962-2023 period, Jets that utilize the Turbo Jet Engine have experienced the fewest amount of fatal incidents, compared to Jets that use other types of Engines.

Conclusions

This analysis resulted in 3 recommendations for investing in a new jet operation.

Implementing these recommendations into the criteria for selecting a Jet operation to invest in will help minimize the risk of undesirable events, such as fatalities and unfavorable flight conditions.

1) Invest in jets that mainly operate in the Northeast region of the USA. In terms of weather conditions, it is more difficult to operate aircraft during Instrument Meteorological Conditions (IMC) than Visual Meteorological Conditions (VMC). According to this dataset, from 1962 to 2023, The Northeast region of America, compared to the other regions of America, has experienced the fewest fatal jet incidents that took place during IMC.

2) Invest in jets that have larger passenger-carrying capacities. According to this dataset, in America, jets with the capacity to carry over 10 people have experienced over 3X fewer fatal incidents than jets that can only carry 10 or less people (Personal Jets). This is even further shown by jets that can carry over 200 people only experiencing around 4% of the number of fatal incidents that Personal Jets experienced,

4) Invest in Airplanes that utilize Turbo Jet Engines as a method of propulsion. According to this dataset, in America, airplanes that use Turbo Jet Engines have experienced a lower amount of fatal incidents, than other jet engine types, over a 60 year span.

Next Steps

Additional analysis could help further minimize the risk our company takes on when selecting a new aircraft operation to invest in by bringing additional insights to light.

1) Jet improvement analysis. This model could display which types of jets have improved the most over the years and now have a smaller chance of experiencing a fatal incident.

2) Flight purpose analysis. This model could display which types of flights are more prone to experiencing fatal incidents.

3) Risk predictor model. Given details about a potential flight, this model could help predict the level of incident severity a flight could result in.