index

February 14, 2025

0.1 Phase-1-Project

0.1.1 Name: Brian Waweru

0.1.2 Topic: Aviation-Accident-Analysis

1 Overview

As the company expands into the aviation industry, it seeks to purchase and operate aircraft for both commercial and private ventures. However, with no prior experience in the sector, the company must carefully assess potential risks associated with different aircraft types. Understanding historical accident data is crucial in determining which aircraft models offer the lowest risk, ensuring safety, regulatory compliance, and cost-effectiveness

1.1 Problem Statement

Aircraft accidents can result from multiple factors, including mechanical failures, human error, and adverse weather conditions. Analyzing historical data will help identify patterns in past incidents, providing valuable insights for risk assessment. The company must evaluate different aircraft models, manufacturers, and operational conditions to minimize the likelihood of accidents and improve decision-making regarding fleet acquisition.

1.2 Data Understanding: Columns and Their Relevance

Date, Location, Country:

- Helps identify trends over time and geographical hotspots for accidents. Useful for assessing how accident frequency varies by region.

DamageLevel:

- Determines the severity of accidents, ranging from minor damage to complete destruction. Crucial for evaluating the resilience of different aircraft models.

TypeOfAircraft & Manufacturer:

- Essential for identifying which aircraft models and manufacturers have the highest or lowest accident rates. Helps in selecting aircraft with strong safety records.

Built & Engines:

- The age of an aircraft and its engine type can impact its reliability and accident risk. Helps determine whether older models or specific engine configurations are riskier.

Passengers, Fatal-Injuries, Serious-Injuries, Minor-Injuries, Uninjured:

- Provides insight into accident severity and survival rates. Essential for assessing passenger safety across different aircraft.

Weather-Condition:

- Helps evaluate how environmental factors contribute to accidents. Useful for identifying whether certain aircraft perform better in adverse conditions.

Flight.Phase:

- Identifies at what stage of flight (takeoff, cruise, landing, etc.) accidents occur most frequently. Assists in understanding operational risks.

Latitude, Longitude:

- Geospatial data that helps map accident locations for further analysis.Useful for identifying high-risk areas and air traffic patterns.

Anticipated Expectations

- Identifying Low-Risk Aircraft Models: The analysis should highlight which aircraft models have historically lower accident rates.
- Understanding Common Risk Factors: Determining key contributors to accidents, such as specific flight phases, weather conditions, or maintenance issues.
- Data-Driven Decision-Making: Ensuring that aircraft purchases align with safety and operational efficiency by using historical data.
- Regulatory Compliance and Safety Standards: Ensuring the fleet meets industry safety regulations to avoid legal and financial liabilities.
- By leveraging this dataset, the company can make informed decisions about its aircraft selection, reducing operational risks while prioritizing passenger safety and business sustainability.

2 Technical Analysis

[1]:
```python
# modules
# Platform
import os
import re

# analysis
import numpy as np
```

```python
import pandas as pd

# visualizations
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```python
# file path
file_path = r'data/AviationData.csv'
# dataframe
df = pd.read_csv(file_path, encoding='ISO-8859-1');
```

```
c:\Users\rurig\anaconda3\envs\learn-env\lib\site-
packages\IPython\core\interactiveshell.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,
```

2.1 1. Shape

[3]:
```python
df.shape # (88889, 31)
```

[3]:
```
(88889, 31)
```

2.2 2. Dataframe Basic Information

[4]:
```python
# Check the first few rows
df.head(2)
```

[4]:
```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24
1  20001218X45447           Accident      LAX94LA336  1962-07-19

          Location        Country Latitude Longitude Airport.Code  \
0  MOOSE CREEK, ID  United States      NaN       NaN          NaN
1   BRIDGEPORT, CA  United States      NaN       NaN          NaN

  Airport.Name  … Purpose.of.flight Air.carrier Total.Fatal.Injuries  \
0          NaN  …          Personal         NaN                  2.0
1          NaN  …          Personal         NaN                  4.0

  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0

  Weather.Condition  Broad.phase.of.flight   Report.Status Publication.Date
0               UNK                 Cruise  Probable Cause              NaN
1               UNK                Unknown  Probable Cause       19-09-1996
```

```
[2 rows x 31 columns]
```

[5]:
```
# Check the last few rows
df.tail(2)
```

[5]:
```
               Event.Id Investigation.Type Accident.Number  Event.Date  \
88887  20221227106498           Accident      WPR23LA076  2022-12-26
88888  20221230106513           Accident      ERA23LA097  2022-12-29

         Location        Country Latitude Longitude Airport.Code Airport.Name  \
88887  Morgan, UT  United States      NaN       NaN          NaN          NaN
88888  Athens, GA  United States      NaN       NaN          NaN          NaN

       … Purpose.of.flight         Air.carrier Total.Fatal.Injuries  \
88887  …          Personal  MC CESSNA 210N LLC                  0.0
88888  …          Personal                 NaN                  0.0

      Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
88887                    0.0                  0.0             0.0
88888                    1.0                  0.0             1.0

      Weather.Condition  Broad.phase.of.flight Report.Status Publication.Date
88887               NaN                    NaN           NaN              NaN
88888               NaN                    NaN           NaN       30-12-2022

[2 rows x 31 columns]
```

[6]:
```
# Get data types of each column
df.dtypes
```

[6]:
```
Event.Id                  object
Investigation.Type        object
Accident.Number           object
Event.Date                object
Location                  object
Country                   object
Latitude                  object
Longitude                 object
Airport.Code              object
Airport.Name              object
Injury.Severity           object
Aircraft.damage           object
Aircraft.Category         object
Registration.Number       object
Make                      object
Model                     object
Amateur.Built             object
```

```
Number.of.Engines          float64
Engine.Type                 object
FAR.Description             object
Schedule                    object
Purpose.of.flight           object
Air.carrier                 object
Total.Fatal.Injuries       float64
Total.Serious.Injuries     float64
Total.Minor.Injuries       float64
Total.Uninjured            float64
Weather.Condition           object
Broad.phase.of.flight       object
Report.Status               object
Publication.Date            object
dtype: object
```

[7]:
```python
# Get the number of columns
len(df.columns)
```

[7]:
```
31
```

[8]:
```python
# Check for missing values
df.isnull().sum().to_frame()
```

[8]:

	0
Event.Id	0
Investigation.Type	0
Accident.Number	0
Event.Date	0
Location	52
Country	226
Latitude	54507
Longitude	54516
Airport.Code	38640
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
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             6381
Publication.Date         13771
```

2.3 3. Summary Statistics

[9]:
```
# General statistics for numerical columns
df.describe()
```

[9]:
```
       Number.of.Engines  Total.Fatal.Injuries  Total.Serious.Injuries  \
count       82805.000000          77488.000000            76379.000000
mean            1.146585              0.647855                0.279881
std             0.446510              5.485960                1.544084
min             0.000000              0.000000                0.000000
25%             1.000000              0.000000                0.000000
50%             1.000000              0.000000                0.000000
75%             1.000000              0.000000                0.000000
max             8.000000            349.000000              161.000000

       Total.Minor.Injuries  Total.Uninjured
count          76956.000000     82977.000000
mean               0.357061         5.325440
std                2.235625        27.913634
min                0.000000         0.000000
25%                0.000000         0.000000
50%                0.000000         1.000000
75%                0.000000         2.000000
max              380.000000       699.000000
```

2.4 4. Structure

[10]:
```
# Check for duplicate rows
df.duplicated().sum() # 0
```

[10]:
```
0
```

[11]:
```
df.columns.tolist()
```

[11]:
```
['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']
```

2.5 5. Missing Values and column analysis

[12]:
```
col_list = list(df.columns)

for i in range(len(list(df.columns))):
    print(f"# column {i + 1} # {col_list[i]}")
```

```
# column 1 # Event.Id
# column 2 # Investigation.Type
# column 3 # Accident.Number
# column 4 # Event.Date
# column 5 # Location
# column 6 # Country
# column 7 # Latitude
# column 8 # Longitude
# column 9 # Airport.Code
# column 10 # Airport.Name
```

```
# column 11 # Injury.Severity
# column 12 # Aircraft.damage
# column 13 # Aircraft.Category
# column 14 # Registration.Number
# column 15 # Make
# column 16 # Model
# column 17 # Amateur.Built
# column 18 # Number.of.Engines
# column 19 # Engine.Type
# column 20 # FAR.Description
# column 21 # Schedule
# column 22 # Purpose.of.flight
# column 23 # Air.carrier
# column 24 # Total.Fatal.Injuries
# column 25 # Total.Serious.Injuries
# column 26 # Total.Minor.Injuries
# column 27 # Total.Uninjured
# column 28 # Weather.Condition
# column 29 # Broad.phase.of.flight
# column 30 # Report.Status
# column 31 # Publication.Date
```

[13]:

```
# Checking the number of missing values
# in each column
df.isnull().sum().to_frame()
df.isnull().sum().to_frame(name='null_count').sort_values(by='null_count',␣
↪ascending=False)
```

[13]:

	null_count
Schedule	76307
Air.carrier	72241
FAR.Description	56866
Aircraft.Category	56602
Longitude	54516
Latitude	54507
Airport.Code	38640
Airport.Name	36099
Broad.phase.of.flight	27165
Publication.Date	13771
Total.Serious.Injuries	12510
Total.Minor.Injuries	11933
Total.Fatal.Injuries	11401
Engine.Type	7077
Report.Status	6381
Purpose.of.flight	6192
Number.of.Engines	6084
Total.Uninjured	5912

```
Weather.Condition          4492
Aircraft.damage            3194
Registration.Number        1317
Injury.Severity            1000
Country                     226
Amateur.Built               102
Model                        92
Make                         63
Location                     52
Investigation.Type            0
Event.Date                    0
Accident.Number               0
Event.Id                      0
```

[14]:
```
# column 1 # Event.Id  #  type: object
df['Event.Id'].describe().to_frame()
df.duplicated(subset='Event.Id').sum() # 938
evt_id_inf = df['Event.Id'].describe().to_frame()

type(evt_id_inf.loc[evt_id_inf.index[0]][0])
evt_count = evt_id_inf.loc[evt_id_inf.index[0]][0]
evt_uniq = df['Event.Id'].nunique()
evt_mis = evt_count - 87951

print(
f'The Column count {evt_count},', # row 0
f'Number of unique values are {evt_uniq}.', # row 1
' ',
f'There are {evt_mis} missing values in "{list(df.columns)[0]}".', # missing
sep = '\n')

# df.drop_duplicates(inplace=True) # subset = 'Event.Id'
df.drop_duplicates(subset=['Event.Id'], inplace=True)

# Drop the column
df = df.drop(columns=['Event.Id'])
```

```
The Column count 88889,
Number of unique values are 87951.

There are 938 missing values in "Event.Id".
```

[15]:
```
# column 2 # 'Investigation.Type'  #  type: object
print(f"The values in the 'Investigation.Type' column are {df['Investigation.
↪Type'].unique().tolist()}",
      end = '\n\n')
df['Investigation.Type'].value_counts().to_frame()
```

```
for i in range(2):
    print(f"Investigation.Type '{df['Investigation.Type'].unique().
 ↪tolist()[i]}' has {df['Investigation.Type'].value_counts()[i] / df.shape[0]␣
 ↪* 100:.2f}%")

# dropping 'Incident'
df = df.loc[(df['Investigation.Type'] == 'Accident')]
# Now, dropping the column
df = df.drop(columns=['Investigation.Type'])
```

```
The values in the 'Investigation.Type' column are ['Accident', 'Incident']

Investigation.Type 'Accident' has 95.72%
Investigation.Type 'Incident' has 4.28%
```

[16]:
```
# column 3 # Accident.Number
df['Accident.Number'].isnull().sum()
df['Accident.Number'].nunique() # 63011
# >>> dropping
df = df.drop(columns=['Accident.Number'])
```

[17]:
```
# column 4 # Event.Date
print(df['Event.Date'].dtype) # object
# check number of missing values
df['Event.Date'].isnull().sum()  # 0
# convert to datetime
df['Event.Date'] = pd.to_datetime(df['Event.Date'])
```

```
object
```

[18]:
```
# column 5 # Location
df.Location.isnull().sum() # 52
df.Location # number of rows # 87951
# >>> dropping
df.dropna(subset=['Location'], inplace=True)
```

[19]:
```
# column 6 # Country
df.Country.isnull().sum()
print(f"The shape if the dataframe is '{df.shape[0]}'.", sep = '\n\n')
# drop all null values in col
df = df.dropna(subset=['Country'])
print(f"""The shape of the new dataframe is {df.shape[0]}
Having lost 222""")
# convert the name to title format
df['Country'] = df['Country'].apply(lambda x: x.title() if isinstance(x, str)␣
 ↪else x)
```

```
# finding out which country stands out
df['Country'].value_counts().idxmax() # 'United States' with 79101 values
# percentage of USA
print()
print(f"Perc of null values: {df['Country'].value_counts()[0] / df.shape[0] *␣
↪100:.1f}%") # 94.2%
# # retaining only 'United States'
# df = df.loc[(df.Country == 'United States')]
```

```
The shape if the dataframe is '84150'.
The shape of the new dataframe is 83947
Having lost 222

Perc of null values: 94.2%
```

[20]:
```
# column 7 # Latitude # and
# column 8 # Longitude
# checking the dtype of Latitude and Longitude column
df.Longitude.dtype # dtype('O')
# inference
print(f"""There are \'{df['Latitude'].isnull().sum()}\' missing values in the␣
↪latitude column,
whilst the longitude column has '{df['Longitude'].isnull().sum()}' missing␣
↪values.""")
```

```
There are '50706' missing values in the latitude column,
whilst the longitude column has '50715' missing values.
```

[21]:
```
# Function to convert DMS to Decimal Degrees
def dms_to_dd(dms):
    if not isinstance(dms, str):  # Ensure input is a string
        return None  # Return None if it's NaN or not a string

    match = re.match(r"(\d{2,3})(\d{2})(\d{2})([NSWE])", dms)

    if not match:
        return None  # Return None if format is incorrect

    degrees, minutes, seconds, direction = match.groups()

    # Convert to decimal degrees
    decimal_degrees = int(degrees) + int(minutes) / 60 + int(seconds) / 3600

    # Apply negative sign for South and West coordinates
    if direction in ['S', 'W']:
        decimal_degrees *= -1
```

```
    return decimal_degrees
```

[22]:
```
# Apply conversion to both Latitude and Longitude columns
df['Latitude_DD'] = df['Latitude'].apply(dms_to_dd)
df['Longitude_DD'] = df['Longitude'].apply(dms_to_dd)

# Handling Null Values:
# Fill NaNs in converted columns
df.fillna({'Latitude_DD': 0, 'Longitude_DD': 0}, inplace=True)
# drop old cols
df.drop(columns=['Latitude', 'Longitude'], inplace=True)
```

[23]:
```
lat_long_rename = {'Latitude_DD': 'Latitude',
                   'Longitude_DD': 'Longitude'
                   }
df.rename(columns=lat_long_rename, inplace=True)
```

[24]:
```
# column 9 # Airport.Code
df['Airport.Code'].unique()
df['Airport.Code'].nunique()
df['Airport.Code'].value_counts()
df['Airport.Code'].isnull().sum() # 38144
df['Airport.Code'].isnull().sum() / df.shape[0] * 100 # 43.5% missing
# > > > dropping
df.drop(columns=['Airport.Code'], inplace = True)
```

[25]:
```
# column 10 # Airport.Name
# > > > dropping col
df.drop(columns=['Airport.Name'], inplace = True)
```

[26]:
```
# column 10 # Injury.Severity
df['Injury.Severity'].isnull().sum() # 50
df['Injury.Severity'].isnull().sum() / df.shape[0] * 100 # 0.06%
# drop the null values
df = df.dropna(subset=['Injury.Severity'])
df['Injury.Severity'].nunique() # 55
# df['Injury.Severity'].unique()
df['Injury.Severity'].value_counts().to_frame()
# drop the `Injury.Severity` column
df = df.drop(columns=['Injury.Severity'], axis=1)
```

[27]:
```
# column 11 # Aircraft.damage
df['Aircraft.damage'].unique()
df['Aircraft.damage'].value_counts().to_frame()
df['Aircraft.damage'].isnull().sum() / df.shape[0] * 100 # 1.38%
# >> dropping null values in columns
df.dropna(subset=['Aircraft.damage'], inplace=True)
```

```
df = df.loc[df['Aircraft.damage'] != 'Unknown']#['Aircraft.damage'].unique()
dict(df['Aircraft.damage'].value_counts())
```

[27]: {'Substantial': 63296, 'Destroyed': 18228, 'Minor': 637}

[28]:
```
# column 12 # Aircraft.Category
df['Aircraft.Category'].isnull().sum() # 50958 values
# which is this perc
df['Aircraft.Category'].isnull().sum() / df.shape[0] * 100 # 65.3%
# dict
print(len(dict(df['Aircraft.Category'].value_counts())))
dict(df['Aircraft.Category'].value_counts())
# >>> dropping the entire col
# df = df.drop(columns=['Aircraft.Category'])
# fill null values with `unknown`
df['Aircraft.Category'].fillna('Unknown', inplace=True)
```

14

[29]:
```
# column 13 # Registration.Number
df['Registration.Number'].nunique() # 73624
# >>>
# dropping column
df.drop('Registration.Number', axis=1, inplace=True)
```

[30]:
```
# column 14 # Make
df.Make.nunique() # 8068
df.Make.value_counts()
# dropping column
# df.drop('Make', axis=1, inplace=True)
df = df.dropna(subset=['Make'])
```

[31]:
```
# column 15 # Model
df.Model.nunique() # 11353
# dropping column
df.drop('Model', axis=1, inplace=True)
```

[32]:
```
# column 16 # Amateur.Built
df['Amateur.Built'].nunique() # 3
# finding the value counts
dict(df['Amateur.Built'].value_counts()) # {'No': 69666, 'Yes': 8228}
# missing values
df['Amateur.Built'].isnull().sum() # 14
# dropping null values
df.dropna(subset=['Amateur.Built'], inplace=True)
```

[33]:
```
# column 13 # Number.of.Engines
df['Number.of.Engines'].unique().tolist() # [1.0, nan, 2.0, 0.0, 4.0, 3.0, 8.0,␣
↪6.0]
df['Number.of.Engines'].nunique() # 7
# perc of null values
df['Number.of.Engines'].isna().sum() / df.shape[0] * 100 # 5.04%
# drop null values
df = df.dropna(subset=['Number.of.Engines'])
# value counts
dict(df['Number.of.Engines'].value_counts()) # {1.0: 67017, 2.0: 8151, 0.0:␣
↪961, 4.0: 146, 3.0: 120, 8.0: 2, 6.0: 1}
# Also, drop planes with 0 engines
# >>makes no sense for a plane with no engine
df = df.loc[(df['Number.of.Engines'] != 0.0)]
# Convert the dtype from `float64` to `int32`
df['Number.of.Engines'] = df['Number.of.Engines'].astype(int)
# checking the type
df['Number.of.Engines'].dtype # dtype('int32')
# print the new values types
df['Number.of.Engines'].unique() # array([1, 2, 4, 3, 8, 6])
```

[33]:
```
array([1, 2, 4, 3, 8, 6])
```

[34]:
```
# column 14 # Engine.Type
df['Engine.Type'].unique().tolist()
# >>>
# ['Reciprocating', 'Turbo Fan', 'Turbo Shaft', 'Turbo Prop', 'Turbo Jet',␣
↪'Unknown', nan, 'Electric', 'Hybrid Rocket', 'None', 'LR', 'UNK']
df['Engine.Type'].nunique() # 11
dict(df['Engine.Type'].value_counts())
# dropping column
df.drop('Engine.Type', axis=1, inplace=True)
```

[35]:
```
# column 15 # FAR.Description
# `
# FAR Desc -- Federal Aviation Regulations (FARs) set by the FAA, essentially
# outlining the aircraft's design and capabilities according to the regulatory
# standards for safe flight operations in the United States.
# `
df['FAR.Description'].nunique() # 27
df['FAR.Description'].value_counts()
df['FAR.Description'].unique()
# no of missing values
df['FAR.Description'].isnull().sum() # 49663
df['FAR.Description'].isnull().sum() / df.shape[0] * 100 # 65.8%
# dropping the column
df.drop('FAR.Description', axis=1, inplace=True)
```

[36]:
```
# column 16 # Schedule
df.Schedule.nunique() # 3
df.Schedule.unique() # array([nan, 'SCHD', 'NSCH', 'UNK'], dtype=object)
dict(df.Schedule.value_counts()) # {'UNK': 3721, 'NSCH': 3204, 'SCHD': 945}

df.Schedule.isnull().sum() # 68786
df.Schedule.isnull().sum() / df.shape[0] * 100 # 89.38%
# >>>
# dropping the columns
df.drop('Schedule', axis=1, inplace=True)
```

[37]:
```
# column 17 # Purpose.of.flight
df['Purpose.of.flight'].value_counts()
# dropping column
df.drop('Purpose.of.flight', axis=1, inplace=True)
```

[38]:
```
# column 18 # Air.carrier
df['Air.carrier'].isnull().sum() # 63242
# perc
df['Air.carrier'].isnull().sum() / df.shape[0] * 100 # 83.8%
# dropping col
df.drop('Air.carrier', axis=1, inplace=True)
```

[39]:
```
# column 19 # Total.Fatal.Injuries
df['Total.Fatal.Injuries'].isnull().sum() # 9702
# perc
df['Total.Fatal.Injuries'].isnull().sum() / df.shape[0] * 100 # 12.8%
# values
df['Total.Fatal.Injuries'].nunique() # 49
# specific
df['Total.Fatal.Injuries'].unique()
# drop null values
df.dropna(subset=['Total.Fatal.Injuries'], inplace=True)
# value count
dict(df['Total.Fatal.Injuries'].value_counts()) # {0.0: 51558, 1.0: 7402, 2.0:␣
↪4267, ..., 265.0: 1}
# reflect
df['Total.Fatal.Injuries'].unique()
# dtype
df['Total.Fatal.Injuries'].dtype
# converting from `float64` to `int32`
df['Total.Fatal.Injuries'] = df['Total.Fatal.Injuries'].astype(int)
# confirmation
df['Total.Fatal.Injuries'].dtype
```

[39]:
```
dtype('int32')
```

[40]:
```
# column 20 # Total.Serious.Injuries
df['Total.Serious.Injuries'].isnull().sum() # 2045
# perc
df['Total.Serious.Injuries'].isnull().sum() / df.shape[0] * 100 # 3.11%
# drop null values
df.dropna(subset=['Total.Serious.Injuries'], inplace=True)
# values
df['Total.Serious.Injuries'].nunique() # 28
# specific
df['Total.Serious.Injuries'].unique()
# value count
dict(df['Total.Serious.Injuries'].value_counts()) # {0.0: 51558, 1.0: 7402, 2.0:
↪ 4267, ..., 265.0: 1}
# reflect
df['Total.Serious.Injuries'].unique()
# # dtype
df['Total.Serious.Injuries'].dtype
# # converting from `float64` to `int32`
df['Total.Serious.Injuries'] = df['Total.Serious.Injuries'].astype(int)
# # confirmation
df['Total.Serious.Injuries'].dtype
```

[40]:
```
dtype('int32')
```

[41]:
```
# column 21 # Total.Minor.Injuries
df['Total.Minor.Injuries'].isnull().sum() # 276
# # perc
df['Total.Minor.Injuries'].isnull().sum() / df.shape[0] * 100 # 0.43%
# # drop null values
df.dropna(subset=['Total.Minor.Injuries'], inplace=True)
# values
df['Total.Minor.Injuries'].nunique() # 40
# specific
df['Total.Minor.Injuries'].unique()
# value count
dict(df['Total.Minor.Injuries'].value_counts())
# reflect
df['Total.Minor.Injuries'].unique()
# dtype
df['Total.Minor.Injuries'].dtype
# # # converting from `float64` to `int32`
df['Total.Minor.Injuries'] = df['Total.Minor.Injuries'].astype(int)
# # # confirmation
df['Total.Minor.Injuries'].dtype
```

[41]:
```
dtype('int32')
```

[42]:
```
# column 22 # Total.Uninjured
df['Total.Uninjured'].isnull().sum() # 43
# perc
df['Total.Uninjured'].isnull().sum() / df.shape[0] * 100 # 0.06%
# drop null values
df.dropna(subset=['Total.Uninjured'], inplace=True)
# dtype
df['Total.Uninjured'].dtype
# # # converting from `float64` to `int32`
df['Total.Uninjured'] = df['Total.Uninjured'].astype(int)
# # # confirmation
df['Total.Uninjured'].dtype
```

[42]:
```
dtype('int32')
```

[43]:
```
# column 23 # Weather.Condition
# no of unique values
df['Weather.Condition'].nunique() # 4
# the value count
dict(df['Weather.Condition'].value_counts()) # {'VMC': 58024, 'IMC': 4445,␣
↪'UNK': 478, 'Unk': 64}
# null values
df['Weather.Condition'].isnull().sum() # 360
# perc
df['Weather.Condition'].isnull().sum() / df.shape[0] * 100 # 0.56%
# drop null values
df.dropna(subset=['Weather.Condition'], inplace=True)
```

[44]:
```
# column 24 # Broad.phase.of.flight
df['Broad.phase.of.flight'].isnull().sum() # 18668
# unique values
df['Broad.phase.of.flight'].unique()
# value count
df['Broad.phase.of.flight'].value_counts()

print(f"The composition of `unknown` and `other` is {(399 + 799) / df.shape[0]␣
↪* 100:.2f}%") # 1.90%
# fill null values with `Unknown`
df['Broad.phase.of.flight'] = df['Broad.phase.of.flight'].fillna('Unknown')
# replace 'Other' with 'Unknown'
df['Broad.phase.of.flight'] = df['Broad.phase.of.flight'].replace('Other',␣
↪'Unknown')
# #
dict(df['Broad.phase.of.flight'].value_counts())
# df.head(4)
```

```
The composition of `unknown` and `other` is 1.88%
```

[44]:
```
{'Unknown': 19694,
 'Landing': 10960,
 'Takeoff': 9386,
 'Cruise': 7613,
 'Maneuvering': 6198,
 'Approach': 4581,
 'Climb': 1394,
 'Descent': 1249,
 'Taxi': 1216,
 'Go-around': 1038,
 'Standing': 439}
```

[45]:
```
# column 25 # Report.Status
df['Report.Status'].nunique() # 15551
df.drop(columns=['Report.Status'], inplace=True)
```

[46]:
```
# column 26 # Publication.Date
# drop column entirely
df.drop(columns=['Publication.Date'], inplace=True)
```

[47]:
```
print(f"Now, there are {len(df.columns)} columns.")
# current columns are:-
df.columns
```

```
Now, there are 16 columns.
```

[47]:
```
Index(['Event.Date', 'Location', 'Country', 'Aircraft.damage',
       'Aircraft.Category', 'Make', 'Amateur.Built', 'Number.of.Engines',
       'Total.Fatal.Injuries', 'Total.Serious.Injuries',
       'Total.Minor.Injuries', 'Total.Uninjured', 'Weather.Condition',
       'Broad.phase.of.flight', 'Latitude', 'Longitude'],
      dtype='object')
```

[48]:
```
# check unique items
print(df.Location.nunique())

# filtering the abbrev
df['Location'] = df['Location'].map(lambda x: x[-2:].upper() if isinstance(x,␣
 ↪str) else x)

# USA State abbreviations and full names
us_states = {
    "Alabama": "AL", "Alaska": "AK", "Arizona": "AZ", "Arkansas": "AR",
    "California": "CA", "Colorado": "CO", "Connecticut": "CT", "Delaware": "DE",
    "Florida": "FL", "Georgia": "GA", "Hawaii": "HI", "Idaho": "ID",
    "Illinois": "IL", "Indiana": "IN", "Iowa": "IA", "Kansas": "KS",
    "Kentucky": "KY", "Louisiana": "LA", "Maine": "ME", "Maryland": "MD",
```

```
    "Massachusetts": "MA", "Michigan": "MI", "Minnesota": "MN", "Mississippi":␣
↪"MS",
    "Missouri": "MO", "Montana": "MT", "Nebraska": "NE", "Nevada": "NV",
    "New Hampshire": "NH", "New Jersey": "NJ", "New Mexico": "NM", "New York":␣
↪"NY",
    "North Carolina": "NC", "North Dakota": "ND", "Ohio": "OH", "Oklahoma":␣
↪"OK",
    "Oregon": "OR", "Pennsylvania": "PA", "Rhode Island": "RI", "South␣
↪Carolina": "SC",
    "South Dakota": "SD", "Tennessee": "TN", "Texas": "TX", "Utah": "UT",
    "Vermont": "VT", "Virginia": "VA", "Washington": "WA", "West Virginia":␣
↪"WV",
    "Wisconsin": "WI", "Wyoming": "WY"
}
# Inverting the dictionary to map abbreviations back to full state names
Abbrev_to_State = {state: abbrev for abbrev, state in us_states.items()}
# Replace abbreviations with full state names
df['Location'] = df['Location'].map(Abbrev_to_State).fillna(df['Location'])
# converting permanently
df.Location.unique()
```

20829

[48]:
```
array(['Idaho', 'California', 'Minnesota', 'Washington', 'New Jersey',
       'Florida', 'New Mexico', 'Alabama', 'Louisiana', 'Texas',
       'Oklahoma', 'Arkansas', 'Utah', 'Alaska', 'Pennsylvania',
       'Michigan', 'Georgia', 'Virginia', 'North Carolina', 'New York',
       'Montana', 'Oregon', 'Nevada', 'Indiana', 'Arizona', 'Missouri',
       'Wyoming', 'Illinois', 'South Carolina', 'Maryland', 'Ohio',
       'Hawaii', 'Colorado', 'Mississippi', 'DC', 'Vermont', 'Kansas',
       'New Hampshire', 'Iowa', 'Wisconsin', 'Massachusetts',
       'Connecticut', 'Kentucky', 'Tennessee', 'Maine', 'AN',
       'South Dakota', 'Nebraska', 'Rhode Island', 'North Dakota', 'LK',
       'West Virginia', '89', 'BO', 'Delaware', 'AS', 'FT', 'PR', 'OF',
       'EN', '95', 'OA', '98', 'DA', 'NG', 'ES', 'NA', 'EA', 'GU', 'OM',
       'DS', '74', '06', 'ZE', 'IC', '1A', 'CE', 'US', 'BA', 'GO', '67',
       '34', 'UA', 'TI', 'RU', 'LY', 'GM', '20', 'LI', 'EY', '16', 'I,',
       'NI', '9,', 'PO', 'AO', 'MY', '8,', 'O,', 'AQ', 'YA', 'N,', 'D,',
       'A,', 'AU', 'LE', 'ON', 'AY', 'JI', 'F)', ',', 'PE', 'S,', 'E,',
       'C,', 'UN', 'AD', 'H,', 'M,', 'G,', '7,', 'X,', 'OS', 'UM', 'CB',
       ', '], dtype=object)
```

[49]:
```
areas_of_interest = ['AS', 'FT', 'PR', 'OF',
       'EN', '95', 'OA', '98', 'DA', 'NG', 'ES', 'NA', 'EA', 'GU', 'OM',
       'DS', '74', '06', 'ZE', 'IC', '1A', 'CE', 'US', 'BA', 'GO', '67',
       '34', 'UA', 'TI', 'RU', 'LY', 'GM', '20', 'LI', 'EY', '16', 'I,',
       'NI', '9,', 'PO', 'AO', 'MY', '8,', 'O,', 'AQ', 'YA', 'N,', 'D,',
```

```python
       'A,', 'AU', 'LE', 'ON', 'AY', 'JI', 'F)', ',', 'PE', 'S,', 'E,',
       'C,', 'UN', 'AD', 'H,', 'M,', 'G,', '7,', 'X,', 'OS', 'UM', 'CB',
       ', ']

df.loc[(df.Location.isin(areas_of_interest))]['Country'].unique()
df.loc[df.Country != 'United States']
```

[49]:

```
      Event.Date  Location        Country Aircraft.damage Aircraft.Category  \
237   1982-02-04  Colorado  Gulf Of Mexico     Substantial        Helicopter
333   1982-02-15        AN     Puerto Rico     Substantial          Airplane
402   1982-02-23        AN  Atlantic Ocean       Destroyed          Airplane
463   1982-03-02        LK     High Island       Destroyed        Helicopter
1391  1982-05-29        89     High Island       Destroyed        Helicopter
…            …         …              …             …                 …
87750 2022-04-30        OF       Venezuela     Substantial          Airplane
87755 2022-05-01         ,         Bolivia     Substantial          Airplane
87823 2022-05-20        OF       Venezuela       Destroyed          Airplane
88712 2022-10-23        OF       Argentina       Destroyed          Airplane
88837 2022-12-01        OF            Cuba     Substantial          Airplane

           Make Amateur.Built  Number.of.Engines  Total.Fatal.Injuries  \
237        Bell            No                  1                     0
333      Cessna            No                  1                     0
402      Cessna            No                  1                     0
463        Bell            No                  1                     2
1391       Bell            No                  1                     0
…           …             …                 …                   …
87750  ROCKWELL            No                  2                     1
87755    CESSNA            No                  1                     0
87823    CESSNA            No                  1                     1
88712    CESSNA            No                  1                     1
88837   LEARJET            No                  2                     0

       Total.Serious.Injuries  Total.Minor.Injuries  Total.Uninjured  \
237                         0                     0                1
333                         0                     0                1
402                         2                     0                0
463                         0                     0                0
1391                        0                     0                4
…                         …                   …              …
87750                       0                     0                0
87755                       0                     0                2
87823                       0                     0                0
88712                       0                     0                0
88837                       0                     0                4

      Weather.Condition Broad.phase.of.flight   Latitude  Longitude
```

```
237                VMC               Takeoff   0.000000   0.000000
333                VMC              Approach   0.000000   0.000000
402                VMC                Cruise   0.000000   0.000000
463                VMC              Approach   0.000000   0.000000
1391               VMC               Landing   0.000000   0.000000
…                  …                   …          …          …
87750              VMC               Unknown   1.059167 -66.840556
87755              VMC               Unknown -14.830000 -64.904722
87823              Unk               Unknown   5.858333 -62.440556
88712              Unk               Unknown -34.636111 -59.458889
88837              VMC               Unknown  19.906111 -75.199722

[765 rows x 16 columns]
```

[50]:
```python
# inference
# Colorado is not in the Gulf of Mexico
df.loc[df['Location'] == 'Colorado', 'Country'] = 'United States'
df.loc[df.Country != 'United States']
```

[50]:
```
      Event.Date Location        Country Aircraft.damage Aircraft.Category  \
333   1982-02-15       AN    Puerto Rico     Substantial          Airplane
402   1982-02-23       AN Atlantic Ocean       Destroyed          Airplane
463   1982-03-02       LK    High Island       Destroyed        Helicopter
1391  1982-05-29       89    High Island       Destroyed        Helicopter
1444  1982-06-03       BO    Puerto Rico     Substantial          Airplane
…          …        …              …               …               …
87750 2022-04-30       OF      Venezuela     Substantial          Airplane
87755 2022-05-01        ,        Bolivia     Substantial          Airplane
87823 2022-05-20       OF      Venezuela       Destroyed          Airplane
88712 2022-10-23       OF      Argentina       Destroyed          Airplane
88837 2022-12-01       OF           Cuba     Substantial          Airplane

          Make Amateur.Built  Number.of.Engines  Total.Fatal.Injuries  \
333     Cessna            No                  1                     0
402     Cessna            No                  1                     0
463       Bell            No                  1                     2
1391      Bell            No                  1                     0
1444    Cessna            No                  1                     0
…          …             …                  …                     …
87750 ROCKWELL            No                  2                     1
87755   CESSNA            No                  1                     0
87823   CESSNA            No                  1                     1
88712   CESSNA            No                  1                     1
88837  LEARJET            No                  2                     0

      Total.Serious.Injuries  Total.Minor.Injuries  Total.Uninjured  \
333                        0                     0                1
```

```
402                          2                      0                 0
463                          0                      0                 0
1391                         0                      0                 4
1444                         0                      0                 1
...                        ...                    ...               ...
87750                        0                      0                 0
87755                        0                      0                 2
87823                        0                      0                 0
88712                        0                      0                 0
88837                        0                      0                 4

      Weather.Condition Broad.phase.of.flight   Latitude  Longitude
333                 VMC              Approach   0.000000   0.000000
402                 VMC                Cruise   0.000000   0.000000
463                 VMC              Approach   0.000000   0.000000
1391                VMC               Landing   0.000000   0.000000
1444                VMC               Descent   0.000000   0.000000
...                 ...                   ...        ...        ...
87750               VMC               Unknown   1.059167 -66.840556
87755               VMC               Unknown -14.830000 -64.904722
87823               Unk               Unknown   5.858333 -62.440556
88712               Unk               Unknown -34.636111 -59.458889
88837               VMC               Unknown  19.906111 -75.199722

[703 rows x 16 columns]
```

[51]:
```
df.Country.value_counts()
```

[51]:
```
United States          63065
Bahamas                   82
Atlantic Ocean            54
Puerto Rico               52
Brazil                    50
                        ...
Chad                       1
Trinidad And Tobago        1
Guyana                     1
Palau                      1
South Sudan                1
Name: Country, Length: 104, dtype: int64
```

[52]:
```
# generating columns number
# for ease of analysis
col_list = list(df.columns)
# for-loop
for i in range(len(list(df.columns))):
    print(f"# column {i + 1} # {col_list[i]}")
```

```
# column 1 # Event.Date
# column 2 # Location
# column 3 # Country
# column 4 # Aircraft.damage
# column 5 # Aircraft.Category
# column 6 # Make
# column 7 # Amateur.Built
# column 8 # Number.of.Engines
# column 9 # Total.Fatal.Injuries
# column 10 # Total.Serious.Injuries
# column 11 # Total.Minor.Injuries
# column 12 # Total.Uninjured
# column 13 # Weather.Condition
# column 14 # Broad.phase.of.flight
# column 15 # Latitude
# column 16 # Longitude
```

[53]:
```
# grimpse so far..
df.head(3)
```

[53]:
```
   Event.Date    Location        Country Aircraft.damage Aircraft.Category  \
0  1948-10-24       Idaho  United States       Destroyed           Unknown
1  1962-07-19  California  United States       Destroyed           Unknown
3  1977-06-19  California  United States       Destroyed           Unknown

        Make Amateur.Built  Number.of.Engines  Total.Fatal.Injuries  \
0    Stinson            No                  1                     2
1      Piper            No                  1                     4
3   Rockwell            No                  1                     2

   Total.Serious.Injuries  Total.Minor.Injuries  Total.Uninjured  \
0                       0                     0                0
1                       0                     0                0
3                       0                     0                0

  Weather.Condition Broad.phase.of.flight  Latitude  Longitude
0               UNK                Cruise       0.0        0.0
1               UNK               Unknown       0.0        0.0
3               IMC                Cruise       0.0        0.0
```

[54]:
```
df.Country.unique()
df.Country.value_counts()[:10]
```

[54]:
```
United States     63065
Bahamas              82
Atlantic Ocean       54
Puerto Rico          52
```

```
Brazil                50
Pacific Ocean         34
Canada                28
Colombia              28
Missing               23
Australia             18
Name: Country, dtype: int64
```

3 Descriptive Analysis

[55]:
```python
# number of columns
print(f'The Number of columns are: {len(df.columns)}')
# columns are:-
print(f'The columns are:- ')
list(df.columns)
```

```
The Number of columns are: 16
The columns are:-
```

[55]:
```
['Event.Date',
 'Location',
 'Country',
 'Aircraft.damage',
 'Aircraft.Category',
 'Make',
 'Amateur.Built',
 'Number.of.Engines',
 'Total.Fatal.Injuries',
 'Total.Serious.Injuries',
 'Total.Minor.Injuries',
 'Total.Uninjured',
 'Weather.Condition',
 'Broad.phase.of.flight',
 'Latitude',
 'Longitude']
```

[56]:
```python
# the shape of the dataframe
df.shape
```

[56]:
```
(63768, 16)
```

[57]:
```python
# description
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 63768 entries, 0 to 88886
Data columns (total 16 columns):
```

```
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Date              63768 non-null  datetime64[ns]
 1   Location                63768 non-null  object
 2   Country                 63768 non-null  object
 3   Aircraft.damage         63768 non-null  object
 4   Aircraft.Category       63768 non-null  object
 5   Make                    63768 non-null  object
 6   Amateur.Built           63768 non-null  object
 7   Number.of.Engines       63768 non-null  int32
 8   Total.Fatal.Injuries    63768 non-null  int32
 9   Total.Serious.Injuries  63768 non-null  int32
 10  Total.Minor.Injuries    63768 non-null  int32
 11  Total.Uninjured         63768 non-null  int32
 12  Weather.Condition       63768 non-null  object
 13  Broad.phase.of.flight   63768 non-null  object
 14  Latitude                63768 non-null  float64
 15  Longitude               63768 non-null  float64
dtypes: datetime64[ns](1), float64(2), int32(5), object(8)
memory usage: 7.1+ MB
```

[58]:

```python
# rename the columns
columns={'Event.Date': 'Date',
         'Make': 'Manufacturer',
         'Number.of.Engines': 'Engines',
         'Aircraft.damage': 'DamageLevel',
         'Amateur.Built': 'Built',
         'Aircraft.Category': 'TypeOfAircraft',
         'Total.Fatal.Injuries': 'Fatal-Injuries',
         'Total.Serious.Injuries': 'Serious-Injuries',
         'Total.Minor.Injuries': 'Minor-Injuries',
         'Total.Uninjured': 'Uninjured',
         'Weather.Condition': 'Weather-Condition',
         'Broad.phase.of.flight': 'Flight.Phase'
         }

df = df.rename(columns=columns)
list(df.columns)
```

[58]:

```
['Date',
 'Location',
 'Country',
 'DamageLevel',
 'TypeOfAircraft',
 'Manufacturer',
 'Built',
 'Engines',
```

```
 'Fatal-Injuries',
 'Serious-Injuries',
 'Minor-Injuries',
 'Uninjured',
 'Weather-Condition',
 'Flight.Phase',
 'Latitude',
 'Longitude']
```

[59]:
```
#  check num dtype
df[['Fatal-Injuries', 'Serious-Injuries', 'Minor-Injuries', 'Uninjured']].
 ↪describe()
# creating a new column
df['Passengers'] = df[['Fatal-Injuries', 'Serious-Injuries', 'Minor-Injuries',␣
 ↪'Uninjured']].sum(axis=1)#.unique()
# columns
df.columns
# rearranging columns
df = df[['Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',␣
 ↪'Manufacturer',
       'Built', 'Engines', 'Passengers', 'Fatal-Injuries', 'Serious-Injuries',
       'Minor-Injuries', 'Uninjured', 'Weather-Condition', 'Flight.Phase',
       'Latitude', 'Longitude']]

# checking order of columns
df.columns
```

[59]:
```
Index(['Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
       'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
       'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
       'Flight.Phase', 'Latitude', 'Longitude'],
      dtype='object')
```

[60]:
```
# value_counts of manufacture column
# inference
# ----------
# some names are not consistent
# ----------
print(f"""Before:-
----------------------
{df.Manufacturer.value_counts().to_frame()[:10]}""",
end='\n\n')

# Capitalize the first letter of each word in 'Manufacturer' column
df['Manufacturer'] = df['Manufacturer'].str.lower().str.title()
# confirming
print("""After:-
```

```
----------------------""")
print(df.Manufacturer.value_counts().to_frame()[:10])
```

```
Before:-
----------------------
          Manufacturer
Cessna           17286
Piper             9383
CESSNA            4128
Beech             3195
PIPER             2443
Bell              1453
Grumman            947
BEECH              839
Mooney             822
Bellanca           728

After:-
----------------------
          Manufacturer
Cessna           21414
Piper            11826
Beech             4034
Bell              1848
Mooney            1029
Grumman           1011
Bellanca           875
Hughes             706
Robinson           637
Aeronca            531
```

4 Desciptional Analysis 2

[61]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 63768 entries, 0 to 88886
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Date                63768 non-null  datetime64[ns]
 1   Location            63768 non-null  object
 2   Country             63768 non-null  object
 3   DamageLevel         63768 non-null  object
 4   TypeOfAircraft      63768 non-null  object
 5   Manufacturer        63768 non-null  object
 6   Built               63768 non-null  object
```

```
 7   Engines            63768 non-null  int32
 8   Passengers         63768 non-null  int64
 9   Fatal-Injuries     63768 non-null  int32
 10  Serious-Injuries   63768 non-null  int32
 11  Minor-Injuries     63768 non-null  int32
 12  Uninjured          63768 non-null  int32
 13  Weather-Condition  63768 non-null  object
 14  Flight.Phase       63768 non-null  object
 15  Latitude           63768 non-null  float64
 16  Longitude          63768 non-null  float64
dtypes: datetime64[ns](1), float64(2), int32(5), int64(1), object(8)
memory usage: 7.5+ MB
```

[62]:
```
# Description
df.describe()
```

[62]:
```
            Engines    Passengers  Fatal-Injuries  Serious-Injuries  \
count  63768.000000  63768.000000    63768.000000      63768.000000
mean       1.118774      2.659814        0.400687          0.222478
std        0.349752     11.943647        2.769290          1.104898
min        1.000000      0.000000        0.000000          0.000000
25%        1.000000      1.000000        0.000000          0.000000
50%        1.000000      2.000000        0.000000          0.000000
75%        1.000000      2.000000        0.000000          0.000000
max        8.000000    576.000000      270.000000        137.000000

       Minor-Injuries     Uninjured      Latitude     Longitude
count    63768.000000  63768.000000  63768.000000  63768.000000
mean         0.281599      1.755050      8.075773    -20.324925
std          1.257196     11.168593     15.883390     40.505289
min          0.000000      0.000000    -48.571389   -170.711389
25%          0.000000      0.000000      0.000000     -9.378472
50%          0.000000      1.000000      0.000000      0.000000
75%          0.000000      2.000000      3.993194      0.000000
max        125.000000    576.000000     71.474444    815.588889
```

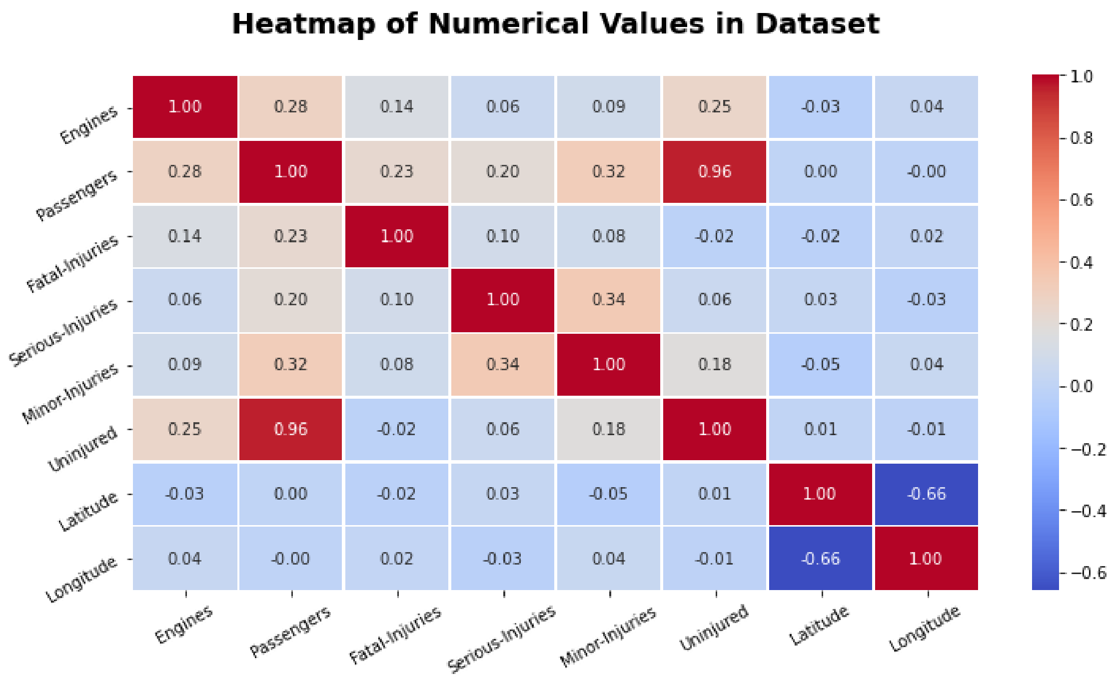
[63]:
```
# Corr-Matrix
df.corr()
```

[63]:
```
                   Engines  Passengers  Fatal-Injuries  Serious-Injuries  \
Engines           1.000000    0.284867        0.139910          0.055594
Passengers        0.284867    1.000000        0.233736          0.204158
Fatal-Injuries    0.139910    0.233736        1.000000          0.098033
Serious-Injuries  0.055594    0.204158        0.098033          1.000000
Minor-Injuries    0.089097    0.321414        0.082217          0.340731
Uninjured         0.254416    0.955063       -0.016950          0.056735
Latitude         -0.034466    0.003639       -0.018851          0.028131
```

```
Longitude          0.037014   -0.000610        0.018118          -0.028428

                  Minor-Injuries  Uninjured  Latitude  Longitude
Engines                 0.089097   0.254416 -0.034466   0.037014
Passengers              0.321414   0.955063  0.003639  -0.000610
Fatal-Injuries          0.082217  -0.016950 -0.018851   0.018118
Serious-Injuries        0.340731   0.056735  0.028131  -0.028428
Minor-Injuries          1.000000   0.177059 -0.045173   0.042025
Uninjured               0.177059   1.000000  0.010867  -0.007063
Latitude               -0.045173   0.010867  1.000000  -0.660415
Longitude               0.042025  -0.007063 -0.660415   1.000000
```

[64]:

```python
# corr matrix
corr_matrix = df.corr()

# figure size
plt.figure(figsize=(12, 6))  # w, h
# heatmap
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=0.5)

# Rotation of the axis labels
plt.xticks(rotation=30)
plt.yticks(rotation=30)

# Labels
plt.title('\nHeatmap of Numerical Values in Dataset\n', fontsize=18,␣
 ↪fontweight='bold')

# teh Plot
plt.show();
```



4.1 Visualizations

[65]:
```
df.columns
```

[65]:
```
Index(['Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
       'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
       'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
       'Flight.Phase', 'Latitude', 'Longitude'],
      dtype='object')
```

[66]:
```
# Assuming your DataFrame is named df
df['Date'] = pd.to_datetime(df['Date'])
df['Year'] = df['Date'].dt.year
# confirming
df.columns
# rearranging columns again
columns = ['Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
'Flight.Phase', 'Latitude', 'Longitude', 'Year']
# cementing
df = df[['Year', 'Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
```

```
'Flight.Phase', 'Latitude', 'Longitude']]
# check
df.columns
```

[66]:
```
Index(['Year', 'Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
       'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
       'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
       'Flight.Phase', 'Latitude', 'Longitude'],
      dtype='object')
```

[67]:
```
# Weather-Condition
df['Weather-Condition'].value_counts()

# corrections
weather_correction = {'UNK': 'Unknown',
'IMC': 'Bad',
'VMC': 'Good',
'Unk': 'Unknown'
}

df['Weather-Condition'] = df['Weather-Condition'].replace(weather_correction)
# cementing changes
df['Weather-Condition'].unique()
```

[67]:
```
array(['Unknown', 'Bad', 'Good'], dtype=object)
```

5 Exporting csv

[68]:
```
# exporting csv
filename = 'final-output.csv'

try:
    # Check if file exists and overwrite or create it
    if os.path.exists(filename):
        print(f"File '{filename}' previously existed but overwritten.",␣
 ↪end='\n')
    else:
        df.to_csv(filename, index=False)
        print(f"The csv-file '{filename}' was not found, so it has been created.
 ↪", end='\n')

except PermissionError as e:
    print(f"PermissionError: Unable to write to '{filename}'. Please check file␣
 ↪permissions.")
    print(f"Error details: {e}", end='\n')
```

```
#   The End!
print('')
print('The End!')
```

```
File 'final-output.csv' previously existed but overwritten.

The End!
```

[69]:
```
df.columns
```

[69]:
```
Index(['Year', 'Date', 'Location', 'Country', 'DamageLevel', 'TypeOfAircraft',
       'Manufacturer', 'Built', 'Engines', 'Passengers', 'Fatal-Injuries',
       'Serious-Injuries', 'Minor-Injuries', 'Uninjured', 'Weather-Condition',
       'Flight.Phase', 'Latitude', 'Longitude'],
      dtype='object')
```

5.1 The Research Questions are:-

5.1.1 SPECIFIC OBJECTIVES

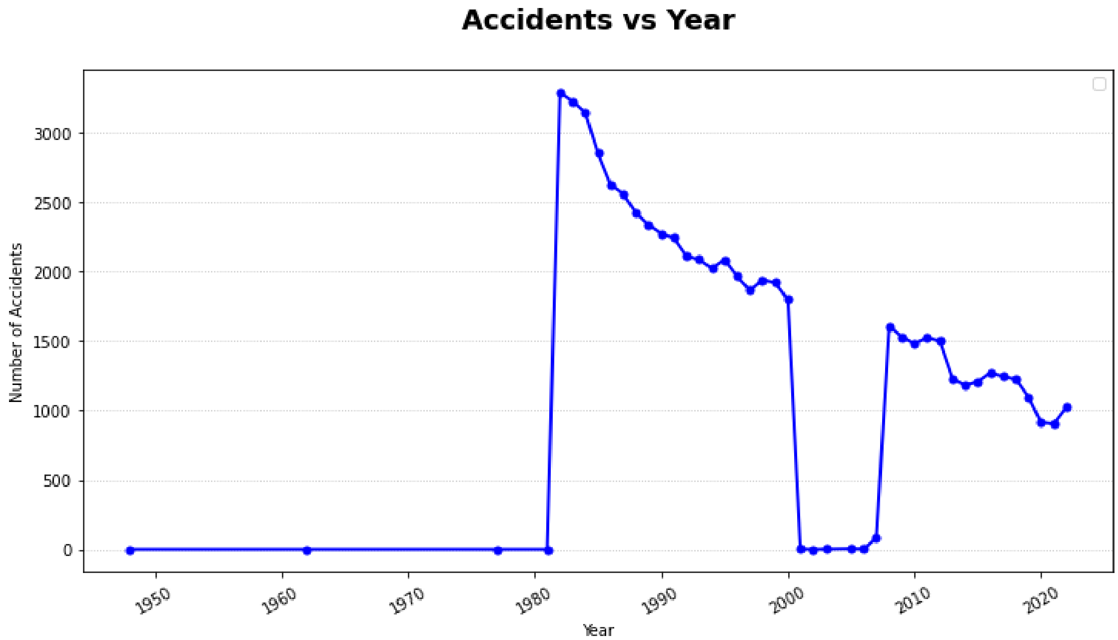
1. Analyse Aircraft Safety Records – Examine historical accident data to identify aircraft models with the lowest accident and fatality rates.
2. Evaluate Risk Factors by Aircraft Type – Assess how factors such as aircraft age, manufacturer, engine type, and passenger capacity influence accident frequency and severity.
3. Assess the Impact of Weather and Geographic Location – Determine how different weather conditions and regions contribute to aircraft accidents and identify aircraft best suited for various environments.

5.1.2 Line Graph Of Accident Vs Year

[70]:
```
# Step 1: Group by 'Year' and count the accidents per year
accidents_per_year = df.groupby(df['Date'].dt.year).size()

# figure size
plt.figure(figsize=(12, 6))
# Step 2: Plot a line graph
plt.plot(accidents_per_year.index, accidents_per_year.values, marker='o',␣
 ↪color='b', linestyle='-', linewidth=2, markersize=5)
# labels
plt.title('Accidents vs Year\n',
          fontsize = 18,
          fontweight = 'bold'
          )
plt.xlabel('Year')
plt.ylabel('Number of Accidents')
# Show
plt.xticks(rotation=30)
```

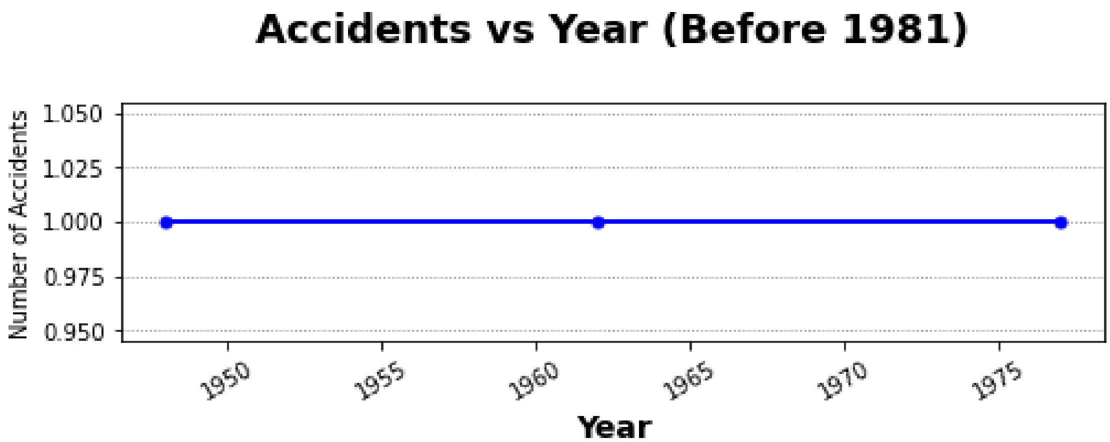
```
plt.grid(axis='y', linestyle=':', color='gray', alpha = 0.5)
plt.legend()
plt.show();
```

```
No handles with labels found to put in legend.
```



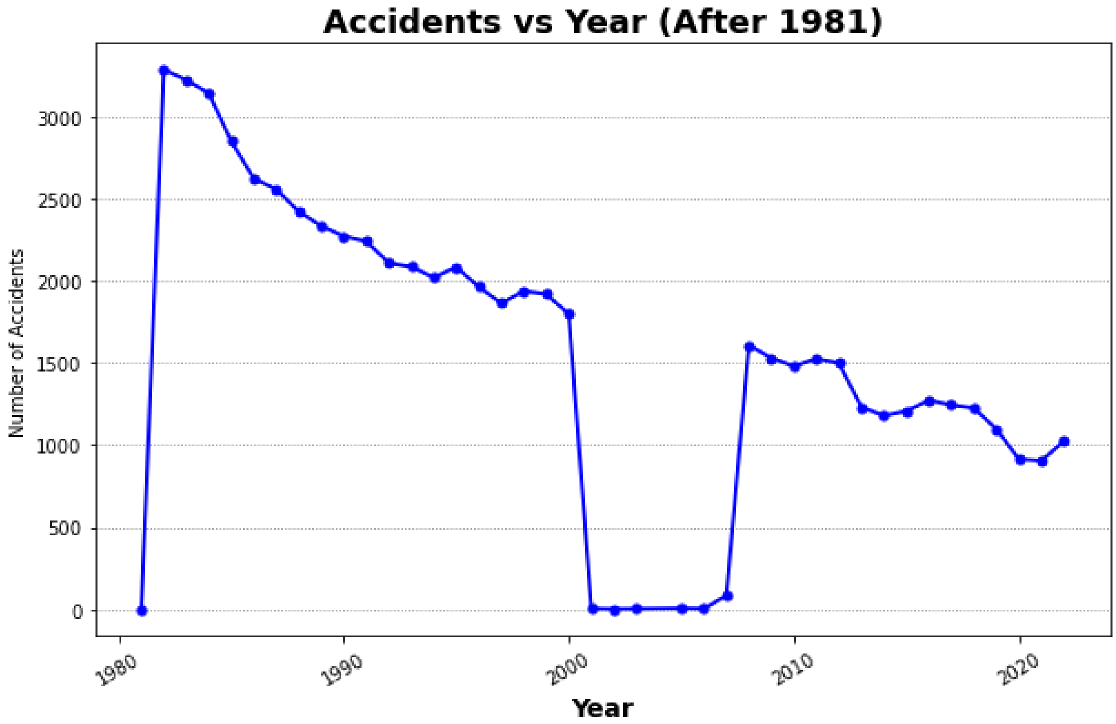
[71]:
```
# Step 2: Filter for years before 1981
df_filter = df[df['Date'].dt.year < 1981]

# Step 3: Group by 'Year' and count the accidents per year
accidents_per_year = df_filter.groupby(df_filter['Date'].dt.year).size()

# Step 4: Plot a line graph
plt.figure(figsize=(8, 2))
plt.plot(accidents_per_year.index, accidents_per_year.values, marker='o',␣
↪color='b', linestyle='-', linewidth=2, markersize=5)
plt.title('Accidents vs Year (Before 1981)\n',
          fontsize = 18,
          fontweight = 'bold'
          )
plt.xlabel('Year', fontsize=14, fontweight='bold')  # Make x-axis label bigger␣
↪and bold
plt.ylabel('Number of Accidents')

# Show only the y-axis grid with dotted lines
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
```

```
plt.xticks(rotation=30)
plt.show()
```



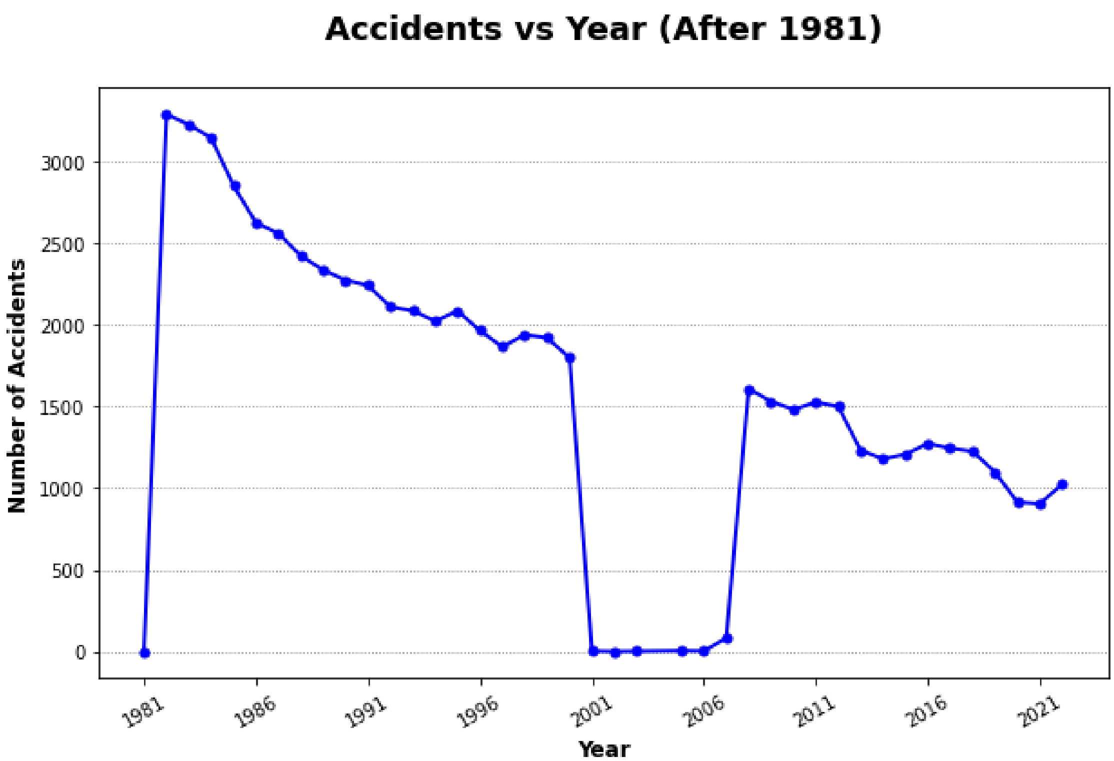
[72]:

```
# Step 2: Filter for years before 1981
df_filter = df[df['Date'].dt.year >= 1981]

# Step 3: Group by 'Year' and count the accidents per year
accidents_per_year = df_filter.groupby(df_filter['Date'].dt.year).size()

# Step 4: Plot a line graph
plt.figure(figsize=(10, 6))
plt.plot(accidents_per_year.index, accidents_per_year.values, marker='o',␣
↪color='b', linestyle='-', linewidth=2, markersize=5)
plt.title('Accidents vs Year (After 1981)',
          fontsize = 18,
          fontweight = 'bold')
plt.xlabel('Year', fontsize=14, fontweight='bold')  # Make x-axis label bigger␣
↪and bold
plt.ylabel('Number of Accidents')

# Show only the y-axis grid with dotted lines
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.xticks(rotation=30)
plt.show()
```



[73]:
```
# Step 2: Filter for years before 1981
df_filter = df[df['Date'].dt.year >= 1981]

# Step 3: Group by 'Year' and count the accidents per year
accidents_per_year = df_filter.groupby(df_filter['Date'].dt.year).size()

# Step 4: Plot a line graph
plt.figure(figsize=(10, 6))
plt.plot(accidents_per_year.index, accidents_per_year.values, marker='o',␣
 ↪color='b', linestyle='-', linewidth=2, markersize=5)
plt.title('Accidents vs Year (After 1981)\n',
          fontsize = 18,
          fontweight = 'bold'
          )
plt.xlabel('Year',
          fontsize = 12,
          fontweight = 'bold'
          )
plt.ylabel('Number of Accidents',
          fontsize = 12,
          fontweight = 'bold'
          )
# Show only the y-axis grid with dotted lines
```

```
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
# Set x-ticks every 5 years
plt.xticks(range(min(accidents_per_year.index), max(accidents_per_year.index) +␣
 ↪1, 5))
# rotation
plt.xticks(rotation=30)
plt.show();
```

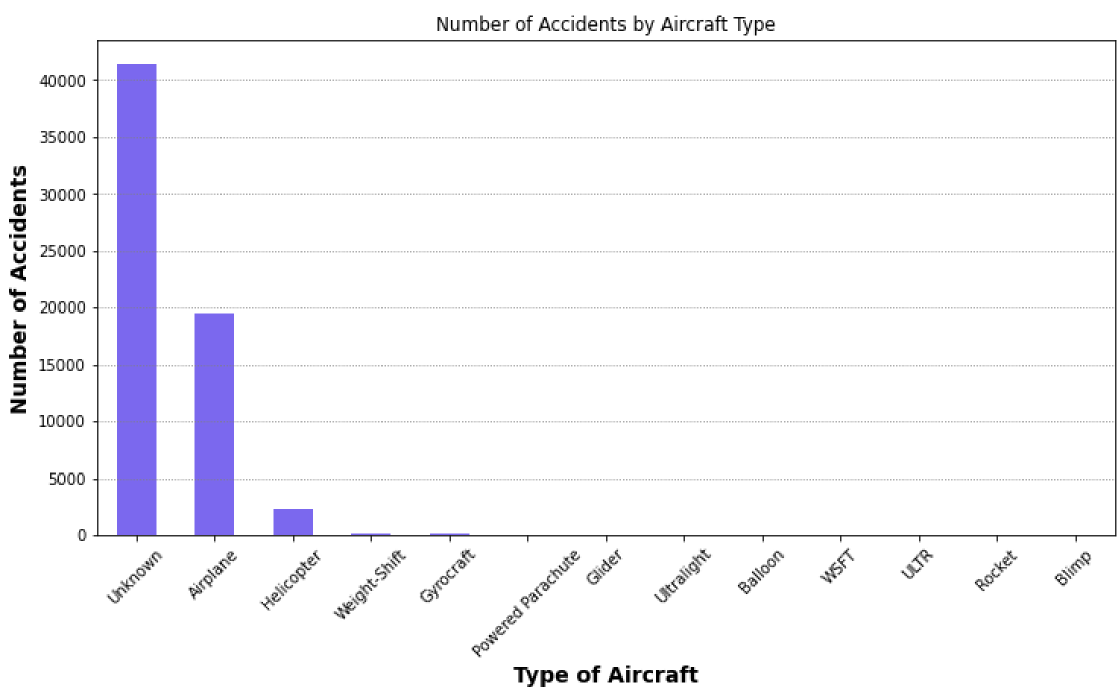


[74]:
```
# Step 2: Filter for years before 1981
df_filter = df[df['Date'].dt.year >= 2005]

# Step 3: Group by 'Year' and count the accidents per year
accidents_per_year = df_filter.groupby(df_filter['Date'].dt.year).size()

# Step 4: Plot a line graph
plt.figure(figsize=(10, 6))
plt.plot(accidents_per_year.index, accidents_per_year.values,
         marker='o',
         color='b',
         linestyle='-',
         linewidth=2,
         markersize=5
```

```
        )
plt.title('Accidents vs Year (last 20 Years)\n',
          fontsize = 18,
          fontweight = 'bold'
          )
plt.xlabel('Year',
          fontsize = 12,
          fontweight = 'bold'
          )
plt.ylabel('Number of Accidents',
          fontsize = 12,
          fontweight = 'bold'
          )
# Show only the y-axis grid with dotted lines
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
# Set x-ticks every 5 years
plt.xticks(range(min(accidents_per_year.index), max(accidents_per_year.index) +␣
 ↪1, 5))
# rotation
plt.xticks(rotation=30)
plt.show();
```

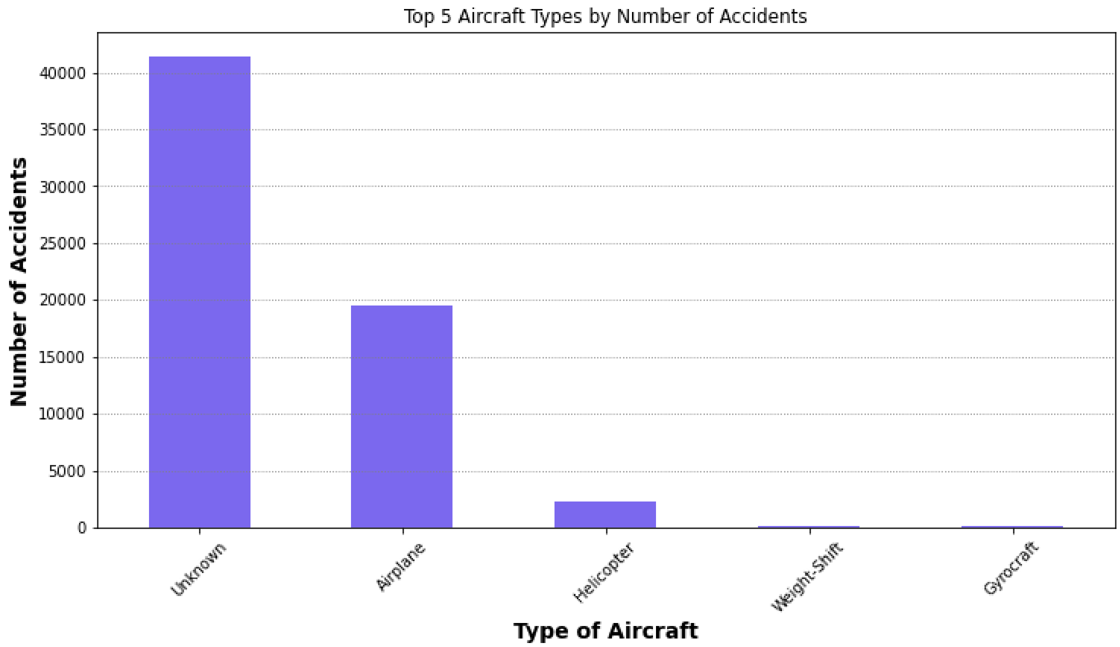
5.1.3 viz-1: TypeOfAircraft vs count the accidents

[75]:
```
# Step 1: Group by 'TypeOfAircraft' and count the accidents
accidents_per_aircraft_type = df.groupby('TypeOfAircraft').size()

# Step 2: Plot a bar graph
plt.figure(figsize=(12, 6))
accidents_per_aircraft_type.sort_values(ascending=False).plot(kind='bar',␣
↪color='mediumslateblue')

# labels and title
plt.title('Number of Accidents by Aircraft Type')
plt.xlabel('Type of Aircraft', fontsize=14, fontweight='bold')  # Make x-axis␣
↪label bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪y-axis label bigger and bold

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show();
```



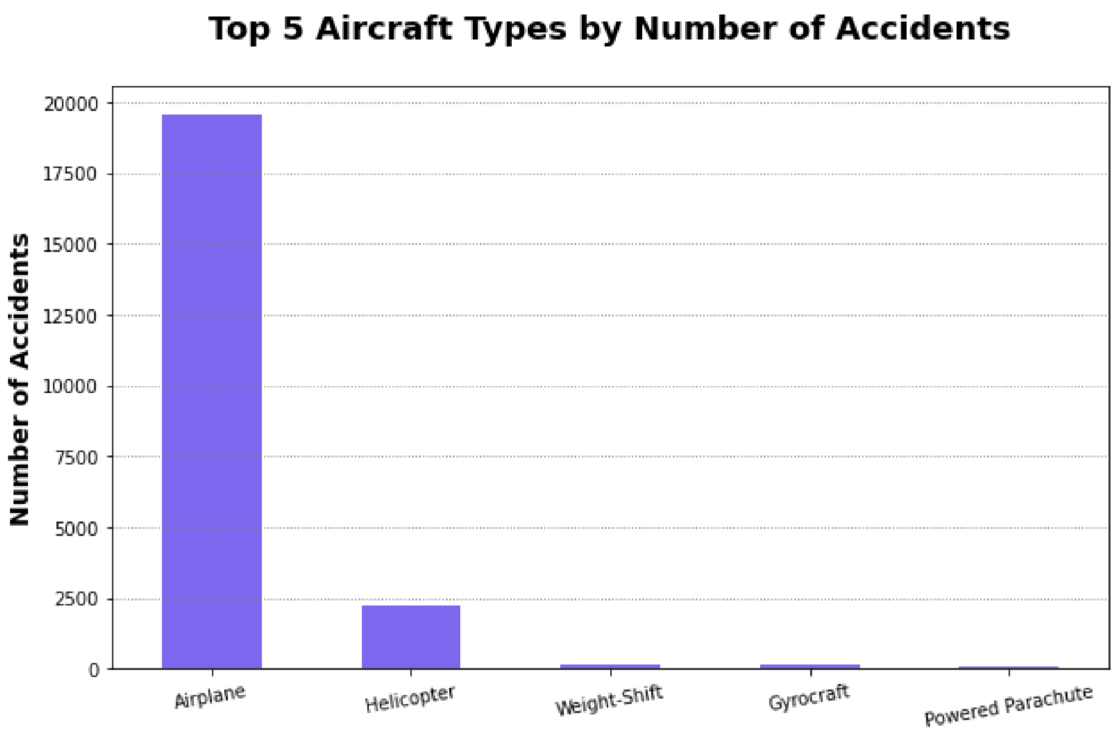
[76]:
```
# Step 1: Group by 'TypeOfAircraft' and count the accidents
accidents_per_aircraft_type = df.groupby('TypeOfAircraft').size()
```

```
# Step 2: Get the top 10 most frequent aircraft types
top_5_accidents = accidents_per_aircraft_type.sort_values(ascending=False).
↪head(5)

# Step 3: Plot a bar graph
plt.figure(figsize=(12, 6))
# top 10
top_5_accidents.plot(kind='bar', color='mediumslateblue')

# labels and title
plt.title('Top 5 Aircraft Types by Number of Accidents')
plt.xlabel('Type of Aircraft', fontsize=14, fontweight='bold')
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```



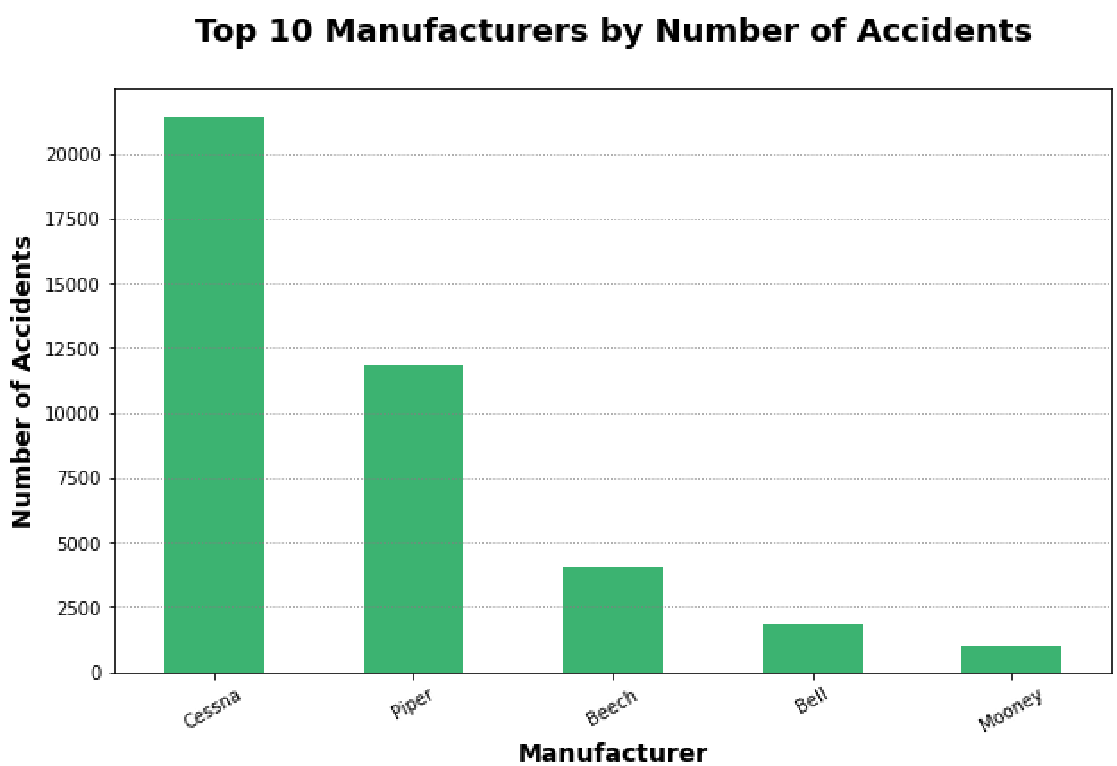
[77]:
```
# Step 1: Filter out 'Unknown' values from 'TypeOfAircraft'
df_filtered = df[df['TypeOfAircraft'] != 'Unknown']

# Step 2: Group by 'TypeOfAircraft' and count the accidents
accidents_per_aircraft_type = df_filtered.groupby('TypeOfAircraft').size()

# Step 3: Get the top 5 most frequent aircraft types
```

```
top_5_accidents = accidents_per_aircraft_type.sort_values(ascending=False).
  ↪head(5)

# Step 4: Plot a bar graph
plt.figure(figsize=(10, 6))
top_5_accidents.plot(kind='bar', color='mediumslateblue')

# labels and title
plt.title('Top 5 Aircraft Types by Number of Accidents\n',
          fontsize=18,
          fontweight='bold'
          )
plt.xlabel('Type of Aircraft', fontsize=14, fontweight='bold')
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=10)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show();
```



5.1.4 viz-2: Manufacturer vs count the accidents

[78]:
```
# Step 1: Group by 'Manufacturer' and count the accidents
accidents_per_manufacturer = df.groupby('Manufacturer').size()

# Step 2: Get the top manufacturers based on accident count (optional if needed)
top_manufacturers = accidents_per_manufacturer.sort_values(ascending=False).
  ↪head(5)   # top 10 for better visualization

# Step 3: Plot a bar graph
plt.figure(figsize=(10, 6))
top_manufacturers.plot(kind='bar', color='mediumseagreen')

# labels and title
plt.title('Top 10 Manufacturers by Number of Accidents\n',
          fontsize=18,
          fontweight='bold'
          )
plt.xlabel('Manufacturer', fontsize=14, fontweight='bold')
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=30)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```

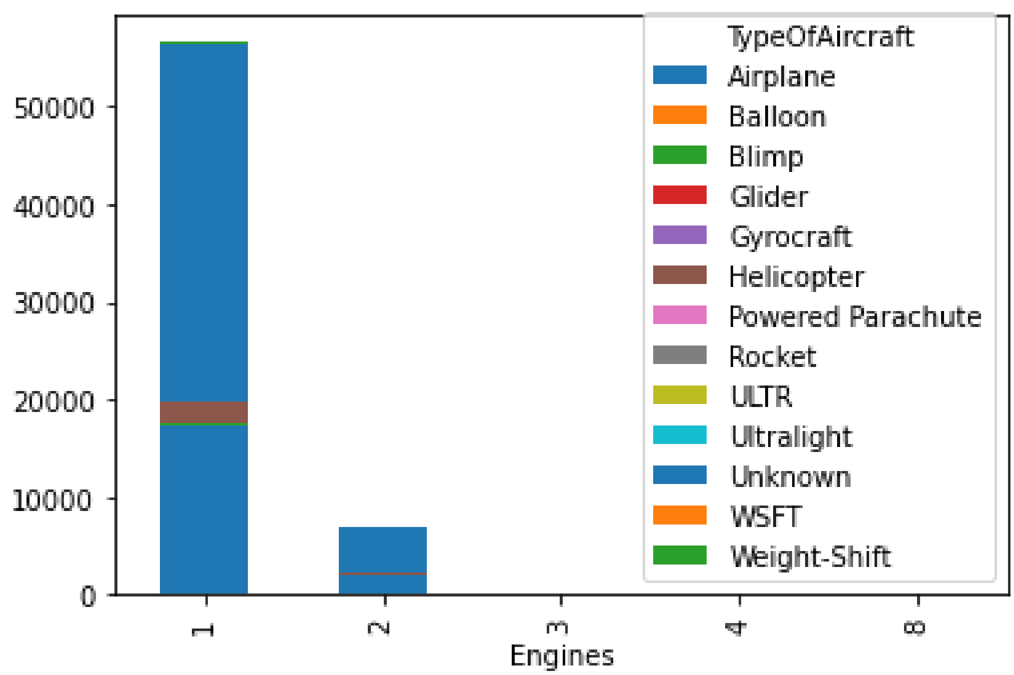


5.2 Objective 2:

5.2.1 Evaluate Risk Factors by Aircraft Type – Assess how factors such as aircraft age, manufacturer, engine type, and passenger capacity influence accident frequency and severity

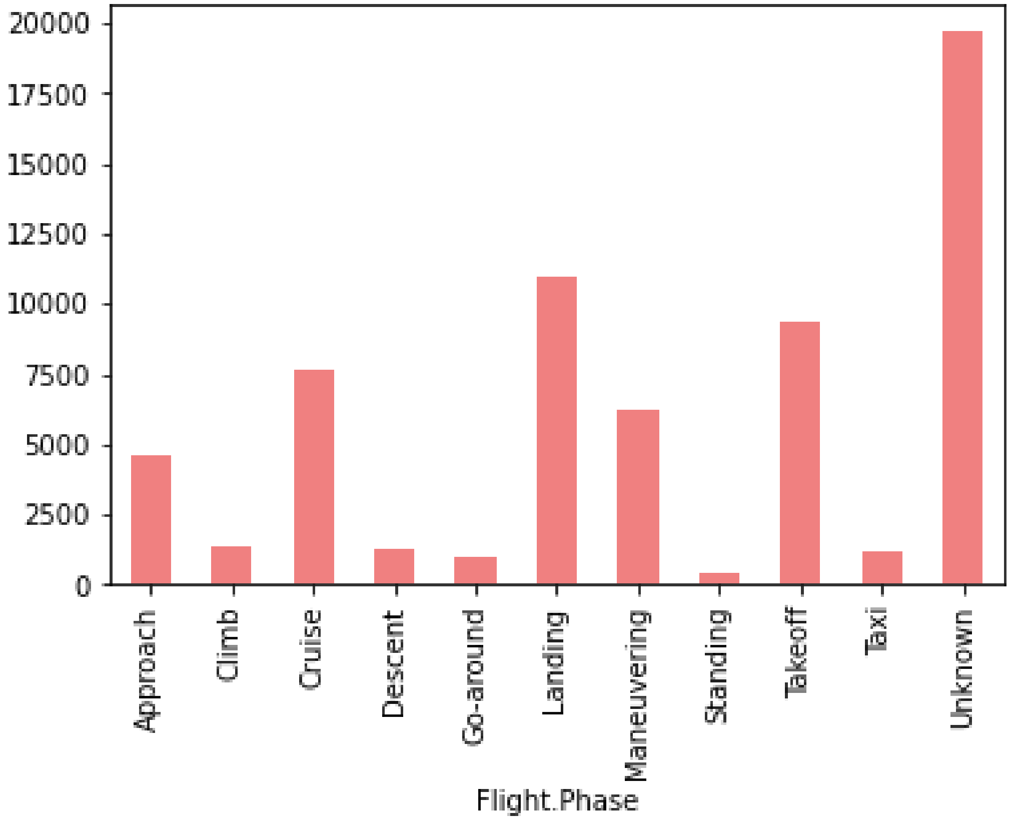
[79]:
```
accidents_by_engine = df.groupby(['Engines', 'TypeOfAircraft']).size().unstack()
accidents_by_engine.plot(kind='bar', stacked=True)
```

[79]: <AxesSubplot:xlabel='Engines'>



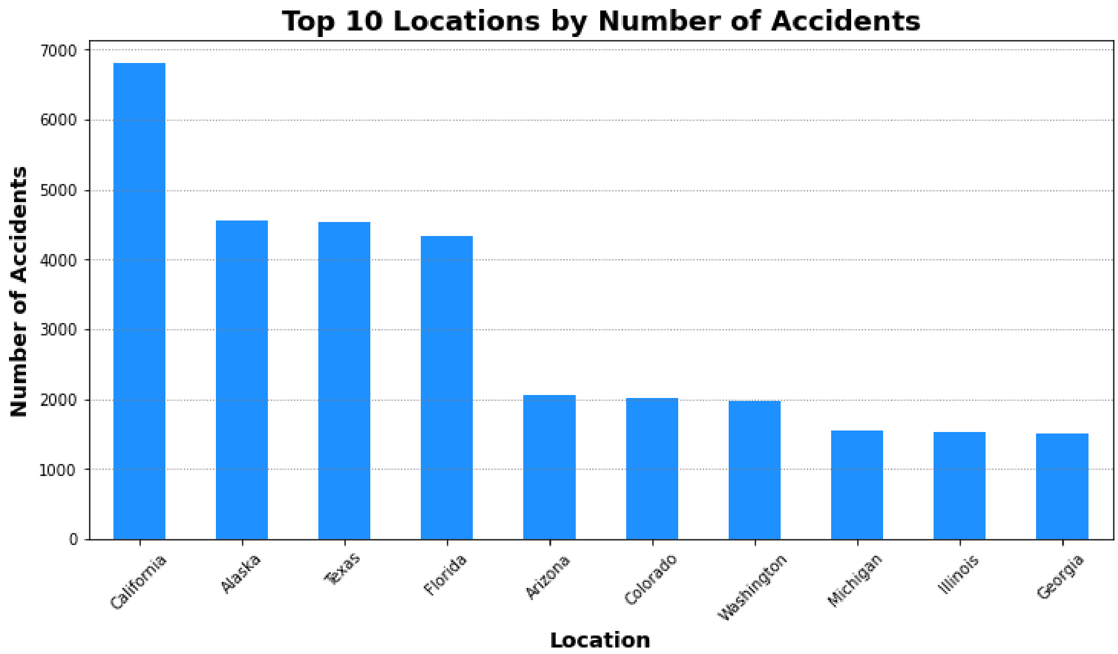
[80]:
```
accidents_by_phase = df.groupby('Flight.Phase').size()
accidents_by_phase.plot(kind='bar', color='lightcoral')
```

[80]: <AxesSubplot:xlabel='Flight.Phase'>



[81]:
```
# Location against Count
# # Step 1: Group by 'Location' and count the accidents
accidents_per_location = df.groupby('Location').size()

# Step 2: Get the top 10 locations based on accident count (optional for better␣
 ↪visualization)
top_10_locations = accidents_per_location.sort_values(ascending=False).head(10)

# Step 3: Plot a bar graph
plt.figure(figsize=(12, 6))
top_10_locations.plot(kind='bar', color='dodgerblue')

# labels and title
plt.title('Top 10 Locations by Number of Accidents', fontsize=18,␣
 ↪fontweight='bold')
plt.xlabel('Location', fontsize=14, fontweight='bold')
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=45)
```

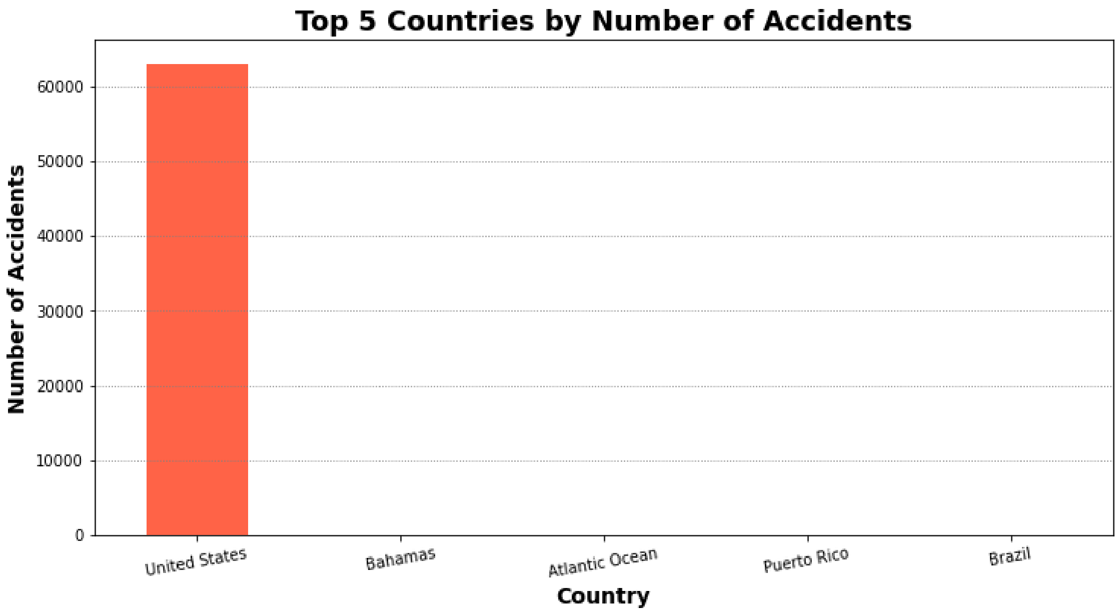
```
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show();
```



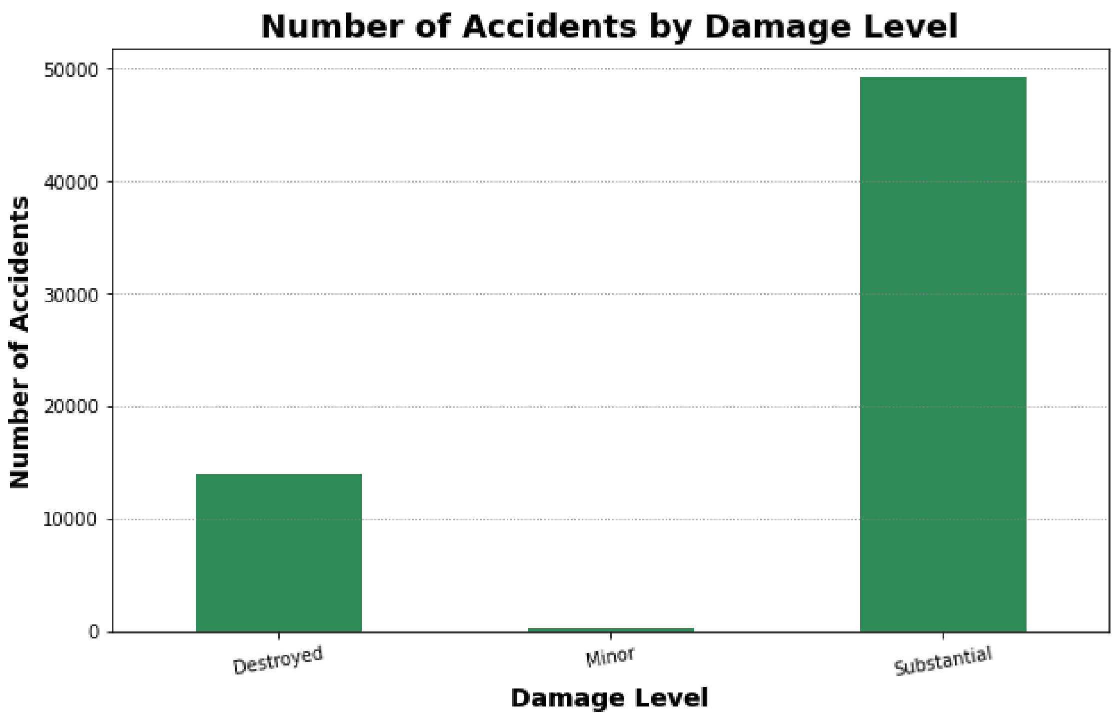
[82]:

```
# country vs count
# Step 1: Group by 'Country' and count the accidents
accidents_per_country = df.groupby('Country').size()

# Step 2: Get the top 10 countries based on accident count (optional for better
↪visualization)
top_5_countries = accidents_per_country.sort_values(ascending=False).head(5)

# Step 3: Plot a bar graph
plt.figure(figsize=(12, 6))
top_5_countries.plot(kind='bar', color='tomato')

# labels and title
plt.title('Top 5 Countries by Number of Accidents', fontsize=18,
↪fontweight='bold')
plt.xlabel('Country', fontsize=14, fontweight='bold')  # Make x-axis label
↪bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make
↪y-axis label bigger and bold

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=10)
```

```
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```

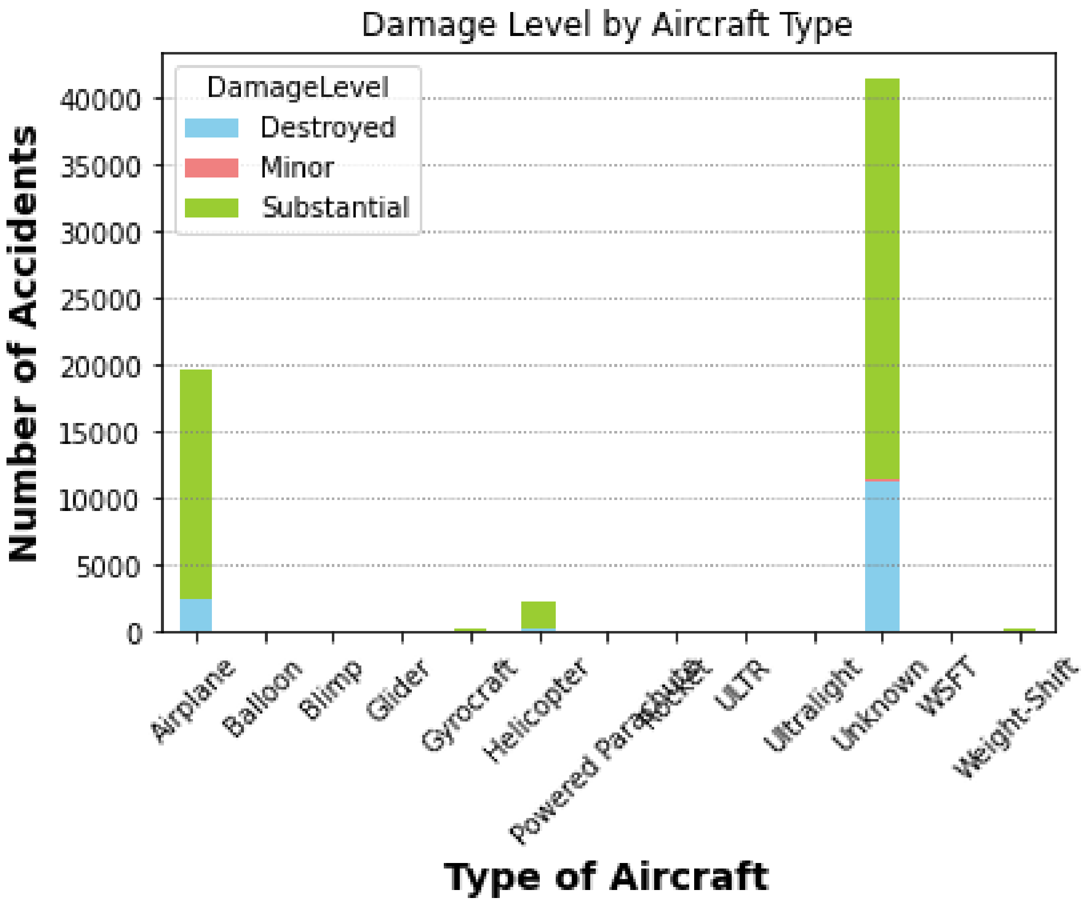


[83]:
```
# damage level agansr count
# Step 1: Group by 'DamageLevel' and count the accidents
accidents_per_damage_level = df.groupby('DamageLevel').size()

# Step 2: Plot a bar graph
plt.figure(figsize=(10, 6))
accidents_per_damage_level.plot(kind='bar', color='seagreen')

# labels and title
plt.title('Number of Accidents by Damage Level', fontsize=18, fontweight='bold')
plt.xlabel('Damage Level', fontsize=14, fontweight='bold')  # Make x-axis label␣
 ↪bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
 ↪y-axis label bigger and bold

# Rotate x-axis labels to avoid overlap if necessary
plt.xticks(rotation=10)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```



[84]:
```
# damagelevel against typeofAircft# Step 1: Group by 'DamageLevel' and␣
↪'TypeOfAircraft' and count the accidents
damage_level_by_aircraft = df.groupby(['TypeOfAircraft', 'DamageLevel']).size().
↪unstack()

# Step 2: Plot a stacked bar chart
plt.figure(figsize=(12, 6))
damage_level_by_aircraft.plot(kind='bar', stacked=True, color=['skyblue',␣
↪'lightcoral', 'yellowgreen', 'lightgrey'])

# labels and title
plt.title('Damage Level by Aircraft Type')
plt.xlabel('Type of Aircraft', fontsize=14, fontweight='bold')  # Make x-axis␣
↪label bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪y-axis label bigger and bold

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```

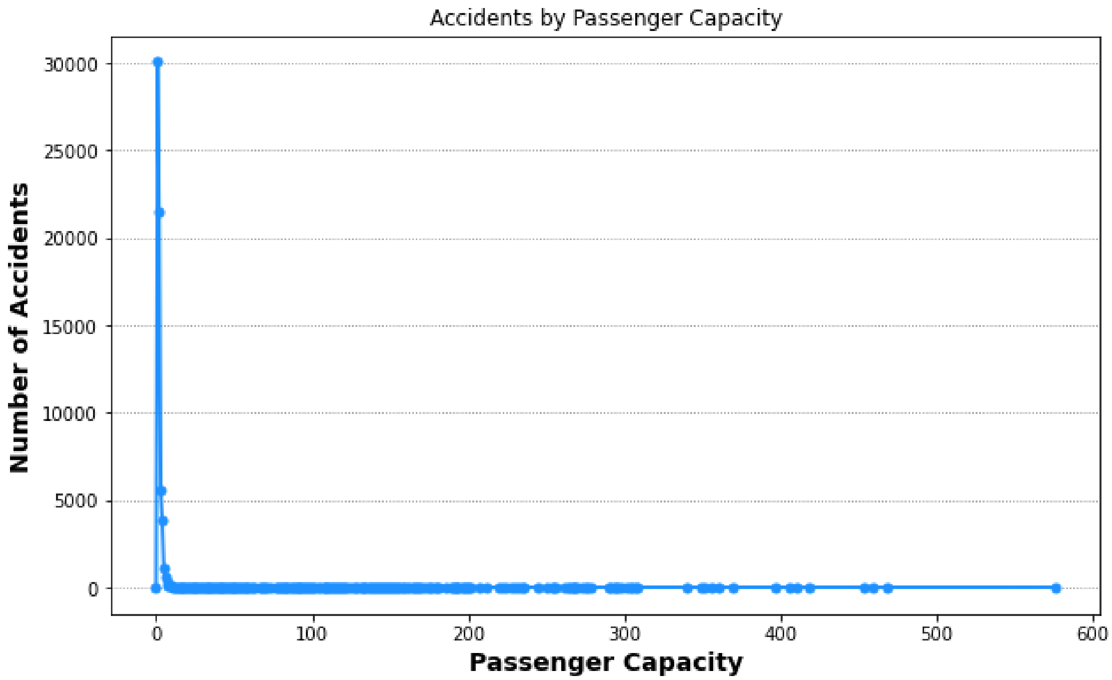
```
<Figure size 864x432 with 0 Axes>
```



[85]:
```
# # Damagelevel against Manufacturer
# ----------------------------
# Takes longs to run
# ----------------------------
# # Step 1: Group by 'DamageLevel' and 'Manufacturer' and count the accidents
# damage_level_by_manufacturer = df.groupby(['Manufacturer', 'DamageLevel']).
↪size().unstack()

# # Step 2: Plot a stacked bar chart
# plt.figure(figsize=(12, 6))
# damage_level_by_manufacturer.plot(kind='bar', stacked=True, color=['skyblue',␣
↪'lightcoral', 'yellowgreen', 'lightgrey'])

# # labels and title
# plt.title('Damage Level by Manufacturer')
# plt.xlabel('Manufacturer', fontsize=14, fontweight='bold')  # Make x-axis␣
↪label bigger and bold
```

```
# plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪y-axis label bigger and bold

# # Rotate x-axis labels to avoid overlap
# plt.xticks(rotation=45)
# plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
# plt.show()
```

[86]:
```
# passenger against number of accidents
# Step 1: Group by 'Passengers' and count the accidents
accidents_by_passenger_capacity = df.groupby('Passengers').size()

# Step 2: Plot a line or scatter plot
plt.figure(figsize=(10, 6))
plt.plot(accidents_by_passenger_capacity.index, accidents_by_passenger_capacity.
↪values, marker='o', color='dodgerblue', linestyle='-', linewidth=2,␣
↪markersize=5)

# labels and title
plt.title('Accidents by Passenger Capacity')
plt.xlabel('Passenger Capacity', fontsize=14, fontweight='bold')  # Make x-axis␣
↪label bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪y-axis label bigger and bold

# Show only the y-axis grid with dotted lines
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
plt.show()
```

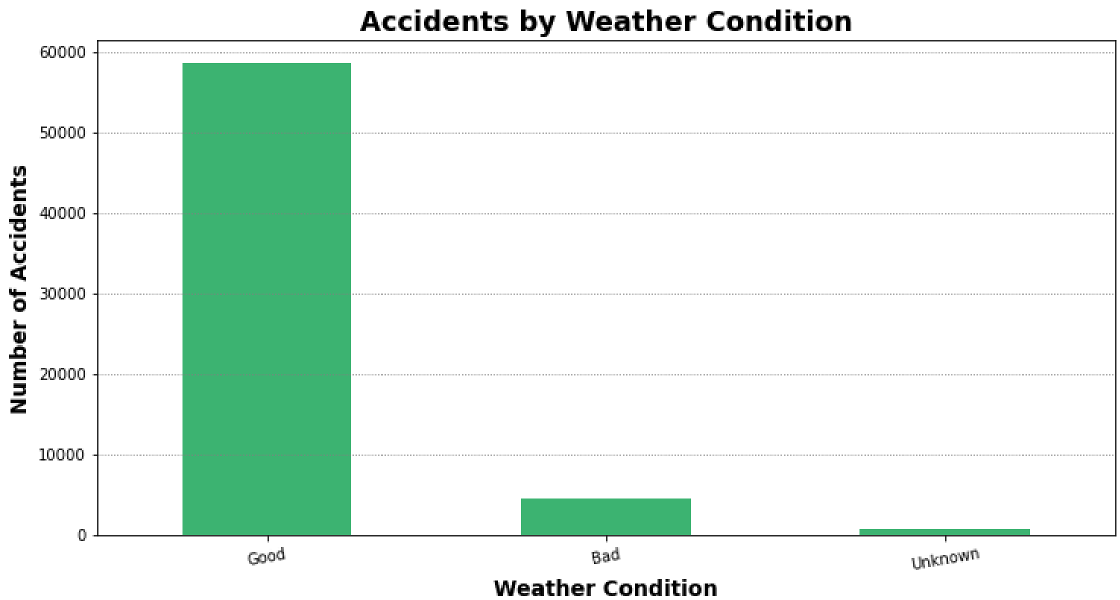


5.3 Objective 3:

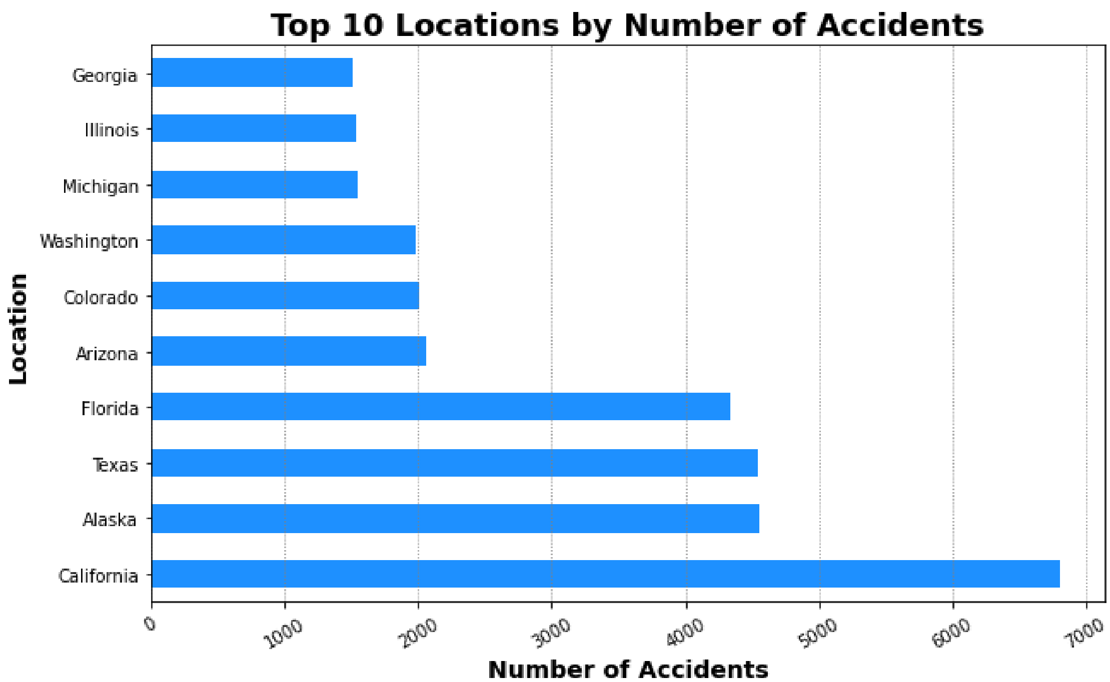
5.3.1 Assess the Impact of Weather and Geographic Location – Determine how different weather conditions and regions contribute to aircraft accidents and identify aircraft best suited for various environments.

[87]:
```
# weather against count of accident
# Step 1: Group by 'Weather-Condition' and count the accidents
accidents_per_weather_condition = df.groupby('Weather-Condition').size()

# Step 2: Plot a bar chart
plt.figure(figsize=(12, 6))
accidents_per_weather_condition.sort_values(ascending=False).plot(kind='bar',␣
↪color='mediumseagreen')

# labels and title
plt.title('Accidents by Weather Condition', fontsize=18, fontweight='bold')
plt.xlabel('Weather Condition', fontsize=14, fontweight='bold')  # Make x-axis␣
↪label bigger and bold
plt.ylabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪y-axis label bigger and bold

# Rotate x-axis labels to avoid overlap
plt.xticks(rotation=10)
plt.grid(axis='y', linestyle=':', color='gray')  # Dotted grid for y-axis
```

```
plt.show()
```



[88]:
```
# Location against count of accident
# Step 1: Group by 'Location' and count the accidents
accidents_per_location = df.groupby('Location').size()

# Step 2: Sort and get the top locations (optional to make the plot more␣
↪readable)
top_locations = accidents_per_location.sort_values(ascending=False).head(10)

# Step 3: Plot a horizontal bar chart
plt.figure(figsize=(10, 6))
top_locations.plot(kind='barh', color='dodgerblue')

# labels and title
plt.title('Top 10 Locations by Number of Accidents', fontsize=18,␣
↪fontweight='bold')
plt.xlabel('Number of Accidents', fontsize=14, fontweight='bold')  # Make␣
↪x-axis label bigger and bold
plt.ylabel('Location', fontsize=14, fontweight='bold')  # Make y-axis label␣
↪bigger and bold

# Grid for better readability
plt.grid(axis='x', linestyle=':', color='gray')  # Dotted grid for x-axis
plt.xticks(rotation=30)
plt.show()
```



Top 10 Locations by Number of Accidents
Georgia
Illinois
Michigan
Washington
Colorado
Arizona
Florida
Texas
Alaska
California
Location
0
1000
2000
3000
4000
5000
6000
7000
Number of Accidents


```
[ ]:
```

```
[ ]:
```