Overview

This dataset consists of aviation accident survey data, which includes information on whether the aircraft was destroyed, the type of injuries sustained by individuals, the location of the accidents along with the year and month, the type of engine involved, weather conditions, the purpose of the flight, and other relevant details.

Business Problem

This analysis aims to identify patterns and trends in aviation accidents to enhance safety measures. By understanding the relationship between weather conditions, engine types, injury severity, and flight purpose, we can develop insights to prevent future accidents. The findings will support data-driven decision-making in aviation safety policies and operational practices. Ultimately, this research seeks to improve overall flight safety and reduce accident-related risks

Data Understanding

In this data analysis, the first step involves importing the necessary libraries and loading the dataset to begin the analysis. Next, I will handle any missing values to ensure the data is complete and reliable. Following this, I will transform the data to enhance its interpretability, such as grouping related categories into broader groups for better clarity. The data will then be explored through various visualizations to uncover relationships and patterns between key variables, such as weather conditions, injury severity, and flight purposes. Finally, I will summarize the findings and provide conclusions that offer insights into aviation safety and accident prevention.

DATA AND LIBRARY IMPORTATION

```
#import libraries
import numpy as np
import pandas as pd
import plotly.express as px
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.cm as cm
```

```
# Loading dataset
df = pd.read_csv('AviationData.csv', encoding='latin-1')
df.head()
```

```
<ipython-input-50-3487004450d9>:2: DtypeWarning: Columns (6,7,28) have mixed types. Specify dtype option on import or set low_memory=Fal
  df = pd.read_csv('AviationData.csv', encoding='latin-1')
```

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

5 rows × 31 columns

DATA UNDERSTANDING

```
# understanding basic information of the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88889 non-null  object
 2   Accident.Number         88889 non-null  object
```

```
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Latitude                34382 non-null  object 
 7   Longitude               34373 non-null  object 
 8   Airport.Code            50132 non-null  object 
 9   Airport.Name            52704 non-null  object 
 10  Injury.Severity         87889 non-null  object 
 11  Aircraft.damage         85695 non-null  object 
 12  Aircraft.Category       32287 non-null  object 
 13  Registration.Number     87507 non-null  object 
 14  Make                    88826 non-null  object 
 15  Model                   88797 non-null  object 
 16  Amateur.Built           88787 non-null  object 
 17  Number.of.Engines       82805 non-null  float64
 18  Engine.Type             81793 non-null  object 
 19  FAR.Description         32023 non-null  object 
 20  Schedule                12582 non-null  object 
 21  Purpose.of.flight       82697 non-null  object 
 22  Air.carrier             16648 non-null  object 
 23  Total.Fatal.Injuries    77488 non-null  float64
 24  Total.Serious.Injuries  76379 non-null  float64
 25  Total.Minor.Injuries    76956 non-null  float64
 26  Total.Uninjured         82977 non-null  float64
 27  Weather.Condition       84397 non-null  object 
 28  Broad.phase.of.flight   61724 non-null  object 
 29  Report.Status           82505 non-null  object 
 30  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

```
# creating a copy of my original data so as not to bring any modification
df1 = df.copy()
```

HANDLING MISSING VALUES

```
# dropping columns that have a lot of missing values
df1.drop(columns=['Latitude'], inplace=True)
df1.drop(columns=['Longitude'],inplace=True)
df1.drop(columns=['Airport.Code'],inplace=True)
df1.drop(columns=['Airport.Name'],inplace=True)
df1.drop(columns=['Aircraft.Category'],inplace=True)
df1.drop(columns=['FAR.Description'],inplace=True)
df1.drop(columns=['Schedule'],inplace=True)
df1.drop(columns=['Air.carrier'],inplace=True)
```

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 23 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   Event.Id                88889 non-null  object 
 1   Investigation.Type      88889 non-null  object 
 2   Accident.Number         88889 non-null  object 
 3   Event.Date              88889 non-null  object 
 4   Location                88837 non-null  object 
 5   Country                 88663 non-null  object 
 6   Injury.Severity         87889 non-null  object 
 7   Aircraft.damage         85695 non-null  object 
 8   Registration.Number     87507 non-null  object 
 9   Make                    88826 non-null  object 
 10  Model                   88797 non-null  object 
 11  Amateur.Built           88787 non-null  object 
 12  Number.of.Engines       82805 non-null  float64
 13  Engine.Type             81793 non-null  object 
 14  Purpose.of.flight       82697 non-null  object 
 15  Total.Fatal.Injuries    77488 non-null  float64
 16  Total.Serious.Injuries  76379 non-null  float64
 17  Total.Minor.Injuries    76956 non-null  float64
 18  Total.Uninjured         82977 non-null  float64
 19  Weather.Condition       84397 non-null  object 
 20  Broad.phase.of.flight   61724 non-null  object 
 21  Report.Status           82505 non-null  object 
 22  Publication.Date        75118 non-null  object 
dtypes: float64(5), object(18)
memory usage: 15.6+ MB
```

```
# checking the number of missing value
df1.isnull().sum()
```

	0
Event.Id	0
Investigation.Type	0
Accident.Number	0
Event.Date	0
Location	52
Country	226
Injury.Severity	1000
Aircraft.damage	3194
Registration.Number	1382
Make	63
Model	92
Amateur.Built	102
Number.of.Engines	6084
Engine.Type	7096
Purpose.of.flight	6192
Total.Fatal.Injuries	11401
Total.Serious.Injuries	12510
Total.Minor.Injuries	11933
Total.Uninjured	5912
Weather.Condition	4492
Broad.phase.of.flight	27165
Report.Status	6384
Publication.Date	13771

dtype: int64

DATA CLEANING

```
# further columns removal
columns_name = ['Publication.Date','Broad.phase.of.flight','Engine.Type']
df1.drop(columns=columns_name,inplace=True)
```

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88889 non-null  object
 2   Accident.Number         88889 non-null  object
 3   Event.Date              88889 non-null  object
 4   Location                88837 non-null  object
 5   Country                 88663 non-null  object
 6   Injury.Severity         87889 non-null  object
 7   Aircraft.damage         85695 non-null  object
 8   Registration.Number     87507 non-null  object
 9   Make                    88826 non-null  object
 10  Model                   88797 non-null  object
 11  Amateur.Built           88787 non-null  object
 12  Number.of.Engines       82805 non-null  float64
 13  Purpose.of.flight       82697 non-null  object
 14  Total.Fatal.Injuries    77488 non-null  float64
 15  Total.Serious.Injuries  76379 non-null  float64
 16  Total.Minor.Injuries    76956 non-null  float64
```

```
 17  Total.Uninjured         82977 non-null  float64
 18  Weather.Condition       84397 non-null  object
 19  Report.Status           82505 non-null  object
dtypes: float64(5), object(15)
memory usage: 13.6+ MB
```

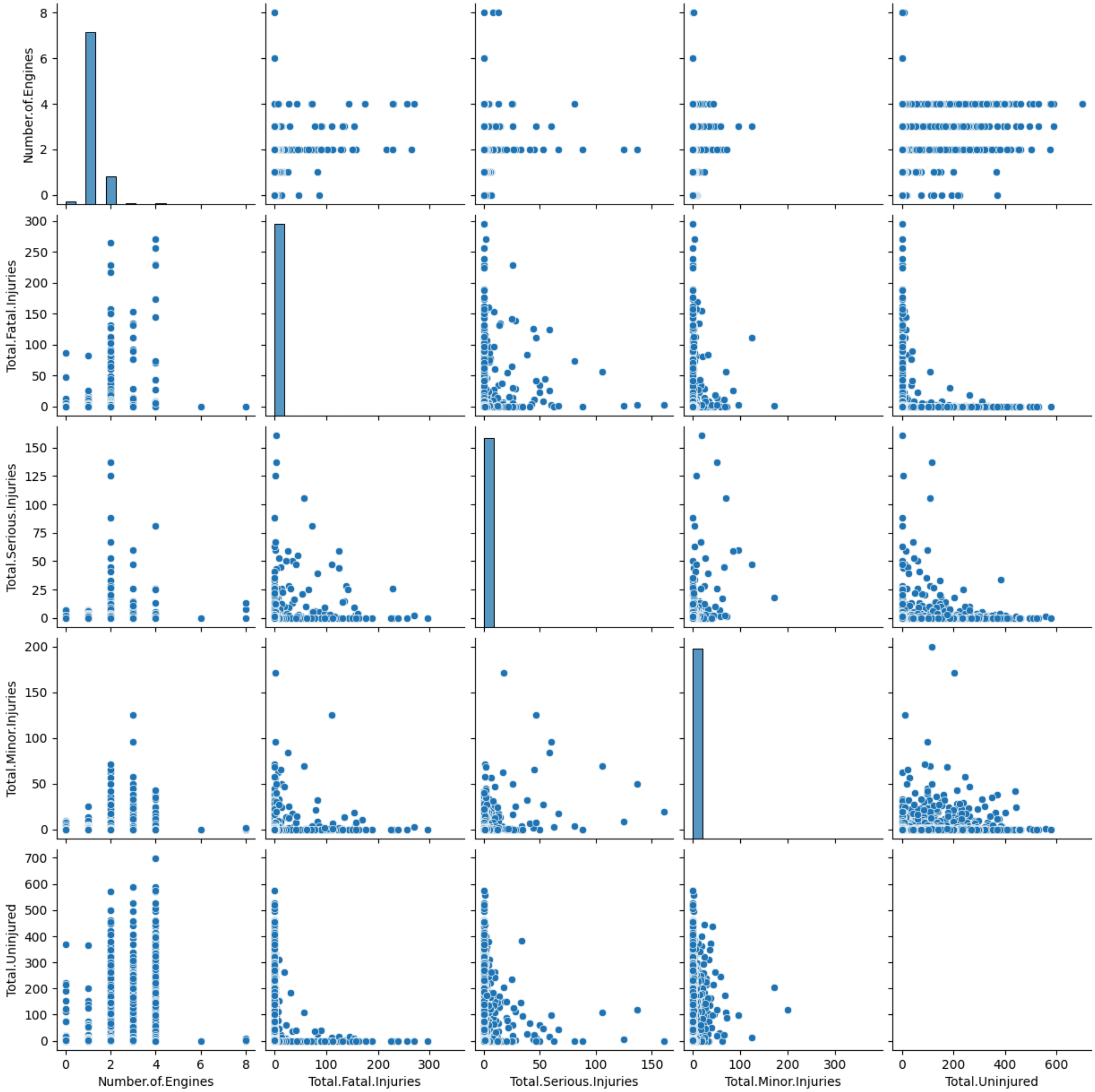
```
# creating a subset with only numerical columns
df1_num = df1.select_dtypes(include=['number'])
```

```
df1_num.corr()
```

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
Number.of.Engines	1.000000	0.098505	0.046157	0.098162	0.406058
Total.Fatal.Injuries	0.098505	1.000000	0.135724	0.073559	-0.015214
Total.Serious.Injuries	0.046157	0.135724	1.000000	0.326849	0.052869
Total.Minor.Injuries	0.098162	0.073559	0.326849	1.000000	0.147770
Total.Uninjured	0.406058	-0.015214	0.052869	0.147770	1.000000

```
# ploting the correlation between the different columns
sns.pairplot(df1_num)
```

```
<seaborn.axisgrid.PairGrid at 0x7c0889abb370>
```



From this plots i can understand that the correlation betweeen the columns is poor,so the correlation can not be used to handle missing values

```
# in order to handle the missing values, the mean,median and mode for each column is computed so as to understand the distribution of the dat

mean1=df1_num['Total.Fatal.Injuries'].mean()
median1=df1_num['Total.Fatal.Injuries'].median()
mode1=df1_num['Total.Fatal.Injuries'].mode()[0]
print(f"Mean: {mean1}, Median: {median1}, Mode: {mode1}")
```

```
Mean: 0.6478551517654346, Median: 0.0, Mode: 0.0
```

```
mean2=df1_num['Total.Serious.Injuries'].mean()
median2=df1_num['Total.Serious.Injuries'].median()
mode2=df1_num['Total.Serious.Injuries'].mode()[0]
print(f"Mean: {mean2}, Median: {median2}, Mode: {mode2}")
```

```
Mean: 0.27988059545162935, Median: 0.0, Mode: 0.0
```

```
mean3=df1_num['Total.Minor.Injuries'].mean()
median3=df1_num['Total.Minor.Injuries'].median()
mode3=df1_num['Total.Minor.Injuries'].mode()[0]
print(f"Mean: {mean3}, Median: {median3}, Mode: {mode3}")
```

```
Mean: 0.3570611778158948, Median: 0.0, Mode: 0.0
```

```
mean4=df1_num['Total.Uninjured'].mean()
median4=df1_num['Total.Uninjured'].median()
mode4=df1_num['Total.Uninjured'].mode()[0]
print(f"Mean: {mean4}, Median: {median4}, Mode: {mode4}")
```

```
Mean: 5.325439579642552, Median: 1.0, Mode: 0.0
```

```
df1_num['Total.Fatal.Injuries'].fillna(median1, inplace=True)
df1_num['Total.Serious.Injuries'].fillna(median2, inplace=True)
df1_num['Total.Minor.Injuries'].fillna(median3, inplace=True)
df1_num['Total.Uninjured'].fillna(median4, inplace=True)
```

```
<ipython-input-65-ebd72580a0f4>:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignm
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting valu

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].me


  df1_num['Total.Fatal.Injuries'].fillna(median1, inplace=True)
<ipython-input-65-ebd72580a0f4>:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignm
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting valu

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].me


  df1_num['Total.Serious.Injuries'].fillna(median2, inplace=True)
<ipython-input-65-ebd72580a0f4>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignm
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting valu

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].me


  df1_num['Total.Minor.Injuries'].fillna(median3, inplace=True)
<ipython-input-65-ebd72580a0f4>:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignm
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting valu

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].me


  df1_num['Total.Uninjured'].fillna(median4, inplace=True)
```

```
df1_num.isnull().sum()
```

	0
Number.of.Engines	6084
Total.Fatal.Injuries	0
Total.Serious.Injuries	0
Total.Minor.Injuries	0
Total.Uninjured	0

dtype: int64

```
# I am returning back to the data frame the numerical columns,where the missing value has just been handled

columns_to_replace = ['Total.Fatal.Injuries', 'Total.Serious.Injuries','Total.Minor.Injuries','Total.Uninjured']
```

```
df1[columns_to_replace] = df1_num[columns_to_replace]
```

```
df1.isnull().sum()
```

	0
Event.Id	0
Investigation.Type	0
Accident.Number	0
Event.Date	0
Location	52
Country	226
Injury.Severity	1000
Aircraft.damage	3194
Registration.Number	1382
Make	63
Model	92
Amateur.Built	102
Number.of.Engines	6084
Purpose.of.flight	6192
Total.Fatal.Injuries	0
Total.Serious.Injuries	0
Total.Minor.Injuries	0
Total.Uninjured	0
Weather.Condition	4492
Report.Status	6384

dtype: int64

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88889 entries, 0 to 88888
Data columns (total 20 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      88889 non-null  object
 2   Accident.Number         88889 non-null  object
 3   Event.Date              88889 non-null  object
 4   Location                88837 non-null  object
 5   Country                 88663 non-null  object
 6   Injury.Severity         87889 non-null  object
 7   Aircraft.damage         85695 non-null  object
 8   Registration.Number     87507 non-null  object
 9   Make                    88826 non-null  object
 10  Model                   88797 non-null  object
 11  Amateur.Built           88787 non-null  object
 12  Number.of.Engines       82805 non-null  float64
 13  Purpose.of.flight       82697 non-null  object
 14  Total.Fatal.Injuries    88889 non-null  float64
 15  Total.Serious.Injuries  88889 non-null  float64
 16  Total.Minor.Injuries    88889 non-null  float64
 17  Total.Uninjured         88889 non-null  float64
 18  Weather.Condition       84397 non-null  object
 19  Report.Status           82505 non-null  object
dtypes: float64(5), object(15)
memory usage: 13.6+ MB
```

```
# Am checking missing value in the columns if they share the same row

num_nulls = df1.isnull().sum(axis=1)
rows_with_nulls = df1[num_nulls == 9].index
rows_with_nulls
```

```
df1= df1.drop(index=rows_with_nulls )
df1.isnull().sum()
```

	0
Event.Id	0
Investigation.Type	0
Accident.Number	0
Event.Date	0
Location	52
Country	226
Injury.Severity	998
Aircraft.damage	3192
Registration.Number	1380
Make	61
Model	90
Amateur.Built	102
Number.of.Engines	6082
Purpose.of.flight	6190
Total.Fatal.Injuries	0
Total.Serious.Injuries	0
Total.Minor.Injuries	0
Total.Uninjured	0
Weather.Condition	4490
Report.Status	6382

dtype: int64

DATA HANDLING

```
# i want to convert the Event.Date to seperate columns year,month,day. So am doing this to compare it year wise,month wise and day wise

df1['Event.Date'] = pd.to_datetime(df['Event.Date'])
df1['Event.Year'] = df1['Event.Date'].dt.year
df1['Event.Month'] = df1['Event.Date'].dt.month
df1['Event.Day'] = df1['Event.Date'].dt.day


# I want to change the Injury.Severity column. When the value is fetal,the number of people injured is written with it so am going to sepera

df1['num_injured'] = df1['Injury.Severity'].str.extract(r'\((\d+)\)').astype(float)
df1['Injury.Severity'] = df1['Injury.Severity'].str.replace(r'\(\d+\)', '', regex=True).str.strip()
df1['Injury.Severity'].unique()
```

```
array(['Fatal', 'Non-Fatal', 'Incident', 'Unavailable', nan, 'Minor',
       'Serious'], dtype=object)
```

```
# So i decided to change the 'Serious' injuries to Fatal while the 'Minor' and 'Incident' to NOn-Fetal. Incident was considered as minor bec
# The purpuse of this is to reduce the categories.

df1['Injury.Severity'] = df1['Injury.Severity'].replace({
    'Serious': 'Fatal',
    'Incident': 'Non-Fatal',
    'Minor': 'Non-Fatal',
    'Unavailable': np.nan
})
df1['Injury.Severity'].unique()
```

```
array(['Fatal', 'Non-Fatal', nan], dtype=object)
```

```
df1['Aircraft.damage'].unique()
```

```
array(['Destroyed', 'Substantial', 'Minor', nan, 'Unknown'], dtype=object)
```

```
# I am going to consider the Substaintial and Minor as Non destroyed,Unknown is going to be considered as nan.

df1["Aircraft.damage"] = df1["Aircraft.damage"].replace({
    'Minor': 'Non-Destroyed',
    'Substantial': 'Non-Destroyed',
    'Unknown': np.nan
})
df1['Aircraft.damage'].unique()
```

```
array(['Destroyed', 'Non-Destroyed', nan], dtype=object)
```

```
df1['Purpose.of.flight'].unique()
```

```
array(['Personal', nan, 'Business', 'Instructional', 'Unknown', 'Ferry',
       'Executive/corporate', 'Aerial Observation', 'Aerial Application',
       'Public Aircraft', 'Skydiving', 'Other Work Use', 'Positioning',
       'Flight Test', 'Air Race/show', 'Air Drop',
       'Public Aircraft - Federal', 'Glider Tow',
       'Public Aircraft - Local', 'External Load',
       'Public Aircraft - State', 'Banner Tow', 'Firefighting',
       'Air Race show', 'PUBS', 'ASHO', 'PUBL'], dtype=object)
```

```
# Since Purpose of has many categorical values, i am going to arrenge them in to 7 categories
category_mapping = {
    'Personal': 'Personal/Business',
    'Business': 'Personal/Business',
    'Executive/corporate': 'Personal/Business',
    'Other Work Use': 'Personal/Business',
    'Positioning': 'Ferry/Positioning',
    'Instructional': 'Flight Training/Testing',
    'Flight Test': 'Flight Training/Testing',
    'Unknown': np.nan,
    'Ferry': 'Ferry/Positioning',
    'Aerial Observation': 'Aerial Work',
    'Aerial Application': 'Aerial Work',
    'Public Aircraft': 'Public Aircraft',
    'Skydiving': 'Recreational/Sport',
    'Air Race/show': 'Recreational/Sport',
    'Air Race show': 'Recreational/Sport',
    'Air Drop': 'Aerial Work',
    'Public Aircraft - Federal': 'Public Aircraft',
    'Glider Tow': 'Aerial Work',
    'Public Aircraft - Local': 'Public Aircraft',
    'External Load': 'Aerial Work',
    'Public Aircraft - State': 'Public Aircraft',
    'Banner Tow': 'Aerial Work',
    'Firefighting': 'Aerial Work',
    'ASHO': 'Recreational/Sport',
    'PUBS': 'Public Aircraft',
    'PUBL': 'Public Aircraft'
}
df1['Purpose.of.flight'] = df1['Purpose.of.flight'].replace(category_mapping)
df1['Purpose.of.flight'].unique()
```

```
array(['Personal/Business', nan, 'Flight Training/Testing',
       'Ferry/Positioning', 'Aerial Work', 'Public Aircraft',
       'Recreational/Sport'], dtype=object)
```

```
df1['Weather.Condition'].unique()
```

```
array(['UNK', 'IMC', 'VMC', nan, 'Unk'], dtype=object)
```

```
# Am changing the UNK value in nan in Weather Condition column

df1['Weather.Condition'] = df1['Weather.Condition'].replace({
    'Unk': np.nan,
    'UNK': np.nan ,
    'Unavailable': np.nan
})
df1['Weather.Condition'].unique()
```

```
array([nan, 'IMC', 'VMC'], dtype=object)
```

```
# The Report.status column is removed because it has entry that has long sentances.

df1.drop(['Report.Status'],axis=1 ,inplace=True)
```

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 88887 entries, 0 to 88888
Data columns (total 23 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88887 non-null  object
 1   Investigation.Type      88887 non-null  object
 2   Accident.Number         88887 non-null  object
 3   Event.Date              88887 non-null  datetime64[ns]
 4   Location                88835 non-null  object
 5   Country                 88661 non-null  object
 6   Injury.Severity         87793 non-null  object
 7   Aircraft.damage         85576 non-null  object
 8   Registration.Number     87507 non-null  object
 9   Make                    88826 non-null  object
 10  Model                   88797 non-null  object
 11  Amateur.Built           88785 non-null  object
 12  Number.of.Engines       82805 non-null  float64
 13  Purpose.of.flight       75895 non-null  object
 14  Total.Fatal.Injuries    88887 non-null  float64
 15  Total.Serious.Injuries  88887 non-null  float64
 16  Total.Minor.Injuries    88887 non-null  float64
 17  Total.Uninjured         88887 non-null  float64
 18  Weather.Condition       83279 non-null  object
 19  Event.Year              88887 non-null  int32
 20  Event.Month             88887 non-null  int32
 21  Event.Day               88887 non-null  int32
 22  num_injured             12564 non-null  float64
dtypes: datetime64[ns](1), float64(6), int32(3), object(13)
memory usage: 15.3+ MB
```

```
# i am filling all the nan values with UNK
df1.fillna("UNK", inplace=True)
```

```
<ipython-input-82-6806396425f5>:2: FutureWarning: Setting an item of incompatible dtype is deprecated and will raise an error in a futur
  df1.fillna("UNK", inplace=True)
```

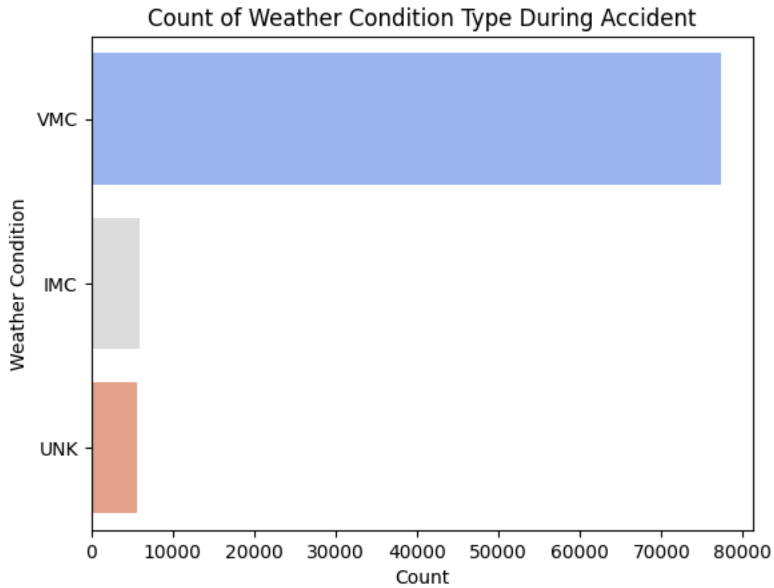
```
df1.drop(['num_injured'],axis=1, inplace=True)
```

```
# The value for location is seperated into city and state

df1['City'] = df['Location'].str.split(',').str[0]
df1['State'] = df['Location'].str.split(',').str[1]
```

DATA VISUALIZATION

```
#In this code i am trying to understand what is the weather like during accidents
weather_condition_counts = df1['Weather.Condition'].value_counts()
sns.barplot(
    x=weather_condition_counts.values,
    y=weather_condition_counts.index,
    palette="coolwarm",
    hue=weather_condition_counts.index,
    dodge=False,
    legend=False
)
plt.xlabel('Count')
plt.ylabel('Weather Condition')
plt.title('Count of Weather Condition Type During Accident')
plt.show()
```



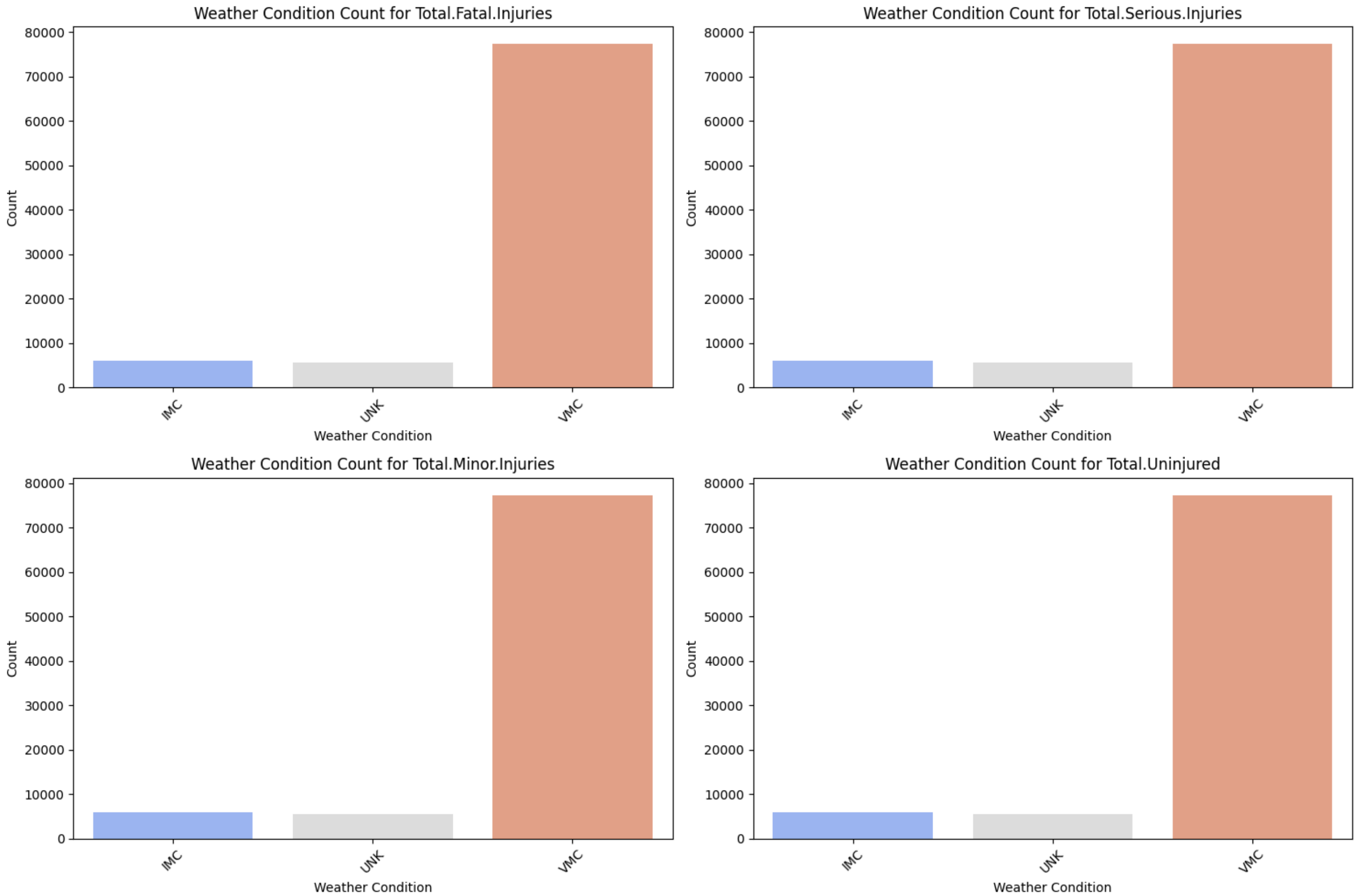
conclusion:i observed that most of the accident occur when the weather condition is VMC meaning the visibility is good.

```
# in this plot i will count the type of weather condition for each type of injury so as to understand what kind of weather prevails for diff

injury_columns = ['Total.Fatal.Injuries', 'Total.Serious.Injuries', 'Total.Minor.Injuries', 'Total.Uninjured']
fig, axes = plt.subplots(2, 2, figsize=(15, 10))

for i, column in enumerate(injury_columns):
    injury_counts_by_weather = df1.groupby('Weather.Condition')[column].count()
    sns.barplot(
        x=injury_counts_by_weather.index,
        y=injury_counts_by_weather.values,
        ax=axes[i // 2, i % 2],
        palette="coolwarm",
        hue=injury_counts_by_weather.index,
        legend=False
    )
    axes[i // 2, i % 2].set_title(f'Weather Condition Count for {column}')
    axes[i // 2, i % 2].set_xlabel('Weather Condition')
    axes[i // 2, i % 2].set_ylabel('Count')
    axes[i // 2, i % 2].tick_params(axis='x', rotation=45)

plt.tight_layout()
plt.show()
```



conclusion: it can be seen that for all the injury the weather condition is VMC

```
df1['Weather.Condition'].unique()
```

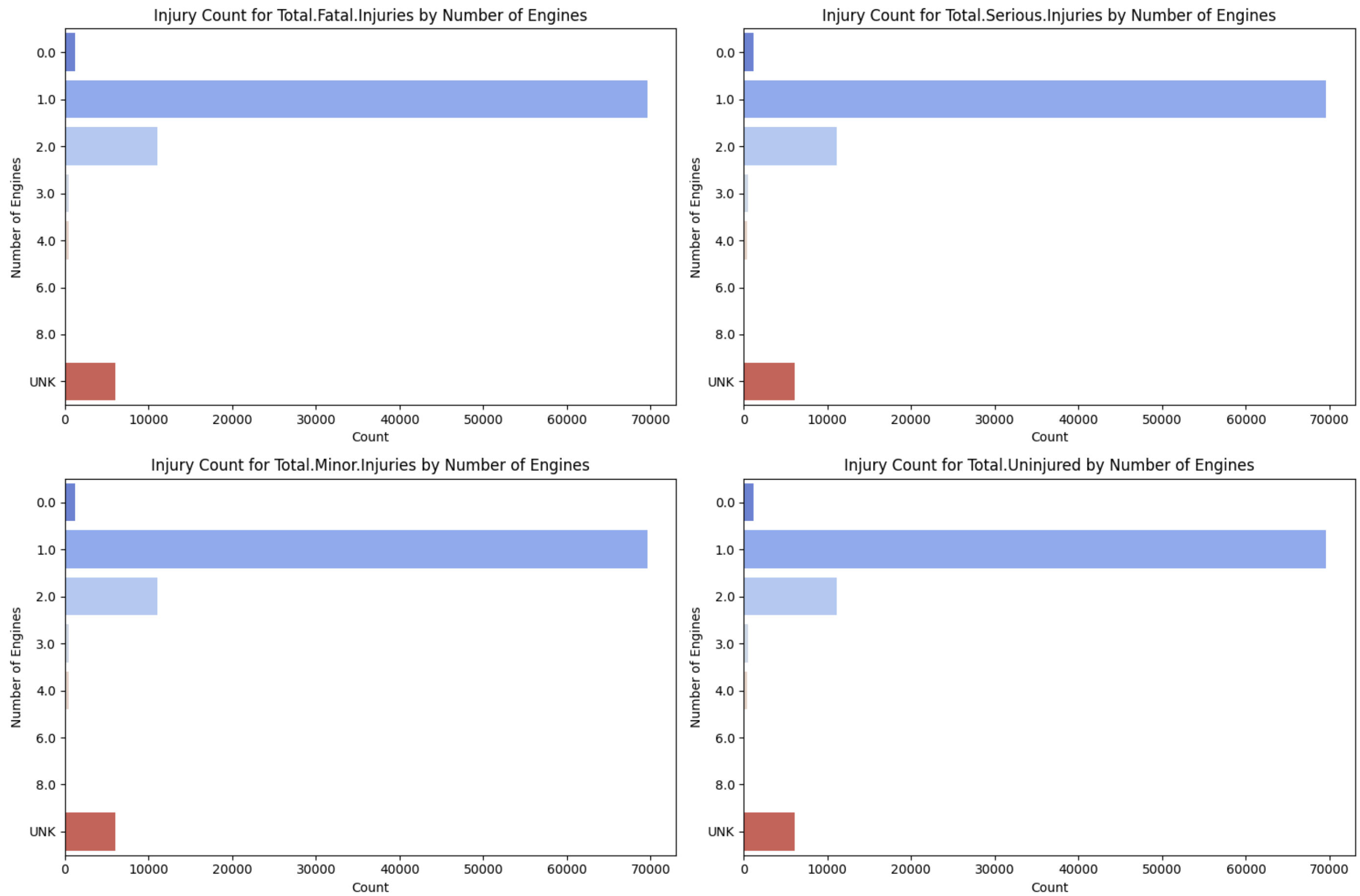
```
array(['UNK', 'IMC', 'VMC'], dtype=object)
```

```
#i want to see the relationship of engine type with the injury type, so as to understand which engine type result in major

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

for i, column in enumerate(injury_columns):
    injury_counts_by_engines = df1.groupby('Number.of.Engines')[column].count()
    sns.barplot(
        x=injury_counts_by_engines.values,
        y=injury_counts_by_engines.index,
        ax=axes[i // 2, i % 2],
        palette="coolwarm",
        hue=injury_counts_by_engines.index,
        legend=False
    )
    axes[i // 2, i % 2].set_title(f'Injury Count for {column} by Number of Engines')
    axes[i // 2, i % 2].set_xlabel('Count')
    axes[i // 2, i % 2].set_ylabel('Number of Engines')
    axes[i // 2, i % 2].tick_params(axis='y', rotation=0)

plt.tight_layout()
plt.show()
```



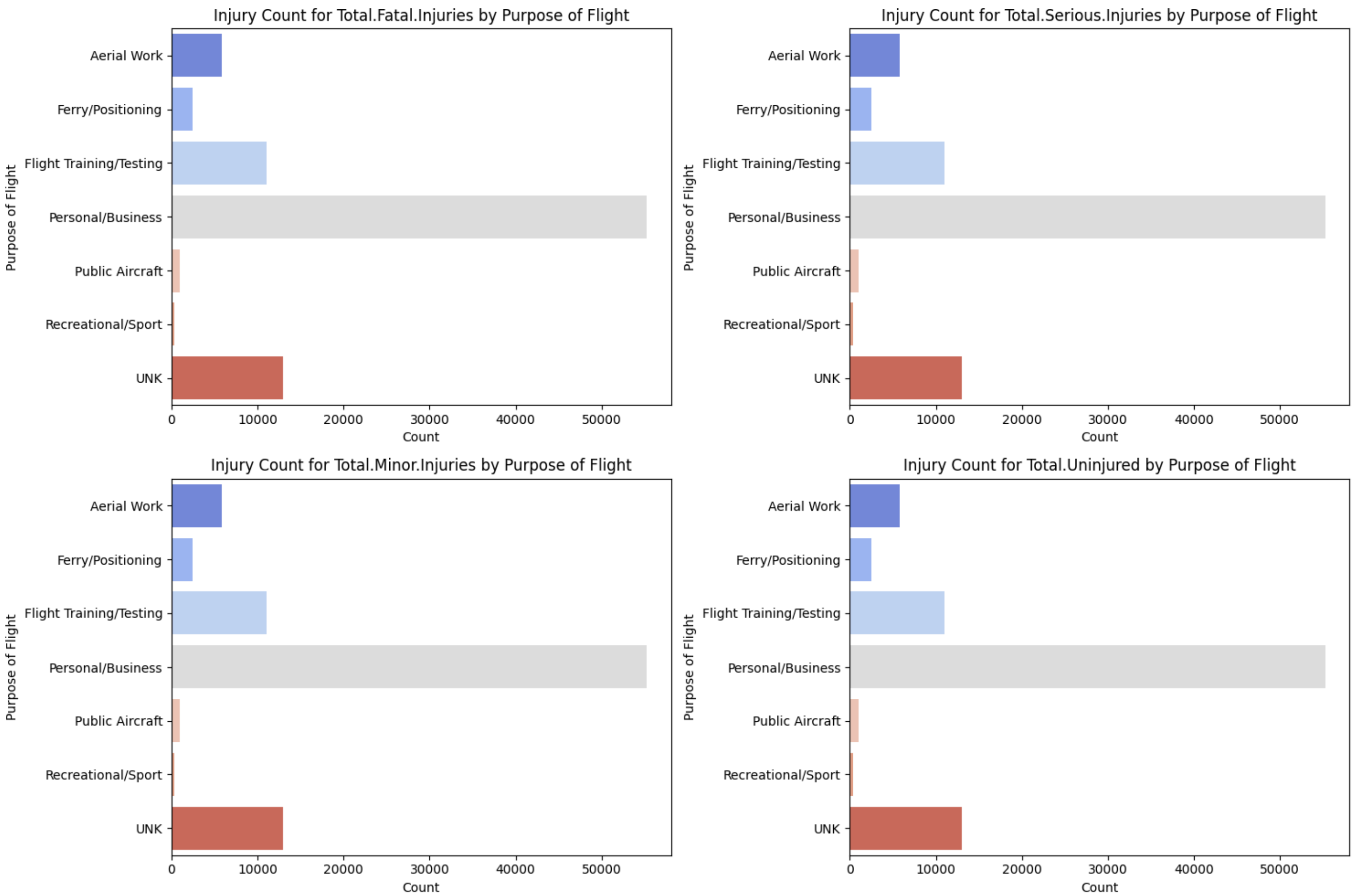
conclusion:engine 1 has the highest number of accidents for the different injuries.

```
#i want to see the relation between type ofinjury and the purpose of flight, to see in what kind of purposes the accident is fatal and in whi

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

for i, column in enumerate(injury_columns):
    injury_counts_by_purpose = df1.groupby('Purpose.of.flight')[column].count()
    sns.barplot(
        x=injury_counts_by_purpose.values,
        y=injury_counts_by_purpose.index,
        ax=axes[i // 2, i % 2],
        palette="coolwarm",
        hue=injury_counts_by_purpose.index,
        legend=False
    )
    axes[i // 2, i % 2].set_title(f'Injury Count for {column} by Purpose of Flight')
    axes[i // 2, i % 2].set_xlabel('Count')
    axes[i // 2, i % 2].set_ylabel('Purpose of Flight')
    axes[i // 2, i % 2].tick_params(axis='y', rotation=0)

plt.tight_layout()
plt.show()
```



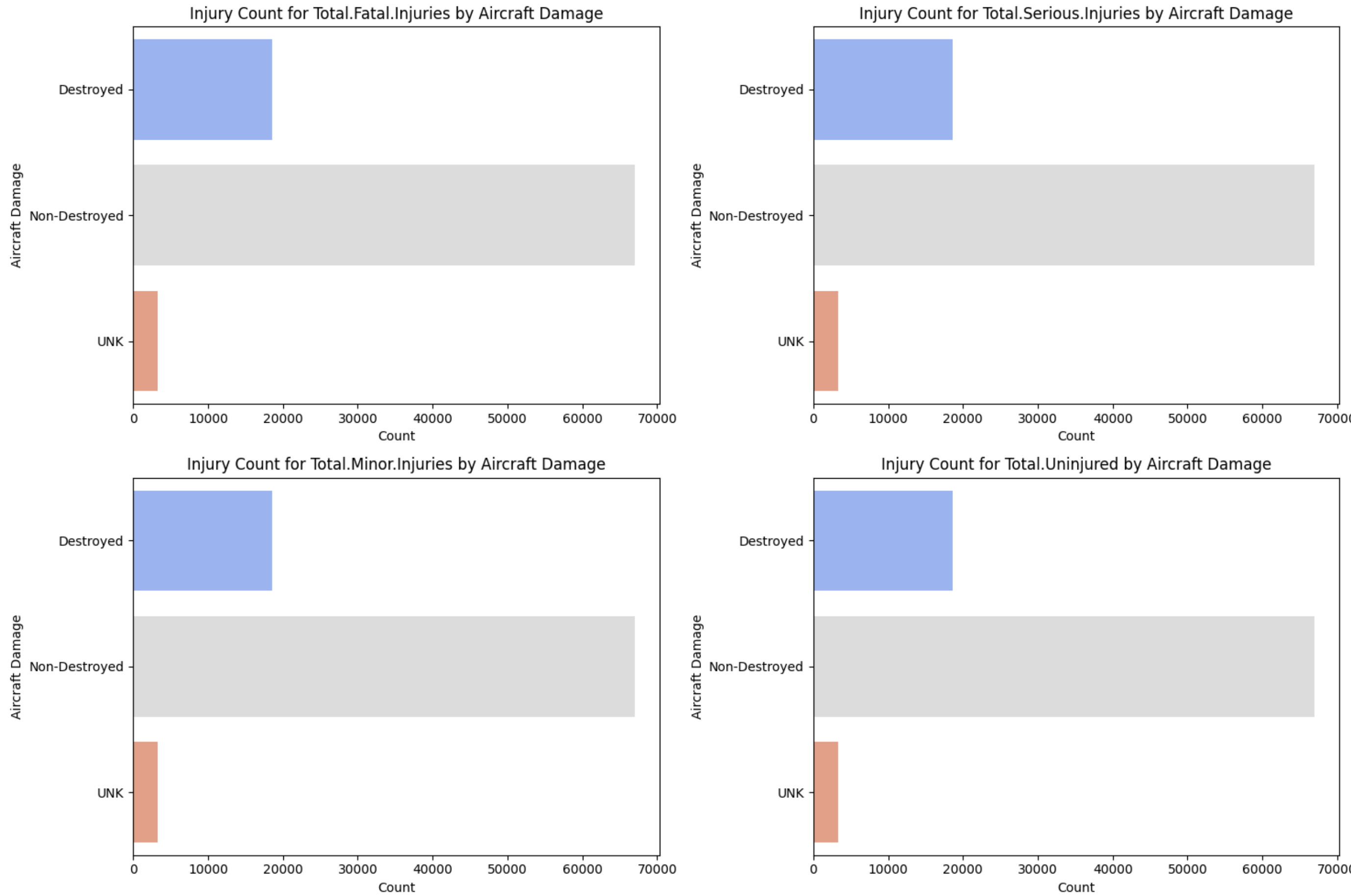
conclusion: most of the injury occur for personal or business. substatial injuries also occur for flight training or testing purpose.

```
#I want to see the relation between the injury type and the degree of damage of the aircraft, so as to see if there is a relation between fat

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

for i, column in enumerate(injury_columns):
    injury_counts_by_damage = df1.groupby('Aircraft.damage')[column].count()
    sns.barplot(
        x=injury_counts_by_damage.values,
        y=injury_counts_by_damage.index,
        ax=axes[i // 2, i % 2],
        palette="coolwarm",
        hue=injury_counts_by_damage.index,
        dodge=False,
        legend=False
    )
    axes[i // 2, i % 2].set_title(f'Injury Count for {column} by Aircraft Damage')
    axes[i // 2, i % 2].set_xlabel('Count')
    axes[i // 2, i % 2].set_ylabel('Aircraft Damage')
    axes[i // 2, i % 2].tick_params(axis='y', rotation=0)

plt.tight_layout()
plt.show()
```



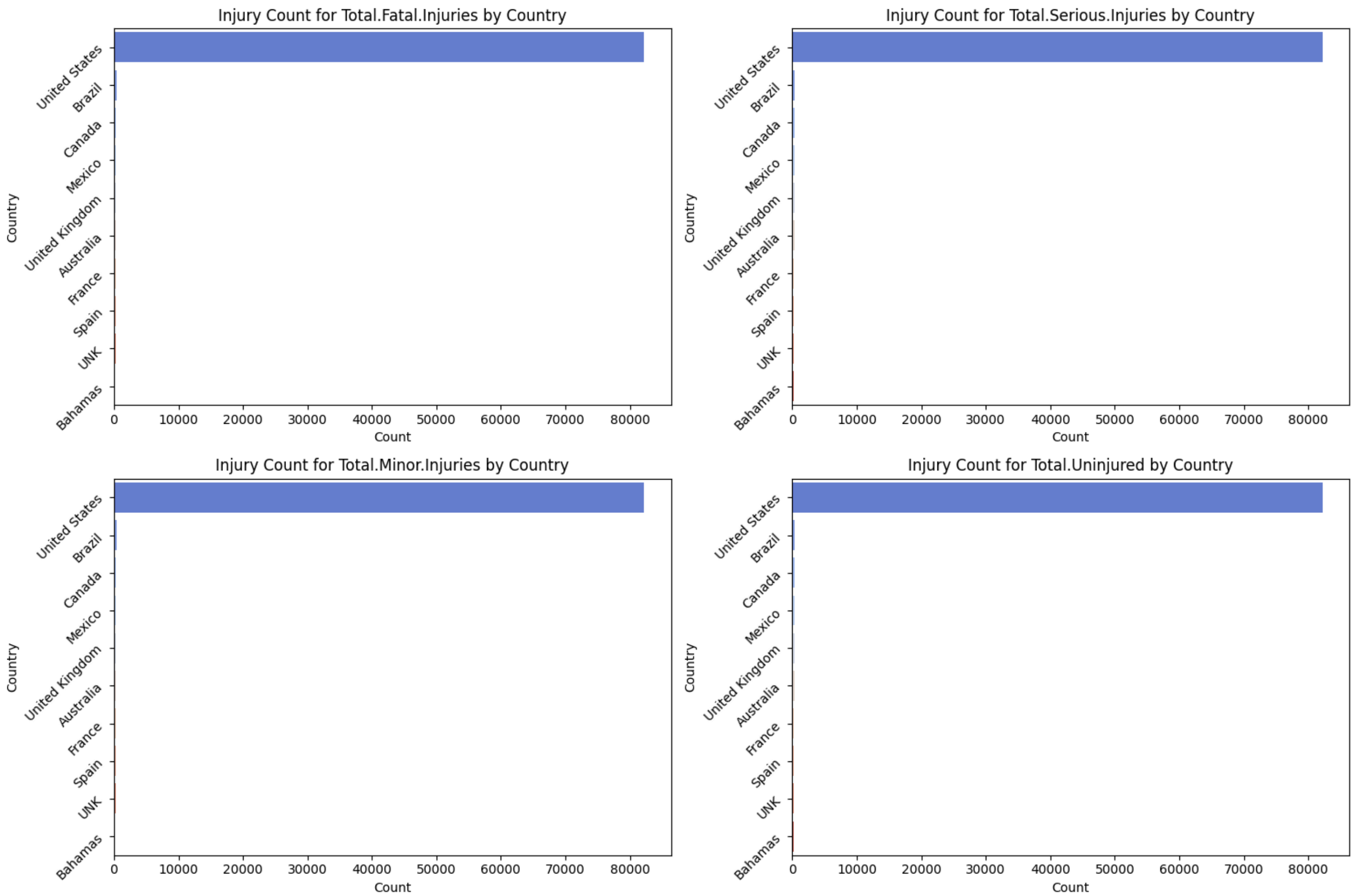
conclusion: most of the aircraft were not destroyed in relation to the different injury that occured.

```
# i want to see the relationship between top 10 country and type of injury, so as to understand which country has highest number of differen

fig, axes = plt.subplots(2, 2, figsize=(15, 10))

for i, column in enumerate(injury_columns):
    injury_counts_by_country = df1.groupby('Country')[column].count()
    top_countries = injury_counts_by_country.nlargest(10)
    sns.barplot(
        x=top_countries.values,
        y=top_countries.index,
        ax=axes[i // 2, i % 2],
        palette="coolwarm",
        hue=top_countries.index,
        dodge=False,
        legend=False
    )
    axes[i // 2, i % 2].set_title(f'Injury Count for {column} by Country')
    axes[i // 2, i % 2].set_xlabel('Count')
    axes[i // 2, i % 2].set_ylabel('Country')
    axes[i // 2, i % 2].tick_params(axis='y', rotation=45)

plt.tight_layout()
plt.show()
```

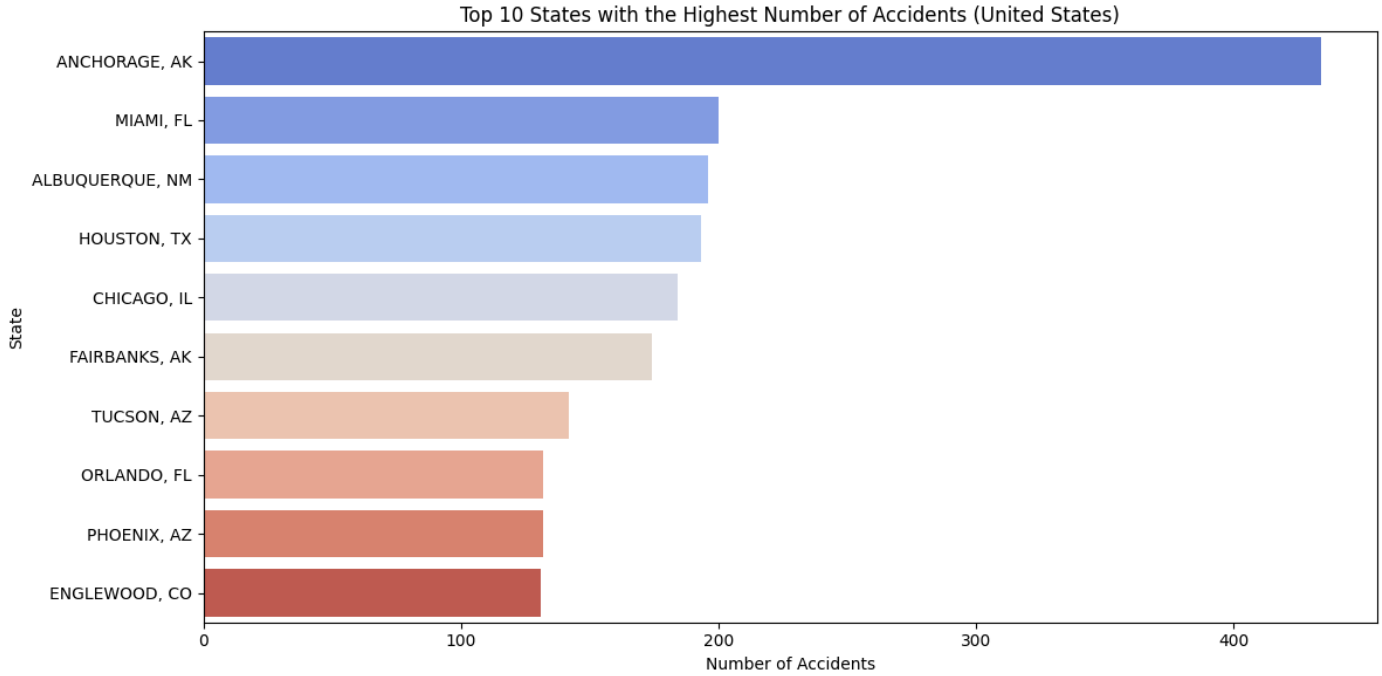


conclusion: it can be seen that USA has the highest count in number of accidents for different injury types.

```
# i want to see the number of accidents for different states in the USA since the country has the highest accidents
usa_accidents = df1[df1['Country'] == 'United States']
accidents_by_state = usa_accidents.groupby('Location').size().nlargest(10)

plt.figure(figsize=(12, 6))
sns.barplot(x=accidents_by_state.values, y=accidents_by_state.index, palette="coolwarm", hue=accidents_by_state.index)

plt.xlabel('Number of Accidents')
plt.ylabel('State')
plt.title('Top 10 States with the Highest Number of Accidents (United States)')
plt.tight_layout()
plt.show()
```



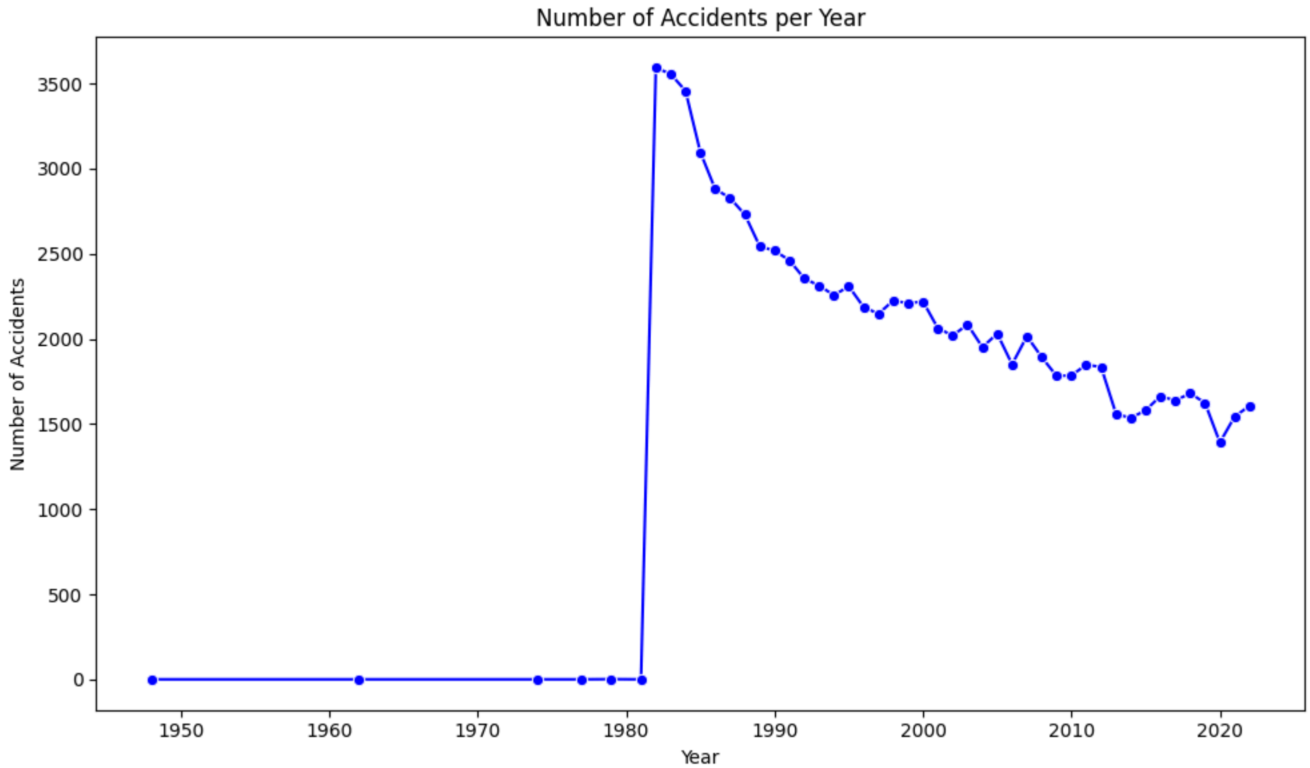
conclusion: Anchorage state has the highest accidents

```
# i want to see the number of accident per year so as to know which years have high value
accidents_per_year = df1.groupby('Event.Year').size()

plt.figure(figsize=(10, 6))
sns.lineplot(x=accidents_per_year.index, y=accidents_per_year.values, marker='o', color='b')

plt.xlabel('Year')
plt.ylabel('Number of Accidents')
plt.title('Number of Accidents per Year')

plt.tight_layout()
plt.show()
```

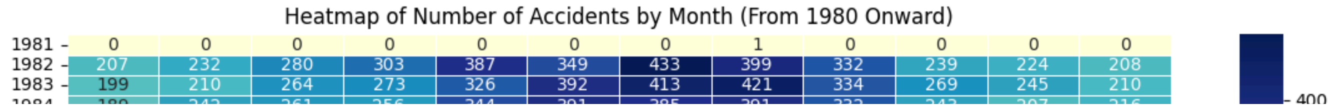


conclusion: there are a lot of accidents after 1980

```
#To visualize the number of accidents by month from the year 1980 onward, to know which month have high accidents
df_filtered = df1[df1['Event.Year'] >= 1980]
accidents_by_month = df_filtered.groupby(['Event.Year', 'Event.Month']).size().unstack(fill_value=0)

plt.figure(figsize=(12, 8))
sns.heatmap(accidents_by_month, cmap='YlGnBu', annot=True, fmt='d', cbar_kws={'label': 'Number of Accidents'}, linewidths=0.5)

plt.xlabel('Month')
plt.ylabel('Year')
plt.title('Heatmap of Number of Accidents by Month (From 1980 Onward)')
plt.xticks(ticks=range(12), labels=['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], rotation=45)
plt.tight_layout()
plt.show()
```


Heatmap of Number of Accidents by Month (From 1980 Onward)
1981
0 0 0 0 0 0 0 1 0 0 0 0
1982
207 232 280 303 387 349 433 399 332 239 224 208
1983
199 210 264 273 326 392 413 421 334 269 245 210
400