

Aircraft Risk Analysis for Portfolio Diversification

Project Goals

This project aims to Identify the safest, lowest-risk aircraft for commercial and private operations to minimize financial and operational risks.

Data Sources

the dataset is from the National Transportation Safety Board that includes aviation accident data from 1962 to 2023 about civil aviation accidents and selected incidents in the United States and international waters.

Business Understanding

Key Questions:

- Which aircraft models have the lowest accident rates?
- What are the common causes of accidents for high-risk aircraft?
- How does aircraft age, manufacturer, and operational use affect safety?
- Which aircraft offer the best cost-safety tradeoff?

1. Importation of necessary libraries

```
In [80]: import pandas as pd  
import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [81]: # open the csv file  
df= pd.read_csv('AviationData.csv', encoding='latin' , low_memory=False , heade
```

```
In [82]: df.head()
```

Out[82]:

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

5 rows × 31 columns

In [83]:

```
# Afficher les 10 premières lignes
df.head(5)

# Afficher 10 lignes aléatoires
#df.sample(10)

# Afficher les 10 dernières lignes
#df.tail(10)
```

Out[83]:

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

5 rows × 31 columns

Exploration of the dataset

In [85]:

```
#See ALL the Columns
df.shape
```

Out[85]: (88889, 31)

In [86]:

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

```
Out[86]: 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
dtype: int64
```

```
In [87]: df= df[['Event.Id','Event.Date','Injury.Severity',
                'Make','Model','Number.of.Engines','Engine.Type','Purpose.of.flight',
                'Total.Fatal.Injuries','Total.Serious.Injuries','Total.Minor.Injuries'],
```

```
In [88]: # Check the Nan Value of the dataset
df.isna().sum()
df
```

Out[88]:

	Event.Id	Event.Date	Injury.Severity	Make	Model	Number.of.Engi
0	20001218X45444	1948-10-24	Fatal(2)	Stinson	108-3	
1	20001218X45447	1962-07-19	Fatal(4)	Piper	PA24-180	
2	20061025X01555	1974-08-30	Fatal(3)	Cessna	172M	
3	20001218X45448	1977-06-19	Fatal(2)	Rockwell	112	
4	20041105X01764	1979-08-02	Fatal(1)	Cessna	501	↑
...	
88884	20221227106491	2022-12-26	Minor	PIPER	PA-28-151	↑
88885	20221227106494	2022-12-26	NaN	BELLANCA	7ECA	↑
88886	20221227106497	2022-12-26	Non-Fatal	AMERICAN CHAMPION AIRCRAFT	8GCBC	
88887	20221227106498	2022-12-26	NaN	CESSNA	210N	↑
88888	20221230106513	2022-12-29	Minor	PIPER	PA-24-260	↑

88889 rows × 14 columns



Eploration of Columns unique values.

```
In [90]: #df['Aircraft.Category'].unique()
#df['Weather.Condition'].unique()

#df['Aircraft.damage'].unique()
#df['Injury.Severity'].unique()
#df['Amateur.Built'].unique()
#df['Engine.Type'].unique()
#df['Aircraft.Category'].unique()
#df['Purpose.of.flight'].unique()
#df['Weather.Condition'].unique()
#df['Broad.phase.of.flight'].unique()
#df['Engine.Type'].unique()
#df['Make'].unique()
```

Data Cleaning

Dealing with rows with unimportant charecters

```
In [93]: # In that columns rows with values (fatal (x) should change into fatal
df['Injury.Severity'] = df['Injury.Severity'].str.replace(r"\(.*\)", "", regex=True)
df['Injury.Severity'].unique()
# In that columns rows with values (UNK is equal to Unk ) should change into Unk
df['Weather.Condition'] = df['Weather.Condition'].str.replace(r"Unk", "UNK", regex=True)
df['Weather.Condition'].unique()

#Rewrite all The Cuntry name in Sentences
df.loc[:, 'Make'] = df['Make'].str.title()

#Rewrite all The Make and Model in Sentences
df['Make'] = df['Make'].str.upper().str.strip()
df['Model'] = df['Model'].str.upper().str.strip()
```

Drop Unecessary columns

```
In [95]: #df=df.drop(['Registration.Number'], axis=1)
df=df.dropna(subset=['Location'])

# Drop columns with excessive missingness (>50%)
##df = df.dropna(thresh=len(df)*0.5, axis=1)
#drop_cols = [
##    'Registration.Number',
#    'Airport.Code', 'Airport.Name'
#]

#df = df.drop(columns=drop_cols)
```

```
In [96]: df.shape
```

```
Out[96]: (88889, 14)
```

Data Imputation

Filling in missing or incomplete values in a dataset. It's a crucial step before analysis, especially when working with real-world data like aircraft specs or incident reports, which often have missing entries.

```
In [98]: #df['Aircraft.damage'].fillna('Unknown', inplace=True)
df['Engine.Type'].fillna('Unknown', inplace=True)
df['Total.Fatal.Injuries'].fillna(0, inplace=True)
df['Total.Serious.Injuries'].fillna(0, inplace=True)
df['Total.Minor.Injuries'].fillna(0, inplace=True)
df['Total.Uninjured'].fillna(0, inplace=True)
df['Broad.phase.of.flight'].fillna('Unknown', inplace=True)
```

```
In [ ]:
```

```
In [99]: df=df.dropna(subset=['Make', 'Model', 'Injury.Severity',
                             'Number.ofEngines', 'Purpose.of.flight',
                             'Weather.Condition'
                             ])

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

```
Out[99]: Event.Id          0
Event.Date          0
Injury.Severity     0
Make                0
Model               0
Number.of.Engines   0
Engine.Type         0
Purpose.of.flight   0
Total.Fatal.Injuries 0
Total.Serious.Injuries 0
Total.Minor.Injuries 0
Total.Uninjured     0
Broad.phase.of.flight 0
Weather.Condition    0
dtype: int64
```

Print of the dataset to see how it look like after Clean it up and Impute it.

```
In [101... df.head()
```

	Event.Id	Event.Date	Injury.Severity	Make	Model	Number.of.Engines
0	20001218X45444	1948-10-24	Fatal	STINSON	108-3	1.0
1	20001218X45447	1962-07-19	Fatal	PIPER	PA24-180	1.0
2	20061025X01555	1974-08-30	Fatal	CESSNA	172M	1.0
3	20001218X45448	1977-06-19	Fatal	ROCKWELL	112	1.0
6	20001218X45446	1981-08-01	Fatal	CESSNA	180	1.0

Operation sur les Date

```
In [103... # Convert to datetime
df.loc[:, 'Event.Date'] = pd.to_datetime(df['Event.Date'])

# Extract year
df.loc[:, 'Event.Year'] = df['Event.Date'].dt.year
df.loc[:, 'Event.Year'].astype(int)
df.head()
```

```
C:\Users\teach\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.p
y:1745: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
    isetter(ilocs[0], value)
C:\Users\teach\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.p
y:1596: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
    self.obj[key] = _infer_fill_value(value)
```

Out[103...

	Event.Id	Event.Date	Injury.Severity	Make	Model	Number.of.Engines
0	20001218X45444	1948-10-24	Fatal	STINSON	108-3	1.0
1	20001218X45447	1962-07-19	Fatal	PIPER	PA24-180	1.0
2	20061025X01555	1974-08-30	Fatal	CESSNA	172M	1.0
3	20001218X45448	1977-06-19	Fatal	ROCKWELL	112	1.0
6	20001218X45446	1981-08-01	Fatal	CESSNA	180	1.0

Number of Injuries

In [105...

```
df.loc[:, 'Total.injured'] = df['Total.Minor.Injuries'] + df['Total.Serious.Injur
```

```
C:\Users\teach\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.p
y:1596: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
    self.obj[key] = _infer_fill_value(value)
C:\Users\teach\anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexing.p
y:1745: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stabl
e/user_guide/indexing.html#returning-a-view-versus-a-copy
    isetter(ilocs[0], value)
```

In [106...

```
Number_of_injuries_perYear = df[['Total.Fatal.Injuries', 'Total.Serious.Injuries'
Number_of_injuries_perYear.head()
```

Out[106...

	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
Event.Year				
1948	2.0	0.0	0.0	0.0
1962	4.0	0.0	0.0	0.0
1974	3.0	0.0	0.0	0.0
1977	2.0	0.0	0.0	0.0
1981	4.0	0.0	0.0	0.0

In [107...

```
df.loc[:, 'Total.Fatal.Injuries'].astype(float)
df.loc[:, 'Total.Minor.Injuries'].astype(float)
df.loc[:, 'Total.Serious.Injuries'].astype(float)
df.loc[:, 'Total.Uninjured'].astype(float)
```

Out[107...

```
0      0.0
1      0.0
2      0.0
3      0.0
6      0.0
...
88859   1.0
88865   1.0
88873   1.0
88877   0.0
88886   1.0
Name: Total.Uninjured, Length: 78822, dtype: float64
```

Number of people involve in accident per Make

In [109...

```
Aircraft_Category_Per_Injuries= df[['Total.Fatal.Injuries','Total.Serious.Injuries','Total.Minor.Injuries','Total.Uninjured']]
Aircraft_Category_Per_Injuries.head()
```

Out[109...

	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
Make				
107.5 FLYING CORPORATION	1.0	0.0	0.0	
1200	0.0	1.0	0.0	
177MF LLC	0.0	2.0	0.0	
1ST FTR GP	1.0	0.0	0.0	
2000 MCCOY	1.0	0.0	0.0	

Number People involve accident per Year

In [111...

```
Number_People_involve_accident_per_Year= df[['Total.Fatal.Injuries','Total.Serious.Injuries','Total.Minor.Injuries','Total.Uninjured']]
Number_People_involve_accident_per_Year.head()
```


Out[111...

	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
Event.Year				
1948	2.0	0.0	0.0	0.0
1962	4.0	0.0	0.0	0.0
1974	3.0	0.0	0.0	0.0
1977	2.0	0.0	0.0	0.0
1981	4.0	0.0	0.0	0.0

mean of unjuries

In [113...

```
Aircraft_Category_Per_Injuries.mean()
```

Out[113...

```
Total.Fatal.Injuries      4.299610
Total.Serious.Injuries     2.296405
Total.Minor.Injuries       3.201087
Total.Uninjured           33.201505
dtype: float64
```

Tendency Measurement

In [115...

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

Out[115...

	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	78822.000000	78822.000000	78822.000000	78822.000000
mean	0.391439	0.209066	0.291429	3.022684
std	2.810573	0.752558	1.271269	19.389403
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	1.000000
75%	0.000000	0.000000	0.000000	2.000000
max	270.000000	81.000000	125.000000	699.000000

Number accident by Phase of flight

In [117...

```
df['Broad.phase.of.flight'].value_counts()
```

```
Out[117... Unknown      19676
Landing      14948
Takeoff      12153
Cruise       9967
Maneuvering   7995
Approach      6235
Climb         1941
Taxi          1819
Descent       1787
Go-around    1342
Standing      848
Other         111
Name: Broad.phase.of.flight, dtype: int64
```

Find the Most Common Aircraft

```
In [119... Common_Aircraft= df['Make'].value_counts()
name=Common_Aircraft.index[0]
NombreAccident=Common_Aircraft.iloc[0]
print('The most Common airplane is ' , name , ' and the of accident', NombreAccident)
```

The most Common airplane is CESSNA and the of accident 25484

Data Preparation to a csv File for analysis with other tools (powerBI)

PowerBI a tools that will help to create beautiful Dashboard for the to represent the data.
After preparing the data now it's ready for analysis.

```
In [121... df.to_csv('Aircraft.csv')
```

Number with fatal uninjured and number of injuries per Make

```
In [123... df.groupby('Make')['Total.Uninjured'].sum().sort_values(ascending=False).head(10)
```

```
Out[123... Make
BOEING      84283.0
CESSNA      32336.0
MCDONNELL DOUGLAS  29652.0
PIPER       17020.0
AIRBUS INDUSTRIE  8499.0
LOCKHEED    7905.0
DOUGLAS     7585.0
BEECH       7056.0
BELL        2512.0
AEROSPATIALE  2231.0
Name: Total.Uninjured, dtype: float64
```

Number of Uninjured by Purpose.of.flight

```
In [125... df.groupby('Purpose.of.flight')['Total.Uninjured'].sum().sort_values(ascending=False)
```

```
Out[125... Purpose.of.flight
Unknown          156843.0
Personal         50467.0
Instructional     12279.0
Business         6073.0
Aerial Application 2887.0
Positioning      2038.0
Public Aircraft  1613.0
Executive/corporate 1541.0
Other Work Use   1487.0
Aerial Observation 777.0
Ferry           604.0
Skydiving        510.0
Flight Test      448.0
Public Aircraft - Federal 262.0
Public Aircraft - Local 91.0
Public Aircraft - State 65.0
Air Race show    57.0
External Load    56.0
Banner Tow       51.0
Air Race/show    36.0
Glider Tow       31.0
Firefighting     20.0
Air Drop         10.0
PUBS             5.0
PUBL             2.0
ASHO             1.0
Name: Total.Uninjured, dtype: float64
```

Total Uninjured

```
In [127... df.groupby('Make')['Total.Uninjured'].sum().sort_values(ascending=False)
```

```
Out[127... Make
BOEING          84283.0
CESSNA          32336.0
MCDONNELL DOUGLAS 29652.0
PIPER           17020.0
AIRBUS INDUSTRIE 8499.0
...
HAPHEY BRUCE FREDERIC 0.0
HANSON ROBERT H      0.0
HANSON LONN          0.0
HANSON GERALD        0.0
107.5 FLYING CORPORATION 0.0
Name: Total.Uninjured, Length: 7176, dtype: float64
```

Calculate the total number of Injuries for each Categories

```
In [129... df['Total.Serious.Injuries'].sum()
```

```
Out[129... 16479.0
```

```
In [130... df['Total.Minor.Injuries'].sum()
```

```
Out[130... 22971.0
```

```
In [131... df['Total.Fatal.Injuries'].sum()
```

```
Out[131... 30854.0
```

Data Visualizations

```
In [133... # Line plot (assuming a time series or ordered data)

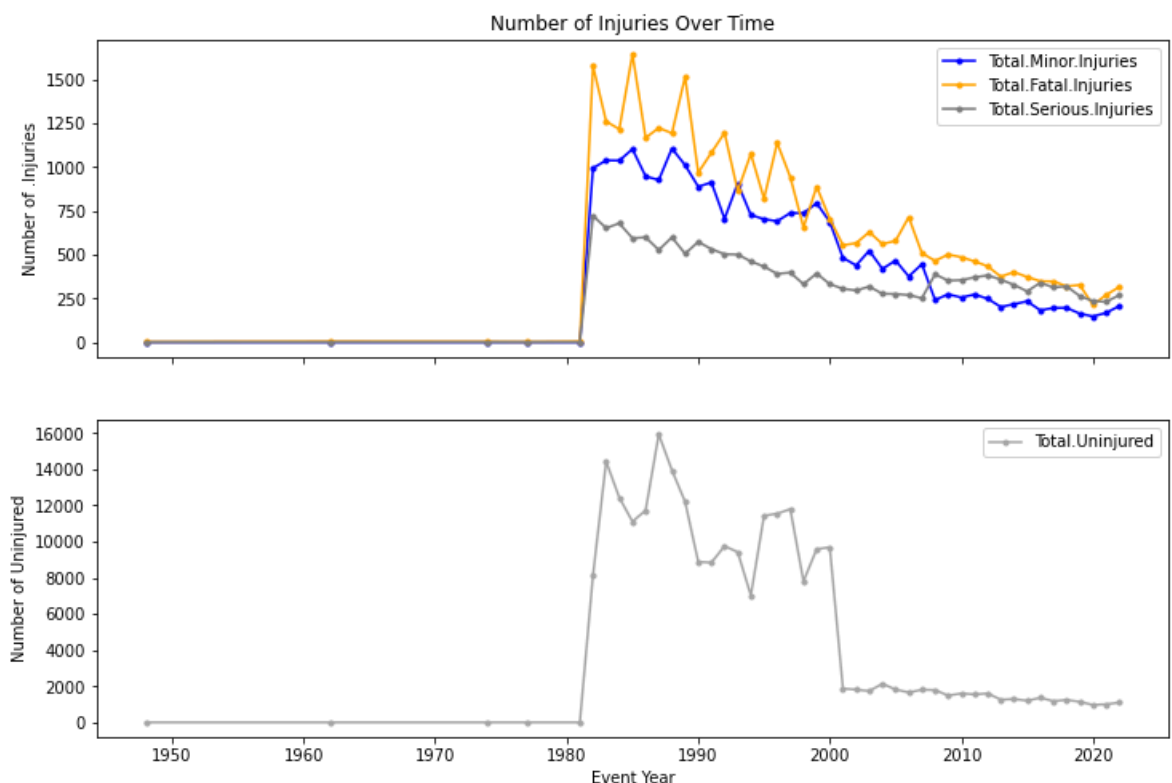
fig , (ax,ax2) = plt.subplots(2, 1, figsize=(12,8), sharex=True)
injuries_by_year = df.groupby('Event.Year')[['Total.Minor.Injuries', 'Total.Fatal.Injuries', 'Total.Serious.Injuries']]

ax.plot(injuries_by_year['Event.Year'], injuries_by_year['Total.Minor.Injuries'])
ax.plot(injuries_by_year['Event.Year'], injuries_by_year['Total.Fatal.Injuries'])
ax.plot(injuries_by_year['Event.Year'], injuries_by_year['Total.Serious.Injuries'])

ax.set_title('Number of Injuries Over Time')
ax.set_ylabel('Number of .Injuries')

ax2.plot(injuries_by_year['Event.Year'], injuries_by_year['Total.Uninjured'], marker='o')
ax2.set_ylabel('Number of Uninjured')
ax2.set_xlabel('Event Year')
ax2.legend()

ax.legend()
plt.savefig("my_plot.png")
plt.show()
```



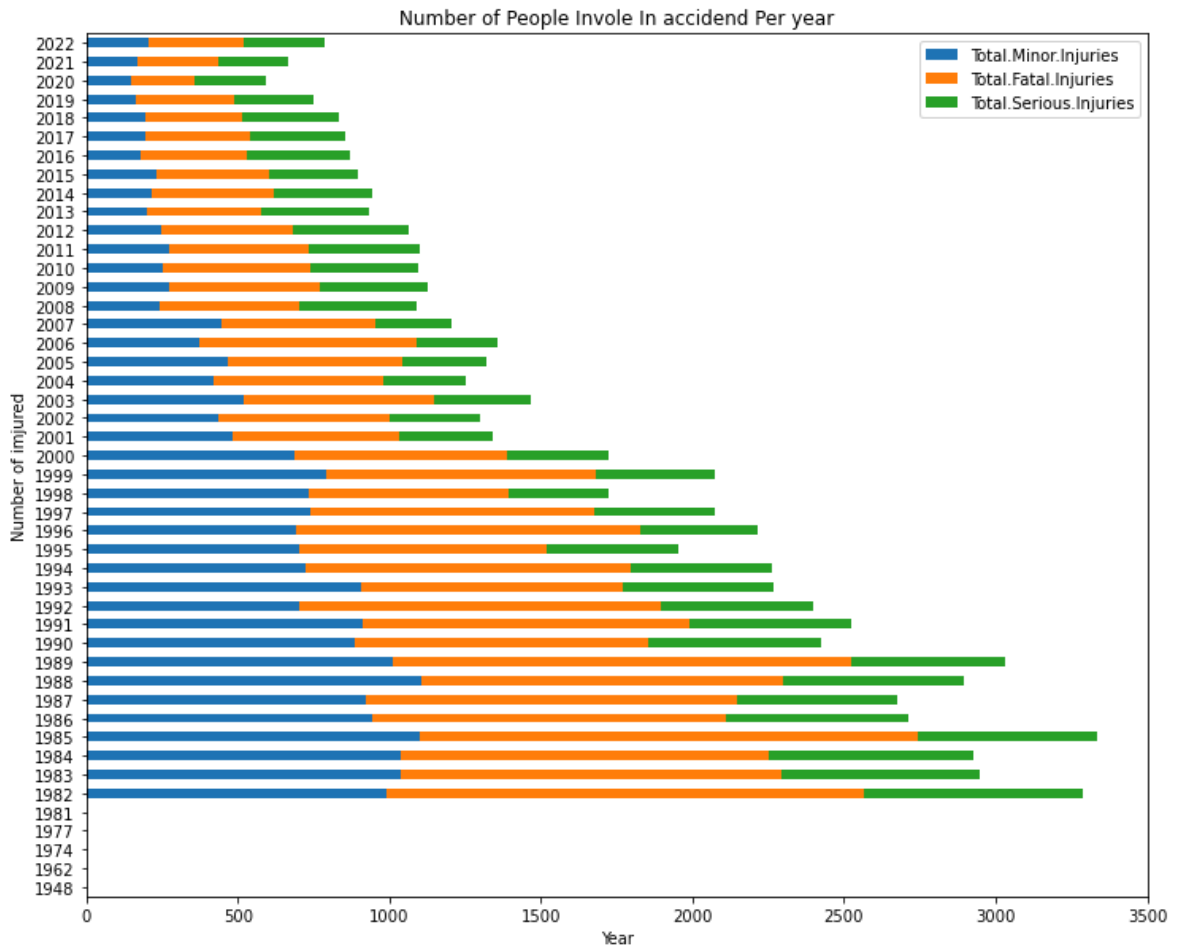
```
In [ ]:
```

```
In [134... injuries_by_year.to_csv('Total Injuries perYear.csv')
```

```
In [135... # Colonnes numériques à agréger
import matplotlib.pyplot as plt
```

```
# Créer un graphique à barres empilées
```

```
injuries_by_year[['Total.Minor.Injuries', 'Total.Fatal.Injuries', 'Total.Serious.I
plt.title('Number of People Involvement in Accident Per year')
plt.ylabel('Number of injured')
plt.xlabel('Year')
plt.show()
```



```
In [136... Summary = df.groupby(['Make'])['Total.Uninjured'].sum().sort_values(ascending=False)
Summary
```

```
Out[136... Make
BOEING 84283.0
CESSNA 32336.0
MCDONNELL DOUGLAS 29652.0
PIPER 17020.0
AIRBUS INDUSTRIE 8499.0
...
HAPHEY BRUCE FREDERIC 0.0
HANSON ROBERT H 0.0
HANSON LONN 0.0
HANSON GERALD 0.0
107.5 FLYING CORPORATION 0.0
Name: Total.Uninjured, Length: 7176, dtype: float64
```

```
In [137... Summary = df.groupby(['Model'])['Total.Uninjured'].sum().sort_values(ascending=False)
Summary
```

```
Out[137... Model
DC-10-10      6710.0
DC-10-30      4053.0
727-200       3695.0
DC-9-82       3161.0
L-1011-385-1  2775.0
...
BA 3101       0.0
S64E          0.0
S6S           0.0
S6S 2-33      0.0
RUTAN         0.0
Name: Total.Uninjured, Length: 10167, dtype: float64
```

Recommend Aircraft Models to the Company

Use a Risk Scoring System Calculation of risk score for each aircraft model based on:

Number of incidents or accidents

Event date, Make and Model

Severity of incidents

Usage type

Based on the frequency and severity of incidents, we recommend considering aircraft such as the Boeing and Cessna. which show low incident rates and minimal injury severity.

In []:

In []: