AIRCRAFT ACCIDENT ANALYSIS

AVIATION SAFETY INSIGHTS from U.S Aviation Accident Data

Author: ***Sharon Kipruto***

Introduction

Our company is expanding into the Aviation industry. For this reason they need to make good decisions on acquiring and operating airplanes for commercial and private enterprises using the recomendations given by us. As they do not know the potential risks involved in the aviation industry, we need to analyze for them the Aviation Data from U.S National Transportation Safety Board(NTSB) to give recomendations. We will do so by exploring, cleaning and studying the Data and use our findings to form actionable insights to the new Aviation department in the company. This advice should help them pick safer aircrafts that will kickstart their new business venture to success.

DATA UNDERSTANDING

This project relies from data from [Kaggle] from the US National Transportation Safety Board(NTSB) For the full context and key questions, refer to [README]

1. DATA EXPLORATION

We load the dataset to understand its structure, contents, size and summary.

In [1]:

```
#importing relevant data Science libraries

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

plt.style.available
plt.style.use('ggplot')
```

In [2]:

```
#importing data into dataframe

df=pd.read_csv('./Data/AviationData.csv' , encoding='Latin1', low_memory=False)

#display the first 5 rows
df.head()
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.C
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	N
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	N
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	N

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Co
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	N
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	N

5 rows × 31 columns

In [3]:

```
#display the last 5 rows
df.tail()
```

Out[3]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Co
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	N
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	N
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	P.
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	N
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	N

5 rows × 31 columns

In [4]:

```
#display the shape of the data to check number of rows and columns in the dataset

df.shape
```

Out[4]:

```
(88889, 31)
```

In [5]:

```
#display the available columns of the dataset
df.columns
```

Out[5]:

```
Index(['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'],
      dtype='object')
```

In [6]:

```
#checking summary 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           50249 non-null  object
 9   Airport.Name           52790 non-null  object
 10  Injury.Severity        87889 non-null  object
 11  Aircraft.damage        85695 non-null  object
 12  Aircraft.Category      32287 non-null  object
 13  Registration.Number    87572 non-null  object
 14  Make                   88826 non-null  object
 15  Model                  88797 non-null  object
 16  Amateur.Built          88787 non-null  object
 17  Number.of.Engines      82805 non-null  float64
 18  Engine.Type            81812 non-null  object
 19  FAR.Description        32023 non-null  object
 20  Schedule               12582 non-null  object
 21  Purpose.of.flight      82697 non-null  object
 22  Air.carrier            16648 non-null  object
 23  Total.Fatal.Injuries   77488 non-null  float64
 24  Total.Serious.Injuries 76379 non-null  float64
 25  Total.Minor.Injuries   76956 non-null  float64
 26  Total.Uninjured        82977 non-null  float64
 27  Weather.Condition      84397 non-null  object
 28  Broad.phase.of.flight  61724 non-null  object
 29  Report.Status          82508 non-null  object
 30  Publication.Date       75118 non-null  object
dtypes: float64(5), object(26)
memory usage: 21.0+ MB
```

In [7]:

```
#display the descriptive statististic to get the overview of the distributions and transf
orm to make it readable
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
Number.of.Engines	82805.0	1.146585	0.446510	0.0	1.0	1.0	1.0	8.0
Total.Fatal.Injuries	77488.0	0.647855	5.485960	0.0	0.0	0.0	0.0	349.0
Total.Serious.Injuries	76379.0	0.279881	1.544084	0.0	0.0	0.0	0.0	161.0
Total.Minor.Injuries	76956.0	0.357061	2.235625	0.0	0.0	0.0	0.0	380.0
Total.Uninjured	82977.0	5.325440	27.913634	0.0	0.0	1.0	2.0	699.0

In [8]:

```
#check for duplicates

duplicates=df.duplicated().sum()

print(f'The number of duplicated values is:{duplicates}')
```

```
The number of duplicated values is:0
```

In [9]:

```
#check for number of unique values in the dataset

print(f'The number of unique values in each column is:')
```

```
df.nunique()
```

The number of unique values in each column is:

Out[9]:

```
Event.Id                  87951
Investigation.Type            2
Accident.Number           88863
Event.Date                14782
Location                  27758
Country                     219
Latitude                  25589
Longitude                 27154
Airport.Code              10375
Airport.Name              24871
Injury.Severity             109
Aircraft.damage               4
Aircraft.Category            15
Registration.Number       79105
Make                       8237
Model                     12318
Amateur.Built                 2
Number.of.Engines             7
Engine.Type                  13
FAR.Description              31
Schedule                      3
Purpose.of.flight            26
Air.carrier               13590
Total.Fatal.Injuries        125
Total.Serious.Injuries       50
Total.Minor.Injuries         57
Total.Uninjured             379
Weather.Condition             4
Broad.phase.of.flight        12
Report.Status             17075
Publication.Date           2924
dtype: int64
```

In [10]:

```
#sort percentage of null values from the highest

(df.isna().sum()/len(df)*100).sort_values(ascending=False)
```

Out[10]:

```
Schedule                  85.845268
Air.carrier               81.271023
FAR.Description           63.974170
Aircraft.Category         63.677170
Longitude                 61.330423
Latitude                  61.320298
Airport.Code              43.469946
Airport.Name              40.611324
Broad.phase.of.flight     30.560587
Publication.Date          15.492356
Total.Serious.Injuries    14.073732
Total.Minor.Injuries      13.424608
Total.Fatal.Injuries      12.826109
Engine.Type                7.961615
Report.Status              7.178616
Purpose.of.flight          6.965991
Number.of.Engines          6.844491
Total.Uninjured            6.650992
Weather.Condition          5.053494
Aircraft.damage            3.593246
Registration.Number        1.481623
Injury.Severity            1.124999
Country                    0.254250
Amateur.Built              0.114750
Model                      0.103500
Make                       0.070875
```

```
Location                  0.058500
Event.Date                0.000000
Accident.Number           0.000000
Investigation.Type        0.000000
Event.Id                  0.000000
dtype: float64
```

Conclusion on the Data Exploration

The aviation dataset contains a mix of numerical and categorical data relating to the aviation accidents. The data has no duplicated values but has alot of missing values in some columns hence it will need some cleaning. The data also has inconsistent column names and some misplaced data types.

2. DATA CLEANING

In this section we will focus on cleaning the data by converting data to their correct types for consistency, cleaning the columns for readability, dealing with null values (categorical and numerical values) for reliability of the analysis.

2.1 Convert the dates to Datetime

The `event_Date` and `Publication_Date` are both stored under Object data type which is not the correct type for dates,we need to convert into proper Datetime format to enable time-based analysis.

In [11]:

```
#check how the dates were before
df.loc[:, ['Event.Date', 'Publication.Date']].head()
```

Out[11]:

	Event.Date	Publication.Date
0	1948-10-24	NaN
1	1962-07-19	19-09-1996
2	1974-08-30	26-02-2007
3	1977-06-19	12-09-2000
4	1979-08-02	16-04-1980

In [12]:

```
#convert Event.Date and publication.date to date time since they are scored as objects

df["Event.Date"] = pd.to_datetime(df["Event.Date"], errors="coerce")
df["Publication.Date"] = pd.to_datetime(df["Publication.Date"], errors="coerce")
```

In [13]:

```
#confirm the changes
df.loc[:, ['Event.Date', 'Publication.Date']].head()
```

Out[13]:

	Event.Date	Publication.Date
0	1948-10-24	NaT
1	1962-07-19	1996-09-19
2	1974-08-30	2007-02-26
3	1977-06-19	2000-12-09
4	1979-08-02	1980-04-16

The dates have been changed accordingly.

2.2 Clean the columns

In [14]:

```
#check the columns
df.columns
```

Out[14]:

```
Index(['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'],
      dtype='object')
```

a) standadize column names

In [15]:

```
#clean the column names for uniformity, easy access and readability
#strip spaces,make it title case ,replace spaces with underscore and replace dot with und
erscore
df.columns=(df.columns.str.strip().str.title().str.replace(' ','_').str.replace('.','_')
)

#check new column names
df.columns
```

Out[15]:

```
Index(['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'],
      dtype='object')
```

b)Extracting new column names and adding to our dataset

It is important to our data analysis that we derive new columns that are relevant, such as `Year` , `Month` , `Day_of_Week` , `Total_Injuries` and `Aircraft type` .Also we will create a column named `Decade` that will hold 10 year intervals that will be relavant when analysing the trends overtime.

In [16]:

```
#Extract year, month and day_of_week from the ['Event_Date] column for easy analysis
df['Year']=df['Event_Date'].dt.year
df['Month']=df['Event_Date'].dt.month
df['Day_of_Week']=df['Event_Date'].dt.day_name()
```

In [17]:

```
#preview after extracting the year day of week and month
df.loc[:, ['Event_Date','Year','Month','Day_of_Week']].head()
```

Out[17]:

	Event_Date	Year	Month	Day_of_Week
0	1948-10-24	1948	10	Sunday
1	1962-07-19	1962	7	Thursday
2	1974-08-30	1974	8	Friday
3	1977-06-19	1977	6	Sunday
4	1979-08-02	1979	8	Thursday

In [18]:

```
# Create column for 10-year intervals
df['Decade'] = (df['Year'] // 10) * 10
```

Create a column for `Total Injuries` that summarises all the Injuries that occured.

In [19]:

```
df['Total_Injuries'] = df['Total_Serious_Injuries'] + df['Total_Minor_Injuries']

#preview after creating the Total_Injuries column
df.loc[:,['Total_Serious_Injuries','Total_Minor_Injuries','Total_Injuries']].head()
```

Out[19]:

	Total_Serious_Injuries	Total_Minor_Injuries	Total_Injuries
0	0.0	0.0	0.0
1	0.0	0.0	0.0
2	NaN	NaN	NaN
3	0.0	0.0	0.0
4	2.0	NaN	NaN

The `make` and `model` of the Aircraft is an important Variable to help determine the aircraft to purchase. For the column with `Model` and `Make` of the aircrafts we will combine to form new column `Aircraft_Type` that can be used in our analysis later.

In [20]:

```
#first lets look at the first 5 rows column mentioned
df.loc[0:5,['Make','Model']]
```

Out[20]:

	Make	Model
0	Stinson	108-3
1	Piper	PA24-180
2	Cessna	172M
3	Rockwell	112
4	Cessna	501
5	Mcdonnell Douglas	DC9

In [21]:

```
#standize the values for Make
df['Make']=df['Make'].str.upper()
```

In [22]:

```
#minimize errors during concatenation by converting type to string
df['Make']=df['Make'].astype(str)
df['Model']=df['Model'].astype(str)

#combine to make new column 'Aircraft_Type'
df['Aircraft_Type']=df['Make']+ ' '+ df['Model']

#replace 'nan' string values with Nan, since some values are missing in both columns
df['Aircraft_Type']=df['Aircraft_Type'].replace('nan nan',np.nan)
```

In [23]:

```
#preview if the column is added and has a combination of make and Model
df.loc[:,['Make','Model','Aircraft_Type']].head()
```

Out[23]:

	Make	Model	Aircraft_Type
0	STINSON	108-3	STINSON 108-3
1	PIPER	PA24-180	PIPER PA24-180
2	CESSNA	172M	CESSNA 172M
3	ROCKWELL	112	ROCKWELL 112
4	CESSNA	501	CESSNA 501

2.3 Dealing with missing values

In [24]:

```
#sort the percentage of null values in descending order
(df.isna().sum()/len(df)*100).sort_values(ascending=False)
```

Out[24]:

```
Schedule                  85.845268
Air_Carrier               81.271023
Far_Description           63.974170
Aircraft_Category         63.677170
Longitude                 61.330423
Latitude                  61.320298
Airport_Code              43.469946
Airport_Name              40.611324
Broad_Phase_Of_Flight     30.560587
Total_Injuries            15.809605
Publication_Date          15.492356
Total_Serious_Injuries    14.073732
Total_Minor_Injuries      13.424608
Total_Fatal_Injuries      12.826109
Engine_Type                7.961615
Report_Status              7.178616
Purpose_Of_Flight          6.965991
Number_Of_Engines          6.844491
Total_Uninjured            6.650992
Weather_Condition          5.053494
Aircraft_Damage            3.593246
Registration_Number        1.481623
Injury_Severity            1.124999
Country                    0.254250
Amateur_Built              0.114750
Location                   0.058500
Aircraft_Type              0.048375
Make                       0.000000
Model                      0.000000
Year                       0.000000
Month                      0.000000
Day_of_Week                0.000000
Decade                     0.000000
Event_Date                 0.000000
Accident_Number            0.000000
```

```
Accident_Number              0.000000
Investigation_Type           0.000000
Event_Id                     0.000000
dtype: float64
```

A) CATEGORICAL DATA

In [25]:

```
#drop full columns with above 60% null values and seem unimportant in our analysis

df.drop(['Schedule','Air_Carrier','Far_Description','Publication_Date','Longitude','Latit
ude'], axis=1, inplace=True)
```

In [26]:

```
#drop the rows of columns with missing values that seem important for our analysis to kee
p
df.dropna(subset=['Location','Country','Aircraft_Type'], inplace=True)
```

Now for the rest of the categorical values of data we will fill the null values with 'Unknown'

In [27]:

```
#fill 'unknown' to null values in some categorial data columns
categorical_cols=['Airport_Code', "Airport_Name","Engine_Type", "Report_Status",
    "Aircraft_Damage",'Injury_Severity','Aircraft_Category','Registration_Number','Amate
ur_Built','Weather_Condition']
for col in categorical_cols:
    df[col]=df[col].fillna('Unknown')
```

`Weather_Condition` **column requires more manipulation to merge the 'Unk' ,'UNK' values with 'Unknown'**

In [28]:

```
df['Weather_Condition'].value_counts()
```

Out[28]:

```
VMC        77074
IMC         5961
Unknown     4448
UNK          825
Unk          262
Name: Weather_Condition, dtype: int64
```

In [29]:

```
#replace the values
df['Weather_Condition'].replace('Unk','Unknown', inplace=True)
df['Weather_Condition'].replace('UNK','Unknown', inplace=True)
```

In [30]:

```
#check if replaced
df['Weather_Condition'].value_counts()
```

Out[30]:

```
VMC        77074
IMC         5961
Unknown     5535
Name: Weather_Condition, dtype: int64
```

For the `Purpose_Of_Flight` **, it will be important to understand if commercial and private flights have different risks later. I will fill it with the most appearing value**

In [31]:

```
#check value counts to detect the most frequent
print(df['Purpose_Of_Flight'].value_counts())

#fill missing values with 'Personal'
df['Purpose_Of_Flight'].fillna('Personal', inplace=True)
```

```
Personal                     49384
Instructional                10587
Unknown                       6677
Aerial Application            4712
Business                      4004
Positioning                   1628
Other Work Use                1259
Ferry                          804
Aerial Observation             785
Public Aircraft                718
Executive/corporate            549
Flight Test                    405
Skydiving                      182
External Load                  123
Public Aircraft - Federal      104
Banner Tow                     101
Air Race show                   99
Public Aircraft - Local         74
Public Aircraft - State         64
Air Race/show                   59
Glider Tow                      53
Firefighting                    40
Air Drop                        11
ASHO                             6
PUBS                             4
PUBL                             1
Name: Purpose_Of_Flight, dtype: int64
```

Now lets clean `Broad phase of Flight` column by filling the `Nan` values with the mode

In [32]:

```
print(df['Broad_Phase_Of_Flight'].mode())

#fill null values
df['Broad_Phase_Of_Flight'].fillna((df['Broad_Phase_Of_Flight'].mode()[0]),inplace=True)
```

```
0    Landing
dtype: object
```

B) NUMERICAL DATA

Now when dealing with numerical values we need to observe what the numbers represent, In this case of injuries while assuming the best case scenario: we have assumed that the columns with null values for `Injured/injuries` means that no injuries were observed or reported hence filling with '0'

In [ ]:

```

```

In [33]:

```
#check the columns mentioned
df.loc[:,["Total_Fatal_Injuries", "Total_Serious_Injuries",
          "Total_Minor_Injuries", "Total_Uninjured",'Total_Injuries']].head()
```

Out[33]:

	Total_Fatal_Injuries	Total_Serious_Injuries	Total_Minor_Injuries	Total_Uninjured	Total_Injuries
0	2.0	0.0	0.0	0.0	0.0
1	4.0	0.0	0.0	0.0	0.0

	Total_Fatal_Injuries	Total_Serious_Injuries	Total_Minor_Injuries	Total_Uninjured	Total_Injuries
2	3.0	NaN	NaN	NaN	NaN
3	2.0	0.0	0.0	0.0	0.0
4	1.0	2.0	NaN	0.0	NaN

In [34]:

```
#fill in 0 or median to null values in columns with numerical value and convert type to i
nterger

num_cols= ["Total_Fatal_Injuries", "Total_Serious_Injuries",
           "Total_Minor_Injuries", "Total_Uninjured",'Total_Injuries']

for col in num_cols:
    if 'Injuries' in col or col=='Total_Uninjured':
        df[col]=df[col].fillna(0)
    else:
        df[col]=df[col].fillna(df[col].median())
    df[col]=df[col].astype(int)
```

In [35]:

```
#check if type has been converted
df[num_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 88570 entries, 0 to 88888
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Total_Fatal_Injuries    88570 non-null  int32
 1   Total_Serious_Injuries  88570 non-null  int32
 2   Total_Minor_Injuries    88570 non-null  int32
 3   Total_Uninjured         88570 non-null  int32
 4   Total_Injuries          88570 non-null  int32
dtypes: int32(5)
memory usage: 2.4 MB
```

Next, looking at the `Number_of_Engines`, these values will be important to know if aircrafts with single or multiple Engines are riskier.

In [36]:

```
#check value counts to see most frequent
print(df['Number_Of_Engines'].value_counts(dropna=False))

#fill the missing values of the Number of Engines with the mode[0]the first most frequent
value
df['Number_Of_Engines'].fillna((df['Number_Of_Engines'].mode()[0]),inplace=True)

#convert dtype to integer
df['Number_Of_Engines']=df['Number_Of_Engines'].astype(int)
```

```
1.0    69433
2.0    11004
NaN     6008
0.0     1220
3.0      476
4.0      425
8.0        3
6.0        1
Name: Number_Of_Engines, dtype: int64
```

In [37]:

```
#recheck missing values
df.isna().sum().sort_values(ascending=False)
```

Out[37]:

```
Aircraft_Type              0
```

```
Aircraft_Type              0
Amateur_Built              0
Investigation_Type         0
Accident_Number            0
Event_Date                 0
Location                   0
Country                    0
Airport_Code               0
Airport_Name               0
Injury_Severity            0
Aircraft_Damage            0
Aircraft_Category          0
Registration_Number        0
Make                       0
Model                      0
Number_Of_Engines          0
Total_Injuries             0
Engine_Type                0
Purpose_Of_Flight          0
Total_Fatal_Injuries       0
Total_Serious_Injuries     0
Total_Minor_Injuries       0
Total_Uninjured            0
Weather_Condition          0
Broad_Phase_Of_Flight      0
Report_Status              0
Year                       0
Month                      0
Day_of_Week                0
Decade                     0
Event_Id                   0
dtype: int64
```

We have eliminated all missing values succesfully.

2.4 Droping columns that are irrelevant to our analysis

Since our analysis is on giving recommendation on what aircraft is the more safer option for purchase and operation, we feel that some columns may be misleading, redundant or irrelevant for our analysis. The following columns did not make the cut:

- **Event_Id**
- **Accident_number**
- **Registration Number**
- **Report status**
- **Investigation type**

In [38]:

```
#drop columns that are not relevant to our analysis
df.drop(['Event_Id','Accident_Number','Investigation_Type','Registration_Number','Report_Status'], axis=1, inplace=True)
```

In [39]:

```
#recheck the final shape we will work with
df.shape
```

Out[39]:

```
(88570, 26)
```

In [40]:

```
#final columns we are working with
df.columns
```

Out[40]:

```
Index(['Event_Date', 'Location', 'Country', 'Airport_Code', 'Airport_Name',
       'Injury_Severity', 'Aircraft_Damage', 'Aircraft_Category', 'Make',
       'Model', 'Amateur_Built', 'Number_Of_Engines', 'Engine_Type',
       'Purpose_Of_Flight', 'Total_Fatal_Injuries', 'Total_Serious_Injuries',
       'Total_Minor_Injuries', 'Total_Uninjured', 'Weather_Condition',
       'Broad_Phase_Of_Flight', 'Year', 'Month', 'Day_of_Week', 'Decade',
       'Total_Injuries', 'Aircraft_Type'],
      dtype='object')
```

In [41]:

```
df.head()
```

Out[41]:

	Event_Date	Location	Country	Airport_Code	Airport_Name	Injury_Severity	Aircraft_Damage	Aircraft_Category	
0	1948-10-24	MOOSE CREEK, ID	United States	Unknown	Unknown	Fatal(2)	Destroyed	Unknown	ST
1	1962-07-19	BRIDGEPORT, CA	United States	Unknown	Unknown	Fatal(4)	Destroyed	Unknown	
2	1974-08-30	Saltville, VA	United States	Unknown	Unknown	Fatal(3)	Destroyed	Unknown	C
3	1977-06-19	EUREKA, CA	United States	Unknown	Unknown	Fatal(2)	Destroyed	Unknown	ROC
4	1979-08-02	Canton, OH	United States	Unknown	Unknown	Fatal(1)	Destroyed	Unknown	C

5 rows × 26 columns

DATA CLEANING CONCLUSION

The Aviation Dataset has been thoroughly cleaned and prepared for exportation. The final dataset we will be working with has 26 columns and 88570 rows of data. Key actions included in this section were:

- **standardizing data**
- **dealing with missing values**
- **deriving columns needed for analysis**
- **removing irrelevant columns**

Our Dataset is now ready for export and Exploratory Data Analysis to identify the low-risk aircrafts.

3. EXPLORATORY DATA ANALYSIS

The next part is essential to every project where we detect and investigate the dataset's main characteristics and study patterns with visualizations to answer the following questions:

1. **Which aircrafts has the highest and lowest accidents,injuries and fatalities?**
2. **Does number of engines in an aircraft impact accidents?**
3. **Which aircrafts are best used for private and commercial flights?**
4. **How have accident trends changed overtime?**

We will explore accident frequencies,counts and impact of type of aircraft, number of Engines, Purpose of flight to cater for SkySafe's goal to identify aircrafts with the least risks for acquisition and .

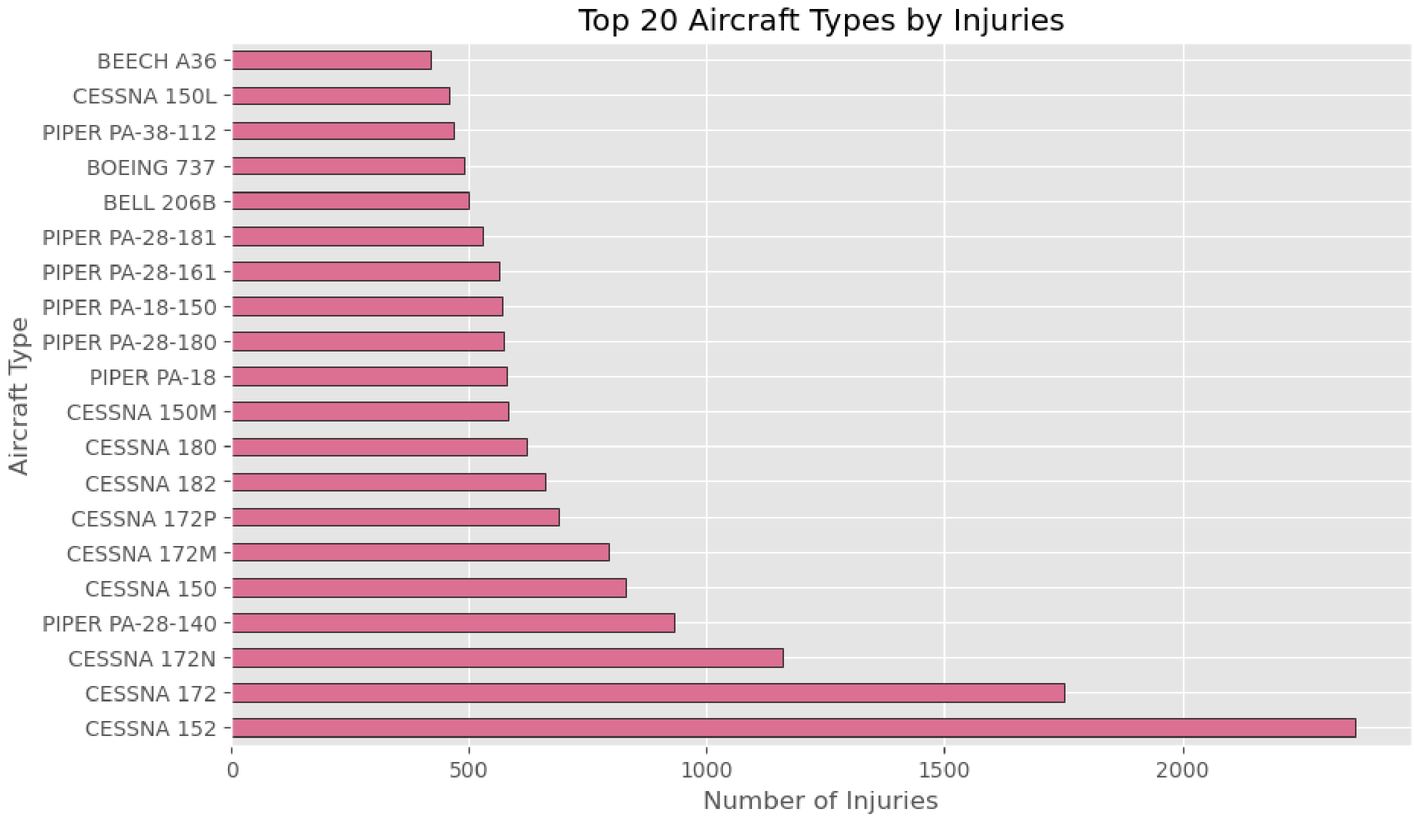
To answer the first question we look at the following plots:*Which aircrafts has the highest and lowest accidents,injuries and fatalities?*

- **Aircraft type with most Injuries**

In [42]:

In [42]:

```
#top 20 aircraft value counts by Injuries
accident_aircraft= df['Aircraft_Type'].value_counts().nlargest(20)

#plotting
plt.figure(figsize=(10, 6))

accident_aircraft.plot(kind='barh',color='palevioletred', edgecolor='black')
plt.title('Top 20 Aircraft Types by Injuries')
plt.xlabel('Number of Injuries')
plt.ylabel('Aircraft Type')

plt.savefig('Images/Aircraft&Injuries.png')
plt.show()
```

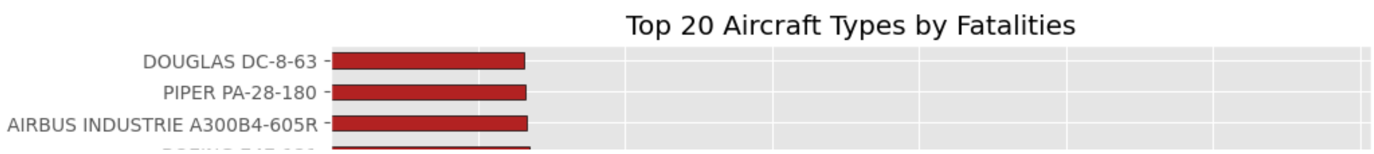


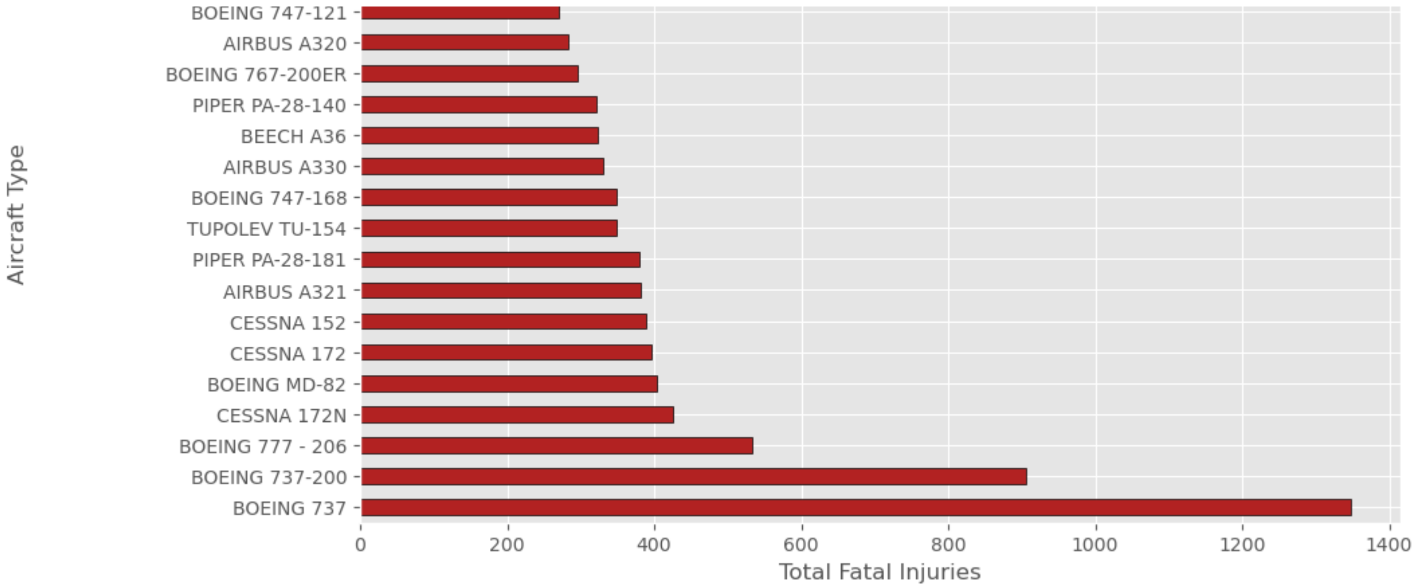
The Cessna types especially Cessna 172 & 152 dominate in injury counts while Piper family seems to have a lower count of injuries in comparison to Cessna. The Boeing737, Beech A36, Cessna 150 and Piper PA-38-112 have shown relatively low accident counts below 500 injuries

- **Fatal injuries Across Aircraft Types**

In [43]:

```
fatal_df= df.groupby('Aircraft_Type')['Total_Fatal_Injuries'].sum().sort_values(ascendin
g=False).head(20)

plt.figure(figsize=(10, 6))

fatal_df.plot(kind='barh',color='firebrick', edgecolor='black')

plt.title('Top 20 Aircraft Types by Fatalities')
plt.xlabel('Total Fatal Injuries')
plt.ylabel('Aircraft Type')

plt.savefig('Images/Aircraft&fatalities_trends.png')
plt.show()
```





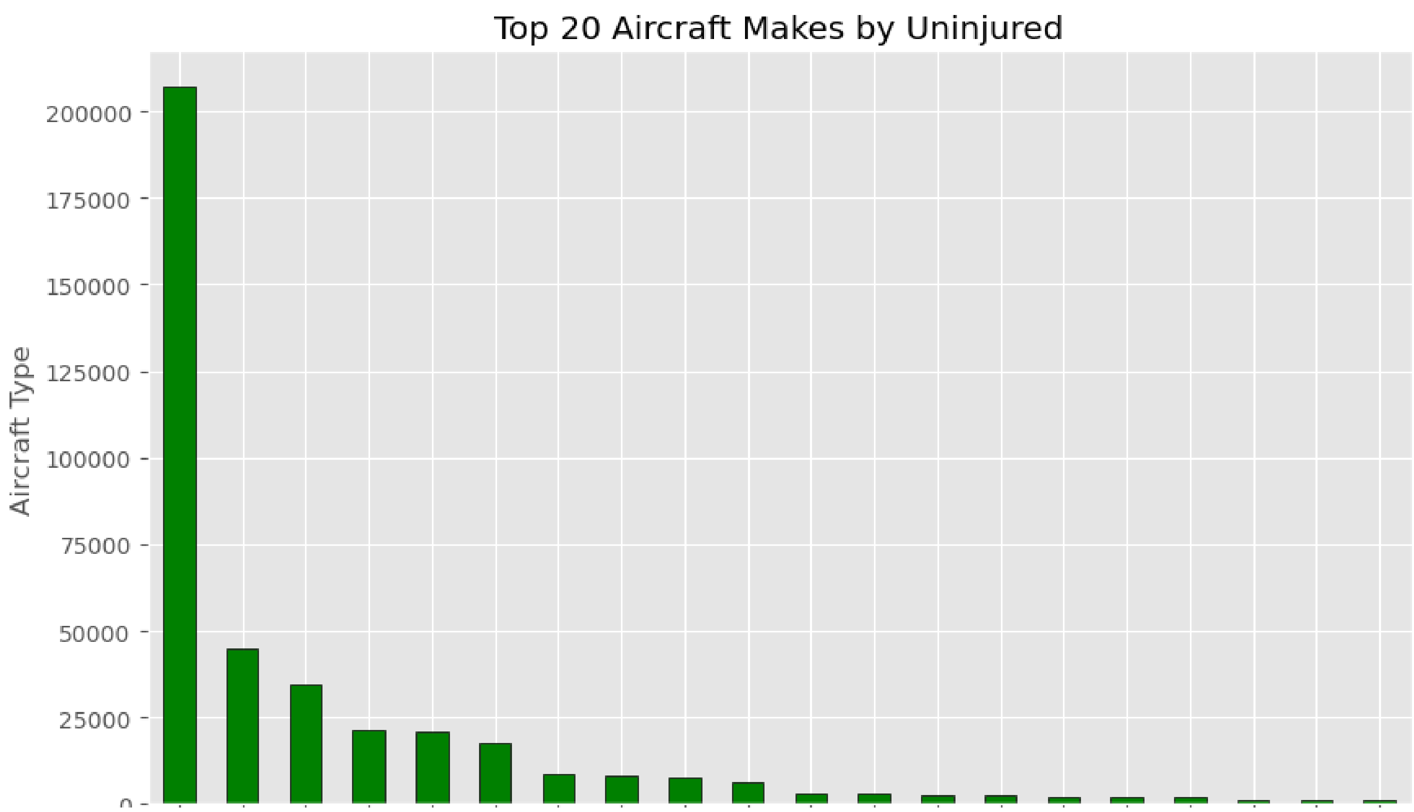
The analysis shows that Boeing 737 and Boeing 737-200 accidents resulted in the highest number of fatalities with a total exceeding 1300 and Douglas showed to have lower fatalities.

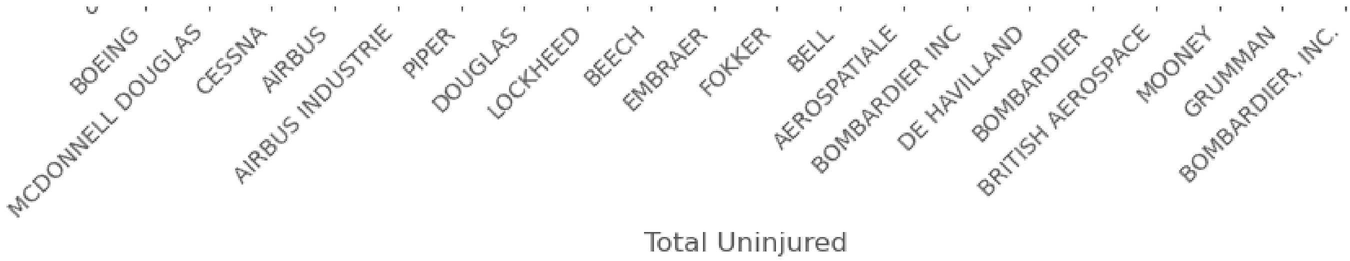
- **Uninjured counts by Make**

So far we have done visualizations on Fatalities and Injuries, now i will make a plot for uninjured vs the make of Aircraft

In [44]:

```
Uninjured_df=df.groupby('Make')['Total_Uninjured'].sum().sort_values(ascending=False).nl
argest(20)

plt.figure(figsize=(10,6))

Uninjured_df.plot(kind='bar',edgecolor='black',color='green')

plt.title('Top 20 Aircraft Makes by Uninjured')
plt.xlabel('Total Uninjured')
plt.ylabel('Aircraft Type')
plt.xticks(rotation=45, ha='right')
plt.savefig('Images/Make&Uninjured.png')
plt.show()
```





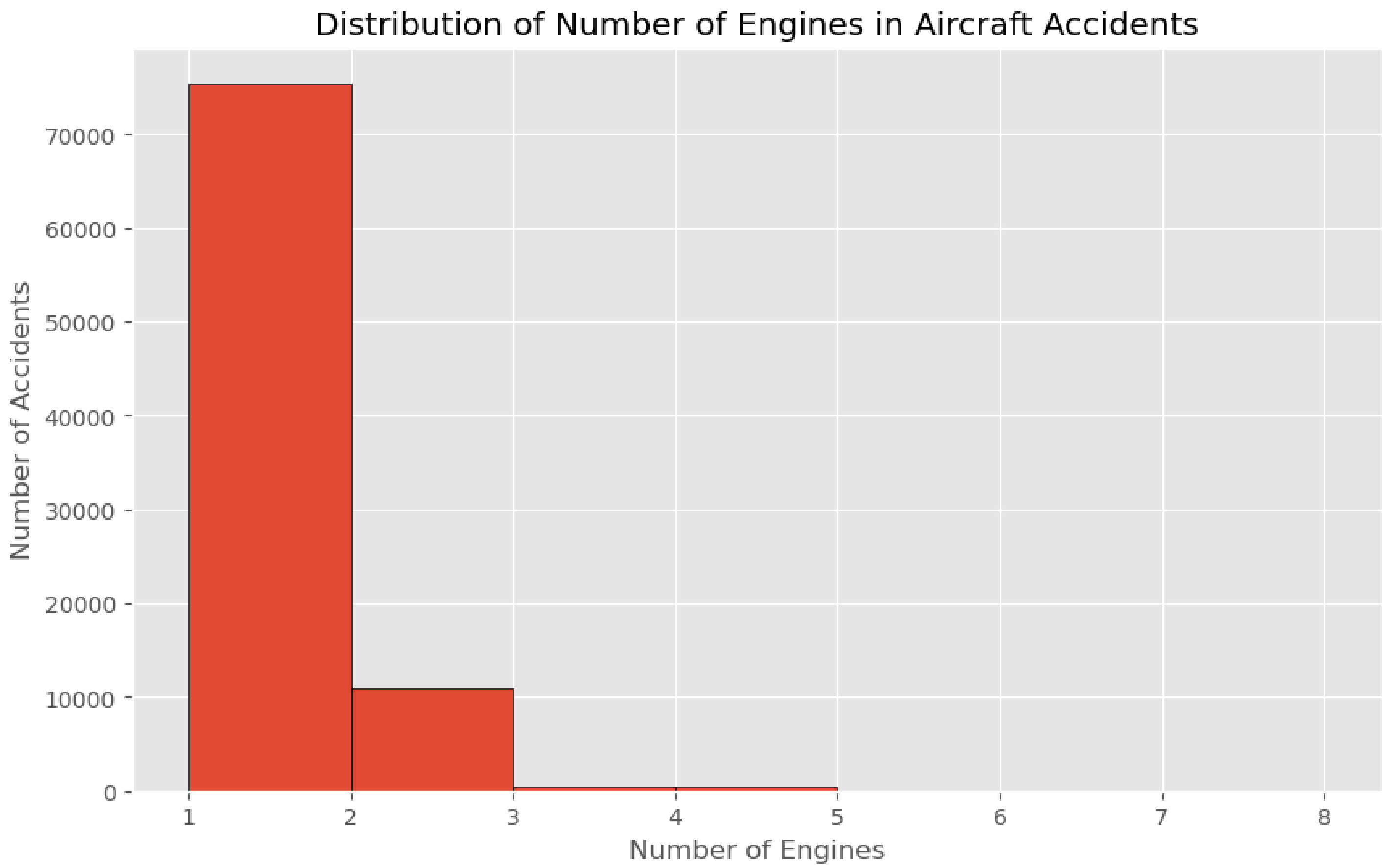
The plot shows that Boieng had the largest number of uninjured people,followed by Mcdonell Douglas ,Cessna,Airbus and PIPER.

To answer the second question: *Does number of engines in an aircraft impact accidents?*

- **Number of engine in accidents**

In [45]:

```
Range_of_engines= len(df['Number_Of_Engines'].unique())

df['Number_Of_Engines'].plot(kind='hist', bins=range(1, Range_of_engines + 2), edgecolor
='black', figsize=(10, 6))
plt.title('Distribution of Number of Engines in Aircraft Accidents')
plt.xlabel('Number of Engines')
plt.ylabel('Number of Accidents')
plt.savefig('Images/engines&Accidents_trends.png')
plt.show()
```



The aircrafts with single Engines caused more accidents resulting to close to 75000 Accidents ,while aircrafts with multiple engines had significantly fewer accidents especially the ones with more than 2 engines.

To answer the third Question: *Which aircrafts are best used for private and commercial flights?*

- **Purpose of Flight**

Since our client wants both private and commercial flights we will analyze accidents trends based on purpose of flight

In [46]:

```
#check the counts in Purpose of flight
df['Purpose_Of_Flight'].value_counts()
```

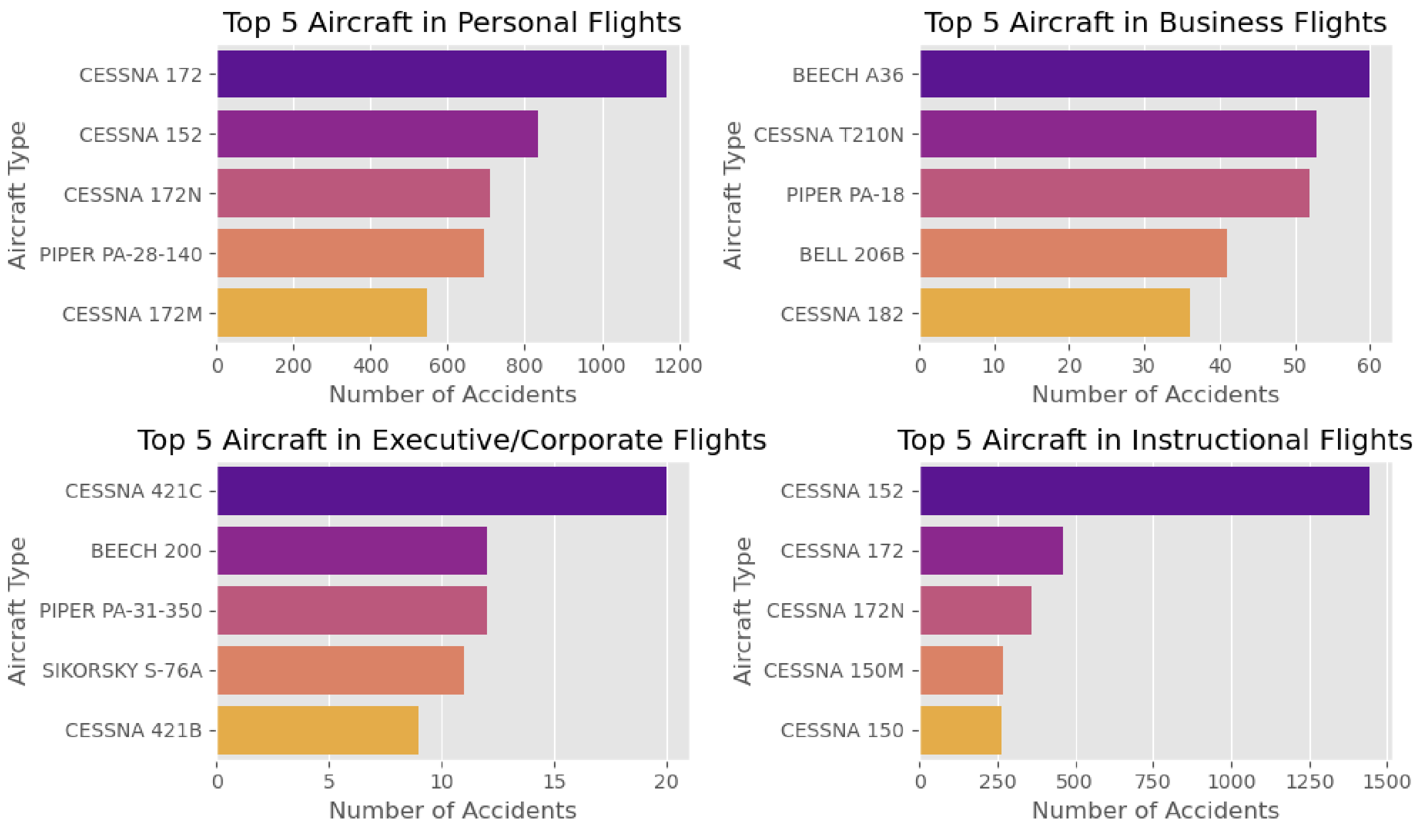
Out[46]:

```
Personal                     55521
Instructional                10587
Unknown                       6677
Aerial Application            4712
Business                      4004
Positioning                   1628
Other Work Use                1259
Ferry                          804
Aerial Observation             785
Public Aircraft                718
Executive/corporate            549
Flight Test                    405
Skydiving                      182
External Load                  123
Public Aircraft - Federal      104
Banner Tow                     101
Air Race show                   99
Public Aircraft - Local         74
Public Aircraft - State         64
Air Race/show                   59
Glider Tow                      53
Firefighting                    40
Air Drop                        11
ASHO                             6
PUBS                             4
PUBL                             1
Name: Purpose_Of_Flight, dtype: int64
```

In [47]:

```
# Make Purpose_Of_Flight uppercase first to standardize for easier manipulation
df['Purpose_Of_Flight'] = df['Purpose_Of_Flight'].str.upper()

# Select relevant purposes of flight for our analysis
relevant_purpose = ['PERSONAL', 'BUSINESS', 'EXECUTIVE/CORPORATE', 'INSTRUCTIONAL']

#create a dataframe with our relevant purposes
df_relevant = df[df['Purpose_Of_Flight'].isin(relevant_purpose)]

# Group by purpose of flight and aircraft type & reset index
group_relevant = (
    df_relevant.groupby(['Purpose_Of_Flight', 'Aircraft_Type'])
    .size()
    .reset_index(name='Count')
)

# Get top 5 aircraft per purpose
top5_per_purpose = (
    group_relevant.groupby('Purpose_Of_Flight', group_keys=False)
    .apply(lambda x: x.nlargest(5, 'Count'))
)

# Plotting 2 rows * 2 columns of subplots
fig, axes = plt.subplots(2, 2, figsize=(10, 6))
axes = axes.flatten()

for i, purpose in enumerate(relevant_purpose):
    data = top5_per_purpose[top5_per_purpose['Purpose_Of_Flight'] == purpose]
```

```
    if data.empty:
        axes[i].text(0.5, 0.5, "No data available", ha='center', va='center')
        axes[i].set_title(f"{purpose.title()} flights")
        axes[i].set_axis_off()
        continue

    sns.barplot(x='Count', y='Aircraft_Type', data=data, ax=axes[i], palette='plasma')
    axes[i].set_title(f"Top 5 Aircraft in {purpose.title()} Flights")
    axes[i].set_xlabel('Number of Accidents')
    axes[i].set_ylabel('Aircraft Type')

plt.tight_layout()
plt.savefig('Images/Aircraft&Purpose_trends.png')
plt.show()
```



The plots above shows that the CESSNA 172 flights has the majority of accidents in both Personal and Instructional flights, while the Cessna 421C leads in accidents on Executive/corporate Flights while Beech A36 leads in Business Flights.

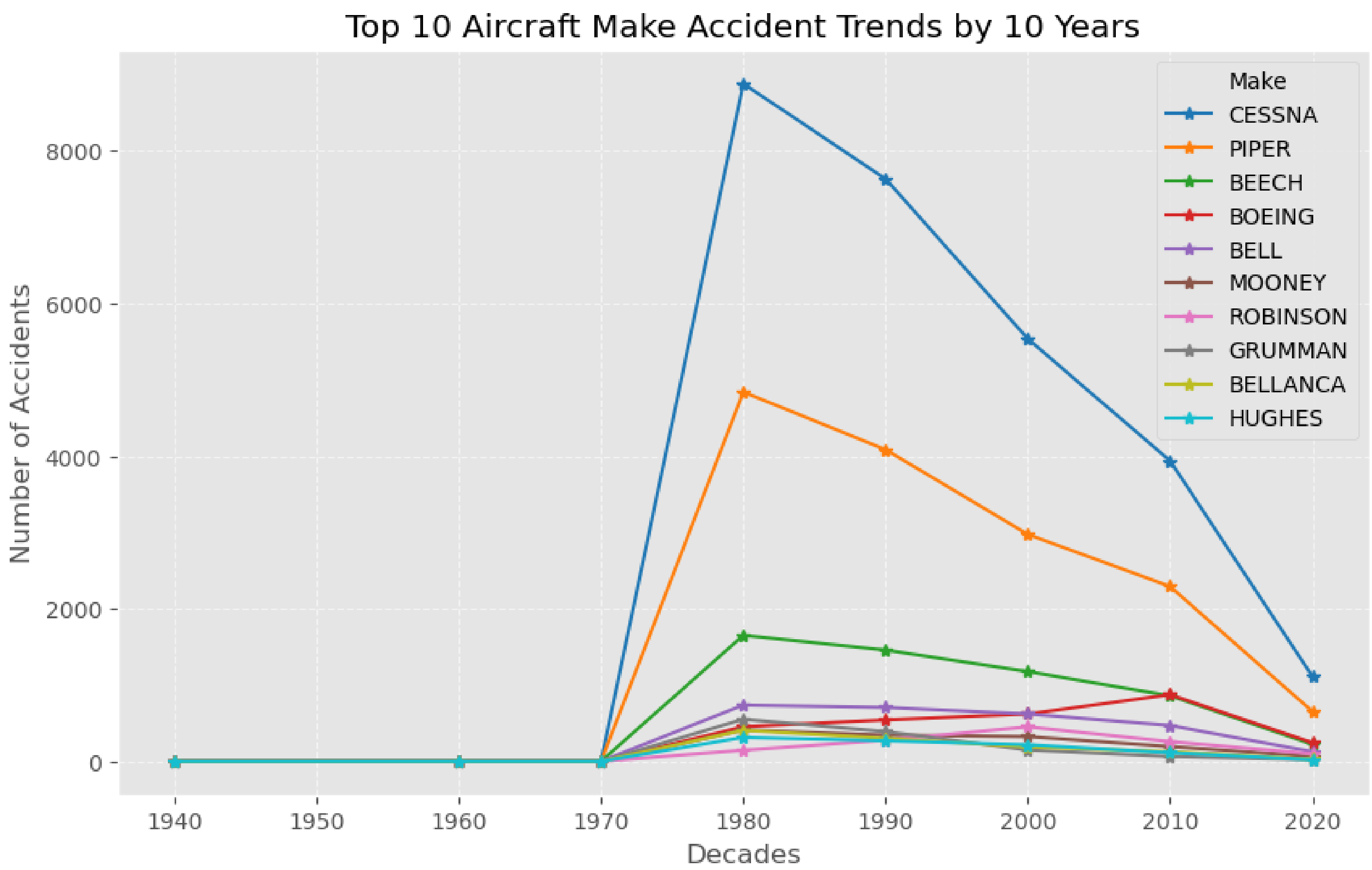
To answer the 4th Question: How have accident trends changed overtime?

- **Accident trends overtime by Make**

In [48]:

```
# Crosstab to count accidents by year and aircraft type
cross_high = pd.crosstab(df['Decade'], df['Make'])

# Keep only top 10 aircraft
top_10_types = df['Make'].value_counts().nlargest(10).index
pivot_top_10 = cross_high[top_10_types]


#Plotting
fig,ax=plt.subplots(figsize=(10,6))

# Plot top 5 aircraft types
pivot_top_10.plot(ax=ax ,kind='line', marker='*',colormap='tab10')
ax.set_title("Top 10 Aircraft Make Accident Trends by 10 Years")
ax.set_xlabel("Decades")
```

```
ax.set_ylabel("Number of Accidents")
ax.grid(True, linestyle='--', alpha=0.5)

plt.savefig('Images/Make&Accident_trends.png')
plt.show()
```



This analysis shows that the Cessna aircraft type has the highest number of accidents with peak in 1980s. while the Robinson,Hughes and Mooney seems to have low accidents over the decades.

Although, overtime the accident counts have declined steadily across all aircraft types especially after the 2000s hence suggesting improvements in safety measures in aviation.

4. CONCLUSION & RECOMENDATIONS

In the visualizations above we were able to visualize the different aircrafts and their occurences on accident data.

1. **Which aircrafts has the highest and lowest accidents,injuries and fatalities?**
   - **Cessna type aircrafts have dominated in Accidents and non-fatal injuries especially Cessna 152 & 172**
   - **Boieng 737 and 737-200 have dominated in highest total fatalities**
   - **Boieng aircraft family showed high counts of uninjured**

1. **Does number of engines in an aircraft impact accidents? *single engine aircrafts account for the most accidents,while aircrafts with more than 2 engines have proved to be safer and have close to no accidents**
2. **Which aircrafts are best used for private and commercial flights?**

   - **Cessna 172&152 are top on personal and instructional flights accidents**
   - **Beech A36 dominated in accidents for the Business flights**
   - **Cessna 421C dominated in accidents for the Executive/corporate flights**
3. **How have accident trends changed overtime?**

   - **Although, focusing on trends overtime the accidents incidents reported/observed have reduced greatly across all aircrafts suggesting safety measures were re-enforced and are working.**

Recommendations

1. Prioritize aircrafts with multiple engines as they have proven to have lower risks for both private ad commercial operations
2. For **Commercial flights** , prioritize larger Boieng Models with strong safety and survival outcomes.
3. For **Private Flights**, steer clear from high incident Makes like Cessna & Beech.
4. for **Instructional Flights** ,intensify pilot training and scenario based safety drills before proceeding.

5. EXPORT CLEANED DATA FOR TABLEAU

In [49]:

```
#Export new cleaned dataframe to a new csv File
df.to_csv('Data/Cleaned_Accident_Data.csv',index=False)
```