Aviation accidents

About Dataset:

The NTSB aviation accident database contains information from 1962 and later about civil aviation accidents and selected incidents within the United States, its territories and possessions, and in international waters.

Project overview

Using incident data from the this dataset to identify risk factors regarding various aircrafts in the dataset. This is to be used identfy the lowest risk aircraft that can be used upon entering the aviation market, with a particular focus on the private and commercial sector

In [1]:
```
# Importing relevant libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

%matplotlib inline
```

Importing data and creating dataframes

In [2]:
```
# Import data into dataframe and preview
df1 = pd.read_csv('Data/AviationData.csv', encoding='latin1')
df1.head()
```

```
/Users/georgenyangaya/anaconda3/envs/learn-env/lib/python3.8/site-packages/IPython/core/interactiveshell.py:314
5: 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,
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	...	Purpos
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	NaN	NaN	...	
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	NaN	NaN	...	
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.9222	-81.8781	NaN	NaN	...	
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	NaN	NaN	...	
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	NaN	NaN	...	

5 rows × 31 columns

In [3]:
```
# Import and preview second set of data
df2 = pd.read_csv('Data/USState_Codes.csv')
df2.head()
```

Out[3]:

	US_State	Abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA

Previewing Dataframes

In [4]:
```
df1.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 [5]:
```
df1.describe()
```

Out[5]:

	Number.of.Engines	Total.Fatal.Injuries	Total.Serious.Injuries	Total.Minor.Injuries	Total.Uninjured
count	82805.000000	77488.000000	76379.000000	76956.000000	82977.000000
mean	1.146585	0.647855	0.279881	0.357061	5.325440
std	0.446510	5.485960	1.544084	2.235625	27.913634
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000	1.000000
75%	1.000000	0.000000	0.000000	0.000000	2.000000
max	8.000000	349.000000	161.000000	380.000000	699.000000

In [6]:
```
# Checking for duplicated rows
print(df1.duplicated().value_counts())
```

```
False    88889
dtype: int64
```

Checking for extraneous/erronous values

In this section, we are looking for data that isn't an accurate represention of what is being analysed. This ranges from mispelled categories to values that are too extreme to be realistic

In [7]:
```
# Check for extraneous/erronous values
for col in df1.columns:
    print(col, '\n', df1[col].value_counts(normalize=True).sort_values(ascending=False).head(10), '\n', df1[col]
```

```
Latitude
 332739N      0.000553
335219N      0.000524
334118N      0.000494
32.815556    0.000494
039405N      0.000465
324934N      0.000465
34.654444    0.000436
393412N      0.000407
391132N      0.000407
61.174445    0.000407
Name: Latitude, dtype: float64
 28.221111    0.000029
434645N      0.000029
045170N      0.000029
045235S      0.000029
462510N      0.000029
355148N      0.000029
60.817223    0.000029
048525N      0.000029
```

From the data above, we have identified a few columns that are worth examining deeper for extraneous/erroneous values

Columns to check

- Airport name
- Injury Severity
- Aircraft.Category
- Registration.Number
- Make
- Engine.Type
- FAR.Description
- Purpose.of.flight
- Air.carrier
- Weather.Condition

In [8]:
```
columns_to_check = ['Airport.Name', 'Injury.Severity', 'Aircraft.Category', 'Registration.Number', 'Make',
                    'Engine.Type', 'FAR.Description', 'Purpose.of.flight', 'Air.carrier', 'Weather.Condition']
```

In [9]:
```
for col in columns_to_check:
    print(f'column: {col}')
    print(df1[col].value_counts())
```

```
column: Airport.Name
Private                           240
PRIVATE                           224
Private Airstrip                  153
NONE                              146
PRIVATE STRIP                     111
                                 ...
VASHON MUNICIPAL                    1
SONOMA SKYPARK AIRPORT              1
St. Pete-Clearwater Internatio      1
Calaveras CO-Maury Rasmussen        1
George Bryan Airport                1
Name: Airport.Name, Length: 24871, dtype: int64
column: Injury.Severity
Non-Fatal     67357
Fatal(1)       6167
Fatal          5262
Fatal(2)       3711
Incident       2219
```

Simple fixes:

Title: Airport.Name, Make, Air.carrier

Upper: Weather.Condition, Registration.Number

Replace unknowns: Aircraft.Category, Registration.Number, Engine.Type

Replace values: Injury.Severity, Purpose.of.flight, FAR.Description

In [10]:
```
# Create a copy of df1 to clean data
df1_clean = df1.copy()
```

In [11]:
```
# Title
df1_clean['Airport.Name'] = df1_clean['Airport.Name'].str.title()
df1_clean['Make'] = df1_clean['Make'].str.title()
df1_clean['Air.carrier'] = df1_clean['Air.carrier'].str.title()

# Upper
df1_clean['Weather.Condition'] = df1_clean['Weather.Condition'].str.upper()

# Replace unknowns
df1_clean['Aircraft.Category'] = df1_clean['Aircraft.Category'].replace('UNK','Unknown')
df1_clean['Engine.Type'] = df1_clean['Engine.Type'].str.title().replace(['None','Unk'],'Unknown')
df1_clean['Registration.Number'] = df1_clean['Registration.Number'].str.upper().replace(['NONE','UNK','UNREG'],'

# Replacing 'Fatal(*)' with 'Fatal' for ['Injury.Severity']
df1_clean['Injury.Severity'] = df1_clean['Injury.Severity'].apply(lambda x: 'Fatal' if str(x).startswith('Fatal'

# Replacing values in Purpose.of.flight
df1_clean['Purpose.of.flight'] = df1_clean['Purpose.of.flight'].replace('Air Race show','Air Race/show')
df1_clean['Purpose.of.flight'] = df1_clean['Purpose.of.flight'].replace('PUBS','Public Aircraft - State')
df1_clean['Purpose.of.flight'] = df1_clean['Purpose.of.flight'].replace('PUBL','Public Aircraft - Local')

# Replacing values in FAR.description
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('UNK','Unknown')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('091','Part 91: General Aviation')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('NUSN','Non-U.S., Non-Commercial')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('NUSC','Non-U.S., Commercial')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('137','Part 137: Agricultural')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('135','Part 135: Air Taxi & Commuter')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('121','Part 121: Air Carrier')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('129','Part 129: Foreign')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('133','Part 133: Rotorcraft Ext. Load')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('125','Part 125: 20+ Pax,6000+ lbs')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('ARMF','Armed Forces')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('PUBU','Public Use')
df1_clean['FAR.Description'] = df1_clean['FAR.Description'].replace('091K','Part 91 Subpart K: Fractional')
```

In [12]:
```
# Rechecking for extraneous/erronous values in 'Columns to check'
for col in columns_to_check:
    print(f'column: {col}')
    print(df1_clean[col].value_counts(normalize=True))
```

```
Geared Turbofan    0.000147
Electric           0.000122
Lr                 0.000024
Hybrid Rocket      0.000012
Name: Engine.Type, dtype: float64
column: FAR.Description
Part 91: General Aviation        0.771539
Non-U.S., Non-Commercial         0.052494
Part 137: Agricultural           0.045186
Non-U.S., Commercial             0.034538
Part 135: Air Taxi & Commuter    0.032602
Part 121: Air Carrier            0.026356
Unknown                          0.012272
Part 129: Foreign                0.010805
Public Use                       0.008494
Part 133: Rotorcraft Ext. Load   0.004341
Part 91 Subpart K: Fractional    0.000468
Part 125: 20+ Pax,6000+ lbs      0.000312
Armed Forces                     0.000281
107                              0.000125
```

Missing Data

The next step is to deal with null values within the data set

In [13]:
```
# Check for missing values
df1_clean.isna().sum()
```

Out[13]:
```
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
```

Plan for null values

'Location' = replace with Unknown

'Country' = replace with Unknown

'Latitude' = ignore column

'Longitude' = ignore column

'Airport.Code' = replace with Unknown

'Airport.Name' = replace with Unknown

'Injury.Severity' = replace with Unknown

'Aircraft.damage' = replace with Unknown

'Aircraft.Category' = replace with Unknown

'Registration.Number' = replace with Unknown

'Make' = replace with Unknown

'Model' = replace with Unknown

'Amateur.Built' = replace with Mode

'Number.of.Engines' = replace with Median

'Engine.Type' = replace with Unknown

'FAR.Description' = replace with Unknown

'Schedule' = ignore column

'Purpose.of.flight' = replace with Unknown

'Air.carrier' = ignore column

'Total.Fatal.Injuries' = replace with 0

'Total.Serious.Injuries' = replace with 0

'Total.Minor.Injuries' = replace with 0

'Total.Uninjured' = replace with 0

'Weather.Condition' = replace with Unknown

'Broad.phase.of.flight' = replace with Unknown

'Report.Status' = replace with Unknown

'Publication.Date' = drop column

In [14]:
```
# fill null values
df1_clean.fillna({
    'Location': 'Unknown',
    'Country': 'Unknown',
    'Airport.Code': 'Unknown',
    'Airport.Name': 'Unknown',
    'Injury.Severity': 'Unknown',
    'Aircraft.damage': 'Unknown',
    'Aircraft.Category': 'Unknown',
    'Registration.Number': 'Unknown',
    'Make': 'Unknown',
    'Model': 'Unknown',
    'Amateur.Built': df1_clean['Amateur.Built'].mode()[0],
    'Number.of.Engines': df1_clean['Number.of.Engines'].median(),
    'Engine.Type': 'Unknown',
    'FAR.Description': 'Unknown',
    'Purpose.of.flight': 'Unknown',
    'Total.Fatal.Injuries': 0,
    'Total.Serious.Injuries': 0,
    'Total.Minor.Injuries': 0,
    'Total.Uninjured': 0,
    'Weather.Condition': 'Unknown',
    'Broad.phase.of.flight': 'Unknown',
    'Report.Status': 'Unknown'
}, inplace=True)
```

In [15]:
```
# Drop unneeded columns
df1_clean = df1_clean.drop(columns = ['Latitude','Longitude','Schedule','Air.carrier','Publication.Date'])
```

In [16]:
```
# Recheck for missing values
df1_clean.isna().sum()
```

Out[16]:
```
Event.Id                  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
Amateur.Built             0
Number.of.Engines         0
Engine.Type               0
FAR.Description           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
dtype: int64
```

Adding flight category column

Due to the focus being on buying planes for private and commercial use it would be useful to also categorise flights in these bins for further analysis.

These categories will stem from the Purpose.of.flight column as shown below:

1. Private:

- Personal
- Executive/Corporate
- Business
- Skydiving
- Air Race/Show
- Glider Tow
- ASHO

2. Commercial:

- Aerial Application
- Aerial Observation
- Banner Tow
- External Load
- Ferry
- Air Drop

3. Public/Government:

- Public Aircraft
- Public Aircraft - Federal
- Public Aircraft - Local
- Public Aircraft - State
- Firefighting

4. Other:

- Instructional
- Flight Test
- Positioning
- Other Work Use

5. Unknown:

- Unknown

In [17]:
```
Flight_category = []

private = ['Personal', 'Executive/corporate', 'Business', 'Skydiving', 'Air Race/show', 'Glider Tow', 'ASHO']
commercial =['Aerial Application', 'Aerial Observation', 'Banner Tow', 'External Load', 'Ferry', 'Air Drop']
public = ['Public Aircraft', 'Public Aircraft - Federal', 'Public Aircraft - Local', 'Public Aircraft - State',

for item in df1_clean['Purpose.of.flight']:
    if item in private:
        Flight_category.append('Private')
    elif item in commercial:
        Flight_category.append('Commercial')
    elif item in public:
        Flight_category.append('Public')
    elif item == 'Unknown':
        Flight_category.append('Unknown')
    else:
        Flight_category.append('Other')

df1_clean['Flight.category'] = Flight_category
# Picking a random sample from the two to confirm it worked as expected
df1_clean.loc[600:650,['Flight.category','Purpose.of.flight']]
```

Out[17]:

	Flight.category	Purpose.of.flight
600	Private	Personal
601	Private	Business
602	Other	Instructional
603	Private	Business
604	Commercial	Aerial Application
605	Unknown	Unknown
606	Private	Personal
607	Unknown	Unknown
608	Private	Personal
609	Private	Business
610	Private	Personal
611	Private	Business
612	Private	Personal
613	Private	Executive/corporate
614	Private	Personal
615	Commercial	Aerial Application
616	Unknown	Unknown
617	Private	Personal
618	Private	Personal
619	Private	Executive/corporate
620	Private	Personal
621	Private	Personal
622	Private	Personal
623	Private	Executive/corporate
624	Private	Personal
625	Private	Personal
626	Private	Personal
627	Private	Personal
628	Private	Personal
629	Private	Personal
630	Commercial	Ferry
631	Private	Personal
632	Private	Personal
633	Private	Personal
634	Private	Business
635	Private	Personal
636	Private	Personal
637	Other	Instructional
638	Private	Personal
639	Private	Personal
640	Private	Personal
641	Other	Instructional
642	Other	Instructional
643	Private	Personal
644	Private	Personal
645	Private	Personal
646	Private	Personal
647	Other	Instructional
648	Unknown	Unknown
649	Private	Business
650	Private	Personal

Exporting the data

Now that the data has been cleaned, exploratory data analysis can be formed. But first this cleaned data will be exported to allow for its use on an interactive Tableau Dashboard.

In [18]:
```
# Save the DataFrame to a CSV file
df1_clean.to_csv('cleaned.csv')
```

Exploratory Data Analysis (EDA)

In [19]:
```
# Preview clean dataframe
df1_clean.head(10)
```

Out[19]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Airport.Code	Airport.Name	Injury.Severity	Aircraft.damage
0	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	Unknown	Unknown	Fatal	Destroye
1	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	Unknown	Unknown	Fatal	Destroye
2	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	Unknown	Unknown	Fatal	Destroye
3	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	Unknown	Unknown	Fatal	Destroye
4	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	Unknown	Unknown	Fatal	Destroye
5	20170710X52551	Accident	NYC79AA106	1979-09-17	BOSTON, MA	United States	Unknown	Unknown	Non-Fatal	Substantia
6	20001218X45446	Accident	CHI81LA106	1981-08-01	COTTON, MN	United States	Unknown	Unknown	Fatal	Destroye
7	20020909X01562	Accident	SEA82DA022	1982-01-01	PULLMAN, WA	United States	Unknown	Blackburn Ag Strip	Non-Fatal	Substantia
8	20020909X01561	Accident	NYC82DA015	1982-01-01	EAST HANOVER, NJ	United States	N58	Hanover	Non-Fatal	Substantia
9	20020909X01560	Accident	MIA82DA029	1982-01-01	JACKSONVILLE, FL	United States	JAX	Jacksonville Intl	Non-Fatal	Substantia

10 rows × 27 columns

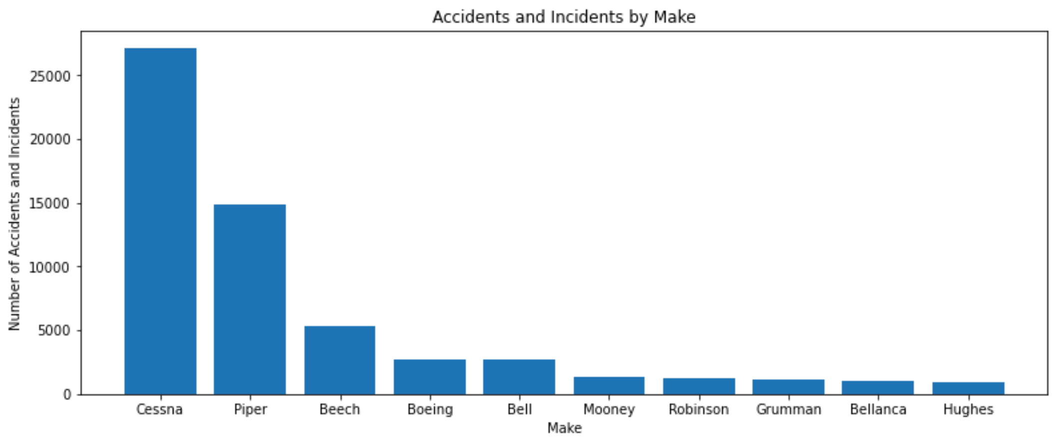
Basic EDA

Incidents by make

In [20]:
```
# Selecting top 10 aircraft makes by frequency of incidents
df1_clean['Make'].value_counts(normalize = True)[0:10]
```

Out[20]:
```
Cessna      0.305426
Piper       0.167287
Beech       0.060435
Boeing      0.030881
Bell        0.030622
Mooney      0.015007
Robinson    0.013837
Grumman     0.013185
Bellanca    0.011756
Hughes      0.010485
Name: Make, dtype: float64
```

In [21]:
```
# Plotting barchart for this data
fig, ax = plt.subplots(figsize = (13,5))
ax.bar(x = df1_clean['Make'].value_counts()[0:10].index, height=df1_clean['Make'].value_counts()[0:10])
ax.set_title('Accidents and Incidents by Make')
ax.set_xlabel('Make')
ax.set_ylabel('Number of Accidents and Incidents');
```



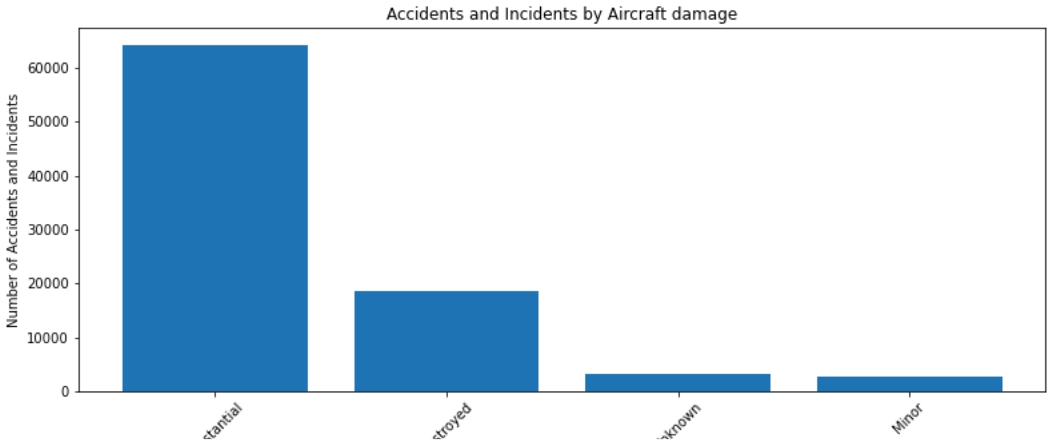
Cessna's are the make most common reported to have an incident. However, since we only have incident data we can't assume this means it's the most risky aircraft. It is more likely an indicator of the frequency of the aircraft's use

Incidents by Aircraft.damage

In [22]:
```
# Frequency of incidents by aircraft damage
df1_clean['Aircraft.damage'].value_counts(normalize = True)
```

Out[22]:
```
Substantial    0.721664
Destroyed      0.209508
Unknown        0.037271
Minor          0.031556
Name: Aircraft.damage, dtype: float64
```

In [23]:
```
# Plotting barchart for this data
fig, ax = plt.subplots(figsize = (13,5))
ax.bar(x = df1_clean['Aircraft.damage'].value_counts().index, height=df1_clean['Aircraft.damage'].value_counts()
ax.set_title('Accidents and Incidents by Aircraft damage')
ax.set_xlabel('Aircraft damage')
ax.set_ylabel('Number of Accidents and Incidents')
plt.xticks(rotation=45);
```

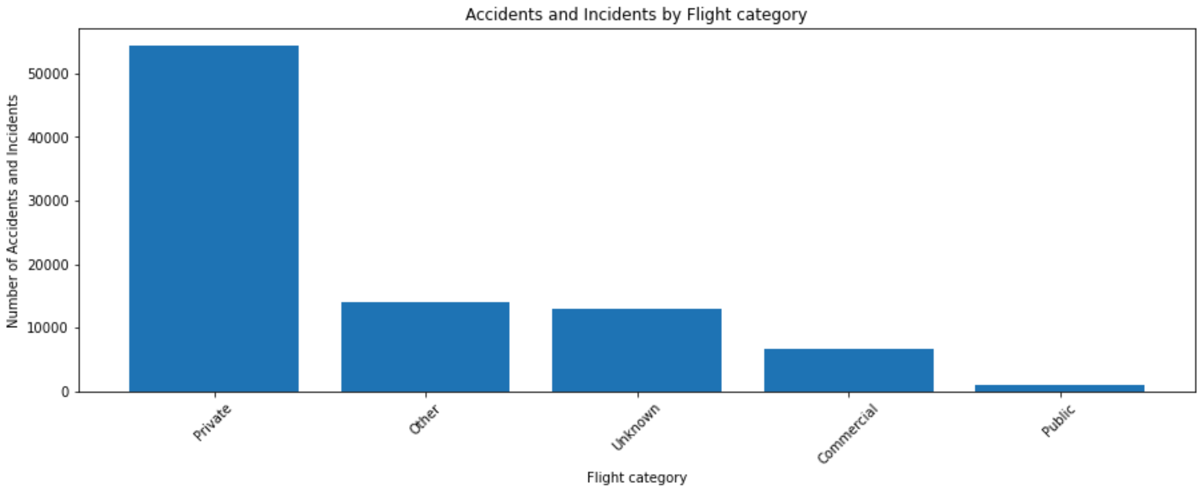


Incidents by Flight.category

In [24]:
```
# Frequency of incidents by flight category
df1_clean['Flight.category'].value_counts(normalize = True)
```

Out[24]:
```
Private       0.612202
Other         0.156555
Unknown       0.146182
Commercial    0.073721
Public        0.011340
Name: Flight.category, dtype: float64
```

In [25]:
```
# Plotting barchart for this data
fig, ax = plt.subplots(figsize = (15,5))
ax.bar(x = df1_clean['Flight.category'].value_counts().index, height=df1_clean['Flight.category'].value_counts()
ax.set_title('Accidents and Incidents by Flight category')
ax.set_xlabel('Flight category')
ax.set_ylabel('Number of Accidents and Incidents')
plt.xticks(rotation=45);
```

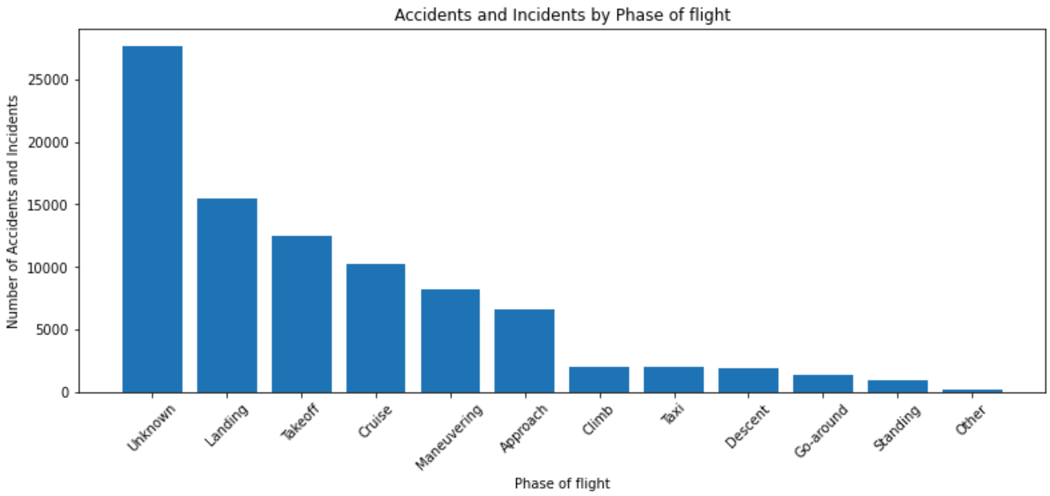


Incidents by phase of flight

In [26]:
```
# Value counts of phase of flight excluding Unknown values
df1_clean['Broad.phase.of.flight'].value_counts(normalize = True)
```

Out[26]:
```
Unknown        0.311771
Landing        0.173565
Takeoff        0.140546
Cruise         0.115526
Maneuvering    0.091620
Approach       0.073642
Climb          0.022882
Taxi           0.022027
Descent        0.021229
Go-around      0.015221
Standing       0.010631
Other          0.001339
Name: Broad.phase.of.flight, dtype: float64
```

In [27]:
```
# Plotting barchart for this data, filtering out Unknown values
fig, ax = plt.subplots(figsize = (13,5))
ax.bar(x = df1_clean['Broad.phase.of.flight'].value_counts().index, height=df1_clean['Broad.phase.of.flight'].va
ax.set_title('Accidents and Incidents by Phase of flight')
ax.set_xlabel('Phase of flight')
ax.set_ylabel('Number of Accidents and Incidents')
plt.xticks(rotation=45);
```



Ignoring unknown we can see that the most common time for an incident to take place is during complex phases for an aircraft such as landing and takeoff. Naturally, during less complex phases such as standing and go-around there are minimal incidents

Further EDA

Damage by Make analysis

In [28]:
```
# Make a list on the makes on flight with most incidents
most_inc_make = list(df1_clean['Make'].value_counts(normalize = True)[0:5].index)
most_inc_make
```

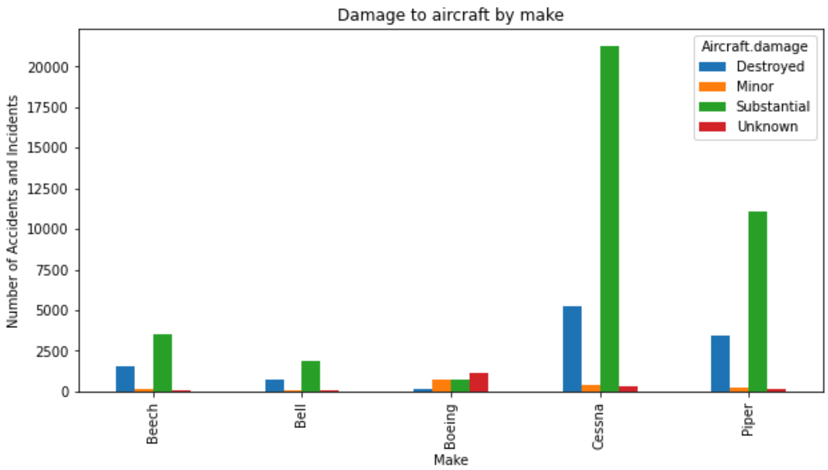
Out[28]:
```
['Cessna', 'Piper', 'Beech', 'Boeing', 'Bell']
```

In [29]:
```
# Create a dataframe only including incidents with those makes
most_inc_make_df = df1_clean[df1_clean['Make'].isin(most_inc_make)]
```

In [30]:
```
# Categories the incidents by damage to the aircraft and break it down by make
most_inc_make_df.groupby(['Make','Aircraft.damage'])['Event.Id'].count()
```

Out[30]:
```
Make    Aircraft.damage
Beech   Destroyed           1585
        Minor                170
        Substantial         3539
        Unknown               78
Bell    Destroyed            708
        Minor                 47
        Substantial         1900
        Unknown               67
Boeing  Destroyed            170
        Minor                711
        Substantial          739
        Unknown             1125
Cessna  Destroyed           5202
        Minor                387
        Substantial        21268
        Unknown              292
Piper   Destroyed           3428
        Minor                204
        Substantial        11100
        Unknown              138
Name: Event.Id, dtype: int64
```

In [31]:
```
# Plot this data
make_damage_grouped = most_inc_make_df.groupby(['Make','Aircraft.damage'])['Event.Id'].count()
make_damage_grouped.unstack('Aircraft.damage').plot.bar(figsize=(10, 5))
plt.xlabel('Make')
plt.ylabel('Number of Accidents and Incidents')
plt.title('Damage to aircraft by make');
```



Findings

At a brief glance we can see when an incident occurs the damage to the aircraft is most commonly 'Substantial' followed by the aircraft being 'Destroyed'

Only Boeing differs from this where the damage is most commonly 'Substantial' but this data is likely skewed by the proportion of unknown values for Boeing

Further info

It would be beneficial to know the proportion of each 'Aircraft.damage' outcome for each 'make'

In [32]:
```
# Seeing the percentage breakdown of aircraft damage by Make
most_inc_make_df.groupby(['Make','Aircraft.damage'])['Event.Id'].count()/most_inc_make_df.groupby(['Make'])['Eve
```

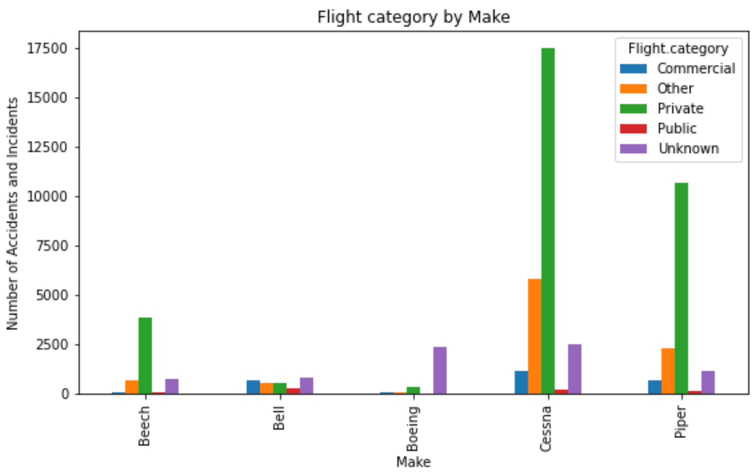
Out[32]:
```
Make    Aircraft.damage
Beech   Destroyed          0.295048
        Minor              0.031646
        Substantial        0.658786
        Unknown            0.014520
Bell    Destroyed          0.260103
        Minor              0.017267
        Substantial        0.698016
        Unknown            0.024614
Boeing  Destroyed          0.061931
        Minor              0.259016
        Substantial        0.269217
        Unknown            0.409836
Cessna  Destroyed          0.191609
        Minor              0.014255
        Substantial        0.783381
        Unknown            0.010755
Piper   Destroyed          0.230531
        Minor              0.013719
        Substantial        0.746469
        Unknown            0.009280
Name: Event.Id, dtype: float64
```

Make by flight category

In [33]:
```
category_make_grouped = most_inc_make_df.groupby(['Flight.category', 'Make'])['Event.Id'].count()
category_make_grouped
```

Out[33]:
```
Flight.category  Make
Commercial       Beech        78
                 Bell        645
                 Boeing       31
                 Cessna     1157
                 Piper       672
Other            Beech       682
                 Bell        561
                 Boeing       49
                 Cessna     5819
                 Piper      2283
Private          Beech      3873
                 Bell        500
                 Boeing      313
                 Cessna    17514
                 Piper     10657
Public           Beech        29
                 Bell        235
                 Boeing        2
                 Cessna      172
                 Piper        93
Unknown          Beech       710
                 Bell        781
                 Boeing     2350
                 Cessna     2487
                 Piper      1165
Name: Event.Id, dtype: int64
```

In [34]:
```
category_make_grouped.unstack('Flight.category').plot.bar(figsize=(9, 5))
plt.xlabel('Make')
plt.ylabel('Number of Accidents and Incidents')
plt.title('Flight category by Make');
```



Findings

Cessna's, Piper's and Beech's aircraft has the most commonly reported incidents for private and commercial flight suggesting they are the

Further info

It would be beneficial to know the proportion of each 'make' for each 'Flight.category'

In [35]:
```
most_inc_make_df.groupby(['Flight.category', 'Make'])['Event.Id'].count()/most_inc_make_df.groupby(['Flight.cate
```

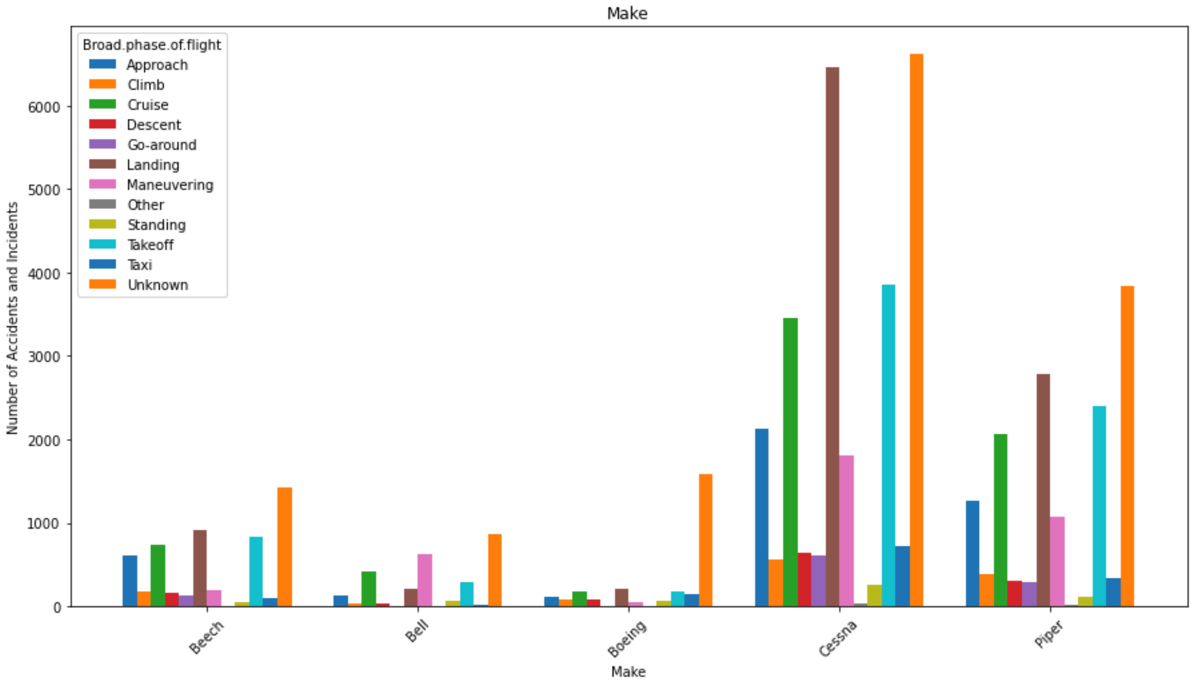
Out[35]:
```
Flight.category  Make
Commercial       Beech     0.030197
                 Bell      0.249710
                 Boeing    0.012002
                 Cessna    0.447929
                 Piper     0.260163
Other            Beech     0.072600
                 Bell      0.059719
                 Boeing    0.005216
                 Cessna    0.619438
                 Piper     0.243027
Private          Beech     0.117874
                 Bell      0.015217
                 Boeing    0.009526
                 Cessna    0.533037
                 Piper     0.324345
Public           Beech     0.054614
                 Bell      0.442561
                 Boeing    0.003766
                 Cessna    0.323917
                 Piper     0.175141
Unknown          Beech     0.094755
                 Bell      0.104231
                 Boeing    0.313626
                 Cessna    0.331910
                 Piper     0.155478
Name: Event.Id, dtype: float64
```

Phase of flight by Make

In [36]:
```
make_phase_grouped = most_inc_make_df.groupby(['Make', 'Broad.phase.of.flight'])['Event.Id'].count()
make_phase_grouped
```

Out[36]:
```
Make    Broad.phase.of.flight
Beech   Approach                  606
        Climb                     177
        Cruise                    733
        Descent                   158
        Go-around                 140
        Landing                   914
        Maneuvering               204
        Other                       6
        Standing                   57
        Takeoff                   841
        Taxi                      107
        Unknown                  1429
Bell    Approach                  138
        Climb                      33
        Cruise                    419
        Descent                    42
        Go-around                   3
        Landing                   220
        Maneuvering               624
        Other                       5
        Standing                   62
        Takeoff                   289
        Taxi                       23
        Unknown                   864
Boeing  Approach                  113
        Climb                      83
        Cruise                    184
        Descent                    88
        Go-around                  12
        Landing                   205
        Maneuvering                49
        Other                       1
        Standing                   74
        Takeoff                   187
        Taxi                      156
        Unknown                  1593
Cessna  Approach                 2127
        Climb                     560
        Cruise                   3448
        Descent                   637
        Go-around                 610
        Landing                  6453
        Maneuvering              1814
        Other                      30
        Standing                  262
        Takeoff                  3861
        Taxi                      730
        Unknown                  6617
Piper   Approach                 1261
        Climb                     390
        Cruise                   2058
        Descent                   314
        Go-around                 298
        Landing                  2779
        Maneuvering              1068
        Other                      17
        Standing                  113
        Takeoff                  2401
        Taxi                      337
        Unknown                  3834
Name: Event.Id, dtype: int64
```

In [37]:
```
make_phase_grouped.unstack('Broad.phase.of.flight').plot.bar(figsize=(15, 8), width = 0.8)
plt.xlabel('Make')
plt.ylabel('Number of Accidents and Incidents')
plt.title('Make')
plt.xticks(rotation=45);
```



Findings

Across different makes the trend is consistent with the overall trend. The only exception is Bell aircraft with a high number of incidents whilst maneuevering suggest an issue with the aircraft

Further info

It would be beneficial to know the proportion of each incidents occuring at each 'Broad.phase.of.flight' for each 'make'

In [38]:
```
make_phase_grouped/most_inc_make_df.groupby(['Make'])['Event.Id'].count()
```

Out[38]:
```
Make    Broad.phase.of.flight
Beech   Approach                 0.112807
        Climb                    0.032949
        Cruise                   0.136448
        Descent                  0.029412
        Go-around                0.026061
        Landing                  0.170141
        Maneuvering              0.037975
        Other                    0.001117
        Standing                 0.010611
        Takeoff                  0.156552
        Taxi                     0.019918
        Unknown                  0.266009
Bell    Approach                 0.050698
        Climb                    0.012123
        Cruise                   0.153931
        Descent                  0.015430
        Go-around                0.001102
        Landing                  0.080823
        Maneuvering              0.229243
        Other                    0.001837
        Standing                 0.022777
        Takeoff                  0.106172
        Taxi                     0.008450
        Unknown                  0.317414
Boeing  Approach                 0.041166
        Climb                    0.030237
        Cruise                   0.067031
        Descent                  0.032058
        Go-around                0.004372
        Landing                  0.074681
        Maneuvering              0.017851
        Other                    0.000364
        Standing                 0.026958
        Takeoff                  0.068124
        Taxi                     0.056831
        Unknown                  0.580328
Cessna  Approach                 0.078345
        Climb                    0.020627
        Cruise                   0.127003
        Descent                  0.023463
        Go-around                0.022469
        Landing                  0.237688
        Maneuvering              0.066816
        Other                    0.001105
        Standing                 0.009650
        Takeoff                  0.142215
        Taxi                     0.026889
        Unknown                  0.243729
Piper   Approach                 0.084802
        Climb                    0.026227
        Cruise                   0.138399
        Descent                  0.021116
        Go-around                0.020040
        Landing                  0.186886
        Maneuvering              0.071822
        Other                    0.001143
        Standing                 0.007599
        Takeoff                  0.161466
        Taxi                     0.022663
        Unknown                  0.257835
Name: Event.Id, dtype: float64
```

In [ ]: