Project Overview

This project analyzes the NTSB Aviation Accident dataset, which contains aviation accidents from 1962 to 2023. It contains over 80,000 records. This analysis can be used to see the safest airlines with the least accidents, fatalities, and areas that can be improved to reduce such calamities.

Business Understanding

We have been hired by Sky High Corp. They are interested in **purchasing and operating airplanes** for **commercial and private activities** and they want to know the **potential of risks involved in aviation**.

We have been tasked to find **which aircraft have the lowest risk** for the company to start with as they get into this business venture.

In [1]:
```
# Importing the necessary libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
plt.style.use('ggplot')

# To display all columns
pd.set_option('display.max_columns', None)

# To ensure all visualizations stay within the notebook
%matplotlib inline
```

In [2]:
```
# Loading the dataset
aviation_df = pd.read_csv("./data/AviationData.csv", encoding = 'latin-1',
                          dtype = {6: str, 7:str, 28: str})
# dtype = {6: str, 7:str, 28: str}: was used to set the data type for those specific columns to str to avoid errors
aviation_df
```

Out[2]:

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Code	Airport.Name	Inju
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	36.922223	-81.878056	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	
...	...	...	...	...	...	...	...	...	...	...	
88884	20221227106491	Accident	ERA23LA093	2022-12-26	Annapolis, MD	United States	NaN	NaN	NaN	NaN	
88885	20221227106494	Accident	ERA23LA095	2022-12-26	Hampton, NH	United States	NaN	NaN	NaN	NaN	
88886	20221227106497	Accident	WPR23LA075	2022-12-26	Payson, AZ	United States	341525N	1112021W	PAN	PAYSON	
88887	20221227106498	Accident	WPR23LA076	2022-12-26	Morgan, UT	United States	NaN	NaN	NaN	NaN	
88888	20221230106513	Accident	ERA23LA097	2022-12-29	Athens, GA	United States	NaN	NaN	NaN	NaN	

88889 rows × 31 columns

Data Understanding

In [3]:
```
print(f"The Accident Aviation dataset contains {aviation_df.shape[0]} rows and {aviation_df.shape[1]} columns")
```

The Accident Aviation dataset contains 88889 rows and 31 columns

In [4]:
```
aviation_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 [5]:
```
# Checking the percentage of null values in all columns
aviation_df.isna().mean()*100
```

Out[5]:
```
Event.Id                  0.000000
Investigation.Type        0.000000
Accident.Number           0.000000
Event.Date                0.000000
Location                  0.058500
Country                   0.254250
Latitude                 61.320298
Longitude                61.330423
Airport.Code             43.469946
Airport.Name             40.611324
Injury.Severity           1.124999
Aircraft.damage           3.593246
Aircraft.Category        63.677170
Registration.Number       1.481623
Make                      0.070875
Model                     0.103500
Amateur.Built             0.114750
Number.of.Engines         6.844491
Engine.Type               7.961615
FAR.Description          63.974170
Schedule                 85.845268
Purpose.of.flight         6.965991
Air.carrier              81.271023
Total.Fatal.Injuries     12.826109
Total.Serious.Injuries   14.073732
Total.Minor.Injuries     13.424608
Total.Uninjured           6.650992
Weather.Condition         5.053494
Broad.phase.of.flight    30.560587
Report.Status             7.178616
Publication.Date         15.492356
dtype: float64
```

Data Preparation

In [6]:
```
# Converting all column names to lower and replacing dots with underscores
aviation_df.columns = aviation_df.columns.str.lower().str.replace('.', "_", regex = True)
aviation_df.columns
```

Out[6]:
```
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 [7]:
```
aviation_df.isna().sum()
```

Out[7]:
```
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 [8]:
```
# To get only accidents that happen in the United States and its territories
us_territories = ["United States",'American Samoa','Guam',"Marshall Islands","Micronesia",
                  "Northern Marianas","Palau","Puerto Rico","Virgin Islands","Washington_DC",
                  "Gulf of Mexico","Atlantic Ocean","Pacific Ocean"]
us_accidents = aviation_df[aviation_df['country'].isin(us_territories)]
```

In [9]:
```
us_accidents.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 82373 entries, 0 to 88888
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   event_id                82373 non-null  object 
 1   investigation_type      82373 non-null  object 
 2   accident_number         82373 non-null  object 
 3   event_date              82373 non-null  object 
 4   location                82360 non-null  object 
 5   country                 82373 non-null  object 
 6   latitude                32286 non-null  object 
 7   longitude               32276 non-null  object 
 8   airport_code            49247 non-null  object 
 9   airport_name            51714 non-null  object 
 10  injury_severity         82253 non-null  object 
 11  aircraft_damage         80371 non-null  object 
 12  aircraft_category       28195 non-null  object 
 13  registration_number     82322 non-null  object 
 14  make                    82352 non-null  object 
 15  model                   82335 non-null  object 
 16  amateur_built           82352 non-null  object 
 17  number_of_engines       80460 non-null  float64
 18  engine_type             79311 non-null  object 
 19  far_description         28266 non-null  object 
 20  schedule                10338 non-null  object 
 21  purpose_of_flight       79901 non-null  object 
 22  air_carrier             14530 non-null  object 
 23  total_fatal_injuries    71716 non-null  float64
 24  total_serious_injuries  70996 non-null  float64
 25  total_minor_injuries    71641 non-null  float64
 26  total_uninjured         77368 non-null  float64
 27  weather_condition       81687 non-null  object 
 28  broad_phase_of_flight   61238 non-null  object 
 29  report_status           79719 non-null  object 
 30  publication_date        69658 non-null  object 
dtypes: float64(5), object(26)
memory usage: 20.1+ MB
```

In [10]:
```
# Checking for the percentage of null values in each column
us_accidents.isna().mean()*100
```

Out[10]:
```
event_id                  0.000000
investigation_type        0.000000
accident_number           0.000000
event_date                0.000000
location                  0.015782
country                   0.000000
latitude                 60.805118
longitude                60.817258
airport_code             40.214633
airport_name             37.219720
injury_severity           0.145679
aircraft_damage           2.430408
aircraft_category        65.771551
registration_number       0.061913
make                      0.025494
model                     0.046132
amateur_built             0.025494
number_of_engines         2.322363
engine_type               3.717237
far_description          65.685358
schedule                 87.449771
purpose_of_flight         3.000983
air_carrier              82.360725
total_fatal_injuries     12.937492
total_serious_injuries   13.811564
total_minor_injuries     13.028541
total_uninjured           6.076020
weather_condition         0.832797
broad_phase_of_flight    25.657679
report_status             3.221930
publication_date         15.435883
dtype: float64
```

In [11]:
```
# Dropping unnecessary columns
us_accidents = us_accidents.copy()
us_accidents.drop(['latitude',
                   'longitude',
                   'schedule',
                   'far_description',
                   'airport_code',
                   'report_status',
                   'publication_date',
                   'air_carrier',
                   'airport_name',], axis = 1, inplace = True)
```

Some columns had to be changed to appropriate data types:

- `number_of_engines`, `total_fatal_injuries`, `total_serious_injuries`, `total_minor_injuries` and `total_uninjured` had to be changed as people and number of engines cannot be continuous data
- `event_date` had to be changed to a datetime format and the year extracted

In [12]:
```
# Filling null values with 0 and changing data type to int
# 0 becomes a placeholder
us_accidents['number_of_engines'] = us_accidents['number_of_engines'].fillna(0).astype(int)
us_accidents['total_fatal_injuries'] = us_accidents['total_fatal_injuries'].fillna(0).astype(int)
us_accidents['total_serious_injuries'] = us_accidents['total_serious_injuries'].fillna(0).astype(int)
us_accidents['total_minor_injuries'] = us_accidents['total_minor_injuries'].fillna(0).astype(int)
us_accidents['total_uninjured'] = us_accidents['total_uninjured'].fillna(0).astype(int)

# Only getting the Year the incident/accident happened
us_accidents['event_date'] = pd.to_datetime(us_accidents['event_date'], format='%Y-%m-%d').dt.strftime('%Y')
us_accidents.columns = us_accidents.columns.str.replace('event_date', "event_year")
us_accidents['event_year'] = us_accidents['event_year'].astype(int)
```

In [13]:
```
# Checking for duplicated using the event_id
us_accidents[us_accidents.duplicated(subset = 'event_id', keep = False)].head(50)
```

Out[13]:

	event_id	investigation_type	accident_number	event_year	location	country	injury_severity	aircraft_damage	aircraft_category	registr
117	20020917X01908	Accident	DCA82AA012B	1982	ROCKPORT, TX	United States	Fatal(3)	Destroyed	Airplane	
118	20020917X01908	Accident	DCA82AA012A	1982	ROCKPORT, TX	United States	Fatal(3)	Destroyed	Airplane	
153	20020917X02259	Accident	LAX82FA049A	1982	VICTORVILLE, CA	United States	Fatal(2)	Destroyed	Airplane	
158	20020917X02400	Accident	MIA82FA038B	1982	NEWPORT RICHEY, FL	United States	Non-Fatal	Substantial	Airplane	
159	20020917X02400	Accident	MIA82FA038A	1982	NEWPORT RICHEY, FL	United States	Non-Fatal	Substantial	Airplane	
160	20020917X02259	Accident	LAX82FA049B	1982	VICTORVILLE, CA	United States	Fatal(2)	Substantial	Airplane	
242	20020917X02585	Accident	SEA82DA028A	1982	MEDFORD, OR	United States	Non-Fatal	Minor	Airplane	
244	20020917X02173	Accident	LAX82DA065B	1982	SAN JOSE, CA	United States	Non-Fatal	Minor	Airplane	
245	20020917X02585	Accident	SEA82DA028B	1982	MEDFORD, OR	United States	Non-Fatal	Substantial	Airplane	
248	20020917X02173	Accident	LAX82DA065A	1982	SAN JOSE, CA	United States	Non-Fatal	Substantial	Airplane	
254	20020917X02402	Accident	MIA82FA044B	1982	W. OF HOMESTEAD, FL	United States	Fatal(8)	Destroyed	Airplane	
255	20020917X02402	Accident	MIA82FA044A	1982	W. OF HOMESTEAD, FL	United States	Fatal(8)	Destroyed	Airplane	
490	20020917X02189	Accident	LAX82DA097B	1982	HALF MOON BAY, CA	United States	Non-Fatal	Substantial	Airplane	
491	20020917X02189	Accident	LAX82DA097A	1982	HALF MOON BAY, CA	United States	Non-Fatal	Substantial	Airplane	

	event_id	investigation_type	accident_number	event_year	location	country	injury_severity	aircraft_damage	aircraft_category	registr
535	20020917X01716	Accident	ATL82DKW06B	1982	NASHVILLE, TN	United States	Non-Fatal	Minor	Airplane	
539	20020917X01716	Accident	ATL82DKW06A	1982	NASHVILLE, TN	United States	Non-Fatal	Substantial	Airplane	
557	20020917X02154	Accident	LAX82AA106B	1982	GLENDALE, AZ	United States	Fatal(6)	Destroyed	Airplane	
558	20020917X02154	Accident	LAX82AA106A	1982	GLENDALE, AZ	United States	Fatal(6)	Destroyed	Airplane	
844	20020917X02282	Accident	LAX82FA136B	1982	TULARE, CA	United States	Fatal(1)	Substantial	Glider	
845	20020917X02282	Accident	LAX82FA136A	1982	TULARE, CA	United States	Fatal(1)	Substantial	Glider	
961	20020917X02558	Accident	NYC82FHJ04B	1982	NEW YORK, NY	United States	Non-Fatal	Minor	Helicopter	
981	20020917X02558	Accident	NYC82FHJ04A	1982	NEW YORK, NY	United States	Non-Fatal	Substantial	Helicopter	
1031	20020917X03642	Accident	LAX82FA156B	1982	CAMARILLO, CA	United States	Non-Fatal	Minor	Airplane	
1036	20020917X02721	Accident	ATL82DA123B	1982	MARIETTA, GA	United States	Non-Fatal	Minor	Airplane	
1041	20020917X03642	Accident	LAX82FA156A	1982	CAMARILLO, CA	United States	Non-Fatal	Substantial	Airplane	
1047	20020917X02721	Accident	ATL82DA123A	1982	MARIETTA, GA	United States	Non-Fatal	Substantial	Airplane	
1160	20020917X04016	Accident	NYC82FA091B	1982	SANFORD, ME	United States	Non-Fatal	Destroyed	Airplane	
1171	20020917X04016	Accident	NYC82FA091A	1982	SANFORD, ME	United States	Non-Fatal	Substantial	Airplane	
1370	20020917X02935	Accident	CHI82DA189B	1982	EVANSVILLE, IN	United States	Non-Fatal	Substantial	Airplane	

	event_id	investigation_type	accident_number	event_year	location	country	injury_severity	aircraft_damage	aircraft_category	registr
1371	20020917X02935	Accident	CHI82DA189A	1982	EVANSVILLE, IN	United States	Non-Fatal	Substantial	Airplane	
1426	20020917X03553	Accident	LAX82DA207A	1982	SANTA CRUZ, CA	United States	Non-Fatal	NaN	Airplane	
1431	20020917X03553	Accident	LAX82DA207B	1982	SANTA CRUZ, CA	United States	Non-Fatal	Substantial	Airplane	
1529	20020917X03659	Accident	LAX82FA218B	1982	CORONA, CA	United States	Fatal(4)	Destroyed	Airplane	
1530	20020917X03659	Accident	LAX82FA218A	1982	CORONA, CA	United States	Fatal(4)	Destroyed	Airplane	
1710	20020917X03514	Accident	LAX82AA235B	1982	SAN JOSE, CA	United States	Fatal(3)	Destroyed	Airplane	
1711	20020917X03514	Accident	LAX82AA235A	1982	SAN JOSE, CA	United States	Fatal(3)	Destroyed	Airplane	
1731	20020917X03442	Accident	FTW82DRJ19A	1982	LUFKIN, TX	United States	Non-Fatal	Minor	Airplane	
1738	20020917X03442	Accident	FTW82DRJ19B	1982	LUFKIN, TX	United States	Non-Fatal	Substantial	Airplane	
1880	20020917X03351	Accident	FTW82DA275B	1982	AUSTIN, TX	United States	Non-Fatal	Substantial	Airplane	
1892	20020917X03351	Accident	FTW82DA275A	1982	AUSTIN, TX	United States	Non-Fatal	Substantial	Airplane	
1918	20020917X03353	Accident	FTW82DA277A	1982	JUSTIN, TX	United States	Non-Fatal	Destroyed	Airplane	
1931	20020917X03353	Accident	FTW82DA277B	1982	JUSTIN, TX	United States	Non-Fatal	Substantial	Airplane	
2052	20020917X04070	Accident	SEA82AA126B	1982	MERCER ISLAND, WA	United States	Fatal(6)	Destroyed	Airplane	
2053	20020917X04070	Accident	SEA82AA126A	1982	MERCER ISLAND, WA	United States	Fatal(6)	Destroyed	Airplane	

	event_id	investigation_type	accident_number	event_year	location	country	injury_severity	aircraft_damage	aircraft_category	registr
2125	20020917X03685	Accident	LAX82FA279B	1982	MORGAN HILL, CA	United States	Fatal(2)	Destroyed	Airplane	
2127	20020917X03685	Accident	LAX82FA279A	1982	MORGAN HILL, CA	United States	Fatal(2)	Substantial	Airplane	
2223	20020917X03083	Accident	CHI82FA290B	1982	OSHKOSH, WI	United States	Fatal(3)	Destroyed	Airplane	
2224	20020917X03083	Accident	CHI82FA290A	1982	OSHKOSH, WI	United States	Fatal(3)	Destroyed	Airplane	
2264	20020917X03176	Accident	DEN82DA157B	1982	GRAFTON, ND	United States	Non-Fatal	Minor	Airplane	
2272	20020917X03176	Accident	DEN82DA157A	1982	GRAFTON, ND	United States	Non-Fatal	Substantial	Airplane	

While trying to check for duplicates in `event_id`, it was discovered that in cases where the `event_id` was duplicated, two aircrafts were involved in the accident. They were both logged in one event_id but different accident_number

Aircraft Category Column

The Aircraft Category Column started with around 65% of null values in the column. Since our client mostly wants airplanes data, we had to try to minimize the null values.

The following were done after a lot of research:

- The type of aircraft had to be identified using the `make` and `model` columns.
- Some duplicates were removed in the `make` and `model` columns by converting all values into Title case.
- Depending on the aircrafts we have in the dataset, we determined all that were helicopters, airplanes and some gliders
- Some naming conventions were changed to ensure uniformity in the dataset.

Once most of the data in the `aircraft_category` was cleaned, we were able to reduce the null values from 65% to 13%. The rest of the null values were then dropped

In [14]:
```
us_accidents.isna().mean()*100
```

Out[14]:
```
event_id                  0.000000
investigation_type        0.000000
accident_number           0.000000
event_year                0.000000
location                  0.015782
country                   0.000000
injury_severity           0.145679
aircraft_damage           2.430408
aircraft_category        65.771551
registration_number       0.061913
make                      0.025494
model                     0.046132
amateur_built             0.025494
number_of_engines         0.000000
engine_type               3.717237
purpose_of_flight         3.000983
total_fatal_injuries      0.000000
total_serious_injuries    0.000000
total_minor_injuries      0.000000
total_uninjured           0.000000
weather_condition         0.832797
broad_phase_of_flight    25.657679
dtype: float64
```

In [15]:
```
us_accidents['make'].value_counts()
```

Out[15]:
```
Cessna               21597
Piper                11670
CESSNA                4287
Beech                 4168
PIPER                 2509
                     ...
Hallett                  1
Steven R. Jackson        1
Weste                    1
Arthur P. Matthews       1
ROYSE RALPH L            1
Name: make, Length: 8003, dtype: int64
```

In [16]:
```
# Converting all values into Title case
us_accidents['make'] = us_accidents['make'].str.title()
#pd.set_option('display.max_rows', None)
us_accidents['make'].value_counts().head(56)
```

Out[16]:

Cessna	25884
Piper	14179
Beech	5061
Bell	2296
Boeing	1496
Mooney	1294
Grumman	1142
Bellanca	1040
Robinson	926
Hughes	875
Schweizer	745
Air Tractor	645
Aeronca	635
Maule	577
Champion	514
Mcdonnell Douglas	467
Stinson	439
Luscombe	413
Aero Commander	397
De Havilland	386
Taylorcraft	382
North American	374
Aerospatiale	351
Hiller	345
Rockwell	337
Enstrom	285
Robinson Helicopter	228
Douglas	226
Grumman American	224
Air Tractor Inc	218
Ayres	217
Cirrus Design Corp	206
Eurocopter	189
Robinson Helicopter Company	181
Sikorsky	162
Ercoupe (Eng & Research Corp.)	160
Embraer	158
Swearingen	156
Balloon Works	147
Pitts	145
Schleicher	144
Fairchild	142
Lake	142
Waco	141

```
Aviat                          137
Mitsubishi                     136
Let                            132
Grumman-Schweizer              127
Burkhart Grob                  121
Airbus Industrie               114
Vans                           112
Airbus                         111
Ryan                           110
Helio                          109
Socata                         104
Cirrus                         103
Name: make, dtype: int64
```

In [17]:

```
# Imputing the appropriate aircraft category depending on make and model columns
us_accidents.loc[us_accidents['make'] == 'Cessna', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Piper', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Beech', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Mooney', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Bellanca', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Boeing', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'American Champion Aircraft', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Aeronca', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Maule', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Stinson', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Luscombe', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Aero Commander', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Taylorcraft', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'Rockwell International', 'aircraft_category'] = 'Airplane'
us_accidents.loc[us_accidents['make'] == 'North American', 'aircraft_category'] = 'Helicopter'
us_accidents.loc[us_accidents['make'] == 'Hiller', 'aircraft_category'] = 'Helicopter'
us_accidents.loc[us_accidents['make'] == 'Bell', 'aircraft_category'] = 'Helicopter'
us_accidents.loc[us_accidents['make'] == 'Hughes', 'aircraft_category'] = 'Helicopter'

# Streamlining naming conventions for Robinson Helicopter Company
us_accidents['make'] = us_accidents['make'].replace(['Robinson','Robinson Helicopter','Robinson Helicopter Company'], "Robinson H
us_accidents.loc[us_accidents['make'] == 'Robinson Helicopter Company', 'aircraft_category'] = 'Helicopter'

# Streamlining naming conventions for Northrop Grumman
us_accidents['make'] = us_accidents['make'].replace(['Grumman','Grumman American','Grumman American Avn. Corp.'], "Northrop Grumm
us_accidents.loc[us_accidents['make'] == 'Northrop Grumman', 'aircraft_category'] = 'Airplane'

# Streamlining naming conventions for De Havilland
us_accidents['make'] = us_accidents['make'].replace(['Dehavilland','De Havilland'], "De Havilland")
```

```
us_accidents.loc[us_accidents['make'] == 'De Havilland', 'aircraft_category'] = 'Airplane'

# Streamlining naming conventions for Air Tractor Inc
us_accidents['make'] = us_accidents['make'].replace(['Air Tractor','Air Tractor Inc'], "Air Tractor Inc")
us_accidents.loc[us_accidents['make'] == 'Air Tractor Inc', 'aircraft_category'] = 'Airplane'

# Streamlining naming conventions for American Champion Aircraft
us_accidents['make'] = us_accidents['make'].replace(['American Champion Aircraft','Champion'], "American Champion Aircraft")

# Streamlining naming conventions for Rockwell International
us_accidents['make'] = us_accidents['make'].replace(['Rockwell','Rockwell International'], "Rockwell International")

# Streamlining naming conventions for Cirrus Design Corp
us_accidents['make'] = us_accidents['make'].replace(['Cirrus Design Corp','Cirrus'], "Cirrus Design Corp")

# Streamlining naming conventions for Aviat Aircraft Inc
us_accidents['make'] = us_accidents['make'].replace(['Aviat Aircraft Inc','Aviat'], "Aviat Aircraft Inc")

# Streamlining naming conventions for Rockwell International
us_accidents['make'] = us_accidents['make'].replace(['Ayres Corporation','Ayres'], "Ayres Corporation")

# Streamlining naming conventions for Diamond Aircraft Ind Inc
us_accidents['make'] = us_accidents['make'].replace(['Diamond Aircraft Ind Inc','Diamond'], "Diamond Aircraft Ind Inc")

# Imputing the appropriate aircraft category depending on make and model columns for Schweizer
us_accidents.loc[(us_accidents['aircraft_category'].isna()) &
                 (us_accidents['make'] == "Schweizer") &
                 (us_accidents['model'].str.contains('269|300', na = False, case = False)), 'aircraft_category'] = "Helicopter"
us_accidents.loc[(us_accidents['aircraft_category'].isna()) &
                 (us_accidents['make'] == "Schweizer") &
                 (us_accidents['model'].str.contains('2-3|1-2|2-2|1-3|SGS', na = False, case = False)), 'aircraft_category'] = "C
us_accidents.loc[(us_accidents['aircraft_category'].isna()) &
                 (us_accidents['make'] == "Schweizer") &
                 (us_accidents['model'].str.contains('164', na = False, case = False)), 'aircraft_category'] = "Airplane"

# Imputing the appropriate aircraft category depending on make and model columns for McDonnell Douglas
us_accidents.loc[(us_accidents['aircraft_category'].isna()) &
                 (us_accidents['make'] == "Mcdonnell Douglas") &
                 (us_accidents['model'].str.contains('DC|MD-8|MD-11|MD-9|MD8|MD-10|MD11', na = False, case = False)), 'aircraft_c
us_accidents.loc[(us_accidents['aircraft_category'].isna()) &
                 (us_accidents['make'] == "Mcdonnell Douglas") &
                 (us_accidents['model'].str.contains('369|500|600|269|520|90', na = False, case = False)), 'aircraft_category'] =
us_accidents['make'] = us_accidents['make'].replace('Mcdonnell Douglas', "McDonnell Douglas")
```

```
# Replacing UNK with Unknown
us_accidents['aircraft_category'] = us_accidents['aircraft_category'].replace('UNK', "Unknown")

# Dropping the rest of the values
us_accidents.dropna(subset = ['make', 'model','aircraft_category'], inplace = True)
```

In [18]:
```
# Final Results
us_accidents['aircraft_category'].value_counts()
```

Out[18]:
```
Airplane            62544
Helicopter           6465
Glider                756
Balloon               229
Gyrocraft             172
Weight-Shift          161
Powered Parachute      89
Ultralight             25
WSFT                    9
Unknown                 5
Blimp                   4
Powered-Lift            3
Rocket                  1
ULTR                    1
Name: aircraft_category, dtype: int64
```

Location and State Columns

New column had to be computed to get the states and the area that the accident happened

- `area` was to contain the genral area where the accident occured
- `state_short_code` contains the abbreviation for the states and the territories

Due to input errors, especially among the US Territories, manual replacements had to be done to get the correct data. In cases where the area could not be fetched, **UN** is put to represent **Unknown**

In [19]:
```
# Creating and cleaning up the created columns
new_cols = us_accidents['location'].str.rsplit(',',n = 1, expand = True)
us_accidents['area'] = new_cols[0]
us_accidents['state_abbrev'] = new_cols[1].str.strip()
```

In [20]:
```
# pd.set_option('display.max_rows', None)
us_accidents['state_abbrev'].value_counts()
```

Out[20]:
```
CA                                7417
AK                                5264
TX                                5130
FL                                4912
AZ                                2407
                                  ...
Micronesia (Federated States of)     2
Marshall Islands                     1
MARSHALL ISLANDS                     1
Palau                                1
CB                                   1
Name: state_abbrev, Length: 68, dtype: int64
```

In [21]:
```
# Renaming the short codes accordingly
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace(["Virgin Islands (British)", 'CB'], 'VI')
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace(["American Samoa","AMERICAN SAMOA"], 'AS')
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace("Micronesia (Federated States of)", 'FM')
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace(["Marshall Islands","MARSHALL ISLANDS"], 'MH')
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace("Palau", 'PW')

# All Empty Values replaced with UN for Unknown
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].replace("", 'UN')
us_accidents['state_abbrev'] = us_accidents['state_abbrev'].fillna('UN')
```

In [22]:
```
# pd.set_option('display.max_rows', None)
us_accidents['state_abbrev'].value_counts()
```

Out[22]:
```
CA    7417
AK    5264
TX    5130
FL    4912
AZ    2407
      ...
VI       7
AS       4
MH       2
FM       2
PW       1
Name: state_abbrev, Length: 63, dtype: int64
```

All good

In [23]:
```
# This dictionary contains thee long form of the state abbreviations
state_abbreviation = {
    "AL": "Alabama",
    "AK": "Alaska",
    "AZ": "Arizona",
    "AR": "Arkansas",
    "CA": "California",
    "CO": "Colorado",
    "CT": "Connecticut",
    "DE": "Delaware",
    "FL": "Florida",
    "GA": "Georgia",
    "HI": "Hawaii",
    "ID": "Idaho",
    "IL": "Illinois",
    "IN": "Indiana",
    "IA": "Iowa",
    "KS": "Kansas",
    "KY": "Kentucky",
    "LA": "Louisiana",
    "ME": "Maine",
    "MD": "Maryland",
    "MA": "Massachusetts",
    "MI": "Michigan",
    "MN": "Minnesota",
    "MS": "Mississippi",
    "MO": "Missouri",
    "MT": "Montana",
    "NE": "Nebraska",
    "NV": "Nevada",
    "NH": "New Hampshire",
    "NJ": "New Jersey",
    "NM": "New Mexico",
    "NY": "New York",
    "NC": "North Carolina",
    "ND": "North Dakota",
    "OH": "Ohio",
    "OK": "Oklahoma",
    "OR": "Oregon",
    "PA": "Pennsylvania",
    "RI": "Rhode Island",
```

```
    "SC": "South Carolina",
    "SD": "South Dakota",
    "TN": "Tennessee",
    "TX": "Texas",
    "UT": "Utah",
    "VT": "Vermont",
    "VA": "Virginia",
    "WA": "Washington",
    "WV": "West Virginia",
    "WI": "Wisconsin",
    "WY": "Wyoming",
    "AS": "American Samoa",
    "GU": "Guam",
    "MH": "Marshall Islands",
    "FM": "Micronesia",
    "MP": "Northern Marianas",
    "PW": "Palau",
    "PR": "Puerto Rico",
    "VI": "Virgin Islands",
    "DC": "Washington DC",
    "GM": "Gulf of Mexico",
    "AO": "Atlantic Ocean",
    "PO": "Atlantic Ocean",
    "UN": "Unknown"
}
```

In [24]:
```
# Making a new column with the abbreviations
us_accidents['state'] = us_accidents['state_abbrev'].map(state_abbreviation)
```

In [25]:
```
us_accidents.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 70464 entries, 0 to 88888
Data columns (total 25 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   event_id                70464 non-null  object
 1   investigation_type      70464 non-null  object
 2   accident_number         70464 non-null  object
 3   event_year              70464 non-null  int32 
 4   location                70453 non-null  object
 5   country                 70464 non-null  object
 6   injury_severity         70358 non-null  object
 7   aircraft_damage         69049 non-null  object
 8   aircraft_category       70464 non-null  object
 9   registration_number     70441 non-null  object
 10  make                    70464 non-null  object
 11  model                   70464 non-null  object
 12  amateur_built           70449 non-null  object
 13  number_of_engines       70464 non-null  int32 
 14  engine_type             67650 non-null  object
 15  purpose_of_flight       68335 non-null  object
 16  total_fatal_injuries    70464 non-null  int32 
 17  total_serious_injuries  70464 non-null  int32 
 18  total_minor_injuries    70464 non-null  int32 
 19  total_uninjured         70464 non-null  int32 
 20  weather_condition       69821 non-null  object
 21  broad_phase_of_flight   49407 non-null  object
 22  area                    70453 non-null  object
 23  state_abbrev            70464 non-null  object
 24  state                   70442 non-null  object
dtypes: int32(6), object(19)
memory usage: 12.4+ MB
```

While investigating the state null values, it was discovered that some columns had the **OF** abbreviation that is not attched to any state and territory as they are not in the United States. They were thus dropped.

In [26]:
```
us_accidents.drop(us_accidents[us_accidents['state'].isna()].index, inplace = True)
```

Injury Columns

A new column, `'total_injured'`, is created. It contains the sum of all the injured columns.

In [27]:
```
us_accidents['total_injured'] = us_accidents[['total_fatal_injuries',
                                              'total_serious_injuries',
                                              'total_minor_injuries']].sum(axis = 1)

us_accidents
```

Out[27]:

	event_id	investigation_type	accident_number	event_year	location	country	injury_severity	aircraft_damage	aircraft_category	regist
0	20001218X45444	Accident	SEA87LA080	1948	MOOSE CREEK, ID	United States	Fatal(2)	Destroyed	Airplane	
1	20001218X45447	Accident	LAX94LA336	1962	BRIDGEPORT, CA	United States	Fatal(4)	Destroyed	Airplane	
2	20061025X01555	Accident	NYC07LA005	1974	Saltville, VA	United States	Fatal(3)	Destroyed	Airplane	
4	20041105X01764	Accident	CHI79FA064	1979	Canton, OH	United States	Fatal(1)	Destroyed	Airplane	
5	20170710X52551	Accident	NYC79AA106	1979	BOSTON, MA	United States	Non-Fatal	Substantial	Airplane	
...	...	...	...	...	...	...	...	...	...	
88884	20221227106491	Accident	ERA23LA093	2022	Annapolis, MD	United States	Minor	NaN	Airplane	
88885	20221227106494	Accident	ERA23LA095	2022	Hampton, NH	United States	NaN	NaN	Airplane	
88886	20221227106497	Accident	WPR23LA075	2022	Payson, AZ	United States	Non-Fatal	Substantial	Airplane	
88887	20221227106498	Accident	WPR23LA076	2022	Morgan, UT	United States	NaN	NaN	Airplane	
88888	20221230106513	Accident	ERA23LA097	2022	Athens, GA	United States	Minor	NaN	Airplane	

70442 rows × 26 columns

Injury Severity Column

Cleaning up the `'injury_severity'` column has a lot of fatal rows but contains a number. Let us only remain with **Fatal** and not Fatal(1), Fatal(4) etc.

In [28]:
```
# Before
us_accidents['injury_severity'].value_counts()
```

Out[28]:
```
Non-Fatal      56438
Fatal(1)        4013
Fatal           3558
Fatal(2)        2703
Incident        1343
Fatal(3)         899
Fatal(4)         644
Minor            203
Fatal(5)         162
Serious          154
Fatal(6)          97
Fatal(7)          26
Fatal(8)          24
Fatal(10)         14
Unavailable       14
Fatal(9)           6
Fatal(11)          5
Fatal(14)          5
Fatal(25)          3
Fatal(12)          3
Fatal(82)          2
Fatal(17)          2
Fatal(18)          2
Fatal(20)          2
Fatal(13)          2
Fatal(228)         1
Fatal(78)          1
Fatal(21)          1
Fatal(92)          1
Fatal(65)          1
Fatal(64)          1
Fatal(44)          1
Fatal(73)          1
Fatal(230)         1
Fatal(132)         1
Fatal(16)          1
Fatal(27)          1
Fatal(34)          1
Fatal(153)         1
Fatal(111)         1
Fatal(28)          1
Fatal(156)         1
Name: injury_severity, dtype: int64
```

In [29]:
```
us_accidents['injury_severity'] = us_accidents['injury_severity'].str.replace(r'\(\d+\)', '', regex = True)
```

In [30]:
```
# After
us_accidents['injury_severity'].value_counts()
```

Out[30]:
```
Non-Fatal      56438
Fatal          12189
Incident        1343
Minor            203
Serious          154
Unavailable       14
Name: injury_severity, dtype: int64
```

Make and Model Column

The model column is mostly clean. The biggest worry in this column is user input error where some users have put hyphens or spaces where there shouldn't be or they have been used interchangeably. To curb this and get a more accurate description, removing of the hyphens and whitespaces might be the best way to solve this issue.

It was also seen important to concatenate the two columns for simpler analysis and to explore granularity

In [31]:
```
us_accidents['model'] = us_accidents['model'].str.replace(r"[-\s]", '', regex = True)
# -: removes hyphens
# s: removes whitespaces
```

In [32]:
```
us_accidents['make_model'] = us_accidents['make'] + " " + us_accidents['model']
```

In [33]:
```
#pd.set_option('display.max_rows', None)
us_accidents[['make','model']].value_counts()
```

Out[33]:
```
make                model
Cessna              152                   2328
                    172                   1636
                    172N                  1144
Piper               PA28140                978
Cessna              172M                   805
                                           ...
Experimental        QuadCityChallenger       1
                    Nieuport12               1
                    Boland                   1
Excalibur Aircraft  Excalibur                1
Zwicker Murray R    GLASTAR                  1
Length: 8728, dtype: int64
```

In [34]:
```
# Dropping rows with "Unavailable" and NaN values
us_accidents.drop(us_accidents[(us_accidents['injury_severity'].isna()) |
                  (us_accidents['injury_severity'] == "Unavailable") |
                   (us_accidents['amateur_built'] == "Yes") |
                    (us_accidents['amateur_built'].isna())].index, inplace = True)
```

Cleaning Up Null Values

In [35]:
```
# Filling NaN in aircraft_damage with Unknown
us_accidents['aircraft_damage'] =  us_accidents['aircraft_damage'].fillna('Unknown')

# Filling NaN in engine_type with Unknown
us_accidents['engine_type'] = us_accidents['engine_type'].replace("UNK", "Unknown")
us_accidents['engine_type'] = us_accidents['engine_type'].fillna('Unknown')

# Filling NaN in purpose_of_flight with Unknown
us_accidents['purpose_of_flight'] = us_accidents['purpose_of_flight'].fillna("Unkown")

# Dropping unnecessary Columns
us_accidents.drop(['location',
                   'broad_phase_of_flight',
                   'registration_number',
                   'area',
                   'amateur_built',
                   'accident_number',
                   'weather_condition'
                  ], axis = 1, inplace = True)
```

In [36]:
```
# Only remaining with columns which contain Airplane and Helicopters only
us_accidents = us_accidents[(us_accidents['aircraft_category'] == "Airplane") |
                            (us_accidents['aircraft_category'] == "Helicopter")]
```

In [37]:
```
# Filtering us_accidents to only get the top 30 planes
considered_planes = list(us_accidents['make'].value_counts().head(30).index)

us_accidents = us_accidents[us_accidents['make'].isin(considered_planes)]
```

In [38]:
```
# Reordering Columns and resetting the index
col_order = ['event_id', 'investigation_type', 'event_year','state_abbrev', 'state','country',
             'aircraft_category', 'make','model','make_model', 'number_of_engines', 'engine_type','purpose_of_flight',
            'total_fatal_injuries', 'total_serious_injuries','total_minor_injuries', 'total_injured', 'total_uninjured',
            'injury_severity', 'aircraft_damage']
us_accidents = us_accidents[col_order].reset_index(drop = True)
```

This is our cleaned data

In [39]:
```
us_accidents
```

Out[39]:

	event_id	investigation_type	event_year	state_abbrev	state	country	aircraft_category	make	model	make_model	numbe
0	20001218X45444	Accident	1948	ID	Idaho	United States	Airplane	Stinson	1083	Stinson 1083	
1	20001218X45447	Accident	1962	CA	California	United States	Airplane	Piper	PA24180	Piper PA24180	
2	20061025X01555	Accident	1974	VA	Virginia	United States	Airplane	Cessna	172M	Cessna 172M	
3	20041105X01764	Accident	1979	OH	Ohio	United States	Airplane	Cessna	501	Cessna 501	
4	20170710X52551	Accident	1979	MA	Massachusetts	United States	Airplane	McDonnell Douglas	DC9	McDonnell Douglas DC9	
...	...	...	...	...	...	...	...	...	...	...	
61498	20221221106483	Accident	2022	MI	Michigan	United States	Airplane	Cessna	172F	Cessna 172F	
61499	20221222106486	Accident	2022	LA	Louisiana	United States	Airplane	Northrop Grumman	AA5B	Northrop Grumman AA5B	
61500	20221227106491	Accident	2022	MD	Maryland	United States	Airplane	Piper	PA28151	Piper PA28151	
61501	20221227106497	Accident	2022	AZ	Arizona	United States	Airplane	American Champion Aircraft	8GCBC	American Champion Aircraft 8GCBC	
61502	20221230106513	Accident	2022	GA	Georgia	United States	Airplane	Piper	PA24260	Piper PA24260	

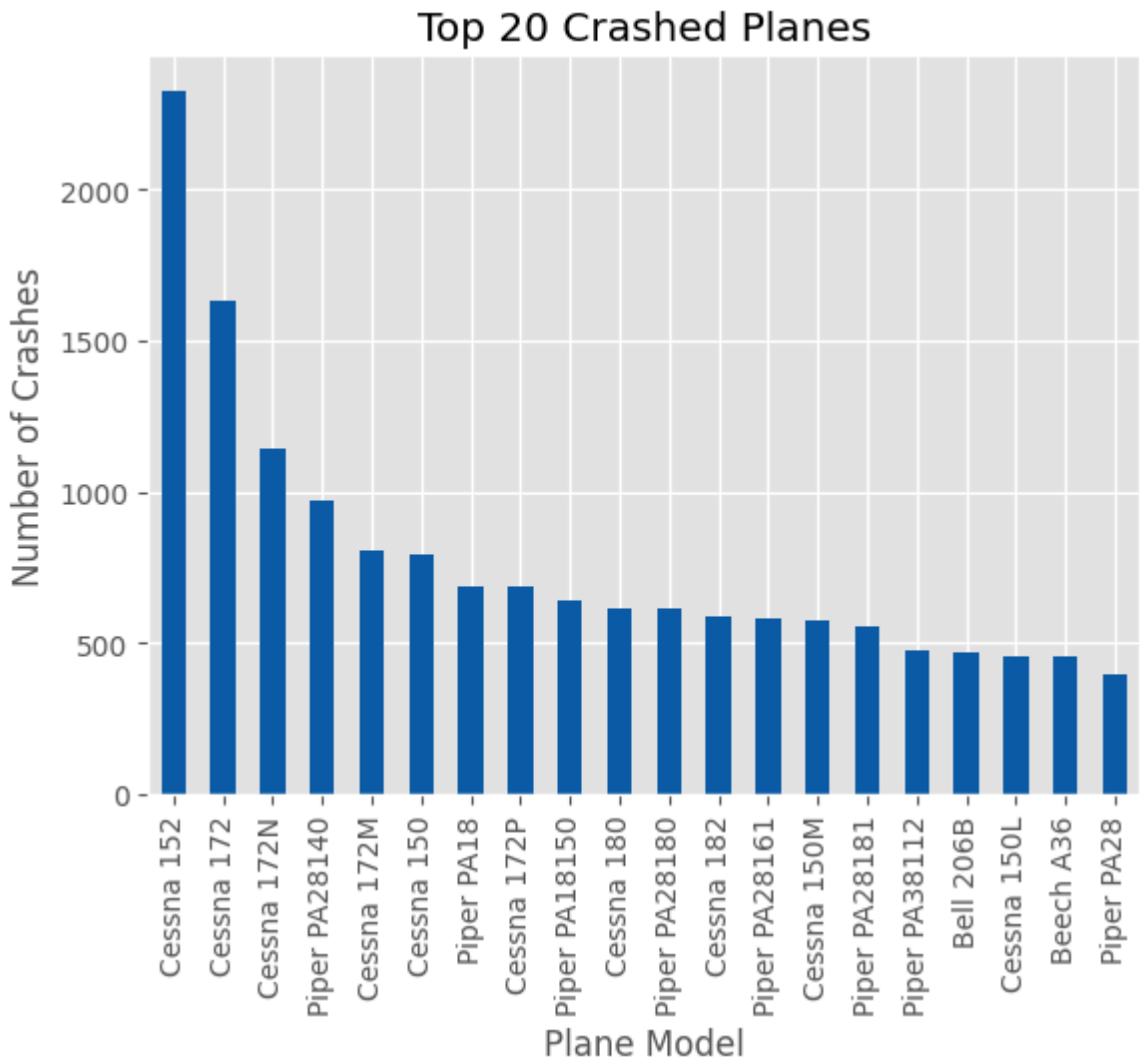
61503 rows × 20 columns

In [40]:
```
# Saving the file
us_accidents.to_csv("./data/US_Aviation_Accidents.csv", encoding = 'latin-1', index = False)
```

Data Analysis

Q: Which planes have recorded the highest number of crashes?

In [41]:
```
top20_planes = us_accidents['make_model'].value_counts().head(20)
top20_planes.plot(kind = 'bar', color = '#0D5EA6')
plt.title("Top 20 Crashed Planes")
plt.xlabel('Plane Model')
plt.ylabel("Number of Crashes");
```



Observations

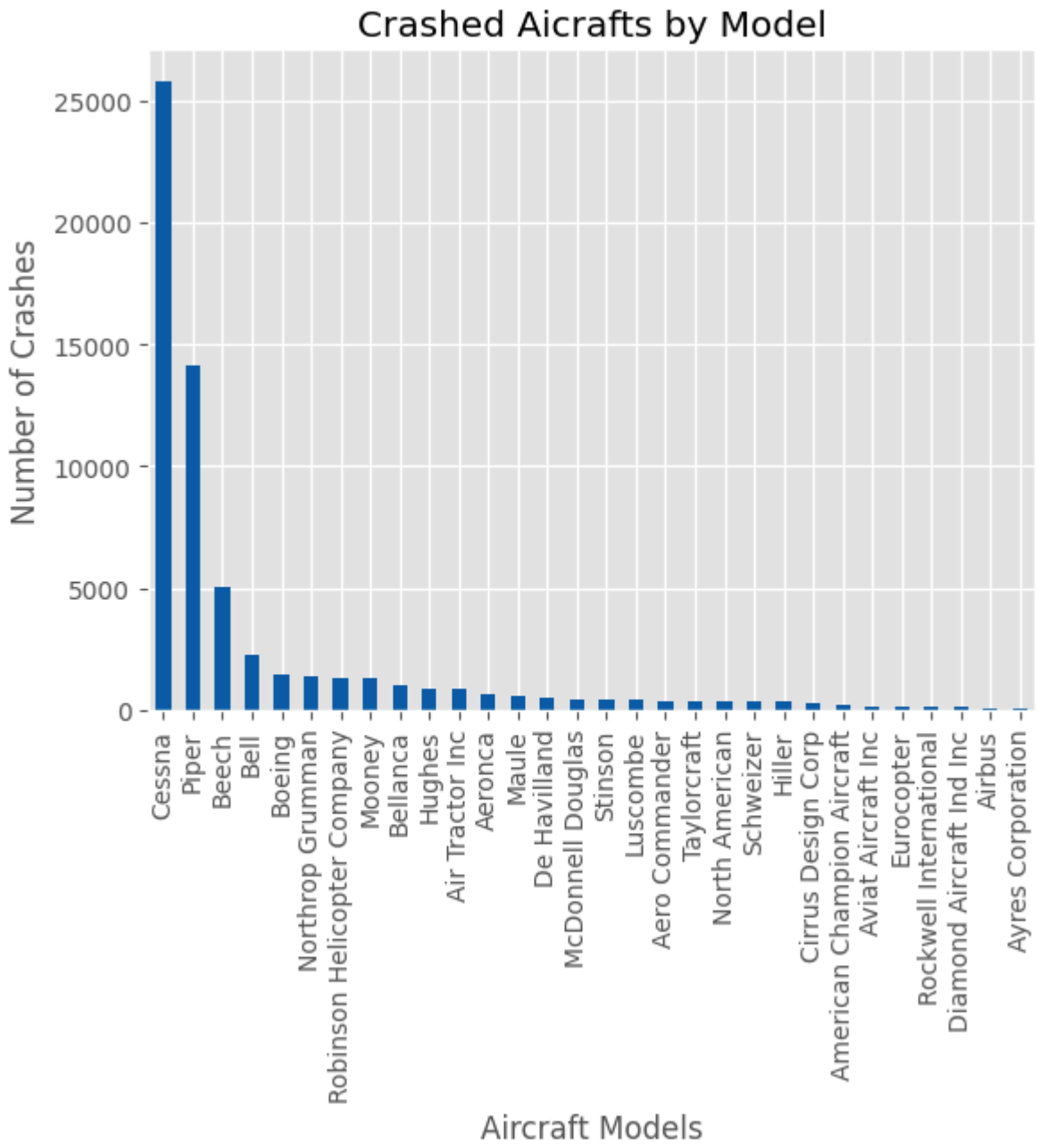
The Cessna is the most crashed airplane. From the 20 above, it appears in half of the occurences

The Cessna 172 and its variants have crashed the most. Specifically, the 172, 172N, 172M, and 172P models.

Piper models are also in this list, but 10% less than Cessna.

Q: Which aircrafts have had the most and the least number of crashes? Does it mean that the aircraft with the least number of crashes is the safest?

In [42]:
```
us_accidents['make'].value_counts().plot(kind = 'bar', color = '#0D5EA6')
plt.title("Crashed Aicrafts by Model")
plt.xlabel('Aircraft Models')
plt.ylabel("Number of Crashes");
```



Observations

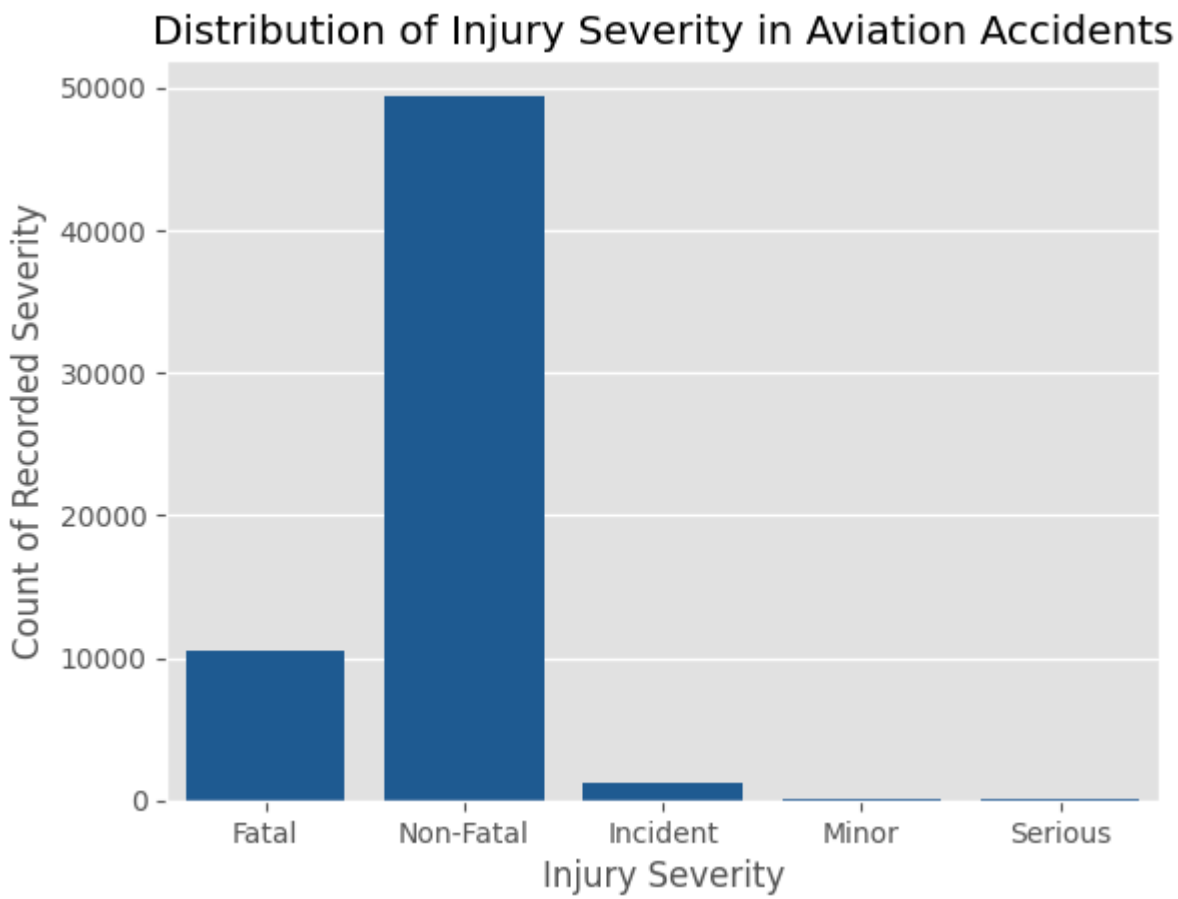
Cessna, Piper and Beech lead the pack when it comes to the most aircraft crashes with over 5,000 crashes each.

Diamond, Airbus and Ayres have had the least number of crashes since 1948.

However, this doesn't mean that the bottom three are the safest. The above can show that the top 3 are the most preferred planes of the bunch as they are bought more for various reasons.

Q: Which types of injury severity have been recorded the most?

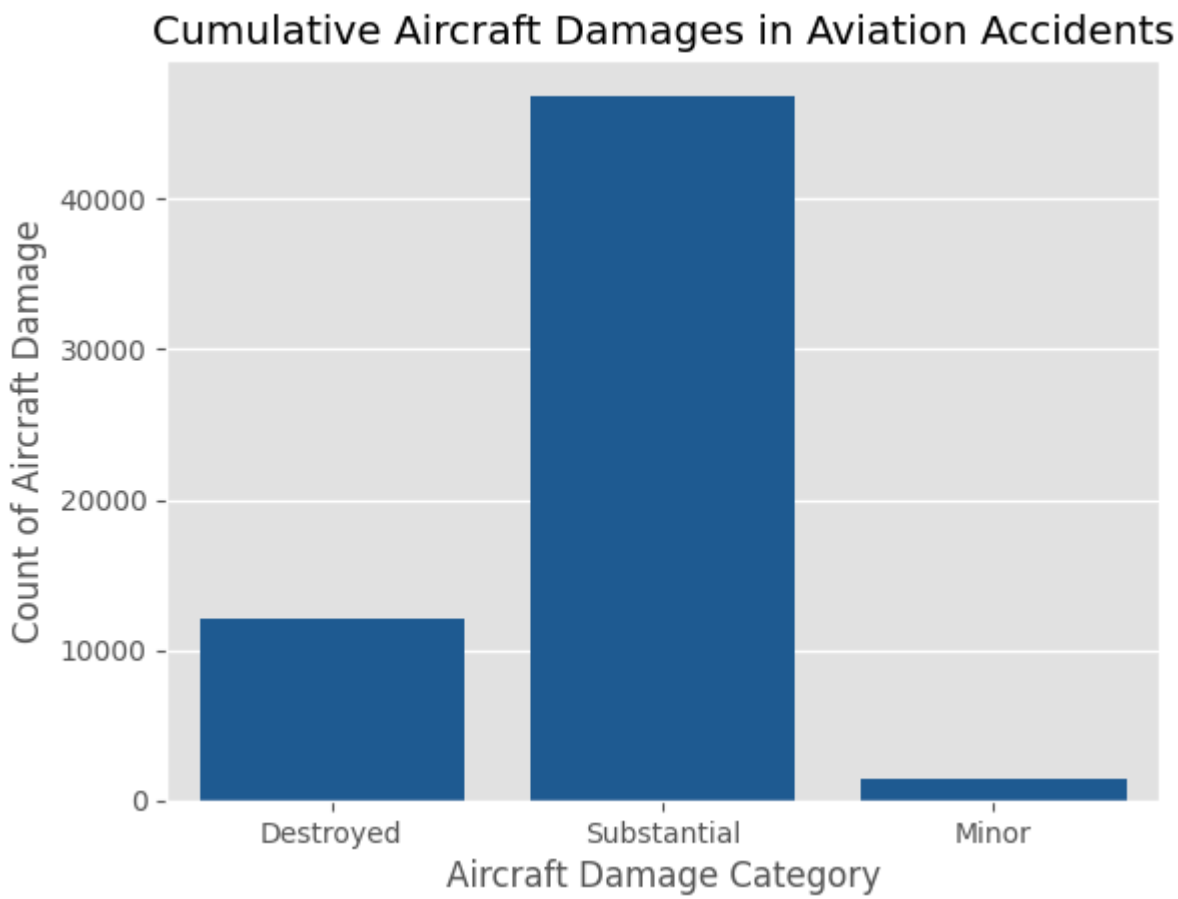
In [43]:
```
sns.countplot(x ='injury_severity', data = us_accidents, color = '#0D5EA6')
plt.title('Distribution of Injury Severity in Aviation Accidents')
plt.xlabel("Injury Severity")
plt.ylabel("Count of Recorded Severity");
```



Observations

Most accidents have been non-fatal. Only around 10,000 cases have been considered fatal since 1962.

In [44]:
```
damage = us_accidents.query("aircraft_damage != 'Unknown'")
sns.countplot(x ='aircraft_damage', data = damage, color = '#0D5EA6')
plt.title('Cumulative Aircraft Damages in Aviation Accidents')
plt.xlabel("Aircraft Damage Category")
plt.ylabel("Count of Aircraft Damage");
```

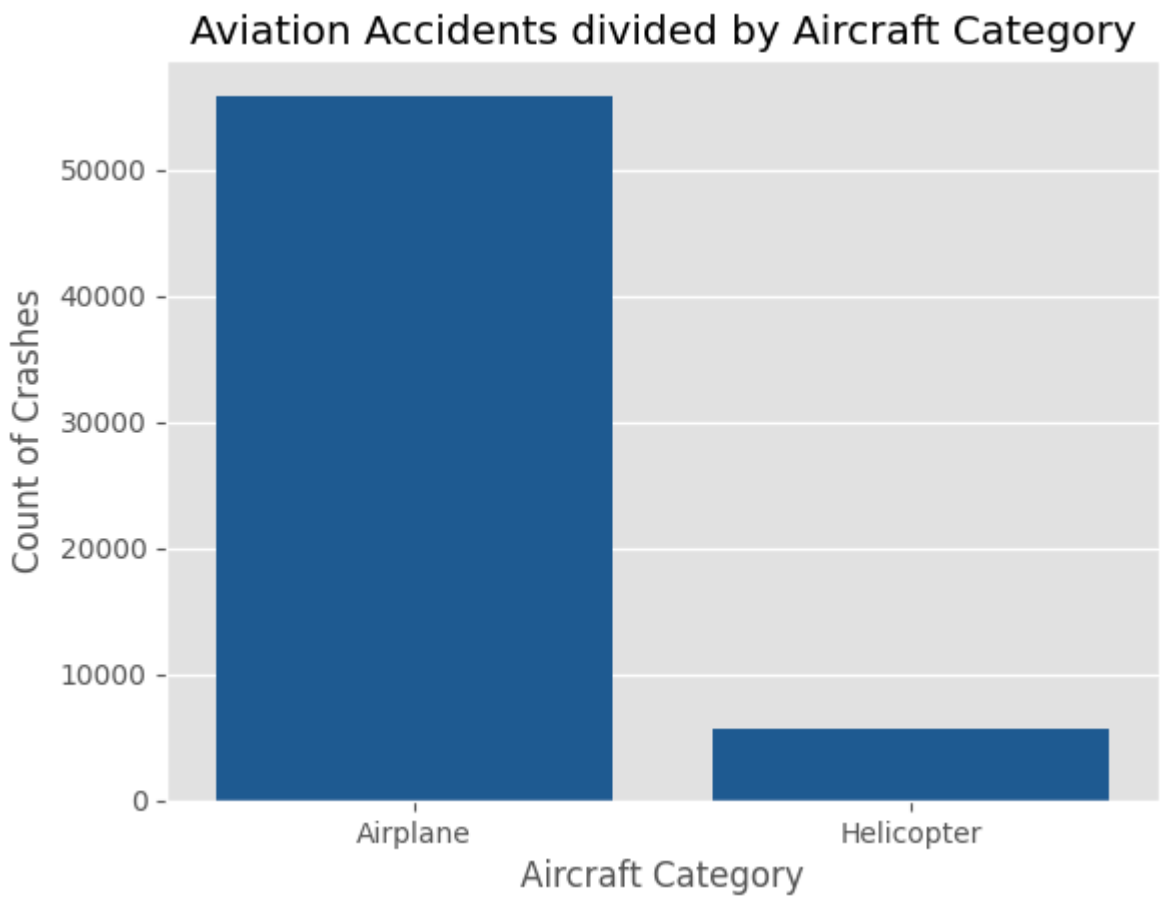


Observations

Most aircraft damages are substantial where the damage greatly affects the structural integrity and lifespan of the aircraft. Such damages also need high costs and great experience to return the aircraft to its former glory, if possible.

Q: Which aircraft category have recorded the most accidents?

In [45]:
```
sns.countplot(data = us_accidents, x = 'aircraft_category', color = '#0D5EA6')
plt.title('Aviation Accidents divided by Aircraft Category')
plt.xlabel("Aircraft Category")
plt.ylabel("Count of Crashes");
```

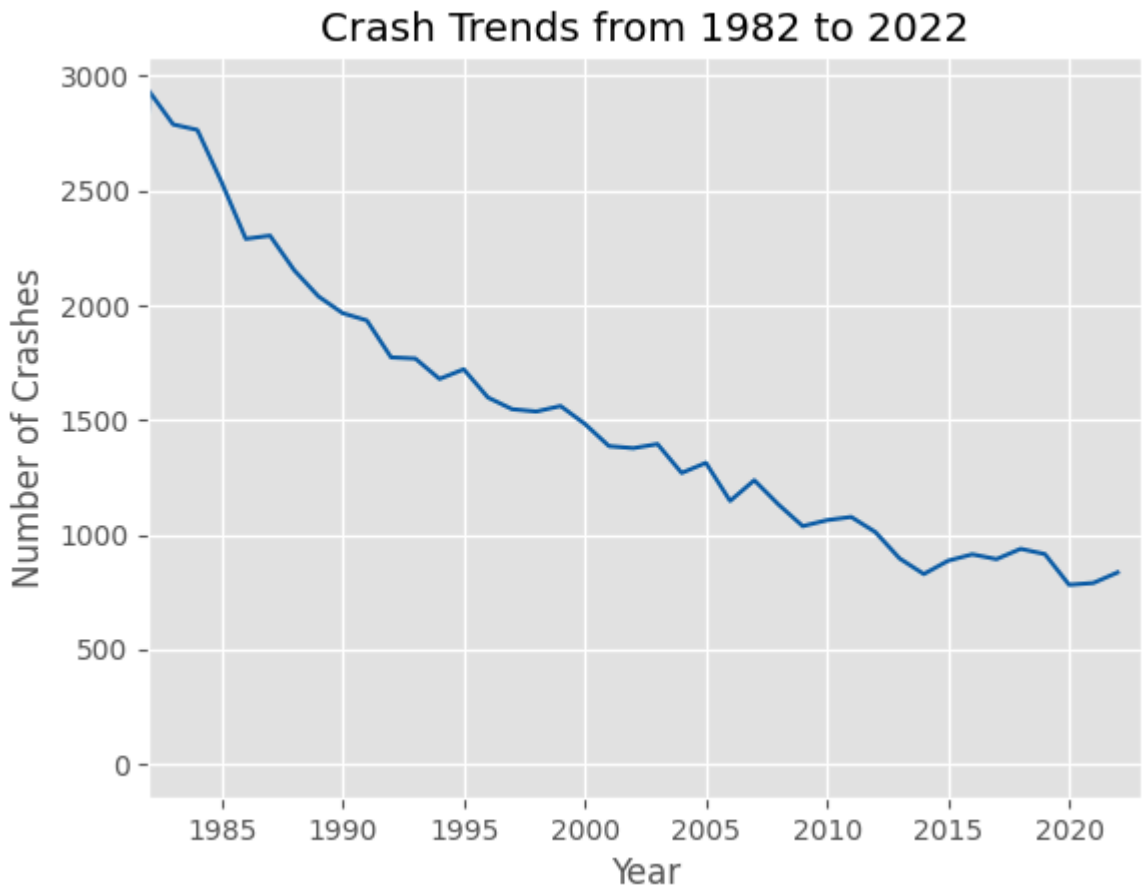


Observations

Airplanes record almost ten times more accidents than helicopters.

Q: How is the trend of airplane crashes from 1982 to date?

In [46]:
```
crashes_per_year = us_accidents['event_year'].value_counts().sort_index(ascending = True)
crashes_per_year.plot(color = '#0D5EA6')
plt.title("Crash Trends from 1982 to 2022")
plt.xlabel('Year')
plt.ylabel("Number of Crashes")
plt.xlim(1982, 2023);
```



Observations

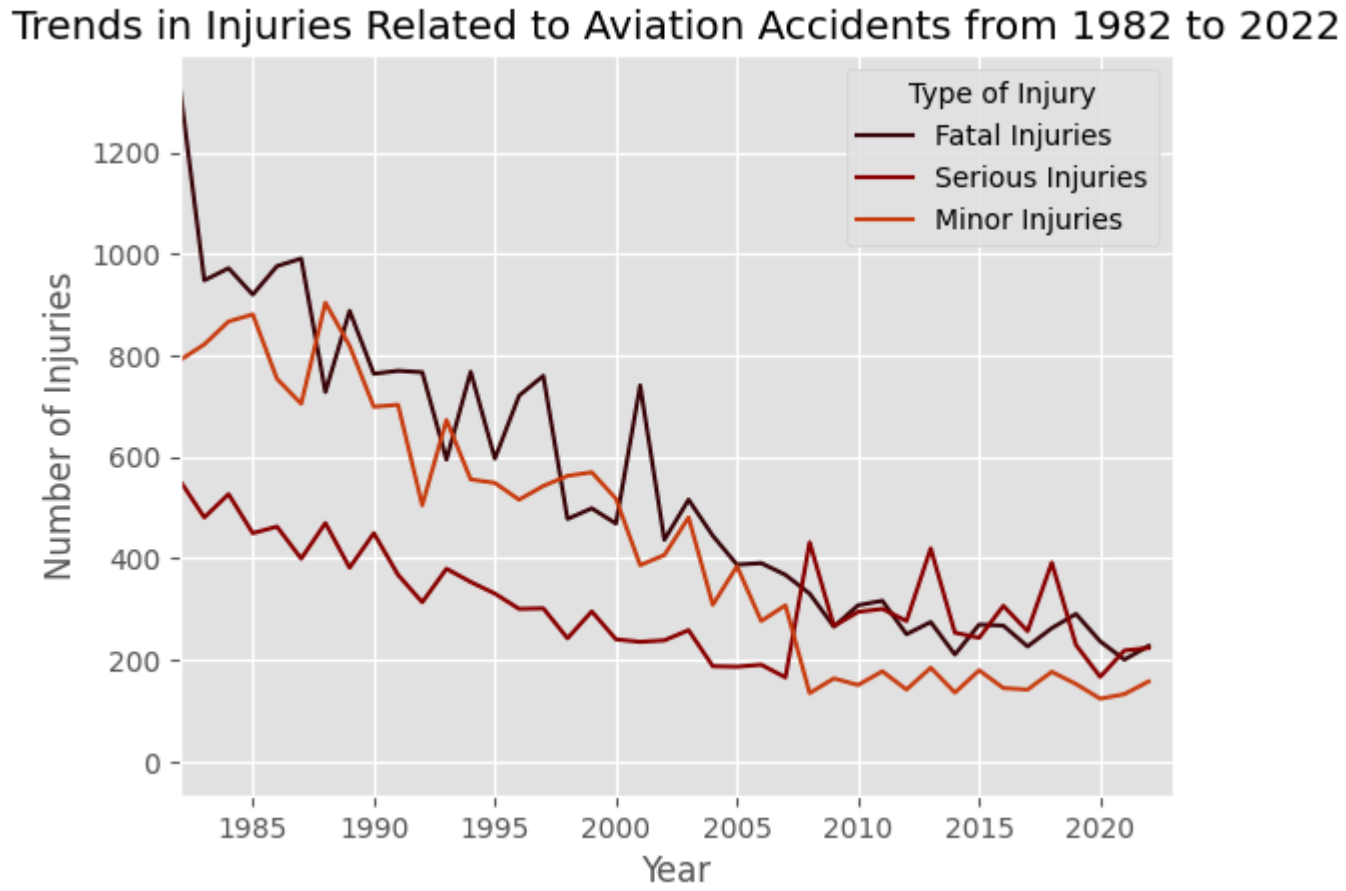
Airplane crashes have been on a continuous decline since 1982, showing that planes have become safer as more technology advances and more aviation laws have been passed.

Planes have thus become safer.

Q: How have casualties from airplane crashes changed from 1982 to date?

In [47]:
```
injuries_per_year = us_accidents.groupby('event_year')[['total_fatal_injuries','total_serious_injuries','total_minor_injuries']].
injuries_per_year.plot(color = ['#3B060A','#8A0000','#C83F12'])
plt.title("Trends in Injuries Related to Aviation Accidents from 1982 to 2022")
```

```
plt.xlabel('Year')
plt.ylabel("Number of Injuries")
plt.legend(title= 'Type of Injury', labels =['Fatal Injuries', 'Serious Injuries','Minor Injuries'])
plt.xlim(1982, 2023);
```

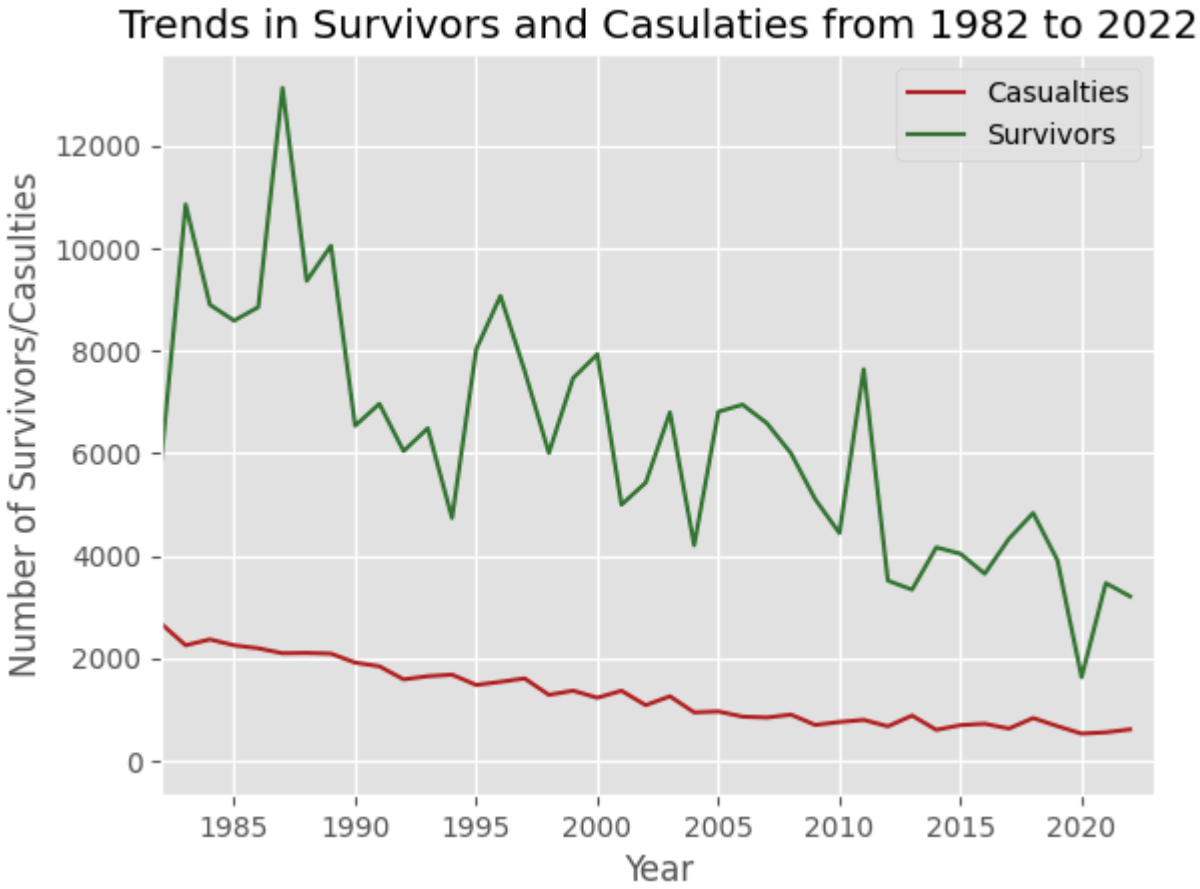


Observations

Similar to airplane crashes, casualties as a result of plane crashes have also declined since 1982 due to advancements in technology and aviation laws, which have made air travel safer.

Q: What is the trend of casualties and survivors from 1982 to date?

In [48]:
```
injuries_per_year = us_accidents.groupby('event_year')[['total_injured','total_uninjured']].sum().sort_index(ascending = True)
injuries_per_year.plot(color = ["#B22222","#347433"])
plt.title("Trends in Survivors and Casulaties from 1982 to 2022")
plt.xlabel('Year')
plt.ylabel("Number of Survivors/Casulties")
plt.legend(['Casualties', 'Survivors'])
plt.xlim(1982, 2023);
```

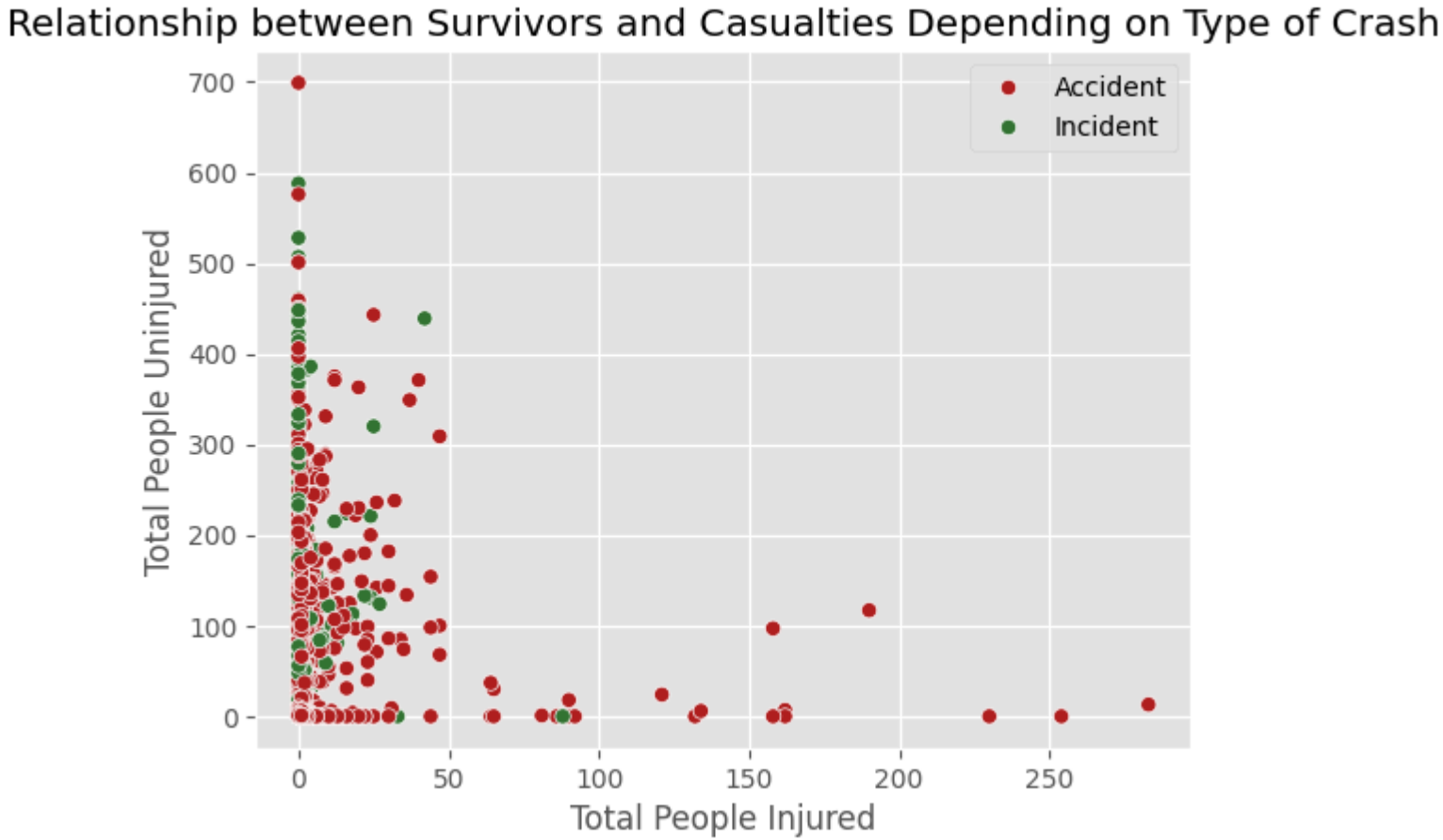


Observations

There has always been a higher number of survivors than casualties over the years. There has been a recorded decline in both survivors and casualties as the accidents have also become fewer.

Q: What is the relationship between the survivors and the casualties

In [49]:
```
sns.scatterplot(x = "total_injured",
                y = "total_uninjured",
                hue = 'investigation_type',
                data = us_accidents,
                palette = ["#B22222","#347433"])
plt.title("Relationship between Survivors and Casualties Depending on Type of Crash")
plt.xlabel('Total People Injured')
plt.ylabel('Total People Uninjured')
plt.legend();
```

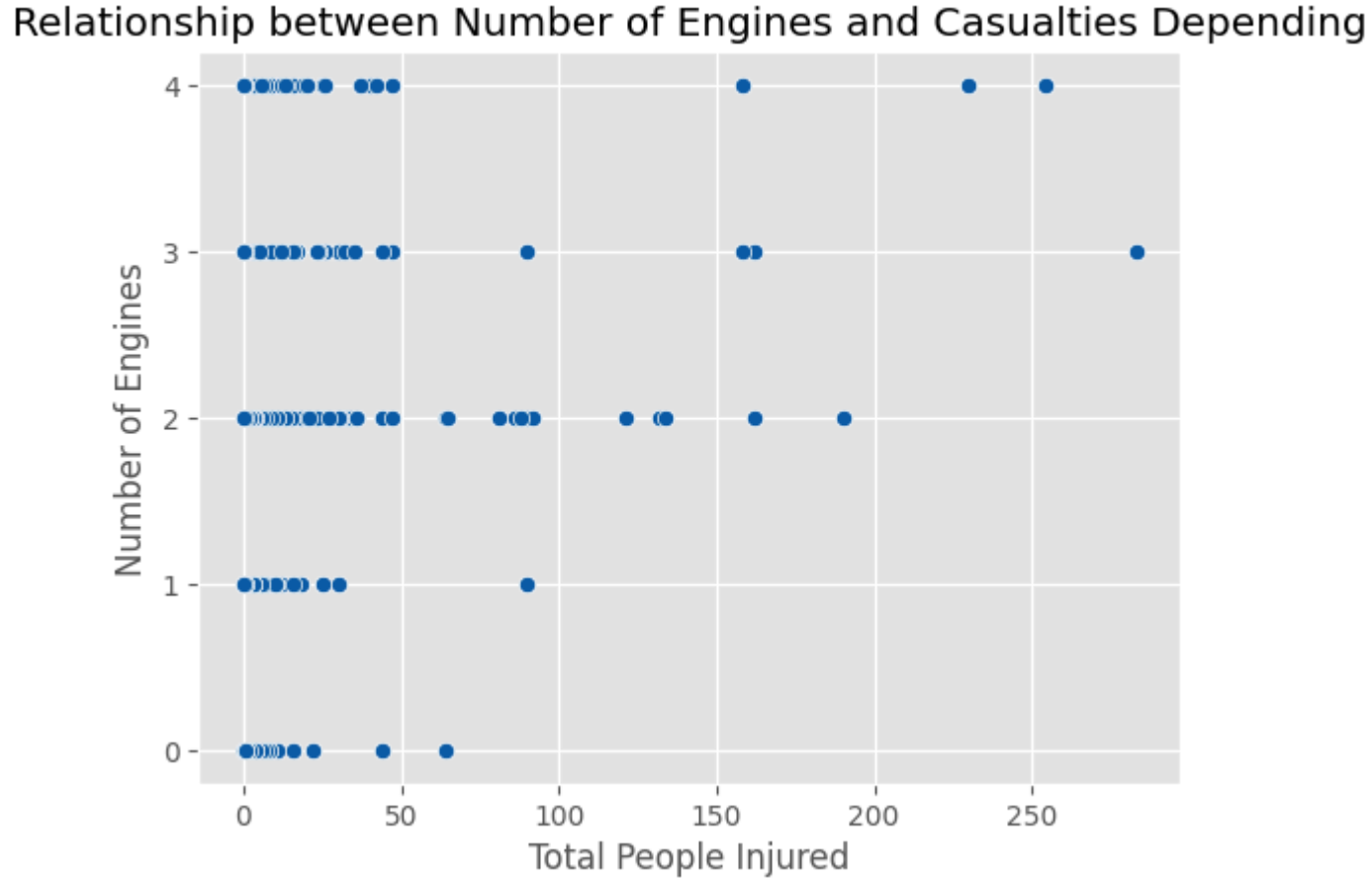


Observations

There is no correlation between those who were injured and those who survived.

Q: Is there a relationship between the casualties and number of engines in planes?

In [50]:
```
sns.scatterplot(x = "total_injured",
                y = "number_of_engines",
                data = us_accidents,
                color = '#0D5EA6')
plt.title("Relationship between Number of Engines and Casualties Depending")
plt.xlabel('Total People Injured')
plt.ylabel('Number of Engines')
plt.yticks(range(us_accidents['number_of_engines'].min(), us_accidents['number_of_engines'].max()+1))
plt.show()
```

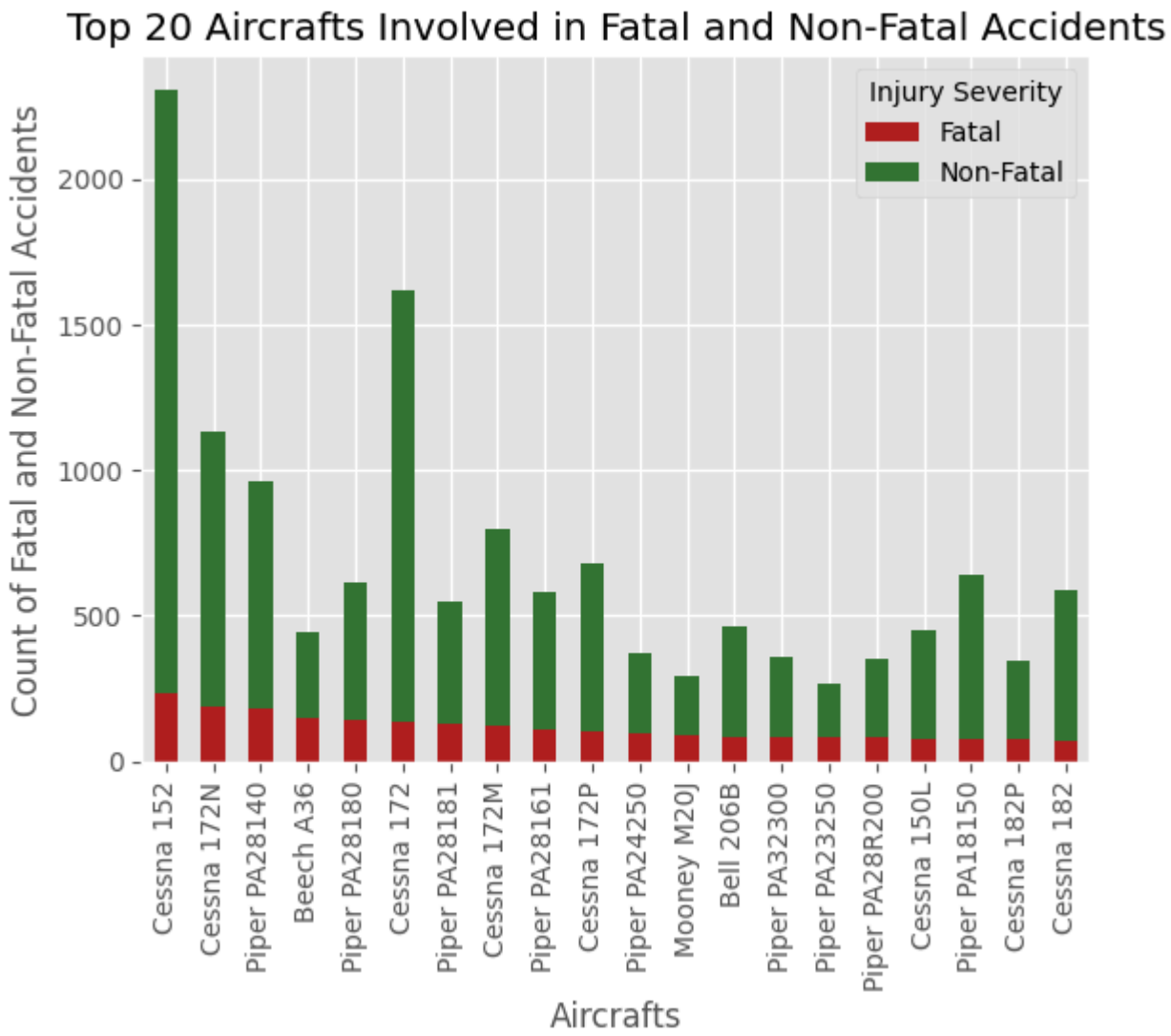


Observations

There is no correlation number of engines and casualties recorded in plane crashes.

Q: Which aircraft model has the fatal and non-fatal casualties?

In [51]:
```
accidents = us_accidents.query("injury_severity == 'Fatal' | injury_severity == 'Non-Fatal'")
accidents = accidents.groupby(['make_model','injury_severity']).size().unstack(fill_value=0)
accidents = accidents.sort_values(by = 'Fatal',ascending = False).head(20)
accidents.plot(color = ["#B22222","#347433"], kind = "bar", stacked = True)
plt.title("Top 20 Aircrafts Involved in Fatal and Non-Fatal Accidents")
plt.xlabel('Aircrafts')
plt.ylabel("Count of Fatal and Non-Fatal Accidents")
plt.legend(title = "Injury Severity");
```



Observations

Most airplane crashes are usually non-fatal. Non-fatal accidents are accidents that do not lead to fatalities.

Out of the top 20, Piper planes constitute 45% of the planes, and Cessna constitutes 40%. It can be argued that both of these aircraft manufacturers are the safest since they have the highest survival rate.

Conclusion

- Airplane crashes and aviation casualties have become rarer and rarer with each passing year as technology keeps advancing and better aviation laws get passed.
- Most accidents that do occur do not lead to loss of life but do have a great impact on the aircraft's lifespan and structural integrity.
- Most crashes involve aircraft from Cessna and Piper Aircraft. However, they seem to be the most preferred when it comes to personal aircraft. Specifically, the Cessna 172 and the Piper PA-28 lineups of aircraft.

Business Recommendations

- As a starting business venture, it is recommended to start with aircraft with proven track records. Cessnas have been seen as the market leader, from small commercial trips to personal aircraft with the Cessna Citation and the Cessna 172 lineups of aircraft, respectively.
- The Cessna 172 and Piper PA-28 aircraft have been shown to lead the pack when it comes to personal use aircraft. Both have a wide variety of models that have been improving technologically to offer safety and peace of mind. The latest models for both are the Cessna 172 Skyhawk and Piper PA-28 Cherokee.
- It should also be noted that, according to NASA and Husain Law, almost 80% of aviation accidents are caused by pilot error and not mechanical error. Therefore, Sky High Corp should greatly focus on hiring pilots with great track records and keep them trained and satisfied to reduce the risk of pilot error