Compiling Data on Aviation with the Least Amount of Risk

Project Goals

Data

Methods

Exploring the Data

Cleaning The Data

Handling the NaN's for the Make and Model Columns

Drop the Missing Values from the Make and Model columns

Comparing the two Data Frames

Cleaning The Data

Handling the Four Injury Rows

Convert datetime from a string to a datetime object

Cleaning The Engines Column

Checking out the make and model

Trying to fix the names of the make column

Combine the Injuries columns into a total injuries column

So there are 21991 nulls, and 542 unknowns

Looking into aircraft damage and doing the same thing

Splitting The Data

Airplanes

```
Out[33]: Airplane              24831
         Helicopter             2907
         Glider                  431
         Gyrocraft               168
         Balloon                 166
         Weight-Shift            154
         Powered Parachute        87
         Ultralight               26
         WSFT                      9
         Blimp                     4
         Unknown                   4
         Powered-Lift              4
         Rocket                    1
         ULTR                      1
         Name: aircraft_category, dtype: int64
```

```
In [34]: df_clean_airplanes = df_clean.loc[df_clean['aircraft_category'] == 'Airplane']
```

```
In [35]: # What are the top 10 makes of airplanes?

         top_10_makes = df_clean_airplanes['make'].value_counts().head(10)
         top_10_makes
```

```
Out[35]: cessna      7948
         piper       4495
         beech       1531
         boeing       679
         mooney       446
         air          410
         grumman      390
         cirrus       356
         bellanca     272
         aeronca      228
         Name: make, dtype: int64
```

We are going to drop

the null and unknown values from engine_type for the dataframe because it is relevant to the safety of airplanes.

Dropping Null Values From engine_type

```
In [36]: df_clean_airplanes.dropna(subset=['engine_type'], inplace=True)
         df_clean_airplanes['engine_type'].isna().sum()

<ipython-input-36-c9c9cb67ffda>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  df_clean_airplanes.dropna(subset=['engine_type'], inplace=True)

Out[36]: 0
```

Dropping unknown values from engine_type

```
In [37]: df_clean_airplanes.drop(df_clean[(df_clean['engine_type'] == 'unknown')].index, inplac
         df_clean_airplanes

C:\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

Out[37]:

	event_id	investigation_type	accident_number	event_date	location	country	latitude
5	20170710X52551	Accident	NYC79AA106	1979-09-17	BOSTON, MA	United States	42.445277
7	20020909X01562	Accident	SEA82DA022	1982-01-01	PULLMAN, WA	United States	NaN
8	20020909X01561	Accident	NYC82DA015	1982-01-01	EAST HANOVER, NJ	United States	NaN
12	20020917X02148	Accident	FTW82FRJ07	1982-01-02	HOMER, LA	United States	NaN
13	20020917X02134	Accident	FTW82FRA14	1982-01-02	HEARNE, TX	United States	NaN
...	...	...	...	...	...	...	...
88639	20221011106092	Accident	CEN23LA008	2022-10-06	Iola, TX	United States	304354N
88647	20221011106098	Accident	ERA23LA014	2022-10-08	Dacula, GA	United States	034055N
88661	20221018106153	Accident	CEN23LA015	2022-10-13	Ardmore, OK	United States	034849N
88735	20221031106231	Accident	CEN23LA023	2022-10-29	Houston, TX	United States	293620N
88767	20221109106272	Accident	CEN23LA033	2022-11-09	Bridgeport, TX	United States	331026N

22700 rows × 32 columns

Filtering down the engines

Engines we don't want: Reciprocating Engines

```
In [38]: df_clean_airplanes['engine_type'].value_counts().index

Out[38]: Index(['Reciprocating', 'Turbo Prop', 'Turbo Fan', 'Turbo Jet', 'Unknown',
                'Geared Turbofan', 'Turbo Shaft', 'Electric', 'UNK'],
               dtype='object')
```

How to handle the Reciprocating engines?

Remove the rows with reciprocating engines.

```
In [39]: # This code works by:
         # Calling the drop() method and passing it the filtered rows we want to drop

         # I want to drop the rows of df_clean_airplanes where the engine_type is Reciprocatin
         df_clean_airplanes.drop( df_clean_airplanes[df_clean_airplanes['engine_type'] == 'Rec

C:\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py:4163: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
r_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

```
In [40]: # export .csv file to look at in Tableau

         df_clean_airplanes.to_csv('./Data/clean_airplanes.csv')
```

```
In [41]: ### Exploring airplanes and the differing number of engines for their makes
```

This is a filter for planes with two engines and a new dataframe consiting of data only for planes with 2 engines:

```
In [42]: df_clean_airplanes_w_2_engines = df_clean_airplanes.loc[df_clean_airplanes['number_of_
```

```
In [43]: # df to csv

         df_clean_airplanes_w_2_engines.to_csv('./Data/two_engine_planes.csv')
```

This is a filter for planes with three engines and a new dataframe consiting of data only for planes with 3 engines:

```
In [44]: df_clean_airplanes_w_3_engines = df_clean_airplanes.loc[df_clean_airplanes['number_of_
```

```
In [45]: # df to csv

         df_clean_airplanes_w_3_engines.to_csv('./Data/three_engine_plane.csv')
```

```
In [ ]:
```

```
In [ ]:
```

Investigating the Carriers

```
In [46]: df_clean_airplanes['model'].value_counts()

Out[46]: 208B                  60
         208                   44
         AT-502B               36
         737                   36
         A320                  33
                               ..
         BOEING 777-228 IGW     1
         DHC 6 200              1
         LANCAIR IV P           1
         DHC-2                  1
         CL600-2A12             1
         Name: model, Length: 875, dtype: int64
```

```
In [47]: df_737 = df_clean_airplanes.query("model == '737' | model == '747' | model == '340'| r
         df_737 = df_737.query("make == 'boeing' | make == 'airbus'")

         df_737['model']

Out[47]: 4150     747
         52199    747
         54167    747
         55630    737
         64807    737
         65457    737
         65538    320
         66356    737
         66556    737
         66965    737
         67027    737
         67151    737
         67271    737
         67743    747
         67994    737
         68146    747
         68353    737
         68738    737
         69156    737
         69358    737
         69741    737
         69916    747
         70924    737
         71199    737
         71882    747
         73233    747
         73533    320
         73586    747
         74633    737
         74747    737
         75823    747
         77087    737
         77411    747
         77705    737
         77887    737
         77906    737
         80518    747
         81107    737
         81327    747
         82042    737
         82151    737
         82165    737
         82437    737
         82655    737
         82850    737
         82857    737
         82987    737
         83134    737
         84372    737
         84538    737
         85070    737
         Name: model, dtype: object
```

```
In [48]: df_737['model'].value_counts()

Out[48]: 737    36
         747    13
         320     2
         Name: model, dtype: int64
```

```
In [49]: df_737['make'].value_counts()

Out[49]: boeing    49
         airbus     2
         Name: make, dtype: int64
```

```
In [50]: number_of_planes_737 = df_737['model'].value_counts().values[0]
         number_of_planes_747 = df_737['model'].value_counts().values[1]
```

```
In [51]: df_737_accidents = df_737[df_737['model'] == '737']
         df_747_accidents = df_737[df_737['model'] == '747']

         df_737_substantial = df_737_accidents[df_737_accidents['aircraft_damage'] == 'Substant

         df_747_substantial = df_747_accidents[df_747_accidents['aircraft_damage'] == 'Substant

         df_737_minor = df_737_accidents[df_737_accidents['aircraft_damage'] == 'Minor'].shape

         df_747_minor = df_747_accidents[df_747_accidents['aircraft_damage'] == 'Minor'].shape
```

```
In [52]: # export .csv file to look at further in Tableau
         df_737.to_csv('./Data/carriers.csv')
```

Helicopters

```
In [53]: df_clean_helicopters = df_clean.loc[df_clean['aircraft_category'] == 'Helicopter']
```

```
In [54]: df_clean_helicopters[df_clean_helicopters['engine_type'] == 'Reciprocating'].sort_valu
```

Out[54]:

	event_id	investigation_type	accident_number	event_date	location	country	latitude
88414	20220831105841	Accident	WPR22LA329	2022-08-26	Deadhorse, AK	United States	684126N
88341	20220811105721	Accident	WPR22LA299	2022-08-11	Palmer, AK	United States	612618N
88309	20220808105687	Accident	CEN22LA366	2022-08-05	Maynard, IA	United States	424912N
88281	20220801105634	Accident	CEN22LA350	2022-07-31	Marshall, MO	United States	039633N
88256	20220729105620	Accident	CEN22LA345	2022-07-28	Ithaca, NE	United States	041946N
...	...	...	...	...	...	...	...
151	20020917X02578	Accident	SEA82DA020	1982-01-22	NEAR KINGSTON, ID	United States	NaN
137	20020917X01915	Accident	DEN82DA021	1982-01-20	BONDURANT, WY	United States	NaN
91	20020917X02577	Accident	SEA82DA019	1982-01-15	S.E. OF MALTA, ID	United States	NaN
19	20020917X02339	Accident	MIA82DA028	1982-01-02	MIAMI, FL	United States	NaN
16	20020917X01962	Accident	DEN82DTM08	1982-01-02	MIDWAY, UT	United States	NaN

1375 rows × 32 columns

It looks like reciprocating engines are still being used for helicopters today, so we will not drop those engines for this dataframe.

```
In [55]: # What models have the highest average of uninjured passengers?

         df_clean_helicopters.groupby('model')['total_uninjured'].mean().sort_values(ascending

Out[55]: model
         92              18.0
         S-92A           14.0
         SA-330J         13.0
         214ST           11.0
         412 - EP        11.0
         S 76B           10.0
         AS 350 BA FX1    7.0
         BV234            7.0
         S-76C++          7.0
         EC 130B4         6.0
         Name: total_uninjured, dtype: float64
```

```
In [56]: # turn into .csv file to visualize in Tableau
         df_clean_helicopters.to_csv('./Data/clean_helicopters.csv')
```

Results

Question Statement:

Which aircrafts are the lowest risk?

What are our three concrete business recommendations

After anaylising our data we are able to come to the results that;

Passenger Transportation

- The Boeing 727 model is ideal for passenger transportaion because out of all 2407 plane crashes only 345 of them were a Boeing make
- Out of all 345 Boeing crashes, only 16 of them were with the Boeing 727 model the only Boeing make with three engines.
- Out of all 16 Boeing crashes only 3 had any injuries related none of them being fatal.
- We were able to reach this conclusion by analyzing the data set and filtering it down o specific compenents we were interested in looking at and then comparing the data sets with information like total crashes for makes or total crashes for a specific number of engined plane.

Cargo Transportation

- The Boeing 747 model is ideal for cargo transportation.
- We came to this conclusion by making a ratio of number of accidents to number of planes.
- When comparing the aircraft damage severity between the Boeings the 737 is smaller than the 747.
- The Boeing 747 has 107 ton of capacity.
- The nose of the 747 opens (really cool).
- The 747 has a wide body which means more space.
- The 747 also has 4 engines making it much safer.

Private Enterprises

- The Sikorsky S-92A is ideal for private enterprises
- Since certain makes and models have more crash occurrences than others
- Used the mean to show the ratio of uninjured passengers to the number of accidents.

```
In [ ]:
```