# Aviation Incidents

## Overview

This project analyzes aviation incidents to identify airplane models with the least amount of incidents and their engine counts. By cleaning and examining the aviation dataset, the goal is to highlight the safest airplane models for the aviation division.

## Business Understanding

The project aims to assist the aviation division in selecting low-risk airplane models based on incident frequency and engine count, promoting company growth in the aviation sector.

# Data Understanding

The dataset includes airplane models, engine counts, and injury reports from aviation accidents.

```
import pandas as pd
import numpy as np
import csv

aviation_data = pd.read_csv("./data/Aviation_Data.csv",
low_memory=False)

aviation_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90348 entries, 0 to 90347
Data columns (total 31 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Event.Id                88889 non-null  object
 1   Investigation.Type      90348 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            50132 non-null  object 
 9   Airport.Name            52704 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     87507 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             81793 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           82505 non-null  object 
 30  Publication.Date        73659 non-null  object 
dtypes: float64(5), object(26)
memory usage: 21.4+ MB
```

# Aviation Data

The aviation dataset includes records from 1962 to 2023, and includes models of plane, number of engines, and injury severity.

```
aviation_data.head()
```

```
         Event.Id Investigation.Type Accident.Number  Event.Date  \
0  20001218X45444           Accident      SEA87LA080  1948-10-24   
1  20001218X45447           Accident      LAX94LA336  1962-07-19   
2  20061025X01555           Accident      NYC07LA005  1974-08-30   
3  20001218X45448           Accident      LAX96LA321  1977-06-19   
4  20041105X01764           Accident      CHI79FA064  1979-08-02   

          Location        Country   Latitude   Longitude Airport.Code 
\
0  MOOSE CREEK, ID  United States        NaN         NaN          NaN 

1   BRIDGEPORT, CA  United States        NaN         NaN          NaN 

2    Saltville, VA  United States  36.922223  -81.878056          NaN 
```

```
3       EUREKA, CA  United States        NaN         NaN         NaN

4       Canton, OH  United States        NaN         NaN         NaN


  Airport.Name  ... Purpose.of.flight Air.carrier Total.Fatal.Injuries
\
0          NaN  ...          Personal         NaN                  2.0

1          NaN  ...          Personal         NaN                  4.0

2          NaN  ...          Personal         NaN                  3.0

3          NaN  ...          Personal         NaN                  2.0

4          NaN  ...          Personal         NaN                  1.0


  Total.Serious.Injuries Total.Minor.Injuries Total.Uninjured  \
0                    0.0                  0.0             0.0
1                    0.0                  0.0             0.0
2                    NaN                  NaN             NaN
3                    0.0                  0.0             0.0
4                    2.0                  NaN             0.0

  Weather.Condition  Broad.phase.of.flight   Report.Status
Publication.Date
0               UNK                 Cruise  Probable Cause
NaN
1               UNK                Unknown  Probable Cause       19-
09-1996
2               IMC                 Cruise  Probable Cause       26-
02-2007
3               IMC                 Cruise  Probable Cause       12-
09-2000
4               VMC               Approach  Probable Cause       16-
04-1980

[5 rows x 31 columns]
```

```
aviation_data['Accident Date'] =
pd.to_datetime(aviation_data['Event.Date'])
aviation_data['Accident Date'].describe()
```

```
count                            88889
mean     1999-09-17 17:13:39.354476032
min                1948-10-24 00:00:00
25%                1989-01-15 00:00:00
50%                1998-07-18 00:00:00
75%                2009-07-01 00:00:00
```

```
max                   2022-12-29 00:00:00
Name: Accident Date, dtype: object
```

## Number of Engines data

```
aviation_data['Number.of.Engines'].value_counts()
```

```
Number.of.Engines
1.0    69582
2.0    11079
0.0     1226
3.0      483
4.0      431
8.0        3
6.0        1
Name: count, dtype: int64
```

## Model

```
aviation_data['Model'].value_counts()
```

```
Model
152              2367
172              1756
172N             1164
PA-28-140         932
150               829
                 ...
GC-1-A              1
737-3S3             1
MBB-BK117-B2        1
GLASSAIR GL25       1
M-8 EAGLE           1
Name: count, Length: 12318, dtype: int64
```

## Injury Severity

```
aviation_data['Injury.Severity'].value_counts()
```

```
Injury.Severity
Non-Fatal     67357
Fatal(1)       6167
Fatal          5262
Fatal(2)       3711
Incident       2219
              ...
Fatal(270)        1
Fatal(60)         1
Fatal(43)         1
```

```
Fatal(143)        1
Fatal(230)        1
Name: count, Length: 109, dtype: int64
```

# Data Preperation

## Data Cleaning

The analysis focuses on identifying airplanes with average engine counts and the lowest risk, using data cleaning and descriptive statistics.

```
# look up columns
aviation_data.columns

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', 'Accident Date'],
      dtype='object')

# Narrowing down the dataset to 3 columns
aviation_data = aviation_data[['Model', 'Injury.Severity',
'Number.of.Engines']]

aviation_data.head()

      Model Injury.Severity  Number.of.Engines
0     108-3        Fatal(2)                1.0
1  PA24-180        Fatal(4)                1.0
2      172M        Fatal(3)                1.0
3       112        Fatal(2)                1.0
4       501        Fatal(1)                NaN

# I will drop NaN from the dataset
aviation_data = aviation_data.dropna(inplace=False,how='any',axis=0)
aviation_data

          Model Injury.Severity  Number.of.Engines
0         108-3        Fatal(2)                1.0
```

```
1      PA24-180        Fatal(4)                1.0
2          172M        Fatal(3)                1.0
3           112        Fatal(2)                1.0
5           DC9       Non-Fatal                2.0
...         ...             ...                ...
90328      PA42       Non-Fatal                2.0
90332      SR22       Non-Fatal                1.0
90335   SA226TC       Non-Fatal                2.0
90336     R172K           Minor                1.0
90345     8GCBC       Non-Fatal                1.0

[82488 rows x 3 columns]
```

```
aviation_data.head()
```

```
      Model Injury.Severity  Number.of.Engines
0     108-3        Fatal(2)                1.0
1  PA24-180        Fatal(4)                1.0
2      172M        Fatal(3)                1.0
3       112        Fatal(2)                1.0
5       DC9       Non-Fatal                2.0
```

Looking for duplicates to reduce any inaccurate data.

```
# look for duplicates in dataset
aviation_data.duplicated()
```

```
0        False
1        False
2        False
3        False
5        False
         ...
90328     True
90332     True
90335     True
90336     True
90345     True
Length: 82488, dtype: bool
```

```
# Drop duplicates
aviation_data.drop_duplicates(inplace=True)
aviation_data
```

```
          Model Injury.Severity  Number.of.Engines
0         108-3        Fatal(2)                1.0
1      PA24-180        Fatal(4)                1.0
2          172M        Fatal(3)                1.0
3           112        Fatal(2)                1.0
5           DC9       Non-Fatal                2.0
```

```
...          ...              ...                  ...
90306  KITFOX S5       Non-Fatal                  1.0
90307  M-8 EAGLE           Minor                  1.0
90313  EC 130 B4           Minor                  1.0
90317      PA-44           Minor                  2.0
90326  EC 130 T2           Minor                  1.0

[17149 rows x 3 columns]
```

```
aviation_data.head(15)
```

```
           Model Injury.Severity  Number.of.Engines
0          108-3        Fatal(2)                1.0
1       PA24-180        Fatal(4)                1.0
2           172M        Fatal(3)                1.0
3            112        Fatal(2)                1.0
5            DC9       Non-Fatal                2.0
6            180        Fatal(4)                1.0
7            140       Non-Fatal                1.0
8           401B       Non-Fatal                2.0
9    NAVION L-17B      Non-Fatal                1.0
10     PA-28-161       Non-Fatal                1.0
11          V35B       Non-Fatal                1.0
12        17-30A       Non-Fatal                1.0
13         R172K        Fatal(1)                1.0
14             A        Fatal(1)                1.0
15            19        Fatal(2)                1.0
```

```
# Group the columns together
aviation_data.groupby(['Injury.Severity','Number.of.Engines'])
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at
0x00000220CE2D5C70>
```

```
aviation_data.groupby(['Injury.Severity','Number.of.Engines']).mean(nu
meric_only=True)
```

```
Empty DataFrame
Columns: []
Index: [(Fatal, 0.0), (Fatal, 1.0), (Fatal, 2.0), (Fatal, 3.0),
(Fatal, 4.0), (Fatal(1), 0.0), (Fatal(1), 1.0), (Fatal(1), 2.0),
(Fatal(1), 3.0), (Fatal(1), 4.0), (Fatal(10), 0.0), (Fatal(10), 1.0),
(Fatal(10), 2.0), (Fatal(102), 2.0), (Fatal(11), 2.0), (Fatal(110),
2.0), (Fatal(111), 3.0), (Fatal(113), 2.0), (Fatal(12), 2.0),
(Fatal(13), 0.0), (Fatal(13), 2.0), (Fatal(131), 3.0), (Fatal(132),
2.0), (Fatal(135), 3.0), (Fatal(14), 2.0), (Fatal(14), 3.0),
(Fatal(144), 4.0), (Fatal(15), 2.0), (Fatal(153), 3.0), (Fatal(154),
2.0), (Fatal(156), 2.0), (Fatal(16), 2.0), (Fatal(17), 1.0),
(Fatal(17), 2.0), (Fatal(174), 4.0), (Fatal(18), 2.0), (Fatal(19),
2.0), (Fatal(2), 0.0), (Fatal(2), 1.0), (Fatal(2), 2.0), (Fatal(2),
3.0), (Fatal(2), 4.0), (Fatal(20), 2.0), (Fatal(21), 2.0),
```

```
(Fatal(217), 2.0), (Fatal(228), 4.0), (Fatal(23), 2.0), (Fatal(230),
4.0), (Fatal(25), 1.0), (Fatal(25), 2.0), (Fatal(256), 4.0),
(Fatal(265), 2.0), (Fatal(27), 2.0), (Fatal(27), 4.0), (Fatal(270),
4.0), (Fatal(28), 2.0), (Fatal(29), 2.0), (Fatal(29), 3.0), (Fatal(3),
0.0), (Fatal(3), 1.0), (Fatal(3), 2.0), (Fatal(3), 4.0), (Fatal(30),
2.0), (Fatal(31), 2.0), (Fatal(34), 2.0), (Fatal(37), 2.0), (Fatal(4),
0.0), (Fatal(4), 1.0), (Fatal(4), 2.0), (Fatal(4), 4.0), (Fatal(43),
4.0), (Fatal(47), 0.0), (Fatal(49), 2.0), (Fatal(5), 0.0), (Fatal(5),
1.0), (Fatal(5), 2.0), (Fatal(5), 3.0), (Fatal(5), 4.0), (Fatal(6),
0.0), (Fatal(6), 1.0), (Fatal(6), 2.0), (Fatal(6), 3.0), (Fatal(6),
4.0), (Fatal(60), 2.0), (Fatal(65), 2.0), (Fatal(68), 2.0), (Fatal(7),
1.0), (Fatal(7), 2.0), (Fatal(7), 4.0), (Fatal(70), 2.0), (Fatal(70),
4.0), (Fatal(73), 4.0), (Fatal(78), 2.0), (Fatal(8), 0.0), (Fatal(8),
1.0), (Fatal(8), 2.0), (Fatal(8), 3.0), (Fatal(82), 1.0), (Fatal(82),
2.0), (Fatal(87), 0.0), ...]

[127 rows x 0 columns]
```

```
aviation_data.groupby('Number.of.Engines').sum().agg(['count'])
```

```
       Model  Injury.Severity
count      7                7
```

```
# Save cleaned dataset as csv
aviation_data.to_csv('aviation_datamodelenginjur.csv')
```

# Exploratory Data Analysiss

```
import matplotlib
import matplotlib.pyplot as plt

%matplotlib inline
```

## Number of Engines, Models, and Injury Severity

```
# Summarize Number of Engines
aviation_data['Number.of.Engines'].describe(include = "all")
```

```
count    17149.000000
mean         1.230976
std          0.618984
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          8.000000
Name: Number.of.Engines, dtype: float64
```

```
# Summarize Model of plane
aviation_data['Model'].describe(include = "all")
```

```
count          17149
unique         11309
top        PA-23-250
freq              17
Name: Model, dtype: object
```

```
# Summarize Injury Severity
aviation_data['Injury.Severity'].describe(include = "all")
```

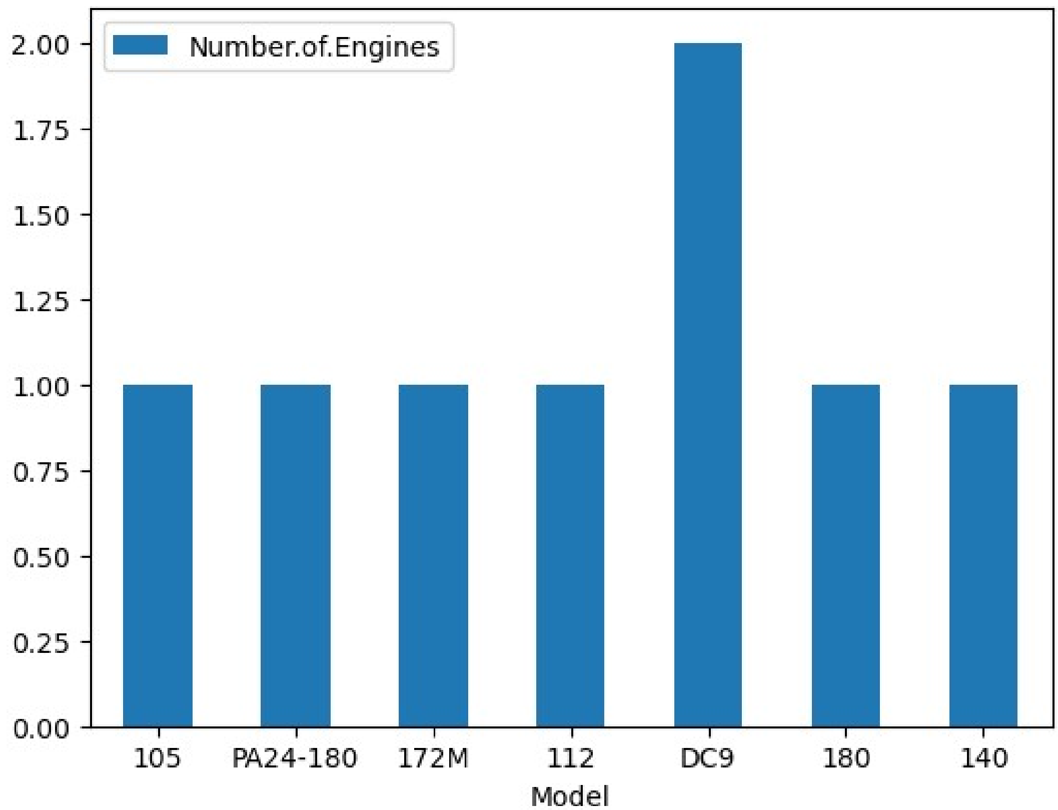
```
count          17149
unique            67
top        Non-Fatal
freq            9448
Name: Injury.Severity, dtype: object
```

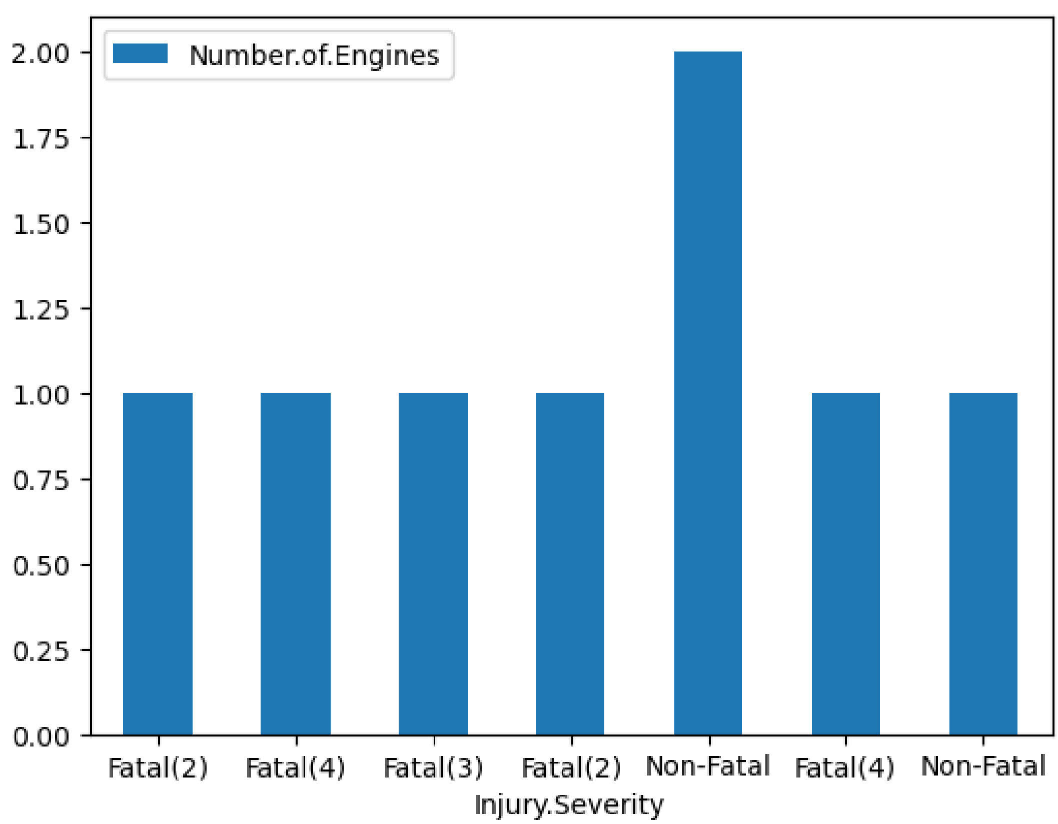
```
# Create a plot
aviation_data = pd.core.frame.DataFrame({'Model':[108-3,'PA24-
180','172M','112','DC9','180','140'],'Number.of.Engines':
[1.0,1.0,1.0,1.0,2.0,1.0,1.0]})

ax = aviation_data.plot.bar(x='Model', y='Number.of.Engines', rot=0)

aviation_data = pd.core.frame.DataFrame({'Injury.Severity':
['Fatal(2)','Fatal(4)','Fatal(3)','Fatal(2)','Non-
Fatal','Fatal(4)','Non-Fatal'], 'Number.of.Engines':
[1.0,1.0,1.0,1.0,2.0,1.0,1.0]})

ax = aviation_data.plot.bar(x='Injury.Severity',
y='Number.of.Engines', rot=0)
```


Number.of.Engines
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
105
PA24-180
172M
112
DC9
180
140
Model

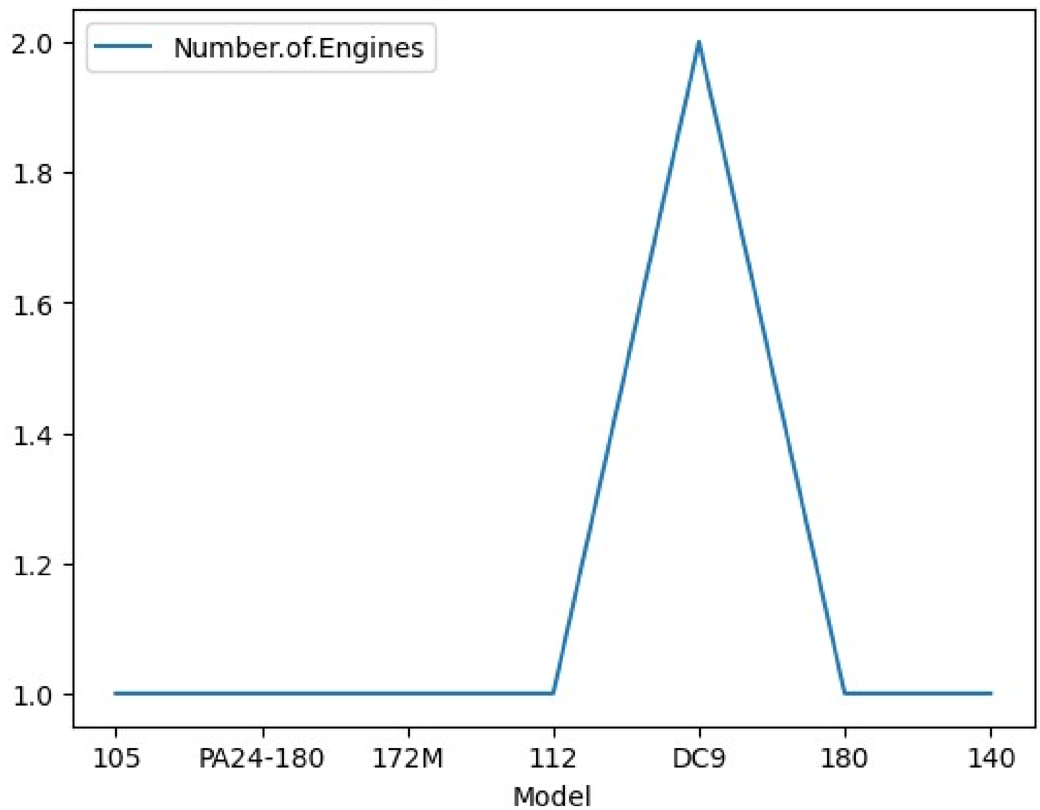

Number.of.Engines
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Fatal(2)
Fatal(4)
Fatal(3)
Fatal(2)
Non-Fatal
Fatal(4)
Non-Fatal
Injury.Severity

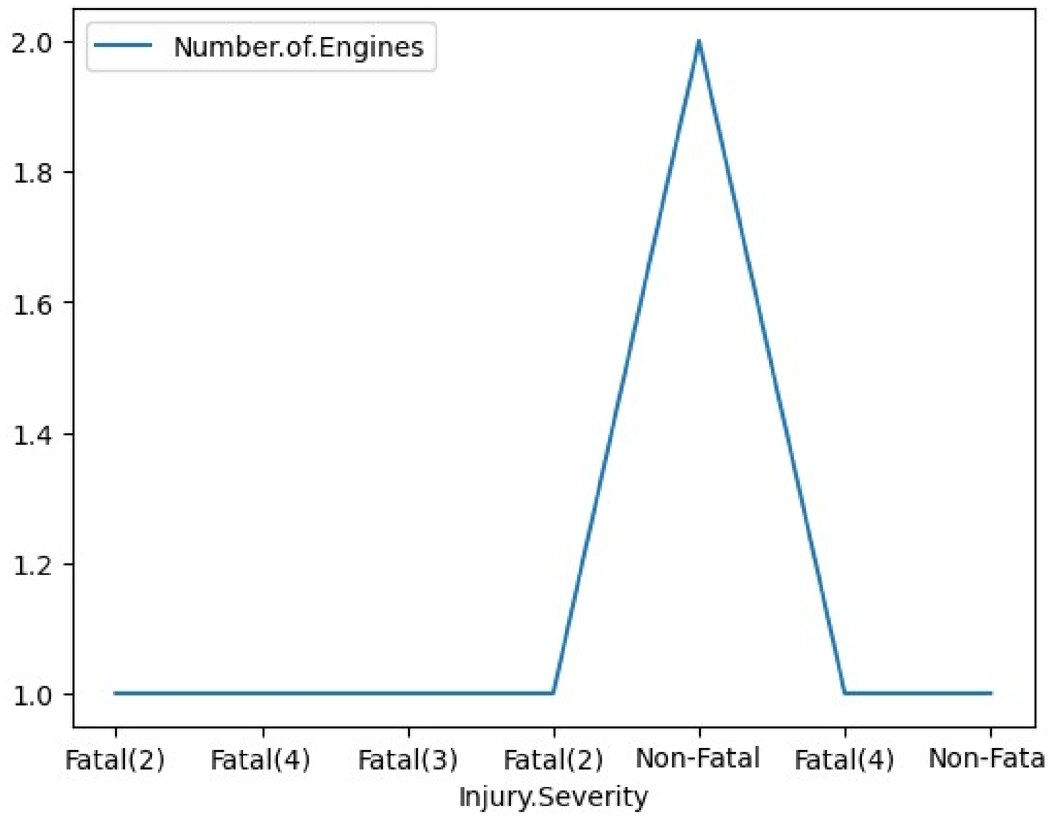
```python
# Create a plot
aviation_data = pd.core.frame.DataFrame({'Model':[108-3,'PA24-
180','172M','112','DC9','180','140'],'Number.of.Engines':
[1.0,1.0,1.0,1.0,2.0,1.0,1.0]})

ax = aviation_data.plot.line(x='Model', y='Number.of.Engines', rot=0)

aviation_data = pd.core.frame.DataFrame({'Injury.Severity':
['Fatal(2)','Fatal(4)','Fatal(3)','Fatal(2)','Non-
Fatal','Fatal(4)','Non-Fatal'], 'Number.of.Engines':
[1.0,1.0,1.0,1.0,2.0,1.0,1.0]})

ax = aviation_data.plot.line(x='Injury.Severity',
y='Number.of.Engines', rot=0)
```






# Conclusions

This analysis leads with the model of plane with the least amount incidents with the ideal amount of number of engines:

- **Number of Engines.** On average each plane with the least amount of incidents had only one engine.
- **Model of plane.** DC-9 model plane has the most engines with the least amount of incidents
- **Injury Severity.** all injury incidents were non-fatal for the planes that fit the companies risk free decision.

# Recommendations

- **The planes with the least amount of incidents.** The company should go with the plane with non-fatal injuries for safety precautions.
- **Saving money based on how many engines there is.** The plane that has less engines and low incident reports will cost less in the future.

- **Every year evaluation.** Every year the company can expand their aviation side to gather more planes for business projects/improvements.

# Limitations

- **The data set lacks the know how.** In the data set doesn't show you how a plane had an incident, knowing that would help narrow down malfunctions or weather.
- **Cost of each plane.** The lack of cost for each individual plane and how much it would cost to repair them/salvage them.

# Next Steps

Further analyses could yield additional insights to further improve choice of model plane:

- **Better predictions for model plane based off repairing cost.** This modeling could already use avaialable data such as how bad the crash was.
- **Predicting undesirable outcomes.** Knowing that the weather is really bad should delay the flight until further notice