COMP 4447 Final Project

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Data Motivation

For some people, the most frightening experience is flying in a metal object, tens of thousands of miles above the Earths surface. One small error and your life is over.

Since 1962 there have been 82,634 aircraft accidents documented across the globe in vehicles like planes, helicopters, gyro-aircraft, hot air balloons, and pretty much anything that can can sustain flight.

Our dataset originates from Kaggle.com (https://www.kaggle.com/khsamaha/aviation-accident-database-synopses) and contains 82,634 rows with 31 columns.

Task Definition/Research Question

We decided to task ourselves with uncovering which factors may lead to a higher chance of resulting in an aircraft accident. Our group will be focused mostly on the location of the incident, whether or not the aircraft was an ameteur build or not, and the weather conditions during the accident.

Literature Review

In general, most aircraft accidents that have been investigated usually focus on the aircraft it occurred in, the reason for the flight, or the severity of the crash (fatality or not focus). Our goal was to focus more on the location of the accident to see if there are areas of the world one should try and not fly in. Also, we wanted to see if amateur builders contribute to more accidents than professionals given there should be more trust in the professionally built aircraft than the amateur built ones. Lastly, we wanted to investigate how weather conditions plays a role in aircraft accidents regardless that this subject is widely studied.

Quality Cleaning

In [100…

```
# importing for df
import warnings

from pandas.core.common import SettingWithCopyWarning

warnings.simplefilter(action="ignore", category=SettingWithCopyWarning)

import pandas as pd
import numpy as np
aviation_df = pd.read_csv('AviationData.csv', encoding="ISO-8859-1")  # explain local grab
aviation_df
```

Out[100…

	Event.Id	Investigation.Type	Accident.Number	Event.Date	Location	Country	Latitude	Longitude	Airport.Coc
0	20181217X10943	Accident	GAA19CA098	2018-12-16	Grangville, ID	United States	45.583611	-115.681667	PV
1	20181217X25746	Accident	GAA19CA097	2018-12-15	MORIARTY, NM	United States	34.970000	-106.000000	Na
2	20181213X41114	Accident	ERA19LA065	2018-12-13	Punta Gorda, FL	United States	26.925278	-82.001111	PG
3	20181213X45528	Accident	CEN19FA044	2018-12-13	Valparaiso, IN	United States	41.451667	-87.004444	VF
4	20181214X90303	Accident	GAA19CA096	2018-12-11	Hartford, WI	United States	43.330278	-88.326111	HX
...	...	...	...	...	...	...	...	...	
82630	20041105X01764	Accident	CHI79FA064	1979-08-02	Canton, OH	United States	NaN	NaN	Na
82631	20001218X45448	Accident	LAX96LA321	1977-06-19	EUREKA, CA	United States	NaN	NaN	Na
82632	20061025X01555	Accident	NYC07LA005	1974-08-30	Saltville, VA	United States	36.922223	-81.878056	Na
82633	20001218X45447	Accident	LAX94LA336	1962-07-19	BRIDGEPORT, CA	United States	NaN	NaN	Na
82634	20001218X45444	Accident	SEA87LA080	1948-10-24	MOOSE CREEK, ID	United States	NaN	NaN	Na

82635 rows × 31 columns

In order to narrow our view of data we will review the number of NULLS and NANs in the data set to ensure that we are analyzing quality data.

In [101…

```
# Count the number of Nulls in each column
aviation_df.isna().sum()
```

Out[101…

```
Event.Id                    0
Investigation.Type          1
Accident.Number             0
Event.Date                  0
Location                   75
Country                   507
Latitude                53903
Longitude               53912
Airport.Code            35859
Airport.Name            33121
Injury.Severity             0
Aircraft.Damage          2592
Aircraft.Category       56735
Registration.Number      3582
Make                       73
Model                     102
Amateur.Built             627
Number.of.Engines        4609
Engine.Type              3982
FAR.Description         57068
Schedule                70905
Purpose.of.Flight        4550
Air.Carrier             78545
Total.Fatal.Injuries    25967
Total.Serious.Injuries  28466
Total.Minor.Injuries    27288
Total.Uninjured         13795
Weather.Condition        2708
Broad.Phase.of.Flight    6503
Report.Status               0
Publication.Date        14014
dtype: int64
```

There are multiple columns with data that is primarily NULL/missing or the data is not pertinant to our investigation. We will remove the following columns from the dataframe:

- Ivestigation.Type only has two options that are basically the same.

- Airport.Code and Airport.Name contain mostly NULL values, do not pertain to our analysis, and do not contain matching NULL counts indications that they might not match up properly.
- Engine.Type was not an interest to our groups investigation.
- FAR.Description more than half were NULL.
- Schedule conatains mostly NULL values and most of other values are UNK, which means unknown.
- Air.Carrier mostly NULL values.
- Total.Fatal.Injuries outside of our analysis.
- Total.Serious.Injuries outside of our analysis.
- Total.Minor.Injuries outside of our analysis.
- Total.Uninjured outside of our analysis.
- Report.Status most were 'Preliminary', never fully investigated, opted to remove.
- Publication.Date not pertinant to our analysis.

In [102…

```
# Columns that we've identified as not being useful for our project
drops = ['Investigation.Type', 'Airport.Code', 'Airport.Name',
         'Engine.Type', 'FAR.Description', 'Schedule',
         'Air.Carrier', 'Total.Fatal.Injuries', 'Total.Serious.Injuries',
         'Total.Minor.Injuries', 'Total.Uninjured', 'Report.Status',
         'Publication.Date']
aviation_df.drop(columns=drops, inplace=True)  # dropping columns we agreed upon
```

In [103…

```
aviation_df['Country'].value_counts()
```

Out[103…

```
United States     77528
Canada              286
Brazil              266
Mexico              248
United Kingdom      247
                   ...
Senegal               1
Isle of Man           1
Cambodia              1
Nauru                 1
Oman                  1
Name: Country, Length: 178, dtype: int64
```

In order to refine our data further, we decided to only focus on accidents that occurred in the United States. Accidents in the United States account for approximately 94% of all documented accidents.

In [104…
```
aviation_df.drop(aviation_df[aviation_df['Country'] != 'United States'].index, inplace=True)  # 80132/85976 ent
```

In order to remain with best practices, column names will be formatted to the appropriate standards; the '.' will be replaced with '_'.

In [105…
```
# Renaming the columns to be more conventional:
aviation_df = aviation_df.rename(columns={"Event.Id":"Event_ID", "Accident.Number":"Accident_Number",
                                          "Event.Date":"Event_Date", "Injury.Severity":"Injury_Severity",
                                          "Aircraft.Damage":"Aircraft_Damage", "Aircraft.Category":"Aircraft_Ca
                                          "Registration.Number":"Registration_Number", "Amateur.Built":"Amateur
                                          "Number.of.Engines":"Number_Engines", "Purpose.of.Flight":"Purpose_Fl
                                          "Weather.Condition":"Weather_Condition", "Broad.Phase.of.Flight":"Bro

aviation_df.dtypes
```

Out[105…
```
Event_ID               object
Accident_Number        object
Event_Date             object
Location               object
Country                object
Latitude              float64
Longitude             float64
Injury_Severity        object
Aircraft_Damage        object
Aircraft_Category      object
Registration_Number    object
Make                   object
Model                  object
Amateur_Built          object
Number_Engines        float64
Purpose_Flight         object
Weather_Condition      object
Broad_Phase_Flight     object
dtype: object
```

Apon review of the data types in our set it was discovered that there is need to convert Event_Date from an object to a datetime.

In [106…
```
aviation_df['Event_Date'] = pd.to_datetime(aviation_df['Event_Date']) #Converting all date fields to datetime i
aviation_df.dtypes
```

Out[106…
```
Event_ID                      object
Accident_Number               object
Event_Date            datetime64[ns]
Location                      object
Country                       object
Latitude                     float64
```

```
Longitude                float64
Injury_Severity           object
Aircraft_Damage           object
Aircraft_Category         object
Registration_Number       object
Make                      object
Model                     object
Amateur_Built             object
Number_Engines           float64
Purpose_Flight            object
Weather_Condition         object
Broad_Phase_Flight        object
dtype: object
```

Reducing our dataset even further by select fewer columns to continue our analysis.

We will fully clean the small dataframe we are left with of NULLS/Nans and remove data that is incorrect (ie, latitudes and longitudes that are larger than possible).

In [107…

```
# Columns we opted to keep for analysis
keeps = ['Event_ID','Accident_Number', 'Event_Date', 'Location', 'Latitude',
         'Longitude', 'Amateur_Built', 'Weather_Condition']

small_df = aviation_df[keeps]

# dropping NAs for Location (30), Amateur Built (95), Weather Condition (608)
small_df.dropna(subset=['Location', 'Amateur_Built',
                        'Weather_Condition'], inplace=True)
# dropping UNK/Unk (Unknown) weather condition (638/79431)
small_df.drop(small_df[small_df['Weather_Condition'] == 'UNK'].index, inplace=True)
small_df.drop(small_df[small_df['Weather_Condition'] == 'Unk'].index, inplace=True)

small_df.head()
```

Out[107…

	Event_ID	Accident_Number	Event_Date	Location	Latitude	Longitude	Amateur_Built	Weather_Condition
1	20181217X25746	GAA19CA097	2018-12-15	MORIARTY, NM	34.970000	-106.000000	No	VMC
2	20181213X41114	ERA19LA065	2018-12-13	Punta Gorda, FL	26.925278	-82.001111	No	VMC
3	20181213X45528	CEN19FA044	2018-12-13	Valparaiso, IN	41.451667	-87.004444	No	VMC
4	20181214X90303	GAA19CA096	2018-12-11	Hartford, WI	43.330278	-88.326111	No	VMC
6	20181208X53536	GAA19CA090	2018-12-08	Hesperia, CA	34.376945	-117.316111	Yes	VMC

In [108…

```
# removing invalid latitude and longitude values AND 1 based on Location
small_df.drop(small_df[small_df['Latitude'] < -90].index, inplace=True)
small_df.drop(small_df[small_df['Latitude'] > 90].index, inplace=True)
small_df.drop(small_df[small_df['Longitude'] < -180].index, inplace=True)
small_df.drop(small_df[small_df['Longitude'] > 180].index, inplace=True)
```

In addition to cleansing our data, we need to derive new columns from existing columns.

From our newly converted datetime column, Event_Date, we will extract the year of accident occurence and add it to a new column, Year.

From the Location column we will extract the state code value and validate that it is indeed in one of the 50 US states. The new column will be State_Code.

In [109…

```
# deduced columns
small_df['Year'] = pd.DatetimeIndex(small_df['Event_Date']).year  # extracting year field

def code_strip(row):  # extracts the state [or territory] tag
    slice = row['Location'][-4:]
    if slice[0] == ',':
        return slice[-2:]
    else:  # single unique case for 'GULF OF MEXICO,' entry
        return 'GM'

small_df['State_Code'] = small_df.apply(lambda row: code_strip(row), axis=1)

# trimming down to the 50 states and DC
states = ["AL", "AK", "AZ", "AR", "CA", "CO", "CT", "DC", "DE", "FL", "GA",
          "HI", "ID", "IL", "IN", "IA", "KS", "KY", "LA", "ME", "MD",
          "MA", "MI", "MN", "MS", "MO", "MT", "NE", "NV", "NH", "NJ",
          "NM", "NY", "NC", "ND", "OH", "OK", "OR", "PA", "RI", "SC",
          "SD", "TN", "TX", "UT", "VT", "VA", "WA", "WV", "WI", "WY"]

small_df = small_df[small_df['State_Code'].isin(states)]

small_df.drop(small_df[small_df['Year'] < 1982].index, inplace=True)  # only 7 entries before 1982...

small_df.head()
```

Out[109…

	Event_ID	Accident_Number	Event_Date	Location	Latitude	Longitude	Amateur_Built	Weather_Condition	Year	Stat

	Event_ID	Accident_Number	Event_Date	Location	Latitude	Longitude	Amateur_Built	Weather_Condition	Year	Stat
1	20181217X25746	GAA19CA097	2018-12-15	MORIARTY, NM	34.970000	-106.000000	No	VMC	2018	
2	20181213X41114	ERA19LA065	2018-12-13	Punta Gorda, FL	26.925278	-82.001111	No	VMC	2018	
3	20181213X45528	CEN19FA044	2018-12-13	Valparaiso, IN	41.451667	-87.004444	No	VMC	2018	
4	20181214X90303	GAA19CA096	2018-12-11	Hartford, WI	43.330278	-88.326111	No	VMC	2018	
6	20181208X53536	GAA19CA090	2018-12-08	Hesperia, CA	34.376945	-117.316111	Yes	VMC	2018	

Visual Analysis of Data

The main goal of our analysis is to indicate which locations may have a higher likelihood of an aircraft accident, which weather type plays a greater role in accidents, and does the aircraft being an amateur build have an affect on accidents given the locations.

The following will displat a heat map of all accidents' latitudes and longitudes in the United States.

In [110…

```
# importing for heatmap
import folium
from folium.plugins import HeatMap  # creating HeatMap object
import webbrowser  # to open .html file if saved
import os  # to find cwd
```

In [111…

```
# HEATMAP
latlon_df = small_df[['Latitude', 'Longitude', 'Year']]
latlon_df = latlon_df.drop(latlon_df[latlon_df['Year'] < 1999].index)  # 2000-present
latlon_df = latlon_df.dropna(subset=['Latitude', 'Longitude'])  # Lat (50133), Long (50143)

latitude_avg = latlon_df['Latitude'].mean()
longitude_avg = latlon_df['Longitude'].mean()
heat_map = folium.Map([latitude_avg, longitude_avg], zoom_start=2)
title = 'Aircraft Accidents in the United States'
html = ''' <h3 align="center" style="font-size:16px"><b>{}</b></h3>
       '''.format(title)
heat_map.get_root().html.add_child(folium.Element(html))
```

```
# adding heatmap data
coord_data = [[row['Latitude'], row['Longitude']] for idx, row in latlon_df.iterrows()]
HeatMap(coord_data).add_to(heat_map)

# saving to .html and opening in browser
file_name = 'Accidents_Heat.html'
heat_map.save(file_name)
abs_path = os.path.abspath(os.getcwd())
url = f'file:///{abs_path}/{file_name}'
webbrowser.open(url, new=1, autoraise=True)
```

Out[111… True

As depicted in the heatmap from the hearmap above, the latitudes and longitudes appear to be incorrect as their locations indicate the United States but their geographical locations indicate places like Asia, Europe and the middle of the Atlantic. Assuming the geolocations are correct, when zoomed in the, the heat map displays accidents well. However, to avoid the likelihood that geolocations are all incorrect, we'll move on to other location based columns.

The State_Codes of the accident will now be used as our plot our accidents to ensure the accidents are at least generalized to a US state level.

In [112…

```
# importing for choropleth
import geopandas as gpd  # reading json of state geometry
from geojson import Feature, FeatureCollection  # creating hovering interaction on the states
```

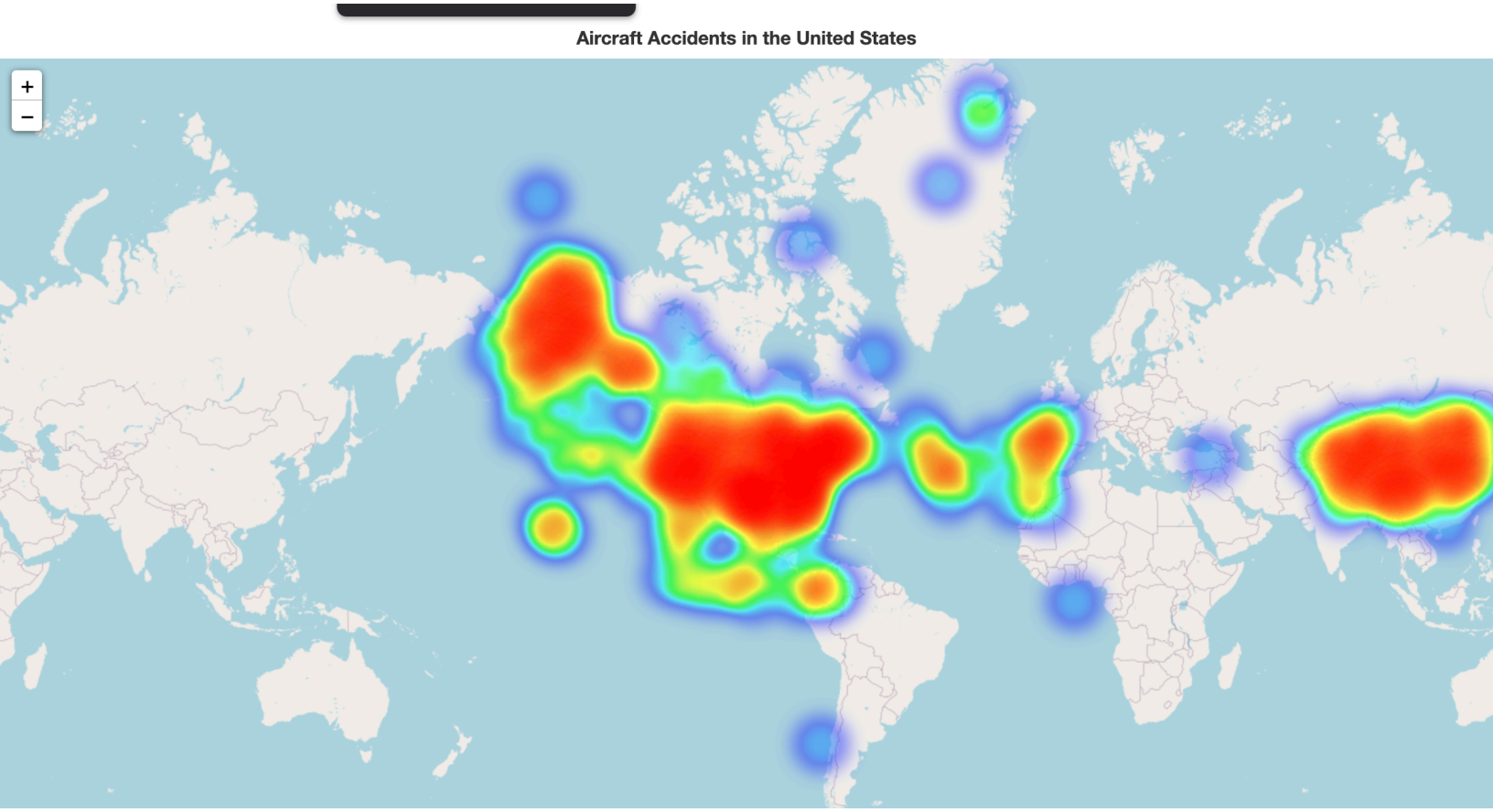
In [113…

```
# CHOROPLETH
count_df = pd.DataFrame({'Accidents': small_df.groupby(["State_Code"]).size()}).reset_index()
url = "https://raw.githubusercontent.com/python-visualization/folium/master/examples/data"
state_geo = f"{url}/us-states.json"
geoJSON_df = gpd.read_file(state_geo)
geoJSON_df = geoJSON_df.rename(columns = {'id': 'State_Code'})
choro_df = geoJSON_df.merge(count_df, on='State_Code')
choro_df = choro_df.rename({'State_Code': 'state'}, axis=1)

accident_map = folium.Map(location=[50, -100], zoom_start=4)
title = 'Aircraft Accidents in the United States'
html = ''' <h3 align="center" style="font-size:16px"><b>{}</b></h3>
       '''.format(title)
accident_map.get_root().html.add_child(folium.Element(html))

# adding choropleth data
```

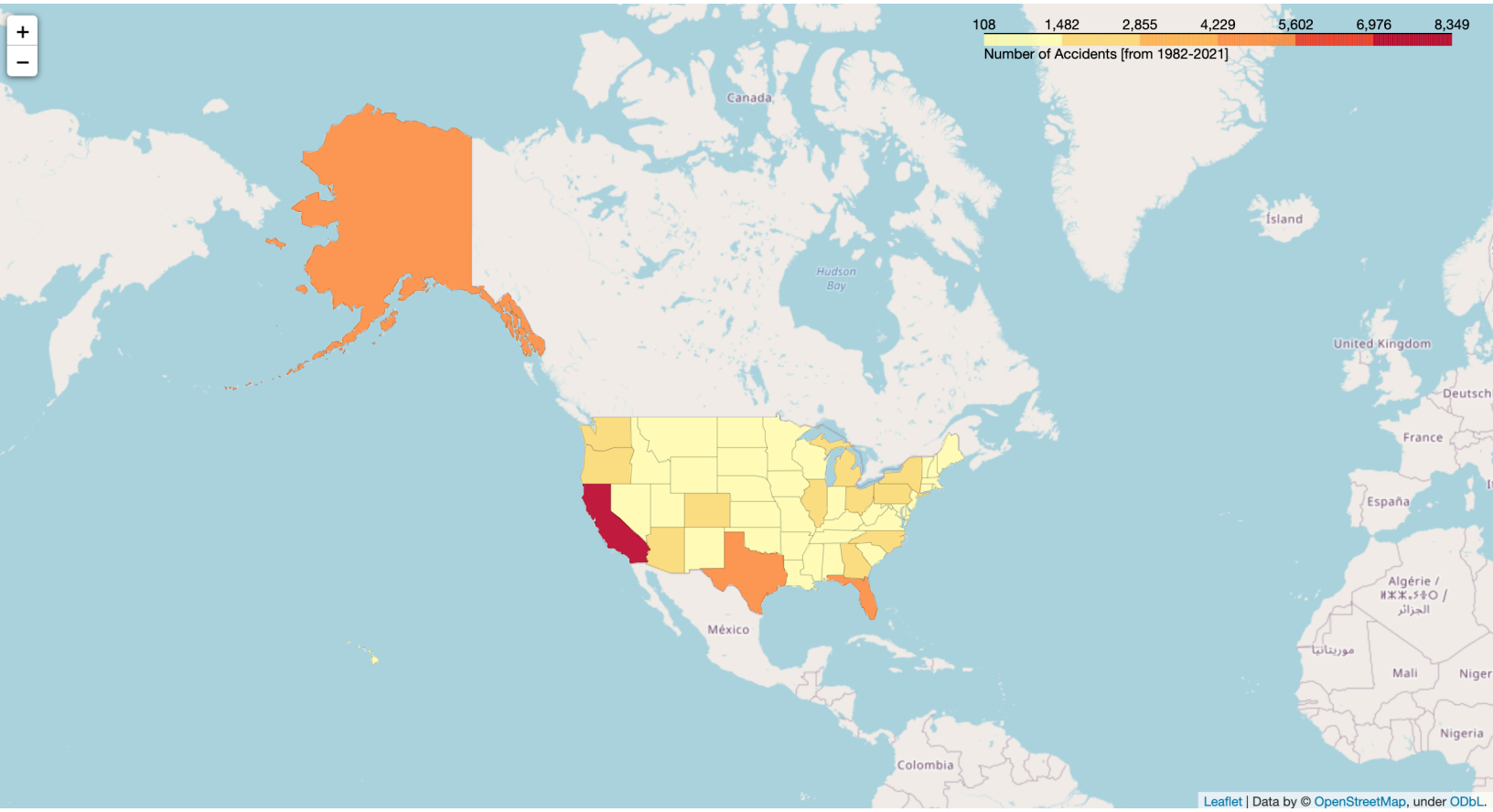
Heat Map



```
folium.Choropleth(geo_data=choro_df,
                  data=choro_df,
                  columns=['state', 'Accidents'],
                  key_on="feature.properties.state",
                  fill_color='YlOrRd',
                  fill_opacity=1,
                  nan_fill_color="White",
                  line_opacity=1,
                  legend_name="Number of Accidents [from 1982-2021]",
                  smooth_factor=0,
                  Highlight= True,
                  line_color="#0000",
                  name='Accident Count',
                  show=True,
                  overlay=True).add_to(accident_map)

# hover functionality for state level granularity
style_function = lambda x: {'fillColor': '#ffffff',
                            'color':'#000000',
                            'fillOpacity': 0.1,
                            'weight': 0.1}
highlight_function = lambda x: {'fillColor': '#000000',
                                'color':'#000000',
                                'fillOpacity': 0.50,
                                'weight': 0.1}
NIL = folium.features.GeoJson(
    data=choro_df,
    style_function=style_function,
    control=False,
    highlight_function=highlight_function,
    tooltip=folium.features.GeoJsonTooltip(
        fields=['state', 'Accidents'],
        aliases=['State:', 'Count:'],
        style=("background-color: white; color: #333333; font-family: arial; font-size: 12px; padding: 10px;")
    )
)
accident_map.add_child(NIL)
accident_map.keep_in_front(NIL)

# saving to .html and opening in browser
file_name = 'Accidents_Choro.html'
accident_map.save(file_name)
abs_path = os.path.abspath(os.getcwd())
url = f'file:///{abs_path}/{file_name}'
webbrowser.open(url, new=1, autoraise=True)
```


108
1,482
2,855
4,229
5,602
6,976
8,349
Number of Accidents [from 1982-2021]
Canada
Hudson Bay
Ísland
United Kingdom
Deutsch
France
España
Algérie / ⵍⵣⵣⴰⵢⴻⵔ / الجزائر
موريتانيا
Mali
Niger
Nigeria
México
Colombia
Leaflet | Data by © OpenStreetMap, under ODbL.

Out[113… True

The choropleth map above shows the concentration of accidents per states. It appears that there could be potential outliers in states like California, Alaska, Texas, and Florida. Seeing as the states that appear to be ouliers for accidents all are coastal states and could experience drastic weather, we opted to combine our analysis of weather conditions and locations.

In [114…

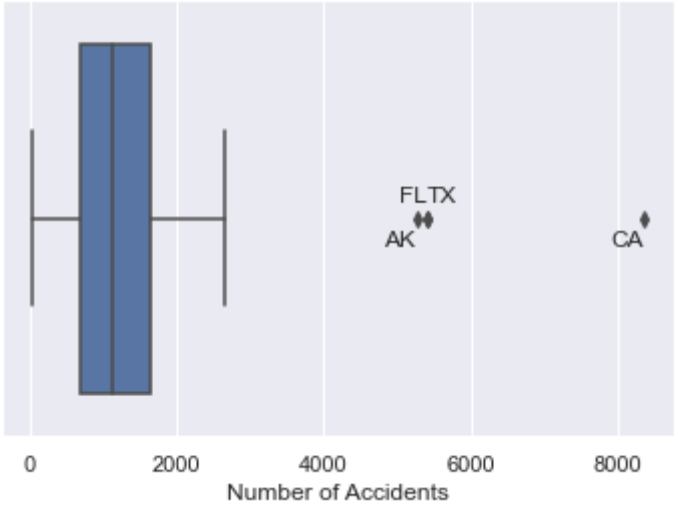
```
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.cbook import boxplot_stats
sns.set(style='darkgrid')
```

In [115…

```
### BOX & WHISKER
ax = sns.boxplot(x=count_df['Accidents'])

# manual calculation of quantiles for labeling purposes
month_q1 = count_df.quantile(0.25)['Accidents']
month_q3 = count_df.quantile(0.75)['Accidents']
outlier_top_lim = month_q3 + 1.5 * (month_q3 - month_q1)
outlier_bottom_lim = month_q1 - 1.5 * (month_q3 - month_q1)
ax.set(xlabel='Number of Accidents', ylabel='',
       title='')

# iterating through df to label the outliers
for row in count_df.itertuples():
    val = row[2]
    if val > outlier_top_lim or val < outlier_bottom_lim:
        if row[1] in ['AK', 'CA']:
            x = val
            y = 0.05
        else:
            if row[1] == 'TX':
                x = val + 400
            else:
                x = val
            y = -0.05
        plt.text(x, y, row[1], ha='right', va='center')
plt.show()
```



The states of California, Alaska, Texas, and Florida are in fact all outliers. To "equalize" our analysis we will compare our outliear coastal states to the remaining states.

In [116…

```
# creation of outliers column
def outlier_detection(row, num_call):
    outliers = ['AK', 'FL', 'TX', 'CA']
    if row['State_Code'] in outliers:
        if num_call == 0:
            return 'Outlier'
        else:
            return 1
    else:
        if num_call == 0:
            return 'Non-Outlier'
        else:
            return 1
small_df['Outliers'] = small_df.apply(lambda row: outlier_detection(row, 0), axis=1)
small_df.head()
```

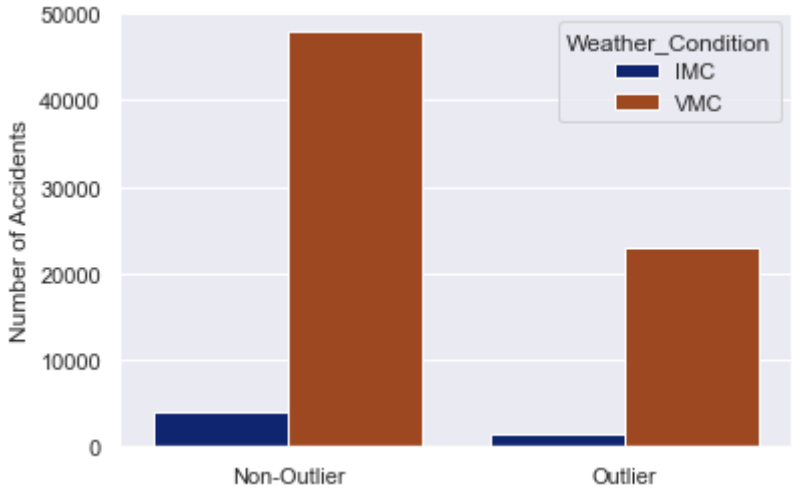
Out [116…

	Event_ID	Accident_Number	Event_Date	Location	Latitude	Longitude	Amateur_Built	Weather_Condition	Year	Stat
1	20181217X25746	GAA19CA097	2018-12-15	MORIARTY, NM	34.970000	-106.000000	No	VMC	2018	
2	20181213X41114	ERA19LA065	2018-12-13	Punta Gorda, FL	26.925278	-82.001111	No	VMC	2018	

	Event_ID	Accident_Number	Event_Date	Location	Latitude	Longitude	Amateur_Built	Weather_Condition	Year	Stat
3	20181213X45528	CEN19FA044	2018-12-13	Valparaiso, IN	41.451667	-87.004444	No	VMC	2018	
4	20181214X90303	GAA19CA096	2018-12-11	Hartford, WI	43.330278	-88.326111	No	VMC	2018	
6	20181208X53536	GAA19CA090	2018-12-08	Hesperia, CA	34.376945	-117.316111	Yes	VMC	2018	

In [117…

```
# OUTLIERS VS NON-OUTLIERS (WEATHER CONDITIONS)
weather_df = small_df[['Outliers', 'Weather_Condition']]
weather_df = weather_df.groupby(['Outliers', 'Weather_Condition']).size().reset_index(name='Count')
ax1 = sns.barplot(data=weather_df,
                  x='Outliers',
                  y='Count',
                  hue='Weather_Condition',
                  palette='dark')
ax1.set(xlabel='', ylabel='Number of Accidents',
        title='')
plt.show()
```



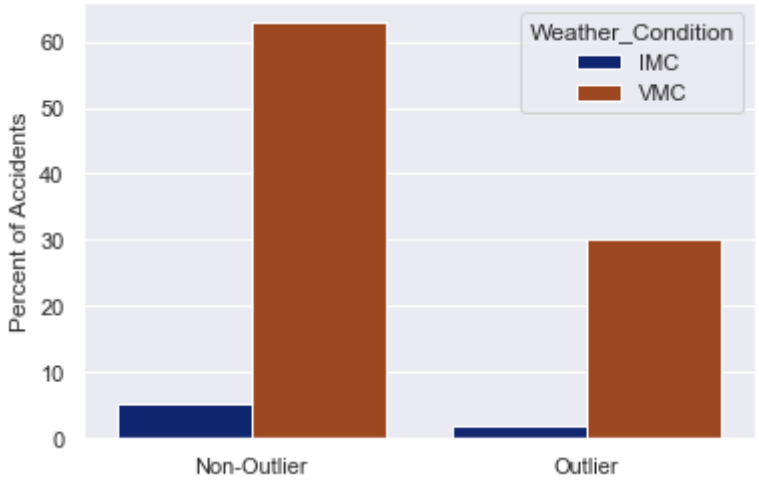
The outliers account for about one third of all accidents, regardless of weather conditions. Comparing our accidents weather conditions in terms of percents may make lucid the role weather may play in aircraft accidents.

In [118…

```
# OUTLIERS VS NON-OUTLIERS (WEATHER CONDITIONS)
```

```
weather_df['Whole_Percent'] = (weather_df['Count'] /
                  weather_df['Count'].sum()) * 100

ax1 = sns.barplot(data=weather_df,
                  x='Outliers',
                  y='Whole_Percent',
                  hue='Weather_Condition',
                  palette='dark')
ax1.set(xlabel='', ylabel='Percent of Accidents',
        title='')
plt.show()
```



In [119…

```
Non_Out_IMC = weather_df.iloc[0, 2] / (weather_df.iloc[0, 2] + weather_df.iloc[1, 2]) * 100
Out_IMC = weather_df.iloc[2, 2] / (weather_df.iloc[2, 2] + weather_df.iloc[3, 2]) * 100
Non_Out_VMC = 100.0 - Non_Out_IMC
Out_VMC = 100.0 - Out_IMC
Percentages = [Non_Out_IMC, Non_Out_VMC, Out_IMC, Out_VMC]
Percentages = [round(val, 2) for val in Percentages]
weather_df['Grouped_Percent'] = Percentages
weather_df.head()
```

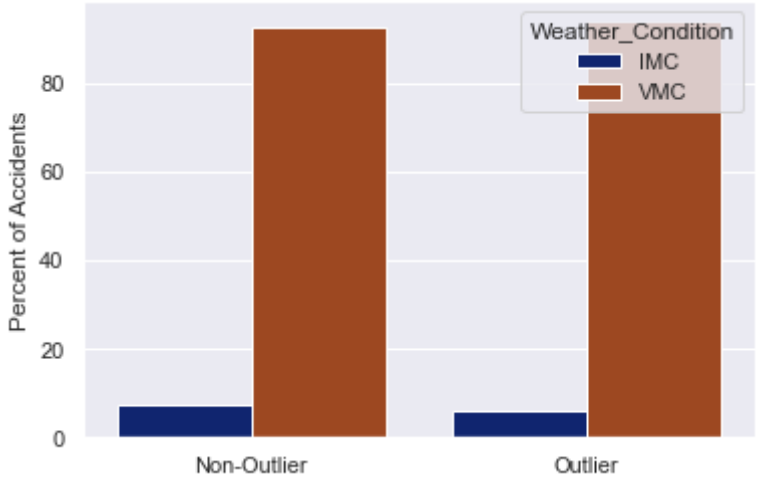
Out[119…

	Outliers	Weather_Condition	Count	Whole_Percent	Grouped_Percent
0	Non-Outlier	IMC	3901	5.116804	7.53
1	Non-Outlier	VMC	47915	62.848411	92.47
2	Outlier	IMC	1496	1.962250	6.13

	Outliers	Weather_Condition	Count	Whole_Percent	Grouped_Percent
3	Outlier	VMC	22927	30.072535	93.87

In [120…

```
ax1 = sns.barplot(data=weather_df,
                  x='Outliers',
                  y='Grouped_Percent',
                  hue='Weather_Condition',
                  palette='dark')
ax1.set(xlabel='', ylabel='Percent of Accidents',
        title='')
plt.show()
```



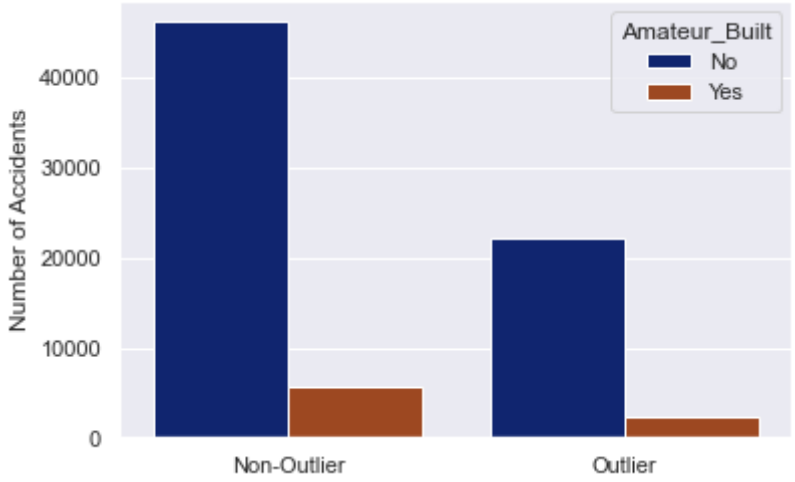
When comparing based on percents of the whole, the role weather conditions may play was still unclear. From here we opted to analyze the Outlier and Non-Outliers directly.

When comparing the percent of weather conditions per Outlier or Non-Outlier we see that the distribution between our outlier states and non-outlier states appear to be mostly equal, indicating that the location of the accident is mostly negligible. On the other side, it does appear that most accidents, regardless of which state the accident occurred in, were more likely to occur in VMC, visual meterlogical conditions. These conditions are in which pilots do not need to fly directly off their instruments. In contrast, IMC, instrument meterlogical conditions, are conditions in which pilots must fly using their instruments. In general, more accident occurred when the conditions were fair/visible.

In [121…

```
# OUTLIERS VS NON-OUTLIERS (AMATEUR BUILT)
```

```
amateur_df = small_df[['Outliers', 'Amateur_Built']]
amateur_df = amateur_df.groupby(['Outliers', 'Amateur_Built']).size().reset_index(name='Count')
ax1 = sns.barplot(data=amateur_df,
                  x='Outliers',
                  y='Count',
                  hue='Amateur_Built',
                  palette='dark')
ax1.set(xlabel='', ylabel='Number of Accidents',
        title='')
plt.show()
```



In [122…

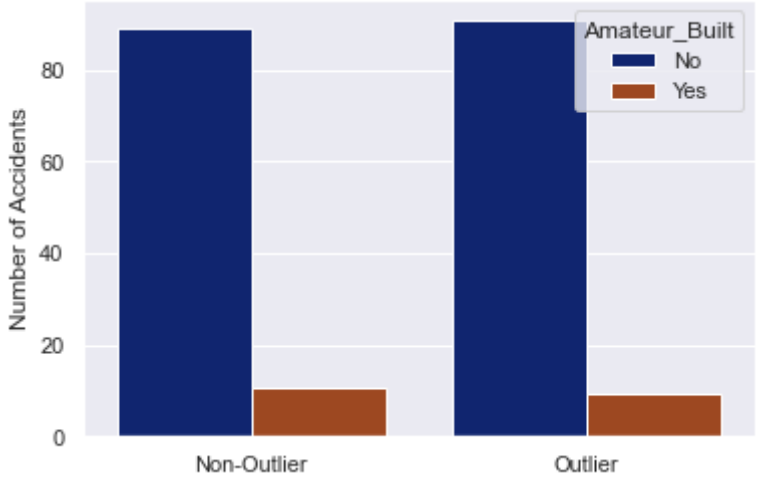
```
Non_Out_No = amateur_df.iloc[0, 2] / (amateur_df.iloc[0, 2] + amateur_df.iloc[1, 2]) * 100
Out_No = amateur_df.iloc[2, 2] / (amateur_df.iloc[2, 2] + amateur_df.iloc[3, 2]) * 100
Non_Out_Yes = 100.0 - Non_Out_No
Out_Yes = 100.0 - Out_No
Percentages = [Non_Out_No, Non_Out_Yes, Out_No, Out_Yes]
Percentages = [round(val, 2) for val in Percentages]
amateur_df['Percent'] = Percentages
amateur_df.head()
```

Out[122…

	Outliers	Amateur_Built	Count	Percent
0	Non-Outlier	No	46232	89.22
1	Non-Outlier	Yes	5584	10.78
2	Outlier	No	22163	90.75
3	Outlier	Yes	2260	9.25

In [123…

```
ax1 = sns.barplot(data=amateur_df,
                  x='Outliers',
                  y='Percent',
                  hue='Amateur_Built',
                  palette='dark')
ax1.set(xlabel='', ylabel='Number of Accidents',
        title='')
plt.show()
```



Continuing our analysis, the interest of the build of the aircraft comes into question. From the graphs above, regardless of the states (outlier, non-outliers), it appears that majority of all aircraft accidents resulted from aircraft that were not made by amateurs, meaning they were professionally built by larger companies.

In [124…

```
import pyproj
from shapely.geometry import Polygon, Point
from shapely.ops import transform
from functools import partial
```

In [125…

```
# BERMUDA SQAURE (JUST GOOFIN)
poly = Polygon([[-80.190262, 25.774252], [-66.118292, 18.466465], [-64.75737, 32.321384]))  # bermuda triangle
def bermuda(row, shape):
    coord = Point(row['Latitude'], row['Longitude'])
    return shape.contains(coord)  # check if the given point is within the triangle
```

```
small_df['Bermuda'] = small_df.apply(lambda row: bermuda(row, poly), axis=1)
small_df['Bermuda'].value_counts()  # zero crashes in the bermuda triangle :(
```

Out[125…

```
False    76239
Name: Bermuda, dtype: int64
```

In addtion to our location analysis, we wanted to see how many aircraft accidents happened in the Bermuda Triangle. Unfortunately, there were no flight accidents that occurred in the Triangle.

Conclusion

In conclusion, the location of the accident does not play a significant role. When investigating the affect weather plays on accidents the majority of accidents happen during VMC or conditions that do not requiring indstruments to fly in; conditions that are usually more clear, fewer clouds, no storms, etc. When accounting for the build of the aircraft, amateur or not, most of the accidents happened in professionally build aircraft. Lastly, when investigating the number of aircraft accidents that took place in the Bermuda Triangle we did not find a single one; whihc makes sense as they do not crash in the triangle, they disappear....(just kidding).