NOAA Weather Data

Obtaining the Data

In [1]:

```
#Importing libraries needed
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import pyplot
%matplotlib inline
import numpy as np
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Data Understanding

Data was obtained from the National Oceanic and Atmospheric Administration (NOAA) National Climatic Data Center (NCDC) using the Climate Data Online (CDO) database. The CDO provides free access to NCDC's archive of global historical weather and climate data in addition to station history information. These data include quality controlled daily, monthly, seasonal, and yearly measurements of temperature, precipitation, wind, and degree days as well as radar data and 30-year Climate Normals.

Data from NOAA was selected because it provides daily summaries for average wind speed and fastest 2 minute wind gust for the five hurricanes we wanted to examine.

For the purpose of this project we will be looking at six hurricanes:

- Charley
- Dennis
- Matthew
- Irma
- Michael
- Ian

We will be using information from hurricane Charley, Dennis, Matthew, Irma, Michael to create our models and validating our model with recent data from Hurricane Ian.

NOAA Data Column Descriptions

Column Name	Description
NAME	is the name of the station (usually city/airport name).
LATITUDE	latitude (decimated degrees w/northern hemisphere values > 0, southern hemisphere values < 0)

Column Name	Description
LONGITUDE	longitude (decimated degrees w/western hemisphere values < 0, eastern hemisphere values > 0)
DATE	is the year of the record (4 digits) followed by month (2 digits) and day (2 digits).
AWND	Average daily wind speed (meters per second)
WSF2	Fastest 2-minute wind speed (in meters per second)
HurricaneName	Numerical label given to each hurricane. 1 = Charley, 2 = Dennis, 3 = Matthew, 4 = Irma, 5= Michael
COORD	Engineered column representing coordinates created by combining LATITUDE and LONGITDE
City	Engineered column representing cities created by running coordinates through geopy reverse geolocater.

Citations:

Centers N. Select a Location | Data Tools | Climate Data Online (CDO) | National Climatic Data Center (NCDC). Noaa.gov. Published 2019. https://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation (https://www.ncdc.noaa.gov/cdo-web/datatools/selectlocation)

Hurricanes. coast.noaa.gov. https://coast.noaa.gov/hurricanes/ (https://coast.noaa.gov/hurricanes/)

National Centers for Environmental Information (NCEI. Climate Data Online (CDO) - The National Climatic Data Center's (NCDC) Climate Data Online (CDO) provides free access to

In [2]:
```
#opening the datasets
ian = pd.read_csv(r'data\ian.csv')
matthew = pd.read_csv(r'data\matthew.csv')
irma =  pd.read_csv(r'data\irma.csv')
michael =  pd.read_csv(r'data\michael.csv')
charley = pd.read_csv(r'data\charley.csv')
dennis = pd.read_csv(r'data\dennis.csv')
```

Data Cleaning

Let's remove duplicate values and keep only the value with the highest wind speed.

In [3]:
```
#removing duplicates
charley = charley.sort_values('AWND', ascending=False).drop_duplicates
dennis = dennis.sort_values('AWND', ascending=False).drop_duplicates('
matthew = matthew.sort_values('AWND', ascending=False).drop_duplicates
irma = irma.sort_values('AWND', ascending=False).drop_duplicates('NAME
michael = michael.sort_values('AWND', ascending=False).drop_duplicates
ian = ian.sort_values('AWND', ascending=False).drop_duplicates('NAME')
```

Data Engineering

We want to be able to compare data from all five hurricanes against home value. So we are

Concating the Hurricane Dataframes

In [4]:

```
#creating a column with a label for each hurricane
#this way we can still know which hurricane we are referencing

#charley
charley['HurricaneName'] = 'charley'

#dennis
dennis['HurricaneName'] = 'dennis'

#matthew
matthew['HurricaneName'] = 'matthew'

#irma
irma['HurricaneName'] = 'irma'

#michael
michael['HurricaneName'] = 'michael'

#ian
ian['HurricaneName'] = 'ian'

```

In [5]:

```
#making sure it looks good
charley.head()
```

Out[5]:

	NAME	LATITUDE	LONGITUDE	DATE	AWND	WSF2	HurricaneName
0	FORT PIERCE, FL US	27.4419	-80.3508	8/13/2004	NaN	NaN	charley
2	FORT PIERCE ARC, FL US	27.4272	-80.4053	8/13/2004	NaN	NaN	charley
4	BIG CYPRESS, FL US	26.3283	-80.9958	8/13/2004	NaN	NaN	charley
6	HOMESTEAD GEN AVIATION AIRPORT, FL US	25.5011	-80.5500	8/13/2004	NaN	NaN	charley
8	LOXAHATCHEE NWR, FL US	26.4985	-80.2160	8/13/2004	NaN	NaN	charley

In [6]:
```
#concating the six dataframes into one
hurricane = pd.concat([charley, dennis, matthew, irma, michael, ian],
hurricane.head()
```

Out[6]:

	NAME	LATITUDE	LONGITUDE	DATE	AWND	WSF2	HurricaneName
0	FORT PIERCE, FL US	27.4419	-80.3508	8/13/2004	NaN	NaN	charley
1	FORT PIERCE ARC, FL US	27.4272	-80.4053	8/13/2004	NaN	NaN	charley
2	BIG CYPRESS, FL US	26.3283	-80.9958	8/13/2004	NaN	NaN	charley
3	HOMESTEAD GEN AVIATION AIRPORT, FL US	25.5011	-80.5500	8/13/2004	NaN	NaN	charley
4	LOXAHATCHEE NWR, FL US	26.4985	-80.2160	8/13/2004	NaN	NaN	charley

In [7]:
```
hurricane.describe()
```

Out[7]:

	LATITUDE	LONGITUDE	AWND	WSF2
count	2494.000000	2494.000000	266.000000	264.000000
mean	28.311389	-82.073998	17.902218	33.542045
std	1.600142	1.672985	7.781214	13.890268
min	24.550659	-87.467244	2.910000	0.000000
25%	27.150977	-82.514912	12.805000	23.900000
50%	28.298745	-81.757617	15.660000	30.000000
75%	29.729953	-80.906335	21.920000	42.900000
max	30.964030	-80.034979	40.710000	87.000000

In [8]:
```
#data types are object and float
#currently have 5571 entries
#AWND is missing a lot of values
hurricane.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2494 entries, 0 to 2493
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   NAME           2494 non-null   object
 1   LATITUDE       2494 non-null   float64
 2   LONGITUDE      2494 non-null   float64
 3   DATE           2494 non-null   object
 4   AWND           266 non-null    float64
 5   WSF2           264 non-null    float64
 6   HurricaneName  2494 non-null   object
dtypes: float64(4), object(3)
memory usage: 136.5+ KB
```

Scrubbing the Data

In [9]:
```
#AWND is missing 5070
#We are going to drop any rows where wind speed is missing
#Dropping is the best solution here because wind speed
#Will not be accurately reflected by the mean in cities hit by the hur
hurricane.isnull().sum()
```

Out[9]:
```
NAME               0
LATITUDE           0
LONGITUDE          0
DATE               0
AWND            2228
WSF2            2230
HurricaneName      0
dtype: int64
```

In [10]:
```
#dropping all rows with missing values
hurricane.dropna(inplace= True)
```

In [11]:
```
#checking that dataframe is clean
hurricane.isnull().sum()
```

Out[11]:
```
NAME            0
LATITUDE        0
LONGITUDE       0
DATE            0
AWND            0
WSF2            0
HurricaneName   0
dtype: int64
```

In [12]:
```
#currently AWND and WSF2 are in meter per second
#let's change that to miles per hour for user understanding
#meter per second * 2.2369 = miles per hour
hurricane['AWND'] = (hurricane['AWND']*2.2369)
hurricane['WSF2'] = (hurricane['WSF2']*2.2369)
```

Data Exploration

Exploring all hurricanes

The fastest average wind speed accross all hurricanes was 91 mph and fastest two minute wind gust was 194 mph.

In [13]:
```
#Looking at stats for all hurricanes
hurricane.describe()
```

Out[13]:

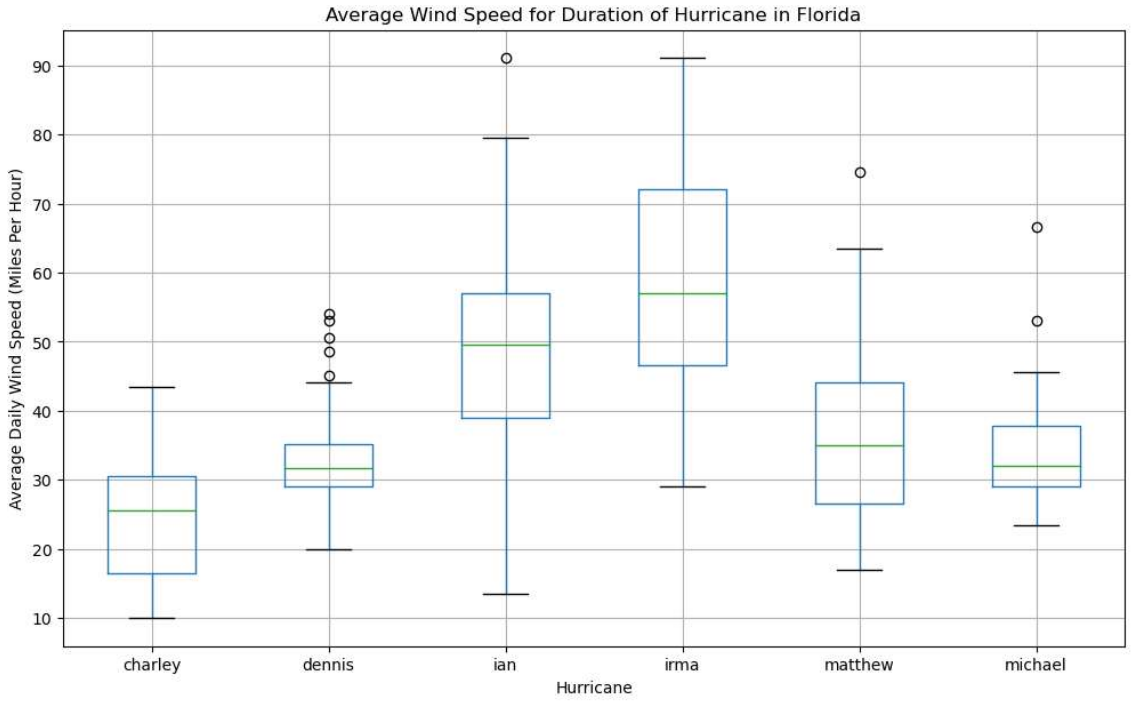
	LATITUDE	LONGITUDE	AWND	WSF2
count	260.000000	260.00000	260.000000	260.000000
mean	28.178982	-82.31930	40.430763	74.971424
std	1.886234	2.03567	17.180567	31.242263
min	24.557060	-87.31667	9.998943	0.000000
25%	26.538050	-82.68555	29.012593	53.461910
50%	28.061370	-81.75684	35.029854	66.100395
75%	30.233330	-80.63560	49.161470	95.963010
max	30.843150	-80.09918	91.064199	194.610300

Visualizing Wind Speed

As we can see from the box and whisker plot below the largest hurricane was Irma and Ian. The variable of average wind speed is a recording of the average wind speed for the whole day. While other hurricanes may have had significant wind gusts and max speeds, what made hurricanes like Irma and Ian unique devastating was that they were extremely slow moving and stagnant. We can also see from the scatterplots below that each hurricane has a unique path. While coastal cities do tend to take more damage, at times inland regions can also experience severe damage.

In [14]:

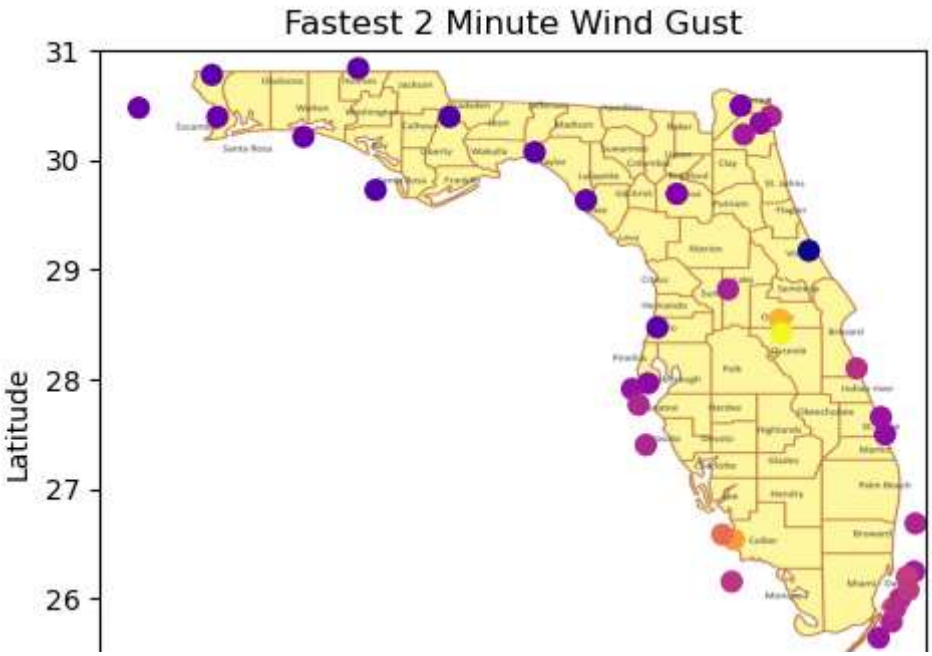
```
#Generate a box and whiskers plot for all six hurricanes
#creating a dataframe that has just HurricaneName and AWND
hurricane_bw = hurricane[['HurricaneName', 'AWND']]
#pivoting the values
hurricane_bw = hurricane_bw.pivot(columns='HurricaneName', values='AWN
#plotting
box = hurricane_bw.boxplot(figsize = (12,7,));
box.plot()
#adding title
plt.title('Average Wind Speed for Duration of Hurricane in Florida')
#adding xlabel
plt.xlabel('Hurricane')
#adding ylabel
plt.ylabel('Average Daily Wind Speed (Miles Per Hour)');
```



In [15]:

```
#creating a scatterplot function
def scatterplot(df):
    #importing image for background
    img = plt.imread(r"data\images\floridamap.jpg")
    fig, ax = plt.subplots()
    ax.imshow(img, extent=[-87, -80, 25, 31])
    #plotting scatter plot
    plt.scatter(x=df['LONGITUDE'], y=df['LATITUDE'], s=50, c=df['WSF2'
    #title
    plt.title('Fastest 2 Minute Wind Gust')
    #xlabel
    plt.xlabel('Longitude')
    #y label
    plt.ylabel('Latitude')
    #legend
    ax.legend(df['HurricaneName'])
    return plt.show()
```

In [16]:
```
#applying scatterplot function to our hurricanes
scatterplot(charley)
scatterplot(dennis)
scatterplot(matthew)
scatterplot(irma)
scatterplot(michael)
scatterplot(ian)
```



Data Engingeering

Using Geopy to Get Cities

In order to join the hurricane dataframe to the housing dataframe we will need to know the city names. Using the coordinates provided by the NOAA dataset we can use geopy to reverse geolocate the city names.

Due to this being an API not all request could be completed and some city names had to be annoitated in excel.

Citation:
kumar_satyam. Get the city, state, and country names from latitude and longitude using Python. GeeksforGeeks. Published October 15, 2020. https://www.geeksforgeeks.org/get-the-city-state-and-country-names-from-latitude-and-longitude-using-python/ (https://www.geeksforgeeks.org/get-the-city-state-and-country-names-from-latitude-and-longitude-using-python/)

In [17]:
```
#importing libraries
from tkinter import *
from geopy.geocoders import Nominatim
from geopy.geocoders import Photon

# Create an instance of tkinter frame
win = Tk()

# Define geometry of the window
win.geometry("700x350")
```

Out[17]: ''

Getting Coordinates

In [18]:
```
#Engingeering a coordinates column out of latitude and longitude
#We need coordinates to use geopy

hurricane['COORD'] = list(zip(hurricane.LATITUDE, hurricane.LONGITUDE))

hurricane.head()
```

Out[18]:

	NAME	LATITUDE	LONGITUDE	DATE	AWND	WSF2	HurricaneName
5	JACKSONVILLE INTERNATIONAL AIRPORT, FL US	30.49529	-81.69374	8/14/2004	14.517481	44.51431	charley
9	CRESTVIEW FAA AP, FL US	30.77715	-86.51938	8/13/2004	16.016204	29.07970	charley
15	MARIANNA MUNICIPAL AIRPORT, FL US	30.83696	-85.18352	8/13/2004	15.501717	29.07970	charley
16	PENSACOLA REGIONAL AIRPORT, FL US	30.47612	-87.18575	8/13/2004	22.011096	36.01409	charley
25	NAPLES MUNICIPAL AIRPORT, FL US	26.15498	-81.77514	8/13/2004	20.512373	78.06781	charley

In [19]:
```
#creating a function
def get_city(coords):
    #instantiate the Nominatim API
    geolocator = Nominatim(user_agent="MyApp")
    #get the city from the coordinates
    location = geolocator.reverse(coords)
    address = location.raw['address']
    city = address.get('city', '')
    #return the city
    return city
```

In [20]:
```
#applying function to dataframe
hurricane['City'] = hurricane['COORD'].apply(get_city)
```

In [21]:
```
#looks good
hurricane.isnull().sum()
```

Out[21]:
```
NAME            0
LATITUDE        0
LONGITUDE       0
DATE            0
AWND            0
WSF2            0
HurricaneName   0
COORD           0
City            0
dtype: int64
```

Saving the Dataframe

In [22]:
```
#saving the dataframe
hurricane.to_csv(r'data\hurricane.csv', index=False)
```