# WeatherPy

### Note

• Instructions have been included for each segment. You do not have to follow them exactly, but they are included to help you think through the steps,

```
In [1]: # Dependencies and Setup
        import matplotlib.pyplot as plt
        import pandas as pd
        import numpy as np
        import requests
        import time
         from datetime import datetime
        from scipy.stats import linregress
        # Import API key
        from api_keys import weather_api_key
         # Incorporated citipy to determine city based on latitude and longitude
        from citipy import citipy
        # Output File (CSV)
        output_data_file = "../output_data/cities.csv"
        # Range of latitudes and longitudes
        lat_range = (-90, 90)
lng_range = (-180, 180)
```

### **Generate Cities List**

```
In [25]: # List for holding lat_Ings and cities
lat_Ings = []
cities = []

# Create a set of random lat and Ing combinations
lats = np.random.uniform(lat_range[0], lat_range[1], size=1500)
lngs = np.random.uniform(lng_range[0], lng_range[1], size=1500)
lat_Ings = zip(lats, lngs)

# Identify nearest city for each lat, Ing combination
for lat_Ing in lat_Ings:
    city = citipy.nearest_city(lat_Ing[0], lat_Ing[1]).city_name

# If the city is unique, then add it to a our cities list
    if city not in cities:
        cities.append(city)

# Print the city count to confirm sufficient count
print(f"The total number of cities is {len(cities)}")
```

The total number of cities is 625

### **Perform API Calls**

- Perform a weather check on each city using a series of successive API calls.
- . Include a print log of each city as it'sbeing processed (with the city number and city name).

```
In [3]: # Set variables
         c_data_list = []
          set_no = 1
          rec_no = 1
          num_of_set = 50
          units = "imperial"
          print("Beginning Data Retrieval")
          print("
          # Put city data into the list
          for city in cities:
              url = f"http://api.openweathermap.org/data/2.5/weather?q={city}&appid={weather_api_key}&units={units}"
               response = requests.get(url).json()
                   c_data_list.append({"City" : city.
                                            "Lat": response["coord"]["lat"],
"Lng": response["coord"]["lon"],
                                           "Max Temp" : response["main"]["temp_max"],
"Humidity" : response["main"]["humidity"],
"Cloudiness" : response["clouds"]["all"],
"Wind Speed" : response["wind"]["speed"],
                                            "Country" : response["sys"]["country"],
                                            "Date" : response["dt"]})
                   print(f"Processing Record {rec_no} of Set {set_no} | {city}")
                    if (len(c_data_list)) % num_of_set == 0:
                        rec_no = 1
                        set_no += 1
                    else:
                        rec_no += 1
              except KeyError:
                   print("City not found, Skipping...")
          print("Data Retrieval Complete")
          print("-
```

.

```
Processing Record 25 of Set 12 | bijie
Processing Record 26 of Set 12 | aguimes
Processing Record 27 of Set 12 | ushtobe
Processing Record 28 of Set 12 | mumford
Processing Record 29 of Set 12 | paamiut
Processing Record 30 of Set 12 | banamba
Processing Record 31 of Set 12 | henties bay
```

Data Retrieval Complete

### Convert Raw Data to DataFrame

- . Export the city data into a .csv.
- . Display the DataFrame

```
In [4]: # Create a dataframe to store the city data
cities_df = pd.DataFrame(c_data_list)
cities_df.count()
```

Out [4]: City Lat 581 Lna Max Temp 581 581 Humidity Cloudiness 581 Wind Speed 581 Country 581 Date 581

dtype: int64

In [5]: # Show five cities cities\_df.head()

Out [5]:

	City	Lat	Lng	Max Temp	Humidity	Cloudiness	Wind Speed	Country	Date
0	hermanus	-34.42	19.23	53.01	90	17	1.99	ZA	1595126828
1	yar-sale	66.83	70.83	49.01	91	100	12.64	RU	1595126588
2	evansville	37.97	-87.56	84.20	70	1	6.93	US	1595126613
3	fort saint james	54.43	-124.25	60.55	81	74	4.72	CA	1595127017
4	ushuaia	-54.80	-68.30	32.00	94	75	9.17	AR	1595126619

## Inspect the data and remove the cities where the humidity > 100%.

Skip this step if there are no cities that have humidity > 100%.

In [6]: # Describe the city data cities\_df.describe()

Out [6]:

	Lat	Lng	Max Temp	Humidity	Cloudiness	Wind Speed	Date
count	581.000000	581.000000	581.000000	581.000000	581.000000	581.000000	5.810000e+02
mean	19.581756	15.249948	69.617590	70.695353	45.500861	7.475800	1.595127e+09
std	33.084487	90.732088	13.312144	19.158462	38.521719	5.111438	1.432299e+02
min	-54.800000	-179.170000	24.800000	8.000000	0.000000	0.160000	1.595126e+09
25%	-7.710000	-69.260000	59.900000	60.000000	1.000000	3.740000	1.595127e+09
50%	21.200000	23.040000	71.080000	74.000000	40.000000	5.990000	1.595127e+09
75%	47.850000	97.520000	80.560000	85.000000	82.000000	10.250000	1.595127e+09
max	78.220000	179.320000	107.600000	100.000000	100.000000	33.910000	1.595127e+09

In [7]: # Get the indices of cities that have humidity over 100%,
humidity\_idx = cities\_df.loc[(cities\_df.iloc[:, 4] > 100)].index
humidity\_idx

Out[7]: Int64Index([], dtype='int64')

In [8]: # Make a new DataFrame equal to the city data to drop all humidity outliers by index.
# Passing "inplace=False" will make a copy of the city\_data DataFrame, which we call "clean\_city\_data".
filtered\_df = cities\_df.drop(index = humidity\_idx)
filtered\_df.head()

Out [8]:

	City	Lat	Lng	Max Temp	Humidity	Cloudiness	Wind Speed	Country	Date
0	hermanus	-34.42	19.23	53.01	90	17	1.99	ZA	1595126828
1	yar-sale	66.83	70.83	49.01	91	100	12.64	RU	1595126588
2	evansville	37.97	-87.56	84.20	70	1	6.93	US	1595126613
3	fort saint james	54.43	-124.25	60.55	81	74	4.72	CA	1595127017
4	ushuaia	-54.80	-68.30	32.00	94	75	9.17	AR	1595126619

```
In [9]: # Extract relevant fields from the data frame
to_csv_df = cities_df.iloc[:, [0, 5, 7, 8, 4, 1, 2, 3, 6]]
to_csv_df.index.name = "City_lD"
# Export the City_Data into a csv
to_csv_df.to_csv(output_data_file)
```

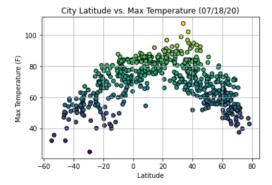
# **Plotting the Data**

- Use proper labeling of the plots using plot titles (including date of analysis) and axes labels.
- · Save the plotted figures as .pngs.

## Latitude vs. Temperature Plot

```
In [10]: # Get data to make a scatter plot from the city data
latitude = cities_df.iloc[:, 1]
max_temp = cities_df.iloc[:, 3]

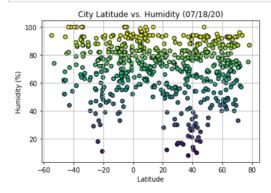
# Create a scatter plot - Latitude vs. Max Temperature
plt.scatter(latitude, max_temp, c = max_temp, cmap = "viridis", edgecolors = "black")
plt.grid()
plt.xlabel("Latitude")
plt.ylabel("Max Temperature (F)")
plt.title(f"City Latitude vs. Max Temperature ({datetime.today().strftime('%m/%d/%y')})")
plt.savefig("../output_data/max_temp.png")
plt.show()
```



# Latitude vs. Humidity Plot

```
In [11]: # Get humidity data from the city data
humidity = cities_df.iloc[:, 4]

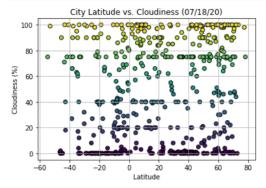
# Create a scatter plot - Latitude vs. Humidity
plt.scatter(latitude, humidity, c = humidity, cmap = "viridis", edgecolors = "black")
plt.grid()
plt.xlabel("Latitude")
plt.ylabel("Humidity (%)")
plt.title(f"City Latitude vs. Humidity ({datetime.today().strftime('%m/%d/%y')})")
plt.savefig("../output_data/humidity.png")
plt.show()
```



## Latitude vs. Cloudiness Plot

```
In [12]: # Get cloudiness from the city data
cloudiness = cities_df.iloc[:, 5]

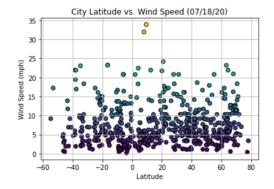
# Create a scatter plot - Latitude vs. Cloudiness
plt.scatter(latitude, cloudiness, c = cloudiness, cmap = "viridis", edgecolors = "black")
plt.grid()
plt.xlabel("Latitude")
plt.ylabel("Cloudiness (%)")
plt.title(f"City Latitude vs. Cloudiness ({datetime.today().strftime('%m/%d/%y')})")
plt.savefig("../output_data/cloudiness.png")
plt.show()
```



# Latitude vs. Wind Speed Plot

```
In [13]: # Get wind speed from the city data
wind_speed = cities_df.iloc[:, 6]

# Create a scatter plot - Latitude vs. Cloudiness
plt.scatter(latitude, wind_speed, c = wind_speed, cmap = "viridis", edgecolors = "black")
plt.grid()
plt.xlabel("Latitude")
plt.xlabel("Latitude")
plt.vlabel("Wind Speed (mph)")
plt.title(f"City Latitude vs. Wind Speed ({datetime.today().strftime('%m/%d/%y')})")
plt.savefig("../output_data/wind_speed.png")
plt.show()
```



## **Linear Regression**

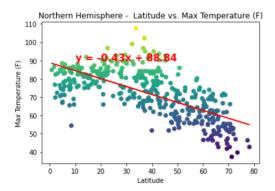
```
In [15]: # Create Northern and Southern Hemisphere DataFrames
north_df = cities_df.loc[cities_df.iloc[:, 1] >= 0]
south_df = cities_df.loc[cities_df.iloc[:, 1] < 0]</pre>
```

### Northern Hemisphere - Max Temp vs. Latitude Linear Regression

```
In [16]: # Get latitude and max temperature data on Northern Hemisphere
    north_lat = north_df.iloc[:, 1]
    north_max_temp = north_df.iloc[:, 3]

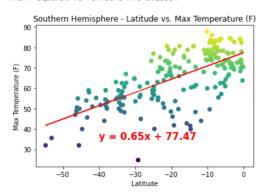
# Create a scatter plot with a linear regression - Latitude vs. Max temperature
    plt.scatter(north_lat, north_max_temp, c = north_max_temp, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Max Temperature (F)")
    plt.title("Northern Hemisphere - Latitude vs. Max Temperature (F)")
    plt.annotate(linear_r_plot(north_lat, north_max_temp), (10, 90), fontsize = 15, color = "red", weight = "bold")
    plt.savefig(".../output_data/northern_max_temp.png")
    plt.show()
```

The r-squared is: 0.47007889389017865



### Southern Hemisphere - Max Temp vs. Latitude Linear Regression

The r-squared is: 0.46943417348125094

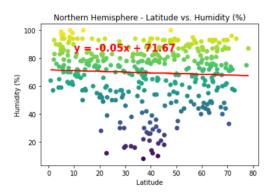


### Northern Hemisphere - Humidity (%) vs. Latitude Linear Regression

```
In [18]: # Get humidity data on Northern Hemisphere
    north_humidity = north_df.iloc[:, 4]

# Create a scatter plot with a linear regression - Latitude vs. Humidity
    plt.scatter(north_lat, north_humidity, c = north_humidity, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Humidity (%)")
    plt.ylabel("Homidity (%)")
    plt.title("Northern Hemisphere - Latitude vs. Humidity (%)")
    plt.annotate(linear_r_plot(north_lat, north_humidity), (10, 85), fontsize = 15, color = "red", weight = "bold")
    plt.savefig("../output_data/northern_humidity.png")
    plt.show()
```

The r-squared is: 0.003023514192657079

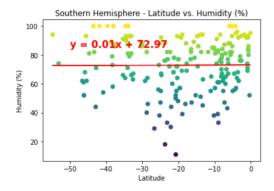


### Southern Hemisphere - Humidity (%) vs. Latitude Linear Regression

```
In [19]: # Get humidity data on Southern Hemisphere
    south_humidity = south_df.iloc[:, 4]

# Create a scatter plot with a linear regression - Latitude vs. Humidity
    plt.scatter(south_lat, south_humidity, c = south_humidity, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Humidity (%)")
    plt.title("Southern Hemisphere - Latitude vs. Humidity (%)")
    plt.annotate(linear_r_plot(south_lat, south_humidity), (-50, 85), fontsize = 15, color = "red", weight = "bold")
    plt.snwefig("../output_data/southern_humidity.png")
    plt.show()
```

The r-squared is: 2.4464026951950943e-05

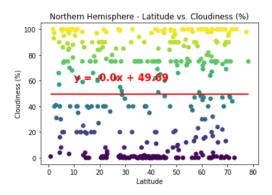


### Northern Hemisphere - Cloudiness (%) vs. Latitude Linear Regression

```
In [20]: # Get oloudiness data on Northern Hemisphere
    north_cloudiness = north_df.iloc[:, 5]

# Create a scatter plot with a linear regression - Latitude vs. Cloudiness
    plt.scatter(north_lat, north_cloudiness, c = north_cloudiness, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Cloudiness (%)")
    plt.title("Northern Hemisphere - Latitude vs. Cloudiness (%)")
    plt.annotate(linear_r_plot(north_lat, north_cloudiness), (10, 60), fontsize = 15, color = "red", weight = "bold")
    plt.savefig("../output_data/northern_cloudiness.png")
    plt.show()
```

The r-squared is: 9.300700810529933e-07

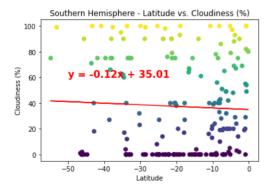


### Southern Hemisphere - Cloudiness (%) vs. Latitude Linear Regression

```
In [21]: # Get cloudiness data on Southern Hemisphere
    south_cloudiness = south_df.iloc[:, 5]

# Create a scatter plot with a linear regression - Latitude vs. Cloudiness
    plt.scatter(south_lat, south_cloudiness, c = south_cloudiness, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Cloudiness (%)")
    plt.ylabel("Cloudiness (%)")
    plt.title("Southern Hemisphere - Latitude vs. Cloudiness (%)")
    plt.annotate(linear_r_plot(south_lat, south_cloudiness), (-50, 60), fontsize = 15, color = "red", weight = "bold")
    plt.savefig("../output_data/southern_cloudiness.png")
    plt.show()
```

The r-squared is: 0.0020876397068019053

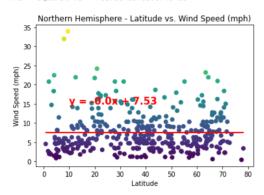


### Northern Hemisphere - Wind Speed (mph) vs. Latitude Linear Regression

```
In [22]: # Get wind speed data on Northern Hemisphere
    north_wind_speed = north_df.iloc[:, 6]

# Create a scatter plot with a linear regression - Latitude vs. Cloudiness
    plt.scatter(north_lat, north_wind_speed, c = north_wind_speed, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Wind Speed (mph)")
    plt.title("Northern Hemisphere - Latitude vs. Wind Speed (mph)")
    plt.annotate(linear_r_plot(north_lat, north_wind_speed), (10, 15), fontsize = 15, color = "red", weight = "bold")
    plt.savefig("../output_data/northern_wind_speed.png")
    plt.show()
```

The r-squared is: 7.587334531907874e-06

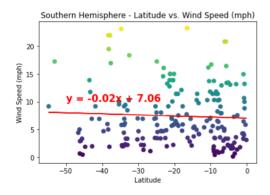


#### Southern Hemisphere - Wind Speed (mph) vs. Latitude Linear Regression

```
In [23]: # Get wind speed data on Southern Hemisphere
    south_wind_speed = south_df.iloc[:, 6]

# Create a scatter plot with a linear regression - Latitude vs. Cloudiness
    plt.scatter(south_lat, south_wind_speed, c = south_wind_speed, cmap = "viridis")
    plt.xlabel("Latitude")
    plt.ylabel("Wind Speed (mph)")
    plt.title("Southern Hemisphere - Latitude vs. Wind Speed (mph)")
    plt.annotate(linear__plot(south_lat, south_wind_speed), (-50, 10), fontsize = 15, color = "red", weight = "bold")
    plt.savefig("../output_data/southern_wind_speed.png")
    plt.show()
```

The r-squared is: 0.002331632699647725



## Result

- The closer to the equator it is, the hotter weather it is.
  - The amount of sunshine received at the equator is more than other places.
- The higher latitude on the northern hemisphere and the lower latitude on the southern hemisphere it is, the colder temperature it is.
  - The reflection of the sun's rays and the amount of sunshine will affect the temperature.
- I wasn't able to find any correlation between latitude and wind speed, humidity, cloudiness.
  - I suppose wind speed, humidity and cloudiness would be affected by other factors such as precipitation or whether inland or waterfront.