Merging Data and Storing in a Database / Data Visualization

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```
In [62]: # Importing required packages
import sqlite3
import pands as pd
from matplotlib import pyplot as plt
```

Loading data into database

```
In [6]: # Read temperature_data csv into environment
temperature_data = pd.read_csv("C:/Users/kayly/OneDrive/Desktop/MSDS/DSC540/Tem Project/TemperatureData")
temperature_data
```

5]:		City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp
	0	Abidjan	Ivory Coast	1	1996	Africa	1	79.6	1996-01-01	80.513774	80.754839
	1	Abidjan	Ivory Coast	1	1996	Africa	2	81.2	1996-01-02	80.513774	80.754839
	2	Abidjan	Ivory Coast	1	1996	Africa	3	82.2	1996-01-03	80.513774	80.754839
	3	Abidjan	Ivory Coast	1	1996	Africa	4	83.0	1996-01-04	80.513774	80.754839
	4	Abidjan	Ivory Coast	1	1996	Africa	5	82.1	1996-01-05	80.513774	80.754839
	952982	Zurich	Switzerland	12	2019	Europe	27	40.8	2019-12-27	51.086908	38.848387
	952983	Zurich	Switzerland	12	2019	Europe	28	35.5	2019-12-28	51.086908	38.848387
	952984	Zurich	Switzerland	12	2019	Europe	29	30.4	2019-12-29	51.086908	38.848387
	952985	Zurich	Switzerland	12	2019	Europe	30	29.9	2019-12-30	51.086908	38.848387
	952986	Zurich	Switzerland	12	2019	Europe	31	31.4	2019-12-31	51.086908	38.848387

952987 rows × 10 columns

```
In [20]: # Adding data from csv file to table called temperaturedata in database
with sqlite3.connect("milestonedata.db") as conn:
    temperature_data.to_sql('temperaturedata', conn, index=True)
    conn.commit()
```

```
In [21]: # Checking that dataframe was added to database table correctly
# Prints first row of each column
with sqlite3.connect("milestonedata.dh") as conn:
cursor = conn.cursor()
rows = cursor.execute("SELECT city, country, month, year, region, day, avgdailytemp, dateofobservation, avgyearlytemp, avgmonthlytemp FROM temperaturedata")
for row in rows:
    print(row)
    break
cursor.close()
```

('Abidjan', 'Ivory Coast', 1, 1996, 'Africa', 1, 79.6, '1996-01-01', 80.5137741046832, 80.75483870967743)

In [9]: # Read development_data csv into environment
development_data = pd.read_csv("C:/Users/kayly/OneDrive/Desktop/MSDS/DSC540/Tem Project/DevelopmentData")
development_data

0 Albania 8.0 8.0 2.8 18.6 8.0 44.0 4.0 3.0 1 Algeria 17.0 20.0 0.1 4.6 15.0 41.0 22.0 14.0 2 American Samoa 0.0 0.0 8.7 15.8 8.0 12.0 1.0 1.0 3 Angola 793.0 661.0 0.0 7.0 32.0 53.0 34.0 18.0 4 Antigua and Barbuda 0.0 0.0 0.3 19.9 3.0 31.0 4.0 2.0 166 Europe & Central Asia 1023.0 10576.0 10.7 14.2 678.0 1239.0 1360.0 350.0 167 Latin America & Caribbean 10700.0 9296.0 19.4 24.1 1117.0 1716.0 5439.0 629.0 168 Middle East & North Africa 205.0 230.0 13 5.1 290.0 672.0 374.0 228.0 169 North Am		Country	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	Marine protected areas (% of total territorial waters) 2022	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatened Higher Plants	Threatened Mammals	Change in Forest Area 1990 to 2021
2 American Samos 0.0 0.0 8.7 15.8 8.0 12.0 1.0 1.0 3 Angola 793.0 661.0 0.0 7.0 32.0 53.0 34.0 18.0 4 Antigua and Barbuda 0.0 0.0 0.3 19.9 3.0 31.0 4.0 2.0 <th>0</th> <th>Albania</th> <th>8.0</th> <th>8.0</th> <th>2.8</th> <th>18.6</th> <th>8.0</th> <th>44.0</th> <th>4.0</th> <th>3.0</th> <th>0.0</th>	0	Albania	8.0	8.0	2.8	18.6	8.0	44.0	4.0	3.0	0.0
3 Angola 793.0 661.0 0.0 7.0 32.0 53.0 34.0 18.0 4 Antigua and Barbuda 0.0 0.0 0.3 19.9 3.0 31.0 4.0 2.0 <td>1</td> <td>Algeria</td> <td>17.0</td> <td>20.0</td> <td>0.1</td> <td>4.6</td> <td>15.0</td> <td>41.0</td> <td>22.0</td> <td>14.0</td> <td>-3.0</td>	1	Algeria	17.0	20.0	0.1	4.6	15.0	41.0	22.0	14.0	-3.0
4 Antigua and Barbuda 0.0 0.0 0.3 19.9 3.0 31.0 4.0 2.0 <	2	American Samoa	0.0	0.0	8.7	15.8	8.0	12.0	1.0	1.0	0.0
4 Barbuda 0.0 0.0 0.3 19.9 3.0 51.0 4.0 2.0 </td <td>3</td> <td>Angola</td> <td>793.0</td> <td>661.0</td> <td>0.0</td> <td>7.0</td> <td>32.0</td> <td>53.0</td> <td>34.0</td> <td>18.0</td> <td>132.0</td>	3	Angola	793.0	661.0	0.0	7.0	32.0	53.0	34.0	18.0	132.0
166 Europe & Central Asia 10232.0 10576.0 10.7 14.2 678.0 1239.0 1306.0 350.0 167 Latin America & Caribbean 10700.0 9296.0 19.4 24.1 1117.0 1716.0 5439.0 629.0 168 Middle East & North Africa 205.0 230.0 1.3 5.1 290.0 672.0 374.0 228.0 169 North America 6507.0 6567.0 12.8 12.3 118.0 322.0 536.0 62.0	4		0.0	0.0	0.3	19.9	3.0	31.0	4.0	2.0	0.0
167 Latin America & Caribbean 10700 19.4 24.1 1117.0 1716.0 5439.0 629.0 168 Middle East & North Africa 205.0 230.0 1.3 5.1 290.0 672.0 374.0 228.0 169 North America 6507.0 6567.0 12.8 12.3 118.0 322.0 536.0 62.0					***			***			
167 Caribbean 10/00.0 9296.0 19.4 24.1 1117.0 1716.0 5439.0 629.0 168 Middle East & North Africa 205.0 230.0 1.3 5.1 290.0 672.0 374.0 228.0 169 North America 6507.0 6567.0 12.8 12.3 118.0 322.0 536.0 62.0	166		10232.0	10576.0	10.7	14.2	678.0	1239.0	1306.0	350.0	-344.0
North Africa 2000 2300 1.3 3.1 2900 6720 374.0 226.0 169 North America 6507.0 6567.0 12.8 12.3 118.0 322.0 536.0 62.0	167		10700.0	9296.0	19.4	24.1	1117.0	1716.0	5439.0	629.0	1404.0
	168		205.0	230.0	1.3	5.1	290.0	672.0	374.0	228.0	-25.0
170 South Asia 826.0 900.0 0.5 8.7 253.0 397.0 794.0 252.0	169	North America	6507.0	6567.0	12.8	12.3	118.0	322.0	536.0	62.0	-60.0
	170	South Asia	826.0	900.0	0.5	8.7	253.0	397.0	794.0	252.0	-74.0

171 rows × 10 columns

('Albania', 'Forest Area (sq.km thousands) 1990')

```
In [12]: # Read air_pollution_data csv into environment
air_pollution_data * pd.read_csv("C:/Users/kayly/OneDrive/Desktop/MSDS/DSC540/Tem Project/AirPollutionData")
air_pollution_data
```

2]:		Country	Country Code	City	Quality Rating	Concentration CO	Concentration NO	Concentration NO2	Concentration NH3	Concentration O3	Concentration SO2	Concentration PM2.5	Concentration PM10	DateTime	Qualitative Name
	0	Albania	AL	Tirana	1	208.62	0.00	3.90	2.95	40.41	0.30	8.70	10.92	2024-05-30 01:58:36	Good
	1	Armenia	AM	Yerevan	1	175.24	0.00	6.86	5.00	38.62	0.60	6.12	15.66	2024-05-30 01:59:07	Good
	2	Austria	AT	Vienna	1	216.96	0.00	7.28	3.01	28.61	0.66	5.24	6.72	2024-05-30 01:58:36	Good
	3	Australia	AU	Brisbane	2	247.00	1.72	6.94	0.58	62.94	5.54	2.28	3.93	2024-05-30 01:58:29	Fair
	4	Australia	AU	Canberra	1	223.64	0.09	0.39	0.13	47.92	0.23	3.46	3.73	2024-05-30 01:58:32	Good
11	13	Uganda	UG	Kampala	5	1628.88	0.09	7.45	6.59	2.48	2.27	98.01	132.54	2024-05-30 01:57:42	Very Poor
11		States of erica (the)	US	Capetown	2	196.93	0.05	0.34	0.00	87.98	0.45	0.79	2.25	2024-05-30 01:57:34	Fair
11	15 Uz	zbekistan	UZ	Tashkent	1	367.17	23.69	35.30	3.77	11.36	2.92	9.00	14.01	2024-05-30 01:58:28	Good
11	16	Viet Nam	VN	Hanoi	3	827.79	1.30	25.71	9.12	9.66	13.95	34.47	47.49	2024-05-30 01:50:24	Moderate
11	17	Zambia	ZM	Lusaka	2	1415.25	0.00	6.34	11.65	37.19	6.14	11.48	19.94	2024-05-30 01:57:44	Fair

118 rows × 14 columns

Joining Datasets

]:		Index1	City1	Country1	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	 Concentration CO	Concentration NO	Concentration NO2	Concentration NH3	Concentration O3	Concentration SO2	Concentratic PM2
	0	0	Abidjan	Ivory Coast	1	1996	Africa	1	79.6	1996-01-01	80.513774	 327.11	0.00	0.83	1.03	22.89	0.43	6.7
	1	1	Abidjan	Ivory Coast	1	1996	Africa	2	81.2	1996-01-02	80.513774	 327.11	0.00	0.83	1.03	22.89	0.43	6.7
	2	2	Abidjan	Ivory Coast	1	1996	Africa	3	82.2	1996-01-03	80.513774	 327.11	0.00	0.83	1.03	22.89	0.43	6.7
	3	3	Abidjan	Ivory Coast	1	1996	Africa	4	83.0	1996-01-04	80.513774	 327.11	0.00	0.83	1.03	22.89	0.43	6.7
	4	4	Abidjan	Ivory Coast	1	1996	Africa	5	82.1	1996-01-05	80.513774	 327.11	0.00	0.83	1.03	22.89	0.43	6.7
9	52982	952982	Zurich	Switzerland	12	2019	Europe	27	40.8	2019-12-27	51.086908	 198.60	0.02	6.43	1.65	21.64	0.80	2.1
9	52983	952983	Zurich	Switzerland	12	2019	Europe	28	35.5	2019-12-28	51.086908	 198.60	0.02	6.43	1.65	21.64	0.80	2.8
9	52984	952984	Zurich	Switzerland	12	2019	Europe	29	30.4	2019-12-29	51.086908	 198.60	0.02	6.43	1.65	21.64	0.80	2.8
9	52985	952985	Zurich	Switzerland	12	2019	Europe	30	29.9	2019-12-30	51.086908	 198.60	0.02	6.43	1.65	21.64	0.80	2.8
9	52986	952986	Zurich	Switzerland	12	2019	Europe	31	31.4	2019-12-31	51.086908	 198.60	0.02	6.43	1.65	21.64	0.80	2.1

952987 rows × 26 columns

1

In [39]: # Delete repeated columns
temp_pollution_frame = temp_pollution_frame.drop(['Index1', 'Index2', 'City2', 'Country2'], axis=1)
temp_pollution_frame

Out[39]:

]:		City1	Country1	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Concentration CO	Concentration NO	Concentration NO2	Concentration NH3	Concentration O3	Concentration C SO2
	0	Abidjan	Ivory Coast	1	1996	Africa	1	79.6	1996-01-01	80.513774	80.754839	 327.11	0.00	0.83	1.03	22.89	0.43
	1	Abidjan	Ivory Coast	1	1996	Africa	2	81.2	1996-01-02	80.513774	80.754839	 327.11	0.00	0.83	1.03	22.89	0.43
	2	Abidjan	Ivory Coast	1	1996	Africa	3	82.2	1996-01-03	80.513774	80.754839	 327.11	0.00	0.83	1.03	22.89	0.43
	3	Abidjan	Ivory Coast	1	1996	Africa	4	83.0	1996-01-04	80.513774	80.754839	 327.11	0.00	0.83	1.03	22.89	0.43
	4	Abidjan	Ivory Coast	1	1996	Africa	5	82.1	1996-01-05	80.513774	80.754839	 327.11	0.00	0.83	1.03	22.89	0.43
										***		 ***	***				
9	52982	Zurich	Switzerland	12	2019	Europe	27	40.8	2019-12-27	51.086908	38.848387	 198.60	0.02	6.43	1.65	21.64	0.80
9	52983	Zurich	Switzerland	12	2019	Europe	28	35.5	2019-12-28	51.086908	38.848387	 198.60	0.02	6.43	1.65	21.64	0.80
9	952984	Zurich	Switzerland	12	2019	Europe	29	30.4	2019-12-29	51.086908	38.848387	 198.60	0.02	6.43	1.65	21.64	0.80
9	52985	Zurich	Switzerland	12	2019	Europe	30	29.9	2019-12-30	51.086908	38.848387	 198.60	0.02	6.43	1.65	21.64	0.80
9	952986	Zurich	Switzerland	12	2019	Europe	31	31.4	2019-12-31	51.086908	38.848387	 198.60	0.02	6.43	1.65	21.64	0.80

952987 rows × 22 columns

1

In [45]: # Checking number of NA's
temp_pollutation_frame.isna().sum()

```
Country1
                              Month
                              Year
Region
                             Dav
                             AvgDailyTemp
DateOfObservation
                             AvgYearlyTemp
AvgMonthlyTemp
Country Code
Quality Rating
                                                                                         11166
                             Concentration CO
Concentration NO
Concentration NO2
Concentration NH3
                                                                                         11166
                                                                                         11166
                              Concentration 03
                                                                                         11166
                              Concentration SO2
                                                                                         11166
                             Concentration PM2.5
Concentration PM10
DateTime
Qualitative Name
                                                                                         11166
                             dtype: int64
    In [40]: # Load new dataasaet into database
                            with sqlite3.connect("milestonedata.db") as conn:
temp_pollution_frame.to_sql('temp_pollution_data', conn, index=True)
conn.commit()
     In [41]: # Checking that dataframe was added to database table correctly
                            # Prints city and one column from each of the original dataframes to make sure join actually happened with sqlite3.connect("milestonedata.db") as conn:
                                      cursor = Conn.cursor()
for row in cursor.execute("SELECT City1, AvgDailyTemp, 'Concentration CO' FROM temp_pollution_data"):
    print(row)
    break
                            cursor.close()
                          ('Abidjan', 79.6, 'Concentration CO')
    In [43]: # Testing join before creating dataframe
                            # Join temp_polltuton_data with developmentdata on country by Left join
with sqlitest_connect("milestonedata.db") as conn:
    cursor = conn.cursor()
    cursor.execute("PRAGMA foreign_keys = 1")
    sql = ""SELECT * FROM temp_pollution_data LEFT JOIN developmentdata ON temp_pollution_data.Country1 * developmentdata.Country""
    rows = cursor.execute(sql)
    for row in rows:
                                        for row in rows:
                                             print(row)
                            cursor.close()
                         (0, 'Abidjan', 'Ivory Coast', 1, 1996, 'Africa', 1, 79.6, '1996-01-01', 80.5137741046832, 80.75483870967743, 'CI', 2.0, 327.11, 0.0, 0.83, 1.03, 22.89, 0.43, 6.29, 25.43, '2024-05-30 01:57:20', 'Fair', None, No
with sqlite3.connect("milestonedata.db") as conn:
                                       squises.commect( milestomedata.up ) as comm:
cursor = conn.cursor()
cursor.execute("PRAGMA foreign_keys = 1")
full temp_oplution_data to developmentdata (keeps all entries from temp_pollution_data)
sql = """SELECT * FROM temp_pollution_data LEFT JOIN developmentdata ON temp_pollution_data.Country1 = developmentdata.Country"""
                                        rows = cursor.execute(sql)
                                        for row in rows:
                            data2.append(row) # Appends each row to data List
cursor.close()
                             # Create dataframe from columns and rows
final_dataset = pd.DataFrame(data2,columns=columns2)
                             final_dataset
                                                                                                                                                                                                                                                                                                                                                                                                                         Marine
```

	Index1	City1	Country1	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	 Country2	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	areas (%	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatened Higher Plants	Threat Mam
0	0	Abidjan	Ivory Coast	1	1996	Africa	1	79.6	1996-01-01	80.513774	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	1	Abidjan	Ivory Coast	1	1996	Africa	2	81.2	1996-01-02	80.513774	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	2	Abidjan	Ivory Coast	1	1996	Africa	3	82.2	1996-01-03	80.513774	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	3	Abidjan	Ivory Coast	1	1996	Africa	4	83.0	1996-01-04	80.513774	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	4	Abidjan	Ivory Coast	1	1996	Africa	5	82.1	1996-01-05	80.513774	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952982	952982	Zurich	Switzerland	12	2019	Europe	27	40.8	2019-12-27	51.086908	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952983	952983	Zurich	Switzerland	12	2019	Europe	28	35.5	2019-12-28	51.086908	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952984	952984	Zurich	Switzerland	12	2019	Europe	29	30.4	2019-12-29	51.086908	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952985	952985	Zurich	Switzerland	12	2019	Europe	30	29.9	2019-12-30	51.086908	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952986	952986	Zurich	Switzerland	12	2019	Europe	31	31.4	2019-12-31	51.086908	 None	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
952987 r	nws x 33	columns																	

952987 rows × 33 columns

1

Out[45]: City1

Data Transformation / Cleaning

```
In [163_ # Drop repetative columns
final_dataset = final_dataset.drop(['Index1', 'Country2'],axis=1)

In [164_ # Rename columns
final_dataset.rename(columns={'City1':'City', 'Country1':'Country'}, inplace=True)
final_dataset
```

	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Qualitative Name	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	areas (%	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threate Hig Pla
0	Abidjan	Ivory Coast	1	1996	Africa	1	79.6	1996-01-01	80.513774	80.754839	 Fair	NaN	NaN	NaN	NaN	NaN	NaN	1
1	Abidjan	Ivory Coast	1	1996	Africa	2	81.2	1996-01-02	80.513774	80.754839	 Fair	NaN	NaN	NaN	NaN	NaN	NaN	1
2	Abidjan	Ivory Coast	1	1996	Africa	3	82.2	1996-01-03	80.513774	80.754839	 Fair	NaN	NaN	NaN	NaN	NaN	NaN	1
3	Abidjan	Ivory Coast	1	1996	Africa	4	83.0	1996-01-04	80.513774	80.754839	 Fair	NaN	NaN	NaN	NaN	NaN	NaN	1
4	Abidjan	Ivory Coast	1	1996	Africa	5	82.1	1996-01-05	80.513774	80.754839	 Fair	NaN	NaN	NaN	NaN	NaN	NaN	1
952982	Zurich	Switzerland	12	2019	Europe	27	40.8	2019-12-27	51.086908	38.848387	 Good	NaN	NaN	NaN	NaN	NaN	NaN	1
952983	Zurich	Switzerland	12	2019	Europe	28	35.5	2019-12-28	51.086908	38.848387	 Good	NaN	NaN	NaN	NaN	NaN	NaN	1
952984	Zurich	Switzerland	12	2019	Europe	29	30.4	2019-12-29	51.086908	38.848387	 Good	NaN	NaN	NaN	NaN	NaN	NaN	1
952985	Zurich	Switzerland	12	2019	Europe	30	29.9	2019-12-30	51.086908	38.848387	 Good	NaN	NaN	NaN	NaN	NaN	NaN	1
952986	Zurich	Switzerland	12	2019	Europe	31	31.4	2019-12-31	51.086908	38.848387	 Good	NaN	NaN	NaN	NaN	NaN	NaN	1

Marine

Marine

952987 rows × 31 columns

4

In [165... # Checking number of Na values
final_dataset.isna().sum()

Out[165... City Country Month Month
Year
Region
Day
AvgBailyTemp
DateOfObservation
AvgYearlyTemp
AvgWonthlyTemp
Concentration NO
Concentration NO
Concentration NO
Concentration NO
Concentration NO
Concentration NB3
Concentration NB3
Concentration NB3
Concentration PM10
DateTime
Qualitative Name
Porest Area (sq.km thousands) 1990
Forest Area (sq.km thousands) 2021
Marine protected areas (% of total territorial waters) 2022
Terresterial protected areas (% of total transparence of the second pm10
Threatened Birds
Threatened Higher Plants
Threatened Higher Plants
Threatened Mammals
Change in Forest Area 1990 to 2021
dtype: int64
Due to my joins not being perfect, there are a lot of rows that do not ha Year 11166 11166 11166 11166 11166 11166 11166 11166 11166 11166 11166 11166 279725 279725 279725 279725 279725 279725 279725 279725 279725 279725

Due to my joins not being perfect, there are a lot of rows that do not have data. I have a large dataset right now, so for the sake of this project, I am going to drop any rows that contain Na values. In the real world, I would likely try to make my joins work a little better but I think this works for what I need to do now.

In [166... # Drop all rows that contain NA values
final_dataset = final_dataset.dropna()
final_dataset

Out[166...

	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Qualitative Name	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	protected areas (% of total territorial waters) 2022	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatenec Higher Plants
15421	Algiers	Algeria	1	1996	Africa	1	67.4	1996-01-01	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15422	Algiers	Algeria	1	1996	Africa	2	60.0	1996-01-02	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15423	Algiers	Algeria	1	1996	Africa	3	54.4	1996-01-03	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15424	Algiers	Algeria	1	1996	Africa	4	57.7	1996-01-04	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15425	Algiers	Algeria	1	1996	Africa	5	57.6	1996-01-05	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
											 							-
944116	Zagreb	Croatia	12	2019	Europe	27	38.9	2019-12-27	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	3.8
944117	Zagreb	Croatia	12	2019	Europe	28	37.8	2019-12-28	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944118	Zagreb	Croatia	12	2019	Europe	29	35.0	2019-12-29	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	3.8
944119	Zagreb	Croatia	12	2019	Europe	30	30.3	2019-12-30	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944120	Zagreb	Croatia	12	2019	Europe	31	30.2	2019-12-31	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	3.8

664979 rows × 31 columns

4

In [167_ # Checking unique cities
unique_cities = final_dataset['City'].unique()
unique_cities

```
Out[167_ array(['Algiers', 'Almaty', 'Amman', 'Antananarivo', 'Ashabad', 'Athens', 'Burkland', 'Bangkok', 'Barcelona', 'Beljing', 'Beirut', 'Belfast', 'Bilbao', 'Bissau', 'Bombay (Mumbai)', 'Bonn', 'Bordeaux', 'Brisbane', 'Buchaset', 'Calcuta', 'Canbera', 'Capetown', 'Chengdu', 'Chennai (Madras)', 'Colombo', 'Conakry', 'Copenhagen', 'Cotonou', 'Dakah', 'Oar Es Salaam', 'Delhi', 'Dhaka', 'Dublin', 'Frankfurt', 'Freetown', 'Guargehou', 'Hamburg', 'Hanoi', 'Helsinki', 'Islamabad', 'Jakarta', 'Karachi', 'Kiev', 'Kuala Lumpur', 'Kuwait', 'Lagos', 'Libreville', 'Lisbon', 'Lome', 'London', 'Madrid', 'Manama', 'Manila', 'Maputo', 'Melbourne', 'Milan', 'Munich', 'Nairobi', 'Naimey', 'Nicosia', 'Nouakchott', 'Osaka', 'Oslo', 'Paris', 'Perth', 'Rabat', 'Reykjavk', 'Riga', 'Rome', 'Sapporo', 'Shanghai', 'Shenyang', 'Singapore', 'Sofia', 'Stockholm', 'Sydney', 'Tbilisi', 'Tel Aviv', 'Tirana', 'Tokyo', 'Tunis', 'Marsaw', 'Zagreb'], dtype=object)
```

The most granular dataset I have works with dialy values. However, I have calculated averages by month and year. I will drop all data that is not Day 28 from the dataset. I chose day 28 because the shortest month on a non-leap year has 28 days. My average monthly temperature will then be calculated from the largest number of days possible in the shortest month. By doing this, I will capture all averyage monthly and yearly temperatures and significantly slim down my dataset.

Marine

```
in [168... # Subsetting data to contain only rows where Day is equal to 28 final_dataset = final_dataset[final_dataset.Day==28] final_dataset
```

944024 Zagreb Croatia 12 2016 Europe 28

944086 Zagreb Croatia 12 2018 Europe 28

12 2017 Europe 28

12 2019 Europe 28

	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Qualitative Name	Forest Area (sq.km thousands) 1990	Area (sq.km	areas (%	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatenec Higher Plants
15448	Algiers	Algeria	1	1996	Africa	28	62.8	1996-01-28	63.530220	57.370968	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15479	Algiers	Algeria	1	1997	Africa	28	50.1	1997-01-28	64.926301	55.719355	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15510	Algiers	Algeria	1	1998	Africa	28	58.4	1998-01-28	63.619668	53.590323	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15540	Algiers	Algeria	1	1999	Africa	28	55.7	1999-01-28	64.923626	52.280000	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
15571	Algiers	Algeria	1	2000	Africa	28	54.0	2000-01-28	64.182787	47.235484	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
							***				 	***					***	
943994	Zagreh	Croatia	12	2015	Furone	28	30.6	2015-12-28	55 704945	38 223333	Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0

54.832133

55.572055

56.492758

56.557103

31.748387 ...

39.277419 ...

37.122581 ...

40.554839 ...

Good

Good

Good

Good

19.0

19.0

19.0

19.0

19.0

19.0

19.0

9.0

9.0

9.0

9.0

38.5

38.5

38.5

38.5

14.0

14.0

14.0

14.0

64.0

64.0

64.0

64.0

8.0

3.8

8.0

3.8

944117 Zagreb Croatia 21822 rows × 31 columns

944055 Zagreb Croatia

4

Visualizations

In [67]: # Import matplotlib package
import matplotlib.pyplot as plt

Visualization 1- Histogram of Qualitative Name for all cities combined

35.7

43.6

37.8

32.6

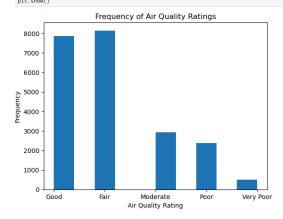
2016-12-28

2017-12-28

2018-12-28

2019-12-28

```
plt.hist(final_dataset['Qualitative Name'])
plt.xlabel('Air Quality Rating')
plt.ylabel('Frequency')
plt.title('Frequency of Air Quality Ratings')
plt.show()
```



Visualization 2- Line graph of average yearly temperature of Madrid

In [170... # Create a subset of the data that only shows month 12
subset1 = final_dataset[final_dataset.Month==12]
subset1

	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Qualitative Name	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	protected areas (% of total territorial waters) 2022	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatenec Higher Plants
23577	Algiers	Algeria	12	1996	Africa	28	43.9	1996-12-28	63.530220	55.787097	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
23608	Algiers	Algeria	12	1997	Africa	28	50.7	1997-12-28	64.926301	54.964516	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
23637	Algiers	Algeria	12	1998	Africa	28	54.6	1998-12-28	63.619668	51.348148	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
23666	Algiers	Algeria	12	1999	Africa	28	58.9	1999-12-28	64.923626	53.003226	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
23697	Algiers	Algeria	12	2000	Africa	28	57.9	2000-12-28	64.182787	55.519355	 Good	17.0	20.0	0.1	4.6	15.0	41.0	22.0
943994	Zagreb	Croatia	12	2015	Europe	28	30.6	2015-12-28	55.704945	38.223333	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944024	Zagreb	Croatia	12	2016	Europe	28	35.7	2016-12-28	54.832133	31.748387	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944055	Zagreb	Croatia	12	2017	Europe	28	43.6	2017-12-28	55.572055	39.277419	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944086	Zagreb	Croatia	12	2018	Europe	28	32.6	2018-12-28	56.492758	37.122581	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0
944117	Zagreb	Croatia	12	2019	Europe	28	37.8	2019-12-28	56.557103	40.554839	 Good	19.0	19.0	9.0	38.5	14.0	64.0	8.0

Marine

1772 rows × 31 columns

4

In [171_ # Creates a subset that contains only rows with Madrid for the city column
madrid_subset = subset1[subset1.City=='Madrid']
madrid_subset

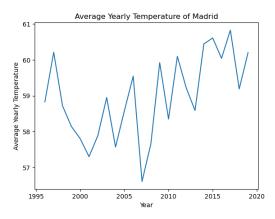
Out[171...

	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	 Qualitative Name	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	Marine protected areas (% of total territorial waters) 2022	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threatened Highe Plant
560850	Madrid	Spain	12	1996	Europe	28	33.0	1996-12-28	58.828962	45.948387	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
560881	Madrid	Spain	12	1997	Europe	28	39.8	1997-12-28	60.210959	44.241935	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
560910	Madrid	Spain	12	1998	Europe	28	33.1	1998-12-28	58.719668	38.944444	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.
560939	Madrid	Spain	12	1999	Europe	28	46.9	1999-12-28	58.146429	42.274194	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
560970	Madrid	Spain	12	2000	Europe	28	42.6	2000-12-28	57.804372	44.016129	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561001	Madrid	Spain	12	2001	Europe	28	30.8	2001-12-28	57.303562	35.096774	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561032	Madrid	Spain	12	2002	Europe	28	47.2	2002-12-28	57.889197	45.977419	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561063	Madrid	Spain	12	2003	Europe	28	44.5	2003-12-28	58.951781	42.051613	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561094	Madrid	Spain	12	2004	Europe	28	34.6	2004-12-28	57.572678	42.829032	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561125	Madrid	Spain	12	2005	Europe	28	38.8	2005-12-28	58.578630	40.870968	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561156	Madrid	Spain	12	2006	Europe	28	36.6	2006-12-28	59.545753	41.241935	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561187	Madrid	Spain	12	2007	Europe	28	37.2	2007-12-28	56.614011	39.845161	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561218	Madrid	Spain	12	2008	Europe	28	42.0	2008-12-28	57.658516	41.900000	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561249	Madrid	Spain	12	2009	Europe	28	45.5	2009-12-28	59.922253	43.700000	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561280	Madrid	Spain	12	2010	Europe	28	37.8	2010-12-28	58.352603	42.851613	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561311	Madrid	Spain	12	2011	Europe	28	37.9	2011-12-28	60.097260	41.974194	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561342	Madrid	Spain	12	2012	Europe	28	38.9	2012-12-28	59.221038	42.619355	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561373	Madrid	Spain	12	2013	Europe	28	47.7	2013-12-28	58.589863	40.512903	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561404	Madrid	Spain	12	2014	Europe	28	46.7	2014-12-28	60.443681	42.180645	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561435	Madrid	Spain	12	2015	Europe	28	46.2	2015-12-28	60.608242	45.173333	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561465	Madrid	Spain	12	2016	Europe	28	42.7	2016-12-28	60.042541	44.203226	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561496	Madrid	Spain	12	2017	Europe	28	52.0	2017-12-28	60.827123	42.474194	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561527	Madrid	Spain	12	2018	Europe	28	40.8	2018-12-28	59.189503	42.735484	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0
561558	Madrid	Spain	12	2019	Europe	28	39.7	2019-12-28	60.198889	46.080645	 Fair	139.0	186.0	12.8	28.1	19.0	83.0	247.0

24 rows × 31 columns



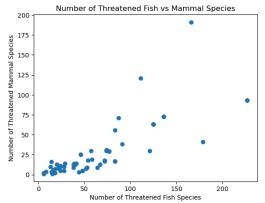
In [172_ # Plot AvgYearlyTemp by Year for each Madrid plt.plot(madrid_subset['Year'], madrid_subset['AvgYearlyTemp']) plt.xlabel('Year') plt.ylabel('Average Yearly Temperature') plt.title('Average Yearly Temperature of Madrid') plt.show()



Visualization 3- Scatter plot of Threatened Fish Species vs Threatened Mammal Species in 2020 for each City

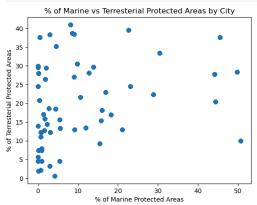
```
In [249_ # Subset of dataframe that contains rows where Month equis 1
species_subset = final_dataset[final_dataset.Month=1]
# Subset of previous subsets where Year equals 2820
species_subset2 = species_subset[species_subset.Year==2020]

In [250_ # Plot scatter plot of Threatened Fishes vs Threatened mammals in 2020 for each city
plt.scatter(species_subset2['Threatened Fishes'], species_subset2['Threatened Mammals'])
plt.valabel('Number of Threatened Fishes'), species')
plt.yalabel('Number of Threatened Mammal Species')
plt.title('Number of Threatened Fish vs Mammal Species')
plt.show()
```



Visualization 4- Scatter plot of Marine Protected Areas and Terresterial Protected Areas

```
In [252... # Plots scatter plot of Marine Protected areas vs Terresterial protested areas of all cities plt.scatter(final_dataset['Marine protected areas (% of total territorial waters) 2022'], final_dataset['Terresterial protected areas (% of total land area) 2022']) plt.ylabel('% of Marine Protected Areas') plt.ylabel('% of Marine vs Terresterial Protected Areas by City') plt.show()
```



Visualization 5- Bar Graph of Concentration CO for each City in 2020

```
In [251. # Subset1 is a subset of the final_dataset that only contains rows where Month equals 12
# Subset2 is a subset of subset1 that contains only rows where Year equals 2000
subset3 = subset1[subset1.Year==2000]

# Subset3 is a subset of subset2 that contains only rows where Qualitative Name is Poor
subset3 = subset2[subset2['Qualitative Name'] == 'Poor']
subset3
```

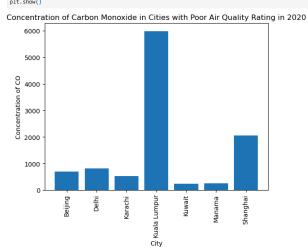
	City	Country	Month	Year	Region	Day	AvgDailyTemp	DateOfObservation	AvgYearlyTemp	AvgMonthlyTemp	•••	Qualitative Name	Forest Area (sq.km thousands) 1990	Forest Area (sq.km thousands) 2021	protected areas (% of total territorial waters) 2022	Terresterial protected areas (% of total land area) 2022	Threatened Birds	Threatened Fishes	Threaten High Plai
121861	Beijing	China	12	2000	Asia	28	23.6	2000-12-28	54.774317	29.970968		Poor	1571.0	2219.0	5.5	15.6	96.0	136.0	59
363836	Delhi	India	12	2000	Asia	28	55.7	2000-12-28	76.595355	58.429032		Poor	639.0	724.0	0.2	7.5	93.0	227.0	39
468479	Karachi	Pakistan	12	2000	Asia	28	72.2	2000-12-28	82.247557	70.361290		Poor	50.0	37.0	0.8	12.3	33.0	46.0	1
494146	Kuala Lumpur	Malaysia	12	2000	Asia	28	81.0	2000-12-28	81.777072	81.132258		Poor	206.0	191.0	5.6	13.3	63.0	87.0	72
502993	Kuwait	Kuwait	12	2000	Middle East	28	53.2	2000-12-28	80.282240	59.251613		Poor	0.0	0.0	1.4	17.1	11.0	18.0	
569841	Manama	Bahrain	12	2000	Middle East	28	62.0	2000-12-28	80.606011	67.248387		Poor	0.0	0.0	21.1	13.0	7.0	14.0	
784784	Shanghai	China	12	2000	Asia	28	47.8	2000-12-28	63.381096	47.893548		Poor	1571.0	2219.0	5.5	15.6	96.0	136.0	59

Marine

7 rows × 31 columns

•

Plots bar graph of Concentration of CO by City
plt.bar(subset3['City'], subset3['Concentration CO'])
plt.xlabel('City')
plt.ylabel('Concentration of CO')
plt.title('Concentration of CO')
plt.title('Concentration of Carbon Monoxide in Cities with Poor Air Quality Rating in 2020')
plt.xticks(rotation=90) # Rotate x-labels to be verticle
plt.show()



Ethical Implications

As in my previous steps, I avoided making any major changes to my dataset. I did choose to reduce the granularity of my final dataset because one dataset was much more granular than my others and went into more detail than was necessary. I did utilize a lot of subsetting and filtering for my visualizations. It's possible that in doing so, I lost some critical pieces of information. If I were drawing conclusions from this data, I would need to be more careful with my filtering. It would also be helpful to plot multiple variations of some of my plots. For example, my final plot is a bar graph of Concentration of CO in cities that had a poor air quality rating in 2020. It would likely be useful to also plot concentration of CO in cities that had other ratings of air quality (very poor, moderate, fair, and good). This would allow more accurate comparison to see if there is a relationship between air quality rating and concentration of CO. I also chose to drill down on a few cities rather than visualizing all of my cities. If I were to draw conclusions from these visualizations, I would need to be careful to note which cities the visualization represent because others could make incorrect assumptions about the data without that information.

Through this semester long project I've seen how difficult working with different data sources can be. During each step, I had to continually remind myself how I planned to join my datasets in the final step to help guide my transformations. I had a lot of difficulty with the HTML milestone, but I feel much more comfortable with web scraping now. I also now realize the importance of using a well documented API. Thankfully, I chose an API that has great documentation but I saw the struggles of my classmates who were not as fortunate. This class has been a great way to build on my foundational Python skills while building new skills such as SQL.