ml-project

June 25, 2024

0.1 ML Capstone Project on Air Pollution Datatracker

0.1.1 Introduction

The provided dataset on Kaggle offers comprehensive insights into air quality analysis in the U

0.1.2 Business Problem:

Comprehensive Analysis and Mitigation Strategy Development for Air Pollution in the United

0.1.3 Title:

Comprehensive Analysis and Mitigation Strategy Development for Air Pollution in the United Sta

0.1.4 Data Dictionary

Date: Date of data collection.
Address: Specific location of data collection.
State: U.S. state where data was collected.
County: County within the state of data collection.
City: City where data was collected.
O3 Mean: Average Ozone level for the day.
O3 1st Max Value: Highest Ozone level for the day.
O3 1st Max Hour: Hour of highest Ozone level.
O3 AQI: Air Quality Index for Ozone.
CO Mean: Average Carbon Monoxide level for the day.
CO 1st Max Value: Highest Carbon Monoxide level for the day.
CO 1st Max Hour: Hour of highest Carbon Monoxide level.
CO AQI: Air Quality Index for Carbon Monoxide.
SO2 Mean: Average Sulphur Dioxide level for the day.
SO2 1st Max Value: Highest Sulphur Dioxide level for the day.
SO2 1st Max Hour: Hour of highest Sulphur Dioxide level.
SO2 AQI: Air Quality Index for Sulphur Dioxide.
NO2 Mean: Average Nitrogen Dioxide level for the day.
NO2 1st Max Value: Highest Nitrogen Dioxide level for the day.
NO2 1st Max Hour: Hour of highest Nitrogen Dioxide level.

1 Necessary Imports

[1]:
```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2 Data ingestion

[5]:
```
# Load the dataset
df = pd.read_csv('../Data/pollution_2000_2023.csv')

# Display the first few rows of the dataset
df.head()
```

[5]:
```
   Unnamed: 0        Date                                    Address    State  \
0           0  2000-01-01  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona
1           1  2000-01-02  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona
2           2  2000-01-03  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona
3           3  2000-01-04  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona
4           4  2000-01-05  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona

     County     City   O3 Mean  O3 1st Max Value  O3 1st Max Hour  O3 AQI  \
0  Maricopa  Phoenix  0.019765             0.040               10      37
1  Maricopa  Phoenix  0.015882             0.032               10      30
2  Maricopa  Phoenix  0.009353             0.016                9      15
3  Maricopa  Phoenix  0.015882             0.033                9      31
4  Maricopa  Phoenix  0.007353             0.012                9      11

   …  CO 1st Max Hour  CO AQI  SO2 Mean  SO2 1st Max Value  \
0  …               23    25.0  3.000000                9.0
1  …                0    26.0  1.958333                3.0
2  …                8    28.0  5.250000               11.0
3  …               23    34.0  7.083333               16.0
4  …                2    42.0  8.708333               15.0

   SO2 1st Max Hour  SO2 AQI   NO2 Mean  NO2 1st Max Value  NO2 1st Max Hour  \
0                21     13.0  19.041667               49.0                19
1                22      4.0  22.958333               36.0                19
2                19     16.0  38.125000               51.0                 8
3                 8     23.0  40.260870               74.0                 8
4                 7     21.0  48.450000               61.0                22

   NO2 AQI
0       46
```

```
1        34
2        48
3        72
4        58

[5 rows x 22 columns]
```

2.0.1 Data Understanding

[9]:
```
df.shape
```

[9]:
```
(665414, 22)
```

[11]:
```
# here we check data types null values an all
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 665414 entries, 0 to 665413
Data columns (total 22 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   Unnamed: 0         665414 non-null  int64
 1   Date               665414 non-null  object
 2   Address            665414 non-null  object
 3   State              665414 non-null  object
 4   County             665414 non-null  object
 5   City               665414 non-null  object
 6   O3 Mean            665414 non-null  float64
 7   O3 1st Max Value   665414 non-null  float64
 8   O3 1st Max Hour    665414 non-null  int64
 9   O3 AQI             665414 non-null  int64
 10  CO Mean            665414 non-null  float64
 11  CO 1st Max Value   665414 non-null  float64
 12  CO 1st Max Hour    665414 non-null  int64
 13  CO AQI             665414 non-null  float64
 14  SO2 Mean           665414 non-null  float64
 15  SO2 1st Max Value  665414 non-null  float64
 16  SO2 1st Max Hour   665414 non-null  int64
 17  SO2 AQI            665414 non-null  float64
 18  NO2 Mean           665414 non-null  float64
 19  NO2 1st Max Value  665414 non-null  float64
 20  NO2 1st Max Hour   665414 non-null  int64
 21  NO2 AQI            665414 non-null  int64
dtypes: float64(10), int64(7), object(5)
memory usage: 111.7+ MB
```

Drop unrelated columns

[12]:
```
df.drop(['Unnamed: 0'],axis=1,inplace=True)
df.head()
```

[12]:
```
         Date                               Address    State    County  \
0  2000-01-01  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona  Maricopa
1  2000-01-02  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona  Maricopa
2  2000-01-03  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona  Maricopa
3  2000-01-04  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona  Maricopa
4  2000-01-05  1645 E ROOSEVELT ST-CENTRAL PHOENIX STN  Arizona  Maricopa

      City   O3 Mean  O3 1st Max Value  O3 1st Max Hour  O3 AQI   CO Mean  \
0  Phoenix  0.019765             0.040               10      37  0.878947
1  Phoenix  0.015882             0.032               10      30  1.066667
2  Phoenix  0.009353             0.016                9      15  1.762500
3  Phoenix  0.015882             0.033                9      31  1.829167
4  Phoenix  0.007353             0.012                9      11  2.700000

   …  CO 1st Max Hour  CO AQI  SO2 Mean  SO2 1st Max Value  \
0  …               23    25.0  3.000000                9.0
1  …                0    26.0  1.958333                3.0
2  …                8    28.0  5.250000               11.0
3  …               23    34.0  7.083333               16.0
4  …                2    42.0  8.708333               15.0

   SO2 1st Max Hour  SO2 AQI   NO2 Mean  NO2 1st Max Value  NO2 1st Max Hour  \
0                21     13.0  19.041667               49.0                19
1                22      4.0  22.958333               36.0                19
2                19     16.0  38.125000               51.0                 8
3                 8     23.0  40.260870               74.0                 8
4                 7     21.0  48.450000               61.0                22

   NO2 AQI
0       46
1       34
2       48
3       72
4       58

[5 rows x 21 columns]
```

[16]:
```
df.dtypes
```

[16]:
```
Date                      object
Address                   object
State                     object
County                    object
City                      object
```

```
O3 Mean               float64
O3 1st Max Value      float64
O3 1st Max Hour         int64
O3 AQI                  int64
CO Mean               float64
CO 1st Max Value      float64
CO 1st Max Hour         int64
CO AQI                float64
SO2 Mean              float64
SO2 1st Max Value     float64
SO2 1st Max Hour        int64
SO2 AQI               float64
NO2 Mean              float64
NO2 1st Max Value     float64
NO2 1st Max Hour        int64
NO2 AQI                 int64
dtype: object
```

Change Datatypes of some columns

[17]:
```
col = ['CO AQI', 'SO2 AQI']
for i in col:
    df[i] = df[i].astype('int')
```

[18]:
```
df['CO AQI'].dtype
```

[18]:
```
dtype('int32')
```

[20]:
```
df['SO2 AQI'].dtype
```

[20]:
```
dtype('int32')
```

[21]:
```
df.describe()
```

[21]:
```
             O3 Mean  O3 1st Max Value  O3 1st Max Hour         O3 AQI  \
count  665414.000000     665414.000000    665414.000000  665414.000000
mean        0.028605          0.038980        10.766409      39.137872
std         0.012151          0.014912         3.297315      22.253413
min        -0.000706          0.000000         7.000000       0.000000
25%         0.019824          0.029000         9.000000      27.000000
50%         0.028353          0.038000        10.000000      35.000000
75%         0.036882          0.048000        11.000000      44.000000
max         0.107353          0.140000        23.000000     237.000000

             CO Mean  CO 1st Max Value  CO 1st Max Hour         CO AQI  \
count  665414.000000     665414.000000    665414.000000  665414.000000
mean        0.329459          0.465604         5.922553       5.247399
```

std	0.275725	0.434542	7.719537	5.010467
min	-0.437500	-0.400000	0.000000	0.000000
25%	0.175000	0.200000	0.000000	2.000000
50%	0.258333	0.300000	1.000000	3.000000
75%	0.408696	0.600000	9.000000	7.000000
max	7.508333	15.500000	23.000000	201.000000

	SO2 Mean	SO2 1st Max Value	SO2 1st Max Hour	SO2 AQI \
count	665414.000000	665414.000000	665414.000000	665414.000000
mean	1.428759	3.931057	8.867280	5.154743
std	2.410071	7.700799	6.776779	10.371465
min	-2.508333	-2.300000	0.000000	0.000000
25%	0.173913	0.600000	3.000000	0.000000
50%	0.604167	1.400000	8.000000	1.000000
75%	1.604545	4.000000	13.000000	6.000000
max	321.625000	351.000000	23.000000	200.000000

	NO2 Mean	NO2 1st Max Value	NO2 1st Max Hour	NO2 AQI
count	665414.000000	665414.000000	665414.000000	665414.000000
mean	11.510561	23.253519	11.588897	21.766209
std	8.957527	15.264335	7.888301	14.447780
min	-4.629167	-4.400000	0.000000	0.000000
25%	4.860870	11.000000	5.000000	10.000000
50%	9.304348	21.000000	9.000000	20.000000
75%	15.958333	33.000000	20.000000	31.000000
max	140.650000	371.700000	23.000000	153.000000

2.1 EDA

Here are 15 exploratory data analysis (EDA) questions tailored to my dataset on air quality

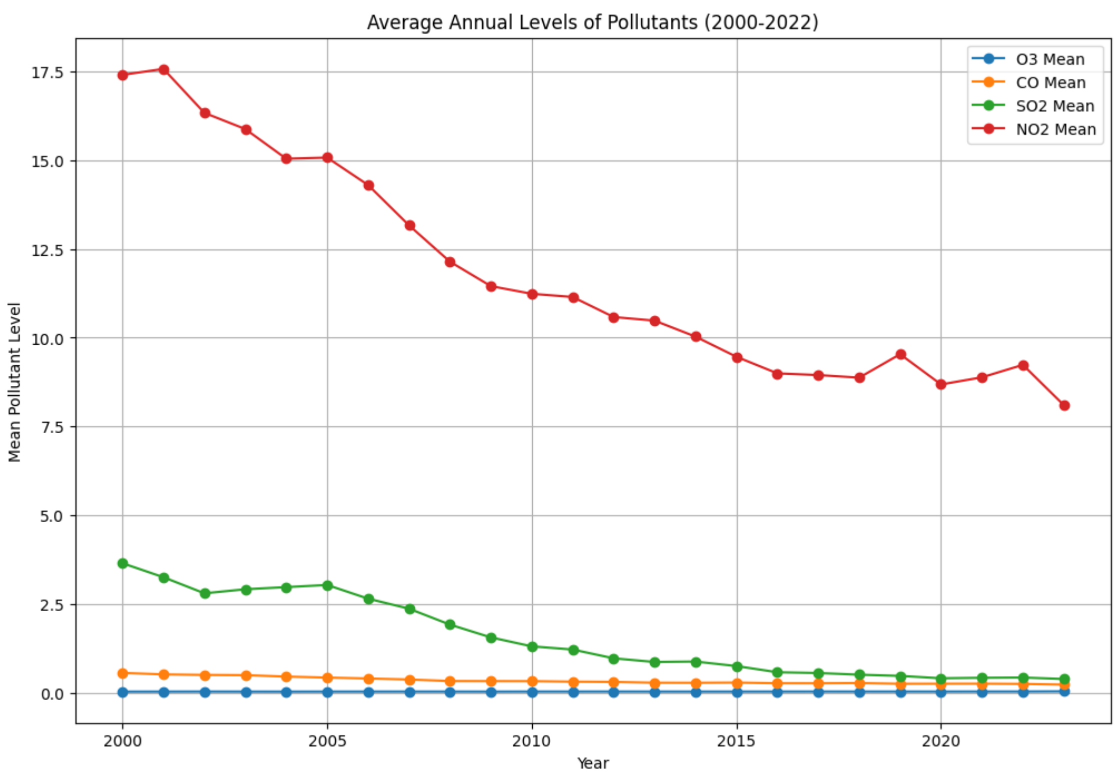
2.1.1 Temporal Analysis:

Problem 1: What are the trends in the average annual levels of O3, CO, SO2, and NO2 from 2000 to 2022?

[35]:
```python
# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Extract year from Date
df['Year'] = df['Date'].dt.year

# Convert relevant columns to numeric, coercing errors
numeric_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Check for non-numeric values that couldn't be converted
```

```
print(df[numeric_columns].dtypes)

# Drop rows with any NaN values in numeric columns (if necessary)
df_clean = df.dropna(subset=numeric_columns)

# Group by Year and calculate mean values for each pollutant
annual_means = df_clean.groupby('Year')[numeric_columns].mean()

# Plotting the trends
annual_means.plot(figsize=(12, 8), marker='o', title='Average Annual Levels of␣
↪Pollutants (2000-2022)')
plt.xlabel('Year')
plt.ylabel('Mean Pollutant Level')
plt.grid(True)
plt.show()
```

```
O3 Mean     float64
CO Mean     float64
SO2 Mean    float64
NO2 Mean    float64
dtype: object
```



2.1.2 Geographical Distribution:

Problem 2: States with the Highest Average Pollutant Levels

[38]:
```
# Group by State and calculate mean values for each pollutant
state_means = df.groupby('State').mean(numeric_only=True)[['O3 Mean', 'CO␣
↪Mean', 'SO2 Mean', 'NO2 Mean']]

# Sort the states by the highest average O3 levels and display the top 10
top_states_o3 = state_means.sort_values(by='O3 Mean', ascending=False).head(10)
top_states_o3
```

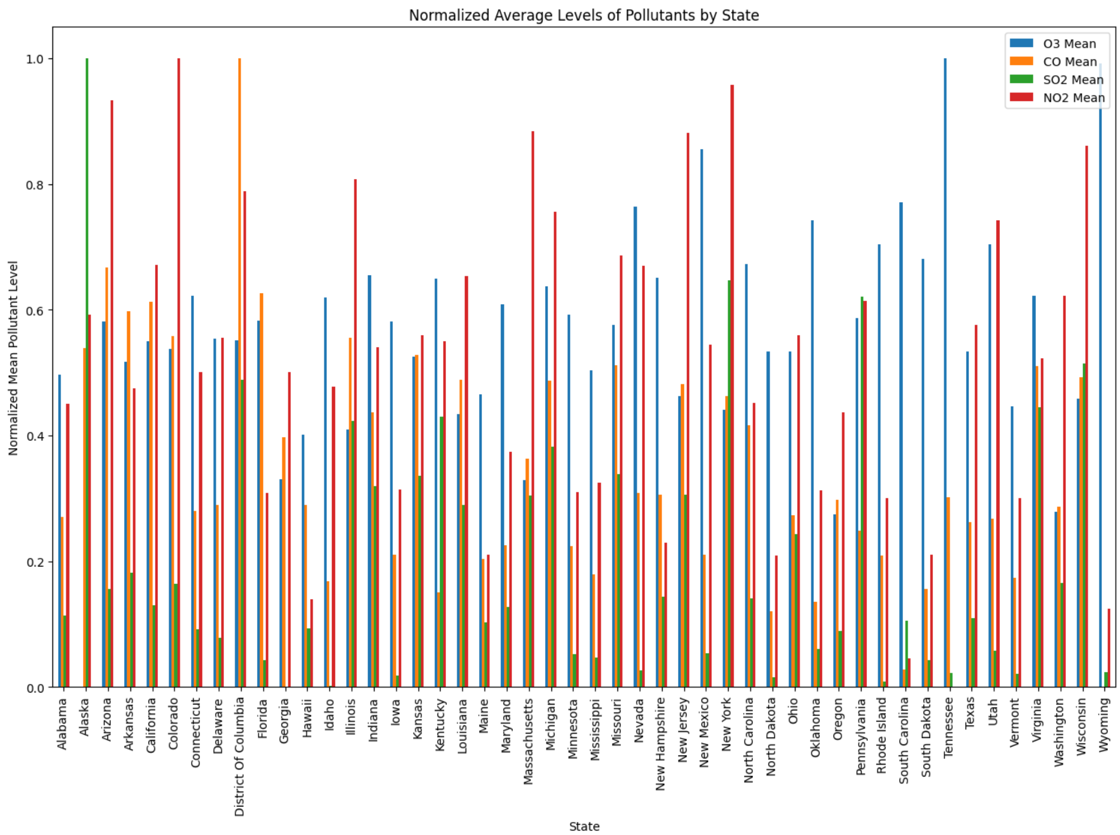
[38]:

	O3 Mean	CO Mean	SO2 Mean	NO2 Mean
State				
Tennessee	0.039083	0.258443	0.367047	1.254657
Wyoming	0.038877	0.110682	0.370953	3.351865
New Mexico	0.035650	0.214087	0.533809	10.438319
South Carolina	0.033644	0.124513	0.813247	2.016696
Nevada	0.033467	0.261808	0.389834	12.567614
Oklahoma	0.032963	0.176805	0.574495	6.533284
Utah	0.032040	0.242020	0.555488	13.773945
Rhode Island	0.032034	0.213029	0.294245	6.319832
South Dakota	0.031504	0.186906	0.474933	4.806641
North Carolina	0.031291	0.314893	1.003756	8.867809

2.1.3 Pollutant Comparison Across States

Problem 3: Let's compare the average levels of O3, CO, SO2, and NO2 across different states.

[41]:
```
# Normalize the data for better comparison
state_means_normalized = (state_means - state_means.min()) / (state_means.max()␣
↪- state_means.min())

# Plot the normalized values
state_means_normalized.plot(kind='bar', figsize=(16, 10), title='Normalized␣
↪Average Levels of Pollutants by State')
plt.xlabel('State')
plt.ylabel('Normalized Mean Pollutant Level')
plt.legend(loc='upper right')
plt.show()
```

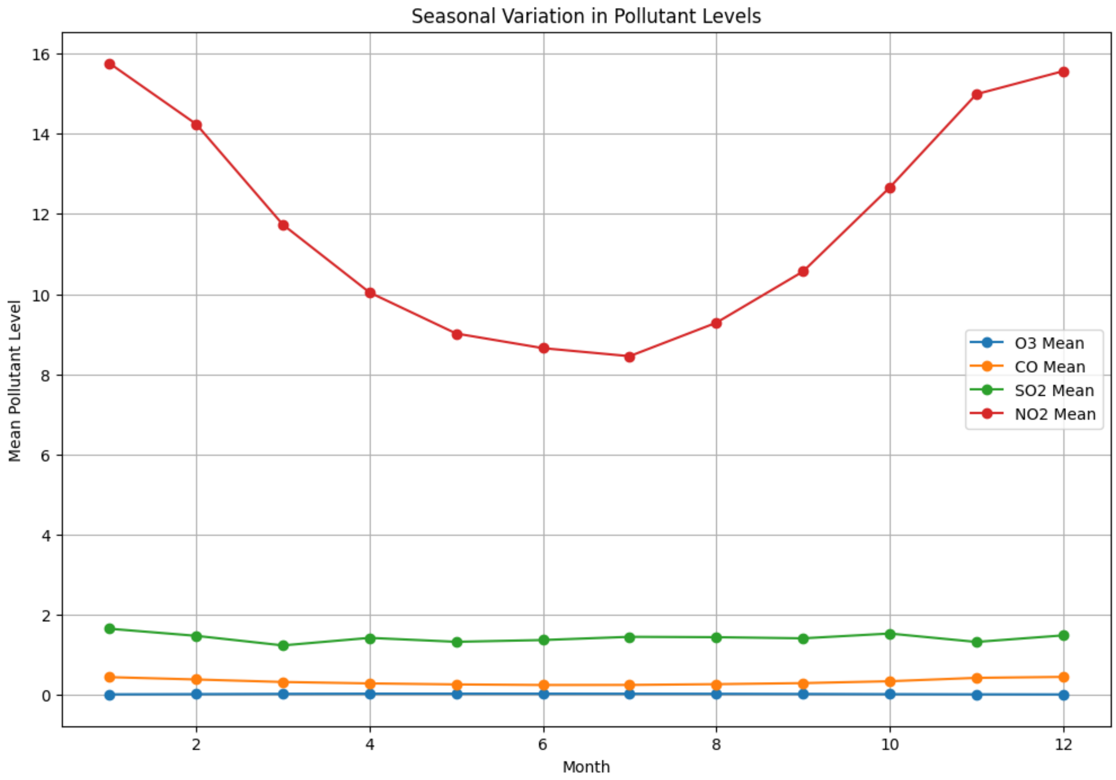


2.1.4 Seasonal Variation in Pollutant Levels

Problem 4 :To analyze how pollutant levels vary seasonally:

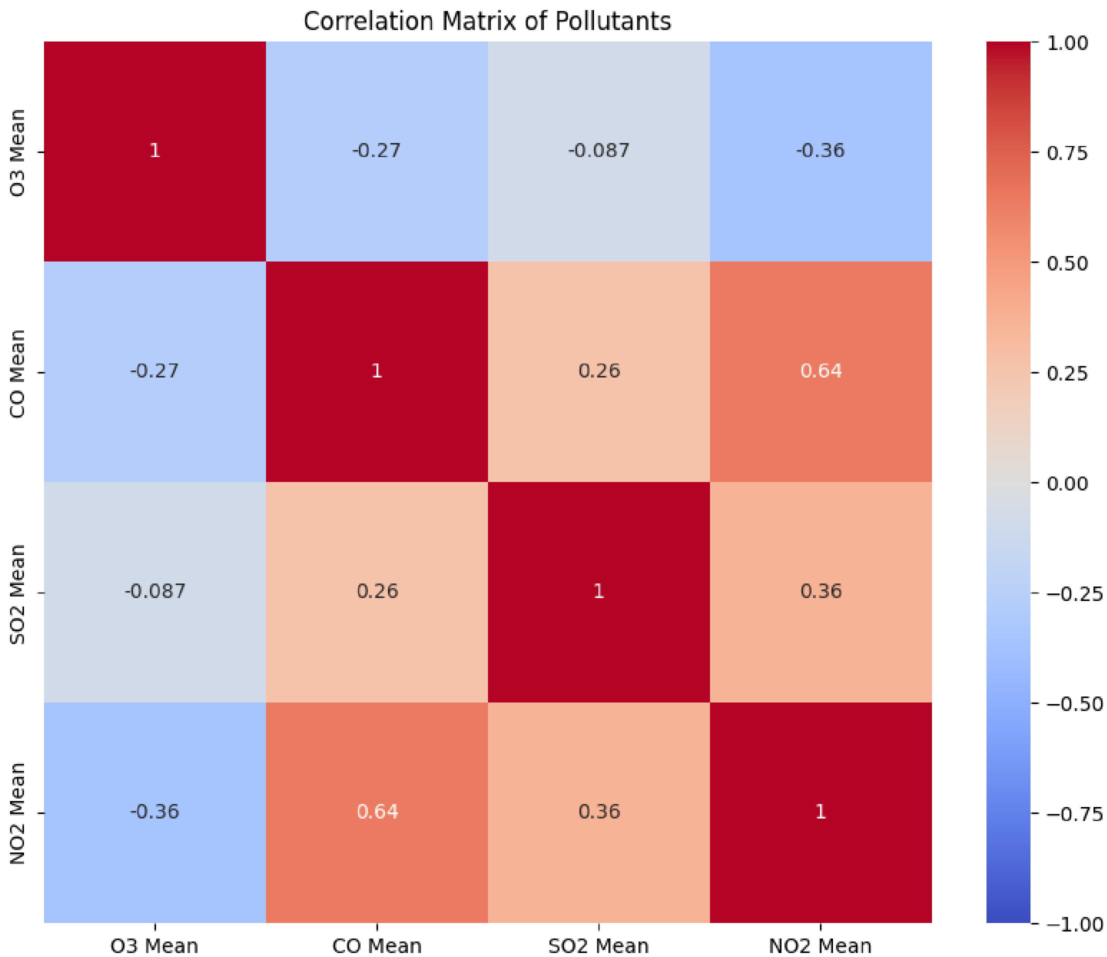
[43]:
```
# Extract month from Date
df['Month'] = df['Date'].dt.month

# Convert relevant columns to numeric, coercing errors
numeric_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Drop rows with any NaN values in numeric columns (if necessary)
df_clean = df.dropna(subset=numeric_columns)

# Group by Month and calculate mean values for each pollutant
monthly_means = df_clean.groupby('Month')[numeric_columns].mean()

# Plot the seasonal variations
monthly_means.plot(figsize=(12, 8), marker='o', title='Seasonal Variation in␣
↪Pollutant Levels')
plt.xlabel('Month')
```

```
plt.ylabel('Mean Pollutant Level')
plt.grid(True)
plt.show()
```



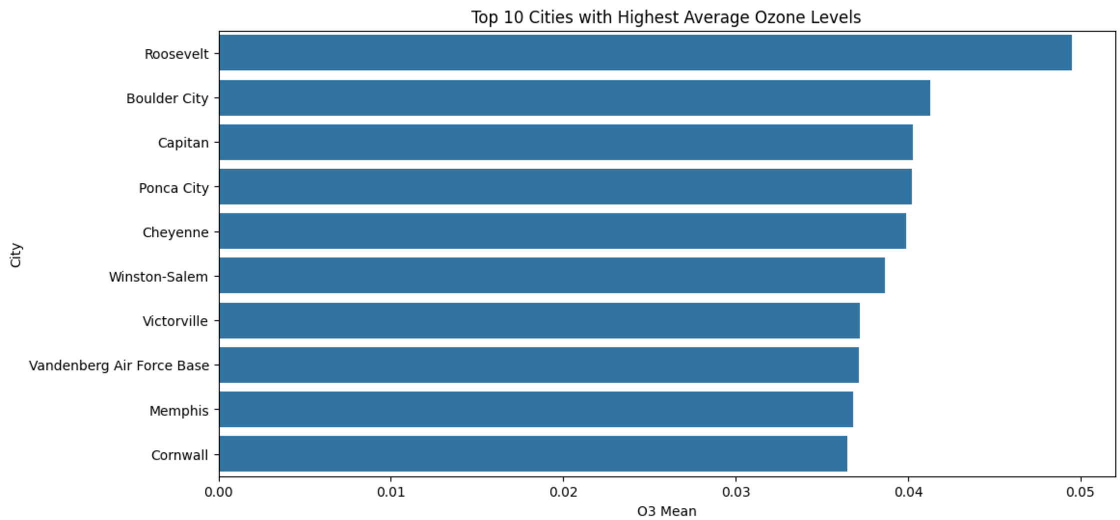
Correlation Analysis Between Pollutants Problem 5:Analyze the correlation between different pollutants.

[45]:
```
# Calculate correlation matrix
correlation_matrix = df[['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']].corr()

# Plot the correlation matrix
import seaborn as sns
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix of Pollutants')
plt.show()
```



Problem 6 : Identify the top 10 cities with the highest average Ozone levels throughout the dataset's timeframe.

[46]:
```
# Calculate the average Ozone levels for each city
avg_ozone_by_city = df.groupby('City')['O3 Mean'].mean()

# Sort the cities based on average Ozone levels in descending order
top_10_cities = avg_ozone_by_city.sort_values(ascending=False).head(10).
↪reset_index()

# Plotting
plt.figure(figsize=(12, 6))
sns.barplot(data = top_10_cities, x = 'O3 Mean', y = 'City')
plt.title('Top 10 Cities with Highest Average Ozone Levels')
plt.show()
```

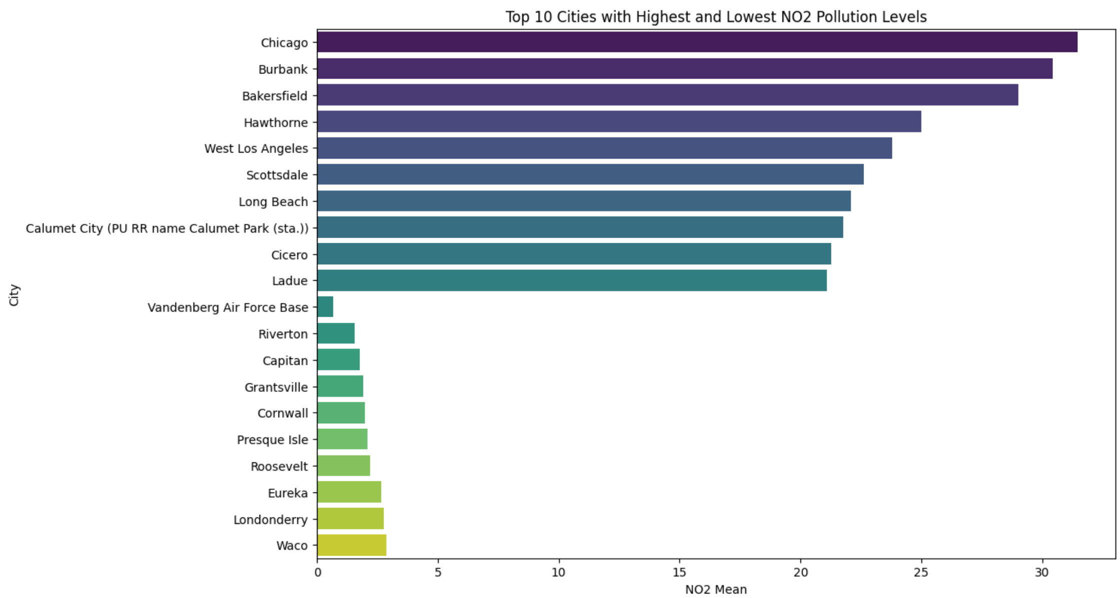


Problem 7 : Identify the top 10 cities with the highest and lowest levels of Nitrogen Dioxide (NO2) pollution over the entire dataset period.

[47]:
```
# Filter data for NO2 levels and relevant columns
no2_data = df.loc[:,('City', 'NO2 Mean')]

# Group by city and calculate the mean NO2 levels
mean_no2_by_city = no2_data.groupby('City')['NO2 Mean'].mean().reset_index()

# Sort cities by mean NO2 levels
top_10_highest_no2_cities = mean_no2_by_city.sort_values(by='NO2 Mean',␣
 ↪ascending=False).head(10)
top_10_lowest_no2_cities = mean_no2_by_city.sort_values(by='NO2 Mean').head(10)

# Concatenate the top 10 highest and lowest cities
top_10_no2_cities = pd.concat([top_10_highest_no2_cities,␣
 ↪top_10_lowest_no2_cities])

# Plotting using Seaborn
plt.figure(figsize=(12, 8))
sns.barplot(data=top_10_no2_cities, x='NO2 Mean', y='City',palette='viridis')
plt.title('Top 10 Cities with Highest and Lowest NO2 Pollution Levels')
plt.show()
```

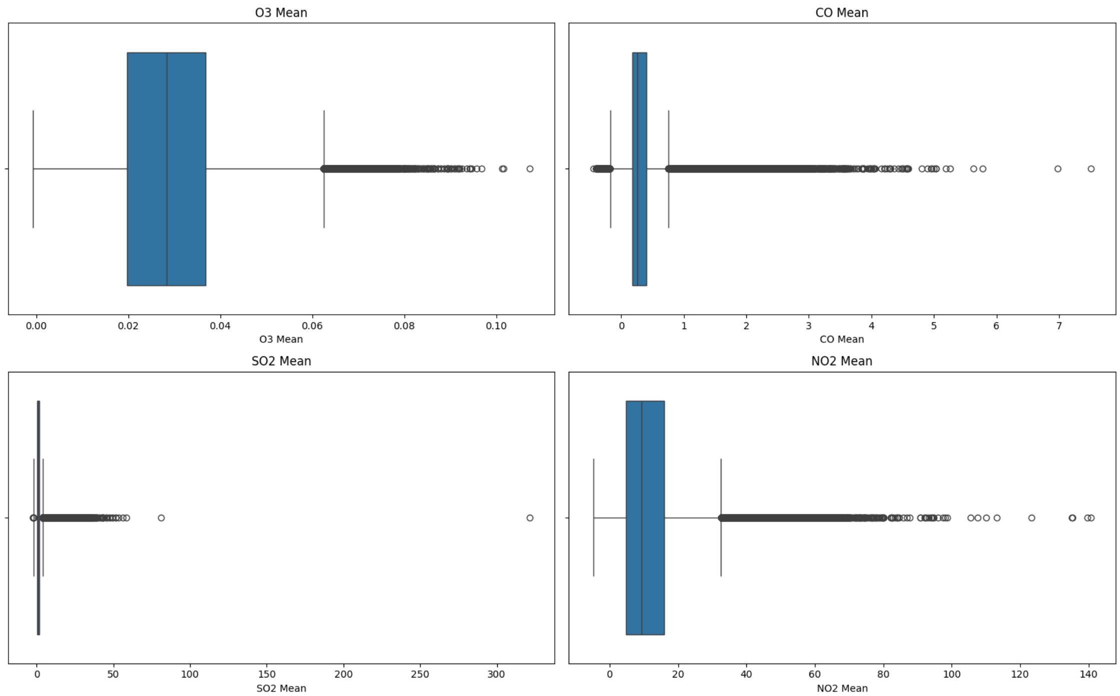
```
C:\Users\kapil\AppData\Local\Temp\ipykernel_1876\480866270.py:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
sns.barplot(data=top_10_no2_cities, x='NO2 Mean', y='City',palette='viridis')
```



Outliers and Anomalies Detection Problem 8: Detect outliers and anomalies in the pollutant data.

[48]:
```
# Using box plots to detect outliers
plt.figure(figsize=(16, 10))

plt.subplot(2, 2, 1)
sns.boxplot(data=df, x='O3 Mean')
plt.title('O3 Mean')

plt.subplot(2, 2, 2)
sns.boxplot(data=df, x='CO Mean')
plt.title('CO Mean')

plt.subplot(2, 2, 3)
sns.boxplot(data=df, x='SO2 Mean')
plt.title('SO2 Mean')

plt.subplot(2, 2, 4)
sns.boxplot(data=df, x='NO2 Mean')
plt.title('NO2 Mean')

plt.tight_layout()
plt.show()
```



Identify Hotspots of Pollution Problem 9: Identify cities with the highest levels of NO2 pollution

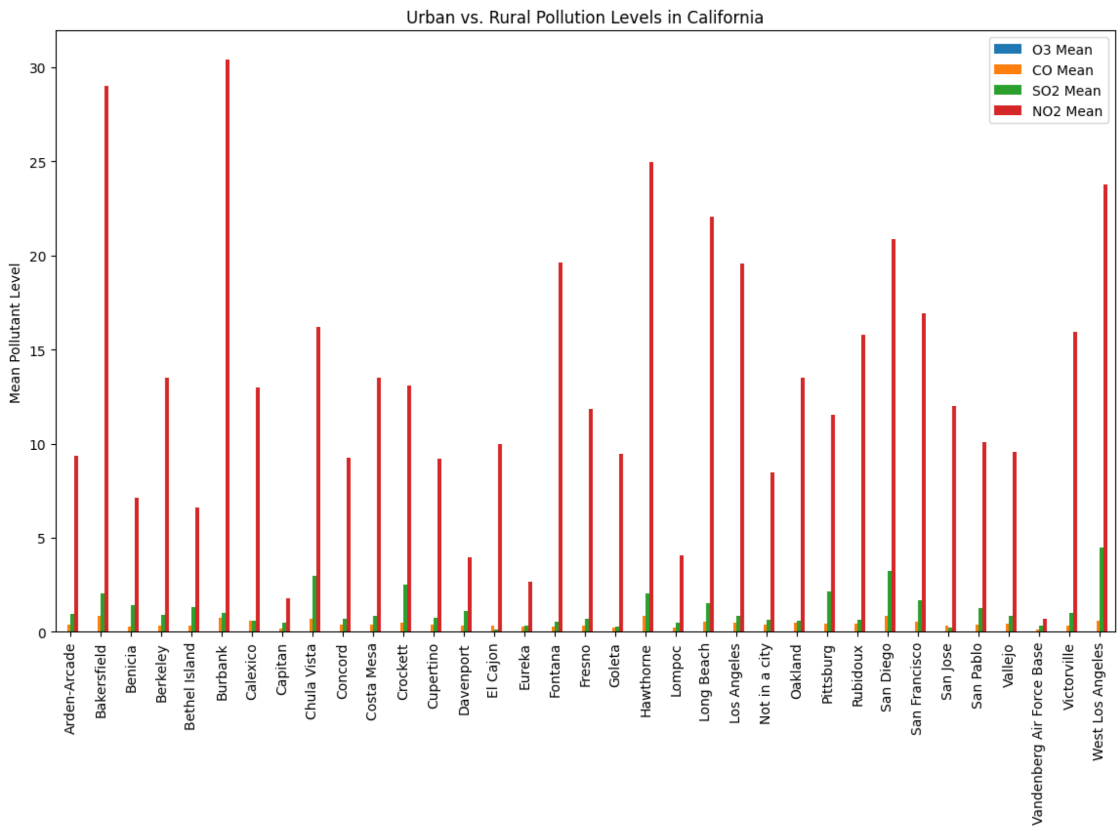
[50]:
```python
# Convert relevant columns to numeric, coercing errors
numeric_columns = ['NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Drop rows with any NaN values in the 'NO2 Mean' column (if necessary)
df_clean = df.dropna(subset=numeric_columns)

# Group by City and calculate mean NO2 levels
city_no2_means = df_clean.groupby('City')['NO2 Mean'].mean()

# Sort cities by the highest average NO2 levels and display the top 10
top_cities_no2 = city_no2_means.sort_values(ascending=False).head(10)
top_cities_no2
```

[50]:
```
City
Chicago                                     31.451528
Burbank                                     30.431702
Bakersfield                                 29.022370
Hawthorne                                   24.985028
West Los Angeles                            23.778210
Scottsdale                                  22.619903
```

```
Long Beach                                      22.071382
Calumet City (PU RR name Calumet Park (sta.))   21.777969
Cicero                                          21.262820
Ladue                                           21.093291
Name: NO2 Mean, dtype: float64
```

Urban vs. Rural Comparison Problem 10:Compare pollution levels between urban and rural areas within the same state or county.

[52]:
```python
# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Convert relevant columns to numeric, coercing errors
numeric_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Drop rows with any NaN values in numeric columns (if necessary)
df_clean = df.dropna(subset=numeric_columns)

# Group by State and City, then calculate mean values for each pollutant
urban_rural_means = df_clean.groupby(['State', 'City'])[numeric_columns].mean()

# Plotting the comparison for a selected state (e.g., California)
urban_rural_means.loc['California'].plot(kind='bar', figsize=(14, 8),␣
↪title='Urban vs. Rural Pollution Levels in California')
plt.xlabel('City')
plt.ylabel('Mean Pollutant Level')
plt.show()
```



Problem 11 : Calculate daily, monthly, and yearly averages of each air pollutant (NO2, SO2, CO, O3) across all states.

[54]:
```
# Adding month and day in dataset
df['Month'] = df['Date'].dt.month
df['Day'] = df['Date'].dt.day
```

[55]:
```
data = df.loc[:,('Day','Month','Year','O3 Mean','CO Mean','SO2 Mean','NO2␣
↪Mean')]
def calculate_averages(data):

    # Calculate daily averages
    daily_averages = data.groupby(['Year', 'Month','Day']).mean().reset_index()

    # Calculate monthly averages
    monthly_averages = data.groupby(['Year','Month']).mean().reset_index()

    # Calculate yearly averages
    yearly_averages = data.groupby('Year').mean().reset_index()
```

```
    return daily_averages, monthly_averages, yearly_averages

# Calculate averages
daily_avg, monthly_avg, yearly_avg = calculate_averages(data)

# Print the results
print("Daily Averages:")
print(daily_avg.head())
print("\nMonthly Averages:")
print(monthly_avg.head())
print("\nYearly Averages:")
print(yearly_avg.head())
```

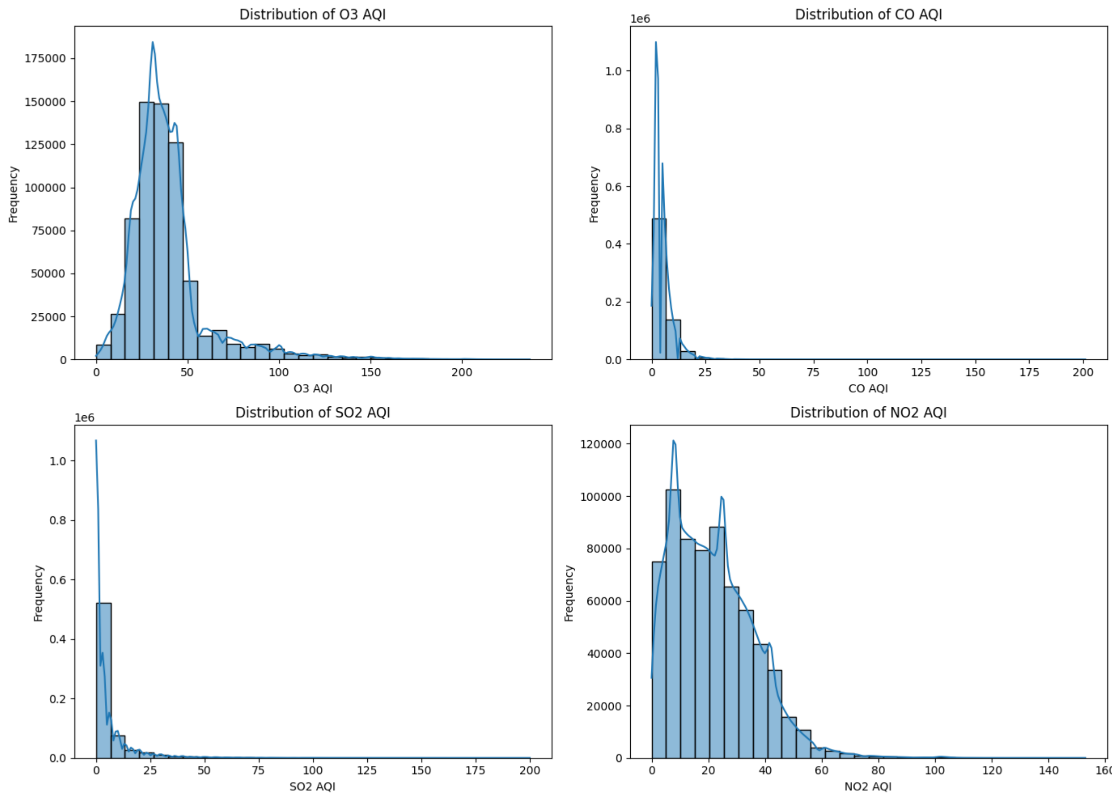
```
Daily Averages:
   Year  Month  Day   O3 Mean   CO Mean  SO2 Mean   NO2 Mean
0  2000      1    1  0.020742  0.773897  4.346910  18.508666
1  2000      1    2  0.021207  0.590316  3.438415  14.692258
2  2000      1    3  0.013568  0.880811  3.390395  23.830700
3  2000      1    4  0.013322  1.006128  2.758615  24.160910
4  2000      1    5  0.016361  1.009010  3.006528  23.804671

Monthly Averages:
   Year  Month        Day   O3 Mean   CO Mean  SO2 Mean   NO2 Mean
0  2000      1  16.118017  0.014521  0.948309  3.866951  23.425019
1  2000      2  14.895746  0.021125  0.715586  3.426367  20.960138
2  2000      3  16.300063  0.027074  0.537657  3.161874  17.715628
3  2000      4  15.586100  0.030665  0.469062  3.377199  16.140980
4  2000      5  16.091484  0.034551  0.421474  3.389836  15.031685

Yearly Averages:
   Year        Day     Month   O3 Mean   CO Mean  SO2 Mean   NO2 Mean
0  2000  15.761562  6.667127  0.026569  0.554411  3.643767  17.404993
1  2001  15.769339  6.730470  0.027640  0.512427  3.249895  17.572878
2  2002  15.736885  6.510978  0.029079  0.497511  2.796563  16.334337
3  2003  15.723803  6.480783  0.027643  0.490883  2.910570  15.877995
4  2004  15.792296  6.607470  0.026913  0.450355  2.971342  15.042115
```

Problem 12: What is the distribution of the Air Quality Index (AQI) for each pollutant over the years?

This question aims to analyze the distribution of AQI for Ozone (O3), Carbon Monoxide (CO), Su

[23]:
```
import seaborn as sns

# Ensure columns are numeric, coercing errors to NaN and then dropping NaNs
aqi_columns = ['O3 AQI', 'CO AQI', 'SO2 AQI', 'NO2 AQI']
df_clean[aqi_columns] = df_clean[aqi_columns].apply(pd.to_numeric,␣
 ↪errors='coerce')
```

```python
df_clean = df_clean.dropna(subset=aqi_columns)

# Plotting the distribution of AQI for each pollutant
plt.figure(figsize=(14, 10))

# O3 AQI
plt.subplot(2, 2, 1)
sns.histplot(df_clean['O3 AQI'], kde=True, bins=30)
plt.title('Distribution of O3 AQI')
plt.xlabel('O3 AQI')
plt.ylabel('Frequency')

# CO AQI
plt.subplot(2, 2, 2)
sns.histplot(df_clean['CO AQI'], kde=True, bins=30)
plt.title('Distribution of CO AQI')
plt.xlabel('CO AQI')
plt.ylabel('Frequency')

# SO2 AQI
plt.subplot(2, 2, 3)
sns.histplot(df_clean['SO2 AQI'], kde=True, bins=30)
plt.title('Distribution of SO2 AQI')
plt.xlabel('SO2 AQI')
plt.ylabel('Frequency')

# NO2 AQI
plt.subplot(2, 2, 4)
sns.histplot(df_clean['NO2 AQI'], kde=True, bins=30)
plt.title('Distribution of NO2 AQI')
plt.xlabel('NO2 AQI')
plt.ylabel('Frequency')

plt.tight_layout()
plt.show()
```



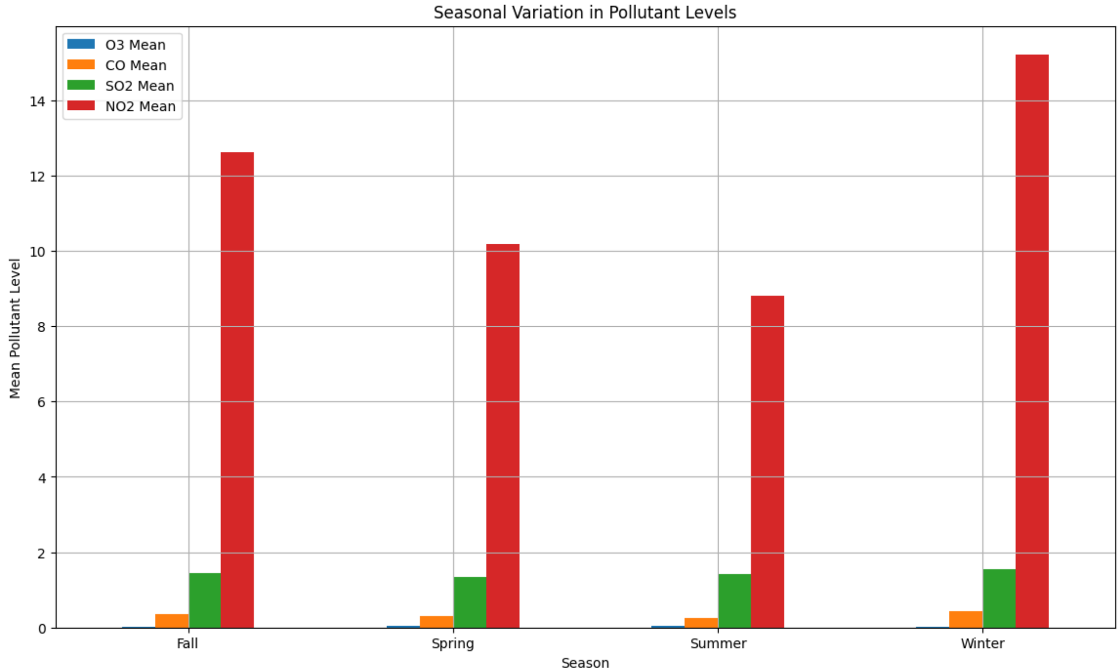
Problem 13: How do the mean levels of each pollutant vary by season (Spring, Summer, Fall, Winter)?

This question aims to explore the seasonal variations in the mean levels of Ozone (O3), Carbon

[27]:
```python
# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Extract month from Date
df['Month'] = df['Date'].dt.month

# Define seasons based on months
def get_season(month):
    if month in [3, 4, 5]:
        return 'Spring'
    elif month in [6, 7, 8]:
        return 'Summer'
    elif month in [9, 10, 11]:
        return 'Fall'
    else:
        return 'Winter'
```

```python
# Add a season column
df['Season'] = df['Month'].apply(get_season)

# Ensure columns are numeric, coercing errors to NaN and then dropping NaNs
pollutant_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[pollutant_columns] = df[pollutant_columns].apply(pd.to_numeric,␣
 ↪errors='coerce')
df_clean = df.dropna(subset=pollutant_columns + ['Season'])

# Verify data types
print(df_clean[pollutant_columns].dtypes)

# Group by Season and calculate mean values for each pollutant
seasonal_means = df_clean.groupby('Season')[pollutant_columns].mean()

# Plotting the seasonal variations
seasonal_means.plot(kind='bar', figsize=(14, 8), title='Seasonal Variation in␣
 ↪Pollutant Levels')
plt.xlabel('Season')
plt.ylabel('Mean Pollutant Level')
plt.xticks(rotation=0)
plt.grid(True)
plt.show()
```

```
O3 Mean     float64
CO Mean     float64
SO2 Mean    float64
NO2 Mean    float64
dtype: object
```



2.2 Machine Learning Model

Problem 14:Linear Regression model to predict the average NO2 levels based on date features (year, month).

[4]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Load the dataset
df = pd.read_csv('../data/pollution_2000_2023.csv')

# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Extract year and month from Date
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month

# Convert relevant columns to numeric, coercing errors
numeric_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Drop rows with any NaN values in relevant columns
df_clean = df.dropna(subset=numeric_columns + ['Year', 'Month'])
```

```python
# Select features and target variable
X = df_clean[['Year', 'Month']]
y = df_clean['NO2 Mean']

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

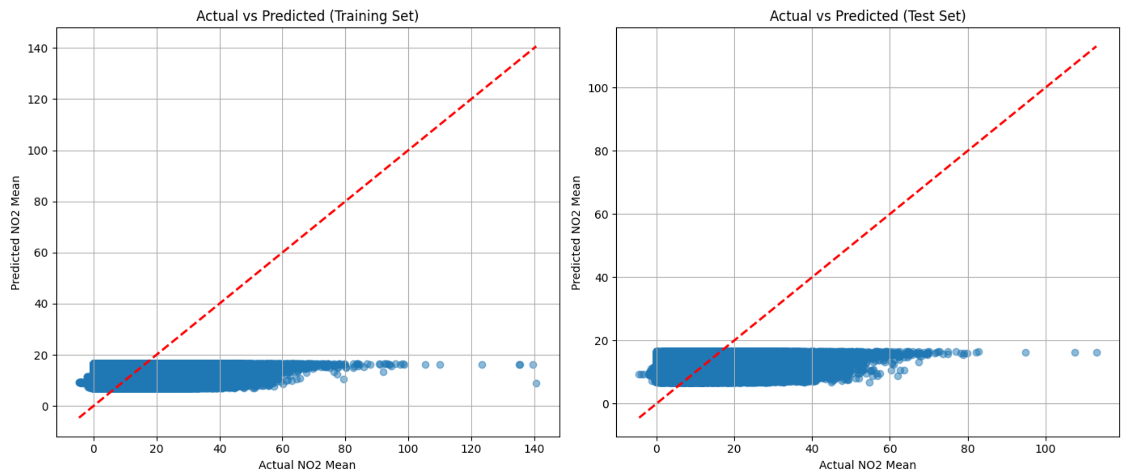
[5]:
```python
# Initialize and train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
```

[6]:
```python
# Evaluate the model
train_rmse = np.sqrt(mean_squared_error(y_train, y_pred_train))
test_rmse = np.sqrt(mean_squared_error(y_test, y_pred_test))

print(f'Train RMSE: {train_rmse}')
print(f'Test RMSE: {test_rmse}')
```

```
Train RMSE: 8.546798872811287
Test RMSE: 8.540854680565833
```

[7]:
```python
# Plotting actual vs predicted values for the training set
plt.figure(figsize=(14, 6))

# Training set
plt.subplot(1, 2, 1)
plt.scatter(y_train, y_pred_train, alpha=0.5)
plt.plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], 'r--',␣
↪lw=2)
plt.xlabel('Actual NO2 Mean')
plt.ylabel('Predicted NO2 Mean')
plt.title('Actual vs Predicted (Training Set)')
plt.grid(True)

# Test set
plt.subplot(1, 2, 2)
plt.scatter(y_test, y_pred_test, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'r--',␣
↪lw=2)
plt.xlabel('Actual NO2 Mean')
plt.ylabel('Predicted NO2 Mean')
plt.title('Actual vs Predicted (Test Set)')
```

```
plt.grid(True)

plt.tight_layout()
plt.show()
```



Problem 15: Build a predictive model in Python to forecast O3 Mean levels for the next year based on historical data from 2000-2022.

[10]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error

# Load the dataset
df = pd.read_csv('../data/pollution_2000_2023.csv')

# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')

# Extract year and month from Date
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month

# Convert relevant columns to numeric, coercing errors
numeric_columns = ['O3 Mean', 'CO Mean', 'SO2 Mean', 'NO2 Mean']
df[numeric_columns] = df[numeric_columns].apply(pd.to_numeric, errors='coerce')

# Drop rows with any NaN values in relevant columns
df_clean = df.dropna(subset=numeric_columns + ['Year', 'Month'])
```

[11]:
```
# Create lag features for O3 Mean
df_clean['O3 Mean Lag1'] = df_clean['O3 Mean'].shift(1)
```

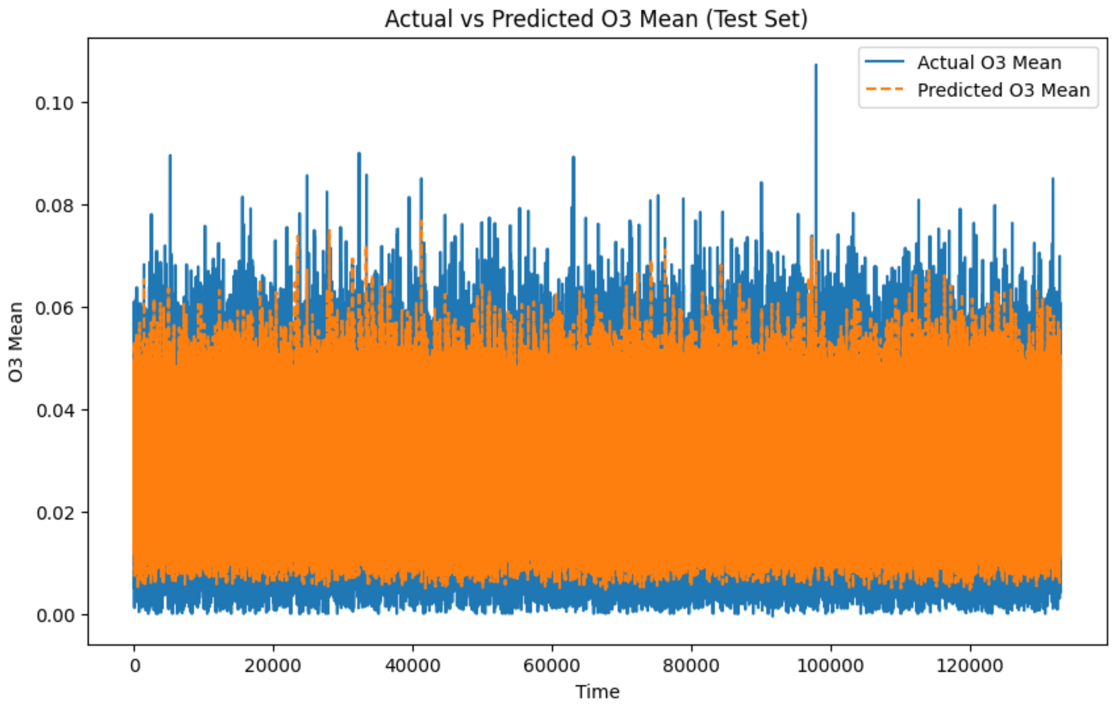
```python
df_clean['O3 Mean Lag2'] = df_clean['O3 Mean'].shift(2)
df_clean['O3 Mean Lag3'] = df_clean['O3 Mean'].shift(3)

# Drop rows with NaN values due to lagging
df_clean = df_clean.dropna()

# Select features and target variable
X = df_clean[['Year', 'Month', 'O3 Mean Lag1', 'O3 Mean Lag2', 'O3 Mean Lag3']]
y = df_clean['O3 Mean']
```

[12]:
```python
# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

[13]:
```python
# Initialize and train the model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred_train = model.predict(X_train)
y_pred_test = model.predict(X_test)
```

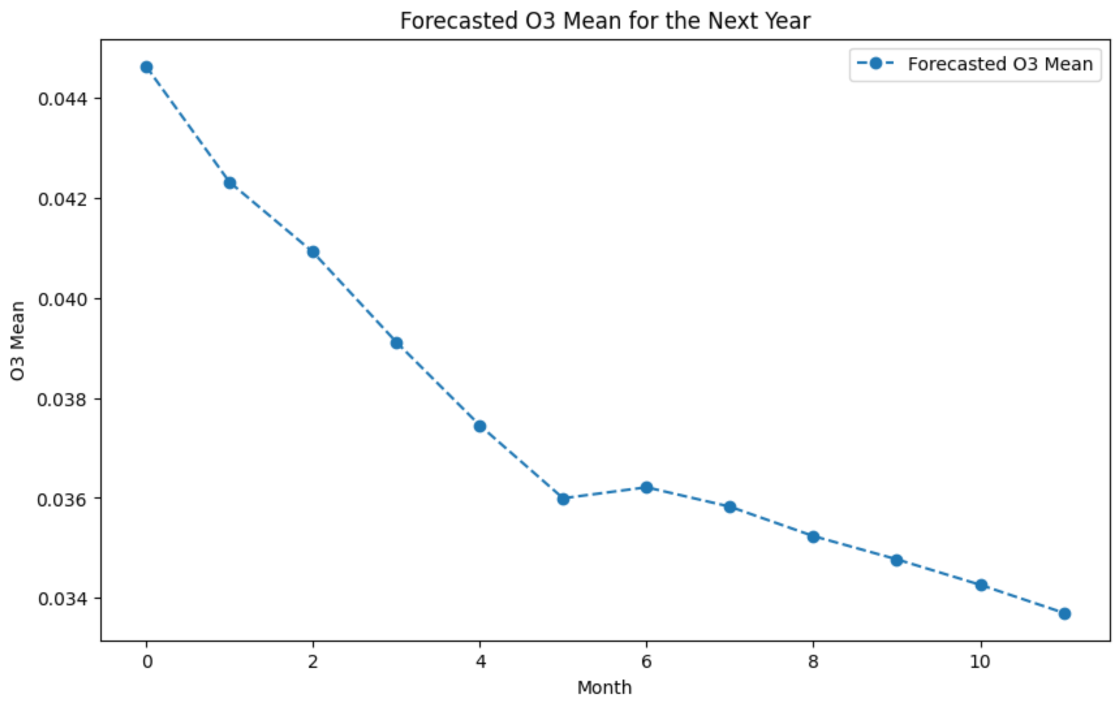
[14]:
```python
# Evaluate the model
train_rmse = np.sqrt(mean_squared_error(y_train, y_pred_train))
test_rmse = np.sqrt(mean_squared_error(y_test, y_pred_test))

print(f'Train RMSE: {train_rmse}')
print(f'Test RMSE: {test_rmse}')

# Plotting actual vs predicted values for the test set
plt.figure(figsize=(10, 6))
plt.plot(y_test.values, label='Actual O3 Mean')
plt.plot(y_pred_test, label='Predicted O3 Mean', linestyle='--')
plt.xlabel('Time')
plt.ylabel('O3 Mean')
plt.title('Actual vs Predicted O3 Mean (Test Set)')
plt.legend()
plt.show()
```

```
Train RMSE: 0.0078543513480357
Test RMSE: 0.007826618947392327
```



[20]:
```python
# Get the last available data point
last_data_point = df_clean[['Year', 'Month', 'O3 Mean Lag1', 'O3 Mean Lag2',␣
↪'O3 Mean Lag3']].iloc[-1]

# Initialize list to store forecasts
forecasts = []

# Forecast for the next 12 months
for i in range(12):
    # Increment month and year
    next_month = last_data_point['Month'] + 1
    next_year = last_data_point['Year']
    if next_month > 12:
        next_month = 1
        next_year += 1

    # Prepare the data for prediction
    data_for_prediction = pd.DataFrame({
        'Year': [next_year],
        'Month': [next_month],
        'O3 Mean Lag1': [last_data_point['O3 Mean Lag1']],
        'O3 Mean Lag2': [last_data_point['O3 Mean Lag2']],
        'O3 Mean Lag3': [last_data_point['O3 Mean Lag3']]
    })
```

```
    # Predict
    next_forecast = model.predict(data_for_prediction)[0]

    # Append to forecasts
    forecasts.append(next_forecast)

    # Update last_data_point for next prediction
    last_data_point = {
        'Year': next_year,
        'Month': next_month,
        'O3 Mean Lag1': next_forecast,
        'O3 Mean Lag2': last_data_point['O3 Mean Lag1'],
        'O3 Mean Lag3': last_data_point['O3 Mean Lag2']
    }

# Plot the forecasts
plt.figure(figsize=(10, 6))
plt.plot(forecasts, marker='o', linestyle='--', label='Forecasted O3 Mean')
plt.xlabel('Month')
plt.ylabel('O3 Mean')
plt.title('Forecasted O3 Mean for the Next Year')
plt.legend()
plt.show()
```



2.3 Conclusion

Temporal Trends: There are noticeable temporal trends in air pollutant levels over the years. Some pollutants may exhibit seasonal patterns, while others may show long-term trends.

Geographical Variations: Air pollutant levels vary significantly across different states and cities in the United States. Certain regions may consistently exhibit higher or lower levels of pollutants compared to others.

Outlier Detection: Outliers or extreme events in air pollutant levels can be identified and analyzed using visualization techniques such as box plots. These outliers may be indicative of unusual environmental conditions or specific events affecting air quality.

Predictive Modeling: Predictive models, such as linear regression, can be used to forecast future air pollutant levels based on historical data. These models can provide valuable insights for decision-making and planning related to environmental health and pollution control.

Policy Implications: The analysis of air quality data can inform the development of environmental policies and regulations aimed at reducing air pollution and mitigating its adverse effects on public health and the environment.

Overall, the dataset provides valuable information for understanding air quality trends, identifying areas of concern, and guiding efforts to improve air quality and public health outcomes.