Experiment No. 11

Aim : Data Visualization using matplotlib.

Problem Statement: Analyzing Air Quality Index (AQI) Trends in a City, and perform following tasks – 1. Import dataset. 2. Explore dataset. 3. Identify the relevant variables for visualizing AQI trends. 4. Create line plots or time series plots. 5. Plot individual pollutant levels. 6. Use bar plots or stacked bar plots to compare the AQI values. 7. Create box plots or violin plots to analyze the distribution of AQI values. 8. Use scatter plots or bubble charts to explore the relationship. 9. Customize the visualizations.

Dataset: "City_Air_Quality.csv"

Software Requirements : Python, and Jupyter Notebook.

Hardware Requirements : 8GB RAM, Storage and Processor.

Objectives : i) Import and explore the "City_Air_Quality.csv" dataset to understand it's structure. ii) Identify and extract relevant variables for visualizing AQI trends. iii) Customize visualizations for better reliability and interpretation.

Theory : The Air Quality Index (AQI) is a numerical scale used to communicate how polluted the air currently is or how polluted it is forecasted to become. It is designed to provide the public with a clear and easily understandable measure of air quality, helping individuals make informed decisions about their health and activities.

Data Visualization

Data visualization is the graphical representation of information and data. It uses visual elements like charts, graphs, and maps to make complex data more accessible, understandable, and actionable. Effective data visualization helps to uncover insights, reveal patterns, and communicate findings in a clear and compelling way.

Matplotlib

Matplotlib is a powerful and widely used plotting library for the Python programming language. It provides a flexible and comprehensive way to create static, animated, and interactive visualizations in Python.

Customization in Matplotlib

Customizing visualizations in Matplotlib allows you to tailor plots to specific needs, enhance readability, and effectively communicate insights. Matplotlib provides a rich set of customization options for various elements of your plots.

Types of plots for AQI Analysis

1 . Line Plot

Purpose: To display trends over time and track changes in AQI values.

Application: Time Series Analysis: Use line plots to show how AQI values fluctuate over time, such as daily, monthly, or yearly trends. This helps in identifying patterns, seasonal variations, and long-term changes.

2. Bar Plot

Purpose: To compare AQI values across different categories or locations.

Application: Comparative Analysis: Use bar plots to compare average AQI values for different locations, cities, or time periods. This can highlight areas with higher or lower air quality.

3.Box Plot

Purpose: To summarize the distribution of AQI values and identify outliers.

Application: Distribution Analysis: Use box plots to visualize the spread of AQI values and to detect any anomalies or outliers in the data. It provides a concise summary of the data's minimum, first quartile, median, third quartile, and maximum.

4.Scatter Plot

Purpose: To examine the relationship between AQI and another variable (e.g., temperature, humidity).

Application: Correlation Analysis: Use scatter plots to visualize how AQI correlates with other environmental factors. This can help identify patterns or trends in how AQI changes with different conditions.

5.Violin Plot

Purpose: To visualize the distribution of AQI values across different categories, showing both the distribution shape and density.

Application: Distribution Comparison: Use violin plots to compare the distribution of AQI values across different locations or time periods. It provides a deeper understanding of the data distribution beyond just summary statistics.

Implementation

Step No.1 - Import The Dataset.

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import seaborn as sns

df = pd.read_csv(r"C:\Users\saira\Downloads\city_day.csv\city_day.csv")

df
```

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	AQI_Bucket
0	Ahmedabad	2015-01-01	NaN	NaN	0.92	18.22	17.15	NaN	0.92	27.64	133.36	0.00	0.02	0.00	NaN	NaN
1	Ahmedabad	2015-01-02	NaN	NaN	0.97	15.69	16.46	NaN	0.97	24.55	34.06	3.68	5.50	3.77	NaN	NaN
2	Ahmedabad	2015-01-03	NaN	NaN	17.40	19.30	29.70	NaN	17.40	29.07	30.70	6.80	16.40	2.25	NaN	NaN
3	Ahmedabad	2015-01-04	NaN	NaN	1.70	18.48	17.97	NaN	1.70	18.59	36.08	4.43	10.14	1.00	NaN	NaN
4	Ahmedabad	2015-01-05	NaN	NaN	22.10	21.42	37.76	NaN	22.10	39.33	39.31	7.01	18.89	2.78	NaN	NaN

... ...
... ...

29526 Visakhapatnam 2020-06-27 15.02 50.94 7.68 25.06 19.54 12.47
0.47 8.55 23.30 2.24 12.07 0.73 41.0 Good

29527 Visakhapatnam 2020-06-28 24.38 74.09 3.42 26.06 16.53 11.99
0.52 12.72 30.14 0.74 2.21 0.38 70.0 Satisfactory

29528 Visakhapatnam 2020-06-29 22.91 65.73 3.45 29.53 18.33 10.71
0.48 8.42 30.96 0.01 0.01 0.00 68.0 Satisfactory

29529 Visakhapatnam 2020-06-30 16.64 49.97 4.05 29.26 18.80 10.03
0.52 9.84 28.30 0.00 0.00 0.00 54.0 Satisfactory

29530 Visakhapatnam 2020-07-01 15.00 66.00 0.40 26.85 14.05 5.20
0.59 2.10 17.05 NaN NaN NaN 50.0 Good

df.head()

City Date PM2.5 PM10 NO NO2 NOx NH3 CO SO2 O3 Benzene
Toluene Xylene AQI AQI_Bucket

0 Ahmedabad 2015-01-01 NaN NaN 0.92 18.22 17.15 NaN 0.92
27.64 133.36 0.00 0.02 0.00 NaN NaN

1 Ahmedabad 2015-01-02 NaN NaN 0.97 15.69 16.46 NaN 0.97
24.55 34.06 3.68 5.50 3.77 NaN NaN

2 Ahmedabad 2015-01-03 NaN NaN 17.40 19.30 29.70 NaN 17.40
29.07 30.70 6.80 16.40 2.25 NaN NaN

3 Ahmedabad 2015-01-04 NaN NaN 1.70 18.48 17.97 NaN 1.70
18.59 36.08 4.43 10.14 1.00 NaN NaN

4 Ahmedabad 2015-01-05 NaN NaN 22.10 21.42 37.76 NaN 22.10
39.33 39.31 7.01 18.89 2.78 NaN NaN

df.tail()

City Date PM2.5 PM10 NO NO2 NOx NH3 CO SO2 O3 Benzene
Toluene Xylene AQI AQI_Bucket

29526 Visakhapatnam 2020-06-27 15.02 50.94 7.68 25.06 19.54 12.47
0.47 8.55 23.30 2.24 12.07 0.73 41.0 Good

29527 Visakhapatnam 2020-06-28 24.38 74.09 3.42 26.06 16.53 11.99
0.52 12.72 30.14 0.74 2.21 0.38 70.0 Satisfactory

29528 Visakhapatnam 2020-06-29 22.91 65.73 3.45 29.53 18.33 10.71
0.48 8.42 30.96 0.01 0.01 0.00 68.0 Satisfactory

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0.52 9.84 28.30 0.00 0.00 0.00 54.0 Satisfactory

29530 Visakhapatnam 2020-07-01 15.00 66.00 0.40 26.85 14.05 5.20
0.59 2.10 17.05 NaN NaN NaN 50.0 Good

Step No.2 - Explore the Structure and Content Of Dataset.

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29531 entries, 0 to 29530
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   City        29531 non-null  object
 1   Date        29531 non-null  object
 2   PM2.5       24933 non-null  float64
 3   PM10        18391 non-null  float64
 4   NO          25949 non-null  float64
 5   NO2         25946 non-null  float64
 6   NOx         25346 non-null  float64
 7   NH3         19203 non-null  float64
 8   CO          27472 non-null  float64
```

9 SO2 25677 non-null float64

10 O3 25509 non-null float64

11 Benzene 23908 non-null float64

12 Toluene 21490 non-null float64

13 Xylene 11422 non-null float64

14 AQI 24850 non-null float64

15 AQI_Bucket 24850 non-null object

dtypes: float64(13), object(3)

memory usage: 3.6+ MB

df.describe()

PM2.5 PM10 NO NO2 NOx NH3 CO SO2 O3 Benzene Toluene
Xylene AQI

count 24933.000000 18391.000000 25949.000000 25946.000000 25346.000000
19203.000000 27472.000000 25677.000000 25509.000000 23908.000000
21490.000000 11422.000000 24850.000000

mean 67.450578 118.127103 17.574730 28.560659 32.309123 23.483476
2.248598 14.531977 34.491430 3.280840 8.700972 3.070128
166.463581

std 64.661449 90.605110 22.785846 24.474746 31.646011 25.684275
6.962884 18.133775 21.694928 15.811136 19.969164 6.323247
140.696585

min 0.040000 0.010000 0.020000 0.010000 0.000000 0.010000
0.000000 0.010000 0.010000 0.000000 0.000000 0.000000
13.000000

25% 28.820000 56.255000 5.630000 11.750000 12.820000 8.580000
0.510000 5.670000 18.860000 0.120000 0.600000 0.140000
81.000000

50% 48.570000 95.680000 9.890000 21.690000 23.520000 15.850000
0.890000 9.160000 30.840000 1.070000 2.970000 0.980000
118.000000

75% 80.590000 149.745000 19.950000 37.620000 40.127500 30.020000
1.450000 15.220000 45.570000 3.080000 9.150000 3.350000
208.000000

max 949.990000 1000.000000 390.680000 362.210000 467.630000
352.890000 175.810000 193.860000 257.730000 455.030000
454.850000 170.370000 2049.000000

df.isnull().sum()

City 0

Date 0

PM2.5 4598

PM10 11140

NO 3582

NO2 3585

NOx 4185

NH3 10328

CO 2059

SO2 3854

O3 4022

Benzene 5623

Toluene 8041

Xylene 18109

AQI 4681

AQI_Bucket 4681

dtype: int64

df.dropna(inplace=True)

df.isnull().sum()

City 0

Date 0

PM2.5 0

PM10 0

NO 0

NO2 0

NOx 0

NH3 0

CO 0

SO2 0

O3 0

Benzene 0

Toluene 0

Xylene 0

AQI 0

AQI_Bucket 0

dtype: int64

df.columns

Index(['City', 'Date', 'PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2',

'O3', 'Benzene', 'Toluene', 'Xylene', 'AQI', 'AQI_Bucket'],

dtype='object')

Step No.3 - Identify the relevant variables for visualizing AQI trends.

```
# Based on typical air quality datasets, relevant columns are identified as:
# - Date: To track AQI and pollutant levels over time
# - AQI: The Air Quality Index values
# - Pollutant levels: Including PM2.5, PM10, CO, NO2, SO2, O3
relevant_columns = ['Date', 'AQI', 'PM2.5', 'PM10', 'CO', 'NO2', 'SO2', 'O3']
relevant_columns
```

['Date', 'AQI', 'PM2.5', 'PM10', 'CO', 'NO2', 'SO2', 'O3']

```
# Identify the available relevant columns in the dataset
available_relevant_columns = [col for col in relevant_columns if col in df.columns]
available_relevant_columns
```

['Date', 'AQI', 'PM2.5', 'PM10', 'CO', 'NO2', 'SO2', 'O3']

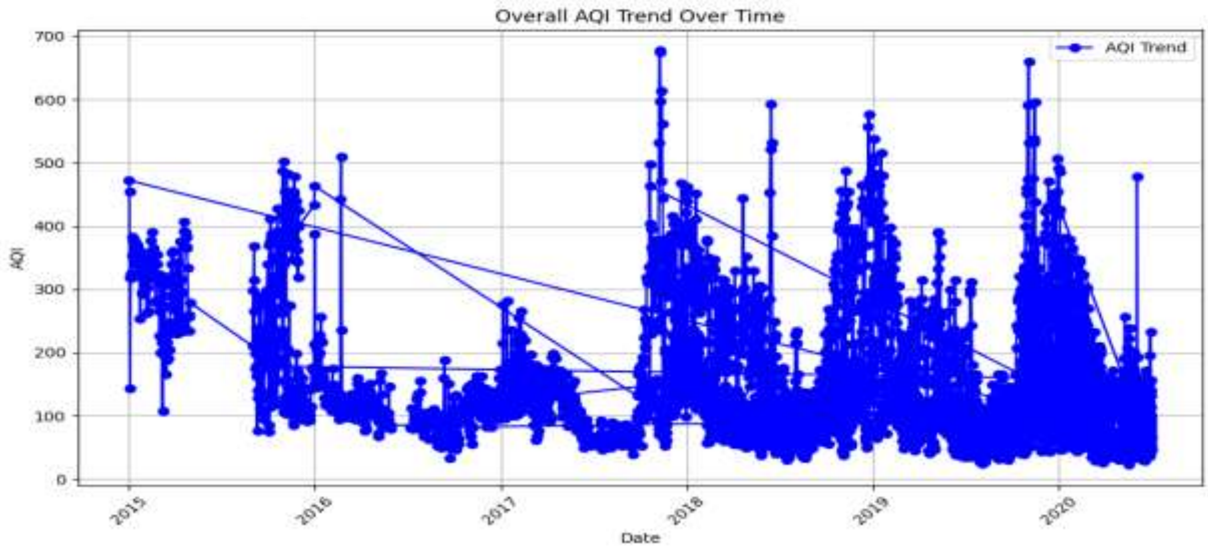
```
if 'Date' in available_relevant_columns:
    df['Date'] = pd.to_datetime(df['Date'])
df[available_relevant_columns].head()
```

	Date	AQI	PM2.5	PM10	CO	NO2	SO2	O3
2123	2017-11-25	184.0	81.40	124.50	0.12	20.50	15.24	127.09
2124	2017-11-26	197.0	78.32	129.06	0.14	26.00	26.96	117.44
2125	2017-11-27	198.0	88.76	135.32	0.11	30.85	33.59	111.81
2126	2017-11-28	188.0	64.18	104.09	0.09	28.07	19.00	138.18
2127	2017-11-29	173.0	72.47	114.84	0.16	23.20	10.55	109.74

Step No.4 - Create line plots or time series plots to visualize the overall AQI trend over time.

```
plt.figure(figsize=(10, 6))
plt.plot(df['Date'], df['AQI'], marker='o', linestyle='-', color='b', label='AQI Trend')
```

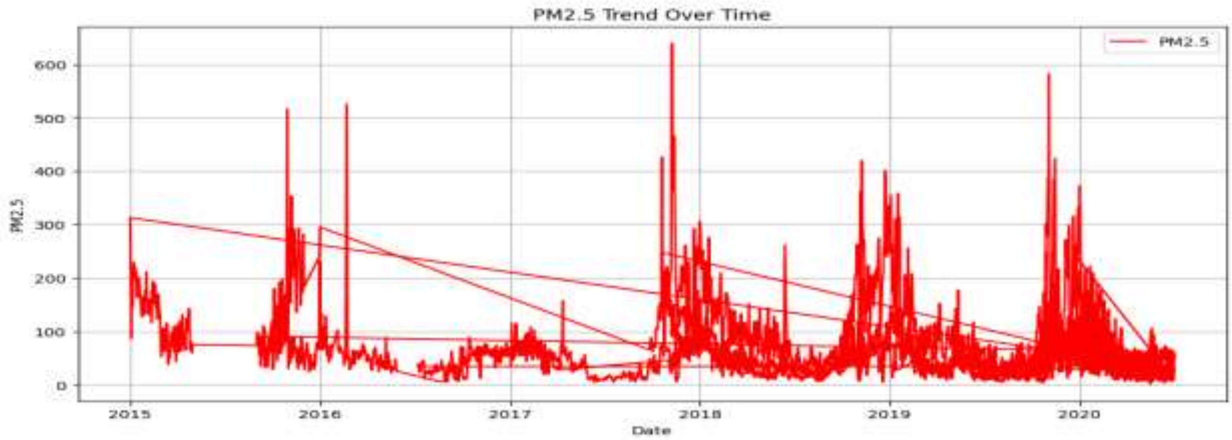
```
plt.xlabel('Date')
plt.ylabel('AQI')
plt.title('Overall AQI Trend Over Time')
plt.xticks(rotation=45)
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()
```

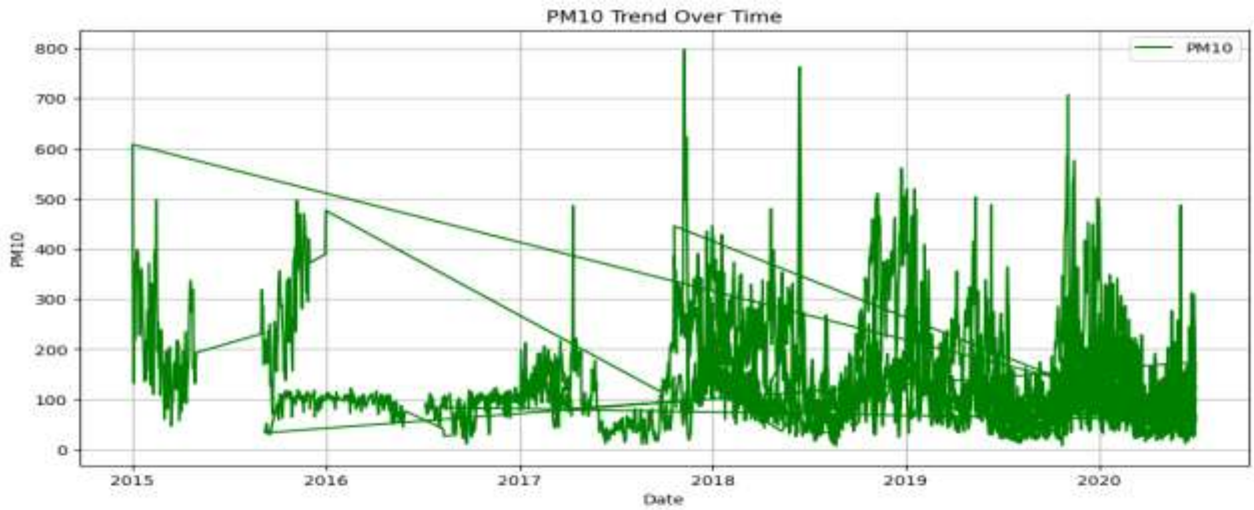


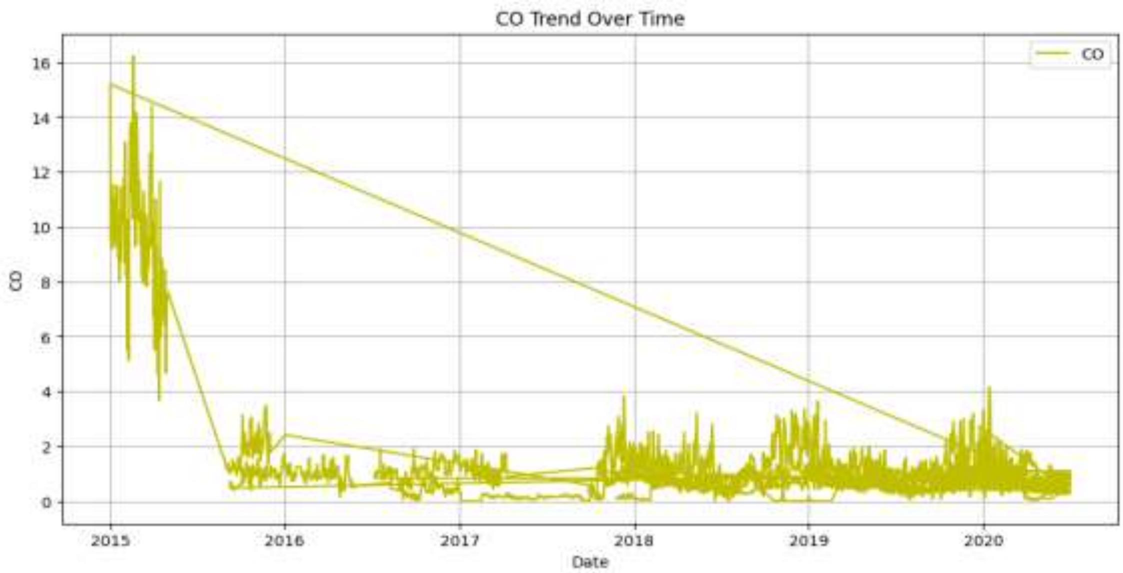
Step No.5 - Plot individual pollutant levels over time.

```
pollutants = ['PM2.5', 'PM10', 'CO']
for pollutant in pollutants:
    plt.figure(figsize=(12, 6))
    plt.plot(df['Date'], df[pollutant], label=pollutant, color='r' if pollutant == 'PM2.5' else 'g' if pollutant == 'PM10' else 'y')
    plt.xlabel('Date')
    plt.ylabel(pollutant)
    plt.title(f'{pollutant} Trend Over Time')
```

```
plt.legend()

plt.grid(True)

plt.show()
```

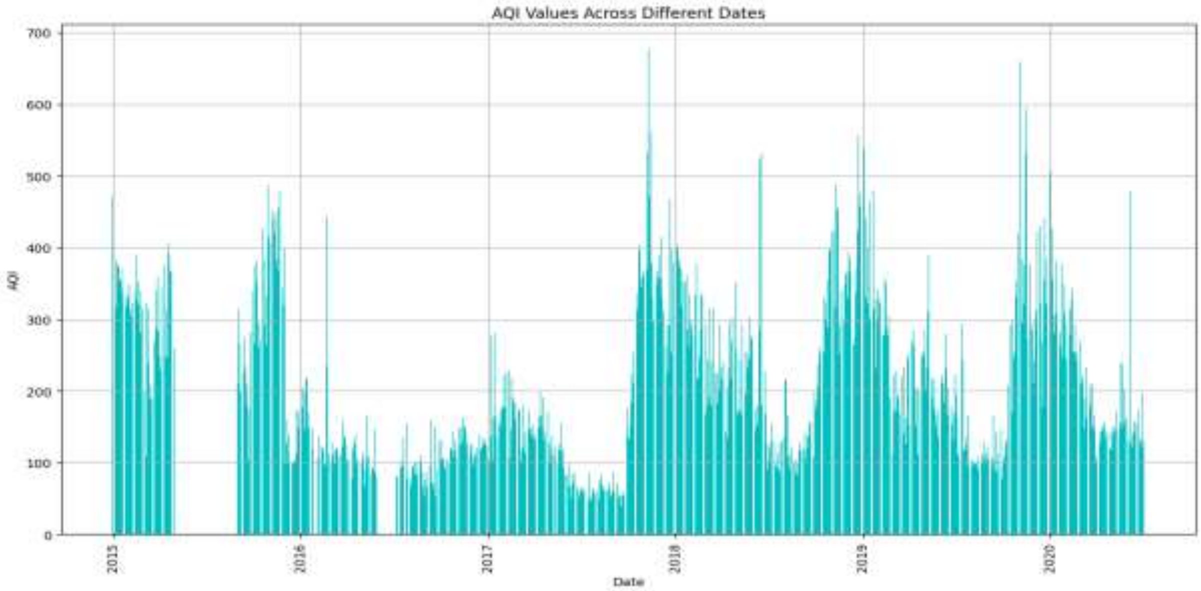






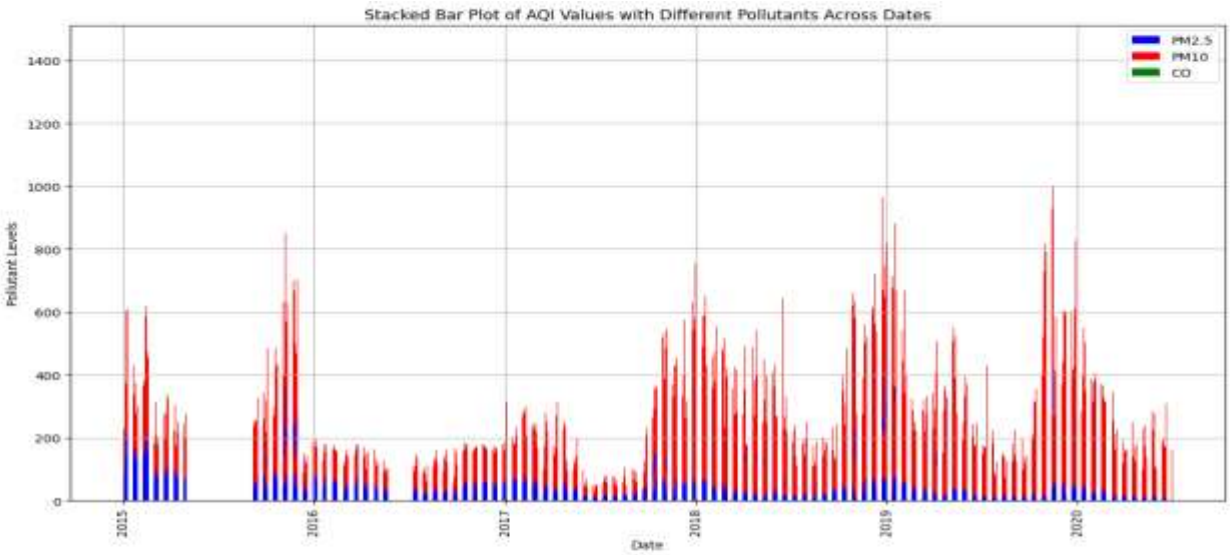
Step No. 6 - Use bar plots or stacked bar plots to compare the AQI values across different dates or time periods.

```
# Plot bar plot for AQI values across different dates
plt.figure(figsize=(15, 8))
plt.bar(df['Date'], df['AQI'], color='c')
plt.xlabel('Date')
plt.ylabel('AQI')
plt.title('AQI Values Across Different Dates')
plt.xticks(rotation=90)
plt.grid(True)
plt.show()
```




```
# Plot stacked bar plot for AQI values with different pollutants
plt.figure(figsize=(15, 8))
bar_width = 0.5
plt.bar(df['Date'], df['PM2.5'], label='PM2.5', color='b', width=bar_width)
plt.bar(df['Date'], df['PM10'], bottom=df['PM2.5'], label='PM10', color='r', width=bar_width)
```

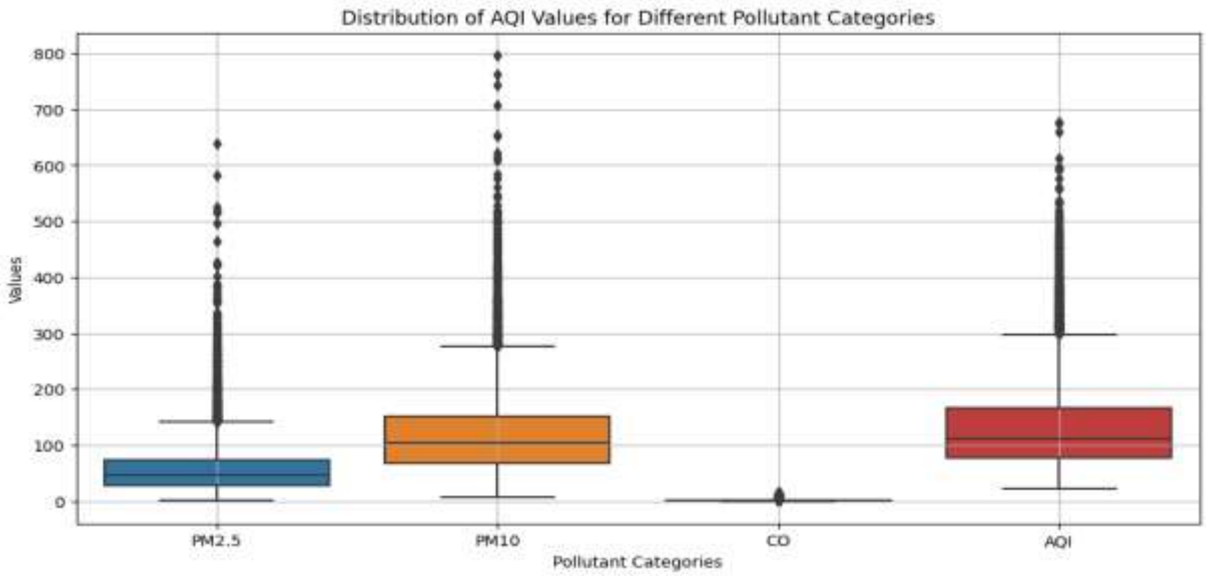
```
plt.bar(df['Date'], df['CO'], bottom=df['PM2.5'] + df['PM10'], label='CO', color='g', width=bar_width)

plt.xlabel('Date')

plt.ylabel('Pollutant Levels')

plt.title('Stacked Bar Plot of AQI Values with Different Pollutants Across Dates')

plt.xticks(rotation=90)

plt.legend()

plt.grid(True)

plt.show()
```



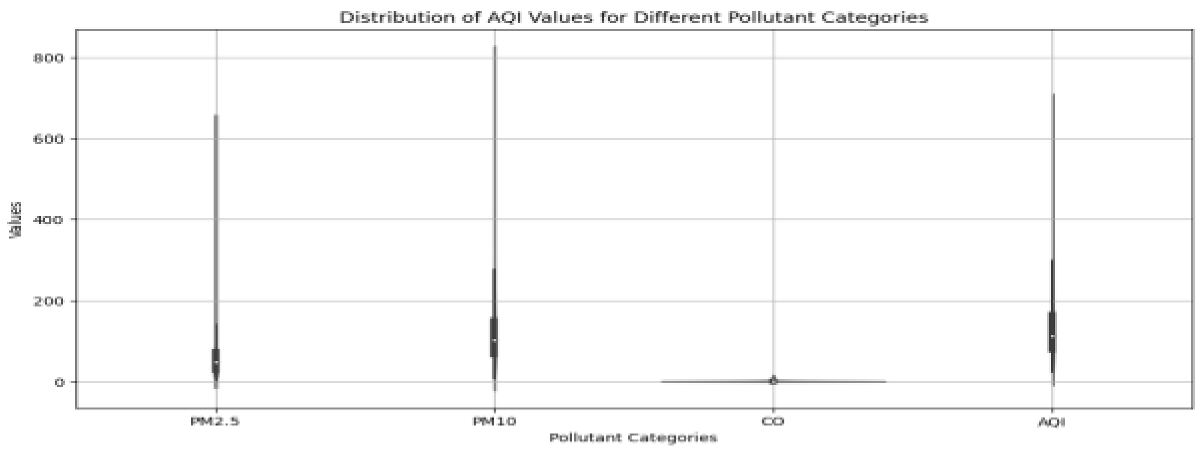
Step No. 7 - Create box plots or violin plots to analyze the distribution of AQI values for different pollutant categories.

```
# Create box plot for AQI values by pollutant categories

plt.figure(figsize=(12, 6))

sns.boxplot(data=df[['PM2.5', 'PM10', 'CO', 'AQI']])

plt.xlabel('Pollutant Categories')

plt.ylabel('Values')

plt.title('Distribution of AQI Values for Different Pollutant Categories')
```

```
plt.grid(True)

plt.show()
```

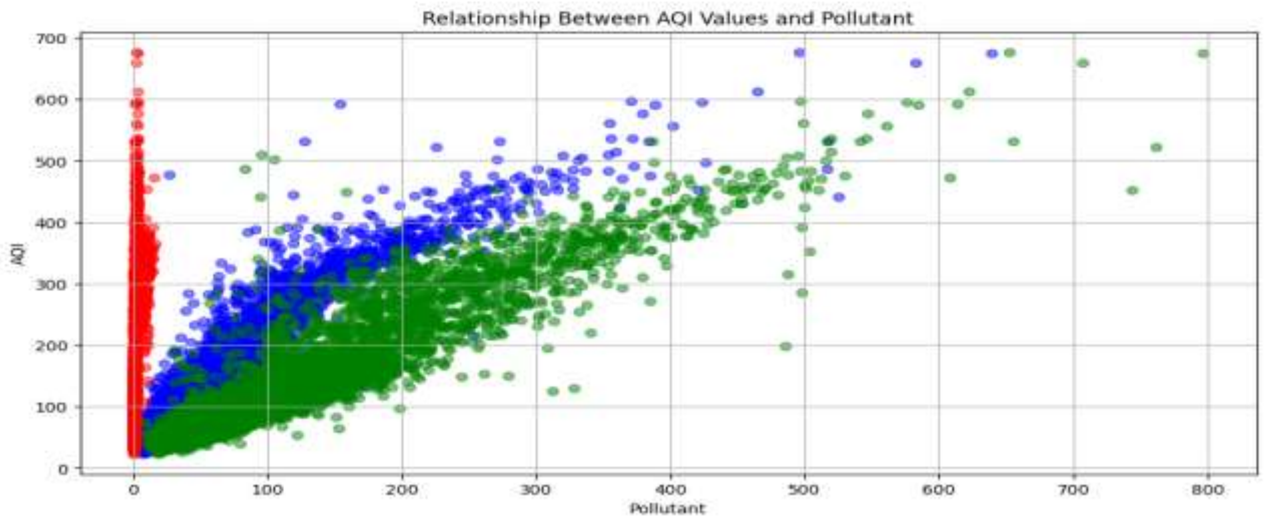



```
# Create violin plot for AQI values by pollutant categories

plt.figure(figsize=(12, 6))

sns.violinplot(data=df[['PM2.5', 'PM10', 'CO', 'AQI']])

plt.xlabel('Pollutant Categories')

plt.ylabel('Values')

plt.title('Distribution of AQI Values for Different Pollutant Categories')

plt.grid(True)

plt.show()
```



Step No. 8 - Use scatter plots or bubble charts to explore the relationship between AQI values and pollutant levels.

```
# Scatter plot for AQI values vs. Pollutants

plt.figure(figsize=(12, 6))

plt.scatter(df['PM2.5'], df['AQI'], alpha=0.5, color='b')

plt.scatter(df['PM10'], df['AQI'], alpha=0.5, color='g')

plt.scatter(df['CO'], df['AQI'], alpha=0.5, color='r')

plt.xlabel('Pollutant')

plt.ylabel('AQI')

plt.title('Relationship Between AQI Values and Pollutant')

plt.grid(True)

plt.show()
```




```
plt.figure(figsize=(12, 6))

plt.scatter(df['PM2.5'], df['AQI'], s=df['CO']*10, alpha=0.5, color='b', edgecolors='w', linewidth=0.5, label='PM2.5')

plt.scatter(df['PM10'], df['AQI'], s=df['CO']*10, alpha=0.5, color='g', edgecolors='w', linewidth=0.5, label='PM10')
```

plt.scatter(df['CO'], df['AQI'], s=df['CO']*10, alpha=0.5, color='r', edgecolors='w', linewidth=0.5, label='CO')

plt.xlabel('Pollutant Level')

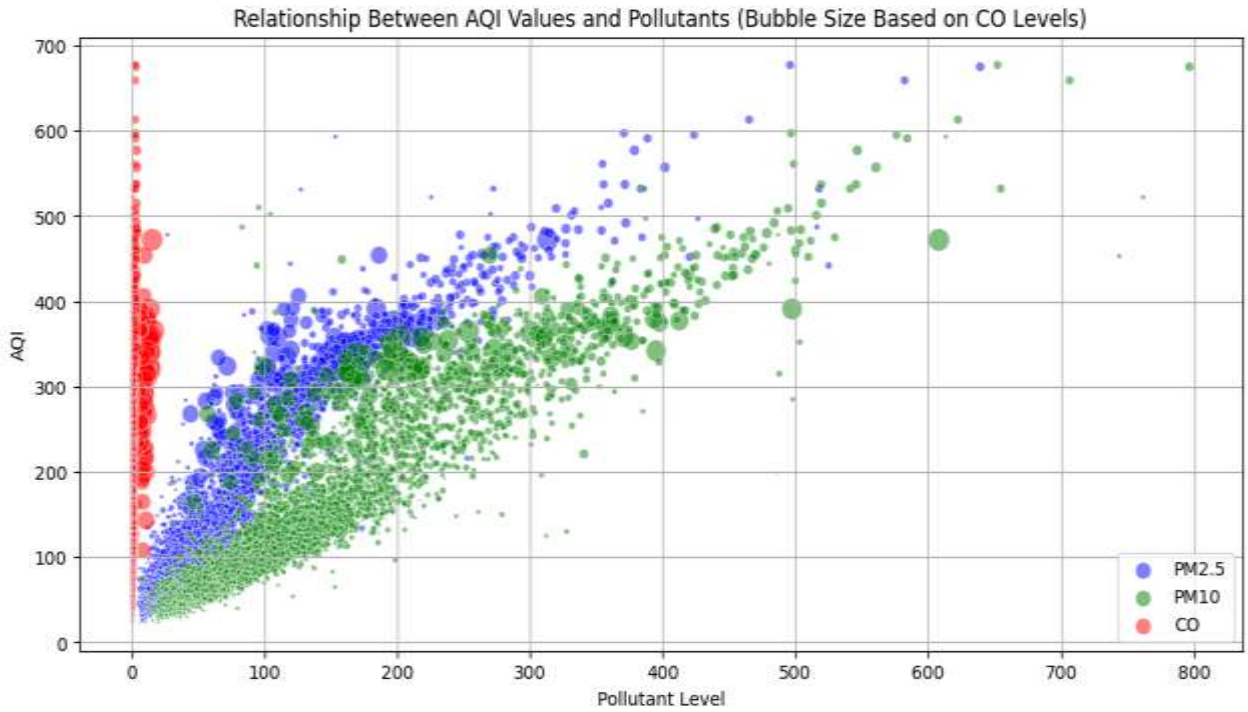
plt.ylabel('AQI')

plt.title('Relationship Between AQI Values and Pollutants (Bubble Size Based on CO Levels)')

plt.legend(loc='best')

plt.grid(True)

plt.show()



Conclusion : We can successfully analyzing Air Quality Index [AQI] trends in a city on a "Air_Quality.csv" dataset, also we can visualizing various AQI trends easily by using matplotlib.