```python
# Importing libraries and Dataset
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
from sklearn.preprocessing import LabelEncoder
warnings.filterwarnings("ignore")
AQI_df= pd.read_csv('Datasets/AQI Dataset.csv')
AQI_df.sample(10)
```

```
             City             Datetime  PM2.5    PM10     NO    NO2
NOx  \
526783     Mumbai  2015-05-02 18:00:00    NaN     NaN    NaN    NaN
29.00
407418     Jaipur  2018-07-29 03:00:00  37.78  125.08   8.72  20.62
29.34
293150      Delhi  2020-06-22 03:00:00  48.31   90.54   4.64  16.67
14.20
74207    Amritsar  2017-03-22 11:00:00  75.69  129.66  10.21  27.24
NaN
335905   Gurugram  2020-04-26 16:00:00  50.64   73.66   2.55   7.72
5.30
138833  Bengaluru  2019-02-05 05:00:00  35.30   65.40   4.20  18.83
15.99
399734     Jaipur  2017-09-11 23:00:00  34.80  165.30   4.21  27.33
NaN
480421    Lucknow  2015-07-18 00:00:00  24.47     NaN   3.72   9.73
4.22
709178  Ahmedabad           2018-07-27  35.80     NaN  29.72  48.89
46.03
206629    Chennai  2017-02-25 15:00:00  35.43     NaN   6.68  12.05
11.37

          NH3     CO    SO2     O3  Benzene  Toluene  Xylene    AQI  \
526783    NaN   0.00    NaN    NaN     0.00     0.00    0.00    NaN
407418   7.23   0.36   8.55  10.73     0.30     1.07     NaN  112.0
293150  36.33   0.81  10.95  27.25     1.52    10.69    0.27   97.0
74207   12.73   0.00   0.86  13.87      NaN      NaN     NaN   86.0
335905  24.93   0.48   6.60  68.23     5.96     1.36    2.15  128.0
138833  15.48   0.47   4.22  66.08     0.35     0.85     NaN   76.0
399734  17.09   0.24   8.30  47.87     0.00     0.36     NaN  113.0
480421    NaN   5.43   3.18  29.47     0.04     0.06     NaN  134.0
709178    NaN  29.72  19.94    NaN     5.77    26.88    0.65  458.0
206629    NaN   0.35   4.52  28.20     0.46     0.00     NaN   65.0

       AQI_Bucket
526783        NaN
407418   Moderate
```

```
293150  Satisfactory
74207   Satisfactory
335905      Moderate
138833  Satisfactory
399734      Moderate
480421      Moderate
709178        Severe
206629  Satisfactory
```

```
AQI_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 737406 entries, 0 to 737405
Data columns (total 16 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   City        737406 non-null  object 
 1   Datetime    737406 non-null  object 
 2   PM2.5       587720 non-null  float64
 3   PM10        429529 non-null  float64
 4   NO          617192 non-null  float64
 5   NO2         616699 non-null  float64
 6   NOx         609997 non-null  float64
 7   NH3         454536 non-null  float64
 8   CO          648830 non-null  float64
 9   SO2         603179 non-null  float64
 10  O3          604176 non-null  float64
 11  Benzene     568137 non-null  float64
 12  Toluene     508758 non-null  float64
 13  Xylene      263468 non-null  float64
 14  AQI         603645 non-null  float64
 15  AQI_Bucket  603645 non-null  object 
dtypes: float64(13), object(3)
memory usage: 90.0+ MB
```

```
AQI_df.shape
```

```
(737406, 16)
```

```
#Checking null values
null_values=AQI_df.isnull().sum()
missing_percentage = (AQI_df.isnull().sum() / len(AQI_df)) * 100
print(null_values)
print(missing_percentage)
```

```
City                0
Datetime            0
PM2.5          149686
PM10           307877
NO             120214
NO2            120707
```

```
NOx             127409
NH3             282870
CO               88576
SO2             134227
O3              133230
Benzene         169269
Toluene         228648
Xylene          473938
AQI             133761
AQI_Bucket      133761
dtype: int64
City             0.000000
Datetime         0.000000
PM2.5           20.298994
PM10            41.751355
NO              16.302281
NO2             16.369137
NOx             17.277999
NH3             38.360144
CO              12.011836
SO2             18.202591
O3              18.067388
Benzene         22.954655
Toluene         31.007071
Xylene          64.270971
AQI             18.139397
AQI_Bucket      18.139397
dtype: float64

# Since Xylene column has almost 64% null values therefore we remove
it from our dataset
AQI_df.drop(['Xylene'], axis=1, inplace=True)

AQI_df.head()

        City             Datetime  PM2.5  PM10    NO    NO2    NOx
NH3    CO  \
0  Ahmedabad  2015-01-01 01:00:00    NaN   NaN  1.00  40.01  36.37
NaN  1.00
1  Ahmedabad  2015-01-01 02:00:00    NaN   NaN  0.02  27.75  19.73
NaN  0.02
2  Ahmedabad  2015-01-01 03:00:00    NaN   NaN  0.08  19.32  11.08
NaN  0.08
3  Ahmedabad  2015-01-01 04:00:00    NaN   NaN  0.30  16.45   9.20
NaN  0.30
4  Ahmedabad  2015-01-01 05:00:00    NaN   NaN  0.12  14.90   7.85
NaN  0.12

      SO2      O3  Benzene  Toluene  AQI AQI_Bucket
0  122.07     NaN      0.0      0.0  NaN        NaN
```

```
1   85.90     NaN      0.0      0.0  NaN         NaN
2   52.83     NaN      0.0      0.0  NaN         NaN
3   39.53  153.58      0.0      0.0  NaN         NaN
4   32.63     NaN      0.0      0.0  NaN         NaN
```

```
AQI_df.isnull().sum()
```

```
City               0
Datetime           0
PM2.5         149686
PM10          307877
NO            120214
NO2           120707
NOx           127409
NH3           282870
CO             88576
SO2           134227
O3            133230
Benzene       169269
Toluene       228648
AQI           133761
AQI_Bucket    133761
dtype: int64
```

```
AQI_df.dropna(inplace=True)
```

```
AQI_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 239322 entries, 48220 to 737404
Data columns (total 15 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   City        239322 non-null  object
 1   Datetime    239322 non-null  object
 2   PM2.5       239322 non-null  float64
 3   PM10        239322 non-null  float64
 4   NO          239322 non-null  float64
 5   NO2         239322 non-null  float64
 6   NOx         239322 non-null  float64
 7   NH3         239322 non-null  float64
 8   CO          239322 non-null  float64
 9   SO2         239322 non-null  float64
 10  O3          239322 non-null  float64
 11  Benzene     239322 non-null  float64
 12  Toluene     239322 non-null  float64
 13  AQI         239322 non-null  float64
 14  AQI_Bucket  239322 non-null  object
dtypes: float64(12), object(3)
memory usage: 29.2+ MB
```

```python
# Detecting numerical and categorical columns
numerical_cols = AQI_df.select_dtypes(include=['number']).columns
categorical_cols = AQI_df.select_dtypes(include=['object']).columns
print(numerical_cols)
print(categorical_cols)
```

```
Index(['PM2.5', 'PM10', 'NO', 'NO2', 'NOx', 'NH3', 'CO', 'SO2', 'O3',
       'Benzene', 'Toluene', 'AQI'],
      dtype='object')
Index(['City', 'Datetime', 'AQI_Bucket'], dtype='object')
```

```python
AQI_df.shape
```

```
(239322, 15)
```

```python
AQI_df.isnull().sum()
```

```
City          0
Datetime      0
PM2.5         0
PM10          0
NO            0
NO2           0
NOx           0
NH3           0
CO            0
SO2           0
O3            0
Benzene       0
Toluene       0
AQI           0
AQI_Bucket    0
dtype: int64
```

```python
AQI_df.head()
```

```
        City            Datetime  PM2.5   PM10    NO   NO2    NOx
NH3  \
48220  Aizawl  2020-03-12 13:00:00   25.0  31.11  7.14  1.86  11.28
24.00
48221  Aizawl  2020-03-12 14:00:00   19.0  29.17  7.32  1.15  10.85
27.59
48222  Aizawl  2020-03-12 15:00:00   24.0  30.00  7.14  1.04  10.51
31.13
48223  Aizawl  2020-03-12 16:00:00   25.0  32.08  7.20  1.19  10.74
33.31
48224  Aizawl  2020-03-12 17:00:00   33.0  41.00  7.22  1.37  10.93
30.05

        CO   SO2    O3  Benzene  Toluene   AQI    AQI_Bucket
48220  0.42  4.31  0.76      0.0      0.0  51.0  Satisfactory
```

```
48221  0.44  4.65  0.07      0.0      0.0  52.0  Satisfactory
48222  0.43  4.83  0.67      0.0      0.0  52.0  Satisfactory
48223  0.46  5.26  0.05      0.0      0.0  53.0  Satisfactory
48224  0.50  5.39  0.02      0.0      0.0  54.0  Satisfactory
```

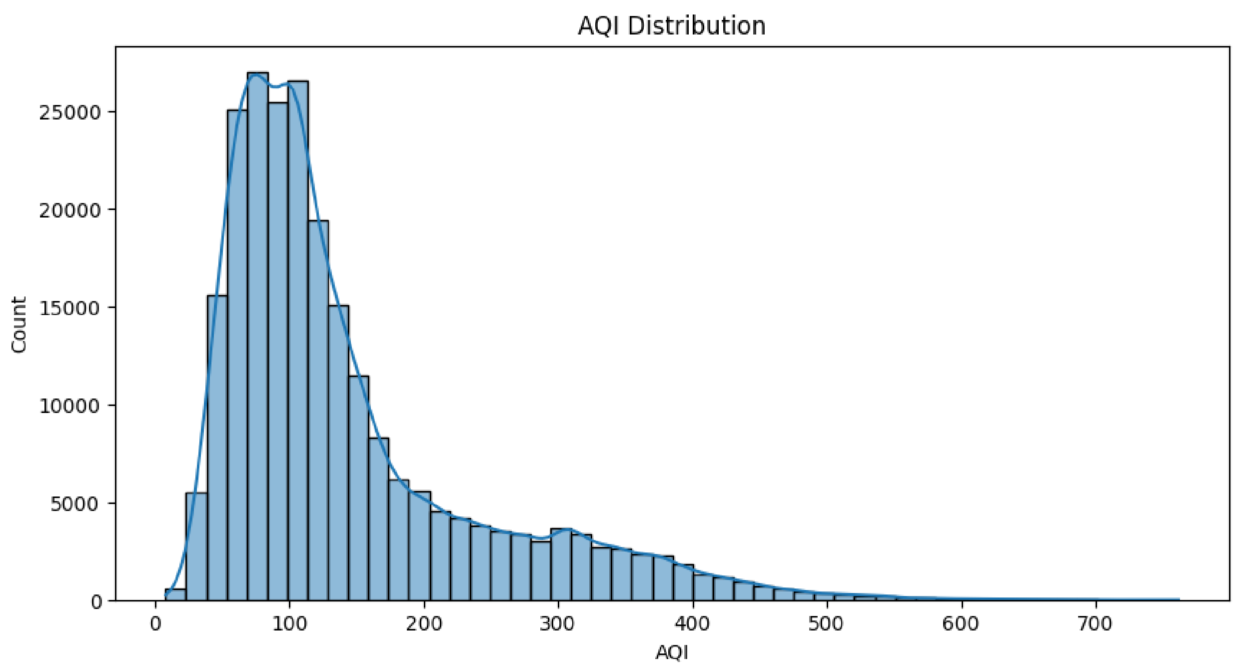
```
AQI_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 239322 entries, 48220 to 737404
Data columns (total 15 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   City        239322 non-null  object
 1   Datetime    239322 non-null  object
 2   PM2.5       239322 non-null  float64
 3   PM10        239322 non-null  float64
 4   NO          239322 non-null  float64
 5   NO2         239322 non-null  float64
 6   NOx         239322 non-null  float64
 7   NH3         239322 non-null  float64
 8   CO          239322 non-null  float64
 9   SO2         239322 non-null  float64
 10  O3          239322 non-null  float64
 11  Benzene     239322 non-null  float64
 12  Toluene     239322 non-null  float64
 13  AQI         239322 non-null  float64
 14  AQI_Bucket  239322 non-null  object
dtypes: float64(12), object(3)
memory usage: 29.2+ MB
```

```
# Printing the mean and median values of all the numerical columns
mean_values=AQI_df[numerical_cols].mean()
median_values=AQI_df[numerical_cols].median()
print(mean_values)
print(median_values)
```

```
PM2.5       61.813510
PM10       125.092535
NO          18.531356
NO2         33.339782
NOx         36.262404
NH3         23.418141
CO           1.027775
SO2         11.270571
O3          38.721834
Benzene      4.055001
Toluene      9.854879
AQI        143.422594
dtype: float64
PM2.5       44.12
```

```
PM10           95.80
NO              7.98
NO2            26.88
NOx            24.49
NH3            18.05
CO              0.74
SO2             8.64
O3             31.05
Benzene         1.50
Toluene         4.33
AQI           110.00
dtype: float64

# Plot for frequency of AQI
plt.figure(figsize=(10, 5))
sns.histplot(AQI_df['AQI'], bins=50, kde=True)
plt.title("AQI Distribution")
plt.show()
```



The above graph shows that:-

1. The highest frequency is for AQI values between 0 and 100, suggesting that most recorded air quality falls within Good to Satisfactory levels
2. The frequency sharply declines as AQI increases beyond 400, meaning that severe pollution events are rare but present
3. A few data points exceed 550+ AQI, which are extreme pollution levels (possibly due to industrial areas, wildfires, duststorms, etc.)

```
AQI_df.shape
```

```
(239322, 15)

# Check for any null values remaining
(AQI_df[numerical_cols]==0.0).sum()

PM2.5          0
PM10           0
NO             0
NO2            0
NOx         4365
NH3            0
CO          3900
SO2            0
O3             0
Benzene    13790
Toluene    11598
AQI            0
dtype: int64

#Since the distribution is skewed we will use median to replace the
0.0 values of the dataset
AQI_df[numerical_cols] = AQI_df[numerical_cols].replace(0.0,
AQI_df[numerical_cols].median())

(AQI_df[numerical_cols]==0.0).sum()

PM2.5      0
PM10       0
NO         0
NO2        0
NOx        0
NH3        0
CO         0
SO2        0
O3         0
Benzene    0
Toluene    0
AQI        0
dtype: int64

AQI_df.head()

         City             Datetime  PM2.5   PM10    NO   NO2    NOx
NH3  \
48220  Aizawl  2020-03-12 13:00:00   25.0  31.11  7.14  1.86  11.28
24.00
48221  Aizawl  2020-03-12 14:00:00   19.0  29.17  7.32  1.15  10.85
27.59
48222  Aizawl  2020-03-12 15:00:00   24.0  30.00  7.14  1.04  10.51
31.13
48223  Aizawl  2020-03-12 16:00:00   25.0  32.08  7.20  1.19  10.74
```

```
33.31
48224  Aizawl  2020-03-12 17:00:00   33.0  41.00  7.22  1.37  10.93
30.05

         CO   SO2    O3  Benzene  Toluene   AQI    AQI_Bucket
48220  0.42  4.31  0.76      1.5     4.33  51.0  Satisfactory
48221  0.44  4.65  0.07      1.5     4.33  52.0  Satisfactory
48222  0.43  4.83  0.67      1.5     4.33  52.0  Satisfactory
48223  0.46  5.26  0.05      1.5     4.33  53.0  Satisfactory
48224  0.50  5.39  0.02      1.5     4.33  54.0  Satisfactory
```

```python
AQI_df.info()
```

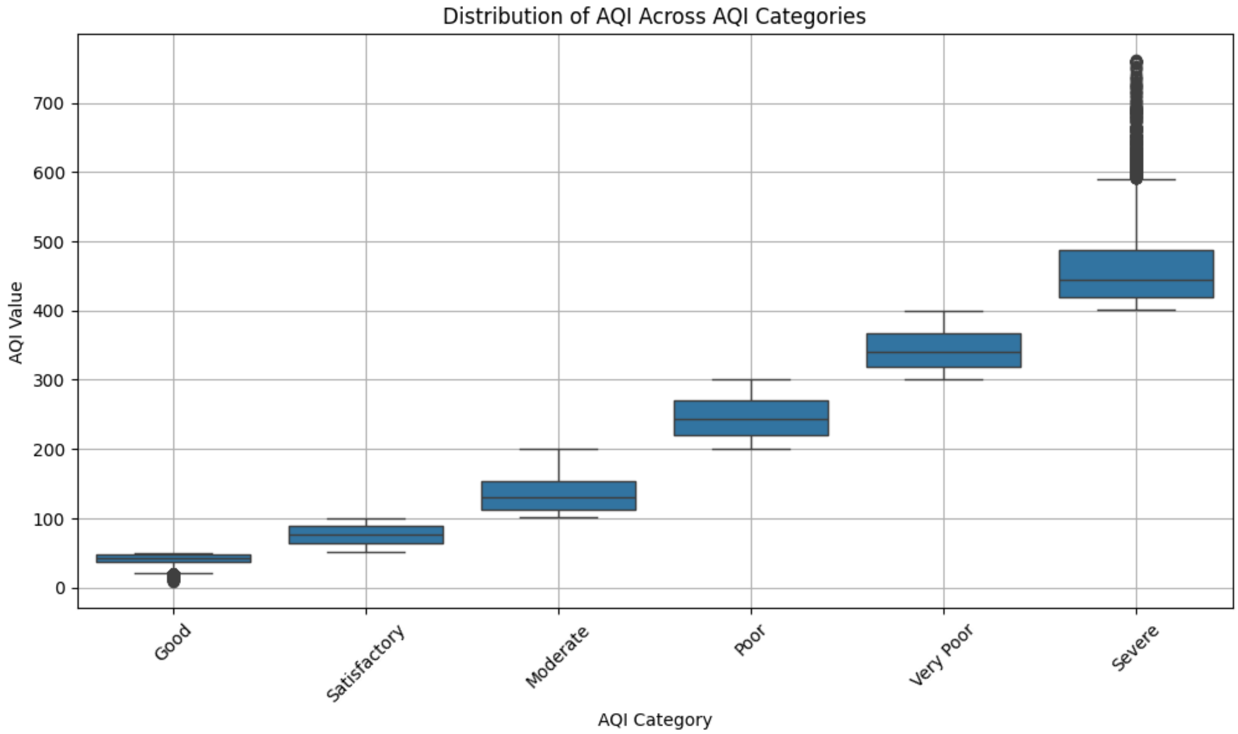
```
<class 'pandas.core.frame.DataFrame'>
Index: 239322 entries, 48220 to 737404
Data columns (total 15 columns):
 #   Column      Non-Null Count   Dtype  
---  ------      --------------   -----  
 0   City        239322 non-null  object 
 1   Datetime    239322 non-null  object 
 2   PM2.5       239322 non-null  float64
 3   PM10        239322 non-null  float64
 4   NO          239322 non-null  float64
 5   NO2         239322 non-null  float64
 6   NOx         239322 non-null  float64
 7   NH3         239322 non-null  float64
 8   CO          239322 non-null  float64
 9   SO2         239322 non-null  float64
 10  O3          239322 non-null  float64
 11  Benzene     239322 non-null  float64
 12  Toluene     239322 non-null  float64
 13  AQI         239322 non-null  float64
 14  AQI_Bucket  239322 non-null  object 
dtypes: float64(12), object(3)
memory usage: 29.2+ MB
```

```python
#Identifying unique AQI categories
aqi_buckets = AQI_df['AQI_Bucket'].unique()
print("Unique AQI Categories:", aqi_buckets)
```

```
Unique AQI Categories: ['Satisfactory' 'Good' 'Moderate' 'Poor' 'Very
Poor' 'Severe']
```

```python
# Plot to show how AQI is distributed among diff AQI categories
plt.figure(figsize=(12, 6))
sns.boxplot(x='AQI_Bucket', y='AQI', data=AQI_df, order=['Good',
'Satisfactory', 'Moderate', 'Poor', 'Very Poor', 'Severe'])
plt.title("Distribution of AQI Across AQI Categories")
plt.xlabel("AQI Category")
plt.ylabel("AQI Value")
```

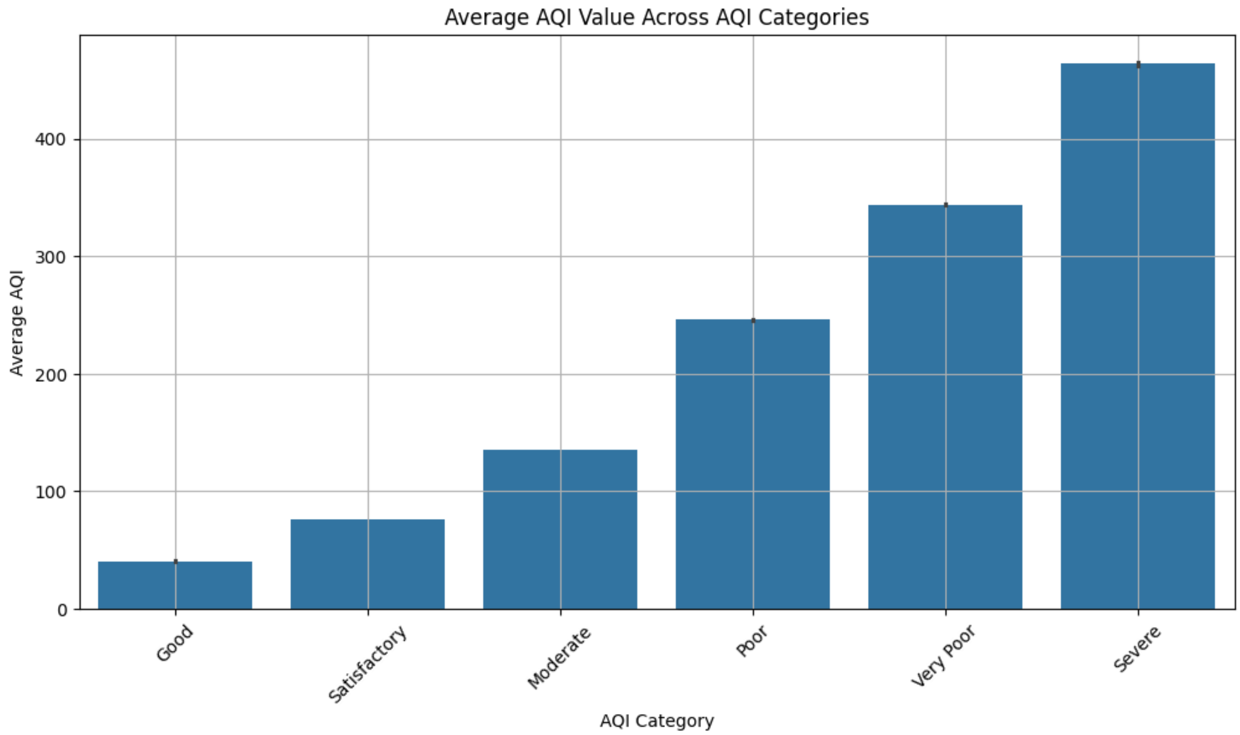
```
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



The above graph shows that:-

1. AQI lying in Severe pollution is highly variable (500<AQI<700+).
2. Box sizes increase with pollution severity, indicating higher variation in bad air quality.
3. Some unexpectedly high AQI values appear even in the Satisfactory and Moderate categories.

```
# Plot to show average AQI values in all the categories
plt.figure(figsize=(12, 6))
sns.barplot(x='AQI_Bucket', y='AQI', data=AQI_df, estimator=lambda x:
x.mean(), order=['Good', 'Satisfactory', 'Moderate', 'Poor', 'Very
Poor', 'Severe'])
plt.title("Average AQI Value Across AQI Categories")
plt.xlabel("AQI Category")
plt.ylabel("Average AQI")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



The above graph shows that:-

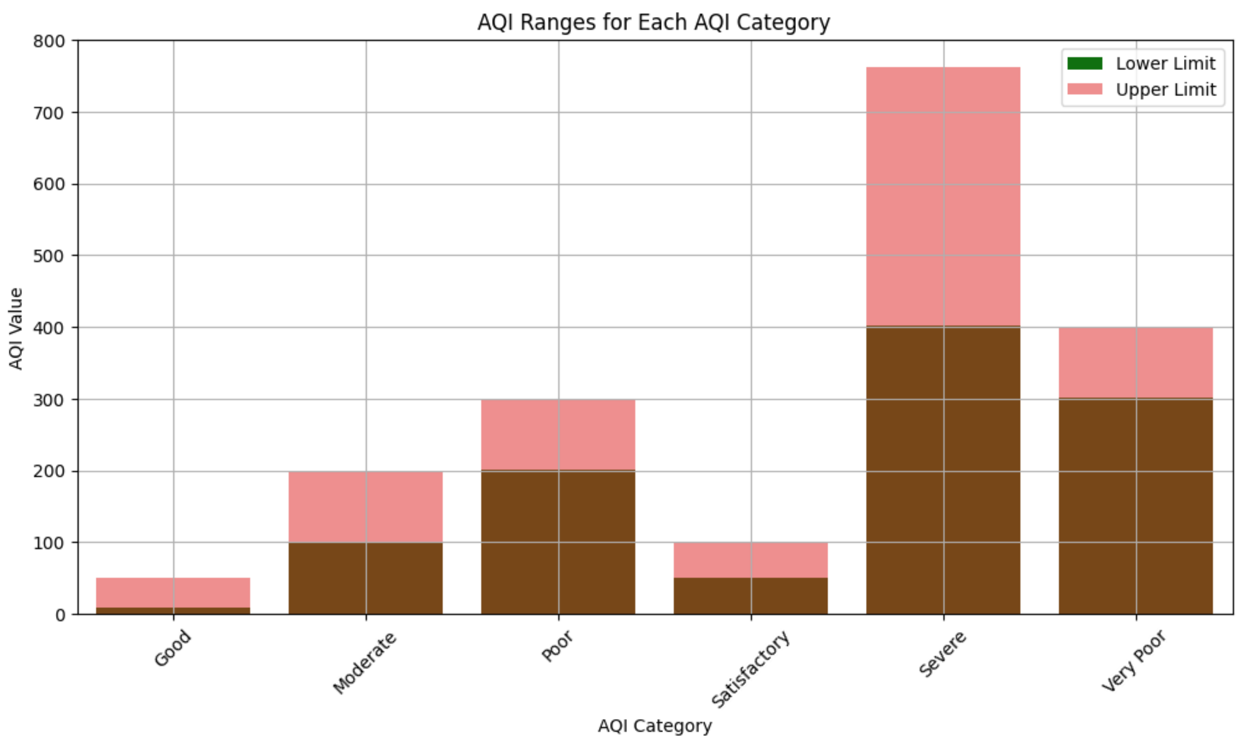
1. The transition from Good to Satisfactory to Moderate is more gradual.
2. The largest jumps occur in "Very Poor" and "Severe" categories.

```
# Finding the limits of AQI lying into AQI categories
aqi_limits = AQI_df.groupby('AQI_Bucket')['AQI'].agg(['min',
'max']).reset_index()
aqi_limits.columns = ['AQI_Bucket', 'Lower_Limit', 'Upper_Limit']
print(aqi_limits)
```

```
     AQI_Bucket  Lower_Limit  Upper_Limit
0          Good          8.0         50.0
1      Moderate        101.0        200.0
2          Poor        201.0        300.0
3  Satisfactory         51.0        100.0
4        Severe        401.0        762.0
5     Very Poor        301.0        400.0
```

```
# Plot to show upper limit and lower limit for each AQI category
plt.figure(figsize=(12, 6))
sns.barplot(x='AQI_Bucket', y='Lower_Limit', data=aqi_limits,
color='green', label="Lower Limit")
sns.barplot(x='AQI_Bucket', y='Upper_Limit', data=aqi_limits,
color='red', alpha=0.5, label="Upper Limit")
plt.title("AQI Ranges for Each AQI Category")
plt.xlabel("AQI Category")
plt.ylabel("AQI Value")
```

```
plt.xticks(rotation=45)
plt.legend()
plt.grid(True)
plt.show()
```



The above graph shows that:-

1. The Severe category has a massive spread, with AQI going far beyond 500. This suggests some extreme pollution events or highly polluted cities.
2. Lower & Upper Limits Vary for Each Category
3. Lower limits (brown) are consistent with AQI guidelines.
4. Upper limits (pink) are much higher in "Severe" due to outliers.
5. Most categories have stable AQI ranges, but the "Severe" category is highly volatile.

```
AQI_df['AQI_Bucket'].isnull().sum()
```

```
np.int64(0)
```

```
AQI_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 239322 entries, 48220 to 737404
Data columns (total 15 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   City        239322 non-null  object
 1   Datetime    239322 non-null  object
```

```
 2   PM2.5       239322 non-null  float64
 3   PM10        239322 non-null  float64
 4   NO          239322 non-null  float64
 5   NO2         239322 non-null  float64
 6   NOx         239322 non-null  float64
 7   NH3         239322 non-null  float64
 8   CO          239322 non-null  float64
 9   SO2         239322 non-null  float64
 10  O3          239322 non-null  float64
 11  Benzene     239322 non-null  float64
 12  Toluene     239322 non-null  float64
 13  AQI         239322 non-null  float64
 14  AQI_Bucket  239322 non-null  object
dtypes: float64(12), object(3)
memory usage: 29.2+ MB
```

```
AQI_df.shape
```

```
(239322, 15)
```

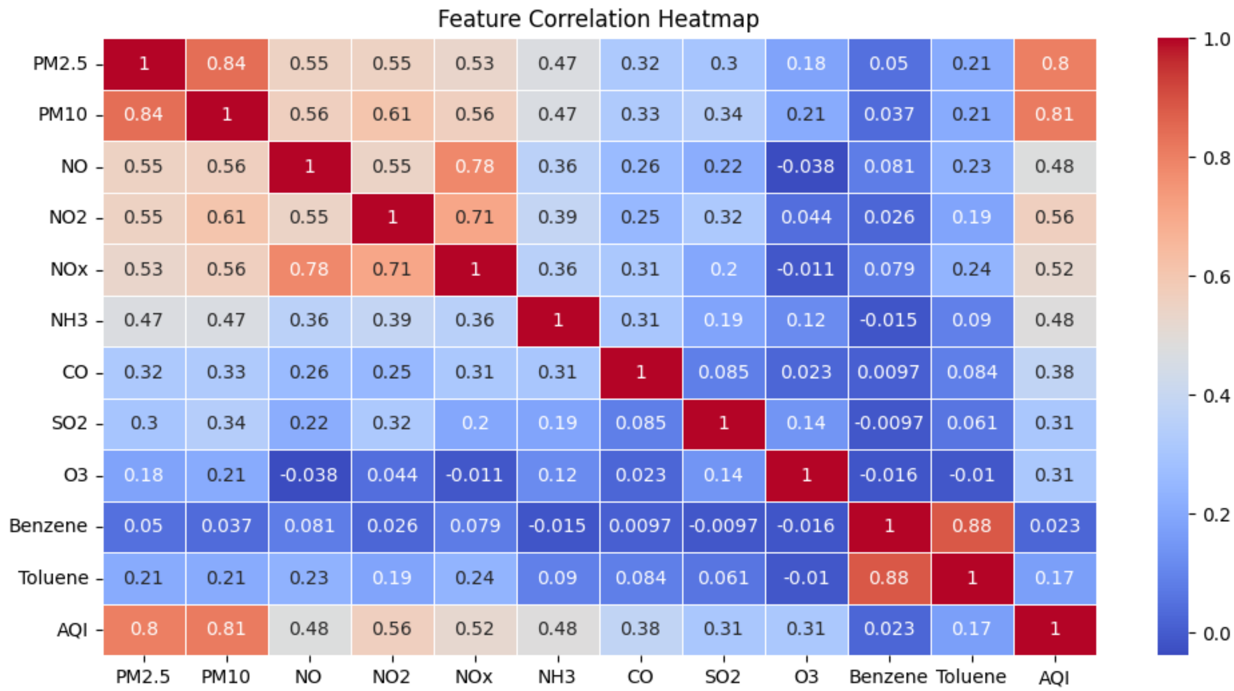
```
AQI_df.isnull().sum()
```

```
City          0
Datetime      0
PM2.5         0
PM10          0
NO            0
NO2           0
NOx           0
NH3           0
CO            0
SO2           0
O3            0
Benzene       0
Toluene       0
AQI           0
AQI_Bucket    0
dtype: int64
```

```
AQI_df.head()
```

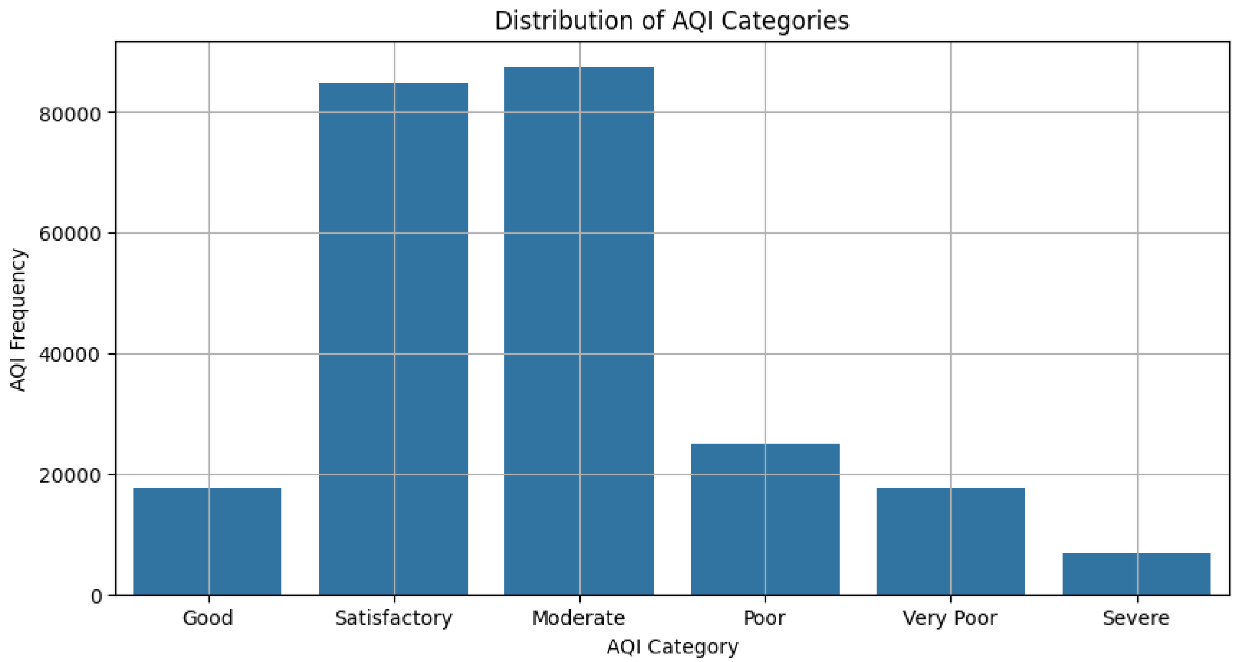
```
         City             Datetime  PM2.5   PM10    NO   NO2    NOx
NH3  \
48220  Aizawl  2020-03-12 13:00:00   25.0  31.11  7.14  1.86  11.28
24.00
48221  Aizawl  2020-03-12 14:00:00   19.0  29.17  7.32  1.15  10.85
27.59
48222  Aizawl  2020-03-12 15:00:00   24.0  30.00  7.14  1.04  10.51
31.13
48223  Aizawl  2020-03-12 16:00:00   25.0  32.08  7.20  1.19  10.74
33.31
```

```
48224  Aizawl  2020-03-12 17:00:00   33.0  41.00  7.22  1.37  10.93
30.05

         CO   SO2    O3  Benzene  Toluene   AQI    AQI_Bucket
48220  0.42  4.31  0.76      1.5     4.33  51.0  Satisfactory
48221  0.44  4.65  0.07      1.5     4.33  52.0  Satisfactory
48222  0.43  4.83  0.67      1.5     4.33  52.0  Satisfactory
48223  0.46  5.26  0.05      1.5     4.33  53.0  Satisfactory
48224  0.50  5.39  0.02      1.5     4.33  54.0  Satisfactory

AQI_df.describe()

               PM2.5           PM10             NO            NO2  \
count  239322.000000  239322.000000  239322.000000  239322.000000
mean       61.813510     125.092535      18.531356      33.339782
std        62.803755     103.770181      33.829649      25.601033
min         0.010000       0.010000       0.010000       0.010000
25%        25.550000      58.000000       3.800000      15.340000
50%        44.120000      95.800000       7.980000      26.880000
75%        72.980000     153.190000      16.770000      43.930000
max       999.990000    1000.000000     498.970000     380.020000

                 NOx            NH3             CO            SO2  \
count  239322.000000  239322.000000  239322.000000  239322.000000
mean       36.709078      23.418141       1.039834      11.270571
std        40.002762      18.960396       1.464409      10.426656
min         0.010000       0.010000       0.010000       0.010000
25%        14.780000      11.140000       0.500000       5.530000
50%        24.490000      18.050000       0.740000       8.640000
75%        41.900000      30.600000       1.090000      13.330000
max       493.400000     485.820000      47.420000     199.930000

                  O3        Benzene        Toluene            AQI
count  239322.000000  239322.000000  239322.000000  239322.000000
mean       38.721834       4.141433      10.064720     143.422594
std        29.183399      21.101855      23.906228      99.630428
min         0.010000       0.010000       0.010000       8.000000
25%        17.810000       0.630000       1.820000      76.000000
50%        31.050000       1.500000       4.330000     110.000000
75%        52.430000       3.630000      10.910000     173.000000
max       497.620000     498.070000     498.070000     762.000000

# Plot ot show the correlation between the pollutants and AQI
plt.figure(figsize=(12, 6))
numerical_columns = AQI_df.select_dtypes(include=['number'])
correlation=numerical_columns.corr()
sns.heatmap(correlation, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title("Feature Correlation Heatmap")
plt.show()
```

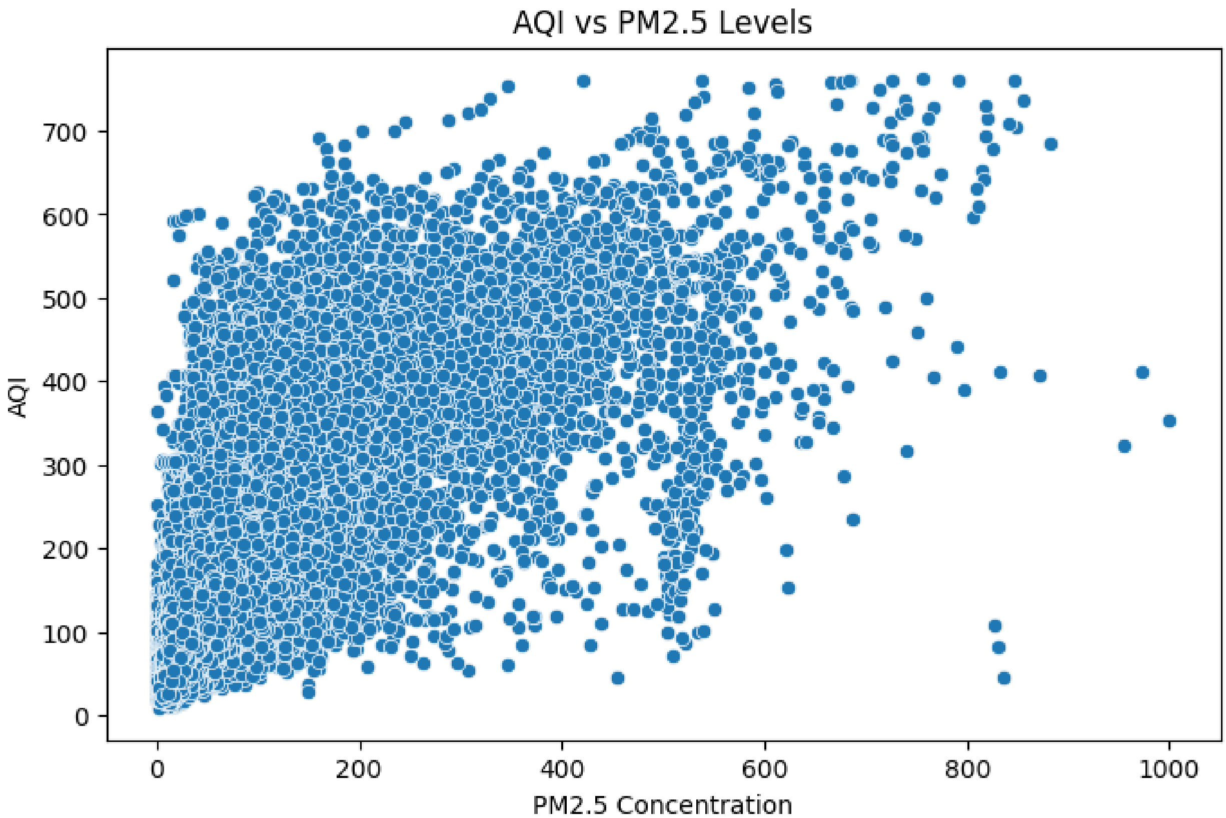


1. PM10 and PM2.5 Has the Highest Correlation with AQI (0.80). Indicates that PM10 and PM2.5 is a major contributor to AQI levels incerasing pollution.
2. NO2 also Strongly Correlates with AQI (0.56).
3. NH3 and NOx Show Moderate Correlation with AQI (~0.48-0.52). NH3 (Ammonia) and NOx (Nitrogen Oxides) have a moderate impact on air quality.
4. Toluene and Benzene Are Highly Correlated (0.68) same for NOx and NO (0.78)
5. Other Pollutants Show Lower Correlation with AQI. Like toluene (0.17), SO_2 (0.31), and Benzene (0.023)

```
# Frequencies of AQI in diff AQI categories
plt.figure(figsize=(10, 5))
sns.countplot(x='AQI_Bucket', data=AQI_df, order=['Good',
'Satisfactory', 'Moderate', 'Poor', 'Very Poor', 'Severe'])
plt.title("Distribution of AQI Categories")
plt.xlabel("AQI Category")
plt.ylabel("AQI Frequency")
plt.grid(True)
plt.show()
```

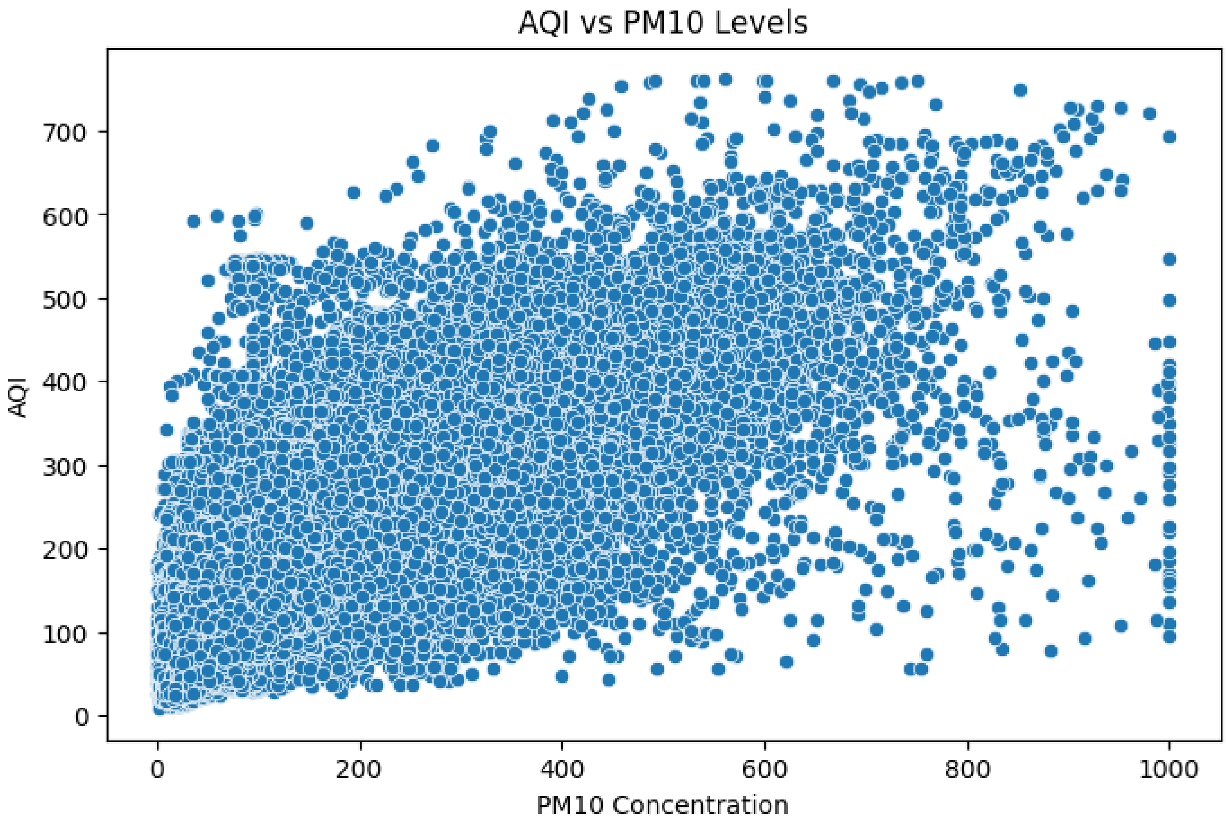



```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='PM2.5', y='AQI', data=AQI_df)
plt.title("AQI vs PM2.5 Levels")
plt.xlabel("PM2.5 Concentration")
plt.ylabel("AQI")
plt.show()
```

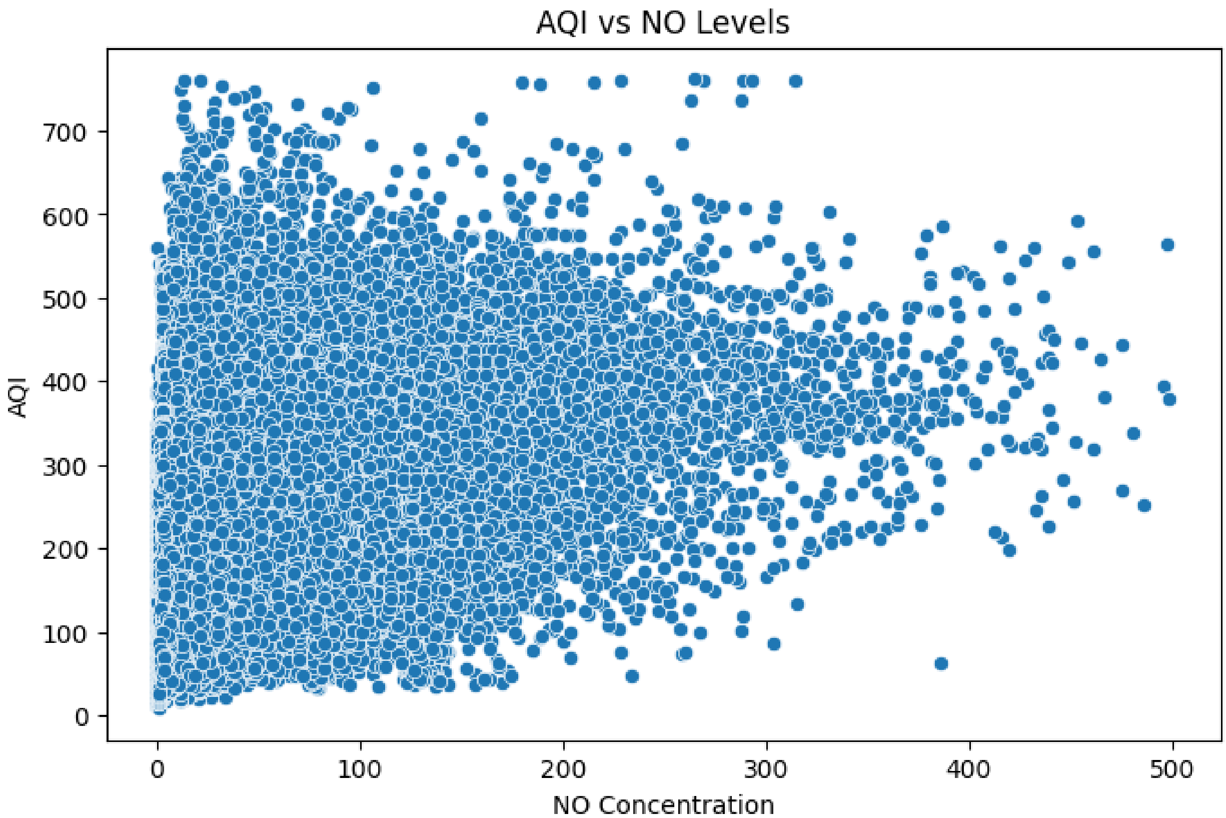


1. AQI increases significantly as PM2.5 concentration rises up to ~200 µg/m³. Indicates that PM2.5 is a major contributor to AQI levels in this ranges.
2. After 200 µg/m³, AQI does not increase proportionally with PM2.5. This suggests a saturation effect, where other pollutants (like CO, NO_2) also play a role
3. A few points show extreme AQI values (>700), despite lower PM2.5 concentrations.

```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='PM10', y='AQI', data=AQI_df)
plt.title("AQI vs PM10 Levels")
plt.xlabel("PM10 Concentration")
plt.ylabel("AQI")
plt.show()
```

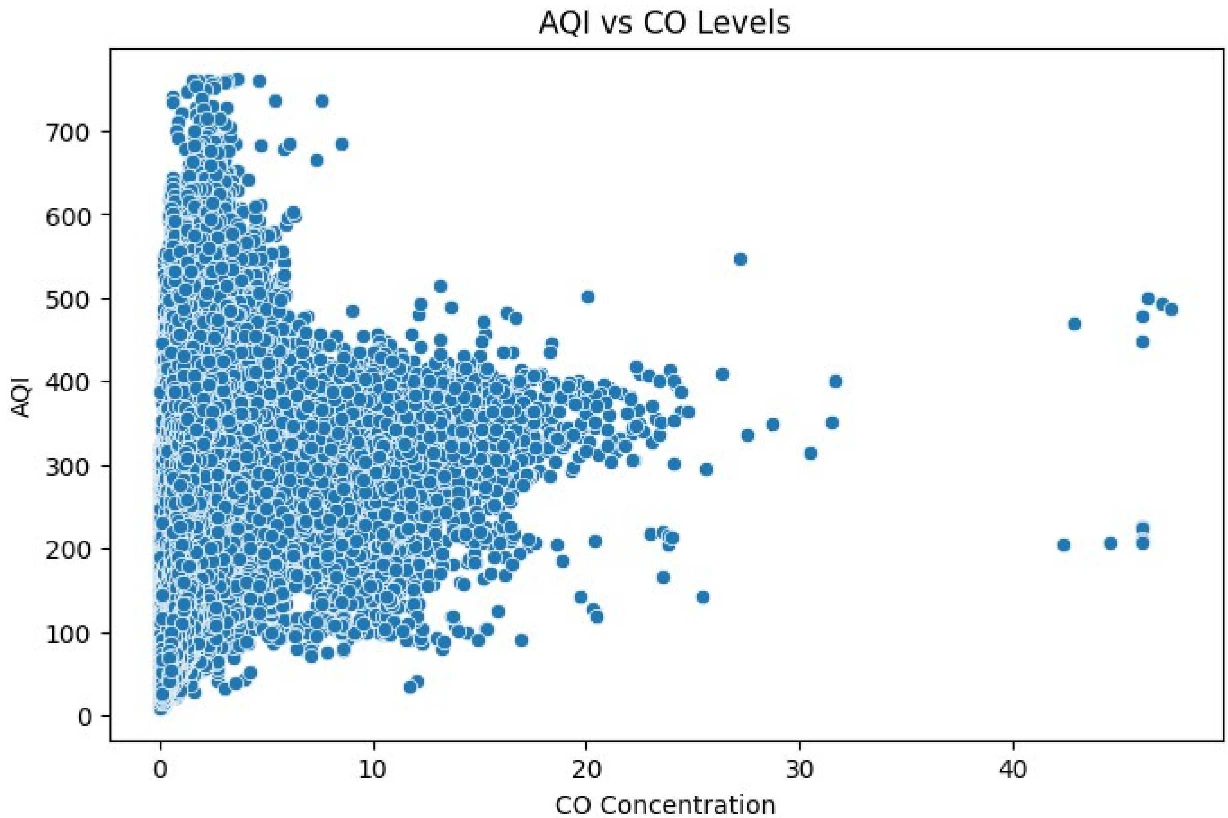



```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='NO', y='AQI', data=AQI_df)
plt.title("AQI vs NO Levels")
plt.xlabel("NO Concentration")
plt.ylabel("AQI")
plt.show()
```

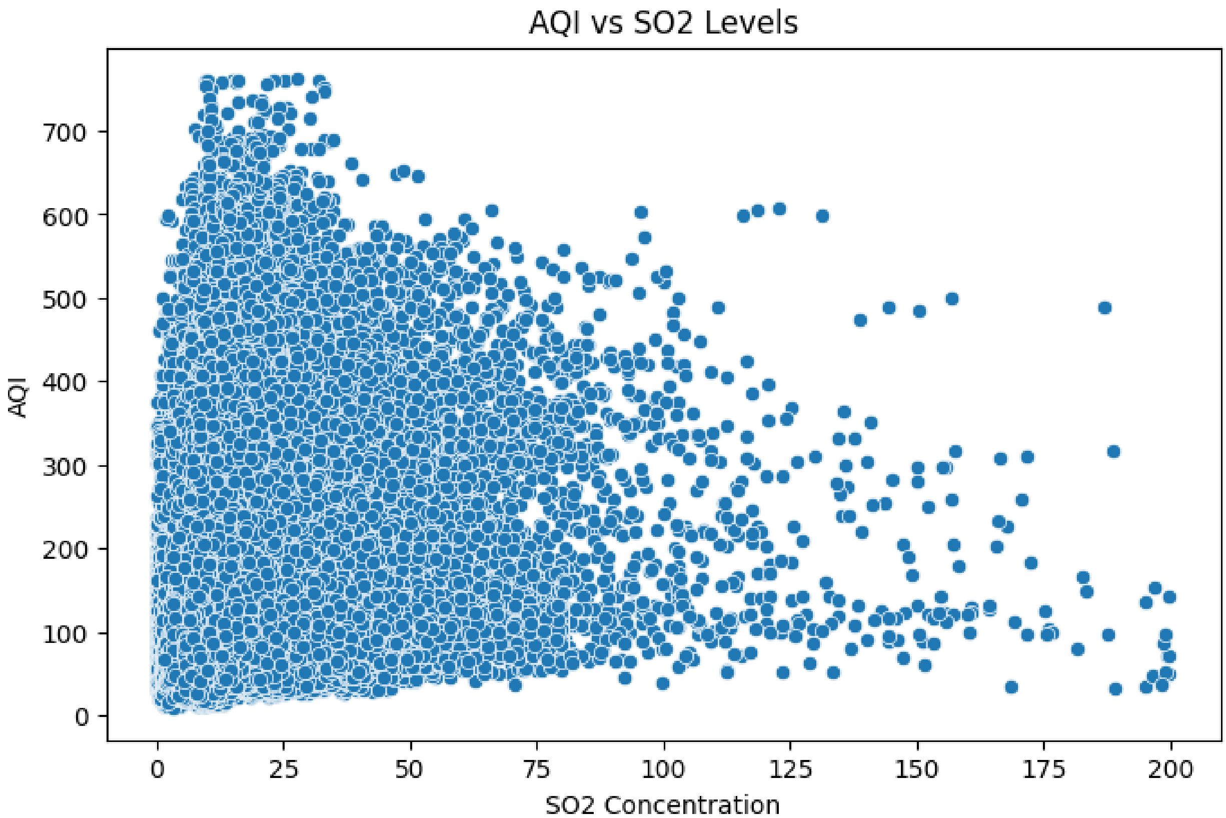


1. As NO concentration increases AQI also tends to decrease, but the pattern is not strictly linear. Suggests that NO contributes to air pollution moderately.

```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='CO', y='AQI', data=AQI_df)
plt.title("AQI vs CO Levels")
plt.xlabel("CO Concentration")
plt.ylabel("AQI")
plt.show()
```




```
plt.figure(figsize=(8, 5))
sns.scatterplot(x='SO2', y='AQI', data=AQI_df)
plt.title("AQI vs SO2 Levels")
plt.xlabel("SO2 Concentration")
plt.ylabel("AQI")
plt.show()
```



1. The plot shows a widely spread distribution with no strong upward trend. Indicates that SO_2 does not have a significant direct impact on AQI.
2. This indicates that SO_2 levels are generally lower compared to other pollutants in the dataset.

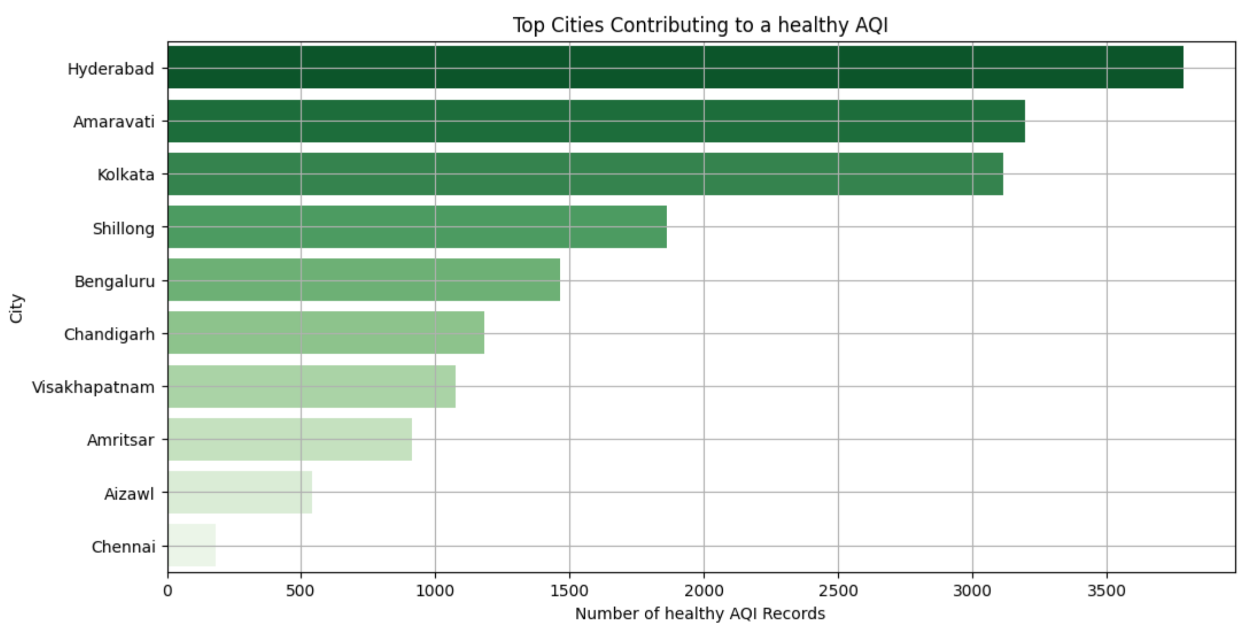
```
# Converting datetime column from object datatype to datetime64
datatype
AQI_df['Datetime'] = pd.to_datetime(AQI_df['Datetime'],
errors='coerce')

# Printing datatype of all the columns
print(AQI_df.dtypes)

City                    object
Datetime        datetime64[ns]
PM2.5                  float64
PM10                   float64
NO                     float64
NO2                    float64
NOx                    float64
NH3                    float64
CO                     float64
SO2                    float64
O3                     float64
Benzene                float64
```

```
Toluene                   float64
AQI                       float64
AQI_Bucket                 object
dtype: object
```

```
# Determinnig the cities present in the dataset
Cities = AQI_df['City'].unique()
print("Unique Cities:- ", Cities)
```

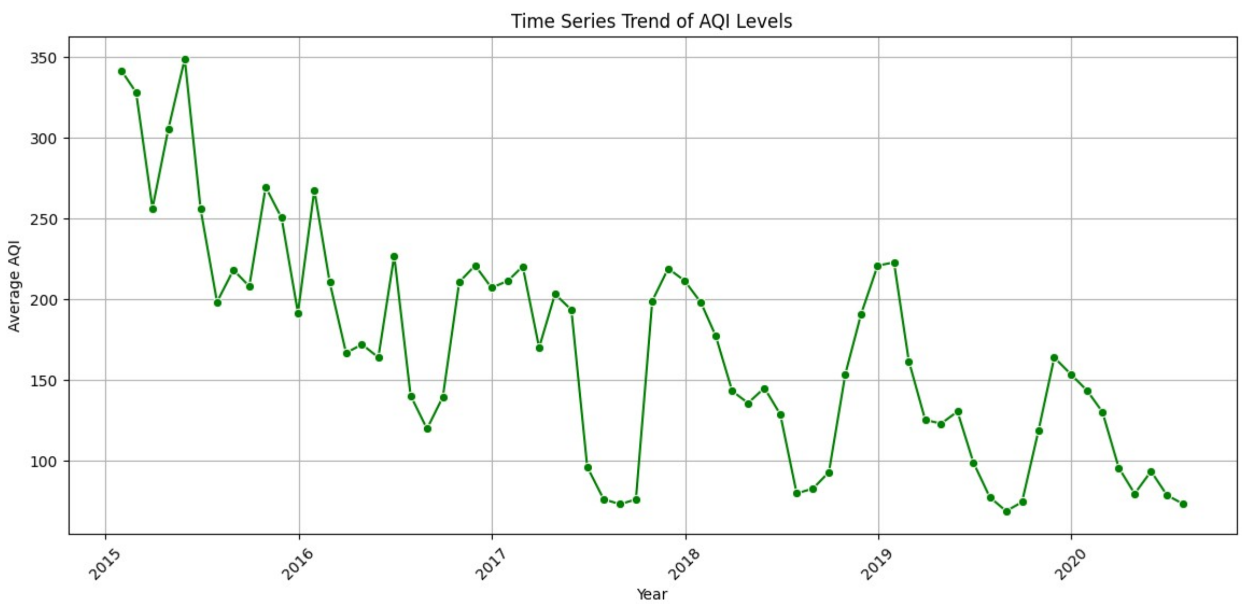
```
Unique Cities:-  ['Aizawl' 'Amaravati' 'Amritsar' 'Bengaluru'
'Chandigarh' 'Chennai'
 'Coimbatore' 'Delhi' 'Gurugram' 'Hyderabad' 'Jaipur' 'Kolkata'
'Patna'
 'Shillong' 'Talcher' 'Visakhapatnam']
```

```
# Plot to show cities have a haealthy AQI
managable_aqi_cities = AQI_df[AQI_df['AQI_Bucket'] == 'Good']
city_counts = managable_aqi_cities['City'].value_counts().head(10)
plt.figure(figsize=(12, 6))
sns.barplot(x=city_counts.values, y=city_counts.index,
palette="Greens_r")
plt.title("Top Cities Contributing to a healthy AQI")
plt.xlabel("Number of healthy AQI Records")
plt.ylabel("City")
plt.grid(True)
plt.show()
```

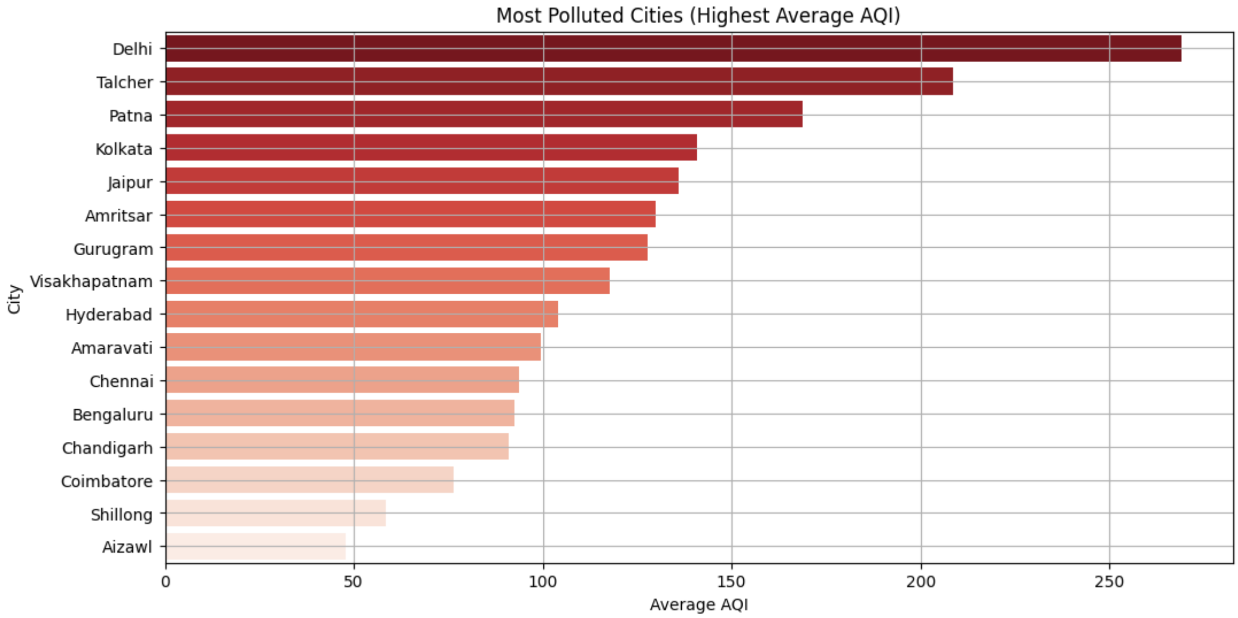



```
AQI_df.set_index('Datetime', inplace=True)
monthly_aqi_trend = AQI_df['AQI'].resample('M').mean()
plt.figure(figsize=(14, 6))
```

```
sns.lineplot(x=monthly_aqi_trend.index, y=monthly_aqi_trend.values,
marker="o", color='green')
plt.title("Time Series Trend of AQI Levels")
plt.xlabel("Year")
plt.ylabel("Average AQI")
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```




```
city_aqi = AQI_df.groupby('City')
['AQI'].mean().sort_values(ascending=False).head(26)
plt.figure(figsize=(12, 6))
sns.barplot(x=city_aqi.values, y=city_aqi.index, palette="Reds_r")
plt.title("Most Polluted Cities (Highest Average AQI)")
plt.xlabel("Average AQI")
plt.ylabel("City")
plt.grid(True)
plt.show()
```




```
AQI_df.head(15)
```

```
                           City  PM2.5   PM10    NO   NO2    NOx    NH3
CO  \
Datetime

2020-03-12 13:00:00  Aizawl   25.0  31.11  7.14  1.86  11.28  24.00
0.42
2020-03-12 14:00:00  Aizawl   19.0  29.17  7.32  1.15  10.85  27.59
0.44
2020-03-12 15:00:00  Aizawl   24.0  30.00  7.14  1.04  10.51  31.13
0.43
2020-03-12 16:00:00  Aizawl   25.0  32.08  7.20  1.19  10.74  33.31
0.46
2020-03-12 17:00:00  Aizawl   33.0  41.00  7.22  1.37  10.93  30.05
0.50
2020-03-13 04:00:00  Aizawl   39.0  42.78  7.06  0.04   9.07  20.85
0.51
2020-03-13 05:00:00  Aizawl   41.0  42.00  7.02  0.02   8.96  19.35
0.51
2020-03-13 12:00:00  Aizawl   26.0  34.00  7.25  1.37  10.96  31.94
0.53
2020-03-13 13:00:00  Aizawl   32.0  46.00  7.07  1.30  10.64  33.39
0.51
2020-03-13 14:00:00  Aizawl   22.0  31.11  7.28  1.17  10.81  32.70
0.47
2020-03-13 15:00:00  Aizawl   27.0  38.00  7.32  1.46  11.13  35.07
0.49
2020-03-13 20:00:00  Aizawl   67.0  75.00  7.11  1.92  11.28  37.99
0.76
2020-03-13 21:00:00  Aizawl   52.0  59.30  7.12  1.41  10.82  33.64
```

```
0.70
2020-03-13 22:00:00  Aizawl   39.0  50.00  6.90  1.21  10.34  31.83
0.61
2020-03-14 01:00:00  Aizawl   33.0  41.00  6.97  0.73  10.01  24.98
0.47

                      SO2    O3  Benzene  Toluene   AQI    AQI_Bucket

Datetime

2020-03-12 13:00:00  4.31  0.76      1.5     4.33  51.0  Satisfactory

2020-03-12 14:00:00  4.65  0.07      1.5     4.33  52.0  Satisfactory

2020-03-12 15:00:00  4.83  0.67      1.5     4.33  52.0  Satisfactory

2020-03-12 16:00:00  5.26  0.05      1.5     4.33  53.0  Satisfactory

2020-03-12 17:00:00  5.39  0.02      1.5     4.33  54.0  Satisfactory

2020-03-13 04:00:00  3.73  0.02      1.5     4.33  56.0  Satisfactory

2020-03-13 05:00:00  3.39  0.02      1.5     4.33  57.0  Satisfactory

2020-03-13 12:00:00  4.52  0.47      1.5     4.33  61.0  Satisfactory

2020-03-13 13:00:00  5.02  0.45      1.5     4.33  61.0  Satisfactory

2020-03-13 14:00:00  5.12  0.18      1.5     4.33  61.0  Satisfactory

2020-03-13 15:00:00  5.22  0.16      1.5     4.33  62.0  Satisfactory

2020-03-13 20:00:00  5.27  0.10      1.5     4.33  64.0  Satisfactory

2020-03-13 21:00:00  4.92  0.07      1.5     4.33  65.0  Satisfactory

2020-03-13 22:00:00  4.56  0.11      1.5     4.33  64.0  Satisfactory

2020-03-14 01:00:00  4.00  0.44      1.5     4.33  64.0  Satisfactory

AQI_df.info()

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 239322 entries, 2020-03-12 13:00:00 to NaT
Data columns (total 14 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   City        239322 non-null  object
 1   PM2.5       239322 non-null  float64
 2   PM10        239322 non-null  float64
 3   NO          239322 non-null  float64
```

```
 4   NO2         239322 non-null  float64
 5   NOx         239322 non-null  float64
 6   NH3         239322 non-null  float64
 7   CO          239322 non-null  float64
 8   SO2         239322 non-null  float64
 9   O3          239322 non-null  float64
 10  Benzene     239322 non-null  float64
 11  Toluene     239322 non-null  float64
 12  AQI         239322 non-null  float64
 13  AQI_Bucket  239322 non-null  object
dtypes: float64(12), object(2)
memory usage: 27.4+ MB
```

```
AQI_df.shape
```

```
(239322, 14)
```

```
#Saving the updated dataset into final.csv
AQI_df.to_csv('final.csv',index=True)
```