

Delhi AQI Analysis

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from scipy import stats
import statsmodels.api as sm
```

Load Dataset

```
# Example - adjust path if needed
df = pd.read_csv("delhiaqi.csv")
```

```
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 561 entries, 0 to 560
```

```
Data columns (total 9 columns):
```

#	Column	Non-Null Count	Dtype
0	date	561 non-null	object
1	co	561 non-null	float64
2	no	561 non-null	float64
3	no2	561 non-null	float64
4	o3	561 non-null	float64
5	so2	561 non-null	float64
6	pm2_5	561 non-null	float64
7	pm10	561 non-null	float64
8	nh3	561 non-null	float64

```
dtypes: float64(8), object(1)
```

```
memory usage: 39.6+ KB
```

	co	no	no2	o3	so2	\
count	561.000000	561.000000	561.000000	561.000000	561.000000	
mean	3814.942210	51.181979	75.292496	30.141943	64.655936	
std	3227.744681	83.904476	42.473791	39.979405	61.073080	
min	654.220000	0.000000	13.370000	0.000000	5.250000	
25%	1708.980000	3.380000	44.550000	0.070000	28.130000	
50%	2590.180000	13.300000	63.750000	11.800000	47.210000	
75%	4432.680000	59.010000	97.330000	47.210000	77.250000	
max	16876.220000	425.580000	263.210000	164.510000	511.170000	
	pm2_5	pm10	nh3			

count	561.000000	561.000000	561.000000
mean	358.256364	420.988414	26.425062
std	227.359117	271.287026	36.563094
min	60.100000	69.080000	0.630000
25%	204.450000	240.900000	8.230000
50%	301.170000	340.900000	14.820000
75%	416.650000	482.570000	26.350000
max	1310.200000	1499.270000	267.510000

```
df.head()
```

	date	co	no	no2	o3	so2	pm2_5
pm10 \							
0	2023-01-01 00:00:00	1655.58	1.66	39.41	5.90	17.88	169.29
							194.64
1	2023-01-01 01:00:00	1869.20	6.82	42.16	1.99	22.17	182.84
							211.08
2	2023-01-01 02:00:00	2510.07	27.72	43.87	0.02	30.04	220.25
							260.68
3	2023-01-01 03:00:00	3150.94	55.43	44.55	0.85	35.76	252.90
							304.12
4	2023-01-01 04:00:00	3471.37	68.84	45.24	5.45	39.10	266.36
							322.80

	nh3
0	5.83
1	7.66
2	11.40
3	13.55
4	14.19

Data Cleaning (Handle Nulls, Duplicates, Date formatting)

```
# Drop duplicates
```

```
df = df.drop_duplicates()
```

```
# Check missing values
```

```
print(df.isnull().sum())
```

```
# Convert date column (adjust column name if different)
```

```
df['date'] = pd.to_datetime(df['date'])
```

date	0
co	0
no	0
no2	0
o3	0
so2	0
pm2_5	0

```
pm10      0
nh3        0
dtype: int64
```

Feature Engineering (Extract month, season etc.)

```
# Extract month & year
df['month'] = df['date'].dt.month
df['year'] = df['date'].dt.year
df['day'] = df['date'].dt.day

# Define seasons for Delhi
def season(month):
    if month in [12,1,2]:
        return 'Winter'
    elif month in [3,4,5]:
        return 'Summer'
    elif month in [6,7,8,9]:
        return 'Monsoon'
    else:
        return 'Post-Monsoon'

df['season'] = df['month'].apply(season)
```

AQI Calculation

```
df['AQI'] = df['pm2_5']

# Composite AQI
df['AQI_composite'] =
df[['pm2_5', 'pm10', 'no2', 'o3', 'so2']].max(axis=1)

df[['date', 'AQI', 'AQI_composite']].head()
```

	date	AQI	AQI_composite
0	2023-01-01 00:00:00	169.29	194.64
1	2023-01-01 01:00:00	182.84	211.08
2	2023-01-01 02:00:00	220.25	260.68
3	2023-01-01 03:00:00	252.90	304.12
4	2023-01-01 04:00:00	266.36	322.80

EDA - Visualizations

```
df.describe()
```

	date	co	no	no2
o3 \				
count	561	561.000000	561.000000	561.000000
561.000000				

mean	2023-01-12 16:00:00	3814.942210	51.181979	75.292496
30.141943				
min	2023-01-01 00:00:00	654.220000	0.000000	13.370000
0.000000				
25%	2023-01-06 20:00:00	1708.980000	3.380000	44.550000
0.070000				
50%	2023-01-12 16:00:00	2590.180000	13.300000	63.750000
11.800000				
75%	2023-01-18 12:00:00	4432.680000	59.010000	97.330000
47.210000				
max	2023-01-24 08:00:00	16876.220000	425.580000	263.210000
164.510000				
std		NaN	3227.744681	83.904476
39.979405				42.473791

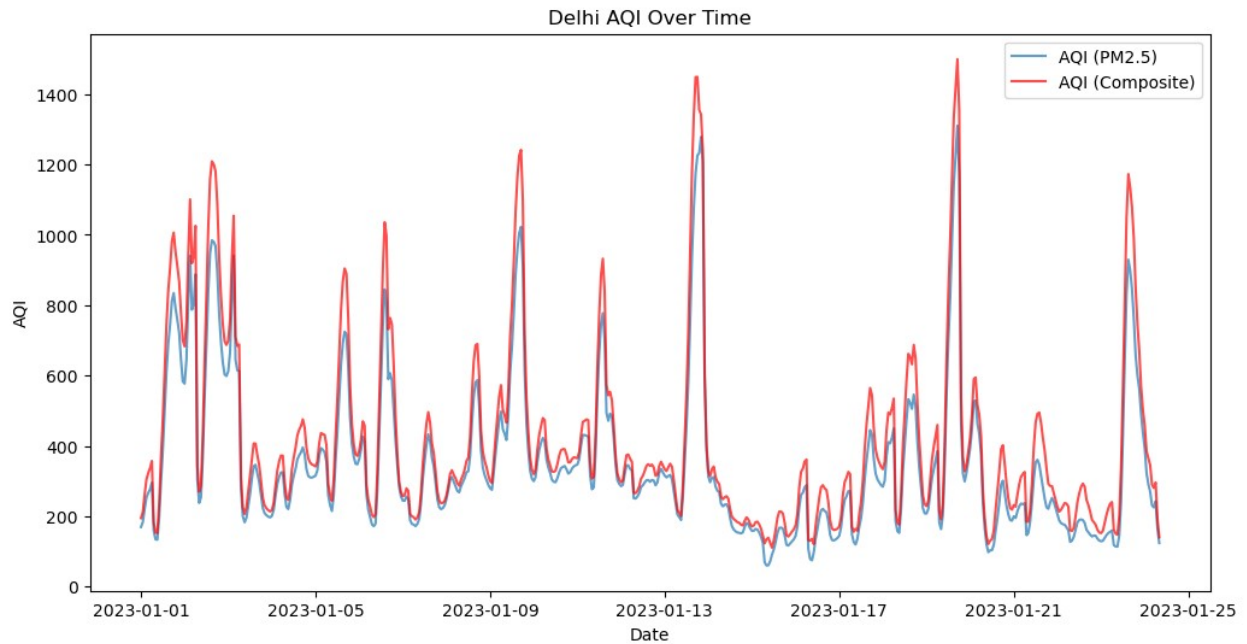
	so2	pm2_5	pm10	nh3	month	year
\						
count	561.000000	561.000000	561.000000	561.000000	561.0	561.0
mean	64.655936	358.256364	420.988414	26.425062	1.0	2023.0
min	5.250000	60.100000	69.080000	0.630000	1.0	2023.0
25%	28.130000	204.450000	240.900000	8.230000	1.0	2023.0
50%	47.210000	301.170000	340.900000	14.820000	1.0	2023.0
75%	77.250000	416.650000	482.570000	26.350000	1.0	2023.0
max	511.170000	1310.200000	1499.270000	267.510000	1.0	2023.0
std	61.073080	227.359117	271.287026	36.563094	0.0	0.0

	day	AQI	AQI_composite
count	561.000000	561.000000	561.000000
mean	12.192513	358.256364	421.589537
min	1.000000	60.100000	110.640000
25%	6.000000	204.450000	240.900000
50%	12.000000	301.170000	340.900000
75%	18.000000	416.650000	482.570000
max	24.000000	1310.200000	1499.270000
std	6.756374	227.359117	270.597421

AQI Over Time (Code)

```
plt.figure(figsize=(12,6))
plt.plot(df['date'], df['AQI'], label="AQI (PM2.5)", alpha=0.7)
plt.plot(df['date'], df['AQI_composite'], label="AQI (Composite)",
alpha=0.7, color='red')
```

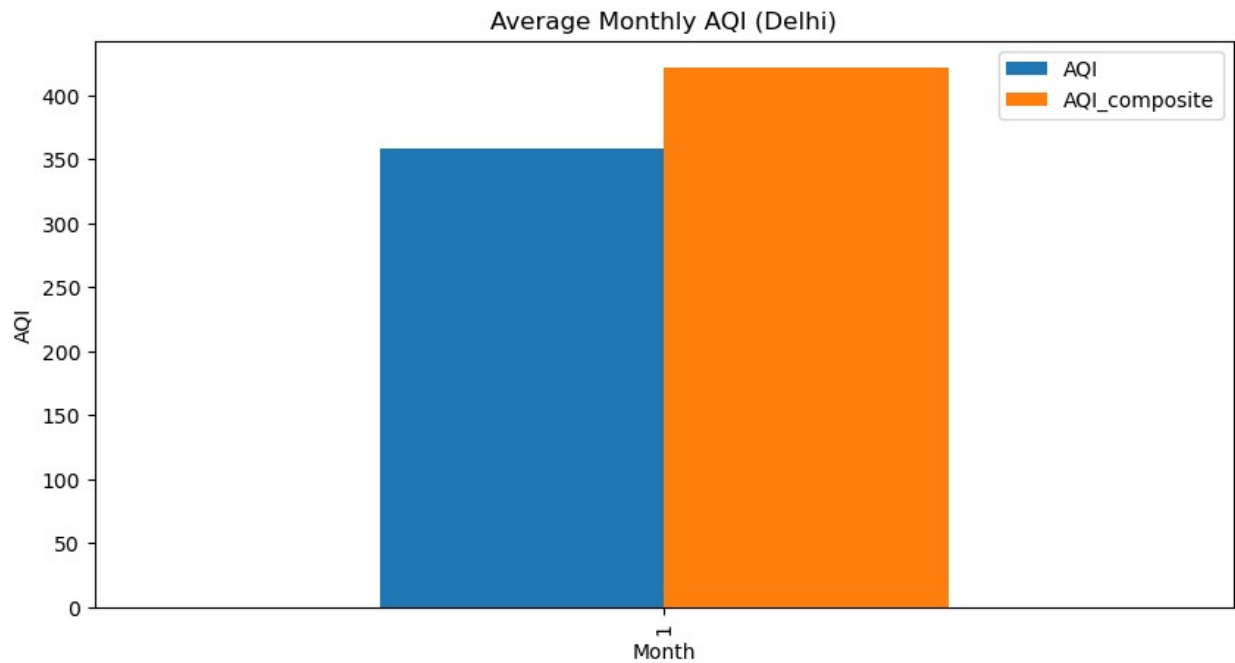
```
plt.title("Delhi AQI Over Time")
plt.xlabel("Date")
plt.ylabel("AQI")
plt.legend()
plt.show()
```



Seasonal Trends

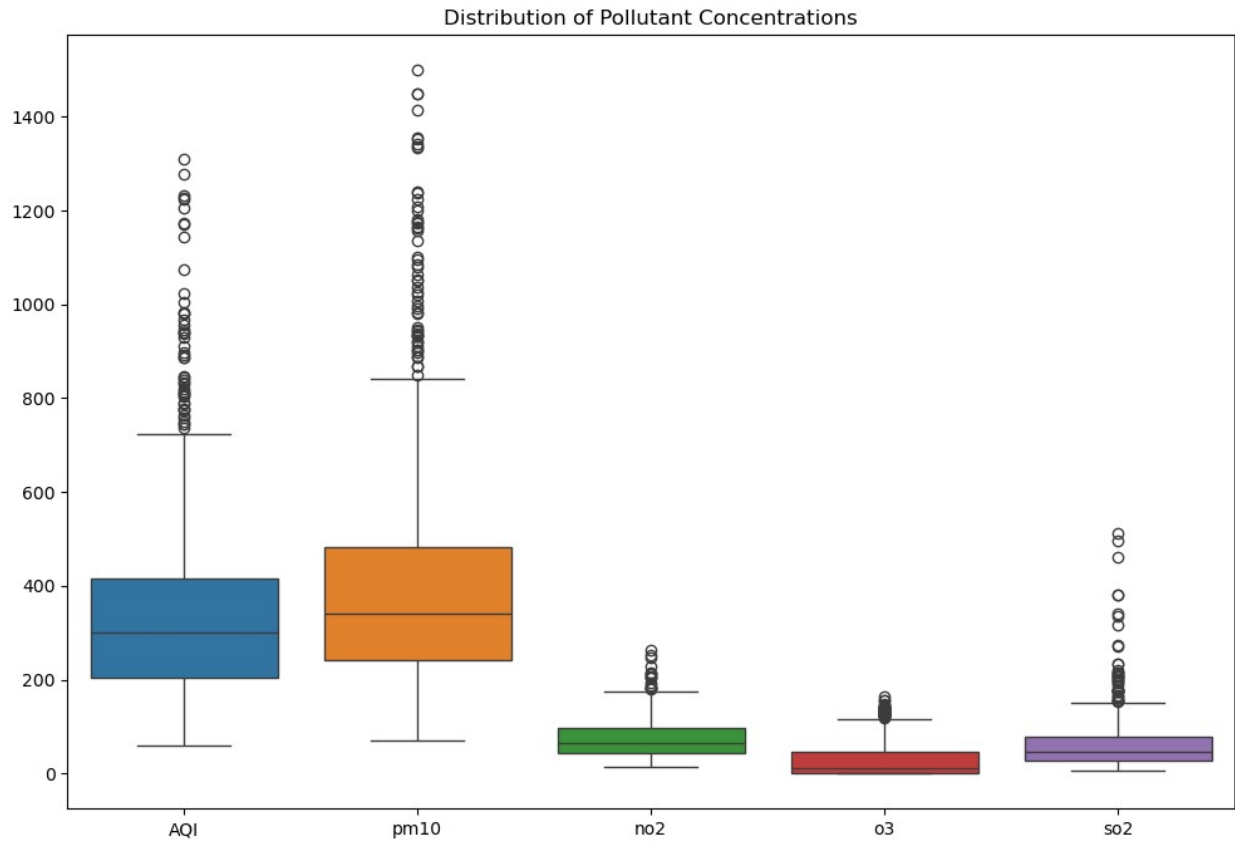
```
df['month'] = df['date'].dt.month
monthly = df.groupby('month')[['AQI', 'AQI_composite']].mean()

monthly.plot(kind='bar', figsize=(10,5))
plt.title("Average Monthly AQI (Delhi)")
plt.xlabel("Month")
plt.ylabel("AQI")
plt.show()
```



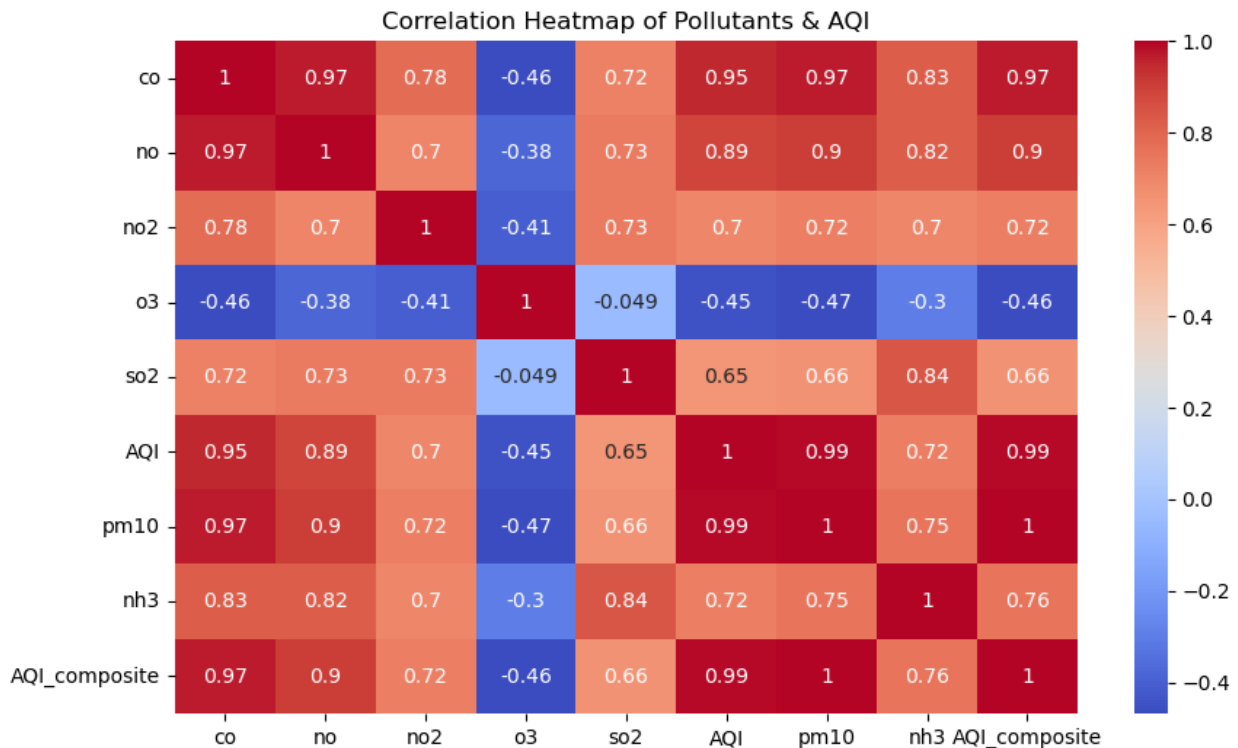
Pollutant Distributions

```
plt.figure(figsize=(12,8))
sns.boxplot(data=df[['AQI','pm10','no2','o3','so2']])
plt.title("Distribution of Pollutant Concentrations")
plt.show()
```



Correlation Heatmap

```
plt.figure(figsize=(10,6))
sns.heatmap(df[['co', 'no', 'no2', 'o3', 'so2', 'AQI', 'pm10', 'nh3', 'AQI_composite']].corr(),
            annot=True, cmap="coolwarm")
plt.title("Correlation Heatmap of Pollutants & AQI")
plt.show()
```



Insights & Observations

- **PM10 ($r = 0.99$)** is the strongest contributor to AQI, showing an almost perfect positive correlation.
- **CO ($r = 0.95$)** and **NO ($r = 0.89$)** also have very strong positive correlations with AQI, indicating they are major pollutants driving poor air quality.
- **NO2 ($r = 0.70$)**, **NH3 ($r = 0.72$)**, and **SO2 ($r = 0.65$ – 0.66)** show moderate positive correlations with AQI.
- **Ozone (O3, $r \approx -0.45$)** shows a negative correlation, suggesting higher O3 levels may coincide with slightly improved AQI conditions.
- **Multicollinearity is high** among CO, PM10, and NO (correlations > 0.9), meaning these pollutants often rise together and may act as overlapping indicators.
- Overall, **PM10, CO, and NO** are the dominant pollutants influencing AQI in this dataset, consistent with common sources like traffic emissions, industrial activities, and road dust in urban areas.