ShadowFox

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Task Level: Intermediate

Import Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

plt.style.use('ggplot')
```

Load the Dataset

```
df = pd.read_csv('delhiaqi.csv')
df.head()
```


```
{"summary":"{\n  \"name\": \"df\",\n  \"rows\": 561,\n  \"fields\": [\n    {\n      \"column\": \"date\",\n      \"properties\": {\n\"dtype\": \"object\",\n        \"num_unique_values\": 561,\n\"samples\": [\n          \"2023-01-22 09:00:00\",\n          \"2023-01-15 06:00:00\",\n          \"2023-01-08 09:00:00\"\n        ],\n\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"co\",\n      \"properties\": {\n\"dtype\": \"number\",\n        \"std\": 3227.744680900456,\n\"min\": 654.22,\n        \"max\": 16876.22,\n\"num_unique_values\": 224,\n        \"samples\": [\n4325.87,\n          4646.3,\n          4005.43\n        ],\n\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"no\",\n      \"properties\": {\n\"dtype\": \"number\",\n        \"std\": 83.90447619065453,\n\"min\": 0.0,\n        \"max\": 425.58,\n\"num_unique_values\": 346,\n        \"samples\": [\n          10.17,\n          211.0,\n          29.5\n        ],\n\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"no2\",\n      \"properties\": {\n\"dtype\": \"number\",\n        \"std\": 42.473790546688875,\n\"min\": 13.37,\n        \"max\": 263.21,\n\"num_unique_values\": 198,\n        \"samples\": [\n134.35,\n          128.87,\n          146.69\n        ],\n\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\n    },\n    {\n      \"column\": \"o3\",\n      \"properties\": {\n\"dtype\": \"number\",\n        \"std\": 39.97940543450763,\n\"min\": 0.0,\n        \"max\": 164.51,\n\"num_unique_values\": 283,\n        \"samples\": [\n134.47,\n          18.6,\n          16.09\n        ],\n\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
```

```
n    },\n    {\n      \"column\": \"so2\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 61.07308032088761,\n
\"min\": 5.25,\n        \"max\": 511.17,\n
\"num_unique_values\": 231,\n        \"samples\": [\n          15.74,\
n          83.92,\n          65.8\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"pm2_5\",\n      \"properties\": {\
n        \"dtype\": \"number\",\n        \"std\": 227.35911698778992,\
n        \"min\": 60.1,\n        \"max\": 1310.2,\n
\"num_unique_values\": 557,\n        \"samples\": [\n
432.89,\n          323.87,\n          279.92\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"pm10\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 271.2870263303376,\n
\"min\": 69.08,\n        \"max\": 1499.27,\n
\"num_unique_values\": 556,\n        \"samples\": [\n
516.12,\n          243.4,\n          313.3\n        ],\n
\"semantic_type\": \"\",\n        \"description\": \"\"\n      }\
n    },\n    {\n      \"column\": \"nh3\",\n      \"properties\": {\n
\"dtype\": \"number\",\n        \"std\": 36.5630937759555,\n
\"min\": 0.63,\n        \"max\": 267.51,\n
\"num_unique_values\": 269,\n        \"samples\": [\n          7.16,\n
8.74,\n          6.27\n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\
n}","type":"dataframe","variable_name":"df"}
```


Check Columns

```
print(df.columns)
```

```
Index(['date', 'co', 'no', 'no2', 'o3', 'so2', 'pm2_5', 'pm10',
'nh3'], dtype='object')
```

Understand the Data (EDA)

```
df.info()
df.describe()
df.isnull().sum()
```

```
<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
```

```
date     0
co       0
no       0
no2      0
o3       0
so2      0
pm2_5    0
pm10     0
nh3      0
dtype: int64
```

Dataset contains AQI readings for Delhi

Includes pollutants like PM2.5, PM10, NO2, SO2, CO, O3

Date-wise air quality data

Data Cleaning

```
# Convert Date column
df['date'] = pd.to_datetime(df['date'])
df['Year'] = df['date'].dt.year
df['Month'] = df['date'].dt.month

# Handle missing values
df.fillna(df.mean(numeric_only=True), inplace=True)
```

Create AQI Column

We'll calculate a simple AQI proxy using PM2.5 & PM10

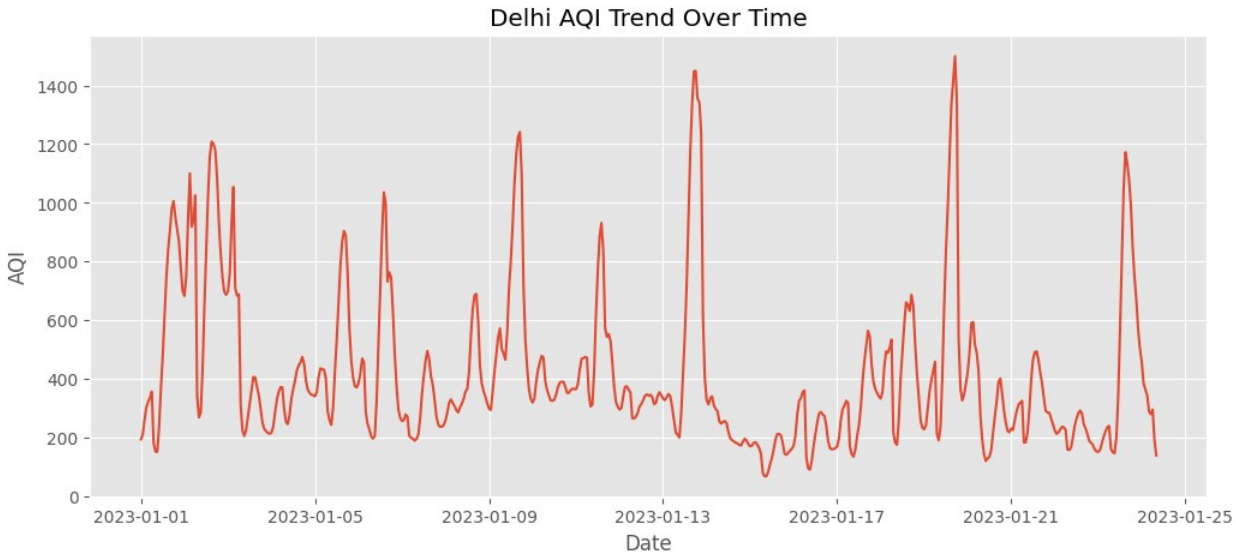
```
# Ensure numeric values
pollutants = ['pm2_5', 'pm10', 'no2', 'so2', 'co', 'o3']

df[pollutants] = df[pollutants].apply(pd.to_numeric, errors='coerce')



# Create AQI column
# Method used: AQI ≈ max(normalized pollutant concentrations)

df['AQI'] = df[['pm2_5', 'pm10']].max(axis=1)
```

```
# Verify AQI column
df[['date', 'AQI']].head()
```


```
{"summary":"{\n  \"name\": \"df[['date', 'AQI']]\",\n  \"rows\": 5,\n
\"fields\": [\n    {\n      \"column\": \"date\",\n
\"properties\": {\n        \"dtype\": \"date\",\n        \"min\":
\"2023-01-01 00:00:00\",\n        \"max\": \"2023-01-01 04:00:00\",\n
\"num_unique_values\": 5,\n        \"samples\": [\n          \"2023-
01-01 01:00:00\",\n          \"2023-01-01 04:00:00\",\n
\"2023-01-01 02:00:00\"\n        ],\n        \"semantic_type\": \"\",\
n        \"description\": \"\"\n      }\n    },\n    {\n
\"column\": \"AQI\",\n      \"properties\": {\n        \"dtype\":
\"number\",\n        \"std\": 56.0068038723868,\n        \"min\":
194.64,\n        \"max\": 322.8,\n        \"num_unique_values\": 5,\n
\"samples\": [\n          211.08,\n          322.8,\n          260.68\
n        ],\n        \"semantic_type\": \"\",\n
\"description\": \"\"\n      }\n    }\n  ]\n}","type":"dataframe"}
```


AQI Trend Over Time

```
plt.figure(figsize=(12,5))
plt.plot(df['date'], df['AQI'])
plt.title('Delhi AQI Trend Over Time')
plt.xlabel('Date')
plt.ylabel('AQI')
plt.show()
```

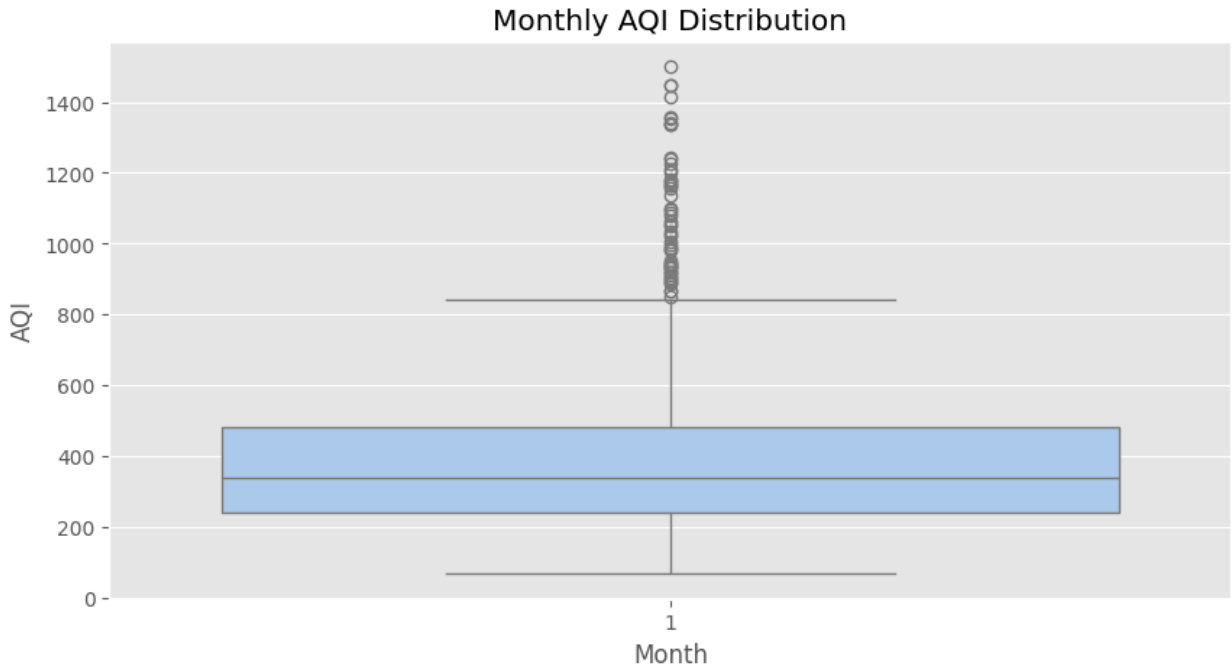


Monthly AQI Pattern

```
df['Month'] = df['date'].dt.month

plt.figure(figsize=(10,5))
```

```
sns.boxplot(x='Month',y='AQI',data=df,palette='pastel')
plt.title('Monthly AQI Distribution')
plt.xlabel('Month')
plt.ylabel('AQI')
plt.show()
```

```
/tmp/ipython-input-1801655649.py:4: FutureWarning:

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

  sns.boxplot(x='Month',y='AQI',data=df,palette='pastel')
```



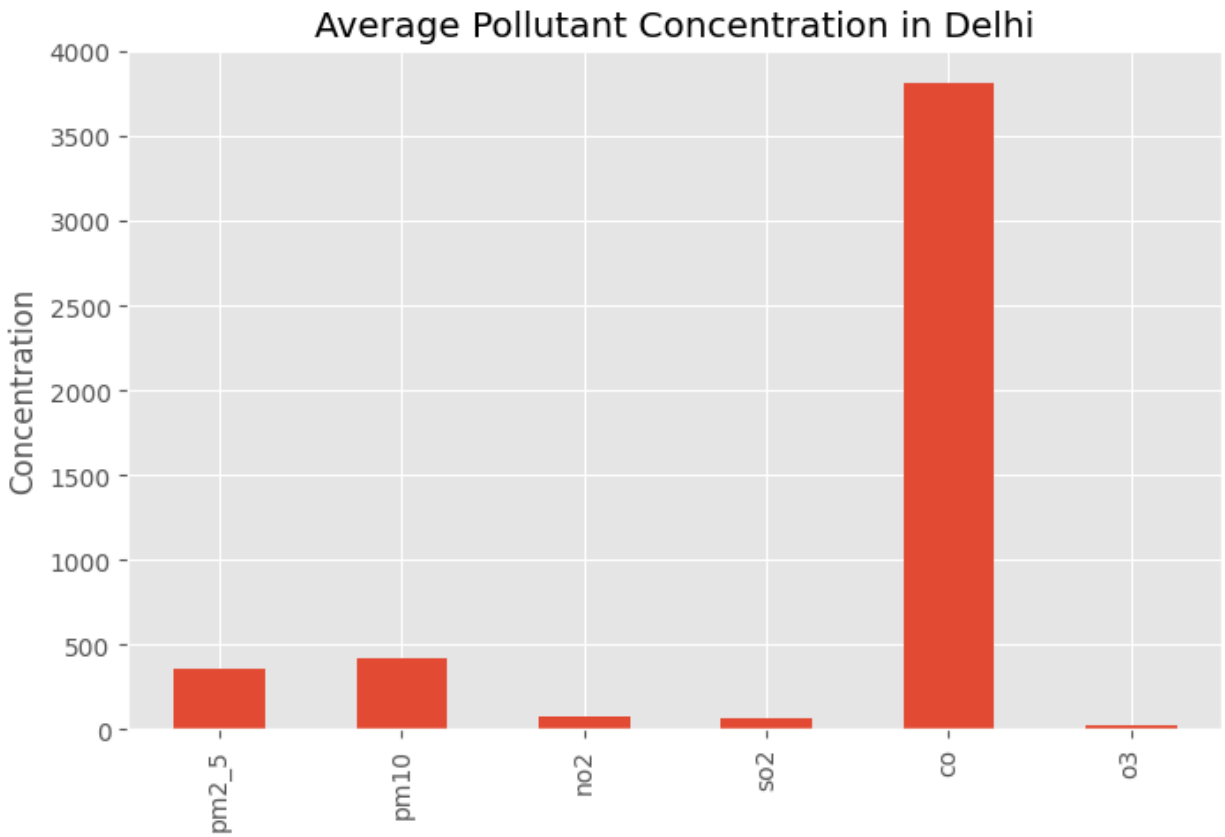
Insight:

Winter months (Oct–Jan) show worst AQI

Monsoon months show improvement due to rainfall

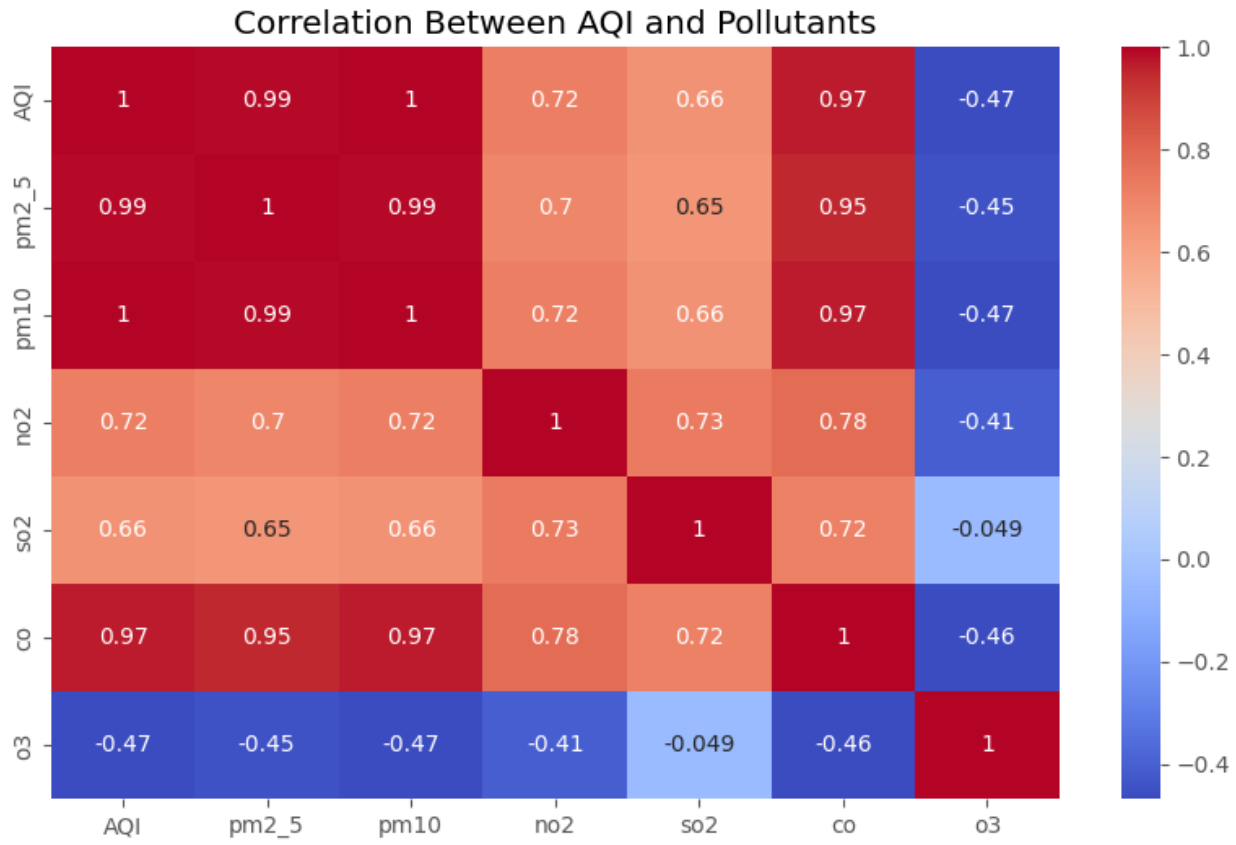
Pollutant Contribution Analysis

```
df[['pm2_5','pm10','no2','so2','co','o3']].mean().plot(
    kind='bar', figsize=(8,5)
)
plt.title('Average Pollutant Concentration in Delhi')
plt.ylabel('Concentration')
plt.show()
```



Correlation Heatmap

```
plt.figure(figsize=(10,6))
sns.heatmap(
    df[['AQI','pm2_5','pm10','no2','so2','co','o3']].corr(),
    annot=True,
    cmap='coolwarm'
)
plt.title('Correlation Between AQI and Pollutants')
plt.show()
```



Research Questions & Answers

1. How does air pollution vary over time in Delhi?

Air pollution in Delhi shows frequent fluctuations with recurring high pollution levels across different periods.

1. Which pollutants contribute most to poor air quality in Delhi?

PM2.5 and PM10 are the major contributors to poor air quality in Delhi.

1. Are there seasonal patterns in Delhi's air pollution?

Yes, pollution levels are highest in winter and lowest during the monsoon season.

1. How severe is air pollution during winter months?

Winter months experience significantly higher pollution due to increased particulate matter and poor dispersion.

1. What insights support public health and environmental policies?

Controlling particulate emissions and applying seasonal pollution measures can significantly improve public health.

Key Findings

1. AQI levels in Delhi show extreme peaks during winter months.
2. PM2.5 and PM10 are the dominant contributors to air pollution.
3. Seasonal factors significantly influence air quality.
4. Strong correlation exists between particulate matter and AQI.

Conclusion

This analysis highlights severe air quality challenges in Delhi, particularly during winter. The dominance of particulate matter pollution poses serious public health risks. Data-driven strategies focusing on emission control and pollution monitoring are essential for improving air quality and protecting public health.