Lab 1: Data Visualization, Data Preprocessing, and Statistical Analysis

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Lab 1: Data Visualization, Data Preprocessing, and Statistical Analysis

Github Link

https://github.com/ndhinaharan36295/MSCS-634_Lab-1

1. Data Collection

Lab 1: Data Visualization, Data Preprocessing, and Statistical Analysis Using Python in Jupyter Notebook

[14] 0s
```python
# Imports
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
```

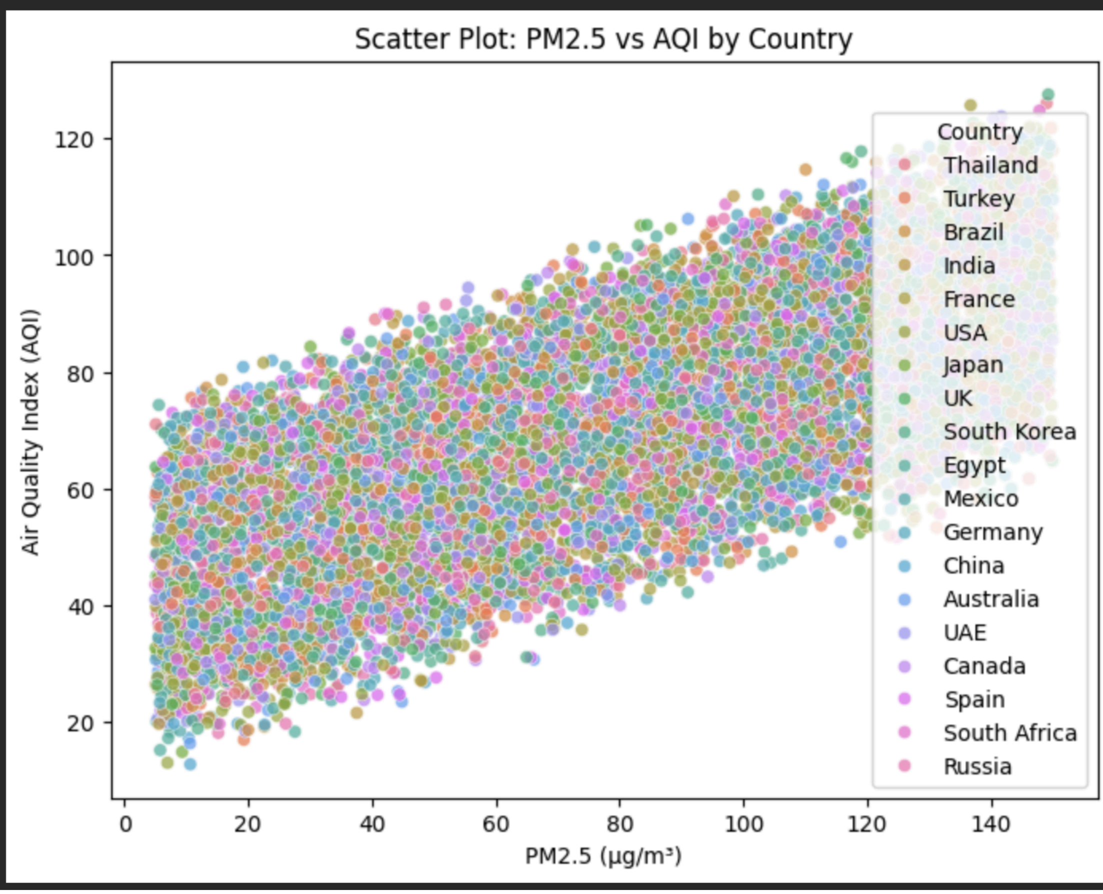
[4] 0s
```python
# Step 1: Data Collection

# Load dataset
df = pd.read_csv("global_air_quality.csv")

# Display first five rows
df.head()
```

	City	Country	Date	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed
0	Bangkok	Thailand	2023-03-19	86.57	25.19	99.88	30.63	4.46	36.29	17.67	59.35	13.76
1	Istanbul	Turkey	2023-02-16	50.63	97.39	48.14	8.71	3.40	144.16	3.46	67.51	6.36
2	Rio de Janeiro	Brazil	2023-11-13	130.21	57.22	98.51	9.92	0.12	179.31	25.29	29.30	12.87
3	Mumbai	India	2023-03-16	119.70	130.52	10.96	33.03	7.74	38.65	23.15	99.97	7.71
4	Paris	France	2023-04-04	55.20	36.62	76.85	21.85	2.00	67.09	16.02	90.28	14.16

2. Data Visualization

1) Scatter Plot: PM2.5 vs AQI

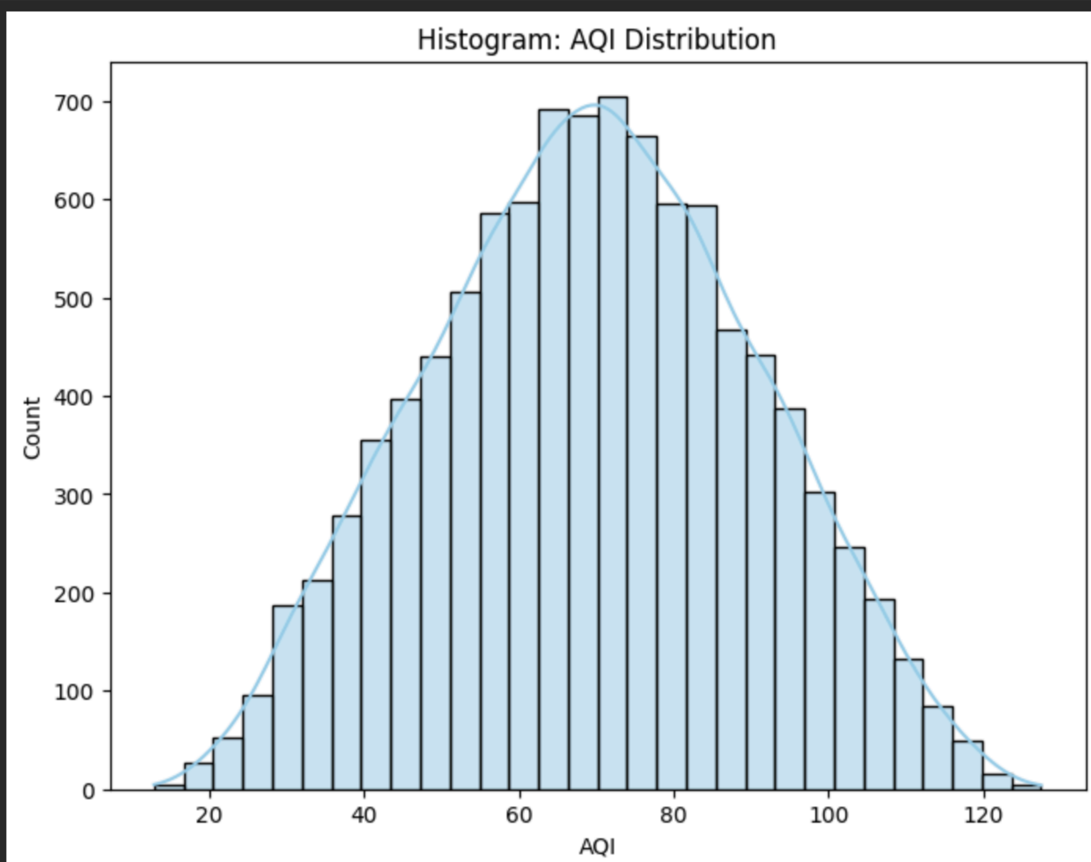
```python
# Scatter Plot: PM2.5 vs AQI
plt.figure(figsize=(8,6))
sns.scatterplot(data=df, x="PM2.5", y="AQI", hue="Country", alpha=0.7)
plt.title("Scatter Plot: PM2.5 vs AQI by Country")
plt.xlabel("PM2.5 (µg/m³)")
plt.ylabel("Air Quality Index (AQI)")
plt.show()
```



The scatter plot of PM2.5 versus AQI by country reveals a strong positive correlation, indicating that as PM2.5 concentrations increase, air quality deteriorates correspondingly. Most data points cluster between 20–80 µg/m³ of PM2.5 and 40–100 AQI, representing moderate pollution levels common across regions. The consistent upward trend across countries suggests that PM2.5 is a dominant factor influencing overall air quality worldwide. Some vertical dispersion at similar PM2.5 levels implies the impact of secondary pollutants or meteorological variations, while a few outliers at higher values likely reflect severe pollution episodes in specific urban or industrial areas.

2) Distribution of AQI Histogram

```
# Histogram: Distribution of AQI
plt.figure(figsize=(8,6))
sns.histplot(df["AQI"], bins=30, kde=True, color="skyblue")
plt.title("Histogram: AQI Distribution")
plt.xlabel("AQI")
plt.show()
```



The histogram of AQI values shows a roughly bell-shaped distribution, indicating that most regions experience moderate air quality conditions centered around AQI values of 60 to 80. The symmetry of the distribution suggests that extreme pollution or exceptionally clean air events are relatively uncommon. The smooth, near-normal pattern also implies a stable environmental range across locations, with only a small number of observations falling into high-AQI categories that represent more severe pollution levels.

3. Data Preprocessing

1) **Handling missing values**

Before:

Step 3: Data Preprocessing

[21] 0s

```
# Handling missing values

# Check for missing values before
print(df.isnull().sum())
```

```
City           0
Country        0
Date           0
PM2.5          0
PM10           0
NO2            0
SO2            0
CO             0
O3             0
Temperature    0
Humidity       0
Wind Speed     0
AQI            0
dtype: int64
```

After:

```
[22]
# Fill missing values of pollutant & AQI columns with median
cols = ["PM2.5", "PM10", "NO2", "SO2", "CO", "O3", "AQI"]
for c in cols:
    df[c] = df[c].fillna(df[c].median())

# verify no missing values after
print(df.isnull().sum())
```

```
City           0
Country        0
Date           0
PM2.5          0
PM10           0
NO2            0
SO2            0
CO             0
O3             0
Temperature    0
Humidity       0
Wind Speed     0
AQI            0
dtype: int64
```

2) Outlier Detection & Removal (IQR method)

```
[27]
# 2) Outlier Detection and Removal

# Example for PM2.5
Q1 = df["PM2.5"].quantile(0.25)
Q3 = df["PM2.5"].quantile(0.75)
IQR = Q3 - Q1
lower = Q1 - 1.5 * IQR
upper = Q3 + 1.5 * IQR

print("IQR:", IQR)

print("Before removing outliers:", df.shape)

outliers = df[(df["PM2.5"] < lower) | (df["PM2.5"] > upper)]
print("Outliers count:", outliers.shape[0])

df_no_outliers = df[(df["PM2.5"] >= lower) & (df["PM2.5"] <= upper)]
print("After removing outliers:", df_no_outliers.shape)
```

```
IQR: 72.2075
Before removing outliers: (10000, 13)
Outliers count: 0
After removing outliers: (10000, 13)
```

3) Data Reduction

[30]
✓ 0s

```python
# 3) Data Reduction
df.head()
```

	City	Country	Date	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed	AQI
0	Bangkok	Thailand	2023-03-19	86.57	25.19	99.88	30.63	4.46	36.29	17.67	59.35	13.76	56.9025
1	Istanbul	Turkey	2023-02-16	50.63	97.39	48.14	8.71	3.40	144.16	3.46	67.51	6.36	57.7080
2	Rio de Janeiro	Brazil	2023-11-13	130.21	57.22	98.51	9.92	0.12	179.31	25.29	29.30	12.87	84.6245
3	Mumbai	India	2023-03-16	119.70	130.52	10.96	33.03	7.74	38.65	23.15	99.97	7.71	82.1785
4	Paris	France	2023-04-04	55.20	36.62	76.85	21.85	2.00	67.09	16.02	90.28	14.16	45.7420

Next steps: Generate code with df New interactive sheet

[31]
✓ 0s

```python
# Sampling (e.g., 20%)
df_sample = df_no_outliers.sample(n=int(0.2 * len(df_no_outliers)), random_state=42)

# Dropping columns less relevant (e.g., "Date")
df_reduced = df_sample.drop(["Date"], axis=1)  # adjust column list as needed
df_reduced.head()
```

	City	Country	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed	AQI
6252	Beijing	China	111.92	32.08	7.95	37.45	9.43	45.77	23.68	30.31	5.91	55.3610
4684	Berlin	Germany	62.62	153.88	22.76	22.12	0.45	112.53	1.93	66.61	1.22	71.6845
1731	Bangkok	Thailand	77.06	114.31	24.99	45.80	8.55	64.48	-1.39	27.47	6.25	67.9560
4742	Istanbul	Turkey	72.75	38.79	31.58	35.59	2.63	186.67	16.51	28.25	16.90	53.0525
4521	Sydney	Australia	18.25	186.45	27.36	45.47	8.91	170.28	-0.68	90.85	5.72	71.0560

Next steps: Generate code with df_reduced New interactive sheet

4) Data Scaling & Discretization

Before:

	City	Country	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed	AQI
6252	Beijing	China	111.92	32.08	7.95	37.45	9.43	45.77	23.68	30.31	5.91	55.3610
4684	Berlin	Germany	62.62	153.88	22.76	22.12	0.45	112.53	1.93	66.61	1.22	71.6845
1731	Bangkok	Thailand	77.06	114.31	24.99	45.80	8.55	64.48	-1.39	27.47	6.25	67.9560
4742	Istanbul	Turkey	72.75	38.79	31.58	35.59	2.63	186.67	16.51	28.25	16.90	53.0525
4521	Sydney	Australia	18.25	186.45	27.36	45.47	8.91	170.28	-0.68	90.85	5.72	71.0560

After:

[37]
0s

```python
# 4) Data Scaling and Discretization

scaler = MinMaxScaler()
num_cols = ["PM2.5", "PM10", "NO2", "SO2", "CO", "O3", "AQI"]
df_reduced[num_cols] = scaler.fit_transform(df_reduced[num_cols])

# Discretize AQI into categories
df_reduced["AQI_Category"] = pd.cut(
    df_reduced["AQI"],
    bins=[0, 0.3, 0.6, 0.8, 1.0],
    labels=["Good", "Moderate", "Unhealthy", "Hazardous"]
)
df_reduced.head()
```

	City	Country	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed	AQI	AQI_Category
6252	Beijing	China	0.737390	0.115983	0.030983	0.744181	0.942424	0.187997	23.68	30.31	5.91	0.369557	Moderate
4684	Berlin	Germany	0.397226	0.757812	0.187059	0.431196	0.035354	0.539754	1.93	66.61	1.22	0.512216	Moderate
1731	Bangkok	Thailand	0.496861	0.549297	0.210560	0.914659	0.853535	0.286580	-1.39	27.47	6.25	0.479630	Moderate
4742	Istanbul	Turkey	0.467122	0.151341	0.280008	0.706207	0.255556	0.930397	16.51	28.25	16.90	0.349382	Moderate
4521	Sydney	Australia	0.091078	0.929441	0.235536	0.907922	0.889899	0.844038	-0.68	90.85	5.72	0.506723	Moderate

4. Statistical Analysis

1) General overview

```python
# General overview
df_reduced.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2000 entries, 6252 to 6929
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   City          2000 non-null   object
 1   Country       2000 non-null   object
 2   PM2.5         2000 non-null   float64
 3   PM10          2000 non-null   float64
 4   NO2           2000 non-null   float64
 5   SO2           2000 non-null   float64
 6   CO            2000 non-null   float64
 7   O3            2000 non-null   float64
 8   Temperature   2000 non-null   float64
 9   Humidity      2000 non-null   float64
 10  Wind Speed    2000 non-null   float64
 11  AQI           2000 non-null   float64
 12  AQI_Category  1999 non-null   category
dtypes: category(1), float64(10), object(2)
memory usage: 205.3+ KB
```

[40]

```
df_reduced.describe()
```

	PM2.5	PM10	NO2	SO2	CO	O3	Temperature	Humidity	Wind Speed	AQI
count	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.000000	2000.00000	2000.000000	2000.000000	2000.000000
mean	0.501342	0.503600	0.491887	0.494081	0.507387	0.508792	14.43329	55.030790	10.205715	0.495096
std	0.288942	0.293132	0.285086	0.287523	0.286817	0.291054	14.50690	26.102797	5.633121	0.180474
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	-9.97000	10.010000	0.500000	0.000000
25%	0.254675	0.253557	0.245732	0.239026	0.263384	0.246733	1.42750	32.827500	5.237500	0.366880
50%	0.501069	0.503452	0.481768	0.488975	0.508081	0.518125	14.43500	54.990000	10.290000	0.497188
75%	0.746447	0.756626	0.736379	0.751837	0.760859	0.762264	27.11250	77.675000	14.900000	0.623202
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	39.97000	99.970000	19.990000	1.000000

2) Central Tendency Measures

[44]

```python
# Central Tendency Measures
mean_pm25 = df_reduced["PM2.5"].mean()
median_pm25 = df_reduced["PM2.5"].median()
mode_pm25 = df_reduced["PM2.5"].mode()[0]
min_pm25 = df_reduced["PM2.5"].min()
max_pm25 = df_reduced["PM2.5"].max()

print("PM2.5 – \n Min:", min_pm25,
      "\n Max:", max_pm25,
      "\n Mean:", mean_pm25,
      "\n Median:", median_pm25,
      "\n Mode:", mode_pm25)
```

```
PM2.5 –
 Min: 0.0
 Max: 1.0
 Mean: 0.5013420961843649
 Median: 0.5010694818188091
 Mode: 0.9833022838611745
```

3) Dispersion Measures

```
[47]
0s
# Dispersion Measures
range_pm25 = max_pm25 - min_pm25
variance_pm25 = df_reduced["PM2.5"].var()
std_pm25 = df_reduced["PM2.5"].std()
Q1_pm25, Q3_pm25 = df_reduced["PM2.5"].quantile([0.25, 0.75])
IQR_pm25 = Q3_pm25 - Q1_pm25

print(" Range:", range_pm25,
      "\n Variance:", variance_pm25,
      "\n StdDev:", std_pm25,
      "\n IQR:", IQR_pm25)
```

```
Range: 1.0
Variance: 0.08348766571104879
StdDev: 0.2889423224642745
IQR: 0.4917718898778721
```

4) Correction Analysis

```
[48]
✓ 2s
# Correction Analysis
corr_matrix = df_reduced.corr(numeric_only=True)
plt.figure(figsize=(10,8))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Matrix: Pollutants & AQI")
plt.show()
```