# Assignment No. 4

**Problem Statement:** Perform the following operations using Python on the Air quality data sets a. Data cleaning b. Data transformation

## Objective:

This analysis aims to enhance the quality and consistency of a 16,219-row air quality dataset by performing data cleaning and preprocessing. Key steps include handling missing values, removing duplicates, addressing outliers, and applying normalization and encoding as needed. By standardizing the data, we can ensure reliable analysis and meaningful insights into air quality trends. Visualizations will be created to reveal key patterns, helping to interpret the data effectively.

## Prerequisite :

1. Basic understanding of Python programming.
2. Understanding of Data cleaning and Data Preprocessing.
3. Understanding of libraries like Pandas, NumPy, Matplotlib, and Seaborn.
4. Knowledge of libraries such as NumPy and Matplotlib for data generation and visualization

## Theory :

## Data Preprocessing:

Data preprocessing, commonly known as data preparation, involves the systematic identification and correction of errors and inconsistencies in datasets. This step is crucial for transforming raw data into a format that is clean, structured, and ready for analysis, particularly in machine learning applications.

The process of data preprocessing encompasses four main categories:

## 1. Data Cleaning:

Datasets from the real world often suffer from issues such as missing information, noise, and inconsistencies. Data cleaning addresses these problems by filling in gaps, reducing noise, spotting outliers, and fixing any discrepancies. If left unaddressed, raw data can result in misleading analysis and flawed models. Therefore, implementing data cleaning strategies is vital for ensuring the reliability and quality of the dataset.

a) **Handling Missing Data**

In datasets, missing values are a common issue, often arising from data collection processes or validation requirements. It's important to address these gaps appropriately to improve the accuracy and reliability of analysis.

- **Dropping Rows/Columns:** Rows or columns with only NaN values or those with over 65% missing data can often be safely removed to avoid compromising data quality.
- **Removing Duplicates:** Duplicated rows or columns should be deleted, keeping only the first instance to prevent biases that could impact machine learning outcomes.
- **Estimating Missing Values:** For datasets with a smaller proportion of missing values, interpolation techniques can help bridge these gaps. A typical method is to fill in missing data with the mean, median, or mode of the feature, depending on the nature of the data.

b) **Addressing Noisy Data**

Noisy data, often the result of collection errors or poor data entry, lacks valuable information and can mislead analyses. To manage noisy data effectively, several strategies are available:

- **Binning Method:** This technique organizes sorted data into equal-sized bins and replaces the values in each bin with either the mean or boundary values, smoothing the dataset.
- **Clustering:** By grouping similar data points, clustering helps identify and isolate outliers, reducing noise in the data.
- **Regression:** Fitting data to a regression model—whether simple (one variable) or multiple (several variables)—can help smooth data by approximating relationships and reducing variability.

## 2. Data Integration:

Data integration involves consolidating data from diverse sources into a single, cohesive data repository, making it suitable for analysis. This process often requires addressing issues like schema alignment and entity identification to ensure consistency and accuracy across datasets.

a) **Purpose**: Integrates data from different sources to create a unified, comprehensive dataset suitable for analysis.
b) **Schema Integration**: Ensures alignment between varying data structures and formats, promoting compatibility across datasets.
c) **Entity Identification**: Matches entities across sources, such as recognizing that `customer_id` and `cust_number` refer to the same real-world entity.
d) **Role of Metadata**: Metadata, or data about data, helps prevent integration errors by providing essential context.
e) **Redundancy Issues**: When attributes are derived from other tables, redundancy can occur, leading to duplicate data entries.
f) **Inconsistencies**: Variations in naming conventions or dimensions between sources can introduce redundancies and inconsistencies, affecting data quality in the unified dataset.

## 3. Data Transformation:

Data transformation is the process of reformatting data to make it suitable for analysis and data mining. Key transformation methods include:

1. **Normalization**: Scales data values within a specific range, such as 0.0 to 1.0 or -1.0 to 1.0, to standardize the dataset.
2. **Concept Hierarchy Generation**: Replaces detailed or raw data with broader concepts by generalizing categorical data (e.g., converting specific streets to cities) or converting numeric values into categories (e.g., grouping ages into categories like youth, middle-aged, and elderly).
3. **Smoothing**: Reduces noise in the data through methods like binning, clustering, or regression, enhancing data quality.
4. **Aggregation**: Summarizes data by computing higher-level statistics, such as aggregating daily sales to monthly or yearly totals. Feature aggregation can also combine related features, like deriving area from height and width, which reduces dimensionality and multicollinearity.

## 4. Data Reduction:

Data reduction encompasses techniques designed to simplify and minimize the volume of data processed in analysis. This approach is essential for enhancing storage efficiency and reducing costs related to data storage and analysis, especially when working with large datasets.

**Techniques of Data Reduction**:

a) **Dimensionality Reduction:**
- Reduces the number of features in a dataset without merely selecting a subset.
- Techniques like Principal Component Analysis (PCA) transform data into a lower-dimensional space, preserving essential patterns.

b) **Numerosity Reduction:**
- Replaces or estimates data with smaller representations.
- Uses parametric models (e.g., regression, log-linear) to store essential parameters and non-parametric methods (e.g., clustering, sampling) for data summarization.

c) **Data Cube Aggregation:**
- Applies aggregation operations during data cube construction for efficient multi-dimensional analysis.
- Summarizes data to facilitate quicker insights across dimensions.

d) **Data Compression:**
- Reduces dataset size using encoding techniques.
- Methods like Wavelet Transform and PCA retain core information while saving space.

e) **Discretization and Concept Hierarchy Generation:**
- Simplifies analysis by replacing raw values with ranges or high-level concepts.
- Supports mining at various abstraction levels, enhancing interpretability in data analysis.

## Code & Output:

```
import pandas as pd
# Load the dataset
df = pd.read_csv('C:/Users/vishal_2/Assignments/Datasets/Air_Quality.csv')
data = df.iloc[:, 4]
print(data.head())
```

```
0    ppb
1    ppb
2    ppb
3    ppb
4    ppb
Name: Measure Info, dtype: object
```

```python
#Step 1: Data Cleaning
# Check for missing values
print("Missing values in each column:")
print(df.isnull().sum())
```

```
Missing values in each column:
Unique ID            0
Indicator ID         0
Name                 0
Measure              0
Measure Info         0
Geo Type Name        0
Geo Join ID          0
Geo Place Name       0
Time Period          0
Start_Date           0
Data Value           0
Message          16218
dtype: int64
```

```python
dataset_null = df.isnull()
print(dataset_null)
```

```
      Unique ID  Indicator ID   Name  Measure  Measure Info  Geo Type Name  \
0         False         False  False    False         False          False
1         False         False  False    False         False          False
2         False         False  False    False         False          False
3         False         False  False    False         False          False
4         False         False  False    False         False          False
...         ...           ...    ...      ...           ...            ...
16213     False         False  False    False         False          False
16214     False         False  False    False         False          False
16215     False         False  False    False         False          False
16216     False         False  False    False         False          False
16217     False         False  False    False         False          False

      Geo Join ID  Geo Place Name  Time Period  Start_Date  Data Value  \
0           False           False        False       False       False
1           False           False        False       False       False
2           False           False        False       False       False
3           False           False        False       False       False
4           False           False        False       False       False
...           ...             ...          ...         ...         ...
16213       False           False        False       False       False
16214       False           False        False       False       False
16215       False           False        False       False       False
16216       False           False        False       False       False
16217       False           False        False       False       False
```

```python
#Message column have almost 100% missing vlaue so we can drop it
df = df.drop('Message', axis=1)
```

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16218 entries, 0 to 16217
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Unique ID       16218 non-null  int64
 1   Indicator ID    16218 non-null  int64
 2   Name            16218 non-null  object
 3   Measure         16218 non-null  object
 4   Measure Info    16218 non-null  object
 5   Geo Type Name   16218 non-null  object
 6   Geo Join ID     16218 non-null  int64
 7   Geo Place Name  16218 non-null  object
 8   Time Period     16218 non-null  object
 9   Start_Date      16218 non-null  object
 10  Data Value      16218 non-null  float64
dtypes: float64(1), int64(3), object(7)
memory usage: 1.4+ MB
```

```python
#converting Data into Numerical Format
# Convert 'Start_Date' to datetime format
df['Start_Date'] = pd.to_datetime(df['Start_Date'], errors='coerce')

# For categorical columns, apply one-hot encoding
categorical_columns = ['Name', 'Measure', 'Measure Info', 'Geo Type Name', 'Geo Place Name', 'Time Period']

# One-Hot Encoding
df_encoded = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Check the first few rows of the transformed DataFrame
print(df_encoded.head())

# Optionally, check the data types after conversion
print(df_encoded.dtypes)
```

```
   Unique ID  Indicator ID  Geo Join ID Start_Date  Data Value  \
0     172653           375          203 2010-12-01       25.30
1     172585           375          203 2008-12-01       26.93
2     336637           375          204 2015-01-01       19.09
3     336622           375          103 2015-01-01       19.76
4     172582           375          104 2008-12-01       22.83
```

```
   Name_Annual vehicle miles travelled (cars)  \
0                                     False
1                                     False
2                                     False
3                                     False
4                                     False

   Name_Annual vehicle miles travelled (trucks)  \
0                                       False
1                                       False
2                                       False
3                                       False
4                                       False

   Name_Asthma emergency department visits due to PM2.5  \
0                                                 False
1                                                 False
2                                                 False
...
Time Period_Winter 2018-19             bool
Time Period_Winter 2019-20             bool
Time Period_Winter 2020-21             bool
Length: 202, dtype: object
```

*Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...*

```python
# Check for duplicates again
duplicates = df_encoded.duplicated().sum()
print(f"Number of duplicate rows: {duplicates}")
```

```
Number of duplicate rows: 0
```

```python
# Check for missing values again
missing_values = df_encoded.isnull().sum()
print("Missing values in each column:")
print(missing_values[missing_values > 0])
```

```
Missing values in each column:
Series([], dtype: int64)
```

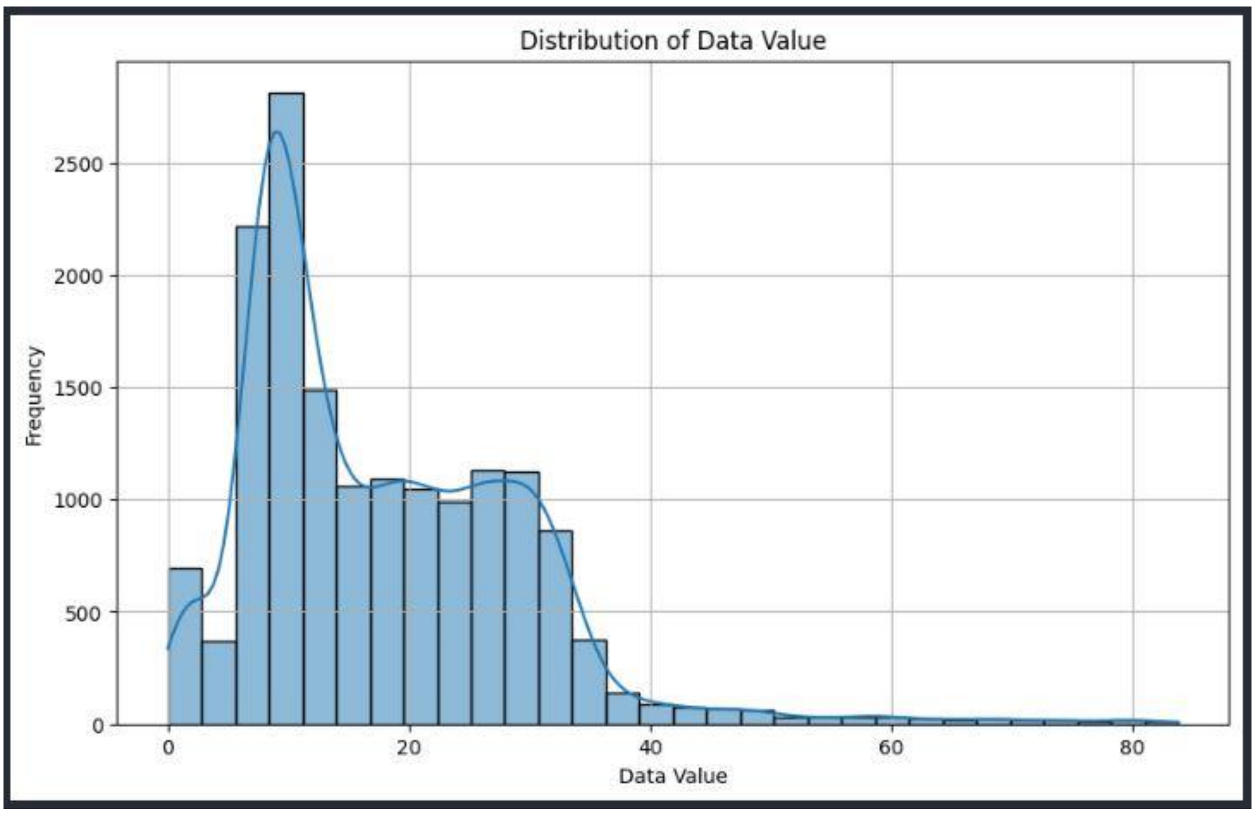
```python
# Outlier detection (example using Z-score)
from scipy import stats

# You can choose to check for outliers in 'Data Value'
z_scores = stats.zscore(df_encoded['Data Value'])
abs_z_scores = abs(z_scores)
outliers = (abs_z_scores > 3).sum()  # threshold can be adjusted

print(f"Number of outliers in 'Data Value': {outliers}")

# Optionally, you can remove outliers
df_encoded = df_encoded[(abs_z_scores <= 3)]
print(f"New shape after removing outliers: {df_encoded.shape}")
```

```
Number of outliers in 'Data Value': 274
New shape after removing outliers: (15944, 202)
```

```python
#Re-verify after handling the missing values
# Check for missing values
missing_values = df_encoded.isnull().sum()
print("Missing values in each column:")
print(missing_values[missing_values > 0])

# Summary statistics
print("Summary statistics of the DataFrame:")
print(df_encoded.describe())
```

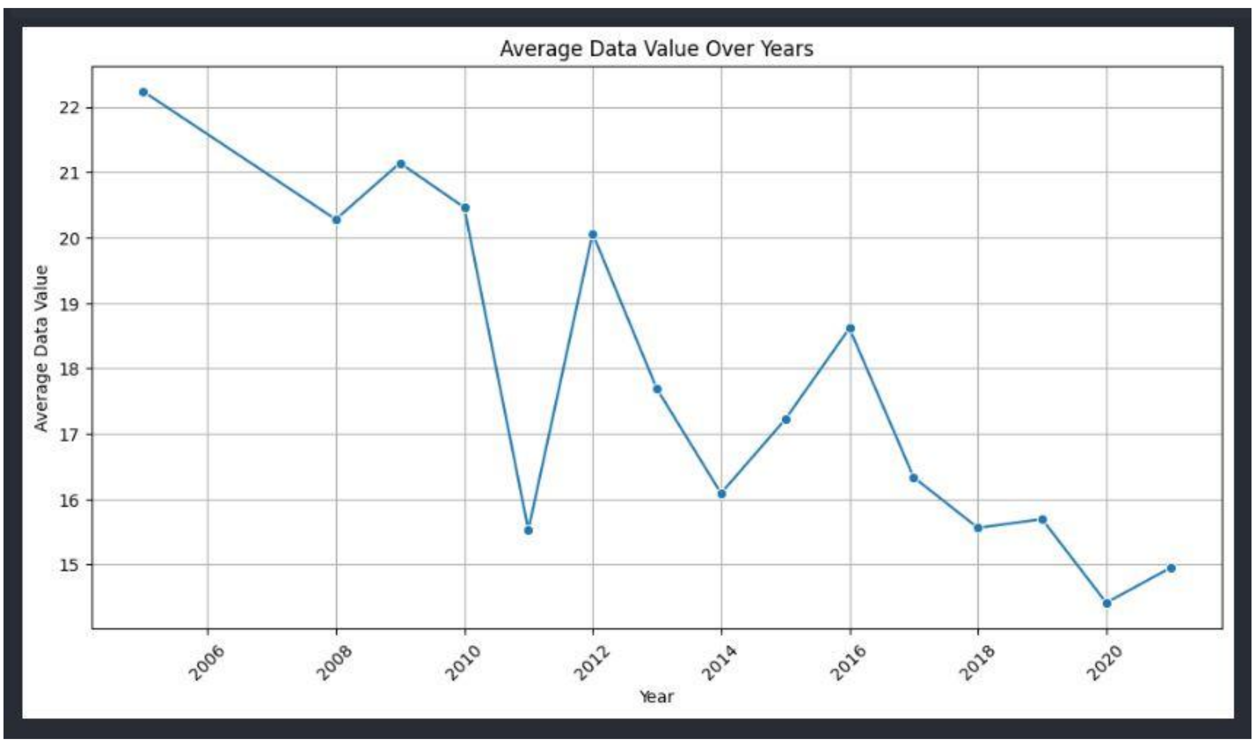
```
Missing values in each column:
Series([], dtype: int64)
Summary statistics of the DataFrame:
           Unique ID  Indicator ID   Geo Join ID  \
count   15944.000000  15944.000000  1.594400e+04
mean   373678.183705    423.956222  6.201849e+05
min    121644.000000    365.000000  1.000000e+00
25%    173633.750000    365.000000  2.020000e+02
50%    325285.500000    375.000000  3.030000e+02
75%    605287.250000    386.000000  4.040000e+02
max    799868.000000    661.000000  1.051061e+08
std    215387.957752    107.881226  7.960520e+06

                          Start_Date    Data Value
count                          15944  15944.000000
mean   2014-04-07 10:34:49.914701568     17.826834
min              2005-01-01 00:00:00      0.000000
25%              2011-01-01 00:00:00      8.980000
50%              2014-06-01 00:00:00     14.820000
75%              2017-06-01 00:00:00     25.570000
max              2021-06-01 00:00:00     83.800000
std                              NaN     11.623999
```

```python
#now data is in good shape and clean so we can do data transformation
#Distribution Plot of Data Value
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 6))
sns.histplot(df_encoded['Data Value'], bins=30, kde=True)
plt.title('Distribution of Data Value')
plt.xlabel('Data Value')
plt.ylabel('Frequency')
plt.grid()
plt.show()
```

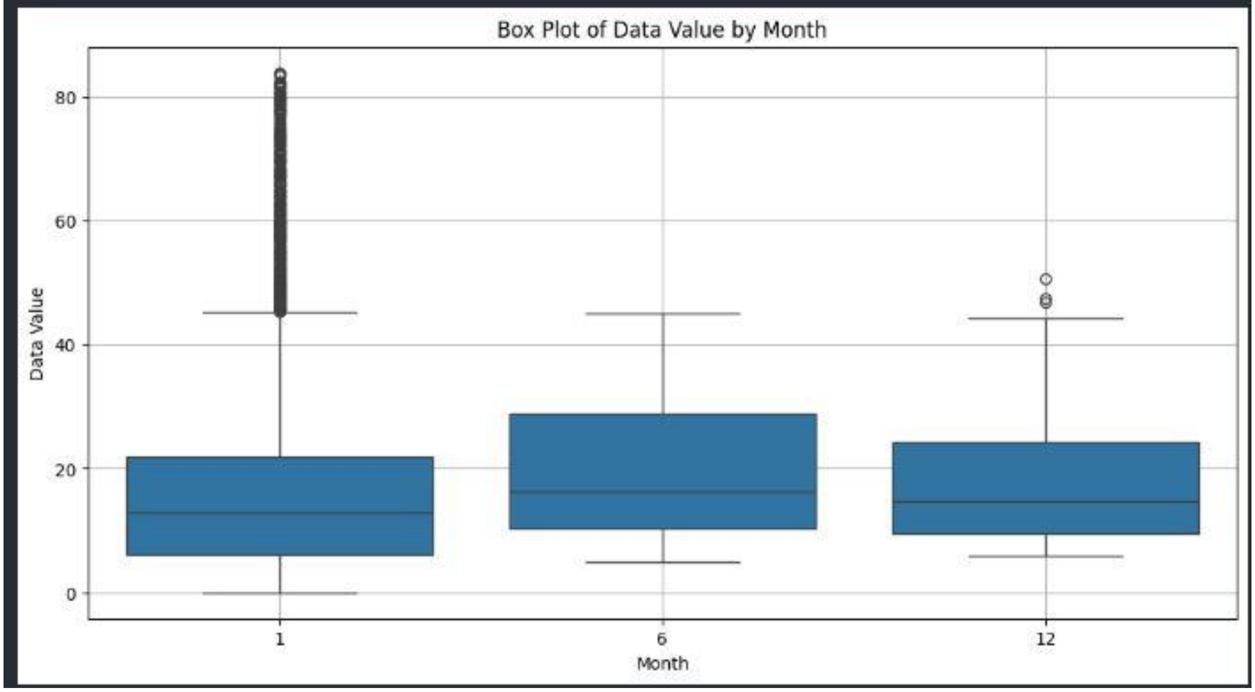


```
#feature selection
# Drop irrelevant columns
# Assuming Unique ID, Indicator ID, and Geo Join ID are not directly relevant for your analysis
df_transformed = df_encoded.drop(['Unique ID', 'Indicator ID', 'Geo Join ID'], axis=1)

# Extracting year and month from Start_Date
df_transformed['Year'] = df_transformed['Start_Date'].dt.year
df_transformed['Month'] = df_transformed['Start_Date'].dt.month

# we can Drop Start_Date if it's not needed anymore
df_transformed = df_transformed.drop('Start_Date', axis=1)
```

```
# Grouping by Year to find the average Data Value
average_data_value_per_year = df_transformed.groupby('Year')['Data Value'].mean().reset_index()

plt.figure(figsize=(12, 6))
sns.lineplot(data=average_data_value_per_year, x='Year', y='Data Value', marker='o')
plt.title('Average Data Value Over Years')
plt.xlabel('Year')
plt.ylabel('Average Data Value')
plt.xticks(rotation=45)
plt.grid()
plt.show()
```



```python
plt.figure(figsize=(12, 6))
sns.boxplot(x='Month', y='Data Value', data=df_transformed)
plt.title('Box Plot of Data Value by Month')
plt.xlabel('Month')
plt.ylabel('Data Value')
plt.grid()
plt.show()
```




## Another case study for cleaning handling missing values:

```python
import pandas as pd

# Load the dataset
df = pd.read_csv('C:/Users/vishal_2/Assignments/Datasets/city_day.csv')

# Assuming 'pm2.5' is the 5th column, assign it to a new variable
data = df.iloc[:, 4]

# Display a few rows of PM2.5 data
print(data.head())
```

```
0     0.92
1     0.97
2    17.40
3     1.70
4    22.10
Name: NO, dtype: float64
```

```
dataset_null = df.isnull()
print(dataset_null)
```

```
        City   Date  PM2.5   PM10     NO    NO2    NOx    NH3     CO    SO2  \
0      False  False   True   True  False  False  False   True  False  False
1      False  False   True   True  False  False  False   True  False  False
2      False  False   True   True  False  False  False   True  False  False
3      False  False   True   True  False  False  False   True  False  False
4      False  False   True   True  False  False  False   True  False  False
...      ...    ...    ...    ...    ...    ...    ...    ...    ...    ...
29526  False  False  False  False  False  False  False  False  False  False
29527  False  False  False  False  False  False  False  False  False  False
29528  False  False  False  False  False  False  False  False  False  False
29529  False  False  False  False  False  False  False  False  False  False
29530  False  False  False  False  False  False  False  False  False  False

          O3  Benzene  Toluene  Xylene    AQI  AQI_Bucket
0      False    False    False   False   True        True
1      False    False    False   False   True        True
2      False    False    False   False   True        True
3      False    False    False   False   True        True
4      False    False    False   False   True        True
...      ...      ...      ...     ...    ...         ...
29526  False    False    False   False  False       False
29527  False    False    False   False  False       False
29528  False    False    False   False  False       False
29529  False    False    False   False  False       False
29530  False     True     True    True  False       False

[29531 rows x 16 columns]
```

```
print(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
```

```
percent_missing_dataset = df.isnull().mean()*100
print(percent_missing_dataset)
```

```
City           0.000000
Date           0.000000
PM2.5         15.570079
PM10          37.723071
NO            12.129626
NO2           12.139785
NOx           14.171549
NH3           34.973418
CO             6.972334
SO2           13.050692
O3            13.619586
Benzene       19.041008
Toluene       27.229014
Xylene        61.322001
AQI           15.851139
AQI_Bucket    15.851139
dtype: float64
```

```
#  function to fill in missing values using median
def data_imputation(data, column_grouping, column_selected):
    # Parameter meaning
    # data => The name of the dataframe to be processed
    # column_grouping => The column used to group values and take the median
    # column_selected => The column in which we will fill its NaN values

    # Get unique category groups
    group = data[column_grouping].unique()

    # Loop through each value in the group category
    for value in group:
        # get median
        median = data.loc[(data[column_grouping]==value) & ~(data[column_selected].isna()), column_selected].median()

        # change missing value
        data.loc[(data[column_grouping]==value) & (data[column_selected].isna()), column_selected] = median

    # Return the dataframe after filling the missing values
    return data
```

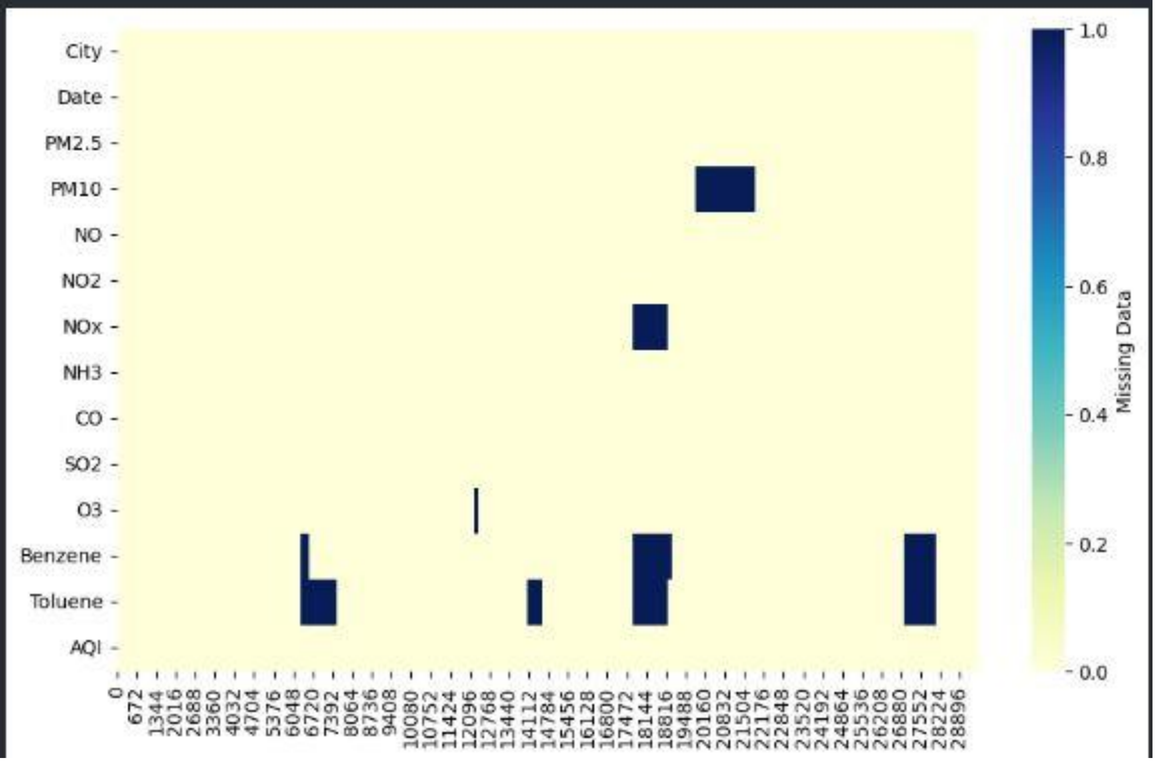
```python
# apply the function to 'PM2.5' column
df = data_imputation(data=df, column_grouping='City', column_selected='PM2.5')

# apply the function to 'Xylene' column
df = data_imputation(data=df, column_grouping='City', column_selected='Xylene')

# apply the function to 'PM2.5' column
df = data_imputation(data=df, column_grouping='City', column_selected='PM10')

# apply the function to 'NO' column
df = data_imputation(data=df, column_grouping='City', column_selected='NO')

# apply the function to 'NO2' column
df = data_imputation(data=df, column_grouping='City', column_selected='NO2')
```

```python
n = df.isna()
missing_counts = n.sum()
missing_per = missing_counts / len(df)

print(missing_per)
```

```
City        0.000000
Date        0.000000
PM2.5       0.000000
PM10        0.068030
NO          0.000000
NO2         0.000000
NOx         0.039586
NH3         0.000000
CO          0.000000
SO2         0.000000
O3          0.005486
Benzene     0.092513
Toluene     0.135790
Xylene      0.441807
AQI         0.000000
dtype: float64
```

```python
# Visualizing Missing Data using a seaborn heatmap.
plt.figure(figsize=(10,6))
sns.heatmap(df.isna().transpose(),
            cmap="YlGnBu",
            cbar_kws={'label': 'Missing Data'})
```

```
<Axes: >
```




## References :


https://medium.easyread.co/basics-of-data-preprocessing-71c314bc7188
https://medium.com/almabetter/data-preprocessing-techniques-6ea145684812
https://medium.com/@yogeshojha/data-preprocessing-75485c7188c4
https://medium.com/womenintechnology/data-preprocessing-steps-for-machine-learning-in-phyton-part-1-18009c6f1153


**Github-** https://github.com/Vishalgodalkar/Data-Science

## Conclusion :

The dataset has undergone cleaning by removing outliers and filling in any missing values. Categorical features have been transformed into numerical formats, and relevant temporal features have been extracted. Additionally, the average data value has been analyzed over time, making the dataset fully prepared for deeper analysis.