INDEX

ACKNOWLEDGEMENT

We would like to express our gratitude towards Dr. Richa Sharma and our honorable Principal Dr. Madhu Pruthi, of Keshav Mahavidyalaya for her support in accomplishment of our project on Exploratory Data Analysis on AQI Data Set.

we would like to extend our deep appreciation to all group members, without support and coordination we would not have been able to complete this project.

Group Members: Satyandra, Puneet , Saurabh.

INSPIRATION

Concern about quality of air we breathe. To study the different element responsible for the deteoriation of the inhaling elements. The health of the public, especially those who are the most vulnerable, such as children, the elderly and the sick, is at risk from air pollution, but it is difficult to say how large the risk is. It is possible that the problem has been over-stressed in relation to other challenges in the field of public health.

Link to the Dataset:

https://www.kaggle.com/rohanrao/air-quality-data-in-india

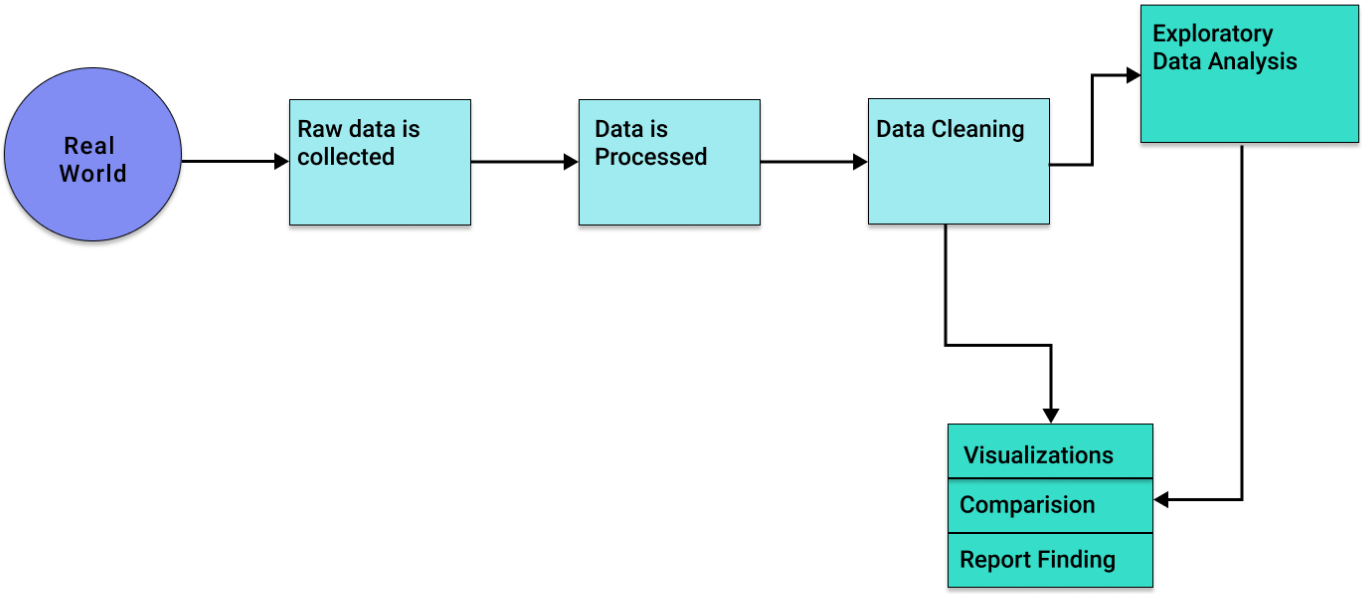
Data Description:

The data-set consists of 16 Columns. The columns, and their descriptions were as listed below:

1. **City**: Contains the Data of various Cities.
2. **Date**: Contains the date from 01-01-2015 – 01-07-2020.
3. **PM2.5**: Particulate Matter 2.5-Micrometer in ug/m^3.
4. **PM10**: Particulate Matter 10-Micrometer in ug/m^3.
5. **NO**: Nitric Oxide in ug/m^3.
6. **NO2**: Nitric Dioxide in ug/m^3.
7. **NOx**: Any Nitric x-oxide in ppb.
8. **NH3**: Ammonia in ug/m^3.
9. **CO**: Carbon Monoxide in mg/m^3.
10. **SO2**: Sulphur Dioxide in ug/m^3.
11. **O3**: Ozone
12. **Benzene**: Benzene in ppb.
13. **Xylene**: Xylene in ppb.

14. **Tolune**: Tolune in ppb.
15. **AQI**: Contains the calculated value of AQI of all days
16. **AQI Bucket**: Contains the Category of Aqi: -
    - Good 0-50
    - Moderate 51-100
    - Satisfactory 101-150
    - Poor 151-200
    - Very Poor 201-300
    - Severe 301-Higher

Flowchart:



LIBRARIES:

- **NumPy** aims to provide an array object that is up to 50x faster than traditional Python lists. The array object in NumPy is called ndarray, it provides a lot of supporting functions that make #working with ndarray very easy
- **Pandas** is an open-source library that is built on top of NumPy library. It is a Python package that offers various data structures and operations for manipulating numerical data and time series. It is mainly popular for importing and analyzing data much easier.
- **Seaborn** is an open-source Python library built on top of matplotlib. It is used for data visualization and exploratory data analysis. Seaborn works easily with data frames and the Pandas library. The graphs created can also be customized easily.
- **Matplotlib** comes with a wide variety of plots. Plots helps to understand trends, patterns, and to make correlations. They're typically instruments for reasoning about quantitative information.

FUNCTIONS:

1) **MERGE**

- pandas.merge(left, right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True, indicator=False, validate=None)[source]
- Merge DataFrame or named Series objects with a database-style join.
-
- A named Series object is treated as a DataFrame with a single named column.
-
- The join is done on columns or indexes. If joining columns on columns, the DataFrame indexes will be ignored. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on. When performing a cross merge, no column specifications to merge on are allowed.

Parameters:

- Left DataFrame
- right DataFrame or named Series
- Object to merge with.

How{'left', 'right', 'outer', 'inner', 'cross'}, default 'inner'
Type of merge to be performed.

- left: use only keys from left frame, similar to a SQL left outer join; preserve key order.
- right: use only keys from right frame, similar to a SQL right outer join; preserve key order.
- outer: use union of keys from both frames, similar to a SQL full outer join; sort keys lexicographically.

- inner: use intersection of keys from both frames, similar to a SQL inner join; preserve the order of the left keys.
- cross: creates the cartesian product from both frames, preserves the order of the left keys.

2) **PD.DATAFRAME**

- Pandas DataFrame is two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows andcolumns).

3)**VALUES**

- values() is an inbuilt method in Python programming language that returns a list of all the values available in a given dictionary.
- Returns: returns a list of all the values available in a given dictionary. the values have been stored in a reversed manner.There are no parameters

4) **SORT_VALUES**

- Pandas sort_values() function sorts a data frame in Ascending or Descending order of passed Column. It's different than the sorted Python function since it cannot sort a data frame and particular column cannot be selected.
- DataFrame.sort_values(by, axis=0, ascending=True, inplace=False, kind='quicksort', na_position='last')
- by: Single/List of column names to sort Data Frame by.
- axis: 0 or 'index' for rows and 1 or 'columns' for Column.
- ascending: Boolean value which sorts Data frame in ascending order if True.
- inplace: Boolean value. Makes the changes in passed data frame itself if True.
- kind: String which can have three inputs('quicksort', 'mergesort' or 'heapsort') of algorithm used to sort data frame.
- na_position: Takes two string input 'last' or 'first' to set position of Null values. Default is 'last'.

5) **RENAME_FUNCTION**

- rename() method in Python is used to rename a file or directory. This method renames a source file/ directory to specified
- destination file/directory. Parameters: source: A path-like object representing the file system path

6) **READ_CSV**

- This function reads a csv file in a dataframe. The Pandas read_csv() function returns a new DataFrame with the data and labels from the file data. csv , which you specifiedwith the first argument. This string can be any valid path, including URLs.

7)**HEAD**

- This function returns the first 5 rows.The head() function is used to get the first n rows. It is useful for quickly testing if your object has the right type of data in it. For negative values of n , the head() function returns all rows except the last n rows, equivalent to df[:-n].

8)**FIGURE(FIGSIZE=(X,Y))**

- The purpose of using plt. figure() is to create a figure object. The whole figure is regarded as the figure object. It isnecessary to explicitly use plt. figure() when we want to tweak the size of the figure and when we want to add multiple Axes objects in a single figure.
- figsize(float, float): These parameter are the width, height in inches

9) **BARPLOT**

- function calculates a summary statistic for each category
- x, y: This parameter take names of variables in data or vector data, Inputs for plotting long-form data.
- hue: (optional) This parameter take column name for colour encoding.
- data: (optional) This parameter take DataFrame, array, or list of arrays, Dataset for plotting.
- We use plt.xticks(rotation=#) where # can be any angle by which we want to rotate the x labels
- The title () function in python is the Python String Method which is used to convert the first character in each word to Uppercase and remaining characters to Lowercase in the string and returns a new string.
- plt. show () starts an event loop, looks for all currently active figure objects, and opens one or more interactive windows that display your figure or figures.

10) **INFO**

- The info() function is **used to print a concise summary of a DataFrame**.
- This method prints information about a DataFrame including the index dtype and column dtypes, non-null values and memory usage.

11) **ISNULL**

- ***Syntax:*** *Series.isnull()*
- ***Parameter :*** *None*
- ***Returns :*** *boolean*
- isnull() function has returned an object containing boolean values. All missing values have been mapped to True.

12) **SUM**

- **sum(iterable, start)**
- **iterable :** iterable can be anything list , tuples or dictionaries ,
- but most importantly it should be numbers.
- **start** : this start is added to the sum of
- numbers in the iterable.
- If start is not given in the syntax , it is assumed to be 0.

Possible two syntaxes:

. **sum(a)**
a is the list , it adds up all the numbers in the
list a and takes start to be 0, so returning
only the sum of the numbers in the list.

. **sum(a, start)**

this returns the sum of the list + start

13) **VALUE_COUNT**

- **Index.value_counts()** function returns object containing counts of unique values. The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.
- **Syntax:** Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)
- **Parameters :**
  normalize : If True then the object returned will contain the relative frequencies of the unique values .
  sort : Sort by values
  ascending : Sort in ascending order
  bins : Rather than count values, group them into half-open bins, a convenience for pd.cut, only works with numeric data
  dropna : Don't include counts of NaN.
- **Returns:** counts : Series

Code:

Original file is located at

https://colab.research.google.com/drive/1AxZj-xjlVCNmcjHeYlweLnBmBhXzucFA

Importing Libraries

"""

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
#import matplotlib.dates as mdates
```

"""# **Importing the Dataset**"""

```
df = pd.read_csv("AQI.csv").sort_values(by=['City','Date'])#sorting by city and date.
df.head()
```

```
"""# **Check Null Values**"""

df.info() #Print a Concise Summary of Dataframe

df.isnull().sum() #sum(count) of null values.

"""# **Unique values and Count of columns**"""

for i in df.columns:
  print('column name:{}     unique values:{}'.format(i,len(df[i].unique())))  #Finds all the Unique Values Within the df.

cities = df['City'].value_counts()   #Return a Series containing counts of unique values.
print(f'Total no. of different cities in the dataset : {len(cities)}')
print(cities.index)  #priting the unique values of column 'City'

"""# **Filling Null Values**"""

df['PM2.5']=df['PM2.5'].fillna(df['PM2.5'].mean())
df['PM10']=df['PM10'].fillna(df['PM10'].mean())
df['NO']=df['NO'].fillna(df['NO'].mean())
df['NO2']=df['NO2'].fillna(df['NO2'].mean())
df['NOx']=df['NOx'].fillna(df['NOx'].mean())
df['NH3']=df['NH3'].fillna(df['NH3'].mean())
df['CO']=df['CO'].fillna(df['CO'].mean())
df['SO2']=df['SO2'].fillna(df['SO2'].mean())
df['O3']=df['O3'].fillna(df['O3'].mean())
df['Benzene']=df['Benzene'].fillna(df['Benzene'].mean())
df['Toluene']=df['Toluene'].fillna(df['Toluene'].mean())
df['Xylene']=df['Xylene'].fillna(df['Xylene'].mean())
df['AQI']=df['AQI'].fillna(df['AQI'].mode()[0])
df['AQI_Bucket']=df['AQI_Bucket'].fillna('Moderate')
```

```
df.info()
```

```
"""# **Average Amount Of Pollution In Every City**"""
```

```
df.describe()   #Generate descriptive statistics.
```

```
df.reset_index(drop=True,inplace=True)
df.head()
```

```
"""# **Most Polluted cities**"""
```

```
most_polluted = df[['City', 'AQI', 'PM10','PM2.5', 'CO','NO', 'NO2','SO2','O3']].groupby(['City']).mean().sort_values(by = 'AQI', ascending = False)
most_polluted
```

```
"""## **Plotting graph of most polluted cities**"""
```

```
plt.style.use('seaborn-whitegrid')
f, ax_ = plt.subplots(1,7, figsize = (20,8))
bar1=sns.barplot(x = most_polluted.AQI, y = most_polluted.index, palette='RdBu',ax=ax_[0]);
bar1=sns.barplot(x = most_polluted.sort_values(by="PM10",ascending=False)['PM10'] , y = most_polluted.index, palette='RdBu',ax=ax_[1]);
bar1=sns.barplot(x = most_polluted.sort_values(by="PM2.5",ascending=False)['PM2.5'] , y = most_polluted.index, palette='RdBu',ax=ax_[2]);
bar1=sns.barplot(x = most_polluted.sort_values(by='CO',ascending=False)['CO'], y = most_polluted.index, palette='RdBu',ax=ax_[3]);
bar1=sns.barplot(x = most_polluted.sort_values(by='NO',ascending=False)['NO'] , y = most_polluted.index, palette='RdBu',ax=ax_[4]);
bar1=sns.barplot(x = most_polluted.sort_values(by='SO2',ascending=False)['SO2'] , y = most_polluted.index, palette='RdBu',ax=ax_[5]);
bar1=sns.barplot(x = most_polluted.sort_values(by='O3',ascending=False)['O3'] , y = most_polluted.index, palette='RdBu',ax=ax_[6]);
```

```
titles = ['AirQualityIndex', 'ParticulateMatter10','ParticulateMatter2.5', 'CO', 'NO', 'SO2', 'O3']
for i in range(7) :
```

```
    ax_[i].set_ylabel('')
    ax_[i].set_yticklabels(labels = ax_[i].get_yticklabels(),fontsize = 10);
    ax_[i].set_title(titles[i])
    f.tight_layout()


"""### Correlation"""


cor = df.corr()
heatmap_df= cor.drop(['NOx', 'NH3','O3','Toluene','Xylene', 'AQI']).drop(['NOx', 'NH3','O3','Toluene','Xylene', 'AQI'], axis=1)
f, ax = plt.subplots(figsize = (10,10))
sns.heatmap(heatmap_df, vmax = 1, square = True, annot = True)


"""# **Graph of Pollutants in every City.**"""


df[['PM2.5','City']].groupby(['City']).median().sort_values("PM2.5", ascending = False).plot.bar(color='#2C2891')
df[['PM10','City']].groupby(['City']).median().sort_values("PM10", ascending = False).plot.bar(color='#FFB319')
df[['NO','City']].groupby(['City']).median().sort_values("NO", ascending = False).plot.bar(color='#39A388')
df[['NO2','City']].groupby(['City']).median().sort_values("NO2", ascending = False).plot.bar(color='#FFB830')
df[['CO','City']].groupby(['City']).median().sort_values("CO", ascending = False).plot.bar(color='#FF2442')
df[['SO2','City']].groupby(['City']).median().sort_values("SO2", ascending = False).plot.bar(color='#80ED99')
df[['O3','City']].groupby(['City']).median().sort_values("O3", ascending = False).plot.bar(color='#EC9CD3')
df[['Benzene','City']].groupby(['City']).median().sort_values("Benzene", ascending = False).plot.bar(color='#F037A5')


"""# **Analaysis of data using Time Series**"""


# convert column to datetime
df['Date'] = pd.to_datetime(df['Date'])


pollutants = ['PM2.5','PM10','NO','NO2','NOx','NH3','CO','SO2','O3','Benzene','Toluene','Xylene','AQI'] #Creating a list for Pollutants


"""## Plotting the Color Map for Every Month throughout the years"""
```

```
df['month'] = pd.DatetimeIndex(df['Date']).month       #Returns Immutable ndarray-like of datetime64 data

mth_dic = {1:'Jan',2:'Feb',3:'Mar',4:'Apr',5:'May',6:'Jun',7:'Jul',8:'Aug',9:'Sep',10:'Oct',11:'Nov',12:'Dec'} #Creating a dict of months

df['month']=df['month'].map(mth_dic)            #Mapping of dict with index

df.groupby('month')[pollutants].mean().plot(figsize=(12,6), cmap='Spectral')

plt.legend(bbox_to_anchor=(1.0, 1.0))

plt.xticks(np.arange(12), mth_dic.values())

plt.ylabel('Concentration per Cubic Meter')


"""# **Analysis of AQI during Covid 19 Pandemic of Major Cities**"""


cities = ['Ahmedabad','Delhi','Bengaluru','Mumbai','Hyderabad','Chennai','Lucknow']  #Major Cities

filter_city_date = df[df['Date'] >= '2019-01-01']

AQI = filter_city_date[filter_city_date.City.isin(cities)][['Date','City','AQI','AQI_Bucket']] #taking values only after 2019

AQI.head()


"""# Comparing AQI Before and After Lockdown using Line Graph"""


subplot_titles=["Bengaluru","Chennai","Delhi",'Hyderabad','Mumbai', "Ahmedabad","Lucknow"]     #Create a figure and a set of subplots

x_line_annotation = datetime.date(2020, 3, 25)    #Lockdown Date

f, axes = plt.subplots(7, 1, figsize=(15, 15), sharex=True)       #Sharex controls sharing of properties among x or y axes

for count, title in enumerate(subplot_titles):

    ax = AQI[AQI['City']==title].plot(x='Date', y='AQI', kind='line', ax=axes[count], color='#161E54')

    ax.title.set_text(title)

    ax.set_xlim([datetime.date(2019, 1, 1), datetime.date(2020, 7, 1)])

    ax.axvline(x=x_line_annotation, linestyle='dashed', alpha=1, color='#FF0000')


"""From Above Line Graphs we can conclude that:


-The Value Of Aqi gradually increases during January to May


-The Value Of Aqi gradually decreases during June to September
```

-But After the Lockdown, the value decreses drastically over the all major cities

Creating Pivot Tables

"""

```
AQI_pivot = AQI.pivot(index='Date', columns='City', values='AQI')      #Pivot returns reshaped DataFrame
AQI_pivot.head()

AQI_beforeLockdown = AQI_pivot['2020-01-01':'2020-03-25']
AQI_afterLockdown = AQI_pivot['2020-03-26':'2020-07-01']
df1= pd.DataFrame(AQI_beforeLockdown.mean().reset_index())
df2= pd.DataFrame(AQI_afterLockdown.mean().reset_index())
df3=df1.merge(df2, on='City')
df3 = df3.rename({'0_x': 'BeforeLockdown', '0_y': 'AfterLockdown'}, axis=1)
```

"""## **Bar Plot for Comparision**"""

```
df3.reset_index().plot(x="City", y=["BeforeLockdown", "AfterLockdown"], kind="bar",figsize=(16,8))
plt.title("Comparision Of AQI Before and After Lockdown")
plt.xlabel("Cities")
plt.ylabel("AQI")
plt.show()
```

"""-The mean AQI value for Mumbai went from moderate(148.77) to satisfactory(64.35)

-The mean AQI value for Ahmedabad went from very poor(372.4) to moderate(118.8)

-The mean AQI value for Delhi went from poor(246.3) to moderate(125.27)

-The mean AQI value for Hyderabad went from moderate(94.43) to satisfactory(64.67)

-The mean AQI value for Bengaluru went from moderate(96) to satisfactory(65.4)

-The mean AQI value for Chennai went from moderate(80.31) to satisfactory(80.1)

Creating a copy of dataframe

"""

```
df_cpy=df.copy()
sub_set=df_cpy[df_cpy['City'].isin(['Ahmedabad','Delhi','Mumbai','Chennai','Hyderabad','Lucknow'])]

sub_set.head()

sub_set.groupby('City')['AQI_Bucket'].value_counts().to_frame()   #Creating a dataframe

plt.figure(figsize=(20,10))
sub_set.groupby('City')['AQI_Bucket'].value_counts().sort_values(ascending=False).plot.bar(color=['#ff4000','#ff8000','#ffbf00','#ffff00','#bfff00','#80ff00','#40ff00','#00ff00','#00ff40','#00ff80','#00ffbf','#00ffff','#00bfff','#0080ff','#0040ff','#0000ff','#4000ff','#8000ff','#bf00ff','#ff00ff','#ff00bf','#ff0080','#ff0040','#ff0000','#660000','#4d0000','#330000'],edgecolor='black')
plt.show()

list=['Good','Moderate','Satisfactory','Poor','Very Poor','Severe']

plt.figure(figsize=(12,12))
plt.pie(df_cpy['AQI_Bucket'].value_counts()
[0:6],labels=(df_cpy['AQI_Bucket'].value_counts()
[0:6].keys()),autopct='%0.1f%%')

plt.figure(figsize=(20,10))
pollutants1 = ['NO','NO2','NOx','NH3','CO','SO2','O3','Benzene','Toluene','Xylene']
df_cpy.boxplot(pollutants1)
```

OUTPUT

Importing Libraries

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

import matplotlib.dates as mdates

Importing the Dataset

df = pd.read_csv("AQI.csv").sort_values(by=['City','Date'])#sorting by city and date. df.head()

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3	CO	SO2	O3
0	Ahmedabad	1/1/2015	NaN	NaN	0.92	18.22	17.15	NaN	0.92	27.64	133.36
365	Ahmedabad	1/1/2016	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
731	Ahmedabad	1/1/2017	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1096	Ahmedabad	1/1/2018	84.46	NaN	7.58	87.62	48.40	NaN	7.58	102.36	69.02
1461	Ahmedabad	1/1/2019	110.71	NaN	63.03	111.56	100.04	NaN	63.03	80.15	57.12

Check Null Values

df.info() #Print a Concise Summary of Dataframe

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 29531 entries, 0 to 29234
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
0    City        29531 non-null  object 
1    Date        29531 non-null  object 
2    PM2.5       24933 non-null  float64
3    PM10        18391 non-null  float64
4    NO          25949 non-null  float64
5    NO2         25946 non-null  float64
6    NOx         25346 non-null  float64
7    NH3         19203 non-null  float64
8    CO          27472 non-null  float64
9    SO2         25677 non-null  float64
10   O3          25509 non-null  float64
```

11 Benzene 23908 non-null float64

12 Toluene 21490 non-null float64

13 Xylene 11422 non-null float64

14 AQI 24850 non-null float64 15 AQI_Bucket 24850 non-null object dtypes: float64(13), object(3) memory usage: 3.8+ MB

df.isnull().sum() #sum(count) of null values.

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

Unique values and Count of columns

for i in df.columns: print('column name:{} unique values:{}'.format(i,len(df[i].unique()))) #Finds all th

column name:City unique values:26 column
name:Date unique values:2009 column name:PM2.5
unique values:11717 column name:PM10 unique
values:12572 column name:NO unique values:5777
column name:NO2 unique values:7405 column
name:NOx unique values:8157 column name:NH3
unique values:5923 column name:CO unique
values:1780 column name:SO2 unique values:4762
column name:O3 unique values:7700 column
name:Benzene unique values:1874 column
name:Toluene unique values:3609 column

```
name:Xylene     unique values:1562 column name:AQI
unique values:830 column name:AQI_Bucket     unique
values:7 cities = df['City'].value_counts()   #Return a
Series containing counts of unique values.
```

```
print(f'Total no. of different cities in the dataset : {len(cities)}') print(cities.index)  #priting the unique values of column 'City'
```

```
Total no. of different cities in the dataset : 26

Index(['Chennai', 'Bengaluru', 'Lucknow', 'Delhi', 'Mumbai', 'Ahmedabad',

    'Hyderabad', 'Patna', 'Gurugram', 'Visakhapatnam', 'Amritsar',

    'Jorapokhar', 'Jaipur', 'Thiruvananthapuram', 'Amaravati',

    'Brajrajnagar', 'Talcher', 'Kolkata', 'Guwahati', 'Coimbatore',

    'Shillong', 'Chandigarh', 'Bhopal', 'Kochi', 'Ernakulam', 'Aizawl'],      dtype='object')
```

Filling Null Values

```
df['PM2.5']=df['PM2.5'].fillna(df['PM2.5'].mean()) df['PM10']=df['PM10'].fillna(df['PM10'].mean())
df['NO']=df['NO'].fillna(df['NO'].mean()) df['NO2']=df['NO2'].fillna(df['NO2'].mean())
df['NOx']=df['NOx'].fillna(df['NOx'].mean()) df['NH3']=df['NH3'].fillna(df['NH3'].mean())
df['CO']=df['CO'].fillna(df['CO'].mean()) df['SO2']=df['SO2'].fillna(df['SO2'].mean())
df['O3']=df['O3'].fillna(df['O3'].mean()) df['Benzene']=df['Benzene'].fillna(df['Benzene'].mean())
df['Toluene']=df['Toluene'].fillna(df['Toluene'].mean()) df['Xylene']=df['Xylene'].fillna(df['Xylene'].mean())
df['AQI']=df['AQI'].fillna(df['AQI'].mode()[0]) df['AQI_Bucket']=df['AQI_Bucket'].fillna('Moderate')
```

```
df.info()
```

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

Int64Index: 29531 entries, 0 to 29234

Data columns (total 16 columns):

 #   Column      Non-Null Count  Dtype

---  ------      --------------  -----

0     City       29531 non-null  object

1     Date       29531 non-null  object

2     PM2.5      29531 non-null  float64

3     PM10       29531 non-null  float64

4     NO         29531 non-null  float64

5     NO2        29531 non-null  float64

6     NOx        29531 non-null  float64

7     NH3        29531 non-null  float64
```

8 CO 29531 non-null float64

9 SO2 29531 non-null float64

10 O3 29531 non-null float64

11 Benzene 29531 non-null float64

12 Toluene 29531 non-null float64

13 Xylene 29531 non-null float64

14 AQI 29531 non-null float64 15 AQI_Bucket 29531 non-null object dtypes: float64(13), object(3) memory usage: 3.8+ MB

Average Amount Of Pollution In Every City

df.describe() #Generate descriptive statistics.

	PM2.5	PM10	NO	NO2	NOx	NH3
count	29531.000000	29531.000000	29531.00000	29531.000000	29531.000000	29531.000000
mean	67.450578	118.127103	17.57473	28.560659	32.309123	23.483476
std	59.414476	71.500953	21.35922	22.941051	29.317936	20.711370
min	0.040000	0.010000	0.02000	0.010000	0.000000	0.010000
25%	32.150000	79.315000	6.21000	12.980000	14.670000	12.040000
50%	58.030000	118.127103	11.53000	25.240000	27.550000	23.483476
75%	72.450000	118.127103	17.57473	34.665000	36.015000	23.483476
max	949.990000	1000.000000	390.68000	362.210000	467.630000	352.890000

df.reset_index(drop=True,inplace=True) df.head()

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3
0	Ahmedabad	1/1/2015	67.450578	118.127103	0.92000	18.220000	17.150000	23.483476
1	Ahmedabad	1/1/2016	67.450578	118.127103	17.57473	28.560659	32.309123	23.483476
2	Ahmedabad	1/1/2017	67.450578	118.127103	17.57473	28.560659	32.309123	23.483476

3	Ahmedabad	1/1/2018	84.460000	118.127103	7.58000	87.620000	48.400000	23.483476
4	Ahmedabad	1/1/2019	110.710000	118.127103	63.03000	111.560000	100.040000	23.483476

Most Polluted cities

most_polluted = df[['City', 'AQI', 'PM10','PM2.5', 'CO','NO', 'NO2','SO2','O3']].groupby(['Ci most_polluted

	AQI	PM10	PM2.5	CO	NO	NO2	
City							
Ahmedabad	334.485814	117.409318	67.728234	16.147420	20.956815	49.805675	4
Delhi	258.703833	228.413747	117.146631	1.976053	38.964280	50.763057	1

Lucknow	211.276755	118.127103	107.568277	2.131976	15.261301	33.188450	1
Patna	210.979010	119.013316	113.815353	1.591700	30.283315	36.507494	2
Gurugram	208.550923	150.467320	112.549731	1.321857	17.537607	23.797951	
Talcher	155.490811	156.552639	62.607920	1.911862	28.071044	17.343337	2
Jorapokhar	139.759624	142.240508	66.406088	1.358846	12.530220	13.781598	2
Guwahati	139.579681	116.604900	63.692929	0.738284	20.038456	13.598607	1
Brajrajnagar	138.699360	123.094114	64.726798	1.870288	17.372515	19.524152	1
Kolkata	137.723587	115.798256	64.571464	0.799251	26.550753	40.032711	
Jaipur	133.110413	123.416193	54.640204	0.809991	14.675238	32.370143	1
Bhopal	131.653979	119.287038	50.601160	0.923001	7.365372	31.258602	
Amritsar	118.526618	115.353495	56.724459	0.656948	18.640090	18.883865	
Visakhapatnam	114.230506	107.916796	50.191650	0.777069	13.480745	35.728846	1
Chennai	113.724739	109.815308	51.417112	1.082048	9.340802	17.067334	
Hyderabad	108.754736	96.567339	48.205721	0.594912	7.953391	28.389182	
Kochi	104.228395	67.335432	31.428519	1.296667	71.102528	15.449963	1
Mumbai	103.293181	110.006396	54.864359	0.589271	22.705652	27.429689	1
Chandigarh	96.588816	85.656546	42.428943	0.631349	10.594503	11.834088	1
Amaravati	96.074658	78.777456	39.614400	0.793211	5.195931	22.545012	1
Bengaluru	94.696864	89.494244	38.118529	1.840878	9.433523	27.996732	
Ernakulam	92.895062	50.058879	25.994274	1.643175	23.045302	12.157631	
Thiruvananthapuram	77.287770	55.093885	29.525274	0.970043	3.848603	9.914812	
Coimbatore	76.176166	39.435543	29.945349	0.959419	8.830156	28.778153	
Shillong	70.122581	59.099258	38.385603	0.453528	4.087416	7.663125	
Aizawl	35.955752	24.191567	18.020630	0.283628	9.408053	0.388496	

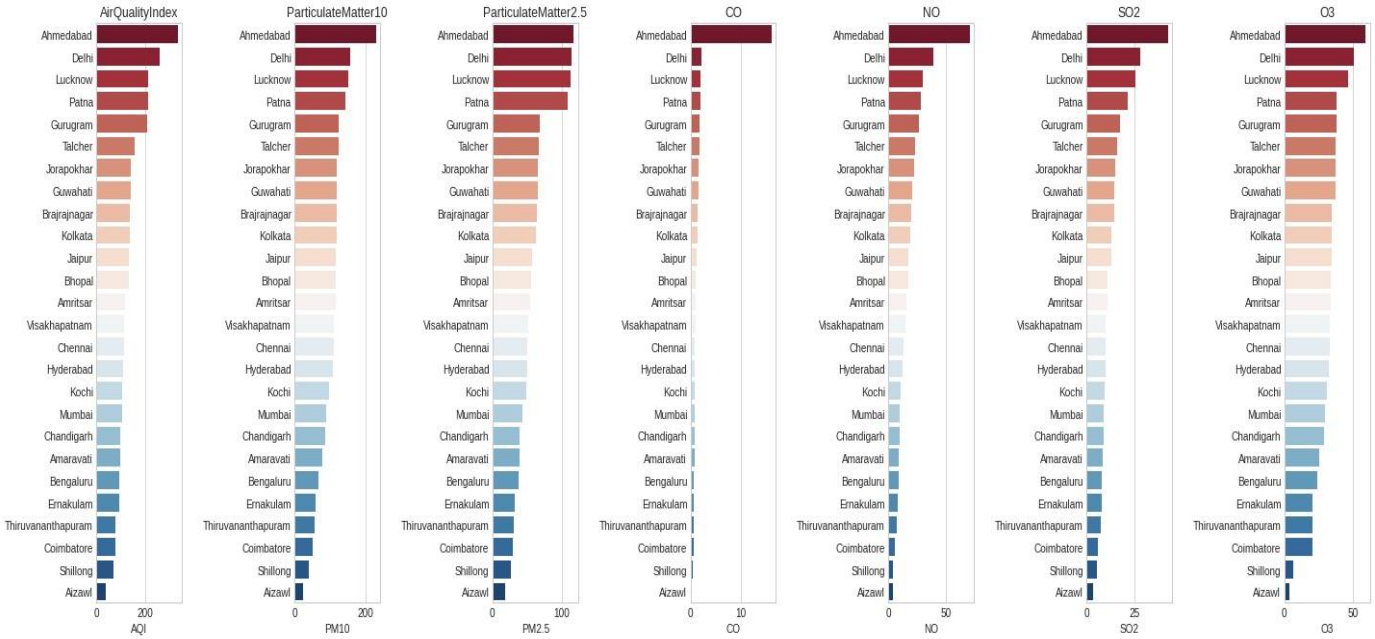
Plotting graph of most polluted cities

plt.style.use('seaborn-whitegrid') f, ax_ = plt.subplots(1,7, figsize = (20,8)) bar1=sns.barplot(x = most_polluted.AQI, y = most_polluted.index, palette='RdBu',ax=ax_[0]); bar1=sns.barplot(x = most_polluted.sort_values(by="PM10",ascending=False)['PM10'] , y = most_ bar1=sns.barplot(x = most_polluted.sort_values(by="PM2.5",ascending=False)['PM2.5'] , y = mos bar1=sns.barplot(x = most_polluted.sort_values(by='CO',ascending=False)['CO'], y = most_pollu bar1=sns.barplot(x = most_polluted.sort_values(by='NO',ascending=False)['NO'] , y = most_poll bar1=sns.barplot(x = most_polluted.sort_values(by='SO2',ascending=False)['SO2'] , y = most_po bar1=sns.barplot(x = most_polluted.sort_values(by='O3',ascending=False)['O3'] , y = most_poll

titles = ['AirQualityIndex', 'ParticulateMatter10','ParticulateMatter2.5', 'CO', 'NO', 'SO2', for i in range(7) :

```
    ax_[i].set_ylabel('')      ax_[i].set_yticklabels(labels = ax_[i].get_yticklabels(),fontsize = 10);
ax_[i].set_title(titles[i])

    f.tight_layout()
```



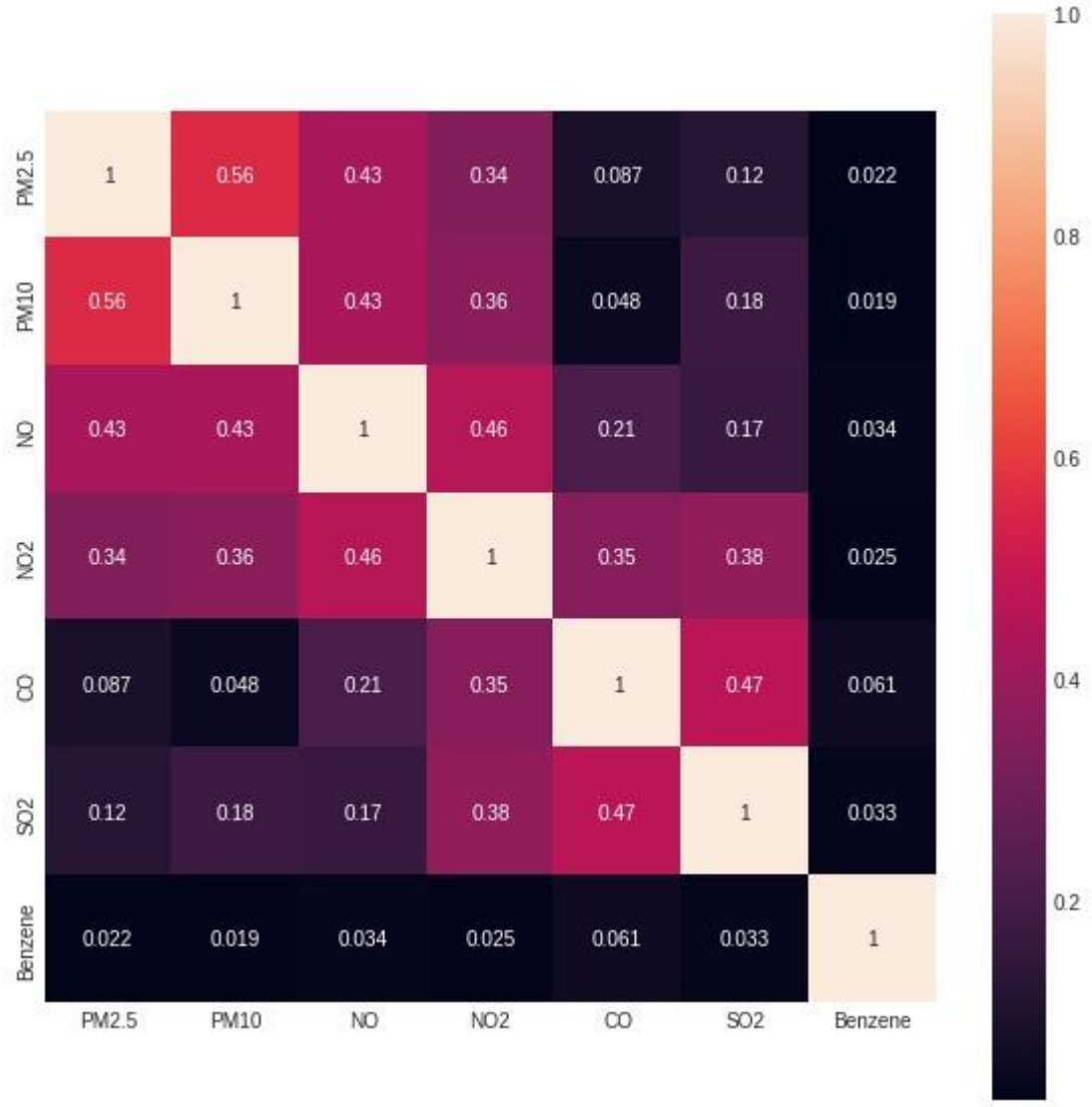
Correlation

```
cor = df.corr() heatmap_df= cor.drop(['NOx', 'NH3','O3','Toluene','Xylene', 'AQI']).drop(['NOx', 'NH3','O3',' f, ax =
plt.subplots(figsize = (10,10))

        h t          (h t          df                  1                    T                    t T )
```

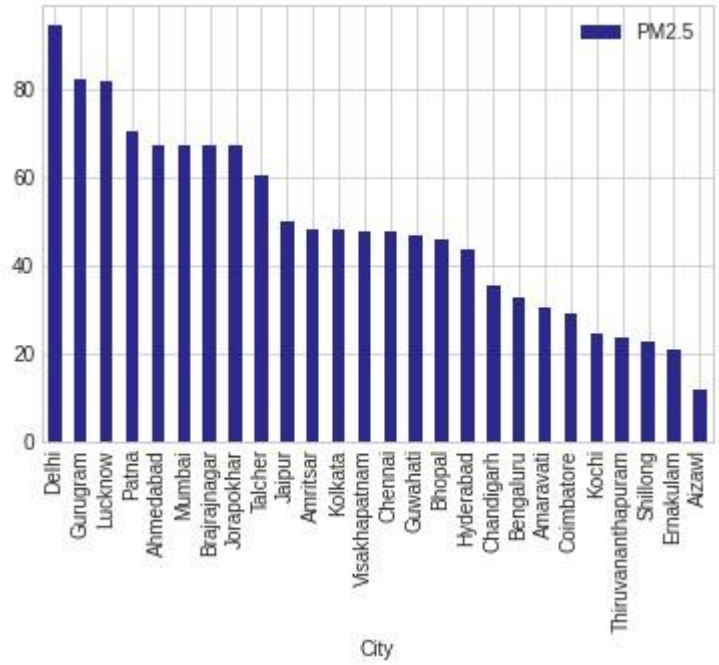
```
sns.heatmap(heatmap_df, vmax = 1, square = True, annot = True)
```

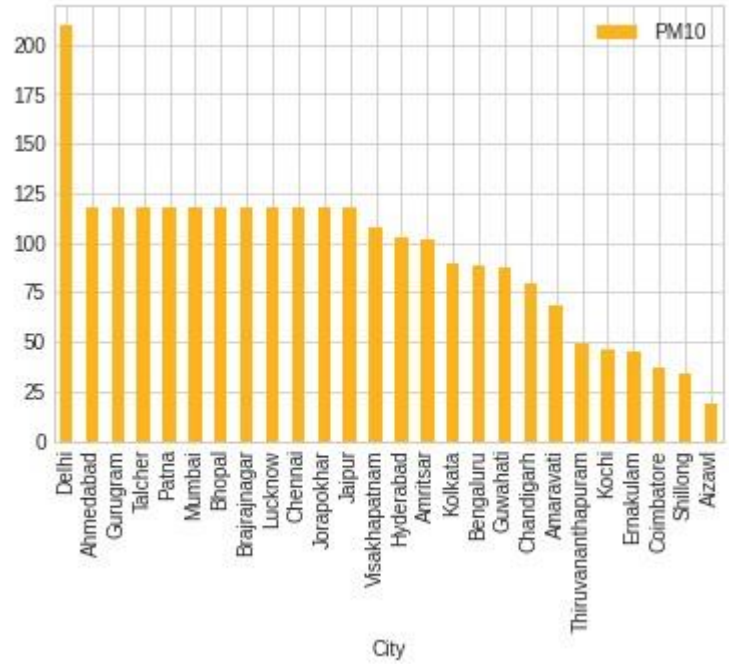
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fde9928fc90>
```

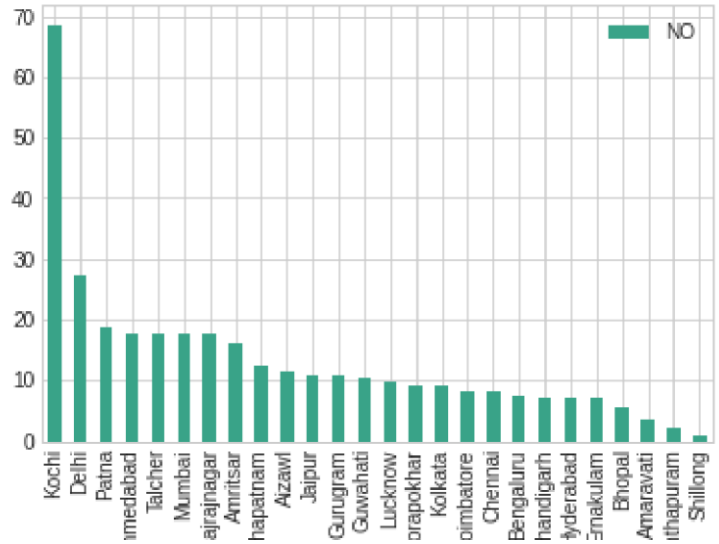


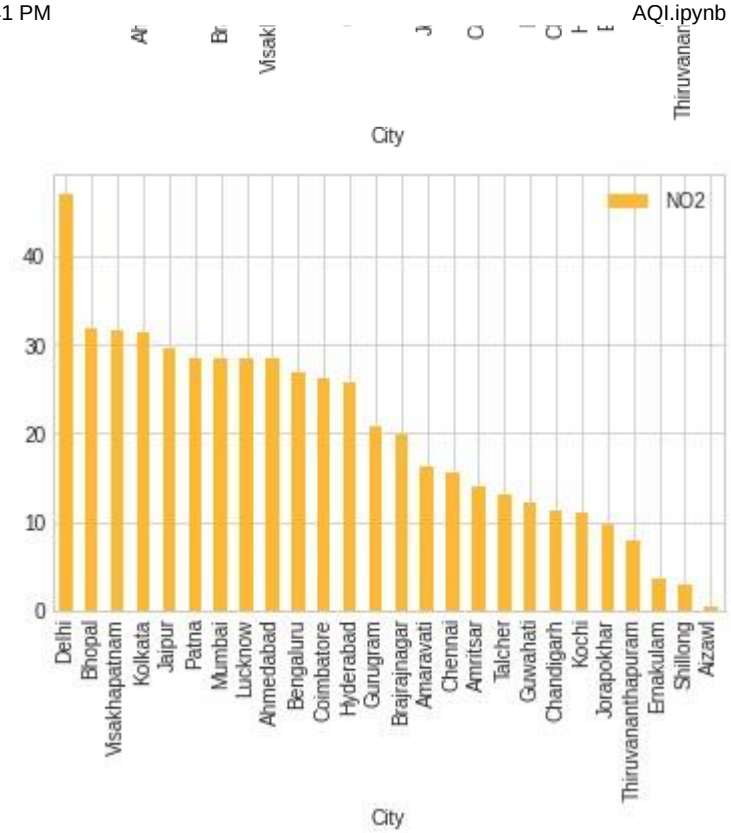
Graph of Pollutants in every City.

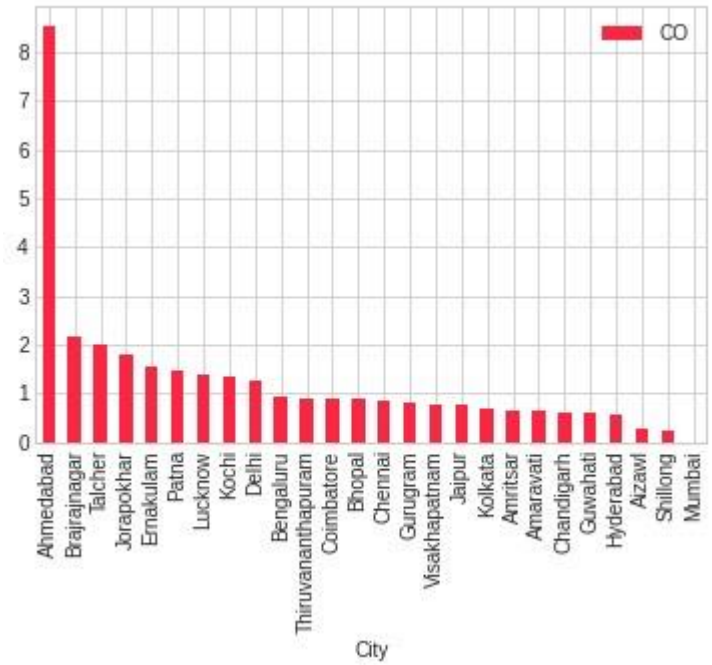
```
df[['PM2.5','City']].groupby(['City']).median().sort_values("PM2.5", ascending = False).plot.
df[['PM10','City']].groupby(['City']).median().sort_values("PM10", ascending = False).plot.ba
df[['NO','City']].groupby(['City']).median().sort_values("NO", ascending = False).plot.bar(co
df[['NO2','City']].groupby(['City']).median().sort_values("NO2", ascending = False).plot.bar(
df[['CO','City']].groupby(['City']).median().sort_values("CO", ascending = False).plot.bar(co
df[['SO2','City']].groupby(['City']).median().sort_values("SO2", ascending = False).plot.bar(
df[['O3','City']].groupby(['City']).median().sort_values("O3", ascending = False).plot.bar(co
df[['Benzene','City']].groupby(['City']).median().sort_values("Benzene", ascending = False).p
<matplotlib.axes._subplots.AxesSubplot at 0x7fde9bda2350>
```

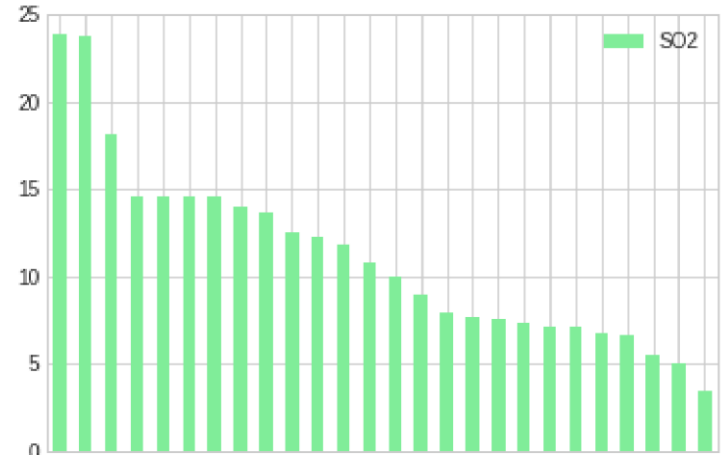

PM2.5
0
20
40
60
80
Delhi
Gurugram
Lucknow
Patna
Ahmedabad
Mumbai
Brajrajnagar
Jorapokhar
Talcher
Jaipur
Amritsar
Kolkata
Visakhapatnam
Chennai
Guwahati
Bhopal
Hyderabad
Chandigarh
Bengaluru
Amaravati
Coimbatore
Kochi
Thiruvananthapuram
Shillong
Ernakulam
Aizawl
City

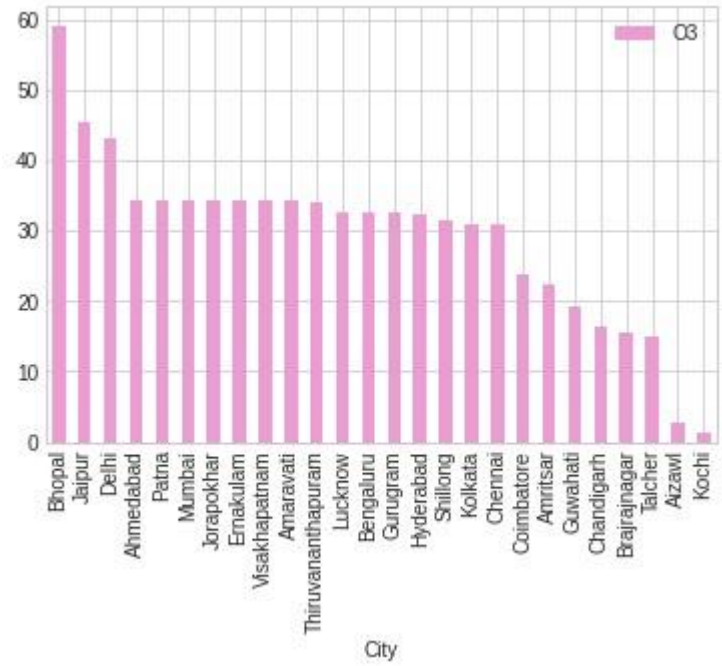

PM10
0
25
50
75
100
125
150
175
200
Delhi
Ahmedabad
Gurugram
Talcher
Patna
Mumbai
Bhopal
Brajrajnagar
Lucknow
Chennai
Jorapokhar
Jaipur
Visakhapatnam
Hyderabad
Amritsar
Kolkata
Bengaluru
Guwahati
Chandigarh
Amaravati
Thiruvananthapuram
Kochi
Ernakulam
Coimbatore
Shillong
Aizawl
City

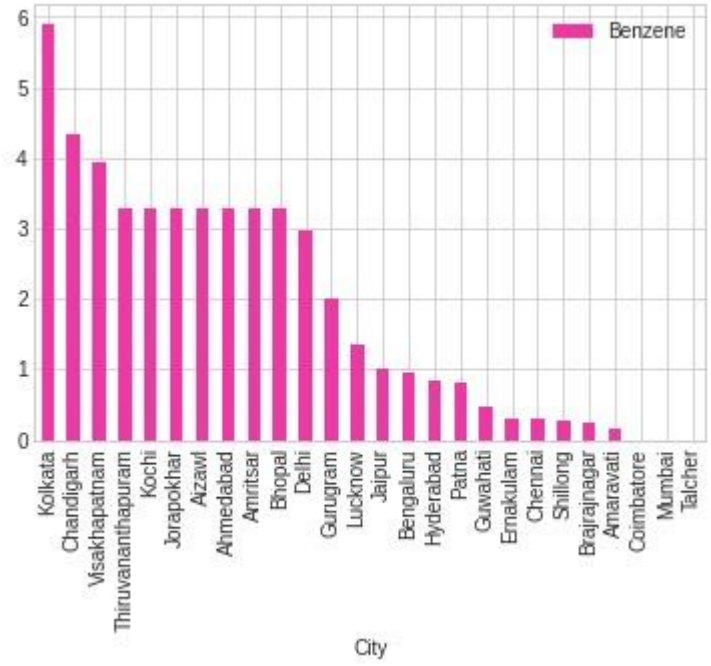

NO
0
10
20
30
40
50
60
70
Kochi
Delhi
Patna
Talcher
Mumbai
Amritsar
Aizawl
Jaipur
Gurugram
Guwahati
Lucknow
Kolkata
Chennai
Bengaluru
Bhopal
Amaravati
Shillong


City
NO2
0
10
20
30
40
Delhi
Bhopal
Visakhapatnam
Kolkata
Jaipur
Patna
Mumbai
Lucknow
Ahmedabad
Bengaluru
Coimbatore
Hyderabad
Gurugram
Brajrajnagar
Amaravati
Chennai
Amritsar
Talcher
Guwahati
Chandigarh
Kochi
Jorapokhar
Thiruvananthapuram
Ernakulam
Shillong
Aizawl


City
CO
0
1
2
3
4
5
6
7
8
Ahmedabad
Brajrajnagar
Talcher
Jorapokhar
Ernakulam
Patna
Lucknow
Kochi
Delhi
Bengaluru
Thiruvananthapuram
Coimbatore
Bhopal
Chennai
Gurugram
Visakhapatnam
Jaipur
Kolkata
Amritsar
Amaravati
Chandigarh
Guwahati
Hyderabad
Aizawl
Shillong
Mumbai


SO2
0
5
10
15
20
25





Analaysis of data using Time Series

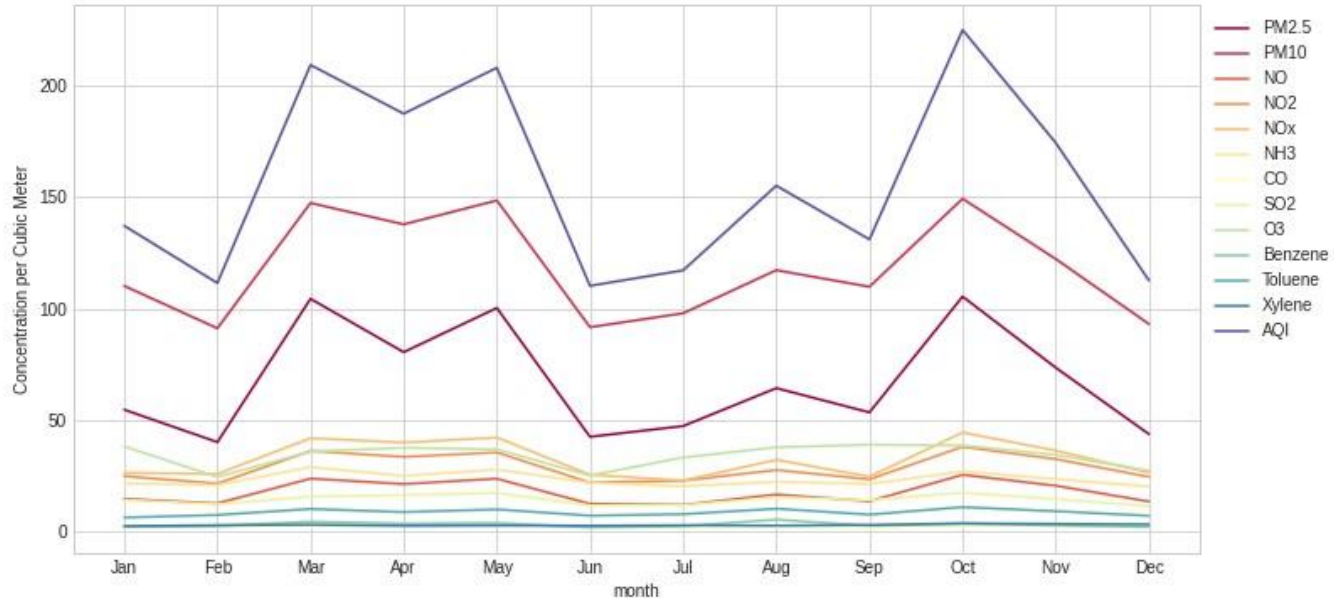
# convert column to datetime df['Date'] =
pd.to_datetime(df['Date'])

pollutants = ['PM2.5','PM10','NO','NO2','NOx','NH3','CO','SO2','O3','Benzene','Toluene','Xyle

Plotting the Color Map for Every Month throughout the years

df['month'] = pd.DatetimeIndex(df['Date']).month #Returns Immutable ndarray-like of da mth_dic = {1:'Jan',2:'Feb',3:'Mar',4:'Apr',5:'May',6:'Jun',7:'Jul',8:'Aug',9:'Sep',10:'Oct',1 df['month']=df['month'].map(mth_dic) #Mapping of dict with index df.groupby('month')[pollutants].mean().plot(figsize=(12,6), cmap='Spectral') plt.legend(bbox_to_anchor=(1.0, 1.0)) plt.xticks(np.arange(12), mth_dic.values()) plt.ylabel('Concentration per Cubic Meter')

```
Text(0, 0.5, 'Concentration per Cubic Meter')
```



Analysis of AQI during Covid 19 Pandemic of Major Cities

cities = ['Ahmedabad','Delhi','Bengaluru','Mumbai','Hyderabad','Chennai','Lucknow'] #Major C filter_city_date = df[df['Date'] >= '2019-01-01']

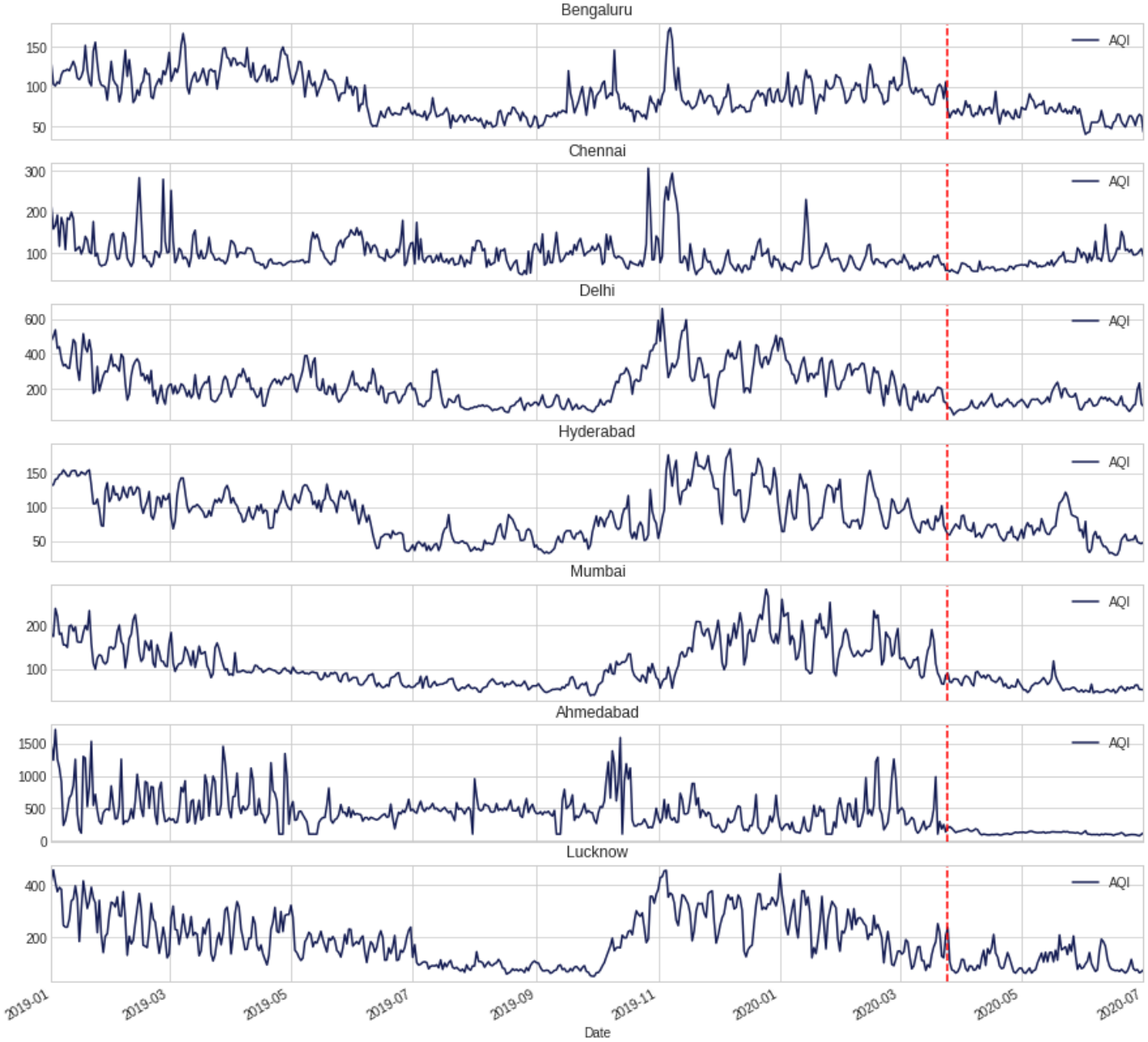
AQI = filter_city_date[filter_city_date.City.isin(cities)][['Date','City','AQI','AQI_Bucket'] AQI.head()

	Date	City	AQI	AQI_Bucket
4	2019-01-01	Ahmedabad	1474.0	Severe
5	2020-01-01	Ahmedabad	216.0	Poor
10	2019-01-10	Ahmedabad	661.0	Severe
11	2020-01-10	Ahmedabad	129.0	Moderate
16	2019-01-11	Ahmedabad	711.0	Severe

Comparing AQI Before and After Lockdown using Line Graph

```
subplot_titles=["Bengaluru","Chennai","Delhi",'Hyderabad','Mumbai', "Ahmedabad","Lucknow"]    x_line_annotation = datetime.date(2020, 3, 25)    #Lockdown Date f, axes = plt.subplots(7, 1, figsize=(15, 15), sharex=True)      #Sharex controls sharing of for count, title in enumerate(subplot_titles):

    ax = AQI[AQI['City']==title].plot(x='Date', y='AQI', kind='line', ax=axes[count], color='     ax.title.set_text(title) ax.set_xlim([datetime.date(2019, 1, 1), datetime.date(2020, 7, 1)])     ax.axvline(x=x_line_annotation, linestyle='dashed', alpha=1, color='#FF0000')
```


Bengaluru
AQI
150
100
50
Chennai
AQI
300
200
100
Delhi
AQI
600
400
200
Hyderabad
AQI
150
100
50
Mumbai
AQI
200
100
Ahmedabad
AQI
1500
1000
500
0
Lucknow
AQI
400
200
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01
2020-03
2020-05
2020-07
Date

From Above Line Graphs we can conclude that:

-The Value Of Aqi gradually increases during January to May

-The Value Of Aqi gradually decreases during June to September

-But After the Lockdown, the value decreses drastically over the all major cities

Creating Pivot Tables

```
AQI_pivot = AQI.pivot(index='Date', columns='City', values='AQI')  #Pivot returns reshaped DataFrame
```

City	Ahmedabad	Bengaluru	Chennai	Delhi	Hyderabad	Lucknow	Mumbai
Date							
2019-01-01	1474.0	128.0	212.0	475.0	132.0	413.0	181.0
2019-01-02	1246.0	103.0	158.0	501.0	133.0	457.0	175.0
2019-01-03	1719.0	101.0	167.0	537.0	141.0	410.0	239.0
2019-01-04	1264.0	106.0	192.0	432.0	142.0	374.0	221.0
2019-01-05	1127.0	104.0	116.0	440.0	148.0	390.0	180.0

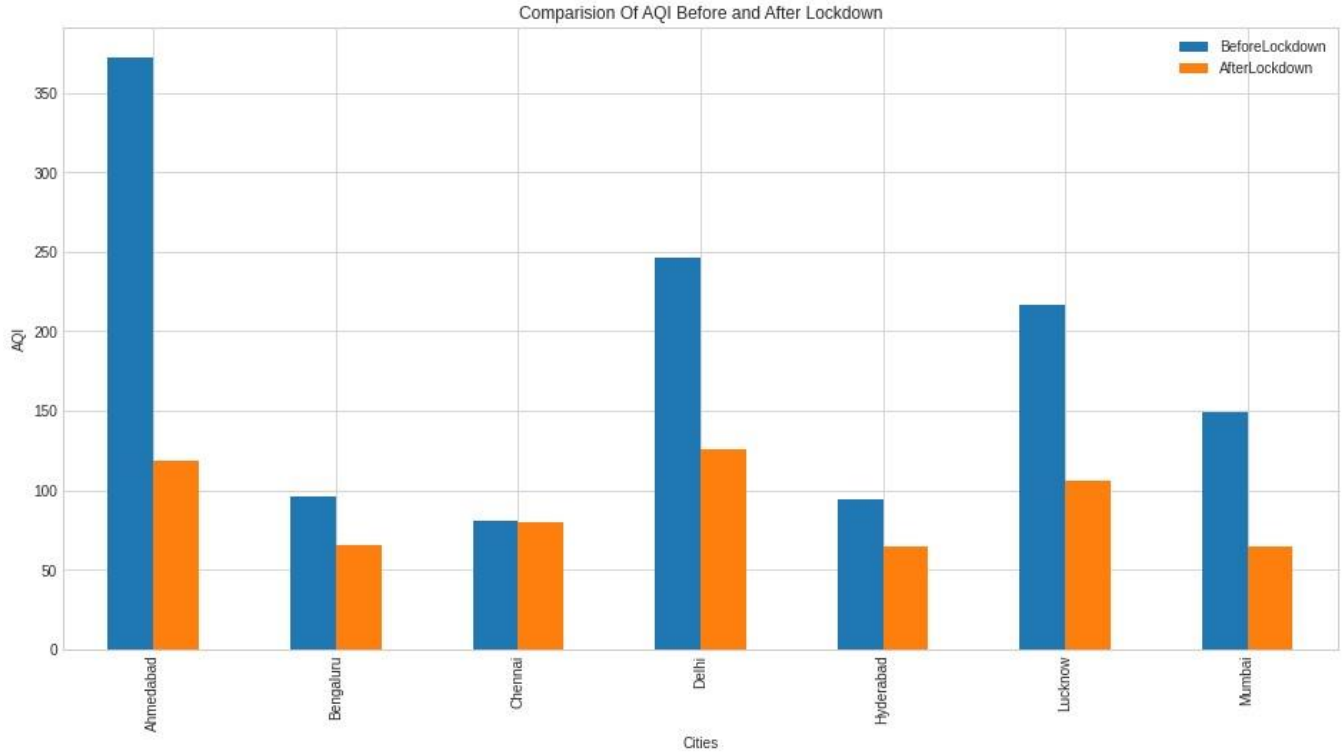
```
AQI_beforeLockdown = AQI_pivot['2020-01-01':'2020-03-25']
AQI_afterLockdown = AQI_pivot['2020-03-26':'2020-07-01'] df1=
pd.DataFrame(AQI_beforeLockdown.mean().reset_index()) df2=
pd.DataFrame(AQI_afterLockdown.mean().reset_index()) df3=df1.merge(df2,
on='City')

df3 = df3.rename({'0_x': 'BeforeLockdown', '0_y': 'AfterLockdown'}, axis=1)
```

Bar Plot for Comparision

```
df3.reset_index().plot(x="City", y=["BeforeLockdown", "AfterLockdown"], kind="bar",figsize=(1 plt.title("Comparision Of AQI Before and After Lockdown") plt.xlabel("Cities") plt.ylabel("AQI") plt.show()
```

```
plt.show()
```



-The mean AQI value for Mumbai went from moderate(148.77) to satisfactory(64.35)

-The mean AQI value for Ahmedabad went from very poor(372.4) to moderate(118.8)

-The mean AQI value for Delhi went from poor(246.3) to moderate(125.27)

-The mean AQI value for Hyderabad went from moderate(94.43) to satisfactory(64.67)

-The mean AQI value for Bengaluru went from moderate(96) to satisfactory(65.4)

-The mean AQI value for Chennai went from moderate(80.31) to satisfactory(80.1) **Creating a copy**

of dataframe

df_cpy=df.copy() sub_set=df_cpy[df_cpy['City'].isin(['Ahmedabad','Delhi','Mumbai','Chennai','Hyderabad','Luckn

```
sub_set.head()
```

	City	Date	PM2.5	PM10	NO	NO2	NOx	NH3
0	Ahmedabad	2015-01-01	67.450578	118.127103	0.92000	18.220000	17.150000	23.483476
1	Ahmedabad	2016-01-01	67.450578	118.127103	17.57473	28.560659	32.309123	23.483476
2	Ahmedabad	2017-01-01	67.450578	118.127103	17.57473	28.560659	32.309123	23.483476
3	Ahmedabad	2018-01-01	84.460000	118.127103	7.58000	87.620000	48.400000	23.483476
4	Ahmedabad	2019-01-01	110.710000	118.127103	63.03000	111.560000	100.040000	23.483476

```
sub_set.groupby('City')['AQI_Bucket'].value_counts().to_frame()   #Creating a dataframe
```

AQI_Bucket City

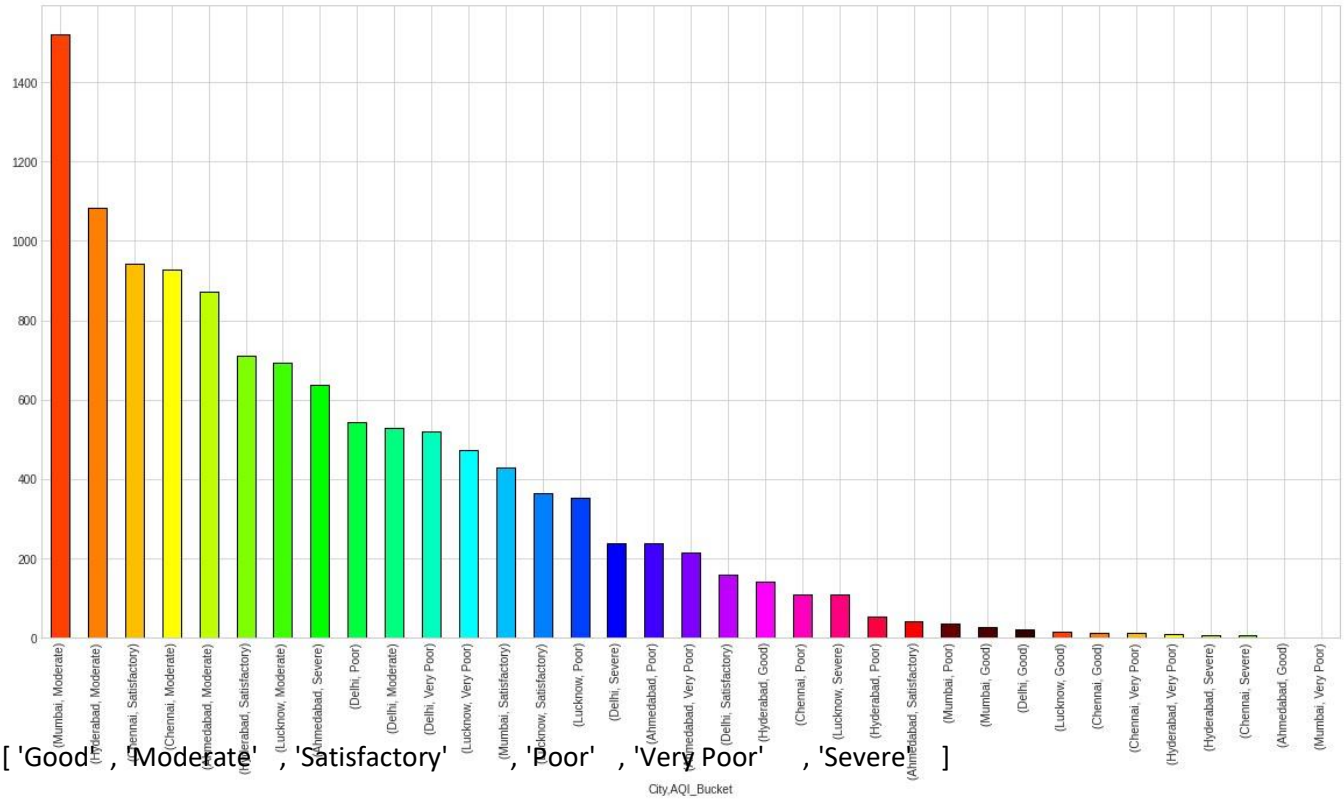
AQI_Bucket

Ahmedabad	**Moderate**	873
	Severe	638
	Poor	238
	Very Poor	216
	Satisfactory	43
	Good	1
Chennai	**Satisfactory**	941
	Moderate	929
	Poor	110
	Good	12
	Very Poor	11
	Severe	6
Delhi	**Poor**	542
	Moderate	529
	Very Poor	520
	Severe	239

```
plt.figure(figsize=(20,10))
sub_set.groupby('City'[**Satisfactory**)['AQI_Bucket'].value_counts().sort_values(ascending158 =False).plot.bar(co
plt.show()
```

	Good	21
Hyderabad	**Moderate**	1084
	Satisfactory	710
	Good	141
	Poor	54
	Very Poor	10
	Severe	7
Lucknow	**Moderate**	694
	Very Poor	473
	Satisfactory	365

Poor	352
Severe	110
G d	15
Good	15



list =['Good' , 'Moderate' , 'Satisfactory' , 'Poor' , 'Very Poor' , 'Severe']

plt.figure(figsize=(12,12)) plt.pie(df_cpy['AQI_Bucket'].value_counts()

[0:6],labels=(df_cpy['AQI_Bucket'].value_counts()

[0:6].keys()),autopct='%0.1f%%') ([<matplotlib.patches.Wedge at 0x7fdea4c6f3d0>,

<matplotlib.patches.Wedge at 0x7fdea4c6f790>,

<matplotlib.patches.Wedge at 0x7fdea48b1410>,

<matplotlib.patches.Wedge at 0x7fdea4e26310>,

<matplotlib.patches.Wedge at 0x7fdea4973990>,

<matplotlib.patches.Wedge at 0x7fdea49afb10>],

[Text(0.14648365529584692, 1.090202980518384, 'Moderate'),

Text(-0.9030187349109592, -0.6281378546145829, 'Satisfactory'),

Text(0.22684442834538193, -1.0763557057630424, 'Poor'),

Text(0.7515555545124892, -0.8032211703394184, 'Very Poor'),

Text(1.0010785557733146, -0.4558966167573687, 'Good'),

Text(1.0888753883698952, -0.15604611050042272, 'Severe')],

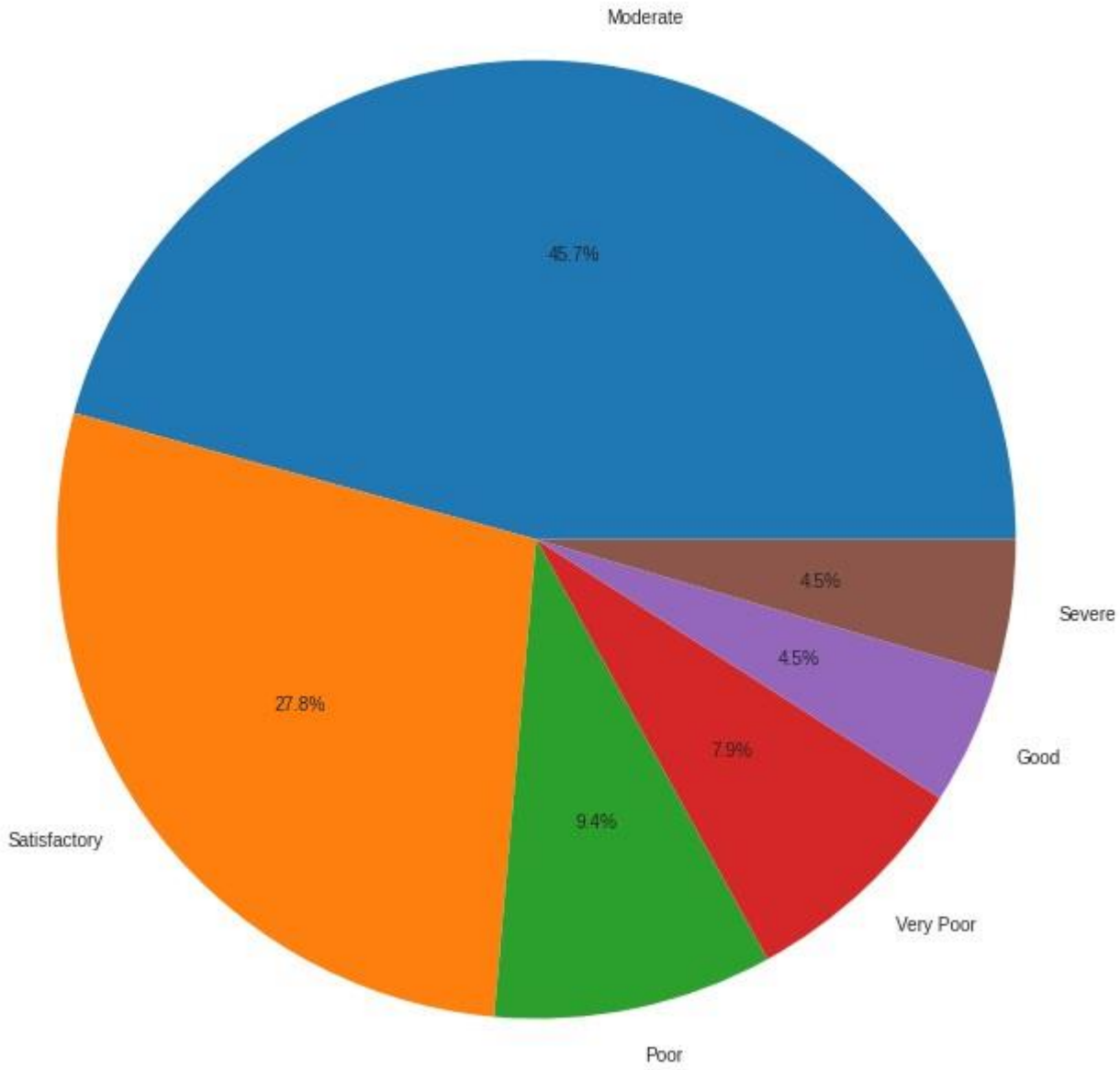
[Text(0.0799001756159165, 0.5946561711918457, '45.7%'),

Text(-0.49255567358779584, -0.3426206479715907, '27.8%'),

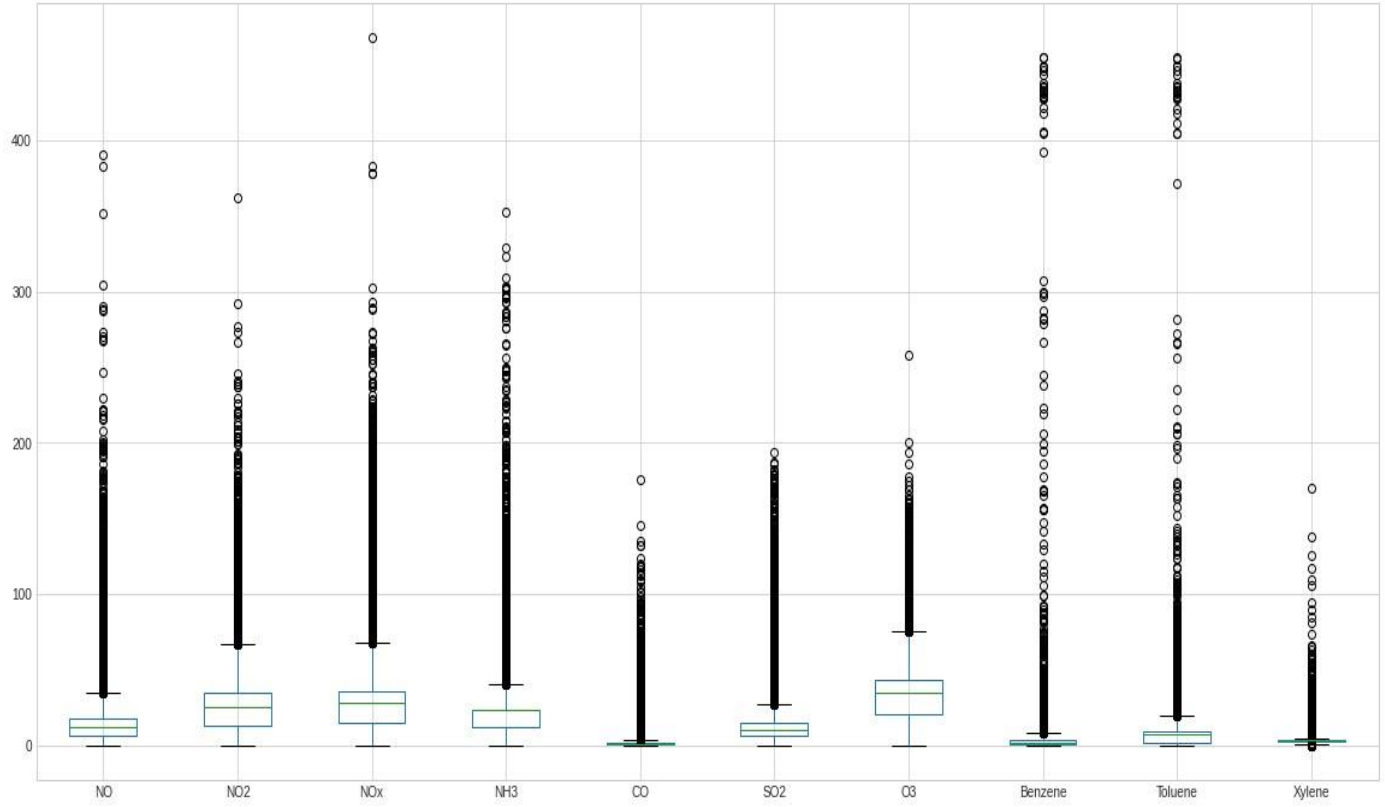
Text(0.1237333245520265, -0.5871031122343867, '9.4%'),

Text(0.4099393933704486, -0.4381206383669555, '7.9%'),

Text(0.5460428486036261, -0.24867088186765562, '4.5%'), Text(0.5939320300199428, -0.08511606027295783, '4.5%')])




```
plt.figure(figsize=(20,10))
pollutants1 = ['NO','NO2','NOx','NH3','CO','SO2','O3','Benzene','Toluene','Xylene']
df_cpy.boxplot(pollutants1)
```


400
300
200
100
0
NO
NO2
NOx
NH3
CO
SO2
O3
Benzene
Toluene
Xylene

Inferences:

1. Most polluted City is Ahmedabad with AQi of 334.48.
2. On the basis of analysis, the city with lowest AQI is Aizwal.
3. Followed by Shillong and other North-Eastern State, that conclude that North-Eastern States have better Quality Of Air than any other metro/urban areas.
4. AQI majorly depends on PM2.5 and PM10, CO, NO, SO3.
5. Delhi has highest value of PM2.5, PM10 and NO2 over the period of this dataset which is 1-1-2015 – 1-7-2019.
6. Ahmedabad has highest concentration of SO2 and CO in the air among other 26 cities. Burning of fossil fuels in the industries could be the main reason behind emission of S02 and CO in the air.
7. Talcher is at second place in terms of SO2 Concentration and also has placed among top 5 in Concentration of CO, NO, PM10. This is because Talcher is highest coal reserve of India.
8. With the help of Time-Series and graph Plotting Utilities, Before Lockdown it can be said that the value of AQI Gradually increases during January to May in metro cities during the period of January 2019 and March 2020, and decreases during June to September, But after the Lockdown the value of AQI decreases drastically.
9. The more accurate data is listed below:-
    - -The mean AQI value for Mumbai went from moderate(148.77) to satisfactory(64.35)
    - -The mean AQI value for Ahmedabad went from very poor(372.4) to moderate(118.8)
    - -The mean AQI value for Delhi went from poor(246.3) to moderate(125.27)
    - -The mean AQI value for Hyderabad went from moderate(94.43) to satisfactory(64.67)
    - -The mean AQI value for Bengaluru went from moderate(96) to satisfactory(65.4)
    - -The mean AQI value for Chennai went from moderate(80.31) to satisfactory(80.1)
10. On the basis of pie plot-
    - The AQI of around 45.7% values over each day are Moderate.
    - The AQI of around 27.8% values over each day are Satisfactory.
    - The AQI of around 9.4% values over each day are Poor.
    - The AQI of around 7.9% values over each day are Very Poor.
    - The AQI of around 4.5% values over each day are Good.
    - The AQI of around 4.5% values over each day are Severe.

Future Scope:

- This data can be further processed in machine learning model.
- Visualization can be done on the basis of week days vs weekends.
- Each City can be visualized separately.
- More reasons for the sudden rise and fall of the level of AQI and other pollutants could be given if we do further EDA on the dataset.

Conclusion:

1. This EDA gave us the idea of the rate of increase of pollution in India.
2. Different measures to lower the air pollution in India by lowering emission of fossil fuels to emit less carbon dioxide. by shifting to electric vehicle rather than fossil fuels (petrol, diesel) based vehicle.
3. The health of the public, especially those who are the most vulnerable, such as children, the elderly and the sick, is at risk from air pollution, but it is difficult to say how large the risk is. It is possible that the problem has been over-stressed in relation to other challenges in the field of public health.
4. As we have seen, there are considerable uncertainties in estimating both exposures and effects and their relationships. It may be, for example, that the effects of long-term exposure to lower concentrations of air pollutants could be more damaging to public health than short-term exposure to higher concentrations. For this reason alone, local authorities could take action to assess and improve local air quality. It is not sufficient to wait for an episode of severe air pollution and then try to deal with its effects.
5. On an individual level, the risk to health from air pollution is very much smaller than that posed by active cigarette smoking or accidents. It is also true that healthy individuals are rather unlikely to be affected by exposure to the concentrations of outdoor air pollutants in many European countries on most days of the year. However, the old and the young, and especially those suffering from respiratory or heart diseases, are the groups who are most vulnerable to the effects of air pollution. It is only right that cost effective action should be taken to provide them with clean air, which The Times of 1881 described as "the first necessity of our existence.
6. Another reason for action on air pollution is that we do not know the contribution which exposure to air pollutants may make to deaths from, for example, heart disease. In many countries heart disease is a leading cause of death and even a small contribution from air pollution could mean a significant and important effect on public health.

References:

1. Air Quality Data in India (2015 - 2020) | Kaggle
2. National Air Quality Index (AQI) launched by the Environment Minister AQI is a huge initiative under ‘Swachh Bharat’ (pib.gov.in)
3. https://www.thehindu.com/society/where-paddy-fields-sink-houses-cave-in-life-in-indias-largest-coalfield/article26744915.ece#:~:text=Black%20diamond-,Talcher%20coalfield%20has%20the%20country's%20highest%20coal%20reserve%20of%2051.163,underground%20and%20open%2Dcast%20mining.
4. Our Documentation | Python.org
5. McKinney, W. (2017). Python for Data Analysis: Data Wrangling with Pandas, NumPy and I Python. 2nd edition. O’Reilly Media.