#### **Major Project Synopsis**

on

#### AIR QUALITY INDEX PREDICTOR

In partial fulfilment of requirements for the degree

of

**BACHELOR OF TECHNOLOGY** 

IN

**COMPUTER SCIENCE & ENGINEERING** 

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### INTRODUCTION

#### Let's see what you breath.

- Clean air is one of the basic requirement for good human health and well-being of the humanity. The problem of air pollution has become a new challenge for the world.
- Air pollution continues to be a well-known environmental problem worldwide
- The quality of the air is the result of complex interaction of many factors that involve the chemistry and the meteorology of the atmosphere, as well as the emissions of variety of pollutants both from natural and man-made sources
- This project uses supervised learning to predict Air Quality Index of India.
- The air quality is measured by the Air Quality Index. Let's know what is the Air Quality Index (AQI) in India?



### National Air Quality Index

### 91% of the World's Population Are Breathing in Polluted Air Every Day

- India uses the National Air Quality Index (AQI), Canada uses the Air Quality Health Index, Singapore uses the Pollutant Standards Index and Malaysia uses the Air Pollution Index.
- The National Air Quality Index (AQI) in India was launched on 17 September 2014 in New Delhi under the Swachh Bharat Abhiyan by the Environment Minister Shri PrakashJavadekar.
- The air quality index is composed of 8 pollutants ((PM10, PM2.5, NO2, SO2, CO, O3, NH3, and Pb).



### Air Quality Index

#### The Quality of Air we breath

- AQI is the air quality index; it gives you the index value that what is the current pollution status in the city, how polluted the air currently is.
- The Air Quality Index (AQI) is a widely used concept to communicate with the public on air quality.
- The Air Quality Index is acquired by measuring emissions of eight major pollutants present in the air: Particulate matter (PM2.5 and PM10), Ozone (O3), Carbon Monoxide (C0), Nitrogen Dioxide (NO2), Sulphur Dioxide (SO2), Lead (Pb) and Ammonia (NH3) emissions.



### 6 Categories air of quality index

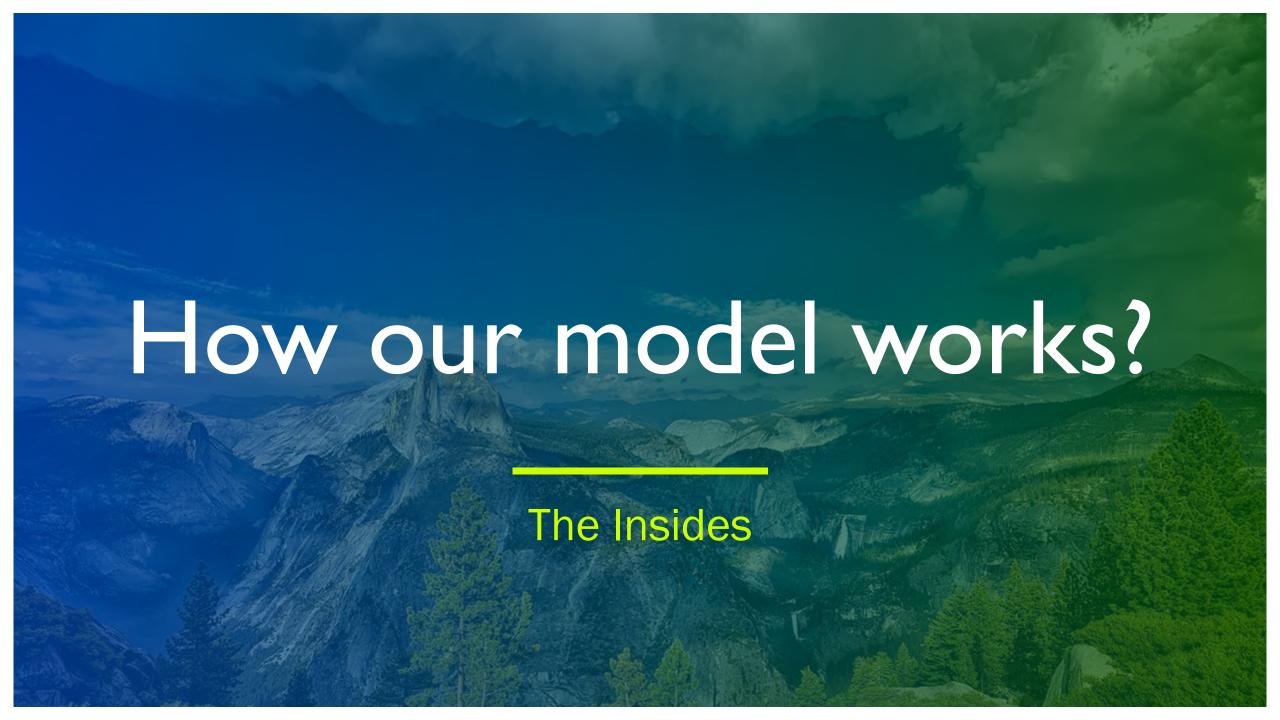
- The Air Quality Index measures the quality of air. It shows the amount and types of gases dissolved in the air. There are 6 categories of the air have been created in this air quality index.
- These categories are based on air quality. These categories are: good, satisfactory, moderate, poor, very poor and severe.



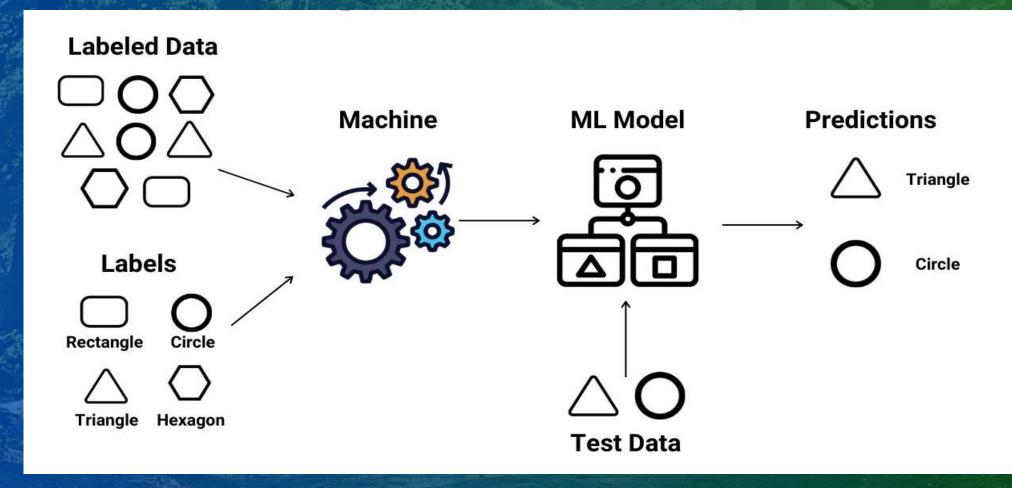
# CENTRAL POLLUTION CONTROL'S BOARD

AIR QUALITY STANDARDS

|                   | A STATE OF THE PARTY OF THE PAR |
|-------------------|--|
| AIR QUALITY INDEX | CATEGORY   |
| 0-50              | Good   |
| 51-100            | Satisfactory   |
| 101-200           | Moderate   |
| 201-300           | Poor   |
| 301-400           | Very Poor  |
| 401-500           | Severe   |



### Supervised Machine Learning



### Preface

- "Supervised learning means that a model learns from previous examples and is trained on labeled data. In other words, the dataset has tags that tell the model which patterns are related to fraud and which represent normal behavior".
- In supervised learning, models are trained using labelled dataset, where the model learns about each type of data.
   Once the training process is completed, the model is tested on the basis of test data (a subset of the training set), and then it predicts the output.



# Steps Involved in Supervised Learning:

- 1. Import the libraries
- 2. Read Dataset
- 3. Data Analysis
- 4. Label encoding of the categorical columns if have
- 5. Defining x and y
- 6. Splitting x and y into train and test data
- 7. Import the model
- 8. Train the model with x\_train and y\_train
- Predict with x test and got predicted y
- 10. Evaluation with accuracy score and confusion matrix



## Importing the libraries:

We can import libraries by following syntax:

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



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

# 2. Reading the dataset:

Reading the dataset by read\_csv('File\_name') function

df=pd.read\_csv(io.BytesIO(uploaded['city\_day.csv']))

C+ city\_day.csv

city\_day.csv(text/csv) - 2574056 bytes, last modified: 7/28/2020 - 100% done
 Saving city\_day.csv to city\_day.csv

### 3. Data Analysis:

#### Extracting the first ten values from the Data Frame

| pr | print(df.head(10)) |       |                    |          |      |       |     |       |        |     |        |  |  |
|----|--------------------|-------|--------------------|----------|------|-------|-----|-------|--------|-----|--------|--|--|
|    | c                  | ity   | Date               | PM2.5    | PM10 |       | NO  | NO2   | NOx    | NH3 | со     |  |  |
| 0  | Ahmeda             | bad : | 2015-01-01         | . NaN    | NaN  | 0.    | 92  | 18.22 | 17.15  | NaN | 0.92   |  |  |
| 1  | Ahmeda             | bad : | 2015-01-02         | . NaN    | NaN  | 0.    | 97  | 15.69 | 16.46  | NaN | 0.97   |  |  |
| 2  | Ahmeda             | bad : | <b>2015-01-0</b> 3 | NaN      | NaN  | 17.   | 40  | 19.30 | 29.70  | NaN | 17.40  |  |  |
| 3  | Ahmeda             | bad : | 2015-01-04         | NaN      | NaN  | 1.    | 70  | 18.48 | 17.97  | NaN | 1.70   |  |  |
| 4  | Ahmeda             | bad : | 2015-01-05         | NaN      | NaN  | 22.   | 10  | 21.42 | 37.76  | NaN | 22.10  |  |  |
| 5  | Ahmeda             | bad : | 2015-01-06         | NaN      | NaN  | 45.   | 41  | 38.48 | 81.50  | NaN | 45.41  |  |  |
| 6  | Ahmeda             | bad : | 2015-01-07         | ' NaN    | NaN  | 112.  | 16  | 40.62 | 130.77 | NaN | 112.16 |  |  |
| 7  | Ahmeda             | bad : | 2015-01-08         | NaN      | NaN  | 80.   | 87  | 36.74 | 96.75  | NaN | 80.87  |  |  |
| 8  | Ahmeda             | bad : | 2015-01-09         | ) NaN    | NaN  | 29.   | 16  | 31.00 | 48.00  | NaN | 29.16  |  |  |
| 9  | Ahmeda             | bad : | 2015-01-10         | ) NaN    | NaN  | N     | aN  | 7.04  | 0.00   | NaN | NaN    |  |  |
|    |                    |       |                    |          |      |       |     |       |        |     |        |  |  |
|    | S02                |       | 03 Benzer          |          |      | ylene |     | AQI_E |        |     |        |  |  |
| 0  | 27.64              | 133.  |                    |          | .02  | 0.00  | NaN |       | NaN    |     |        |  |  |
| 1  | 24.55              | 34.0  |                    |          | .50  | 3.77  | NaN |       | NaN    |     |        |  |  |
| 2  | 29.07              | 30.   |                    |          | .40  | 2.25  | NaN |       | NaN    |     |        |  |  |
| 3  | 18.59              | 36.0  |                    |          | .14  | 1.00  | NaN |       | NaN    |     |        |  |  |
| 4  | 39.33              | 39.   |                    |          | .89  | 2.78  | NaN |       | NaN    |     |        |  |  |
| 5  | 45.76              | 46.   |                    |          | .83  | 1.93  | NaN |       | NaN    |     |        |  |  |
| 6  | 32.28              | 33.4  |                    |          | .00  | 0.00  | NaN |       | NaN    |     |        |  |  |
| 7  | 38.54              | 31.8  |                    |          | .00  | 0.00  | NaN |       | NaN    |     |        |  |  |
| 8  | 58.68              | 25.   |                    |          | .00  | 0.00  | NaN |       | NaN    |     |        |  |  |
| 9  | 8.29               | 4.    | 55 0.0             | <u>ט</u> | .00  | 0.00  | NaN |       | NaN    |     |        |  |  |

#### Extracting the last ten values from the Data Frame

| print(df.tail(10)) |       |         |        |          |       |        |              |       |               |       |  |
|--------------------|-------|---------|--------|----------|-------|--------|--------------|-------|---------------|-------|--|
|                    |       | Cit     | v      | Date I   | PM2.5 | PM10   | NO           | NO2   | . NOx         | NH3   |  |
| 29521              | Visak | hapatna | -      |          | 33.17 | 108.22 | 5.58         | 42.45 | 27.06         | 13.70 |  |
| 29522              |       | hapatna |        | -06-23   | 25.40 | 83.38  | 2.76         | 34.09 | 19.92         | 13.13 |  |
| 29523              | Visak | hapatna | m 2020 | -06-24   | 34.36 | 90.90  | 1.22         | 23.38 | 3 13.12       | 14.45 |  |
| 29524              | Visak | hapatna | m 2020 | -06-25 : | 13.45 | 58.54  | 2.30         | 21.60 | 13.09         | 12.27 |  |
| 29525              | Visak | hapatna | m 2020 | -06-26   | 7.63  | 32.27  | 5.91         | 23.27 | 7 17.19       | 11.15 |  |
| 29526              | Visak | hapatna | m 2020 | -06-27   | 15.02 | 50.94  | 7.68         | 25.06 | 19.54         | 12.47 |  |
| 29527              | Visak | hapatna | m 2020 | -06-28   | 24.38 | 74.09  | 3.42         | 26.06 | 16.53         | 11.99 |  |
| 29528              | Visak | hapatna | m 2020 | -06-29   | 22.91 | 65.73  | 3.45         | 29.53 | <b>18.</b> 33 | 10.71 |  |
| 29529              | Visak | hapatna | m 2020 | -06-30   | 16.64 | 49.97  | 4.05         | 29.26 | 18.80         | 10.03 |  |
| 29530              | Visak | hapatna | m 2020 | -07-01   | 15.00 | 66.00  | 0.40         | 26.85 | 14.05         | 5.20  |  |
|                    |       |         |        | _        | - 1   |        |              |       |               |       |  |
| 20524              | CO    | S02     | 03     | Benzene  | Tolue |        | lene         | AQI   | AQI_Bu        |       |  |
| 29521              | 0.73  | 13.65   | 34.85  | 3.99     | 10.   |        | 2.32         | 95.0  | Satisfac      |       |  |
| 29522              | 0.54  | 10.40   | 43.27  | 2.88     | 12.   |        | 1.33         | 100.0 | Satisfac      |       |  |
| 29523              | 0.56  | 10.92   | 35.12  | 2.99     |       |        | 1.60         | 86.0  | Satisfac      |       |  |
| 29524              | 0.41  | 8.19    | 29.38  | 1.28     |       |        | 3.92         | 77.0  | Satisfac      |       |  |
| 29525              | 0.46  | 6.87    | 19.90  | 1.45     |       |        | 1.45         | 47.0  |               | Good  |  |
| 29526              | 0.47  | 8.55    | 23.30  | 2.24     | 12.   |        | <b>3.7</b> 3 | 41.0  |               | Good  |  |
| 29527              | 0.52  | 12.72   | 30.14  | 0.74     |       |        | 3.38         | 70.0  | Satisfac      |       |  |
| 29528              | 0.48  | 8.42    | 30.96  | 0.01     |       |        | 0.00         | 68.0  | Satisfac      |       |  |
| 29529              | 0.52  | 9.84    | 28.30  | 0.00     |       |        | 0.00         | 54.0  | Satisfac      |       |  |
| 29530              | 0.59  | 2.10    | 17.05  | NaN      | N     | laN    | NaN          | 50.0  |               | Good  |  |

#### Describing the data frame statistically

| print( | df.describe() | ı            |              |              |              |
|--------|---------------|--------------|--------------|--------------|--------------|
|        |               | •            |              |              |              |
|        | PM2.5         | PM10         | NO           | NO2          | NOx          |
| count  | 24933.000000  | 18391.000000 | 25949.000000 | 25946.000000 | 25346.000000 |
| mean   | 67.450578     | 118.127103   | 17.574730    | 28.560659    | 32.309123    |
| std    | 64.661449     | 90.605110    | 22.785846    | 24.474746    | 31.646011    |
| min    | 0.040000      | 0.010000     | 0.020000     | 0.010000     | 0.000000     |
| 25%    | 28.820000     | 56.255000    | 5.630000     | 11.750000    | 12.820000    |
| 50%    | 48.570000     | 95.680000    | 9.890000     | 21.690000    | 23.520000    |
| 75%    | 80.590000     | 149.745000   | 19.950000    | 37.620000    | 40.127500    |
| max    | 949.990000    | 1000.000000  | 390.680000   | 362.210000   | 467.630000   |
|        |               |              |              |              |              |
|        | NH3           | CO           | S02          | 03           | Benzene      |
| count  | 19203.000000  | 27472.000000 | 25677.000000 | 25509.000000 | 23908.000000 |
| mean   | 23.483476     | 2.248598     | 14.531977    | 34.491430    | 3.280840     |
| std    | 25.684275     | 6.962884     | 18.133775    | 21.694928    | 15.811136    |
| min    | 0.010000      | 0.000000     | 0.010000     | 0.010000     | 0.000000     |
| 25%    | 8.580000      | 0.510000     | 5.670000     | 18.860000    | 0.120000     |
| 50%    | 15.850000     | 0.890000     | 9.160000     | 30.840000    | 1.070000     |
| 75%    | 30.020000     | 1.450000     | 15.220000    | 45.570000    | 3.080000     |
| max    | 352.890000    | 175.810000   | 193.860000   | 257.730000   | 455.030000   |
|        | _             |              |              |              |              |
|        | Toluene       | Xylene       | AQI          |              |              |
| count  | 21490.000000  | 11422.000000 | 24850.000000 |              |              |
| mean   | 8.700972      | 3.070128     | 166.463581   |              |              |
| std    | 19.969164     | 6.323247     | 140.696585   |              |              |
| min    | 0.000000      | 0.000000     | 13.000000    |              |              |
| 25%    | 0.600000      | 0.140000     | 81.000000    |              |              |
| 50%    | 2.970000      | 0.980000     | 118.000000   |              |              |
| 75%    | 9.150000      | 3.350000     | 208.000000   |              |              |
| max    | 454.850000    | 170.370000   | 2049.000000  |              |              |



#### Summing the null values column wise

| • | <pre>print(df.isnull().sum()</pre> |
|---|------------------------------------|
|   |                                    |

| _→ | City         | 0     |
|----|--------------|-------|
|    | Date         | 0     |
|    | PM2.5        | 4598  |
|    | PM10         | 11140 |
|    | NO           | 3582  |
|    | NO2          | 3585  |
|    | NOx          | 4185  |
|    | NH3          | 10328 |
|    | CO           | 2059  |
|    | S02          | 3854  |
|    | 03           | 4022  |
|    | Benzene      | 5623  |
|    | Toluene      | 8041  |
|    | Xylene       | 18109 |
|    | AQI          | 4681  |
|    | AQI Bucket   | 4681  |
|    | dtvpe: int64 |       |

#### Calculating the relationship between each column in the data set.

| 1 | 0  | print(df | f.corr()  |          |           |          |           |           |          |   |
|---|----|----------|-----------|----------|-----------|----------|-----------|-----------|----------|---|
|   |    | ļ        | .,,       |          |           |          |           |           |          |   |
|   | С→ |          | PM2.5     | PM10     | NO        | NO2      | NOx       | NH3       | со       | \ |
|   | _  | PM2.5    | 1.000000  | 0.846498 | 0.433491  | 0.350709 | 0.436792  | 0.275086  | 0.089912 |   |
|   |    | PM10     | 0.846498  | 1.000000 | 0.502349  | 0.464380 | 0.527768  | 0.376816  | 0.112588 |   |
|   |    | NO       | 0.433491  | 0.502349 | 1.000000  | 0.478070 | 0.794890  | 0.185621  | 0.212607 |   |
|   |    | NO2      | 0.350709  | 0.464380 | 0.478070  | 1.000000 | 0.627627  | 0.234938  | 0.356521 |   |
|   |    | NOx      | 0.436792  | 0.527768 | 0.794890  | 0.627627 | 1.000000  | 0.166224  | 0.226992 |   |
|   |    | NH3      | 0.275086  | 0.376816 | 0.185621  | 0.234938 | 0.166224  | 1.000000  | 0.104891 |   |
|   |    | со       | 0.089912  | 0.112588 | 0.212607  | 0.356521 | 0.226992  | 0.104891  | 1.000000 |   |
|   |    | S02      | 0.132325  | 0.256974 | 0.170322  | 0.392233 | 0.238397  | -0.038998 | 0.489697 |   |
|   |    | 03       | 0.161238  | 0.244919 | 0.014580  | 0.293349 | 0.093170  | 0.094972  | 0.041736 |   |
|   |    | Benzene  | 0.023911  | 0.022265 | 0.035771  | 0.025260 | 0.039121  | -0.015650 | 0.061861 |   |
|   |    | Toluene  | 0.117080  | 0.169335 | 0.150857  | 0.273926 | 0.189386  | 0.013227  | 0.277904 |   |
|   |    | Xylene   | 0.114579  | 0.081700 | 0.094237  | 0.171701 | 0.087398  | -0.019813 | 0.154889 |   |
|   |    | AQI      | 0.659181  | 0.803313 | 0.452191  | 0.537071 | 0.486450  | 0.252019  | 0.683346 |   |
|   |    |          |           |          |           |          |           |           |          |   |
|   |    |          | S02       | 03       | Benzene   | Toluene  | Xylene    | AQI       |          |   |
|   |    | PM2.5    | 0.132325  | 0.161238 | 0.023911  | 0.117080 | 0.114579  | 0.659181  |          |   |
|   |    | PM10     | 0.256974  | 0.244919 | 0.022265  | 0.169335 | 0.081700  | 0.803313  |          |   |
|   |    | NO       | 0.170322  | 0.014580 | 0.035771  | 0.150857 | 0.094237  | 0.452191  |          |   |
|   |    | NO2      | 0.392233  | 0.293349 | 0.025260  | 0.273926 | 0.171701  | 0.537071  |          |   |
|   |    | NOx      | 0.238397  | 0.093170 | 0.039121  | 0.189386 | 0.087398  | 0.486450  |          |   |
|   |    | NH3      | -0.038998 | 0.094972 | -0.015650 | 0.013227 | -0.019813 | 0.252019  |          |   |
|   |    | co       | 0.489697  | 0.041736 | 0.061861  | 0.277904 | 0.154889  | 0.683346  |          |   |
|   |    | S02      | 1.000000  | 0.162142 | 0.036110  | 0.296139 | 0.251195  | 0.490586  |          |   |
|   |    | 03       | 0.162142  | 1.000000 | 0.020255  | 0.130209 | 0.111410  | 0.198991  |          |   |
|   |    | Benzene  | 0.036110  | 0.020255 | 1.000000  | 0.739286 | 0.415427  | 0.044407  |          |   |
|   |    | Toluene  | 0.296139  | 0.130209 | 0.739286  | 1.000000 | 0.421432  | 0.279992  |          |   |
|   |    | Xylene   | 0.251195  | 0.111410 | 0.415427  | 0.421432 | 1.000000  | 0.165532  |          |   |
|   |    | AQI      | 0.490586  | 0.198991 | 0.044407  | 0.279992 | 0.165532  | 1.000000  |          |   |
|   |    |          |           |          |           |          |           |           |          |   |

### Labelling columns of the data frame

```
0
```

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

#### Replacing null values with "Good".

```
df['AQI_Bucket'].fillna('Good')
₽
                     Good
                     Good
                     Good
                     Good
                     Good
    29526
                     Good
             Satisfactory
    29527
             Satisfactory
    29528
    29529
             Satisfactory
    29530
                     Good
    Name: AQI_Bucket, Length: 29531, dtype: object
```

#### Printing the dataframe

|   | _      |        |         |        |      |       |        |        |       |         |        |   |
|---|--------|--------|---------|--------|------|-------|--------|--------|-------|---------|--------|---|
| 0 | print( | df)    |         |        |      |       |        |        |       |         |        |   |
|   | _      |        |         |        |      |       |        |        |       |         |        |   |
| ₽ |        |        | City    |        | Date | PM2.5 |        | NO     | NO2   | NOx     | NH3    | \ |
|   | 0      |        | medabad | 2015-0 |      | NaN   |        |        | 18.22 | 17.15   | NaN    |   |
|   | 1      |        | medabad | 2015-0 |      | NaN   |        | 0.97   | 15.69 | 16.46   | NaN    |   |
|   | 2      |        | medabad | 2015-0 |      | NaN   |        | 17.40  | 19.30 | 29.70   | NaN    |   |
|   | 3      |        | medabad | 2015-0 |      | NaN   |        | 1.70   | 18.48 | 17.97   | NaN    |   |
|   | 4      | Ah     | medabad | 2015-0 | 1-05 | NaN   | NaN    | 22.10  | 21.42 | 37.76   | NaN    |   |
|   |        |        |         |        |      |       |        |        |       |         |        |   |
|   | 29526  |        | apatnam | 2020-0 |      | 15.02 |        |        | 25.06 | 19.54   | 12.47  |   |
|   | 29527  |        | apatnam | 2020-0 |      | 24.38 |        | 3.42   | 26.06 | 16.53   | 11.99  |   |
|   | 29528  |        | apatnam | 2020-0 |      | 22.91 |        |        | 29.53 | 18.33   | 10.71  |   |
|   | 29529  |        | apatnam | 2020-0 |      | 16.64 | 49.97  |        | 29.26 | 18.80   | 10.03  |   |
|   | 29530  | Visakh | apatnam | 2020-0 | 7-01 | 15.00 | 66.00  | 0.40   | 26.85 | 14.05   | 5.20   |   |
|   |        |        |         |        |      |       |        |        |       |         |        |   |
|   |        | co     | S02     | 03     | Benz |       | oluene | Xylene | AQI   | AQI_E   | Bucket |   |
|   | 0      | 0.92   | 27.64   | 133.36 |      | .00   | 0.02   | 0.00   | NaN   |         | NaN    |   |
|   | 1      | 0.97   | 24.55   | 34.06  |      | .68   | 5.50   | 3.77   | NaN   |         | NaN    |   |
|   | 2      | 17.40  | 29.07   | 30.70  |      | .80   | 16.40  | 2.25   | NaN   |         | NaN    |   |
|   | 3      | 1.70   | 18.59   | 36.08  | 4    | .43   | 10.14  | 1.00   | NaN   |         | NaN    |   |
|   | 4      | 22.10  | 39.33   | 39.31  | 7    | .01   | 18.89  | 2.78   | NaN   |         | NaN    |   |
|   |        |        |         |        |      |       |        |        |       |         |        |   |
|   | 29526  | 0.47   | 8.55    | 23.30  |      | .24   | 12.07  | 0.73   | 41.0  |         | Good   |   |
|   | 29527  | 0.52   | 12.72   | 30.14  |      | .74   | 2.21   | 0.38   | 70.0  | Satisfa |        |   |
|   | 29528  | 0.48   | 8.42    | 30.96  |      | .01   | 0.01   | 0.00   | 68.0  | Satisfa |        |   |
|   | 29529  | 0.52   | 9.84    | 28.30  | 0    | .00   | 0.00   | 0.00   | 54.0  | Satisfa | ictory |   |
|   | 29530  | 0.59   | 2.10    | 17.05  |      | NaN   | NaN    | NaN    | 50.0  |         | Good   |   |
|   |        |        |         |        |      |       |        |        |       |         |        |   |
|   | [29531 | rows x | 16 colı | umns]  |      |       |        |        |       |         |        |   |
|   |        |        |         |        |      |       |        |        |       |         |        |   |

# 4.. Label encoding of the categorical column if have:

Label Encoding is a popular encoding technique for handling categorical variables. In this technique, each label
is assigned a unique integer based on alphabetical ordering. We do his by following syntax:

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df['AQI_Bucket']=le.fit_transform(df['AQI_Bucket'])
print(df['AQI_Bucket'].value_counts())

1 8829
3 8224
6 4681
2 2781
5 2337
0 1341
4 1338
Name: AQI_Bucket, dtype: int64
```

## 5.Defining x and y

```
x=df.iloc[:,2:14]
y=df.iloc[:,0:16:15]
print(x)
print(y)
```

### df.iloc helps us to select a specific row or column from the data set.

```
PM2.5
                PM10
                         NO
                                NO2
                                       NOx
                                               NH3
                                                       co
                                                              502
                                                                       03
         NaN
                       0.92
                             18.22
                                     17.15
                                               NaN
                                                     0.92
                                                           27.64
                                                                   133.36
                                                                    34.06
                                     29.70
                                                           29.07
                                                                    30.70
                                                                    36.08
         NaN
                      22.10
                             21.42
                                    37.76
                                                           39.33
                                                                    39.31
       15.02
                                     19.54
                                                                    30.14
                                     18.33
                                                                    30.96
                                                                    28.30
       15.00
               66.00
                       0.40
                             26.85
                                     14.05
                                                     0.59
                                                            2.10
                                                                    17.05
       Benzene
                Toluene Xvlene
          3.68
                            3.77
          6.80
                   16.40
                            2.25
          4.43
                   10.14
                            1.00
          7.01
                   18.89
                            2.78
29526
          2.24
                   12.07
                            0.73
29527
          0.74
                    2.21
                            0.38
29528
                            0.00
          0.01
                    0.01
29529
          0.00
                    0.00
                            0.00
29530
           NaN
                     NaN
                             NaN
[29531 rows x 12 columns]
                 City AOI Bucket
           Ahmedabad
           Ahmedabad
           Ahmedabad
           Ahmedabad
            Ahmedabad
       Visakhapatnam
       Visakhapatnam
       Visakhapatnam
       Visakhapatnam
29530 Visakhapatnam
```

## 6. Splitting the x and y in train and test:

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model. Splitting your dataset is essential for an unbiased evaluation of prediction performance.

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x, y, test_size = .25)
print(x_train.shape, x_test.shape, y_train.shape,y_test.shape)

(22148, 12) (7383, 12) (22148, 2) (7383, 2)
```

## 7. Import the model:



from sklearn.linear\_model import LogisticRegression
lr=LogisticRegression()
print(lr)

LogisticRegression()

### 8. Train the model with x\_train and y\_train:

from sklearn.linear\_model import LogisticRegression
lr=LogisticRegression()

lr.fit(x\_train,y\_train)

### 9. Predict with x\_test and get predicted y

```
y_pred_lr = lr.predict(x_test)
print(y_pred_lr[:5],y_test.values[:5] )

print(lr.score(x_train,y_train))
print(lr.score(x_test, y_test))
```

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### 10. Evaluation

```
print(lr.score(x_train,y_train))
print(lr.score(x_test, y_test))

from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
print(confusion_matrix(y_pred_lr, y_test))
print(classification_report(y_pred_lr, y_test))
print(f'model_score- {lr.score(x_test,y_test)}')
print(f'accuracy_score- {accuracy_score(y_pred_lr, y_test)}')

0.5736583279880265
accuracy
```

```
0.5567671584348942
                 0 01
     1 0 11
                 3 16]
   3 464 71 248
   0 61 45 2
                 4 35]
  84 89 0 267
     3 6 0 11
     12 24
                 9 49]]
            precision
                        recall f1-score
                                         support
                          0.73
         0
                 0.27
                                   0.39
                                              44
                 0.74
                          0.58
                                   0.65
                                             805
                 0.31
                          0.31
                                   0.31
                                             147
                 0.50
                          0.61
                                   0.55
                                             441
                 0.41
                          0.42
                                   0.42
                                              26
         5
                 0.46
                          0.51
                                   0.48
                                              96
```

```
accuracy 0.56 1559
macro avg 0.45 0.52 0.47 1559
weighted avg 0.59 0.56 0.57 1559
```

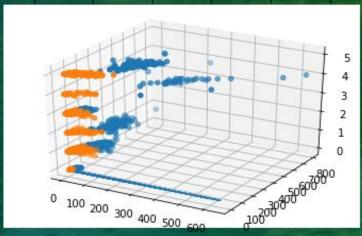
model\_score- 0.5567671584348942 accuracy\_score- 0.5567671584348942

### Confusion matrix and Accuracy

```
cm=confusion_matrix(y_pred_lr,y_test)
sns.heatmap(cm,annot=True)
plt.show()

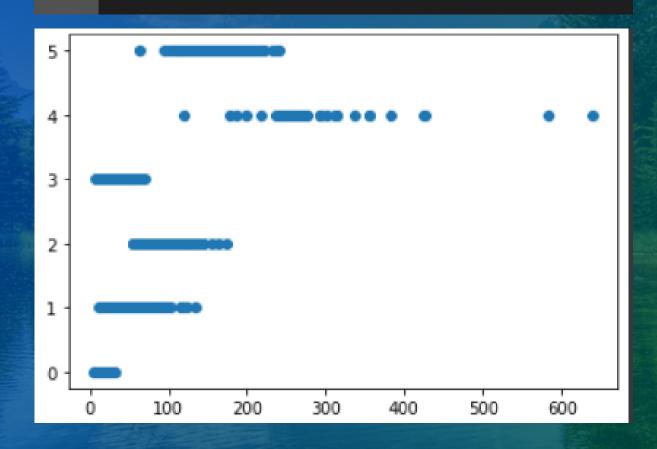
ax = plt.axes(projection = '3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['N0'],x_test['N02'],y_pred_lr, 'black')
plt.plot(x_test['PM2.5'], y_pred_lr)
plt.show()
```

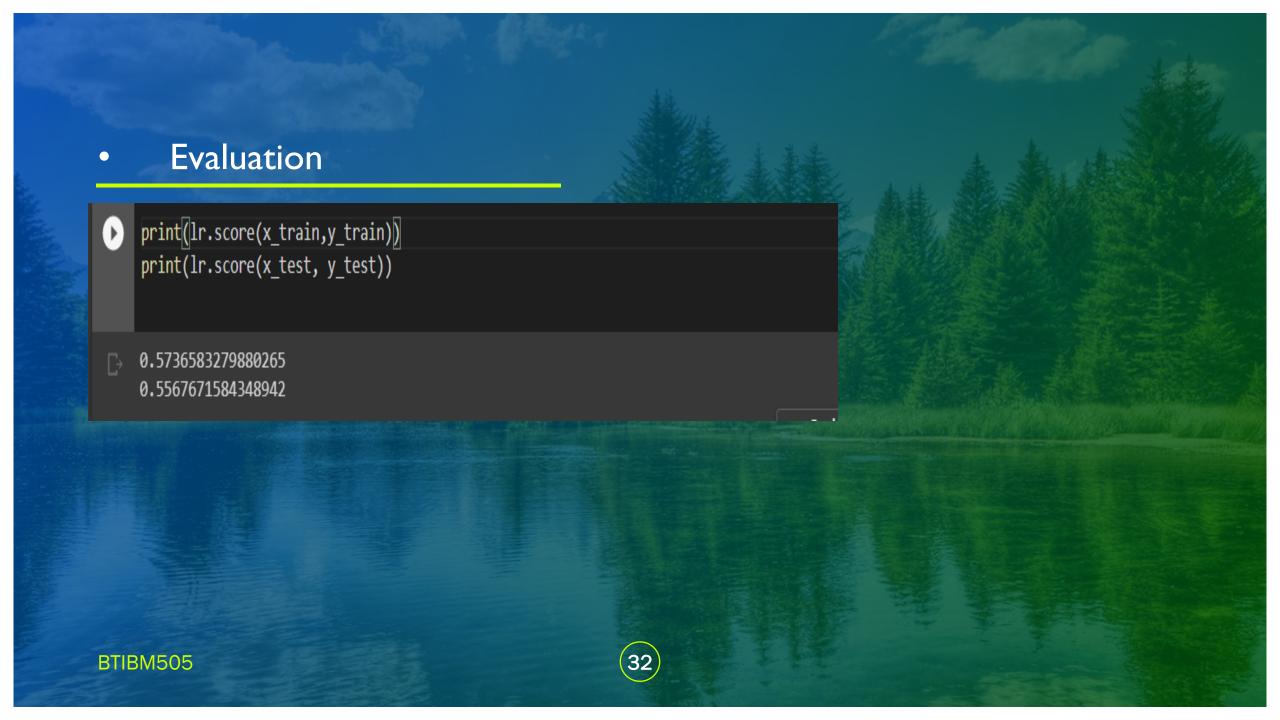
|      | 28 | 0     | 0  | 7       | 0  | 0  |
|------|----|-------|----|---------|----|----|
|      | 7  | 5e+02 | 89 | 2.5e+02 | 0  | 17 |
| 子子学者 | 0  | 45    | 33 | 2       | 8  | 28 |
|      | 74 | 77    | 1  | 2.5e+02 | 0  | 0  |
|      | 0  | 4     | 8  | 0       | 11 | 2  |
| E ST | 0  | 11    | 30 | 0       | 20 | 55 |





plt.scatter(x\_test['PM2.5'], y\_test)
plt.show()

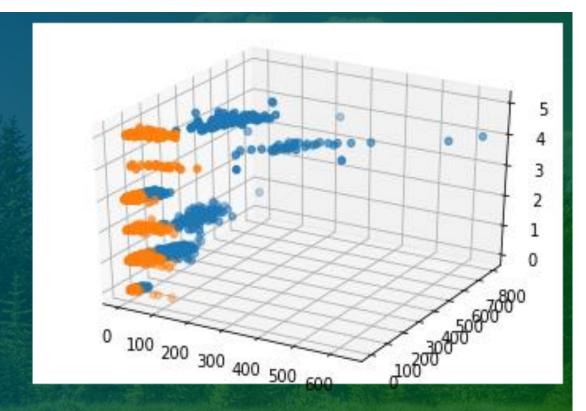




# Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier()
dtc.fit(x train,y train)
y pred dtc=dtc.predict(x test)
print(f'Predicted_y{y_pred_dtc[:5]} Actual_y{y_test.values[:5]}')
print(confusion_matrix(y_pred_dtc,y_test))
from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
cm=confusion_matrix(y_pred_dtc, y_test)
plt.figure(figsize=(7,5))
print(sns.heatmap(cm, annot=True))
plt.show()
print(classification report(y pred dtc, y test))
print(f'model_score- {dtc.score(x_test, y_test)} ')
print(f'accuracy_score- {accuracy_score(y_pred_dtc, y_test)}')
ax = plt.axes (projection ='3d')
ax.scatter3D(x test['PM2.5'],x test['PM10'],y test)
ax.scatter3D(x test['NO'],x test['NO2'], y pred_dtc,'black')
plt.show()
```

```
Predicted_y[0 4 0 3 1] Actual_y[[3]
 [4]
 [8]
 [3]
 [1]]
                        0]
6]
              31
               97
                       18]
           97
                        Ø]
            0 381
                        0]
                0 16 78]]
          25
AxesSubplot(0.125,0.125;0.62x0.755)
```



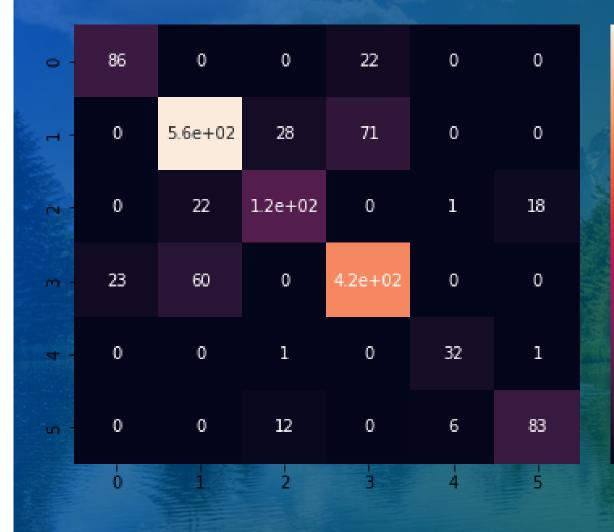


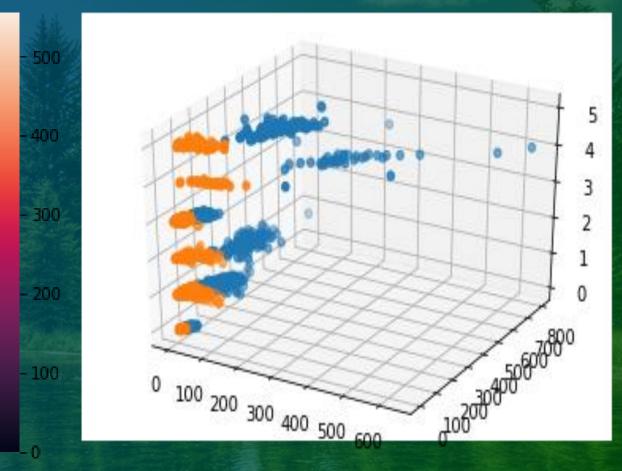
# Random forest

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(x train, y train)
y pred rfc = rfc.predict(x test)
print(f'predicted_y-{y_pred_rfc} actual_y-{y_test.values}')
print(confusion_matrix(y_pred_rfc,y_test))
cm=confusion_matrix(y_pred_rfc,y_test)
plt.figure(figsize=(7,5))
sns.heatmap(cm, annot=True)
plt.show()
print(classification_report(y_pred_rfc, y_test))
print(f'model_score- {rfc.score(x_test,y_test)}')
print(f'accuracy_score- {accuracy_score(y_pred_rfc, y_test)}')
ax = plt.axes (projection ='3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['NO'],x_test['NO2'],y_pred_rfc,'black')
plt.show()
```

```
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier()
rfc.fit(x train, y train)
y pred rfc = rfc.predict(x test)
print(f'predicted_y-{y_pred_rfc} actual_y-{y_test.values}')
print(confusion_matrix(y_pred_rfc,y_test))
cm=confusion matrix(y pred rfc,y test)
plt.figure(figsize=(7,5))
sns.heatmap(cm, annot=True)
plt.show()
print(classification report(y pred rfc, y test))
print(f'model score- {rfc.score(x test,y test)}')
print(f'accuracy_score- {accuracy_score(y_pred_rfc, y_test)}')
ax = plt.axes (projection ='3d')
ax.scatter3D(x test['PM2.5'],x test['PM10'],y test)
ax.scatter3D(x test['NO'],x test['NO2'],y pred rfc,'black')
plt.show()
```

```
/usr/local/lib/python3.7/dist-packag
 This is separate from the ipykerne
predicted y-[3 4 0 ... 3 0 3] actual
[4]
[0]
[3]
[0]
[3]]
[[ 86 0 0 22 0
   0 556 28 71 0
   0 22 120 0
                 1 181
 [ 23 60 0 417 0
      0 12
                    8311
```





# K-Nearest Neighbors Classifier

```
from sklearn.neighbors import KNeighborsClassifier
knc=KNeighborsClassifier()
knc.fit(x train, y train)
y pred knc=knc.predict(x test)
print(f'Predicted_y{y_pred_knc[:5]} Actual_y{y_test.values[:5]}')
print(confusion_matrix(y_pred_knc,y_test))
from sklearn.metrics import confusion_matrix,classification_report, accuracy_score
cm=confusion_matrix(y_pred_knc,y_test)
plt.figure(figsize=(7,5))
print(sns.heatmap(cm, annot=True))
plt.show()
print(classification_report(y_pred_knc, y_test))
print(f'model_score- {dtc.score(x_test, y_test)} ')
print(f'accuracy_score- {accuracy_score(y_pred_knc, y_test)}')
ax = plt.axes(projection = '3d')
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_test)
ax.scatter3D(x_test['PM2.5'],x_test['PM10'],y_pred_knc, 'black')
plt.show()
```



/usr/local/lib/python3.7/dist-packages/sklearn
return self.\_fit(X, y)

Predicted\_y[0 4 0 3 1] Actual\_y[[3]

[4]

L.

[0]

[3]

[1]]

[[87 1 0 30 0 0] [0525 33 65 0 1]

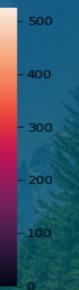
[ 0 29 117 0 0 19]

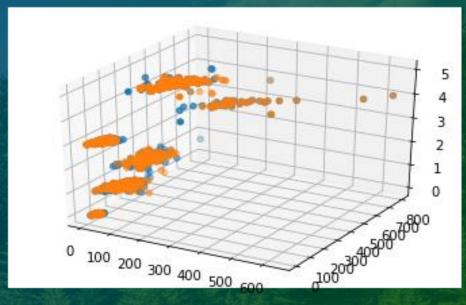
[ 22 83 1 415 0 01

[ 0 0 1 0 31 4]

[ 0 0 9 0 8 78]]

AxesSubplot(0.125,0.125;0.62x0.755)





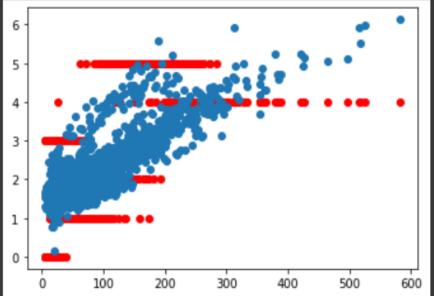
| 200000       | PERSONAL STATES | 28/20  | 75%      | 1 46    |
|--------------|-----------------|--------|----------|---------|
|              | precision       | recall | f1-score | support |
| 0            | 0.80            | 0.74   | 0.77     | 118     |
| 1            | 0.82            | 0.84   | 0.83     | 624     |
| 2            | 0.73            | 0.71   | 0.72     | 165     |
| 3            | 0.81            | 0.80   | 0.81     | 521     |
| 4            | 0.79            | 0.86   | 0.83     | 36      |
| 5            | 0.76            | 0.82   | 0.79     | 95      |
|              |                 |        |          |         |
| accuracy     |                 |        | 0.80     | 1559    |
| macro avg    | 0.79            | 0.79   | 0.79     | 1559    |
| weighted avg | 0.80            | 0.80   | 0.80     | 1559    |
|              |                 |        |          |         |

model\_score- 0.7498396407953817 accuracy\_score- 0.8037203335471456

# Simple linear Regressor

```
from sklearn.linear model import LinearRegression
slr=LinearRegression()
slr.fit(x train, y train)
y_pred=slr.predict(x_test)
print(slr.score(x train,y train))
print(slr.score(x_test,y_test))
from sklearn.metrics import mean absolute error, mean squared error, r2 score
print("Mean Absolute Error:- ",mean absolute error(y test, y pred))
print("Mean Squared Error:- ",mean squared error(y test,y pred))
print("r2 score:- ",r2 score(y test,y pred))
a=slr.coef
b=slr.intercept
plt.scatter(x test['PM2.5'],y test,color='r')
plt.scatter(x test['PM2.5'],y pred)
plt.show()
```

0.1961930096682737
 0.18946593484141327
 Mean Absolute Error: - 1.0708636884898894
 Mean Squared Error: - 1.384272714993072
 r2\_score: - 0.18946593484141327





Dataset: <a href="https://www.kaggle.com/datasets/rohanrao/air-quality-data-in-india?resource=download">https://www.kaggle.com/datasets/rohanrao/air-quality-data-in-india?resource=download</a>

Google Drive: <a href="https://drive.google.com/drive/folders/1j5hfguD4NrOGAMA\_rhelORpP6-1Ux2gL">https://drive.google.com/drive/folders/1j5hfguD4NrOGAMA\_rhelORpP6-1Ux2gL</a>

Google Colab 2: https://colab.research.google.com/drive/1Hi1ur89p4DdpjSAWjd0gJV-

LGjHSG7e-#scrollTo=-teNaxQN-B01

Google Colab 1:

Click on the link for the source codes

https://colab.research.google.com/drive/1G00JBNjDj\_WMdzNqXu0\_kbl8TKzHRsyE

