Predicting air pollutants

In [1]:
```
!pip3 install pyreadr
```

```
Collecting pyreadr
  Downloading https://files.pythonhosted.org/packages/c8/09/52ca21f4888
ca56731dbe15ca59cda5ccbea72ec2e4a3b97c286de533bde/pyreadr-0.2.9-cp36-cp
36m-manylinux1_x86_64.whl (261kB)
     |████████████████████████████████| 266kB 4.6MB/s
Requirement already satisfied: pandas>0.24.0 in /usr/local/lib/python3.
6/dist-packages (from pyreadr) (1.0.5)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.
6/dist-packages (from pandas>0.24.0->pyreadr) (1.18.5)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.
6/dist-packages (from pandas>0.24.0->pyreadr) (2018.9)
Requirement already satisfied: python-dateutil>=2.6.1 in /usr/local/li
b/python3.6/dist-packages (from pandas>0.24.0->pyreadr) (2.8.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dis
t-packages (from python-dateutil>=2.6.1->pandas>0.24.0->pyreadr) (1.15.
0)
Installing collected packages: pyreadr
Successfully installed pyreadr-0.2.9
```

In [2]:
```
import pyreadr
```

Downloading data from UK air

In [3]:
```
metadata_url='http://uk-air.defra.gov.uk/openair/R_data/AURN_metadata.R
Data'

fn = metadata_url.split('/')[-1]
```

In [4]:
```
!wget $metadata_url
```

```
--2020-08-13 05:17:50--  http://uk-air.defra.gov.uk/openair/R_data/AURN
_metadata.RData
Resolving uk-air.defra.gov.uk (uk-air.defra.gov.uk)... 213.251.9.44
Connecting to uk-air.defra.gov.uk (uk-air.defra.gov.uk)|213.251.9.44|:8
0... connected.
HTTP request sent, awaiting response... 301 Moved Permanently
Location: https://uk-air.defra.gov.uk/openair/R_data/AURN_metadata.RDat
a [following]
--2020-08-13 05:17:50--  https://uk-air.defra.gov.uk/openair/R_data/AUR
N_metadata.RData
Connecting to uk-air.defra.gov.uk (uk-air.defra.gov.uk)|213.251.9.44|:4
43... connected.
HTTP request sent, awaiting response... 200 OK
Length: 31218 (30K) [application/octet-stream]
Saving to: 'AURN_metadata.RData'

AURN_metadata.RData 100%[===================>]  30.49K  --.-KB/s    in
0s

2020-08-13 05:17:51 (257 MB/s) - 'AURN_metadata.RData' saved [31218/312
18]
```

In [5]:
```
import pandas as pd
pyreadr.read_r(fn)['AURN_metadata'].head()
```

Out[5]:

	site_id	site_name	location_type	latitude	longitude	parameter	Parameter_name	start_date
0	ABD	Aberdeen	Urban Background	57.15736	-2.094278	O3	Ozone	2003-08-01
1	ABD	Aberdeen	Urban Background	57.15736	-2.094278	NO	Nitric oxide	1999-09-18
2	ABD	Aberdeen	Urban Background	57.15736	-2.094278	NO2	Nitrogen dioxide	1999-09-18

	site_id	site_name	location_type	latitude	longitude	parameter	Parameter_name	start_date
3	ABD	Aberdeen	Urban Background	57.15736	-2.094278	NOXasNO2	Nitrogen oxides as nitrogen dioxide	1999-09-18
4	ABD	Aberdeen	Urban Background	57.15736	-2.094278	SO2	Sulphur dioxide	2001-01-01

In [6]:

```
package_url_base = 'https://uk-air.defra.gov.uk/openair/R_data/{fn}'
```

In [7]:

```
site = 'kc1'
year = 2020

fn = '{site}_{year}.RData'.format(site=site.upper(), year=year)

url = package_url_base.format(fn=fn)
!wget $url
```

```
--2020-08-13 05:17:53--  https://uk-air.defra.gov.uk/openair/R_data/KC1
_2020.RData
Resolving uk-air.defra.gov.uk (uk-air.defra.gov.uk)... 213.251.9.44
Connecting to uk-air.defra.gov.uk (uk-air.defra.gov.uk)|213.251.9.44|:4
43... connected.
HTTP request sent, awaiting response... 200 OK
Length: 204431 (200K) [application/octet-stream]
Saving to: ‘KC1_2020.RData’

KC1_2020.RData      100%[===================>] 199.64K   486KB/s    in
0.4s

2020-08-13 05:17:55 (486 KB/s) - ‘KC1_2020.RData’ saved [204431/204431]
```

In [8]:

```
df = pyreadr.read_r(fn)[fn.split('.')[0]]
```

In [9]:

```
df.head()
```

Out[9]:

	date	O3	NO2	CO	SO2	PM10	NOXasNO2	NO	PM2.5	temp	ws
0	2020-01-01 00:00:00	1.13090	46.22164	0.213586	NaN	41.850	64.75051	12.08422	35.189	2.3	2.1
1	2020-01-01 01:00:00	1.19742	45.01138	0.236887	NaN	43.000	74.07898	18.95739	36.250	1.4	2.1
2	2020-01-01 02:00:00	1.49678	41.43513	0.203878	NaN	46.025	60.49783	12.43237	39.623	1.0	2.3
3	2020-01-01 03:00:00	1.59656	39.81147	0.203878	NaN	48.525	53.50148	8.92839	41.179	0.8	1.8
4	2020-01-01 04:00:00	5.78753	33.62730	0.168928	NaN	45.400	37.65681	2.62798	40.118	0.8	1.7

Data preparation

We are trying to predict CO, NO, PM2.5, PM10 .

Our dataset consists of date, CO , PM10, PM2.5, NO ,TEMPERATURE , Wind Speed(WS), Wind Direction(WD).

In [12]:

```
df.describe()
```

Out[12]:

	O3	NO2	CO	SO2	PM10	NOXasNO2	N
count	5189.000000	5340.000000	5348.000000	5332.000000	5371.000000	5341.000000	5340.0000
mean	59.947588	18.335906	0.284959	5.021545	13.685726	24.267710	3.8670
std	27.198648	15.183808	0.167791	4.091021	10.072496	32.420114	14.0524

	O3	NO2	CO	SO2	PM10	NOXasNO2	N
min	-0.049890	-0.683720	-0.011642	-2.554460	0.700000	0.052590	-0.1715(
25%	45.003040	8.326380	0.117425	1.872490	7.325000	9.747380	0.5488'
50%	60.968640	13.181735	0.309545	3.500285	10.900000	15.357380	1.0477:
75%	74.289930	22.993118	0.416202	7.450520	16.625000	26.535940	2.2295!
max	212.941190	105.952500	0.969197	17.761510	160.450000	449.581260	241.8417!

We could see that the values are missing for the columns , we could fill this using mean sampling

Mean sampling

In [13]:
```
mean = df['CO'].mean()
```

In [14]:
```
mean
```

Out[14]:
```
0.2849588167539257
```

In [15]:
```
df['CO'] = df ['CO'].fillna(mean)
```

In [16]:
```
mean_temp= df['temp'].mean()
```

In [17]:
```
df['temp']=df['temp'].fillna(mean_temp)
```

In [18]:
```
mean_ws = df['ws'].mean()
```

In [19]:
```
df['ws'] = df['ws'].fillna(mean_ws)
```

In [20]:
```
mean_wd = df['wd'].mean()
```

In [21]:
```
df['wd'] = df['wd'].fillna(mean_wd)
```

In [22]:
```
mean_1 = df['PM10'].mean()
```

In [23]:
```
df['PM10'] = df['PM10'].fillna(mean_1)
```

In [24]:
```
mean_2  = df ['NO'].mean()
```

In [25]:
```
df['NO'] = df ['NO'].fillna(mean_2)
```

In [26]:
```
mean_3 = df['PM2.5'].mean()
```

In [27]:
```
df['PM2.5'] = df['PM2.5'].fillna(mean_3)
```

In [28]:
```
mean_o3=df['O3'].mean()
df['O3'] = df ['O3'].fillna(mean_o3)
```

In [29]:
```
mean_no2=df['NO2'].mean()
df['NO2'] = df ['NO2'].fillna(mean_no2)
```

In [30]:
```
mean_nox=df['NOXasNO2'].mean()
df['NOXasNO2'] = df ['NOXasNO2'].fillna(mean_nox)
```

In [31]:
```
mean_raw=df['RAWPM25'].mean()
df['RAWPM25'] = df ['RAWPM25'].fillna(mean_raw)
```

In [32]:
```
df.describe()
```

Out[32]:

	O3	NO2	CO	SO2	PM10	NOXasNO2	N
count	5400.000000	5400.000000	5400.000000	5332.000000	5400.000000	5400.000000	5400.00000
mean	59.947588	18.335906	0.284959	5.021545	13.685726	24.267710	3.8670

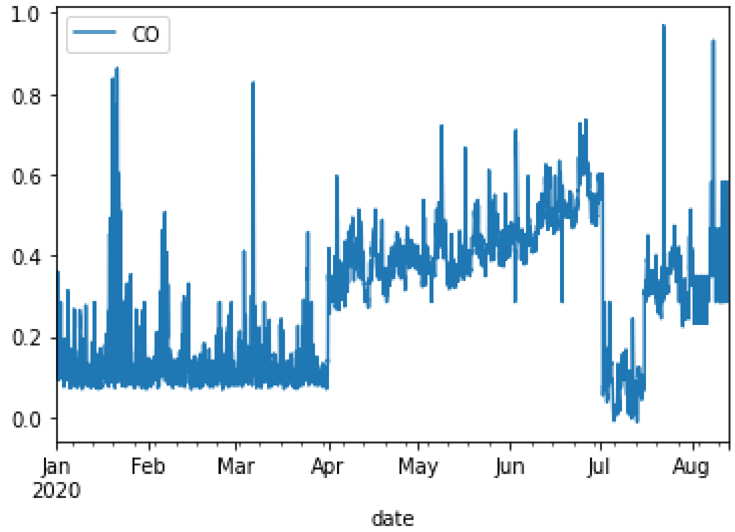
	O3	NO2	CO	SO2	PM10	NOXasNO2	N
std	26.661871	15.099202	0.166981	4.091021	10.045408	32.242485	13.97419
min	-0.049890	-0.683720	-0.011642	-2.554460	0.700000	0.052590	-0.17150
25%	46.050780	8.401650	0.117561	1.872490	7.325000	9.810665	0.5488
50%	59.959189	13.353870	0.305603	3.500285	10.925000	15.496175	1.0633
75%	73.741120	22.871370	0.413291	7.450520	16.600000	26.296880	2.2935
max	212.941190	105.952500	0.969197	17.761510	160.450000	449.581260	241.8417

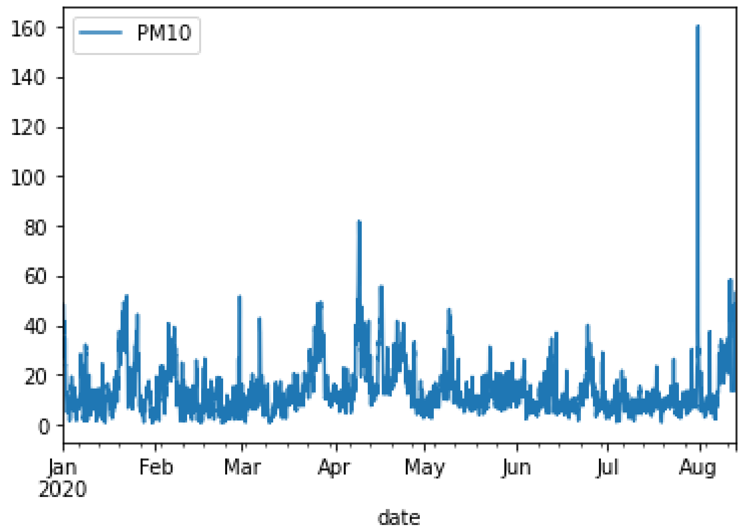
EXPLORATORY DATA ANALYSIS

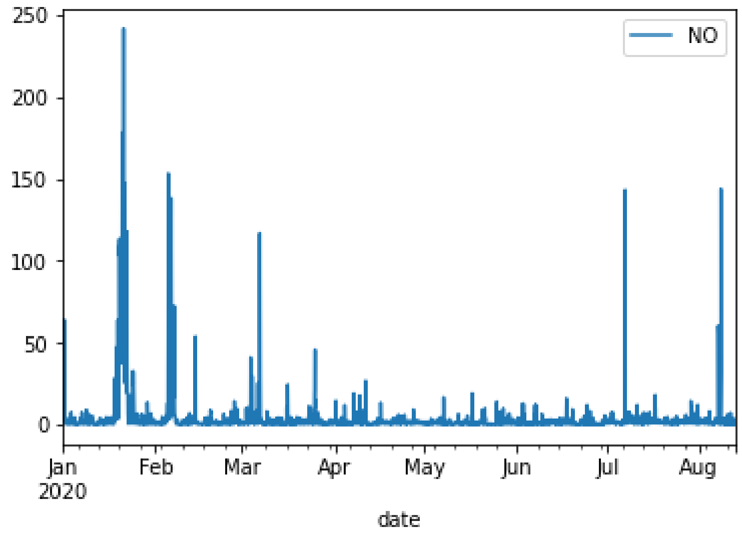
In [33]:
```
from matplotlib import pyplot
```

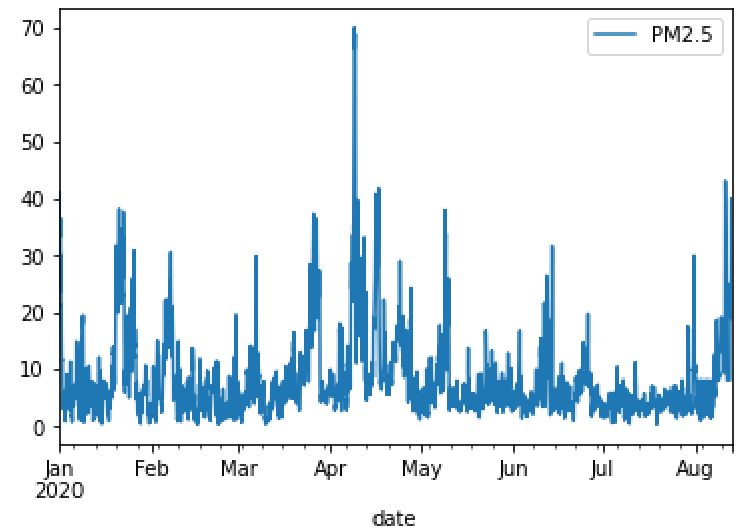
In [34]:
```
df.plot(x='date', y='CO')
df.plot(x='date', y ='PM10')
df.plot(x='date', y = 'NO')
df.plot(x= 'date', y = 'PM2.5')
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a570ac400>


CO
1.0
0.8
0.6
0.4
0.2
0.0
Jan
2020
Feb
Mar
Apr
May
Jun
Jul
Aug
date


PM10
160
140
120
100
80
60
40
20
0
Jan
2020
Feb
Mar
Apr
May
Jun
Jul
Aug
date



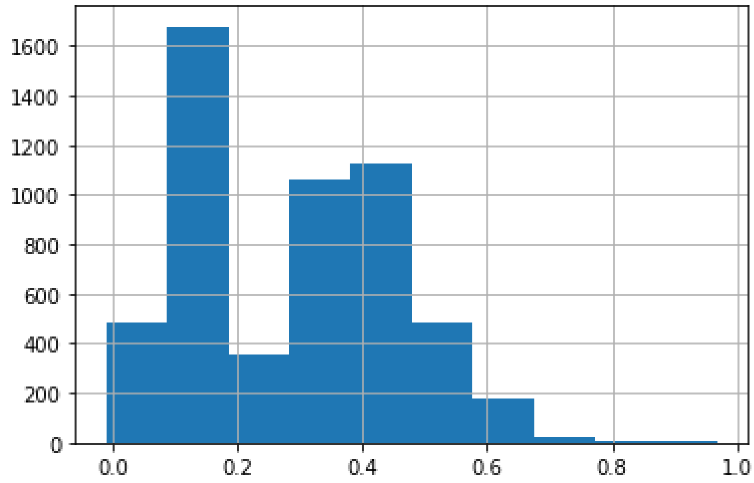


Observation

We can see the variation of pollutant values , throuhout the year

In [35]:
```
df['CO'].hist()
```

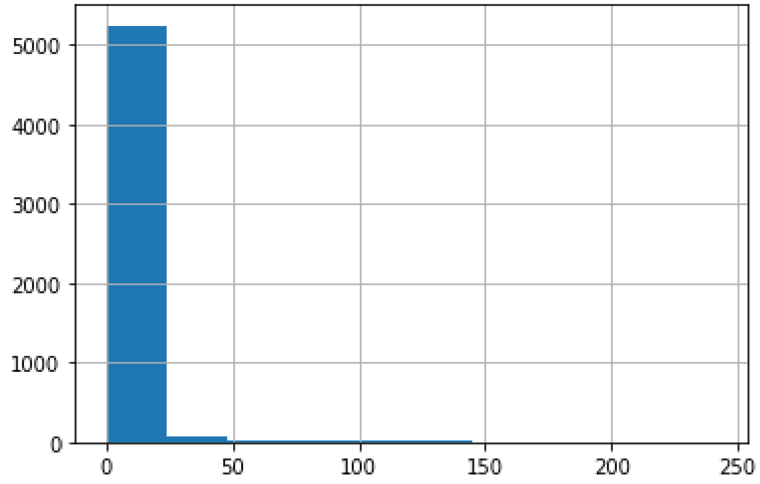
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a586deac8>



From the above plot we could see most of the CO values are around 0.2 .

In [36]:
```
df['NO'].hist()
```

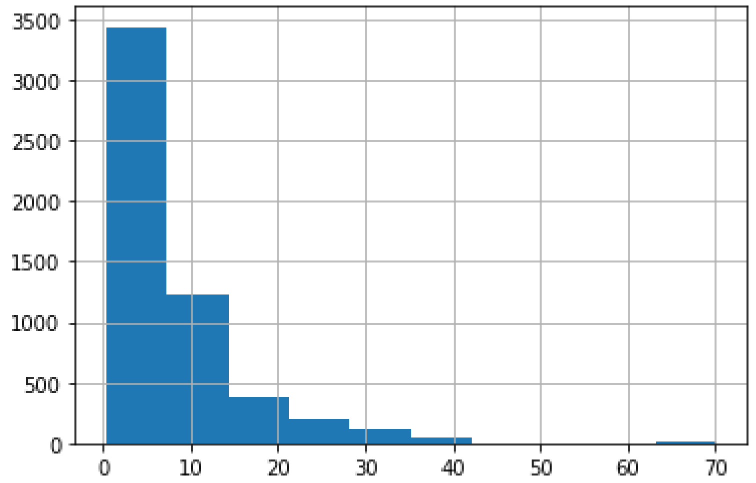
Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a586deef0>



From the above plot we could see most of the NO values are around 0 to 50 .

In [37]:
```
df['PM2.5'].hist()
```

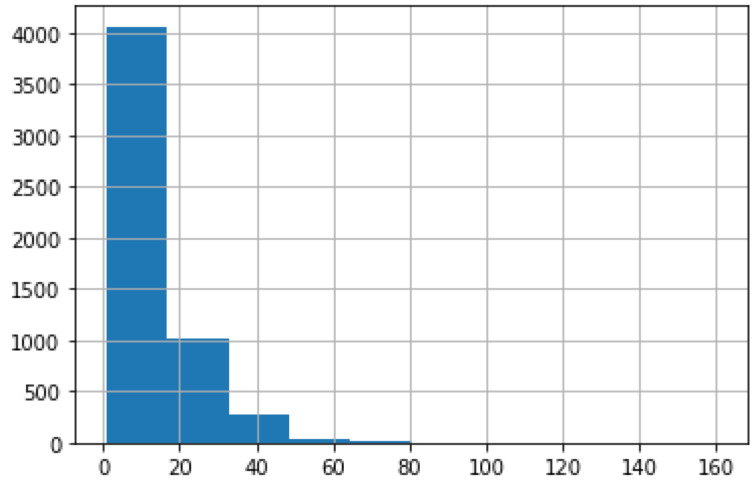
Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a56977208>



From the above plot we could see most of the PM2.5 values are around 0 to 5 .

In [38]:
```
df['PM10'].hist()
```

Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3a569cb780>
```



From the above plot we could see most of the PM10 values are around 0 to 20 .

In [39]:
```
df.head()
```

Out[39]:

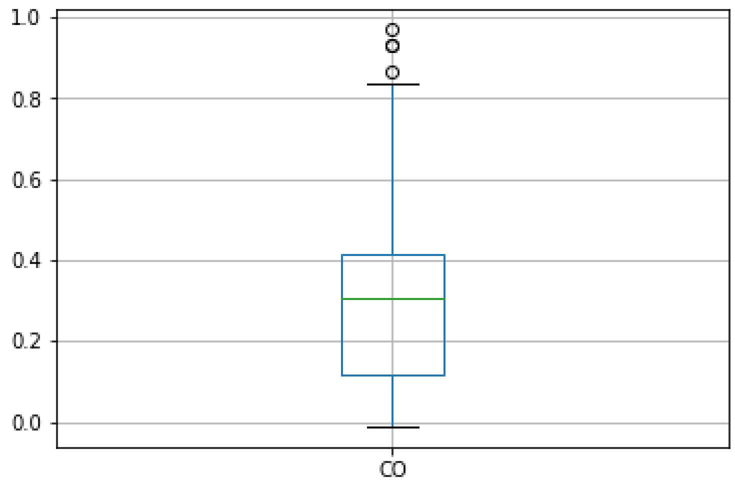
	date	O3	NO2	CO	SO2	PM10	NOXasNO2	NO	PM2.5	temp	ws
0	2020-01-01 00:00:00	1.13090	46.22164	0.213586	NaN	41.850	64.75051	12.08422	35.189	2.3	2.1
1	2020-01-01 01:00:00	1.19742	45.01138	0.236887	NaN	43.000	74.07898	18.95739	36.250	1.4	2.1
2	2020-01-01 02:00:00	1.49678	41.43513	0.203878	NaN	46.025	60.49783	12.43237	39.623	1.0	2.3
3	2020-01-01 03:00:00	1.59656	39.81147	0.203878	NaN	48.525	53.50148	8.92839	41.179	0.8	1.8

	date	O3	NO2	CO	SO2	PM10	NOXasNO2	NO	PM2.5	temp	ws
4	2020-01-01 04:00:00	5.78753	33.62730	0.168928	NaN	45.400	37.65681	2.62798	40.118	0.8	1.7

Highlighting the outliers

In [40]:
```
df['CO'].plot.box(grid='True')
```

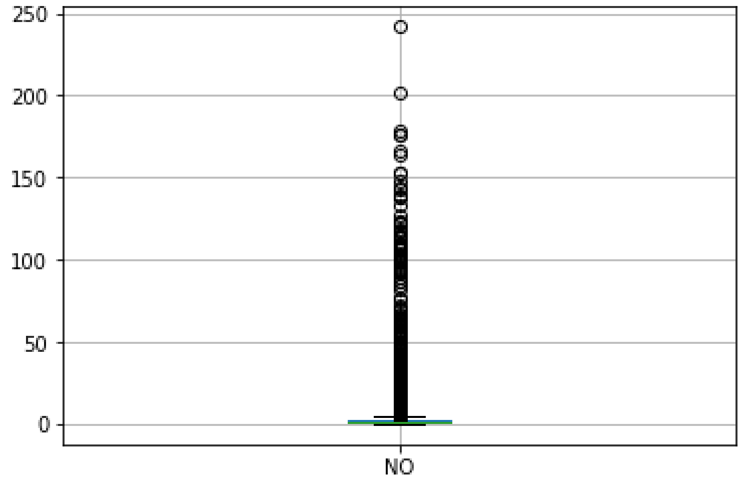
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a56884240>



We could see that the IQR lies between 0 to 0.8 , and the points above or below it are outliers

In [41]:
```
df['NO'].plot.box(grid='True')
```

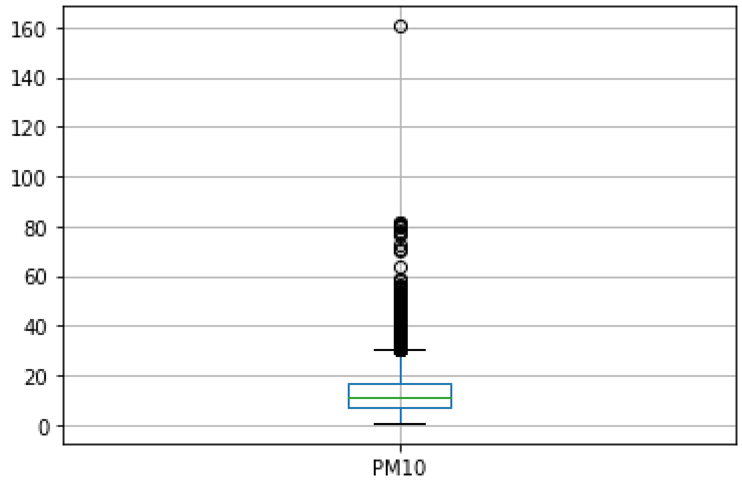
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a567e5390>



We could see that the IQR lies between 0 to 10 , and the points above or below it are outliers

In [42]:
```
df['PM10'].plot.box(grid='True')
```

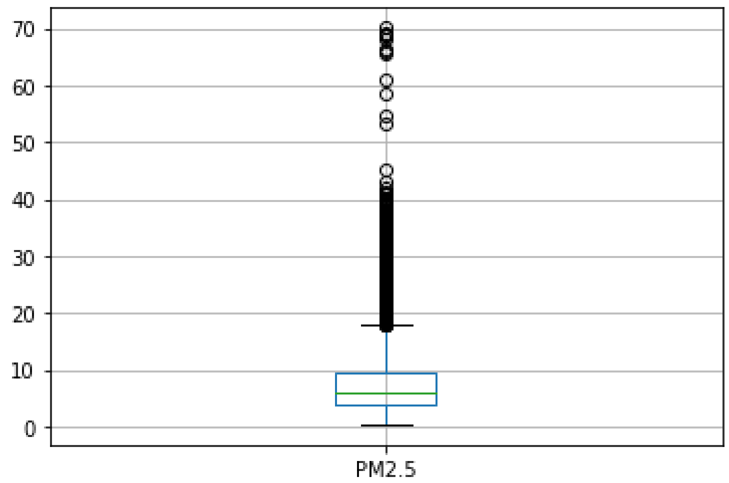
Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7f3a567d0470>



We could see that the IQR lies between 0 to 30 , and the points above or below it are outliers

In [43]:
```
df['PM2.5'].plot.box(grid='True')
```

Out[43]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3a570f3278>
```



We could see that the IQR lies between 0 to 188 , and the points above or below it are outliers

In [44]:
```
df = df[['date','temp', 'ws','wd','PM10','PM2.5','NO','CO','O3','NO2',
'NOXasNO2','RAWPM25']]
```

splitting the datetime values to two columns as date and time seperately

In [45]:
```
df['date'] = pd.to_datetime(df['date'])
df['Date'] = df['date'].dt.strftime('%d/%m/%Y')
df['Time'] = df['date'].dt.strftime('%H:%M:%S')
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

```
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imp
orts until
```

In [46]:
```
df
```

Out[46]:

	date	temp	ws	wd	PM10	PM2.5	NO	CO	O3	NO2	NOXas
0	2020-01-01 00:00:00	2.3	2.1	92.7	41.850	35.189	12.08422	0.213586	1.13090	46.22164	64.7
1	2020-01-01 01:00:00	1.4	2.1	98.3	43.000	36.250	18.95739	0.236887	1.19742	45.01138	74.0
2	2020-01-01 02:00:00	1.0	2.3	116.6	46.025	39.623	12.43237	0.203878	1.49678	41.43513	60.4
3	2020-01-01 03:00:00	0.8	1.8	131.1	48.525	41.179	8.92839	0.203878	1.59656	39.81147	53.5

	date	temp	ws	wd	PM10	PM2.5	NO	CO	O3	NO2	NOXas
4	2020-01-01 04:00:00	0.8	1.7	108.8	45.400	40.118	2.62798	0.168928	5.78753	33.62730	37.6
...	...	...	...	...	...	...	...	...	...	...	
5395	2020-08-12 19:00:00	24.0	2.5	81.4	32.000	20.755	0.24946	0.465680	153.26976	31.17375	31.5
5396	2020-08-12 20:00:00	23.1	2.6	61.2	27.700	18.962	0.24946	0.465680	148.08094	31.93875	32.3
5397	2020-08-12 21:00:00	22.3	2.8	77.5	37.400	26.793	0.24946	0.284959	148.67965	30.02625	30.4
5398	2020-08-12 22:00:00	22.1	3.4	182.5	42.000	31.227	0.62365	0.523890	137.10459	34.80750	35.7
5399	2020-08-12 23:00:00	21.9	2.3	123.3	53.200	40.095	0.49892	0.512248	131.51663	30.98250	31.7

5400 rows × 14 columns

In [47]:

```
df = df[['Date','Time','temp','ws','wd','PM10','PM2.5','NO','CO','O3',
'NO2','NOXasNO2','RAWPM25']]
```

In [48]:

```
from datetime import datetime
Date= []
for i in df['Date']:
    Date.append(datetime.strptime(i,'%d/%m/%Y'))
df.dtypes
```

Out[48]:

```
Date         object
Time         object
temp        float64
ws          float64
```

```
wd            float64
PM10          float64
PM2.5         float64
NO            float64
CO            float64
O3            float64
NO2           float64
NOXasNO2      float64
RAWPM25       float64
dtype: object
```

Date and time values are of object datatype , converting it to float type.

In [49]:
```
date=pd.Series(Date)
df['Date']=pd.to_numeric(date)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:2: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

In [50]:
```
df['Date']=df['Date'].astype(float)
df.dtypes
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

Out[50]:
```
Date          float64
```

```
Time            object
temp           float64
ws             float64
wd             float64
PM10           float64
PM2.5          float64
NO             float64
CO             float64
O3             float64
NO2            float64
NOXasNO2       float64
RAWPM25        float64
dtype: object
```

In [51]:
```
df.loc[:,'Time']=df['Time']
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/indexing.py:966: Set
tingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  self.obj[item] = s
```

In [52]:
```
from datetime import datetime
Time= []
for i in df['Time']:
    Time.append(datetime.strptime(i,'%H:%M:%S'))
df.dtypes
```

Out[52]:
```
Date           float64
Time            object
temp           float64
ws             float64
wd             float64
PM10           float64
PM2.5          float64
NO             float64
```

```
CO           float64
O3           float64
NO2          float64
NOXasNO2     float64
RAWPM25      float64
dtype: object
```

In [53]:
```
time=pd.Series(Time)
df['Time']=pd.to_numeric(time)
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:3: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imp
orts until
```

In [54]:
```
df['Time']=df['Time'].astype(float)
df.dtypes
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:1: Setting
WithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

Out[54]:
```
Date         float64
Time         float64
temp         float64
ws           float64
wd           float64
PM10         float64
PM2.5        float64
```

```
NO           float64
CO           float64
O3           float64
NO2          float64
NOXasNO2     float64
RAWPM25      float64
dtype: object
```

All column values in the dataframe are float values.

In [55]:
```
import seaborn as sns
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:1
9: FutureWarning: pandas.util.testing is deprecated. Use the functions
in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

Visualizing the data using pair plots to determine whether the data is linear.

In [56]:
```
sns.pairplot(df[["Date","Time","CO","PM2.5","PM10","NO",'O3','NO2','NOX
asNO2','RAWPM25']],diag_kind = "auto")
```

Out[56]:
```
<seaborn.axisgrid.PairGrid at 0x7f3a4beb12b0>
```

Using the Pearson correlation to find out what features contribute most to predicting our target.

In [57]:
```
df_45=df.corr('pearson')
df_45
```

Out[57]:

	Date	Time	temp	ws	wd	PM10	PM2.5	
Date	1.000000e+00	-7.175127e-18	0.726525	-0.208231	-0.101286	-0.077177	-0.154311	-0
Time	-7.175127e-18	1.000000e+00	0.119706	0.038549	0.025290	-0.015263	-0.037685	-0
temp	7.265252e-01	1.197056e-01	1.000000	0.029214	-0.019913	-0.048034	-0.155942	-0
ws	-2.082307e-01	3.854920e-02	0.029214	1.000000	0.116873	-0.254469	-0.312547	-0
wd	-1.012861e-01	2.528979e-02	-0.019913	0.116873	1.000000	-0.338792	-0.323025	0
PM10	-7.717687e-02	-1.526338e-02	-0.048034	-0.254469	-0.338792	1.000000	0.934253	0
PM2.5	-1.543113e-01	-3.768474e-02	-0.155942	-0.312547	-0.323025	0.934253	1.000000	0
NO	-1.748028e-01	-3.698464e-02	-0.213222	-0.208945	0.076699	0.304891	0.343863	1
CO	5.355923e-01	1.616974e-02	0.428485	-0.374376	-0.247085	0.243006	0.227018	0
O3	1.748115e-01	1.749172e-01	0.467904	0.252520	-0.216385	-0.018354	-0.120339	-0
NO2	-2.910968e-01	6.828484e-02	-0.345716	-0.440947	-0.025270	0.456301	0.501895	0
NOXasNO2	-2.524193e-01	7.372132e-03	-0.303551	-0.345395	0.039202	0.416230	0.463487	0
RAWPM25	-1.543116e-01	-3.768547e-02	-0.155943	-0.312547	-0.323024	0.934254	1.000000	0

Predicting CO

In [58]:
```
abs(df_45['CO']).sort_values(ascending=False)
```

Out[58]:
```
CO           1.000000
Date         0.535592
temp         0.428485
ws           0.374376
wd           0.247085
PM10         0.243006
PM2.5        0.227018
RAWPM25      0.227018
NOXasNO2     0.141956
NO           0.139816
O3           0.108220
NO2          0.104721
Time         0.016170
Name: CO, dtype: float64
```

In [102]:
```
features=df
target=df['CO']
```

Deleting features wich have very high and very low correlation values .

In [103]:
```
features=features.drop('Time',axis=1)
features=features.drop('O3',axis=1)
features=features.drop('NO2',axis=1)
features=features.drop('CO',axis=1)

features.tail()
```

Out[103]:

	Date	temp	ws	wd	PM10	PM2.5	NO	NOXasNO2	RAWPM25
5395	1.597190e+18	24.0	2.5	81.4	32.0	20.755	0.24946	31.55625	22.0
5396	1.597190e+18	23.1	2.6	61.2	27.7	18.962	0.24946	32.32125	20.1
5397	1.597190e+18	22.3	2.8	77.5	37.4	26.793	0.24946	30.40875	28.4
5398	1.597190e+18	22.1	3.4	182.5	42.0	31.227	0.62365	35.76375	33.1

	Date	temp	ws	wd	PM10	PM2.5	NO	NOXasNO2	RAWPM25
5399	1.597190e+18	21.9	2.3	123.3	53.2	40.095	0.49892	31.74750	42.5

In [104]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target)
```

In [105]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(4050, 9) (1350, 9) (4050,) (1350,)
```

Linear Regression

In [106]:
```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression(normalize=True)
regressor.fit(X_train, y_train)
```

Out[106]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=True)
```

In [107]:
```
print("Predicted values:", regressor.predict(X_test))
y_pred = regressor.predict(X_test)
y_pred.shape
```

```
Predicted values: [0.20152648 0.25745209 0.38096121 ... 0.37786929 0.28
198935 0.14553014]
```

Out[107]:
```
(1350,)
```

In [108]:
```
print("R^2 score for liner regression: ", regressor.score(X_test, y_tes
t))
```

```
R^2 score for liner regression:  0.45069441311030134
```

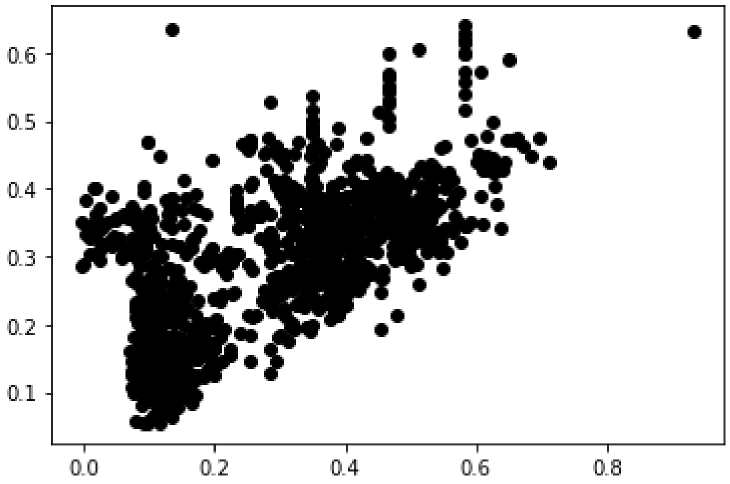
In [109]:
```
from sklearn.metrics import mean_squared_error
```

```
mean_squared_error(y_test, y_pred)
```

Out[109]: 0.014952659496861547

In [110]:
```
import matplotlib.pyplot as plt
```

In [111]:
```
plt.scatter(y_test,y_pred,color='black')
plt.show()
```



Decision Tree Regression

In [112]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [113]:
```
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

Out[113]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
```

```
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [114]:
```
print("Coefficient of determination R^2 <-- on train set: {}".format(dt
r.score(X_train, y_train)))
```

```
Coefficient of determination R^2 <-- on train set: 0.9999999483967442
```

In [115]:
```
print("Coefficient of determination R^2 <-- on test set: {}".format(dtr
.score(X_test, y_test)))
```

```
Coefficient of determination R^2 <-- on test set: 0.9422464833582939
```

In [116]:
```
print("Predicted values:", dtr.predict(X_test))
y_pred = dtr.predict(X_test)
y_pred.shape
```

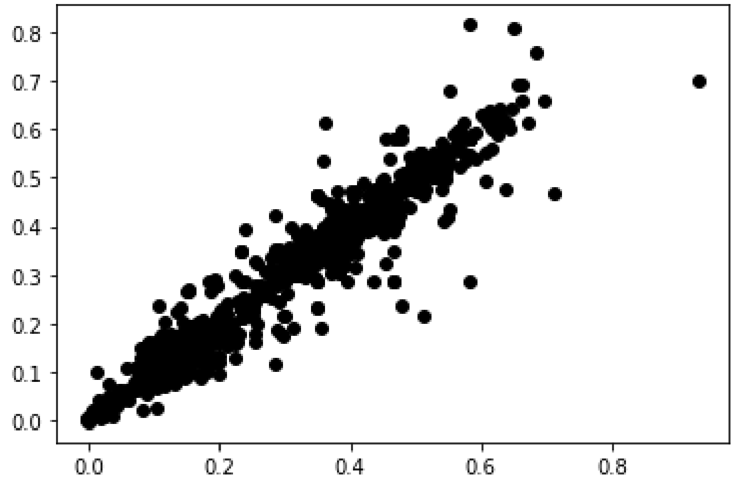
```
Predicted values: [0.102866 0.398739 0.436575 ... 0.34926  0.094049 0.0
98526]
```

Out[116]:
```
(1350,)
```

In [117]:
```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, y_pred)
```

Out[117]:
```
0.001572109750384107
```

In [118]:
```
plt.scatter(y_test,y_pred,color='black')
plt.show()
```



Prediction NO

In [69]:
```
abs(df_45['NO']).sort_values(ascending=False)
```

Out[69]:
```
NO          1.000000
NOXasNO2    0.919636
NO2         0.544702
O3          0.381443
PM2.5       0.343863
RAWPM25     0.343863
PM10        0.304891
temp        0.213222
ws          0.208945
Date        0.174803
CO          0.139816
wd          0.076699
Time        0.036985
Name: NO, dtype: float64
```

In [119]:
```
features=df
target=df['NO']
```

In [120]:
```
features=features.drop('NOXasNO2',axis=1)

features=features.drop('wd',axis=1)
features=features.drop('Time',axis=1)
features=features.drop('CO',axis=1)
features=features.drop('NO',axis=1)

features.tail()
```

Out[120]:

	Date	temp	ws	PM10	PM2.5	O3	NO2	RAWPM25
5395	1.597190e+18	24.0	2.5	32.0	20.755	153.26976	31.17375	22.0
5396	1.597190e+18	23.1	2.6	27.7	18.962	148.08094	31.93875	20.1
5397	1.597190e+18	22.3	2.8	37.4	26.793	148.67965	30.02625	28.4
5398	1.597190e+18	22.1	3.4	42.0	31.227	137.10459	34.80750	33.1
5399	1.597190e+18	21.9	2.3	53.2	40.095	131.51663	30.98250	42.5

In [72]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target)
```

In [73]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

```
(4050, 8) (1350, 8) (4050,) (1350,)
```

Linear Regression

In [74]:
```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression(normalize=True)
regressor.fit(X_train, y_train)
```

Out[74]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=True)
```

In [75]:
```
print("Predicted values:", regressor.predict(X_test))
y_pred = regressor.predict(X_test)
y_pred.shape
```

```
Predicted values: [13.6679862  15.79897684 -2.68124423 ... -5.46781358
-0.40777158
 -3.00529578]
```

Out[75]: (1350,)

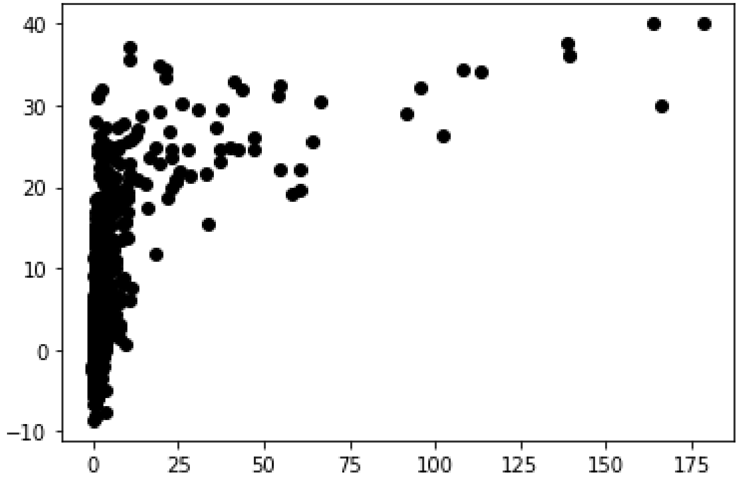
In [76]:
```
print("R^2 score for liner regression: ", regressor.score(X_test, y_tes
t))
```

```
R^2 score for liner regression:  0.2973493659868801
```

In [77]:
```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, y_pred)
```

Out[77]: 117.66082659090041

In [78]:
```
plt.scatter(y_test,y_pred,color='black')
plt.show()
```



Decision Tree Regression

In [121]:
```
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

Out[121]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [122]:
```
print("Coefficient of determination R^2 <-- on train set: {}".format(dt
r.score(X_train, y_train)))
```

```
Coefficient of determination R^2 <-- on train set: 0.9999999483967442
```

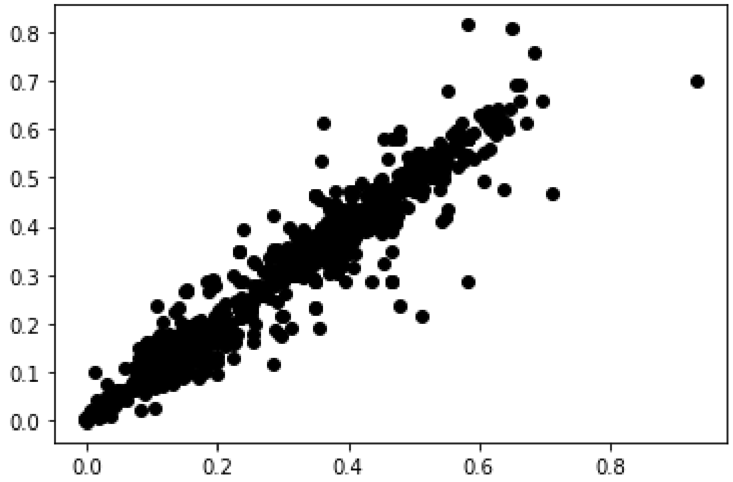
In [123]:
```
print("Coefficient of determination R^2 <-- on train set: {}".format(dt
r.score(X_test, y_test)))
```

```
Coefficient of determination R^2 <-- on train set: 0.939265747914148
```

In [124]:
```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, y_pred)
```

Out[124]:
```
0.001572109750384107
```

In [125]:
```
plt.scatter(y_test,y_pred,color='black')
plt.show()
```



Predicting PM10

In [79]:
```
abs(df_45['PM10']).sort_values(ascending=False)
```

Out[79]:
```
PM10        1.000000
RAWPM25     0.934254
PM2.5       0.934253
NO2         0.456301
NOXasNO2    0.416230
wd          0.338792
NO          0.304891
ws          0.254469
CO          0.243006
Date        0.077177
temp        0.048034
O3          0.018354
Time        0.015263
Name: PM10, dtype: float64
```

In [126]:
```
features=df
target=df['PM10']
```

In [127]:
```
features=features.drop('PM2.5',axis=1)
features=features.drop('RAWPM25',axis=1)
features=features.drop('Time',axis=1)
features=features.drop('O3',axis=1)
features=features.drop('PM10',axis=1)

features.tail()
```

Out[127]:

	Date	temp	ws	wd	NO	CO	NO2	NOXasNO2
5395	1.597190e+18	24.0	2.5	81.4	0.24946	0.465680	31.17375	31.55625
5396	1.597190e+18	23.1	2.6	61.2	0.24946	0.465680	31.93875	32.32125
5397	1.597190e+18	22.3	2.8	77.5	0.24946	0.284959	30.02625	30.40875
5398	1.597190e+18	22.1	3.4	182.5	0.62365	0.523890	34.80750	35.76375
5399	1.597190e+18	21.9	2.3	123.3	0.49892	0.512248	30.98250	31.74750

Linear Regression

In [128]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
from sklearn.linear_model import LinearRegression

regressor = LinearRegression(normalize=True)
regressor.fit(X_train, y_train)
```

```
(4050, 8) (1350, 8) (4050,) (1350,)
```

Out[128]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=True)
```

In [129]:
```
print("Predicted values:", regressor.predict(X_test))
y_pred = regressor.predict(X_test)
y_pred.shape
```

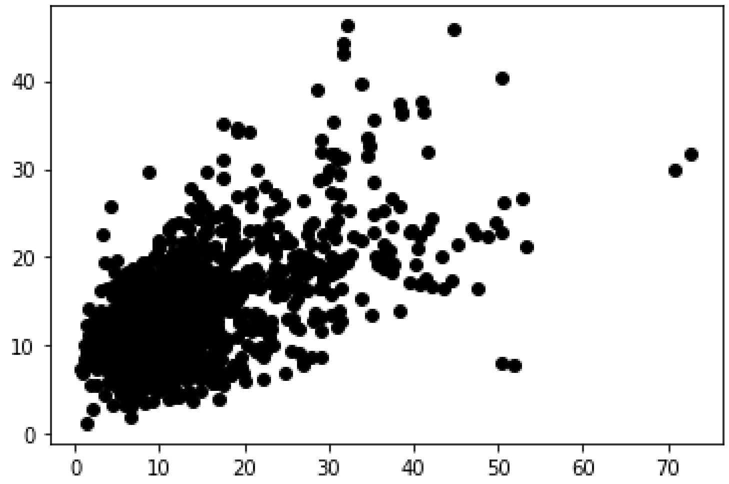
```
Predicted values: [ 9.16359431 14.9317549  14.19188089 ... 15.73757943
9.75595561
 10.25833411]
```

Out[129]:
```
(1350,)
```

In [130]:
```
print("R^2 score for liner regression: ", regressor.score(X_test, y_tes
t))

plt.scatter(y_test,y_pred,color='black')
plt.show()
```

```
R^2 score for liner regression:  0.3502602452585487
```



Decision Tree Regression

In [132]:
```
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

Out[132]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
```

```
e,
                              min_samples_leaf=1, min_samples_split=2,
                              min_weight_fraction_leaf=0.0, presort='deprecate
d',
                              random_state=None, splitter='best')
```

In [133]:
```
print("Predicted values:", dtr.predict(X_test))
y_pred = dtr.predict(X_test)
y_pred.shape
```

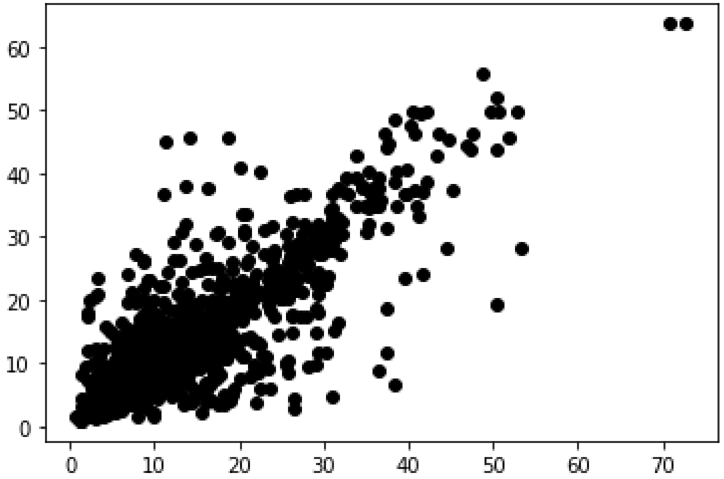
```
Predicted values: [ 3.05   15.975 11.025 ... 18.2    17.325  4.55 ]
```

Out[133]:
```
(1350,)
```

In [135]:
```
print("R^2 score for decision tree regression: ", dtr.score(X_test, y_t
est))

plt.scatter(y_test,y_pred,color='black')
plt.show()
```

```
R^2 score for decision tree regression:  0.6289571781504768
```



Predicting PM2.5

In [86]:
```
abs(df_45['PM2.5']).sort_values(ascending=False)
```

Out[86]:
```
PM2.5        1.000000
RAWPM25      1.000000
PM10         0.934253
NO2          0.501895
NOXasNO2     0.463487
NO           0.343863
wd           0.323025
ws           0.312547
CO           0.227018
temp         0.155942
Date         0.154311
O3           0.120339
Time         0.037685
Name: PM2.5, dtype: float64
```

In [136]:
```
features=df
target=df['PM2.5']
```

In [137]:
```
features=features.drop('PM2.5',axis=1)
features=features.drop('RAWPM25',axis=1)
```

linear regression

In [138]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(features, target)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
from sklearn.linear_model import LinearRegression

regressor = LinearRegression(normalize=True)
regressor.fit(X_train, y_train)
```

```
(4050, 11) (1350, 11) (4050,) (1350,)
```

Out[138]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normaliz
e=True)

In [139]:
```
print("Predicted values:", regressor.predict(X_test))
y_pred = regressor.predict(X_test)
y_pred.shape
```

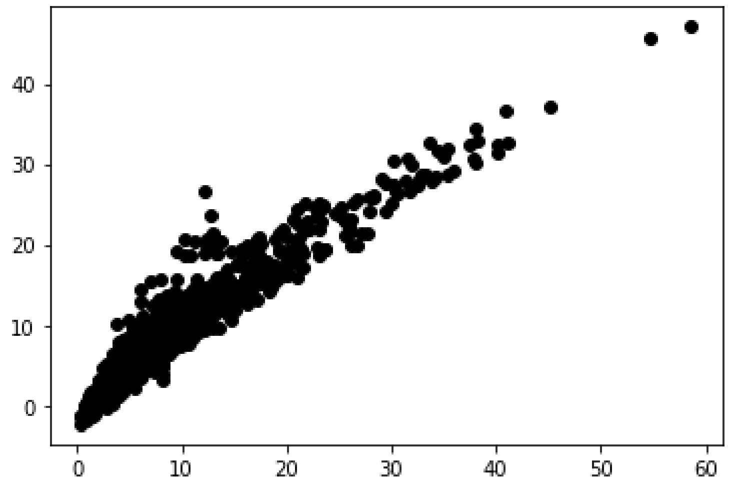
```
Predicted values: [ 5.01843172 13.22355267  3.87021066 ...  7.47070939
4.60965215
  9.20345245]
```

Out[139]: (1350,)

In [140]:
```
print("R^2 score for liner regression: ", regressor.score(X_test, y_tes
t))

plt.scatter(y_test,y_pred,color='black')
plt.show()
```

```
R^2 score for liner regression:  0.9088709006448249
```



In [141]:
```
from sklearn.metrics import mean_squared_error
mean_squared_error(y_test, y_pred)
```

Out[141]: 4.513404434029614

Decision Tree Regression

In [142]:
```
dtr = DecisionTreeRegressor()
dtr.fit(X_train, y_train)
```

Out[142]:
```
DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=Non
e,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecate
d',
                      random_state=None, splitter='best')
```

In [143]:
```
print("Predicted values:", dtr.predict(X_test))
y_pred = dtr.predict(X_test)
y_pred.shape
```

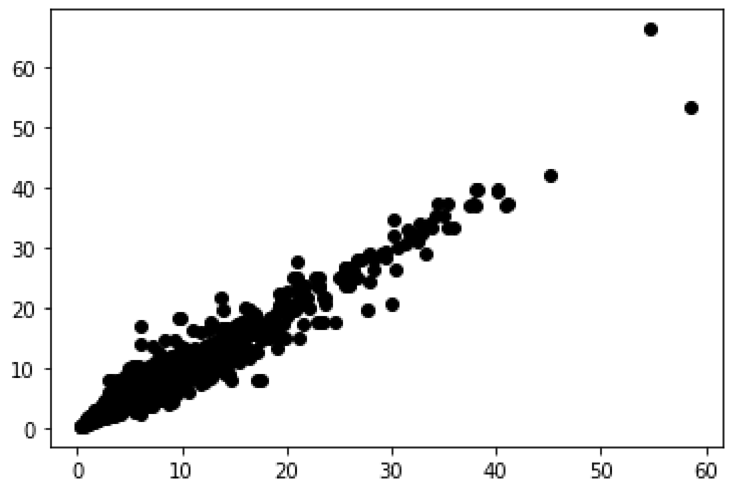
```
Predicted values: [ 3.09       12.618       8.13952937 ...  7.193
4.505
  7.406     ]
```

Out[143]: (1350,)

In [144]:
```
print("R^2 score for decision tree regression: ", dtr.score(X_test, y_t
est))

plt.scatter(y_test,y_pred,color='black')
plt.show()
```

```
R^2 score for decision tree regression:  0.9387604267503846
```



Conclusion

1. I have worked on linear regression and decision tree to predict the pollutant , we could also work on other regression techniques like LASSO .
2. I have tried mean sampling to fill the missing values in the data, we could also try other thecniques like forward fill and backward fill.
3. We could try regression after removing the outliers .