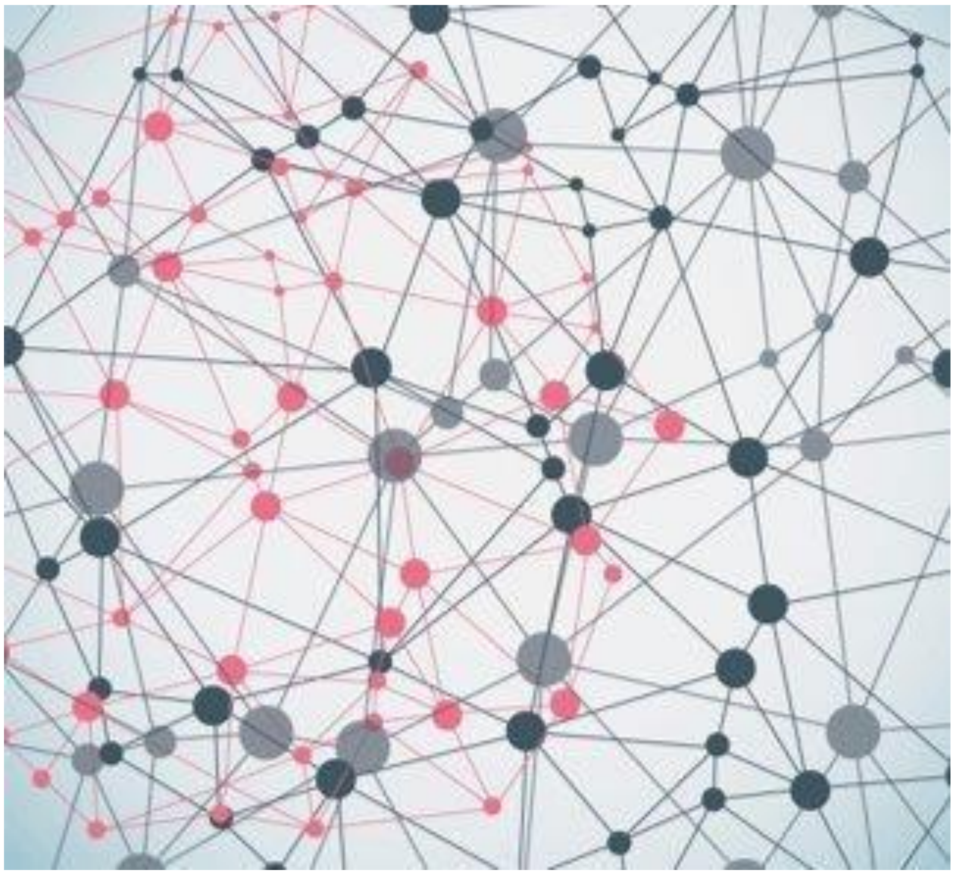
AIR QUALITY ANALYSIS AND PREDICTION IN TAMIL NADU



PROJECT REPORT PHASE- 4

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INTRODUCTION

Air pollution is one of the greatest environmental risk to health. By reducing air pollution levels, countriescan reduce the burden of disease from stroke, heart disease, lung cancer, and both chronic and acute respiratory diseases, including asthma. Here we are studied about the air quality analysis methods in Tamil Nadu

Content for Project Phase 4:

For analyzing data, we need some libraries. In this section, we are importing all the required libraries like pandas NumPy, matplotlib, plotly, seaborn, and word cloud that are required for data analysis. Check the below code to import all the required libraries Data Source: A good data source for credit card fraud detection should be accurate,complete, Covering the geographic area of interest, Accessible.

EXPLORATORY DATA ANALYSIS

Exploratory data analysis is performed on the raw data. The insights gained from the analysis helps to identify the pre-processing tasks that need to be performed to form the dataset for building the air quality prediction model.

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 7)

# Warnings
import warnings
warnings.filterwarnings('ignore')

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directory

import os
print(os.listdir("../input"))

# Any results you write to the current directory are saved as output.
```

```
['lat-lon-indianstates', 'india-air-quality-data', 'indian-states-lat-lon']
```

In [2]:

```
data=pd.read_csv('../input/india-air-quality-data/data.csv',encoding="ISO-8859-1")
data.fillna(0, inplace=True)
data.head()
```

Out[2]:

	stn_code	sampling_date	state	location	agency	type	so2	no2	rspm	spm	location_monitoring_station	pm2_5	date
0	150	February - M021990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	4.8	17.4	0.0	0.0	0	0.0	1990-02-01
1	151	February - M021990	Andhra Pradesh	Hyderabad	0	Industrial Area	3.1	7.0	0.0	0.0	0	0.0	1990-02-01
2	152	February - M021990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	6.2	28.5	0.0	0.0	0	0.0	1990-02-01
3	150	March - M031990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	6.3	14.7	0.0	0.0	0	0.0	1990-03-01

4	151	March - M031990	Andhra Pradesh	Hyderabad	0	Industrial Area	4.7	7.5	0.0	0.0	0	0.0	1990-03-01

In [3]:

```
#Function to calculate so2 individual pollutant index(si)
def calculate_si(so2):
    si=0
    if (so2<=40):
     si= so2*(50/40)
    if (so2>40 and so2<=80):
     si= 50+(so2-40)*(50/40)
    if (so2>80 and so2<=380):
     si= 100+(so2-80)*(100/300)
    if (so2>380 and so2<=800):
     si= 200+(so2-380)*(100/800)
    if (so2>800 and so2<=1600):
     si= 300+(so2-800)*(100/800)
    if (so2>1600):
     si= 400+(so2-1600)*(100/800)
    return si
data['si']=data['so2'].apply(calculate_si)
df= data[['so2','si']]
df.head()
```

Out[3]:

	so2	si

0	4.8	6.000
1	3.1	3.875
2	6.2	7.750
3	6.3	7.875
4	4.7	5.875

In [4]:

```
#Function to calculate no2 individual
pollutant index(ni)
def calculate_ni(no2):
    ni=0
    if(no2<=40):
     ni= no2*50/40
    elif(no2>40 and no2<=80):
     ni= 50+(no2-14)*(50/40)
    elif(no2>80 and no2<=180):
     ni= 100+(no2-80)*(100/100)
    elif(no2>180 and no2<=280):
     ni= 200+(no2-180)*(100/100)
    elif(no2>280 and no2<=400):
     ni= 300+(no2-280)*(100/120)
    else:
     ni= 400+(no2-400)*(100/120)
    return ni
data['ni']=data['no2'].apply(calculate_ni)
df= data[['no2','ni']]
```

```
df.head()
```

Out[4]:

	no2	ni
0	17.4	21.750
1	7.0	8.750
2	28.5	35.625
3	14.7	18.375
4	7.5	9.375

In [5]:

```
#Function to calculate no2 individual pollutant index(rpi)
def calculate_(rspm):
    rpi=0
    if(rpi<=30):
     rpi=rpi*50/30
    elif(rpi>30 and rpi<=60):
     rpi=50+(rpi-30)*50/30
    elif(rpi>60 and rpi<=90):
     rpi=100+(rpi-60)*100/30
    elif(rpi>90 and rpi<=120):
     rpi=200+(rpi-90)*100/30
    elif(rpi>120 and rpi<=250):
     rpi=300+(rpi-120)*(100/130)
    else:
     rpi=400+(rpi-250)*(100/130)
    return rpi
```

```
data['rpi']=data['rspm'].apply(calculate_si
)
df= data[['rspm','rpi']]
df.tail()
#many data values of rspm values is
unawailable since it was not measure before
```

Out[5]:

	rspm	rpi
435737	143.0	121.000000
435738	171.0	130.333333
435739	0.0	0.000000
435740	0.0	0.000000
435741	0.0	0.000000

In [6]:

```
#Function to calculate no2 individual
pollutant index(spi)
def calculate_spi(spm):
    spi=0
    if(spm<=50):
     spi=spm
    if(spm<50 and spm<=100):
     spi=spm
    elif(spm>100 and spm<=250):
     spi= 100+(spm-100)*(100/150)
    elif(spm>250 and spm<=350):
     spi=200+(spm-250)
```

```
    elif(spm>350 and spm<=450):
     spi=300+(spm-350)*(100/80)
    else:
     spi=400+(spm-430)*(100/80)
    return spi
data['spi']=data['spm'].apply(calculate_spi
)
df= data[['spm','spi']]
df.tail()
#many data values of rspm values is
unawailable since it was not measure before
```

Out[6]:

	spm	spi
435737	0.0	0.0
435738	0.0	0.0
435739	0.0	0.0
435740	0.0	0.0
435741	0.0	0.0

In [7]:

```
#function to calculate the air quality index
(AQI) of every data value
#its is calculated as per indian govt
standards
def calculate_aqi(si,ni,spi,rpi):
    aqi=0
    if(si>ni and si>spi and si>rpi):
```

```
        aqi=si
    if(spi>si and spi>ni and spi>rpi):
        aqi=spi
    if(ni>si and ni>spi and ni>rpi):
        aqi=ni
    if(rpi>si and rpi>ni and rpi>spi):
        aqi=rpi
    return aqi
data['AQI']=data.apply(lambda
x:calculate_aqi(x['si'],x['ni'],x['spi'],x[
'rpi']),axis=1)
df=
data[['sampling_date','state','si','ni','rp
i','spi','AQI']]
df.head()
```

Out[7]:

	sampling_date	state	si	ni	rpi	spi	AQI
0	February - M021990	Andhra Pradesh	6.000	21.750	0.0	0.0	21.750
1	February - M021990	Andhra Pradesh	3.875	8.750	0.0	0.0	8.750
2	February - M021990	Andhra Pradesh	7.750	35.625	0.0	0.0	35.625
3	March - M031990	Andhra Pradesh	7.875	18.375	0.0	0.0	18.375
4	March - M031990	Andhra Pradesh	5.875	9.375	0.0	0.0	9.375

In [8]:

```
df.state.unique()
```

Out[8]:

```
array(['Andhra Pradesh', 'Arunachal Pradesh', 'Assam', 'Bihar',
       'Chandigarh', 'Chhattisgarh', 'Dadra & Nagar Haveli',
       'Daman & Diu', 'Delhi', 'Goa', 'Gujarat', 'Haryana',
       'Himachal Pradesh', 'Jammu & Kashmir', 'Jharkhand', 'Karnataka',
       'Kerala', 'Madhya Pradesh', 'Maharashtra', 'Manipur', 'Meghalaya',
       'Mizoram', 'Nagaland', 'Odisha', 'Puducherry', 'Punjab',
       'Rajasthan', 'Sikkim', 'Tamil Nadu', 'Telangana', 'Uttar Pradesh',
       'Uttarakhand', 'Uttaranchal', 'West Bengal',
       'andaman-and-nicobar-islands', 'Lakshadweep', 'Tripura'],
      dtype=object)
```

In [9]:

```
state=pd.read_csv("../input/indian-states-lat-lon/lat.csv")
state.head()
df.head()
```

Out[9]:

	sampling_date	state	si	ni	rpi	spi	AQI
0	February - M021990	Andhra Pradesh	6.000	21.750	0.0	0.0	21.750
1	February - M021990	Andhra Pradesh	3.875	8.750	0.0	0.0	8.750
2	February - M021990	Andhra Pradesh	7.750	35.625	0.0	0.0	35.625
3	March - M031990	Andhra Pradesh	7.875	18.375	0.0	0.0	18.375
4	March - M031990	Andhra Pradesh	5.875	9.375	0.0	0.0	9.375

In [10]:

```
dff=pd.merge(state.set_index("state"),df.set_index("state"), right_index=True,
```

```
left_index=True).reset_index()
dff.head()
```

Out[10]:

	state	lat	lon	sampling_date	si	ni	rpi	spi	AQI
0	Andhra Pradesh	14.750429	78.570026	February - M021990	6.000	21.750	0.0	0.0	21.750
1	Andhra Pradesh	14.750429	78.570026	February - M021990	3.875	8.750	0.0	0.0	8.750
2	Andhra Pradesh	14.750429	78.570026	February - M021990	7.750	35.625	0.0	0.0	35.625
3	Andhra Pradesh	14.750429	78.570026	March - M031990	7.875	18.375	0.0	0.0	18.375
4	Andhra Pradesh	14.750429	78.570026	March - M031990	5.875	9.375	0.0	0.0	9.375

In [11]:

```
from mpl_toolkits.basemap import Basemap
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
%config InlineBackend.figure_format =
'retina'
```

In [12]:

```
m =
Basemap(projection='mill',llcrnrlat=5,urcrn
rlat=40,
```

```
llcrnrlon=60,urcrnrlon=110,lat_ts=20,resolu
tion='c')
```

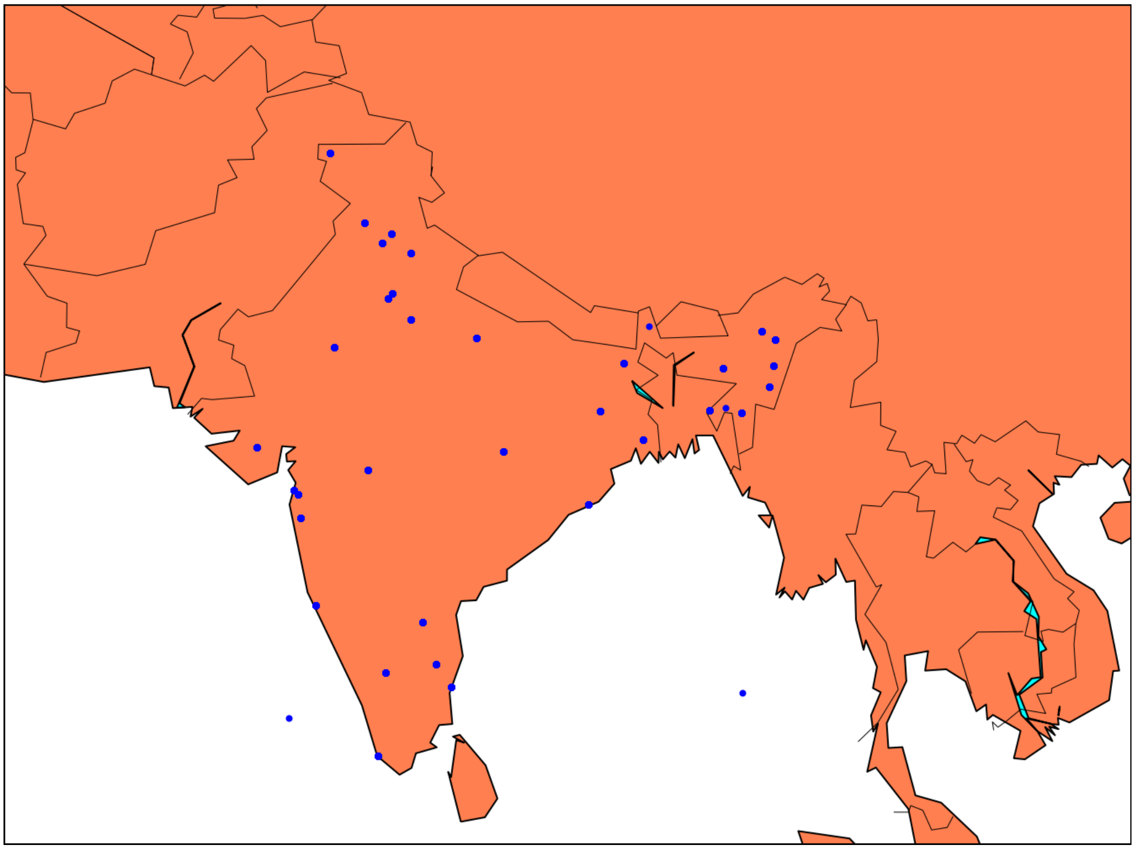
In [13]:

```
longitudes = dff["lon"].tolist()
latitudes = dff["lat"].tolist()
#m =
Basemap(width=12000000,height=9000000,proje
ction='lcc',

#resolution=None,lat_1=80.,lat_2=55,lat_0=80
,lon_0=-107.)
x,y = m(longitudes,latitudes)
```

In [14]:

```
fig = plt.figure(figsize=(12,10))
plt.title("All affected areas")
m.plot(x, y, "o", markersize = 3, color =
'blue')
m.drawcoastlines()
m.fillcontinents(color='coral',lake_color='
aqua')
m.drawmapboundary()
m.drawcountries()
plt.show()
```

All affected areas

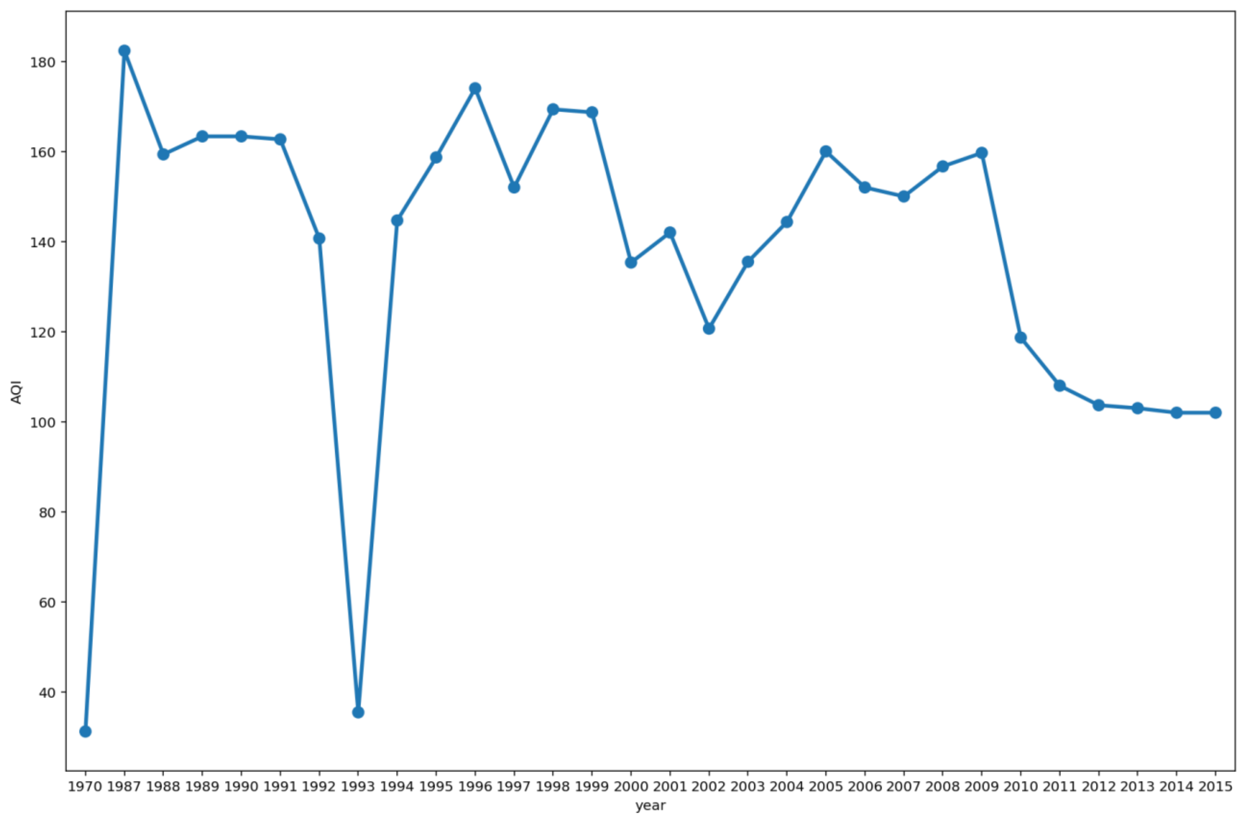


```
data['date'] =
pd.to_datetime(data['date'],format='%Y-%m-
%d') # date parse
data['year'] = data['date'].dt.year # year
data['year'] =
data['year'].fillna(0.0).astype(int)
data = data[(data['year']>0)]

df =
```

```
data[['AQI','year','state']].groupby(["year
"]).median().reset_index().sort_values(by='
year',ascending=False)
f,ax=plt.subplots(figsize=(15,10))
sns.pointplot(x='year', y='AQI', data=df)
```

Out[15]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f72c28f4cc0>
```




```
import warnings
import itertools
import dateutil
```

```
import statsmodels.api as sm
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
%matplotlib inline
df=data[['AQI','date']]
df["date"] = pd.to_datetime(df['date'])
df.tail(20)
```

Out[16]:

	AQI	date
435722	118.333333	2015-11-05
435723	118.666667	2015-11-07
435724	140.666667	2015-11-10
435725	133.666667	2015-11-11
435726	105.000000	2015-11-16
435727	112.666667	2015-11-20
435728	121.333333	2015-11-26
435729	120.000000	2015-11-29
435730	120.666667	2015-12-03
435731	125.000000	2015-12-06
435732	121.666667	2015-12-09
435733	127.000000	2015-12-12
435734	122.666667	2015-12-15
435735	117.000000	2015-12-18
435736	120.000000	2015-12-21
435737	121.000000	2015-12-24
435738	130.333333	2015-12-29

435739	0.000000	1970-01-01
435740	0.000000	1970-01-01
435741	0.000000	1970-01-01

In [17]:

```
#Calculating the yearly mean for the data
df=df.set_index('date').resample('M')["AQI"
].mean()
df.head()
```

Out[17]:

```
date
1970-01-31    49.654762
1970-02-28          NaN
1970-03-31          NaN
1970-04-30          NaN
1970-05-31          NaN
Freq: M, Name: AQI, dtype: float64
```

In [18]:

```
#preprocessing the data values
data=df.reset_index(level=0, inplace=False)
data = data[np.isfinite(data['AQI'])]
data=data[data.date != '1970-01-31']
data = data.reset_index(drop=True)
data.head()
```

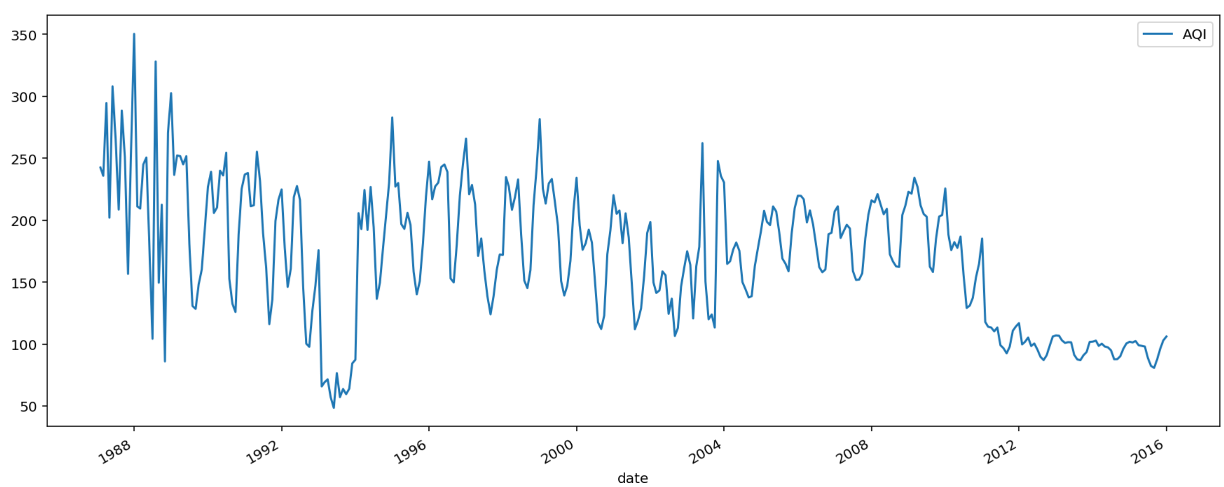
Out[18]:

	date	AQI
0	1987-01-31	242.438652
1	1987-02-28	235.787929
2	1987-03-31	294.558772

3	1987-04-30	202.012681
4	1987-05-31	307.991667

In [19]:

```
#visualizing the processed data of AQI

df=data.set_index('date')
df.sort_values(by='date',ascending=False)
df.plot(figsize=(15, 6))
plt.show()
y=df.AQI
```



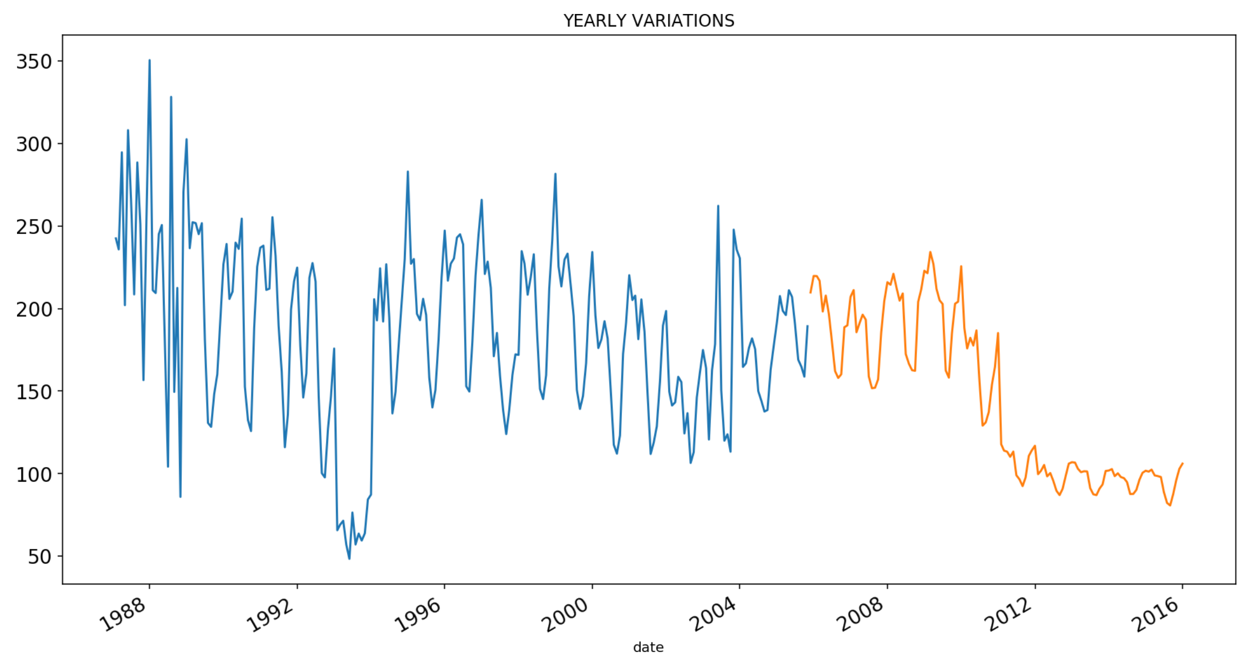
In [20]:

```
#exctracting knowledge about data

#spliting dataframes into test and train
n = df.shape[0]
train_size = 0.65

features_dataframe = df.sort_values('date')
```

```
train = df.iloc[:int(n * train_size)]
test = df.iloc[int(n * train_size):]
```

In [21]:

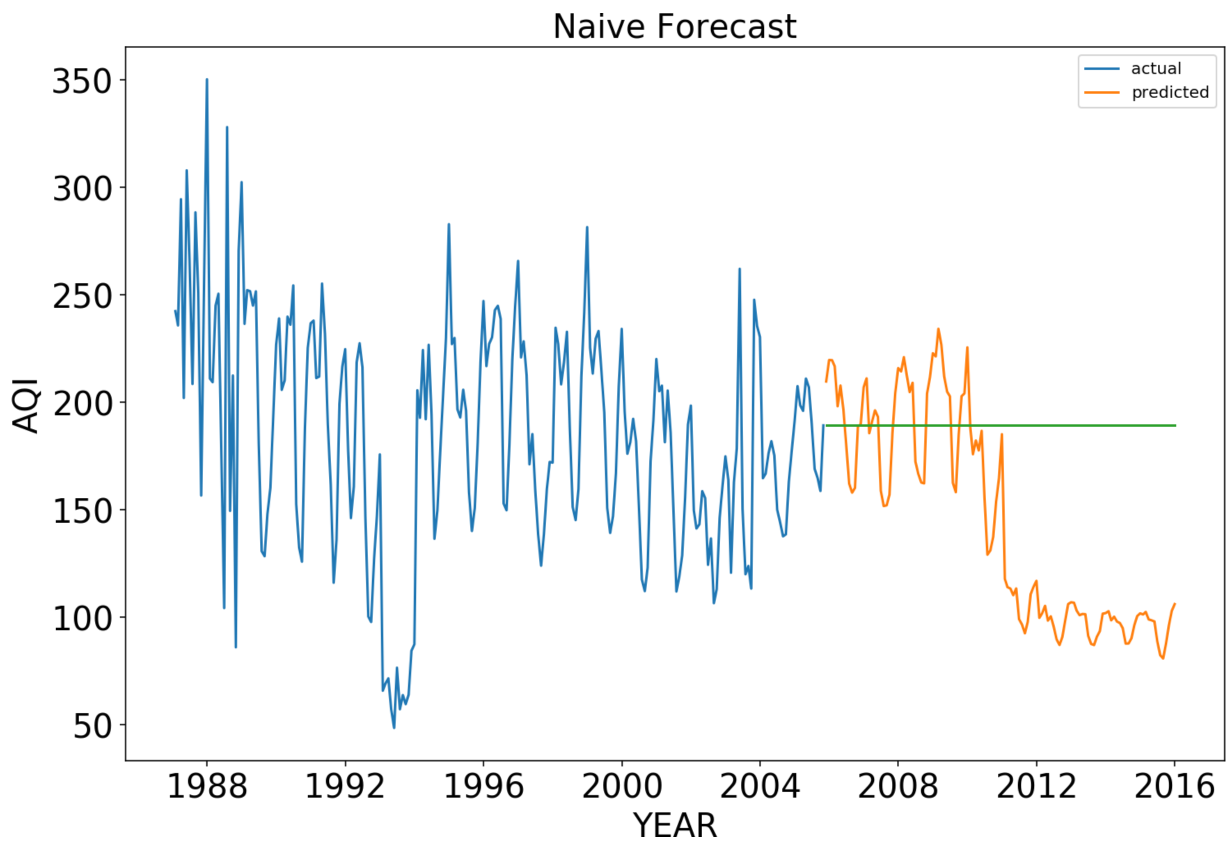
```
#plotting the yearly variations of AQI
train.AQI.plot(figsize=(15,8), title=
'YEARLY VARIATIONS', fontsize=14)
test.AQI.plot(figsize=(15,8), title=
'YEARLY VARIATIONS', fontsize=14)
plt.show()
```



In [22]:

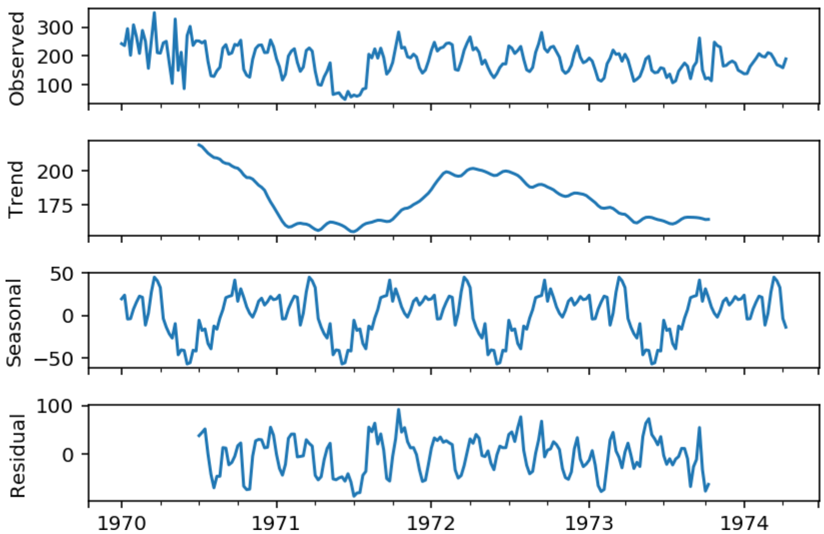
```
#Naive Forecast Approach to find the
variations(trend)
```

```
dd= np.asarray(train.AQI)
y_hat = test.copy()
y_hat['naive'] = dd[len(dd)-1]
plt.figure(figsize=(12,8))
plt.plot(train.index, train['AQI'],
label='Train')
plt.plot(test.index,test['AQI'],
label='Test')
plt.plot(y_hat.index,y_hat['naive'],
label='Naive Forecast')
plt.legend(loc='best')
plt.title("Naive Forecast",fontsize=20)

plt.legend(["actual ","predicted"])
plt.xlabel("YEAR",fontsize=20)
plt.ylabel("AQI",fontsize=20)
plt.tick_params(labelsize=20)
plt.show()
```



In [23]:

```
#various statmodel to identity huge
variations od data values
import statsmodels.api as sm
train.index=pd.DatetimeIndex(freq="w",
start=0 ,periods=224)

sm.tsa.seasonal_decompose(train.AQI).plot()
result =
sm.tsa.stattools.adfuller(train.AQI)
plt.show()
```



In [24]:

```
#resampling the data to predict monthly AQI of india
df=data[['AQI','date']]
df['date']=pd.to_datetime(df['date'])
date=df.groupby(pd.Grouper(key='date',freq='1MS'))["AQI"].mean()
df.count()
```

Out[24]:

```
AQI      346
date     346
dtype: int64
```

In [25]:

```
#splitting the sampling date into month and year accordingly
data['month'] = data['date'].dt.month
```

```
data['year'] = data['date'].dt.year
data=data[['AQI','date','month','year']]
data.head()
```

Out[25]:

	AQI	date	month	year
0	242.438652	1987-01-31	1	1987
1	235.787929	1987-02-28	2	1987
2	294.558772	1987-03-31	3	1987
3	202.012681	1987-04-30	4	1987
4	307.991667	1987-05-31	5	1987

In [26]:

```
#predicting JANUARY-AQI across india
data=data[data['month']==1]
data.head()
```

Out[26]:

	AQI	date	month	year
0	242.438652	1987-01-31	1	1987
12	211.076502	1988-01-31	1	1988
24	236.513310	1989-01-31	1	1989
35	239.071032	1990-01-31	1	1990
47	238.060052	1991-01-31	1	1991

In [27]:

```
#Appling BOXPLOT analysis
df =
data[['AQI','year']].groupby(["year"]).mean
().reset_index().sort_values(by='year',asce
```

```
nding=False)
df=df.dropna()
dd=df
df.describe()
```

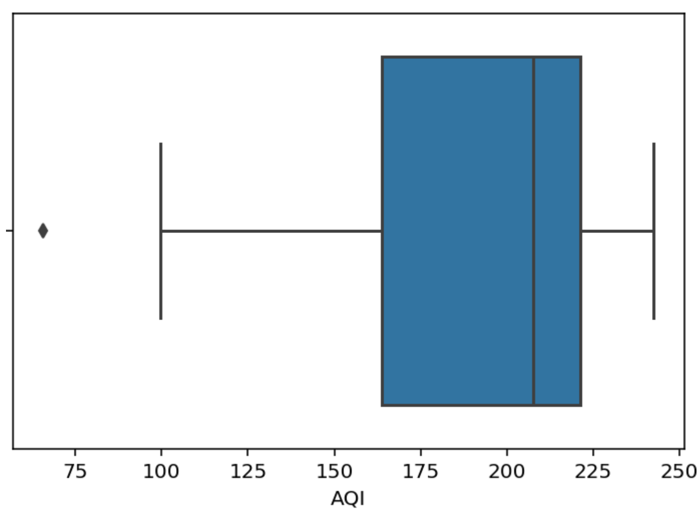
year	AQI	
count	29.000000	29.000000
mean	2001.000000	186.582077
std	8.514693	51.439662
min	1987.000000	65.754613
25%	1994.000000	163.875510
50%	2001.000000	207.546049
75%	2008.000000	221.368166
max	2015.000000	242.438652

In [28]:

```
import seaborn as sns
sns.boxplot(x=df['AQI'])
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f72c268cd30>
```

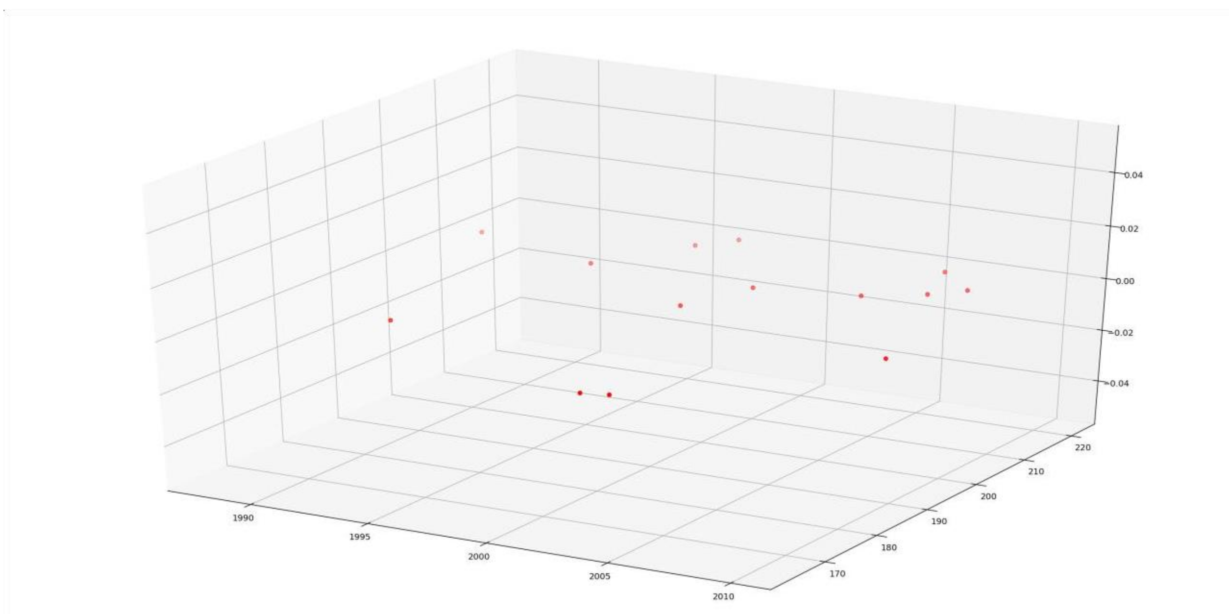


In [29]:

```
#removing Outliers
df = df[np.isfinite(df['AQI'])]
df=df[df.AQI >153]
df=df[df.AQI <221]
```

In [30]:

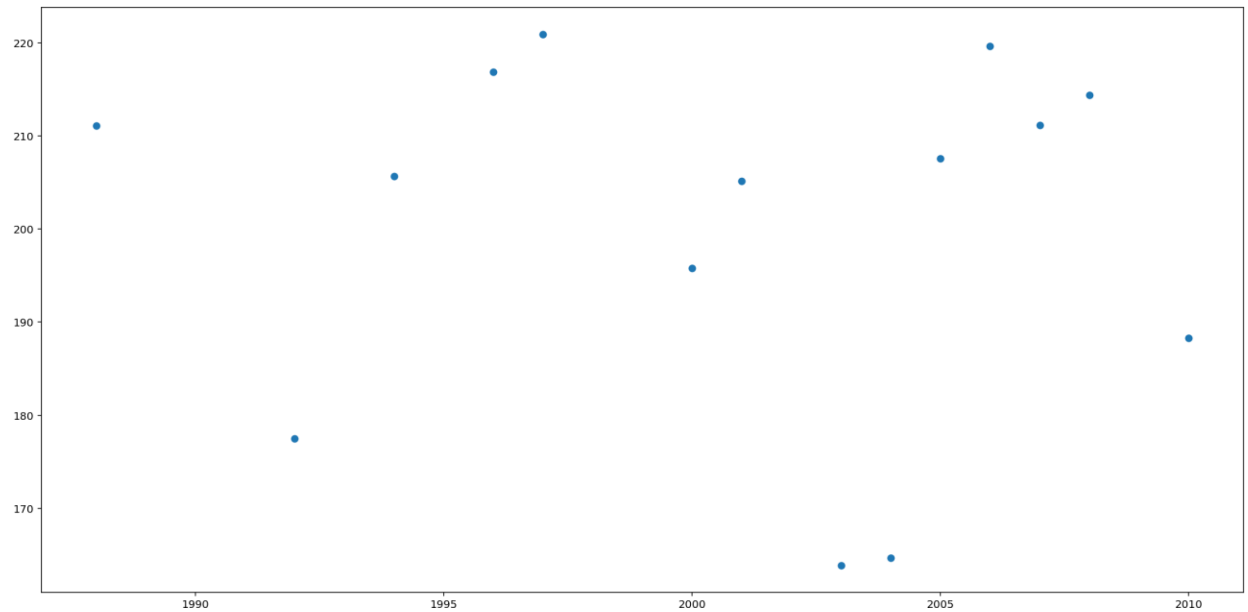
```
#visualizing the filttered data

year=df['year'].values
AQI=df['AQI'].values
df['AQI']=pd.to_numeric(df['AQI'],errors='coerce')
df['year']=pd.to_numeric(df['year'],errors='coerce')

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (20.0, 10.0)
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = Axes3D(fig)
ax.scatter(year,AQI, color='red')
plt.show()
```



In [31]:

```
#scatter plot of data points
cols =['year']
y = df['AQI']
x=df[cols]
```

```
plt.scatter(x,y)
plt.show()
```



In [32]:

```
x = (x - x.mean()) / x.std()
x = np.c_[np.ones(x.shape[0]), x]
x
```

Out[32]:

```
array([[ 1.        ,  1.40346276],
       [ 1.        ,  1.09883519],
       [ 1.        ,  0.9465214 ],
       [ 1.        ,  0.79420761],
       [ 1.        ,  0.64189382],
       [ 1.        ,  0.48958003],
       [ 1.        ,  0.33726625],
       [ 1.        ,  0.03263867],
       [ 1.        , -0.11967512],
       [ 1.        , -0.57661648],
       [ 1.        , -0.72893027],
       [ 1.        , -1.03355785],
       [ 1.        , -1.33818543],
       [ 1.        , -1.94744058]])
```

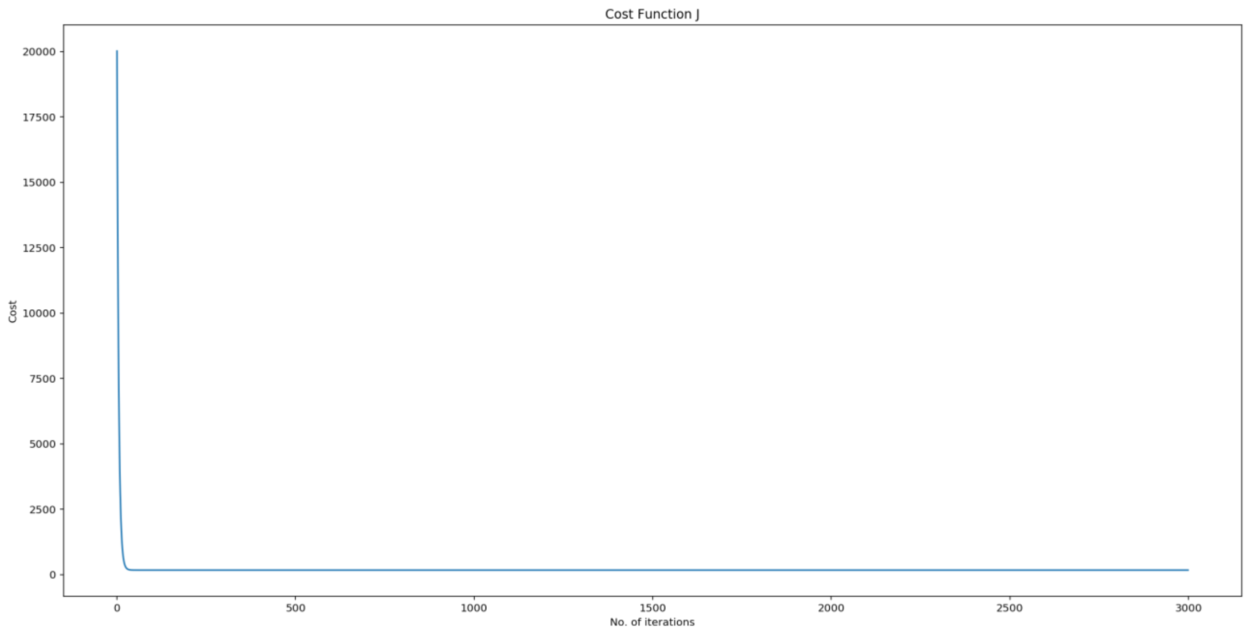
In [33]:

```python
# Applying GRADIENT DESCENT

alpha = 0.1 #Step size
iterations = 3000 #No. of iterations
m = y.size #No. of data points
np.random.seed(4) #Setting the seed
theta = np.random.rand(2) #Picking random values to start with

def gradient_descent(x, y, theta, iterations, alpha):
    past_costs = []
    past_thetas = [theta]
    for i in range(iterations):
        prediction = np.dot(x, theta)
        error = prediction - y
        cost = 1/(2*m) * np.dot(error.T, error)
        past_costs.append(cost)
        theta = theta - (alpha * (1/m) * np.dot(x.T, error))
        past_thetas.append(theta)

    return past_thetas, past_costs
past_thetas, past_costs = gradient_descent(x, y, theta, iterations, alpha)
theta = past_thetas[-1]

#Printing the results...
print("Gradient Descent: {:.2f}, {:.2f}".format(theta[0], theta[1]))
```

```
Gradient Descent: 200.17, -1.54
```

In [34]:

```python
#Plotting the cost function...
plt.title('Cost Function J')
plt.xlabel('No. of iterations')
plt.ylabel('Cost')
plt.plot(past_costs)
plt.show()
```



In [35]:

```
#Predicted val
newB=[ 200.17, -1.54]
def rmse(y,y_pred):
    rmse=np.sqrt(sum(y-y_pred))
    return rmse


y_pred=x.dot(newB)

dt = pd.DataFrame({'Actual': y, 'Predicted': y_pred})
x=pd.concat([df, dt], axis=1)
x
x
```

Out[35]:

	year	AQI	Actual	Predicted
23	2010	188.283360	188.283360	198.008667
21	2008	214.378174	214.378174	198.477794
20	2007	211.160807	211.160807	198.712357
19	2006	219.623267	219.623267	198.946920
18	2005	207.546049	207.546049	199.181484
17	2004	164.661496	164.661496	199.416047

16	2003	163.875510	163.875510	199.650610
14	2001	205.138247	205.138247	200.119736
13	2000	195.772377	195.772377	200.354300
10	1997	220.903571	220.903571	201.057989
9	1996	216.850189	216.850189	201.292553
7	1994	205.636343	205.636343	201.761679
5	1992	177.485106	177.485106	202.230806
1	1988	211.076502	211.076502	203.169058

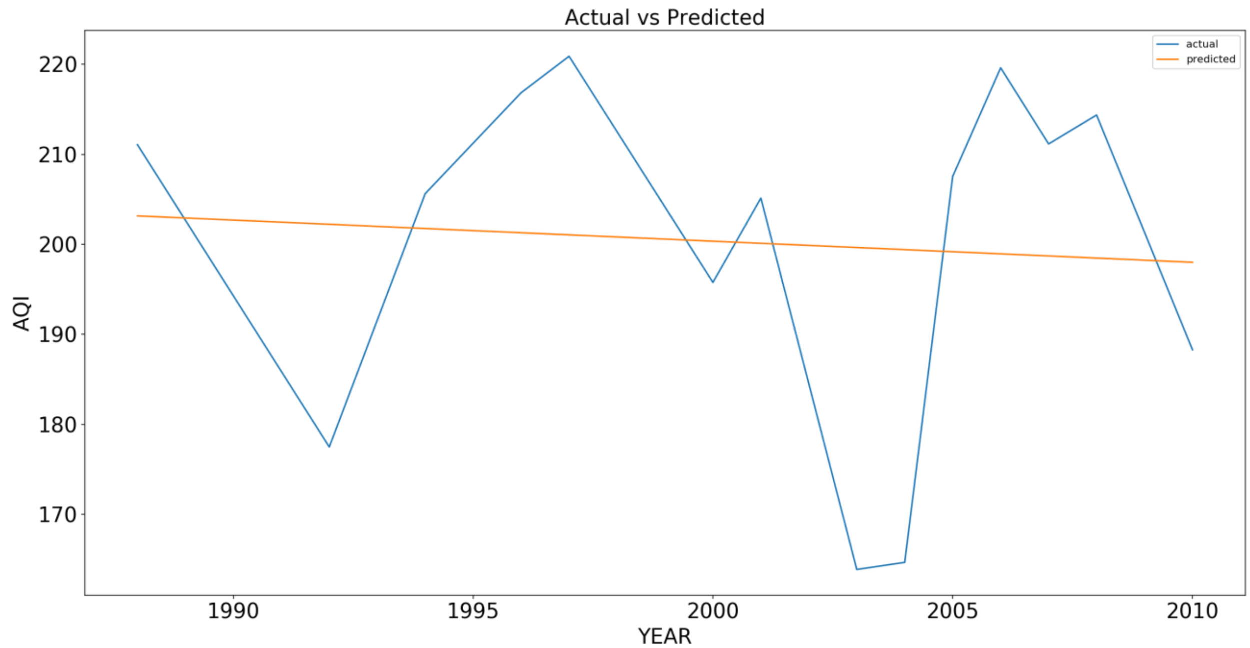
In [36]:

```
#calculating the root mean squared error for the predicted AQi values
from sklearn import metrics
print(np.sqrt(metrics.mean_squared_error(y,y_pred)))
```

```
18.630885273104628
```

In [37]:

```
x_axis=x.year
y_axis=x.Actual
y1_axis=x.Predicted
plt.plot(x_axis,y_axis)
plt.plot(x_axis,y1_axis)
plt.title("Actual vs Predicted",fontsize=20)
plt.legend(["actual ","predicted"])
plt.xlabel("YEAR",fontsize=20)
plt.ylabel("AQI",fontsize=20)
plt.tick_params(labelsize=20)
plt.show()
```



In [38]:

```
#improving the accuracy by splitting the data on heavy variations

df=dd[['year','AQI']]


#huge variations aqi accures on year 2009-2010 (by moving average graph)
df=df[df.year<2011]
df.describe()
```

Out[38]:

	year	AQI
count	24.000000	24.000000
mean	1998.500000	203.441075
std	7.071068	38.624462
min	1987.000000	65.754613
25%	1992.750000	193.900123
50%	1998.500000	212.769491
75%	2004.250000	225.854972
max	2010.000000	242.438652

CONCLUTION

In conclusion, ambient air pollution is a health hazard. It is a global challenge, as evidence shows that adverse effects still exist even at relatively low air pollutant concentrations, and so no threshold values for classical air pollutants can be established based on the available data.