In [1]:

```
# linear algebra
 # data processing, CSV file I/O (e.g. pd.read_csv)

yplot as plt
ns


e.figsize'] = (10, 7)



ings('ignore')

are available in the "../input/" directory.
ing this (by clicking run or pressing Shift+Enter) will list the files in the input directory


./input"))

rite 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_statio
0	150	February - M021990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	4.8	17.4	0.0	0.0	0
1	151	February - M021990	Andhra Pradesh	Hyderabad	0	Industrial Area	3.1	7.0	0.0	0.0	0
2	152	February - M021990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	6.2	28.5	0.0	0.0	0
3	150	March - M031990	Andhra Pradesh	Hyderabad	0	Residential, Rural and other Areas	6.3	14.7	0.0	0.0	0
4	151	March - M031990	Andhra Pradesh	Hyderabad	0	Industrial Area	4.7	7.5	0.0	0.0	0

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','rpi','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=Tru
dff.head()
```

Out [10]:

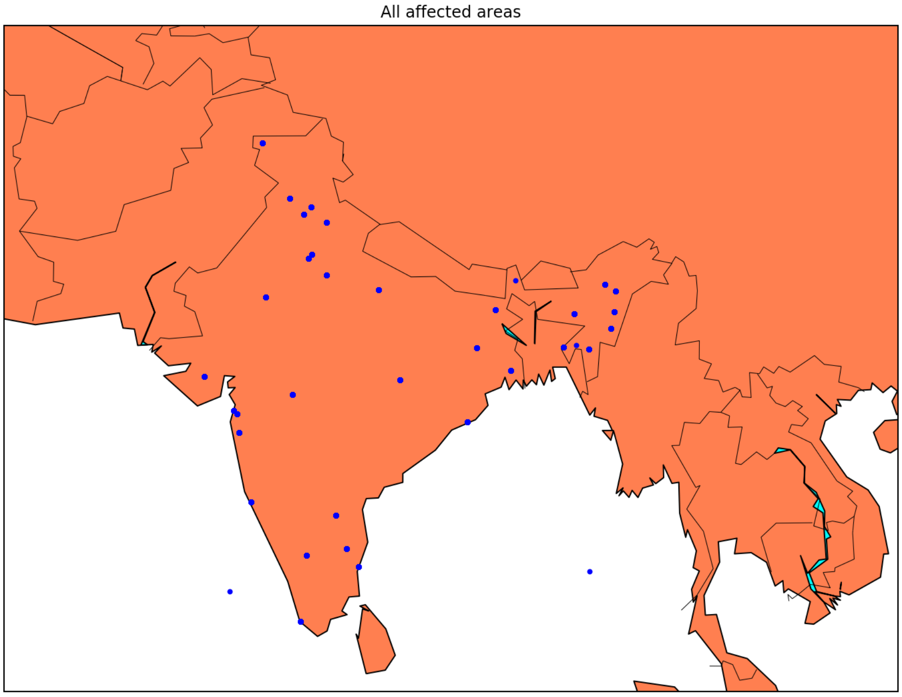
	state	lat	lon	sampling_date	si	ni	rpi	spi	AQI
0	Andhra Pradesh	14.750429	78.570026	February - M021990	6.000	21.750	0.0	0.0	21.750
1	Andhra Pradesh	14.750429	78.570026	February - M021990	3.875	8.750	0.0	0.0	8.750
2	Andhra Pradesh	14.750429	78.570026	February - M021990	7.750	35.625	0.0	0.0	35.625
3	Andhra 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,urcrnrlat=40, llcrnrlon=60,urcrnrlon=110,lat_ts=20,
```

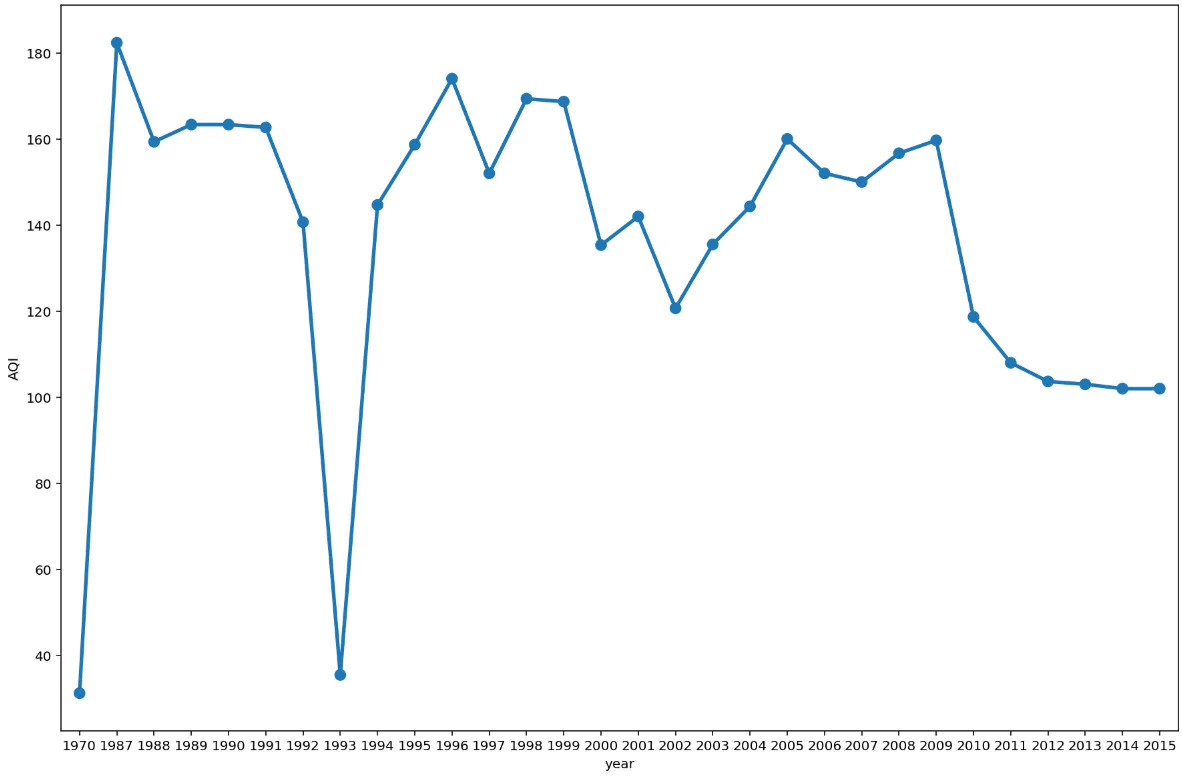
In [13]:
```

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



In [15]:
```
#Visualization of AQI across india

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='ye
f,ax=plt.subplots(figsize=(15,10))
sns.pointplot(x='year', y='AQI', data=df)
```

Out [15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f72c28f4cc0>



In [16]:
```
#setting up date parameter
import warnings
import itertools
import dateutil
```

```python
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]:

```python
#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]:

```python
#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()
```

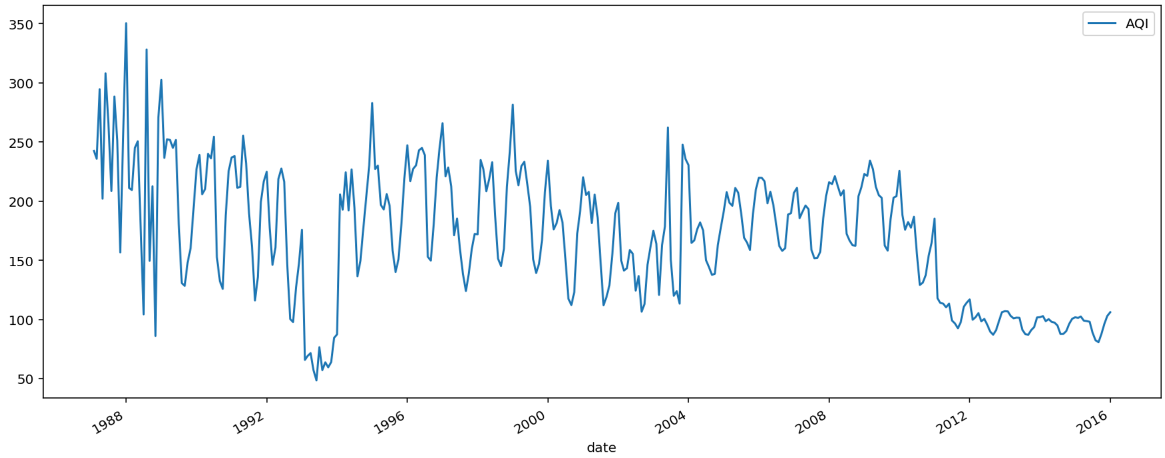
Out [18]:

	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]:

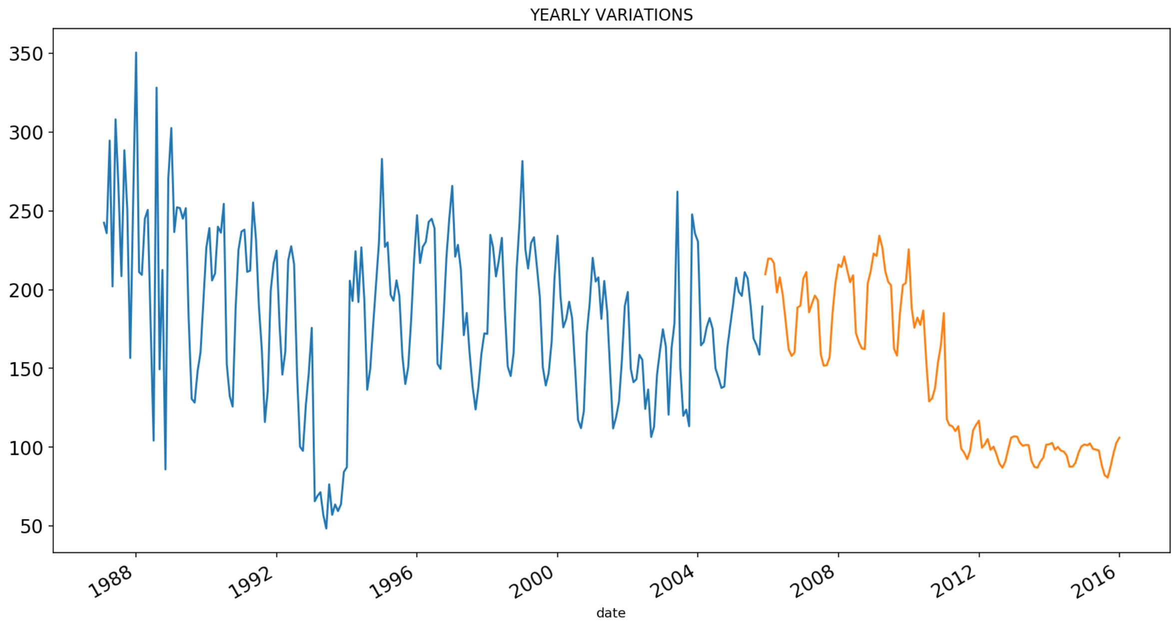
```python
#visualizing the processed data of AQI

df=data.set_index('date')
```

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



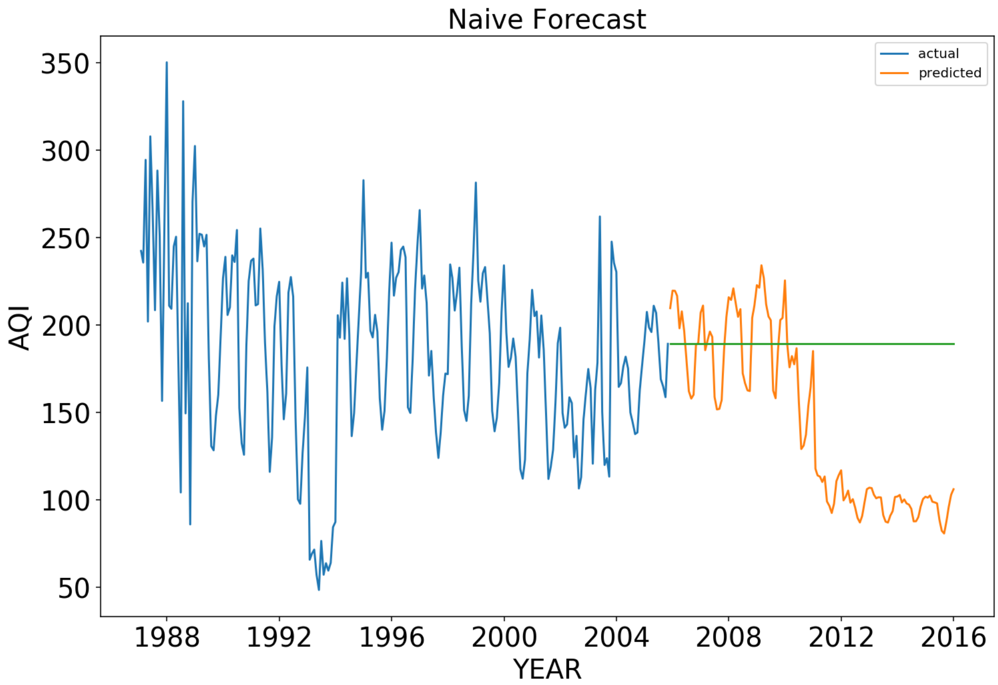
In [20]:
```
#exctracting knowledge about data

#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()
```



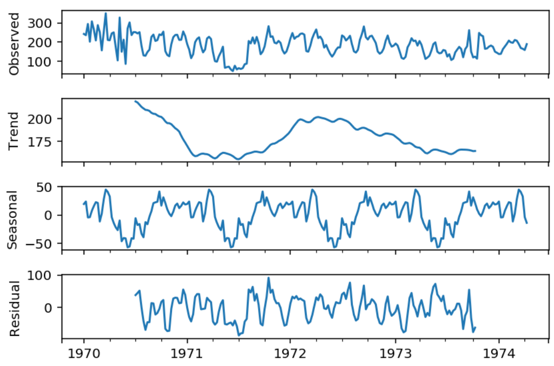
In [22]:
```
#Naive Forecast Approach to find the variations(trend)

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

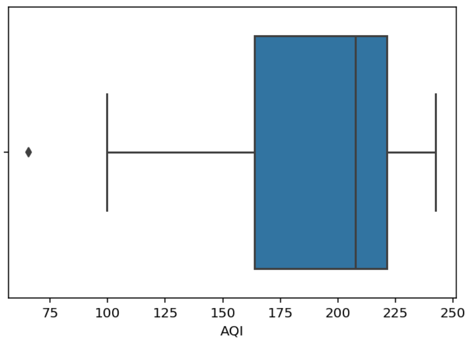
In [27]:
```
#Appling BOXPLOT analysis
df = data[['AQI','year']].groupby(["year"]).mean().reset_index().sort_values(by='year',ascend
df=df.dropna()
dd=df
df.describe()
```

Out [27]:

	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'])
```

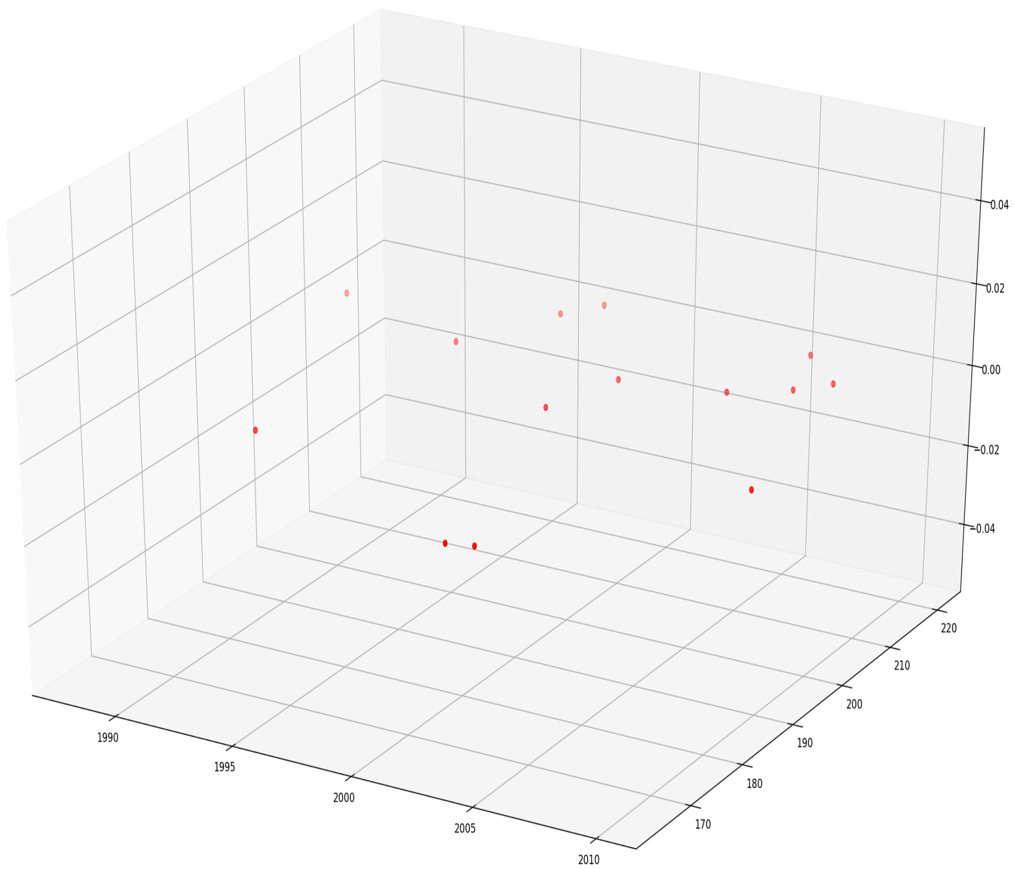
Out [28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f72c268cd30>



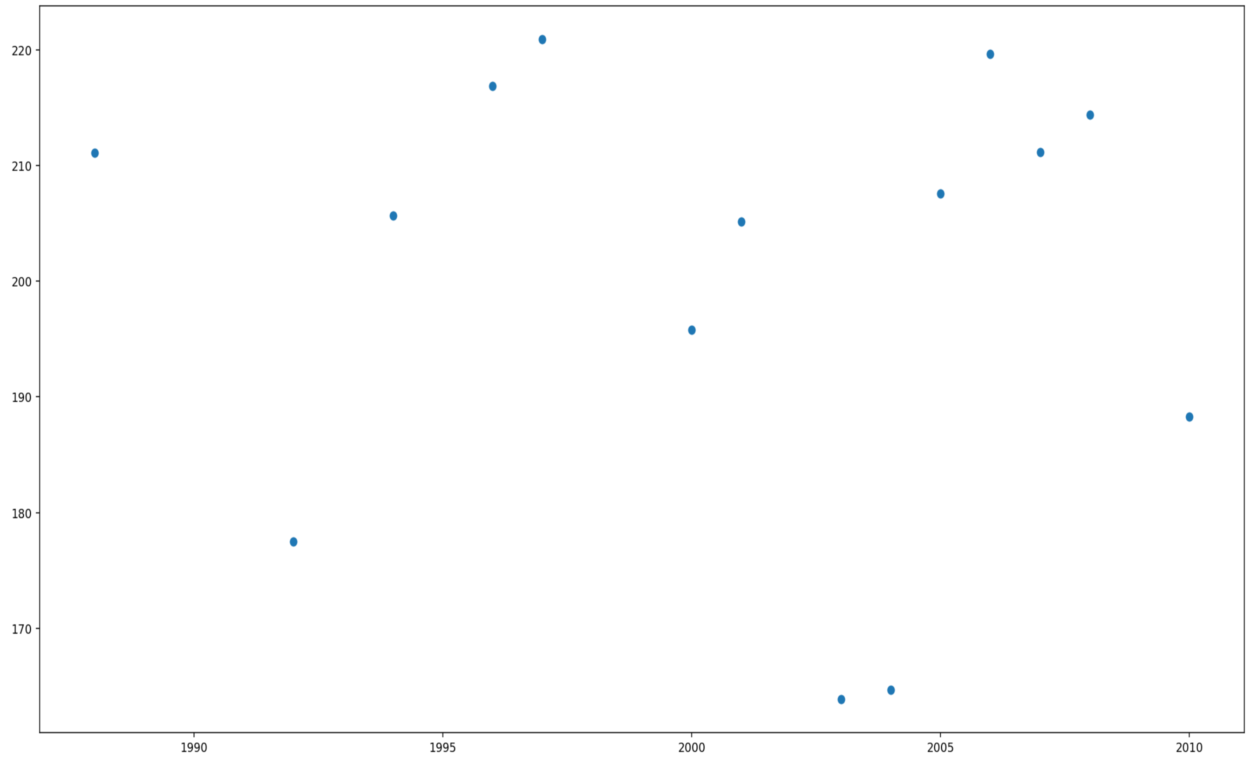
In [29]:
```
#removing Outliers
df = df[np.isfinite(df['AQI'])]
```

```
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]])
```

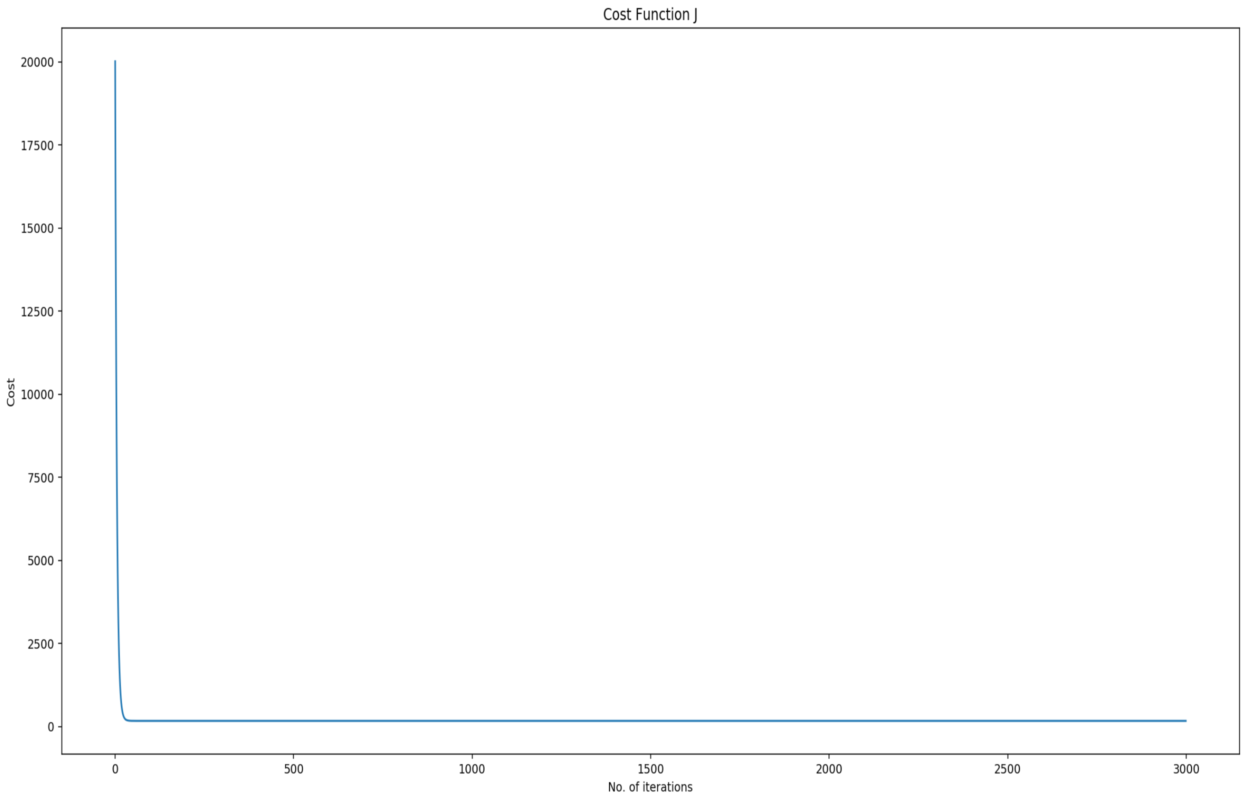
In [33]:

```
# 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]:
```
#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]:

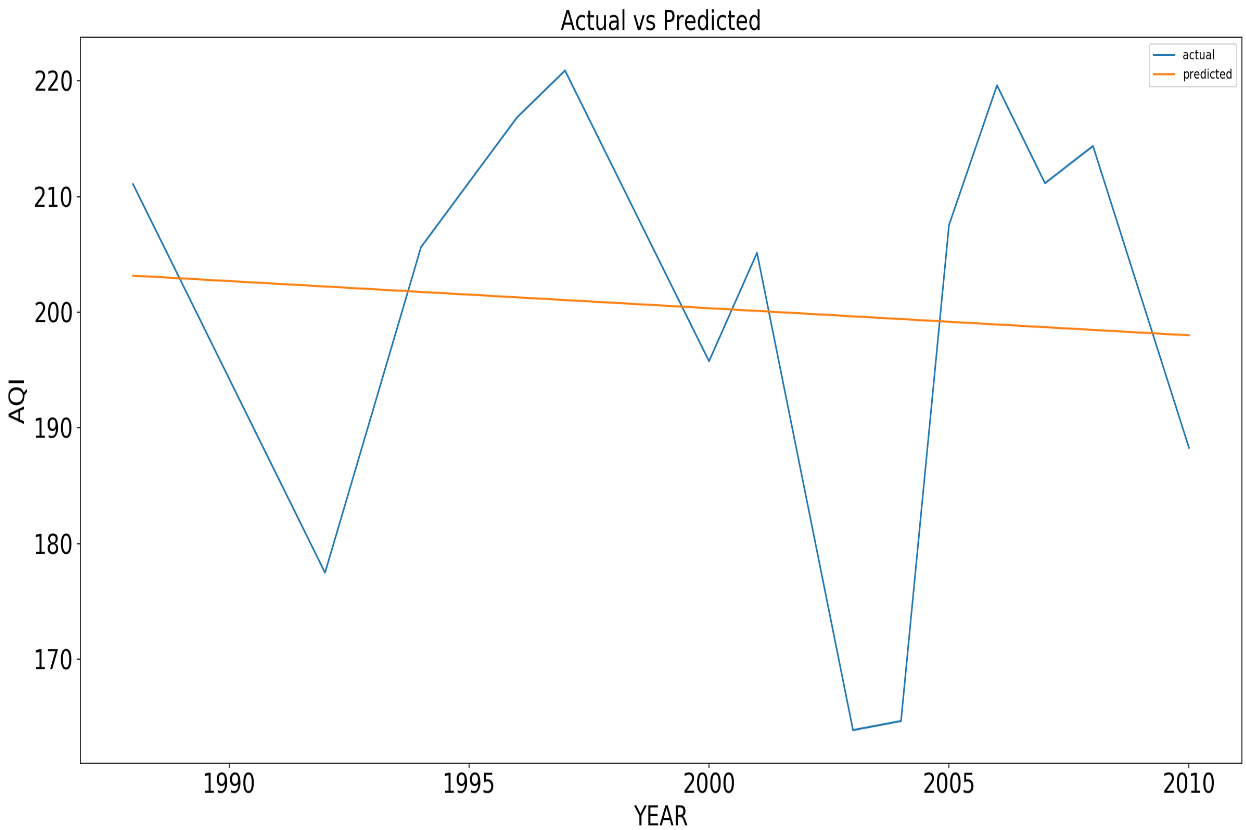
	year	AQI	Actual	Predicted
23	2010	188.283360	188.283360	198.008667
21	2008	214.378174	214.378174	198.477794
20	2007	211.160807	211.160807	198.712357
19	2006	219.623267	219.623267	198.946920
18	2005	207.546049	207.546049	199.181484
17	2004	164.661496	164.661496	199.416047
16	2003	163.875510	163.875510	199.650610
14	2001	205.138247	205.138247	200.119736
13	2000	195.772377	195.772377	200.354300

	year	AQI	Actual	Predicted
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]:

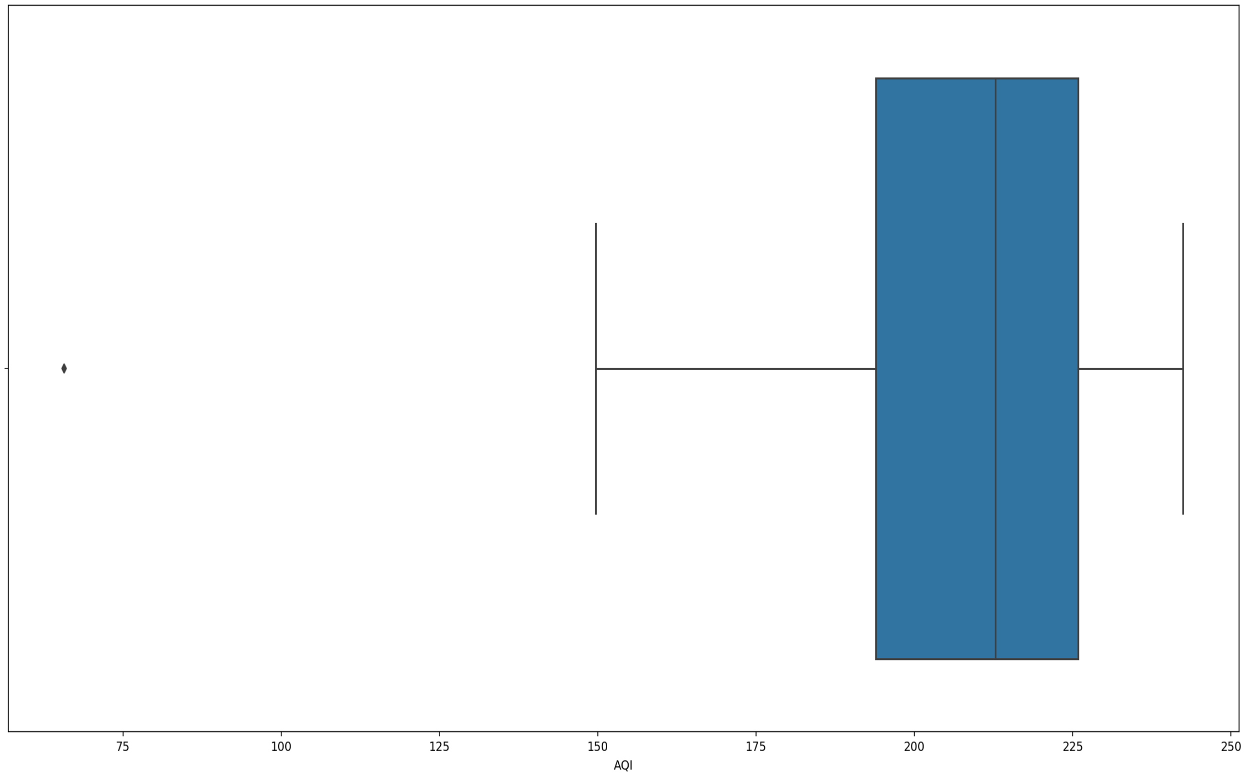
	year	AQI
count	24.000000	24.000000

	year	AQI
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

In [39]:

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

Out [39]: <matplotlib.axes._subplots.AxesSubplot at 0x7f72c0450080>



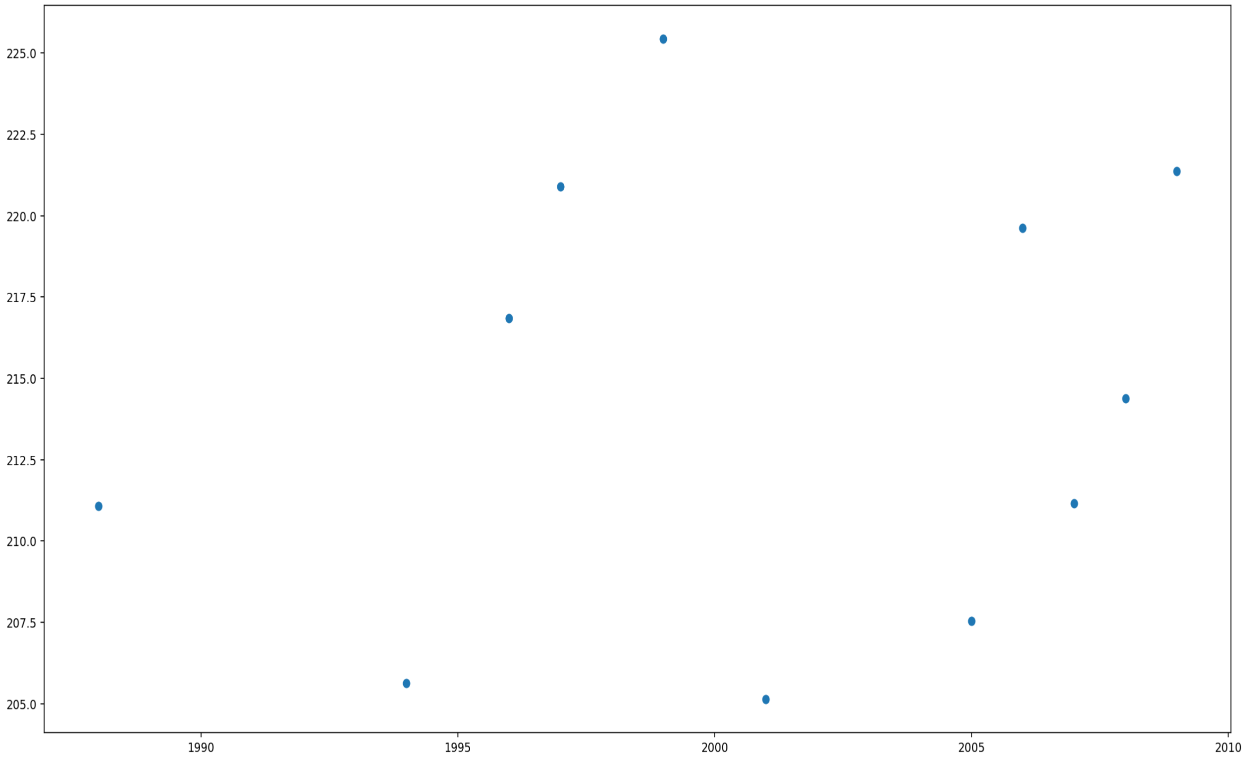
In [40]:

```
#removing outliers
df = df[np.isfinite(df['AQI'])]
df=df[df.AQI >200]
df=df[df.AQI <226]
df
```

Out [40]:

	year	AQI
22	2009	221.368166
21	2008	214.378174
20	2007	211.160807
19	2006	219.623267
18	2005	207.546049
14	2001	205.138247
12	1999	225.439218
10	1997	220.903571
9	1996	216.850189
7	1994	205.636343
1	1988	211.076502

In [41]:
```
#plotting data points
cols =['year']
y = df['AQI']
x=df[cols]

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



In [42]:
```
x = (x - x.mean()) / x.std()
x = np.c_[np.ones(x.shape[0]), x]
x
```

Out [42]:
```
array([[ 1.        ,  1.20224174],
       [ 1.        ,  1.05365007],
       [ 1.        ,  0.90505839],
       [ 1.        ,  0.75646671],
       [ 1.        ,  0.60787504],
       [ 1.        ,  0.01350833],
       [ 1.        , -0.28367502],
       [ 1.        , -0.58085837],
       [ 1.        , -0.72945005],
       [ 1.        , -1.0266334 ],
       [ 1.        , -1.91818345]])
```

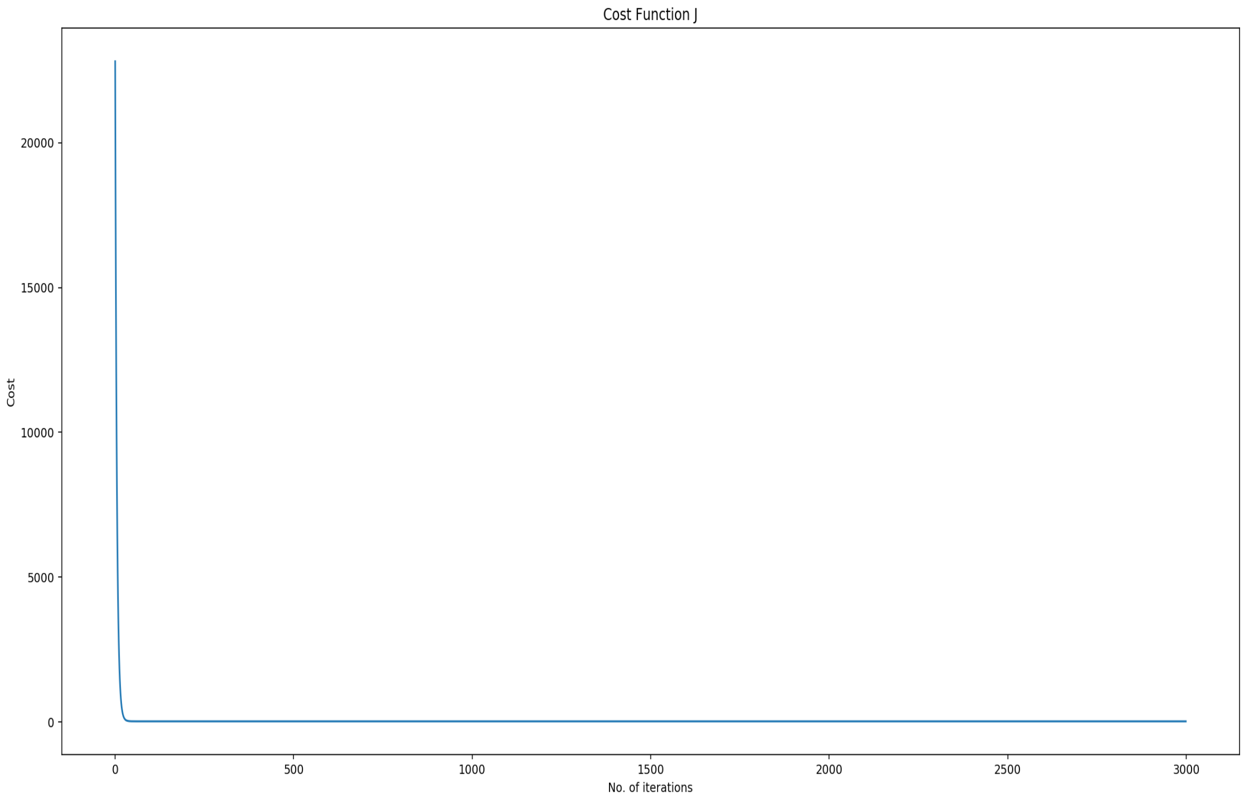
In [43]:
```
#Tunning model with GRADIENT DESCENT

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 some 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]

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

```
Gradient Descent: 214.47, 1.18
```

In [44]:

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



In [45]:

```
#predicting january(1988-2009) AQI across india

import numpy as np
newB=[ 214.47, 1.18]

def rmse(y,y_pred):
    rmse= (np.sqrt(np.mean((y-y_pred)**2)))
    return rmse

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

Out [45]:

	year	AQI	Actual	Predicted
22	2009	221.368166	221.368166	215.888645
21	2008	214.378174	214.378174	215.713307
20	2007	211.160807	211.160807	215.537969
19	2006	219.623267	219.623267	215.362631

	year	AQI	Actual	Predicted
18	2005	207.546049	207.546049	215.187293
14	2001	205.138247	205.138247	214.485940
12	1999	225.439218	225.439218	214.135263
10	1997	220.903571	220.903571	213.784587
9	1996	216.850189	216.850189	213.609249
7	1994	205.636343	205.636343	213.258573
1	1988	211.076502	211.076502	212.206544

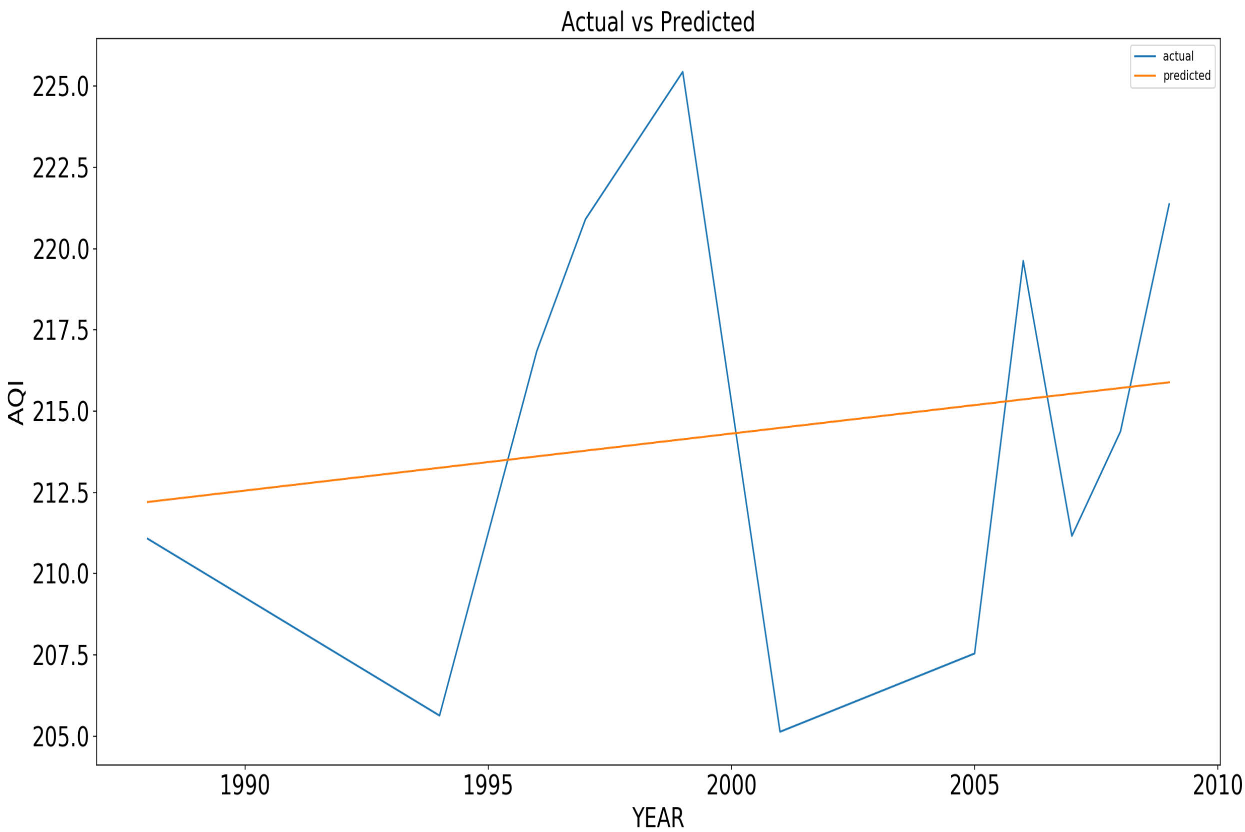
In [46]:

```
#testing the accuracy of the model

from sklearn import metrics
print(np.sqrt(metrics.mean_squared_error(y,y_pred)))
```

```
6.489338584209818
```

In [47]:

```
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 [48]:

```
#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>2010]
df.describe()
```

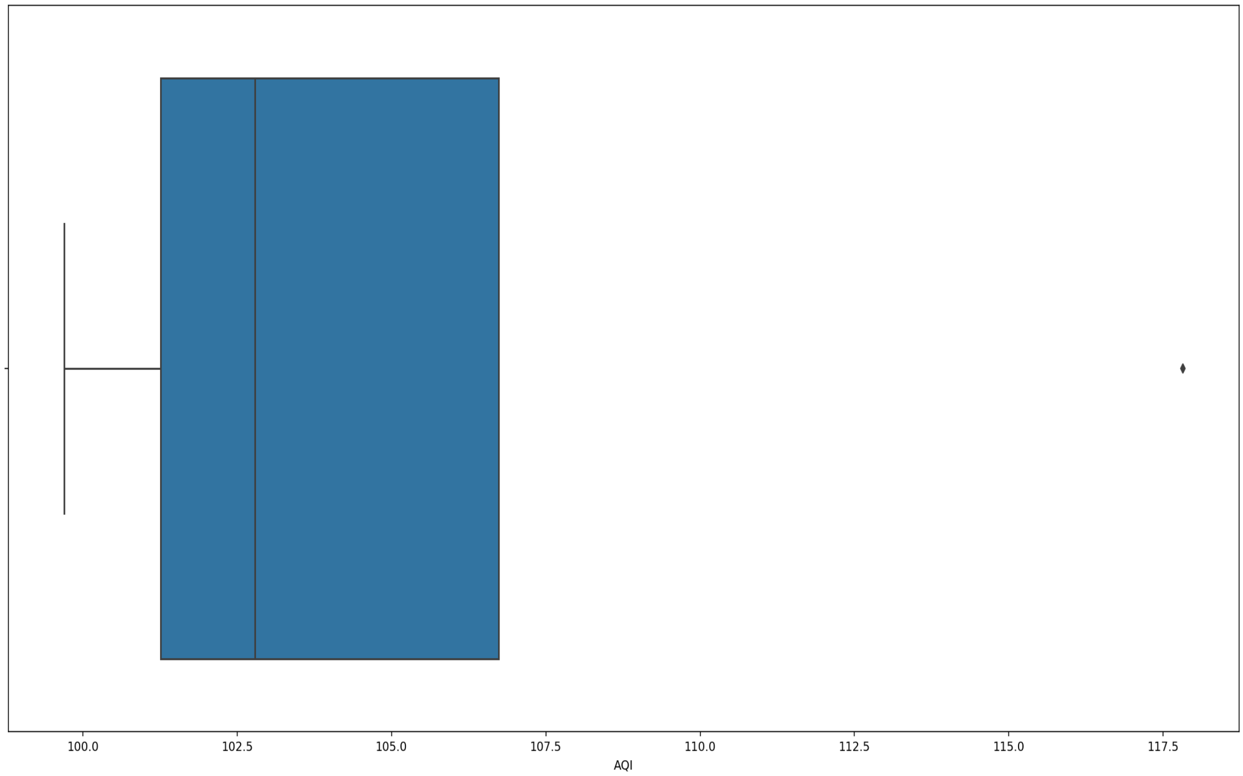
Out [48]:

	year	AQI
count	5.000000	5.000000
mean	2013.000000	105.658889
std	1.581139	7.285694
min	2011.000000	99.696254
25%	2012.000000	101.258882
50%	2013.000000	102.785280
75%	2014.000000	106.729246
max	2015.000000	117.824783

In [49]:

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

Out [49]: <matplotlib.axes._subplots.AxesSubplot at 0x7f72c26a5630>



In [50]:

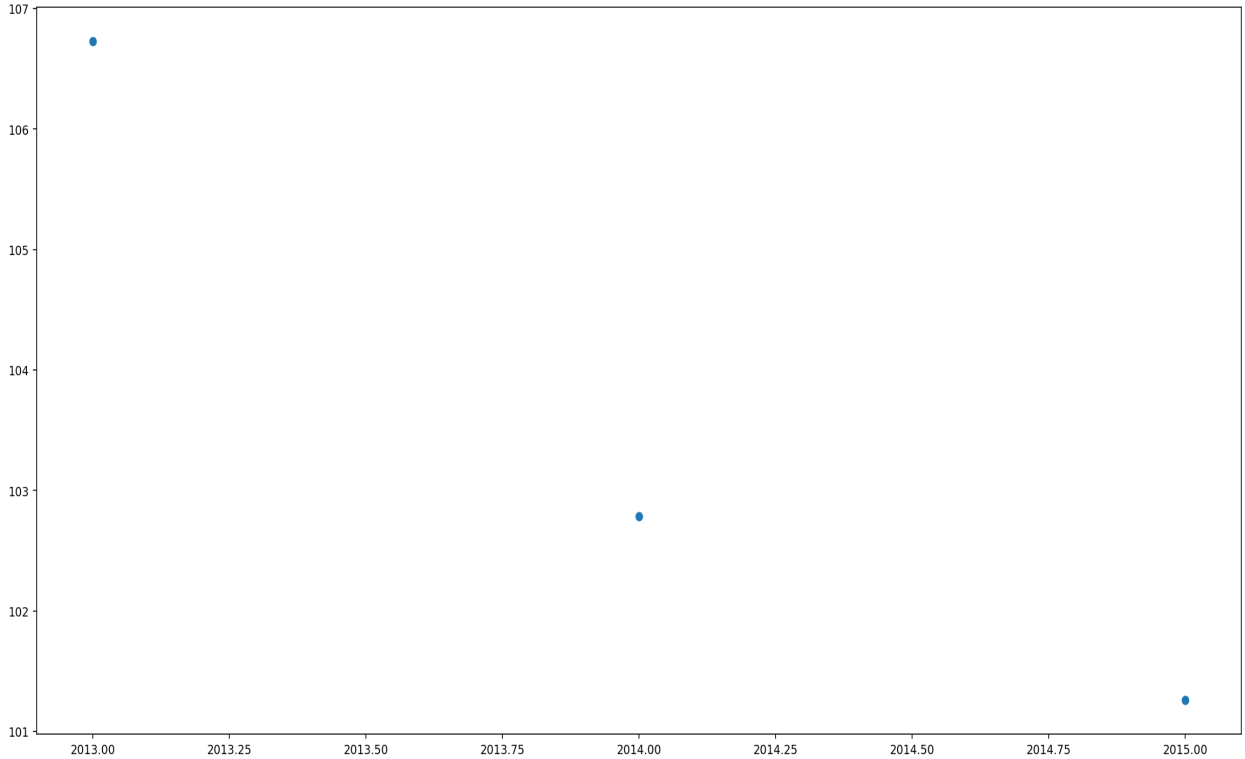
```
df = df[np.isfinite(df['AQI'])]
df=df[df.AQI >101]
df=df[df.AQI <107]
df.head()
```

Out [50]:

	year	AQI
28	2015	101.258882
27	2014	102.785280
26	2013	106.729246

In [51]:

```
cols =['year']
y = df['AQI']
x=df[cols]

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



In [52]:
```
x = (x - x.mean()) / x.std()
x = np.c_[np.ones(x.shape[0]), x]
x
```

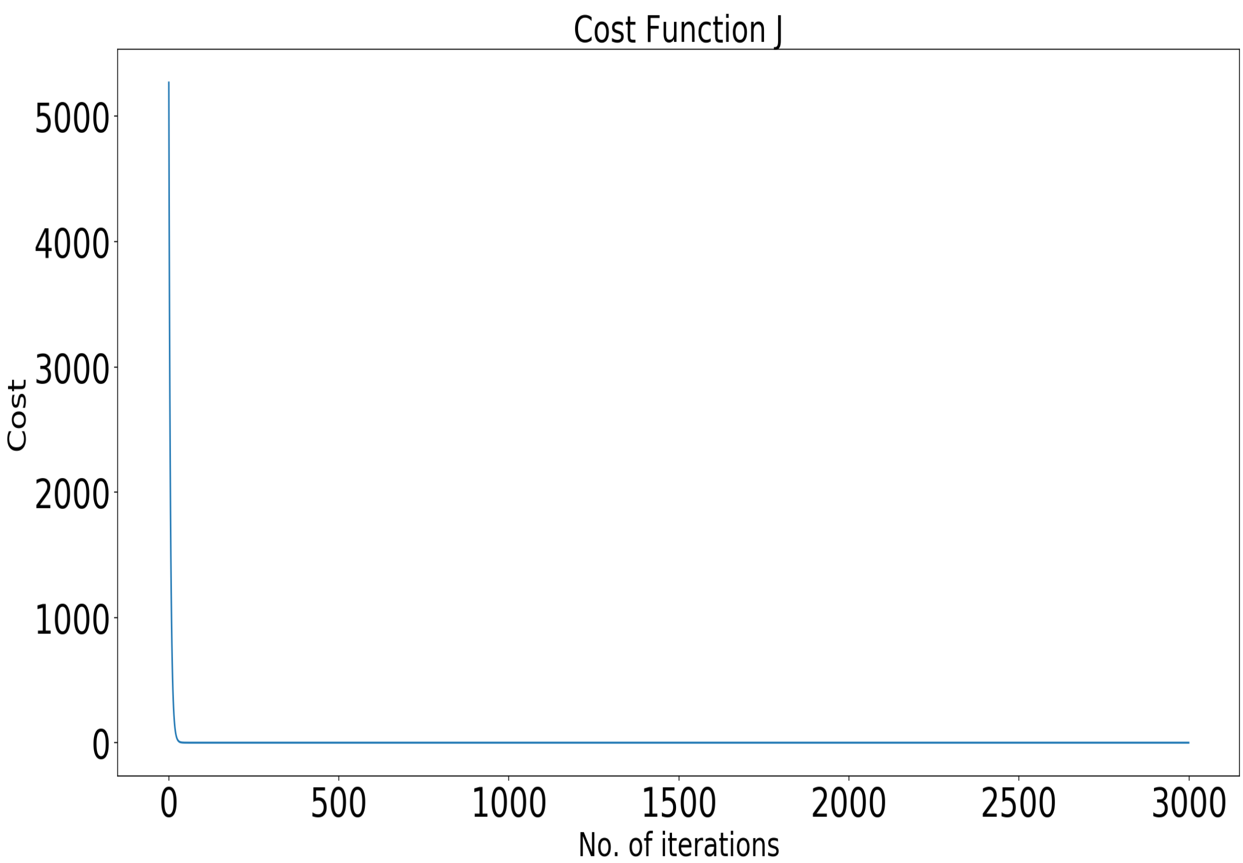
Out [52]:
```
array([[ 1.,  1.],
       [ 1.,  0.],
       [ 1., -1.]])
```

In [53]:
```
#Tunning model with 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 some 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]

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

```
Gradient Descent: 103.59, -2.74
```

In [54]:
```
#Plotting the cost function...
plt.title('Cost Function J',fontsize=28)
plt.xlabel('No. of iterations',fontsize=25)
```

```
plt.ylabel('Cost',fontsize=25)
plt.plot(past_costs)
plt.tick_params(labelsize=30)
plt.show()
```



In [55]:

```
#prediction of january(2013-2015) across india
import numpy as np
newB=[ 103.59, -2.74]

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
```

Out [55]:

	year	AQI	Actual	Predicted
28	2015	101.258882	101.258882	100.85
27	2014	102.785280	102.785280	103.59
26	2013	106.729246	106.729246	106.33

In [56]:

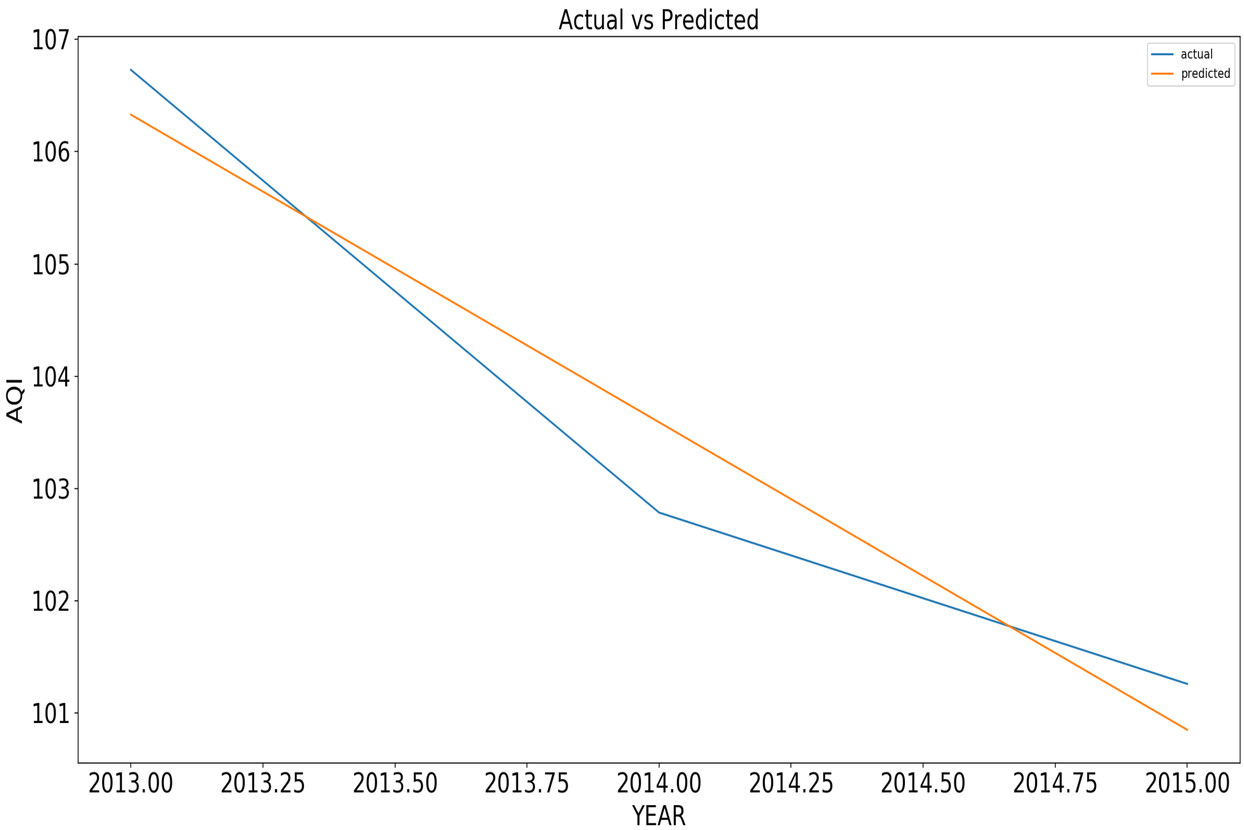
```
#testing the accuracy of the model

from sklearn import metrics
print(np.sqrt(metrics.mean_squared_error(y,y_pred)))
```

```
0.5698410166963634
```

In [57]:

```
#plotting the actual and predicted results
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 [58]:
```
#Prediction for the future
from sklearn.preprocessing import MinMaxScaler
```

In [59]:
```
#feeding in the x value-years
data=[[-1,2016],[-1,2017],[-1,2018],[-1,2019],[-1,2020]]
```

In [60]:
```
#normalization
scaler=MinMaxScaler(feature_range=(-1,1))
scaler.fit(data)
x=scaler.transform(data)
```

In [61]:
```
#calculations
newB=[103.59,-2.74]
ypred=-(x.dot(newB))
```

In [62]:
```
#AQI for the year 2020
print("AQI for the year 2020===>",ypred[-1])
```

```
AQI for the year 2020===> 106.33
```