Preface

This Collab was made in accordance to Data Mining Project for CSE PDEU Sem 5.

Team: DMP_27

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Importing and Downloading Major Libraries

```
!pip install --upgrade scikit-learn

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

```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.7/dist-packages (1
Requirement already satisfied: numpy>=1.14.6 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: scipy>=1.1.0 in /usr/local/lib/python3.7/dist-packages (1
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-packages (1
```

Working on The *Data*

```
#Loading data into variable using Pandas
data_df = pd.read_csv('/content/PM2.5 Global Air Pollution 2010-2017.csv')
```

```
#First Look at Dataset
data_df
```

	Country Name	Country Code	2010	2011	2012	2013	2014	2015
0	Afghanistan	AFG	65.245592	66.835727	66.023174	61.366745	59.010330	61.252656
1	Angola	AGO	33.787247	33.104195	33.415495	34.663923	32.974025	32.729873
2	Albania	ALB	21.277828	22.772537	20.578259	19.938517	18.883955	19.512540
3	Andorra	AND	12.807198	13.273506	12.407053	11.813673	10.830418	11.462178
4	Arab World	ARB	53.787001	52.652279	53.297270	54.053822	52.583603	60.406813
...	...	...	...	...	...	...	...	...
235	Samoa	WSM	14.288094	14.693096	13.627882	13.382522	12.643560	12.321796
236	Yemen, Rep.	YEM	45.979470	50.835291	51.434454	52.998443	48.338653	54.260287

```
#Target Attribute
data_df['2017']
```

```
0      56.910808
1      32.388505
2      18.200603
3      10.307621
4      58.689259
         ...
235    11.548027
236    50.456007
237    25.102205
238    27.438035
239    22.251671
Name: 2017, Length: 240, dtype: float64
```

```
#Features
list(data_df.columns)
```

```
['Country Name',
 'Country Code',
 '2010',
 '2011',
 '2012',
 '2013',
 '2014',
 '2015',
 '2016',
 '2017']
```

```
#checking for null values in whole dataset
data_df.isnull()

#there is no null values found in this dataset
#uncomment respectively if you add an extra to check the validity of project
```

```
#data_df.fillna(method ='pad')
#data_df.fillna(method ='bfill')
#data_df.interpolate(method ='linear', limit_direction ='forward')
#data_df.dropna(axis = 0, how ='any')

#data_df.isnull()

```

	Country Name	Country Code	2010	2011	2012	2013	2014	2015	2016	2017
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
235	False	False	False	False	False	False	False	False	False	False
236	False	False	False	False	False	False	False	False	False	False
237	False	False	False	False	False	False	False	False	False	False
238	False	False	False	False	False	False	False	False	False	False
239	False	False	False	False	False	False	False	False	False	False

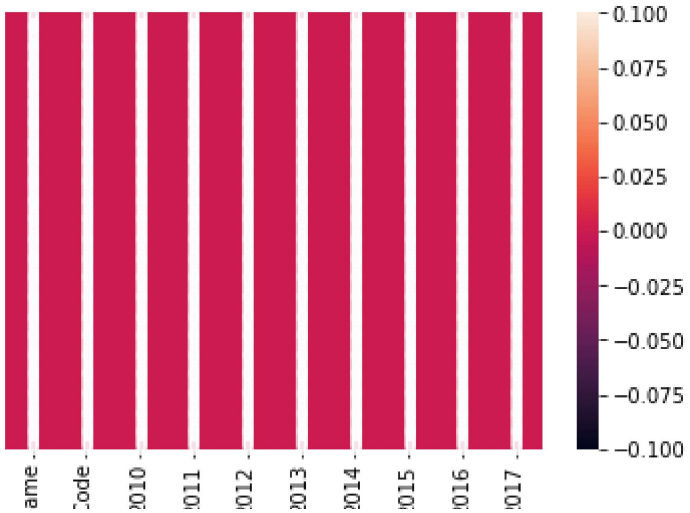
240 rows × 10 columns

```
#Checking for null values/ confirming the previous table using for loop for each column
for i in range(2010,2017):
  i = str(i)
  y = data_df[i].isnull().values.any()
  print(y)
```

```
False
False
False
False
False
False
False
```

```
#heatmap of data proving there is no null values
sns.heatmap(data_df.isnull(),yticklabels=False, annot=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f264f2843d0>
```




```
#Outlier detection
temp = data_df.drop(['Country Name','Country Code'],axis = 1)

#Our data's main label is country rather than the year. So we need to detect outlier row w
for ind,row in temp.head().iterrows():
  sns.boxplot(row.tolist())

#NOTE: If you get the futureWarning error it is because there is no label given. However a
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
  FutureWarning
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass th
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  FutureWarning
```
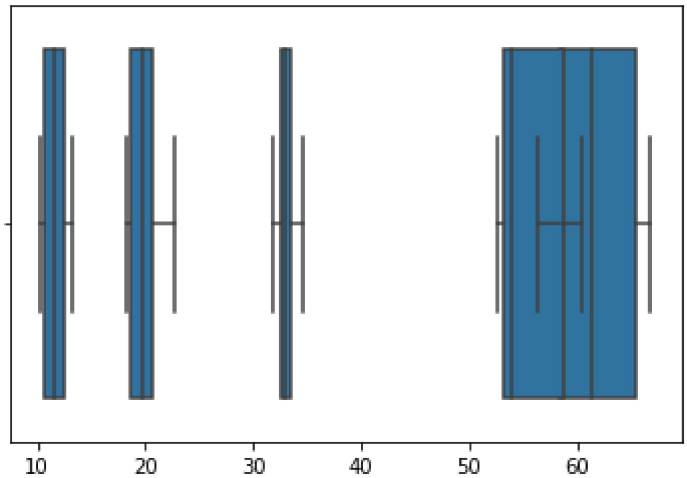



Splitting The Data

```
#Preparing the data to get splitted
x = data_df.drop(['2017'], axis = 1)
y = data_df['2017']

#splitting into train and test
#best output was obtained for 30-70 split with no randomization
from sklearn.model_selection import train_test_split
x_train_temp, x_test_temp, y_train_temp, y_test_temp = train_test_split(x,y,test_size = 0.

#saving country names in different variables
test_countries = x_test_temp['Country Name']
train_countries = x_train_temp['Country Name']
test_codes = x_test_temp['Country Code']
train_codes = x_test_temp['Country Code']
name = data_df['Country Name']
code = data_df['Country Code']

#Preparing the Splitted data to load in Model
x_train = x_train_temp.drop(['Country Name','Country Code'], axis = 1)
y_train = y_train_temp
x_test = x_test_temp.drop(['Country Name','Country Code'], axis = 1)
y_test = y_test_temp


```

Generalized Linear Regression Using Gamma Regression

```
#importing specific library for gama regressor
from sklearn.linear_model import GammaRegressor

#Running the model on our splitted data
modelGamma = GammaRegressor()
modelGamma.fit(x_train, y_train)
```

```
GammaRegressor()
```

```
#Storing the prediction in variable
y_predGamma = modelGamma.predict(x_test)
y_predGamma
```

```
array([ 14.0988688 ,  13.49971036,  20.99165347,  12.98047721,
        13.60711409,  11.86262576, 115.04818148,  29.79830512,
        20.62491967,  37.34549215,  26.50436738,  11.33355307,
        13.53185958,  74.6569349 ,  40.85174596,  15.75310471,
       133.27482464,  19.40765822,  38.29718352,  13.92886687,
        33.32320167,  13.57115482,  34.19451706,  16.27510036,
```

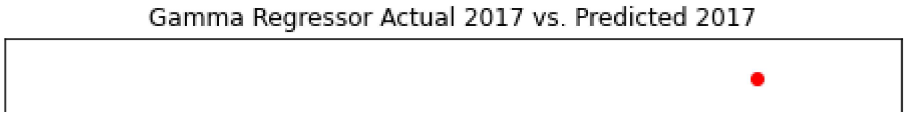
```
34.9700198 ,  16.95284765,  21.26065766,  15.72895591,
18.04237961,  60.19541785,  39.70080345,  15.96454209,
18.88285851,  18.99711332,  32.1260139 ,  25.21202343,
51.36290435,  14.04518271,  12.7676127 ,  15.40463429,
11.83040268,  17.39234703,  20.44012363,  17.96477429,
14.36934486,  29.30495988,  18.6803907 ,  27.24918248,
24.47891932,  19.22302464,  44.95866907,  16.00858757,
13.37108917,  12.88567727,  53.28817982,  16.33113914,
13.01998679,  16.82040653,  16.26074321,  21.58492463,
19.26465089,  51.73601848,  16.57871318,  16.55964474,
15.68418118,  21.56824033,  34.03290304,  37.34309536,
36.33435236,  39.07570428,  60.13570071,  27.92897169])
```

```
#Calculating Accuracy and RMS Error
from sklearn.metrics import r2_score,mean_squared_error
print(r2_score(y_test,y_predGamma))
print(np.sqrt(mean_squared_error(y_test, y_predGamma)))
```

```
0.827720487119502
7.53685235156388
```

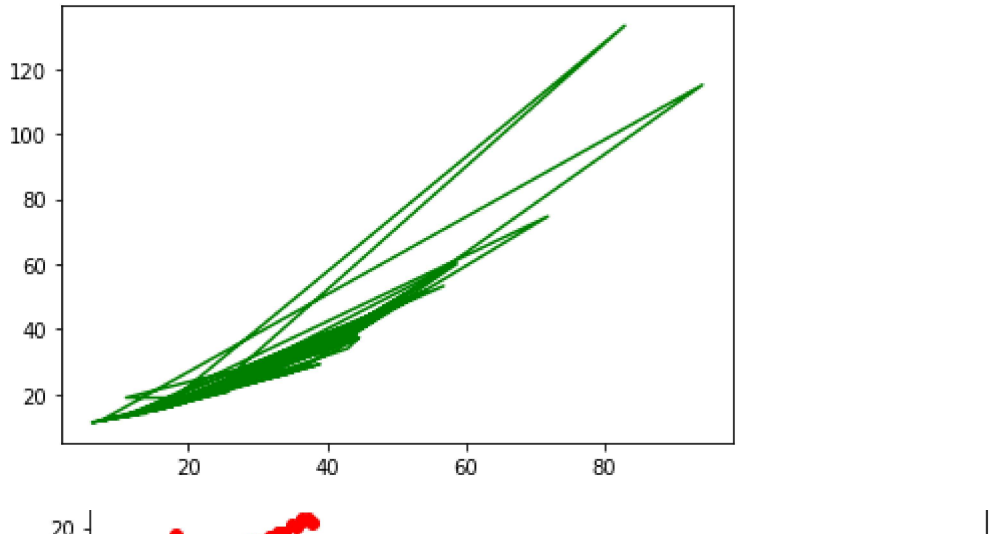
```
#plotting Scatter graph for Actual vs Predicted
plt.figure(figsize=(8,8))
plt.scatter(y_test,y_predGamma, color = 'red')
plt.xlabel('Actual 2017')
plt.ylabel('Predicted 2017')
plt.title('Gamma Regressor Actual 2017 vs. Predicted 2017')
```

```
Text(0.5, 1.0, 'Gamma Regressor Actual 2017 vs. Predicted 2017')
```




```
#plotting continous graph for Actual vs Predicted
plt.plot(y_test,y_predGamma ,'g-')
```

```
[<matplotlib.lines.Line2D at 0x7f264dd0e490>]
```




```
#This model uses Quadratic hypothesis function as evident by graph
#Hence the accuracy is 0.82
#Lets try with a Linear hypothsis function
#best way to address this problem is to use Simple Linear Regression
```

Linear Regression Model

```
#importing LinearRegression Algorithm
from sklearn.linear_model import LinearRegression

#Running the model on our splitted data
modelLR = LinearRegression()
modelLR.fit(x_train,y_train)
```

```
LinearRegression()
```

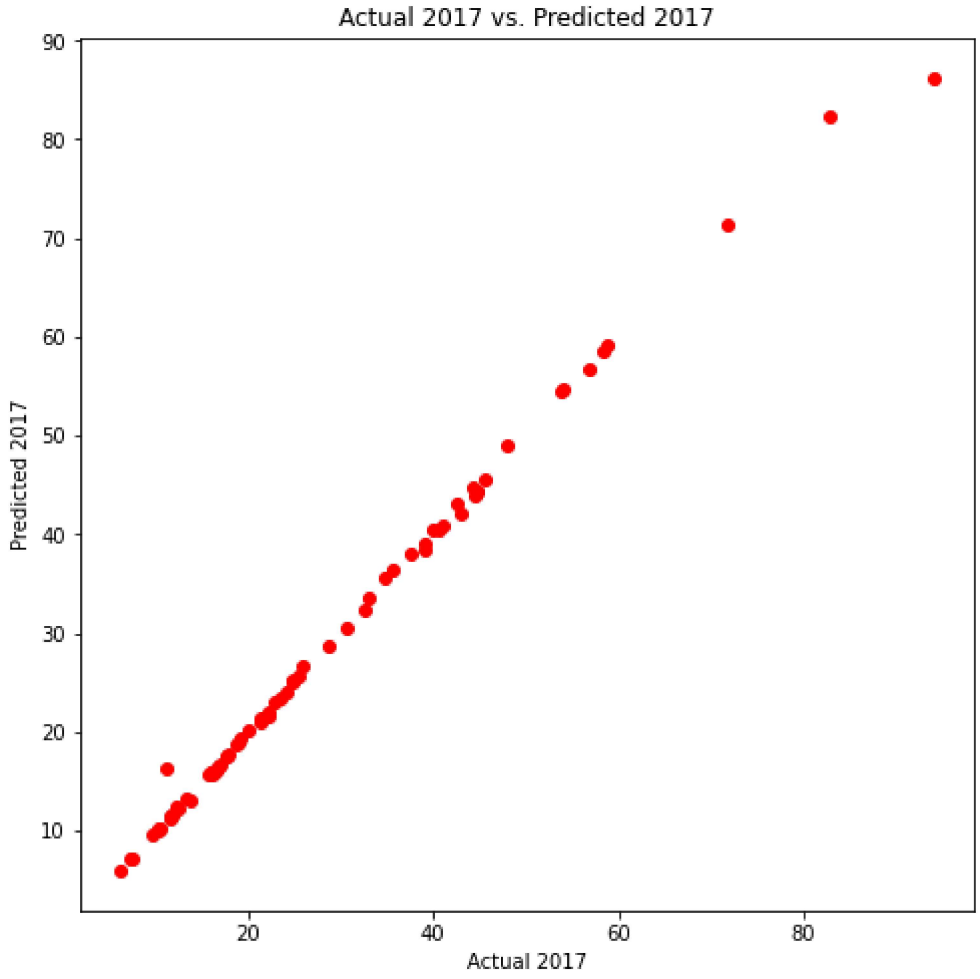
```
#Storing the prediction in variable
y_predLr = modelLR.predict(x_test)
y_predLr
```

```
array([13.10019325, 11.69948933, 26.63994583, 10.2790596 , 11.6363029 ,
        7.28225588, 86.25037088, 38.10419841, 23.34350548, 44.44746746,
       35.5286658 ,  5.96579199, 11.34265401, 71.4308761 , 45.51607481,
       16.18904084, 82.41402299, 23.0995543 , 44.7473802 , 12.2583724 ,
       39.05661248, 11.53728224, 40.56163964, 16.63136052, 40.9433535 ,
```

```
       18.75116897, 25.12407378, 16.12310087, 20.24835239, 58.57560502,
       43.17556351, 15.66878158, 21.46308411, 16.38900482, 36.49974996,
       30.45864552, 54.54517387, 12.4650757 ,  9.59136699, 15.86162737,
        7.1960572 , 18.99141228, 24.00475383, 19.33675658, 13.26729256,
       38.55600602, 21.0400899 , 32.40516543, 28.63893096, 21.66829446,
       49.038065  , 15.81902638, 11.37573827, 10.00296638, 56.72681939,
       17.56434543, 10.15559803, 17.56766161, 16.60605299, 25.31668853,
       22.05232959, 54.80037587, 17.77471344, 16.81332099, 15.93979517,
       25.74691196, 42.03467833, 44.44522388, 40.59612982, 44.01787683,
       59.25316097, 33.50630385])
```

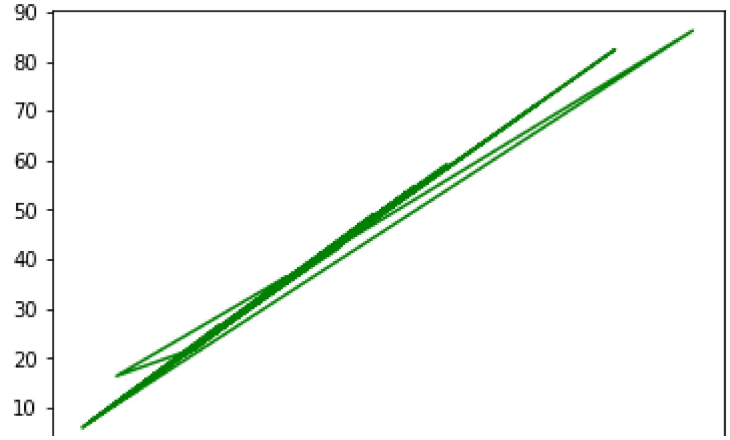
```
1 #plotting Scatter graph for Actual vs Predicted
2 plt.figure(figsize=(8,8))
3 plt.scatter(y_test,y_predLr, color = 'red')
4 plt.xlabel('Actual 2017')
5 plt.ylabel('Predicted 2017')
6 plt.title('Actual 2017 vs. Predicted 2017')
```

```
Text(0.5, 1.0, 'Actual 2017 vs. Predicted 2017')
```




```
1 #plotting continous graph for Actual vs Predicted
2 plt.plot(y_test,y_predLr ,'g-')
```

```
[<matplotlib.lines.Line2D at 0x7f264e6ef850>]
```




```
#Now as we can see in graph we have obtained best results!
#So our accuracy will be better than Gamma Regressor
```

```
#Tabular form of Prediction vs Actual and difference in their values
pred_y_df_Lr = pd.DataFrame({'Country Name':test_countries,'Country Code':test_codes, 'Act

#Saving the comparision table in drive
#You can donwload it from Home Page of Files
pred_y_df_Lr.to_csv('/content/Comparision Table.csv')
pred_y_df_Lr
```

	Country Name	Country Code	Actual Value	predicted value	Difference
109	Kazakhstan	KAZ	13.824288	13.100193	0.724095
71	France	FRA	11.814964	11.699489	0.115474
37	Cote d'Ivoire	CIV	25.886266	26.639946	-0.753679
74	United Kingdom	GBR	10.472690	10.279060	0.193631
108	Japan	JPN	11.704778	11.636303	0.068475
...	...	...	...	...	...
218	Sub-Saharan Africa (IDA & IBRD countries)	TSS	44.602096	44.445224	0.156872
129	Late-demographic dividend	LTE	40.000207	40.596130	-0.595923
73	Gabon	GAB	44.385548	44.017877	0.367672
4	Arab World	ARB	58.689259	59.253161	-0.563902
107	Jordan	JOR	33.006081	33.506304	-0.500223

```
#Calculating Accuracy and RMS Error
from sklearn.metrics import r2_score,mean_squared_error
```

```
print("Accuracy: ",r2_score(y_test,y_predLr))
print("Mean Sqaure Root Error: ",np.sqrt(mean_squared_error(y_test, y_predLr)))
```

```
Accuracy:  0.9958288024910575
```

Conclusion

As the data set was not highly dimensional, the results of simple linear regression is better than advancede linear regressions. Also the data set was squeaky clean and no null values or outliers or redundant values, rows, columns were found. Hence the prediction was 99 percent accurate.

Since all the extensions are useless here we will have final answer from Linear Regression. Uncommnting the data reduction code, changing the directory for your new dataset and dropping respective columns, this code will work for all other datasets as well.

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