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In [ ]:
```
pip install wbgapi
```

In [2]:
```
import pandas as pd
import wbgapi as wb
import sklearn
from sklearn.preprocessing import StandardScaler
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from numpy import array, exp
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit
```

In [4]:
```
#Function to load the world indicators
dfrm=pd.read_csv(r"C:\Users\prasa\Downloads\World Indicator Repository.csv", low_memory=False)
```

In [6]:
```
#Showing some rows of the data
dfrm.head(7)
```

Out[6]:

	Country Name	Country Code	Series Name	Series Code	2017 [YR2017]	2018 [YR2018]	2019 [YR2019]	2020 [YR2020]	2021 [YR2021]
0	Afghanistan	AFG	Access to clean fuels and technologies for coo...	EG.CFT.ACCS.ZS	29.7	30.9	31.9	33.2	..
1	Afghanistan	AFG	Access to clean fuels and technologies for coo...	EG.CFT.ACCS.RU.ZS	13	13.85	15.1	15.9	..
2	Afghanistan	AFG	Access to clean fuels and technologies for coo...	EG.CFT.ACCS.UR.ZS	80.9	81.6	82.3	82.6	..
3	Afghanistan	AFG	Access to electricity (% of population)	EG.ELC.ACCS.ZS	97.69999695	96.61613464	97.69999695	97.69999695	..
4	Afghanistan	AFG	Access to electricity, rural (% of rural popul...	EG.ELC.ACCS.RU.ZS	97.09197235	95.58617401	97.07563019	97.06671143	..
5	Afghanistan	AFG	Access to electricity, urban (% of urban popul...	EG.ELC.ACCS.UR.ZS	99.5	99.62602234	99.5	99.5	..
6	Afghanistan	AFG	Account ownership at a financial institution o...	FX.OWN.TOTL.ZS	14.89331245	..	..	..	..

In [7]:
```
#Description of the dataset
dfrm.describe()
```

Out[7]:

	Country Name	Country Code	Series Name	Series Code	2017 [YR2017]	2018 [YR2018]	2019 [YR2019]	2020 [YR2020]	2021 [YR2021]
count	1864	1862	1862	1862	1862	1862	1862	1862	1862
unique	268	266	7	7	973	825	798	786	1
top	Afghanistan	AFG	Access to clean fuels and technologies for coo...	EG.CFT.ACCS.ZS	100	100	100	100	..
freq	7	7	266	266	511	507	530	583	1862

In [8]:
```
#Data in transpose form
dfrm1=dfrm.transpose()
dfrm1.head(5)
```

Out[8]:

	0	1	2	3	4	5	6	7	
Country Name	Afghanistan	Afghanistan	Afghanistan	Afghanistan	Afghanistan	Afghanistan	Afghanistan	Albania	Albani
Country Code	AFG	AFG	AFG	AFG	AFG	AFG	AFG	ALB	ALI
Series Name	Access to clean fuels and technologies for coo...	Access to clean fuels and technologies for coo...	Access to clean fuels and technologies for coo...	Access to electricity (% of population)	Access to electricity, rural (% of rural popul...	Access to electricity, urban (% of urban popul...	Account ownership at a financial institution o...	Access to clean fuels and technologies for coo...	Access to clean fuel and technologies fc coo.
Series Code	EG.CFT.ACCS.ZS	EG.CFT.ACCS.RU.ZS	EG.CFT.ACCS.UR.ZS	EG.ELC.ACCS.ZS	EG.ELC.ACCS.RU.ZS	EG.ELC.ACCS.UR.ZS	FX.OWN.TOTL.ZS	EG.CFT.ACCS.ZS	EG.CFT.ACCS.RU.Z
2017 [YR2017]	29.7	13	80.9	97.69999695	97.09197235	99.5	14.89331245	78.7	60.

5 rows × 1867 columns

In [2]:
```
ind_id_GDP = ['NY.GDP.MKTP.CD','NE.DAB.TOTL.ZS']
country_codes = ["CHL","GBR",'BGR','DNK','ARG','BRA','CHN','ESP','IND','JAM']
ind_id_Climate=['EG.ELC.ACCS.ZS','EG.USE.ELEC.KH.PC']
data_GDP  = wb.data.DataFrame(ind_id_GDP, country_codes, mrv=7)
data_Climate  = wb.data.DataFrame(ind_id_Climate, country_codes, mrv=7)
#NY.GDP.MKTP.CD    : Current GDP in US$
#NE.DAB.TOTL.ZS : Expenditure
 #EG.ELC.ACCS.ZS        Access to electricity (% of population)
#EG.USE.ELEC.KH.PC      Electric power consumption (kWh per capita)
```

In [3]:
```
# Creating the proper table structure for GDP
data_GDP.columns = [a.replace('YR','') for a in data_GDP.columns]
data_GDP=data_GDP.stack().unstack(level=1)
data_GDP.index.names = ['Country_Code', 'Year']
data_GDP.columns
data_GDP.fillna(0)
data_GDP.head(15)
```

Out[3]:

Country_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD
ARG	2014	99.595836	5.263197e+11
	2015	101.074922	5.947493e+11
	2016	101.039698	5.575314e+11
	2017	102.649034	6.436287e+11
	2018	101.889164	5.248197e+11
	2019	96.994042	4.519324e+11
	2020	93.070816	3.892881e+11
BGR	2014	101.085516	5.708201e+10
	2015	99.100768	5.078200e+10
	2016	95.092863	5.395390e+10
	2017	95.687406	5.919945e+10
	2018	97.459949	6.636342e+10
	2019	96.771743	6.891542e+10
	2020	96.939132	6.988935e+10
BRA	2014	102.661520	2.456044e+12

In [4]:
```
data_GDP.head(5)
```

Out[4]:

Country_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD
ARG	2014	99.595836	5.263197e+11
	2015	101.074922	5.947493e+11
	2016	101.039698	5.575314e+11
	2017	102.649034	6.436287e+11
	2018	101.889164	5.248197e+11

In [5]:
```
# Creating the proper table structure for Climate
data_Climate.columns = [a.replace('YR','') for a in data_Climate.columns]
data_Climate=data_Climate.stack().unstack(level=1)
data_Climate.index.names = ['Country_Code', 'Year']
data_Climate.columns
data_Climate.fillna(0)
data_Climate.head(15)
```

Out[5]:

Country_Code	Year	EG.ELC.ACCS.ZS	EG.USE.ELEC.KH.PC
ARG	2014	100.000000	3074.702071
	2015	99.625389	NaN
	2016	99.849579	NaN
	2017	100.000000	NaN
	2018	99.989578	NaN
	2019	100.000000	NaN
	2020	100.000000	NaN
BGR	2014	100.000000	4708.927458
	2015	100.000000	NaN
	2016	100.000000	NaN
	2017	100.000000	NaN
	2018	100.000000	NaN
	2019	100.000000	NaN
	2020	99.699997	NaN
BRA	2014	99.650246	2619.960499

In [6]:
```
data_Climate.head(15)
```

Out[6]:

Country_Code	Year	EG.ELC.ACCS.ZS	EG.USE.ELEC.KH.PC
ARG	2014	100.000000	3074.702071
	2015	99.625389	NaN
	2016	99.849579	NaN
	2017	100.000000	NaN
	2018	99.989578	NaN
	2019	100.000000	NaN
	2020	100.000000	NaN
BGR	2014	100.000000	4708.927458
	2015	100.000000	NaN
	2016	100.000000	NaN
	2017	100.000000	NaN
	2018	100.000000	NaN
	2019	100.000000	NaN
	2020	99.699997	NaN
BRA	2014	99.650246	2619.960499

In [7]:
```
#Adjusting the dataframe
data1=data_GDP.reset_index()
data2=data_Climate.reset_index()
data3=data1.fillna(0)
data4=data2.fillna(0)
data4.head(10)
```

Out[7]:

series	Country_Code	Year	EG.ELC.ACCS.ZS	EG.USE.ELEC.KH.PC
0	ARG	2014	100.000000	3074.702071
1	ARG	2015	99.625389	0.000000
2	ARG	2016	99.849579	0.000000
3	ARG	2017	100.000000	0.000000
4	ARG	2018	99.989578	0.000000
5	ARG	2019	100.000000	0.000000
6	ARG	2020	100.000000	0.000000
7	BGR	2014	100.000000	4708.927458
8	BGR	2015	100.000000	0.000000
9	BGR	2016	100.000000	0.000000

In [8]:
```
#Joining 2 dataframes
data_concat1 = pd.merge(data3, data4)
data_concat1.head(15)
```

Out[8]:

series	Country_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD	EG.ELC.ACCS.ZS	EG.USE.ELEC.KH.PC
0	ARG	2014	99.595836	5.263197e+11	100.000000	3074.702071
1	ARG	2015	101.074922	5.947493e+11	99.625389	0.000000
2	ARG	2016	101.039698	5.575314e+11	99.849579	0.000000
3	ARG	2017	102.649034	6.436287e+11	100.000000	0.000000
4	ARG	2018	101.889164	5.248197e+11	99.989578	0.000000
5	ARG	2019	96.994042	4.519324e+11	100.000000	0.000000
6	ARG	2020	93.070816	3.892881e+11	100.000000	0.000000
7	BGR	2014	101.085516	5.708201e+10	100.000000	4708.927458
8	BGR	2015	99.100768	5.078200e+10	100.000000	0.000000
9	BGR	2016	95.092863	5.395390e+10	100.000000	0.000000
10	BGR	2017	95.687406	5.919945e+10	100.000000	0.000000
11	BGR	2018	97.459949	6.636342e+10	100.000000	0.000000
12	BGR	2019	96.771743	6.891542e+10	100.000000	0.000000
13	BGR	2020	96.939132	6.988935e+10	99.699997	0.000000
14	BRA	2014	102.661520	2.456044e+12	99.650246	2619.960499

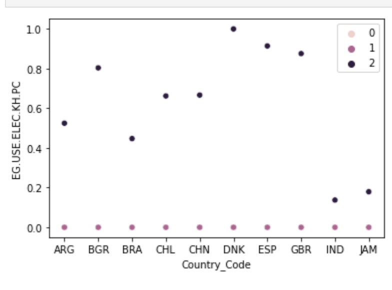
In [9]:
```
#Normalize the values
data_concat2 = data_concat1.iloc[:,2:]
data_concat1.iloc[:,2:] = (data_concat2-data_concat2.min())/ (data_concat2.max() - data_concat2.min())
data_concat1.head(5)
```

Out[9]:

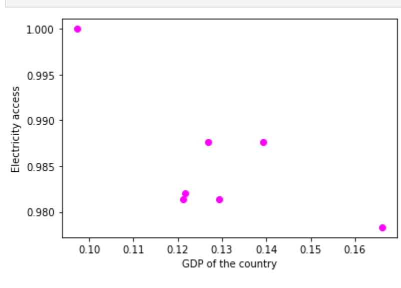
series	Country_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD	EG.ELC.ACCS.ZS	EG.USE.ELEC.KH.PC
0	ARG	2014	0.235884	0.034843	1.000000	0.524801
1	ARG	2015	0.285813	0.039496	0.976772	0.000000
2	ARG	2016	0.284624	0.036965	0.990673	0.000000
3	ARG	2017	0.338950	0.042819	1.000000	0.000000
4	ARG	2018	0.313299	0.034741	0.999354	0.000000

In [10]:
```
#Clustering the dataset using K-means
data_val = data_concat1.drop('Country_Code', axis = 1)
kmn = KMeans(n_clusters=3, init='k-means++', random_state=0).fit(data_val)
```

In [11]:
```
#Clustering the dataset on Electric power consumption
sns.scatterplot(data=data_concat1, x="Country_Code", y="EG.USE.ELEC.KH.PC", hue=kmn.labels_)
plt.legend(loc='best')
plt.show()
```

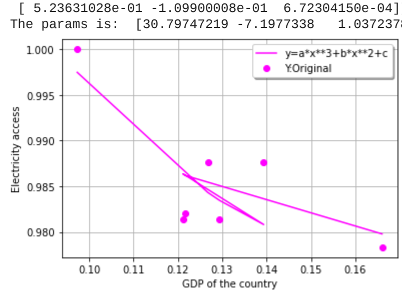


In [12]:
```
#Scatter plot for GDP, PPP vs greenshouse gas emission
country=data_concat1[(data_concat1['Country_Code']=='BRA')]
fnal = country.values
x, y = fnal[:, 3], fnal[:, 4]
plt.scatter(x, y,color="magenta")
plt.ylabel('Electricity access')
plt.xlabel('GDP of the country')
plt.show()
```



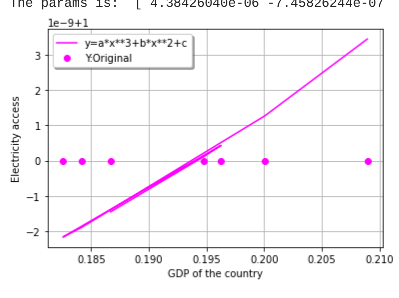
In [13]:
```
#Implementing the curve_fit function for Brazil which has a medium electric power consumption (kWh per capita)

x, y = fnal[:, 3], fnal[:, 4]
def fu(x, a, b, c):
    return a*x**3+b*x**2+c
para, covar = curve_fit(fu, x, y)
print("The covariance is: ", covar)
print("The params is: ", para)
para, _ = curve_fit(fu, x, y)
a, b, c = para[0], para[1], para[2]
yft = a*x**3+b*x**2+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yft, label="y=a*x**3+b*x**2+c",color="magenta")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Y:Original",color="magenta")
    plt.ylabel('Electricity access')
    plt.xlabel('GDP of the country')

    plt.legend(loc='best', fancybox=True, shadow=True)

    plt.show()
```

```
The covariance is:  [[ 4.38518037e+02 -8.99095490e+01  5.23631028e-01]
 [-8.99095490e+01  1.85839542e+01 -1.09900008e-01]
 [ 5.23631028e-01 -1.09900008e-01  6.72304150e-04]]
The params is:  [30.79747219 -7.1977338   1.03723783]
```



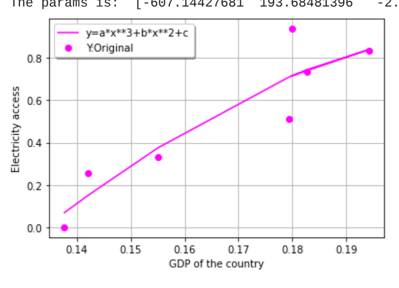
In [17]:
```
#Implementing the curve_fit function for GBR which has a high electric power consumption (kWh per capita)

country1=data_concat1[(data_concat1['Country_Code']=='GBR')]
fnal1 = country1.values

x, y = fnal1[:, 3], fnal1[:, 4]
def fu(x, a, b, c):
    return a*x**3+b*x**2+c
para, covar = curve_fit(fu, x, y)
print("The covariance is: ", covar)
print("The params is: ", para)
para, _ = curve_fit(fu, x, y)
a, b, c = para[0], para[1], para[2]
yft = a*x**3+b*x**2+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yft, label="y=a*x**3+b*x**2+c",color="magenta")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Y:Original",color="magenta")
    plt.ylabel('Electricity access')
    plt.xlabel('GDP of the country')

    plt.legend(loc='best', fancybox=True, shadow=True)

    plt.show()
```

```
The covariance is:  [[-1.27209039e+02 -3.47267469e-07  8.64712520e-01]
 [-3.47267467e-07  1.53028636e-14  2.36057481e-09]
 [ 8.64712520e-01  2.36057482e-09 -5.87794506e-03]]
The params is:  [ 4.38426040e-06 -7.45826244e-07  9.99999996e-01]
```



In [18]:
```
#Implementing the curve_fit function for India which has a low electric power consumption (kWh per capita)

country3=data_concat1[(data_concat1['Country_Code']=='IND')]
fnal3 = country3.values

x, y = fnal3[:, 3], fnal3[:, 4]
def fu(x, a, b, c):
    return a*x**3+b*x**2+c
para, covar = curve_fit(fu, x, y)
print("The covariance is: ", covar)
print("The params is: ", para)
para, _ = curve_fit(fu, x, y)
a, b, c = para[0], para[1], para[2]
yft = a*x**3+b*x**2+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yft, label="y=a*x**3+b*x**2+c",color="magenta")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Y:Original",color="magenta")
    plt.ylabel('Electricity access')
    plt.xlabel('GDP of the country')

    plt.legend(loc='best', fancybox=True, shadow=True)

    plt.show()
```

```
The covariance is:  [[ 8.25394189e+05 -2.05391398e+05  1.79840703e+03]
 [-2.05391398e+05  5.11936244e+04 -4.49900755e+02]
 [ 1.79840703e+03 -4.49900755e+02  3.98998096e+00]]
The params is:  [-607.14427681  193.68481396   -2.01812253]
```



The conclusion which can be derived from the above three comparisons is that for country with high and low electric power consumption (kWh per capita), the relationship between electricity access % and GDP of the country is direct. For the country with medium electric power consumption (kWh per capita), the relationship between electricity access % and GDP of the country is indirect.

In [14]:
```
def err_ranges(x, func, param, sigma):
    import itertools as iter
    # initiate arrays for lower and upper limits
    lower = func(x, *param)
    upper = lower

    uplow = []   # list to hold upper and lower limits for parameters
    for p,s in zip(param, sigma):
        pmin = p - s
        pmax = p + s
        uplow.append((pmin, pmax))

    pmix = list(iter.product(*uplow))

    for p in pmix:
        y = func(x, *p)
        lower = np.minimum(lower, y)
        upper = np.maximum(upper, y)

    return lower, upper
```

In [ ]:

In [ ]: