NAME - Raju

```
In [ ]:
         pip install wbgapi
In [1]:
         import pandas as pd
         import wbgapi as wb
         import sklearn
         import seaborn as sns
         from sklearn.datasets import make_blobs
         from numpy import array, exp
         import itertools as iter
         from sklearn.cluster import KMeans
         import matplotlib.pyplot as plt
         from scipy.optimize import curve_fit
In [2]:
         ecn_indc = ['NE.DAB.TOTL.ZS','NY.GDP.MKTP.CD']
         cod_contry = ["BMU","CHE",'DNK','BGR','BGD','ARG','GBR','IND','BRA','JAM']
         cli indc=['EG.ELC.RNWX.KH','EN.ATM.CO2E.GF.KT']
         ecn_data = wb.data.DataFrame(ecn_indc, cod_contry, mrv=7)
         cli_data = wb.data.DataFrame(cli_indc, cod_contry, mrv=7)
         #NE.DAB.TOTL.ZS: Total expenditure
         #NY.GDP.MKTP.CD: USD GDP of a country
                                  Electricity production from renewable sources %
         #EG.ELC.RNWX.KH:
         #EN.ATM.CO2E.GF.KT: Emissions of Carbon dioxide from fuel
In [3]:
         # ECNMY INDICATOR
         ecn_data.columns = [b.replace('YR','') for b in ecn_data.columns]
         ecn data=ecn data.stack().unstack(level=1)
         ecn_data.index.names = ['Ctry_Code', 'Year']
         ecn_data.columns
         ecn data.fillna(0)
         ecn_data.head(9)
Out[3]:
                   series NE.DAB.TOTL.ZS NY.GDP.MKTP.CD
         Ctry_Code
                    Year
              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
              BGD
                   2014
                              106.487933
                                            1.728855e+11
                   2015
                              106.728219
                                            1.950787e+11
In [4]:
         # CLMATE INDICATOR
         cli_data.columns = [c.replace('YR','') for c in cli_data.columns]
         cli data=cli data.stack().unstack(level=1)
```

cli_data.index.names = ['Ctry_Code', 'Year']

```
cli_data.columns
cli_data.fillna(0)
cli_data.head(9)
```

```
series EG.ELC.RNWX.KH EN.ATM.CO2E.GF.KT
Out[4]:
```

Ctry_Code	Year		
ARG	2010	2.220000e+09	86999.575
	2011	2.155000e+09	92661.423
	2012	2.752000e+09	95459.344
	2013	2.942000e+09	90835.257
	2014	2.719000e+09	96691.456
	2015	2.752000e+09	98359.941
	2016	NaN	102268.963
BGD	2010	0.000000e+00	39431.251
	2011	0.000000e+00	39658.605

```
In [5]:
         #Preprtion of the data
         dfrm1=ecn_data.reset_index()
         dfrm3=dfrm1.fillna(0)
         dfrm2=cli_data.reset_index()
         dfrm4=dfrm2.fillna(0)
```

dfrm = pd.merge(dfrm3, dfrm4) dfrm.head(10)

In [6]: #Getting the indicators for all the countries

```
Out[6]: series Ctry_Code Year NE.DAB.TOTL.ZS NY.GDP.MKTP.CD EG.ELC.RNWX.KH EN.ATM.CO2E.GF.KT
             0
                      ARG 2014
                                        99.595836
                                                      5.263197e+11
                                                                        2.719000e+09
                                                                                                96691.456
                                       101.074922
                      ARG 2015
                                                      5.947493e+11
                                                                        2.752000e+09
                                                                                                98359.941
             2
                      ARG 2016
                                       101.039698
                                                      5.575314e+11
                                                                        0.000000e+00
                                                                                               102268.963
                      BGD 2014
                                       106.487933
                                                      1.728855e+11
                                                                        1.490000e+08
                                                                                                45969.512
              4
                      BGD 2015
                                       106.728219
                                                      1.950787e+11
                                                                        1.580000e+08
                                                                                                48782.101
                      BGD
                           2016
                                       104.674816
                                                      2.214152e+11
                                                                        0.000000e+00
                                                                                                53593.205
             6
                      BGR 2014
                                       101.085516
                                                      5.708201e+10
                                                                        2.783000e+09
                                                                                                5412.492
                      BGR
                           2015
                                        99.100768
                                                      5.078200e+10
                                                                        3.107000e+09
                                                                                                5944.207
             8
                                                      5.395390e+10
                      BGR 2016
                                        95.092863
                                                                        0.000000e+00
                                                                                                6153.226
                      BMU 2014
                                        73.926721
                                                      6.413988e+09
                                                                        0.000000e+00
                                                                                                    0.000
```

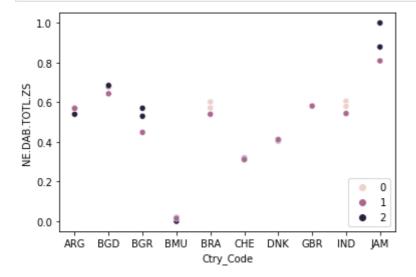
```
In [7]:
         #Normalization of the dfrm values
         df1 = dfrm.iloc[:,2:]
         dfrm.iloc[:,2:] = (df1-df1.min())/ (df1.max() - df1.min())
         dfrm.head(7)
```

Out[7]:	series	Ctry_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD	EG.ELC.RNWX.KH

series	Ctry_Code	Year	NE.DAB.TOTL.ZS	NY.GDP.MKTP.CD	EG.ELC.RNWX.KH	EN.ATM.COZE.GF.KT
0	ARG	2014	0.539749	0.168759	0.035192	0.608272
1	ARG	2015	0.569823	0.190971	0.035619	0.618769
2	ARG	2016	0.569107	0.178891	0.000000	0.643360
3	BGD	2014	0.679885	0.054036	0.001929	0.289188
4	BGD	2015	0.684771	0.061240	0.002045	0.306881
5	BGD	2016	0.643019	0.069789	0.000000	0.337147
6	BGR	2014	0.570039	0.016447	0.036020	0.034049

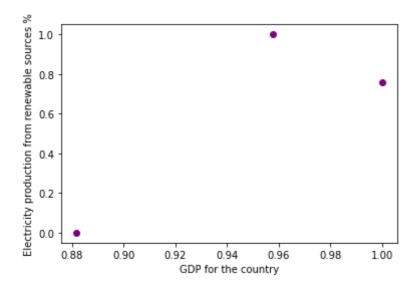
```
In [8]:
#K-means type clustering
df2 = dfrm.drop('Ctry_Code', axis = 1)
kmens = KMeans(n_clusters=3, init='k-means++', random_state=0).fit(df2)
```

```
#Clustering the value of total expenditure for different countries
sns.scatterplot(data=dfrm, x="Ctry_Code", y="NE.DAB.TOTL.ZS", hue=kmens.labels_)
plt.legend(loc='lower right')
plt.show()
```



```
In [10]: #Scatter plot - Electricity production from renewable sources % vs GDP in GBR

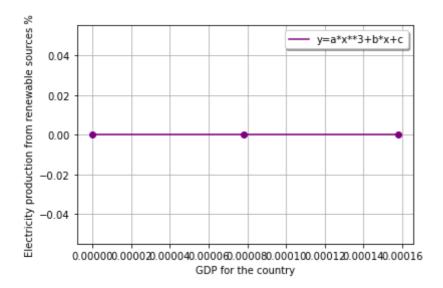
a=dfrm[(dfrm['Ctry_Code']=='GBR')]
b = a.values
x, y = b[:, 3], b[:, 4]
plt.scatter(x, y,color="purple")
plt.xlabel('GDP for the country')
plt.ylabel('Electricity production from renewable sources %')
plt.show()
```



```
In [13]:
          #Using curve fit to do the fitting for Bermuda which has a low total expenditure
          e=dfrm[(dfrm['Ctry_Code']=='BMU')]
          f = e.values
          x, y = f[:, 3], f[:, 4]
          def func(x, a, b, c):
              return a*x**3+b*x+c
          pmtr, cova = curve_fit(func, x, y)
          pmtr, _ = curve_fit(func, x, y)
          print("Parameters value->: ", pmtr)
          a, b, c = pmtr[0], pmtr[1], pmtr[2]
          yfit =a*x**3+b*x+c
          import warnings
          with warnings.catch_warnings(record=True):
              plt.plot(x, yfit, label="y=a*x**3+b*x+c",color="purple")
              plt.grid(True)
              plt.xlabel('GDP for the country')
              plt.legend(loc='best', fancybox=True, shadow=True)
              plt.plot(x, y, 'bo', label="Y orgnl value",color="purple")
              plt.ylabel('Electricity production from renewable sources %')
              plt.show()
```

Parameters value->: [1.52839034e-305 6.62013102e-313 -7.44535683e-317]

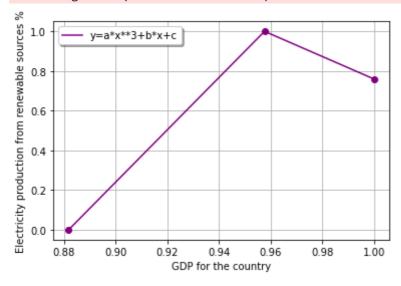
C:\Users\alekh\anaconda3\lib\site-packages\scipy\optimize\minpack.py:833: OptimizeWarning: Covariance of the parameters could not be estimated warnings.warn('Covariance of the parameters could not be estimated',



```
In [11]:
          #Using curve fit to do the fitting for GBR which has a medium total expenditure
          x, y = b[:, 3], b[:, 4]
          def func(x, a, b, c):
              return a*x**3+b*x+c
          pmtr, cova = curve_fit(func, x, y)
          pmtr, _ = curve_fit(func, x, y)
          print("Parameters value->: ", pmtr)
          a, b, c = pmtr[0], pmtr[1], pmtr[2]
          yfit =a*x**3+b*x+c
          import warnings
          with warnings.catch warnings(record=True):
              plt.plot(x, yfit, label="y=a*x**3+b*x+c",color="purple")
              plt.grid(True)
              plt.xlabel('GDP for the country')
              plt.legend(loc='best', fancybox=True, shadow=True)
              plt.plot(x, y, 'bo', label="Y orgnl value",color="purple")
              plt.ylabel('Electricity production from renewable sources %')
              plt.show()
```

Parameters value->: [-56.14217118 155.71842561 -98.81657956]

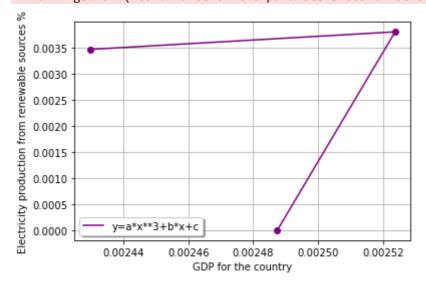
C:\Users\alekh\anaconda3\lib\site-packages\scipy\optimize\minpack.py:833: OptimizeWarning: C
ovariance of the parameters could not be estimated
 warnings.warn('Covariance of the parameters could not be estimated',



```
#Using curve_fit to do the fitting for Jamaica which has a high total expenditure
In [14]:
          h=dfrm[(dfrm['Ctry_Code']=='JAM')]
          j = h.values
          x, y = j[:, 3], j[:, 4]
          def func(x, a, b, c):
              return a*x**3+b*x+c
          pmtr, cova = curve_fit(func, x, y)
          pmtr, _ = curve_fit(func, x, y)
          print("Parameters value->: "
          a, b, c = pmtr[0], pmtr[1], pmtr[2]
          yfit = a*x**3+b*x+c
          import warnings
          with warnings.catch warnings(record=True):
              plt.plot(x, yfit, label="y=a*x**3+b*x+c",color="purple")
              plt.grid(True)
              plt.xlabel('GDP for the country')
              plt.legend(loc='best', fancybox=True, shadow=True)
              plt.plot(x, y, 'bo', label="Y orgnl value",color="purple")
              plt.ylabel('Electricity production from renewable sources %')
              plt.show()
```

Parameters value->: [2.35676711e+08 -4.33389209e+03 7.15307227e+00]

C:\Users\alekh\anaconda3\lib\site-packages\scipy\optimize\minpack.py:833: OptimizeWarning: C
ovariance of the parameters could not be estimated
 warnings.warn('Covariance of the parameters could not be estimated',



It can be understood from the visualisations that the country with a high total expenditure has a direct relationship between GDP of the country and the electricity production from renewable sources %. For the country with a medium total expenditure, the relationship between GDP of the country and the electricity production from renewable sources % is direct till a certain GDP and after than it becomes indirect. For the country with a low total expenditure, the relationship between GDP of the country and the electricity production from renewable sources % is parallel to x axis

```
def err_ranges(x, func, param, sigma):
    # 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
```

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In [ ]:

In [ ]:
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