**NAME - Sai Teja**

In [ ]:

```
pip install wbgapi
```

In [9]:

```
import pandas as pd
import wbgapi as wb
import sklearn
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.optimize import curve_fit
import warnings
from sklearn.preprocessing import StandardScaler
```

In [2]:

```
indi_GD = ['SL.UEM.ADVN.ZS','NY.GDP.MKTP.PP.CD']
conty_cde = ["AFG","IND",'AUS','PAK','BGR','GBR','ESP','LUX','CHL','CHE']
indi_CL=['EN.ATM.PM25.MC.T1.ZS','EN.ATM.CO2E.GF.KT']
G  = wb.data.DataFrame(indi_GD, conty_cde, mrv=7)
C = wb.data.DataFrame(indi_CL, conty_cde, mrv=7)
#SL.UEM.ADVN.ZS: Unemployment with advanced education (% of total labor force with advanced education)
#NY.GDP.MKTP.PP.CD: PPP, GDP of a country
#EN.ATM.PM25.MC.T1.ZS: PM2.5 pollution exceeding WHO target levels
#EN.ATM.CO2E.GF.KT: CO2 emissions from fuel consumptions of gas
```

In [3]:

```
# Economy indicators
G.columns = [s.replace('YR','') for s in G.columns]
G=G.stack().unstack(level=1)
G.index.names = ['Cnt_Cde', 'Year']
G.columns
G.fillna(0)
G.head(10)
```

Out[3]:

| | series | NY.GDP.MKTP.PP.CD | SL.UEM.ADVN.ZS |
|---|---|---|---|
| **Cnt_Cde** | **Year** | | |
| **AFG** | **2014** | 6.905834e+10 | 7.86 |
| | **2015** | 7.183170e+10 | NaN |
| | **2016** | 7.009796e+10 | NaN |
| | **2017** | 7.471192e+10 | 15.46 |
| | **2018** | 7.741557e+10 | NaN |
| | **2019** | 8.187980e+10 | NaN |
| | **2020** | 8.091834e+10 | 14.38 |
| **AUS** | **2014** | 1.100561e+12 | 3.73 |
| | **2015** | 1.101457e+12 | 3.55 |
| | **2016** | 1.143149e+12 | 3.46 |

In [4]:

```
# Cllimate indicators
C.columns = [s.replace('YR','') for s in C.columns]
C=C.stack().unstack(level=1)
C.index.names = ['Cnt_Cde', 'Year']
C.columns
C.fillna(0)
C.head(10)
```

Out[4]:

| | series | EN.ATM.CO2E.GF.KT | EN.ATM.PM25.MC.T1.ZS |
|---|---|---|---|
| **Cnt_Cde** | **Year** | | |
| **AFG** | **2011** | 308.028 | 99.993470 |
| | **2012** | 308.028 | 99.908594 |
| | **2013** | 297.027 | 99.856219 |
| | **2014** | 271.358 | 99.721335 |
| | **2015** | 282.359 | 99.834570 |
| | **2016** | 319.029 | 99.637837 |
| | **2017** | NaN | 99.662950 |
| **AUS** | **2011** | 68525.229 | 0.000000 |
| | **2012** | 65430.281 | 0.000000 |
| | **2013** | 69313.634 | 0.000000 |

In [5]:

```
#Dataset prep
dp1=G.reset_index()
dp2=C.reset_index()
dp3=dp1.fillna(0)
dp4=dp2.fillna(0)
```

In [6]:

```
#Merging the values
dpfinal = pd.merge(dp3, dp4)
dpfinal.head(14)
```

Out[6]:

| series | Cnt_Cde | Year | NY.GDP.MKTP.PP.CD | SL.UEM.ADVN.ZS | EN.ATM.CO2E.GF.KT | EN.ATM.PM25.MC.T1.ZS |
|---|---|---|---|---|---|---|
| **0** | AFG | 2014 | 6.905834e+10 | 7.86 | 271.358 | 99.721335 |
| **1** | AFG | 2015 | 7.183170e+10 | 0.00 | 282.359 | 99.834570 |
| **2** | AFG | 2016 | 7.009796e+10 | 0.00 | 319.029 | 99.637837 |
| **3** | AFG | 2017 | 7.471192e+10 | 15.46 | 0.000 | 99.662950 |
| **4** | AUS | 2014 | 1.100561e+12 | 3.73 | 72606.600 | 0.000000 |
| **5** | AUS | 2015 | 1.101457e+12 | 3.55 | 73809.376 | 0.000000 |
| **6** | AUS | 2016 | 1.143149e+12 | 3.46 | 79122.859 | 0.000000 |
| **7** | AUS | 2017 | 1.190694e+12 | 3.31 | 0.000 | 0.000000 |
| **8** | BGR | 2014 | 1.272635e+11 | 5.10 | 5412.492 | 0.109959 |
| **9** | BGR | 2015 | 1.320171e+11 | 3.95 | 5944.207 | 0.109980 |
| **10** | BGR | 2016 | 1.430866e+11 | 3.37 | 6153.226 | 0.109389 |
| **11** | BGR | 2017 | 1.519202e+11 | 3.03 | 0.000 | 0.108281 |
| **12** | CHE | 2014 | 5.249171e+11 | 3.43 | 6116.556 | 0.000000 |
| **13** | CHE | 2015 | 5.468055e+11 | 3.52 | 6530.927 | 0.000000 |

In [7]:

```
#Value normalization
dpfinal1 = dpfinal.iloc[:,2:]
dpfinal.iloc[:,2:] = (dpfinal1-dpfinal1.min())/ (dpfinal1.max() - dpfinal1.min())
dpfinal.head(6)
```

Out[7]:

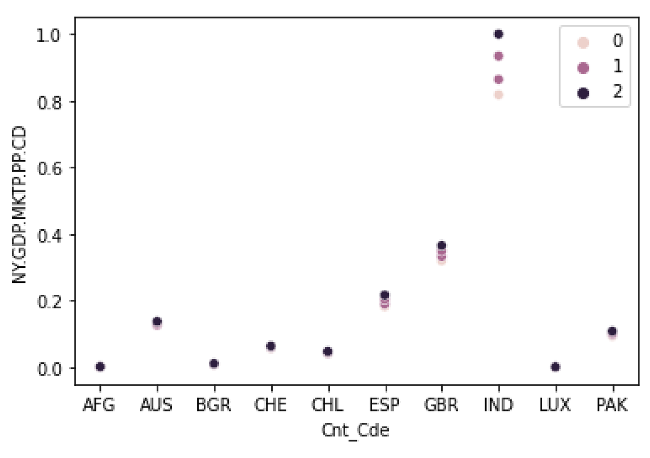
| series | Cnt_Cde | Year | NY.GDP.MKTP.PP.CD | SL.UEM.ADVN.ZS | EN.ATM.CO2E.GF.KT | EN.ATM.PM25.MC.T1.ZS |
|---|---|---|---|---|---|---|
| **0** | AFG | 2014 | 0.001275 | 0.468136 | 0.001707 | 0.998866 |
| **1** | AFG | 2015 | 0.001613 | 0.000000 | 0.001776 | 1.000000 |
| **2** | AFG | 2016 | 0.001402 | 0.000000 | 0.002007 | 0.998029 |
| **3** | AFG | 2017 | 0.001963 | 0.920786 | 0.000000 | 0.998281 |
| **4** | AUS | 2014 | 0.126787 | 0.222156 | 0.456758 | 0.000000 |
| **5** | AUS | 2015 | 0.126896 | 0.211435 | 0.464324 | 0.000000 |

In [11]:

```
#Clustering the full dataset with K-means
dp_value = dpfinal.drop('Cnt_Cde', axis = 1)
kmns = KMeans(n_clusters=3, init='k-means++', random_state=0).fit(dp_value)
```

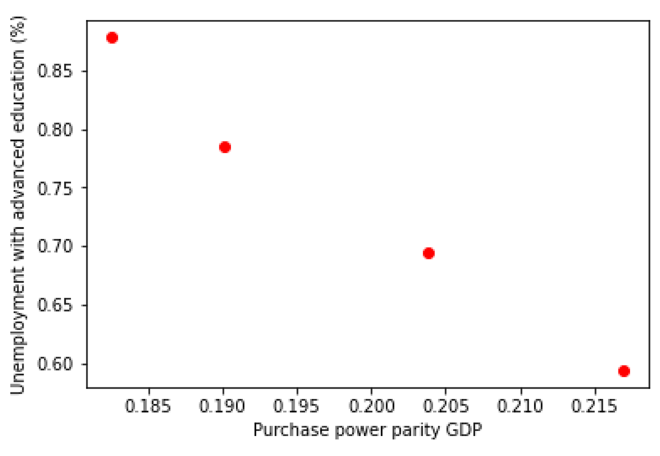
In [17]:

```
#Clustering based on GDP PPP
sns.scatterplot(data=dpfinal, x="Cnt_Cde", y="NY.GDP.MKTP.PP.CD", hue=kmns.labels_)
plt.legend(loc='best')
plt.show()
```




In [18]:

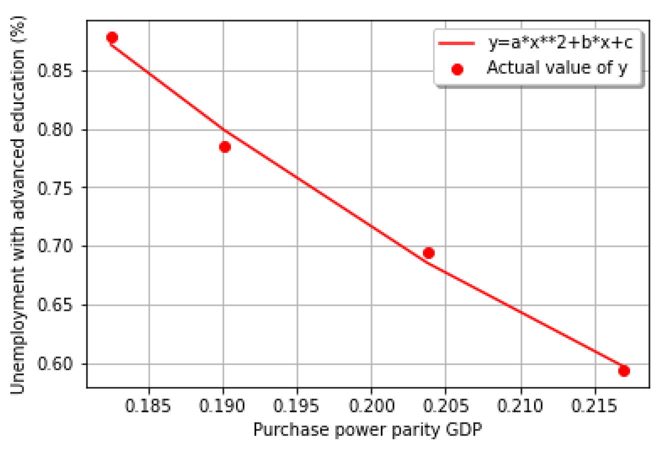
```
#Scatter plot to understand the relation between Unemployment with advanced education (%) and Purchase power parity GDP
ct=dpfinal[(dpfinal['Cnt_Cde']=='ESP')]
dat = ct.values
x, y = dat[:, 2], dat[:, 3]

plt.scatter(x, y,color="red")

plt.ylabel('Unemployment with advanced education (%)')
plt.xlabel('Purchase power parity GDP')
plt.show()
```




In [20]:

```
#Using curve_fit function
x, y = dat[:, 2], dat[:, 3]

def f(x, a, b, c):
    return a*x**2+b*x+c
parm, covr = curve_fit(f, x, y)
print("Covariance value is: ", covr)
print("Params value is: ", parm)
parm, _ = curve_fit(f, x, y)
a, b, c = parm[0], parm[1], parm[2]
yfit = a*x**2+b*x+c

with warnings.catch_warnings(record=True):
    plt.plot(x, yfit, label="y=a*x**2+b*x+c",color="red")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Actual value of y",color="red")
    plt.ylabel('Unemployment with advanced education (%)')
    plt.xlabel('Purchase power parity GDP')

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

    plt.show()
```

```
Covariance value is:  [[ 5154.98116235 -2060.39990878   204.97250741]
 [-2060.39990878   823.98254608   -82.01673938]
 [  204.97250741   -82.01673938     8.16826314]]
Params value is:  [ 59.57530596 -31.77329419   4.68615733]
```




In [83]:

```
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 [ ]: