NAME - Peesari

In [ ]:

```
pip install wbgapi
```

In [10]:

```
import pandas as pd
import wbgapi as wb
import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_blobs
from numpy import array, exp
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
```

In [2]:

```
ecnmy = ['NE.IMP.GNFS.ZS','NY.GDP.MKTP.PP.CD']
contry = ["JPN","AUS",'JAM','PAK','CHE','IND','CHL','GBR','LUX','BGR']
clim=['EN.ATM.CO2E.PC','EN.ATM.GHGT.KT.CE']
dat_ecnmy  = wb.data.DataFrame(ecnmy, contry, mrv=6)
dat_clim = wb.data.DataFrame(clim, contry, mrv=6)
#NE.IMP.GNFS.ZS: Import
#NY.GDP.MKTP.PP.CD: GDP, PPP basis
#EN.ATM.CO2E.PC: CO2 emissions calculated in metric tons per capita
#EN.ATM.GHGT.KT.CE: Greenhouse gas emission
```

In [3]:

```
# Ecnmy of countries
dat_ecnmy.columns = [a.replace('YR','') for a in dat_ecnmy.columns]
dat_ecnmy=dat_ecnmy.stack().unstack(level=1)
dat_ecnmy.index.names = ['Country_Code', 'Year']
dat_ecnmy.fillna(0)
dat_ecnmy.columns
dat_ecnmy.head(5)
```

Out[3]:

	series	NE.IMP.GNFS.ZS	NY.GDP.MKTP.PP.CD
Country_Code	**Year**		
AUS	**2015**	21.556339	1.101457e+12
	2016	21.547899	1.143149e+12
	2017	20.714438	1.190694e+12
	2018	21.512513	1.253361e+12
	2019	21.675312	1.312637e+12

In [4]:

```
# CLIMATE of cnries
dat_clim.columns = [a.replace('YR','') for a in dat_clim.columns]
dat_clim=dat_clim.stack().unstack(level=1)
dat_clim.index.names = ['Country_Code', 'Year']
dat_clim.fillna(0)
dat_clim.columns
dat_clim.head(5)
```

Out[4]:

	series	EN.ATM.CO2E.PC	EN.ATM.GHGT.KT.CE

Country_Code	Year	EN.ATM.CO2E.PC	EN.ATM.GHGT.KT.CE
Country_Code	**Year**		
AUS	**2013**	16.398646	581890.0
	2014	15.755876	593500.0
	2015	15.786449	594580.0
	2016	15.872080	573390.0
	2017	15.738647	619790.0

In [5]:
```
#Cleaning dataset
a=dat_ecnmy.reset_index()
b=dat_clim.reset_index()
c=a.fillna(0)
d=b.fillna(0)
```

In [6]:
```
#Merging the dataframes
e = pd.merge(c, d)
e.head(8)
```

Out[6]:

series	Country_Code	Year	NE.IMP.GNFS.ZS	NY.GDP.MKTP.PP.CD	EN.ATM.CO2E.PC	EN.ATM.GHGT.KT.CE
0	AUS	2015	21.556339	1.101457e+12	15.786449	594580.0
1	AUS	2016	21.547899	1.143149e+12	15.872080	573390.0
2	AUS	2017	20.714438	1.190694e+12	15.738647	619790.0
3	AUS	2018	21.512513	1.253361e+12	15.475516	615380.0
4	BGR	2015	62.900855	1.320171e+11	6.225976	57310.0
5	BGR	2016	58.963344	1.430866e+11	5.855926	54270.0
6	BGR	2017	62.682001	1.519202e+11	6.223902	56450.0
7	BGR	2018	63.155915	1.616873e+11	5.854773	53330.0

In [7]:
```
#Normalization of the dataset
f = e.iloc[:,2:]
e.iloc[:,2:] = (f-f.min())/ (f.max() - f.min())
e.head(10)
```

Out[7]:

series	Country_Code	Year	NE.IMP.GNFS.ZS	NY.GDP.MKTP.PP.CD	EN.ATM.CO2E.PC	EN.ATM.GHGT.KT.CE
0	AUS	2015	0.042463	0.119507	0.984073	0.174046
1	AUS	2016	0.042406	0.124138	0.989703	0.167751
2	AUS	2017	0.036792	0.129418	0.980929	0.181535
3	AUS	2018	0.042168	0.136378	0.963628	0.180225
4	BGR	2015	0.320952	0.011839	0.355441	0.014443
5	BGR	2016	0.294430	0.013069	0.331109	0.013540
6	BGR	2017	0.319478	0.014050	0.355304	0.014188

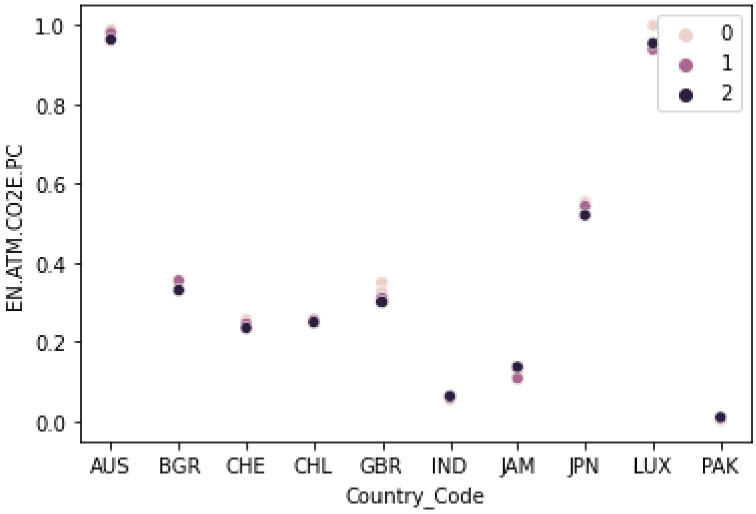
series	Country_Code	Year	NE.IMP.GNFS.ZS	NY.GDP.MKTP.PP.CD	EN.ATM.CO2E.PC	EN.ATM.GHGT.KT.CE
7	BGR	2018	0.322670	0.015134	0.331033	0.013261
8	CHE	2015	0.238941	0.057906	0.255918	0.011591
9	CHE	2016	0.261364	0.060512	0.257108	0.011734

In [8]:

```
#Clustering using K-means
e_v = e.drop('Country_Code', axis = 1)
km = KMeans(n_clusters=3, init='k-means++', random_state=0).fit(e_v)
```

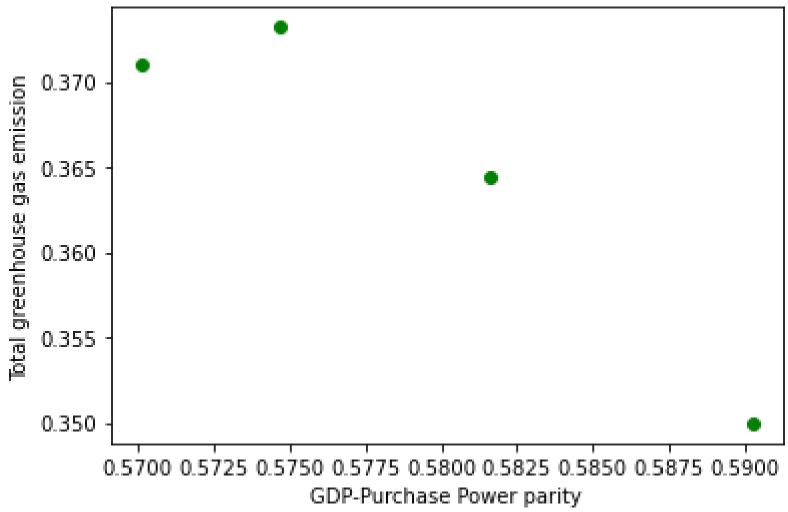
In [11]:

```
#Clustering based on carbon dioxide emission
sns.scatterplot(data=e, x="Country_Code", y="EN.ATM.CO2E.PC", hue=km.labels_)
plt.legend(loc='best')
plt.show()
```



In [12]:

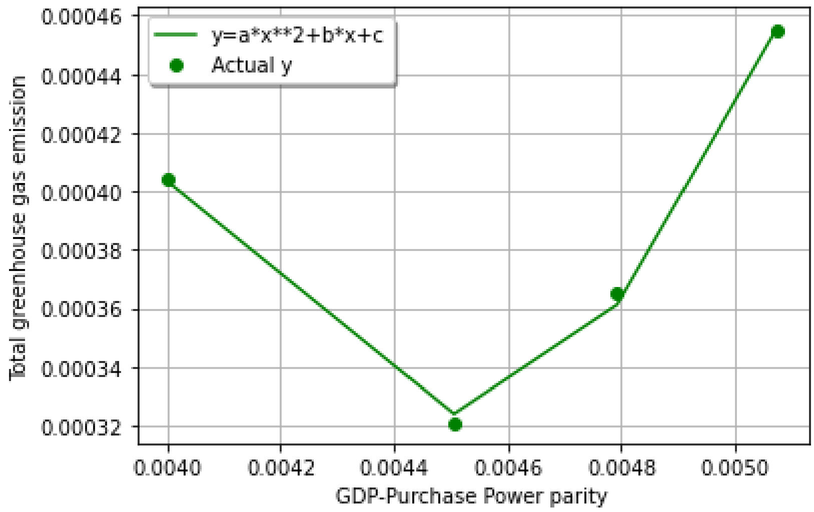
```
#Scatter plot for GDP, PPP vs greenshouse gas emission
import matplotlib.pyplot as plt
from scipy.optimize import curve_fit

t=e[(e['Country_Code']=='JPN')]
fn = t.values
x, y = fn[:, 3], fn[:, 5]

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

plt.ylabel('Total greenhouse gas emission')
plt.xlabel('GDP-Purchase Power parity')
plt.show()
```



In [15]:

```
#Implementing the curve_fit function for Luxembourg with high carbon dioxide emissions calcu
t1=e[(e['Country_Code']=='LUX')]
fn1 = t1.values

x, y = fn1[:, 3], fn1[:, 5]
def funct(x, a, b, c):
    return a*x**2+b*x+c
par, cova = curve_fit(funct, x, y)
print("The covariance is: ", cova)
print("The params is: ", par)
par, _ = curve_fit(funct, x, y)
a, b, c = par[0], par[1], par[2]
yfit = a*x**2+b*x+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yfit, label="y=a*x**2+b*x+c",color="green")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Actual y",color="green")
    plt.ylabel('Total greenhouse gas emission')
    plt.xlabel('GDP-Purchase Power parity')

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

    plt.show()
```

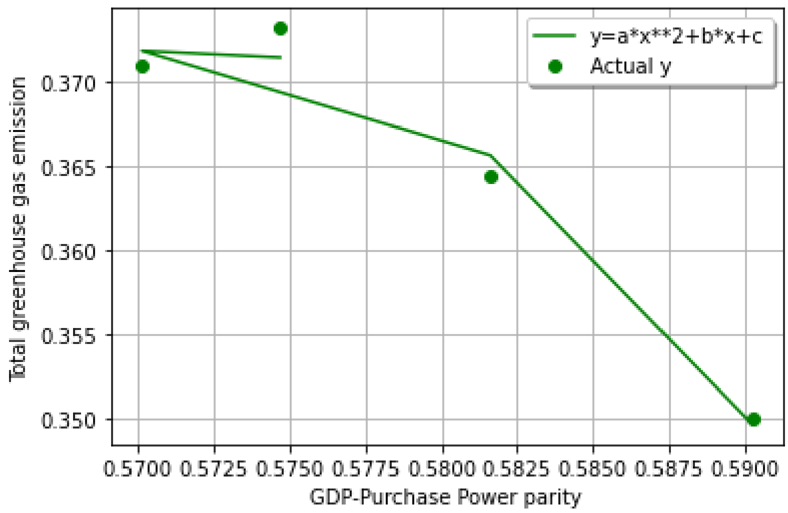
```
The covariance is:  [[ 4.43453597e+02 -4.01081013e+00  8.99678182e-03]
 [-4.01081013e+00  3.63226120e-02 -8.15866593e-05]
 [ 8.99678182e-03 -8.15866593e-05  1.83523300e-07]]
The params is:  [ 3.62225206e+02 -3.23817227e+00  7.56060712e-03]
```



In [13]:

```
#Implementing the curve_fit function for Japan with medium carbon dioxide emissions calculat
x, y = fn[:, 3], fn[:, 5]
def funct(x, a, b, c):
    return a*x**2+b*x+c
par, cova = curve_fit(funct, x, y)
print("The covariance is: ", cova)
print("The params is: ", par)
par, _ = curve_fit(funct, x, y)
a, b, c = par[0], par[1], par[2]
yfit = a*x**2+b*x+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yfit, label="y=a*x**2+b*x+c",color="green")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Actual y",color="green")
    plt.ylabel('Total greenhouse gas emission')
    plt.xlabel('GDP-Purchase Power parity')

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

    plt.show()
```

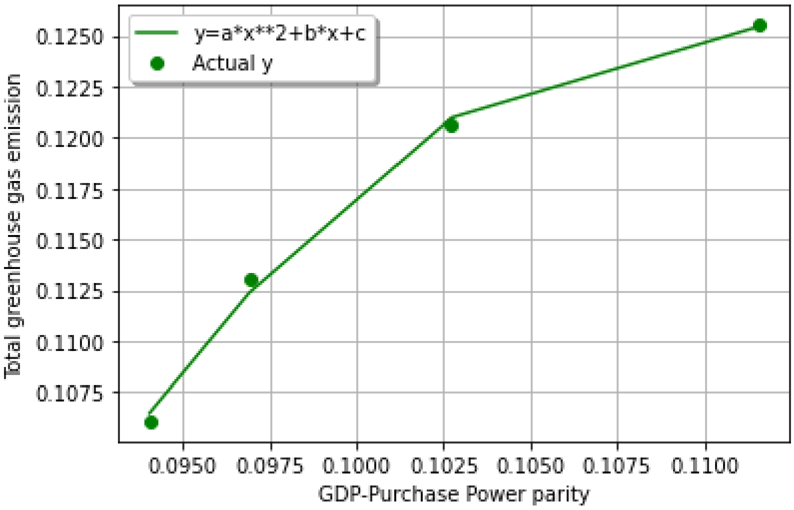
```
The covariance is:  [[ 717.57172341 -832.8805006   241.63739919]
 [-832.8805006   966.74221363 -280.4805251 ]
 [ 241.63739919 -280.4805251    81.37767521]]
The params is:  [-65.59146993  75.00451338 -21.07007305]
```



In [17]:

```
#Implementing the curve_fit function for Pakistan with low carbon dioxide emissions calculat
t2=e[(e['Country_Code']=='PAK')]
fn2 = t2.values

x, y = fn2[:, 3], fn2[:, 5]
def funct(x, a, b, c):
    return a*x**2+b*x+c
par, cova = curve_fit(funct, x, y)
print("The covariance is: ", cova)
print("The params is: ", par)
par, _ = curve_fit(funct, x, y)
a, b, c = par[0], par[1], par[2]
yfit = a*x**2+b*x+c

import warnings

with warnings.catch_warnings(record=True):
    plt.plot(x, yfit, label="y=a*x**2+b*x+c",color="green")
    plt.grid(True)
    plt.plot(x, y, 'bo', label="Actual y",color="green")
    plt.ylabel('Total greenhouse gas emission')
    plt.xlabel('GDP-Purchase Power parity')

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

    plt.show()
```

```
The covariance is:  [[ 1.99756088e+02 -4.11562051e+01  2.11032838e+00]
 [-4.11562051e+01  8.48408323e+00 -4.35259389e-01]
 [ 2.11032838e+00 -4.35259389e-01  2.23417916e-02]]
The params is:  [-66.23932602  14.70060092  -0.6901669 ]
```



From the above line graph visualisations it can be concluded that for country with high carbon dioxide emissions, the relationship between total greenhouse emissions and purchase power parity, GDP is indirect at the beginning and after a certain value of purchase power parity, GDP the relationship is direct. For the country with medium carbon dioxide emissions,the relationship between total greenhouse emissions and purchase power parity, GDP is indirect. For the country with low carbon dioxide emissions the relationship between total greenhouse emissions and purchase power parity, GDP is direct.

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 [ ]:

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In [ ]:

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