Actividad: Análisis exploratorio con técnicas de agrupamiento

Links del Colab: https://colab.research.google.com/drive/1R3Er-mSuHdAurw9B--pi9RDczNQG_jbs?usp=sharing

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs
from sklearn.metrics import silhouette_score
from sklearn.cluster import SpectralClustering
from sklearn.metrics import adjusted_rand_score
from sklearn.metrics import davies_bouldin_score
from sklearn.metrics import calinski_harabasz_score
```

```
data0 = pd.read_csv("/content/drive/MyDrive/7mo Semestre/Colab Notebooks/DataSources/Country-data.csv")
data0
```

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200
...	...	...	...	...	...	...	...	...	...	...
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460

167 rows × 10 columns

```
data = data0.drop('country', axis = 1)
```

1. Aplica k-medias sobre el conjunto de datos para generar un agrupamiento para los países de la base de datos. Utiliza al menos dos métodos para estimar el número óptimo de grupos.

Número Óptimo de clusters (Elbow method y Davies-Bouldin index)

```
# Optimal number of clusters
sum_of_squared_distances = []
sscore = []
chscore = []
dbscore = []

ks = np.arange(2, 21)
for k in ks:
    # Find clustering model
    kmeans = KMeans(n_clusters=k).fit(data)

    # Evaluate sum of squared distances
    sum_of_squared_distances.append(kmeans.inertia_)

    # Evaluate Davies-Bouldin index
    dbscore.append(davies_bouldin_score(data, kmeans.labels_))
```

```
fig, (axs1, axs2) = plt.subplots(2)

axs1.plot(ks, sum_of_squared_distances)
axs1.set_xlabel('Number of clusters')
axs1.set_ylabel('Sum of squared distances (lower is better)')
axs1.set_title('Elbow method')
axs1.set_xticks(ks)

axs2.plot(ks, dbscore)
axs2.set_xlabel('Number of clusters')
axs2.set_ylabel('Score (lower is better)')
axs2.set_title('Davies-Bouldin index')
axs2.set_xticks(ks)

plt.show()
```

```
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  warnings.warn(
```

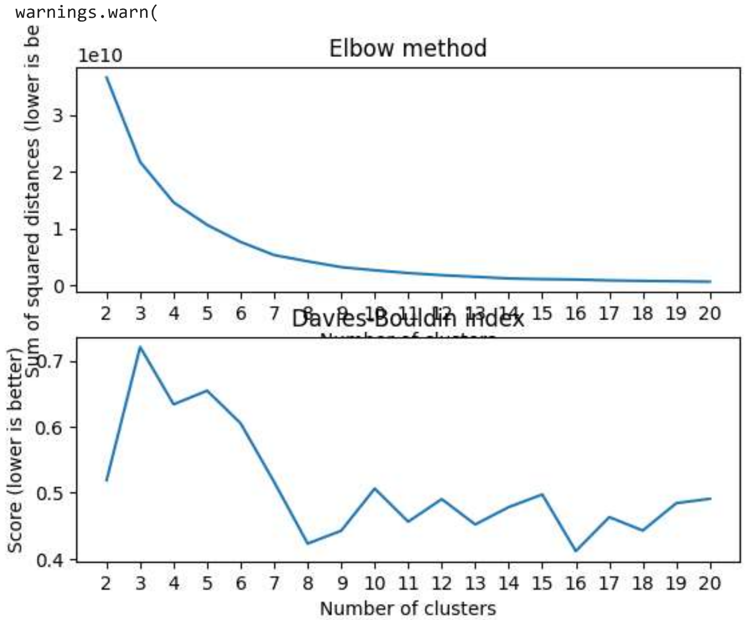

Si observamos detenidamente, notaremos que ambas metricas nos indican que el numero más óptimo de clusters es entre 7 y 8 clusters. Así que esa utilizaremos 8 clusters:

```
kmeans = KMeans(n_clusters=8).fit(data)
clustering_labels = kmeans.labels_
centers = kmeans.cluster_centers_

print('Labels: ', clustering_labels)
print('Centers: ', centers)
```

```
Labels:  [1 1 2 1 2 2 1 0 0 2 5 5 1 2 2 0 1 1 1 1 1 2 2 4 2 1 1 1 1 0 1 1 1 2 1 2 1
 1 1 2 1 2 5 5 0 2 1 1 1 5 1 2 1 0 0 2 1 1 0 1 5 2 1 1 1 1 1 2 0 1 1 2 2 0
 5 0 1 0 1 2 1 1 4 1 1 2 2 1 1 5 2 3 2 1 1 2 2 1 5 1 2 1 1 1 2 1 1 1 1 1 0
 5 1 1 7 5 1 2 1 1 1 2 5 6 2 2 1 1 5 1 2 2 1 4 5 5 1 2 5 5 1 2 1 2 0 7 1 1
 2 1 1 1 1 2 1 1 1 4 0 0 2 1 1 2 1 1 1]
Centers:  [[4.29375000e+00 4.31437500e+01 1.07662500e+01 4.01312500e+01
  4.11250000e+04 1.09125000e+00 8.08062500e+01 1.79625000e+00
  4.61125000e+04]
 [6.30642857e+01 3.10392738e+01 6.14821429e+00 4.59448321e+01
  4.32670238e+03 9.84197619e+00 6.49273810e+01 3.89309524e+00
  1.94778571e+03]
 [1.77357143e+01 4.38476190e+01 6.69952381e+00 4.52071429e+01
  1.61576190e+04 7.26590476e+00 7.33880952e+01 2.06785714e+00
  8.94761905e+03]
 [2.80000000e+00 1.75000000e+02 7.77000000e+00 1.42000000e+02
  9.17000000e+04 3.62000000e+00 8.13000000e+01 1.63000000e+00
  1.05000000e+05]
 [8.17500000e+00 1.02950000e+02 3.27250000e+00 7.40000000e+01
  7.13750000e+04 1.00885000e+01 7.86250000e+01 1.76750000e+00
  3.88500000e+04]
 [1.34058824e+01 5.72470588e+01 7.32235294e+00 5.21705882e+01
  3.19470588e+04 5.47005882e+00 7.73647059e+01 2.08588235e+00
  2.32176471e+04]
 [9.00000000e+00 6.23000000e+01 1.81000000e+00 2.38000000e+01
  1.25000000e+05 6.98000000e+00 7.95000000e+01 2.07000000e+00
  7.03000000e+04]
 [3.85000000e+00 5.18500000e+01 1.04900000e+01 4.09000000e+01
  5.89000000e+04 3.13350000e+00 8.16000000e+01 1.73500000e+00
  8.12000000e+04]]
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
  warnings.warn(
```

```
labels = pd.DataFrame(clustering_labels)
data_km = pd.concat([data0, labels], axis = 1)
data_km
```

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	0
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553	1
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090	1
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460	2
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530	1
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200	2
...	...	...	...	...	...	...	...	...	...	...	...
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970	1
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500	2
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310	1
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310	1
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460	1

167 rows × 11 columns

```
for j in range(8):
  print('\nCluster: ', j, '\nPaises:')
  for i in range(len(data_km)):
    if data_km.iloc[i][0] == j:
      print('\t', data_km.iloc[i]['country'])
```

```
        Mauritius
        Montenegro
        Panama
        Poland
        Romania
        Russia
        Serbia
        Seychelles
        South Africa
        St. Vincent and the Grenadines
        Suriname
        Thailand
        Turkey
        Uruguay
        Venezuela

Cluster:  3
Paises:
        Luxembourg

Cluster:  4
Paises:
        Brunei
        Kuwait
        Singapore
        United Arab Emirates

Cluster:  5
Paises:
        Bahamas
        Bahrain
        Cyprus
        Czech Republic
        Equatorial Guinea
        Greece
        Israel
        Libya
        Malta
        New Zealand
        Oman
        Portugal
        Saudi Arabia
        Slovak Republic
        Slovenia
        South Korea
        Spain

Cluster:  6
Paises:
        Qatar

Cluster:  7
Paises:
        Norway
        Switzerland
```

2. Repita lo anterior, pero con otro método de agrupamiento que elijas.

Utilizaremos Spectral Clustering (Silhouette score y Davies-Bouldin index):

```
sum_of_squared_distances = []
sscore = []
chscore = []
dbscore = []

ks = np.arange(2, 21)
for k in ks:
    # Find clustering model
    spectral = SpectralClustering(n_clusters=k).fit(data)

    # Evaluate Silhouette score
    sscore.append(silhouette_score(data, spectral.labels_))

    # Evaluate Davies-Bouldin index
    dbscore.append(davies_bouldin_score(data, spectral.labels_))

fig, (axs1, axs2) = plt.subplots(2)

axs1.plot(ks, sscore)
axs1.set_xlabel('Number of clusters')
axs1.set_ylabel('Score (greater is better)')
axs1.set_title('Silhouette Coefficient')
axs1.set_xticks(ks)
```

```
axs2.plot(ks, dbscore)
axs2.set_xlabel('Number of clusters')
axs2.set_ylabel('Score (lower is better)')
axs2.set_title('Davies-Bouldin index')
axs2.set_xticks(ks)

plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/manifold/_spectral_embedding.py:274: UserWarning: Graph is not fully connected, spe
  warnings.warn(
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/usr/local/lib/python3.10/dist-packages/sklearn/manifold/_spectral_embedding.py:274: UserWarning: Graph is not fully connected, spe
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```
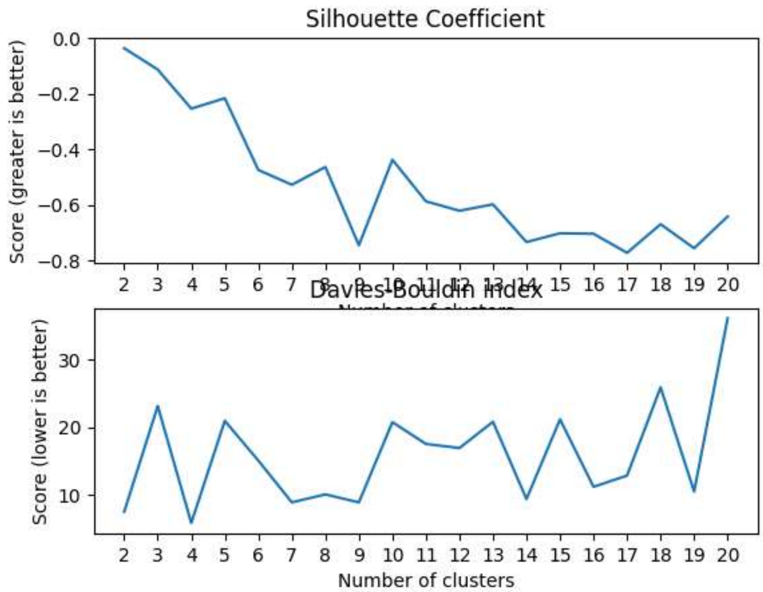



Nuestras dos metricas esta vez estan en cierto desacuerdo. Silhouette indica que lo mejor es 2 o 4; y Davies-Bouldin indica que lo mejor es 6 o 9. En mi opinion, no hay mucho cambio entre el 6 y el 9 de Davies-Boudin, así que eligiré 6 clusters por ser la menor cantidad y estar muy cerca del promedio de los mejores valores de cada métrica.

```
spectral = SpectralClustering(n_clusters=6).fit(data)
clustering_labels = spectral.labels_
print('Labels: ', clustering_labels)
```

```
Labels:  [0 0 5 5 0 0 0 0 3 2 4 0 5 0 0 1 4 5 2 0 5 0 2 5 2 0 5 5 5 0 0 0 0 5 0 5 0
 2 5 4 2 0 0 4 0 3 0 0 4 5 0 0 3 0 5 0 4 5 5 0 0 0 0 0 4 2 5 5 0 5 0 2 0 5
 5 5 0 0 0 5 5 5 2 0 0 0 0 2 3 0 5 5 0 5 0 0 2 0 0 0 0 3 3 0 0 2 3 5 1 2 5
 0 1 0 0 5 5 5 0 0 3 0 2 3 5 5 0 0 0 0 2 0 3 5 5 1 0 0 0 5 0 5 5 0 0 5 0 0
 0 0 0 5 3 0 0 5 3 0 0 0 5 0 5 0 1 0 0]
/usr/local/lib/python3.10/dist-packages/sklearn/manifold/_spectral_embedding.py:274: UserWarning: Graph is not fully connected, spe
  warnings.warn(
```

```
labels = pd.DataFrame(clustering_labels)
data_spec = pd.concat([data0, labels], axis = 1)
data_spec
```

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	0
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553	0
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090	0
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460	5
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530	5
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200	0
...	...	...	...	...	...	...	...	...	...	...	...
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970	5
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500	0
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310	1
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310	0
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460	0

167 rows × 11 columns

```
for j in range(6):
  print('\nCluster: ', j, '\nPaises:')
  for i in range(len(data_spec)):
```

```
    if data_spec.iloc[i][0] == j:
      print('\t', data_spec.iloc[i]['country'])
```

```
Cluster:  4
Paises:
         Bahamas
         Belize
         Costa Rica
         Czech Republic
         El Salvador
         Gambia
         Guinea-Bissau

Cluster:  5
Paises:
         Algeria
         Angola
         Bangladesh
         Benin
         Bosnia and Herzegovina
         Brunei
         Burundi
         Cambodia
         Cameroon
         Chile
         Colombia
         Congo, Rep.
         Equatorial Guinea
         France
         Georgia
         Germany
         Haiti
         Hungary
         India
         Ireland
         Israel
         Italy
         Kazakhstan
         Kenya
         Kiribati
         Lithuania
         Luxembourg
         Madagascar
         Myanmar
         Netherlands
         Oman
         Pakistan
         Panama
         Romania
         Russia
         Singapore
         Slovak Republic
         Spain
         St. Vincent and the Grenadines
         Sudan
         Switzerland
         Tonga
         Uganda
         Uruguay
         Vanuatu
```

3. Investiga qué librerías hay en Python para la implementación de mapas autoorganizados, y selecciona alguna para el agrupamiento de los datos de este ejercicio.

```
pip install -U som-learn
```

```
Requirement already satisfied: som-learn in /usr/local/lib/python3.10/dist-packages (0.1.1)
Requirement already satisfied: scipy>=0.17 in /usr/local/lib/python3.10/dist-packages (from som-learn) (1.10.1)
Requirement already satisfied: numpy>=1.1 in /usr/local/lib/python3.10/dist-packages (from som-learn) (1.23.5)
Requirement already satisfied: scikit-learn>=0.21 in /usr/local/lib/python3.10/dist-packages (from som-learn) (1.2.2)
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.10/dist-packages (from som-learn) (3.7.1)
Requirement already satisfied: somoclu==1.7.5 in /usr/local/lib/python3.10/dist-packages (from som-learn) (1.7.5)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (1.1.0
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (4.42
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (1.4.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (23.1)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (3.1.1
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->som-learn) (2
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.21->som-learn) (1.3.2
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.21->som-learn)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=3.0->som
```

```
from somlearn import SOM


som = SOM(n_columns=2, n_rows=2, random_state=1)
labels = som.fit_predict(data)
print(labels)
```

```
[1 0 0 1 0 0 0 2 2 0 2 2 0 0 0 2 0 1 0 0 0 3 0 2 0 1 1 3 1 2 0 1 1 0 0 0 1
 1 1 0 1 0 2 2 2 0 0 0 0 1 1 2 0 2 2 1 1 0 2 1 2 0 3 1 1 3 1 2 2 0 0 0 3 2
 2 2 0 2 3 0 1 3 2 3 1 0 0 1 1 0 0 2 0 1 1 0 0 1 2 1 0 3 0 0 0 0 1 0 3 0 2
 2 1 1 2 0 1 0 0 0 0 0 2 2 0 0 1 3 0 1 0 0 1 2 2 2 3 3 2 2 0 0 1 0 2 2 3 1
 0 1 1 3 0 0 0 1 0 2 2 2 0 0 3 0 0 1 1]
```

```
labels = pd.DataFrame(labels)
data_som = pd.concat([data0, labels], axis = 1)
data_som
```

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	0
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553	1
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090	0
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460	0
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530	1
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200	0
...	...	...	...	...	...	...	...	...	...	...	...
162	Vanuatu	29.2	46.6	5.25	52.7	2950	2.62	63.0	3.50	2970	3
163	Venezuela	17.1	28.5	4.91	17.6	16500	45.90	75.4	2.47	13500	0
164	Vietnam	23.3	72.0	6.84	80.2	4490	12.10	73.1	1.95	1310	0
165	Yemen	56.3	30.0	5.18	34.4	4480	23.60	67.5	4.67	1310	1
166	Zambia	83.1	37.0	5.89	30.9	3280	14.00	52.0	5.40	1460	1

167 rows × 11 columns

```
data_som[0].unique()
```

```
array([1, 0, 2, 3])
```

+ Code + Text

```
for j in range(4):
  print('\nCluster: ', j, '\nPaises:')
  for i in range(len(data_som)):
    if data_som.iloc[i][0] == j:
      print('\t', data_som.iloc[i]['country'])
```

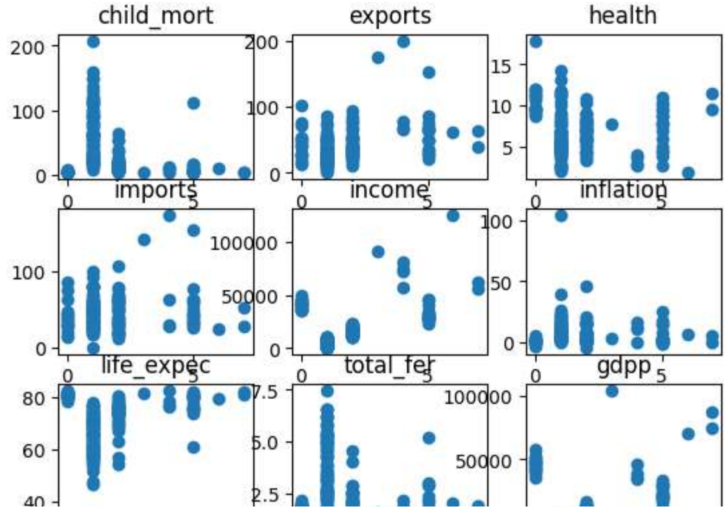
```
Cluster:  0
Paises:
         Albania
         Algeria
         Antigua and Barbuda
         Argentina
         Armenia
         Azerbaijan
         Bangladesh
         Barbados
         Belarus
         Belize
         Bhutan
         Bolivia
         Bosnia and Herzegovina
```

```
            Brazil
            Bulgaria
            Cape Verde
            Chile
            China
            Colombia
            Costa Rica
            Croatia
            Dominican Republic
            Ecuador
            Egypt
            El Salvador
            Fiji
            Georgia
            Grenada
            India
            Indonesia
            Iran
            Jamaica
            Kazakhstan
            Latvia
            Lebanon
            Libya
            Lithuania
            Macedonia, FYR
            Malaysia
            Maldives
            Mauritius
            Moldova
            Mongolia
            Montenegro
            Morocco
            Myanmar
            Nepal
            Oman
            Panama
            Paraguay
            Peru
            Philippines
            Poland
            Romania
            Russia
```

4. De los resultados que se obtienen del agrupamiento, indica si los grupos formados siguen algun patrón que esperabas, o tiene información nueva que no hayas considerado anteriormente.

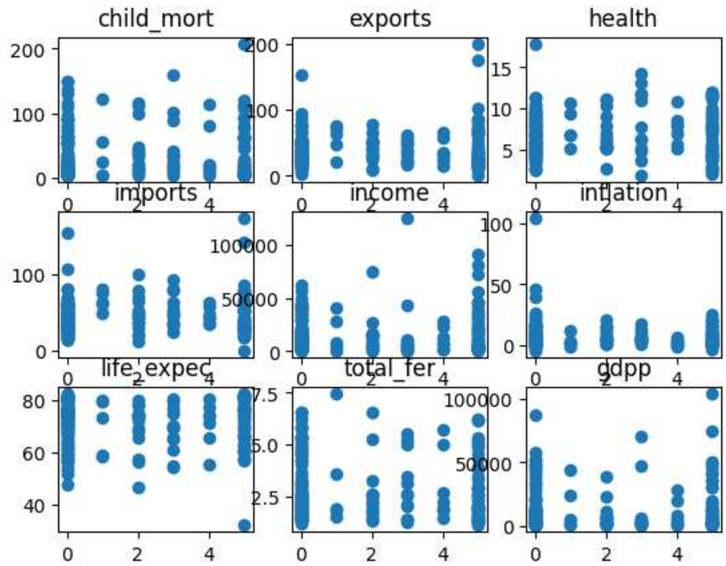
Graficamos por los grupos de kmeans:

```
fig, axs = plt.subplots(3, 3)

axs[0][0].scatter( data_km[0], data_km['child_mort'])
axs[0][0].set_title('child_mort')

axs[0][1].scatter( data_km[0], data_km['exports'])
axs[0][1].set_title('exports')

axs[0][2].scatter( data_km[0], data_km['health'])
axs[0][2].set_title('health')

axs[1][0].scatter( data_km[0], data_km['imports'])
axs[1][0].set_title('imports')

axs[1][1].scatter( data_km[0], data_km['income'])
axs[1][1].set_title('income')

axs[1][2].scatter( data_km[0], data_km['inflation'])
axs[1][2].set_title('inflation')

axs[2][0].scatter( data_km[0], data_km['life_expec'])
axs[2][0].set_title('life_expec')

axs[2][1].scatter( data_km[0], data_km['total_fer'])
axs[2][1].set_title('total_fer')

axs[2][2].scatter( data_km[0], data_km['gdpp'])
axs[2][2].set_title('gdpp')

plt.show()
```



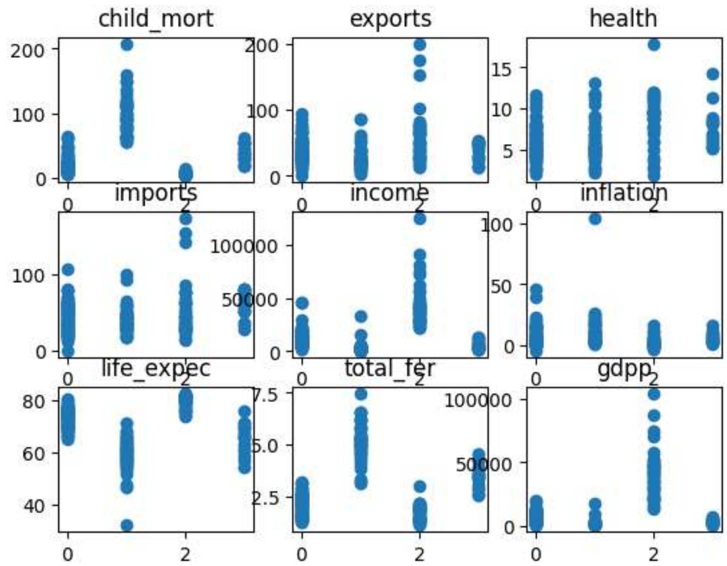
Graficamos por los grupos de spectral:

```
fig, axs = plt.subplots(3, 3)

axs[0][0].scatter( data_spec[0], data_spec['child_mort'])
axs[0][0].set_title('child_mort')

axs[0][1].scatter( data_spec[0], data_spec['exports'])
axs[0][1].set_title('exports')

axs[0][2].scatter( data_spec[0], data_spec['health'])
axs[0][2].set_title('health')

axs[1][0].scatter( data_spec[0], data_spec['imports'])
axs[1][0].set_title('imports')

axs[1][1].scatter( data_spec[0], data_spec['income'])
axs[1][1].set_title('income')

axs[1][2].scatter( data_spec[0], data_spec['inflation'])
axs[1][2].set_title('inflation')

axs[2][0].scatter( data_spec[0], data_spec['life_expec'])
axs[2][0].set_title('life_expec')

axs[2][1].scatter( data_spec[0], data_spec['total_fer'])
axs[2][1].set_title('total_fer')

axs[2][2].scatter( data_spec[0], data_spec['gdpp'])
axs[2][2].set_title('gdpp')

plt.show()
```



Graficamos por los grupos de SOM:

```
fig, axs = plt.subplots(3, 3)

axs[0][0].scatter( data_som[0], data_som['child_mort'])
axs[0][0].set_title('child_mort')

axs[0][1].scatter( data_som[0], data_som['exports'])
axs[0][1].set_title('exports')

axs[0][2].scatter( data_som[0], data_som['health'])
axs[0][2].set_title('health')

axs[1][0].scatter( data_som[0], data_som['imports'])
axs[1][0].set_title('imports')

axs[1][1].scatter( data_som[0], data_som['income'])
axs[1][1].set_title('income')

axs[1][2].scatter( data_som[0], data_som['inflation'])
axs[1][2].set_title('inflation')

axs[2][0].scatter( data_som[0], data_som['life_expec'])
axs[2][0].set_title('life_expec')

axs[2][1].scatter( data_som[0], data_som['total_fer'])
axs[2][1].set_title('total_fer')

axs[2][2].scatter( data_som[0], data_som['gdpp'])
axs[2][2].set_title('gdpp')

plt.show()
```



Los 3 agrupamientos generaron resultados que medianamente muestran un ligero patrón. Pero el que parece que establece más clara una diferencia entre sus valores es el agrupamiento del SOM.

Podemos ver que los paises del grupo 2 de SOM, son los que tienen mas ingresos, exportaciones, gdpp (PIB), expectativa de vida, importaciones; y así mismo son los que menos inflación, mortalidad infantil, y fertilidad; todos estos tienden a ser caracteristicas de paises del primer mundo.

Así que podríamos decir que este agrupamiento mide o relaciona los grupos con el desarrollo de los paises de cada grupo. Claro que no es algo polarizado, pero parece tener esa tendencia.

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