

```
pip install minisom

Collecting minisom
  Downloading MiniSom-2.3.1.tar.gz (10 kB)
  Preparing metadata (setup.py) ... inisom
  Building wheel for minisom (setup.py) ... inisom: filename=MiniSom-
2.3.1-py3-none-any.whl size=10588
sha256=de5e34c4879e34c0681bf83c62ac3cf6e4f7f1d26ac43317c5e70104fe9e452
c
  Stored in directory:
/root/.cache/pip/wheels/c7/92/d2/33bbda5f86fd8830510b16aa98c8dd420129b
5cb24248fd6db
Successfully built minisom
Installing collected packages: minisom
Successfully installed minisom-2.3.1

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from minisom import MiniSom

# clustering methods
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import SpectralClustering
from sklearn.cluster import OPTICS
from sklearn.cluster import DBSCAN

from scipy.cluster.hierarchy import dendrogram, linkage

# Metrics for evaluating clustering results
from sklearn.metrics import adjusted_rand_score
from sklearn.metrics import silhouette_score
from sklearn.metrics import calinski_harabasz_score
from sklearn.metrics import davies_bouldin_score

# Distance metrics
from sklearn.metrics import pairwise_distances

##### Helper function for plotting #####
def plot_data(points, labels, title):
    fig = plt.figure()
    if points.shape[1] > 2:
        ax = fig.add_subplot(projection='3d')
        ax.scatter(points[:,0], points[:,1], points[:,2], c=labels,
cmap='viridis')
        ax.set_xlabel('X')
        ax.set_ylabel('Y')
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        ax.set_zlabel('Z')
        ax.set_title(title)
    else:
        plt.scatter(points[:,0], points[:,1], c=labels,
cmap='viridis')
        plt.xlabel('X')
        plt.ylabel('Y')
        plt.title(title)

    plt.show()

df = pd.read_csv('/content/Country-data.csv')

points = df.iloc[:,1:].to_numpy()
label = df.country.to_numpy()

```

k-medias sobre el conjunto de datos para el agrupamiento de los países de la base de datos.

```

##### K-means #####
print('----- K-means -----')

kmeans = KMeans(n_clusters=10).fit(points)
clustering_labels = kmeans.labels_
centers = kmeans.cluster_centers_

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

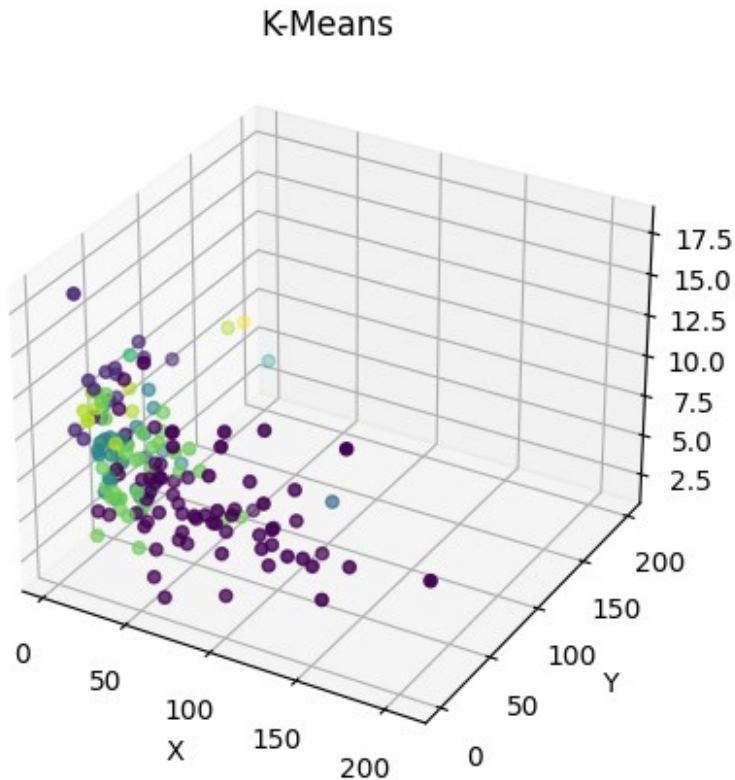
plot_data(points, clustering_labels, 'K-Means')

----- K-means -----
Labels:  [0 7 7 0 4 4 0 1 1 7 8 3 0 4 7 1 7 0 0 0 7 7 4 5 7 0 0 0 0 1
0 0 0 4 7 7 0
0 0 7 0 4 8 8 1 7 7 7 0 3 0 4 0 1 1 7 0 0 1 0 8 7 0 0 0 0 4 1 0 7 7
7 1
8 8 7 1 7 4 0 0 5 0 0 4 4 0 0 4 4 9 7 0 0 4 7 0 8 0 7 0 0 0 7 0 0 0 7
0 1
8 0 0 6 3 0 7 0 7 0 4 8 2 4 4 0 0 3 0 7 4 0 5 4 8 0 7 8 8 7 7 0 7 1 6
0 0
7 0 0 0 7 4 7 0 0 5 1 1 4 0 0 4 0 0 0]
Centers:  [[7.06542857e+01 2.98571286e+01 6.24057143e+00
4.66895129e+01
3.34218571e+03 1.03349429e+01 6.33071429e+01 4.17557143e+00
1.50977143e+03]
[4.31333333e+00 4.43400000e+01 1.08486667e+01 4.09933333e+01
4.14533333e+04 1.14273333e+00 8.07466667e+01 1.81866667e+00
4.68000000e+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]

```

```
[3.67500000e+01 6.76500000e+01 4.12750000e+00 4.60000000e+01  
4.13750000e+04 1.62850000e+01 7.20250000e+01 3.30750000e+00  
1.91000000e+04]  
[1.13363636e+01 4.75227273e+01 6.53681818e+00 4.69000000e+01  
1.99318182e+04 7.32650000e+00 7.51181818e+01 1.86272727e+00  
1.18740909e+04]  
[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]  
[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]  
[2.41861111e+01 4.04250000e+01 6.38472222e+00 4.38305556e+01  
1.17891667e+04 7.27638889e+00 7.23250000e+01 2.34555556e+00  
5.58888889e+03]  
[5.10833333e+00 4.88250000e+01 8.73583333e+00 5.08500000e+01  
2.99166667e+04 1.12375000e+00 7.97666667e+01 1.65416667e+00  
2.71166667e+04]  
[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]]
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/  
_kmeans.py:870: FutureWarning: The default value of `n_init` will  
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly  
to suppress the warning  
warnings.warn(
```



Número optimo de parametros con metodo del codo, y metodo de silueta

```
# 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(points)

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

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

fig, axs = plt.subplots(2)

axs[0].plot(ks, sum_of_squared_distances)
axs[0].set_xlabel('Number of clusters')
axs[0].set_ylabel('Sum of squared distances (lower is better)')
axs[0].set_title('Elbow method')
```

```
axs[0].set_xticks(ks)
```

```

axs[1].plot(ks, dbscore)
axs[1].set_xlabel('Number of clusters')
axs[1].set_ylabel('Score (lower is better)')
axs[1].set_title('Davies-Bouldin index')
axs[1].set_xticks(ks)

```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
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warnings.warn(  
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870  
: FutureWarning: The default value of `n_init` will change from 10 to  
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the  
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warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
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```

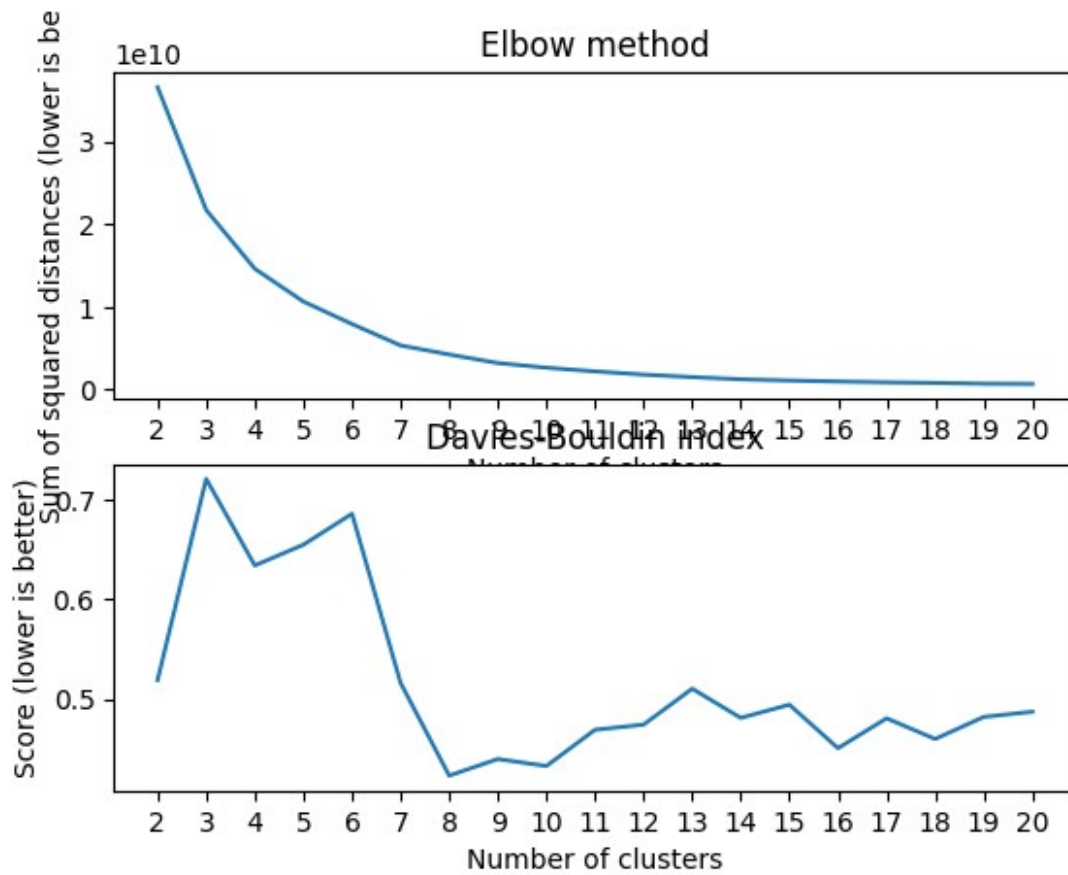
```
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
```

[illegible]

```
: FutureWarning: The default value of `n_init` will change from 10 to  
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the  
warning
```

```
warnings.warn(
```

```
[<matplotlib.axis.XTick at 0x7ae95d1aae00>,  
<matplotlib.axis.XTick at 0x7ae95d1aadd0>,  
<matplotlib.axis.XTick at 0x7ae95d1aace0>,  
<matplotlib.axis.XTick at 0x7ae95d023d00>,  
<matplotlib.axis.XTick at 0x7ae95d0447f0>,  
<matplotlib.axis.XTick at 0x7ae95d0452a0>,  
<matplotlib.axis.XTick at 0x7ae95d00ddb0>,  
<matplotlib.axis.XTick at 0x7ae95d045d50>,  
<matplotlib.axis.XTick at 0x7ae95d046800>,  
<matplotlib.axis.XTick at 0x7ae95d0472b0>,  
<matplotlib.axis.XTick at 0x7ae95d047d60>,  
<matplotlib.axis.XTick at 0x7ae95d046290>,  
<matplotlib.axis.XTick at 0x7ae95d0587c0>,  
<matplotlib.axis.XTick at 0x7ae95d059270>,  
<matplotlib.axis.XTick at 0x7ae95d059d50>,  
<matplotlib.axis.XTick at 0x7ae95d05a830>,  
<matplotlib.axis.XTick at 0x7ae95d059480>,  
<matplotlib.axis.XTick at 0x7ae95d05b130>,  
<matplotlib.axis.XTick at 0x7ae95d05bbe0>]
```



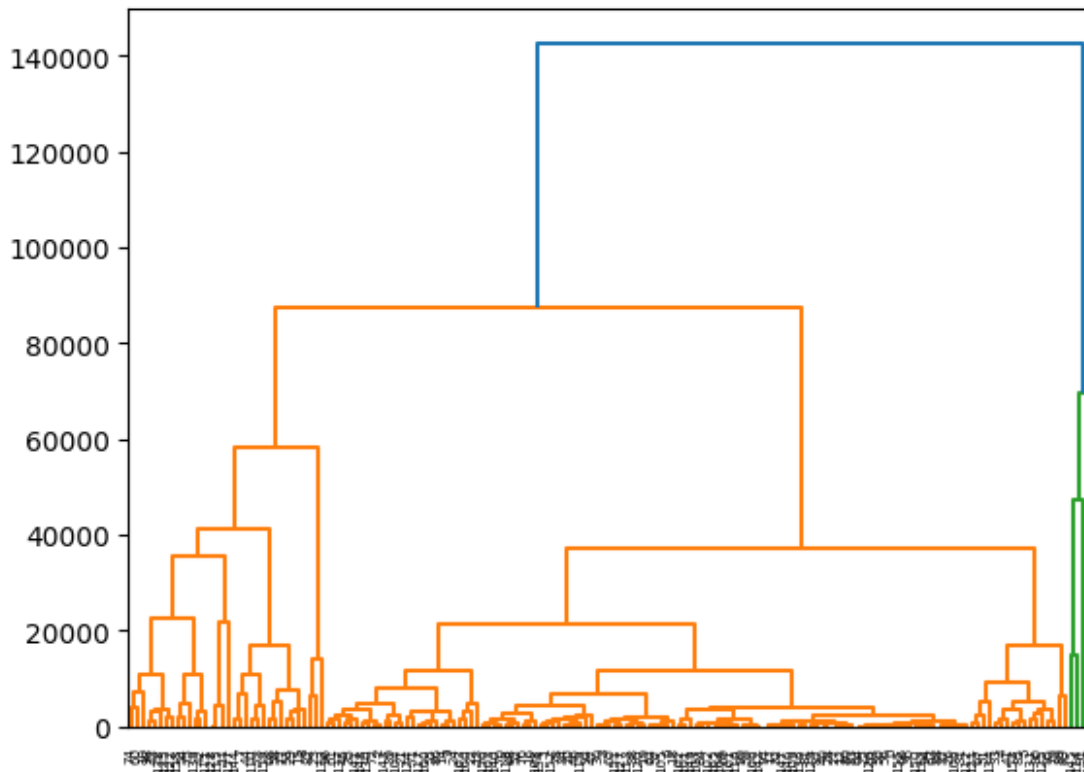
Agrupamiento por otros metodos

```
##### Dendrogram plot #####
print('----- Dendrogram plot -----')

linked = linkage(points, 'complete')
labelList = range(1, 11)

plt.figure()
dendrogram(linked, orientation='top', distance_sort='descending',
show_leaf_counts=True)
plt.show()

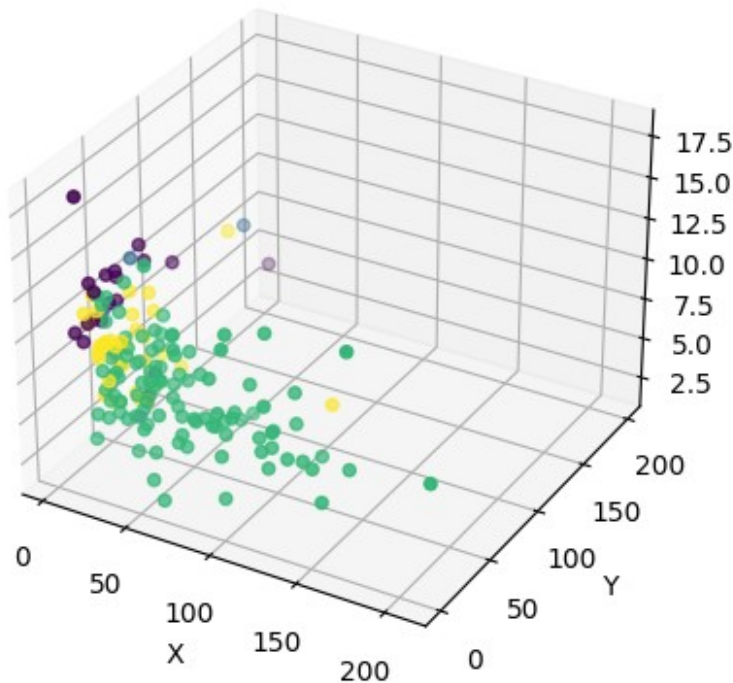
----- Dendrogram plot -----
```

```
##### Agglomerative clustering #####
print('----- Agglomerative clustering -----')
agl = AgglomerativeClustering(n_clusters=4).fit(points)
clustering_labels = agl.labels_
print('Labels: ', clustering_labels)
plot_data(points, clustering_labels, 'Agglomerative clustering')

----- Agglomerative clustering -----
Labels: [2 2 2 2 3 3 2 0 0 2 3 3 2 3 2 0 2 2 2 2 2 2 3 0 2 2 2 2 2 0
2 2 2 3 2 2 2
2 2 2 2 3 3 3 0 2 2 2 2 3 2 3 2 0 0 2 2 2 0 2 3 2 2 2 2 2 3 0 2 2 2
2 0
3 0 2 0 2 3 2 2 0 2 2 3 2 2 2 3 3 1 2 2 2 3 2 2 3 2 2 2 2 2 2 2 2 2
2 0
3 2 2 1 3 2 2 2 2 2 3 3 1 2 3 2 2 3 2 2 3 2 0 3 3 2 2 3 3 2 2 2 2 0 1
2 2
2 2 2 2 2 3 2 2 2 0 0 0 3 2 2 3 2 2 2]
```

Aglomerative clustering



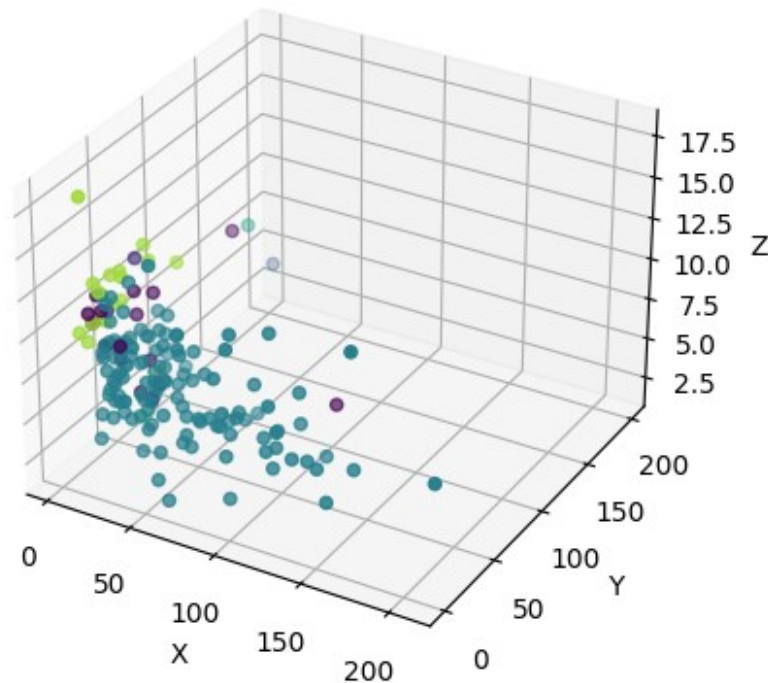
```
# Using custom distance matrix
dist = pairwise_distances(points, metric = 'l1')
agl = AgglomerativeClustering(n_clusters=8, linkage = 'average',
affinity = 'precomputed').fit(dist)
clustering_labels = agl.labels_
print('Labels: ', clustering_labels)
plot_data(points, clustering_labels, 'Agglomerative clustering
(Manhattan affinity & Mean Linkage)')
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_agglomerative.py:983: FutureWarning: Attribute `affinity` was
deprecated in version 1.2 and will be removed in 1.4. Use `metric`
instead
```

```
warnings.warn(
```

```
Labels:  [3 3 3 3 3 3 3 6 6 3 0 0 3 3 3 6 3 3 3 3 3 3 2 3 3 3 3 3 6
3 3 3 3 3 3 3
3 3 3 3 3 0 0 6 3 3 3 3 0 3 3 3 6 6 3 3 3 6 3 0 3 3 3 3 3 3 3 6 3 3 3
3 6
0 6 3 6 3 3 3 3 2 3 3 3 3 3 3 0 3 4 3 3 3 3 3 3 0 3 3 3 3 3 3 3 3 3 3
3 6
0 3 3 1 0 3 3 3 3 3 3 0 5 3 3 3 3 0 3 3 3 3 2 0 0 3 3 0 0 3 3 3 3 6 1
3 3
3 3 3 3 3 3 3 3 3 7 6 6 3 3 3 3 3 3 3]
```

Aglomerative clustering (Manhattan affinity & Mean Linkage)



Mapa autoorganizado con MiniSom

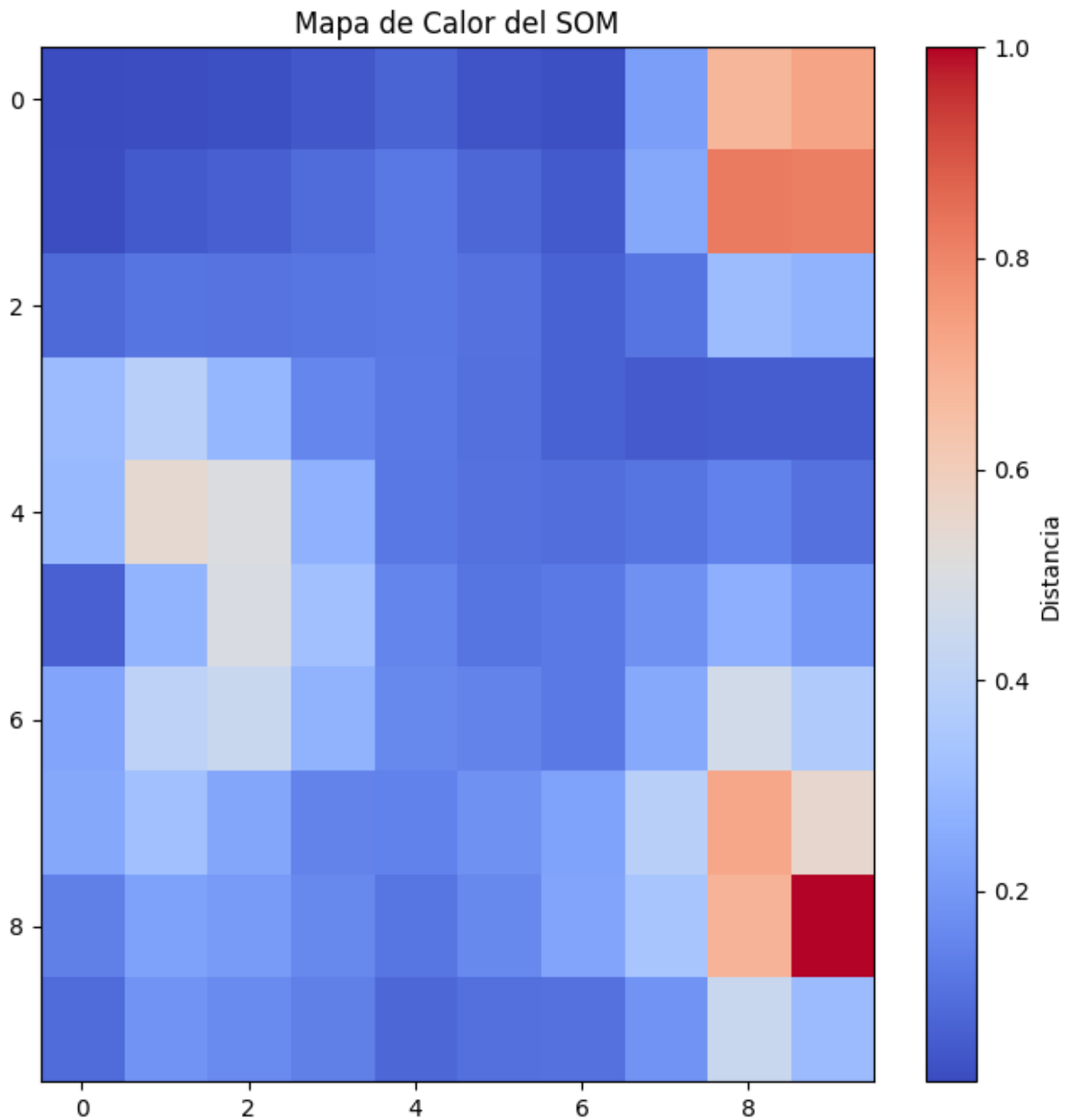
```
# Crear un mapa autoorganizado (SOM)
# Especifica el tamaño de la cuadrícula SOM y otros hiperparámetros
som_shape = (10, 10) # Tamaño de la cuadrícula SOM (10x10)
sigma = 1.0 # Valor de sigma para la función de vecindad
learning_rate = 0.5 # Tasa de aprendizaje inicial

# Crear y entrenar el SOM
data = points
som = MiniSom(som_shape[0], som_shape[1], data.shape[1], sigma=sigma,
              learning_rate=learning_rate)
som.random_weights_init(data)
som.train_random(data, 1000) # Entrenar durante 1000 iteraciones con
                              datos aleatorios

# Calcular la matriz de distancias entre las neuronas en el SOM
distance_map = som.distance_map().T # Transponer para que coincida
                                    con las dimensiones del SOM

# Visualizar el mapa de calor
plt.figure(figsize=(8, 8))
plt.imshow(distance_map, cmap='coolwarm', interpolation='none',
            aspect='auto')
plt.colorbar(label='Distancia')
plt.title('Mapa de Calor del SOM')
```

```
plt.grid(False)  
plt.show()
```



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

Analizando las diferentes gráficas obtenidas se puede observar que en la mayoría de técnicas existe un grupo que cuenta con más dominio que los demás, otra cosa a tomar en cuenta es que los datos se encuentran muy cercanos entre diferentes grupos, lo cual puede llegar a causar algunos problemas al momento de agrupar.