

Clustering jerárquico y dendrogramas

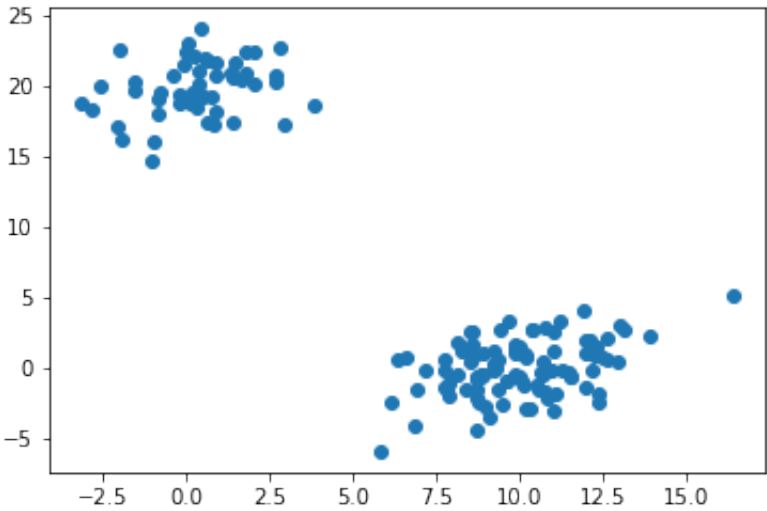
Antes de empezar, pongamos un poco de notación para hablar todos el mismo idioma

- X dataset (array de n x m) de puntos a clusterizar
- n número de datos
- m número de rasgos
- Z array de enlace del cluster con la información de las uniones
- k número de clusters

```
In [1]: import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage
import numpy as np
```

```
In [2]: np.random.seed(4711)
a = np.random.multivariate_normal([10,0],[[3,1],[1,4]], size = [100,])
b = np.random.multivariate_normal([0,20],[[3,1],[1,4]], size = [50,])
X = np.concatenate((a,b))
print(X.shape)
plt.scatter(X[:,0], X[:,1])
plt.show()
```

(150, 2)



```
In [3]: Z = linkage(X, "ward")
```

```
In [4]: from scipy.cluster.hierarchy import cophenet
from scipy.spatial.distance import pdist
```

```
In [5]: c, coph_dist = cophenet(Z, pdist(X))
c
```

Out[5]: 0.9800148387574268

```
In [6]: Z[0]
```

Out[6]: array([5.20000000e+01, 5.30000000e+01, 4.15105485e-02, 2.00000000e+00])

```
In [7]: Z[1]
```

Out[7]: array([1.40000000e+01, 7.90000000e+01, 5.91375926e-02, 2.00000000e+00])

```
In [8]: Z[:20]
```

```
Out[8]: array([[5.20000000e+01, 5.30000000e+01, 4.15105485e-02, 2.00000000e+00],
               [1.40000000e+01, 7.90000000e+01, 5.91375926e-02, 2.00000000e+00],
               [3.30000000e+01, 6.80000000e+01, 7.10677929e-02, 2.00000000e+00],
               [1.70000000e+01, 7.30000000e+01, 7.13712071e-02, 2.00000000e+00],
               [1.00000000e+00, 8.00000000e+00, 7.54313099e-02, 2.00000000e+00],
               [8.50000000e+01, 9.50000000e+01, 1.09277896e-01, 2.00000000e+00],
               [1.08000000e+02, 1.31000000e+02, 1.10071548e-01, 2.00000000e+00],
               [9.00000000e+00, 6.60000000e+01, 1.13022407e-01, 2.00000000e+00],
               [1.50000000e+01, 6.90000000e+01, 1.14289714e-01, 2.00000000e+00],
               [6.30000000e+01, 9.80000000e+01, 1.21200766e-01, 2.00000000e+00],
               [1.07000000e+02, 1.15000000e+02, 1.21671017e-01, 2.00000000e+00],
               [6.50000000e+01, 7.40000000e+01, 1.24900190e-01, 2.00000000e+00],
               [5.80000000e+01, 6.10000000e+01, 1.40277358e-01, 2.00000000e+00],
               [6.20000000e+01, 1.52000000e+02, 1.72599535e-01, 3.00000000e+00],
               [4.10000000e+01, 1.58000000e+02, 1.77901377e-01, 3.00000000e+00],
               [1.00000000e+01, 8.30000000e+01, 1.86354938e-01, 2.00000000e+00],
               [1.14000000e+02, 1.39000000e+02, 2.04186147e-01, 2.00000000e+00],
               [3.90000000e+01, 8.80000000e+01, 2.06282849e-01, 2.00000000e+00],
               [7.00000000e+01, 9.60000000e+01, 2.19312547e-01, 2.00000000e+00],
               [4.60000000e+01, 5.00000000e+01, 2.20492804e-01, 2.00000000e+00]])
```

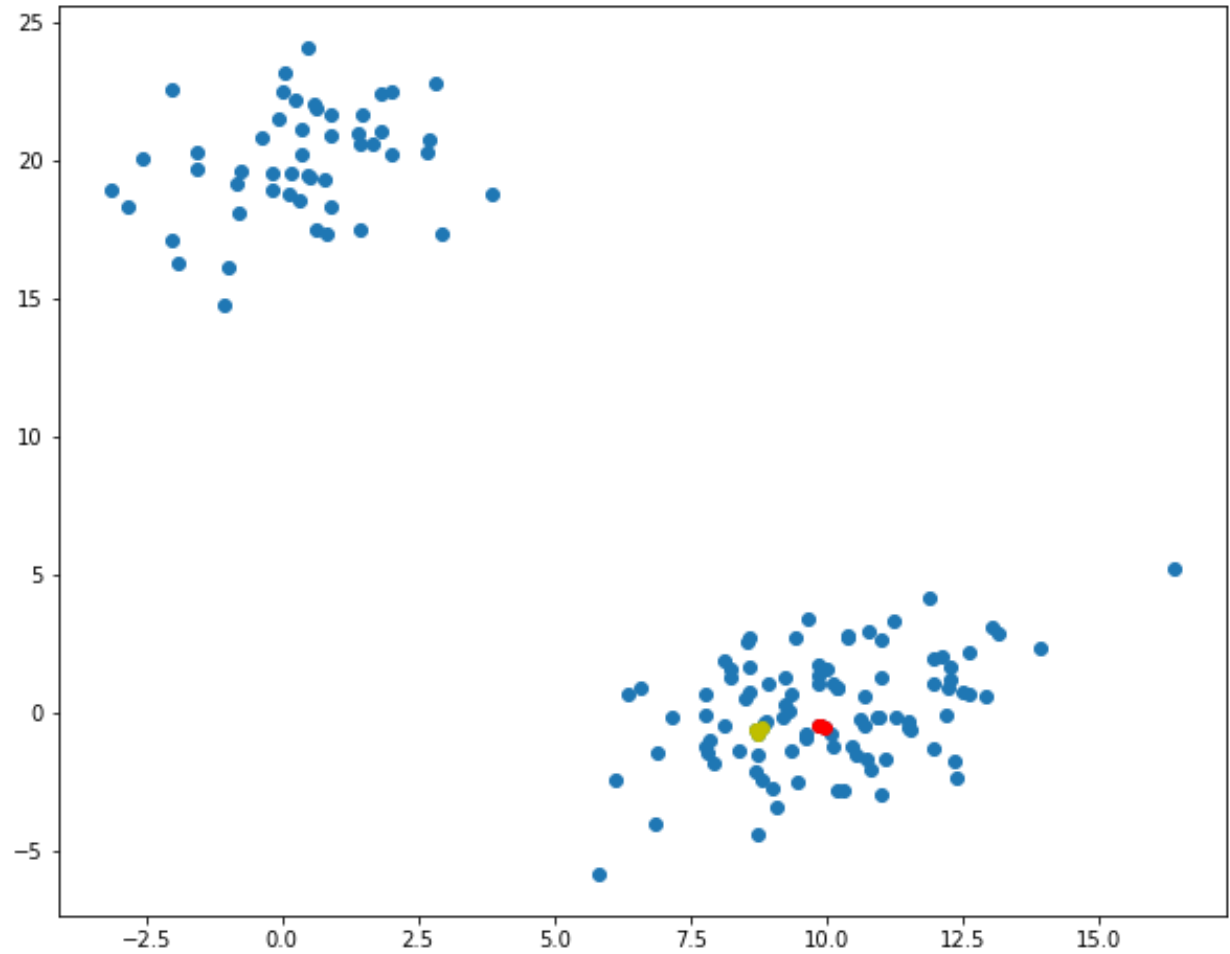
```
In [9]: print(Z[152-len(X)])# cluster 152
        print(Z[158-len(X)])#cluster 158
```

```
[33.      68.      0.07106779  2.      ]
[15.      69.      0.11428971  2.      ]
```

```
In [10]: X[[33,62,68]]
```

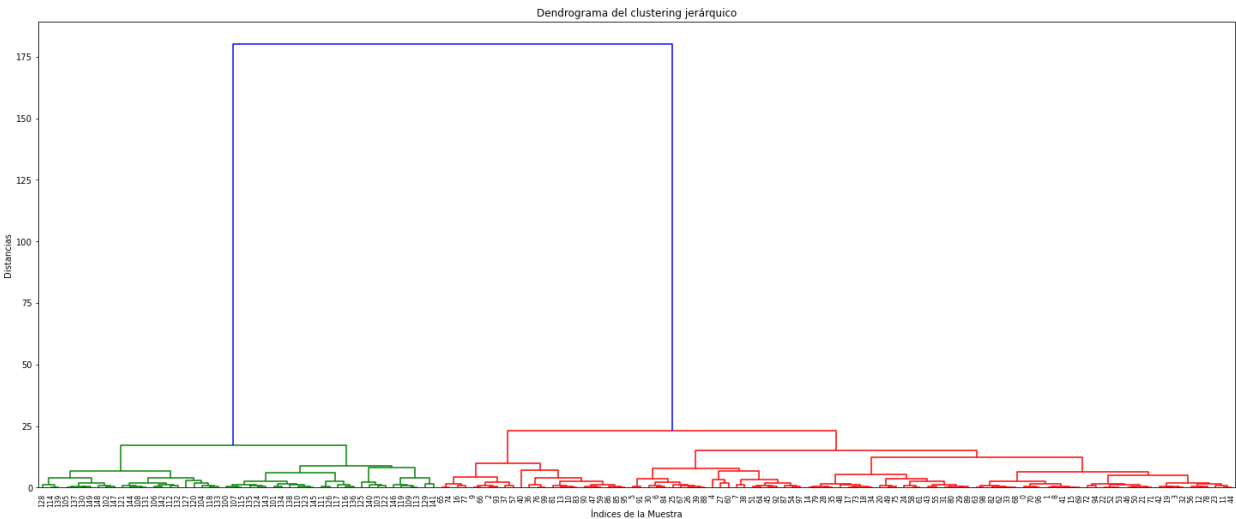
```
Out[10]: array([[ 9.83913054, -0.48729797],
                 [ 9.97792822, -0.56383202],
                 [ 9.8934927 , -0.44152257]])
```

```
In [11]: idx = [33,62,68]
idx2 = [15,69,41]
plt.figure(figsize=(10,8))
plt.scatter(X[:,0], X[:,1])##pintar todos los puntos
plt.scatter(X[idx,0], X[idx,1], c='r')##destacamos en rojo los puntos
plt.scatter(X[idx2,0], X[idx2,1], c='y')##destacamos en amarillo el se
plt.show()
```



Representación gráfica de un dendrograma

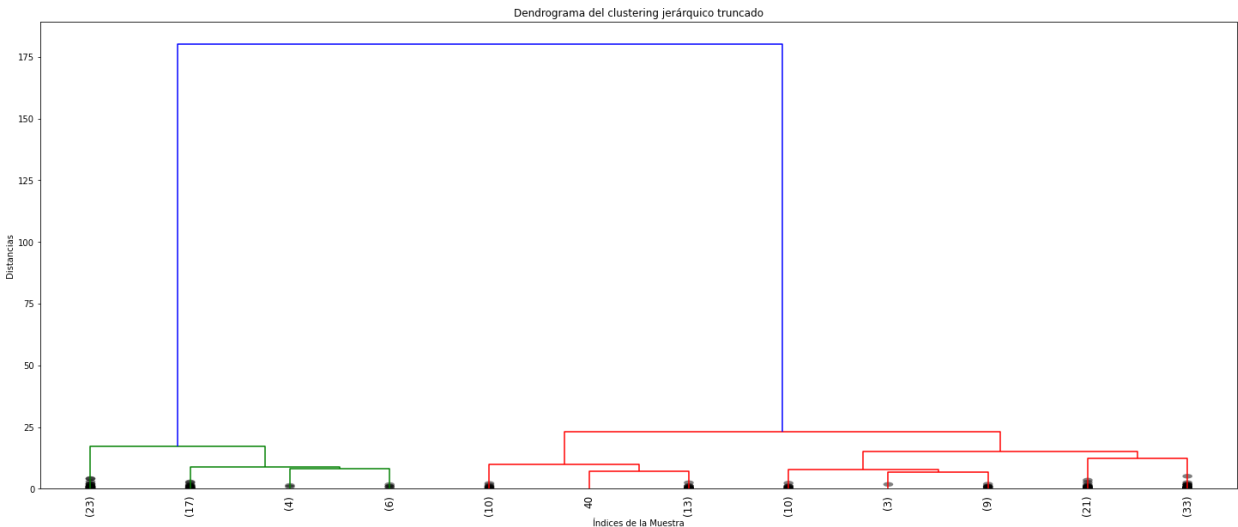
```
In [12]: plt.figure(figsize=(25,10))
plt.title("Dendrograma del clustering jerárquico")
plt.xlabel("Índices de la Muestra")
plt.ylabel("Distancias")
dendrogram(Z, leaf_rotation=90., leaf_font_size=8.0,
            color_threshold=0.7*180)
plt.show()
```



```
In [13]: Z[-4:,]
Out[13]: array([[290.      , 294.      , 15.11533118, 76.      ],
                [287.      , 292.      , 17.11527362, 50.      ],
                [293.      , 295.      , 23.12198936, 100.     ],
                [296.      , 297.      , 180.27043021, 150.     ]])
```

Truncar el dendrograma

```
In [14]: plt.figure(figsize=(25,10))
plt.title("Dendrograma del clustering jerárquico truncado")
plt.xlabel("Índices de la Muestra")
plt.ylabel("Distancias")
dendrogram(Z, leaf_rotation=90., leaf_font_size=12.0,
           color_threshold=0.7*180,
           truncate_mode="lastp", p=12, show_leaf_counts=True,
           show_contracted=True,)
plt.show()
```



Dendrograma tuneado

```
In [15]: def dendrogram_tune(*args, **kwargs):

    max_d=kwargs.pop("max_d", None)
    if max_d and 'color_threshold' not in kwargs:
        kwargs['color_threshold'] = max_d
    annotate_above = kwargs.pop('annotate_above', 0)

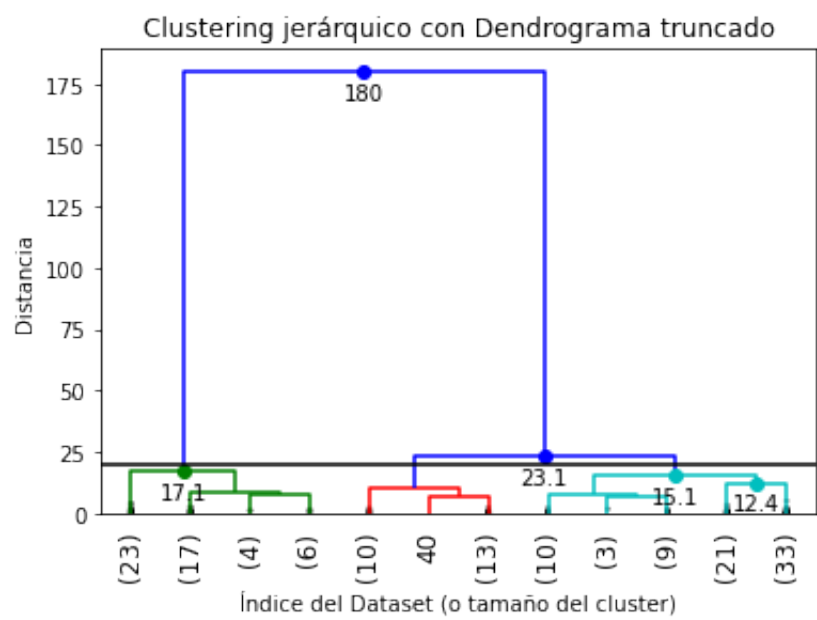
    ddata = dendrogram(*args,**kwargs)

    if not kwargs.get('no_plot', False):
        plt.title("Clustering jerárquico con Dendrograma truncado")
        plt.xlabel("Índice del Dataset (o tamaño del cluster)")
        plt.ylabel("Distancia")
        for i, d, c in zip(ddata['icoord'], ddata['dcoord'],
                           ddata['color_list']):
            x = 0.5 * sum(i[1:3])
            y = d[1]
            if y>annotate_above:
                plt.plot(x,y, 'o',c=c)
                plt.annotate('%.3g'%y, (x,y), xytext=(0,-5),
                             textcoords="offset points", va="top",
                             ha="center")

        if max_d:
            plt.axhline(y=max_d, c='k')

    return ddata
```

```
In [16]: dendrogram_tune(Z,truncate_mode='lastp',p=12, leaf_rotation=90.,
                        leaf_font_size=12.,
                        show_contracted=True,annotate_above=10, max_d=20)
plt.show()
```



Corte automático del dendrograma

$$\text{inconsistency}_i = (h_i - \text{avg}(h_j)) / \text{std}(h_j)$$

```
In [17]: from scipy.cluster.hierarchy import inconsistent
```

```
In [18]: depth = 3
incons = inconsistent(Z, depth)
incons[-10:]
```

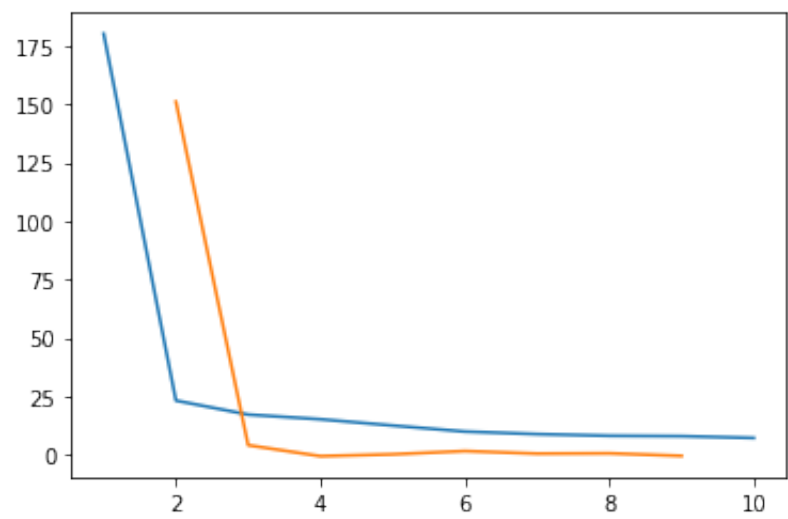
Out[18]: array([[3.63777835, 2.5556114 , 4. , 1.35908084],
[3.89767268, 2.57216151, 7. , 1.54388156],
[3.05885714, 2.66707272, 6. , 1.87115096],
[4.92746418, 2.73259589, 7. , 1.39821573],
[4.76943311, 3.16276553, 6. , 1.60455941],
[5.27287862, 3.56604844, 7. , 2.00627335],
[8.22057081, 4.07583053, 7. , 1.69162096],
[7.83287032, 4.46681266, 7. , 2.07808207],
[11.38091435, 6.29430022, 7. , 1.86535033],
[37.25844589, 63.31539362, 7. , 2.25872377]])

Método del codo

```
In [19]: last = Z[-10:,2]
last_rev = last[::-1]
print(last_rev)
idx = np.arange(1, len(last)+1)
plt.plot(idx, last_rev)

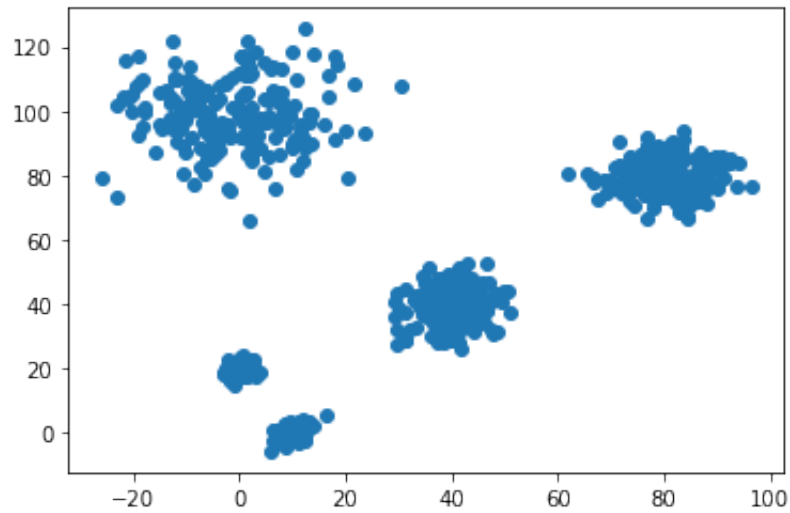
acc = np.diff(last,2)
acc_rev = acc[::-1]
plt.plot(idx[:-2]+1, acc_rev)
plt.show()
k = acc_rev.argmax() +2
print("El número óptimo de cluster es %s"%str(k))
```

[180.27043021 23.12198936 17.11527362 15.11533118 12.42734657
 9.84427829 8.74822275 8.04935282 7.86878542 7.11106083]



El número óptimo de cluster es 2

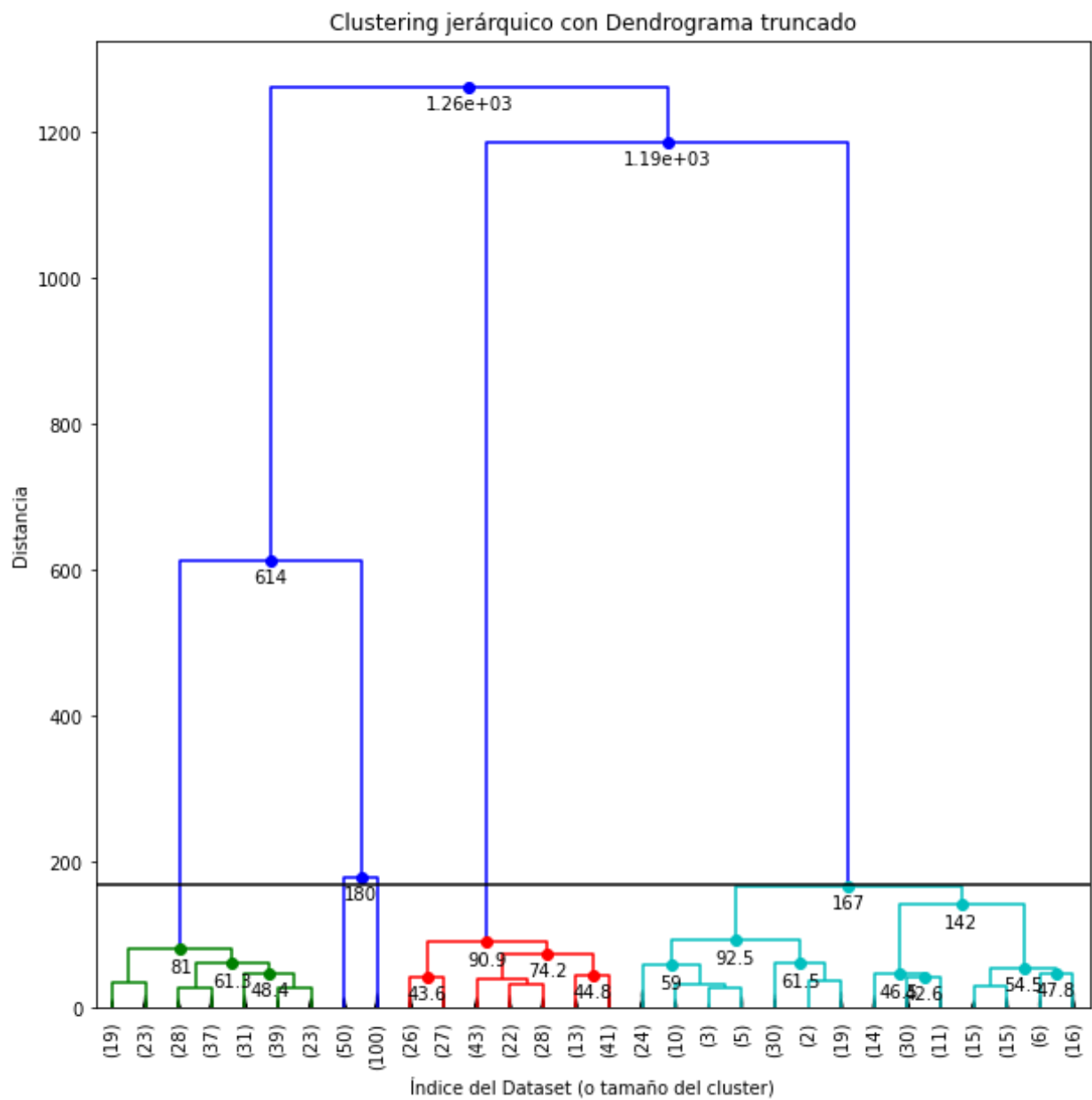
```
In [20]: c = np.random.multivariate_normal([40,40],[[20,1],[1,30]], size=[200,])  
d = np.random.multivariate_normal([80,80],[[30,1],[1,30]], size=[200,])  
e = np.random.multivariate_normal([0,100],[[100,1],[1,100]],  
                                   size=[200,])  
  
X2 = np.concatenate((X,c,d,e),)  
plt.scatter(X2[:,0], X2[:,1])  
plt.show()
```



```
In [21]: Z2 = linkage(X2,"ward")
```

```
In [22]: plt.figure(figsize=(10,10))
dendrogram_tune(
    Z2,
    truncate_mode="lastp",
    p=30,
    leaf_rotation=90.,
    leaf_font_size=10.,
    show_contracted=True,
    annotate_above = 40,
    max_d = 170
)

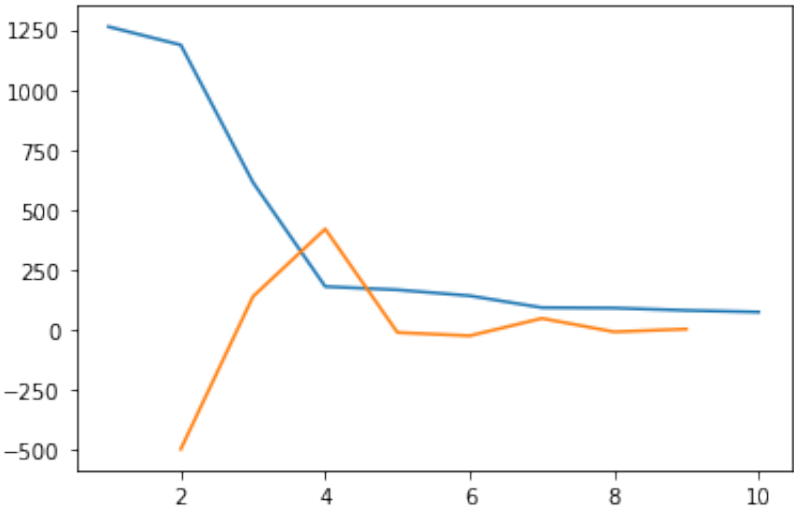
plt.show()
```




```
In [23]: last = Z2[-10:,2]
last_rev = last[::-1]
print(last_rev)
idx = np.arange(1, len(last)+1)
plt.plot(idx, last_rev)

acc = np.diff(last,2)
acc_rev = acc[::-1]
plt.plot(idx[:-2]+1, acc_rev)
plt.show()
k = acc_rev.argmax() +2
print("El número óptimo de cluster es %s"%str(k))
```

```
[1262.52130994 1186.7588235   614.06504667  180.27043021  166.6643465
8
 141.92437181   92.54599212   90.91214341   80.96733501   74.1701531
2]
```



El número óptimo de cluster es 4

```
In [24]: print(inconsistent(Z2, 5)[-10:])
```

```
[ [ 13.99221995  15.56655759  30.          3.8658472 ]
 [ 16.73940735  18.56390061  30.          3.45982932]
 [ 19.05945013  20.53210626  31.          3.49952861]
 [ 19.25573887  20.8265769   29.          3.51907342]
 [ 21.36116189  26.77659523  30.          4.50255938]
 [ 36.58100874  37.08602393  31.          3.50761079]
 [ 12.12200256  32.15467931  30.          5.22936105]
 [ 42.61369802 111.38576865  31.          5.13038026]
 [ 81.75198678 208.31582073  31.          5.30447871]
 [147.25602023 307.95700562  31.          3.62149673]]
```

Recuperar los clusters y sus elementos

```
In [25]: from scipy.cluster.hierarchy import fcluster
```

```
In [26]: max_d=25
clusters = fcluster(Z, max_d, criterion="distance")
clusters
```

[illegible]

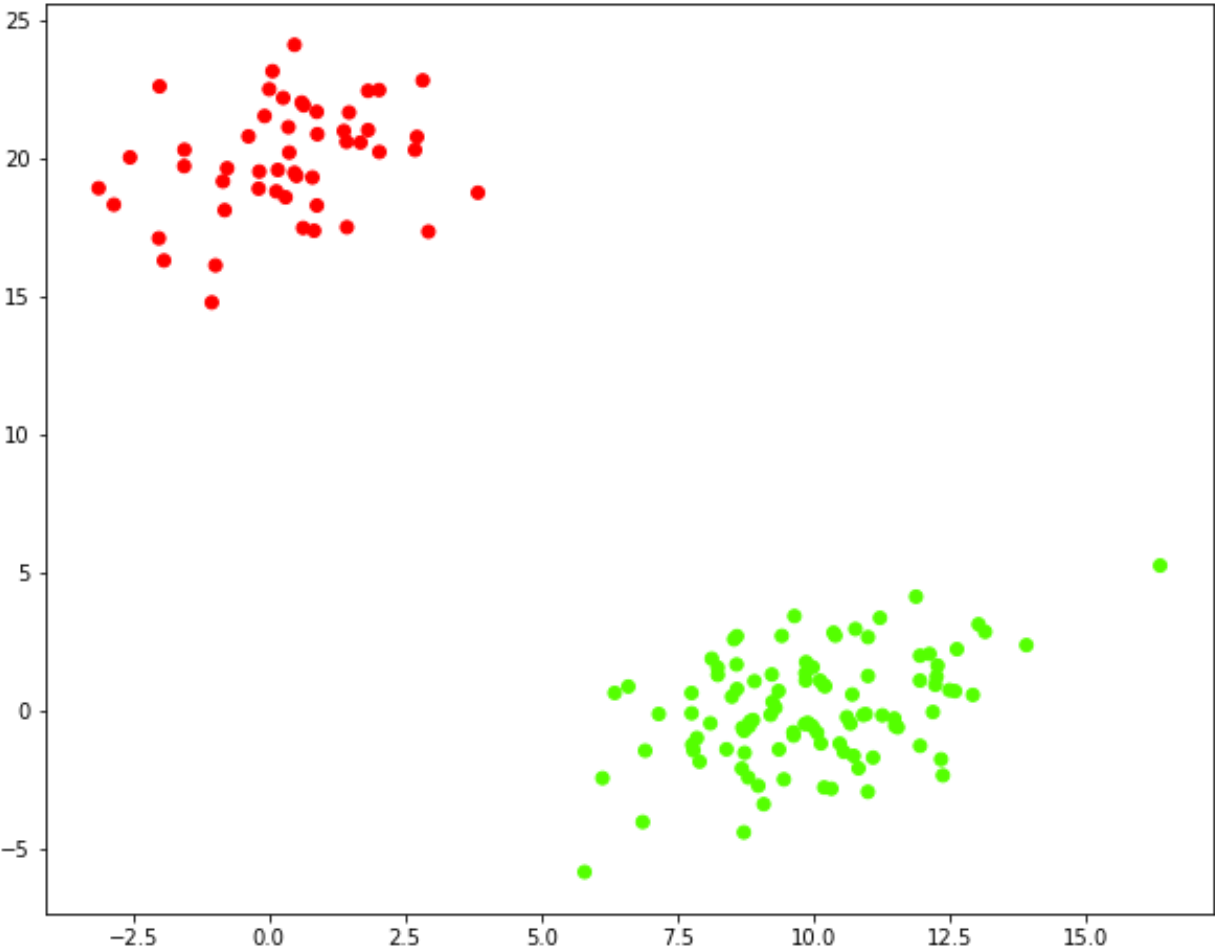
```
In [27]: k=2
clusters = fcluster(Z, k, criterion="maxclust")
clusters
```

[illegible]

```
In [28]: fcluster(Z, 8, depth=10)
```

[illegible]

```
In [29]: plt.figure(figsize=(10,8))
plt.scatter(X[:,0], X[:,1], c = clusters, cmap="prism")
plt.show()
```



```
In [30]: max_d=170  
clusters = fcluster(Z2, max_d, criterion="distance")  
clusters  
  
plt.figure(figsize=(10,8))  
plt.scatter(X2[:,0], X2[:,1], c = clusters, cmap="prism")  
plt.show()
```

