Clustering

January 5, 2022

0.1 Clustering

[12]:
```
#----- Librerías a emplear -----
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from scipy.spatial import distance_matrix

#from jupyterthemes import jtplot
#jtplot.style(theme='onedork')
```

[13]:
```
#----- Cargamos nuestra data -----
data = pd.read_csv("GitHub/python-ml-course/datasets/movies/movies.csv", sep =␣
↪";")
data
```

[13]:

	user_id	star_wars	lord_of_the_rings	harry_potter
0	1	1.2	4.9	2.1
1	2	2.1	8.1	7.9
2	3	7.4	3.0	9.9
3	4	5.6	0.5	1.8
4	5	1.5	8.3	2.6
5	6	2.5	3.7	6.5
6	7	2.0	8.2	8.5
7	8	1.8	9.3	4.5
8	9	2.6	1.7	3.1
9	10	1.5	4.7	2.3

[14]:
```
#----- Tomamos únicamente lo que nos interesa -----
movies = data.columns.values.tolist()[1:]
movies
```

[14]: ['star_wars', 'lord_of_the_rings', 'harry_potter']

[15]:
```
#----- DISTANCIAS -----
# En base a la distancia de Minkowsi tenemos:
# p=1 -> Distancia de Manhattan   |   p=2 -> Distancia Euclidea
```

```
dd1 = distance_matrix(data[movies], data[movies], p = 1)
dd2 = distance_matrix(data[movies], data[movies], p = 2)
dd10 = distance_matrix(data[movies], data[movies], p = 10)
```

[16]:
```
#----- Pasamos la matriz de distancias a dataframe -----
def dm_to_df(dd, col_name):
    import pandas as pd
    return pd.DataFrame(dd, index = col_name, columns = col_name)
```

[17]:
```
#---- Visualización de los DataFrames -----
# Observaremos que las distancias más cortas son las de p = 10
dm_to_df(dd1, data["user_id"])
```

[17]:

user_id	1	2	3	4	5	6	7	8	9	10
user_id										
1	0.0	9.9	15.9	9.1	4.2	6.9	10.5	7.4	5.6	0.7
2	9.9	0.0	12.4	17.2	6.1	6.2	0.8	4.9	11.7	9.6
3	15.9	12.4	0.0	12.4	18.5	9.0	12.0	17.3	12.9	15.2
4	9.1	17.2	12.4	0.0	12.7	11.0	18.0	15.3	5.5	8.8
5	4.2	6.1	18.5	12.7	0.0	9.5	6.5	3.2	8.2	3.9
6	6.9	6.2	9.0	11.0	9.5	0.0	7.0	8.3	5.5	6.2
7	10.5	0.8	12.0	18.0	6.5	7.0	0.0	5.3	12.5	10.2
8	7.4	4.9	17.3	15.3	3.2	8.3	5.3	0.0	9.8	7.1
9	5.6	11.7	12.9	5.5	8.2	5.5	12.5	9.8	0.0	4.9
10	0.7	9.6	15.2	8.8	3.9	6.2	10.2	7.1	4.9	0.0

[18]:
```
dm_to_df(dd2, data["user_id"])
```

[18]:

user_id	1	2	3	4	5	6 \
user_id						
1	0.000000	6.685058	10.143471	6.229767	3.449638	4.742362
2	6.685058	0.000000	7.622336	10.354709	5.337602	4.634652
3	10.143471	7.622336	0.000000	8.666026	10.779147	6.004998
4	6.229767	10.354709	8.666026	0.000000	8.848164	6.476110
5	3.449638	5.337602	10.779147	8.848164	0.000000	6.113101
6	4.742362	4.634652	6.004998	6.476110	6.113101	0.000000
7	7.244998	0.616441	7.626270	10.823123	5.921993	4.949747
8	5.047772	3.618011	10.010494	9.958414	2.167948	5.987487
9	3.633180	8.015610	8.424369	3.482815	6.709694	3.945884
10	0.412311	6.578754	9.770363	5.890671	3.612478	4.431704

user_id	7	8	9	10
user_id				
1	7.244998	5.047772	3.633180	0.412311
2	0.616441	3.618011	8.015610	6.578754
3	7.626270	10.010494	8.424369	9.770363

```
4         10.823123   9.958414  3.482815  5.890671
5          5.921993   2.167948  6.709694  3.612478
6          4.949747   5.987487  3.945884  4.431704
7          0.000000   4.153312  8.471718  7.137226
8          4.153312   0.000000  7.769170  5.107837
9          8.471718   7.769170  0.000000  3.293934
10         7.137226   5.107837  3.293934  0.000000
```

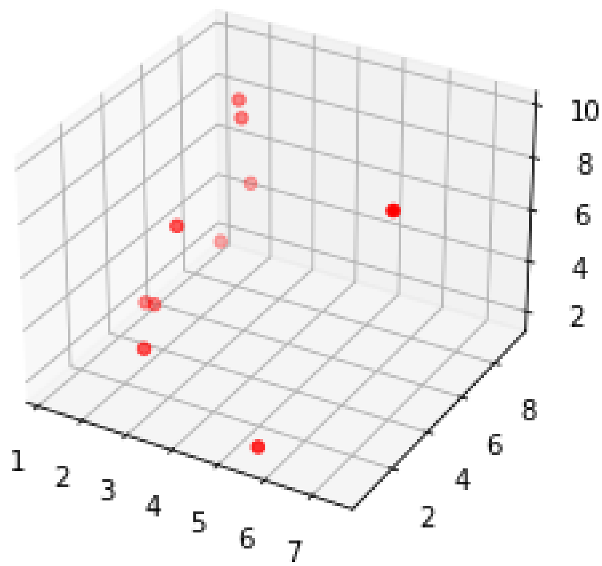
[19]:
```python
dm_to_df(dd10, data["user_id"])
```

[19]:
```
user_id         1         2         3         4         5         6         7  \
user_id
1        0.000000  5.801514  7.875189  4.715803  3.400000  4.400003  6.400850
2        5.801514  0.000000  5.582463  7.680689  5.300000  4.400005  0.600000
3        7.875189  5.582463  0.000000  8.100007  7.408914  4.912532  5.689450
4        4.715803  7.680689  8.100007  0.000000  7.801255  4.717102  7.873307
5        3.400000  5.300000  7.408914  7.801255  0.000000  4.681464  5.900000
6        4.400003  4.400005  4.912532  4.717102  4.681464  0.000000  4.500135
7        6.400850  0.600000  5.689450  7.873307  5.900000  4.500135  0.000000
8        4.401025  3.400010  6.570254  8.800205  1.900310  5.600019  4.000001
9        3.200085  6.435159  6.820602  3.000101  6.600000  3.401683  6.595259
10       0.301025  5.603800  7.658364  4.450759  3.600000  4.200000  6.202035

user_id         8         9        10
user_id
1        4.401025  3.200085  0.301025
2        3.400010  6.435159  5.603800
3        6.570254  6.820602  7.658364
4        8.800205  3.000101  4.450759
5        1.900310  6.600000  3.600000
6        5.600019  3.401683  4.200000
7        4.000001  6.595259  6.202035
8        0.000000  7.600000  4.600288
9        7.600000  0.000000  3.000014
10       4.600288  3.000014  0.000000
```

[20]:
```python
#----- Librería para gráficas 3D -----
from mpl_toolkits.mplot3d import Axes3D
```

[21]:
```python
fig = plt.figure()
ax = fig.add_subplot(111, projection = "3d")
ax.scatter(xs = data["star_wars"], ys = data["lord_of_the_rings"], zs =␣
 ↪data["harry_potter"], c = "red" )
```

[21]:
```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x16ff23cb308>
```



0.1.1 Clustering jerárquico

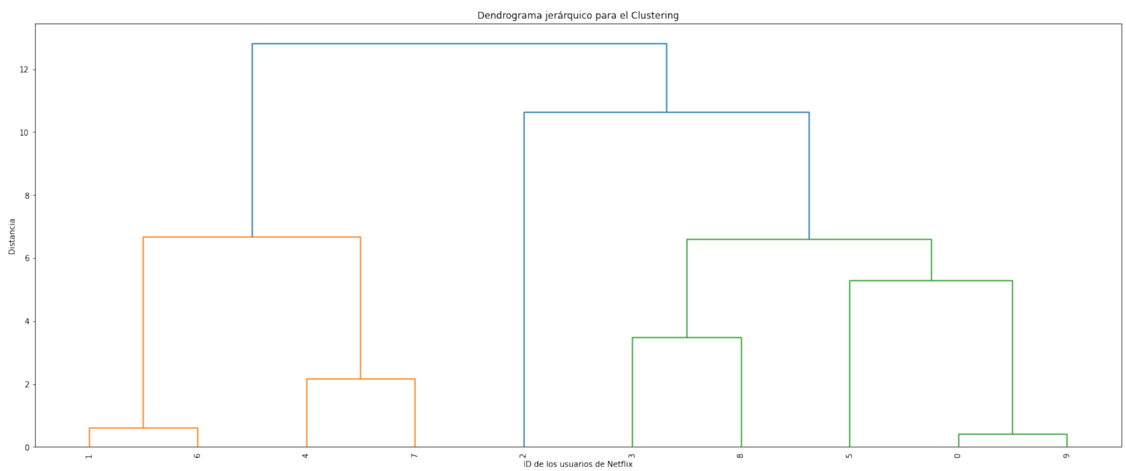
[22]:
```
#----- Importamos las librerías a usar -----
from scipy.cluster.hierarchy import dendrogram, linkage
# dendrogram -> Dendrograma   |   linkage -> enlace de datos
```

[23]:
```
#----- Visualizamos nuestro dataframe -----
print(movies)
print("")
print(data[movies])
```

```
['star_wars', 'lord_of_the_rings', 'harry_potter']

   star_wars  lord_of_the_rings  harry_potter
0        1.2                4.9           2.1
1        2.1                8.1           7.9
2        7.4                3.0           9.9
3        5.6                0.5           1.8
4        1.5                8.3           2.6
5        2.5                3.7           6.5
6        2.0                8.2           8.5
7        1.8                9.3           4.5
8        2.6                1.7           3.1
9        1.5                4.7           2.3
```

[24]:
```
Z = linkage(data[movies], "ward") # Ward es el tipo de enlace
                                  # (single, average, complete, etc)
print(Z)
plt.figure(figsize = (25, 10))
plt.title("Dendrograma jerárquico para el Clustering")
plt.xlabel("ID de los usuarios de Netflix")
plt.ylabel("Distancia")
dendrogram(Z, leaf_rotation = 90, leaf_font_size = 10)
plt.show()
```

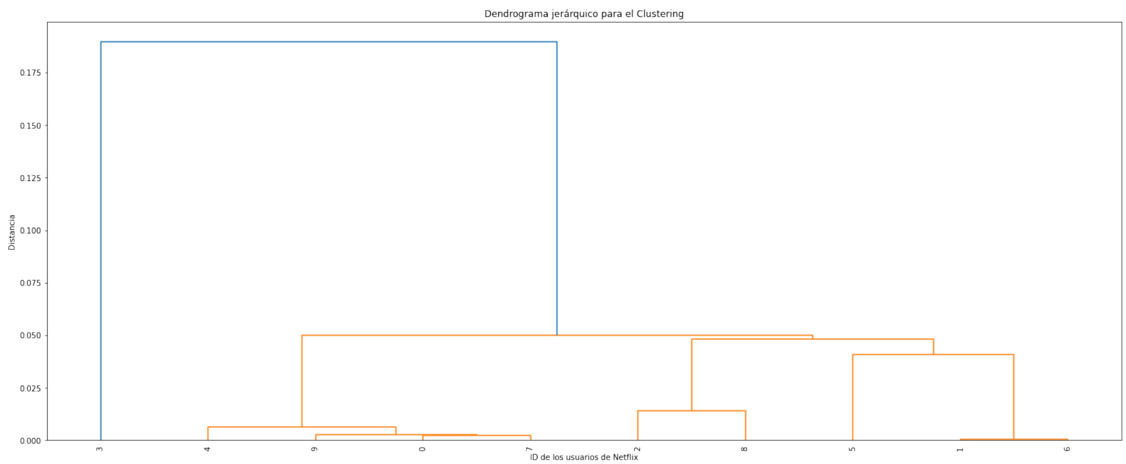
```
[[ 0.          9.          0.41231056  2.        ]
 [ 1.          6.          0.6164414   2.        ]
 [ 4.          7.          2.16794834  2.        ]
 [ 3.          8.          3.48281495  2.        ]
 [ 5.         10.          5.2943366   3.        ]
 [13.         14.          6.59317829  5.        ]
 [11.         12.          6.66408283  4.        ]
 [ 2.         15.         10.62355873  6.        ]
 [16.         17.         12.8156935  10.        ]]
```



[25]:
```
# Podemos crear el enlace especificado en método y función de distancia
Z = linkage(data[movies], method ="single", metric = "cosine")
print(Z)
plt.figure(figsize = (25, 10))
plt.title("Dendrograma jerárquico para el Clustering")
plt.xlabel("ID de los usuarios de Netflix")
plt.ylabel("Distancia")
dendrogram(Z, leaf_rotation = 90, leaf_font_size = 10)
plt.show()
```

```
[[1.00000000e+00 6.00000000e+00 5.73982302e-04 2.00000000e+00]
 [0.00000000e+00 7.00000000e+00 2.20254553e-03 2.00000000e+00]
```

```
[9.00000000e+00 1.10000000e+01 2.85017067e-03 3.00000000e+00]
[4.00000000e+00 1.20000000e+01 6.21188529e-03 4.00000000e+00]
[2.00000000e+00 8.00000000e+00 1.41238086e-02 2.00000000e+00]
[5.00000000e+00 1.00000000e+01 4.10208532e-02 3.00000000e+00]
[1.40000000e+01 1.50000000e+01 4.82230673e-02 5.00000000e+00]
[1.30000000e+01 1.60000000e+01 4.99162497e-02 9.00000000e+00]
[3.00000000e+00 1.70000000e+01 1.89817411e-01 1.00000000e+01]]
```

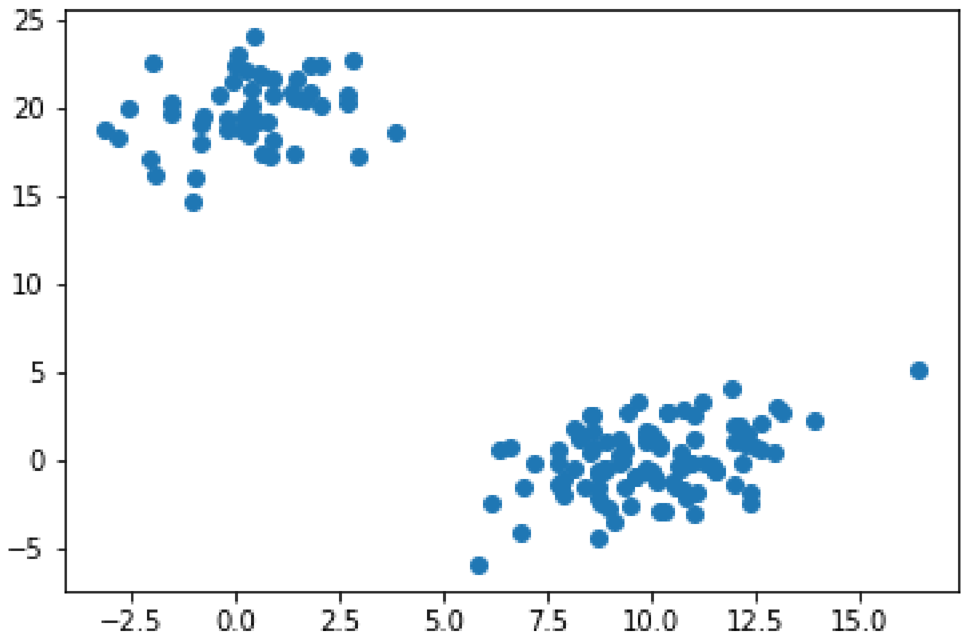


0.1.2 Clustering jerárquico y dendrogramas

[26]:
```python
# Realizamos un nuevo ejemplo con mayor cantidad de datos
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage
import numpy as np

#from jupyterthemes import jtplot
#jtplot.style(theme='onedork')
```

[27]:
```python
np.random.seed(4711) # Colocamos una semilla para nuestros valores aleatorios

# Generamos datos aleatorios
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)) # Concatenamos nuestros datos
print(X.shape) # Tamaño de nuestra matriz
plt.scatter(X[:, 0], X[:, 1]) # Gráfica de datos, todas las filas para las␣
↪columnas 0 y 1
plt.show() # Visualización
```

```
(150, 2)
```



[28]:
```
# Declaramos nuestra matriz de enlace
Z = linkage(X, "ward")
```

[29]:
```
#----- Importación de librerías -----
from scipy.cluster.hierarchy import cophenet
from scipy.spatial.distance import pdist
```

[30]:
```
# Cophenetic distance: ¿Qué tan similares deben ser los datos
# para pertenecer a un mismo cluster?
c, coph_dist = cophenet(Z, pdist(X)) #Cálculo de la distancia euclidiana
c
```

[30]:
```
0.9800148387574268
```

[31]:
```
# Obtenemos nuestros 2 puntos, distancia, número de elementos
Z[0]
```

[31]:
```
array([5.20000000e+01, 5.30000000e+01, 4.15105485e-02, 2.00000000e+00])
```

[32]:
```
# Visualizamos los últimos 20 datos de nuestra matriz de enlace
Z[:20]
```

[32]:
```
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]])
```

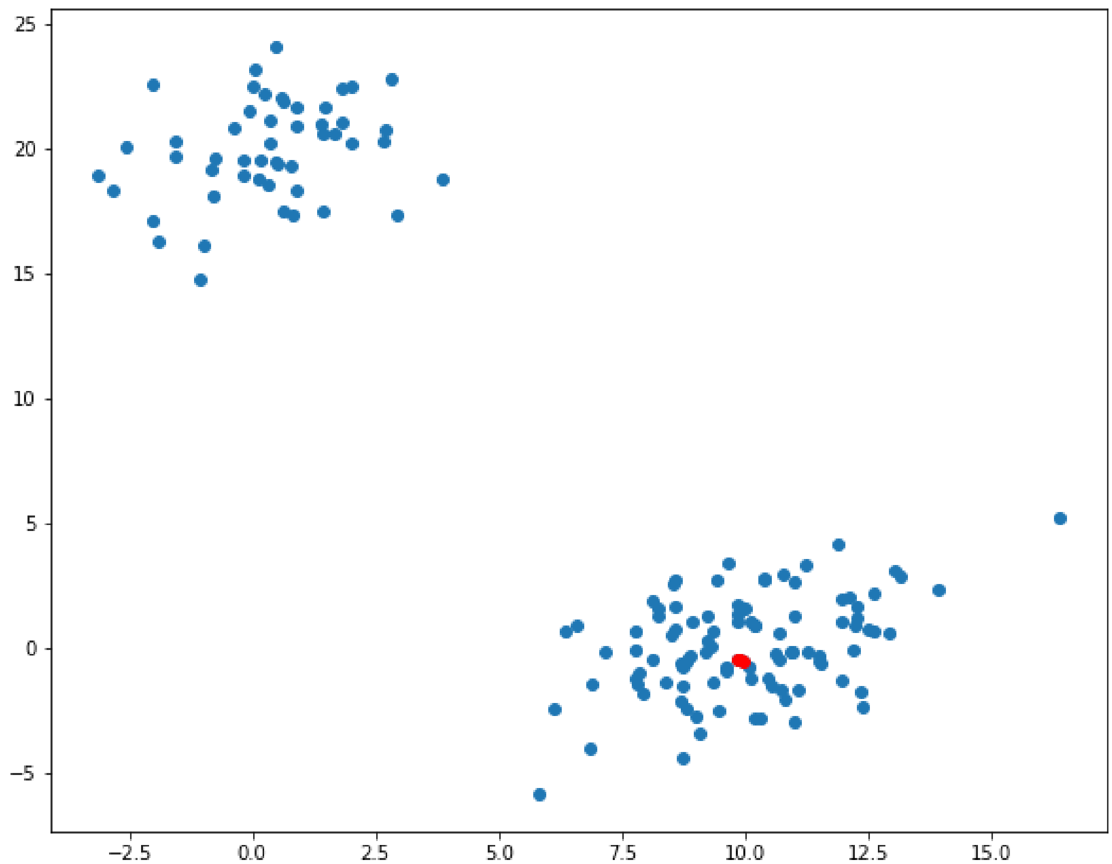
[33]:
```python
print(Z[152 - len(X)]) # Cluster 152
```

```
[33.         68.          0.07106779  2.        ]
```

[34]:
```python
# Además del punto 33 y 68, otro punto cercano a 152 es 62,
# como se puede visualizar en la tabla anterior y aquí:
X[[33, 68, 62]]
```

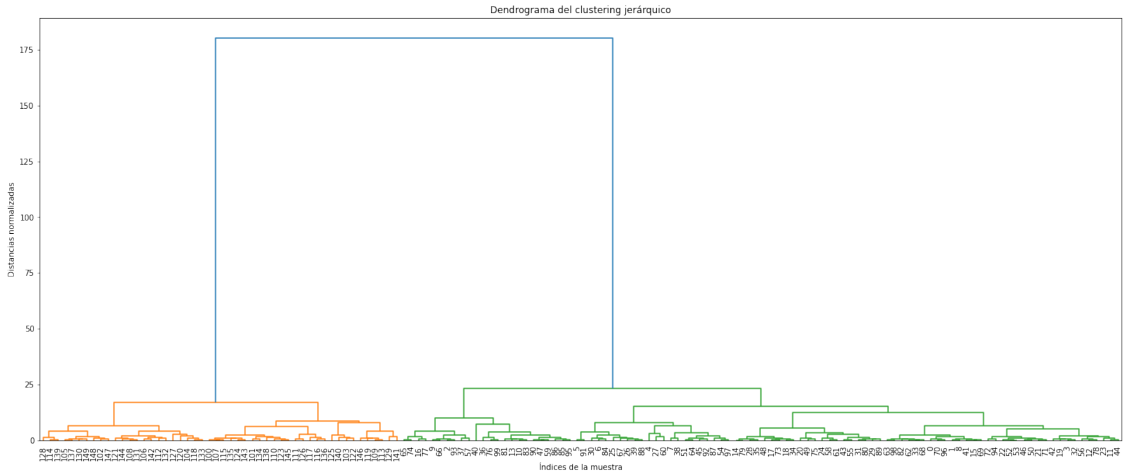
[34]:
```
array([[ 9.83913054, -0.48729797],
       [ 9.8934927 , -0.44152257],
       [ 9.97792822, -0.56383202]])
```

[35]:
```python
idx = [33, 68, 62] # Puntos de interés
plt.figure(figsize = (10, 8))
plt.scatter(X[:, 0], X[:, 1]) # Graficamos todos los puntos
plt.scatter(X[idx, 0], X[idx, 1], c = "r") # Graficamos los puntos de interés
plt.show()
```



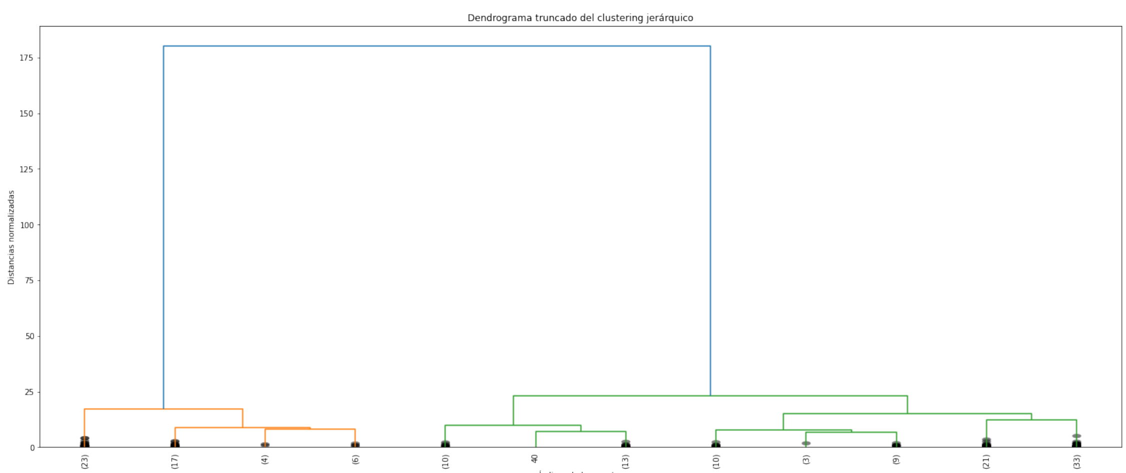
Representación gráfica de un dendrograma

[36]:
```
plt.figure(figsize = (25, 10))
plt.title("Dendrograma del clustering jerárquico")
plt.xlabel("Índices de la muestra")
plt.ylabel("Distancias normalizadas")
# color_threshold: umbral para pintar, por defecto es 70% (180 valor máximo de␣
↪nuestro cluster)
dendrogram(Z, leaf_rotation = 90.0, leaf_font_size = 10.0, color_threshold = 0.
↪7*180)
plt.show()
```



Truncamiento del dendrograma

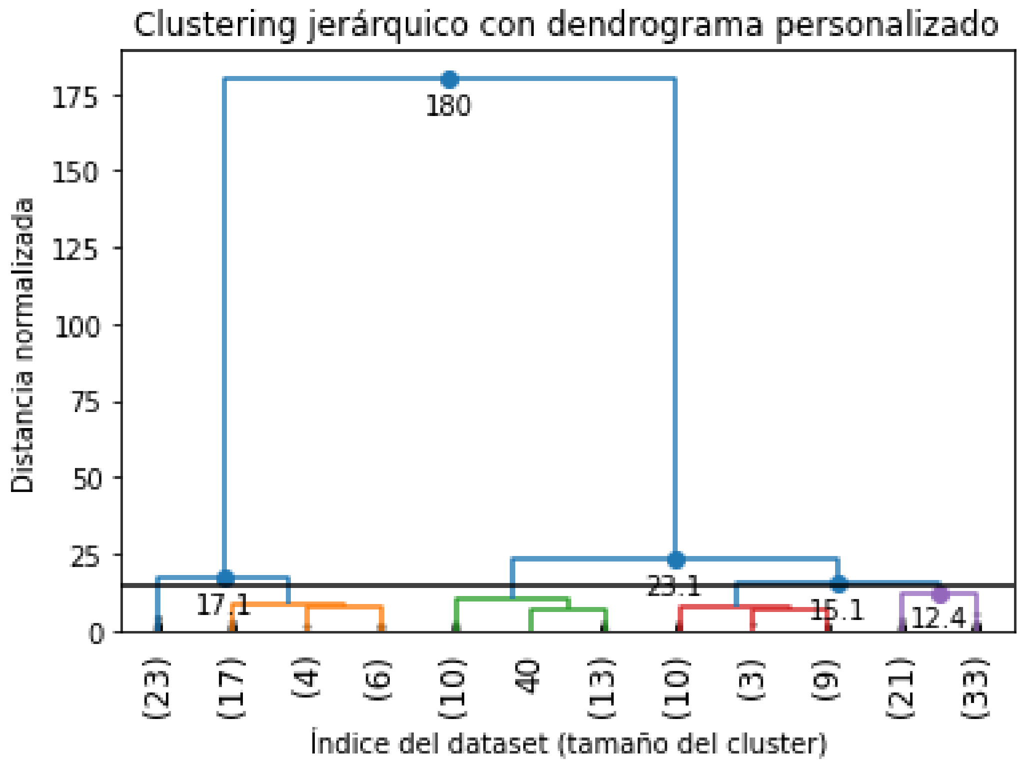
[37]:
```
plt.figure(figsize = (25, 10))
plt.title("Dendrograma truncado del clustering jerárquico")
plt.xlabel("Índices de la muestra")
plt.ylabel("Distancias normalizadas")
# truncate_mode: toma los último p cluster unidos
# show_leaf_counts: Visualización de la data en los ejes
# show_contracted: Visualización del truncamiento
dendrogram(Z, leaf_rotation = 90.0, leaf_font_size = 10.0, color_threshold = 0.
↪7*180,
          truncate_mode = "lastp", p = 12, show_leaf_counts = True,␣
↪show_contracted = True)
plt.show()
```



Dendrograma personalizado

[38]:
```
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 personalizado")
        plt.xlabel("Índice del dataset (tamaño del cluster)")
        plt.ylabel("Distancia normalizada")

        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
```

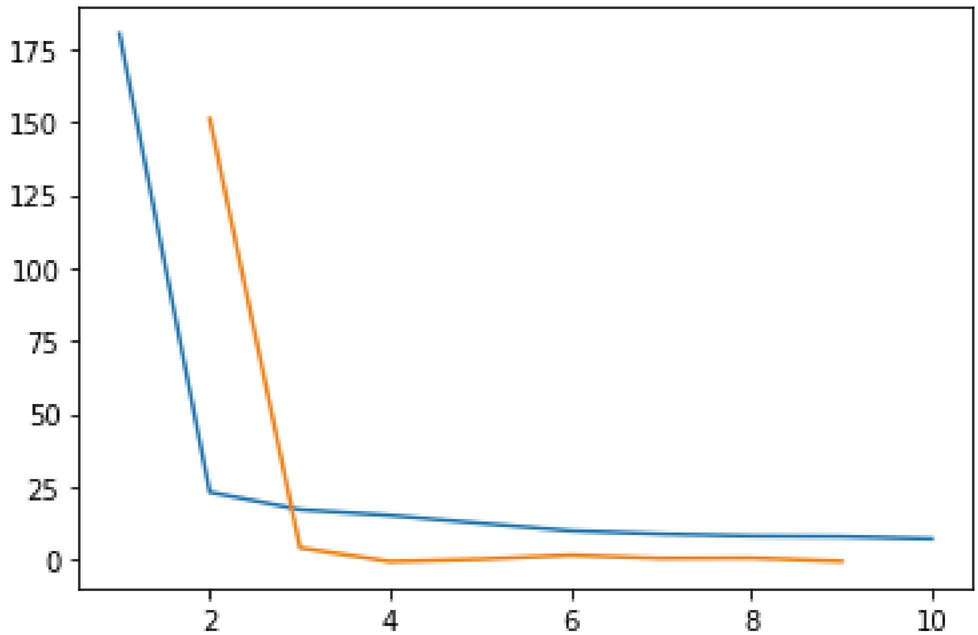
[39]:
```
dendrogram_tune(Z, truncate_mode = "lastp", p = 12, leaf_rotation = 90.0,␣
 ↪leaf_font_size = 12.0,
               show_contracted = True, annotate_above = 10, max_d = 15)
plt.show()
```



0.1.3 Método del codo

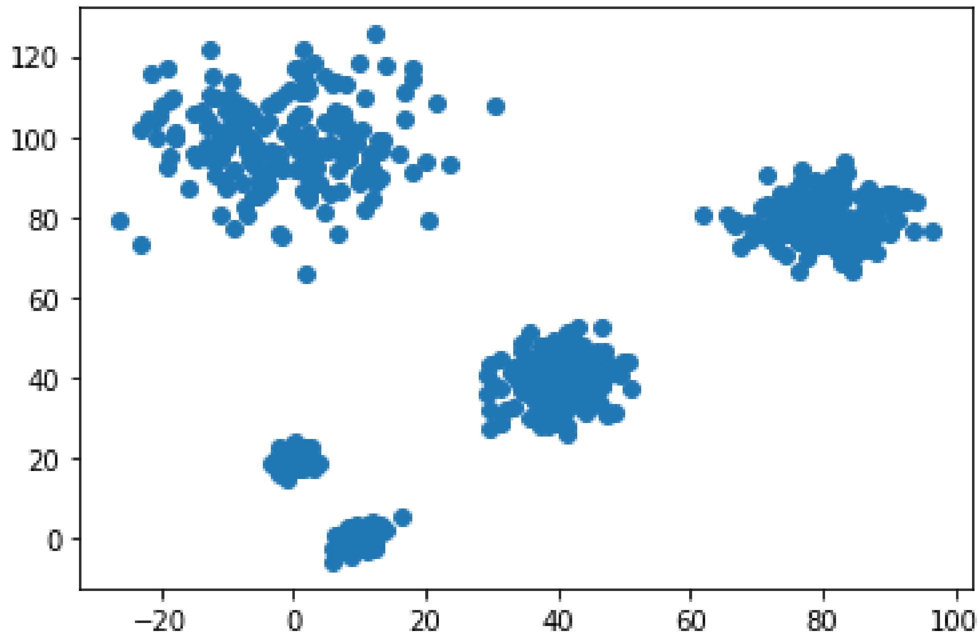
[40]:
```
# Otra perspectiva del clustering y dendrograma
last = Z[-10:, 2] # Tomamos las últimas 10 distancias
last_rev = last[::-1] # Invertimos nuestro vector
print(last_rev) # Imprimimos

# Gráfica de las distancias
idx = np.arange(1, len(last)+1)
plt.plot(idx, last_rev)

acc = np.diff(last, 2) # Restamos cada punto con el siguiente
acc_rev = acc[::-1] # Invertimos
# Graficamos la diferencia de distancias entre puntos
plt.plot(idx[:-2]+1, acc_rev)
plt.show()
```

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



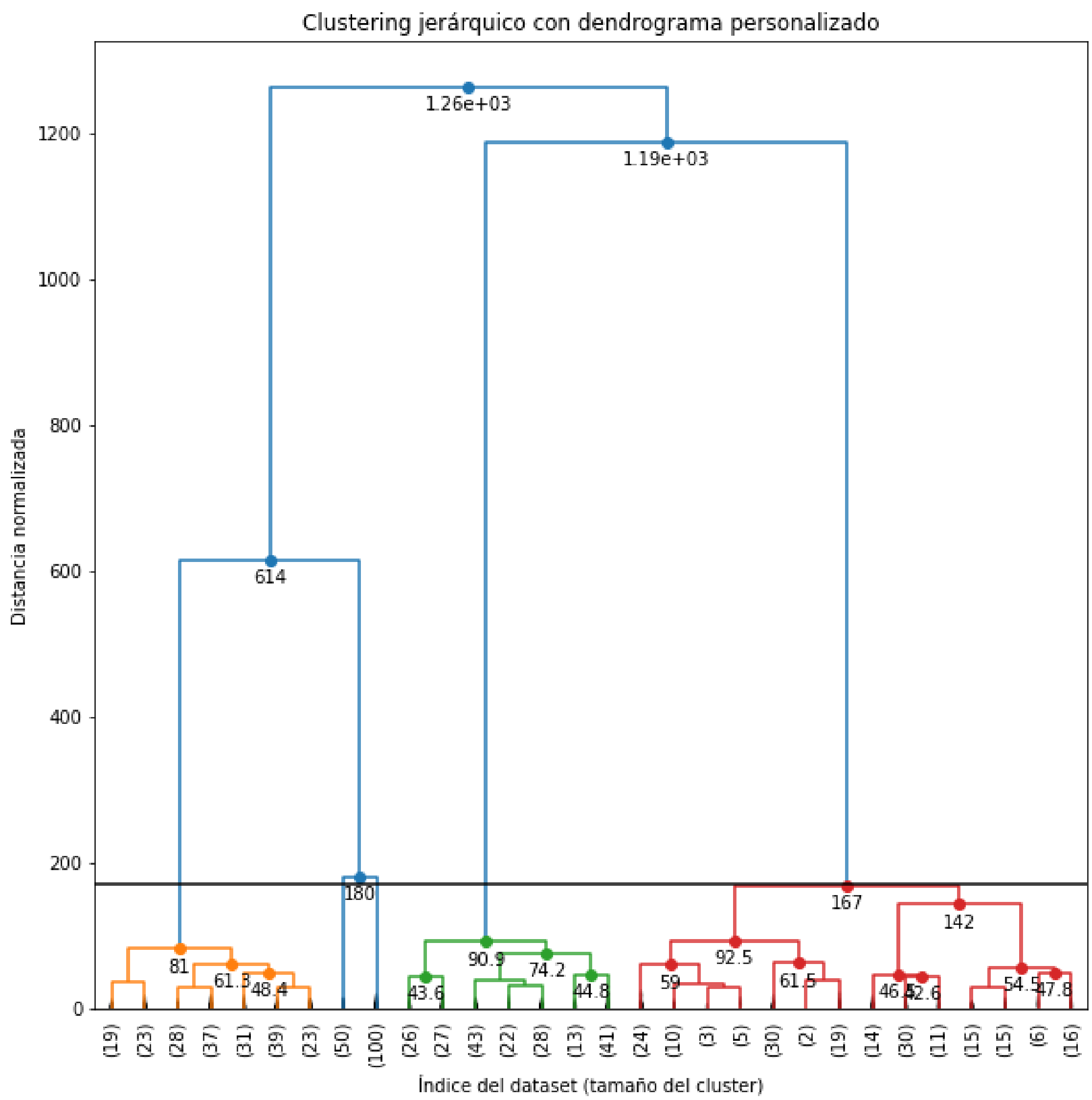
[41]:
```
# Otro ejemplo de clustering
c = np.random.multivariate_normal([40, 40], [[20, 1], [1, 30]], size = [200, ])
d = np.random.multivariate_normal([80, 80], [[30, 1], [1, 30]], size = [200, ])
e = np.random.multivariate_normal([0, 100], [[100, 1], [1, 100]], size = [200,␣
↪])
X2 = np.concatenate((X, c, d, e)) # Concatenamos nuestros datos
print(X2.shape) # Tamaño de nuestra matriz
plt.scatter(X2[:, 0], X2[:, 1]) # Gráfica de datos, todas las filas para las␣
↪columnas 0 y 1
plt.show() # Visualización
```

```
(750, 2)
```



[42]:
```
Z2 = linkage(X2, "ward")
```

[43]:
```
plt.figure(figsize = (10, 10))
dendrogram_tune(Z2, truncate_mode = "lastp", p = 30, leaf_rotation = 90.0,
               leaf_font_size = 10.0, show_contracted = True, annotate_above =␣
 ↪40, max_d = 170)
plt.show()
```

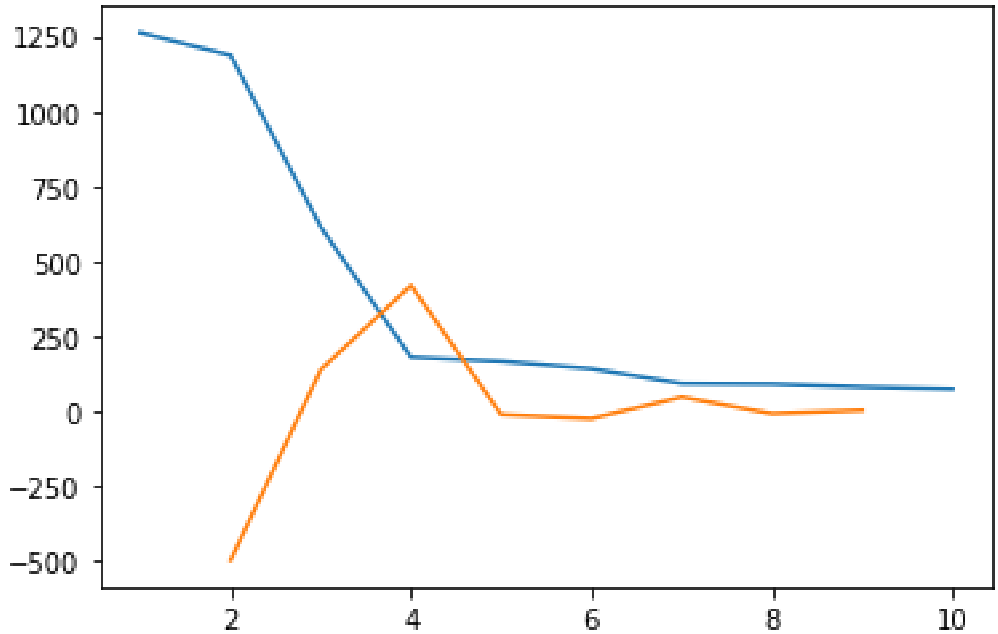


[44]:

```
# Método del codo
last = Z2[-10:, 2] # Tomamos las últimas 10 distancias
last_rev = last[::-1] # Invertimos nuestro vector
print(last_rev) # Imprimimos

# Gráfica de las distancias
idx = np.arange(1, len(last)+1)
plt.plot(idx, last_rev)

acc = np.diff(last, 2) # Restamos cada punto con el siguiente
acc_rev = acc[::-1] # Invertimos
# Graficamos la diferencia de distancias entre puntos
```

```
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  166.66434658
  141.92437181   92.54599212   90.91214341   80.96733501   74.17015312]
```




```
El número óptimo de cluster es 4
```

Recuperación de clusters y sus elementos

[45]:
```
from scipy.cluster.hierarchy import fcluster
```

[46]:
```
max_d = 25 # Corte por distancia
clusters = fcluster(Z, max_d, criterion = "distance")
clusters
```

[46]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

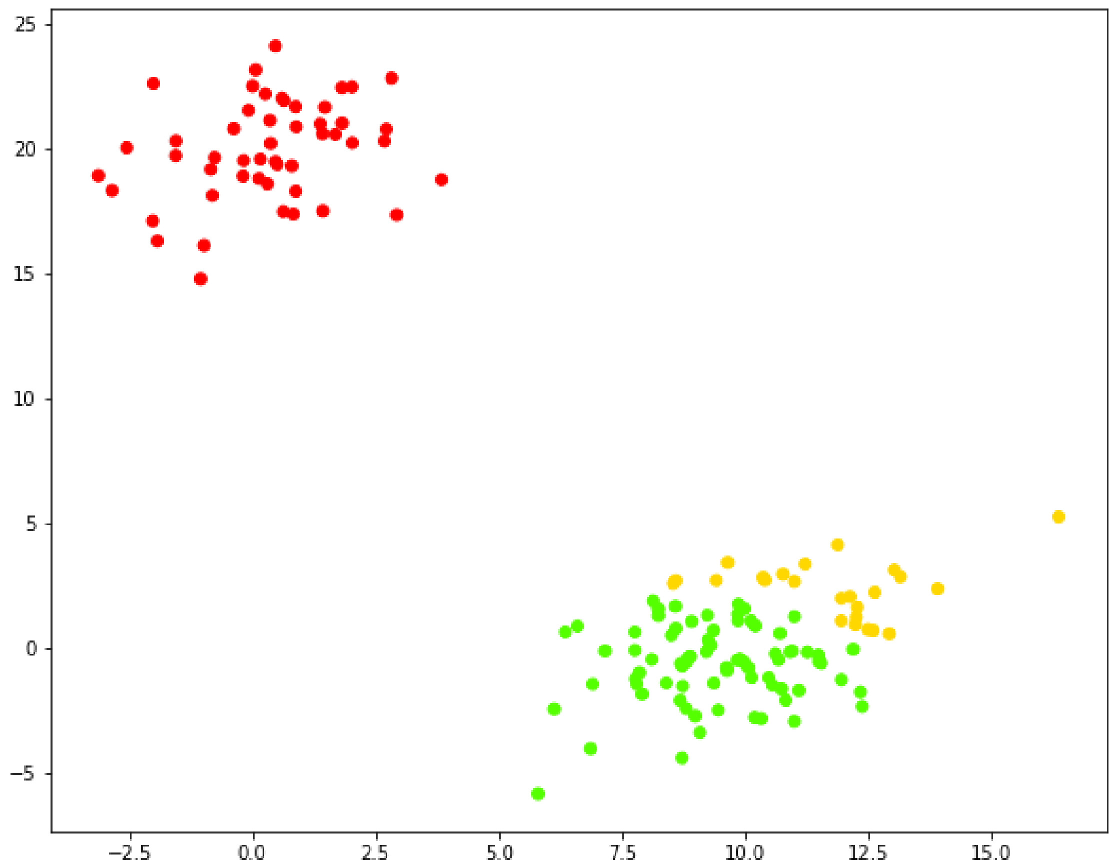
[47]:
```
k = 3 # Corte por número de cluster
clusters = fcluster(Z, k, criterion = "maxclust")
clusters
```

[47]:
```
array([3, 3, 2, 3, 3, 3, 3, 3, 3, 2, 2, 3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 2, 3, 3, 2, 3, 3, 3,
       3, 3, 3, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 2, 3, 2, 3, 3, 3, 3, 3, 2,
       2, 3, 3, 3, 3, 3, 3, 3, 2, 3, 2, 2, 3, 3, 3, 2, 3, 2, 3, 2, 2, 3,
       3, 3, 2, 3, 3, 2, 3, 2, 3, 3, 3, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

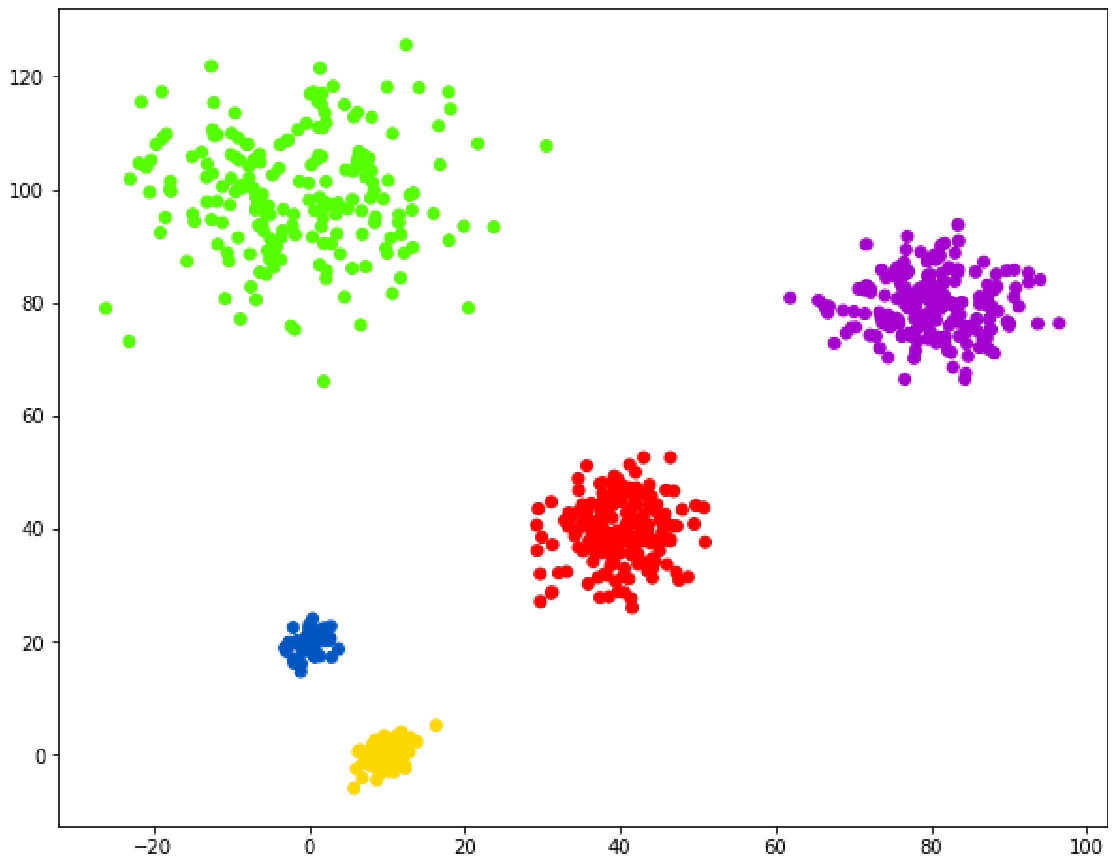
[48]:
```
# Pasamos nuestra matriz enlace, mínimo de elementos para un cluster y␣
↪profundidad
fcluster(Z, 8, depth = 10)
```

[48]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int32)
```

[49]:
```
plt.figure(figsize = (10, 8))
plt.scatter(X[:, 0], X[:, 1], c = clusters, cmap = "prism")
plt.show()
```



[50]:
```
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()
```


120
100
80
60
40
20
0
−20
0
20
40
60
80
100