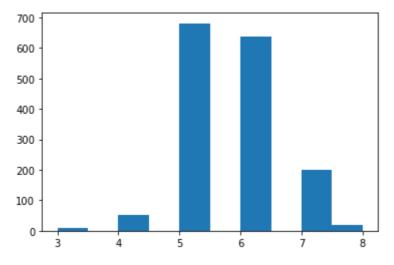
Clustering completo con Python

Importar el dataset

```
In [13]:
            import pandas as pd
            import numpy as np
In [14]:
            df = pd.read_csv("../../Data-Sets/datasets/wine/winequality-red.csv" , sep=";")
            df2 = pd.read_csv("../../Data-Sets/datasets/wine/winequality-white.csv" , sep=";")
            df.shape, df2.shape
           ((1599, 12), (4898, 12))
Out[14]:
In [15]:
            df.head()
                                                                      total
Out[15]:
                                                             free
                fixed volatile
                               citric residual
                                                chlorides
                                                            sulfur
                                                                     sulfur
                                                                            density
                                                                                      pH sulphates alcohol q
              acidity
                       acidity
                                acid
                                        sugar
                                                          dioxide
                                                                   dioxide
           0
                  7.4
                          0.70
                                0.00
                                                   0.076
                                                                      34.0
                                                                             0.9978
                                                                                                0.56
                                           1.9
                                                             11.0
                                                                                    3.51
                                                                                                          9.4
           1
                  7.8
                          0.88
                                0.00
                                           2.6
                                                   0.098
                                                             25.0
                                                                      67.0
                                                                             0.9968
                                                                                    3.20
                                                                                                0.68
                                                                                                          9.8
           2
                  7.8
                          0.76
                                           2.3
                                                   0.092
                                                             15.0
                                                                             0.9970 3.26
                                                                                                0.65
                                                                                                          9.8
                                0.04
                                                                      54.0
           3
                 11.2
                          0.28
                                0.56
                                           1.9
                                                   0.075
                                                              17.0
                                                                      60.0
                                                                             0.9980
                                                                                    3.16
                                                                                                0.58
                                                                                                          9.8
                          0.70
           4
                  7.4
                                0.00
                                           1.9
                                                   0.076
                                                                      34.0
                                                                             0.9978 3.51
                                                                                                0.56
                                                                                                          9.4
                                                             11.0
In [16]:
            df2.head()
Out[16]:
                                                             free
                                                                      total
                fixed
                      volatile
                               citric residual
                                                chlorides
                                                            sulfur
                                                                     sulfur
                                                                            density
                                                                                      pH sulphates alcohol q
              acidity
                       acidity
                                acid
                                        sugar
                                                          dioxide
                                                                   dioxide
           0
                  7.0
                          0.27
                                0.36
                                          20.7
                                                   0.045
                                                             45.0
                                                                     170.0
                                                                             1.0010
                                                                                     3.00
                                                                                                0.45
                                                                                                          8.8
           1
                  6.3
                          0.30
                                0.34
                                                   0.049
                                                             14.0
                                                                                     3.30
                                           1.6
                                                                     132.0
                                                                             0.9940
                                                                                                0.49
                                                                                                          9.5
           2
                  8.1
                          0.28
                                0.40
                                           6.9
                                                   0.050
                                                             30.0
                                                                      97.0
                                                                             0.9951
                                                                                     3.26
                                                                                                0.44
                                                                                                         10.1
           3
                                                                                                0.40
                  7.2
                          0.23
                                0.32
                                           8.5
                                                   0.058
                                                             47.0
                                                                     186.0
                                                                             0.9956
                                                                                     3.19
                                                                                                          9.9
           4
                  7.2
                          0.23
                                0.32
                                           8.5
                                                   0.058
                                                             47.0
                                                                     186.0
                                                                             0.9956 3.19
                                                                                                0.40
                                                                                                          9.9
In [17]:
            import matplotlib.pyplot as plt
In [18]:
            plt.hist(df["quality"])
                                            0., 681.,
                                                          0., 638.,
                                                                        0., 199., 18.]),
           (array([ 10., 0., 53.,
Out[18]:
            array([3., 3.5, 4., 4.5, 5., 5.5, 6., 6.5, 7., 7.5, 8.]),
            <BarContainer object of 10 artists>)
```



In [20]: df.groupby ("quality").mean()

\cap	1701.	
Out	20 .	

•		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	sulfur dioxide	sulfur dioxide	density	рН
	quality									
	3	8.360000	0.884500	0.171000	2.635000	0.122500	11.000000	24.900000	0.997464	3.398000
	4	7.779245	0.693962	0.174151	2.694340	0.090679	12.264151	36.245283	0.996542	3.381509
	5	8.167254	0.577041	0.243686	2.528855	0.092736	16.983847	56.513950	0.997104	3.304949
	6	8.347179	0.497484	0.273824	2.477194	0.084956	15.711599	40.869906	0.996615	3.318072
	7	8.872362	0.403920	0.375176	2.720603	0.076588	14.045226	35.020101	0.996104	3.290754
	8	8.566667	0.423333	0.391111	2.577778	0.068444	13.277778	33.444444	0.995212	3.267222
	4									

Como vemos en la tabla de promedios, la volatilidad del ácido y los cloros influyen negativamente en la calidad del vino. Los sulfatos influyes positivamente al igual que el ácido cítrico. 2-, 2+ y el reso neutras. La idea es ver la influencia de las variables en el resultado final.

Normalización de los datos

In [22]:
 df_norm = (df-df.min())/(df.max()-df.min())
 df_norm.head()

Out[22]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates
0	0.247788	0.397260	0.00	0.068493	0.106845	0.140845	0.098940	0.567548	0.606299	0.137725
1	0.283186	0.520548	0.00	0.116438	0.143573	0.338028	0.215548	0.494126	0.362205	0.209581
2	0.283186	0.438356	0.04	0.095890	0.133556	0.197183	0.169611	0.508811	0.409449	0.191617
3	0.584071	0.109589	0.56	0.068493	0.105175	0.225352	0.190813	0.582232	0.330709	0.149701
4	0.247788	0.397260	0.00	0.068493	0.106845	0.140845	0.098940	0.567548	0.606299	0.137725
4										>

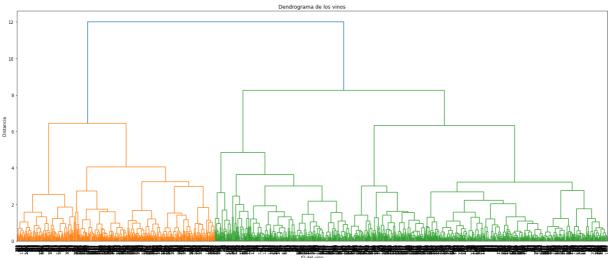
In [24]:

Todos los valores oscilarán entre cero y uno mediante la normalización.

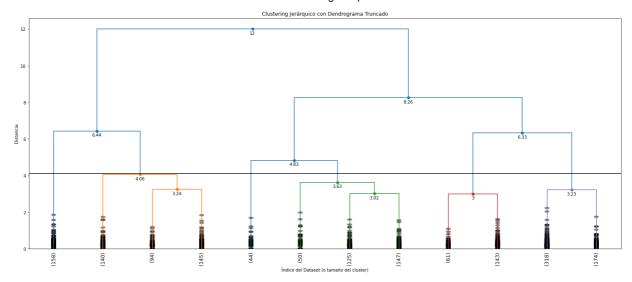
Clustering jerárquico con scikit-learn

```
from sklearn.cluster import AgglomerativeClustering
In [25]:
           clus = AgglomerativeClustering(n_clusters=6, linkage="ward").fit(df_norm)
In [27]:
           clus.labels_
          array([2, 2, 2, ..., 4, 4, 0], dtype=int64)
Out[27]:
In [44]:
           md_h = pd.Series(clus.labels_)
In [45]:
           plt.hist(md_h)
           plt.title("Histograma de los clusters")
           plt.xlabel("Cluster")
           plt.ylabel("Número de vinos del cluster")
          Text(0, 0.5, 'Número de vinos del cluster')
Out[45]:
                              Histograma de los clusters
             500
          Número de vinos del cluster
000 000 000
             300
                                        Cluster
In [30]:
           clus.children
                             4],
          array([[
Out[30]:
                  [ 135,
                           140],
                  [ 750,
                           751],
                  [3179, 3191],
                  [3192, 3193],
                  [3194, 3195]], dtype=int64)
In [31]:
           from scipy.cluster.hierarchy import dendrogram, linkage
In [32]:
           Z = linkage(df_norm, "ward")
```

```
In [34]: plt.figure(figsize=(25,10))
   plt.title("Dendrograma de los vinos")
   plt.xlabel("ID del vino")
   plt.ylabel("Distancia")
   dendrogram(Z, leaf_rotation=90., leaf_font_size=9.)
   plt.show()
```

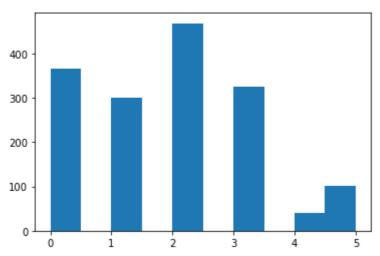


```
In [35]:
          def dendrogram_tuned(*args, **kwargs):
              max_d=kwargs.pop("max_d", None)
              if max_d and 'color_threshold' not in kwargs:
                  kwargs['color_threshold'] = max_d
              annotate_above = kwargs.pop('annotate_above', 0)
              ddata = 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
```



K-means

```
In [69]:
           from sklearn.cluster import KMeans
           from sklearn import datasets
In [70]:
           model = KMeans(n_clusters=6)
           model.fit(df_norm)
          KMeans(n_clusters=6)
Out[70]:
In [71]:
           md_k = pd.Series(model.labels_)
In [72]:
           df_norm["clust_h"]=md_h
           df_norm["clust_k"]=md_k
In [73]:
           df_norm.head()
                                                           free
                                                                    total
Out[73]:
                fixed
                       volatile citric
                                     residual
                                              chlorides
                                                          sulfur
                                                                   sulfur
                                                                                       pH sulphates
                                                                           density
              acidity
                        acidity
                                acid
                                       sugar
                                                        dioxide
                                                                  dioxide
          0 0.247788
                     0.397260
                                0.00
                                     0.068493
                                               0.106845
                                                       0.140845
                                                                0.098940
                                                                          0.567548
                                                                                  0.606299
                                                                                             0.137725
             0.283186 0.520548
                                0.00 0.116438
                                               0.143573
                                                       0.338028
                                                                0.215548
                                                                          0.494126
                                                                                  0.362205
                                                                                             0.209581
          2 0.283186 0.438356
                                0.04 0.095890
                                               0.133556
                                                       0.197183
                                                                0.169611
                                                                          0.508811
                                                                                   0.409449
                                                                                             0.191617
             0.584071 0.109589
                                0.56 0.068493
                                               0.105175 0.225352
                                                                0.190813
                                                                          0.582232 0.330709
                                                                                             0.149701
             0.247788 0.397260
                                0.00 0.068493
                                               0.567548  0.606299
                                                                                             0.137725
In [74]:
           plt.hist(md_k)
          (array([365., 0., 300.,
                                        0., 468.,
                                                    0., 325., 0., 40., 101.]),
Out[74]:
           array([0., 0.5, 1., 1.5, 2., 2.5, 3., 3.5, 4., 4.5, 5.]),
           <BarContainer object of 10 artists>)
```

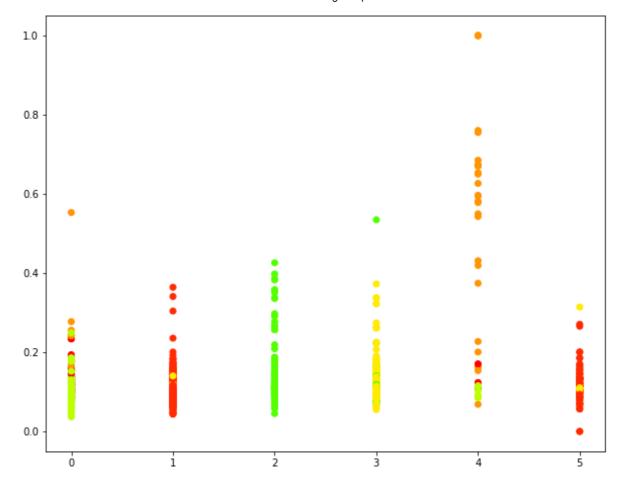


```
In [63]:
          model.cluster_centers_
         array([[3.75027276e-01, 2.82107337e-01, 2.83013699e-01, 1.04531807e-01,
Out[63]:
                 1.11976582e-01, 1.95755354e-01, 1.09347016e-01, 4.84175165e-01,
                 4.61115306e-01, 2.07628578e-01, 3.94836670e-01, 5.67123288e-01,
                 3.61369863e+00, 2.00000000e+00],
                [3.07182800e-01, 2.84845365e-01, 2.92975460e-01, 1.49445332e-01,
                 1.26954945e-01, 3.46496155e-01, 2.83205792e-01, 5.36028306e-01,
                 4.36138351e-01, 1.75636457e-01, 2.05128205e-01, 4.52147239e-01,
                 1.07975460e+00, 3.99693252e+00],
                [2.64368687e-01, 3.60762371e-01, 1.07387580e-01, 9.12264234e-02,
                 1.23735848e-01, 1.44418976e-01, 1.01527682e-01, 4.88513554e-01,
                 4.89571566e-01, 1.52713844e-01, 2.26102235e-01, 4.52676660e-01,
                 2.00214133e+00, 1.01927195e+00],
                [3.61150442e-01, 1.64486301e-01, 4.15266667e-01, 1.05365297e-01,
                 1.07779633e-01, 1.83309859e-01, 9.98586572e-02, 4.27513461e-01,
                 4.26272966e-01, 2.28822355e-01, 4.59743590e-01, 6.76000000e-01,
                 1.66666667e-02, 3.04333333e+00],
                [3.44469027e-01, 3.02054795e-01, 4.27750000e-01, 8.40753425e-02,
                 4.28213689e-01, 2.51760563e-01, 2.08392226e-01, 5.10682819e-01,
                 2.83464567e-01, 4.95359281e-01, 2.17307692e-01, 4.70000000e-01,
                 4.70000000e+00, 5.00000000e+00],
                [4.33014983e-01, 2.07073105e-01, 4.22178218e-01, 1.48853926e-01,
                 1.18299476e-01, 1.79054525e-01, 1.06007067e-01, 5.50115584e-01,
                 4.03211975e-01, 2.11655896e-01, 3.41203351e-01, 5.50495050e-01,
                 1.68316832e-01, 4.44089210e-16]])
In [64]:
          model.inertia
         458.263238598056
Out[64]:
```

Interpretación final

```
In [127...
          df_norm.groupby("clust_k").mean()
Out[127...
                                                                 free
                                                                         total
                    fixed
                           volatile
                                           residual
                                     citric
                                                    chlorides
                                                               sulfur
                                                                        sulfur
                                                                                            pH su
                                                                                density
                  acidity
                           acidity
                                      acid
                                              sugar
                                                              dioxide
                                                                       dioxide
          clust k
                 0.375027 0.282107 0.283014
                                           0.104532
                                                    0.111977 0.195755
                                                                      0.109347
                                                                               0.484175
              1 0.361150 0.164486 0.415267 0.105365
                                                    (
```

```
free
                                                                                   total
                              volatile
                       fixed
                                           citric
                                                  residual
                                                           chlorides
                                                                        sulfur
                                                                                  sulfur
                                                                                           density
                                                                                                         pH su
                     acidity
                               acidity
                                           acid
                                                    sugar
                                                                       dioxide
                                                                                 dioxide
           clust k
                2 0.264447
                             0.360679
                                       0.107500
                                                 0.091163
                                                            0.123661
                                                                      0.144171
                                                                                0.101386
                                                                                          0.488431
                                                                                                   0.489670
                                                                                                              C
                3 0.307202 0.284731
                                       0.293385
                                                 0.149715
                                                            0.127073
                                                                     0.347476
                                                                                0.283968
                                                                                          0.536293
                                                                                                   0.435833
                                                                                                              (
                   0.344469
                             0.302055
                                       0.427750
                                                 0.084075
                                                            0.428214
                                                                      0.251761
                                                                                0.208392
                                                                                         0.510683
                                                                                                   0.283465
                                                                                                              C
                  0.433015 0.207073 0.422178 0.148854
                                                            0.118299
                                                                      0.179055
                                                                                0.106007
                                                                                         0.550116 0.403212
                                                                                                              (
In [80]:
            df_norm.head()
                                                                           total
Out[80]:
                                                                 free
                 fixed
                         volatile citric
                                         residual
                                                   chlorides
                                                                sulfur
                                                                          sulfur
                                                                                  density
                                                                                                рΗ
                                                                                                     sulphates
                acidity
                          acidity
                                   acid
                                           sugar
                                                              dioxide
                                                                        dioxide
              0.247788
                        0.397260
                                   0.00
                                         0.068493
                                                                       0.098940
                                                                                 0.567548
                                                                                           0.606299
                                                   0.106845
                                                             0.140845
                                                                                                      0.137725
              0.283186
                        0.520548
                                        0.116438
                                                             0.338028
                                                                       0.215548
                                                                                                      0.209581
                                   0.00
                                                   0.143573
                                                                                 0.494126
                                                                                           0.362205
                                        0.095890
                                                            0.197183
              0.283186  0.438356
                                   0.04
                                                   0.133556
                                                                       0.169611
                                                                                 0.508811
                                                                                           0.409449
                                                                                                      0.191617
              0.584071
                        0.109589
                                   0.56
                                        0.068493
                                                   0.105175
                                                             0.225352
                                                                       0.190813
                                                                                 0.582232
                                                                                           0.330709
                                                                                                      0.149701
              0.247788 0.397260
                                   0.00 0.068493
                                                   0.106845
                                                            0.140845
                                                                       0.098940
                                                                                 0.567548
                                                                                          0.606299
                                                                                                      0.137725
In [77]:
            from scipy.cluster.hierarchy import fcluster
In [110...
            X = df_norm.columns.values.tolist()[13:]
            X1 = df_norm[X]
In [123...
            df_norm["clust_k"]
                    2
Out[123...
           1
                    2
           2
                    2
           3
                    0
           4
                    2
                    . .
           1594
                    0
           1595
                    0
           1596
                    0
                    0
           1597
           1598
                    1
           Name: clust k, Length: 1599, dtype: int32
In [125...
            max_d=4.2
            clusters = fcluster(Z, max_d, criterion="distance")
            plt.figure(figsize=(10,8))
            plt.scatter(df_norm["clust_k"], df_norm["chlorides"], c= clusters, cmap="prism")
            plt.show()
```



No se puede hacer una representación gráfica con más de una variable, pues requerimos 12 dimensiones para ver la nube de dispersión. Sólo se podría hacer seleccionadado alguna columna contra otra columna.