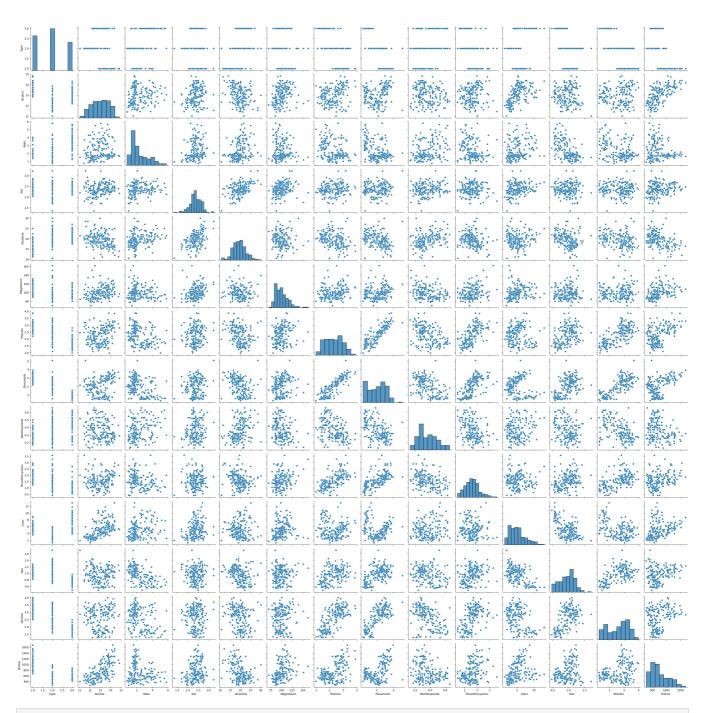
In [23]: import pandas as pd import numpy as np from sklearn.decomposition import PCA import matplotlib.pyplot as plt import seaborn as sn In [2]: wine=pd.read_csv('wine.csv') wine Type Alcohol Malic Ash Alcalinity Magnesium Phenols Flavanoids Nonflavanoids Proanthocyanins Color Hue Dilution Proline Out[2]: 0 14.23 1.71 2.43 15.6 127 2.80 3.06 0.28 2.29 5.64 1.04 3.92 1065 13.20 1.78 2.14 11.2 100 2.65 2.76 0.26 1050 1.28 4.38 1.05 3.40 2 1 13.16 2.36 2.67 18.6 101 2.80 3.24 0.30 2.81 5.68 1.03 3.17 1185 3 14.37 1.95 2.50 16.8 113 3.85 3.49 0.24 2.18 7.80 0.86 3.45 1480 4 13.24 2.59 2.87 21.0 118 2.80 2.69 0.39 1.82 4.32 1.04 2.93 735 13.71 5.65 2.45 173 3 20.5 95 1.68 0.61 0.52 1.06 7.70 0.64 1.74 740 174 3 13.40 3.91 2.48 23.0 102 1.80 0.75 0.43 1.41 7.30 0.70 1.56 750 175 13.27 4.28 2.26 20.0 120 1.59 0.69 10.20 0.59 835 3 0.43 1.35 1.56 120 176 3 13.17 2.59 2.37 20.0 1.65 0.68 0.53 1.46 9.30 0.60 1.62 840 177 14.13 4.10 2.74 24.5 2.05 0.76 0.56 9.20 0.61 560 178 rows × 14 columns In [3]: wine.head() Type Alcohol Malic Ash Alcalinity Magnesium Phenols Flavanoids Nonflavanoids Proanthocyanins Color Hue Dilution Proline 0 14.23 1.71 2.43 15.6 127 2.80 3.06 0.28 2.29 5.64 1.04 3.92 1065 1.78 2.14 2.76 13.20 11.2 100 2.65 0.26 1.28 4.38 1.05 3.40 1050 2 1185 101 2.80 0.30 13.16 2.36 2.67 18.6 3.24 2.81 5.68 1.03 3.17 3 14.37 1.95 2.50 16.8 113 3.85 3.49 0.24 2.18 7.80 0.86 3.45 1480 2.93 13.24 2.59 2.87 21.0 118 2.80 2.69 0.39 1.82 4.32 1.04 735 4 **|** In [4]: wine.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 178 entries, 0 to 177 Data columns (total 14 columns): Dtype Non-Null Count # Column 0 178 non-null Type int64 1 Alcohol 178 non-null float64 2 Malic 178 non-null float64 3 Ash 178 non-null float64 4 Alcalinity 178 non-null float64 5 Magnesium 178 non-null int64 6 Phenols 178 non-null float64 float64 Flavanoids 178 non-null 8 Nonflavanoids 178 non-null float64 9 Proanthocyanins 178 non-null float64 10 Color 178 non-null float64 11 Hue 178 non-null float64 Dilution float64 12 178 non-null 13 Proline 178 non-null int64 dtypes: float64(11), int64(3) memory usage: 19.6 KB sn.pairplot(wine) In [5]:

<seaborn.axisgrid.PairGrid at 0x208540e3dc0>

Out[5]:



In [6]: wine.data = wine.iloc[:,1:]
 data =wine.data.values
 data

C:\Users\ROHIT\AppData\Local\Temp\ipykernel_19804\2901724688.py:1: UserWarning: Pandas doesn't allow columns to be created via a new attribute name - see https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access

wine.data = wine.iloc[:,1:]

```
Out[6]: array([[1.423e+01, 1.710e+00, 2.430e+00, ..., 1.040e+00, 3.920e+00,
                      1.065e+03],
                     [1.320e+01, 1.780e+00, 2.140e+00, ..., 1.050e+00, 3.400e+00,
                      1.050e+03],
                     [1.316e+01, 2.360e+00, 2.670e+00, ..., 1.030e+00, 3.170e+00,
                      1.185e+03],
                     [1.327e+01, 4.280e+00, 2.260e+00, ..., 5.900e-01, 1.560e+00,
                      8.350e+02],
                     [1.317e+01, 2.590e+00, 2.370e+00, ..., 6.000e-01, 1.620e+00,
                      8.400e+02],
                     [1.413e+01, 4.100e+00, 2.740e+00, ..., 6.100e-01, 1.600e+00,
                      5.600e+0211)
In [7]: from sklearn.preprocessing import scale
           wine_normal = scale(data)
           wine normal
Out[7]: array([[ 1.51861254, -0.5622498 , 0.23205254, ..., 0.36217728,
                        1.84791957, 1.01300893],
                     [\ 0.24628963,\ -0.49941338,\ -0.82799632,\ \ldots,\ 0.40605066,
                     1.1134493 , 0.96524152],
[ 0.19687903 , 0.02123125 , 1.10933436 , ... , 0.31830389 ,
                        0.78858745, 1.39514818],
                     [\ 0.33275817,\ 1.74474449,\ -0.38935541,\ \dots,\ -1.61212515,
                     -1.48544548, 0.28057537],
[ 0.20923168, 0.22769377, 0.01273209, ..., -1.56825176,
                     -1.40069891, 0.29649784],
[ 1.39508604, 1.58316512, 1.36520822, ..., -1.52437837, -1.42894777, -0.59516041]])
In [8]: pca = PCA(n_components = 13)
            pca_values = pca.fit_transform(wine_normal)
           pca_values
Out[8]: array([[ 3.31675081e+00, -1.44346263e+00, -1.65739045e-01, ..., -4.51563395e-01, 5.40810414e-01, -6.62386309e-02], [ 2.20946492e+00, 3.33392887e-01, -2.02645737e+00, ..., -1.42657306e-01, 3.88237741e-01, 3.63650247e-03], [ 2.51674015e+00, -1.03115130e+00, 9.82818670e-01, ..., 2.86673847e-01, -2.3171651040, 0.21
                      -2.86672847e-01, 5.83573183e-04, 2.17165104e-02],
                     [-2.67783946e+00, -2.76089913e+00, -9.40941877e-01, ...,
                     5.12492025e-01, 6.98766451e-01, 7.20776948e-02], [-2.38701709e+00, -2.29734668e+00, -5.50696197e-01, ..., 2.99821968e-01, 3.39820654e-01, -2.18657605e-02],
                     [-3.20875816e+00, -2.76891957e+00, 1.01391366e+00, ..., -2.29964331e-01, -1.88787963e-01, -3.23964720e-01]])
In [9]: pca.components_
```

```
Out[9]: array([[ 0.1443294 , -0.24518758, -0.00205106, -0.23932041, 0.14199204,
                                                0.31342949, -0.0886167
                                           \hbox{$[\,\hbox{-0.48365155},\,\,\hbox{-0.22493093},\,\,\hbox{-0.31606881},\,\,\,\hbox{0.0105905}\,\,\,,\,\,\hbox{-0.299634}$}
                                              -0.06503951, \quad 0.00335981, \quad -0.02877949, \quad -0.03930172, \quad -0.52999567, \quad -0.03930172, \quad -0.03
                                                0.27923515, 0.16449619, -0.36490283],
                                           [-0.20738262, 0.08901289, 0.6262239,
                                                                                                                                                      0.61208035, 0.13075693,
                                                                                0.1506819 , 0.17036816,
                                                                                                                                                      0.14945431, -0.13730621,
                                                0.14617896.
                                                0.08522192, 0.16600459, -0.12674592],
                                           [-0.0178563 , 0.53689028, -0.21417556,
                                                                                                                                                      0.06085941, -0.35179658,
                                                0.19806835, 0.15229479, -0.20330102,
                                                                                                                                                      0.39905653, 0.06592568,
                                              -0.42777141, 0.18412074, -0.23207086],
                                           [-0.26566365, 0.03521363, -0.14302547,
                                                                                                                                                      0.06610294, 0.72704851,
                                                                                                                                                      0.13685982, -0.07643678,
                                              -0.14931841, -0.10902584, -0.50070298,
                                              -0.17361452, -0.10116099, -0.1578688 ],
                                           [-0.21353865, \ -0.53681385, \ -0.15447466, \ \ 0.10082451, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0.03814394, \ -0
                                                0.0841223 , 0.01892002, 0.25859401,
                                                                                                                                                      0.53379539, 0.41864414,
                                              -0.10598274, -0.26585107, -0.11972557],
                                           [-0.05639636, \quad 0.42052391, \quad -0.14917061, \quad -0.28696914, \quad 0.3228833
                                               -0.02792498, -0.06068521, 0.59544729, 0.37213935, -0.22771214,
                                                0.23207564, -0.0447637, 0.0768045],
                                           \hbox{$[\,\hbox{-0.39613926}\,,\,\,\hbox{-0.06582674}\,,\quad\hbox{0.17026002}\,,\,\,\hbox{-0.42797018}\,,\quad\hbox{0.15636143}\,,}
                                                0.40593409, 0.18724536, 0.23328465, -0.36822675, 0.03379692,
                                              -0.43662362, 0.07810789, -0.12002267],
                                           [ 0.50861912, -0.07528304, -0.30769445, 0.20044931, 0.27140257, 0.28603452, 0.04957849, 0.19550132, -0.20914487, 0.05621752,
                                                0.08582839, 0.1372269, -0.57578611],
                                           [0.21160473, -0.30907994, -0.02712539, 0.05279942, 0.06787022,
                                              -0.32013135, \ -0.16315051, \ \ 0.21553507, \ \ 0.1341839 \ , \ -0.29077518,
                                              -0.52239889, 0.52370587, 0.162116 ],
                                           [-0.22591696, 0.07648554, -0.49869142, 0.47931378, 0.07128891,
                                                0.30434119, -0.02569409, 0.11689586, -0.23736257, 0.0318388,
                                              -0.04821201, 0.0464233 , 0.53926983],
                                           [-0.26628645, 0.12169604, -0.04962237, -0.05574287, 0.06222011,
                                              -0.30388245\,,\; -0.04289883\,,\;\; 0.04235219\,,\; -0.09555303\,,\;\; 0.60422163\,,
                                                                                0.60095872, -0.07940162],
                                                0.259214
                                           [ 0.01496997, 0.02596375, -0.14121803, 0.09168285, 0.05677422, -0.46390791, 0.83225706, 0.11403985, -0.11691707, -0.0119928,
                                              -0.08988884, -0.15671813, 0.01444734]])
In [10]: var = pca.explained variance ratio
                         \verb"array" ([0.36198848, \ 0.1920749 \ , \ 0.11123631, \ 0.0706903 \ , \ 0.06563294,
                                           0.04935823, 0.04238679, 0.02680749, 0.02222153, 0.01930019,
                                           0.01736836, 0.01298233, 0.00795215])
                         var1 = np.cumsum(np.round(var, decimals = 4)*100)
                         var1
Out[12]: array([ 36.2 , 55.41, 66.53, 73.6 , 80.16, 85.1 , 89.34, 92.02,
                                              94.24, 96.17, 97.91, 99.21, 100.01])
In [13]: plt.plot(var1,color="red")
                        [<matplotlib.lines.Line2D at 0x20864cc4af0>]
In [14]: pca_values[:,0:1]
Out[14]: array([[ 3.31675081],
                                                2.20946492],
                                           [ 2.51674015],
                                                3.75706561],
                                           [ 1.00890849].
                                           [ 3.05025392],
                                               2.449089671.
                                           [ 2.05943687],
                                                2.5108743 ],
                                               2.75362819],
                                           [ 3.47973668],
                                           [ 1.7547529 ],
                                               2.113462341.
                                           [ 3.45815682].
                                           [ 4.31278391],
                                           [ 2.3051882 ],
                                           [ 2.17195527],
                                           [ 1.89897118],
                                               3.541985081.
                                               2.0845222 ],
                                                3.124402541.
                                           [ 1.08657007],
                                           [ 2.53522408],
                                               1.644988341,
                                           [ 1.76157587],
                                           [ 0.9900791 ],
                                           [ 1.77527763].
                                           [ 1.23542396],
                                           [ 2.18840633],
                                           [ 2.25610898],
```

```
[ 2.50022003],
[ 2.67741105],
 1.62857912],
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 1.41038853],
[ 1.90382623],
[ 1.38486223],
[ 1.12220741],
[ 1.5021945 ],
[ 2.52980109],
[ 2.58809543],
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[ 2.10135193],
[ 1.13616618],
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[ 0.7620639 ],
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[ 0.95745536],
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[-0.54395259],
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[ 2.25190942],
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```

[0.48207441], [-0.25288888], [-0.10722764], [-2.4330126],

```
[-0.55108954],
                 [ 0.73962193],
                 [ 1.33632173],
                 [-1.177087
                 [-0.46233501],
                 [ 0.97847408],
                 [-0.09680973],
                 [ 0.03848715],
                 [-1.5971585],
                 [-0.47956492],
                 [-1.79283347],
                 [-1.32710166],
                 [-2.38450083],
                 [-2.9369401],
                 [-2.14681113],
                 [-2.36986949],
                 [-3.06384157],
                 [-3.91575378],
                 [-3.93646339],
                 [-3.09427612],
                 [-2.37447163],
                 [-2.77881295],
                 [-2.28656128],
                 [-2.98563349],
                 [-2.3751947],
                 [-2.20986553],
                 [-2.625621
                 [-4.28063878],
                 [-3.58264137],
                 [-2.80706372],
                 [-2.89965933],
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                 [-2.54983095],
                 [-1.81254128],
                 [-2.76014464],
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                 [-3.60486887],
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                 [-1.60991228],
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                 [-2.59749706],
                 [-2.94929937],
                 [-3.53003227],
                 [-2.40611054],
                 [-2.92908473],
                 [-2.18141278],
                 [-2.38092779],
                 [-3.21161722],
                 [-3.67791872],
                 [-2.4655558],
                 [-3.37052415],
                 [-2.60195585],
                 [-2.67783946],
                 [-2.38701709],
                 [-3.20875816]])
In [15]: final df = pd.concat([pd.DataFrame(pca values[:,0:3],columns=['pc1','pc2','pc3']),wine['Type']], axis=1)
          final_df
Out[15]:
                   pc1
                            pc2
                                     pc3 Type
           0 3.316751 -1.443463 -0.165739
                                            1
              2.209465 0.333393 -2.026457
           2 2.516740 -1.031151 0.982819
           3 3.757066 -2.756372 -0.176192
              1.008908 -0.869831 2.026688
                                            1
          173 -3.370524 -2.216289 -0.342570
                                            3
          174 -2.601956 -1.757229
                                0.207581
                                            3
          175 -2.677839 -2.760899 -0.940942
                                            3
          176 -2.387017 -2.297347 -0.550696
          177 -3.208758 -2.768920 1.013914
                                            3
         178 rows × 4 columns
```

In [16]: sn.scatterplot(data=final_df,x='pc1',y='pc2',hue='Type',s = 100)

```
Out[16]: <AxesSubplot:xlabel='pc1', ylabel='pc2'>
            p1 = sn.scatterplot(data=final_df,x='pc1',y='pc2',s = 100)
for line in range(0,final_df.shape[0]):
In [17]:
                    pl.text(final_df.pc1[line], final_df.pc2[line], final_df.Type[line], horizontalalignment='left', size='med
In [18]:
             from sklearn.cluster import KMeans
             from scipy.cluster.hierarchy import linkage
             import scipy.cluster.hierarchy as sch
             from sklearn.cluster import AgglomerativeClustering
             import warnings
             warnings.filterwarnings('ignore')
 In [ ]:
In [20]: p = np.array(wine_normal)
             z = linkage(wine_normal, method="complete", metric="euclidean")
plt.figure(figsize=(15, 5))
             plt.title('Hierarchical Clustering Dendrogram')
             plt.xlabel('Index')
plt.ylabel('Distance')
             sch.dendrogram(z,)
             plt.show()
                 100
                                1
                                2
                                3
                   80
                   60
             pc2
                   40
                  20
                    0
                                                                   4
                                                                            6
                                                                                      8
                                                                                               10
                                                                                                         12
                                                                pc1
                                                                         Hierarchical Clustering Dendrogram
               10
                8
             Distance
                6
                2
                                                                      Index
             \label{eq:h_complete} $$h\_complete = AgglomerativeClustering(n\_clusters=3, linkage='complete', affinity = "euclidean").fit(wine_normal) $$h\_complete = AgglomerativeClustering(n\_clusters=3, linkage='complete', affinity = "euclidean").fit(wine_normal) $$h\_complete = AgglomerativeClustering(n\_clusters=3, linkage='complete', affinity = "euclidean").fit(wine_normal) $$h\_complete = AgglomerativeClustering(n\_clusters=3, linkage='complete').$$
In [24]:
             cluster_labels=pd.Series(h_complete.labels_)
             cluster labels
             wine['clust']=cluster_labels # creating a new column and assigning it to new column
```

wine

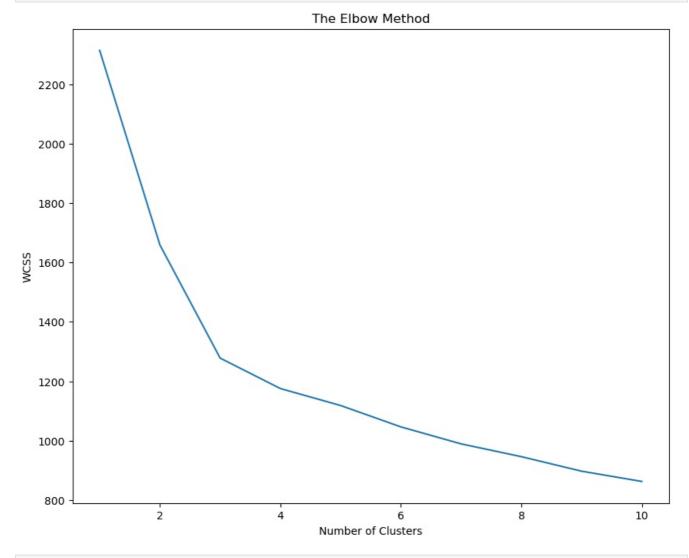
Out[24]:		Type	Alcohol	Malic	Ash	Alcalinity	Magnesium	Phenols	Flavanoids	Nonflavanoids	Proanthocyanins	Color	Hue	Dilution	Proline
	0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	2.29	5.64	1.04	3.92	1065
	1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	1.28	4.38	1.05	3.40	1050
	2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	2.81	5.68	1.03	3.17	1185
	3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	2.18	7.80	0.86	3.45	1480
	4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	1.82	4.32	1.04	2.93	735
	173	3	13.71	5.65	2.45	20.5	95	1.68	0.61	0.52	1.06	7.70	0.64	1.74	740
	174	3	13.40	3.91	2.48	23.0	102	1.80	0.75	0.43	1.41	7.30	0.70	1.56	750
	175	3	13.27	4.28	2.26	20.0	120	1.59	0.69	0.43	1.35	10.20	0.59	1.56	835
	176	3	13.17	2.59	2.37	20.0	120	1.65	0.68	0.53	1.46	9.30	0.60	1.62	840
	177	3	14.13	4.10	2.74	24.5	96	2.05	0.76	0.56	1.35	9.20	0.61	1.60	560

178 rows × 15 columns

```
In [25]: data = wine[(wine.clust==3)]
    data
```

Out[25]: Type Alcohol Malic Ash Alcalinity Magnesium Phenols Flavanoids Nonflavanoids Proanthocyanins Color Hue Dilution Proline clu

```
In [26]: fig = plt.figure(figsize=(10, 8))
WCSS = []
for i in range(1, 11):
        clf = KMeans(n_clusters=i)
        clf.fit(wine_normal)
        WCSS.append(clf.inertia_)
    plt.plot(range(1, 11), WCSS)
    plt.title('The Elbow Method')
    plt.ylabel('WCSS')
    plt.xlabel('Number of Clusters')
    plt.show()
```



```
[2314.0,
Out[27]:
          1659.0079672511501,
          1277.928488844642,
          1175.428333103347,
          1118.3178115480703.
          1046.3669940024863,
          989.1916562037078,
          946.1044545256149.
          897.1892832593963.
          862.6305523869835]
In [28]:
         clf = KMeans(n clusters=3)
         y_kmeans = clf.fit_predict(wine_normal)
In [29]:
         y_kmeans
         clf.labels
                                    Θ,
        array([0, 0, 0, 0, 0, 0, 0,
                                       0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
                                                                    0,
                                                                       0, 0, 0,
                0, 0, 0, 0,
                1,
                                                                    2,
                                                                       2, 2,
                                                                    2,
                2, 2, 2, 2, 2, 2, 0,
                                       2, 2, 2,
                                                2,
                                                  2, 2,
                                                        2, 2, 2, 1,
                                                                       2, 2, 2,
                2, 2, 2, 2, 2, 2, 1, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 1, 1,
                1, 1])
In [30]: clf.cluster_centers_
        array([[ 0.83523208, -0.30380968, 0.36470604, -0.61019129,
                                                                    0.5775868 ,
                 0.88523736,
                              0.97781956, -0.56208965,
                                                                    0.17106348,
                                                       0.58028658.
                                          1.12518529],
                 0.47398365,
                              0.77924711,
                [ 0.16490746,
                              0.87154706,
                                           0.18689833, 0.52436746, -0.07547277,
                                           0.72606354, -0.77970639, 0.94153874,
                 -0.97933029, -1.21524764,
                 -1.16478865, -1.29241163, -0.40708796],
                [-0.92607185, -0.39404154, -0.49451676,
                                                       0.17060184, -0.49171185,
                 \hbox{-0.07598265,} \quad \hbox{0.02081257,} \quad \hbox{-0.03353357,}
                                                       0.0582655 , -0.90191402,
                 0.46180361, 0.27076419, -0.75384618]])
In [31]: clf.inertia
         1277.928488844642
         md=pd.Series(y kmeans)
In [32]:
         wine['clust']=md
         wine
             Type Alcohol Malic Ash Alcalinity Magnesium Phenols Flavanoids Nonflavanoids Proanthocyanins Color Hue Dilution Proline
          0
                    14.23
                          1.71 2.43
                                      15.6
                                                 127
                                                       2.80
                                                                 3.06
                                                                            0.28
                                                                                          2 29
                                                                                                5.64
                                                                                                    1.04
                                                                                                           3.92
                                                                                                                  1065
                    13.20
                          1.78 2.14
                                      11.2
                                                 100
                                                       2.65
                                                                 2.76
                                                                            0.26
                                                                                          1.28
                                                                                                4.38
                                                                                                    1.05
                                                                                                           3.40
                                                                                                                  1050
          1
          2
                          2 36 2 67
                                      18 6
                                                 101
                                                       2 80
                                                                 3 24
                                                                            0.30
                                                                                                    1.03
                                                                                                                  1185
                    13 16
                                                                                          2 81
                                                                                                5 68
                                                                                                           3 17
          3
                    14.37
                          1.95 2.50
                                      16.8
                                                 113
                                                       3.85
                                                                 3.49
                                                                             0.24
                                                                                          2.18
                                                                                                7.80
                                                                                                    0.86
                                                                                                           3.45
                                                                                                                  1480
           4
                    13.24
                          2.59 2.87
                                      21.0
                                                 118
                                                       2.80
                                                                 2.69
                                                                             0.39
                                                                                          1.82
                                                                                                4.32 1.04
                                                                                                           2.93
                                                                                                                  735
         173
                3
                    13.71
                          5.65 2.45
                                      20.5
                                                 95
                                                        1.68
                                                                 0.61
                                                                            0.52
                                                                                          1.06
                                                                                                7.70 0.64
                                                                                                           1.74
                                                                                                                  740
         174
               3
                    13.40
                          3.91 2.48
                                      23.0
                                                 102
                                                        1.80
                                                                 0.75
                                                                             0.43
                                                                                          1.41
                                                                                                7.30 0.70
                                                                                                           1.56
                                                                                                                  750
         175
                3
                    13.27
                          4.28 2.26
                                      20.0
                                                 120
                                                       1.59
                                                                 0.69
                                                                             0.43
                                                                                          1.35
                                                                                               10.20 0.59
                                                                                                           1.56
                                                                                                                  835
         176
                3
                    13.17
                          2.59 2.37
                                      20.0
                                                 120
                                                        1.65
                                                                 0.68
                                                                             0.53
                                                                                          1.46
                                                                                                9.30
                                                                                                    0.60
                                                                                                           1.62
                                                                                                                  840
         177
                3
                    14.13
                         4.10 2.74
                                      24.5
                                                 96
                                                       2.05
                                                                 0.76
                                                                            0.56
                                                                                          1.35
                                                                                                9.20 0.61
                                                                                                           1.60
                                                                                                                  560
        178 rows × 15 columns
In [33]: WCSS
Out[33]: [2314.0,
          1659.0079672511501,
          1277.928488844642,
          1175.428333103347,
          1118.3178115480703.
          1046.3669940024863.
```

Tn []:

989.1916562037078, 946.1044545256149, 897.1892832593963, 862.6305523869835]