PH6130 Project

Principal Component Analysis on a dataset containing chemical analysis of wines

Saurav S Sankhe (ET21MTECH11003), Rahul Ghuge (ET21MTECH11002)

In [1]:

```
# Importing Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [2]:

```
# Importing the Dataset
dataset = pd.read_csv('Wine.csv')
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Alcohol               178 non-null    float64
 1   Malic_Acid            178 non-null    float64
 2   Ash                   178 non-null    float64
 3   Ash_Alcanity          178 non-null    float64
 4   Magnesium             178 non-null    int64  
 5   Total_Phenols         178 non-null    float64
 6   Flavanoids            178 non-null    float64
 7   Nonflavanoid_Phenols  178 non-null    float64
 8   Proanthocyanins       178 non-null    float64
 9   Color_Intensity       178 non-null    float64
 10  Hue                   178 non-null    float64
 11  OD280                 178 non-null    float64
 12  Proline               178 non-null    int64  
 13  Customer_Segment      178 non-null    int64  
dtypes: float64(11), int64(3)
memory usage: 19.6 KB
```

In [3]:

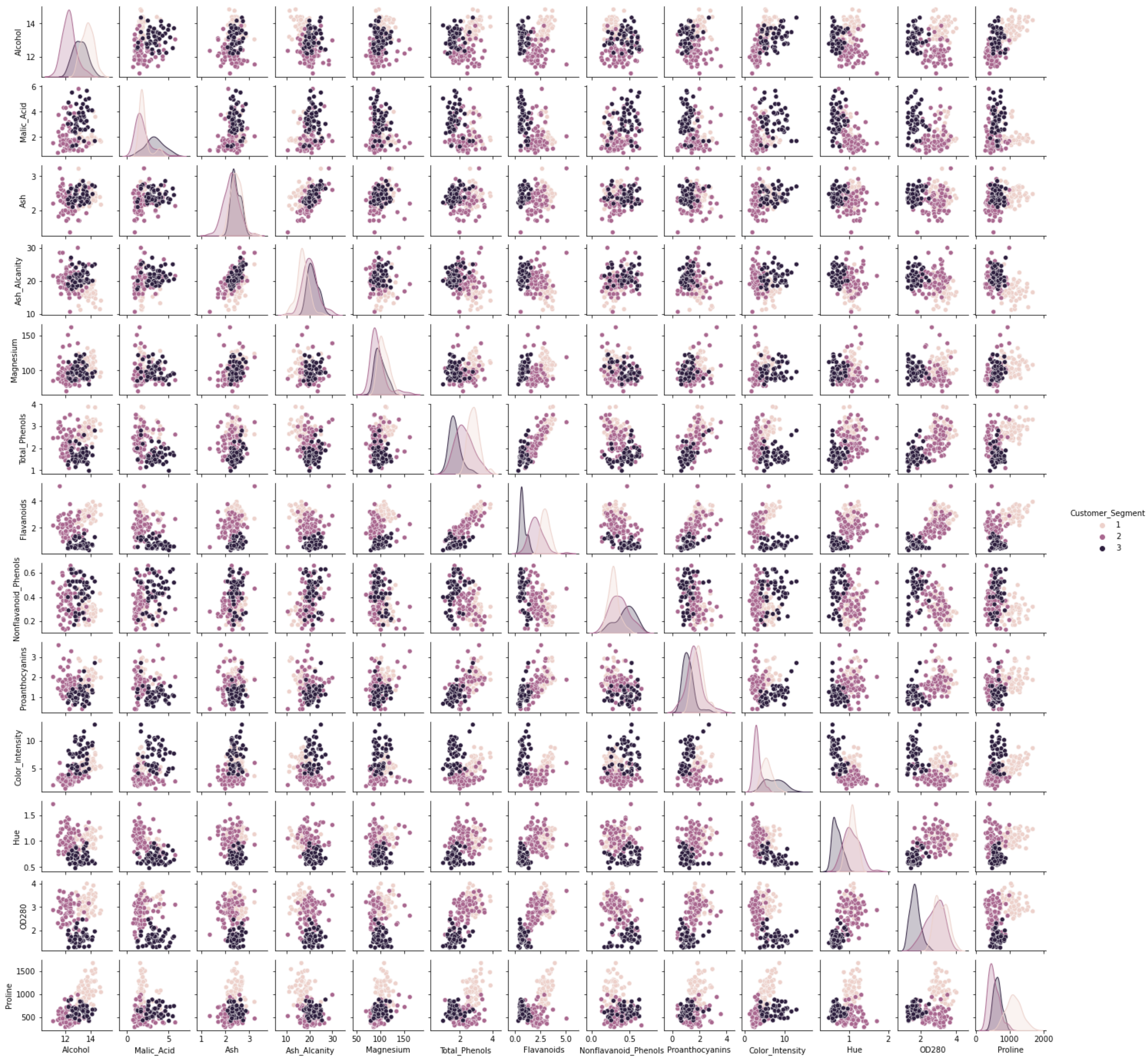
```
dataset.describe()
```

Out[3]:

	Alcohol	Malic_Acid	Ash	Ash_Alcanity	Magnesium	Total_Phenols	Flavanoids	Nonflavanoid_Phenols	Proanthocyanins	Color_Intensity
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.361854	1.590899	5.058090
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.124453	0.572359	2.318286
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.130000	0.410000	1.280000
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.270000	1.250000	3.220000
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.340000	1.555000	4.690000
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.437500	1.950000	6.200000
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.660000	3.580000	13.000000

In [4]:

```
# ============================================================================
# PCA without Sklearn
# ============================================================================
sns.pairplot(dataset, hue = 'Customer_Segment',height=1.5 )
plt.savefig('Pairwise plot')
```



In [5]:

```
# Seperating the Customer_Segment column
Customer_Segment = dataset["Customer_Segment"].tolist()
X = dataset.drop("Customer_Segment", axis = 1)
```

In [6]:

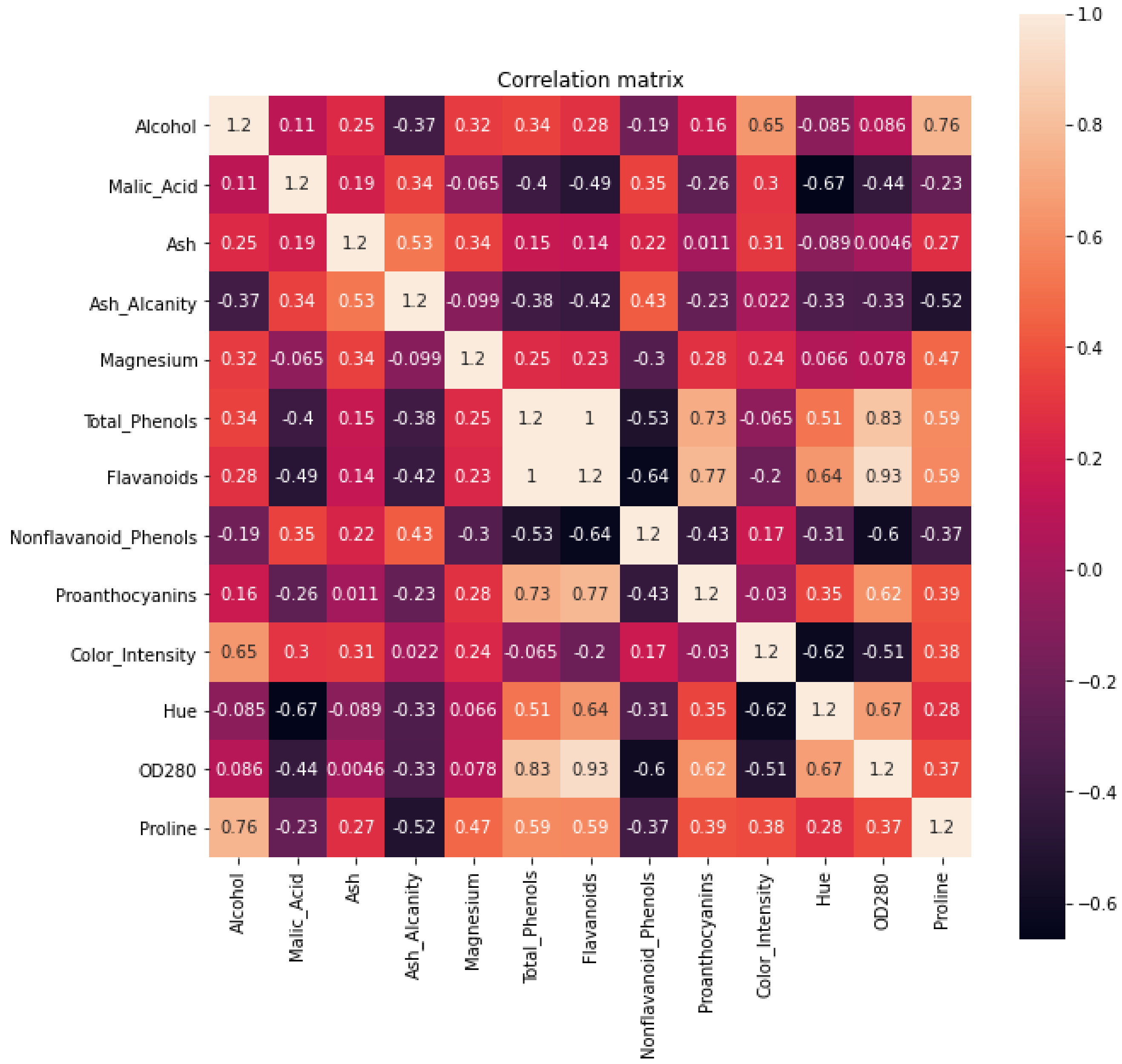
```
# Standardize the data
X = (X - X.mean()) / X.std(ddof=0)
```

In [7]:

```
# Calculating the correlation matrix of the data
X_corr = (1 / 150) * X.T.dot(X)
```

In [8]:

```
# Plotting the correlation matrix
plt.figure(figsize=(10,10))
sns.heatmap(X_corr, vmax=1, square=True,annot=True)
plt.title('Correlation matrix')
plt.savefig('correlation_figure')
```



In [9]:

```
# method1
u,s,v = np.linalg.svd(X_corr)
eig_values, eig_vectors = s, u
eig_values, eig_vectors
```

Out[9]:

```
(array([5.58427563, 2.9630755 , 1.7160054 , 1.09051572, 1.01249744,
        0.76143301, 0.65388693, 0.4135502 , 0.3428042 , 0.29773761,
        0.26793585, 0.20027401, 0.12267515]),
 array([[-0.1443294 , -0.48365155,  0.20738262, -0.0178563 , -0.26566365,
          0.21353865, -0.05639636,  0.39613926, -0.50861912,  0.21160473,
          0.22591696, -0.26628645,  0.01496997],
        [ 0.24518758, -0.22493093, -0.08901289,  0.53689028,  0.03521363,
          0.53681385,  0.42052391,  0.06582674,  0.07528304, -0.30907994,
         -0.07648554,  0.12169604,  0.02596375],
        [ 0.00205106, -0.31606881, -0.6262239 , -0.21417556, -0.14302547,
          0.15447466, -0.14917061, -0.17026002,  0.30769445, -0.02712539,
          0.49869142, -0.04962237, -0.14121803],
        [ 0.23932041,  0.0105905 , -0.61208035,  0.06085941,  0.06610294,
         -0.10082451, -0.28696914,  0.42797018, -0.20044931,  0.05279942,
         -0.47931378, -0.05574287,  0.09168285],
        [-0.14199204, -0.299634  , -0.13075693, -0.35179658,  0.72704851,
          0.03814394,  0.3228833 , -0.15636143, -0.27140257,  0.06787022,
         -0.07128891,  0.06222011,  0.05677422],
        [-0.39466085, -0.06503951, -0.14617896,  0.19806835, -0.14931841,
         -0.0841223 , -0.02792498, -0.40593409, -0.28603452, -0.32013135,
         -0.30434119, -0.30388245, -0.46390791],
        [-0.4229343 ,  0.00335981, -0.1506819 ,  0.15229479, -0.10902584,
         -0.01892002, -0.06068521, -0.18724536, -0.04957849, -0.16315051,
          0.02569409, -0.04289883,  0.83225706],
        [ 0.2985331 , -0.02877949, -0.17036816, -0.20330102, -0.50070298,
         -0.25859401,  0.59544729, -0.23328465, -0.19550132,  0.21553507,
         -0.11689586,  0.04235219,  0.11403985],
        [-0.31342949, -0.03930172, -0.14945431,  0.39905653,  0.13685982,
         -0.53379539,  0.37213935,  0.36822675,  0.20914487,  0.1341839 ,
          0.23736257, -0.09555303, -0.11691707],
        [ 0.0886167 , -0.52999567,  0.13730621,  0.06592568, -0.07643678,
         -0.41864414, -0.22771214, -0.03379692, -0.05621752, -0.29077518,
         -0.0318388 ,  0.60422163, -0.0119928 ],
        [-0.29671456,  0.27923515, -0.08522192, -0.42777141, -0.17361452,
          0.10598274,  0.23207564,  0.43662362, -0.08582839, -0.52239889,
          0.04821201,  0.259214  , -0.08988884],
        [-0.37616741,  0.16449619, -0.16600459,  0.18412074, -0.10116099,
          0.26585107, -0.0447637 , -0.07810789, -0.1372269 ,  0.52370587,
         -0.0464233 ,  0.60095872, -0.15671813],
        [-0.28675223, -0.36490283,  0.12674592, -0.23207086, -0.1578688 ,
          0.11972557,  0.0768045 ,  0.12002267,  0.57578611,  0.162116  ,
         -0.53926983, -0.07940162,  0.01444734]]))
```

In [10]:

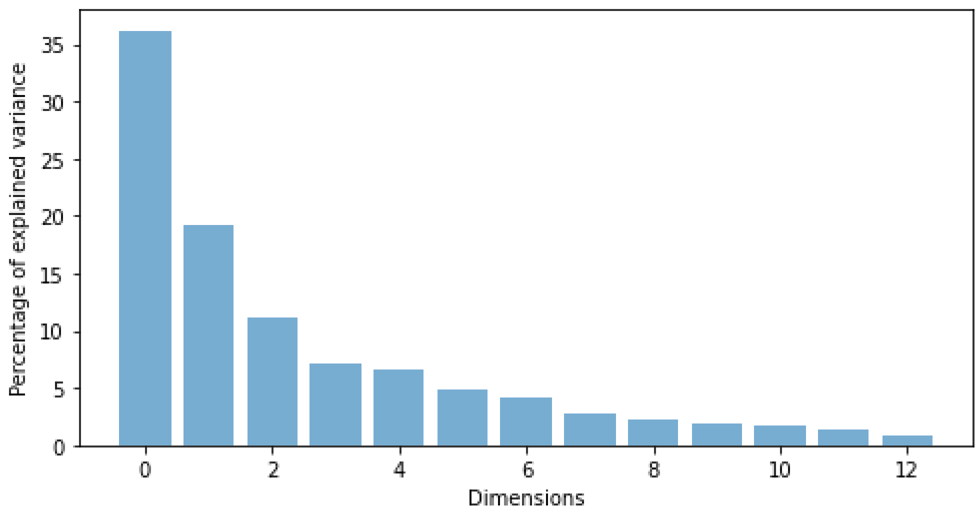
```
# method2
np.linalg.eig(X_corr)
```

Out[10]:
```
(array([5.58427563, 2.9630755 , 1.7160054 , 1.09051572, 1.01249744,
        0.76143301, 0.65388693, 0.12267515, 0.4135502 , 0.20027401,
        0.3428042 , 0.26793585, 0.29773761]),
 array([[-0.1443294 ,  0.48365155,  0.20738262, -0.0178563 , -0.26566365,
          0.21353865,  0.05639636, -0.01496997,  0.39613926, -0.26628645,
         -0.50861912, -0.22591696,  0.21160473],
        [ 0.24518758,  0.22493093, -0.08901289,  0.53689028,  0.03521363,
          0.53681385, -0.42052391, -0.02596375,  0.06582674,  0.12169604,
          0.07528304,  0.07648554, -0.30907994],
        [ 0.00205106,  0.31606881, -0.6262239 , -0.21417556, -0.14302547,
          0.15447466,  0.14917061,  0.14121803, -0.17026002, -0.04962237,
          0.30769445, -0.49869142, -0.02712539],
        [ 0.23932041, -0.0105905 , -0.61208035,  0.06085941,  0.06610294,
         -0.10082451,  0.28696914, -0.09168285,  0.42797018, -0.05574287,
         -0.20044931,  0.47931378,  0.05279942],
        [-0.14199204,  0.299634  , -0.13075693, -0.35179658,  0.72704851,
          0.03814394, -0.3228833 , -0.05677422, -0.15636143,  0.06222011,
         -0.27140257,  0.07128891,  0.06787022],
        [-0.39466085,  0.06503951, -0.14617896,  0.19806835, -0.14931841,
         -0.0841223 ,  0.02792498,  0.46390791, -0.40593409, -0.30388245,
         -0.28603452,  0.30434119, -0.32013135],
        [-0.4229343 , -0.00335981, -0.1506819 ,  0.15229479, -0.10902584,
         -0.01892002,  0.06068521, -0.83225706, -0.18724536, -0.04289883,
         -0.04957849, -0.02569409, -0.16315051],
        [ 0.2985331 ,  0.02877949, -0.17036816, -0.20330102, -0.50070298,
         -0.25859401, -0.59544729, -0.11403985, -0.23328465,  0.04235219,
         -0.19550132,  0.11689586,  0.21553507],
        [-0.31342949,  0.03930172, -0.14945431,  0.39905653,  0.13685982,
         -0.53379539, -0.37213935,  0.11691707,  0.36822675, -0.09555303,
          0.20914487, -0.23736257,  0.1341839 ],
        [ 0.0886167 ,  0.52999567,  0.13730621,  0.06592568, -0.07643678,
         -0.41864414,  0.22771214,  0.0119928 , -0.03379692,  0.60422163,
         -0.05621752,  0.0318388 , -0.29077518],
        [-0.29671456, -0.27923515, -0.08522192, -0.42777141, -0.17361452,
          0.10598274, -0.23207564,  0.08988884,  0.43662362,  0.259214  ,
         -0.08582839, -0.04821201, -0.52239889],
        [-0.37616741, -0.16449619, -0.16600459,  0.18412074, -0.10116099,
          0.26585107,  0.0447637 ,  0.15671813, -0.07810789,  0.60095872,
         -0.1372269 ,  0.0464233 ,  0.52370587],
        [-0.28675223,  0.36490283,  0.12674592, -0.23207086, -0.1578688 ,
          0.11972557, -0.0768045 , -0.01444734,  0.12002267, -0.07940162,
          0.57578611,  0.53926983,  0.162116  ]]))
```

In [11]:
```
np.sum(eig_values)
```

Out[11]:
```
15.426666666666677
```

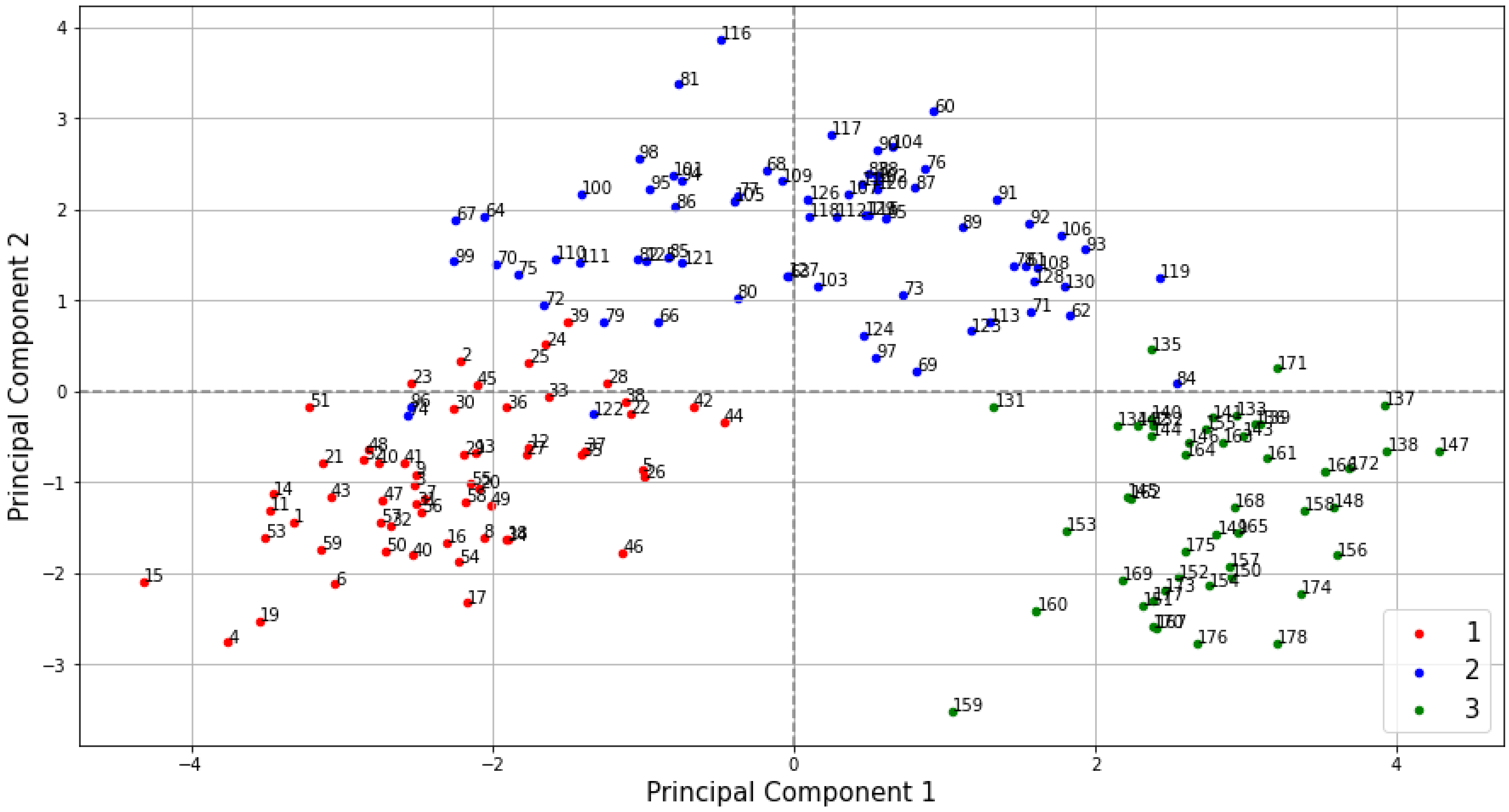
In [12]:
```
# plotting the variance explained by each PC
explained_variance=(eig_values / np.sum(eig_values))*100
plt.figure(figsize=(8,4))
plt.bar(range(13), explained_variance, alpha=0.6)
plt.ylabel('Percentage of explained variance')
plt.xlabel('Dimensions')
plt.savefig('No of Dimensions')
```



In [13]:
```
# calculating our new axis
pc1 = X.dot(eig_vectors[:,0])
pc2 = X.dot(eig_vectors[:,1])
```

In [14]:
```
# plotting in 2D
def plot_scatter(pc1, pc2):
    fig, ax = plt.subplots(figsize=(15, 8))

    species_unique = list(set(Customer_Segment))
    species_colors = ["r","b","g"]

    for i, spec in enumerate(Customer_Segment):
        plt.scatter(pc1[i], pc2[i], label = spec, s = 20, c=species_colors[species_unique.index(spec)])
        ax.annotate(str(i+1), (pc1[i],pc2[i]))

    from collections import OrderedDict
```

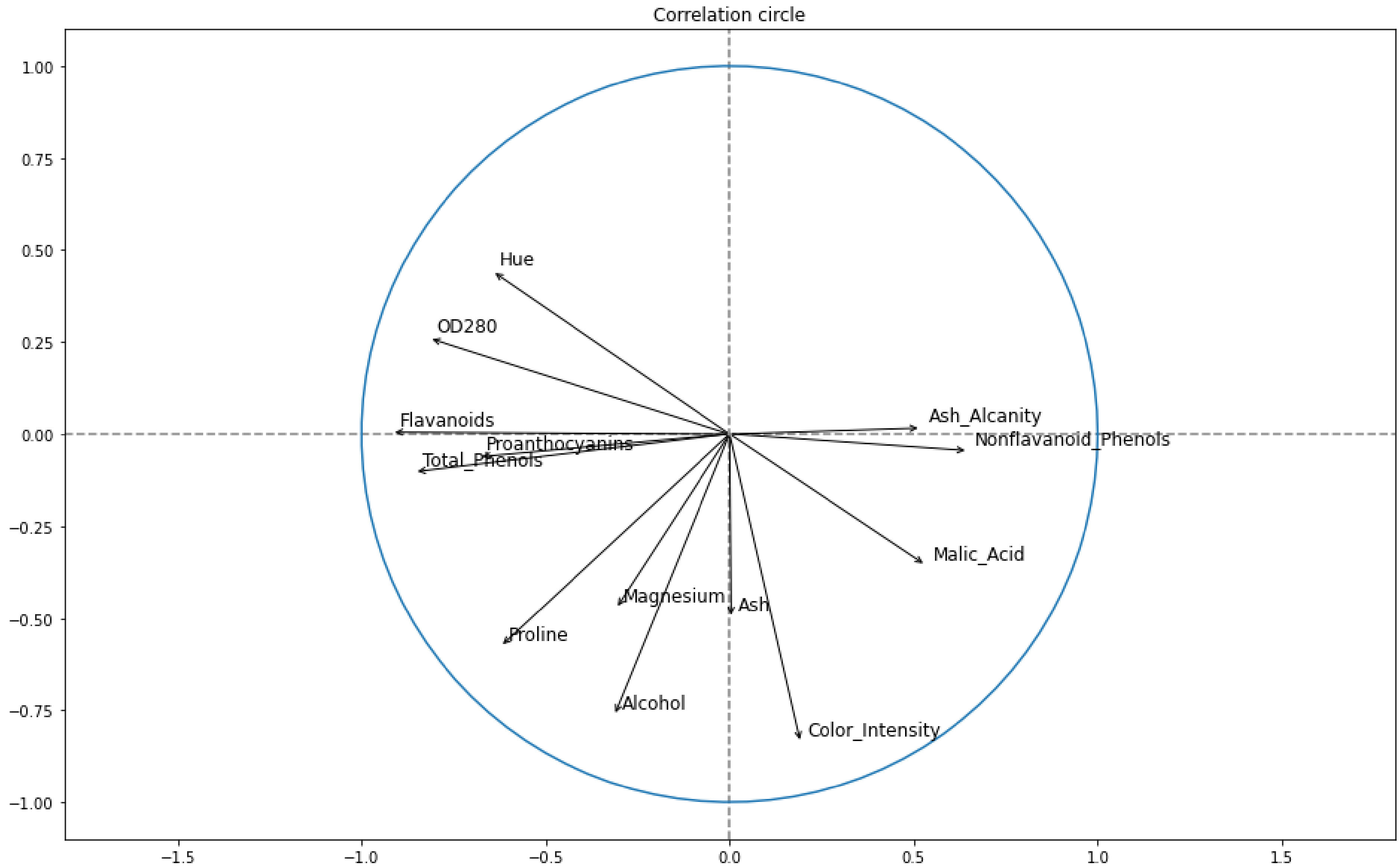
```
    handles, labels = plt.gca().get_legend_handles_labels()
    by_label = OrderedDict(zip(labels, handles))
    plt.legend(by_label.values(), by_label.keys(), prop={'size': 15}, loc=4)

    ax.set_xlabel('Principal Component 1', fontsize = 15)
    ax.set_ylabel('Principal Component 2', fontsize = 15)
    ax.axhline(y=0, color="grey", linestyle="--")
    ax.axvline(x=0, color="grey", linestyle="--")

    plt.grid()
    # plt.axis([-4, 4, -3, 3])
    plt.show()

plot_scatter(pc1, pc2)
plt.savefig('Scatter plot_without sklearn')
```



<Figure size 432x288 with 0 Axes>

In [15]:
```
def plot_correlation_circle(pc1, pc2):
    fig, ax = plt.subplots(figsize=(16, 10))

    for i in range(X.shape[1]):
        x = np.corrcoef(pc1,X[X.columns[i]])[0,1]
        y = np.corrcoef(pc2,X[X.columns[i]])[0,1]
        ax.annotate("", xy= (x,y), xytext=(0, 0),arrowprops=dict(arrowstyle="->"))
        ax.annotate(X.columns[i], (x+0.02,y+0.02), size=12)


    ax.set_title('Correlation circle')
    ax.axhline(y=0, color="grey", linestyle="--")
    ax.axvline(x=0, color="grey", linestyle="--")

    an = np.linspace(0, 2 * np.pi, 100)
    plt.plot(np.cos(an), np.sin(an))
    plt.axis('equal')
    plt.show()
    plt.savefig('Correlation circle')
```

In [16]:
```
plot_correlation_circle(pc1,pc2)
```




```
<Figure size 432x288 with 0 Axes>
```

Well it seems that:Flavanoids & Ash Alcanity are the main things that characterizes the data

PCA with sklearn

In [17]:

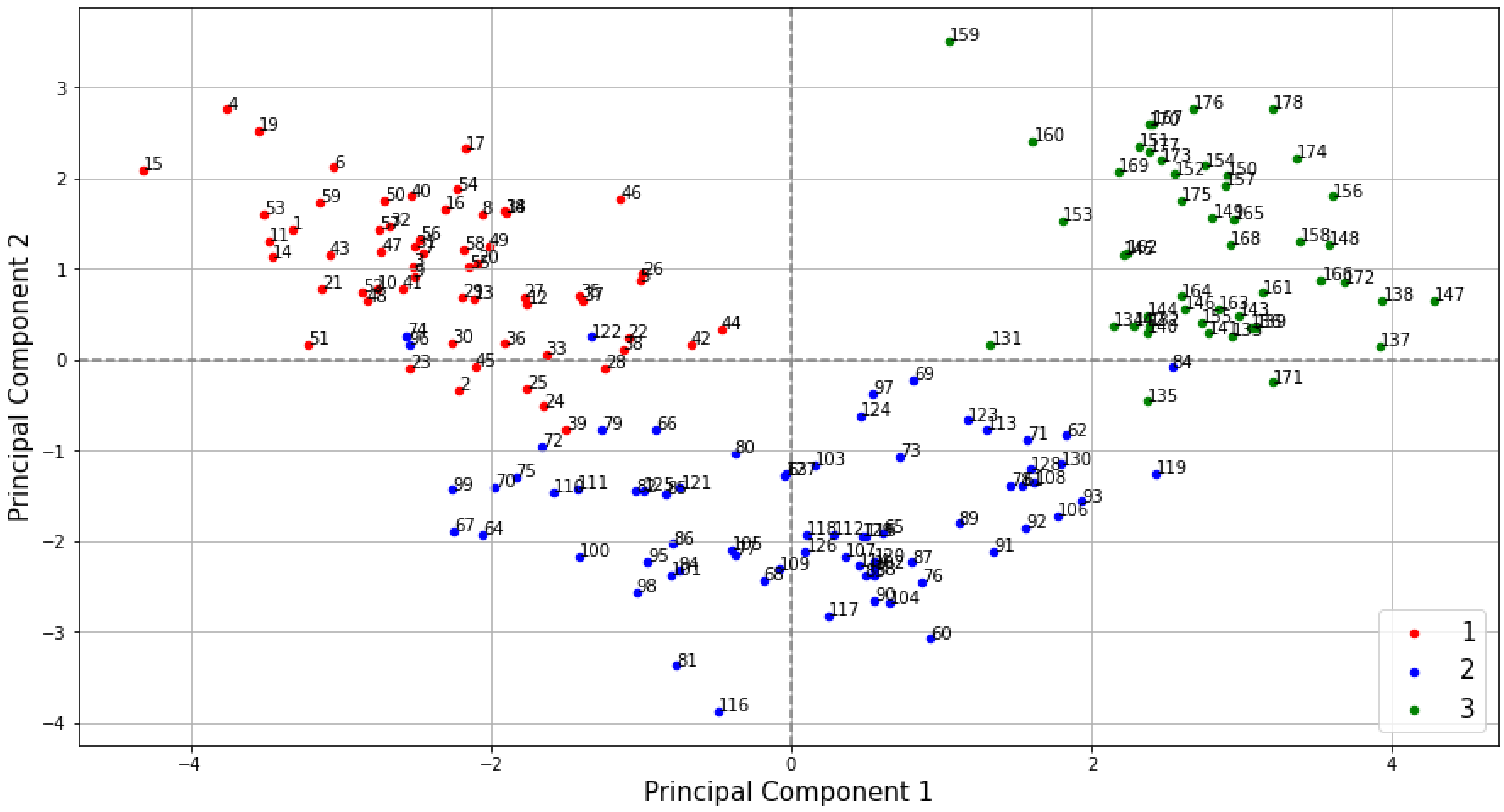
```
# ============================================================================
# PCA with sklearn
# ============================================================================
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

In [18]:

```
X = dataset.drop("Customer_Segment", axis = 1)
X = StandardScaler().fit_transform(X)
pca = PCA()
```

In [19]:

```
result = pca.fit_transform(X)
# Remember what we said about the sign of eigen vectors that might change ?
pc1 = - result[:,0]
pc2 = - result[:,1]
plot_scatter(pc1, pc2)
plt.savefig('Scatter plot_with sklearn')
```




```
<Figure size 432x288 with 0 Axes>
```