```
In [1]: from IPython.display import Image Image(filename='logo.PNG', height=340, width=900)

Out[1]:

TRANSFORM YOURSELF
```

```
In [2]: # Importing Libraries
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt

In [3]: # Import Dataset
    df = pd.read_csv('seeds.csv')
    del df['grain_variety']

In [4]: df.head()
Out[4]:
    area perimeter compactness length width asymmetry_coefficient groove_length
    0 15.26    14.84    0.8710    5.763    3.312     2.221     5.220
```

	area	perimeter	compactness	length	width	asymmetry_coefficient	groove_length
1	14.88	14.57	0.8811	5.554	3.333	1.018	4.956
2	14.29	14.09	0.9050	5.291	3.337	2.699	4.825
3	13.84	13.94	0.8955	5.324	3.379	2.259	4.805
4	16.14	14.99	0.9034	5.658	3.562	1.355	5.175

In [5]: df.tail()

Out[5]:

		area	perimeter	compactness	length	width	asymmetry_coefficient	groove_length
	205	12.19	13.20	0.8783	5.137	2.981	3.631	4.870
	206	11.23	12.88	0.8511	5.140	2.795	4.325	5.003
	207	13.20	13.66	0.8883	5.236	3.232	8.315	5.056
	208	11.84	13.21	0.8521	5.175	2.836	3.598	5.044
	209	12.30	13.34	0.8684	5.243	2.974	5.637	5.063

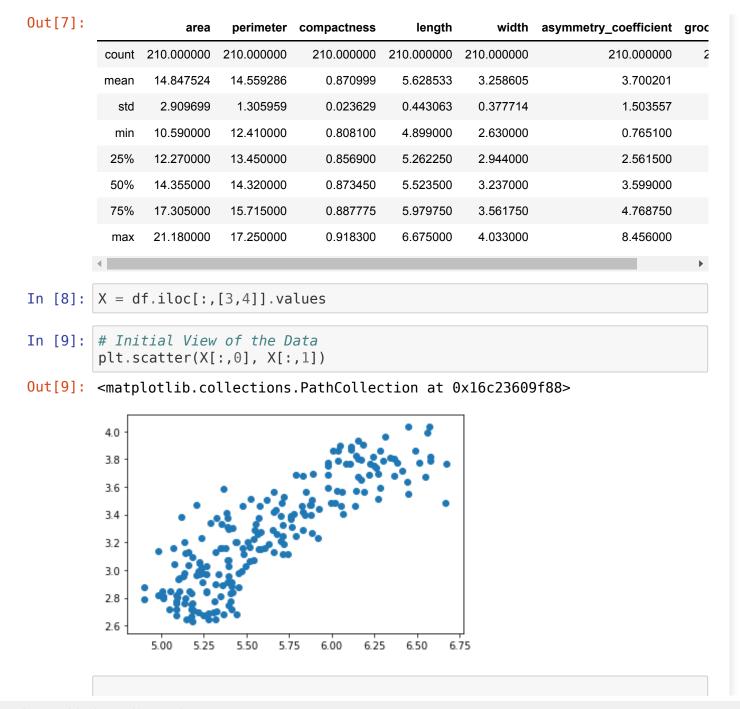
In [6]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210 entries, 0 to 209
Data columns (total 7 columns):
```

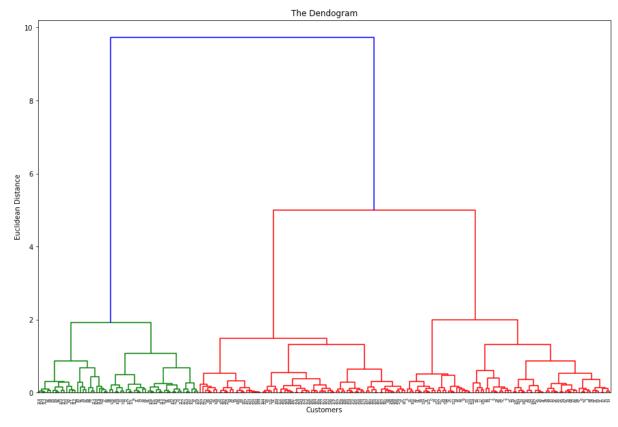
```
area 210 non-null float64
perimeter 210 non-null float64
compactness 210 non-null float64
length 210 non-null float64
width 210 non-null float64
asymmetry_coefficient 210 non-null float64
groove_length 210 non-null float64
```

dtypes: float64(7)
memory usage: 11.6 KB

```
In [7]: df.describe()
```

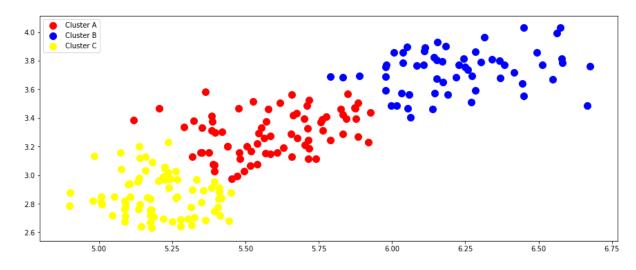


```
In [10]: # Finding the optimum clusters using the DENDOGRAMS
    import scipy.cluster.hierarchy as sch
    plt.figure(figsize = (15,10))
    dendogram = sch.dendrogram(sch.linkage(X, method='ward'))
    plt.title('The Dendogram')
    plt.xlabel('Customers')
    plt.ylabel('Euclidean Distance')
    plt.show()
```



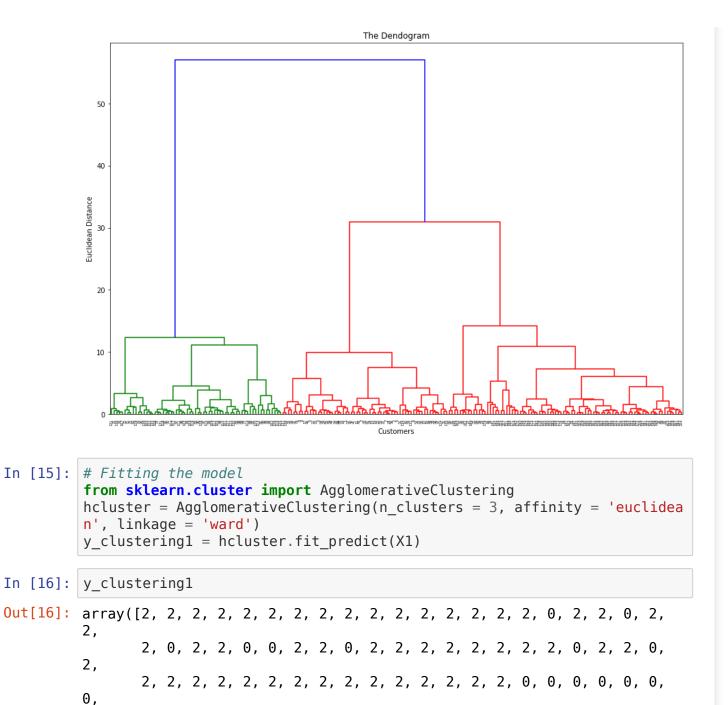
```
In [11]: # Fitting the model
    from sklearn.cluster import AgglomerativeClustering
    hcluster = AgglomerativeClustering(n_clusters = 3, affinity = 'euclidea
    n', linkage = 'ward')
    y_clustering = hcluster.fit_predict(X)
```

```
In [12]: y clustering
Out[12]: array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0,
        0,
              0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 2,
        Θ,
              2,
              0, 0, 0, 2, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1,
        1,
              1. 1. 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
        1,
              1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 0. 1. 1. 1. 1. 1. 1.
        1,
              0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        2,
              2,
              2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
        0,
              2, 2, 2, 2, 2, 2, 2, 2, 2, 2], dtype=int64)
In [13]: # Visualizing Results
        plt.figure(figsize=(15,6))
        plt.scatter(X[y clustering==0, 0], X[y clustering==0, 1], s=100, c='re
        d'. label = 'Cluster A')
        plt.scatter(X[y clustering==1, 0], X[y clustering==1, 1], s=100, c='blu
        e', label = 'Cluster B')
        plt.scatter(X[y clustering==2, 0], X[y clustering==2, 1], s=100, c='yel
        low', label = 'Cluster C')
        #plt.scatter(X[y clustering==3, 0], X[y clustering==3, 1], s=100, c='gr
        een', label = 'Cluster D')
        #plt.scatter(X[y clustering==4, 0], X[y clustering==4, 1], s=100, c='pi
        nk', label = 'Cluster E')
        plt.legend()
Out[13]: <matplotlib.legend.Legend at 0x16c27406b88>
```



```
In []:
In [14]: # Using all the Variables now:
    X1 = df.iloc[:,:].values

# Finding the optimum clusters using the DENDOGRAMS
    import scipy.cluster.hierarchy as sch
    plt.figure(figsize = (15,10))
    dendogram = sch.dendrogram(sch.linkage(X1, method='ward'))
    plt.title('The Dendogram')
    plt.xlabel('Customers')
    plt.ylabel('Euclidean Distance')
    plt.show()
```



```
2, 2, 2, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1,
      1,
          1,
          1,
          0,
          0,
          0,
          0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], dtype=int64)
In [17]: y clustering
Out[17]: array([0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0,
      0,
          0, 2, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 2,
      0,
          2,
          0, 0, 0, 2, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1,
      1,
          1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
      1,
          1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
      1,
          0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
      2,
          2,
          2, 2, 2, 2, 2, 2, 2, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
      0,
          2, 2, 2, 2, 2, 2, 2, 2, 2, 2], dtype=int64)
In [18]: | df['Initial Clustering'] = pd.Series(y clustering)
      df['Final Clustering']= pd.Series(y clustering1)
```

```
In [19]: df
Out[19]:
                  area perimeter compactness length width asymmetry_coefficient groove_length Cluster
              0 15.26
                           14.84
                                       0.8710
                                               5.763 3.312
                                                                           2.221
                                                                                         5.220
                                               5.554 3.333
              1 14.88
                                                                                         4.956
                           14.57
                                       0.8811
                                                                           1.018
              2 14.29
                           14.09
                                       0.9050
                                               5.291
                                                      3.337
                                                                           2.699
                                                                                         4.825
              3 13.84
                           13.94
                                       0.8955
                                               5.324 3.379
                                                                           2.259
                                                                                         4.805
              4 16.14
                                       0.9034
                                                                                         5.175
                           14.99
                                               5.658 3.562
                                                                           1.355
            205 12.19
                           13.20
                                       0.8783
                                               5.137 2.981
                                                                           3.631
                                                                                         4.870
            206 11.23
                           12.88
                                       0.8511
                                               5.140 2.795
                                                                           4.325
                                                                                         5.003
            207 13.20
                           13.66
                                       0.8883
                                               5.236 3.232
                                                                           8.315
                                                                                         5.056
            208 11.84
                                                                                         5.044
                           13.21
                                       0.8521
                                               5.175 2.836
                                                                           3.598
            209 12.30
                           13.34
                                               5.243 2.974
                                                                                         5.063
                                       0.8684
                                                                           5.637
           210 rows × 9 columns
           pd.crosstab(df['Initial Clustering'], df['Final Clustering'])
Out[20]:
             Final Clustering 0 1 2
            Initial Clustering
                         0 10 6 59
                             0 57 2
                         2 76 0 0
 In [ ]:
```