In [1]:

```
from IPython.display import Image
Image(filename='logo.PNG', height=340, width=900)
```

Out[1]:

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')

#Removing Categorical Variable for this dataset
del df['grain_variety']
```

In [4]:

```
df.head()
```

Out[4]:

	area	perimeter	compactness	length	width	asymmetry_coefficient	groove_length

	area	perimeter	compactness	length	width	asymmetry_coefficient	groove_length
0	15.26	14.84	0.8710	5.763	3.312	2.221	5.220
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()
```

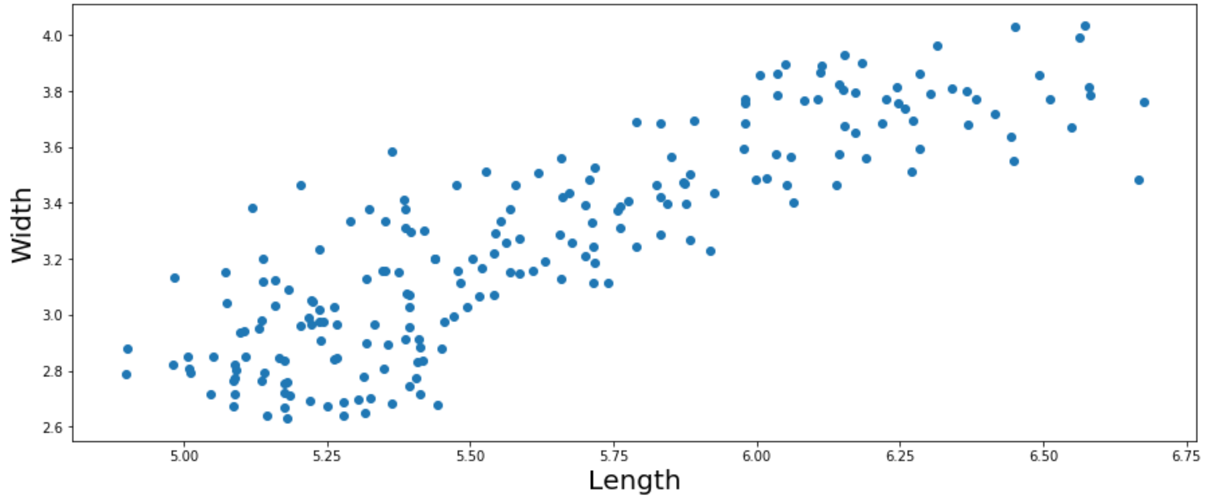
Out[7]:

	area	perimeter	compactness	length	width	asymmetry_coefficient	groo
count	210.000000	210.000000	210.000000	210.000000	210.000000	210.000000	2
mean	14.847524	14.559286	0.870999	5.628533	3.258605	3.700201	
std	2.909699	1.305959	0.023629	0.443063	0.377714	1.503557	
min	10.590000	12.410000	0.808100	4.899000	2.630000	0.765100	
25%	12.270000	13.450000	0.856900	5.262250	2.944000	2.561500	
50%	14.355000	14.320000	0.873450	5.523500	3.237000	3.599000	
75%	17.305000	15.715000	0.887775	5.979750	3.561750	4.768750	
max	21.180000	17.250000	0.918300	6.675000	4.033000	8.456000	

In [8]:
```
X = df.iloc[:,[3,4]].values
```

In [9]:
```
# Initial View of the Data
plt.figure(figsize=(15,6))
plt.scatter(X[:,0], X[:,1])
plt.xlabel('Length', fontsize=20)
plt.ylabel('Width', fontsize=20)
```

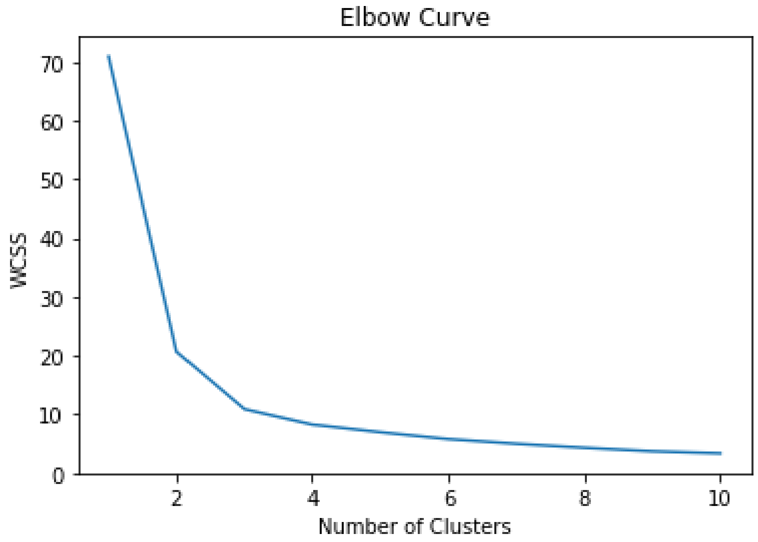
Out[9]:
```
Text(0, 0.5, 'Width')
```



In [10]:

```
# Finding the optimum clusters using the ELBOW curve
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
    kmean = KMeans(n_clusters=i, random_state=0)

    kmean.fit(X)
    wcss.append(kmean.inertia_)
plt.plot(range(1,11), wcss)
plt.title('Elbow Curve')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



In [11]:
```
# Fitting the model
kmean = KMeans(n_clusters=3, random_state=0)
y_kmean_clustering = kmean.fit_predict(X)
```

In [12]:
```
y_kmean_clustering
```

Out[12]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2,
2,
       2, 0, 2, 2, 0, 0, 2, 2, 0, 2, 2, 2, 2, 2, 2, 1, 2, 2, 0, 0, 0,
2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 0, 0, 0,
0,
       2, 2, 2, 0, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 2, 1,
1,
       2, 2, 2, 2, 1, 2, 2, 2, 0, 2, 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, 0, 0, 0, 0, 0, 0, 0, 0,
```

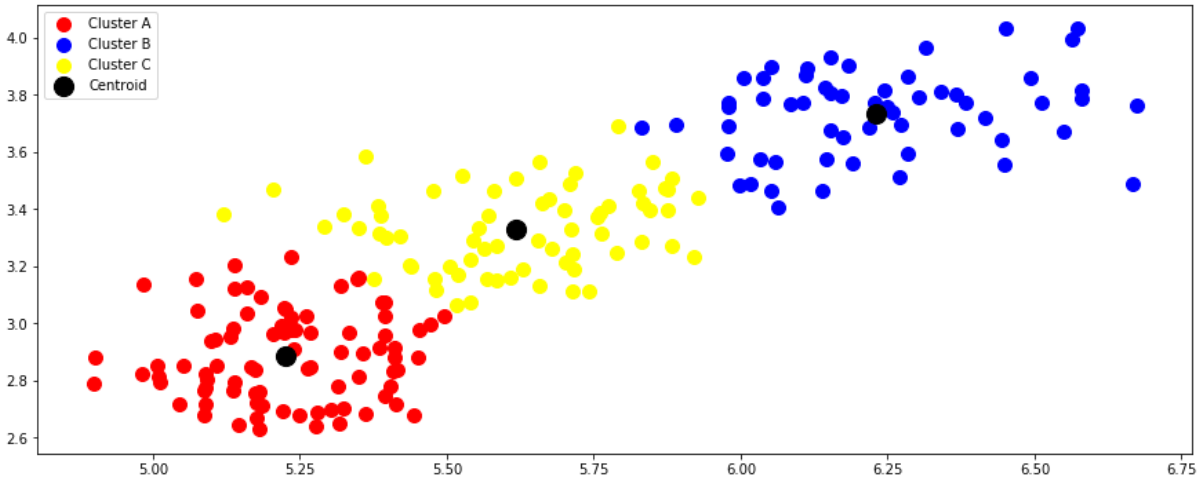
```
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [13]:

```
# Visualizing Results
plt.figure(figsize=(15,6))
plt.scatter(X[y_kmean_clustering==0, 0], X[y_kmean_clustering==0, 1], s
=100, c='red', label = 'Cluster A')
plt.scatter(X[y_kmean_clustering==1, 0], X[y_kmean_clustering==1, 1], s
=100, c='blue', label = 'Cluster B')
plt.scatter(X[y_kmean_clustering==2, 0], X[y_kmean_clustering==2, 1], s
=100, c='yellow', label = 'Cluster C')
#plt.scatter(X[y_kmean_clustering==3, 0], X[y_kmean_clustering==3, 1],
 s=100, c='green', label = 'Cluster D')
# plt.scatter(X[y_kmean_clustering==4, 0], X[y_kmean_clustering==4, 1],
 s=100, c='pink', label = 'Cluster E')
plt.scatter(kmean.cluster_centers_[:,0], kmean.cluster_centers_[:,1], s
 = 200, c = 'black', label = 'Centroid')
plt.legend()
```

Out[13]:

```
<matplotlib.legend.Legend at 0x21594781a08>
```



Implementing the algorithm with all the variables

In [14]:
```
X = df.iloc[:,:].values
```

In [15]:
```
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler()
X = sc_X.fit_transform(X)
```

In [16]:
```
np.set_printoptions(suppress = True)
```

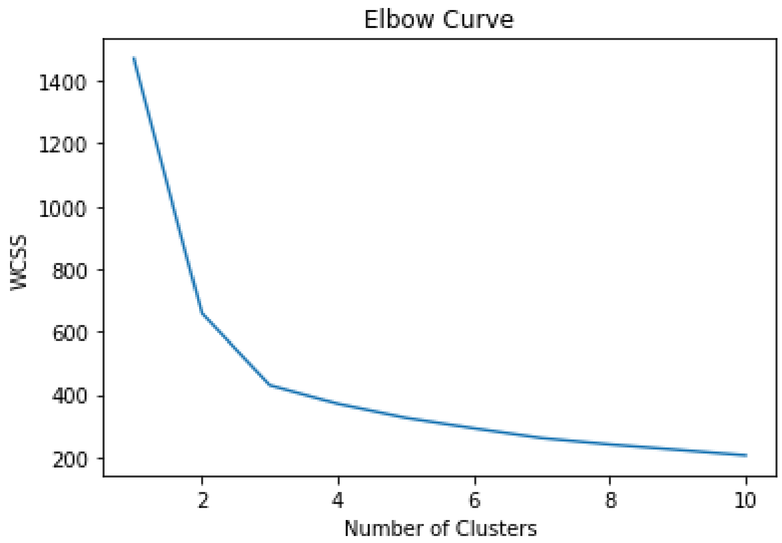
In [17]:
```
X
```

Out[17]:
```
array([[ 0.14209777,  0.21546244,  0.0000606 , ...,  0.14170182,
        -0.98615174, -0.38357742],
       [ 0.01118803,  0.00822376,  0.42851527, ...,  0.19743223,
        -1.7881662 , -0.92201349],
       [-0.19206658, -0.36020056,  1.44238325, ...,  0.20804754,
        -0.66747933, -1.18919199],
       ...,
       [-0.56757084, -0.69024735,  0.7339483 , ..., -0.07060448,
         3.07658816, -0.71806043],
       [-1.03608992, -1.03564515, -0.8017011 , ..., -1.12152071,
        -0.0681352 , -0.7425348 ],
       [-0.87762023, -0.93586356, -0.11023466, ..., -0.75529233,
         1.29122264, -0.70378372]])
```

In [18]:
```
# Finding the optimum clusters using the ELBOW curve
from sklearn.cluster import KMeans
wcss = []
for i in range(1,11):
    kmean = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init
=10, random_state=0)
    # n_clusters = The number of clusters to form as well as the number
 of centroids to generate.
    # init = Method for initialization, defaults to 'k-means++'. It sel
ects initial cluster centers for k-mean clustering
             # in a smart way to speed up convergence
```

```
    # n_init = default: 10, Number of time the k-means algorithm will b
e run with different centroid seeds
    # max_iter : default: 300, Maximum number of iterations of the k-me
ans algorithm for a single run to find the final
                # cluster

    kmean.fit(X)
    wcss.append(kmean.inertia_)
plt.plot(range(1,11), wcss)
plt.title('Elbow Curve')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



In [19]:

```
# Fitting the model
kmean = KMeans(n_clusters=3, init='k-means++', max_iter=300, n_init=10,
 random_state=0)
y_kmean_clustering = kmean.fit_predict(X)
```

In [20]:

```
y_kmean_clustering
```

Out[20]:

```
array([2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 2,
```

```
2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 2, 2, 2, 2,
2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 0, 0, 0, 2, 0, 2,
2,
       2, 2, 2, 0, 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, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1,
1,
       2, 1, 1, 2, 1, 2, 2, 1, 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, 2, 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, 0, 0, 0, 0, 0, 0,
2,
       0, 2, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0])
```

In [21]:
```
df['Cluster']=pd.Series(y_kmean_clustering)
```

In [22]:
```
df
```

Out[22]:

	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	2
1	14.88	14.57	0.8811	5.554	3.333	1.018	4.956	2
2	14.29	14.09	0.9050	5.291	3.337	2.699	4.825	2
3	13.84	13.94	0.8955	5.324	3.379	2.259	4.805	2
4	16.14	14.99	0.9034	5.658	3.562	1.355	5.175	2
...	...	...	...	...	...	...	...	...
205	12.19	13.20	0.8783	5.137	2.981	3.631	4.870	0
206	11.23	12.88	0.8511	5.140	2.795	4.325	5.003	0
207	13.20	13.66	0.8883	5.236	3.232	8.315	5.056	0

	area	perimeter	compactness	length	width	asymmetry_coefficient	groove_length	Cluster
208	11.84	13.21	0.8521	5.175	2.836	3.598	5.044	0
209	12.30	13.34	0.8684	5.243	2.974	5.637	5.063	0

210 rows × 8 columns

In [ ]:

In [ ]: