THE SPARKS FOUNDATION

Data Science and Buisness Analytics Tasks

NAME : M.NIVETHITHAA

TASK 2 - Prediction using UnSupervised ML

DATA AUDIT

Importing Libraries

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

Displaying Raw Dataset

In [2]:
```
data = pd.read_csv("Iris.csv")
data = pd.DataFrame(data)
data
```

Out[2]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

First five rows of the dataset

In [3]:
```
data.head(5)
```

Out[3]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

Last five rows of the dataset

In [4]:
```
data.tail(5)
```

Out[4]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

Shape of the dataset

In [5]:
```
data.shape
```

Out[5]:
```
(150, 6)
```

Columns present in the dataset

In [6]:
```
data.columns
```

Out[6]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

Summary of the dataset

In [7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [8]:
```
data.describe()
```

Out[8]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

Checking Datatypes

In [9]:
```
data.dtypes
```

Out[9]:
```
Id                 int64
SepalLengthCm    float64
SepalWidthCm     float64
PetalLengthCm    float64
PetalWidthCm     float64
Species           object
dtype: object
```

Checking missing values

In [10]:
```
data.isna().sum()
```

Out[10]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

No Missing values

CORRELATION

In [11]:
```
data.corr()
```

Out[11]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
Id	1.000000	0.716676	-0.397729	0.882747	0.899759
SepalLengthCm	0.716676	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.397729	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.882747	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.899759	0.817954	-0.356544	0.962757	1.000000

In [12]:
```
#As this is an Unsupervised Learning we can take features and neglect other columns
data = data.drop(columns=['Id','Species'])
data
```

Out[12]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

Predict the optimum number of clusters

Preparing the Data

Create X

In [13]:
```
X = data.iloc[:, :-1].values
```

Create Y

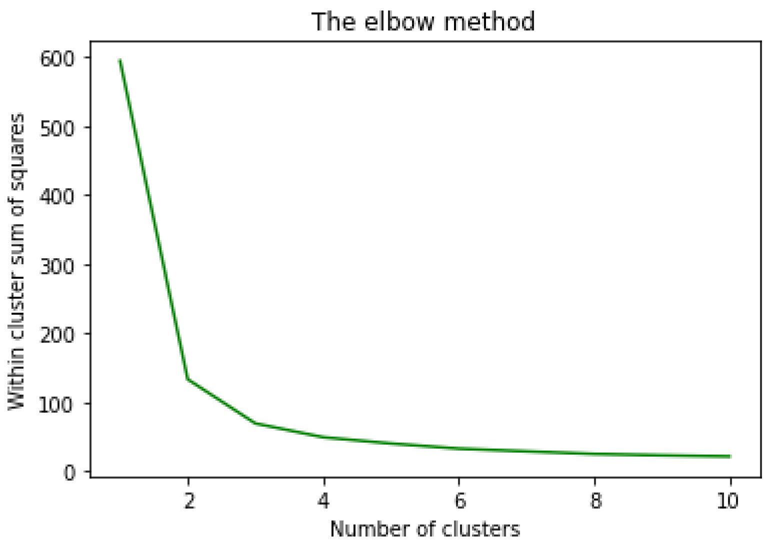
Elbow Method

In [14]:
```
#For creating y we need no of clusters. And we can find the optimum number of clusters using elbow method
```

-> In the Elbow method, we are actually varying the number of clusters (K) from 1 – 10.
-> For each value of K, we are calculating WCSS (Within-Cluster Sum of Square).
-> WCSS is the sum of squared distance between each point and the centroid in a cluster.
-> When we plot the WCSS with the K value, the plot looks like an Elbow.
-> When we analyze the graph we can see that the graph will rapidly change at a point and thus creating an elbow shape.The K value corresponding to this point is the optimal K value or an optimal number of clusters

In [15]:
```
within_cluster_sum_of_squares = []
Range_of_cluster = range(1, 11)
for i in Range_of_cluster:
    kmeans = KMeans(n_clusters = i)
    kmeans.fit(X)
    within_cluster_sum_of_squares.append(kmeans.inertia_)
```

In [16]:
```
plt.plot(Range_of_cluster, within_cluster_sum_of_squares,color="green")
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('Within cluster sum of squares')
plt.show()
```



The point at which the elbow shape is created is 3.Therefore optimal number of clusters is 3

K-Means Clustering

In [17]:
```
y = KMeans(n_clusters=3)
```

Fit K means cluster model

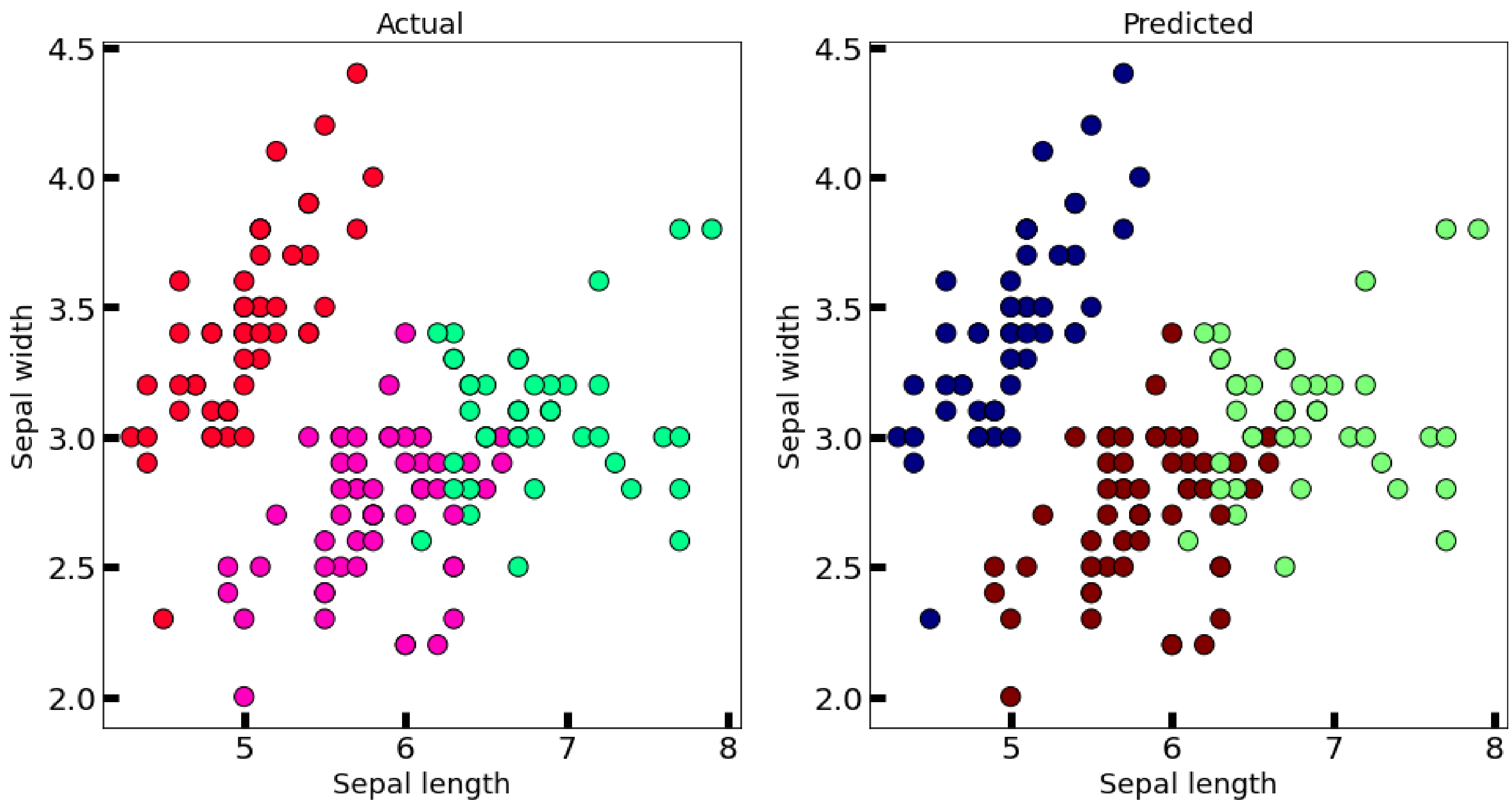
In [18]:
```
y_kmean = y.fit_predict(X)
```

Visualization of Results

Compare our original data vs clustered results

In [19]:
```
new_labels = y.labels_
fig, axes = plt.subplots(1, 2, figsize=(16,8))
axes[0].scatter(X[:, 0], X[:, 1], c=y_kmean, cmap='gist_rainbow',
edgecolor='k', s=150)
axes[1].scatter(X[:, 0], X[:, 1], c=new_labels, cmap='jet',
edgecolor='k', s=150)
axes[0].set_xlabel('Sepal length', fontsize=18)
axes[0].set_ylabel('Sepal width', fontsize=18)
axes[1].set_xlabel('Sepal length', fontsize=18)
axes[1].set_ylabel('Sepal width', fontsize=18)
axes[0].tick_params(direction='in', length=10, width=5, colors='k', labelsize=20)
axes[1].tick_params(direction='in', length=10, width=5, colors='k', labelsize=20)
axes[0].set_title('Actual', fontsize=18)
axes[1].set_title('Predicted', fontsize=18)
```

Out[19]:
```
Text(0.5, 1.0, 'Predicted')
```


Actual
Predicted
4.5
4.0
3.5
3.0
2.5
2.0
Sepal width
5
6
7
8
Sepal length

In [ ]: