

THE SPARKS FOUNDATION

#GRIPMAY21

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DATA SCIENCE AND BUSINESS ANALYTICS INTERNSHIP PROGRAM

PROJECT NAME: GIVEN THE 'IRIS' DATASET, PREDICTING THE OPTIMUM NUMBER OF
CLUSTERS AND TRYING TO VISUALIZE THEM

TOOL USED: PYTHON LANGUAGE

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```
In [ ]: # importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
```



```
In [13]: # loading the dataset
iris = datasets.load_iris()
iris_df = pd.DataFrame(iris.data, columns = iris.feature_names)
iris_df.head() # seeing the first five rows
```

Out[13]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
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



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Run



Code



In [14]: *# finding the optimum number of clusters for k-means classification*

```
x = iris_df.iloc[:, [0, 1, 2, 3]].values
```

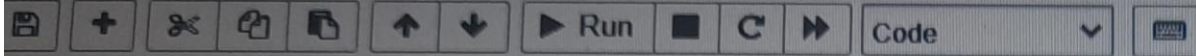
```
wcss = []
```

```
for i in range(1, 11):
```

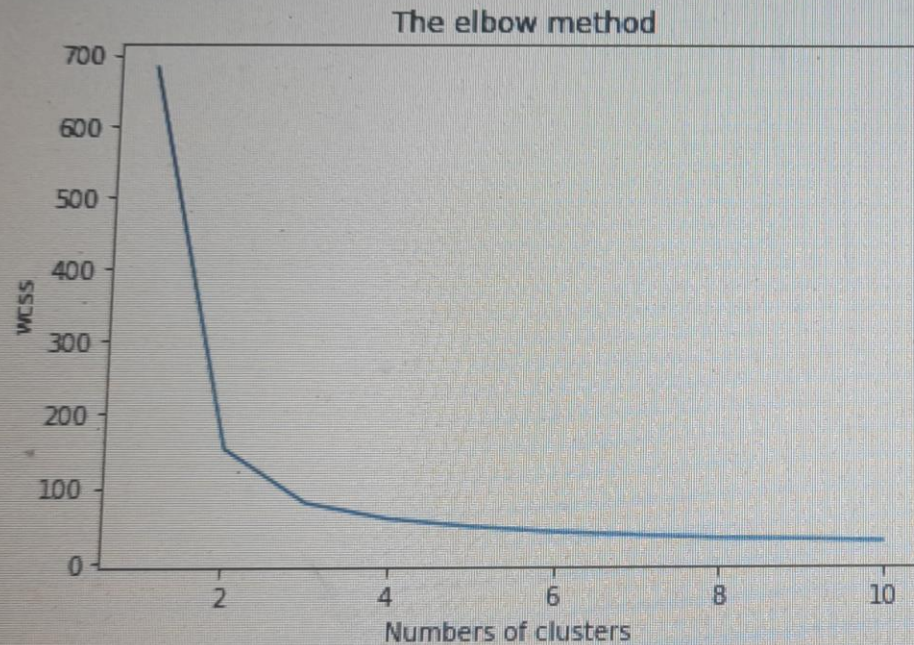
```
    kmeans = KMeans(n_clusters = i, init = 'k-means++',  
                    max_iter = 300, n_init = 10, random_state = 0)
```

```
    kmeans.fit(x)
```

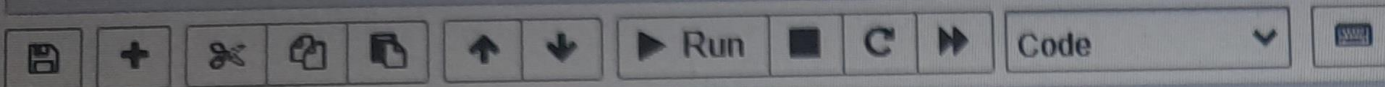
```
    wcss.append(kmeans.inertia_)
```

```
In [15]: # plotting the results in a line graph
# allowing us to observe 'The elbow'
plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Numbers of clusters')
plt.ylabel('wcss')
plt.show()
```



'The elbow method' from the above graph, it is seen the optimum clusters is where the elbow occurs. This is when the within cluster sum of squares (WCSS) does not decrease significantly with every iteration. From this we choose the number of clusters as 3.

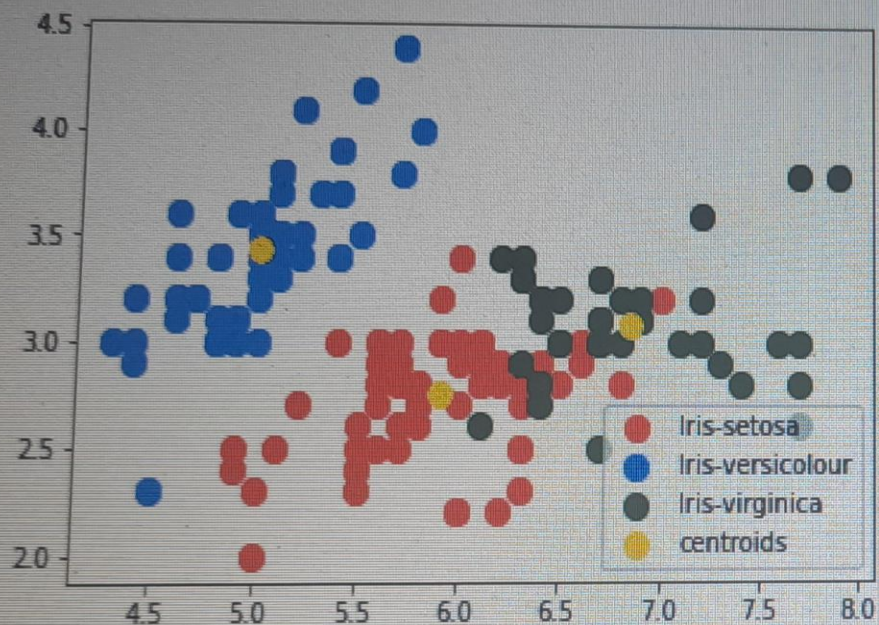


```
In [16]: # applying kmeans to the dataset
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

```
In [17]: # visualizing the clusters on the first two columns
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],
            s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1],
            s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'green', label = 'Iris-virginica')

# plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[0, 0], kmeans.cluster_centers_[0, 1],
            s = 100, c = 'yellow', label = 'centroids')
plt.legend()
```


Out[17]: <matplotlib.legend.Legend at 0x25d825b0490>



We can see that the clustering has done well since most of the reds and blues are separated and the greens are also very close to each other. Also the yellow ones represent the center points of each of the Iris species that we have. Thus, we have been able to find the optimum number of clusters and could visualize them.