Task 2: Prediction using Unsupervised ML

Predict the optimum number of clusters and represent it visually

Name: Praveen Kumar G

Importing necessay libraries

In [72]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
```

Loading data in DataFrame

In [73]:
```
df = pd.read_csv("Iris.csv", index_col = 0)
df.head()
```

Out[73]:

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

In [74]:
```
df.shape
```

Out[74]:
```
(150, 5)
```

In [75]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 150 entries, 1 to 150
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object
dtypes: float64(4), object(1)
memory usage: 7.0+ KB
```

In [76]:
```
df.describe()
```

Out[76]:

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

First we need to find the optimum number of clusters for K-Means. Here we will use `The Elbow Method` to determine the value of k in K-Means.

The Elbow Method

In Elbow method we calculate the `Within-Cluster-Sum of Squared Errors (WCSS)` for different values of k, and choose the k for which WCSS becomes first starts to diminish. In the plot of `WCSS-versus-k`, this is visible as an elbow.

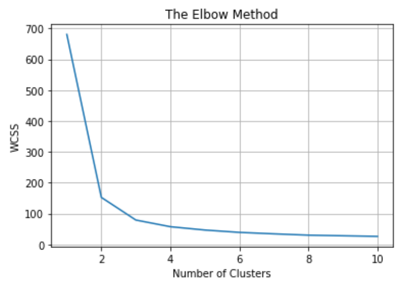
In [77]:
```
x = df.iloc[:, :4].values
from sklearn.cluster import KMeans

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_)

pd.DataFrame({"Number of Clusters":range(1,11),"WCSS":wcss})
```

Out[77]:

	Number of Clusters	WCSS
0	1	680.824400
1	2	152.368706
2	3	78.940841
3	4	57.345409
4	5	46.535582
5	6	38.938740
6	7	34.190688
7	8	29.905374
8	9	27.927882
9	10	25.955497

Plotting Number of Clusters vs. WCSS

In [78]:
```
plt.plot(range(1,11), wcss)
plt.title("The Elbow Method")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS")
plt.grid()
plt.show()
```



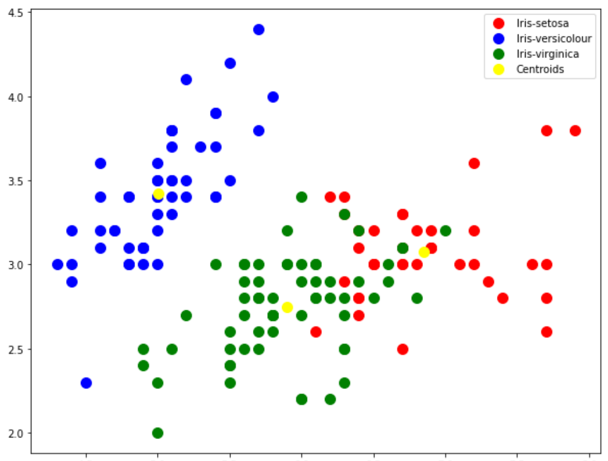
As expected, the plot looks like an arm with a clear elbow at k = 3.

Applying k-means to the dataset with Number of Clusters as k = 3

In [79]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

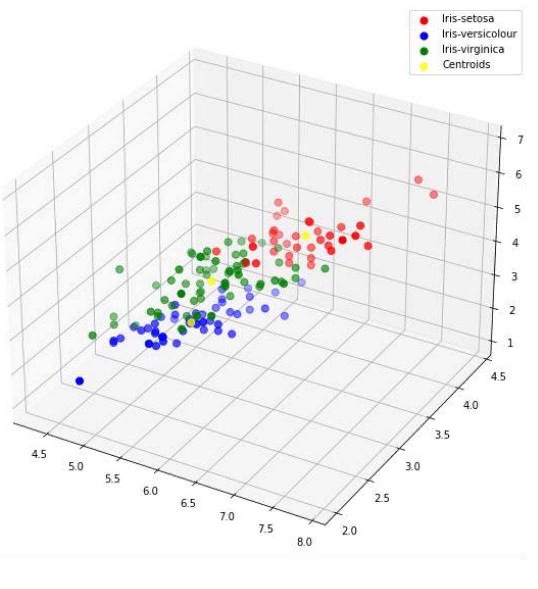
Visualizing the clusters on the first two columns

In [82]:
```
plt.figure(figsize=[10,8])
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')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1],
            s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
plt.show()
```



Visualizing the clusters on the first three columns

In [84]:
```
plt.figure(figsize=[10,10])
ax = plt.axes(projection ="3d")
ax.scatter3D(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], x[y_kmeans == 0, 2],
             s = 50, c = "red", label = 'Iris-setosa')
ax.scatter3D(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], x[y_kmeans == 1, 2],
             s = 50, c = 'blue', label = 'Iris-versicolour')
ax.scatter3D(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1], x[y_kmeans == 2, 2],
             s = 50, c = 'green', label = 'Iris-virginica')

ax.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], kmeans.cluster_centers_[:,2],
            s = 50, c = 'yellow', label = 'Centroids', alpha = 0.8)

plt.legend()
plt.show()
```


Iris-setosa
Iris-versicolour
Iris-virginica
Centroids