Workshop - 1: K- Means Clustering¶

This notebook will walk through some of the basics of K-Means Clustering.

In [14]:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets

# Load the iris dataset
iris = datasets.load_iris()
iris_df = pd.DataFrame(iris.data, columns = iris.feature_names)
iris_df.head() # See the first 5 rows
```

Out[14]:

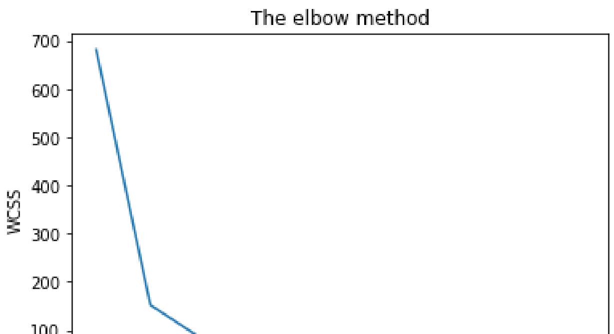
	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

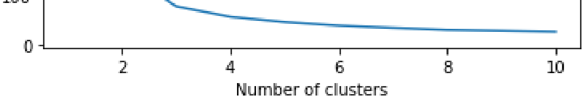
How do you find the optimum number of clusters for K Means? How does one determine the value of K?

In [15]:

```
# Finding the optimum number of clusters for k-means classification

x = iris_df.iloc[:, [0, 1, 2, 3]].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_)

# Plotting the results onto a line graph,
# `allowing us to observe 'The elbow'
plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') # Within cluster sum of squares
plt.show()
```

```
C:\Users\partha sarthi\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:882: UserWarning: KMeans is known to have a memory leak on Win
dows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  f"KMeans is known to have a memory leak on Windows "
```





You can clearly see why it is called 'The elbow method' from the above graph, the optimum clusters is where the elbow occurs. This is when the within cluster sum of squares (WCSS) doesn't decrease significantly with every iteration.

From this we choose the number of clusters as '3'.

In [16]:

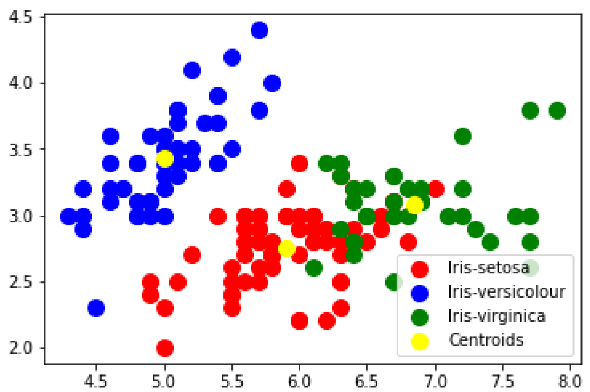
```
# Applying kmeans to the dataset / Creating the kmeans classifier
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

In [17]:

```
# Visualising 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], kmeans.cluster_centers_[:,1],
            s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```

Out[17]:

<matplotlib.legend.Legend at 0x21ff09697c8>



This concludes the K-Means Workshop.