# Prediction using Unsupervised ML

## Task-2 : From the given 'Iris' dataset, predict the optimum number of clusters and represent it visually.

In [ ]:
```
# Importing the required libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
```

### Loading the Iris Dataset into the notebook

In [23]:
```
# Loading the iris dataset
iris = datasets.load_iris()
iris_df = pd.DataFrame(iris.data, columns = iris.feature_names)
iris_df.head() # The first 5 rows
```

Out[23]:

| | 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 |

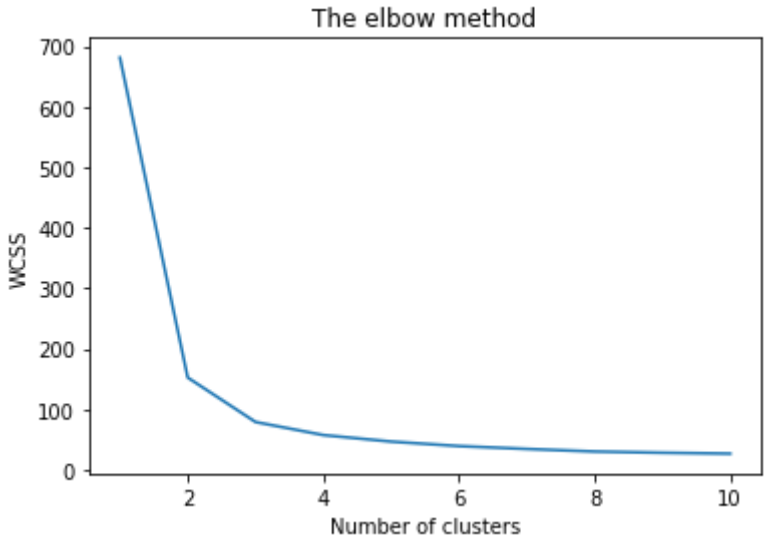
### Finding the optimal number of clusters for K-Means and determining the value of K

In [24]:
```
# 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 graph onto a line graph to observe the pattern

In [25]:
```
# 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()
```



## Creating K-Means Classifier

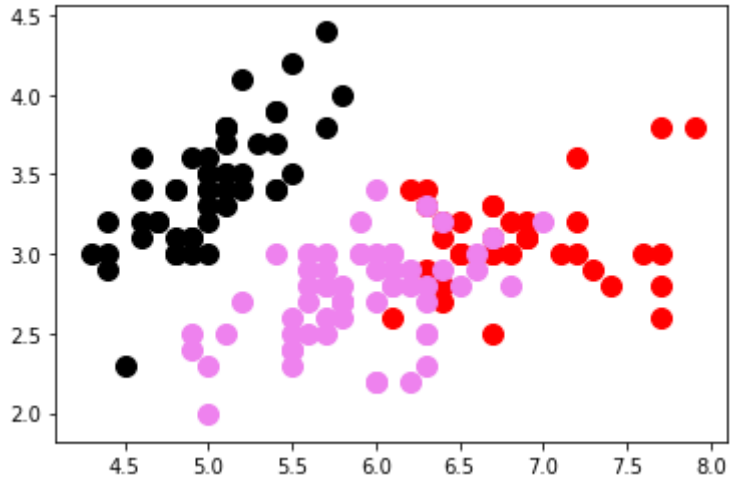
In [26]:
```
# Applying kmeans to the dataset
# Creating the kmeans classifier

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

## Visualizing the cluster data

In [27]:
```
# Visualising the clusters
# Preferably 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 = 'black', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'violet', label = 'Iris-virginica')
```

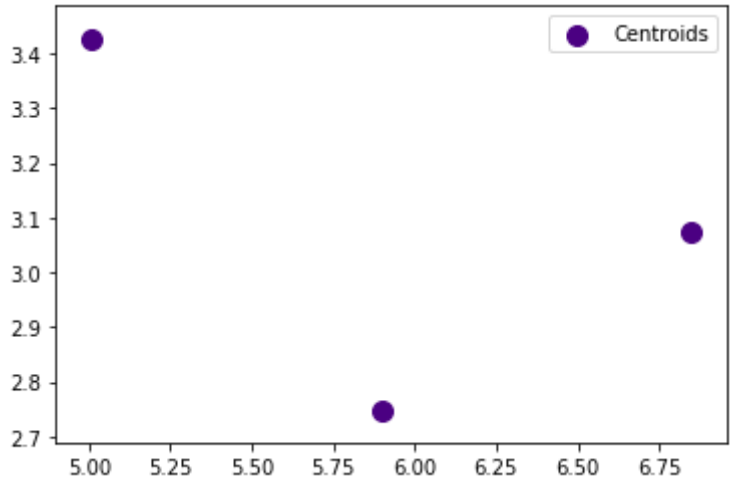
Out[27]: <matplotlib.collections.PathCollection at 0x27b9c31bf88>



In [28]:
```
# Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1],
            s = 100, c = 'indigo', label = 'Centroids')

plt.legend()
```

Out[28]: <matplotlib.legend.Legend at 0x27b9bfe8488>




## Now Combining both the above graphs together

In [29]:
```
# Visualising the clusters
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 = 'red', label = 'Iris-virginica')

# Plotting centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1],
            s = 100, c = 'green', label = 'Centroids')

plt.legend()
```

Out[29]: <matplotlib.legend.Legend at 0x27b9c39bd48>