In [35]:
```
# Importing the necessary Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

In [36]:
```
df = pd.read_csv("Iris.csv")
```

In [37]:
```
# Reading the head of our data
df.head()
```

Out[37]:

	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

In [38]:
```
df.Species.value_counts()
```

Out[38]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

In [5]:
```
df.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 [39]:
```
# Checking for Null Values
df.isnull().sum()
```

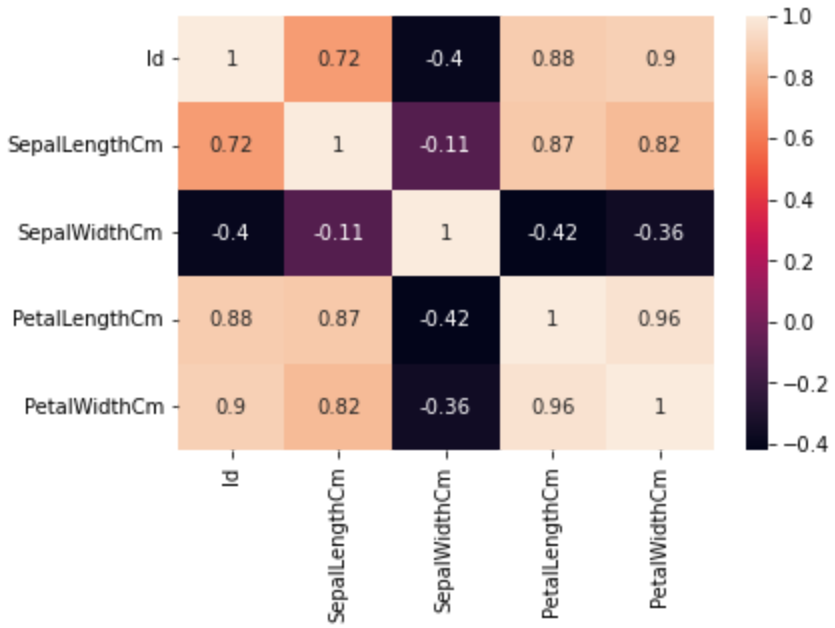
Out[39]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [40]:
```
# Dropping the duplicate rows if any
```

```
df.drop_duplicates(inplace=True)
```

In [42]:
```
# Checking for correlation
corr = df.corr()
sns.heatmap(corr,annot=True)
```

Out[42]:
```
<AxesSubplot:>
```



In [43]:
```
# Selecting the values for predicting the clusters
X = df.iloc[:,:-1].values
```

In [11]:
```
# Importing the cluster
from sklearn.cluster import KMeans
```

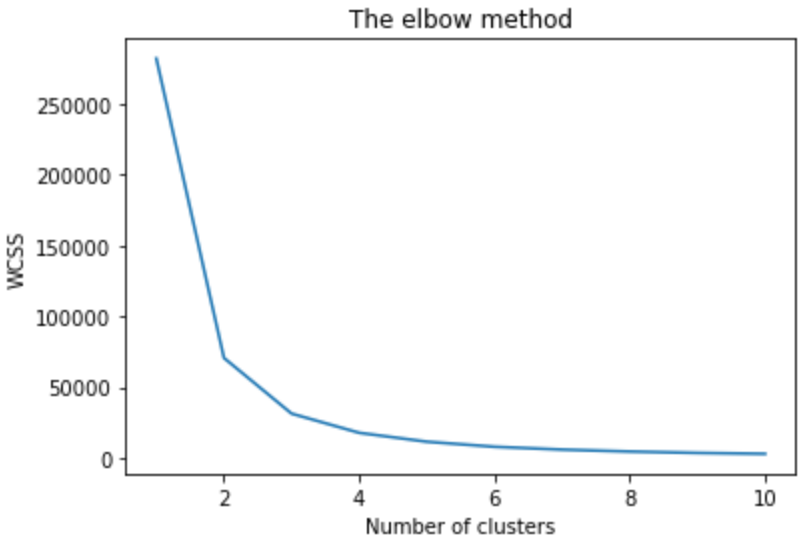
In [12]:
```
# Finding the appropriate number of clusters using Elbow Method

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:\ProgramData\Anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarning: K
Means is known to have a memory leak on Windows with MKL, when there are less chunks than
available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



After the third point we can see there is a smooth decline in the number of clusters so its safe to say that appropriate number of clusters for this data is 3

We will be applying the number of clusters as 3 to the data

In [13]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
kmeans.fit(X)
```

Out[13]:
```
KMeans(n_clusters=3, random_state=0)
```

In [14]:
```
y_kmeans = kmeans.predict(X)
```

In [15]:
```
y_kmeans
```

Out[15]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [16]:
```
labels = kmeans.labels_
```

In [17]:
```
labels
```

Out[17]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [18]:
```
kmeans.inertia_
```

Out[18]:
```
31326.886799999997
```

In [19]:

```
centroids = kmeans.cluster_centers_
```

In [20]:

```
centroids
```

Out[20]:

```
array([[ 25.5  ,   5.006,   3.418,   1.464,   0.244],
       [125.5  ,   6.588,   2.974,   5.552,   2.026],
       [ 75.5  ,   5.936,   2.77 ,   4.26 ,   1.326]])
```

In [21]:

```
# 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(centroids[:, 0], centroids[:,1],
            s = 100, c = 'yellow', label = 'Centroids')

plt.legend()
```

Out[21]:

```
<matplotlib.legend.Legend at 0x18292bcaa30>
```