```
In [1]:
import pandas as pd
import numpy as np
In [2]:
data = pd.read csv('iris.csv')
data.head()
Out[2]:
  sepal_length sepal_width petal_length petal_width target
0
         5.1
                   3.5
                                      0.2
                                             0
                             1.4
1
         4.9
                   3.0
                             1.4
                                      0.2
                                             0
2
         4.7
                   3.2
                             1.3
                                      0.2
                                             0
3
         4.6
                   3.1
                             1.5
                                      0.2
                                             0
         5.0
                   3.6
                             1.4
                                      0.2
                                             0
In [3]:
data.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 # Column
                  Non-Null Count Dtype
   sepal_length 150 non-null
                                 float64
 0
 1 sepal_width 150 non-null float64
 2 petal_length 150 non-null float64
                                 float64
 3 petal_width 150 non-null
 4 target
                                    int64
                   150 non-null
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
In [4]:
data.target.unique()
Out[4]:
array([0, 1, 2])
In [5]:
data.target
Out[5]:
0
       0
1
       0
2
       0
3
       0
4
       0
145
      2
146
      2
      2
147
      2
148
149
Name: target, Length: 150, dtype: int64
In [6]:
```

d = + = = = = = =

```
uata.snape
Out[6]:
(150, 5)
In [7]:
data.isnull().sum()
Out[7]:
sepal_length
                  0
                  0
sepal_width
                  0
petal length
                  0
petal width
                  0
target
dtype: int64
In [8]:
data.describe()
Out[8]:
      sepal_length sepal_width petal_length petal_width
                                                     target
count
       150.000000
                  150.000000
                             150.000000
                                       150.000000 150.000000
         5.843333
                    3.054000
                               3.758667
                                         1.198667
                                                   1.000000
 mean
  std
         0.828066
                    0.433594
                               1.764420
                                         0.763161
                                                   0.819232
  min
         4.300000
                    2.000000
                               1.000000
                                         0.100000
                                                   0.000000
 25%
         5.100000
                    2.800000
                               1.600000
                                         0.300000
                                                   0.000000
         5.800000
                    3.000000
                               4.350000
                                         1.300000
                                                   1.000000
 50%
         6.400000
                    3.300000
                               5.100000
                                         1.800000
                                                   2.000000
 75%
         7.900000
                    4.400000
                               6.900000
                                         2.500000
                                                   2.000000
 max
In [9]:
x = data.iloc[:, [0, 1, 2, 3]].values
Х
Out[9]:
array([[5.1, 3.5, 1.4, 0.2],
        [4.9, 3., 1.4, 0.2],
        [4.7, 3.2, 1.3, 0.2],
        [4.6, 3.1, 1.5, 0.2],
        [5., 3.6, 1.4, 0.2],
        [5.4, 3.9, 1.7, 0.4],
        [4.6, 3.4, 1.4, 0.3],
        [5., 3.4, 1.5, 0.2],
        [4.4, 2.9, 1.4, 0.2],
        [4.9, 3.1, 1.5, 0.1],
        [5.4, 3.7, 1.5, 0.2],
        [4.8, 3.4, 1.6, 0.2],
        [4.8, 3., 1.4, 0.1],
        [4.3, 3. , 1.1, 0.1],
        [5.8, 4., 1.2, 0.2],
        [5.7, 4.4, 1.5, 0.4],
        [5.4, 3.9, 1.3, 0.4],
        [5.1, 3.5, 1.4, 0.3],
        [5.7, 3.8, 1.7, 0.3],
        [5.1, 3.8, 1.5, 0.3],
        [5.4, 3.4, 1.7, 0.2],
        [5.1, 3.7, 1.5, 0.4],
        [4.6, 3.6, 1., 0.2],
        [5.1, 3.3, 1.7, 0.5],
        [4.8, 3.4, 1.9, 0.2],
        [5. . 3. . 1.6. 0.2].
```

```
[5., 3.4, 1.6, 0.4],
[5.2, 3.5, 1.5, 0.2],
[5.2, 3.4, 1.4, 0.2],
[4.7, 3.2, 1.6, 0.2],
[4.8, 3.1, 1.6, 0.2],
[5.4, 3.4, 1.5, 0.4],
[5.2, 4.1, 1.5, 0.1],
[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.1],
[5., 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.1, 1.5, 0.1],
[4.4, 3., 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5., 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5., 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3., 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5., 3.3, 1.4, 0.2],
[7., 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
[5.5, 2.3, 4., 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1.],
[6.6, 2.9, 4.6, 1.3],
[5.2, 2.7, 3.9, 1.4],
[5., 2., 3.5, 1.],
[5.9, 3., 4.2, 1.5],
[6., 2.2, 4., 1.],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3., 4.5, 1.5],
[5.8, 2.7, 4.1, 1.],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4., 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3., 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3., 5., 1.7],
[6., 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1.],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1.],
[5.8, 2.7, 3.9, 1.2],
[6., 2.7, 5.1, 1.6],
[5.4, 3., 4.5, 1.5],
[6., 3.4, 4.5, 1.6],
[6.7, 3.1, 4.7, 1.5],
[6.3, 2.3, 4.4, 1.3],
[5.6, 3., 4.1, 1.3],
[5.5, 2.5, 4., 1.3],
[5.5, 2.6, 4.4, 1.2],
[6.1, 3., 4.6, 1.4],
[5.8, 2.6, 4., 1.2],
[5., 2.3, 3.3, 1.],
[5.6, 2.7, 4.2, 1.3],
[5.7, 3., 4.2, 1.2],
[5.7, 2.9, 4.2, 1.3],
```

[6.2, 2.9, 4.3, 1.3],

```
[5.1, 2.5, 3., 1.1],
[5.7, 2.8, 4.1, 1.3],
[6.3, 3.3, 6., 2.5],
[5.8, 2.7, 5.1, 1.9],
[7.1, 3., 5.9, 2.1],
[6.3, 2.9, 5.6, 1.8],
[6.5, 3., 5.8, 2.2],
[7.6, 3., 6.6, 2.1], [4.9, 2.5, 4.5, 1.7],
[7.3, 2.9, 6.3, 1.8],
[6.7, 2.5, 5.8, 1.8],
[7.2, 3.6, 6.1, 2.5],
[6.5, 3.2, 5.1, 2.],
[6.4, 2.7, 5.3, 1.9],
[6.8, 3., 5.5, 2.1],
[5.7, 2.5, 5., 2.],
[5.8, 2.8, 5.1, 2.4],
[6.4, 3.2, 5.3, 2.3],
[6.5, 3., 5.5, 1.8],
[7.7, 3.8, 6.7, 2.2],
[7.7, 2.6, 6.9, 2.3],
[6., 2.2, 5., 1.5],
[6.9, 3.2, 5.7, 2.3],
[5.6, 2.8, 4.9, 2.],
[7.7, 2.8, 6.7, 2.],
[6.3, 2.7, 4.9, 1.8],
[6.7, 3.3, 5.7, 2.1],
[7.2, 3.2, 6., 1.8],
[6.2, 2.8, 4.8, 1.8],
[6.1, 3., 4.9, 1.8],
[6.4, 2.8, 5.6, 2.1],
[7.2, 3., 5.8, 1.6],
[7.4, 2.8, 6.1, 1.9],
[7.9, 3.8, 6.4, 2.],
[6.4, 2.8, 5.6, 2.2],
[6.3, 2.8, 5.1, 1.5],
[6.1, 2.6, 5.6, 1.4],
[7.7, 3., 6.1, 2.3],
[6.3, 3.4, 5.6, 2.4],
[6.4, 3.1, 5.5, 1.8],
[6., 3., 4.8, 1.8],
[6.9, 3.1, 5.4, 2.1],
[6.7, 3.1, 5.6, 2.4], [6.9, 3.1, 5.1, 2.3],
[5.8, 2.7, 5.1, 1.9],
[6.8, 3.2, 5.9, 2.3],
[6.7, 3.3, 5.7, 2.5], [6.7, 3., 5.2, 2.3],
[6.3, 2.5, 5., 1.9],
[6.5, 3., 5.2, 2.],
[6.2, 3.4, 5.4, 2.3],
[5.9, 3., 5.1, 1.8]])
```

Finding the no. of clusters(k)-Elbow Method

t` explicitly to suppress the warning

warnings.warn(

```
In [10]:

from sklearn.cluster import KMeans
wcss = []
for i in range(1,16):
    kmeans = KMeans(n_clusters=i,random_state=1)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
```

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n init`

```
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
 explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: Th
e default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
```

In [11]:

WCSS

Out[11]:

```
[680.8244000000001,
152.36870647733906,
78.940841426146,
57.34540931571814,
46.53558205128205,
38.95701115711986,
34.326529914529914,
30.227724598930486,
27.766706937799043,
26.072251823340057,
24.721876253132834,
23.100693699231627,
```

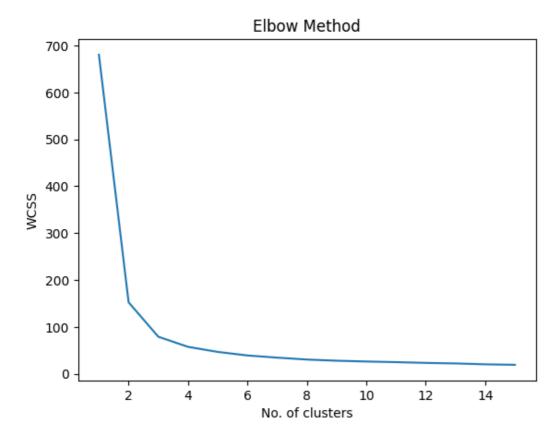
```
21.94/08502331003,
20.045951489686786,
19.009774761186527]
```

In [12]:

```
import matplotlib.pyplot as plt
plt.plot(range(1,16), wcss)
plt.title("Elbow Method")
plt.xlabel("No. of clusters")
plt.ylabel("WCSS")
```

Out[12]:

Text(0, 0.5, 'WCSS')



Building the model

In [13]:

```
kmeans = KMeans(n_clusters=3,random_state=1)
y_predict = kmeans.fit_predict(x)
y_predict

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: Th
e default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
    warnings.warn(
```

Out[13]:

In [14]:

```
kmeans1 = KMeans(n_clusters=4,random_state=1)
y_predict1 = kmeans1.fit_predict(x)
```

```
y predict1
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: Th
e default value of `n init` will change from 10 to 'auto' in 1.4. Set the value of `n ini
t` explicitly to suppress the warning
 warnings.warn(
Out[14]:
0, 0, 0, 0, 0, 0, 1, 1, 1, 2, 1, 2, 1, 2, 1, 2, 2, 2, 2, 1, 2, 1,
     1, 2, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 1, 2, 1, 1, 1,
     2, 2, 2, 1, 2, 2, 2, 2, 2, 1, 2, 2, 3, 1, 3, 3, 3, 3, 3, 3, 3, 3,
     1, 1, 3, 1, 1, 3, 3, 3, 3, 1, 3, 1, 3, 1, 3, 3, 1, 1, 3, 3, 3, 3,
     3, 1, 1, 3, 3, 3, 1, 3, 3, 1, 3, 3, 3, 1, 1, 3, 1], dtype=int32)
In [15]:
kmeans.labels
Out[15]:
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 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, 0, 0, 2, 2, 2, 2, 0, 2, 0, 2, 0, 2, 2, 0, 0, 2, 2, 2, 2,
     2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 0], dtype=int32)
In [16]:
from sklearn.metrics import silhouette score
In [17]:
sil score = silhouette score(x,kmeans.labels )
sil score
Out[17]:
0.5525919445499757
In [18]:
sil score1 = silhouette_score(x,kmeans1.labels_)
sil score1
Out[18]:
0.4972279726640147
Visualizing the clusters with centroids
In [19]:
X
Out[19]:
array([[5.1, 3.5, 1.4, 0.2],
     [4.9, 3., 1.4, 0.2],
     [4.7, 3.2, 1.3, 0.2],
     [4.6, 3.1, 1.5, 0.2],
     [5., 3.6, 1.4, 0.2],
     [5.4, 3.9, 1.7, 0.4],
     [4.6, 3.4, 1.4, 0.3],
     [5., 3.4, 1.5, 0.2],
     [4.4, 2.9, 1.4, 0.2],
     [4.9, 3.1, 1.5, 0.1],
     [5.4, 3.7, 1.5, 0.2],
```

[/ A 2 / 1 6 / 2]

```
[=.0, 0.=, 1.0, 0.2],
[4.8, 3., 1.4, 0.1],
[4.3, 3., 1.1, 0.1],
[5.8, 4., 1.2, 0.2],
[5.7, 4.4, 1.5, 0.4],
[5.4, 3.9, 1.3, 0.4],
[5.1, 3.5, 1.4, 0.3],
[5.7, 3.8, 1.7, 0.3],
[5.1, 3.8, 1.5, 0.3],
[5.4, 3.4, 1.7, 0.2],
[5.1, 3.7, 1.5, 0.4],
[4.6, 3.6, 1., 0.2],
[5.1, 3.3, 1.7, 0.5],
[4.8, 3.4, 1.9, 0.2],
[5., 3., 1.6, 0.2],
[5., 3.4, 1.6, 0.4],
[5.2, 3.5, 1.5, 0.2],
[5.2, 3.4, 1.4, 0.2],
[4.7, 3.2, 1.6, 0.2],
[4.8, 3.1, 1.6, 0.2],
[5.4, 3.4, 1.5, 0.4],
[5.2, 4.1, 1.5, 0.1],
[5.5, 4.2, 1.4, 0.2],
[4.9, 3.1, 1.5, 0.1],
[5., 3.2, 1.2, 0.2],
[5.5, 3.5, 1.3, 0.2],
[4.9, 3.1, 1.5, 0.1],
[4.4, 3., 1.3, 0.2],
[5.1, 3.4, 1.5, 0.2],
[5., 3.5, 1.3, 0.3],
[4.5, 2.3, 1.3, 0.3],
[4.4, 3.2, 1.3, 0.2],
[5., 3.5, 1.6, 0.6],
[5.1, 3.8, 1.9, 0.4],
[4.8, 3., 1.4, 0.3],
[5.1, 3.8, 1.6, 0.2],
[4.6, 3.2, 1.4, 0.2],
[5.3, 3.7, 1.5, 0.2],
[5., 3.3, 1.4, 0.2],
[7. , 3.2, 4.7, 1.4],
[6.4, 3.2, 4.5, 1.5],
[6.9, 3.1, 4.9, 1.5],
[5.5, 2.3, 4., 1.3],
[6.5, 2.8, 4.6, 1.5],
[5.7, 2.8, 4.5, 1.3],
[6.3, 3.3, 4.7, 1.6],
[4.9, 2.4, 3.3, 1.],
[6.6, 2.9, 4.6, 1.3],
[5.2, 2.7, 3.9, 1.4],
[5., 2., 3.5, 1.],
[5.9, 3., 4.2, 1.5],
[6., 2.2, 4., 1.],
[6.1, 2.9, 4.7, 1.4],
[5.6, 2.9, 3.6, 1.3],
[6.7, 3.1, 4.4, 1.4],
[5.6, 3., 4.5, 1.5],
[5.8, 2.7, 4.1, 1.],
[6.2, 2.2, 4.5, 1.5],
[5.6, 2.5, 3.9, 1.1],
[5.9, 3.2, 4.8, 1.8],
[6.1, 2.8, 4., 1.3],
[6.3, 2.5, 4.9, 1.5],
[6.1, 2.8, 4.7, 1.2],
[6.4, 2.9, 4.3, 1.3],
[6.6, 3., 4.4, 1.4],
[6.8, 2.8, 4.8, 1.4],
[6.7, 3., 5., 1.7],
[6., 2.9, 4.5, 1.5],
[5.7, 2.6, 3.5, 1.],
[5.5, 2.4, 3.8, 1.1],
[5.5, 2.4, 3.7, 1.],
[5.8, 2.7, 3.9, 1.2],
```

7 7

Γ6

5 1 1 61

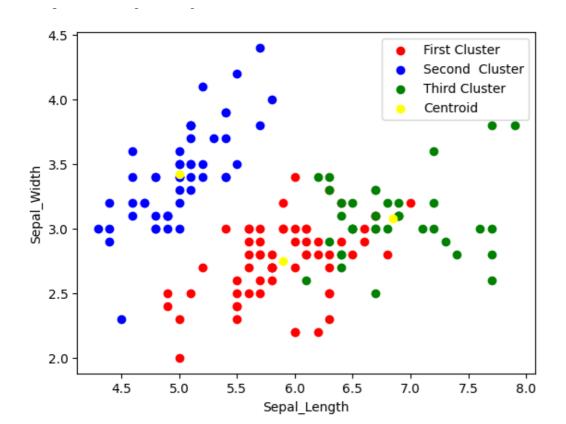
[0. , 2.1, 0.1, 1.0], [5.4, 3., 4.5, 1.5], [6., 3.4, 4.5, 1.6], [6.7, 3.1, 4.7, 1.5], [6.3, 2.3, 4.4, 1.3],[5.6, 3., 4.1, 1.3],[5.5, 2.5, 4., 1.3],[5.5, 2.6, 4.4, 1.2], [6.1, 3., 4.6, 1.4],[5.8, 2.6, 4., 1.2],[5., 2.3, 3.3, 1.], [5.6, 2.7, 4.2, 1.3], [5.7, 3., 4.2, 1.2],[5.7, 2.9, 4.2, 1.3], [6.2, 2.9, 4.3, 1.3],[5.1, 2.5, 3., 1.1], [5.7, 2.8, 4.1, 1.3], [6.3, 3.3, 6., 2.5], [5.8, 2.7, 5.1, 1.9], [7.1, 3., 5.9, 2.1], [6.3, 2.9, 5.6, 1.8],[6.5, 3., 5.8, 2.2],[7.6, 3., 6.6, 2.1], [4.9, 2.5, 4.5, 1.7],[7.3, 2.9, 6.3, 1.8],[6.7, 2.5, 5.8, 1.8],[7.2, 3.6, 6.1, 2.5],[6.5, 3.2, 5.1, 2.],[6.4, 2.7, 5.3, 1.9],[6.8, 3., 5.5, 2.1],[5.7, 2.5, 5., 2.], [5.8, 2.8, 5.1, 2.4], [6.4, 3.2, 5.3, 2.3],[6.5, 3., 5.5, 1.8],[7.7, 3.8, 6.7, 2.2], [7.7, 2.6, 6.9, 2.3], [6., 2.2, 5., 1.5], [6.9, 3.2, 5.7, 2.3], [5.6, 2.8, 4.9, 2.], [7.7, 2.8, 6.7, 2.], [6.3, 2.7, 4.9, 1.8],[6.7, 3.3, 5.7, 2.1],[7.2, 3.2, 6., 1.8],[6.2, 2.8, 4.8, 1.8],[6.1, 3., 4.9, 1.8],[6.4, 2.8, 5.6, 2.1],[7.2, 3., 5.8, 1.6],[7.4, 2.8, 6.1, 1.9],[7.9, 3.8, 6.4, 2.],[6.4, 2.8, 5.6, 2.2],[6.3, 2.8, 5.1, 1.5],[6.1, 2.6, 5.6, 1.4],[7.7, 3., 6.1, 2.3], [6.3, 3.4, 5.6, 2.4], [6.4, 3.1, 5.5, 1.8], [6., 3., 4.8, 1.8],[6.9, 3.1, 5.4, 2.1], [6.7, 3.1, 5.6, 2.4],[6.9, 3.1, 5.1, 2.3],[5.8, 2.7, 5.1, 1.9], [6.8, 3.2, 5.9, 2.3],[6.7, 3.3, 5.7, 2.5],[6.7, 3., 5.2, 2.3],[6.3, 2.5, 5., 1.9],[6.5, 3., 5.2, 2.],[6.2, 3.4, 5.4, 2.3],[5.9, 3., 5.1, 1.8]])

In [20]:

```
Juc[20] .
array([5.1, 4.9, 4.7, 4.6, 5. , 5.4, 4.6, 5. , 4.4, 4.9, 5.4, 4.8, 4.8,
      4.3, 5.8, 5.7, 5.4, 5.1, 5.7, 5.1, 5.4, 5.1, 4.6, 5.1, 4.8, 5.
      5. , 5.2, 5.2, 4.7, 4.8, 5.4, 5.2, 5.5, 4.9, 5. , 5.5, 4.9, 4.4,
      5.1, 5. , 4.5, 4.4, 5. , 5.1, 4.8, 5.1, 4.6, 5.3, 5. , 7. , 6.4,
      6.9, 5.5, 6.5, 5.7, 6.3, 4.9, 6.6, 5.2, 5. , 5.9, 6. , 6.1, 5.6,
      6.7, 5.6, 5.8, 6.2, 5.6, 5.9, 6.1, 6.3, 6.1, 6.4, 6.6, 6.8, 6.7,
      6. , 5.7, 5.5, 5.5, 5.8, 6. , 5.4, 6. , 6.7, 6.3, 5.6, 5.5, 5.5,
      6.1, 5.8, 5. , 5.6, 5.7, 5.7, 6.2, 5.1, 5.7, 6.3, 5.8, 7.1, 6.3,
      6.5, 7.6, 4.9, 7.3, 6.7, 7.2, 6.5, 6.4, 6.8, 5.7, 5.8, 6.4, 6.5,
      7.7, 7.7, 6., 6.9, 5.6, 7.7, 6.3, 6.7, 7.2, 6.2, 6.1, 6.4, 7.2,
      7.4, 7.9, 6.4, 6.3, 6.1, 7.7, 6.3, 6.4, 6. , 6.9, 6.7, 6.9, 5.8,
      6.8, 6.7, 6.7, 6.3, 6.5, 6.2, 5.9])
In [21]:
y_predict
Out[21]:
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 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, 0, 0, 2, 2, 2, 2, 0, 2, 0, 2, 0, 2, 2, 0, 0, 2, 2, 2, 2,
      2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 2, 0, 2, 2, 0], dtype=int32)
In [22]:
x[y predict == 0]
Out[22]:
array([[7., 3.2, 4.7, 1.4],
      [6.4, 3.2, 4.5, 1.5],
      [5.5, 2.3, 4., 1.3],
[6.5, 2.8, 4.6, 1.5],
      [5.7, 2.8, 4.5, 1.3],
      [6.3, 3.3, 4.7, 1.6],
      [4.9, 2.4, 3.3, 1.],
      [6.6, 2.9, 4.6, 1.3],
      [5.2, 2.7, 3.9, 1.4],
      [5., 2., 3.5, 1.],
      [5.9, 3., 4.2, 1.5],
      [6., 2.2, 4., 1.],
      [6.1, 2.9, 4.7, 1.4],
      [5.6, 2.9, 3.6, 1.3],
      [6.7, 3.1, 4.4, 1.4],
      [5.6, 3., 4.5, 1.5],
      [5.8, 2.7, 4.1, 1.],
      [6.2, 2.2, 4.5, 1.5],
      [5.6, 2.5, 3.9, 1.1],
      [5.9, 3.2, 4.8, 1.8],
      [6.1, 2.8, 4., 1.3],
      [6.3, 2.5, 4.9, 1.5],
      [6.1, 2.8, 4.7, 1.2],
      [6.4, 2.9, 4.3, 1.3],
      [6.6, 3., 4.4, 1.4],
      [6.8, 2.8, 4.8, 1.4],
      [6., 2.9, 4.5, 1.5],
      [5.7, 2.6, 3.5, 1.],
      [5.5, 2.4, 3.8, 1.1],
      [5.5, 2.4, 3.7, 1.],
      [5.8, 2.7, 3.9, 1.2],
      [6., 2.7, 5.1, 1.6],
      [5.4, 3., 4.5, 1.5],
      [6., 3.4, 4.5, 1.6],
      [6.7, 3.1, 4.7, 1.5],
      [6.3, 2.3, 4.4, 1.3],
      [5.6, 3., 4.1, 1.3],
      [5.5, 2.5, 4., 1.3],
      [5 5 2 6 A A 1 2]
```

```
[6.1, 3., 4.6, 1.4],
       [5.8, 2.6, 4., 1.2],
       [5., 2.3, 3.3, 1.],
       [5.6, 2.7, 4.2, 1.3],
       [5.7, 3., 4.2, 1.2],
       [5.7, 2.9, 4.2, 1.3],
       [6.2, 2.9, 4.3, 1.3],
       [5.1, 2.5, 3., 1.1],
       [5.7, 2.8, 4.1, 1.3],
       [5.8, 2.7, 5.1, 1.9],
       [4.9, 2.5, 4.5, 1.7],
       [5.7, 2.5, 5., 2.],
       [5.8, 2.8, 5.1, 2.4],
       [6., 2.2, 5., 1.5],
       [5.6, 2.8, 4.9, 2.],
       [6.3, 2.7, 4.9, 1.8],
       [6.2, 2.8, 4.8, 1.8],
       [6.1, 3., 4.9, 1.8],
       [6.3, 2.8, 5.1, 1.5],
       [6., 3., 4.8, 1.8],
       [5.8, 2.7, 5.1, 1.9],
       [6.3, 2.5, 5., 1.9],
       [5.9, 3., 5.1, 1.8]])
In [23]:
x[y predict == 0,3]
Out[23]:
array([1.4, 1.5, 1.3, 1.5, 1.3, 1.6, 1. , 1.3, 1.4, 1. , 1.5, 1. , 1.4,
       1.3, 1.4, 1.5, 1. , 1.5, 1.1, 1.8, 1.3, 1.5, 1.2, 1.3, 1.4, 1.4,
       1.5, 1. , 1.1, 1. , 1.2, 1.6, 1.5, 1.6, 1.5, 1.3, 1.3, 1.3, 1.2,
       1.4, 1.2, 1. , 1.3, 1.2, 1.3, 1.3, 1.1, 1.3, 1.9, 1.7, 2. , 2.4,
       1.5, 2., 1.8, 1.8, 1.8, 1.5, 1.8, 1.9, 1.9, 1.8])
In [24]:
x[y predict == 0,0]
Out[24]:
array([7., 6.4, 5.5, 6.5, 5.7, 6.3, 4.9, 6.6, 5.2, 5., 5.9, 6., 6.1,
       5.6, 6.7, 5.6, 5.8, 6.2, 5.6, 5.9, 6.1, 6.3, 6.1, 6.4, 6.6, 6.8,
       6. , 5.7, 5.5, 5.5, 5.8, 6. , 5.4, 6. , 6.7, 6.3, 5.6, 5.5, 5.5,
       6.1, 5.8, 5. , 5.6, 5.7, 5.7, 6.2, 5.1, 5.7, 5.8, 4.9, 5.7, 5.8,
       6. , 5.6, 6.3, 6.2, 6.1, 6.3, 6. , 5.8, 6.3, 5.9])
In [25]:
x[y predict == 1,0]
Out[25]:
array([5.1, 4.9, 4.7, 4.6, 5. , 5.4, 4.6, 5. , 4.4, 4.9, 5.4, 4.8, 4.8,
       4.3, 5.8, 5.7, 5.4, 5.1, 5.7, 5.1, 5.4, 5.1, 4.6, 5.1, 4.8, 5.
       5. , 5.2, 5.2, 4.7, 4.8, 5.4, 5.2, 5.5, 4.9, 5. , 5.5, 4.9, 4.4,
       5.1, 5., 4.5, 4.4, 5., 5.1, 4.8, 5.1, 4.6, 5.3, 5.])
In [26]:
plt.scatter(x[y predict == 0,0], x[y predict == 0,1],c='red',label='First Cluster')
plt.scatter(x[y_predict == 1,0], x[y_predict == 1,1],c='blue',label='Second Cluster')
plt.scatter(x[y predict == 2,0], x[y predict == 2,1],c='green',label='Third Cluster')
plt.scatter(kmeans.cluster centers [:,0], kmeans.cluster centers [:,1], c='yellow', label='
Centroid')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.legend()
Out[26]:
```

<matplotlib.legend.Legend at 0x7889d1357e80>



In [27]:

```
kmeans.cluster_centers_
```

Out[27]:

In [28]:

```
plt.scatter(x[y_predict == 0,2], x[y_predict == 0,3],c='red',label='First Cluster')
plt.scatter(x[y_predict == 1,2], x[y_predict == 1,3],c='blue',label='Second Cluster')
plt.scatter(x[y_predict == 2,2], x[y_predict == 2,3],c='green',label='Third Cluster')
plt.scatter(kmeans.cluster_centers_[:,2],kmeans.cluster_centers_[:,3],c='yellow',label='Centroid')
plt.xlabel('Petal_Length')
plt.ylabel('Petal_Width')
plt.legend()
```

Out[28]:

<matplotlib.legend.Legend at 0x7889d12465f0>

