THE SPARKS FOUNDATION - GRIP(OCTOBER'21)

Data Science and Business Analytics Internship

Name - Ruchira Sengupta

Task 2 - Prediction using Unsupervised ML

Objective - In this task, we need to predict the optimum number of clusters from the given 'Iris' dataset and represent it visually.

K-Means Clustering

In this task, we will predict the optimum number of clusters from the given 'Iris' dataset.This notebook will walk through some of the basics of K-Means Clustering.

IMPORT THE REQUIRED LIBRARIES

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
import warnings
warnings.filterwarnings('ignore')#Ignore warnings
```

LOAD THE 'IRIS' DATASET

In [2]:
```
iris = datasets.load_iris()
iris_df = pd.DataFrame(iris.data, columns = iris.feature_names)
```

The first 5 rows, last 5 rows, shape, description of the data are displayed

In [3]:
```
iris_df.head() #gives the first 5 rows
```

Out[3]:

	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

In [4]:
```
iris_df.tail() #gives the last 5 rows
```

Out[4]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

In [5]:
```
iris_df.shape #gives the shape of the data
```

Out[5]:
```
(150, 4)
```

In [6]:
```
iris_df.describe() #gives description of the data
```

Out[6]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333
std	0.828066	0.435866	1.765298	0.762238
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

In [7]:
```
iris_df.info() #gives information about the data
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 4 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
dtypes: float64(4)
memory usage: 4.8 KB
```

Checking if there is null element in the dataset

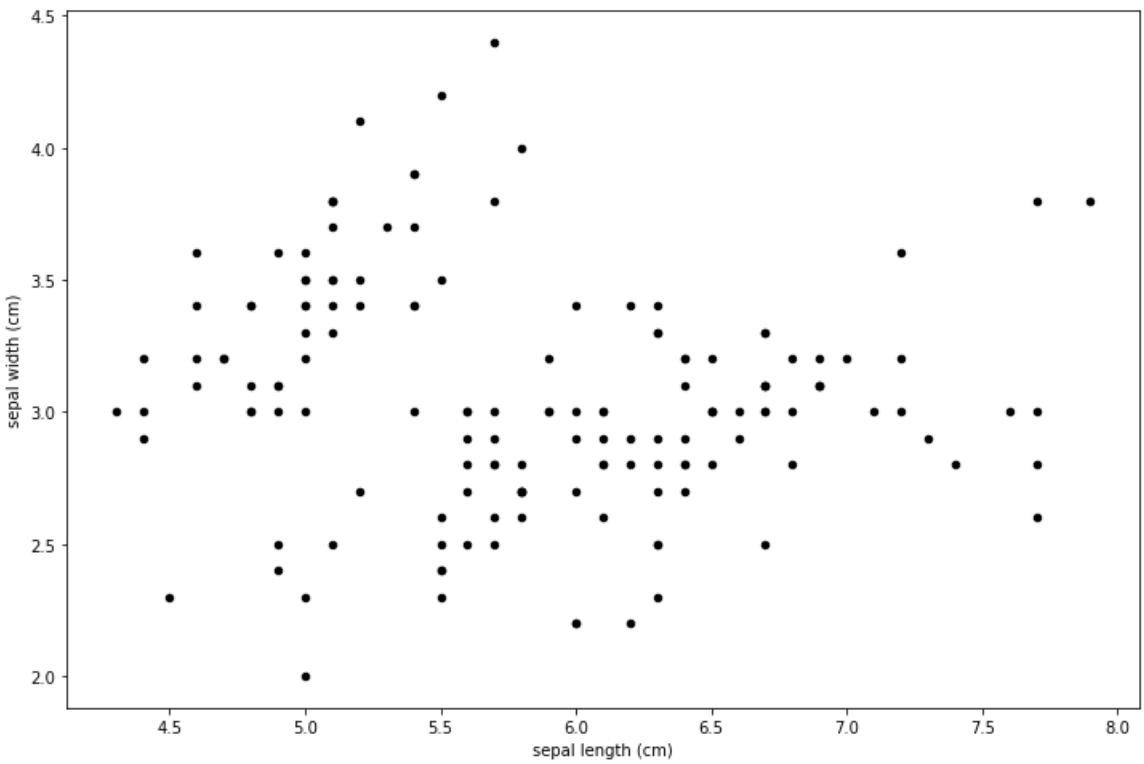
In [8]:
```
print(iris_df.isnull().sum())
```

```
sepal length (cm)    0
sepal width (cm)     0
petal length (cm)    0
petal width (cm)     0
dtype: int64
```

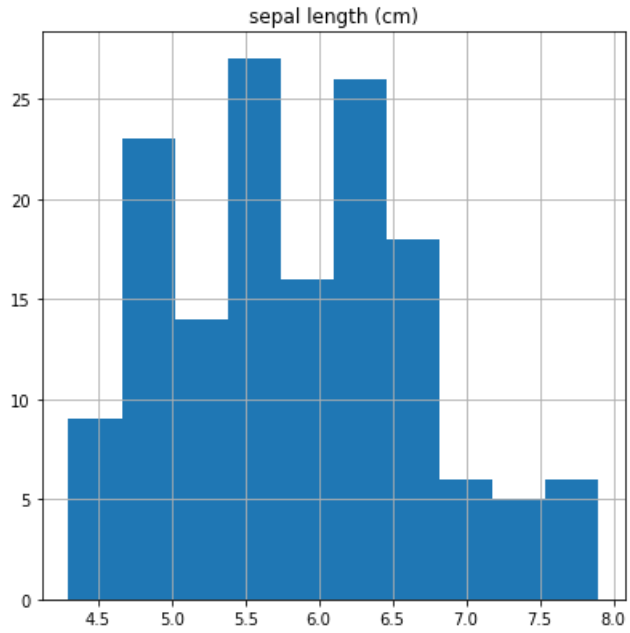
Hence, there are no null elements in the given 'Iris' dataset.

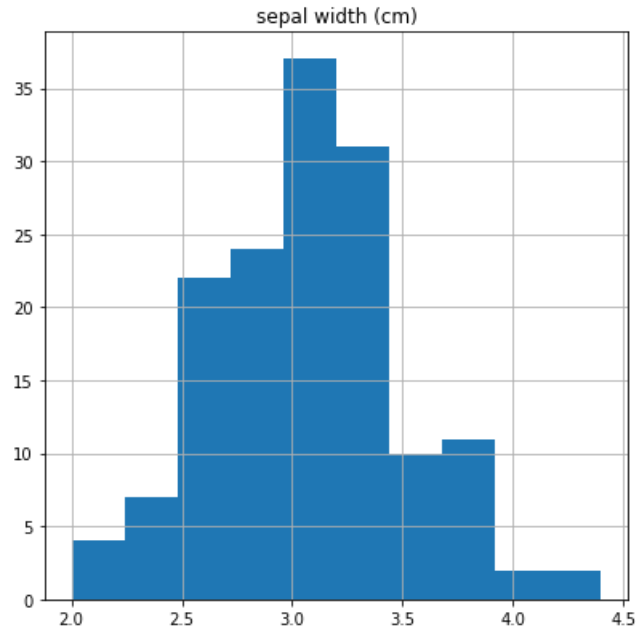
DATA VISUALIZATION

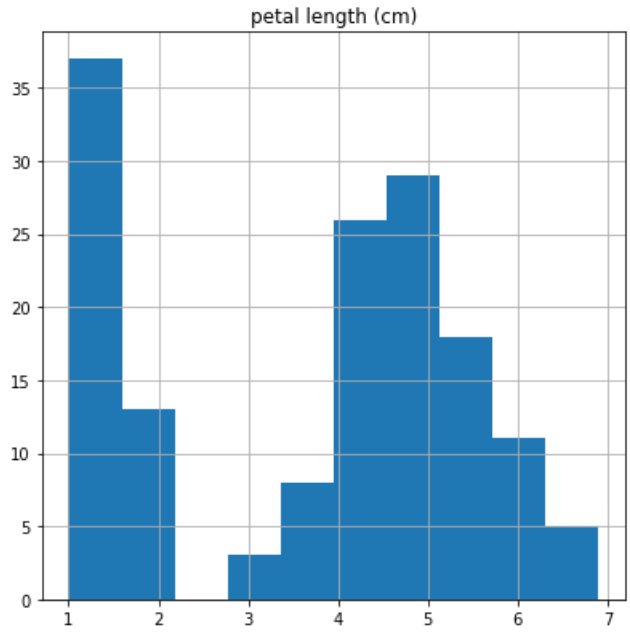
In [9]:
```
#scatter plot

iris_df.plot(kind="scatter", x="sepal length (cm)",   y="sepal width (cm)",figsize=(12,8),color='black')
plt.show()
```

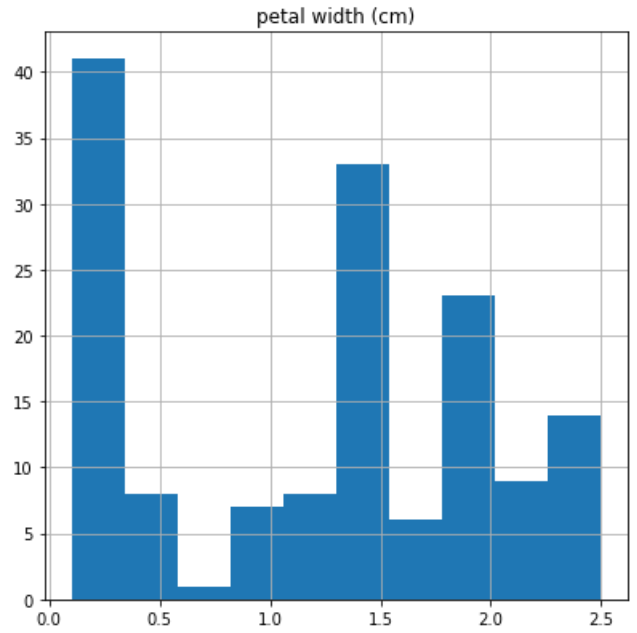


In [10]:
```
p = iris_df.hist(figsize = (15,15)) #histograms
```









The above scatter plot and histograms give a rough representation of the given 'Iris' dataset.

CORRELATION OF THE DATA

In [11]:
```
iris_df.corr()
```

Out[11]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
sepal length (cm)	1.000000	-0.117570	0.871754	0.817941
sepal width (cm)	-0.117570	1.000000	-0.428440	-0.366126
petal length (cm)	0.871754	-0.428440	1.000000	0.962865
petal width (cm)	0.817941	-0.366126	0.962865	1.000000

K-MEANS

K-means is a centroid-based algorithm, or a distance-based algorithm, where we calculate the distances to assign a point to a cluster. In K-Means, each cluster is associated with a centroid.

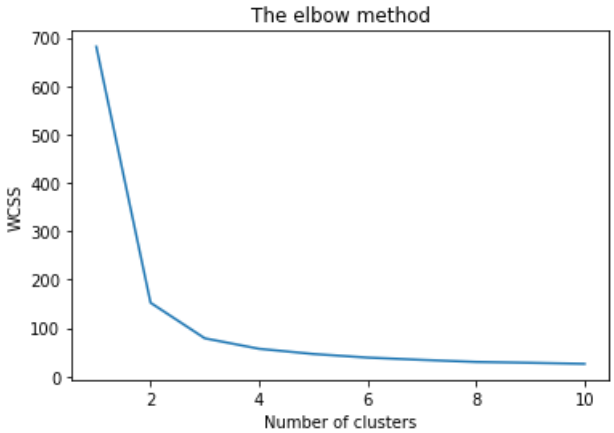
How do you find the optimum number of clusters for K Means? How does one determine the value of K?

In [12]:
```
# 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_)
```

In [13]:

```
# 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()
```



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'.

IMPLEMENTING K-MEANS CLUSTERING

In [14]:

```
# 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 [15]:

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

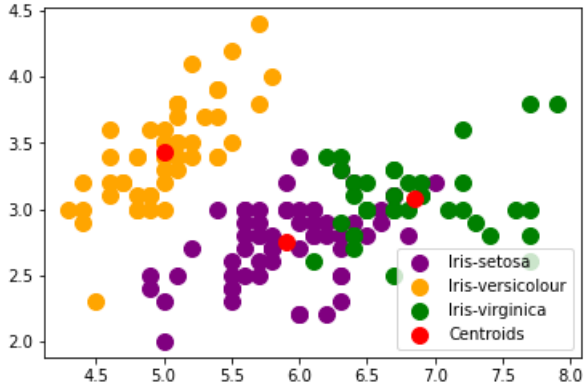
```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 2 2 2 2 0 2 2 2 2
 2 2 0 0 2 2 2 2 0 2 0 2 0 2 2 0 0 2 2 2 2 2 0 2 2 2 2 0 2 2 2 0 2 2 2 0 2
 2 0]
```

In [16]:

```
#Visualising the clusters
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'purple', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'orange', 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 = 'red', label = 'Centroids')

plt.legend()
```

Out[16]:

```
<matplotlib.legend.Legend at 0x1e86fe1eb80>
```



Thus the K-Means Workshop is concluded.

THANK YOU.