# Task 2 - Prediction using Unsupervised ML (K-means Clustering method)

## TSF-GRIP Internship

## Data Science & Business Analytics Tasks

## #GRIPAUG21

## Question:From the given ‘Iris’ dataset, predict the optimum number of clusters and represent it visually.

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## Date: 07/08/2021

In [1]:
```
#Importing Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from matplotlib.pyplot import figure

%matplotlib inline
```

In [2]:
```
#Reading the Data
url = "https://drive.google.com/file/d/11Iq7YvbWZbt8VXjfm06brx66b10YiwK-/view?usp=sharing"
url2='https://drive.google.com/uc?id=' + url.split('/')[-2]
df_iris = pd.read_csv(url2)
```

## Exploratory Data Analysis (EDA)

In [3]:
```
# Data Visualization
df_iris.head(10)
```

Out[3]:

| | 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 |
| 5 | 6 | 5.4 | 3.9 | 1.7 | 0.4 | Iris-setosa |
| 6 | 7 | 4.6 | 3.4 | 1.4 | 0.3 | Iris-setosa |
| 7 | 8 | 5.0 | 3.4 | 1.5 | 0.2 | Iris-setosa |
| 8 | 9 | 4.4 | 2.9 | 1.4 | 0.2 | Iris-setosa |
| 9 | 10 | 4.9 | 3.1 | 1.5 | 0.1 | Iris-setosa |

In [4]:
```
df_iris.shape
```

Out[4]: (150, 6)

In [5]:
```
df_iris.describe()
```

Out[5]:

| | Id | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm |
|---|---|---|---|---|---|
| count | 150.000000 | 150.000000 | 150.000000 | 150.000000 | 150.000000 |
| mean | 75.500000 | 5.843333 | 3.054000 | 3.758667 | 1.198667 |
| std | 43.445368 | 0.828066 | 0.433594 | 1.764420 | 0.763161 |
| min | 1.000000 | 4.300000 | 2.000000 | 1.000000 | 0.100000 |
| 25% | 38.250000 | 5.100000 | 2.800000 | 1.600000 | 0.300000 |
| 50% | 75.500000 | 5.800000 | 3.000000 | 4.350000 | 1.300000 |
| 75% | 112.750000 | 6.400000 | 3.300000 | 5.100000 | 1.800000 |
| max | 150.000000 | 7.900000 | 4.400000 | 6.900000 | 2.500000 |

In [6]:
```
df_iris.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 [7]:
```
# Dropping the Id Column from the dataframe as it is just a serial number and is of no use
df=df_iris.drop(["Id"], axis = 1)
df
```

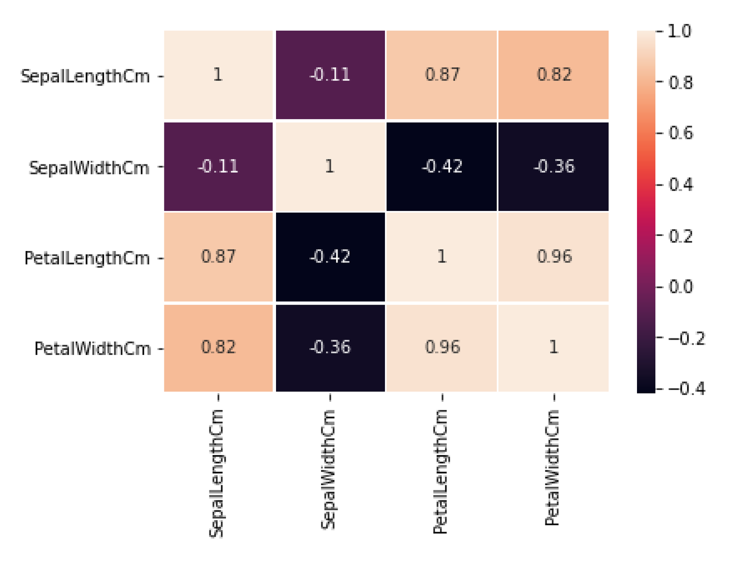
Out[7]:

| | SepalLengthCm | SepalWidthCm | PetalLengthCm | PetalWidthCm | Species |
|---|---|---|---|---|---|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| ... | ... | ... | ... | ... | ... |
| 145 | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| 146 | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| 147 | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| 148 | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| 149 | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 5 columns

In [8]:
```
# Creating a heatmap to understand the correlation between the variables
sns.heatmap(df.corr(), annot = True, linecolor= 'white', linewidths=.5)
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x2a03603ca00>



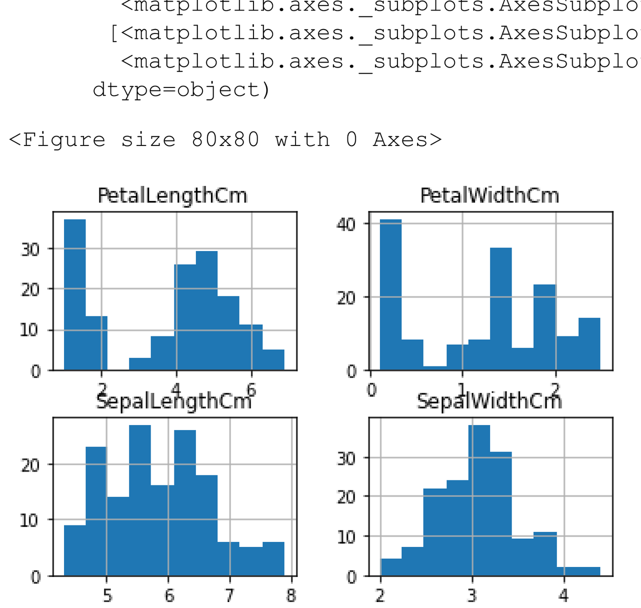

## This graph shows that there is a strong positive correlation between "PetalWidth" with "SepalLength" & "PetalLength"

## while moderate negative correlation between "SepalWidth" with "PetalWidth" & "PetalLength"

In [9]:
```
figure(figsize=(1, 1), dpi=80)
df.hist()
```

Out[9]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000002A0361D99D0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002A036213190>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000002A03623F5E0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000002A03626BA30>]],
      dtype=object)
```

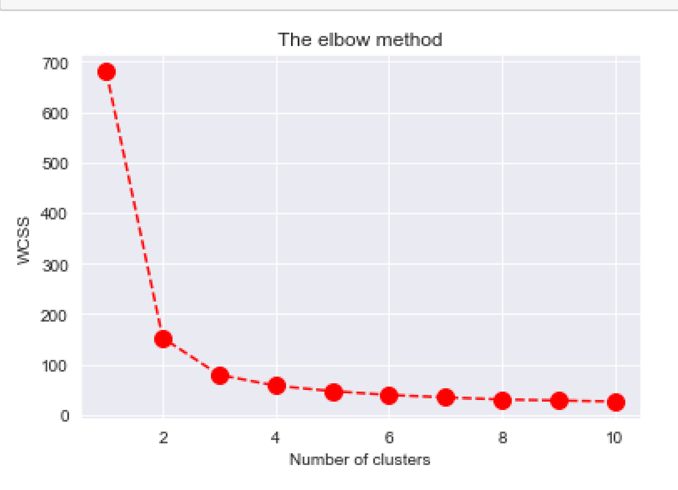
```
<Figure size 80x80 with 0 Axes>
```




## Finding optimum numbers of Clusters for Kmeans classification

In [10]:
```
# Data preparation for K-means clustering
x = df.iloc[:, [0, 1, 2, 3]].values

from sklearn.cluster import KMeans
wcss = []
```

In [11]:
```
# Finding inertia on different k values
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'
sns.set_style('darkgrid')
plt.plot(range(1, 11), wcss, 'r--',marker='o',markersize= 10, color='red')
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') # Within cluster sum of squares
plt.show()
```



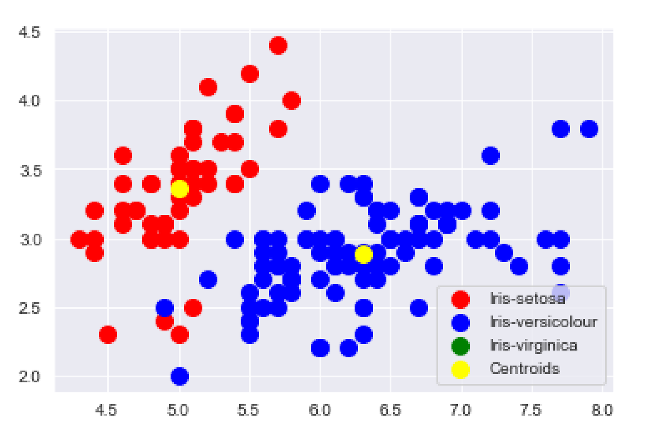

## In Elbow method (from the above graph) optimum clusters is where the elbow occurs. This is when the within cluster sum of squares (WCSS) doesn't decrease significantly with every iteration.

## From this first we choose the number of clusters as * '2

In [12]:
```
# Applying kmeans to the dataset / Creating the kmeans classifier
kmeans = KMeans(n_clusters = 2, init = 'k-means++',max_iter = 300, n_init = 10, random_state = 0)

y_kmeans = kmeans.fit_predict(x)
```

In [13]:
```
# 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[13]: <matplotlib.legend.Legend at 0x2a036d54a30>



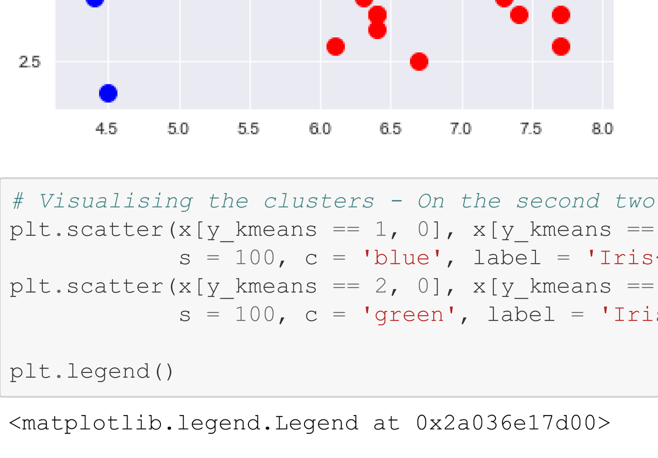

## According to this graph it is clear that model is unable to distinguish Iris-virginica while number of clusters is "2"

## From this now we choose the number of clusters as * '3

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)
```

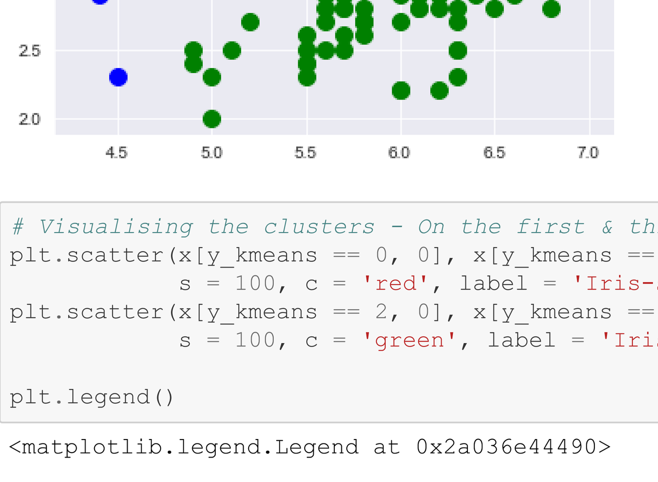
In [15]:
```
# Visualising the clusters - On the first two columns
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],
            s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1],
            s = 100, c = 'blue', label = 'Iris-versicolour')

plt.legend()
```

Out[15]: <matplotlib.legend.Legend at 0x2a036dc46d0>



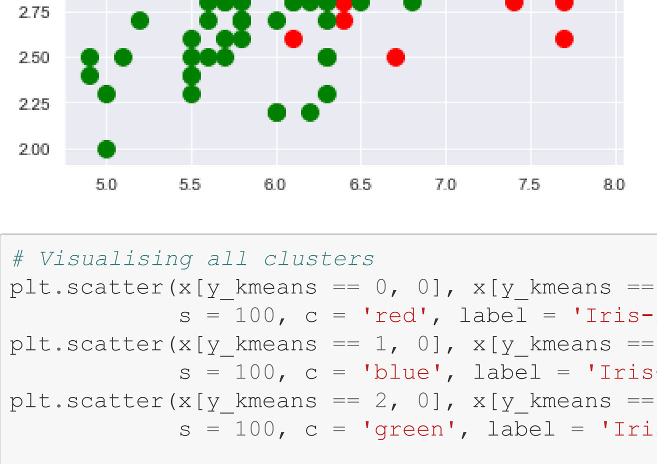

In [16]:
```
# Visualising the clusters - On the second two columns
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1],
            s = 100, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'green', label = 'Iris-virginica')

plt.legend()
```

Out[16]: <matplotlib.legend.Legend at 0x2a036e17d00>



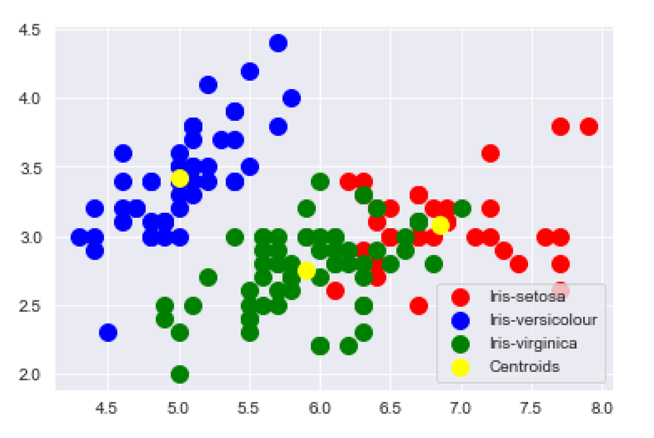

In [17]:
```
# Visualising the clusters - On the first & third columns
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],
            s = 100, c = 'red', label = 'Iris-setosa')
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],
            s = 100, c = 'green', label = 'Iris-virginica')

plt.legend()
```

Out[17]: <matplotlib.legend.Legend at 0x2a036e44490>




In [18]:
```
# Visualising all 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 = '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[18]: <matplotlib.legend.Legend at 0x2a036e40a90>




## Conclusion: So Its clear from the above visualizations that best number of clusters for K-means classifier is "3"