Task - 2 : Prediction using Unupervised ML

K-Means Clustering

In this section we will see how the Python and Scikit-Learn Library for Machine Learning can be used to implement KMeans Clustering functions. Let's start with simple KMeans Clustering involving Four(4) variables named SepalLength, SepalWidth, PetalLength and PetalWidth.

Simple K-Means Clustering

In this Clustering Task we are going to predict the optimum number of clusters. This is a simple K-Means Clustering task.

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In [1]:
```
#Let's import the libraries we are going to use.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import datasets
print("Libraries are imported.")
```

```
Libraries are imported.
```

In [2]:
```
#Import the data from the CSV File
iris = pd.read_csv("Task_2_data.csv")
print("Dataset imported Successfully!")
iris.head(10)
```

```
Dataset imported Successfully!
```

Out[2]:

	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 [3]:
```
iris.drop('Id', inplace = True, axis = 1)
```

In [4]:
```
iris.head(10)
```

Out[4]:

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

In [5]:
```
len(iris)
```

Out[5]:
```
150
```

In [6]:
```
len(iris.columns)
```

Out[6]:
```
5
```

In [7]:
```
iris.shape
```

Out[7]:
```
(150, 5)
```

In [8]:
```
iris.columns
```

Out[8]:
```
Index(['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

In [9]:
```
print('Dataset Info: {}'.format(iris.info()))
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
Dataset Info: None
```

In [10]:
```
print('Dataset Description: \n\n{}'.format(iris.describe()))
```

```
Dataset Description:

       SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidthCm
count     150.000000    150.000000     150.000000    150.000000
mean        5.843333      3.054000       3.758667      1.198667
std         0.828066      0.433594       1.764420      0.763161
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 [11]:
```
iris.nunique()
```

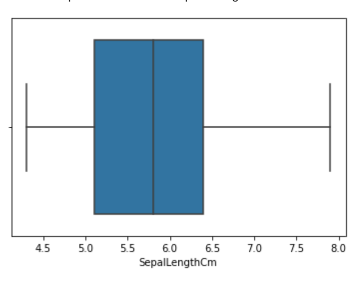
Out[11]:
```
SepalLengthCm    35
SepalWidthCm     23
PetalLengthCm    43
PetalWidthCm     22
Species           3
dtype: int64
```

In [12]:
```
import warnings
warnings.filterwarnings('ignore')
```

Visualising the Data through the BoxPlot

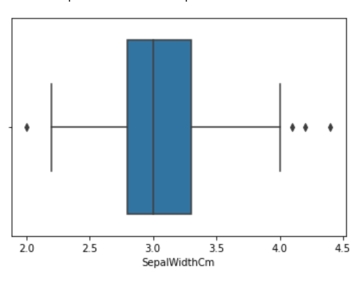
In [13]:
```
sns.boxplot(iris['SepalLengthCm'])
```

Out[13]:
```
<AxesSubplot:xlabel='SepalLengthCm'>
```



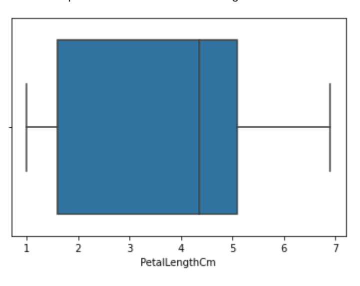
In [14]:
```
sns.boxplot(iris['SepalWidthCm'])
```

Out[14]:
```
<AxesSubplot:xlabel='SepalWidthCm'>
```



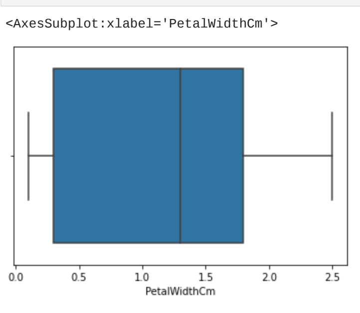
In [15]:
```
sns.boxplot(iris['PetalLengthCm'])
```

Out[15]:
```
<AxesSubplot:xlabel='PetalLengthCm'>
```



In [16]:
```
sns.boxplot(iris['PetalWidthCm'])
```

Out[16]:
```
<AxesSubplot:xlabel='PetalWidthCm'>
```



BoxPlot are usually used in Exploratory Data Analysis (EDA) for specifically indicating whether there are any potential unusual observation or outliers present in the data set or not.

In [17]:
```
def outlier_detect(iris):
    for i in iris.describe().columns:
        Q1 = iris.describe().at['25%', i]
        Q3 = iris.describe().at['75%', i]
        IQR = Q3 - Q1
        LTV = Q1 - 1.5 * IQR
        UTV = Q3 + 1.5 * IQR
        iris[i] = iris[i].mask(iris[i] < LTV, LTV)
        iris[i] = iris[i].mask(iris[i] > UTV, UTV)
    return iris
```

In [18]:
```
iris = outlier_detect(iris)
iris
```

Out[18]:

	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 [19]:
```
iris.isnull().sum()
```

Out[19]:
```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [20]:
```
iris['Species'].value_counts()
```

Out[20]:
```
Iris-virginica     50
Iris-setosa        50
Iris-versicolor    50
Name: Species, dtype: int64
```

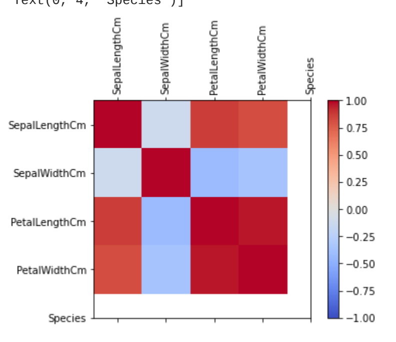
In [21]:
```
iris.corr()
```

Out[21]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.110343	0.871754	0.817954
SepalWidthCm	-0.110343	1.000000	-0.419823	-0.355582
PetalLengthCm	0.871754	-0.419823	1.000000	0.962757
PetalWidthCm	0.817954	-0.355582	0.962757	1.000000

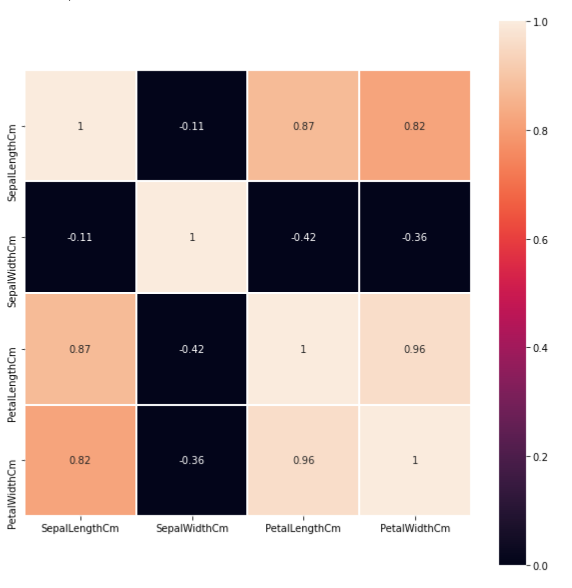
In [22]:
```
iris1 = iris.corr()
fig = plt.figure()
ax = fig.add_subplot(111)
cax = ax.matshow(iris1, cmap = 'coolwarm', vmin = -1, vmax = 1)
fig.colorbar(cax)
ticks = np.arange(0, len(iris.columns), 1)
ax.set_xticks(ticks)
plt.xticks(rotation = 90)
ax.set_yticks(ticks)
ax.set_xticklabels(iris.columns)
ax.set_yticklabels(iris.columns)
```

Out[22]:
```
[Text(0, 0, 'SepalLengthCm'),
 Text(0, 1, 'SepalWidthCm'),
 Text(0, 2, 'PetalLengthCm'),
 Text(0, 3, 'PetalWidthCm'),
 Text(0, 4, 'Species')]
```

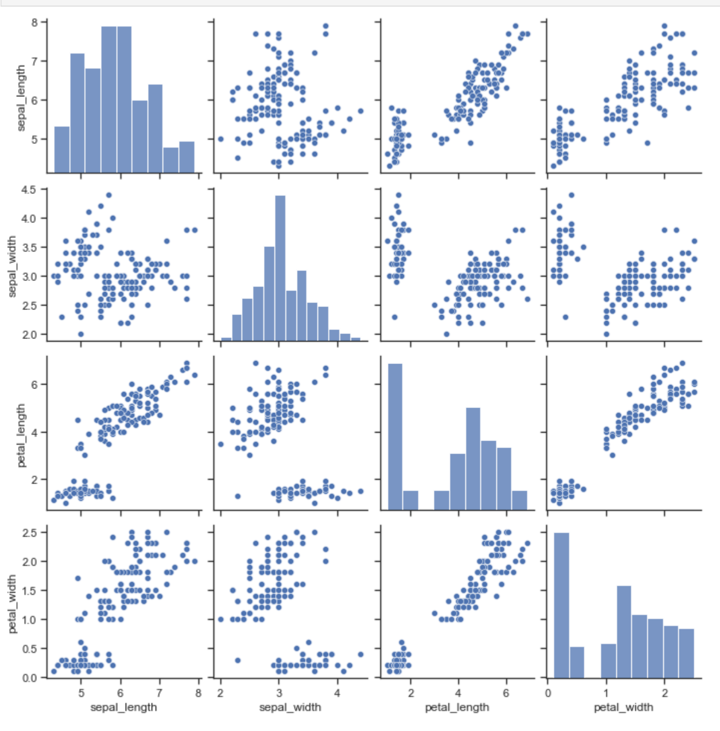


In [23]:
```
fig, ax = plt.subplots(figsize = (10, 10))
sns.heatmap(iris1, vmin = 0, vmax = 1, square = True, annot = True, linewidth = 1)
```

Out[23]:
```
<AxesSubplot:>
```



In [24]:
```
sns.set(style = "ticks", color_codes = True)
iris = sns.load_dataset("iris")
g = sns.pairplot(iris)
plt.show()
```



In [25]:
```
pd.DataFrame.drop_duplicates(iris)
```

Out[25]:

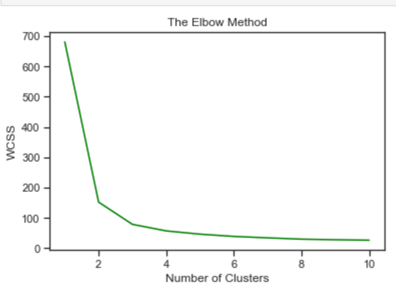
	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

149 rows × 5 columns

Finding the optimum number of Clusters for K_Means Classification

In [26]:
```
x = iris.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_)
```

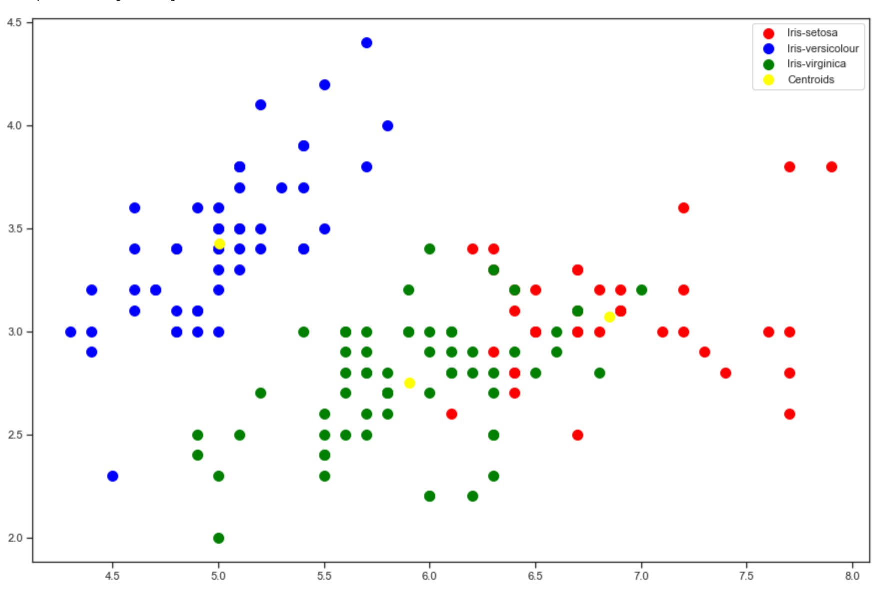
In [27]:
```
plt.plot(range(1, 11), wcss, color = "green")
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



In [28]:
```
kmeans = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

In [29]:
```
plt.figure(figsize=(15,10))
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')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')
plt.legend()
```

Out[29]:
```
<matplotlib.legend.Legend at 0x1b77c17bee0>
```



Thank You!