THE SPARKS FOUNDATION - DATA SCIENCE AND BUSINESS ANALYTICS INTERNSHIP

TASK 2 - Prediction using Unsupervised Machine Learning

In this task the main aim is to predict the optimum number of cluster for the iris data set .Iris data set consists of 3 types of flower namely Iris-setosa Iris-versicolour and Iris-virginica

CONTENT - STEPS INVOLVED

STEP 1:- Importing the Data from Dataset

STEP 2:- VISUALISING THE DATA

STEP 3:- Finding the optimum number of clusters

STEP 4:- Applying k means clustering on the data

STEP 5:- CLUSTER VISUALISATION

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STEP-1 Importing the Data from Dataset

In [1]:
```
# Importing the required libraries

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn import datasets
from sklearn.cluster import KMeans

# In order To ignore the warnings
import warnings as wg
wg.filterwarnings("ignore")
```

In [5]:
```
# Reading data from iris dataset
df = pd.read_csv('C:\\Users\\NOTAM KEDARI\\Desktop\\Iris.csv')
```

In [6]:
```
df.head()
```

Out[6]:

	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

STEP 2: VISUALISING THE DATA

In [7]:
```
df.tail()
```

Out[7]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

In [8]:
```
df.shape
```

Out[8]:
```
(150, 6)
```

In [9]:
```
df.columns
```

Out[9]:
```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
       'Species'],
      dtype='object')
```

In [10]:
```
df['Species'].unique()
```

Out[10]:
```
array(['Iris-setosa', 'Iris-versicolor', 'Iris-virginica'], dtype=object)
```

In [11]:
```
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 [12]:
```
df.describe()
```

Out[12]:

	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 [13]:
```
# now we will drop the label column because it is an unsupervised learning problem
iris = pd.DataFrame(df)
iris_df = iris.drop(columns= ['Species' ,'Id'] )
iris_df.head()
```

Out[13]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
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

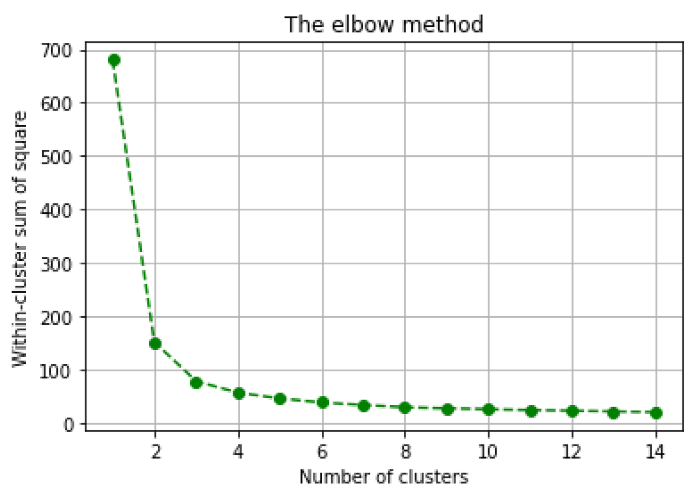
STEP 3:- Finding the optimum number of clusters

ELBOW METHOD

In this method, the number of clusters are varies within a certain range. For each number, within-cluster sum of square (wss) value is calculated and stored in a list. These value are then plotted against the range of number of clusters used before. The location of bend in the 2d plot indicates the appropiate number of clusters.

In [14]:
```
# Calculating the within-cluster sum of square

within_cluster_sum_of_square = []

clusters_range = range(1,15)
for k in clusters_range:
    km = KMeans(n_clusters=k)
    km = km.fit(iris_df)
    within_cluster_sum_of_square.append(km.inertia_)
```

In [15]:
```
# Plotting the "within-cluster sum of square" against clusters range

plt.plot(clusters_range, within_cluster_sum_of_square, 'go--', color='green')
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('Within-cluster sum of square')
plt.grid()
plt.show()
```



In '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.

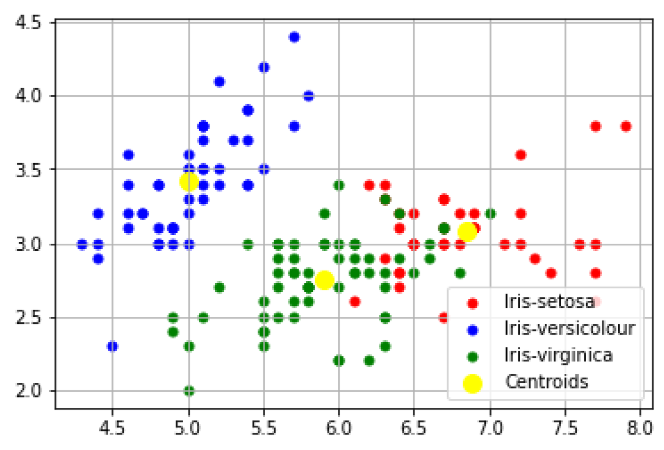
From this we choose the optimum number of clusters as '3'.

STEP 4 :- Applying k means clustering on the data

In [16]:
```
from sklearn.cluster import KMeans

model = KMeans(n_clusters = 3, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
predictions = model.fit_predict(iris_df)
```

STEP 5 - CLUSTER VISUALISATION

In [17]:
```
x = iris_df.iloc[:, [0, 1, 2, 3]].values
plt.scatter(x[predictions == 0, 0], x[predictions == 0, 1], s = 25, c = 'red', label = 'Iris-setosa')
plt.scatter(x[predictions == 1, 0], x[predictions == 1, 1], s = 25, c = 'blue', label = 'Iris-versicolour')
plt.scatter(x[predictions == 2, 0], x[predictions == 2, 1], s = 25, c = 'green', label = 'Iris-virginica')

# Plotting the cluster centers

plt.scatter(model.cluster_centers_[:, 0], model.cluster_centers_[:,1], s = 100, c = 'yellow', label = 'Centroids')
plt.legend()
plt.grid()
plt.show()
```



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In [ ]: