The Sparks Foundation - GRIP - Data Science and Business Analytics Intern - AUGUST-2021

TASK 2 - Prediction the optimum number of clusters From given iris dataset

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DATASET LINK-[https://bit.ly/3cGyP8j (https://bit.ly/3cGyP8j)](https://bit.ly/3cGyP8j)

In this task we are going predict optimum number of clusters formation and visualize it using Elbow method

Step1 Defining objectives

In [12]:
```
#importing nessessary libraries
import sklearn
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn

import warnings
warnings.filterwarnings('ignore')
```

Step2 Data collection

In [13]:
```
#importing the dataset and displaying
dt=pd.read_csv("Iris.csv")
dt
```

Out[13]:

	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
...	...	...	...	...	...	...
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

150 rows × 6 columns

Step3 Data Preprocessing

In [14]:
```
dt.describe()
```

Out[14]:

	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 [15]:

```
dt.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 [16]:

```
print(dt.isnull().sum(),'\n\n Number  of duplicate rows:',dt.duplicated().sum())
```

```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64

 Number  of duplicate rows: 0
```

In [17]:

```
#Removing the duplicates
dt.drop_duplicates(inplace=True)
dt.shape[0]
```

Out[17]:

```
150
```

In [18]:

```
#removing  the id column
dt=dt.iloc[:,1:]
dt.columns
```

Out[18]:

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

Step4 Data divided into clusters

In [19]:
```
x=dt.iloc[:,[0,1,2]].values

from sklearn.cluster import KMeans
km=KMeans(n_clusters=3)
km.fit(x)
```

Out[19]:
```
KMeans(n_clusters=3)
```

In [20]:
```
km.cluster_centers_
#finding nearest values
```

Out[20]:
```
array([[5.006     , 3.418     , 1.464     ],
       [6.83571429, 3.06428571, 5.6547619 ],
       [5.84655172, 2.73275862, 4.3637931 ]])
```

In [21]:
```
#data is labeled as centroid values
pred=km.labels_
pred
```

Out[21]:
```
array([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, 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, 1, 2, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1,
       1, 1, 1, 2, 2, 1, 1, 1, 1, 2, 1, 2, 1, 2, 1, 1, 2, 2, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 2])
```

In [22]:
```
dt['clusters']=pred
dt
```

Out[22]:

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

150 rows × 6 columns

In [23]:
```
display(dt['clusters'].value_counts(),dt['Species'].value_counts())
```

```
2    58
0    50
1    42
Name: clusters, dtype: int64
```

```
Iris-versicolor    50
Iris-setosa        50
Iris-virginica     50
Name: Species, dtype: int64
```

Step 5 Prediction using Elbow method

In [24]:
```
#finding optimum number of clusters
wss=[]
cluster_range=range(1,11)

for k in cluster_range:
    km=KMeans(n_clusters=k,random_state=0)
    km.fit(x)
    inertia=km.inertia_
    wss.append(inertia)
```

In [28]:
```
plt.figure(figsize=(8,5))
plt.xlabel("Here the cluster range")
plt.ylabel("sum of squared error")
plt.title("finding no of clusters in iris dataset")
plt.plot(cluster_range,wss,marker="o")

plt.show()
```

Step 6 Visualization of clusters

In [26]:

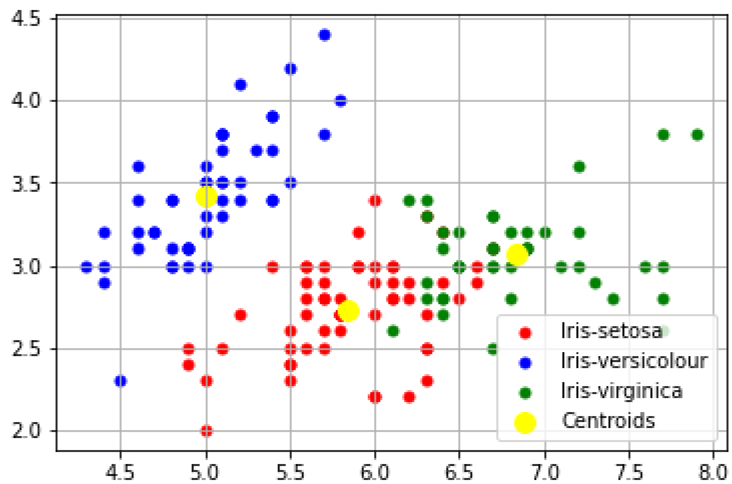
```
#fitting the data
kmeans = KMeans(n_clusters = 3, init = 'k-means++',
                max_iter = 300, n_init = 10, random_state = 0)
y_kmeans = kmeans.fit_predict(x)
```

In [27]:

```
# Visualising the clusters - On the first two columns
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1],  s = 25, c = 'red', label =
plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 25, c = 'blue', label =
plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1],s = 25, c = 'green', label =

# Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0],kmeans.cluster_centers_[:,1],
            s = 100, c = 'yellow', label = 'Centroids')
plt.grid()
plt.legend()
```

Out[27]: <matplotlib.legend.Legend at 0x15f1b6487c0>



In [ ]:

In [ ]: