KDD LAB

Utkarsh Bhangale

20200802124

Aim - To implement Hierarchical Clustering using python

In [1]:
```
# Importing required Libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Loading the dataset
df = pd.read_csv("Iris.csv")
df.head()  # To see the first five rows
```

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

Exploratory Data Analysis

In [3]:
```
df.shape # shape of data
```

Out[3]: (150, 6)

]:

In [4

```
df.info() # Information of data
```

```
<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 [5]:

```
df = df.drop(columns=['Id']) # Dropping Id columns as it is of no use
```

In [6]:

```
df.describe() # Describing the data
```

Out[6]:

	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 [7]:

```
df.isna().sum() # To check is there any null values in dataset
```

Out[7]:

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

In [8]:

```
df.nunique() # No. of unique values in each column
```

Out[8]:

```
SepalLengthCm    35
SepalWidthCm     23
PetalLengthCm    43
PetalWidthCm     22
Species           3
dtype: int64
```

]:

In [9

```
# As it is categorical column it will be used as label,
# We can say that no. of unique value in categorical column
# can be say as no. of clusters

df['Species'].unique()
```

Out[9]:

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

In [10]:

```
df.corr() # Correlation within data
```

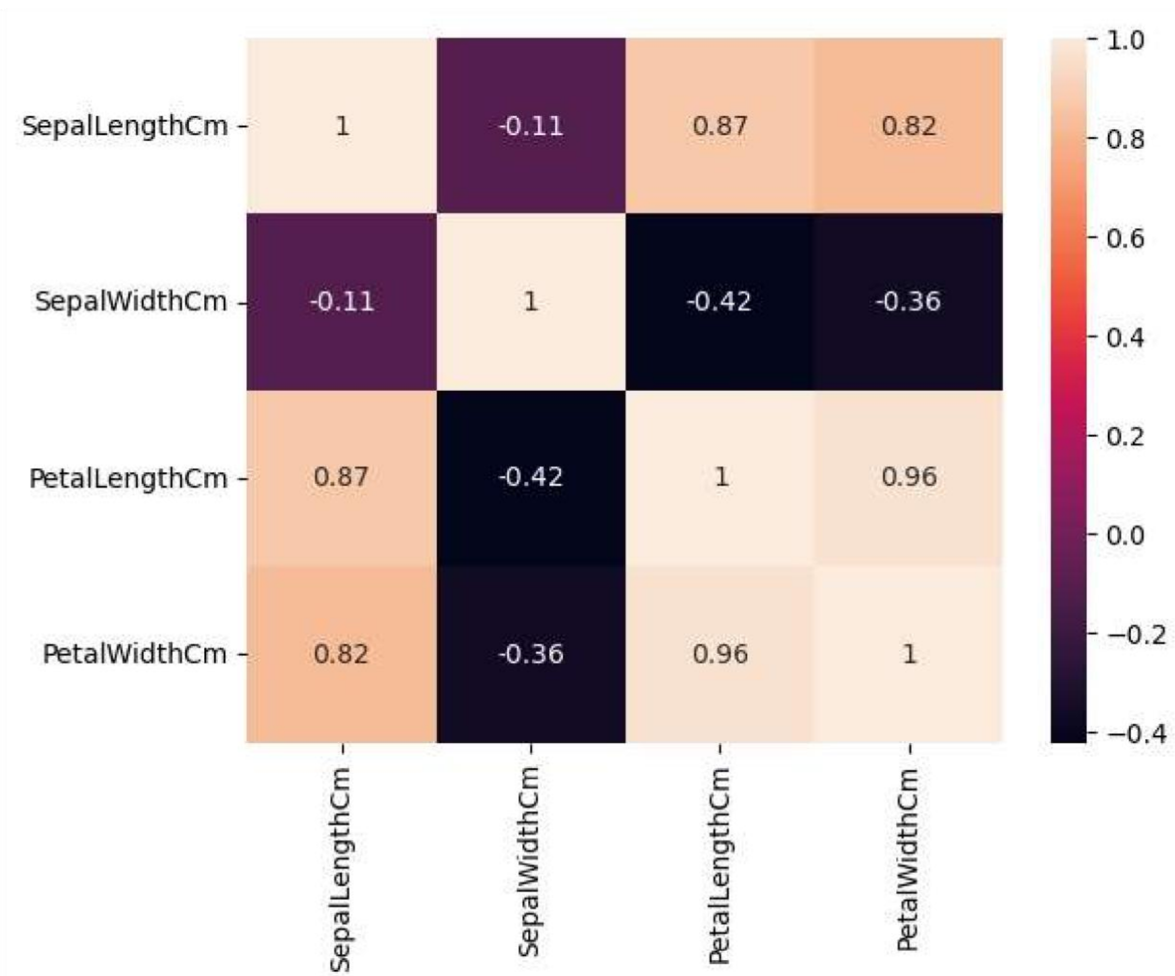
Out[10]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.817954	-0.356544	0.962757	1.000000

In [11]:

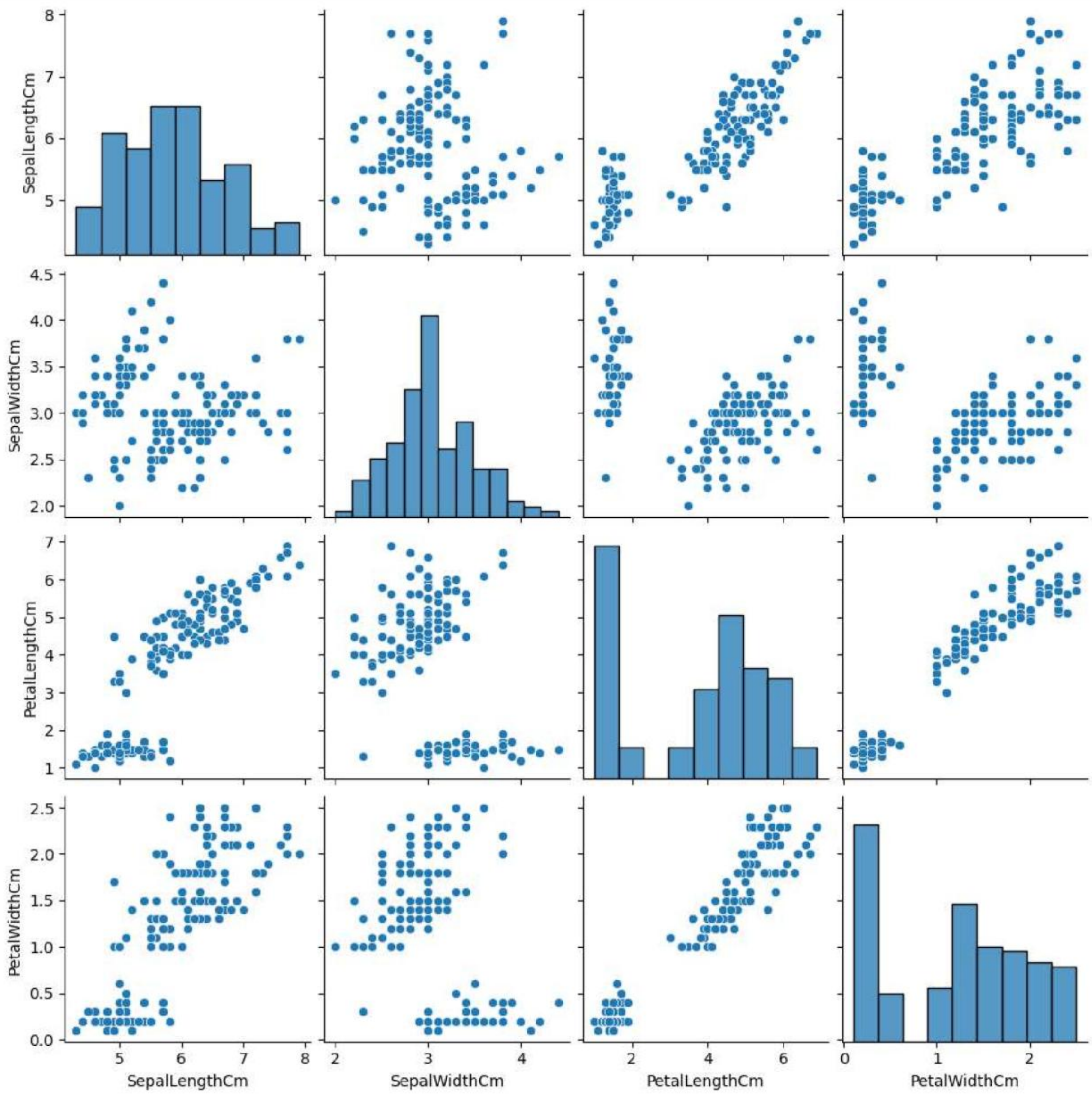
```
sns.heatmap(df.corr(),annot=True)
```

Out[11]: <AxesSubplot:>



In [1]:

```python
# Pairplot of data
sns.pairplot(df)
plt.show()
```



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

In [1]:

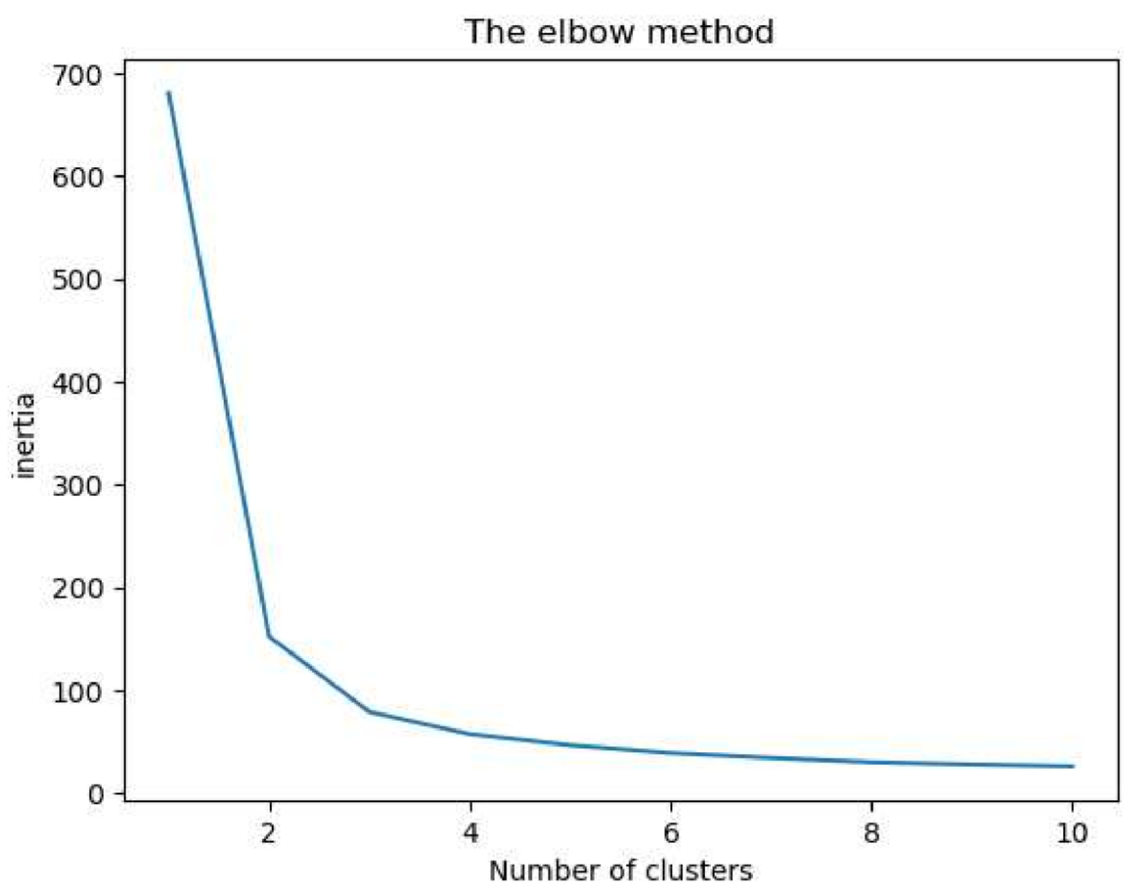
3

```python
# Finding the optimum number of clusters for k-means classification

x = df.iloc[:, [0, 1, 2, 3]].values

from sklearn.cluster import KMeans
inertias = []
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)
    inertias.append(kmeans.inertia_)

plt.plot(range(1, 11), inertias)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('inertia') # Bend Point
plt.show()
```



As the line bends at 3, so n_clusters will be 3

In [1]:

4
```
y_kmeans = kmeans.fit_predict(x)
y_kmeans
```

Out[14]:
```
array([8, 1, 1, 1, 8, 4, 1, 8, 1, 1, 8, 8, 1, 1, 4, 4, 4, 8, 4, 8, 8, 8,
       1, 8, 8, 1, 8, 8, 8, 1, 1, 8, 4, 4, 1, 1, 8, 1, 1, 8, 8, 1, 1, 8,
       8, 1, 8, 1, 8, 8, 3, 3, 3, 2, 3, 2, 3, 9, 3, 2, 9, 2, 2, 3, 2, 3,
       2, 2, 5, 2, 5, 2, 5, 3, 3, 3, 3, 3, 3, 9, 9, 9, 2, 5, 2, 3, 3, 3,
       2, 2, 2, 3, 2, 9, 2, 2, 2, 3, 9, 2, 0, 5, 7, 0, 0, 7, 2, 7, 0, 6,
       0, 5, 0, 5, 5, 0, 0, 6, 7, 5, 0, 5, 7, 5, 0, 7, 5, 5, 0, 7, 7, 6,
       0, 5, 5, 7, 0, 0, 5, 0, 0, 0, 5, 0, 0, 0, 5, 0, 0, 5])
```

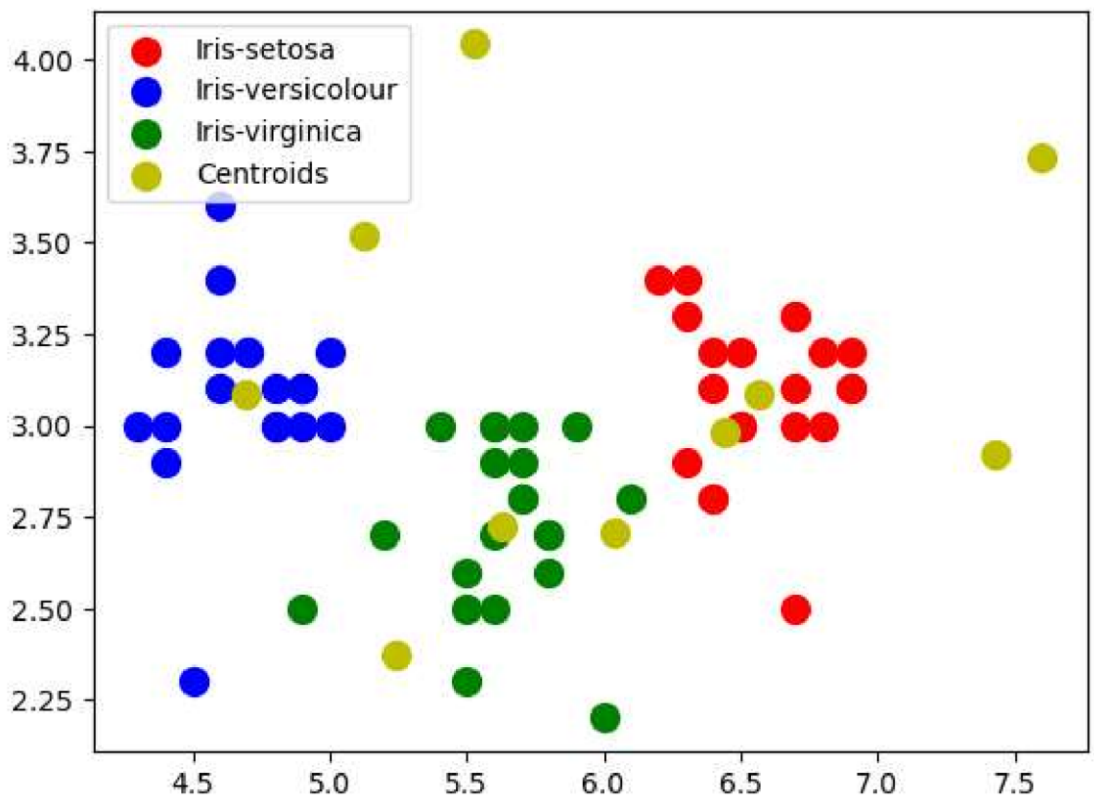
In [15]:
```
plt.scatter(x[y_kmeans == 0, 0], x[y_kmeans == 0, 1], s = 100, c = 'r', label

plt.scatter(x[y_kmeans == 1, 0], x[y_kmeans == 1, 1], s = 100, c = 'b', label

plt.scatter(x[y_kmeans == 2, 0], x[y_kmeans == 2, 1], s = 100, c = 'g', label

# Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 1
plt.legend()
```

Out[15]: <matplotlib.legend.Legend at 0x23e5fd30b80>



Conclusion

i. Successfully From the given ‘Iris’ dataset, predict the optimum number of clusters and represent it visually

ii. The optimium clusters for Iris dataset is 3