

Task 2: Prediction Using Unsupervised ML

- Predict the optimal Number of Clusters and represent it visually.

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Importing Required Libraries

```
In [3]: 1 #importing libraries
2
3 import numpy as np
4 import pandas as pd
5 from sklearn.preprocessing import StandardScaler, LabelEncoder
6
7 #importing visualization libraries
8
9 import matplotlib.pyplot as plt
10 import seaborn as sns
11 import plotly.express as px
12 import plotly.graph_objects as pgo
```

Importing Dataset

```
In [6]: 1 df=pd.read_csv("D:/Harini(christ unniversity)/Internship/Iris.csv")
2 df.head(5)
```

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

```
In [7]: 1 ##dropping the column Id
2
3 df=df.drop('Id',axis=1)
```

```
In [8]: 1 X=df.drop("Species",axis=1)
2 y=df['Species']
```

Exploratory Data Analysis

```
In [9]: 1 ##Finding the shape of the dataset
2
3 X.shape
```

Out[9]: (150, 4)

The dataset contain 150 instances with 4 features.

```
In [10]: 1 ##finding the information of the dataset
2
3 X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 4 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
dtypes: float64(4)
memory usage: 4.8 KB
```

```
In [11]: 1 ##finding the NaN values of the dataset
        2
        3 X.isna().sum()
```

Out[11]: SepalLengthCm 0
SepalWidthCm 0
PetalLengthCm 0
PetalWidthCm 0
dtype: int64

There is no Null values or NaN values in the dataset.

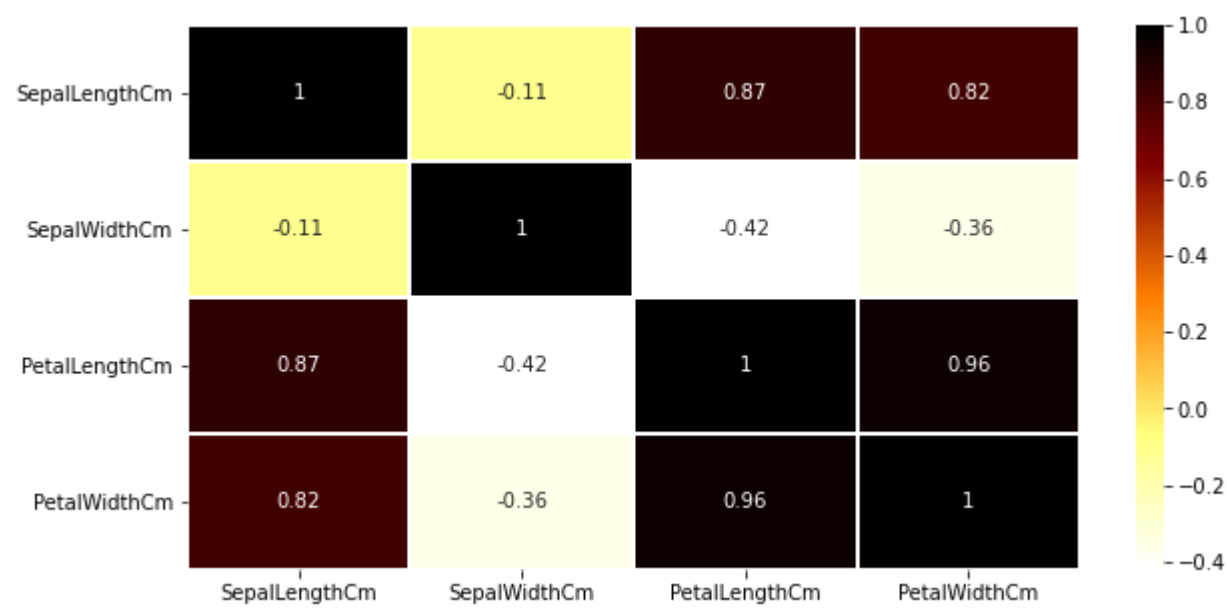
```
In [12]: 1 ##Taking the description of the dataset
        2
        3 X.describe()
```

Out[12]:

	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

Correlation

```
In [13]: 1 plt.figure(figsize = (10, 5))
        2 sns.heatmap(X.corr(), linecolor = 'white', linewidths = 1, cmap = 'afmhot_r', annot = True)
        3 plt.show()
```

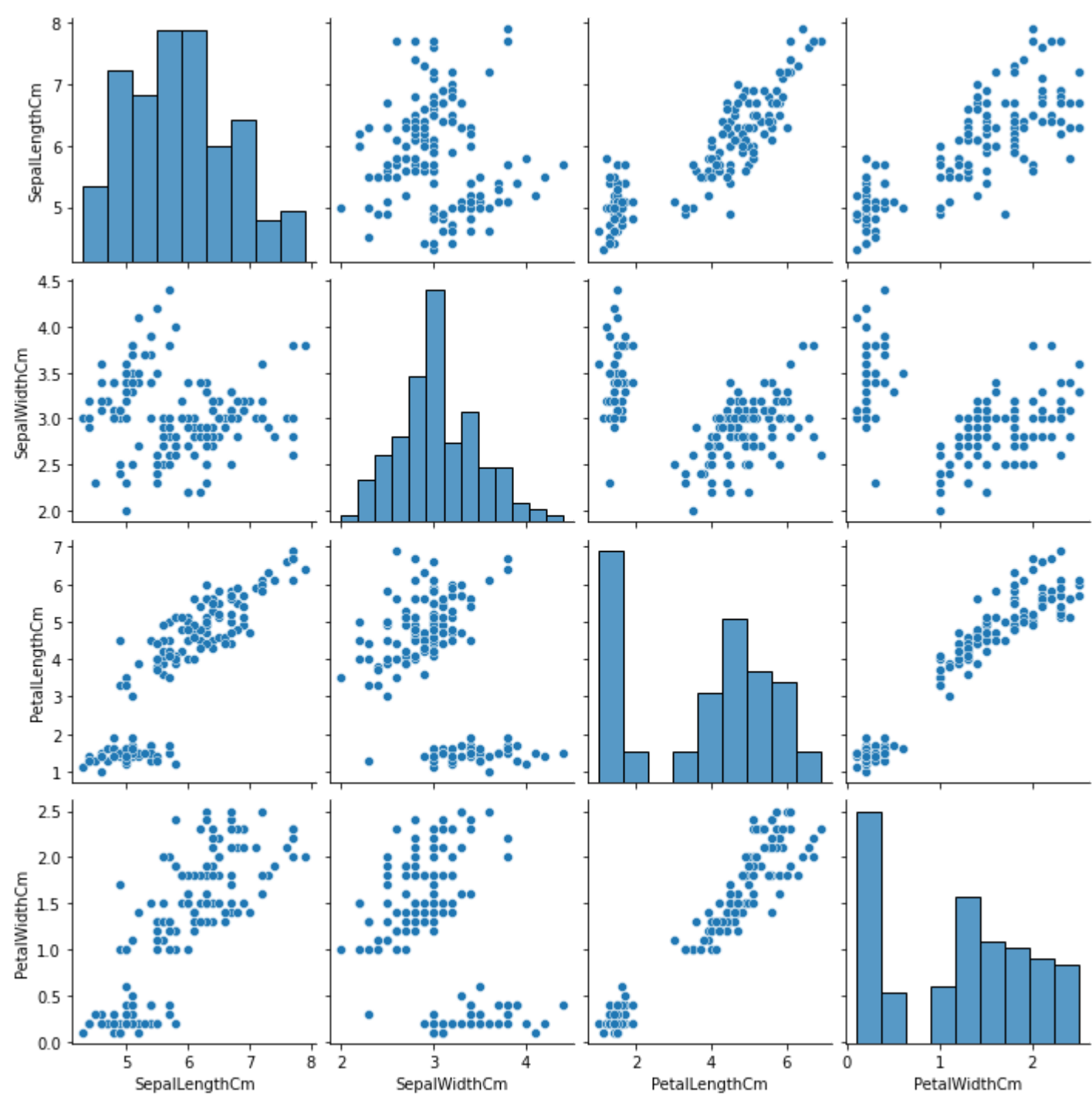


Here, Petal Length and Petal Width are highly correlated.

Pairplot

```
In [14]: 1 sns.pairplot(X)
```

Out[14]: <seaborn.axisgrid.PairGrid at 0x20233583f98>



```
In [15]: 1 x = X.iloc[:, [0, 1, 2, 3]].values
```

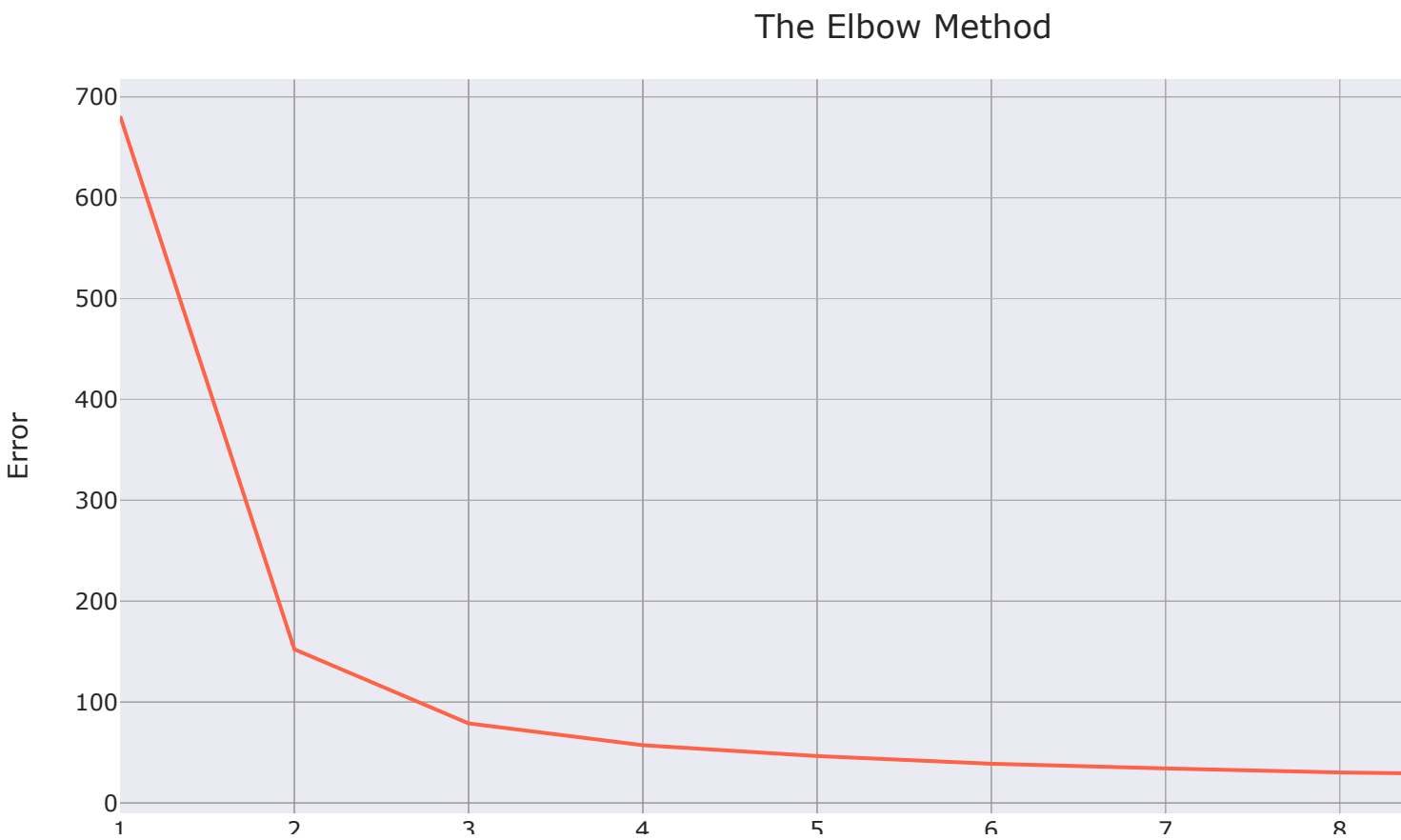
```
In [16]: 1 import warnings
2 warnings.filterwarnings("ignore")
```

Finding the optimum number of clusters for k-means clustering

```
In [17]: 1 #Finding the optimum number of clusters for k-means clustering
2 from sklearn.cluster import KMeans
3 Error = []
4 for i in range(1, 11):
5     kmeans = KMeans(n_clusters = i).fit(x)
6     kmeans.fit(X)
7     Error.append(kmeans.inertia_)
```

```
In [18]: 1 uu=pd.DataFrame(Error)
2         uu.columns=[ 'Error' ]

In [19]: 1 fig =px.line(x=range(1, 11),y=uu['Error'],color_discrete_sequence=[ "tomato"])
2
3         fig.update_layout(title = {'text':'The Elbow Method',
4                                     'y':0.95,
5                                     'x':0.5},
6                               xaxis_title='No.of Clusters',
7                               yaxis_title='Error',
8                               template='seaborn'
9                               )
10
11        fig.show()
```



The Optimal Number of Cluter is 3.

K-Means Clustering

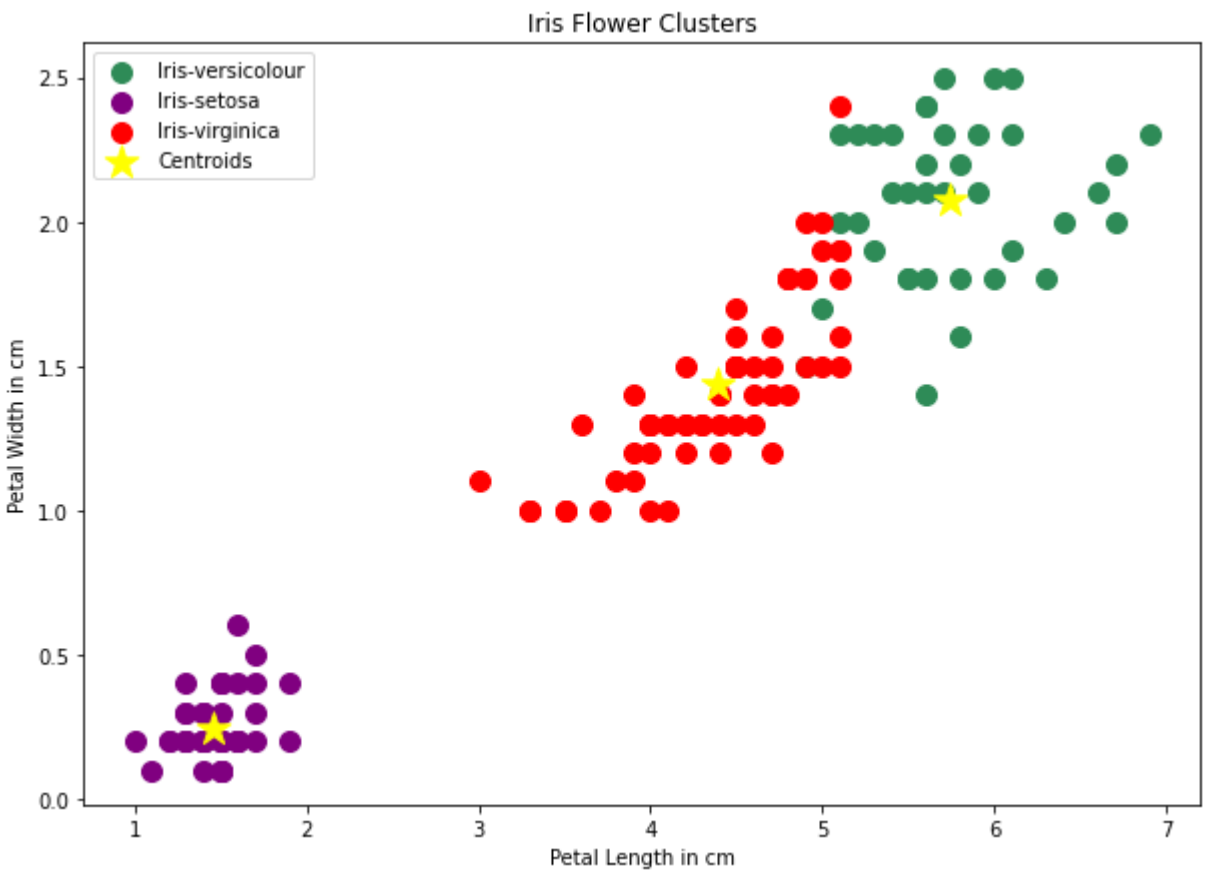
```
In [20]: 1 kmeans = KMeans(n_clusters=3)
2         y_kmeans = kmeans.fit_predict(x)
3         print(y_kmeans)
4
5         kmeans.cluster_centers_

[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 2 2 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 2 0 0 0 0 2 0 0 0 0
 0 0 2 2 0 0 0 0 2 0 2 0 2 0 0 2 2 0 0 0 0 0 2 0 0 0 0 2 0 0 0 2 0
 0 2]
```

```
Out[20]: array([[6.85      , 3.07368421, 5.74210526, 2.07105263],
                [5.006     , 3.418      , 1.464      , 0.244      ],
                [5.9016129 , 2.7483871 , 4.39354839, 1.43387097]])
```

```
In [21]: 1 fig = plt.figure(figsize=(10, 7))
2         plt.title('Clusters with Centroids',fontweight = 'bold', fontsize=20)
3         plt.scatter(x[y_kmeans == 0, 2], x[y_kmeans == 0, 3], s = 100, c = 'seagreen', label = 'Iris-\
4         plt.scatter(x[y_kmeans == 1, 2], x[y_kmeans == 1, 3], s = 100, c = 'purple', label = 'Iris-set
5         plt.scatter(x[y_kmeans == 2, 2], x[y_kmeans == 2, 3],s = 100, c = 'red', label = 'Iris-virgini
6         plt.scatter(kmeans.cluster_centers_[ :, 2], kmeans.cluster_centers_[ :,3], s = 300, c = 'yellow'
7             label = 'Centroids')
8         plt.title('Iris Flower Clusters')
9         plt.ylabel('Petal Width in cm')
10        plt.xlabel('Petal Length in cm')
11        plt.legend()
```

Out[21]: <matplotlib.legend.Legend at 0x20236c7ef60>



```
In [ ]: 1
```