Task 2 : Prediction Using Unsupervised Machine Learning

GRIP @ The Spark Foundation

In this K-means clustering task I tried to predict the optimum numbers of clusters and represents it visually from the given 'Iris' dataset.

Technical Stack : Scikit Learn, Numpy Array, Scipy, Pandas, Matplotlib

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Step 1 - Importing the Libraries..

In [1]:

```
from sklearn import datasets
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
import matplotlib.patches as mpatches
import sklearn.metrics as sm
from mpl_toolkits.mplot3d import Axes3D
from scipy.cluster.hierarchy import linkage,dendrogram
from sklearn.cluster import DBSCAN
from sklearn.decomposition import PCA
import warnings
erwarnings('ignore')
```

Step 2 - Loading the dataset

In [2]:

```
iris = datasets.load_iris()
print(iris.data)
```

```
[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]
 [5.4 3.9 1.7 0.4]
 [4.6 3.4 1.4 0.3]
 [5.  3.4 1.5 0.2]
 [4.4 2.9 1.4 0.2]
 [4.9 3.1 1.5 0.1]
 [5.4 3.7 1.5 0.2]
 [4.8 3.4 1.6 0.2]
 [4.8 3.  1.4 0.1]
 [4.3 3.  1.1 0.1]
 [5.8 4.  1.2 0.2]
 [5.7 4.4 1.5 0.4]
 [5.4 3.9 1.3 0.4]
 [5.1 3.5 1.4 0.3]
 [5.7 3.8 1.7 0.3]
 [5.1 3.8 1.5 0.3]
 [5.4 3.4 1.7 0.2]
 [5.1 3.7 1.5 0.4]
 [4.6 3.6 1.  0.2]
 [5.1 3.3 1.7 0.5]
 [4.8 3.4 1.9 0.2]
 [5.  3.  1.6 0.2]
 [5.  3.4 1.6 0.4]
 [5.2 3.5 1.5 0.2]
 [5.2 3.4 1.4 0.2]
 [4.7 3.2 1.6 0.2]
 [4.8 3.1 1.6 0.2]
 [5.4 3.4 1.5 0.4]
 [5.2 4.1 1.5 0.1]
 [5.5 4.2 1.4 0.2]
 [4.9 3.1 1.5 0.2]
 [5.  3.2 1.2 0.2]
 [5.5 3.5 1.3 0.2]
 [4.9 3.6 1.4 0.1]
 [4.4 3.  1.3 0.2]
 [5.1 3.4 1.5 0.2]
 [5.  3.5 1.3 0.3]
 [4.5 2.3 1.3 0.3]
 [4.4 3.2 1.3 0.2]
 [5.  3.5 1.6 0.6]
 [5.1 3.8 1.9 0.4]
 [4.8 3.  1.4 0.3]
 [5.1 3.8 1.6 0.2]
 [4.6 3.2 1.4 0.2]
 [5.3 3.7 1.5 0.2]
 [5.  3.3 1.4 0.2]
 [7.  3.2 4.7 1.4]
 [6.4 3.2 4.5 1.5]
 [6.9 3.1 4.9 1.5]
 [5.5 2.3 4.  1.3]
 [6.5 2.8 4.6 1.5]
                   1.3]
```

```
 [6.3 3.3 4.7 1.6]
 [4.9 2.4 3.3 1. ]
 [6.6 2.9 4.6 1.3]
 [5.2 2.7 3.9 1.4]
 [5.  2.  3.5 1. ]
 [5.9 3.  4.2 1.5]
 [6.  2.2 4.  1. ]
 [6.1 2.9 4.7 1.4]
 [5.6 2.9 3.6 1.3]
 [6.7 3.1 4.4 1.4]
 [5.6 3.  4.5 1.5]
 [5.8 2.7 4.1 1. ]
 [6.2 2.2 4.5 1.5]
 [5.6 2.5 3.9 1.1]
 [5.9 3.2 4.8 1.8]
 [6.1 2.8 4.  1.3]
 [6.3 2.5 4.9 1.5]
 [6.1 2.8 4.7 1.2]
 [6.4 2.9 4.3 1.3]
 [6.6 3.  4.4 1.4]
 [6.8 2.8 4.8 1.4]
 [6.7 3.  5.  1.7]
 [6.  2.9 4.5 1.5]
 [5.7 2.6 3.5 1. ]
 [5.5 2.4 3.8 1.1]
 [5.5 2.4 3.7 1. ]
 [5.8 2.7 3.9 1.2]
 [6.  2.7 5.1 1.6]
 [5.4 3.  4.5 1.5]
 [6.  3.4 4.5 1.6]
 [6.7 3.1 4.7 1.5]
 [6.3 2.3 4.4 1.3]
 [5.6 3.  4.1 1.3]
 [5.5 2.5 4.  1.3]
 [5.5 2.6 4.4 1.2]
 [6.1 3.  4.6 1.4]
 [5.8 2.6 4.  1.2]
 [5.  2.3 3.3 1. ]
 [5.6 2.7 4.2 1.3]
 [5.7 3.  4.2 1.2]
 [5.7 2.9 4.2 1.3]
 [6.2 2.9 4.3 1.3]
 [5.1 2.5 3.  1.1]
 [5.7 2.8 4.1 1.3]
 [6.3 3.3 6.  2.5]
 [5.8 2.7 5.1 1.9]
 [7.1 3.  5.9 2.1]
 [6.3 2.9 5.6 1.8]
 [6.5 3.  5.8 2.2]
 [7.6 3.  6.6 2.1]
 [4.9 2.5 4.5 1.7]
 [7.3 2.9 6.3 1.8]
 [6.7 2.5 5.8 1.8]
 [7.2 3.6 6.1 2.5]
 [6.5 3.2 5.1 2. ]
 [6.4 2.7 5.3 1.9]
 [6.8 3.  5.5 2.1]
 [5.7 2.5 5.  2. ]
 [5.8 2.8 5.1 2.4]
 [6.4 3.2 5.3 2.3]
 [6.5 3.  5.5 1.8]
 [7.7 3.8 6.7 2.2]
 [7.7 2.6 6.9 2.3]
 [6.  2.2 5.  1.5]
```

```
 [6.9 3.2 5.7 2.3]
 [5.6 2.8 4.9 2. ]
 [7.7 2.8 6.7 2. ]
 [6.3 2.7 4.9 1.8]
 [6.7 3.3 5.7 2.1]
 [7.2 3.2 6.  1.8]
 [6.2 2.8 4.8 1.8]
 [6.1 3.  4.9 1.8]
 [6.4 2.8 5.6 2.1]
 [7.2 3.  5.8 1.6]
 [7.4 2.8 6.1 1.9]
 [7.9 3.8 6.4 2. ]
 [6.4 2.8 5.6 2.2]
 [6.3 2.8 5.1 1.5]
 [6.1 2.6 5.6 1.4]
 [7.7 3.  6.1 2.3]
 [6.3 3.4 5.6 2.4]
 [6.4 3.1 5.5 1.8]
 [6.  3.  4.8 1.8]
 [6.9 3.1 5.4 2.1]
 [6.7 3.1 5.6 2.4]
 [6.9 3.1 5.1 2.3]
 [5.8 2.7 5.1 1.9]
 [6.8 3.2 5.9 2.3]
 [6.7 3.3 5.7 2.5]
 [6.7 3.  5.2 2.3]
 [6.3 2.5 5.  1.9]
 [6.5 3.  5.2 2. ]
 [6.2 3.4 5.4 2.3]
 [5.9 3.  5.1 1.8]]
```

In [3]:

```
print(iris.target_names)
```

```
['setosa' 'versicolor' 'virginica']
```

In [4]:

```
print(iris.target)
```

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

In [5]:

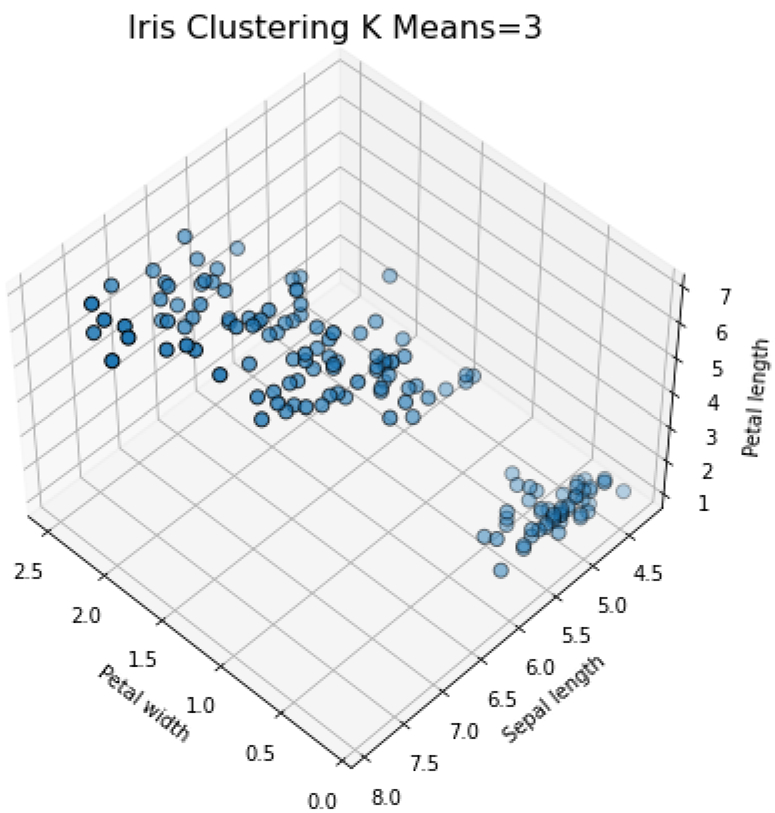
```
x = iris.data
y = iris.target
```

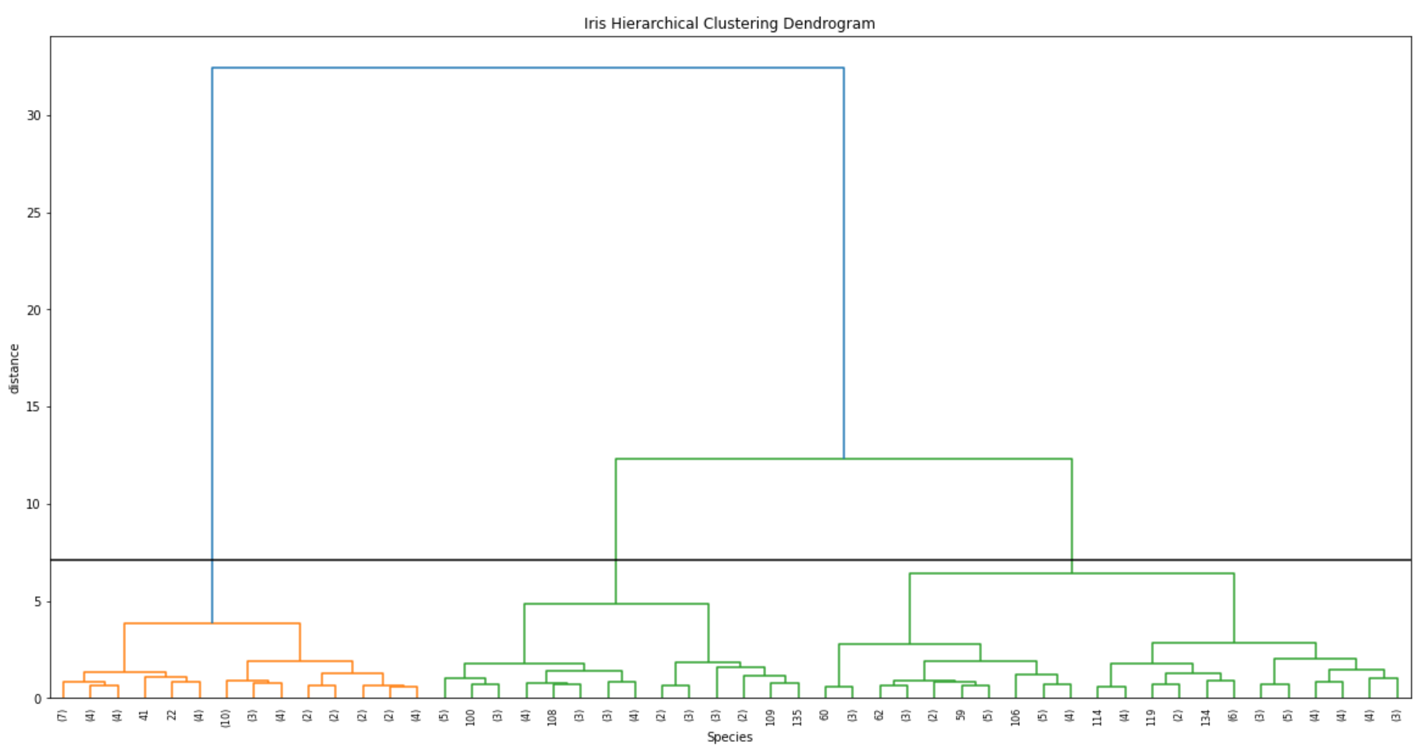
Step 2 - Visualizing the input data and its Hierarchy

In [6]:

```
#Plotting
fig = plt.figure(1, figsize=(7,5))
ax = Axes3D(fig, rect=[0, 0, 0.95, 1], elev=48, azim=134)
ax.scatter(x[:, 3], x[:, 0], x[:, 2], edgecolor="k", s=50)
ax.set_xlabel("Petal width")
ax.set_ylabel("Sepal length")
ax.set_zlabel("Petal length")
plt.title("Iris Clustering K Means=3", fontsize=16)
plt.show()

#Hierachy Clustering
x,"ward")
```

```
max_d=7.08
plt.figure(figsize=(20,10))
plt.title('Iris Hierarchical Clustering Dendrogram')
plt.xlabel('Species')
plt.ylabel('distance')
dendrogram(
    hier,
    truncate_mode='lastp',
    p=50,
    leaf_rotation=90.,
    leaf_font_size=8.,
)
plt.axhline(y=max_d, c='k')
plt.show()
```





Step 3 : Data Preprocessing

In [7]:

```
x = pd.DataFrame(iris.data, columns=['Sepal Length', 'Sepal Width', 'Petal Length', 'Petal
y = pd.DataFrame(iris.target, columns=['Target'])
```

In [8]:

```
x.head()
```

Out[8]:

	Sepal Length	Sepal Width	Petal Length	Petal Width
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

In [9]:

```
y.head()
```

Out[9]:

	Target
0	0
1	0
2	0
3	0
4	0

Step 4 : Model Training

In [10]:

```
iris_k_mean_model = KMeans(n_clusters=3)
iris_k_mean_model.fit(x)
```

Out[10]:

```
KMeans(n_clusters=3)
```

In [11]:

```
print(iris_k_mean_model.labels_)
```

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

In [12]:

```
print(iris_k_mean_model.cluster_centers_)
```

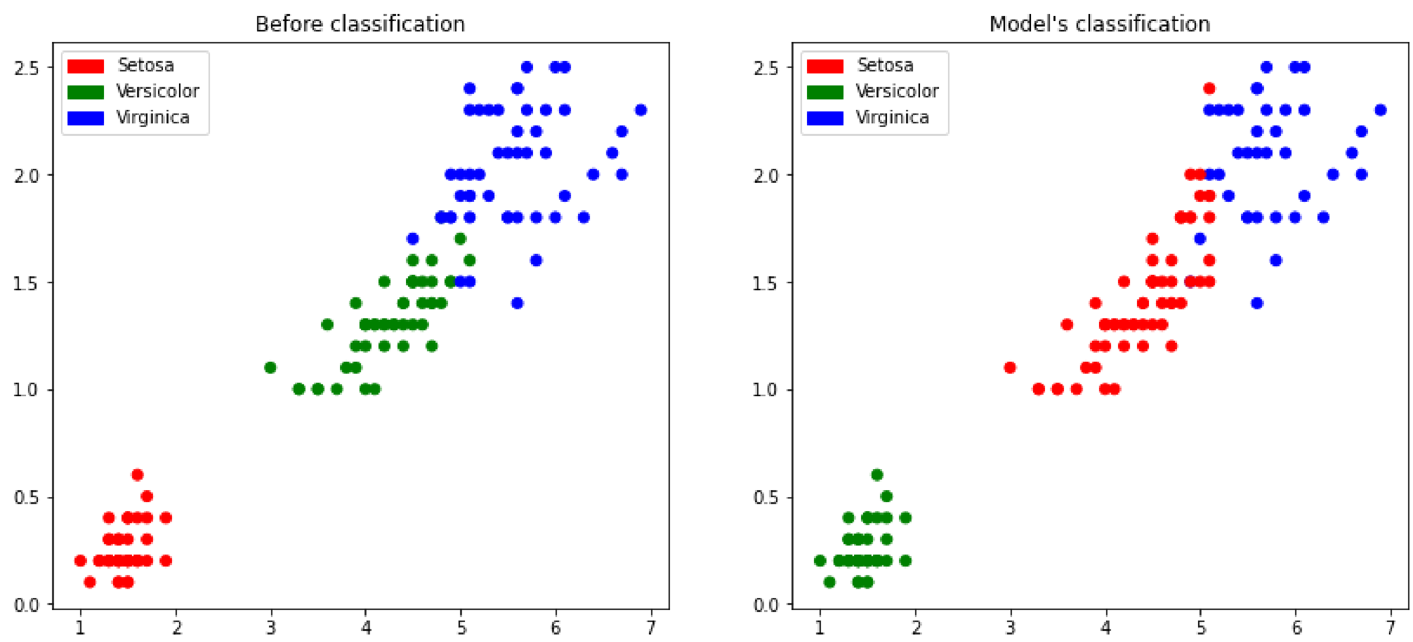
```
[[5.006      3.428      1.462      0.246     ]
 [5.9016129  2.7483871  4.39354839 1.43387097]
 [6.85       3.07368421 5.74210526 2.07105263]]
```

Step 5 : Visualizing the Model Cluster

Loading [MathJax]/extensions/Safe.js

In [13]:

```
import matplotlib.patches as mpatches

colors = ["r", "g", "b"]
texts = ["Setosa", "Versicolor", "Virginica"]
patches = [ mpatches.Patch(color=colors[i], label="{:s}".format(texts[i]) ) for i in range


plt.figure(figsize=(14,6))

colors = np.array(['red', 'green', 'blue'])

predictedY = np.choose(iris_k_mean_model.labels_, [1, 0, 2]).astype(np.int64)

plt.subplot(1, 2, 1)
plt.scatter(x['Petal Length'], x['Petal Width'], c=colors[y['Target']])
plt.title('Before classification')
#plt.legend(handles=[red_patch, green_patch, blue_patch])
#plt.legend(handles= patches)

plt.legend(handles=patches,  loc='best', ncol=1 )
#plt.legend(facecolor="plum")

plt.subplot(1, 2, 2)
plt.scatter(x['Petal Length'], x['Petal Width'], c=colors[predictedY])
plt.title("Model's classification")
#plt.legend(handles= patches)
plt.legend(handles=patches,  loc=2, ncol=1 )

plt.show()
```



Step 6 - Calculating the Accuracy and Confusion Matrix

In [14]:

```
sm.accuracy_score(predictedY, y['Target'])
```

Out[14]: 0.24

In [15]:

```
sm.confusion_matrix(predictedY, y['Target'])
```

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```
Out[15]: array([[ 0, 48, 14],
               [50,  0,  0],
               [ 0,  2, 36]], dtype=int64)
```

In a confusion matrix, the predicted class labels (0, 1, 2) are written along the top (column names). The true class labels (Iris-setosa, etc.) are written along the right side. Each cell in the matrix is a count of how many instances of a true class where classified as each of the predicted classes.

Conclusion

I was able to successfully carry-out prediction using Unsupervised Machine Learning task and was able to evaluate the model's clustering accuracy score.

THANK YOU SO MUCH!!