Importing libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Importing the dataset from drive

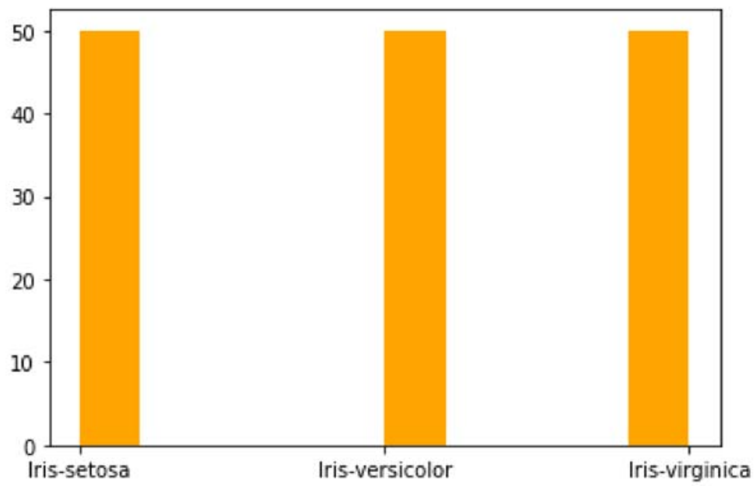
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mou
```

```
dataFrame=pd.read_csv("/content/drive/MyDrive/ML Data/iris data.csv",header=None);
dataFrame.columns=["Petal Length","Petal Width","Sepal Length","Sepal Width","Species"];
print(dataFrame.head(30));
```

```
    Petal Length  Petal Width  Sepal Length  Sepal Width      Species
0            5.1          3.5           1.4          0.2  Iris-setosa
1            4.9          3.0           1.4          0.2  Iris-setosa
2            4.7          3.2           1.3          0.2  Iris-setosa
3            4.6          3.1           1.5          0.2  Iris-setosa
4            5.0          3.6           1.4          0.2  Iris-setosa
5            5.4          3.9           1.7          0.4  Iris-setosa
6            4.6          3.4           1.4          0.3  Iris-setosa
7            5.0          3.4           1.5          0.2  Iris-setosa
8            4.4          2.9           1.4          0.2  Iris-setosa
9            4.9          3.1           1.5          0.1  Iris-setosa
10           5.4          3.7           1.5          0.2  Iris-setosa
11           4.8          3.4           1.6          0.2  Iris-setosa
12           4.8          3.0           1.4          0.1  Iris-setosa
13           4.3          3.0           1.1          0.1  Iris-setosa
14           5.8          4.0           1.2          0.2  Iris-setosa
15           5.7          4.4           1.5          0.4  Iris-setosa
16           5.4          3.9           1.3          0.4  Iris-setosa
17           5.1          3.5           1.4          0.3  Iris-setosa
18           5.7          3.8           1.7          0.3  Iris-setosa
19           5.1          3.8           1.5          0.3  Iris-setosa
20           5.4          3.4           1.7          0.2  Iris-setosa
21           5.1          3.7           1.5          0.4  Iris-setosa
22           4.6          3.6           1.0          0.2  Iris-setosa
23           5.1          3.3           1.7          0.5  Iris-setosa
24           4.8          3.4           1.9          0.2  Iris-setosa
25           5.0          3.0           1.6          0.2  Iris-setosa
26           5.0          3.4           1.6          0.4  Iris-setosa
27           5.2          3.5           1.5          0.2  Iris-setosa
28           5.2          3.4           1.4          0.2  Iris-setosa
29           4.7          3.2           1.6          0.2  Iris-setosa
```

```
plt.hist(dataFrame["Species"],color="Orange")
plt.show()
```




```
import seaborn as sns
sns.FacetGrid(dataFrame,hue="Species",size=3).map(sns.distplot,"Petal Length").add_legend()
sns.FacetGrid(dataFrame,hue="Species",size=3).map(sns.distplot,"Petal Width").add_legend()
sns.FacetGrid(dataFrame,hue="Species",size=3).map(sns.distplot,"Sepal Length").add_legend()
sns.FacetGrid(dataFrame,hue="Species",size=3).map(sns.distplot,"Sepal Width").add_legend()
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/axisgrid.py:316: UserWarning: The `size`
  warnings.warn(msg, UserWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `d
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  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: `d
  warnings.warn(msg, FutureWarning)
```
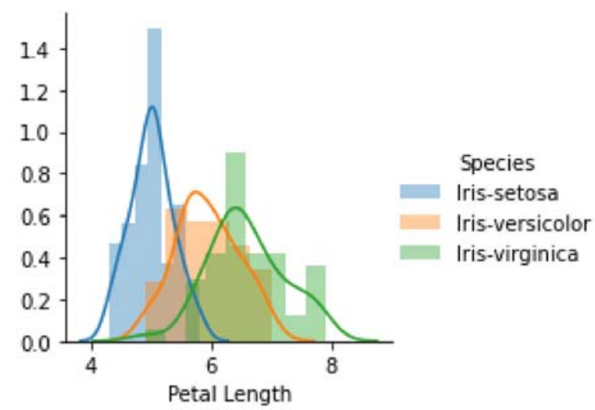
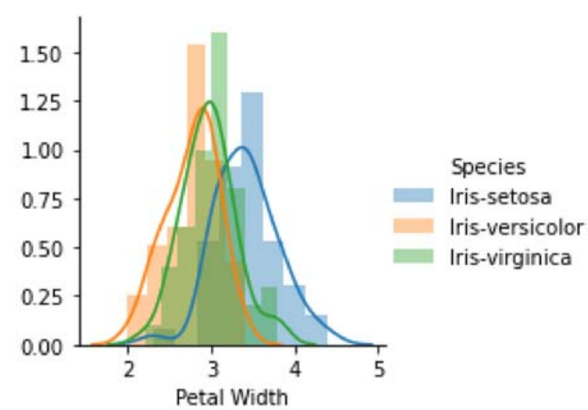





```
dataFrame.describe()
```

	Petal Length	Petal Width	Sepal Length	Sepal Width
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

Assigning Attributes in a numpy array:

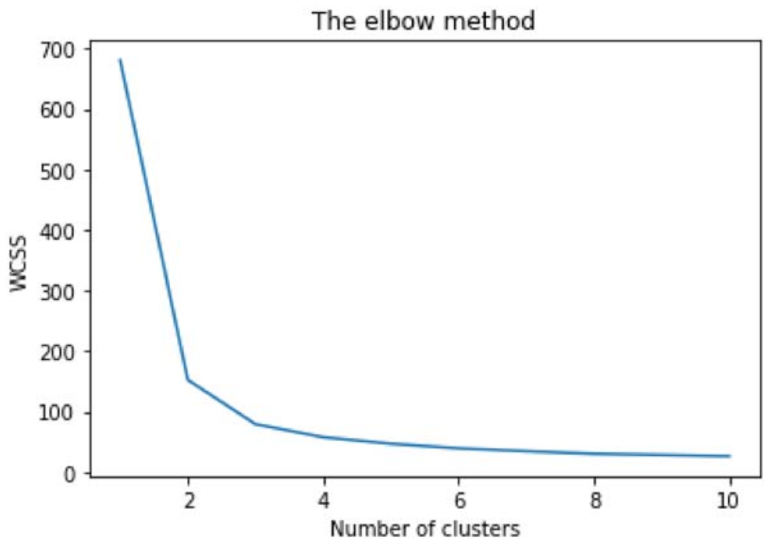
```
attributes = dataFrame.iloc[:, [0, 1, 2, 3]].values
type(attributes)
labels = dataFrame.iloc[:, 4].values
type(labels)
```

```
numpy.ndarray
```

Elbow method

Now we will implement 'The elbow method' on the Iris dataset. The elbow method allows us to pick the optimum amount of clusters for classification

```
#Finding the optimum number of clusters for k-means classification
from sklearn.cluster import KMeans
wcss = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, random_s
    kmeans.fit(attributes)
    wcss.append(kmeans.inertia_)

#Plotting the results onto a line graph, allowing us to observe 'The elbow'
plt.plot(range(1, 11), wcss)
plt.title('The elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') #within cluster sum of squares
plt.show()
```



Model Training

In the above graph, Implementing the elbow method, 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. Now we have the optimum amount of clusters, we can move on to applying K-means clustering to the Iris dataset. Considering the point of occuring of elbow to be 3, i.e. 3 clusters will be the optimum solution for this problem.

Splitting data in 70:30 ratio for training and validation

```
from sklearn.model_selection import train_test_split
validation_size = 0.30

x_train, x_val, y_train, y_val = train_test_split(
    attributes,
    labels,
    test_size=validation_size,
    random_state=10,
    stratify=labels,
)
```

```
print(len(x_train), len(x_val))
```

```
105 45
```

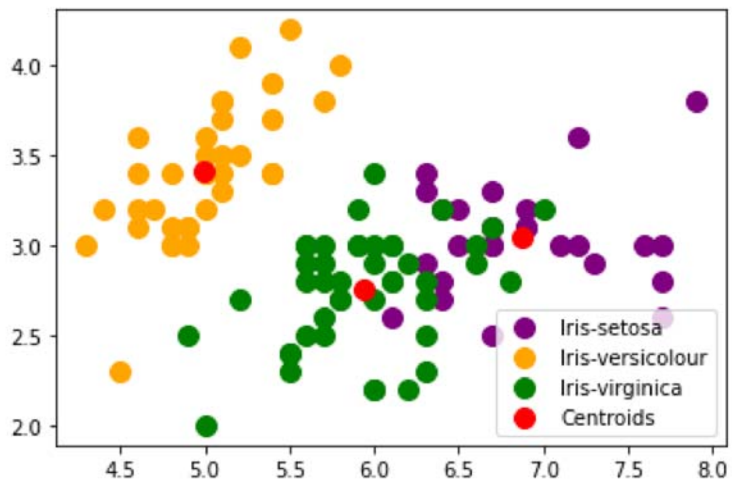
```
#Applying kmeans to the dataset / Creating the kmeans classifier
kmeans = KMeans(n_clusters = 3,init = 'k-means++',max_iter = 300, n_init = 10, random_state =
```

```
y_kmeans = kmeans.fit_predict(x_train)
```

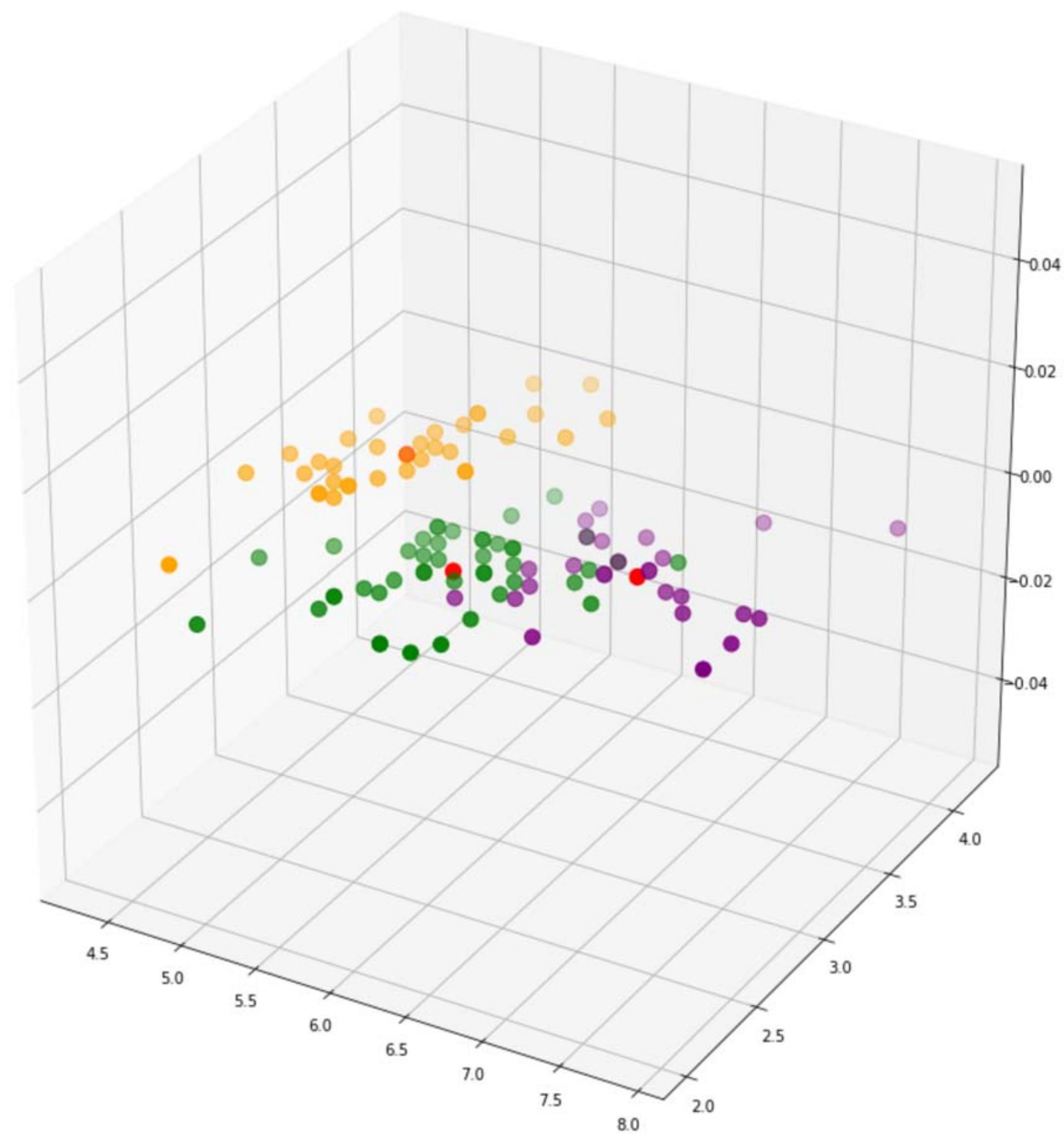
Scatter Plot

```
#Visualising the clusters
plt.scatter(x_train[y_kmeans == 0, 0], x_train[y_kmeans == 0, 1], s = 100, c = 'purple', labe
plt.scatter(x_train[y_kmeans == 1, 0], x_train[y_kmeans == 1, 1], s = 100, c = 'orange', labe
plt.scatter(x_train[y_kmeans == 2, 0], x_train[y_kmeans == 2, 1], s = 100, c = 'green', label

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'red',

plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f73bf326b50>
```




```
# 3d scatterplot using matplotlib

fig = plt.figure(figsize = (15,15))
ax = fig.add_subplot(111, projection='3d')
plt.scatter(x_train[y_kmeans == 0, 0], x_train[y_kmeans == 0, 1], s = 100, c = 'purple', labe
plt.scatter(x_train[y_kmeans == 1, 0], x_train[y_kmeans == 1, 1], s = 100, c = 'orange', labe
plt.scatter(x_train[y_kmeans == 2, 0], x_train[y_kmeans == 2, 1], s = 100, c = 'green', label

#Plotting the centroids of the clusters
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:,1], s = 100, c = 'red',
plt.show()
```



Model accuracy check and classification report

Converting true labels to their respective class numbers:

- Virginica Class 1
- Setosa Class 0
- Versicolor Class 2

```
predictions_train = np.choose(y_kmeans, ["Iris-virginica", "Iris-setosa", "Iris-versicolor"])
print(predictions_train)
```

```
['Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica'
 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-virginica'
 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa' 'Iris-setosa'
 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor' 'Iris-setosa'
 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa'
 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa'
 'Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa' 'Iris-virginica'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-virginica'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa'
 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-setosa' 'Iris-versicolor'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica'
 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica'
 'Iris-setosa' 'Iris-setosa' 'Iris-virginica']
```

```
from sklearn.metrics import classification_report, accuracy_score
accuracy_score(y_train, predictions_train)
```

```
0.8761904761904762
```

```
print(classification_report(y_train, predictions_train, digits=5))
```

	precision	recall	f1-score	support
Iris-setosa	1.00000	1.00000	1.00000	35
Iris-versicolor	0.75000	0.94286	0.83544	35
Iris-virginica	0.92308	0.68571	0.78689	35
accuracy			0.87619	105
macro avg	0.89103	0.87619	0.87411	105
weighted avg	0.89103	0.87619	0.87411	105

Validation Set

```
y_predicted = kmeans.fit_predict(x_val)
```

```
predictions_val = np.choose(y_predicted, ["Iris-versicolor","Iris-virginica","Iris-setosa"])
print(predictions_val)
```

```
['Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica'
 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica'
 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-virginica'
 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa'
 'Iris-virginica' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa'
 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-versicolor']
```

```
print(y_val)
```

```
['Iris-setosa' 'Iris-virginica' 'Iris-setosa' 'Iris-virginica'
 'Iris-versicolor' 'Iris-setosa' 'Iris-versicolor' 'Iris-versicolor'
 'Iris-setosa' 'Iris-versicolor' 'Iris-virginica' 'Iris-virginica'
 'Iris-virginica' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-setosa' 'Iris-virginica' 'Iris-setosa'
 'Iris-virginica' 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor'
 'Iris-setosa' 'Iris-virginica' 'Iris-virginica' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-virginica' 'Iris-versicolor' 'Iris-setosa'
 'Iris-virginica' 'Iris-virginica' 'Iris-setosa' 'Iris-versicolor'
 'Iris-versicolor' 'Iris-versicolor' 'Iris-setosa' 'Iris-setosa'
 'Iris-versicolor']
```

```
accuracy_score(y_val, predictions_val)
```

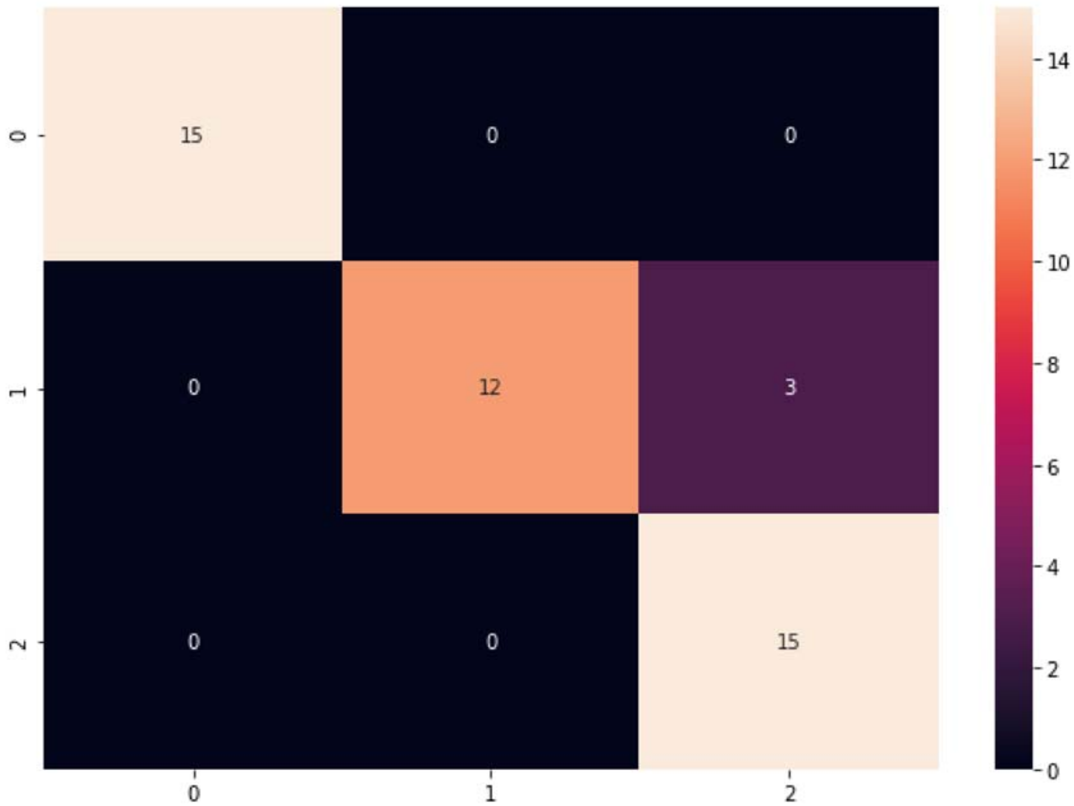
```
0.9333333333333333
```

```
print(classification_report(y_val, predictions_val, digits=5))
```

```
                 precision    recall  f1-score   support

    Iris-setosa    1.00000   1.00000   1.00000        15
Iris-versicolor    1.00000   0.80000   0.88889        15
 Iris-virginica    0.83333   1.00000   0.90909        15

       accuracy                        0.93333        45
      macro avg    0.94444   0.93333   0.93266        45
   weighted avg    0.94444   0.93333   0.93266        45
```

```
import seaborn as sn
import pandas as pd
from sklearn.metrics import confusion_matrix
array = confusion_matrix(y_val,predictions_val)
df_cm = pd.DataFrame(array, index = [i for i in "012"],
                  columns = [i for i in "012"])
```

```
plt.figure(figsize = (10,7))
sn.heatmap(df_cm, annot=True)

plt.show()
```



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