In [ ]:
```
# Import Libraries

import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.cluster import KMeans
```

In [ ]:
```
df = pd.read_csv("/content/Iris (1).csv")
df.head()
```

In [ ]:
```
df.Species.value_counts()
```

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

In [ ]:
```
# Let's check if we have something missing?
df.isnull().sum()
```

Out[ ]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [ ]:
```
df.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
```

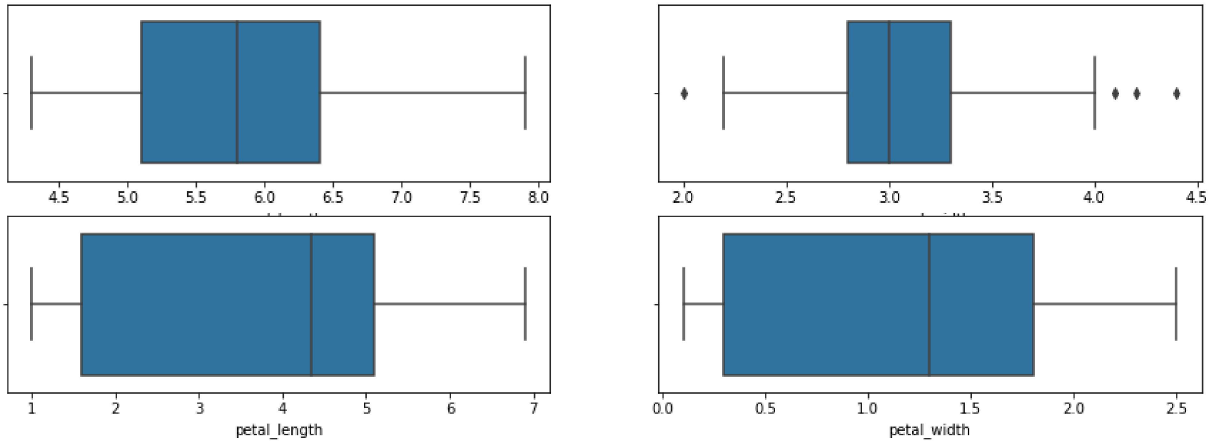
Let's do some EDA

In [ ]:
```
feature = df.columns
```

Let's perfrom Outlier Treatment

In [ ]:
```
plt.figure(figsize = (15, 5))
```

```python
feature = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
for i in enumerate(feature):
    plt.subplot(2,2,i[0]+1)
    sns.boxplot(df[i[1]])
```



In [ ]:

```python
sns.boxplot('sepal_width', data = df)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
s the following variable as a keyword arg: x. From version 0.12, the only valid posi
tional argument will be `data`, and passing other arguments without an explicit keyw
ord will result in an error or misinterpretation.
  FutureWarning
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-18-76ef1ee9ec95> in <module>()
----> 1 sns.boxplot('sepal_width', data = df)

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py in inner_f(*args, **kw
args)
     44             )
     45         kwargs.update({k: arg for k, arg in zip(sig.parameters, args)})
---> 46         return f(**kwargs)
     47     return inner_f
     48

/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py in boxplot(x, y, hue,
 data, order, hue_order, orient, color, palette, saturation, width, dodge, fliersiz
e, linewidth, whis, ax, **kwargs)
   2243     plotter = _BoxPlotter(x, y, hue, data, order, hue_order,
   2244                           orient, color, palette, saturation,
-> 2245                           width, dodge, fliersize, linewidth)
   2246
   2247     if ax is None:

/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py in __init__(self, x,
 y, hue, data, order, hue_order, orient, color, palette, saturation, width, dodge, f
liersize, linewidth)
    404                  width, dodge, fliersize, linewidth):
    405
--> 406         self.establish_variables(x, y, hue, data, orient, order, hue_order)
    407         self.establish_colors(color, palette, saturation)
    408

/usr/local/lib/python3.7/dist-packages/seaborn/categorical.py in establish_variables
(self, x, y, hue, data, orient, order, hue_order, units)
    151                 if isinstance(var, str):
    152                     err = "Could not interpret input '{}'".format(var)
```

```
--> 153                 raise ValueError(err)
    154
    155             # Figure out the plotting orientation

ValueError: Could not interpret input 'sepal_width'
```

In [ ]:
```
# Assignment:

# find out those countries that are in need of the aid
# We should not remove outliers that are in the lower range but we can cap them
# When a column have so many outliers in either upper or lower range, then we can ig
```

Data Preparation

In [ ]:
```
df1 = df.copy()
```

In [ ]:
```
df.drop('id', axis = 1, inplace = True)
```

In [ ]:
```
## Scaling
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
df2 = scale.fit_transform(df)
```

In [ ]:
```
df2 = pd.DataFrame(df2)
df2.columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
df2.head()
```

Out[ ]:

	sepal_length	sepal_width	petal_length	petal_width
0	-0.900681	1.054478	-1.341272	-1.312977
1	-1.143017	-0.125943	-1.341272	-1.312977
2	-1.385353	0.346225	-1.398138	-1.312977
3	-1.506521	0.110141	-1.284407	-1.312977
4	-1.021849	1.290562	-1.341272	-1.312977

In [ ]:
```
## Hopkins Score

from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
import numpy as np
from math import isnan

def hopkins(X):
    d = X.shape[1]
    #d = len(vars) # columns
    n = len(X) # rows
    m = int(0.1 * n)
    nbrs = NearestNeighbors(n_neighbors=1).fit(X.values)

    rand_X = sample(range(0, n, 1), m)
```

```
    ujd = []
    wjd = []
    for j in range(0, m):
        u_dist, _ = nbrs.kneighbors(uniform(np.amin(X,axis=0),np.amax(X,axis=0),d).r
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2, retu
        wjd.append(w_dist[0][1])

    H = sum(ujd) / (sum(ujd) + sum(wjd))
    if isnan(H):
        print(ujd, wjd)
        H = 0

    return H
```

In [ ]:

```
hopkins(df2)
```

Out[ ]:

```
0.8254831861233146
```

In [ ]:

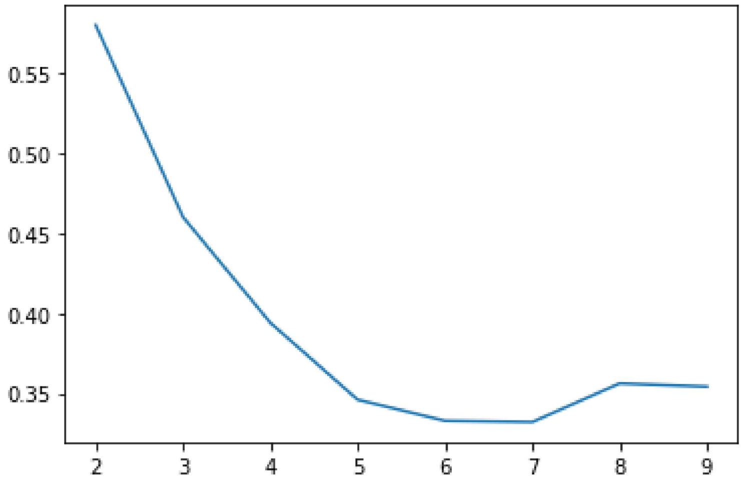
```
# Choose the value of K
# Silhouette
# Elbow Curve

from sklearn.metrics import silhouette_score
ss = []
for k in range(2, 10):
    kmeans = KMeans(n_clusters = k).fit(df2)
    ss.append([k, silhouette_score(df2, kmeans.labels_)])

plt.plot(pd.DataFrame(ss)[0], pd.DataFrame(ss)[1])
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x68d0ad3688>]
```



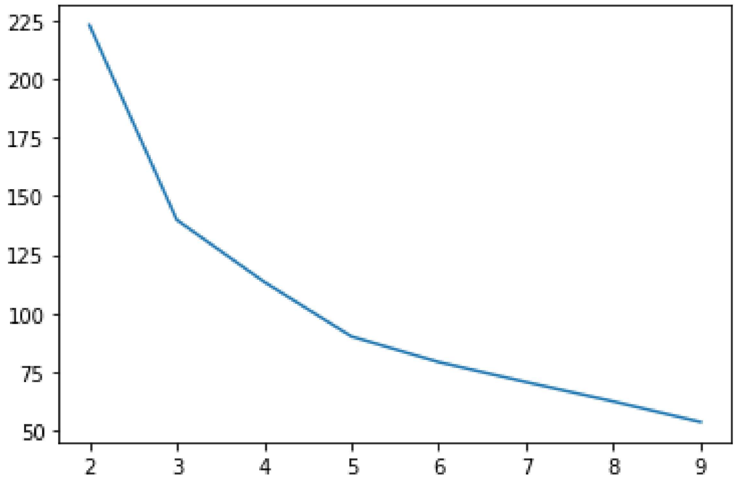
In [ ]:

```
ssd = []
for k in range(2, 10):
    model= KMeans(n_clusters = k).fit(df2)
    ssd.append([k, model.inertia_])

plt.plot(pd.DataFrame(ssd)[0], pd.DataFrame(ssd)[1])
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x68d0bf9108>]
```



In [ ]:

```
# Let's run kmean with 3

kmean = KMeans(n_clusters = 3, random_state = 100)
kmean.fit(df2)
```

Out[ ]:

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=100, tol=0.0001, verbose=0)
```

In [ ]:

```
df1.head()
```

Out[ ]:

	sepal_length	sepal_width	petal_length	petal_width	id
0	5.1	3.5	1.4	0.2	100
1	4.9	3.0	1.4	0.2	101
2	4.7	3.2	1.3	0.2	102
3	4.6	3.1	1.5	0.2	103
4	5.0	3.6	1.4	0.2	104

In [ ]:

```
df_km = pd.concat([df1, pd.Series(kmean.labels_)], axis =1)
```

In [ ]:

```
df_km.head()
```

Out[ ]:

	sepal_length	sepal_width	petal_length	petal_width	id	0
0	5.1	3.5	1.4	0.2	100	0
1	4.9	3.0	1.4	0.2	101	0
2	4.7	3.2	1.3	0.2	102	0
3	4.6	3.1	1.5	0.2	103	0
4	5.0	3.6	1.4	0.2	104	0

Cluster Profiling

In [ ]:

```
# Find the countries that are in need to aid based on 3 column, GDPP, Child_mort, In
```

In [ ]:

```
df_km.columns = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'id',
df_km.head()
```

Out[ ]:

	sepal_length	sepal_width	petal_length	petal_width	id	label
0	5.1	3.5	1.4	0.2	100	0
1	4.9	3.0	1.4	0.2	101	0
2	4.7	3.2	1.3	0.2	102	0
3	4.6	3.1	1.5	0.2	103	0
4	5.0	3.6	1.4	0.2	104	0

In [ ]:

```
df_km.label.value_counts()
```

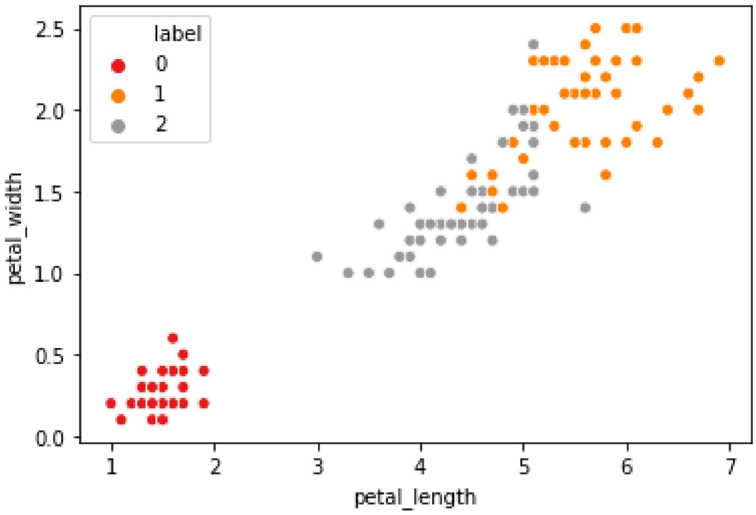
Out[ ]:

```
2    53
0    50
1    47
Name: label, dtype: int64
```

In [ ]:

```
sns.scatterplot(x = "petal_length" , y = "petal_width", hue = 'label', data = df_km,
```

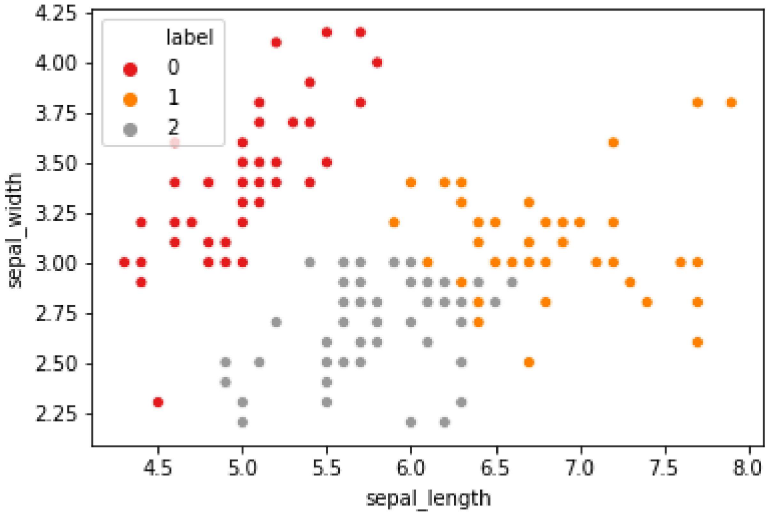
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x68bec1ce88>



In [ ]:

```
sns.scatterplot(x = "sepal_length" , y = "sepal_width", hue = 'label', data = df_km,
```

Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x68ce58e348>

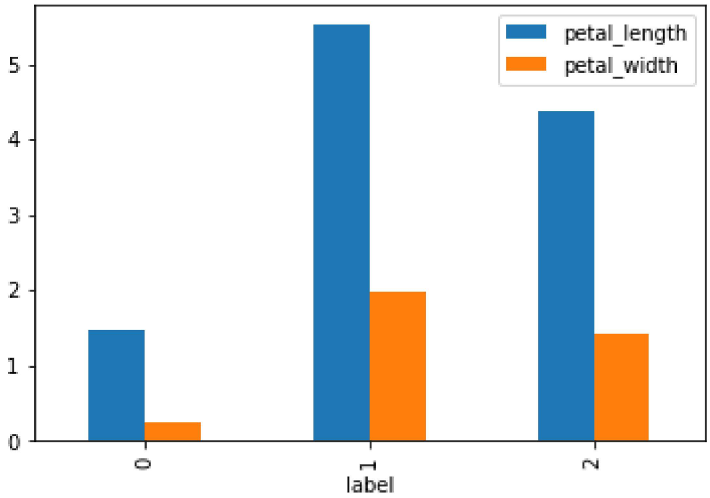


In [ ]:

```
# GDPP, Child_mort, Income
# LOW GDPP
# High Child_mort
# Low Income
df_km[['petal_length', 'petal_width', 'label']].groupby("label").mean().plot(kind =
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x68d0c0aa48>
```



In [ ]:

```
df_km[df_km['label']==0].sort_values(by = ['petal_length', 'petal_width'], ascending
```

Out[ ]:

	sepal_length	sepal_width	petal_length	petal_width	id	label
22	4.6	3.600	1.0	0.2	122	0
13	4.3	3.000	1.1	0.1	113	0
14	5.8	4.000	1.2	0.2	114	0
35	5.0	3.200	1.2	0.2	135	0
2	4.7	3.200	1.3	0.2	102	0
36	5.5	3.500	1.3	0.2	136	0
38	4.4	3.000	1.3	0.2	138	0
42	4.4	3.200	1.3	0.2	142	0
40	5.0	3.500	1.3	0.3	140	0

	sepal_length	sepal_width	petal_length	petal_width	id	label
41	4.5	2.300	1.3	0.3	141	0
16	5.4	3.900	1.3	0.4	116	0
12	4.8	3.000	1.4	0.1	112	0
0	5.1	3.500	1.4	0.2	100	0
1	4.9	3.000	1.4	0.2	101	0
4	5.0	3.600	1.4	0.2	104	0
8	4.4	2.900	1.4	0.2	108	0
28	5.2	3.400	1.4	0.2	128	0
33	5.5	4.151	1.4	0.2	133	0
47	4.6	3.200	1.4	0.2	147	0
49	5.0	3.300	1.4	0.2	149	0
6	4.6	3.400	1.4	0.3	106	0
17	5.1	3.500	1.4	0.3	117	0
45	4.8	3.000	1.4	0.3	145	0
9	4.9	3.100	1.5	0.1	109	0
32	5.2	4.100	1.5	0.1	132	0
34	4.9	3.100	1.5	0.1	134	0
37	4.9	3.100	1.5	0.1	137	0
3	4.6	3.100	1.5	0.2	103	0
7	5.0	3.400	1.5	0.2	107	0
10	5.4	3.700	1.5	0.2	110	0
27	5.2	3.500	1.5	0.2	127	0
39	5.1	3.400	1.5	0.2	139	0
48	5.3	3.700	1.5	0.2	148	0
19	5.1	3.800	1.5	0.3	119	0
15	5.7	4.151	1.5	0.4	115	0
21	5.1	3.700	1.5	0.4	121	0
31	5.4	3.400	1.5	0.4	131	0
11	4.8	3.400	1.6	0.2	111	0
25	5.0	3.000	1.6	0.2	125	0
29	4.7	3.200	1.6	0.2	129	0
30	4.8	3.100	1.6	0.2	130	0
46	5.1	3.800	1.6	0.2	146	0
26	5.0	3.400	1.6	0.4	126	0
43	5.0	3.500	1.6	0.6	143	0
20	5.4	3.400	1.7	0.2	120	0

	sepal_length	sepal_width	petal_length	petal_width	id	label
18	5.7	3.800	1.7	0.3	118	0
5	5.4	3.900	1.7	0.4	105	0
23	5.1	3.300	1.7	0.5	123	0
24	4.8	3.400	1.9	0.2	124	0
44	5.1	3.800	1.9	0.4	144	0

In [ ]:

```
## Hirerachical clustering
```