

```
In [227... import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram, linkage
import warnings
warnings.filterwarnings('ignore')
```

```
In [22]: def print_title(title):
        print(f'\n{'-'*120}\n\033[1m{title}\033[0m')
def print_section(title):
    print(f'\n{'-'*120}\n{title}\n{'-'*120}')
```

# (1) Loading And Preprocessing

## Importing and creating iris data frame form sklearn

```
In [66]: from sklearn.datasets import load_iris
iris_data = load_iris()
iris = pd.DataFrame(data=iris_data.data, columns=iris_data.feature_names)
iris['target'] = iris_data.target
```

```
In [68]: print_title('Data set Head')
print_section(iris.head(3))
```

### Data set Head

```
-----
sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
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

target
0      0
1      0
2      0
-----
```

```
In [70]: print_title('Data set Tail')
print_section(iris.tail(3))
```

### Data set Tail

```
-----
sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)  \
147              6.5              3.0              5.2              2.0
148              6.2              3.4              5.4              2.3
149              5.9              3.0              5.1              1.8

target
147      2
-----
```

```
148      2
149      2
```

```
In [72]: print_title('Data set information')
print_section(iris.info())
```

```
-----
-----
Data set information
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
#   Column                Non-Null Count  Dtype
---  -
0   sepal length (cm)      150 non-null   float64
1   sepal width (cm)       150 non-null   float64
2   petal length (cm)      150 non-null   float64
3   petal width (cm)       150 non-null   float64
4   target                 150 non-null   int32
dtypes: float64(4), int32(1)
memory usage: 5.4 KB
-----
-----
```

```
None
-----
-----
```

```
In [74]: print_title('Data set Description')
print_section(iris.describe())
```

```
-----
-----
Data set Description
-----
-----
      sepal length (cm)  sepal width (cm)  petal length (cm)  \
count      150.000000      150.000000      150.000000
mean         5.843333         3.057333         3.758000
std          0.828066         0.435866         1.765298
min          4.300000         2.000000         1.000000
25%          5.100000         2.800000         1.600000
50%          5.800000         3.000000         4.350000
75%          6.400000         3.300000         5.100000
max          7.900000         4.400000         6.900000

      petal width (cm)      target
count      150.000000  150.000000
mean         1.199333    1.000000
std          0.762238    0.819232
min          0.100000    0.000000
25%          0.300000    0.000000
50%          1.300000    1.000000
75%          1.800000    2.000000
max          2.500000    2.000000
-----
-----
```

```
In [76]: print_title('finding null valuse')
print_section(iris.isnull().sum())
```

```
-----
finding null valuse
-----
```

```
-----
sepal length (cm)      0
sepal width (cm)       0
petal length (cm)      0
petal width (cm)       0
target                 0
dtype: int64
-----
-----
```

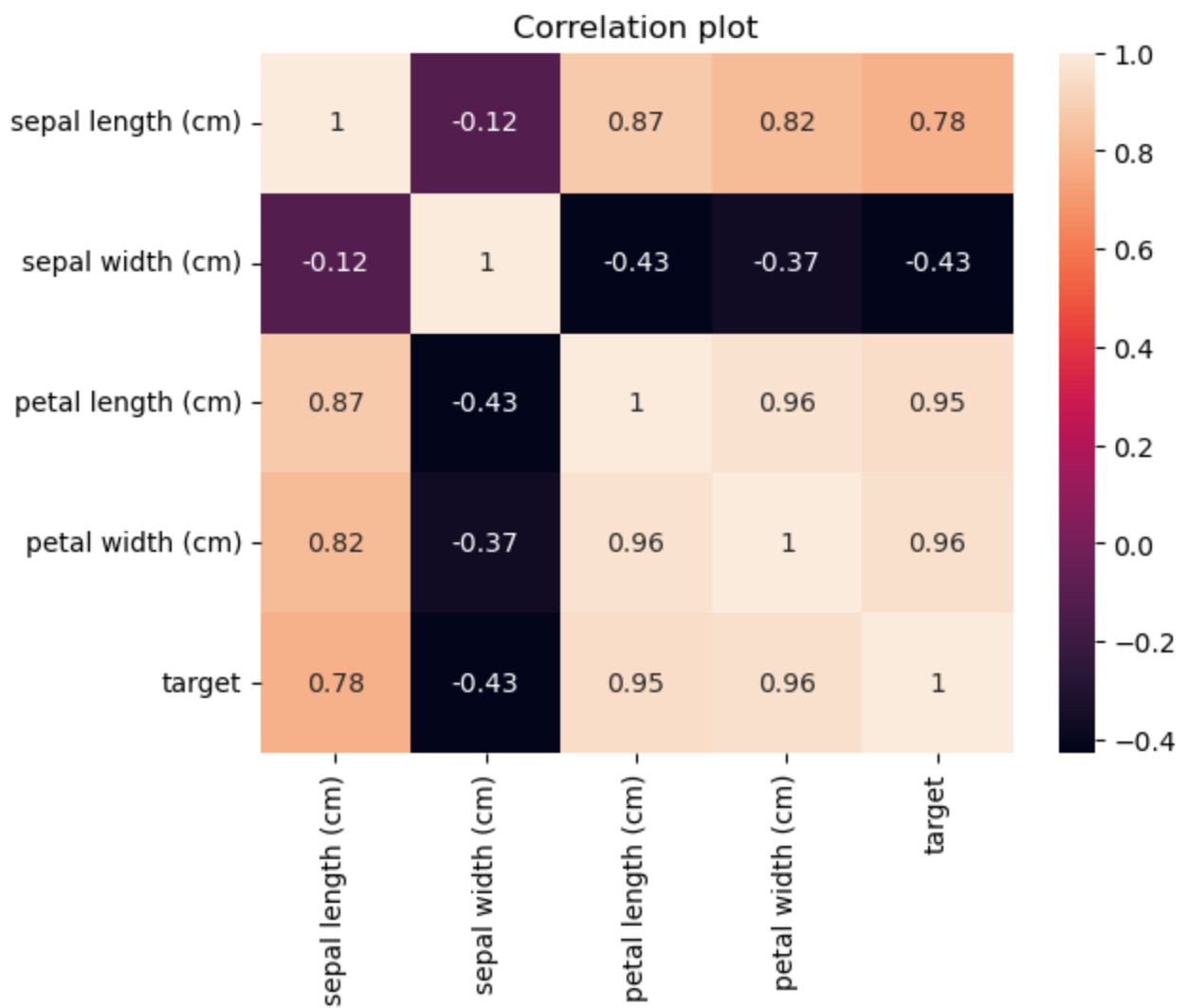
```
In [78]: print_title('Correlation')
print_section(iris.corr())
```

### Correlation

```
-----
-----
sepal length (cm)      sepal width (cm)  petal length (cm)  \
sepal length (cm)      1.000000         -0.117570         0.871754
sepal width (cm)       -0.117570         1.000000         -0.428440
petal length (cm)      0.871754         -0.428440         1.000000
petal width (cm)       0.817941         -0.366126         0.962865
target                 0.782561         -0.426658         0.949035

sepal length (cm)      petal width (cm)  target
sepal length (cm)      0.817941  0.782561
sepal width (cm)       -0.366126 -0.426658
petal length (cm)      0.962865  0.949035
petal width (cm)       1.000000  0.956547
target                 0.956547  1.000000
-----
-----
```

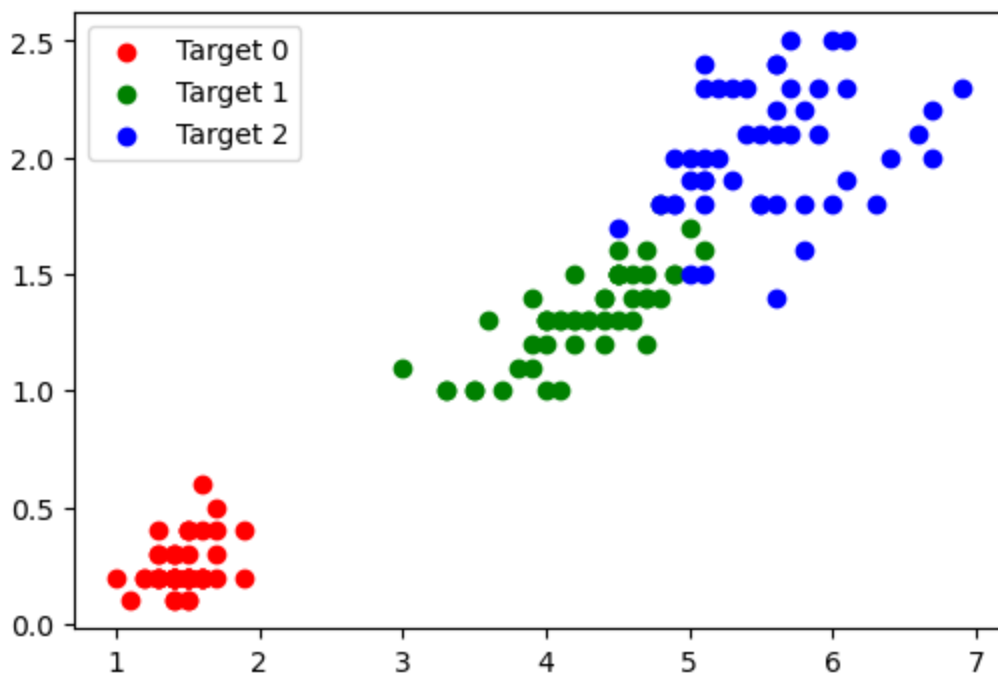
```
In [120... plt.title('Correlation plot')
sns.heatmap(iris.corr(),annot=True)
plt.show()
```



```
In [209...] iris['target'].unique()
```

```
Out[209]: array([0, 1, 2])
```

```
In [211...] plt.figure(figsize=(6,4))
iris1 = iris[iris['target']==0]
iris2 = iris[iris['target']==1]
iris3 = iris[iris['target']==2]
plt.scatter(iris1['petal length (cm)'],iris1['petal width (cm)'],color='r',label='Target
plt.scatter(iris2['petal length (cm)'],iris2['petal width (cm)'],color='g',label='Target
plt.scatter(iris3['petal length (cm)'],iris3['petal width (cm)'],color='b',label='Target
plt.legend()
plt.show()
```



Drping Target column since this is a clustering problem

```
In [122... iris_df=iris.iloc[:,0:4]
```

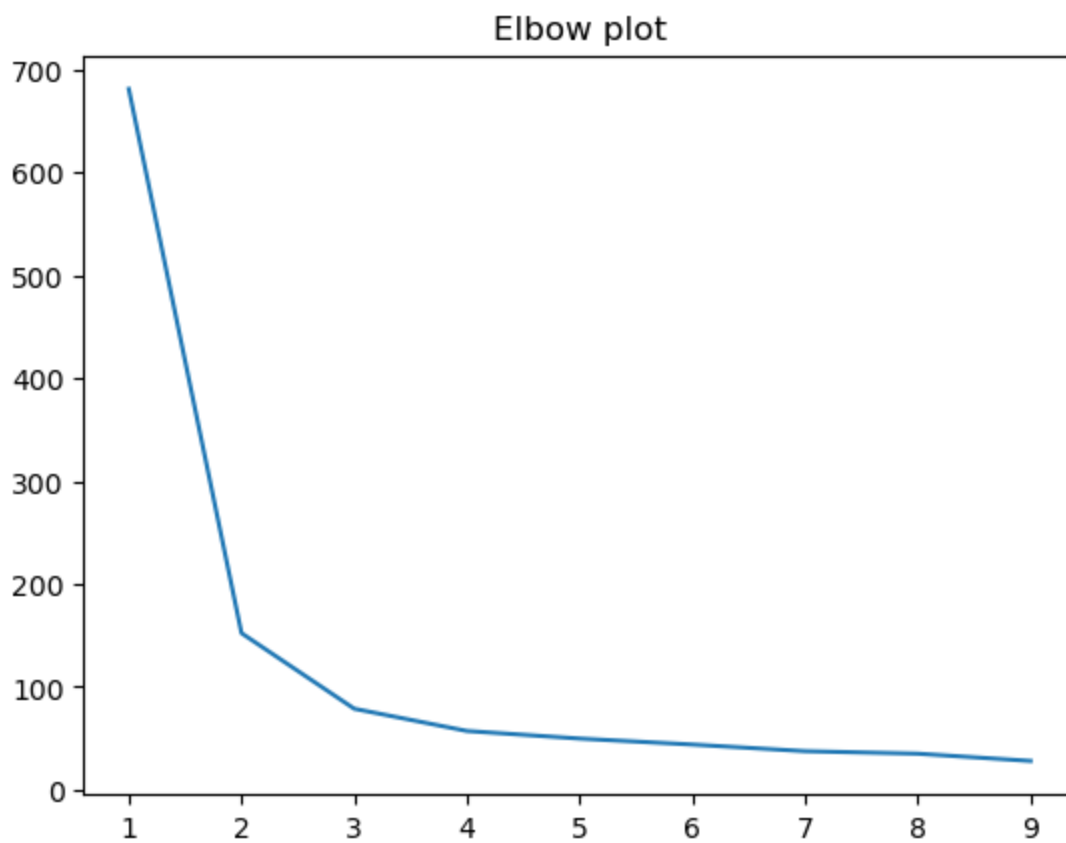
## (2) Clustering Algorithm Implementation

### A)KMeans Clustering

```
In [134... sse
```

```
Out[134]: [681.3706,
152.3479517603579,
78.8556658259773,
57.22847321428571,
49.85280058651026,
44.05522387742976,
37.59275,
35.168657217367745,
28.10249464570517]
```

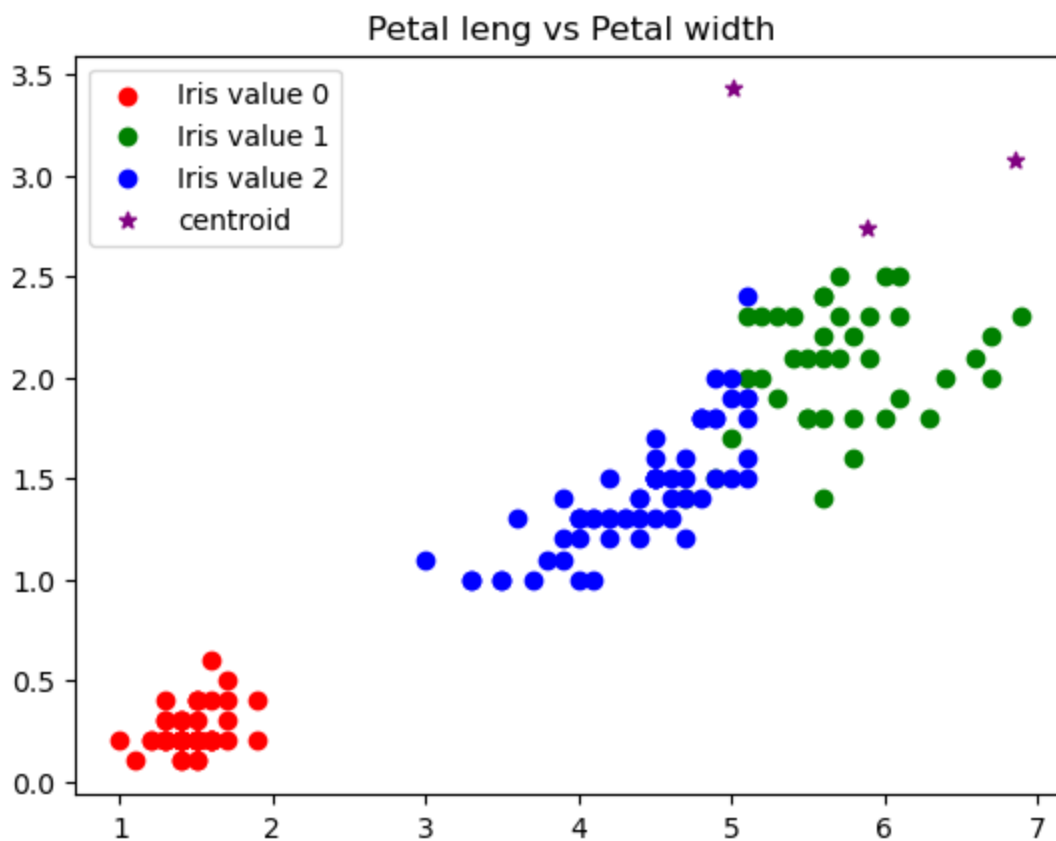
```
In [142... plt.title('Elbow plot')
plt.plot(k_meansclus,sse)
plt.show()
```



## Model implimentation

```
In [165... km1 = KMeans(n_clusters=3,max_iter=300,random_state=0) # crating model using cluster val
y_pred= km1.fit_predict(iris_df) # predicting the model
km1.cluster_centers_ # creating cluster points
iris_df=np.array(iris_df) # converting df to array
```

```
In [187... plt.title('Petal leng vs Petal width')
plt.scatter(iris_df[y_pred==1,2],iris_df[y_pred==1,3],color='r',label='Iris value 0')
plt.scatter(iris_df[y_pred==2,2],iris_df[y_pred==2,3],color='g',label='Iris value 1')
plt.scatter(iris_df[y_pred==0,2],iris_df[y_pred==0,3],color='b',label='Iris value 2')
plt.scatter(km1.cluster_centers_[0,2],km1.cluster_centers_[0,3],color='purple',marker='*')
plt.legend()
plt.show()
```



```
In [132... k_meansclus = range(1,10)      ## creating rage of clistering
sse = []      ##sum of the squared differences between each observation
for k in k_meansclus:
    km = KMeans(n_clusters=k)
    km.fit(iris_df)
    sse.append(km.inertia_)
```

## B)Hierarchical Clustering

```
In [219... # separte features and class labels
x_features = iris_data.data
y_labels = iris_data.target
```

### Model Implimentaion

```
In [229... # Model creation
model = AgglomerativeClustering(linkage='ward',n_clusters = 3)
```

```
In [267... #fitting model to the selected featurss
model.fit(x_features)
predicted_labels = model.labels_ #predicting the model
print(f'Number of unque values in prdicted labels is {np.unique(predicted_labels).sum()})
```

Number of unque values in prdicted labels is 3

### Dendrogram Visualization

The advantage of Dendrogram is that we don't have to presume any spcific number of cluster like KMean

We can get the cluster by cutting Dentrogram at different level

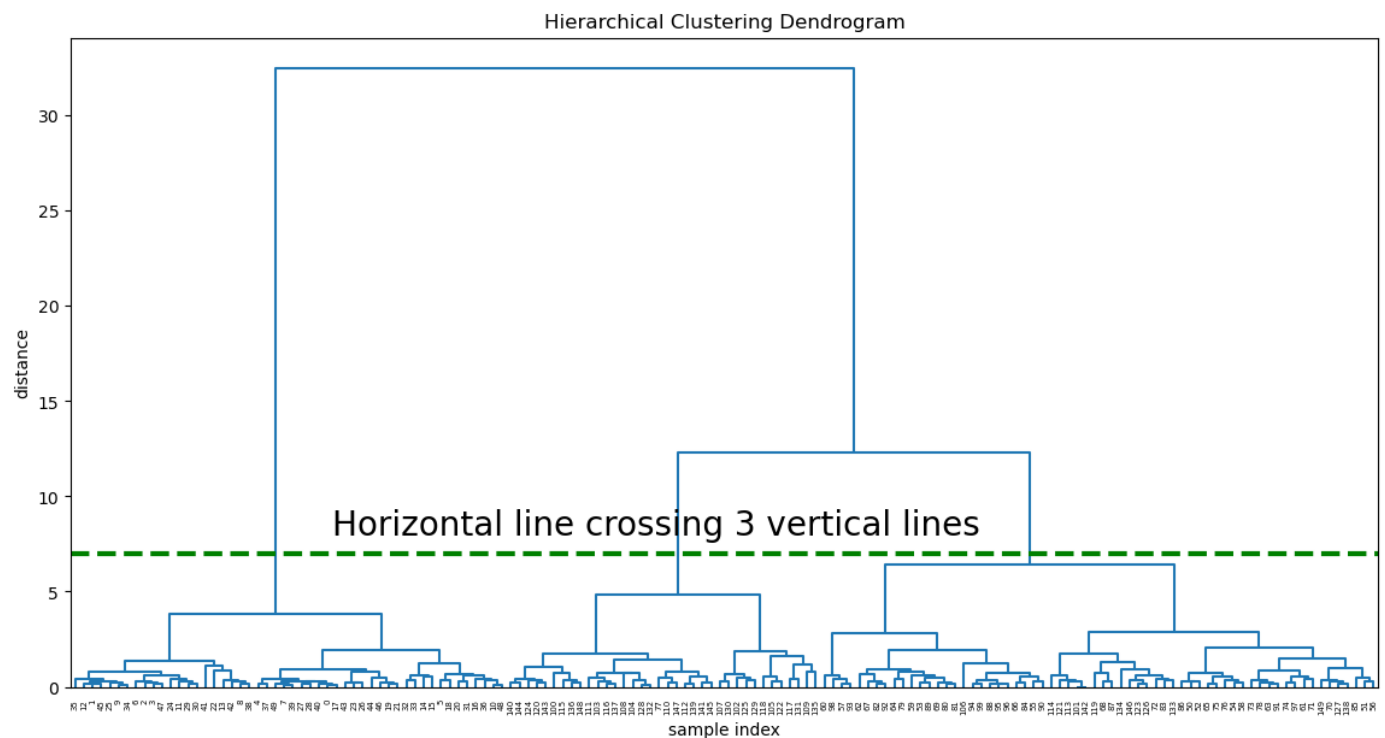
```
In [337... iris_matrix = linkage(x_features,'ward')
plot= plt.figure(figsize = (14,7))
```

```

dendrogram(
    iris_matrix,
    color_threshold=0,
)
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('sample index')
plt.ylabel('distance')
plt.hlines(y=7,xmin=0,xmax=2000,lw=3,linestyle='--',color='g')
plt.text(x=300,y=8,s='Horizontal line crossing 3 vertical lines',fontsize=20)
plt.show()
print_title('Simplifide Hierachical Clustering Dendrogram')
print_section('this plot eliminated the more dense area and shows clean simple visualiza

plot2 = plt.figure(figsize=(14,7))
dendrogram(
    iris_matrix,
    truncate_mode='lastp',
    p=20, #show only the last 20 merged clisters
    leaf_rotation=90, # rotates the x axis labels
    leaf_font_size=12, # font size for x axis
    show_contracted=True #to get a distributin imprssion in trucated branches
)
plt.title('Agglomrative Clustering Dendrogram plot')
plt.xlabel('Clister Size')
plt.ylabel('distance')
plt.hlines(y=7,xmin=0,xmax=2000,lw=3,linestyle='--',color='g')
plt.text(x=30,y=8,s='Horizontal line crossing 3 vertical lines',fontsize=20)
plt.show()

```




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**Simplifide Hierachical Clustering Dendrogram**

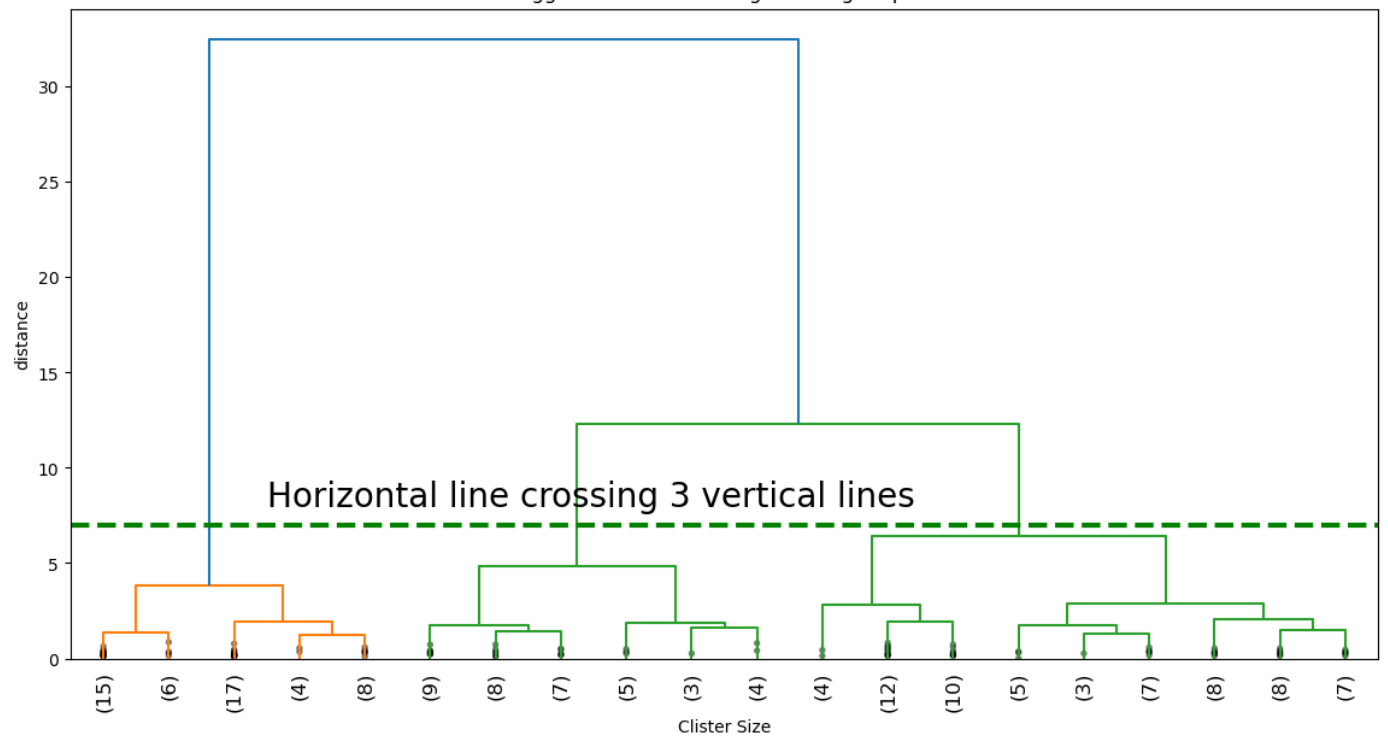
---

this plot eliminated the more dense area and shows clean simple visualization

---



Agglomerative Clustering Dendrogram plot



In [ ]:

In [ ]: