

Hierarchical K-Means

Knowledge Discovery

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1. Convert that data into the numerical values

```

1 data = pd.read_excel("hepatitis_new.xlsx", header=None)
2 data.drop(0, inplace=True, axis=1)
3 data.drop(0, inplace=True, axis=0)
4 data.columns = data.iloc[0]
5 data.drop(1, inplace=True, axis=0)
6 data.columns = [c.replace(' ', '_') for c in data.columns]
7 data = data.replace(to_replace=['no', 'yes'], value=[0, 1])
8 data.CLASS = data.CLASS.replace(to_replace=['Live', 'Die'], value=[0, 1])
9 data = data.replace(to_replace=['?'], value=np.nan)
10 data = data.reset_index()
11 X_temp = data.drop(columns=['CLASS'])
12 X_temp

```

	index	Age	Sex	Steroid	Antivirals	Fatigue	Malaise	Anorexia	Liver_Big	Liver_Firm	Spleen_Palpable	Speiders	Ascites	Varices	Bilirubin	Alk_Phosp
0	2	30	1	0.0	1	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
1	3	50	0	0.0	1	0.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	0.9
2	4	78	0	1.0	1	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7
3	5	31	0	NaN	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7
4	6	34	0	1.0	1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
...
150	152	46	0	1.0	1	0.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	7.6
151	153	44	0	1.0	1	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	0.9
152	154	61	0	0.0	1	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	0.8
153	155	53	1	0.0	1	0.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	1.5
154	156	43	0	1.0	1	0.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	0.0	1.0	1.2

155 rows x 20 columns

```
1 y = data['CLASS'].values  
2 y
```

```
array([0, 0, 0, 0, 0, 0, 1, 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, 0, 0, 0, 1, 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, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,  
       1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1,  
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1,  
       0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0,  
       1], dtype=int64)
```





2. Impute the missing data with the mean values of same attribute in the same class

```
1 X = data.groupby("CLASS").transform(lambda x: x.fillna(x.mean()))
2 X
```

Age	Sex	Steroid	Antivirals	Fatigue	Malaise	Anorexia	Liver_Big	Liver_Firm	Spleen_Palpable	Speiders	Ascites	Varices	Bilirubin	Alk_Phosphate	SGOT
30	1	0.000000	1	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	85.000000	18.0
50	0	0.000000	1	0.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	0.9	135.000000	42.0
78	0	1.000000	1	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7	96.000000	32.0
31	0	0.540984	0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.7	46.000000	52.0
34	0	1.000000	1	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	101.313725	200.0
...
46	0	1.000000	1	0.0	0.0	0.0	1.0	1.0	1.0	0.0	0.0	0.0	7.6	122.375000	242.0
44	0	1.000000	1	0.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.9	126.000000	142.0
61	0	0.000000	1	0.0	0.0	1.0	0.0	0.0	1.0	0.0	1.0	1.0	0.8	75.000000	20.0
53	1	0.000000	1	0.0	1.0	1.0	1.0	1.0	0.0	0.0	1.0	0.0	1.5	81.000000	19.0
43	0	1.000000	1	0.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	1.2	100.000000	19.0

20 columns





3. Hide the class label of the supervised data

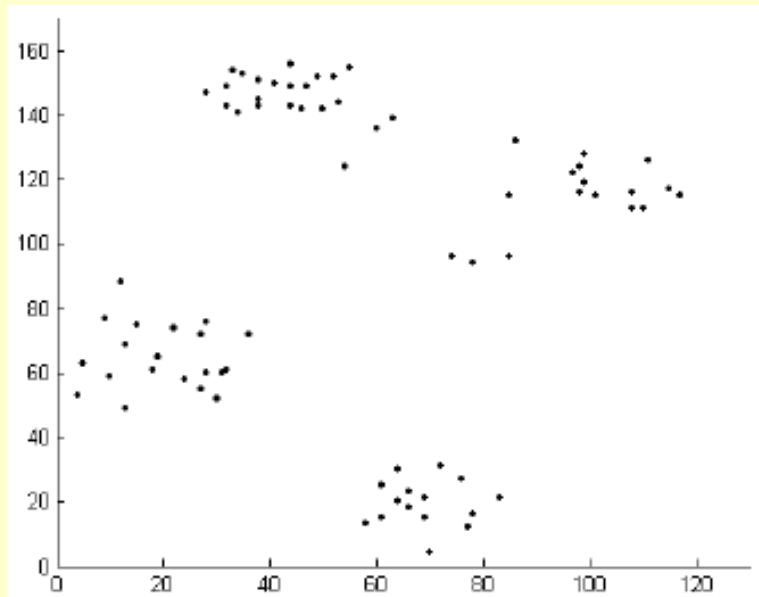
4. Normalize Data

```
1 from sklearn import preprocessing
2 scaler = preprocessing.StandardScaler().fit(X)
3
4 X = scaler.transform(X)
5 X
```

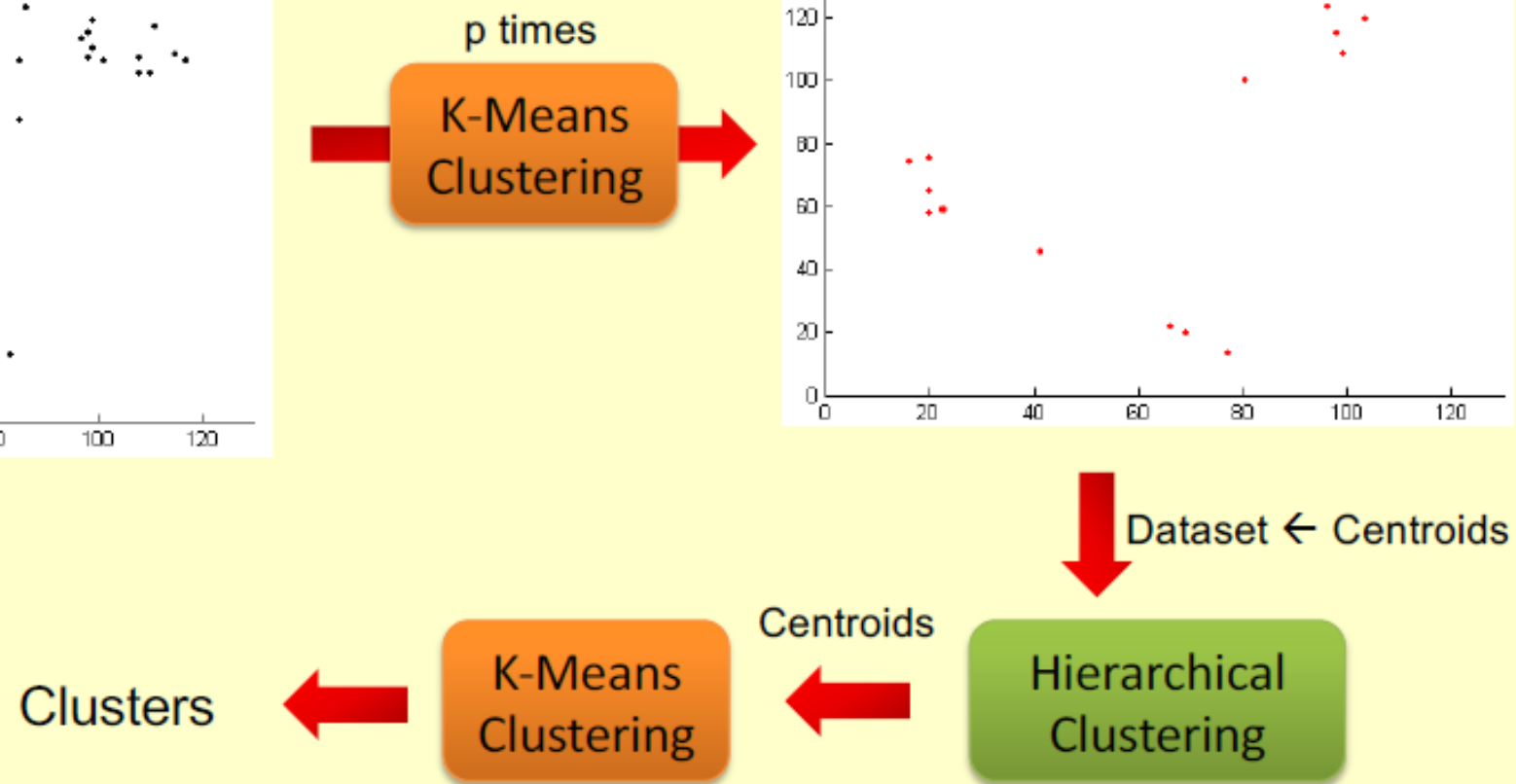
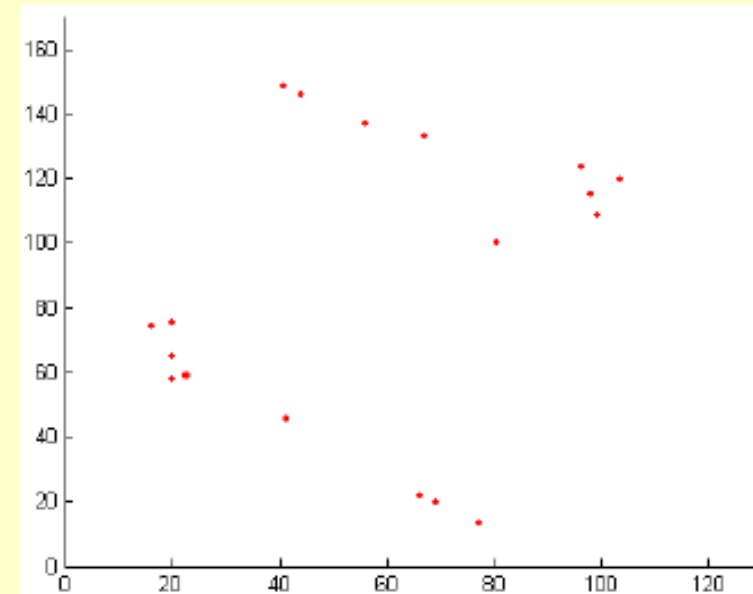
```
array([[ -1.7209121 , -0.89419175,  2.94745653, ...,  0.30720513,
         0.26151157, -0.90748521],
       [-1.69856259,  0.70257923, -0.33927557, ..., -0.48942799,
         0.26151157, -0.90748521],
       [-1.67621309,  2.93805862, -0.33927557, ...,  0.30720513,
         0.26151157, -0.90748521],
       ...,
       [ 1.67621309,  1.58080328, -0.33927557, ...,  0.46653176,
         0.26151157,  1.10194633],
       [ 1.69856259,  0.94209488,  2.94745653, ...,  0.46653176,
        -0.75812043,  1.10194633],
       [ 1.7209121  ,  0.14370939, -0.33927557, ..., -1.1267345 ,
        -1.08753999,  1.10194633]])
```

5. Cluster the data using Hierarchical K-Means into 2 groups

Ruspini Dataset



All centroids from 10 x
K-Means Clustering



5.1 K-Means Random Centroid 10x

```

1 from sklearn.cluster import KMeans
2
3 Cluster_center = []
4 for i in range(1,11):
5     kmeans = KMeans(init="random", n_clusters=2, random_state=i*2).fit(X_scaled)
6     Cluster_center.append(kmeans.cluster_centers_[0])
7     Cluster_center.append(kmeans.cluster_centers_[1])
8     print('==> Loop ke', i, '\n', kmeans.cluster_centers_)
9 #print('==> Cluster Center:\n', Cluster_center)
10 #Cluster_center

```

==> Loop ke 1

```

[[ 0.56036311  0.28016073  0.13879455 -0.21413866  0.32750461 -0.69997079
 -0.71765819 -0.43074567 -0.16076615 -0.39504026 -0.4866123  -0.90514252
 -0.71359843 -0.61387485  0.65168889  0.60233502  0.37742484 -0.82364414
 -0.65116602  0.62698978]

```

Coordinate Centroid for label "0"

```

[[ -0.30819971 -0.1540884  -0.076337  0.11777626 -0.18012753  0.38498393
  0.39471201  0.23691012  0.08842138  0.21727214  0.26763676  0.49782839
  0.39247914  0.33763117 -0.35842889 -0.33128426 -0.20758366  0.45300428
  0.35814131 -0.34484438]]

```

Coordinate Centroid for label "1"

==> Loop ke 2

```

[[ 0.56036311  0.28016073  0.13879455 -0.21413866  0.32750461 -0.69997079
 -0.71765819 -0.43074567 -0.16076615 -0.39504026 -0.4866123  -0.90514252
 -0.71359843 -0.61387485  0.65168889  0.60233502  0.37742484 -0.82364414
 -0.65116602  0.62698978]

```

```

[[ -0.30819971 -0.1540884  -0.076337  0.11777626 -0.18012753  0.38498393
  0.39471201  0.23691012  0.08842138  0.21727214  0.26763676  0.49782839
  0.39247914  0.33763117 -0.35842889 -0.33128426 -0.20758366  0.45300428
  0.35814131 -0.34484438]]

```

==> Loop ke 3

```

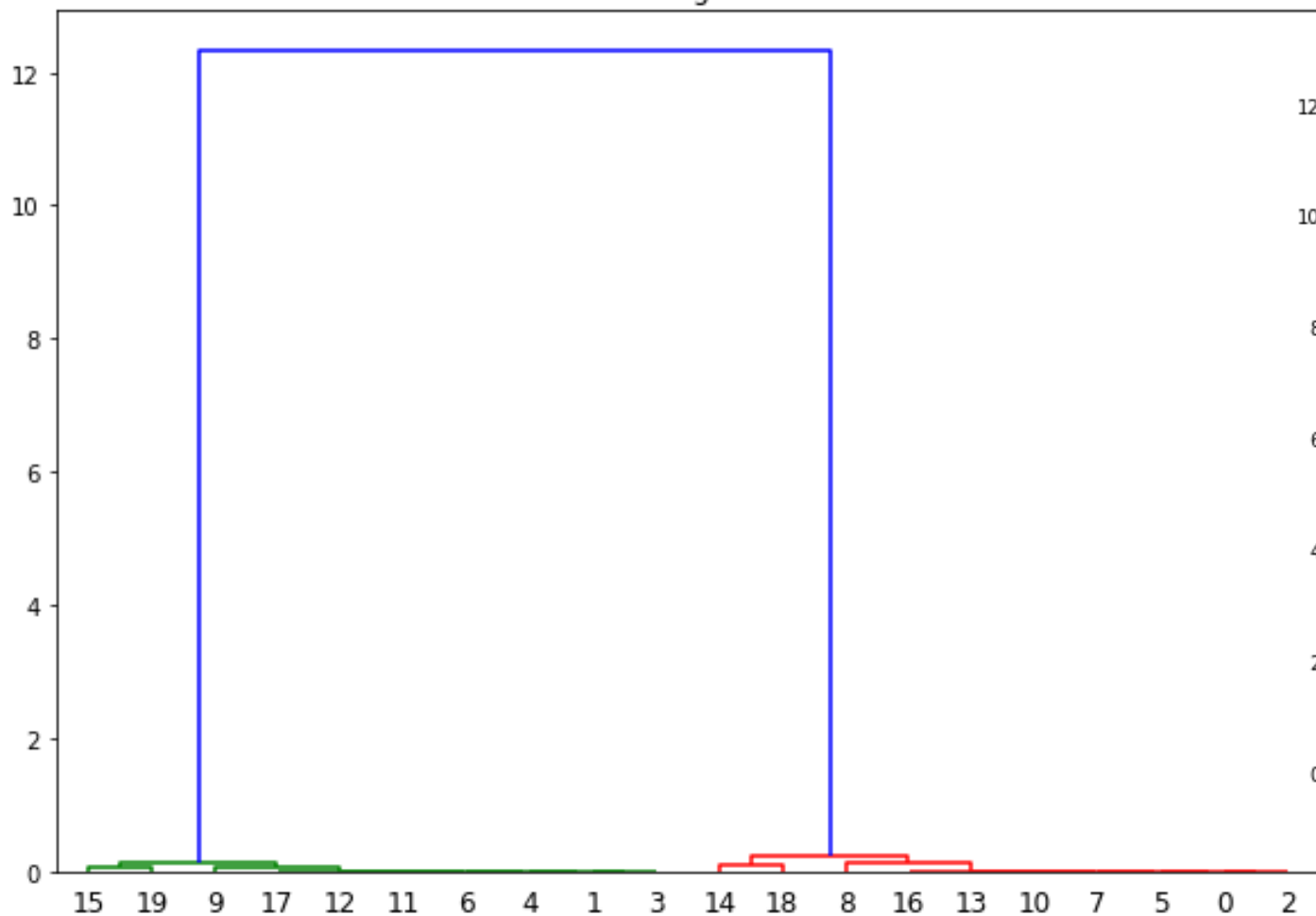
[[ 0.56036311  0.28016073  0.13879455 -0.21413866  0.32750461 -0.69997079
 -0.71765819 -0.43074567 -0.16076615 -0.39504026 -0.4866123  -0.90514252
 -0.71359843 -0.61387485  0.65168889  0.60233502  0.37742484 -0.82364414
 -0.65116602  0.62698978]

```

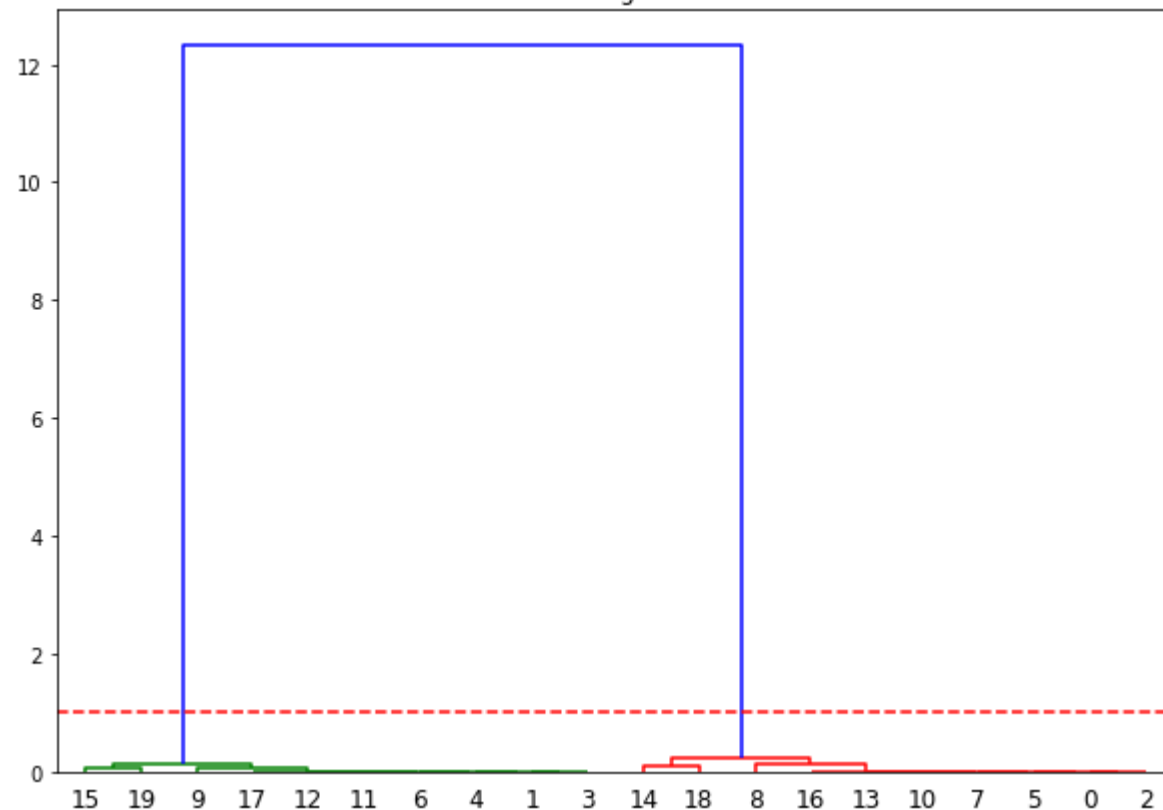
5.2 Dataset for Hierarchical Clustering

```
1 import scipy.cluster.hierarchy as shc
2 import matplotlib.pyplot as plt
3
4 plt.figure(figsize=(10, 7))
5 plt.title("Dendrograms")
6 dend = shc.dendrogram(shc.linkage(Cluster_center, method='ward'))
```

Dendrograms



Dendrograms



5.2 Dataset for Hierarchical Clustering

```
1 from sklearn.cluster import AgglomerativeClustering
2 cluster = AgglomerativeClustering(n_clusters=2, affinity='euclidean', linkage='ward').fit(Cluster_center)
3 cluster
4 print(cluster.n_clusters_)
5 print()
6 print(cluster.labels_)
```

2 → Jumlah Cluster

[0 1 0 1 1 0 1 0 0 1 0 1 1 0 0 1 0 1 0 1] → Cluster Label on Hierarchical Clustering

5.3 Get Centroid from Hierarchical Clustering

Attributes:

`n_clusters_ : int`

The number of clusters found by the algorithm. If `distance_threshold=None`, it will be equal to the given `n_clusters`.

`labels_ : ndarray of shape (n_samples)`

cluster labels for each point

`n_leaves_ : int`

Number of leaves in the hierarchical tree.

`n_connected_components_ : int`

The estimated number of connected components in the graph.

New in version 0.21: `n_connected_components_` was added to replace `n_components_`.

`children_ : array-like of shape (n_samples-1, 2)`

The children of each non-leaf node. Values less than `n_samples` correspond to leaves of the tree which are the original samples. A node `i` greater than or equal to `n_samples` is a non-leaf node and has children `children_[i - n_samples]`. Alternatively at the `i`-th iteration, `children[i][0]` and `children[i][1]` are merged to form node `n_samples + i`.

`distances_ : array-like of shape (n_nodes-1,)`

Distances between nodes in the corresponding place in `children_`. Only computed if `distance_threshold` is used or `compute_distances` is set to `True`.

Can't get Attribute Centroid from Hierarchical Clustering



5.4 Get Centroid from K-Mens

```
1 kmeans = KMeans(n_clusters=2, random_state=i).fit(Cluster_center)
2
3 print(kmeans.cluster_centers_)
4 kmeans.labels_
```

```
[[ 0.56652476  0.28573604  0.14649937 -0.20747346  0.34266922 -0.69982402
 -0.71199092 -0.43437078 -0.16317859 -0.39206989 -0.49043005 -0.90737302
 -0.71786276 -0.61766937  0.65560109  0.59289951  0.37976395 -0.82625723
 -0.64532423  0.63267863]
 [-0.3097843  -0.15631477 -0.08016724  0.11354743 -0.18710447  0.38280409
  0.3894681   0.23744665  0.08915713  0.21441243  0.26810261  0.49617575
  0.39248788  0.33770243 -0.3585674  -0.32445582 -0.20768599  0.45181693
  0.35305676 -0.34599604]]
```

Coordinate
Centroid for label
"0"

Coordinate
Centroid for label
"1"

5.5 Predict Real Data with New Centroid (K-Means)

```
1 y_kmeans = kmeans.predict(X_scaled)
2 print(1-y_kmeans)
3
4 print()
5 print(y)
```

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

Label Hierarchical K-Means

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

Real Label

6. Cluster Analysis (Accuracy)



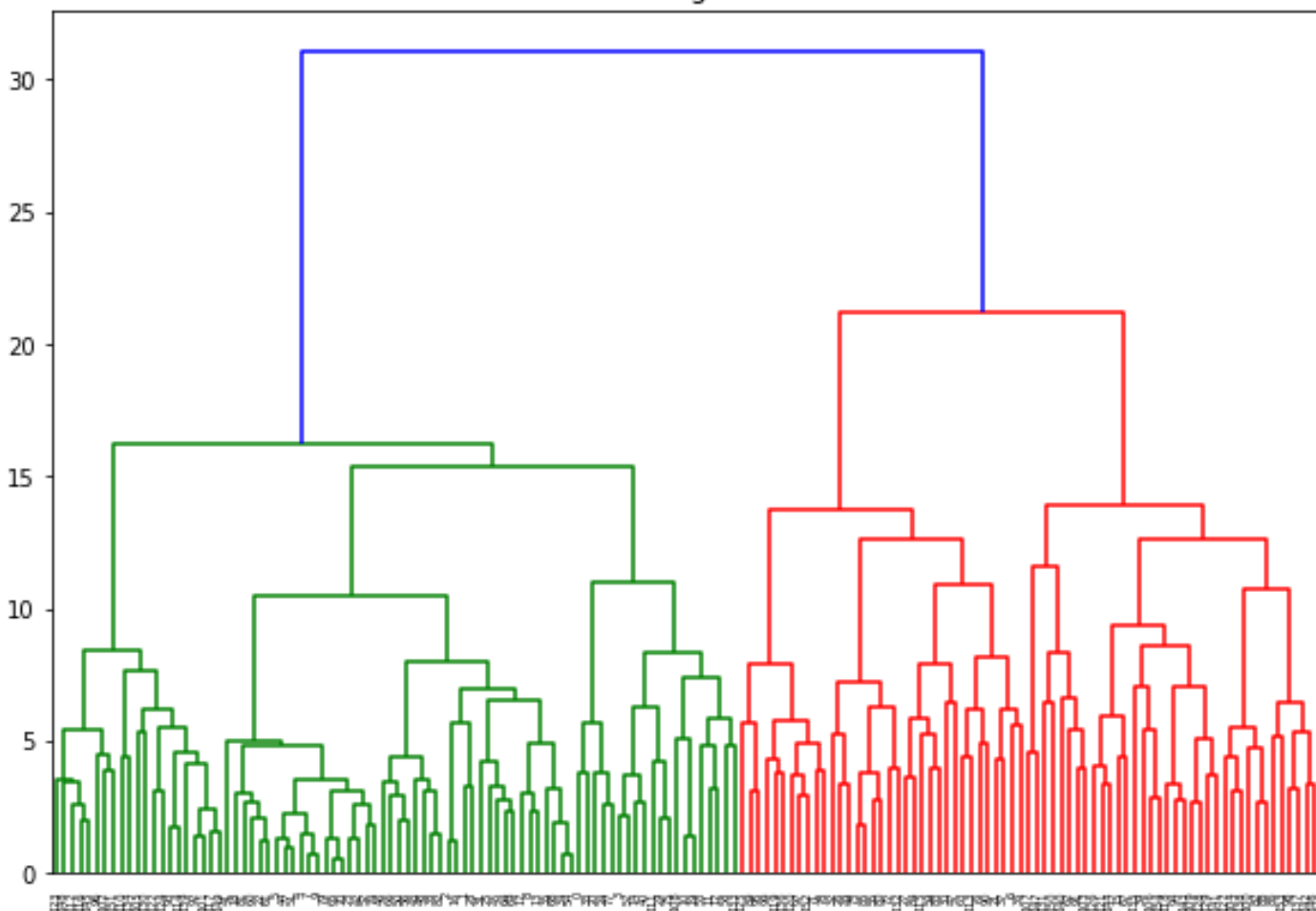
```
1 # Accuracy
2 from sklearn.metrics import accuracy_score
3 acc = accuracy_score(y, 1-y_kmeans)
4 acc*100
```

80.0 → Accuracy Hierarchical K-Means = 80%

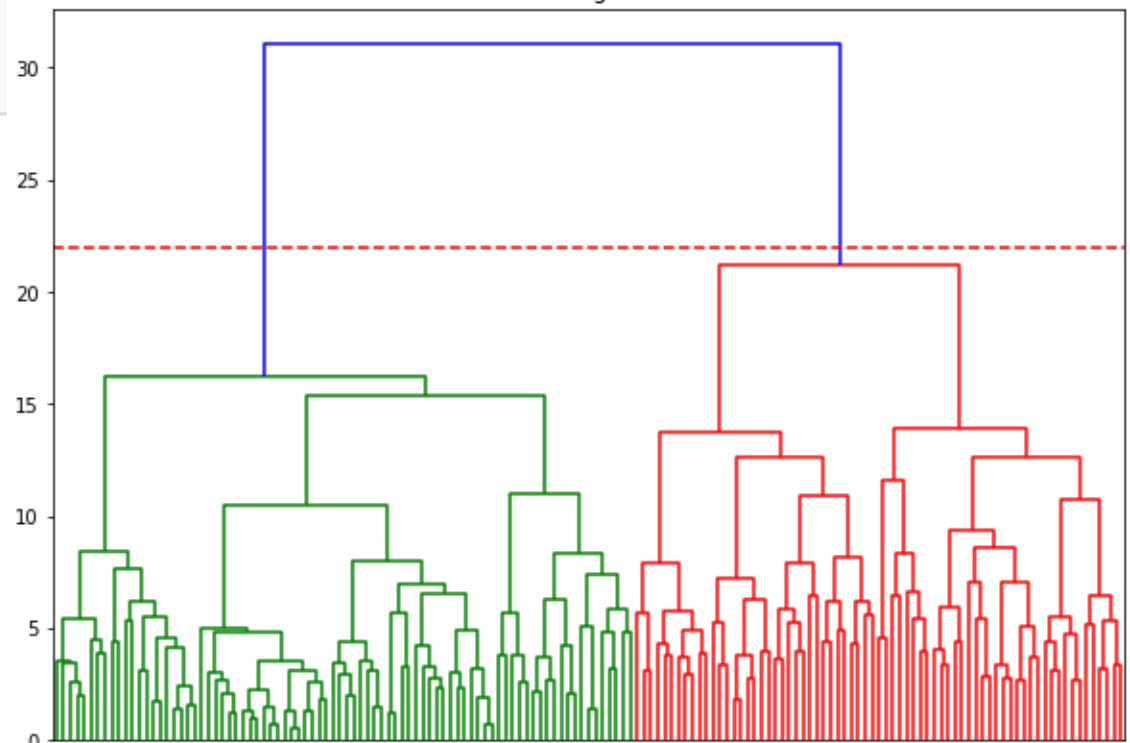
7. Compare to Hierarchical Clustering

```
1 import scipy.cluster.hierarchy as shc
2 import matplotlib.pyplot as plt
3
4 plt.figure(figsize=(10, 7))
5 plt.title("Dendrograms")
6 dend = shc.dendrogram(shc.linkage(X_scaled, method='ward'))
```

Dendrograms



Dendrograms



7.1 Cluster Analysis (Accuracy Hierarchical Clustering)

```
1 from sklearn.cluster import AgglomerativeClustering
2 cluster = AgglomerativeClustering(n_clusters=2, affinity='euclidean', linkage='ward').fit(X_scaled)
3 cluster.labels_
```

```
array([[1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
        1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1,
        1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1,
        1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0,
        0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0,
        1, 1, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 1, 0,
        0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0,
        0], dtype=int64)
```

→ Label Hierarchical Clustering

```
1 # Accuracy
2 from sklearn.metrics import accuracy_score
3 acc = accuracy_score(y, 1-cluster.labels_)
4 acc*100
```

69.6774193548387 → Accuracy Hierarchical Clustering = 69%

Kesimpulan



Pada Hierarchical K-Means, Accuracy yang dihasilkan 80% sedangkan jika menggunakan Hierarchical Clustering saja, Accuracy-nya hanya 69%