Tugas Kecil 1: Eksplorasi scikit-learn untuk Clustering pada Jupyter Notebook

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Overview

1. Load Package Python

In [1]:

```
# Untuk analisis dan mengolah data
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
from matplotlib.patches import Ellipse

# Untuk pembelajaran
from sklearn import metrics
from sklearn import datasets, linear_model, metrics
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
from sklearn.mixture import GaussianMixture
from sklearn.datasets import make_blobs

from pyclustering.cluster.kmedoids import kmedoids
from pyclustering.cluster.bang import bang

from mst_clustering import MSTClustering

# Untuk menyimpan/membaca model/hipotesis
import joblib
import dill

# Lain-lain
from copy import deepcopy
```

2. Pembacaan Dataset Training

2.1 Dataset Iris

In [2]:

```
# load iris dataset
iris_dataset = datasets.load_iris()

print("Number of instances:", len(iris_dataset['data']))
print("Feature names:", iris_dataset['feature_names'])
print()

# print a few samples
print("Sample (10):")
iris_dataset['data'][:10]
```

```
Number of instances: 150
Feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (c
m)', 'petal width (cm)']

Sample (10):
```

Out[2]:

```
array([[ 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]])
```

2.2 Dataset Play Tennis

In [3]:

```
# load tenis dataset
tenis_dataset = pd.read_csv("tennis.csv")
tenis_dataset
```

Out[3]:

	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
6	overcast	cool	normal	True	yes
7	sunny	mild	high	False	no
8	sunny	cool	normal	False	yes
9	rainy	mild	normal	False	yes
10	sunny	mild	normal	True	yes
11	overcast	mild	high	True	yes
12	overcast	hot	normal	False	yes
13	rainy	mild	high	True	no

Dataset play tennis memiliki *instance* dengan nilai atribut berupa *string* dan *boolean* yang dapat diuraikan sebagai berikut.
Atribut 1 - Outlook (string): {0: rainy, 1: overcast, 2: sunny}
Atribut 2 - Temp (string): {0: cool, 1: mild, 2: hot}
Atribut 3 - Humidity (string): {0: normal, 1: high}
Atribut 4 - Windy (boolean): {0: False, 1: True}

Oleh sebab itu, diperlukan *preprocessing* pada *dataset play tennis* menjadi data yang numerik.

In [4]:

```
# Preprocess Play Tennis Dataset (convert to numeric data)
# make backup data
tenis_data_instances = deepcopy(tenis_dataset)
# delete class attribute
del tenis_data_instances['play']

# change attribute value to numeric
tenis_data_instances.outlook.replace(to_replace=['rainy', 'overcast', 'sunny'],value=[0, 1,
tenis_data_instances.temp.replace(to_replace=['cool', 'mild', 'hot'],value=[0, 1, 2], inpla
tenis_data_instances.humidity.replace(to_replace=['normal', 'high'],value=[0, 1], inplace=T
tenis_data_instances.windy.replace(to_replace=[False, True],value=[0, 1], inplace=True)

print("Preprocessed dataset:")
print(tenis_data_instances)
print()

# convert dataframe to list
tenis_data_list = [[0, 0, 0, 0] for i in range(0,14)]
for i in range(0,14):
    tenis_data_list[i][0] = tenis_data_instances.outlook[i]
    tenis_data_list[i][1] = tenis_data_instances.temp[i]
    tenis_data_list[i][2] = tenis_data_instances.humidity[i]
    tenis_data_list[i][3] = tenis_data_instances.windy[i]

tenis_data_nparray = np.array(tenis_data_list)
print("Converted dataset:")
print(tenis_data_nparray)
```

```
Preprocessed dataset:
    outlook  temp  humidity  windy
0         2     2         1      0
1         2     2         1      1
2         1     2         1      0
3         0     1         1      0
4         0     0         0      0
5         0     0         0      1
6         1     0         0      1
7         2     1         1      0
8         2     0         0      0
9         0     1         0      0
10        2     1         0      1
11        1     1         1      1
12        1     2         0      0
13        0     1         1      1

Converted dataset:
[[2 2 1 0]
 [2 2 1 1]
 [1 2 1 0]
 [0 1 1 0]
 [0 0 0 0]
 [0 0 0 1]
 [1 0 0 1]
 [2 1 1 0]
 [2 0 0 0]
 [0 1 0 0]
 [2 1 0 1]
 [1 1 1 1]
```

```
 [1 2 0 0]
 [0 1 1 1]]
```

3. Clustering

3.1 Clustering Dataset Iris

3.1.1 K-Means

In [5]:

```
# fungsi untuk plot hasil clustering
play_tennis_attributes = ['outlook {0: rainy, 1: overcast, 2: sunny}', 'temp {0: cool, 1: m
                                  'humidity {0: normal, 1: high}', 'windy {0: False, 1: Tru
def setLabelAndTitle(i, j, is_tennis=False):
    if(is_tennis):
        plt.title('Play Tennis Dataset Clustering Result - '
                      + play_tennis_attributes[i] + ' ' + play_tennis_attributes[j])
        plt.xlabel(play_tennis_attributes[i])
        plt.ylabel(play_tennis_attributes[j])
    else:
        plt.title('Iris Dataset Clustering Result - '
                      + iris_dataset['feature_names'][i] + ' ' + iris_dataset['feature_name
        plt.xlabel(iris_dataset['feature_names'][i])
        plt.ylabel(iris_dataset['feature_names'][j])

def plotClusteringResult(clustering_result, with_centroid, is_tennis=False):
    for i in range(0, 3):
        for j in range(i+1, 4):
            setLabelAndTitle(i, j, is_tennis)
            plt.scatter(x[clustering_result == 0, i], x[clustering_result == 0, j], s = 100
            plt.scatter(x[clustering_result == 1, i], x[clustering_result == 1, j], s = 100
            if(not is_tennis):
                plt.scatter(x[clustering_result == 2, i], x[clustering_result == 2, j], s =

            if (with_centroid):
                plt.scatter(kmeans.cluster_centers_[:, i], kmeans.cluster_centers_[:,j],
                            s = 100, c = 'yellow', label = 'Centroids')
            plt.legend()
            plt.show()
```

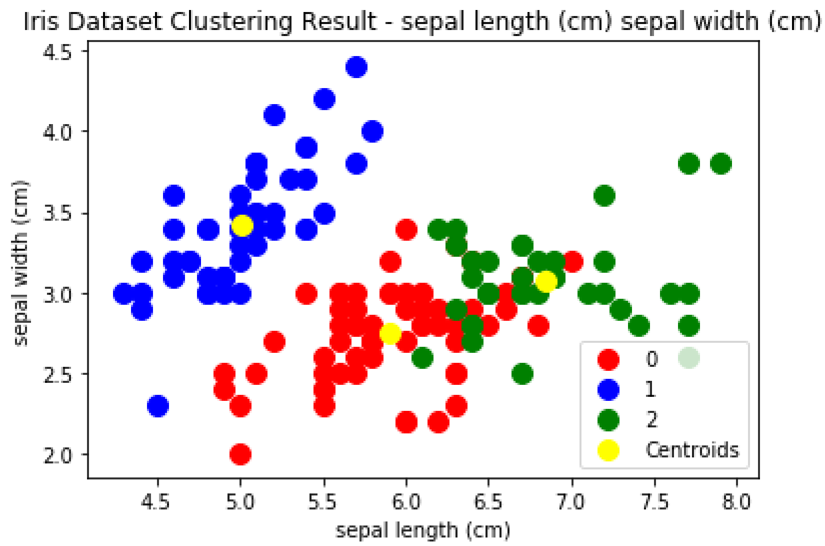
Keterangan parameter penting yang bisa digunakan:

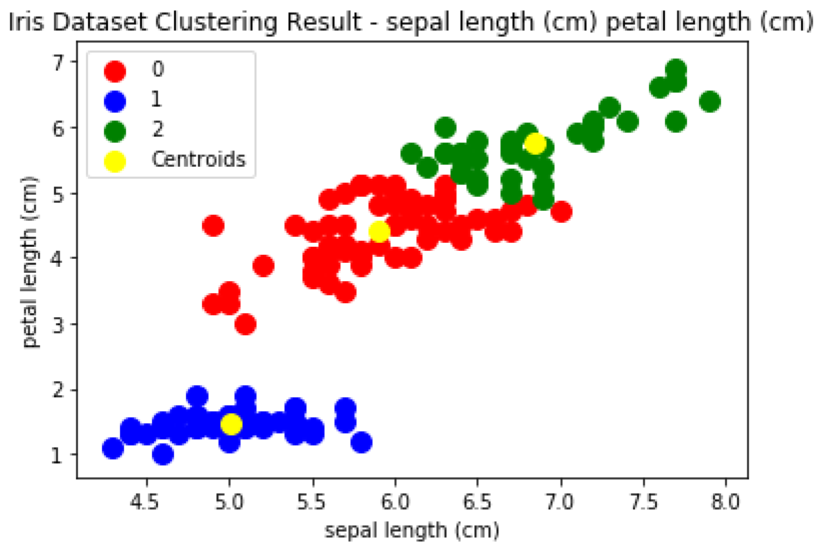
- **n_clusters** : jumlah cluster yang diinginkan; nilai default=8
- **init** : cara menginisialisasi centroid awal (seed); nilai default='k-means++'
  nilai-nilai: **ditentukan manual, random, k-means++** (inisialisasi centroid dengan 'cerdas' untuk mempercepat konvergen, berdasarakan Arthur, D. and Vassilvitskii, S. "k-means++: the advantages of careful seeding". ACM-SIAM symposium on Discrete algorithms. 2007)
- **n_init** : jumlah pengulangan clustering k-means yang dilakukan (dengan seed yang berbeda) untuk memaksimalkan hasil clustering (squared error paling minimum)
- **max_iter** : jumlah iterasi maksimum; nilai default=300
- **tol** : toleransi terhadap squared error untuk menentukan konvergensi; nilai default=0.0001

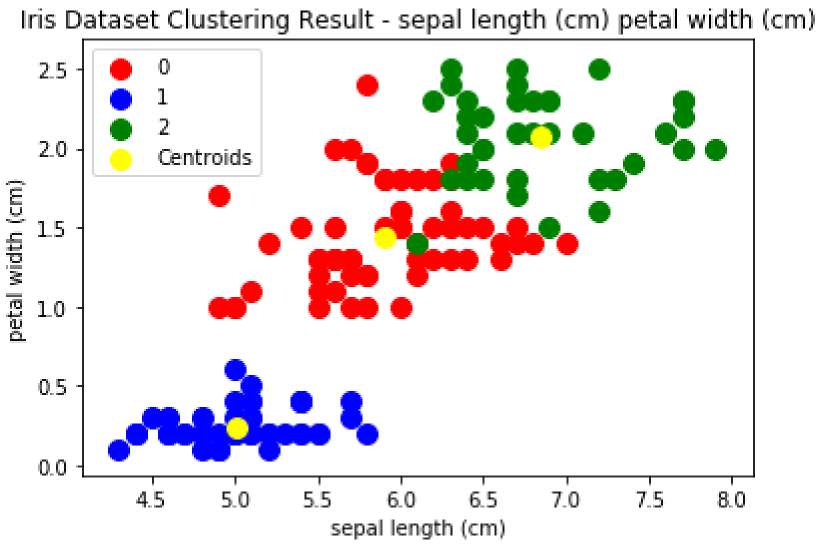
In [6]:

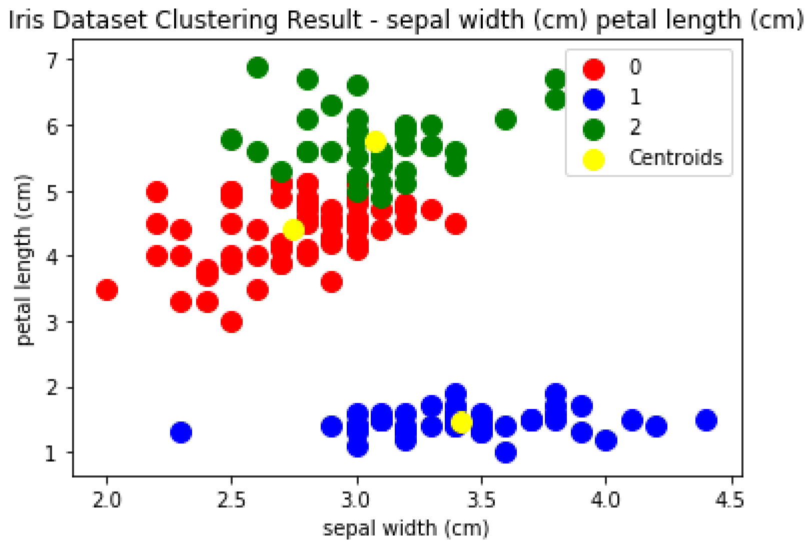
```
# K-Means
x = iris_dataset['data']
kmeans = KMeans(n_clusters=3)
kmeans.fit(x)
clustering_result = kmeans.fit_predict(x)
print("Clustering result:")
print(clustering_result)

#Plotting the centroids of the clusters
plotClusteringResult(clustering_result, 1)
```

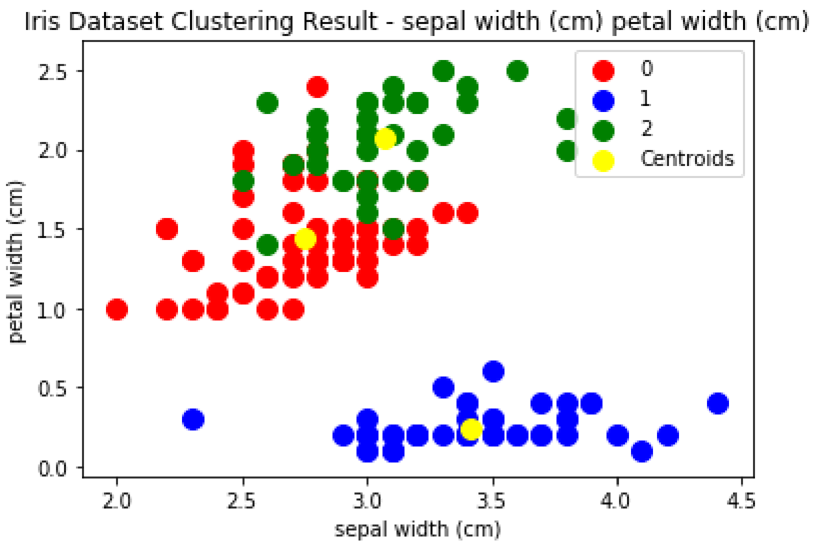
```
Clustering result:
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 2 2 2 2 0 2 2 2 2
 2 2 0 0 2 2 2 2 0 2 0 2 0 2 2 0 0 2 2 2 2 2 0 2 2 2 2 0 2 2 2 0 2 2 2 0 2
 2 0]
```

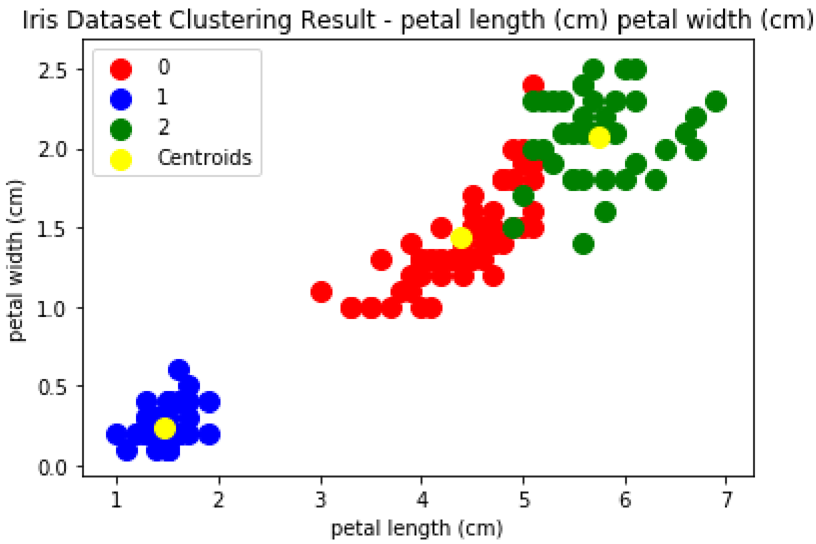





Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
0
1
2
Centroids
petal width (cm)
sepal length (cm)


Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
0
1
2
Centroids
petal length (cm)
sepal width (cm)


Iris Dataset Clustering Result - sepal width (cm) petal width (cm)
0
1
2
Centroids
petal width (cm)
sepal width (cm)



3.1.2 Agglomerative Clustering

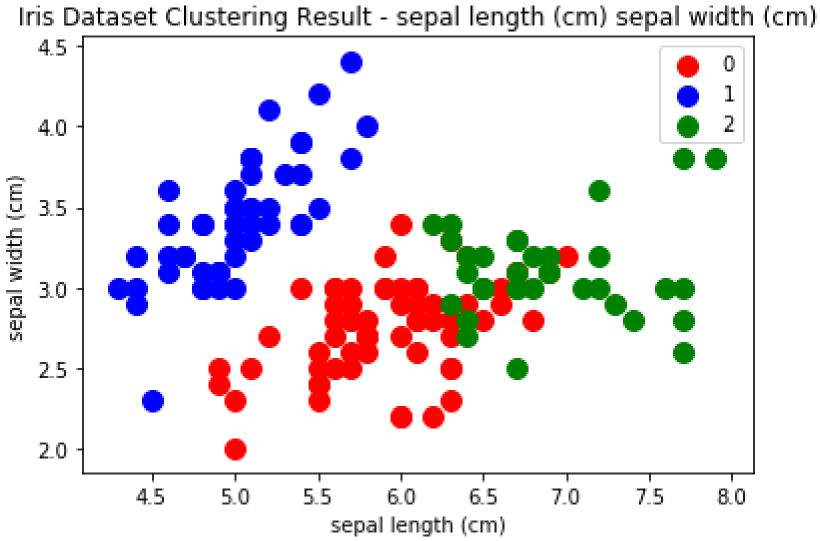
Keterangan parameter penting yang dapat digunakan:

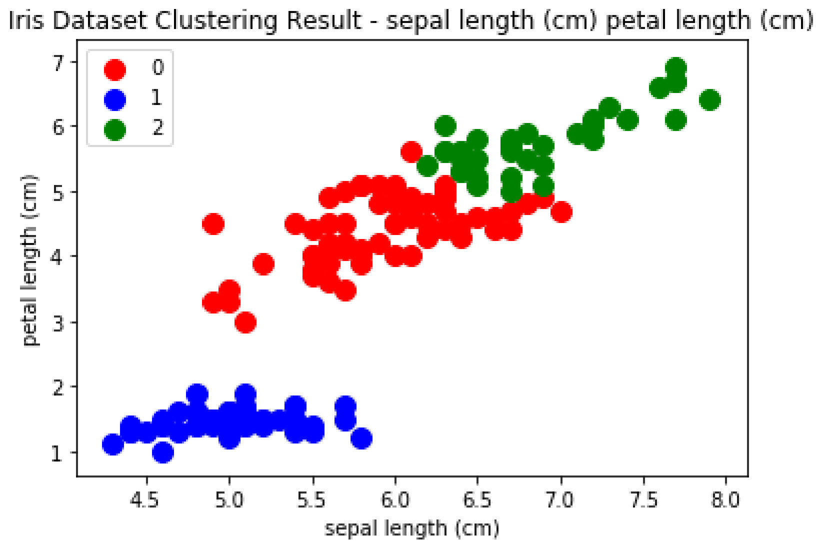
- **n_clusters** : jumlah cluster yang diinginkan
- **affinity** : metode yang digunakan untuk menghitung jarak linkage; default = euclidean
- **linkage** : jenis linkage yang digunakan **(ward/complete/single/average)**; default = 'ward' untuk jenis linkage ward, jenis affinity yang dapat dipilih hanya euclidean

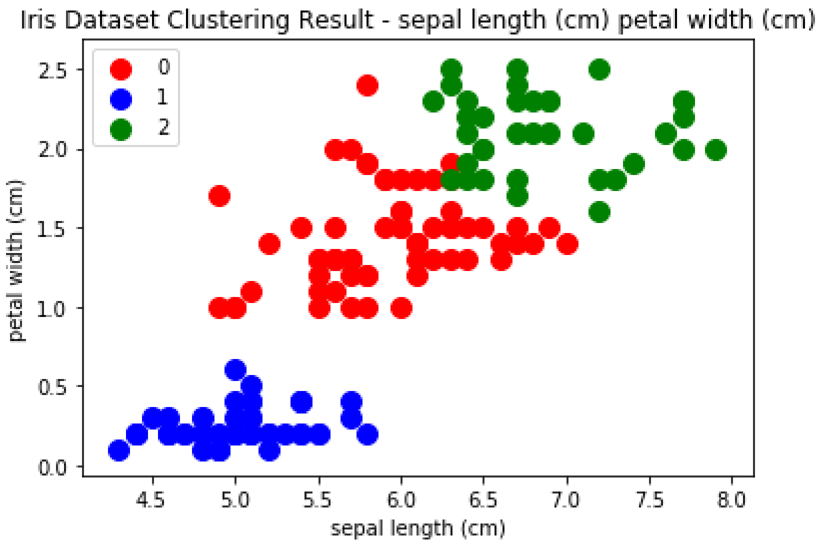
In [7]:

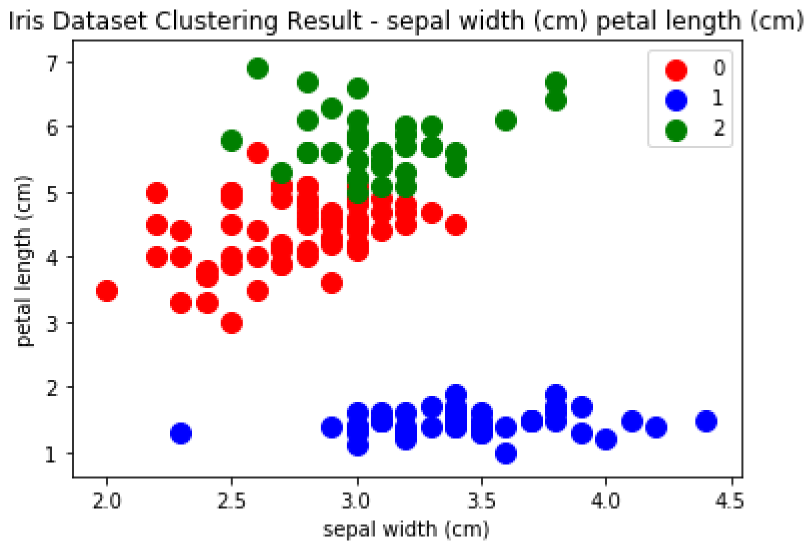
```
agglomerative = AgglomerativeClustering(n_clusters = 3)
agglomerative.fit(x)
clustering_result = agglomerative.fit_predict(x)
print("Clustering result:")
print(clustering_result)

plotClusteringResult(clustering_result, 0)
```

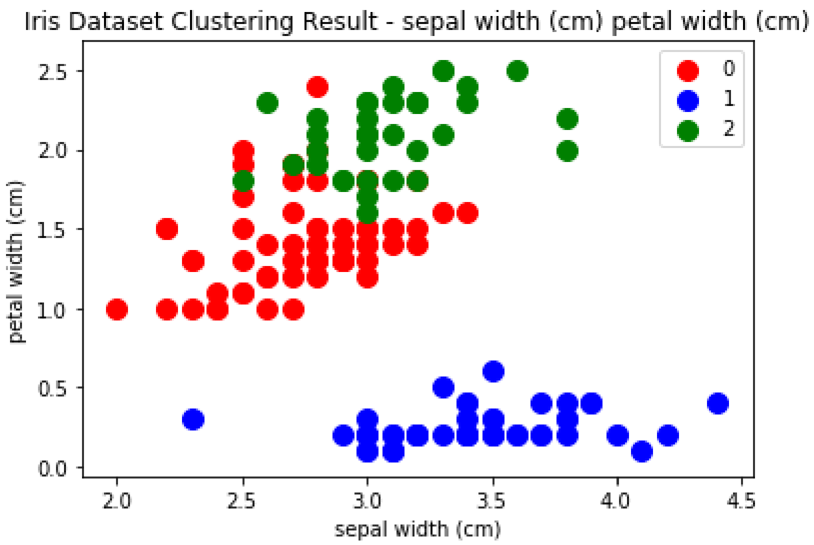
```
Clustering result:
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 2 2 2 2 0 2 2 2 2
 2 2 0 0 2 2 2 2 0 2 0 2 0 2 2 0 0 2 2 2 2 2 0 0 2 2 2 0 2 2 2 0 2 2 2 0 2
 2 0]
```

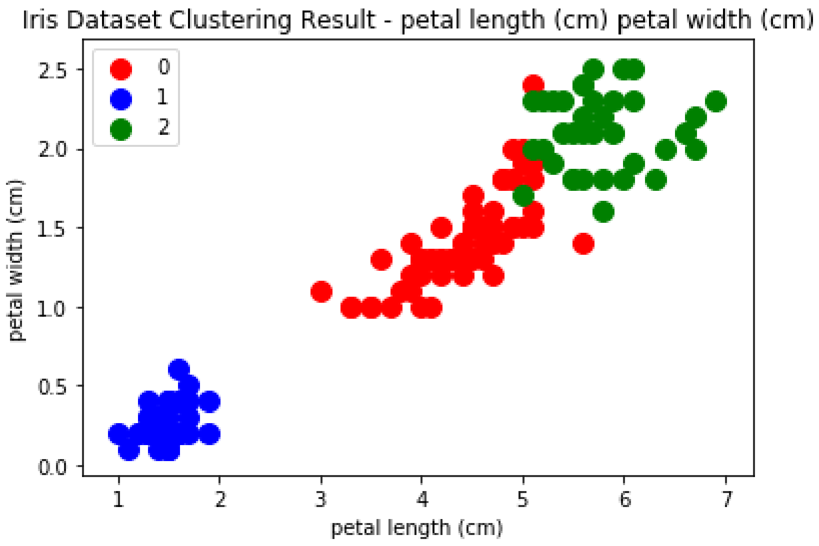





Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
0
1
2
petal width (cm)
sepal length (cm)


Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
0
1
2
petal length (cm)
sepal width (cm)


Iris Dataset Clustering Result - sepal width (cm) petal width (cm)
0
1
2
petal width (cm)
sepal width (cm)



3.1.3 DBSCAN

Keterangan parameter penting yang dapat digunakan:

- **eps** : epsilon
- **min_samples** : minimum poin sampel
- **metric** : cara menghitung jarak antar poin sampel

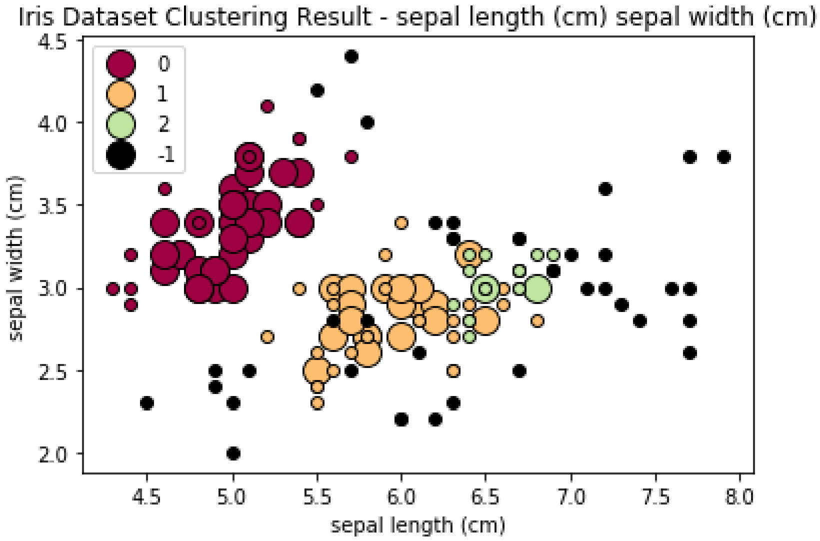
In [8]:

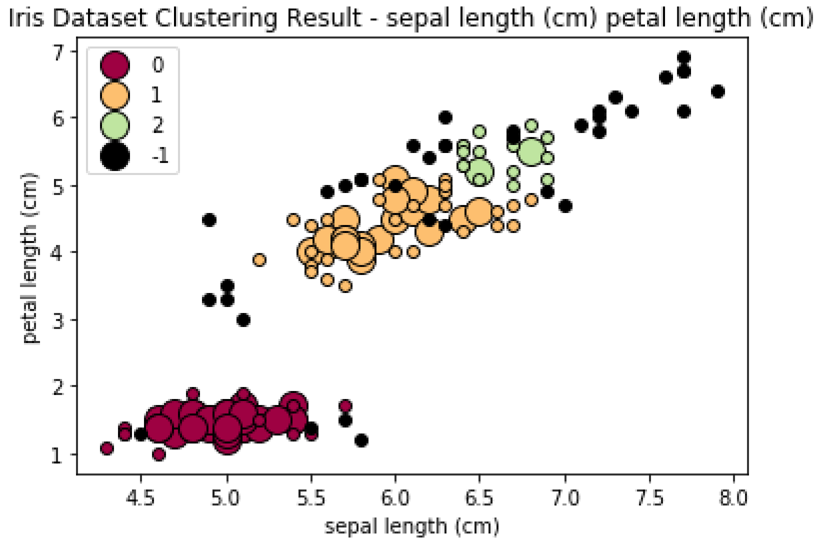
```
# Plot result
# modified from http://scikit-learn.org/stable/auto_examples/cluster/plot_dbscan.html
def plotDBSCAN(i, j, is_tennis=False):
    setLabelAndTitle(i, j, is_tennis)
    unique_labels = set(labels)
    colors = [plt.cm.Spectral(each)
              for each in np.linspace(0, 1, len(unique_labels))]

    for k, col in zip(unique_labels, colors):
        if k == -1:
            # Black used for noise.
            col = [0, 0, 0, 1]

        class_member_mask = (labels == k)

        # Core point
        xy = x[class_member_mask & core_samples_mask]
        plt.plot(xy[:, i], xy[:, j], 'o', markerfacecolor=tuple(col),
                 markeredgecolor='k', markersize=14, label=str(k))
        # Not core point
        xy = x[class_member_mask & ~core_samples_mask]
        plt.plot(xy[:, i], xy[:, j], 'o', markerfacecolor=tuple(col),
                 markeredgecolor='k', markersize=6)

    plt.legend()
    plt.show()
```

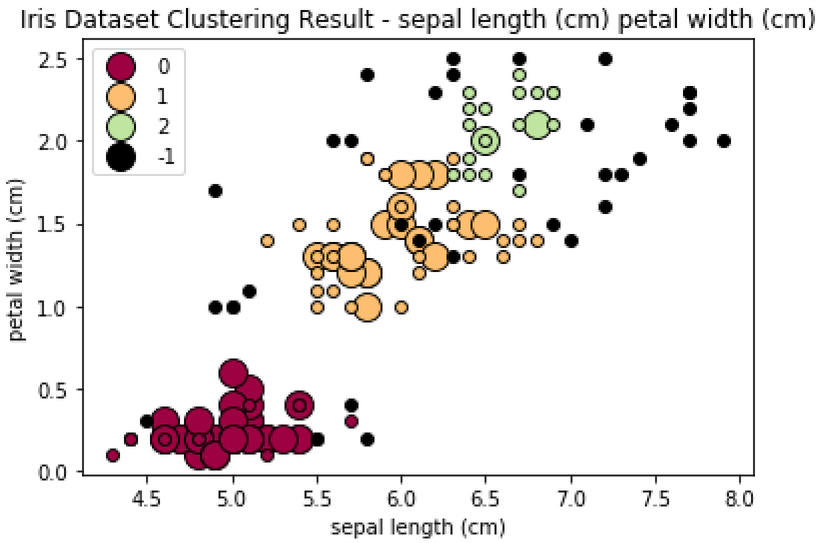
In [9]:

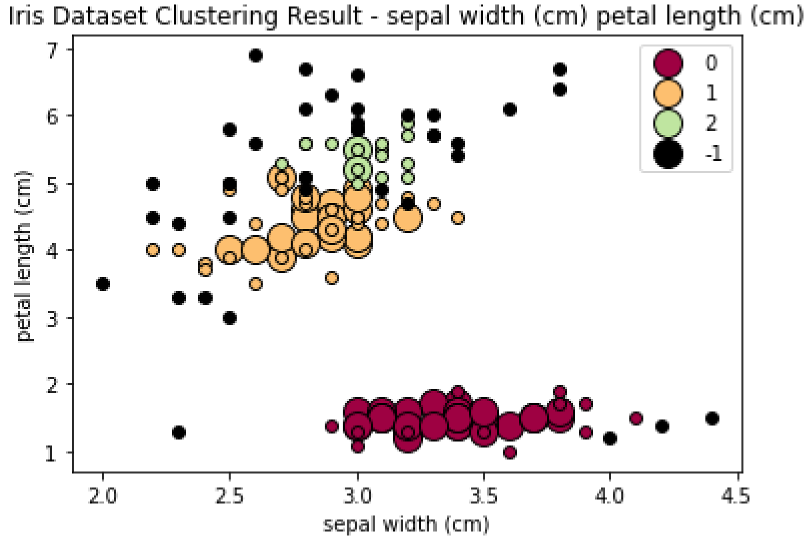
```
# Compute DBSCAN
dbscan = DBSCAN(eps=0.5, min_samples=12)
db = dbscan.fit(x)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_

# Number of clusters in labels
n_clusters = len(set(labels)) - (1 if -1 in labels else 0)

print("eps = 0.5; min_samples = 12")
print("Number of clusters:", n_clusters)
print("Clustering result:")
print("black(-1): outliers")
print(labels)
for i in range(0, 3):
    for j in range(i+1, 4):
        plotDBSCAN(i, j)

db = DBSCAN(eps=0.5, min_samples=13).fit(x)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
print("eps = 0.5; min_samples = 13")
print("Number of clusters:", n_clusters)
print("Clustering result:")
print("black(-1): outliers")
print(labels)
for i in range(0, 3):
    for j in range(i+1, 4):
        plotDBSCAN(i, j)

db = DBSCAN(eps=0.55, min_samples=17).fit(x)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
print("eps = 0.55; min_samples = 17")
print("Number of clusters:", n_clusters)
print("Clustering result:")
print("black(-1): outliers")
print(labels)
for i in range(0, 3):
    for j in range(i+1, 4):
        plotDBSCAN(i, j)
```

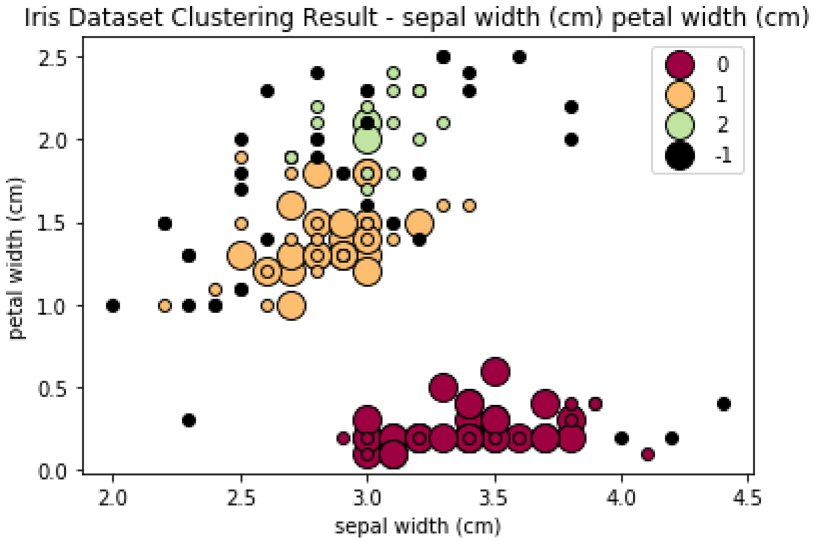
```
eps = 0.5; min_samples = 12
Number of clusters: 3
Clustering result:
black(-1): outliers
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 -1 -1  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0  0
 -1  1 -1  1  1  1  1 -1  1  1 -1  1  1  1  1  1  1  1 -1  1  1  1  1  1  1
  1  1  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 -1  2  2 -1 -1 -1 -1 -1  2  2  2 -1 -1  2  2 -1 -1 -1  2 -1 -1  1  2
 -1  1  1  2 -1 -1 -1  2  1 -1 -1 -1  2  1  2  2  2  1  2 -1  2  1  2 -1  1]
```

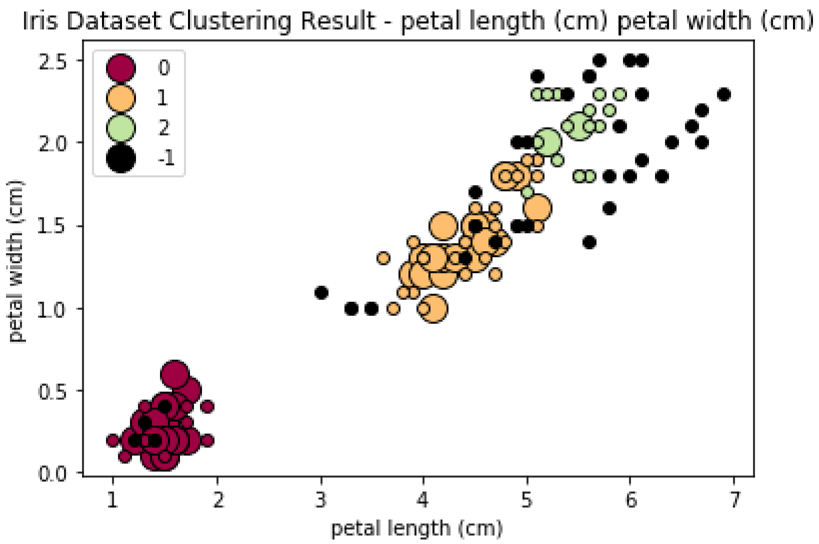

Iris Dataset Clustering Result - sepal length (cm) sepal width (cm)
sepal width (cm)
sepal length (cm)
0
1
2
-1


Iris Dataset Clustering Result - sepal length (cm) petal length (cm)
petal length (cm)
sepal length (cm)
0
1
2
-1


Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
petal width (cm)
sepal length (cm)
0
1
2
-1

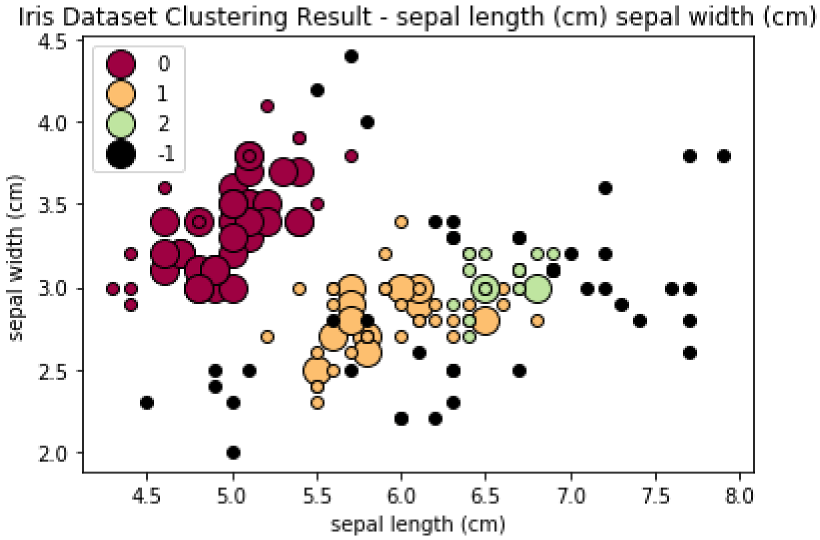


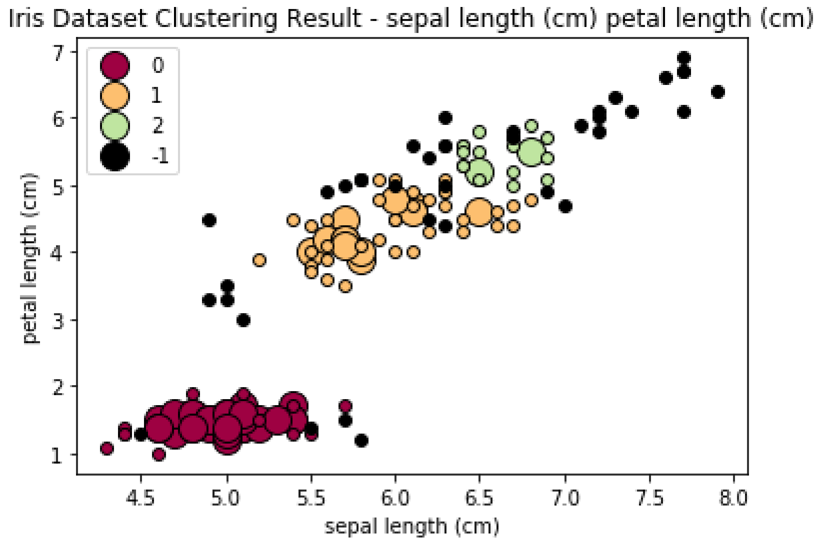


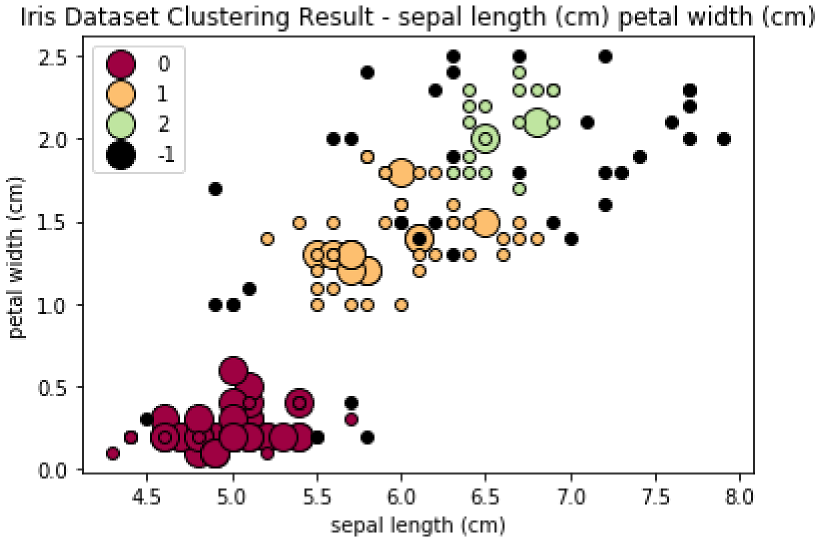


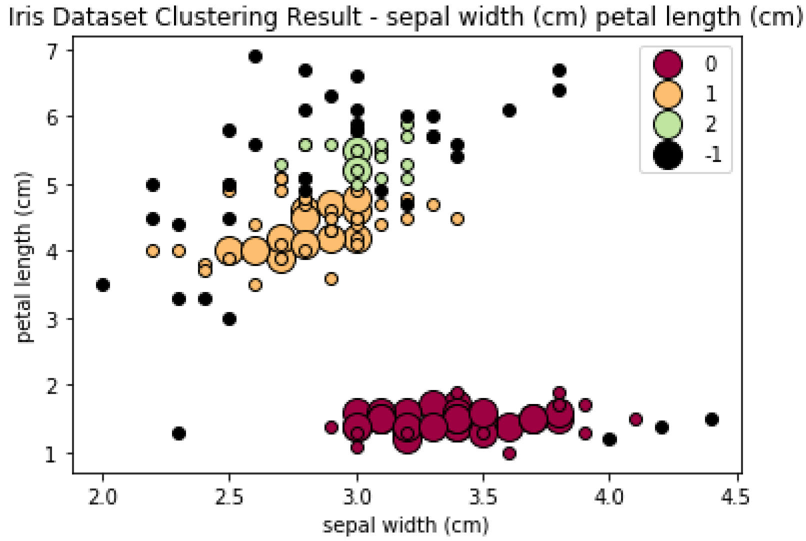

```
eps = 0.5; min_samples = 13
Number of clusters: 3
Clustering result:
black(-1): outliers
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0 -1 -1  0  0  0  0  0  0  0  0
0
  0  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0
```

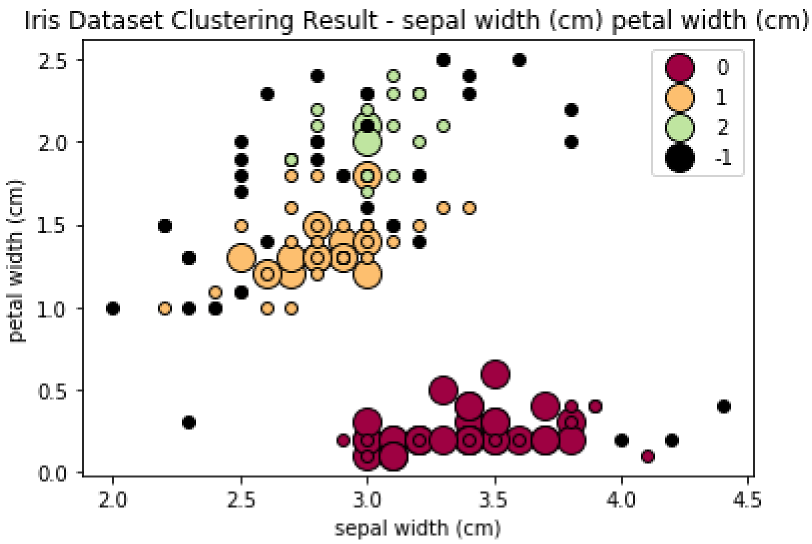
```
0
 -1  1 -1  1  1  1  1 -1  1  1 -1  1  1  1  1  1  1  1 -1  1  1  1  1  1
1
  1  1  2  1  1  1  1  1  1  1  1  1 -1  1  1  1  1  1 -1  1  1  1  1 -1
1
 -1  1 -1  2  2 -1 -1 -1 -1 -1  2  2  2 -1 -1  2  2 -1 -1 -1  2 -1 -1  1
2
 -1  1  1  2 -1 -1 -1  2  1 -1 -1 -1  2  1  2  2  2  1  2 -1  2 -1  2 -1
1]
```

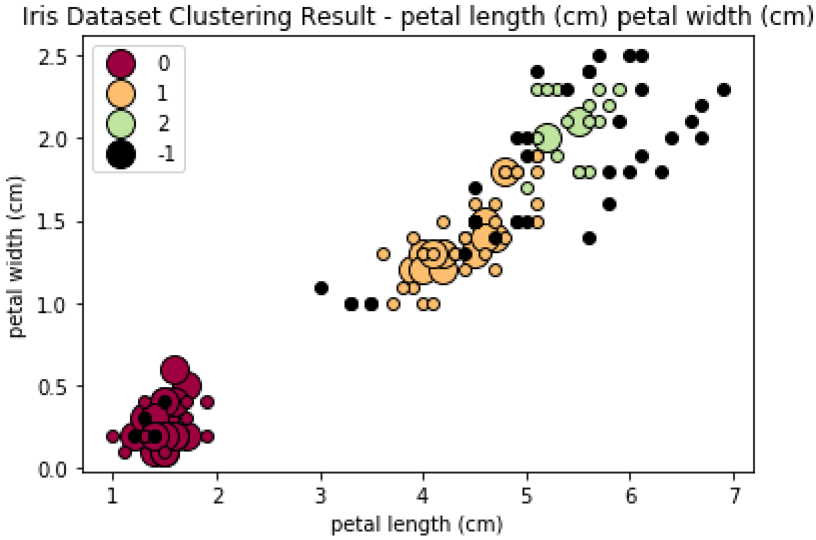




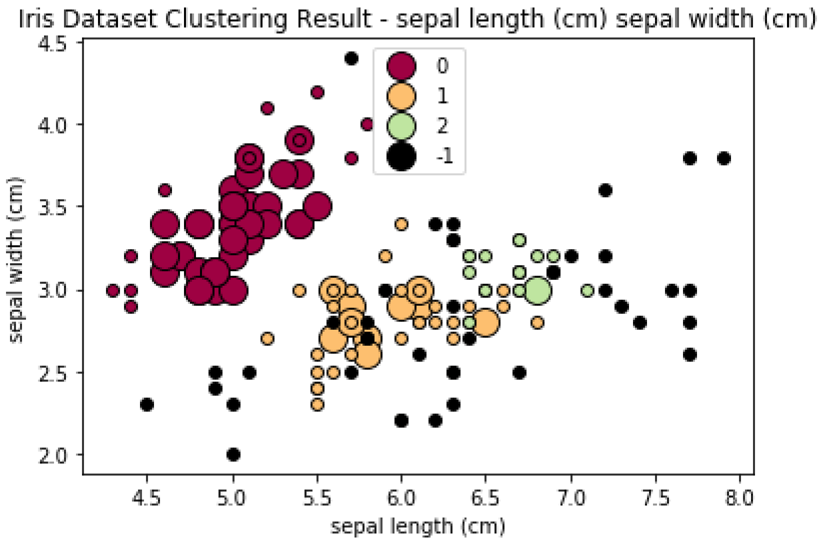

Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
petal width (cm)
sepal length (cm)
0
1
2
-1
0.0
0.5
1.0
1.5
2.0
2.5
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0

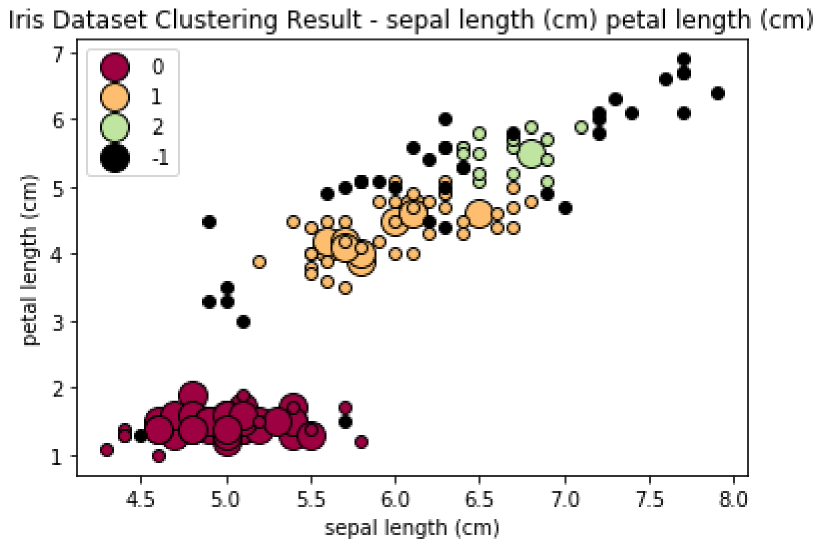

Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
petal length (cm)
sepal width (cm)
0
1
2
-1
1
2
3
4
5
6
7
2.0
2.5
3.0
3.5
4.0
4.5

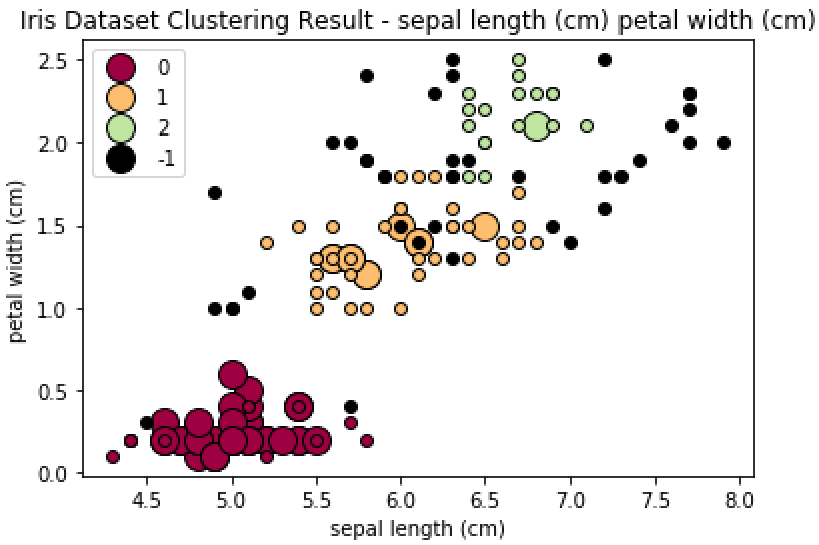

Iris Dataset Clustering Result - sepal width (cm) petal width (cm)
petal width (cm)
sepal width (cm)
0
1
2
-1
0.0
0.5
1.0
1.5
2.0
2.5
2.0
2.5
3.0
3.5
4.0
4.5

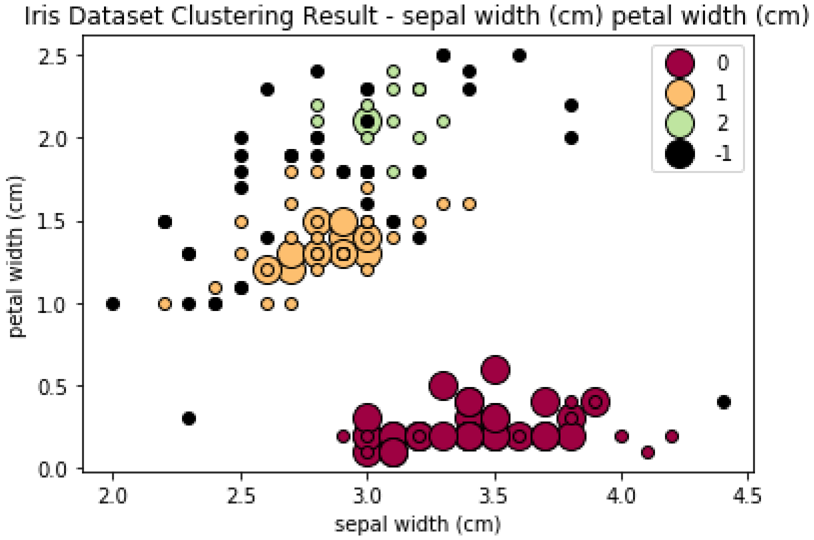


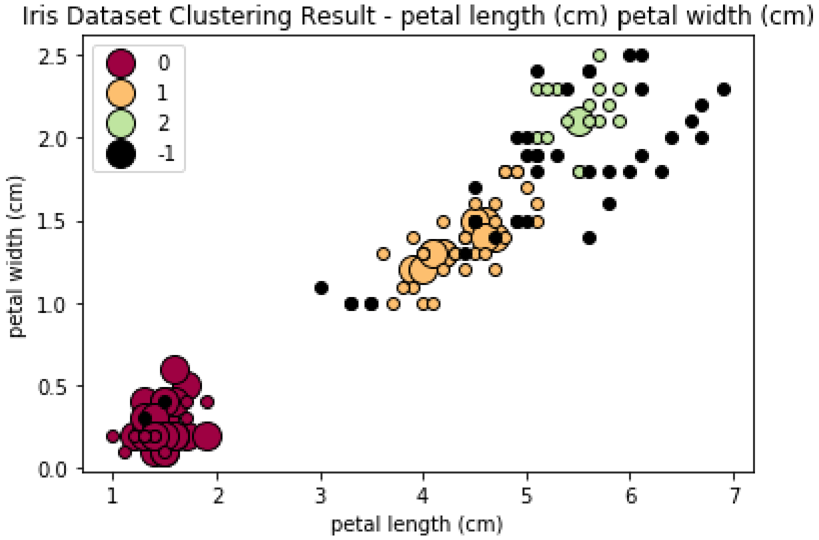

```
eps = 0.55; min_samples = 17
Number of clusters: 3
Clustering result:
black(-1): outliers
[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0  0  0
  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 -1  0  0  0  0  0  0  0  0
 -1  1 -1  1  1  1  1 -1  1  1 -1  1  1  1  1  1  1  1 -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
 -1 -1  2 -1  2 -1 -1 -1 -1 -1  2 -1  2 -1 -1  2  2 -1 -1 -1  2 -1 -1  1  2
 -1  1  1  2 -1 -1 -1  2  1 -1 -1 -1  2  1  2  2  2 -1  2  2  2 -1  2 -1 -1]
```




Iris Dataset Clustering Result - sepal length (cm) petal length (cm)
0
1
2
-1
petal length (cm)
sepal length (cm)


Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
0
1
2
-1
petal width (cm)
sepal length (cm)





3.1.4 Gaussian Mixture

Keterangan parameter penting yang dapat digunakan:

- **n_components** : jumlah komponen mixture
- **covariance_type** : jenis kovariansi (full(default)/tied/diag/spherical)
- **tol** : threshold konvergensi batas bawah average gain

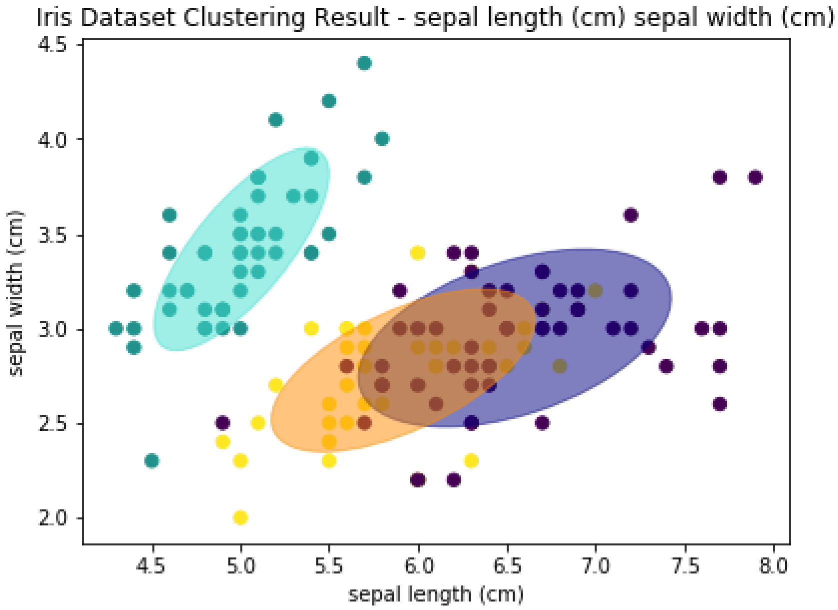
In [10]:

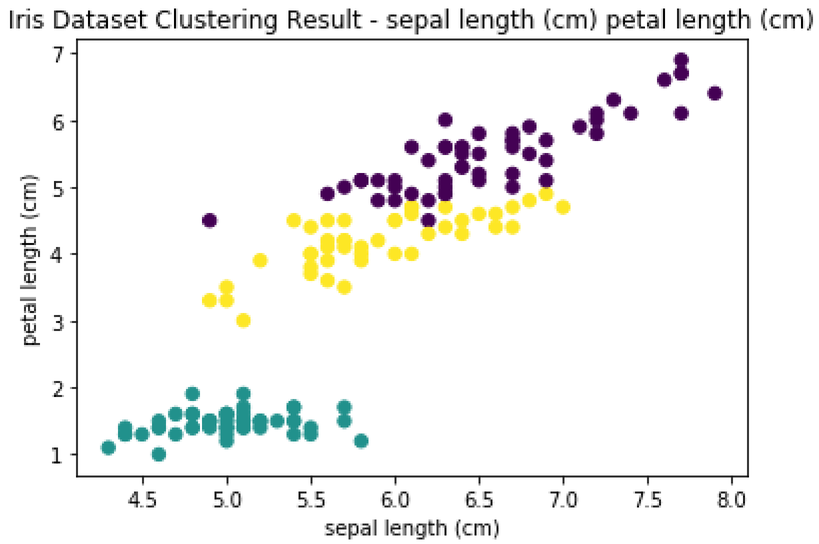
```
# plot function
# modified from http://scikit-learn.org/stable/auto_examples/mixture/plot_gmm_covariances.h
colors = ['navy', 'turquoise', 'darkorange']
def make_ellipses(gmm, n_components, ax, i, j):
    for n, color in enumerate(colors):
        covariances = gmm.covariances_[n][:n_components-1, :n_components-1]
        v, w = np.linalg.eigh(covariances)
        u = w[0] / np.linalg.norm(w[0])
        angle = np.arctan2(u[1], u[0])
        angle = 180 * angle / np.pi  # convert to degrees
        v = 2. * np.sqrt(2.) * np.sqrt(v)
        ell = mpl.patches.Ellipse(gmm.means_[n, :n_components-1], v[0], v[1],
                                  180 + angle, color=color)
        ell.set_clip_box(ax.bbox)
        ell.set_alpha(0.5)
        ax.add_artist(ell)
```

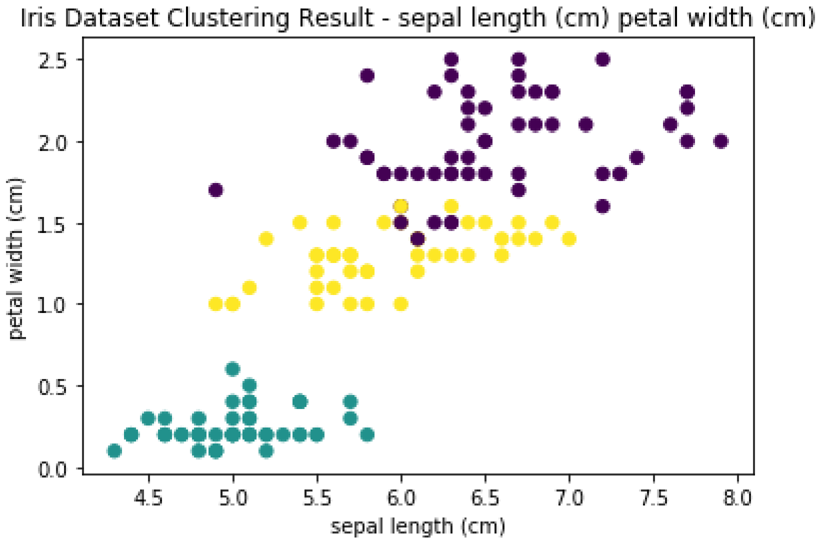
In [11]:

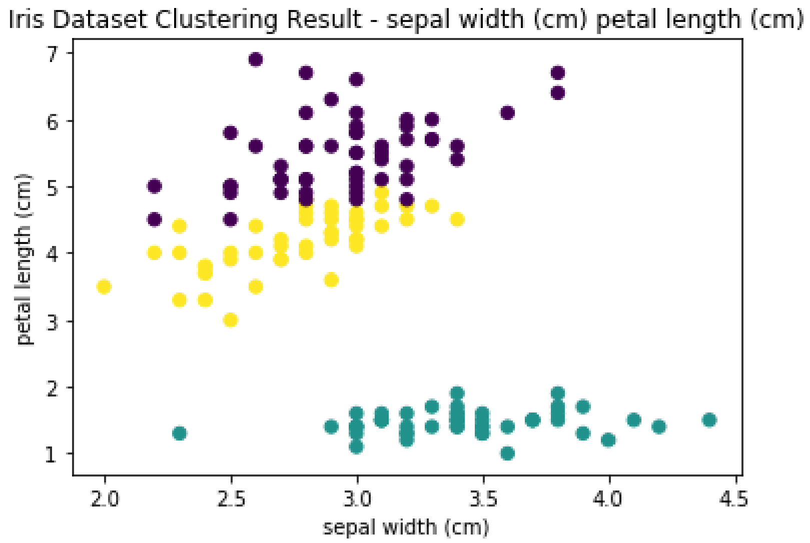
```
gmm = GaussianMixture(n_components=3)
gmm.fit(x)
labels = gmm.predict(x)
print("Clustering result:")
print(labels)

plt.figure(figsize=(5, 8))
plt.subplots_adjust(bottom=.01, top=0.95, hspace=.15, wspace=.05,
                    left=.01, right=.99)

h = plt.subplot(2, 1, 1)
make_ellipses(gmm, 3, h, i, j)
for i in range(0, 3):
    for j in range(i+1, 4):
        setLabelAndTitle(i, j)
        plt.legend(scatterpoints=1, loc='lower right', prop=dict(size=12))
        plt.scatter(x[:, i], x[:, j], c=labels, s=40, cmap='viridis');
        plt.show()
```

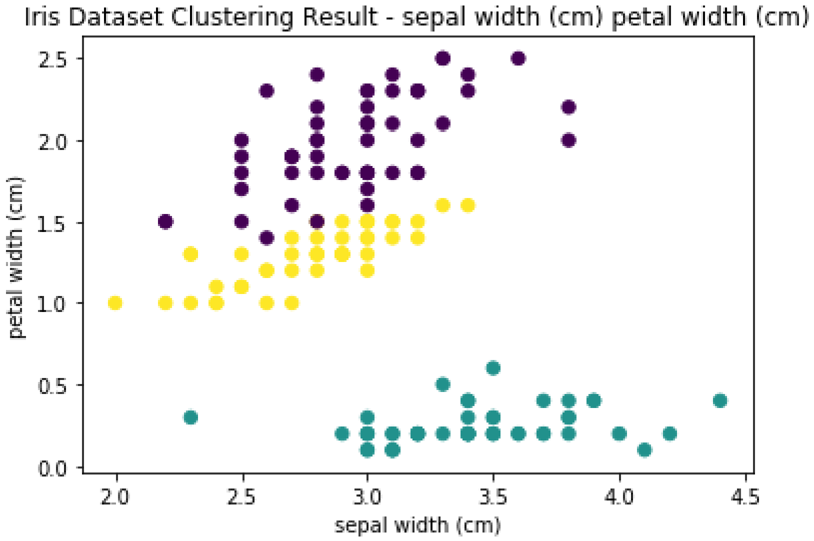
```
Clustering result:
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 2 0 2 0 2
 2 2 2 0 2 2 2 2 2 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0]
```

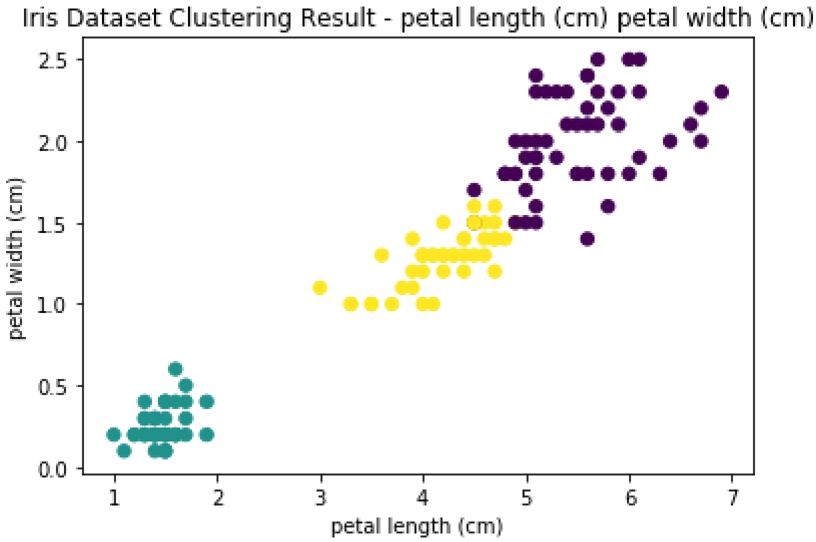



Iris Dataset Clustering Result - sepal length (cm) petal length (cm)
petal length (cm)
sepal length (cm)
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
1
2
3
4
5
6
7


Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
petal width (cm)
sepal length (cm)
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
0.0
0.5
1.0
1.5
2.0
2.5


Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
petal length (cm)
sepal width (cm)
2.0
2.5
3.0
3.5
4.0
4.5
1
2
3
4
5
6
7





3.1.5 K-Medoids

Library yang digunakan untuk *clustering* dengan k-medoids adalah **pyclustering**.

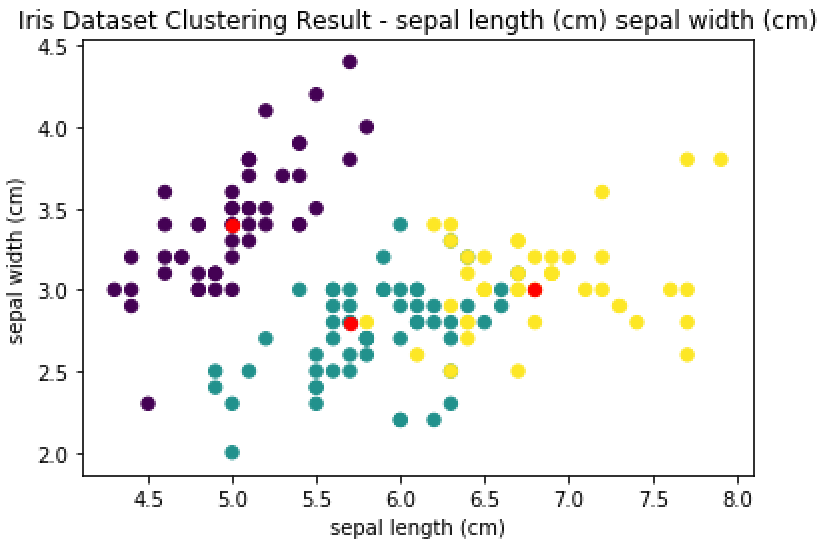
Keterangan parameter penting yang dapat digunakan: (selain data)

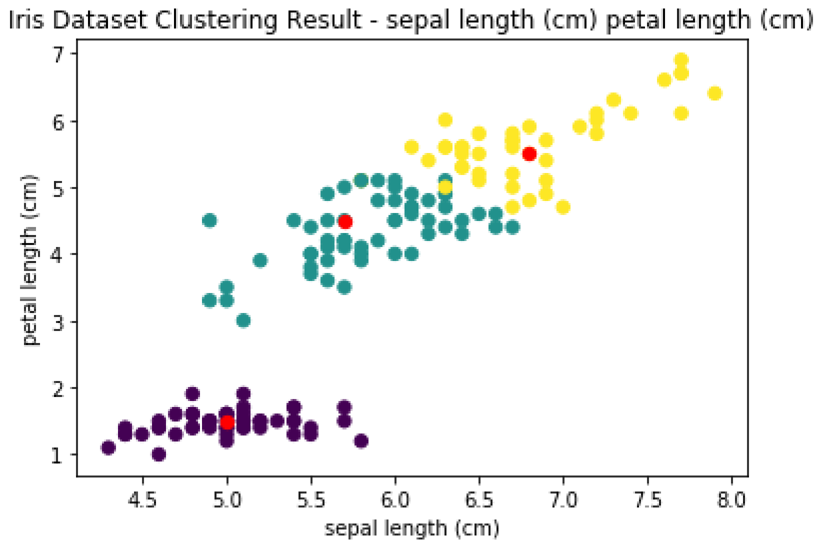
- **initial_index_medoids** : *index instance* medoid awal, ditentukan secara manual oleh pengguna
- **tolerance** : toleransi konvergensi

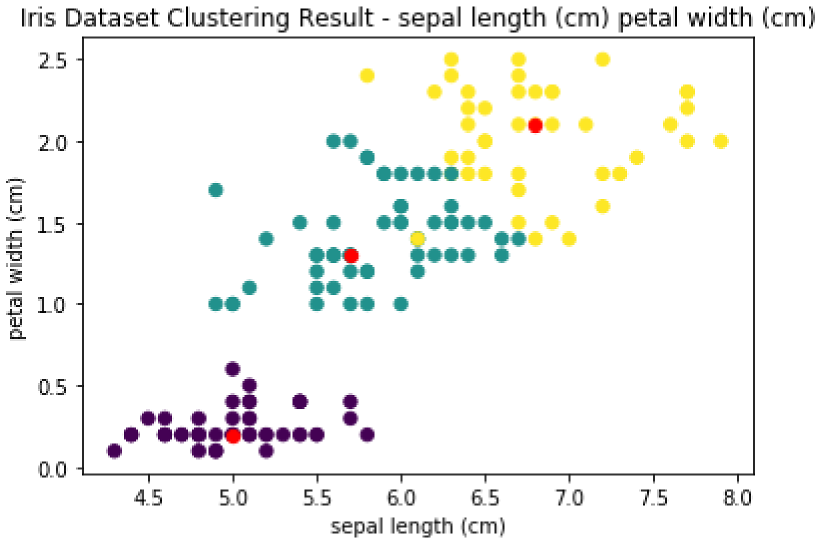
In [12]:

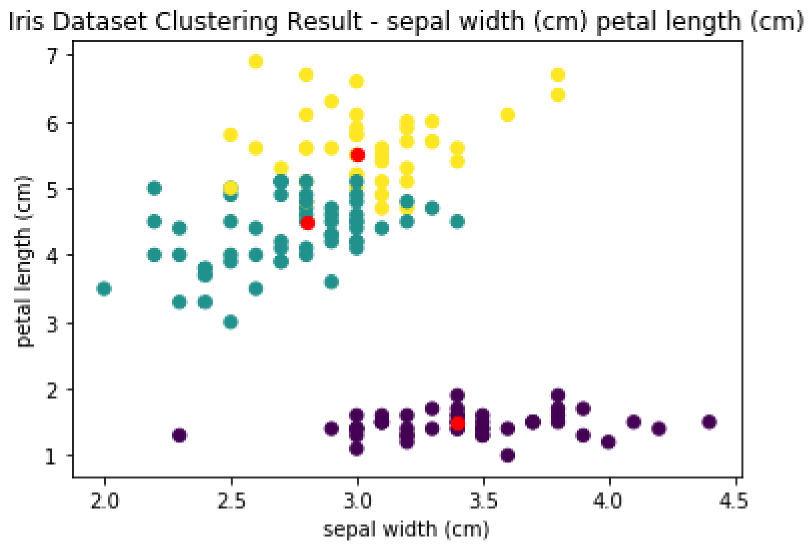
```
kmedoids_instance = kmedoids(x,[20, 70, 111]);
kmedoids_instance.process()
clusters = kmedoids_instance.get_clusters()
medoids = kmedoids_instance.get_medoids()
print("Clustering result:")
print("Medoids:", medoids)
print(clusters)

# plot cluster
labels = [0 for i in range(0,150)]
for i in range(0, len(clusters)):
    for j in range (0, len(clusters[i])):
        labels[clusters[i][j]] = i

for i in range(0, 3):
    for j in range(i+1, 4):
        setLabelAndTitle(i, j)
        plt.scatter(x[:, i], x[:, j], c=labels, s=40, cmap='viridis')
        for l in range(0, len(medoids)):
            plt.scatter(x[medoids[l], i], x[medoids[l], j], c='red', s=40)

        plt.show()
```

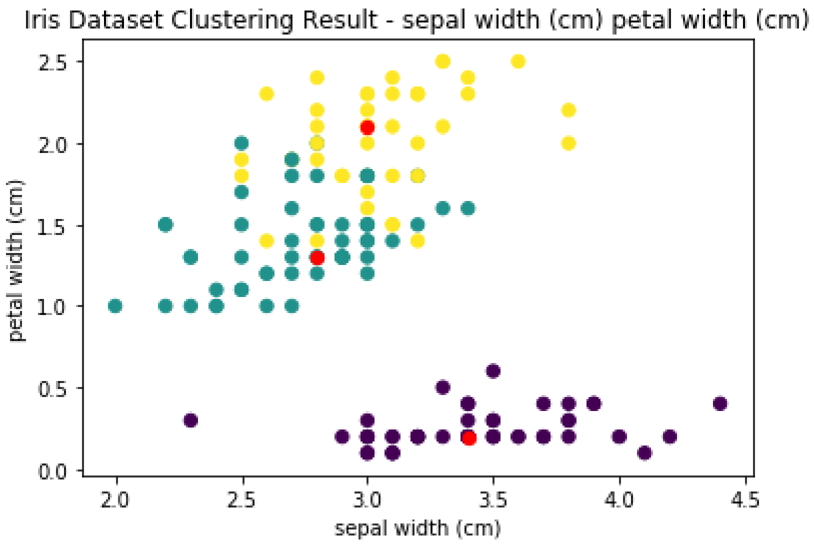
```
Clustering result:
Medoids: [7, 55, 112]
[[7, 0, 1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20,
21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
40, 41, 42, 43, 44, 45, 46, 47, 48, 49], [55, 51, 53, 54, 56, 57, 58, 59, 6
0, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 78, 79, 80, 8
1, 82, 83, 84, 85, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 101,
106, 113, 119, 121, 123, 126, 127, 133, 138, 142, 149], [112, 50, 52, 76, 7
7, 86, 100, 102, 103, 104, 105, 107, 108, 109, 110, 111, 114, 115, 116, 117,
118, 120, 122, 124, 125, 128, 129, 130, 131, 132, 134, 135, 136, 137, 139, 1
40, 141, 143, 144, 145, 146, 147, 148]]
```

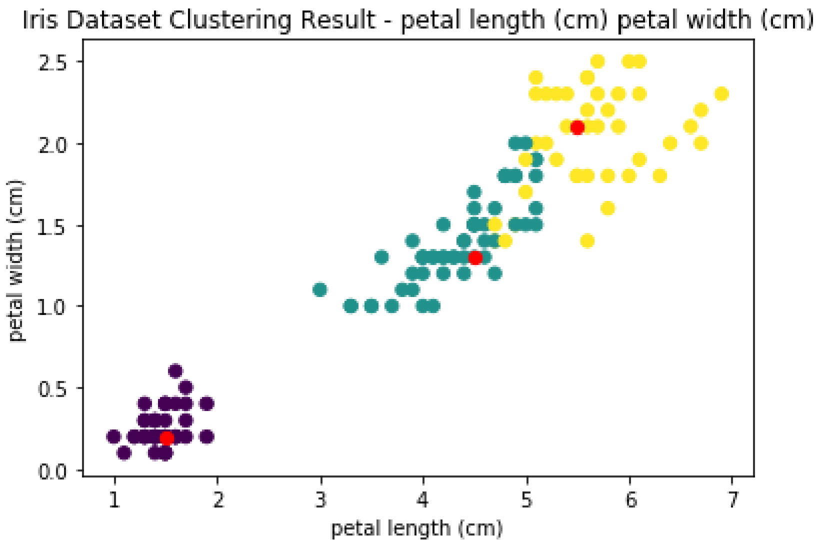



Iris Dataset Clustering Result - sepal length (cm) petal length (cm)
petal length (cm)
sepal length (cm)
1
2
3
4
5
6
7
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
petal width (cm)
sepal length (cm)
0.0
0.5
1.0
1.5
2.0
2.5
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
petal length (cm)
sepal width (cm)
1
2
3
4
5
6
7
2.0
2.5
3.0
3.5
4.0
4.5





3.1.6 Graph Clustering

Library yang digunakan untuk graph clustering adalah **mst_clustering** yang dibuat compatible dengan scikit-learn (https://github.com/jakevdp/mst_clustering/ (https://github.com/jakevdp/mst_clustering/)).

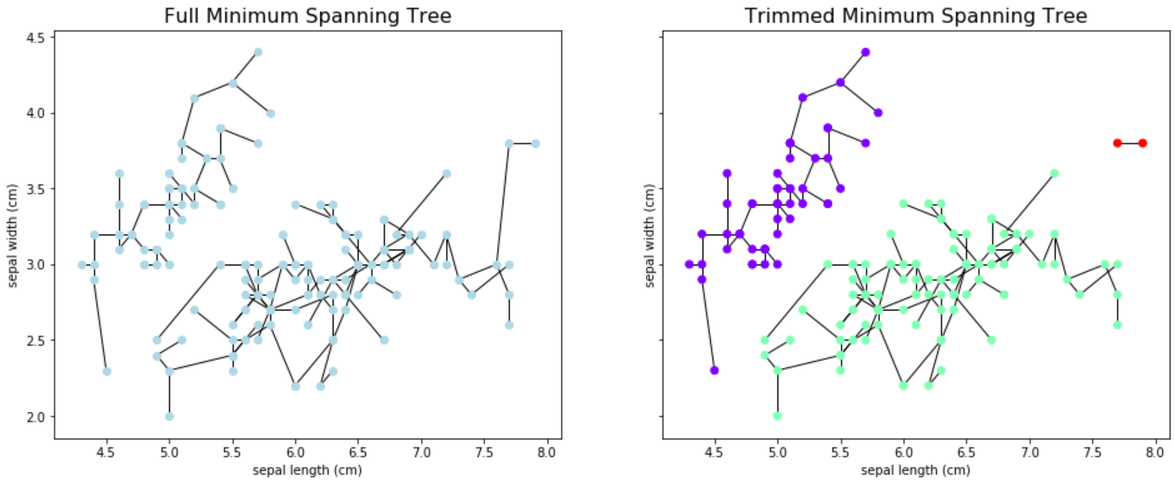
Keterangan parameter penting yang dapat digunakan:

- **cutoff_scale** : panjang edge graf yang akan dipotong
- **min_cluster_size** : jumlah minimum instance dalam satu cluster

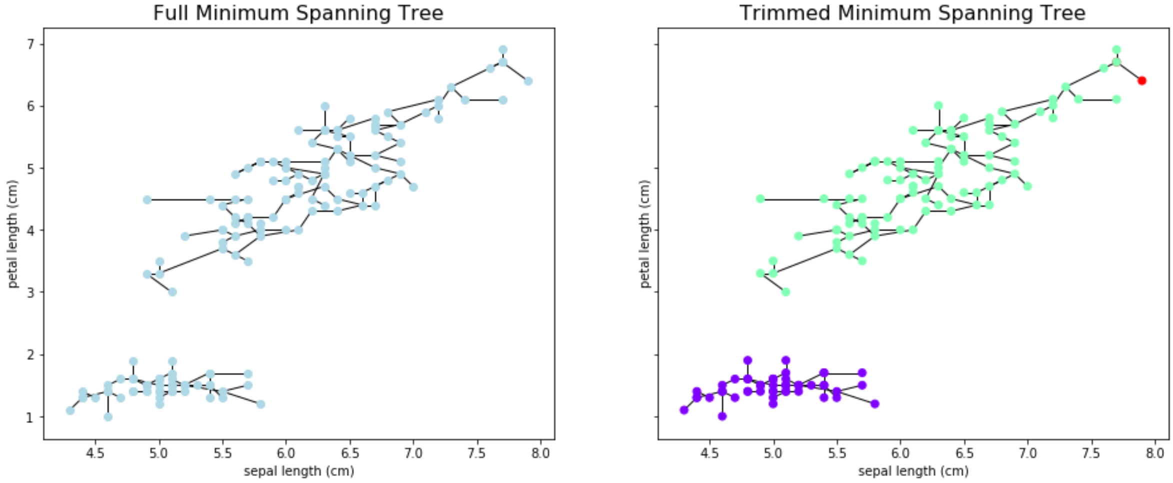
In [13]:

```
def plot_mst(model, i, j, is_tennis=False, cmap='rainbow'):
    if(is_tennis):
        print('Play Tennis Dataset Clustering Result - '
              + play_tennis_attributes[i] + ' ' + play_tennis_attributes[j])
    else:
        print('Iris Dataset Clustering Result - '
              + iris_dataset['feature_names'][i] + ' ' + iris_dataset['feature_names'][j])
    X = model.X_fit_
    fig, ax = plt.subplots(1, 2, figsize=(16, 6), sharex=True, sharey=True)
    for axi, full_graph, colors in zip(ax, [True, False], ['lightblue', model.labels_]):
        segments = model.get_graph_segments(full_graph=full_graph)
        axi.plot(segments[i], segments[j], '-k', zorder=1, lw=1)
        axi.scatter(X[:, i], X[:, j], c=colors, cmap=cmap, zorder=2)
        axi.axis('tight')

    ax[0].set_title('Full Minimum Spanning Tree', size=16)
    ax[1].set_title('Trimmed Minimum Spanning Tree', size=16);
    if(is_tennis):
        ax[0].set_xlabel(play_tennis_attributes[i])
        ax[0].set_ylabel(play_tennis_attributes[j])
        ax[1].set_xlabel(play_tennis_attributes[i])
        ax[1].set_ylabel(play_tennis_attributes[j])
    else:
        ax[0].set_xlabel(iris_dataset['feature_names'][i])
        ax[0].set_ylabel(iris_dataset['feature_names'][j])
        ax[1].set_xlabel(iris_dataset['feature_names'][i])
        ax[1].set_ylabel(iris_dataset['feature_names'][j])
    plt.show()

graph_clustering = MSTClustering(cutoff_scale=0.75)
graph_clustering.fit(x)
for i in range(0, 3):
    for j in range(i+1, 4):
        plot_mst(graph_clustering, i, j)
```

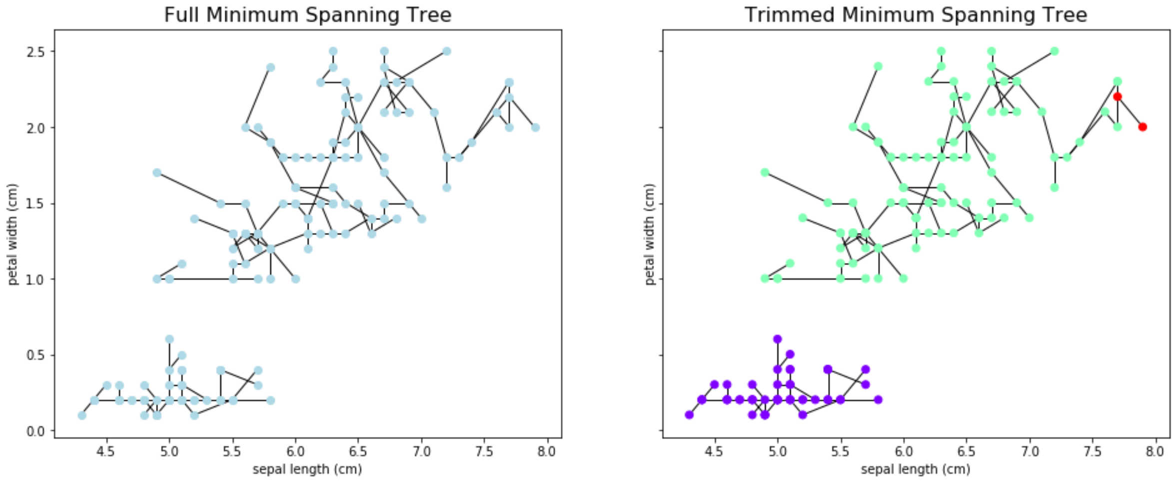
Iris Dataset Clustering Result - sepal length (cm) sepal width (cm)



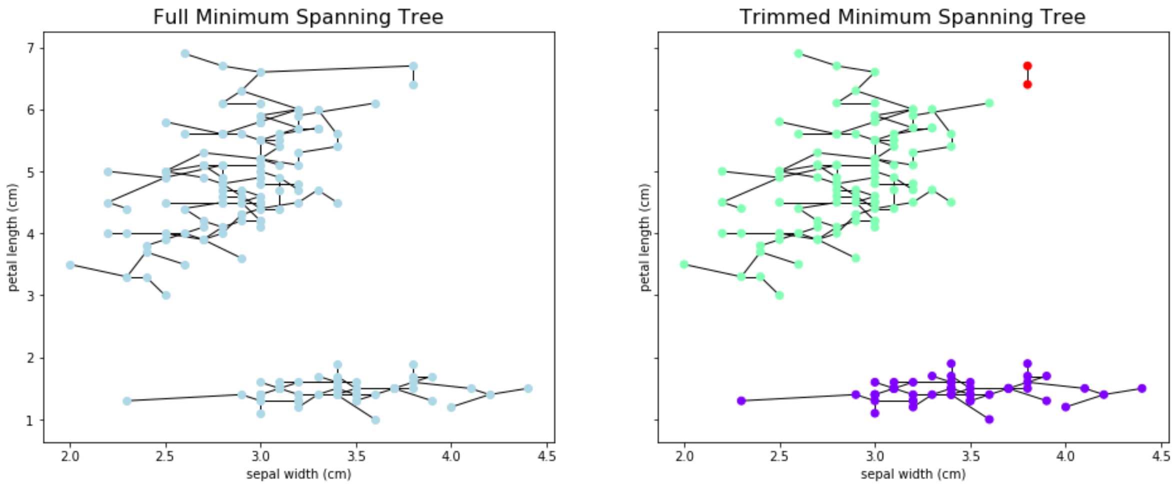
Iris Dataset Clustering Result - sepal length (cm) petal length (cm)



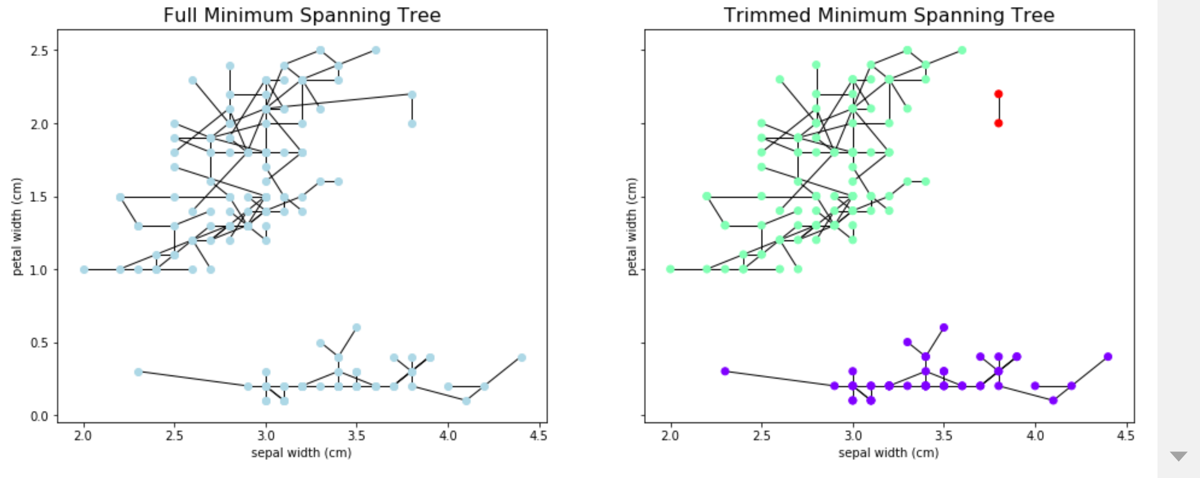
Iris Dataset Clustering Result - sepal length (cm) petal width (cm)



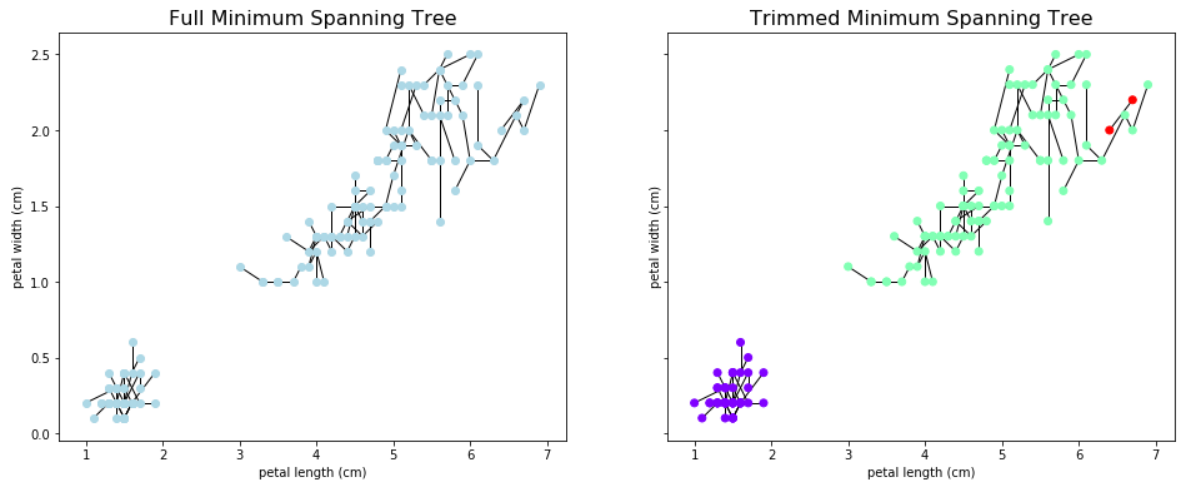
Iris Dataset Clustering Result - sepal width (cm) petal length (cm)



Iris Dataset Clustering Result - sepal width (cm) petal width (cm)




```
Iris Dataset Clustering Result - petal length (cm) petal width (cm)
```



3.1.7 Grid Clustering (BANG Clustering)

Library yang digunakan untuk *clustering* dengan grid clustering adalah **pyclustering** yaitu dengan menggunakan modul BANG clustering.

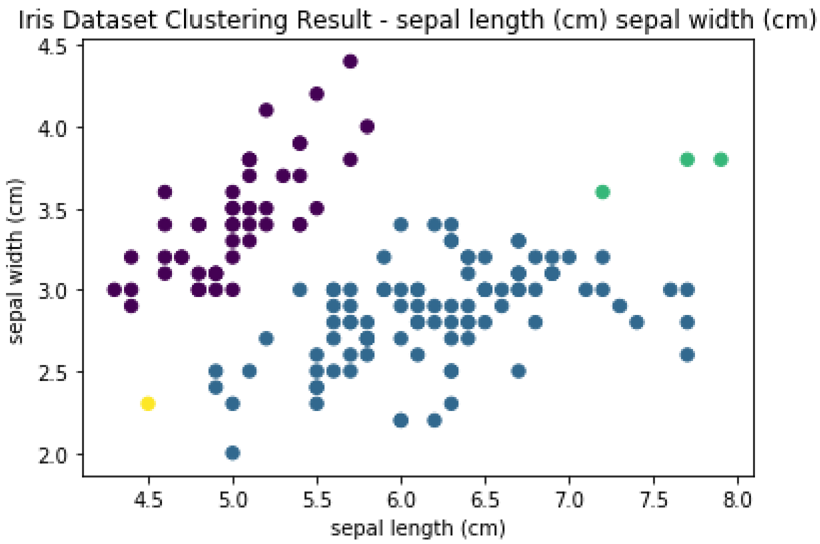
Keterangan parameter penting yang dapat digunakan: (selain data)

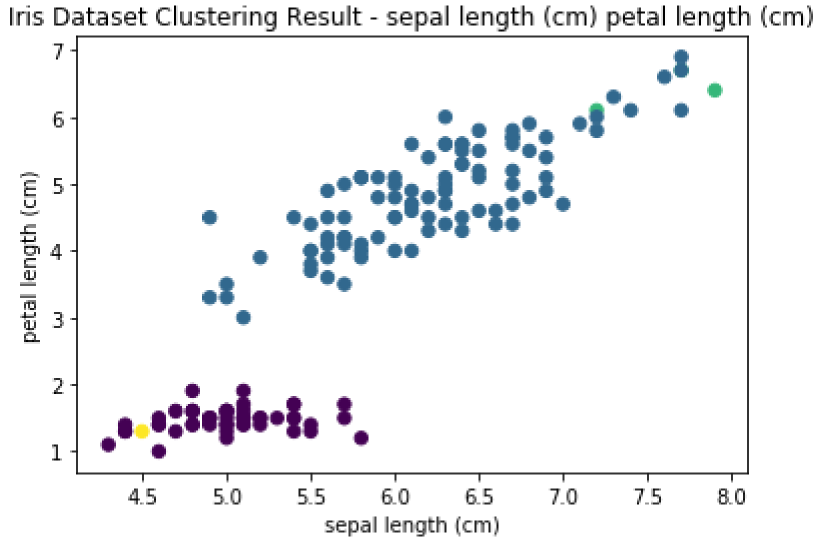
- **levels** : jumlah pembagian yang dilakukan dalam setiap grid

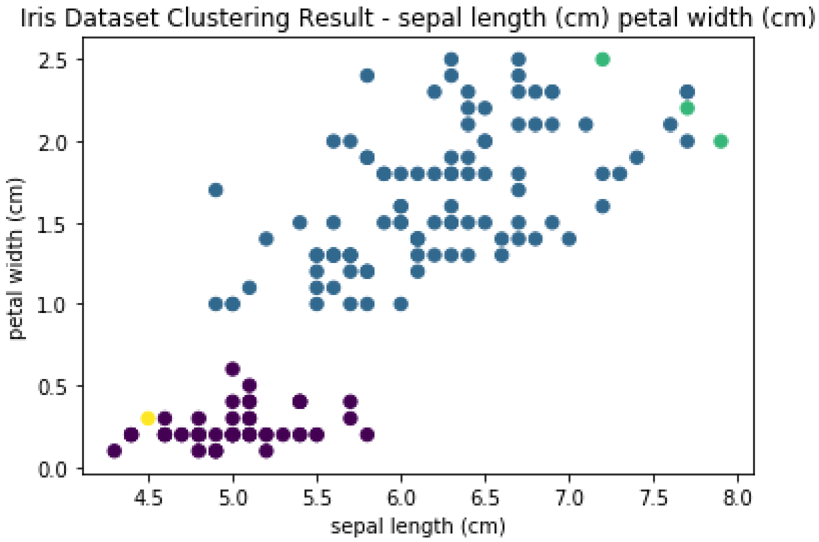
In [14]:

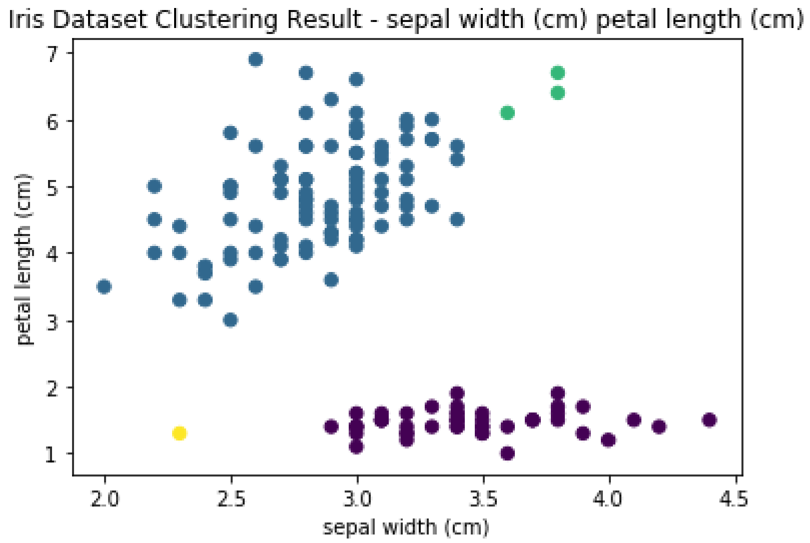
```
# convert numpy array to list
list_dataset = x.tolist()

# clustering using BANG
bang_instance = bang(list_dataset, 14)
bang_instance.process()

clusters = bang_instance.get_clusters()
noise = bang_instance.get_noise()
directory = bang_instance.get_directory()
dendrogram = bang_instance.get_dendrogram()

labels = [0 for i in range(0,150)]
for i in range(0, len(clusters)):
    for j in range (0, len(clusters[i])):
        labels[clusters[i][j]] = i
print("Clustering result:")
print(clusters)

for i in range(0, 3):
    for j in range(i+1, 4):
        setLabelAndTitle(i, j)
        plt.scatter(x[:, i], x[:, j], c=labels, s=40, cmap='viridis')
        plt.show()
```

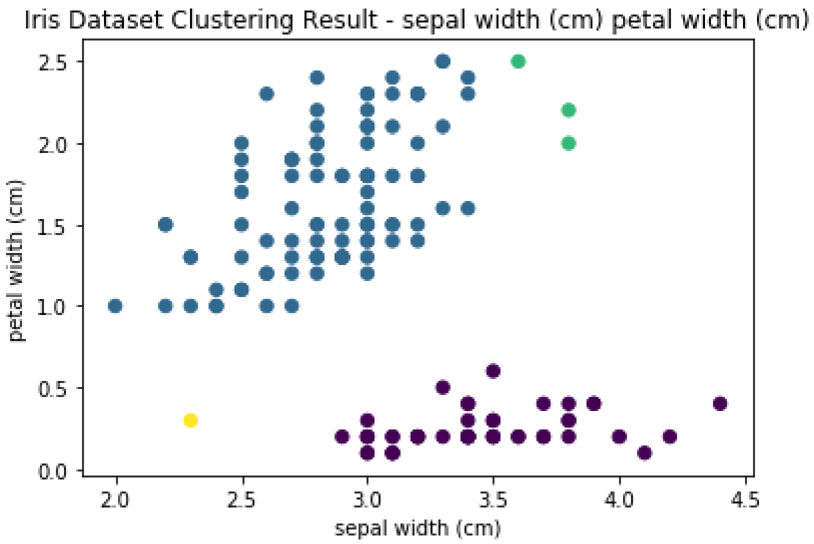
```
Clustering result:
[[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20,
21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39,
40, 42, 43, 44, 45, 46, 47, 48, 49], [50, 51, 52, 53, 54, 55, 56, 57, 58, 5
9, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 7
8, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 9
7, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 110, 111, 112, 113,
114, 115, 116, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 1
30, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 14
6, 147, 148, 149], [117, 131, 109], [41]]
```

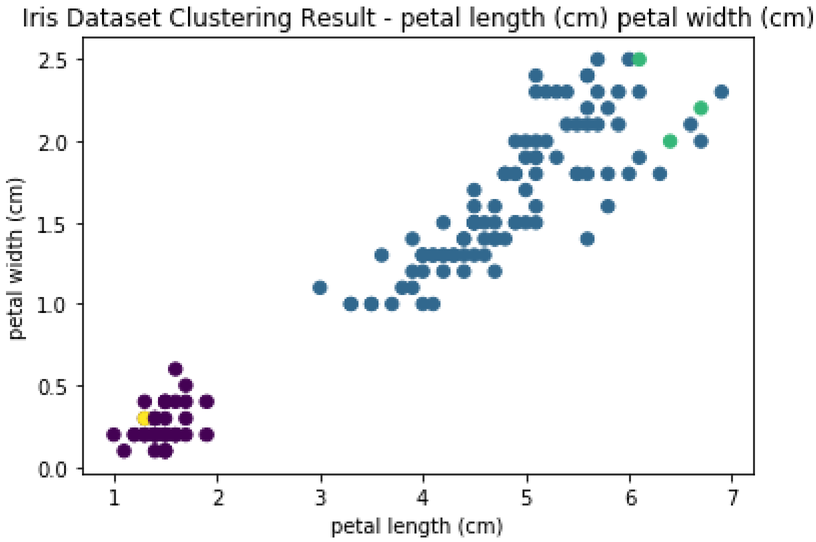



Iris Dataset Clustering Result - sepal length (cm) petal length (cm)
petal length (cm)
sepal length (cm)
1
2
3
4
5
6
7
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Iris Dataset Clustering Result - sepal length (cm) petal width (cm)
petal width (cm)
sepal length (cm)
0.0
0.5
1.0
1.5
2.0
2.5
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0


Iris Dataset Clustering Result - sepal width (cm) petal length (cm)
petal length (cm)
sepal width (cm)
1
2
3
4
5
6
7
2.0
2.5
3.0
3.5
4.0
4.5





3.1.8 Penyimpanan dan Pembacaan Model/Hipotesis pada File Eksternal

1. Penyimpanan Model/Hipotesis

In [15]:

```
joblib.dump(kmeans, 'kmeans_model.pkl')
joblib.dump(agglomerative, 'agglomerative_model.pkl')
joblib.dump(db, 'dbscan_model.pkl')
joblib.dump(gmm, 'gaussian_mixture_model.pkl')
joblib.dump(graph_clustering, 'graph_clustering_model.pkl')

with open('kmedoids_model', "wb") as f:
    dill.dump(kmedoids_instance, f)

with open('bang_model', "wb") as f:
    dill.dump(bang_instance, f)
```

2. Pembacaan Model/Hipotesis

In [16]:

```
kmeans_model = joblib.load('kmeans_model.pkl')
agglomerative_model = joblib.load('agglomerative_model.pkl')
dbscan_model = joblib.load('dbscan_model.pkl')
gaussian_mixture_model = joblib.load('gaussian_mixture_model.pkl')
graph_clustering_model = joblib.load('graph_clustering_model.pkl')

kmedoids_model = dill.load(open('kmedoids_model', "rb"))
bang_model = dill.load(open('bang_model', "rb"))
```

3.1.9 Assignment Cluster Instance Baru dengan Model dari File Eksternal

1. Pembuatan Instance Baru

In [17]:

```
test_instance = [[4.8,  3.1 ,  1.1,  0.4]]

new_dataset = np.append(x, test_instance, axis=0)

# convert numpy array to list for BANG clustering
new_list_dataset = new_dataset.tolist()
```

2. Assignment Cluster Instance Baru

a. K-Means

In [18]:

```
kmeans_cluster_prediction = kmeans_model.predict(test_instance)
print("New instance cluster:", kmeans_cluster_prediction[0])
```

```
New instance cluster: 1
```

b. Agglomerative Clustering

In [19]:

```
agglomerative_prediction = agglomerative_model.fit_predict(new_dataset)
print("New instance cluster:", agglomerative_prediction[150])
```

```
New instance cluster: 1
```

c. DBSCAN

In [20]:

```
dbscan_prediction = dbscan_model.fit_predict(new_dataset)
print("New instance cluster:", dbscan_prediction[150])
```

```
New instance cluster: 0
```

d. Gaussian Mixture

In [21]:

```
gmm_cluster_prediction = gaussian_mixture_model.predict(test_instance)
print("New instance cluster:", gmm_cluster_prediction[0])
```

```
New instance cluster: 1
```

e. Graph Clustering

In [22]:

```
graph_clustering_prediction = graph_clustering_model.fit_predict(new_dataset)
print("New instance cluster:", graph_clustering_prediction[150])
```

```
New instance cluster: 0
```

f. K-Medoids

In [23]:

```
kmedoids_instance = kmedoids(new_dataset,[20, 70, 111]);
kmedoids_instance.process()
clusters = kmedoids_instance.get_clusters()
medoids = kmedoids_instance.get_medoids()
print("Medoids:",medoids)
for i in range(0, len(clusters)):
    if 150 in clusters[i]:
        print("New instance cluster:", i)
        break
```

```
Medoids: [7, 55, 112]
New instance cluster: 0
```

g. Grid Clustering (BANG)

In [24]:

```
bang_model = bang(new_list_dataset, 14)
bang_model.process()

clusters = bang_model.get_clusters()
noise = bang_model.get_noise()
directory = bang_model.get_directory()
dendrogram = bang_model.get_dendrogram()

for i in range(0, len(clusters)):
    if 150 in clusters[i]:
        print("New instance cluster:", i)
        break
```

```
New instance cluster: 0
```

3.2 Clustering Dataset Play Tennis

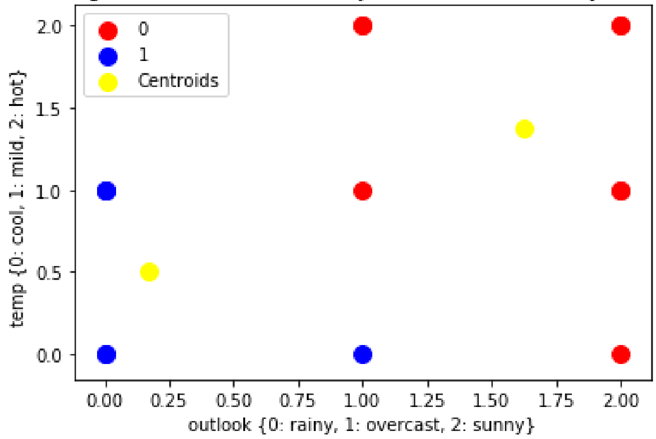
3.2.1 K-Means

In [25]:

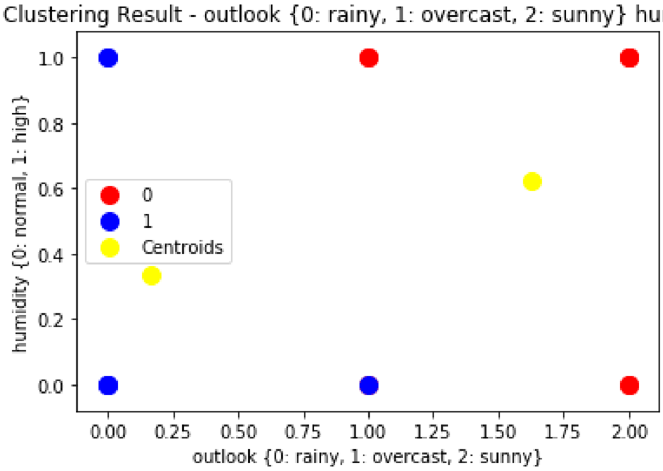
```
# K-Means
x = tenis_data_nparray
kmeans = KMeans(n_clusters=2)
kmeans.fit(x)
clustering_result = kmeans.fit_predict(x)
print("Clustering result:")
print(clustering_result)

plotClusteringResult(clustering_result, 1, True)
plt.show()
```

```
Clustering result:
[0 0 0 1 1 1 1 0 0 1 0 0 0 1]
```

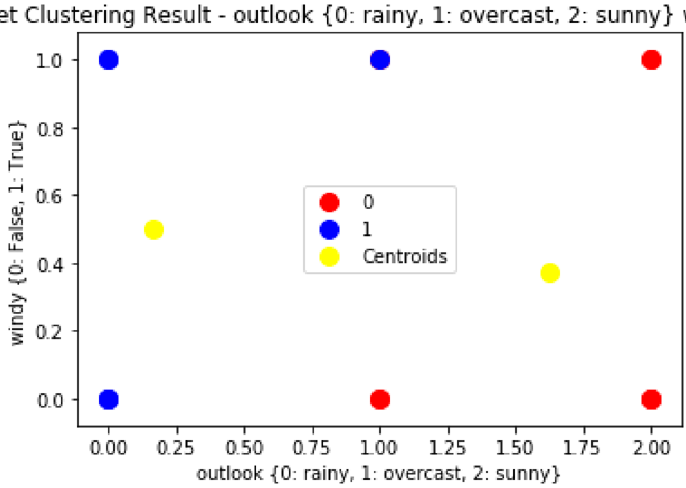
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} temp {0: cool, 1: mild, 2: hot}

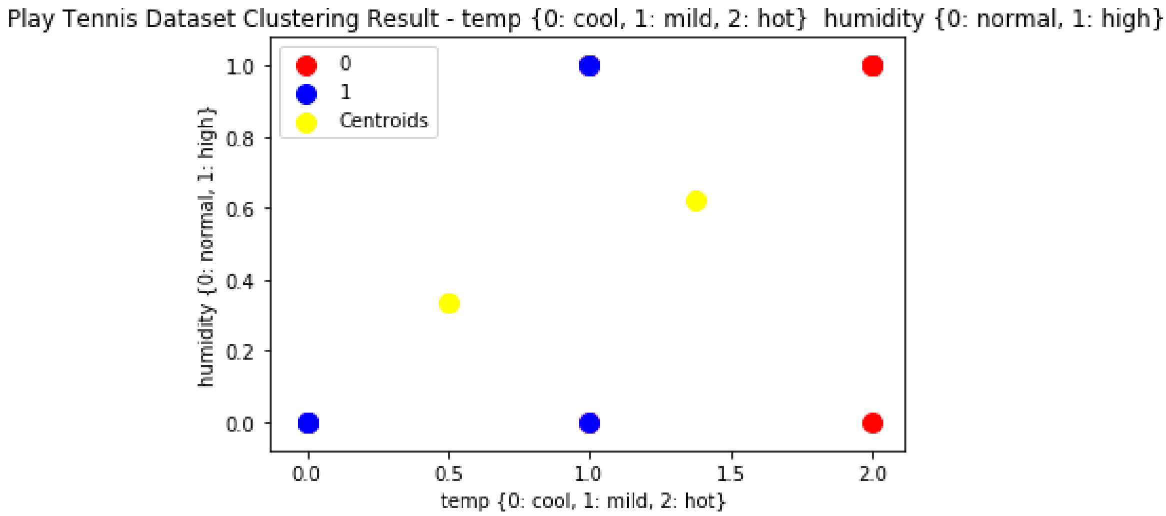


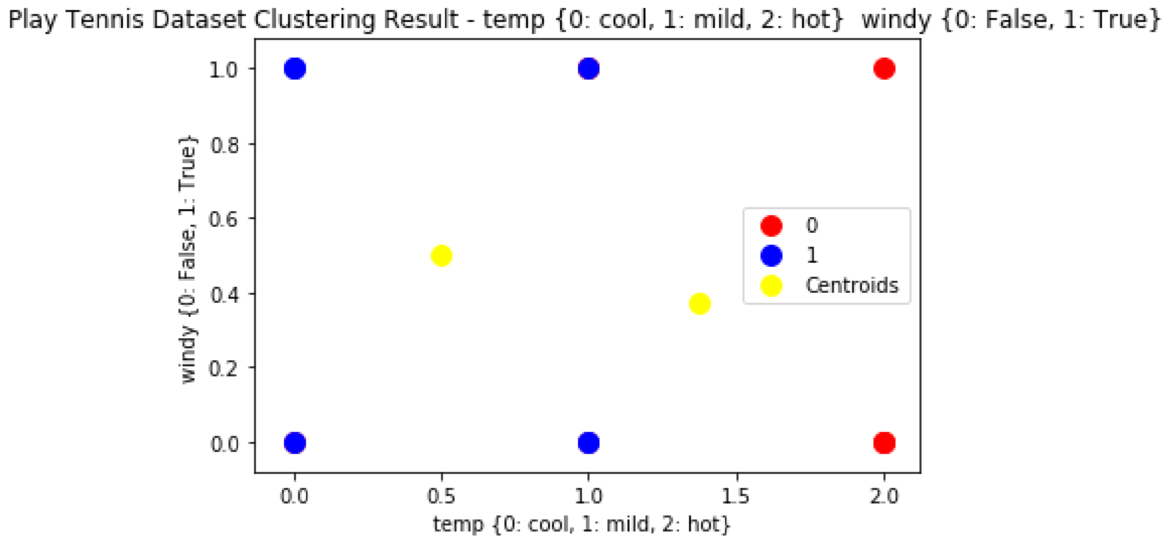
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} humidity {0: normal, 1: high}

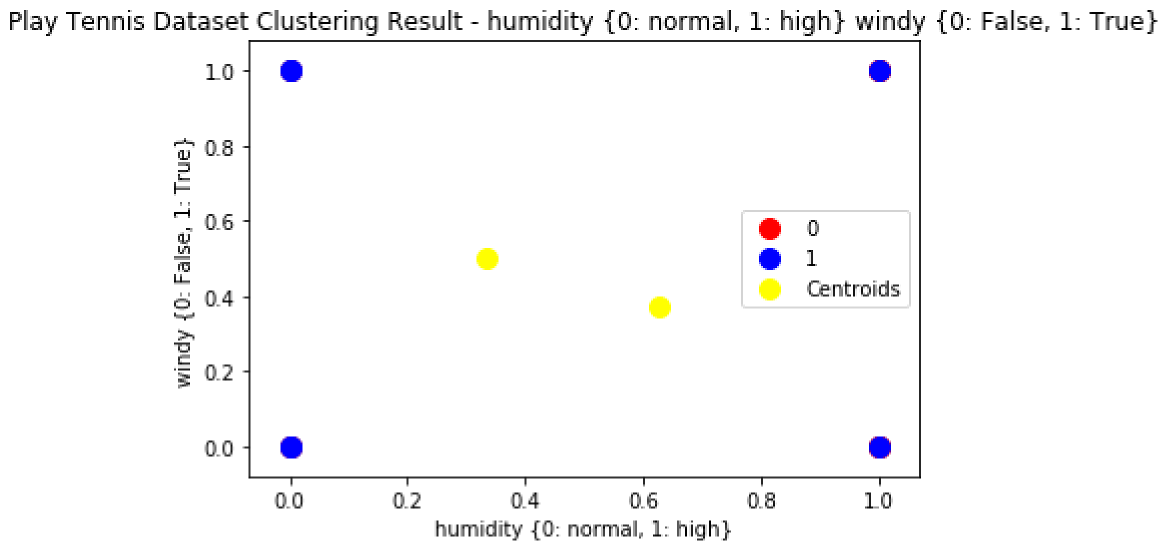


Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} windy {0: False, 1: True}







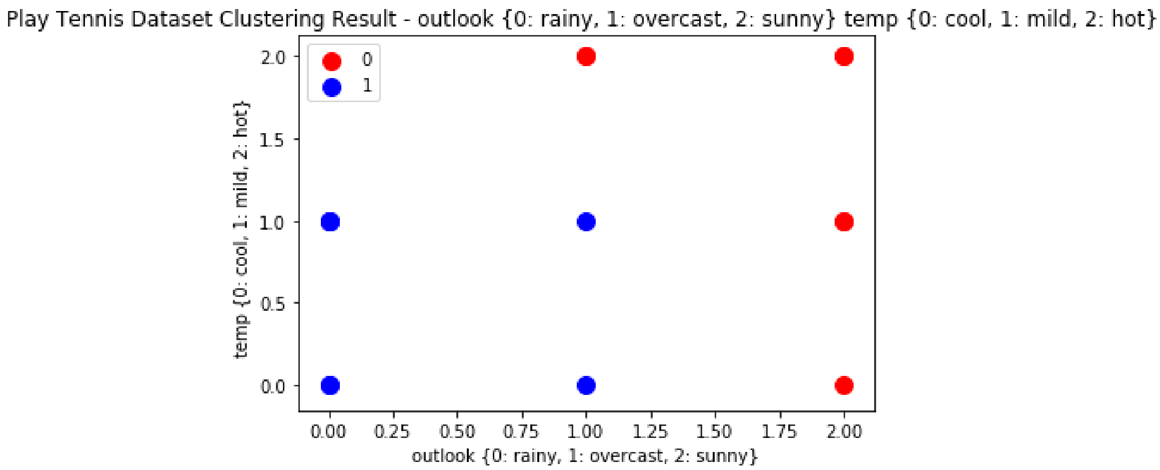


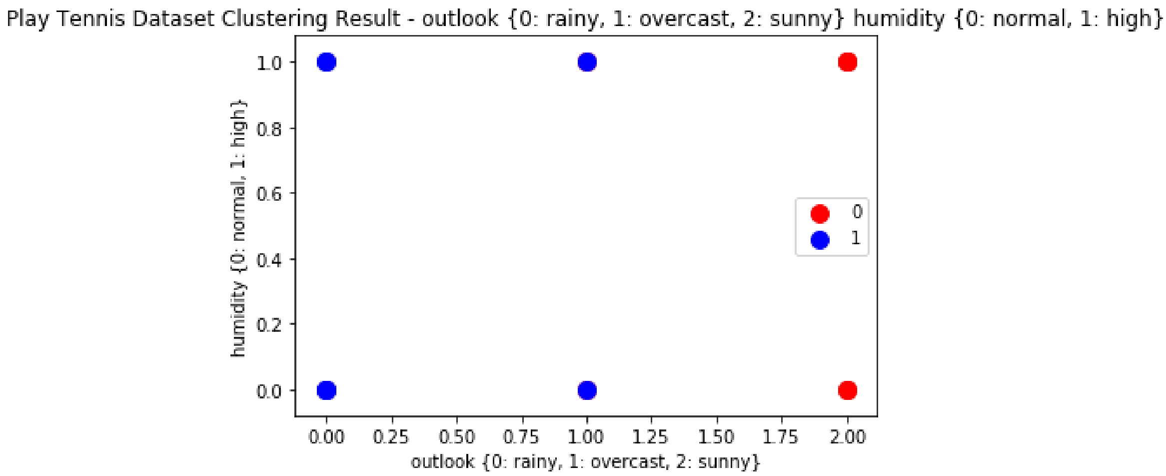
3.2.2 Agglomerative Clustering

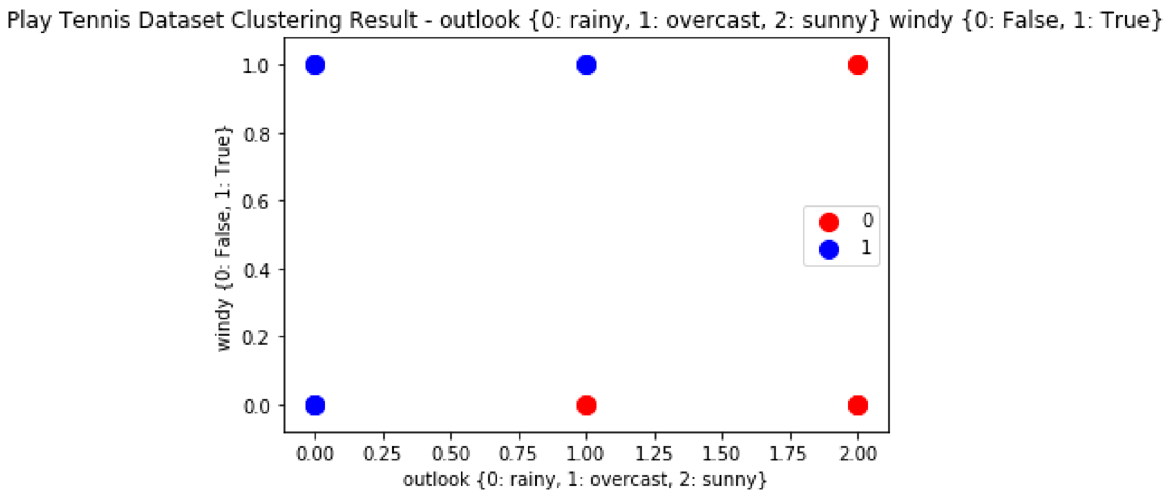
In [26]:

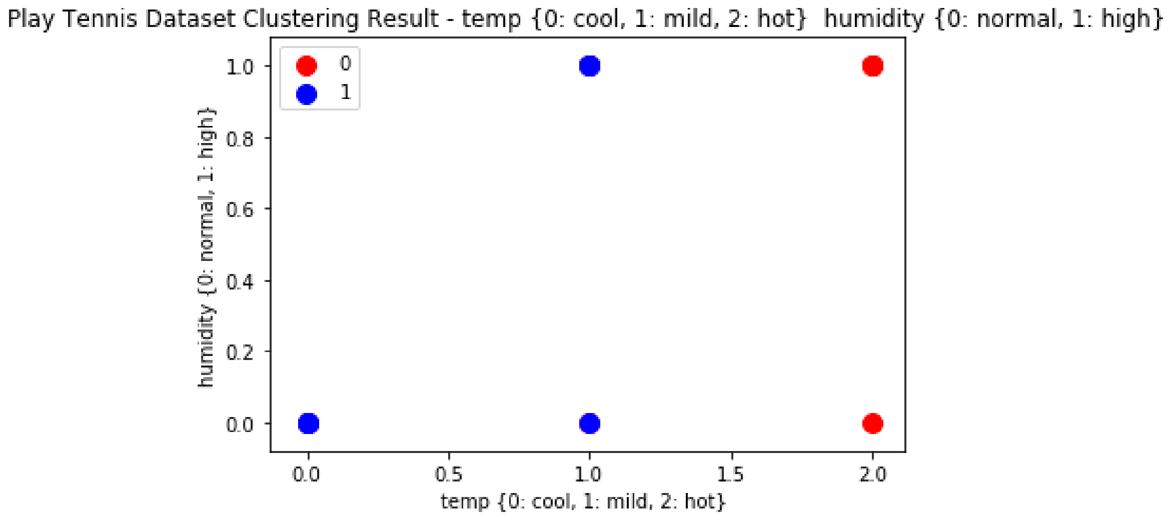
```
agglomerative = AgglomerativeClustering(n_clusters = 2)
agglomerative.fit(x)
clustering_result = agglomerative.fit_predict(x)
print("Clustering result:")
print(clustering_result)

plotClusteringResult(clustering_result, 0, True)
plt.show()
```

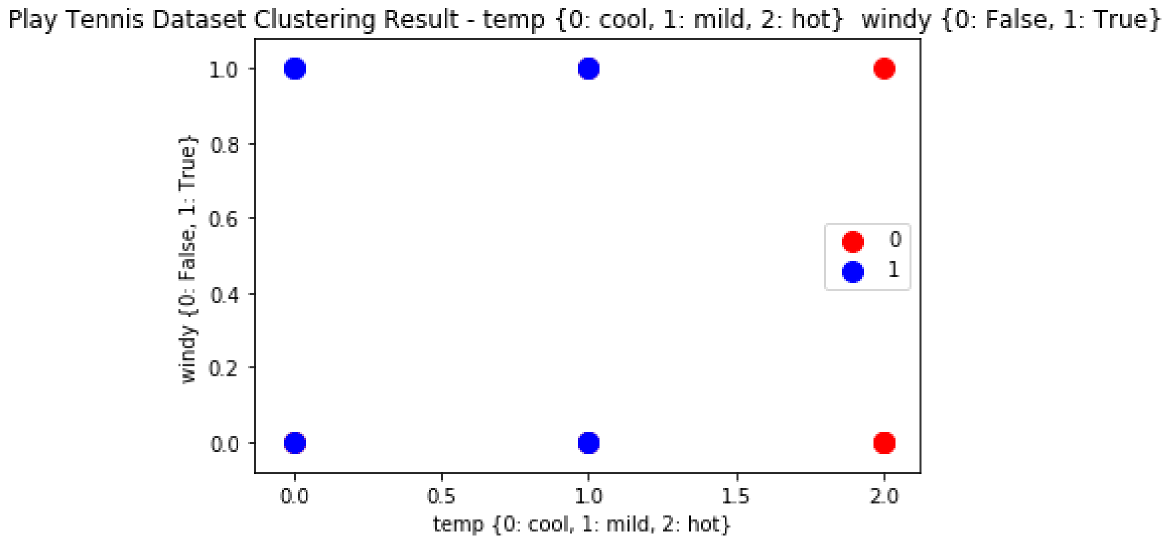
```
Clustering result:
[0 0 0 1 1 1 1 0 0 1 0 1 0 1]
```

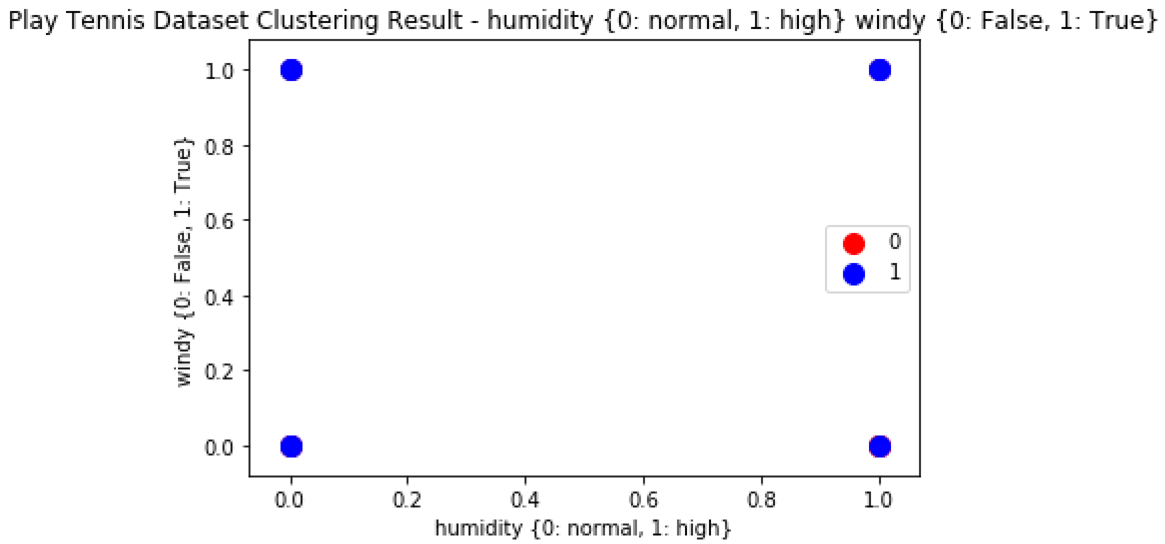







Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} humidity {0: normal, 1: high}
humidity {0: normal, 1: high}
temp {0: cool, 1: mild, 2: hot}
0
1


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} windy {0: False, 1: True}
windy {0: False, 1: True}
temp {0: cool, 1: mild, 2: hot}
0
1

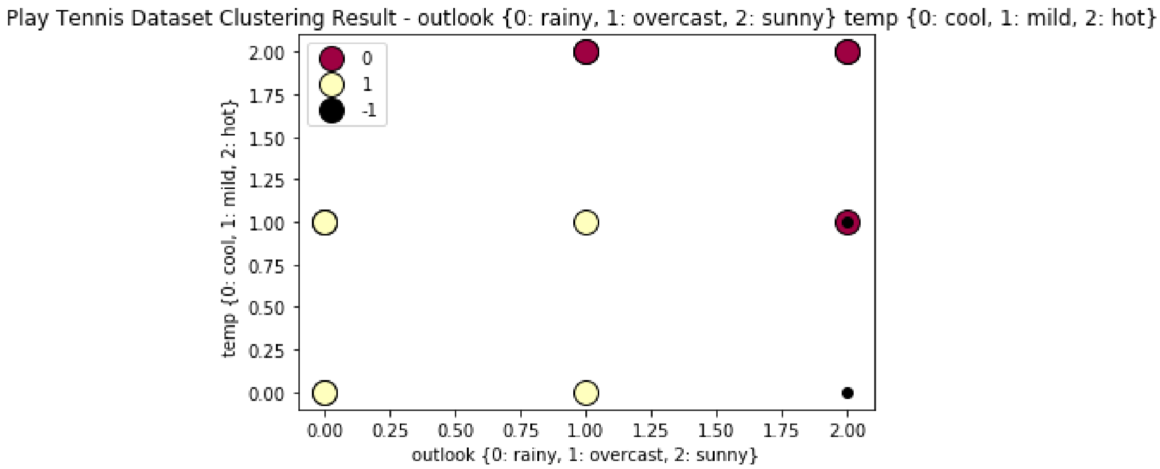

Play Tennis Dataset Clustering Result - humidity {0: normal, 1: high} windy {0: False, 1: True}
windy {0: False, 1: True}
humidity {0: normal, 1: high}
0
1

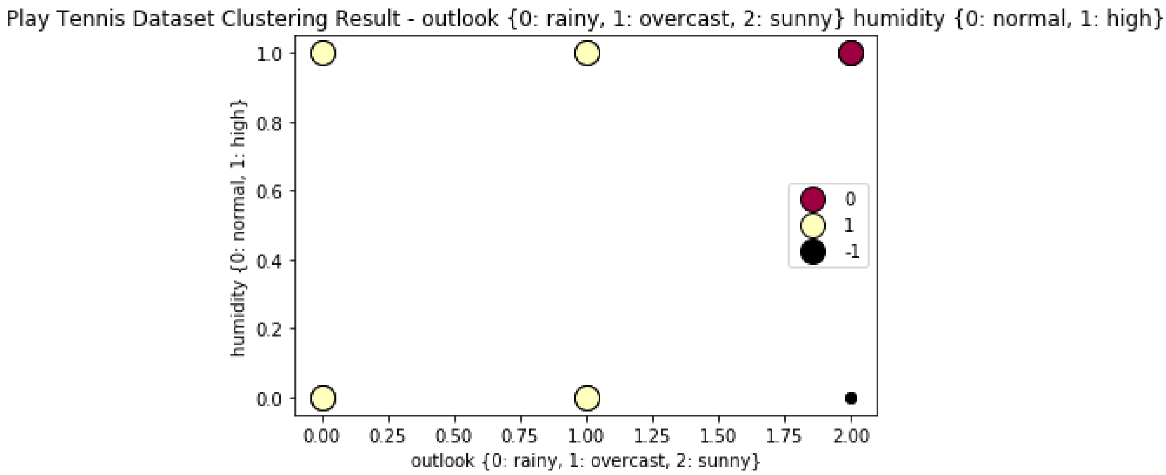
3.2.3 DBSCAN

In [27]:

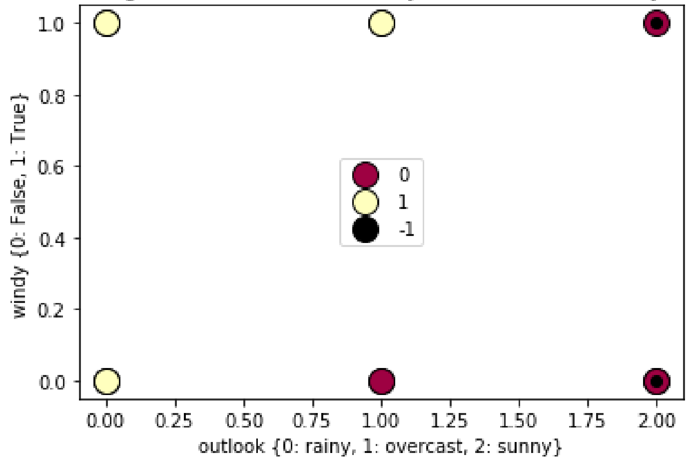
```
dbscan = DBSCAN(eps=1, min_samples=2)
db = dbscan.fit(x)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
print("Clustering result:")
print(labels)
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)

print("eps = 1; min_samples = 2")
for i in range(0, 3):
    for j in range(i+1, 4):
        plotDBSCAN(i, j, True)
```

```
Clustering result:
[ 0  0  0  1  1  1  1  0 -1  1 -1  1  0  1]
eps = 1; min_samples = 2
```

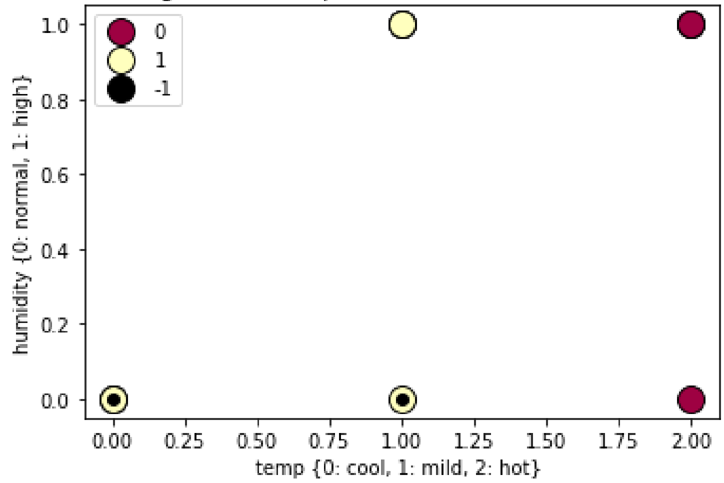




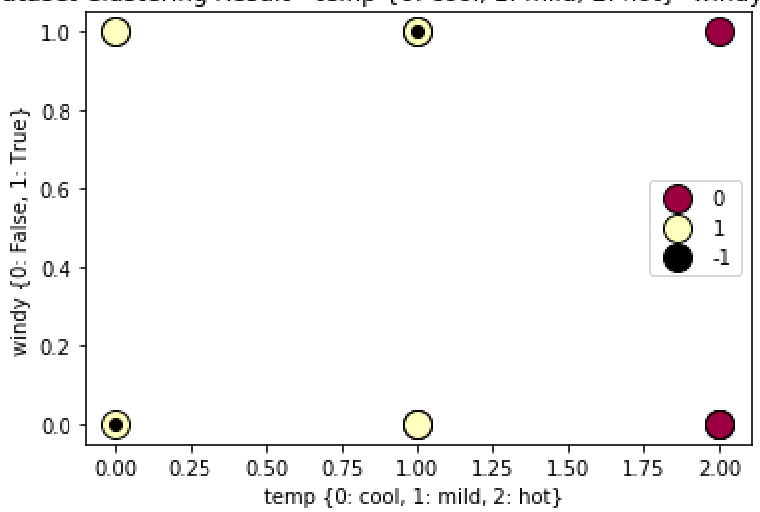
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} windy {0: False, 1: True}

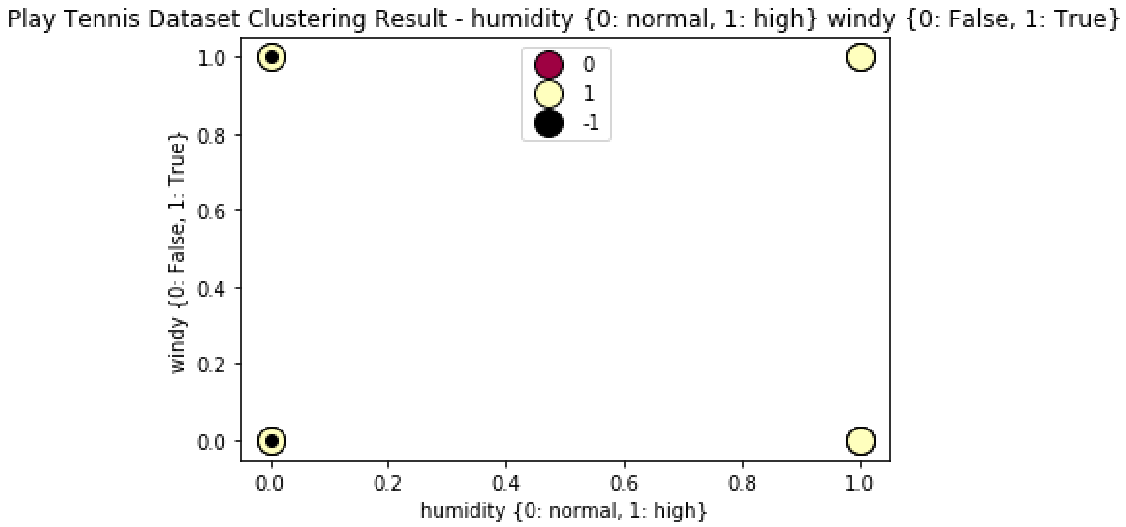


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} humidity {0: normal, 1: high}



Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} windy {0: False, 1: True}





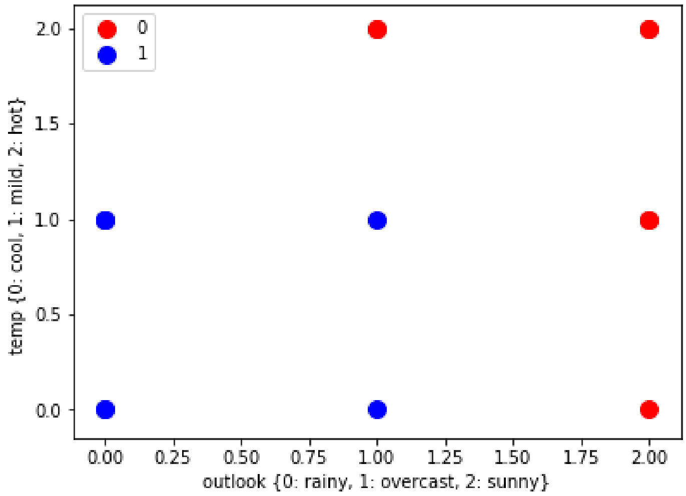
3.2.4 Gaussian Mixture

In [28]:

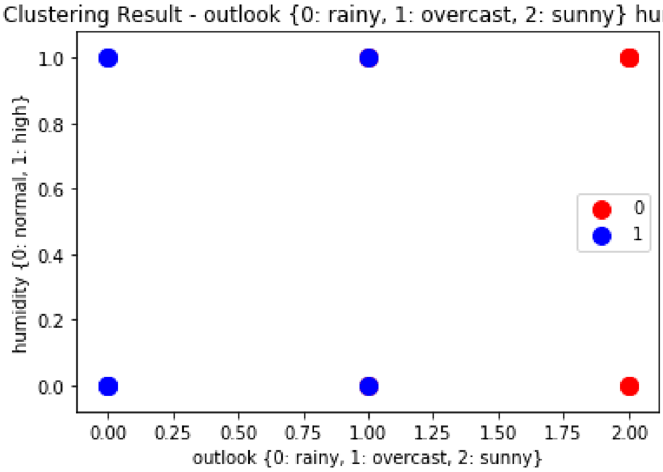
```
gmm = GaussianMixture(n_components=2)
gmm.fit(x)
labels = gmm.predict(x)

plt.figure(figsize=(5, 8))
plt.subplots_adjust(bottom=.01, top=0.95, hspace=.15, wspace=.05,
                    left=.01, right=.99)
# gmm.covariances_

print("Clustering result:")
print(labels)
h = plt.subplot(2, 1, 1)
# make_ellipses(gmm, 2, h)
# plt.legend(scatterpoints=1, loc='lower right', prop=dict(size=12))

# plt.scatter(x[:, 0], x[:, 1], c=labels, s=40, cmap='viridis');
plotClusteringResult(labels, 0, True)
plt.show()
```

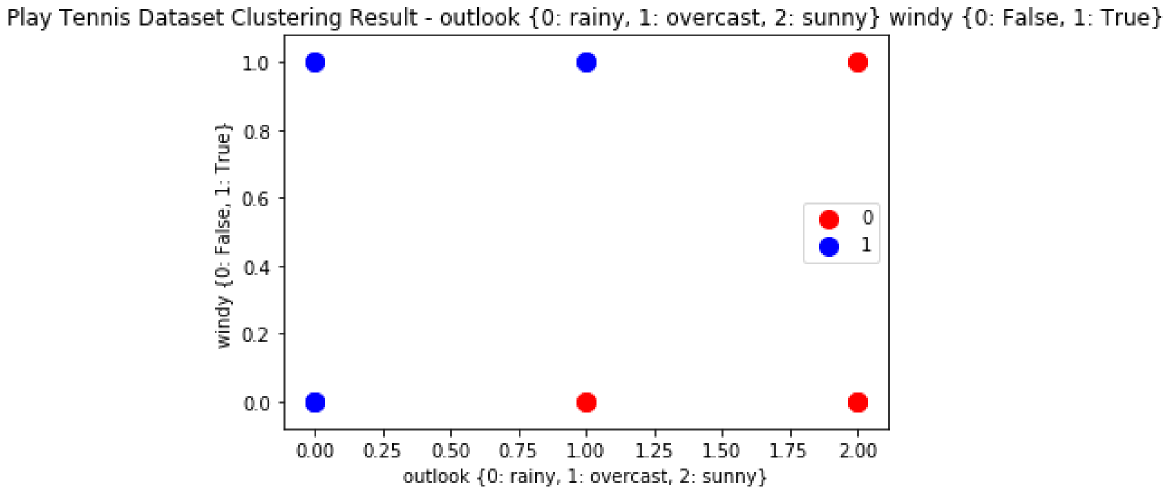
```
Clustering result:
[0 0 0 1 1 1 1 0 0 1 0 1 0 1]
```

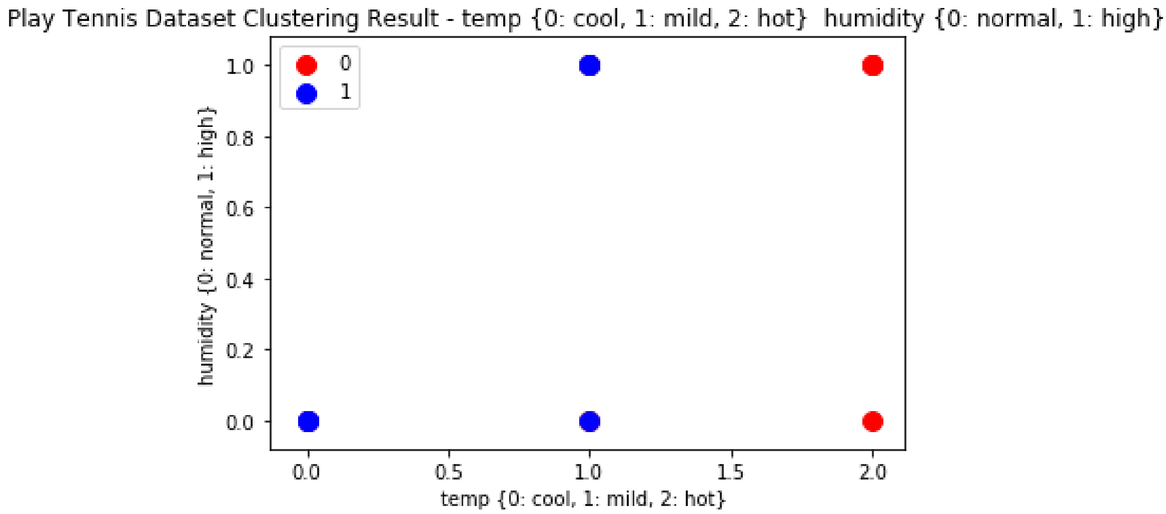
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} temp {0: cool, 1: mild, 2: hot}

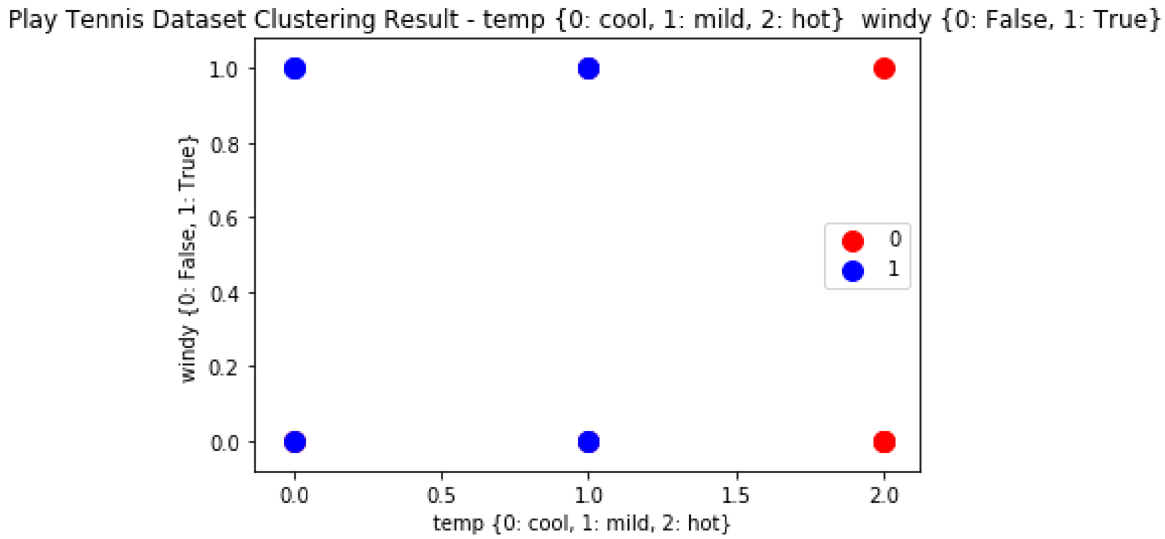


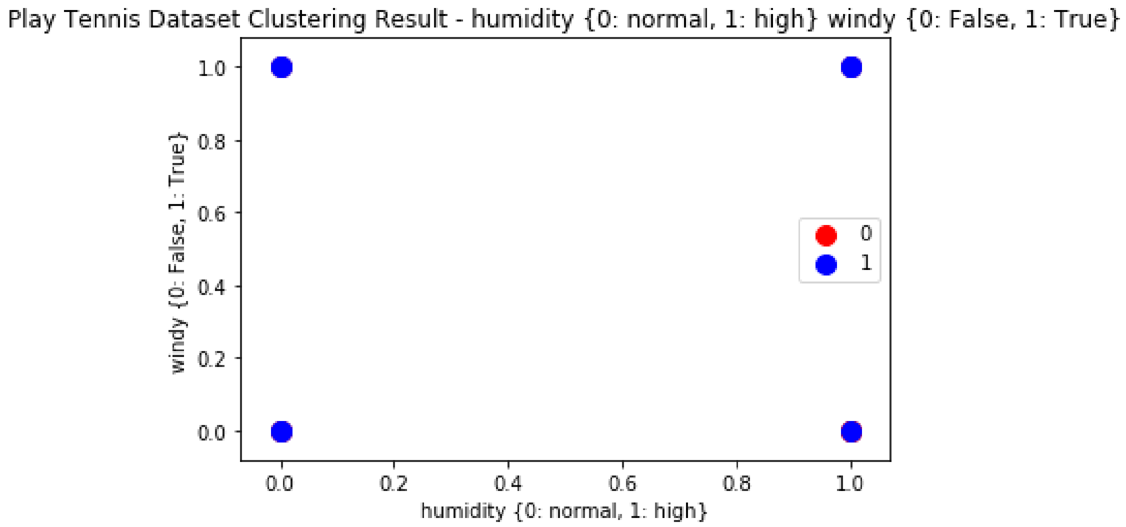
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} humidity {0: normal, 1: high}




Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} windy {0: False, 1: True}
windy {0: False, 1: True}
outlook {0: rainy, 1: overcast, 2: sunny}
0
1
0.0
0.2
0.4
0.6
0.8
1.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} humidity {0: normal, 1: high}
humidity {0: normal, 1: high}
temp {0: cool, 1: mild, 2: hot}
0
1
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} windy {0: False, 1: True}
windy {0: False, 1: True}
temp {0: cool, 1: mild, 2: hot}
0
1
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0



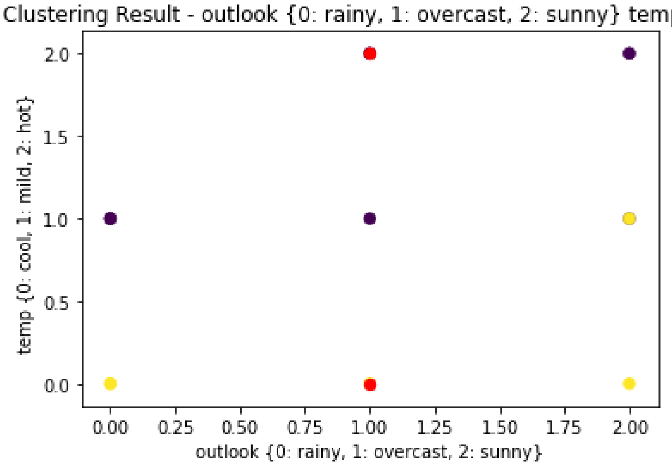
3.2.5 K-Medoids

In [29]:

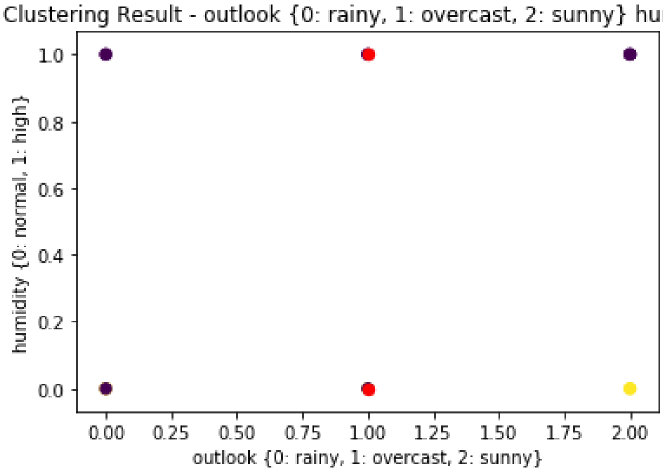
```
kmedoids_instance = kmedoids(x,[1, 10]);
kmedoids_instance.process()
clusters = kmedoids_instance.get_clusters()
medoids = kmedoids_instance.get_medoids()
print(clusters)
print(medoids)

# plot cluster
labels = [0 for i in range(0,14)]
for i in range(0, len(clusters)):
    for j in range (0, len(clusters[i])):
        labels[clusters[i][j]] = i

for i in range(0, 3):
    for j in range(i+1, 4):
        setLabelAndTitle(i, j, True)
        plt.scatter(x[:, i], x[:, j], c=labels, s=40, cmap='viridis')
        for l in range(0, len(medoids)):
            plt.scatter(x[medoids[l], i], x[medoids[l], j], c='red', s=40)

        plt.show()
```

```
[[2, 0, 1, 3, 7, 9, 11, 12, 13], [6, 4, 5, 8, 10]]
[2, 6]
```

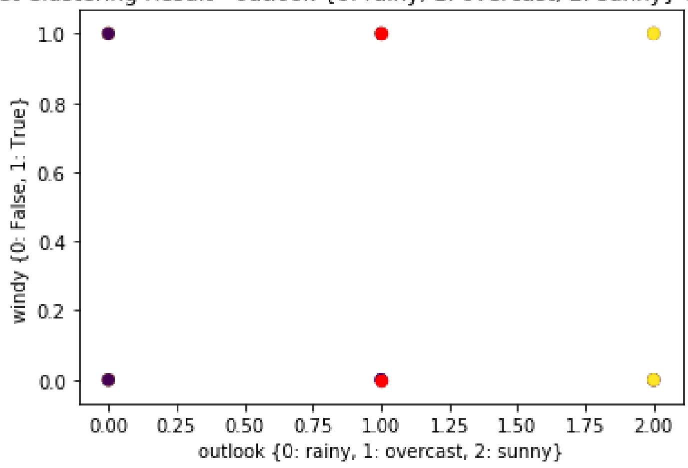
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} temp {0: cool, 1: mild, 2: hot}



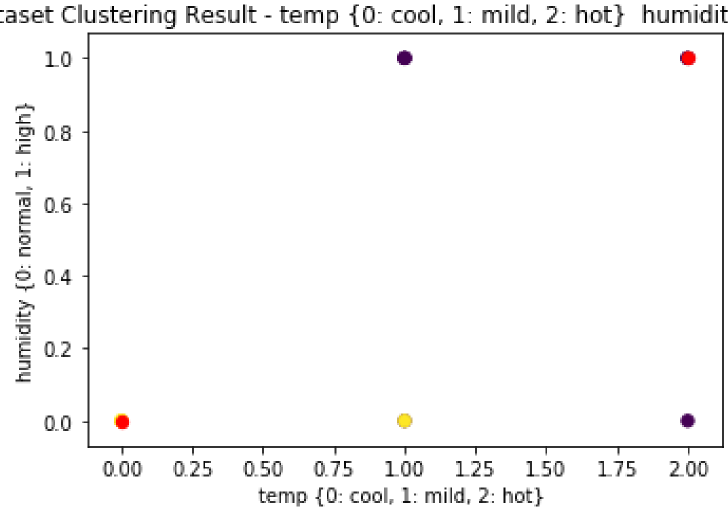
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} humidity {0: normal, 1: high}



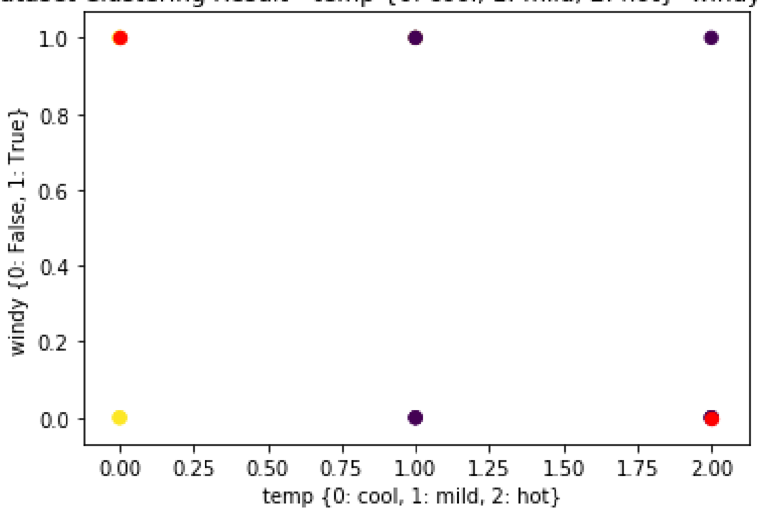
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} windy {0: False, 1: True}

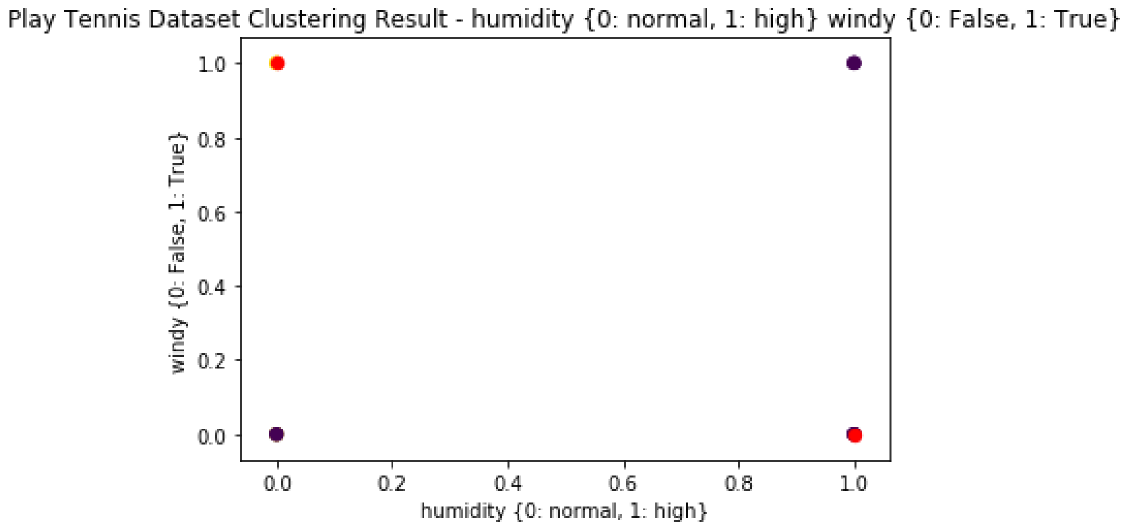


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} humidity {0: normal, 1: high}



Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} windy {0: False, 1: True}



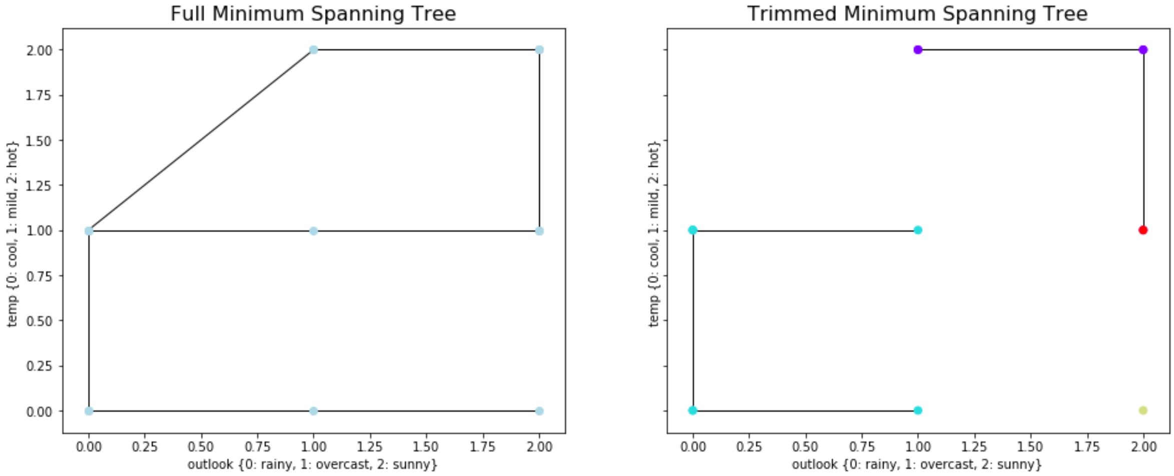


3.2.6 Graph Clustering

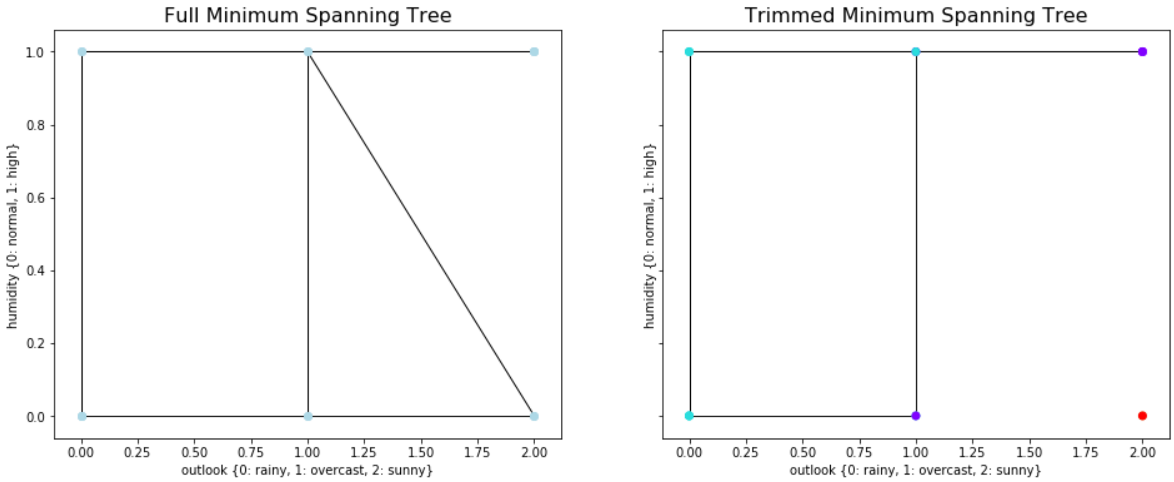
In [30]:

```
graph_clustering = MSTClustering(cutoff_scale=1.4)
graph_clustering.fit(x)
for i in range(0, 3):
    for j in range(i+1, 4):
        plot_mst(graph_clustering, i, j, True)
```

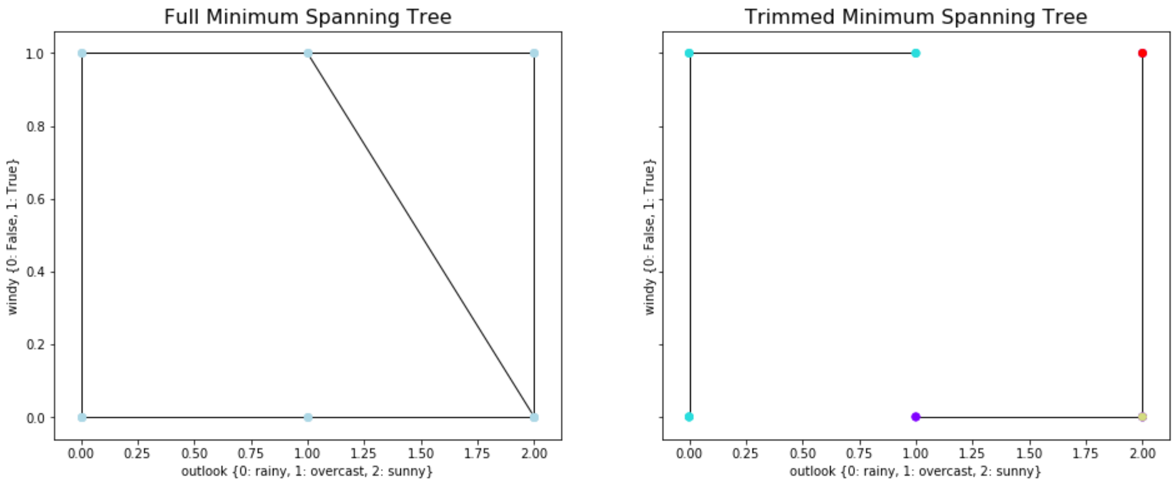
```
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: s
unny} temp {0: cool, 1: mild, 2: hot}
```



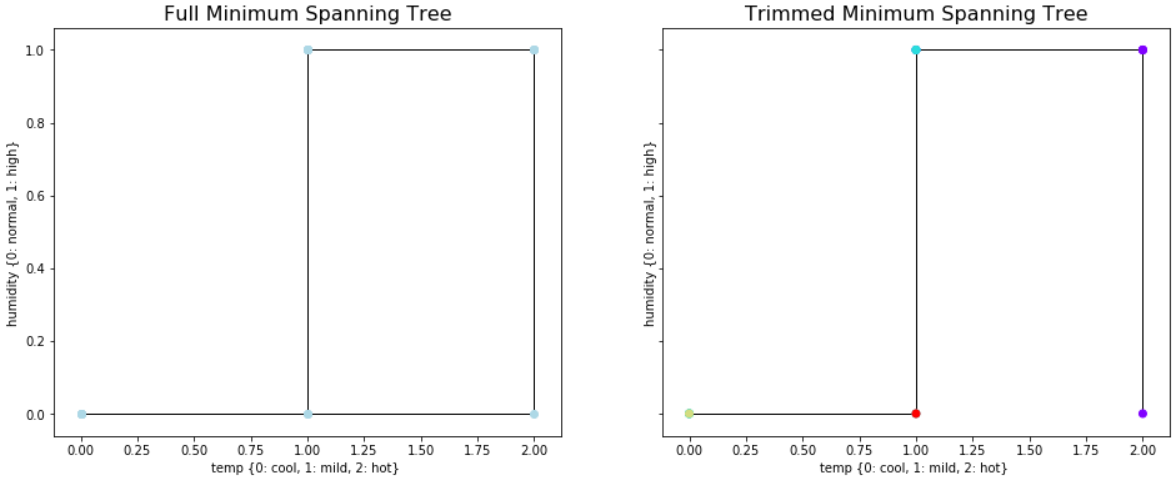

```
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: s
unny} humidity {0: normal, 1: high}
```



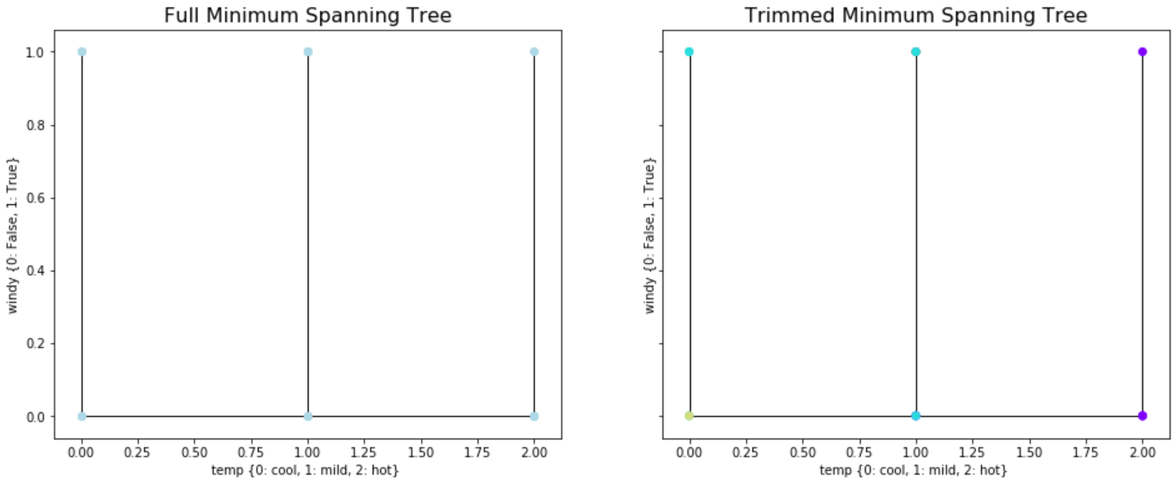

```
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: s
unny} windy {0: False, 1: True}
```



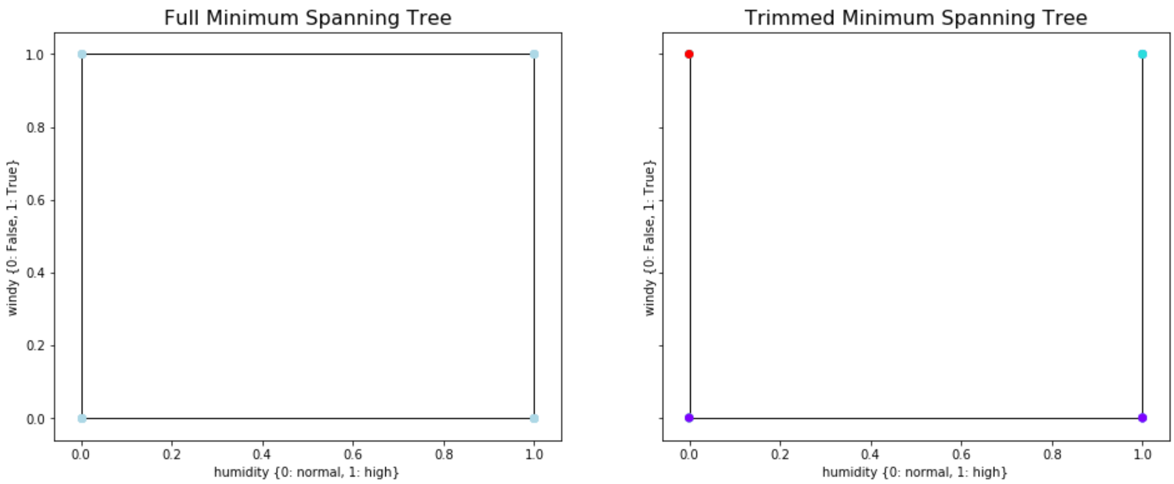
```
Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot}  h
umidity {0: normal, 1: high}
```




```
Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot}  win
dy {0: False, 1: True}
```




```
Play Tennis Dataset Clustering Result - humidity {0: normal, 1: high} windy
{0: False, 1: True}
```



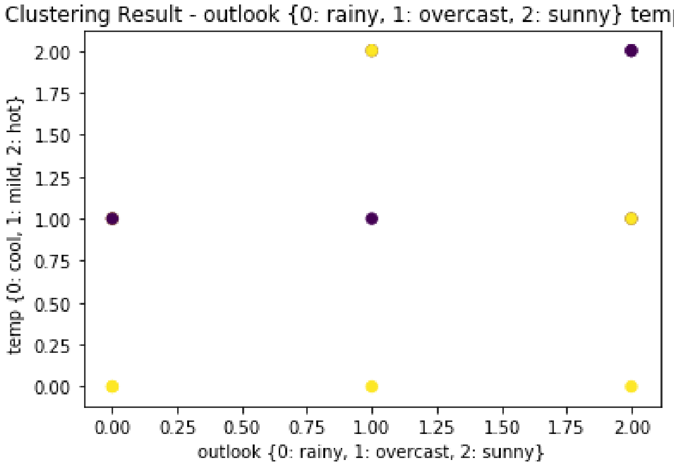
3.2.7 Grid Clustering (BANG Clustering)

In [31]:

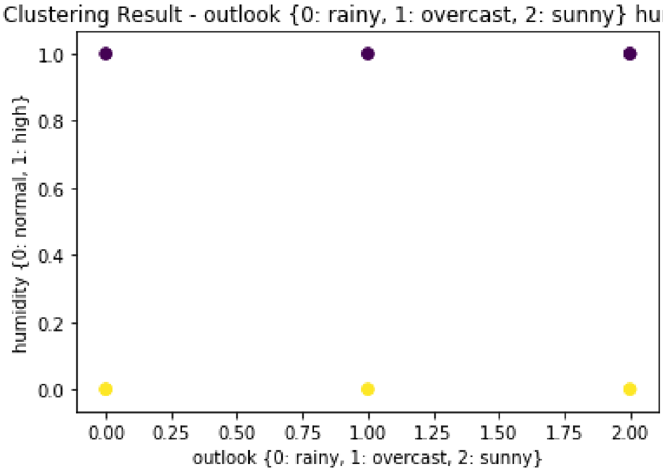
```
bang_instance = bang(tenis_data_list, 7)
bang_instance.process()

clusters = bang_instance.get_clusters()
noise = bang_instance.get_noise()
directory = bang_instance.get_directory()
dendrogram = bang_instance.get_dendrogram()

labels = [0 for i in range(0,14)]
for i in range(0, len(clusters)):
    for j in range (0, len(clusters[i])):
        labels[clusters[i][j]] = i
print("Clustering result:")
print(clusters)

for i in range(0, 3):
    for j in range(i+1, 4):
        setLabelAndTitle(i, j, True)
        plt.scatter(x[:, i], x[:, j], c=labels, s=40, cmap='viridis')
        plt.show()
```

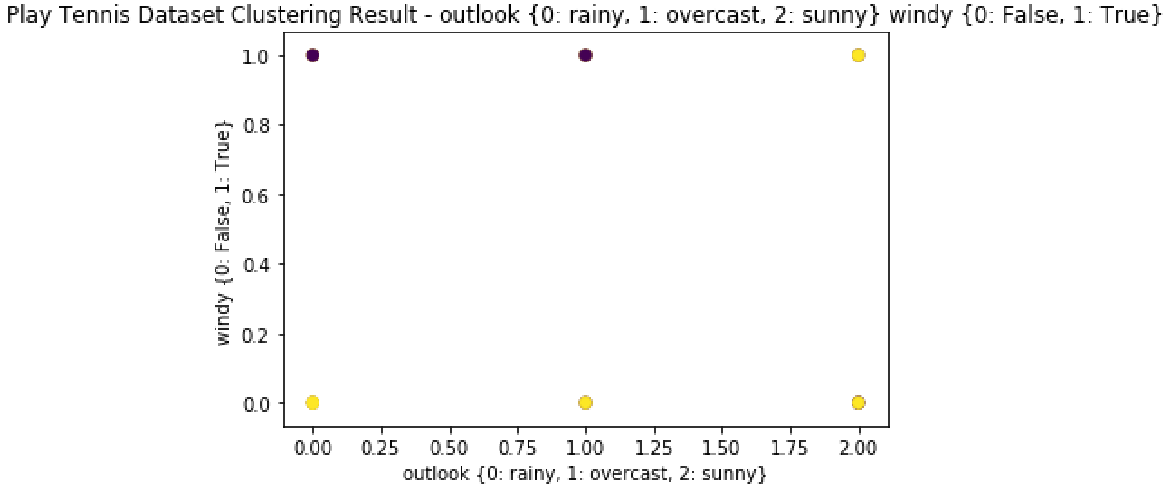
```
Clustering result:
[[0, 1, 2, 3, 7, 11, 13], [4, 5, 6, 8, 9, 10, 12]]
```

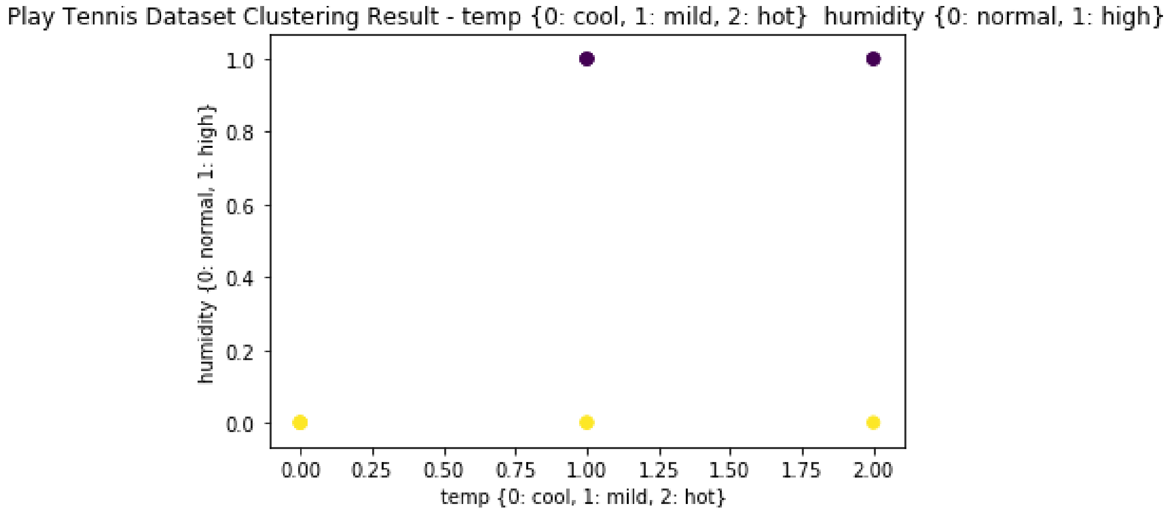
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} temp {0: cool, 1: mild, 2: hot}

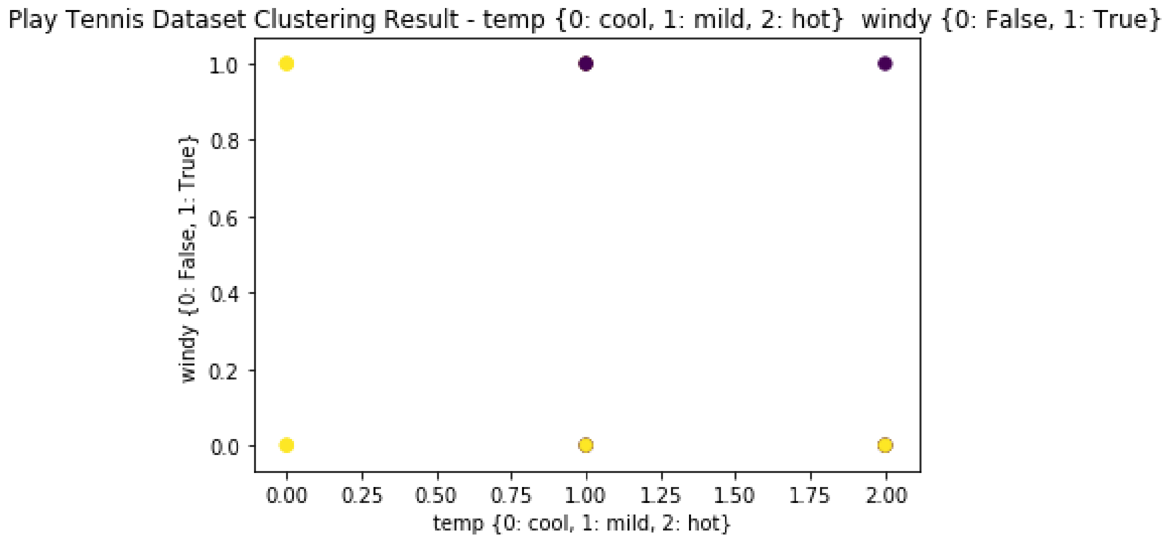


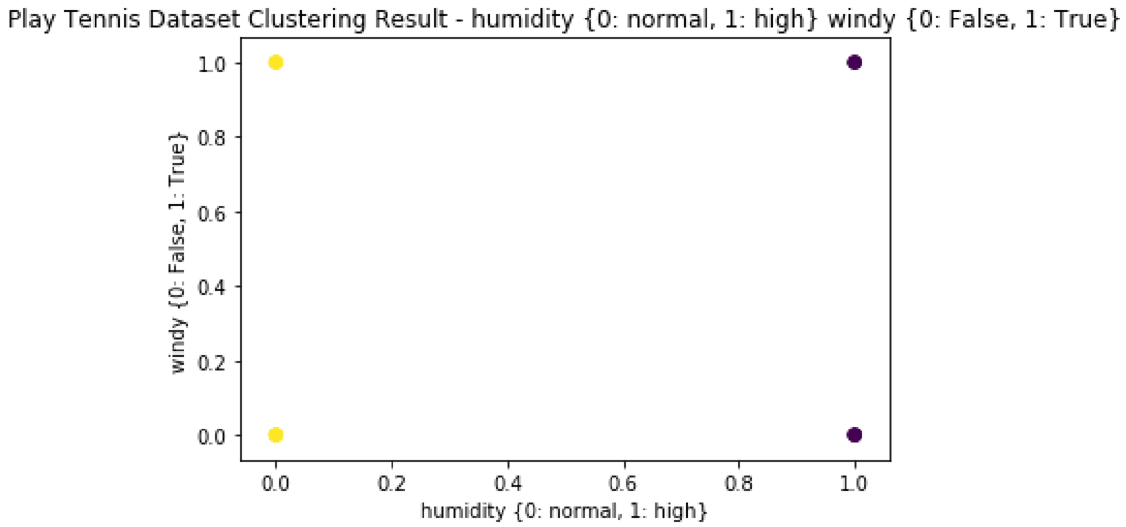
Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} humidity {0: normal, 1: high}




Play Tennis Dataset Clustering Result - outlook {0: rainy, 1: overcast, 2: sunny} windy {0: False, 1: True}
windy {0: False, 1: True}
outlook {0: rainy, 1: overcast, 2: sunny}
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
0.0 0.2 0.4 0.6 0.8 1.0


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} humidity {0: normal, 1: high}
humidity {0: normal, 1: high}
temp {0: cool, 1: mild, 2: hot}
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
0.0 0.2 0.4 0.6 0.8 1.0


Play Tennis Dataset Clustering Result - temp {0: cool, 1: mild, 2: hot} windy {0: False, 1: True}
windy {0: False, 1: True}
temp {0: cool, 1: mild, 2: hot}
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75 2.00
0.0 0.2 0.4 0.6 0.8 1.0



3.2.8 Penyimpanan dan Pembacaan Model/Hipotesis pada File Eksternal

1. Penyimpanan Model/Hipotesis

In [32]:

```
joblib.dump(kmeans, 'tennis_kmeans_model.pkl')
joblib.dump(agglomerative, 'tennis_agglomerative_model.pkl')
joblib.dump(db, 'tennis_dbscan_model.pkl')
joblib.dump(gmm, 'tennis_gaussian_mixture_model.pkl')
joblib.dump(graph_clustering, 'tennis_graph_clustering_model.pkl')

with open('tennis_kmedoids_model', "wb") as f:
    dill.dump(kmedoids_instance, f)

with open('tennis_bang_model', "wb") as f:
    dill.dump(bang_instance, f)
```

2. Pembacaan Model/Hipotesis

In [33]:

```
kmeans_model = joblib.load('tennis_kmeans_model.pkl')
agglomerative_model = joblib.load('tennis_agglomerative_model.pkl')
dbscan_model = joblib.load('tennis_dbscan_model.pkl')
gaussian_mixture_model = joblib.load('tennis_gaussian_mixture_model.pkl')
graph_clustering_model = joblib.load('tennis_graph_clustering_model.pkl')

kmedoids_model = dill.load(open('tennis_kmedoids_model', "rb"))
bang_model = dill.load(open('tennis_bang_model', "rb"))
```

3.2.9 Assignment Cluster Instance Baru dengan Model dari File Eksternal

1. Pembuatan Instance Baru

In [34]:

```
# sunny, cool, normal, True
test_instance = [[2, 0, 0, 1]]

new_dataset = np.append(x, test_instance, axis=0)
print(new_dataset[14])

# convert numpy array to list for BANG clustering
new_list_dataset = new_dataset.tolist()
```

```
[2 0 0 1]
```

2. Assignment Cluster Instance Baru

a. K-Means

In [35]:

```
kmeans_cluster_prediction = kmeans_model.predict(test_instance)
print("New instance cluster:", kmeans_cluster_prediction[0])
```

```
New instance cluster: 0
```

b. Agglomerative Clustering

In [36]:

```
agglomerative_prediction = agglomerative_model.fit_predict(new_dataset)
print("New instance cluster:", agglomerative_prediction[14])
```

```
New instance cluster: 0
```

c. DBSCAN

In [37]:

```
dbscan_prediction = dbscan_model.fit_predict(new_dataset)
print("New instance cluster:", dbscan_prediction[14])
```

```
New instance cluster: 1
```

d. Gaussian Mixture

In [38]:

```
gmm_cluster_prediction = gaussian_mixture_model.predict(test_instance)
print("New instance cluster:", gmm_cluster_prediction[0])
```

```
New instance cluster: 0
```

e. Graph Clustering

In [39]:

```
graph_clustering_prediction = graph_clustering_model.fit_predict(new_dataset)
print("New instance cluster:", graph_clustering_prediction[14])
```

```
New instance cluster: 1
```

f. K-Medoids

In [40]:

```
kmedoids_instance = kmedoids(new_dataset,[1, 10]);
kmedoids_instance.process()
clusters = kmedoids_instance.get_clusters()
medoids = kmedoids_instance.get_medoids()

for i in range(0, len(clusters)):
    if 14 in clusters[i]:
        print("New instance cluster:", i)
        break
```

```
New instance cluster: 1
```

g. Grid Clustering (BANG)

In [41]:

```
bang_model = bang(new_list_dataset, 7)
bang_model.process()

clusters = bang_model.get_clusters()
noise = bang_model.get_noise()
directory = bang_model.get_directory()
dendrogram = bang_model.get_dendrogram()
clusters

for i in range(0, len(clusters)):
    if 14 in clusters[i]:
        print("New instance cluster:", i)
        break
```

```
New instance cluster: 1
```

4. Sumber

[1] http://scikit-learn.org/stable/modules/clustering.html (http://scikit-learn.org/stable/modules/clustering.html)
[2] http://nbviewer.jupyter.org/github/jakevdp/mst_clustering/blob/master/MSTClustering.ipynb (http://nbviewer.jupyter.org/github/jakevdp/mst_clustering/blob/master/MSTClustering.ipynb)
[3] https://codedocs.xyz/annoviko/pyclustering/index.html (https://codedocs.xyz/annoviko/pyclustering/index.html)