IF4091 Pembelajaran Mesin

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

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Import Statements

In [37]:

```
from matplotlib.colors import LogNorm
from mst_clustering import MSTClustering
from pyclustering.cluster.bang import bang, bang_visualizer
from pyclustering.cluster.kmedoids import kmedoids
from sklearn import datasets
from sklearn.decomposition import PCA
from sklearn.externals import joblib
from sklearn.cluster import AgglomerativeClustering, DBSCAN, KMeans
from sklearn.metrics.pairwise import pairwise_distances
from sklearn.mixture import GaussianMixture
from sklearn.preprocessing import LabelEncoder

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

Load Datasets

Pada tahap load, datasets diload kemudian labelnya dihapus karena ingin melakukan clustering (unsupervised learning)

In [38]:

```
# Load iris
iris_data = datasets.load_iris()
iris_df = pd.DataFrame(data= np.c_[iris_data['data'], iris_data['target']],
                    columns= iris_data['feature_names'] + ['target'])
del iris_df["target"]

# Load tennis
tennis_df_raw = pd.read_csv("datasets/tennis.csv")
del tennis_df_raw["play"]
```

Preprocessing

Pada tahap preprocessing, data tennis akan diproses sehingga nilai setiap atribut diubah menjadi atribut integer dengan menggunakan LabelEncoder.

Setelah itu, data iris dan tennis akan ditampilkan dengan menggunakan PCA sehingga data yang memiliki dimensi lebih dari 2 dapat direpresentasikan dengan plot 2 dimensi.

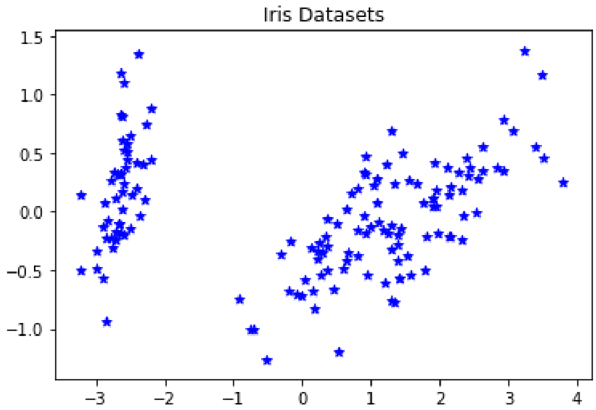
In [39]:

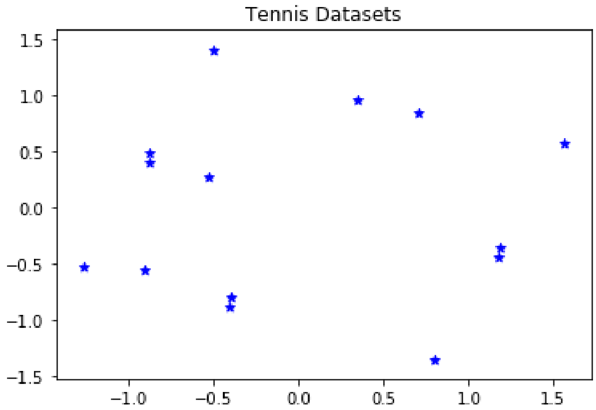
```
# change string/object values to integer
le = LabelEncoder()
tennis_df = pd.DataFrame()
for column in tennis_df_raw:
```

```
    tennis_df[column] = le.fit_transform(tennis_df_raw[column])
```

In [40]:

```
def plot_initial(df, title):
    pca = PCA(n_components=2).fit(df)
    pca_2d = pca.transform(df)
    for i in range(0, pca_2d.shape[0]):
        c = pl.scatter(pca_2d[i,0],pca_2d[i,1],c='b',marker='*')
    pl.title(title)
    pl.show()

plot_initial(iris_df, "Iris Datasets")
plot_initial(tennis_df, "Tennis Datasets")
```





Model Training

In [41]:

```
k_iris = 3
k_tennis = 2
```

In [42]:

```
def plot_cluster(df, model_labels, title):
    pca = PCA(n_components=2).fit(df)
    pca_2d = pca.transform(df)
    unique_labels = list(set(model_labels))
    colors = ['r', 'g', 'b']
    markers = ['+', 'o', '*']
    clusters = [None] * len(unique_labels)
    for i in range(0, pca_2d.shape[0]):
        idx = unique_labels.index(model_labels[i])
        clusters[idx] = pl.scatter(pca_2d[i,0], pca_2d[i,1], c=colors[idx], marker=markers[idx])
    legends = []
    for i, cluster in enumerate(clusters):
        if cluster != None:
            legends.append('Cluster ' + str(i))
    pl.legend(clusters, legends)
    pl.title(title)
```

```
    pl.show()

def plot_cluster_DBSCAN(df, model_labels, title):
    pca = PCA(n_components=2).fit(df)
    pca_2d = pca.transform(df)
    unique_labels = list(set(model_labels))
    colors = ['r', 'g', 'b', 'k']
    markers = ['+', 'o', '*', 'v']
    clusters = [None] * len(unique_labels)
    is_core = [True] * len(unique_labels)
    for i in range(0, pca_2d.shape[0]):
        idx = unique_labels.index(model_labels[i])
        is_core[idx] = model_labels[i] != -1
        clusters[idx] = pl.scatter(pca_2d[i,0], pca_2d[i,1], c=colors[idx], marker=markers[idx])
    legends = []
    for i, cluster in enumerate(clusters):
        if cluster != None:
            if is_core[i]:
                legends.append('Cluster ' + str(i))
            else:
                legends.append('Outlier')
    pl.legend(clusters, legends)
    pl.title(title)
    pl.show()

def plot_cluster_GMM(df, k, title, cov='full', threshold=0.001):
    pca = PCA(n_components=2).fit(df)
    pca_2d = pca.transform(df)
    model = GaussianMixture(n_components=k, covariance_type=cov, tol=threshold).fit(pca_2d)
    x = np.linspace(-20., 30.)
    y = np.linspace(-20., 40.)
    X, Y = np.meshgrid(x, y)
    XX = np.array([X.ravel(), Y.ravel()]).T
    Z = -model.score_samples(XX)
    Z = Z.reshape(X.shape)

    CS = plt.contour(X, Y, Z, norm=LogNorm(vmin=1.0, vmax=1000.0),
                     levels=np.logspace(0, 3, 10))
    CB = plt.colorbar(CS, shrink=0.8, extend='both')
    plt.scatter(pca_2d[:, 0], pca_2d[:, 1], .8)

    plt.title(title)
    plt.axis('tight')
    plt.show()
```

1. Agglomerative Clustering

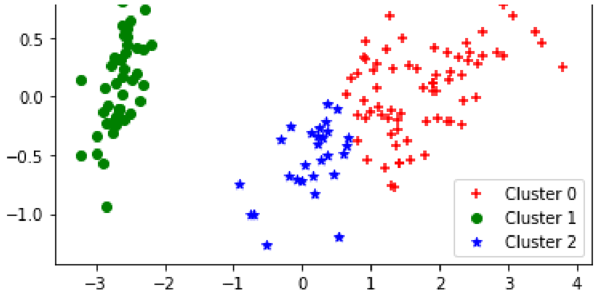
Parameter Agglomerative Clustering:

1. n_clusters: jumlah cluster (default=2)
2. affinity: metrik yang digunakan untuk menghitung jarak linkage (default=euclidean)
3. connectivity: matriks ketetanggan node, untuk structured hierarchical algorithm (default=None)
4. compute_full_tree: apakah proses clustering dihentikan setelah n_cluster iterasi atau tidak (default=auto)
5. linkage: kriteria linkage yang digunakan, misalnya 'ward', 'complete', 'average' (default=ward)

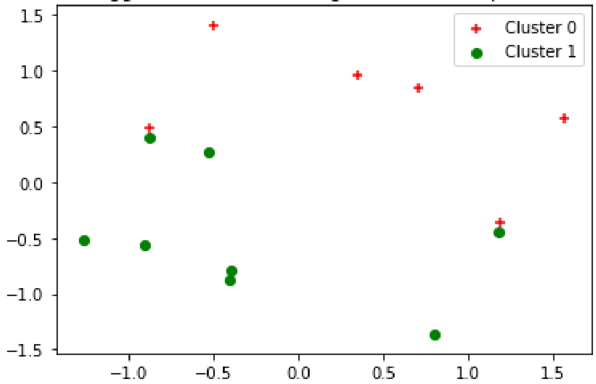
a. Eksperimen Agglomerative Clustering dengan parameter linkage complete

In [43]:

```
iris_agglo1 = AgglomerativeClustering(n_clusters=k_iris, linkage='complete').fit(iris_df)
tennis_agglo1 = AgglomerativeClustering(n_clusters=k_tennis, linkage='complete').fit(tennis_df)

plot_cluster(iris_df, iris_agglo1.labels_, "Iris Agglomerative Clustering Clusters - Complete Link
age")
plot_cluster(tennis_df, tennis_agglo1.labels_, "Tennis Agglomerative Clustering Clusters -
Complete Linkage")
```



Tennis Agglomerative Clustering Clusters - Complete Linkage

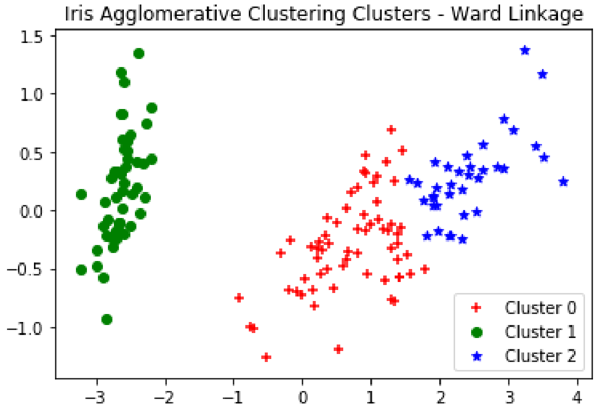


b. Eksperimen Agglomerative Clustering dengan parameter linkage ward

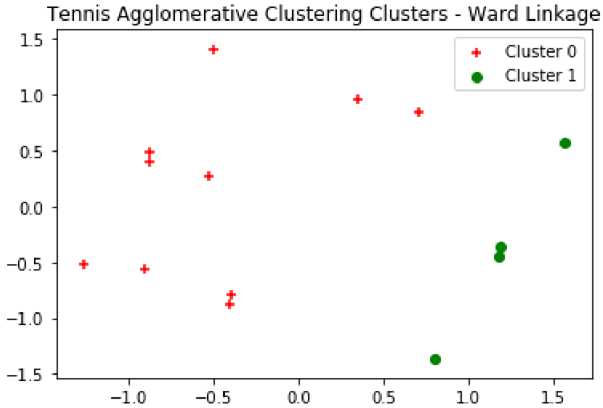
In [44]:

```
iris_agglo = AgglomerativeClustering(n_clusters=k_iris, affinity='euclidean', linkage='ward').fit(i
ris_df)
tennis_agglo = AgglomerativeClustering(n_clusters=k_tennis, affinity='euclidean', linkage='ward').f
it(tennis_df)

plot_cluster(iris_df, iris_agglo.labels_, "Iris Agglomerative Clustering Clusters - Ward Linkage")
plot_cluster(tennis_df, tennis_agglo.labels_, "Tennis Agglomerative Clustering Clusters - Ward Lin
kage")
```

Iris Agglomerative Clustering Clusters - Ward Linkage



Tennis Agglomerative Clustering Clusters - Ward Linkage



c. Simpan model

In [45]:

```
joblib.dump(iris_agglo, 'iris_agglo.pkl')
joblib.dump(tennis_agglo, 'tennis_agglo.pkl')
print("Agglomerative Clustering models saved")
```

```
Agglomerative Clustering models saved
```

2. DBSCAN

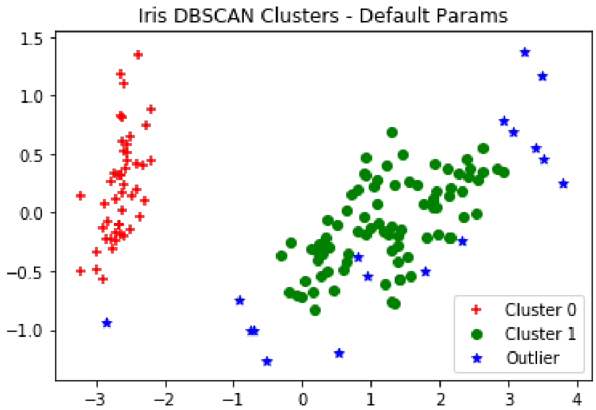
Beberapa parameter DBSCAN:

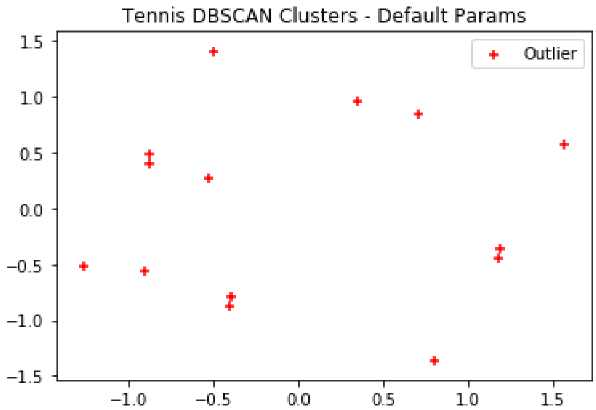
1. eps: jarak maksimum diantara 2 data yang dianggap saling bertetangga (default=0.5)
2. min_samples: jumlah tetangga data minimal untuk dianggap sebagai core point (default=5)
3. metric: metrik yang digunakan untuk menghitung jarak antar data (default=euclidean
4. algorithm: algoritma NN, misalnya 'auto', 'ball_tree', 'kd_tree', 'brute' (default=auto)

a. Eksperimen DBSCAN dengan parameter default

In [46]:

```
iris_dbscan1 = DBSCAN().fit(iris_df)
tennis_dbscan1 = DBSCAN().fit(tennis_df)

plot_cluster_DBSCAN(iris_df, iris_dbscan1.labels_, "Iris DBSCAN Clusters - Default Params")
plot_cluster_DBSCAN(tennis_df, tennis_dbscan1.labels_, "Tennis DBSCAN Clusters - Default Params")
```

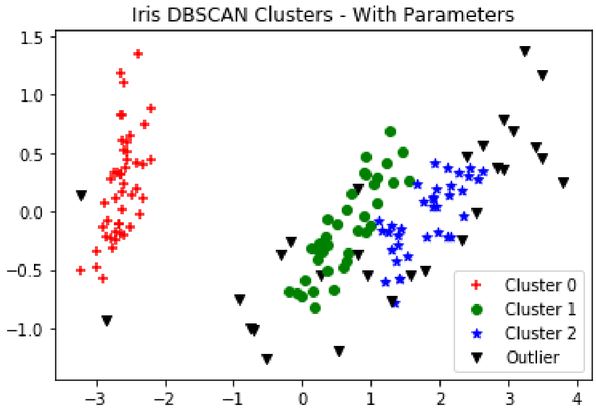


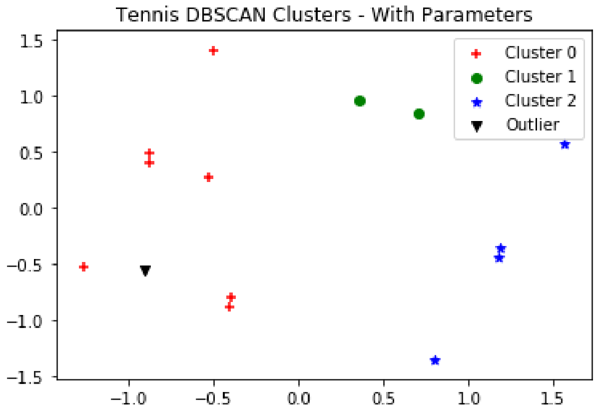


b. Eksperimen DBSCAN dengan parameter epsilon, min samples, dan algoritma DBSCAN

In [47]:

```
iris_dbscan = DBSCAN(eps=0.42, min_samples=5, algorithm='kd_tree').fit(iris_df)
tennis_dbscan = DBSCAN(eps=1, min_samples=2, algorithm='kd_tree').fit(tennis_df)

plot_cluster_DBSCAN(iris_df, iris_dbscan.labels_, "Iris DBSCAN Clusters - With Parameters")
plot_cluster_DBSCAN(tennis_df, tennis_dbscan.labels_, "Tennis DBSCAN Clusters - With Parameters")
```





c. Simpan model

In [48]:

```
joblib.dump(iris_dbscan, 'iris_dbscan.pkl')
joblib.dump(tennis_dbscan, 'tennis_dbscan.pkl')
print("DBSCAN models saved")
```

```
DBSCAN models saved
```

3. K-Means

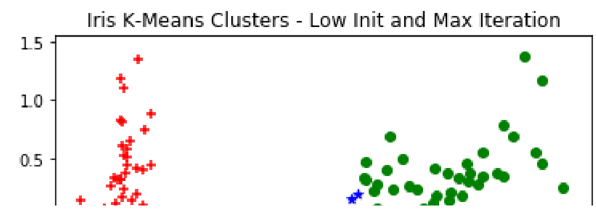
Beberapa parameter K-Means:

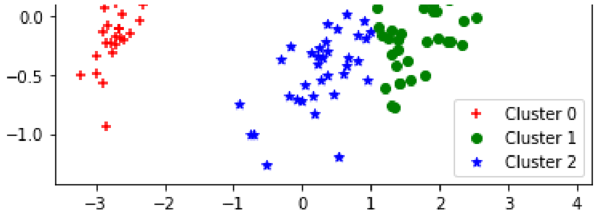
1. n_clusters: jumlah cluster yang dihasilkan (default=8)
2. init: metode inisialisasi, misalnya 'k-means++', 'random', atau ndarray (default=k-means++)
3. n_init: jumlah algoritma k-means akan dijalankan pada seed/centroid yang berbeda untuk menemukan seed terbaik
4. max_iter: jumlah iterasi maksimum (default=300)

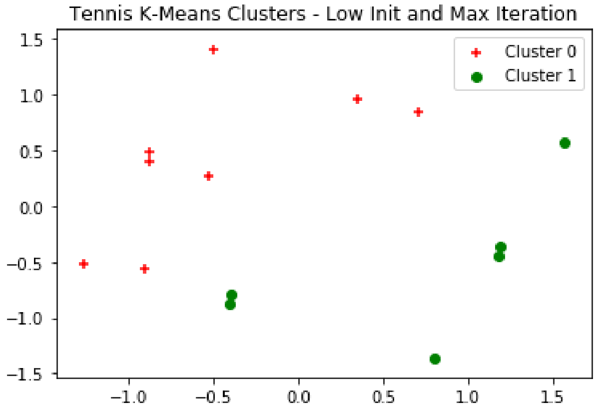
a. Eksperimen K-Means dengan parameter n_init dan jumlah maksimum iterasi yang kecil

In [75]:

```
iris_kmeans1 = KMeans(n_clusters=k_iris, n_init=1, max_iter=2).fit(iris_df)
tennis_kmeans1 = KMeans(n_clusters=k_tennis, n_init=1, max_iter=2).fit(tennis_df)

plot_cluster(iris_df, iris_kmeans1.labels_, "Iris K-Means Clusters - Low Init and Max Iteration")
plot_cluster(tennis_df, tennis_kmeans1.labels_, "Tennis K-Means Clusters - Low Init and Max Iterat
ion")
```



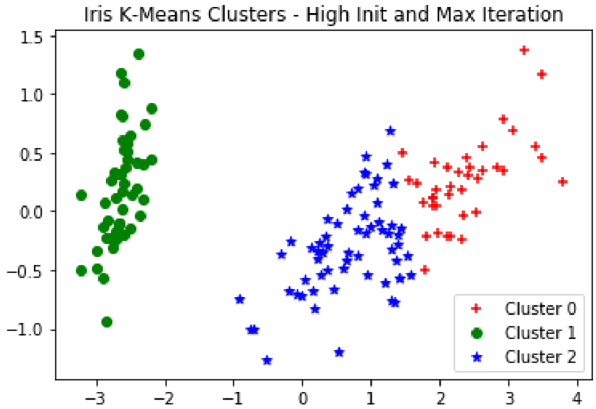


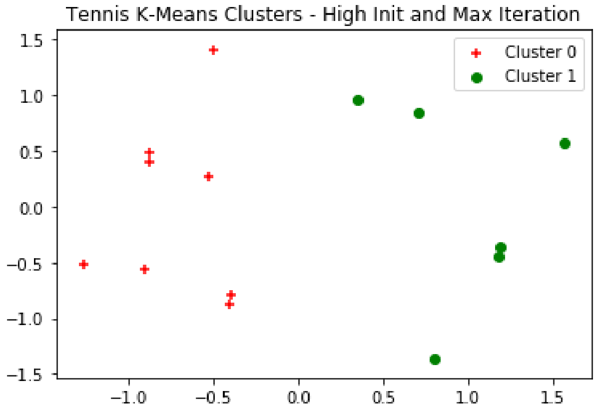


b. Eksperimen K-Means dengan parameter n_init dan jumlah maksimum iterasi besar

In [50]:

```
iris_kmeans = KMeans(n_clusters=k_iris, n_init=20, max_iter=100).fit(iris_df)
tennis_kmeans = KMeans(n_clusters=k_tennis, n_init=20, max_iter=100).fit(tennis_df)

plot_cluster(iris_df, iris_kmeans.labels_, "Iris K-Means Clusters - High Init and Max Iteration")
plot_cluster(tennis_df, tennis_kmeans.labels_, "Tennis K-Means Clusters - High Init and Max Iterat
ion")
```





c. Simpan Model

In [51]:

```
joblib.dump(iris_kmeans, 'iris_kmeans.pkl')
joblib.dump(tennis_kmeans, 'tennis_kmeans.pkl')
```

```
print("K-Means models saved")
```

```
K-Means models saved
```

4. Gaussian Mixture

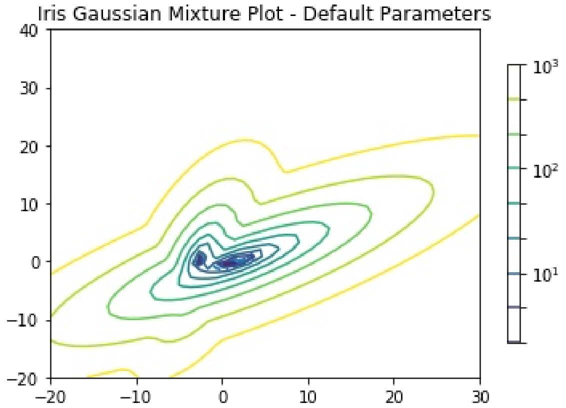
Beberapa parameter GMM:

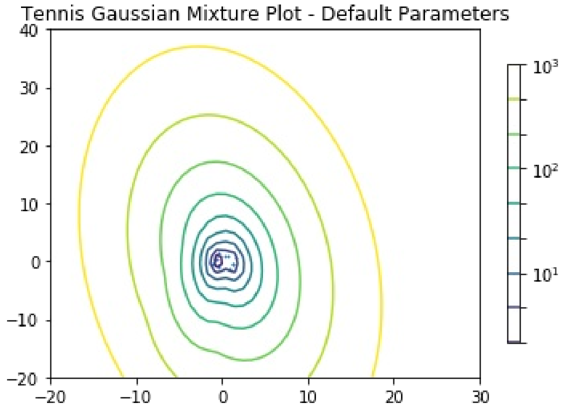
1. n_components: jumlah komponen mixture (default=1)
2. covariance_type: tipe kovariansi, misalnya 'full', 'tied', 'diag', 'spherical' (default=full)
3. tol: threshold konvergensi (default=1e-3)

a. Eksperimen GMM dengan parameter default

In [52]:

```
iris_gauss1 = GaussianMixture(n_components=k_iris).fit(iris_df)
tennis_gauss1 = GaussianMixture(n_components=k_tennis).fit(tennis_df)

plot_cluster_GMM(iris_df, k_iris, "Iris Gaussian Mixture Plot - Default Parameters")
plot_cluster_GMM(tennis_df, k_tennis, "Tennis Gaussian Mixture Plot - Default Parameters")
```

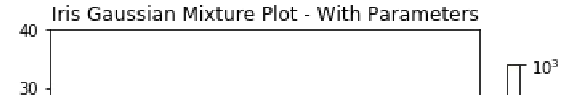


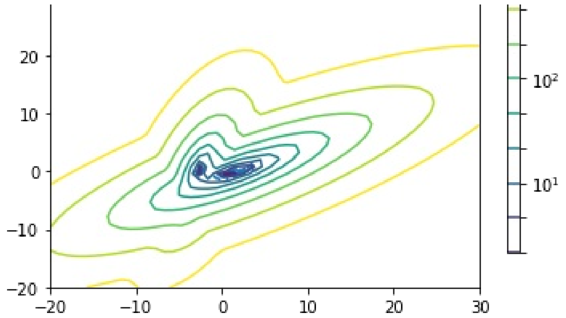


b. Eksperimen GMM dengan parameter komponen, tipe kovarian, dan threshold

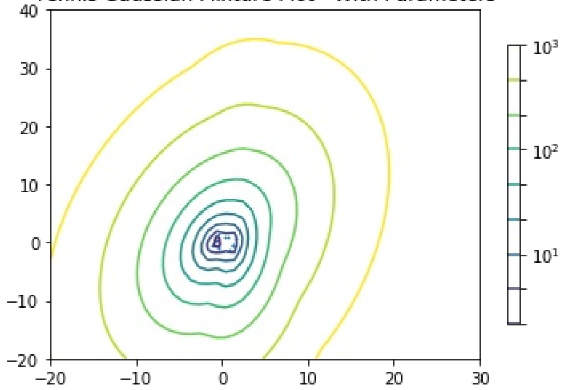
In [78]:

```
iris_gauss = GaussianMixture(n_components=k_iris, covariance_type='spherical', tol=0.0001).fit(iris
_df)
tennis_gauss = GaussianMixture(n_components=k_tennis, covariance_type='spherical', tol=0.0001).fit(
tennis_df)

plot_cluster_GMM(iris_df, k_iris, "Iris Gaussian Mixture Plot - With Parameters")
plot_cluster_GMM(tennis_df, k_tennis, "Tennis Gaussian Mixture Plot - With Parameters")
```





Tennis Gaussian Mixture Plot - With Parameters



c. Simpan model

In [54]:

```
joblib.dump(iris_gauss, 'iris_gauss.pkl')
joblib.dump(tennis_gauss, 'tennis_gauss.pkl')
print("Gaussian Mixture models saved")
```

```
Gaussian Mixture models saved
```

5. K-Medoids

Beberapa parameter K-Medoids:

1. data: data yang ingin diproses
2. initial_index_medoids: titik-titik centroid awal
3. tolerance: threshold untuk konvergensi (default=0.001)
4. ccore: true apabila ingin menggunakan library C dalam proses K-Medoids (default=True)

In [55]:

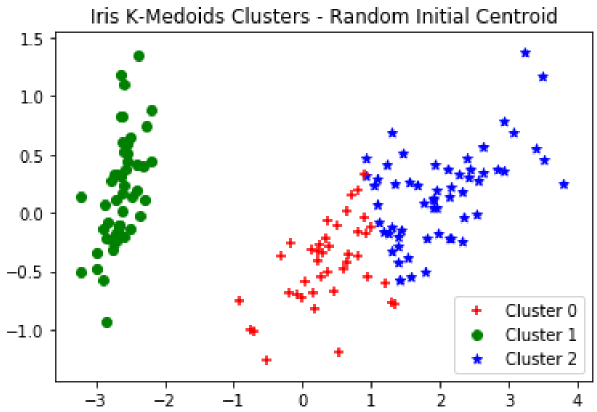
```
def data_clusters_to_cluster(cluster_idxs):
    size = 0
    for i in range(0, len(cluster_idxs)):
        size += len(cluster_idxs[i])
    labels = [0] * size
    for i in range(0, len(cluster_idxs)):
        for j in range(0, len(cluster_idxs[i])):
            labels[cluster_idxs[i][j]] = i
    return labels
```

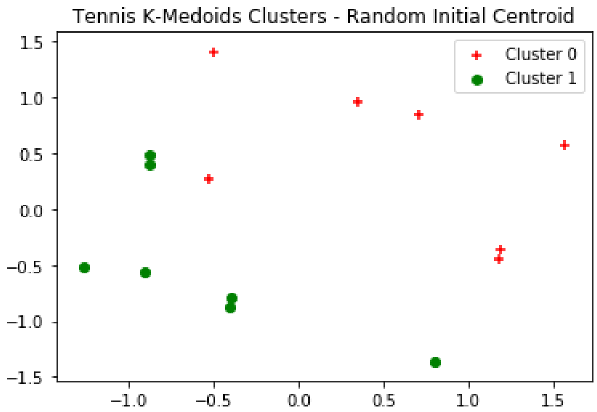
a. Eksperimen K-Medoids dengan parameter initial medoid random dan toleransi tinggi

In [91]:

```
iris_init_medoids1 = np.random.randint(low=0, high=iris_df.shape[0], size=k_iris)
iris_kmedoids1 = kmedoids(data=iris_df.get_values(), initial_index_medoids=iris_init_medoids1,
tolerance=0.5)
iris_kmedoids1.process()

tennis_init_medoids1 = np.random.randint(low=0, high=tennis_df.shape[0], size=k_tennis)
```

```
tennis_kmedoids1 = kmedoids(data=tennis_df.get_values(),
initial_index_medoids=tennis_init_medoids1, tolerance=0.5)
tennis_kmedoids1.process()

plot_cluster(iris_df, data_clusters_to_cluster(
    iris_kmedoids1.get_clusters()), "Iris K-Medoids Clusters - Random Initial Centroid")
plot_cluster(tennis_df, data_clusters_to_cluster(
    tennis_kmedoids1.get_clusters()), "Tennis K-Medoids Clusters - Random Initial Centroid")
```

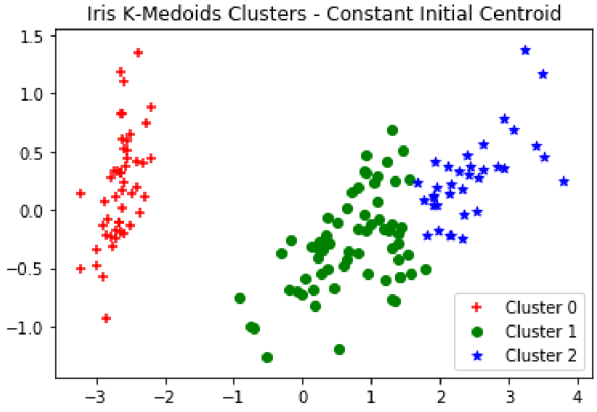


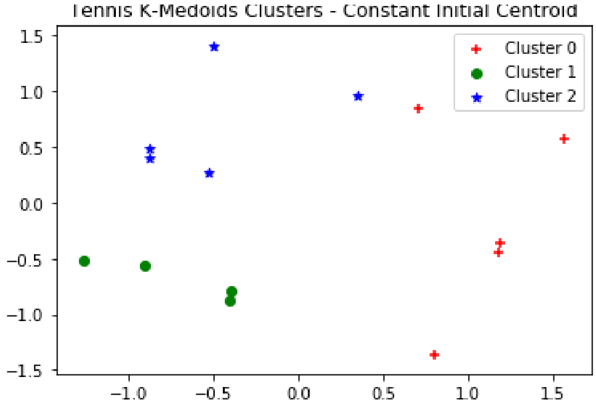


b. Eksperimen K-Medoids dengan initial centroid tetap dan toleransi rendah

In [57]:

```
iris_init_medoids = [25, 75, 125]
iris_kmedoids = kmedoids(data=iris_df.get_values(), initial_index_medoids=iris_init_medoids)
iris_kmedoids.process()

tennis_init_medoids = [4, 8, 12]
tennis_kmedoids = kmedoids(data=tennis_df.get_values(), initial_index_medoids=tennis_init_medoids)
tennis_kmedoids.process()

plot_cluster(iris_df, data_clusters_to_cluster(
    iris_kmedoids.get_clusters()), "Iris K-Medoids Clusters - Constant Initial Centroid")
plot_cluster(tennis_df, data_clusters_to_cluster(
    tennis_kmedoids.get_clusters()), "Tennis K-Medoids Clusters - Constant Initial Centroid")
```





c. Simpan model

In [58]:

```
joblib.dump(iris_kmedoids.get_cluster_encoding(), 'iris_kmedoids.pkl')
joblib.dump(tennis_kmedoids.get_cluster_encoding(), 'tennis_kmedoids.pkl')
print("K-Medoids models saved")
```

```
K-Medoids models saved
```

6. MST Clustering

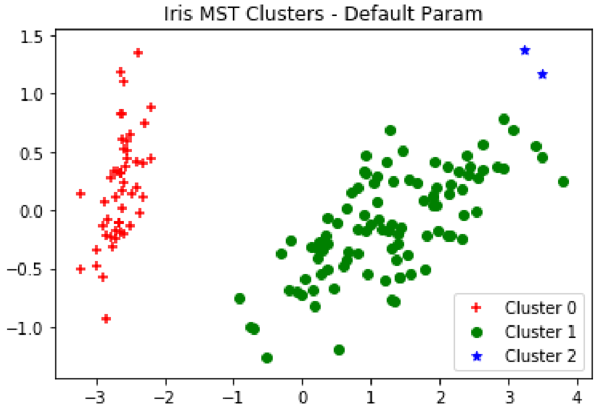
Beberapa parameter MST:

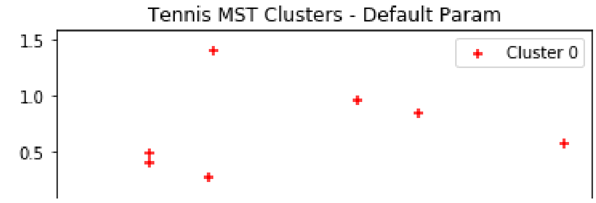
1. cutoff: jumlah edge yang dihapus
2. cutoff_scale: hapus edge dengan jarak melebihi skala
3. min_cluster_size: jumlah minimum data per cluster, bila lebih kecil maka data akan diassign pada background (default=1)
4. metric: metrik untuk menghitung jarak antar data (default=euclidean)

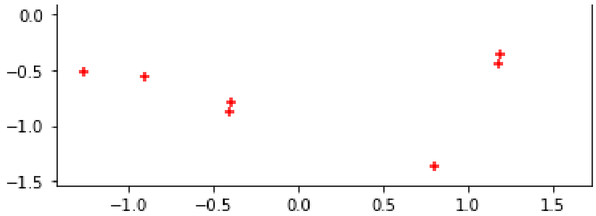
a. Eksperimen MST dengan parameter default

In [59]:

```
iris_mst1 = MSTClustering(cutoff=k_iris-1).fit(iris_df)
tennis_mst1 = MSTClustering(cutoff=k_tennis-1).fit(tennis_df)

plot_cluster(iris_df, iris_mst1.fit_predict(iris_df).tolist(), "Iris MST Clusters - Default Param"
)
plot_cluster(tennis_df, tennis_mst1.fit_predict(iris_df).tolist(), "Tennis MST Clusters - Default
Param")
```



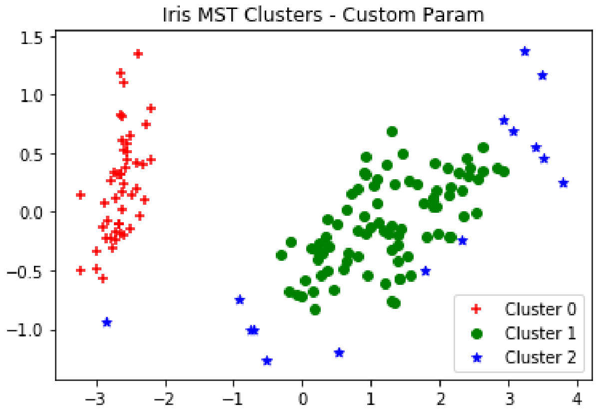


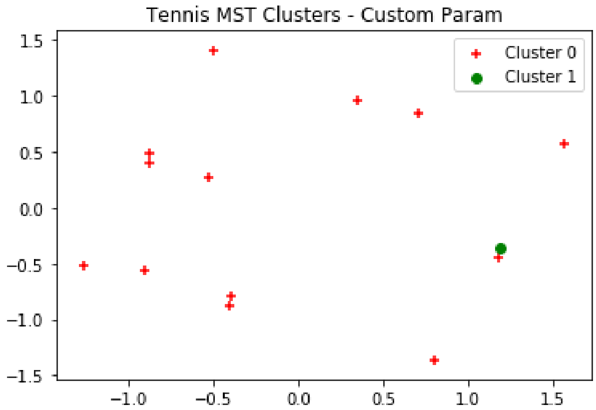


b. Eksperimen MST dengan parameter jumlah cluster dan metrik

In [60]:

```
iris_mst = MSTClustering(cutoff=k_iris-1, cutoff_scale=0.8, min_cluster_size=10, metric='manhattan'
).fit(iris_df)
tennis_mst = MSTClustering(cutoff=k_tennis-1, cutoff_scale=0.5, min_cluster_size=1, metric='manhatt
an').fit(tennis_df)

plot_cluster(iris_df, iris_mst.fit_predict(iris_df).tolist(), "Iris MST Clusters - Custom Param")
plot_cluster(tennis_df, tennis_mst.fit_predict(iris_df).tolist(), "Tennis MST Clusters - Custom Pa
ram")"iris: Cluster"
```





c. Simpan model

In [99]:

```
joblib.dump(iris_mst, 'iris_mst.pkl')
joblib.dump(tennis_mst1, 'tennis_mst.pkl')
print("MST models saved")
```

```
MST models saved
```

7. Grid Clustering

Beberapa parameter Grid:

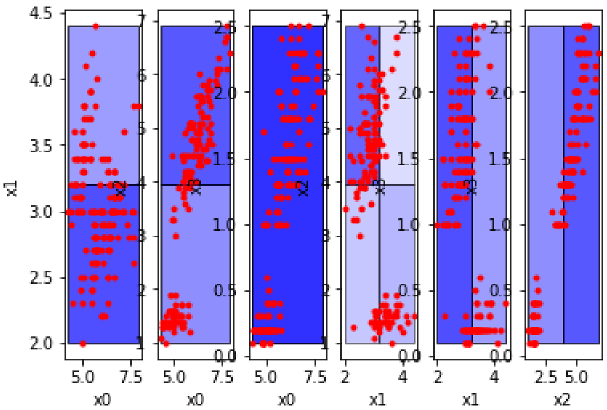
1. data: data yang ingin dicluster
2. levels: jumlah pemisahan 1 blok pada grid

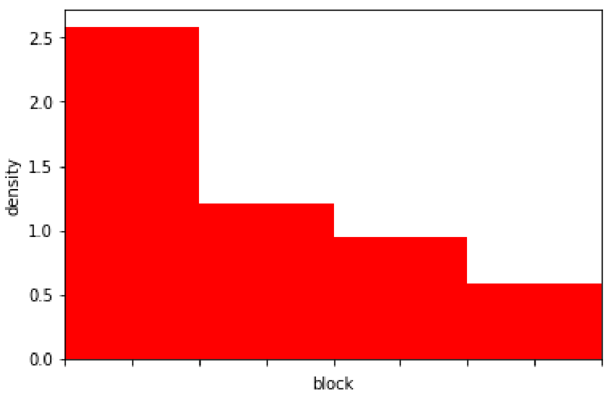
a. Eksperimen Grid Clustering

In [62]:

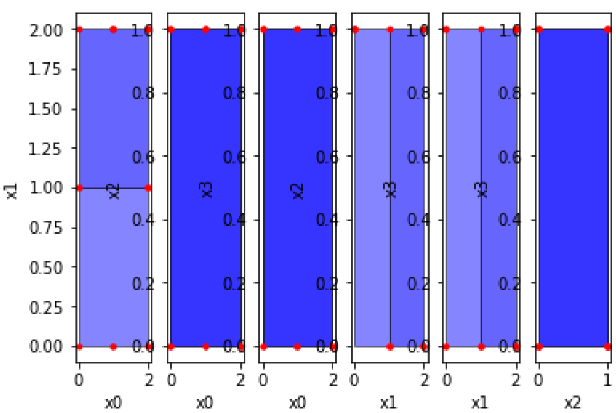
```
iris_grid = bang(data=iris_df.values.tolist(), levels=k_iris)
iris_grid.process()

tennis_grid = bang(data=tennis_df.values.tolist(), levels=k_tennis)
tennis_grid.process()

print("Iris Grid Clustering Blocks and Dendogram")
bang_visualizer.show_blocks(iris_grid.get_directory())
bang_visualizer.show_dendrogram(iris_grid.get_dendrogram())
print()
print("Tennis Grid Clustering Blocks and Dendogram")
bang_visualizer.show_blocks(tennis_grid.get_directory())
bang_visualizer.show_dendrogram(tennis_grid.get_dendrogram())
```

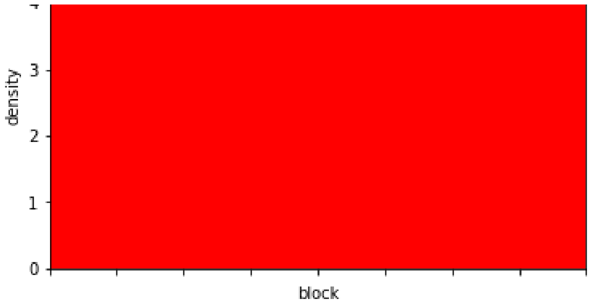
```
Iris Grid Clustering Blocks and Dendogram
```






```
Tennis Grid Clustering Blocks and Dendogram
```





b. Simpan model

In [63]:

```
joblib.dump(iris_grid, 'iris_grid.pkl')
joblib.dump(tennis_grid, 'tennis_grid.pkl')
print("Grid Clustering models saved")
```

```
Grid Clustering models saved
```

Load Models

In [102]:

```
iris_agglo_loaded = joblib.load('iris_agglo.pkl')
tennis_agglo_loaded = joblib.load('tennis_agglo.pkl')
iris_dbscan_loaded = joblib.load('iris_dbscan.pkl')
tennis_dbscan_loaded = joblib.load('tennis_dbscan.pkl')
iris_kmeans_loaded = joblib.load('iris_kmeans.pkl')
tennis_kmeans_loaded = joblib.load('tennis_kmeans.pkl')
iris_gauss_loaded = joblib.load('iris_gauss.pkl')
tennis_gauss_loaded = joblib.load('tennis_gauss.pkl')
iris_kmedoids_loaded = joblib.load('iris_kmedoids.pkl')
tennis_kmedoids_loaded = joblib.load('tennis_kmedoids.pkl')
iris_mst_loaded = joblib.load('iris_mst.pkl')
tennis_mst_loaded = joblib.load('tennis_mst.pkl')
iris_grid_loaded = joblib.load('iris_grid.pkl')
tennis_grid_loaded = joblib.load('tennis_grid.pkl')
```

New Instances

Didefinisikan sebuah instans baru untuk iris dan tennis

In [65]:

```
iris_new = {
    'sepal length (cm)': [5.4],
    'sepal width (cm)' : [3.7],
    'petal length (cm)': [1.5],
    'petal width (cm)' : [0.2]
}
tennis_new = {'outlook': [0], 'temp': [1], 'humidity': [1], 'windy': [0]}

iris_new_df = pd.DataFrame(data=iris_new)
tennis_new_df = pd.DataFrame(data=tennis_new)

iris_new_df_c = pd.concat([iris_df, iris_new_df])
tennis_new_df_c = pd.concat([tennis_df, tennis_new_df])
```

Assigment Cluster

1. Agglomerative Clustering

In [66]:

```
iris_predict_agglo = iris_agglo_loaded.fit_predict(iris_new_df_c)[len(iris_df)]
print("iris: Cluster", iris_predict_agglo)
tennis_predict_agglo = tennis_agglo_loaded.fit_predict(tennis_new_df_c)[len(tennis_df)]
print("tennis: Cluster", tennis_predict_agglo)
```

```
iris: Cluster 1
tennis: Cluster 0
```

2. DBSCAN

In [67]:

```
iris_predict_dbscan = iris_dbscan_loaded.fit_predict(iris_new_df_c)[len(iris_df)]
print("iris: Cluster", iris_predict_dbscan)
tennis_predict_dbscan = tennis_dbscan_loaded.fit_predict(tennis_new_df_c)[len(tennis_df)]
print("tennis: Cluster", tennis_predict_dbscan)
```

```
iris: Cluster 0
tennis: Cluster 1
```

3. K-Means

In [68]:

```
iris_predict_kmeans = iris_kmeans_loaded.predict(iris_new_df)[0]
print("iris: Cluster", iris_predict_kmeans)
tennis_predict_kmeans = tennis_kmeans_loaded.predict(tennis_new_df)[0]
print("tennis: Cluster", tennis_predict_kmeans)
```

```
iris: Cluster 1
tennis: Cluster 1
```

4. Gaussian Mixture

In [69]:

```
iris_predict_gauss = iris_gauss_loaded.predict(iris_new_df)[0]
print("iris: Cluster", iris_predict_gauss)
tennis_predict_gauss = tennis_gauss_loaded.predict(tennis_new_df)[0]
print("tennis: Cluster", tennis_predict_gauss)
```

```
iris: Cluster 1
tennis: Cluster 1
```

5. K-Medoids

In [70]:

```
iris_predict_kmedoids = kmedoids(data=iris_new_df_c.get_values(),
initial_index_medoids=iris_init_medoids)
iris_predict_kmedoids.process()
print("iris: Cluster", data_clusters_to_cluster(iris_predict_kmedoids.get_clusters())[len(iris_df)
])
tennis_predict_kmedoids = kmedoids(data=tennis_new_df_c.get_values(),
initial_index_medoids=tennis_init_medoids)
tennis_predict_kmedoids.process()
print("tennis: Cluster", data_clusters_to_cluster(tennis_predict_kmedoids.get_clusters())
[len(tennis_df)])
```

```
iris: Cluster 0
tennis: Cluster 2
```

6. MST Clustering

In [104]:

```
iris_predict_mst = iris_mst_loaded.fit_predict(iris_new_df_c)[len(iris_df)]
print("iris: Cluster", iris_predict_mst)
tennis_predict_mst = tennis_mst_loaded.fit_predict(tennis_new_df_c)[len(tennis_df)]
print("tennis: Cluster", tennis_predict_mst)
```

```
iris: Cluster 0
tennis: Cluster 1
```

7. Grid Clustering

In [72]:

```
iris_predict_grid = bang(data=iris_new_df_c.values.tolist(), levels=k_iris)
iris_predict_grid.process()
print("iris: Cluster", data_clusters_to_cluster(iris_predict_grid.get_clusters())[len(iris_df)])
tennis_predict_grid = bang(data=tennis_new_df_c.values.tolist(), levels=k_tennis)
tennis_predict_grid.process()
print("tennis: Cluster", data_clusters_to_cluster(tennis_predict_grid.get_clusters())
[len(tennis_df)])
```

```
iris: Cluster 0
tennis: Cluster 0
```