Job Sheet 7: Clustering

Praktikum 1

KMeans

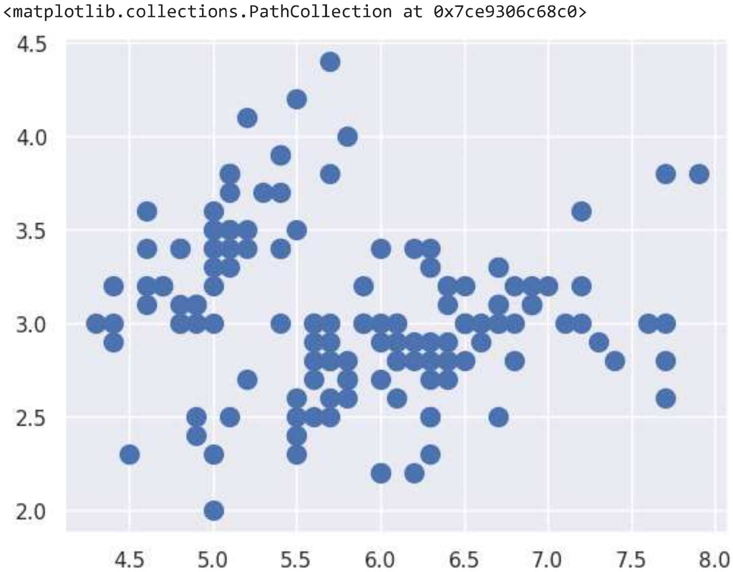
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

df = pd.read_csv('Iris.csv')

df.head()
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

```
# Seleksi Fitur

X = df.iloc[:, 1:-1]
y = df.iloc[:, -1]
```

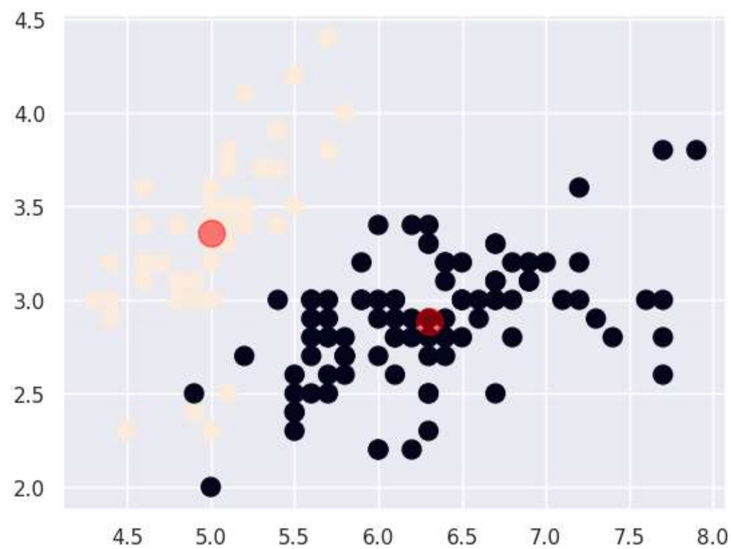
```
# Plot Data
# Karena data 4 dimensi, maka akan kita coba
# plot cluster berdasarkan Sepal Length dan Sepal Width  saja

plt.scatter(X.iloc[:, 0], X.iloc[:, 1], s = 100)
```

```
<matplotlib.collections.PathCollection at 0x7ce9306c68c0>
```



```
# Buat Model KMeans
# Kali ini kita coba menggunakan k=2 - anggap saja kita tidak tahu jumlah label ada 3 :)

from sklearn.cluster import KMeans

# Inisiasi obyek KMeans
cl_kmeans = KMeans(n_clusters=2)

# Fit dan predict model
y_kmeans = cl_kmeans.fit_predict(X)


# Plot hasi cluster berdasarkan Sepal Length dan Sepal Width
plt.scatter(X.iloc[:, 0], X.iloc[:, 1], s = 100, c=y_kmeans)

# Plot centroid
centers = cl_kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='red', s=200, alpha=0.5)
```

```
<matplotlib.collections.PathCollection at 0x7ce9306f38e0>
```




```
# Cek Nilai SSE
print(f'Nilai SSE: {cl_kmeans.inertia_}')
```

```
Nilai SSE: 152.36870647733906
```

```
# Implementasi Metode Elbow

# List nilai SSE
sse = []

# Cari k terbaik dari 1-10
K = range(1,10)

# Cek nilai SSE setiap k
for k in K:
 kmeanModel = KMeans(n_clusters=k)
 kmeanModel.fit(X)
 sse.append(kmeanModel.inertia_)


# Plotting the distortions
plt.figure(figsize=(8,4))
plt.plot(K, sse, "bx-")
plt.xlabel("k")
plt.ylabel("SSE")
plt.title("Metode Elbow untuk Mengetahui Jumlah k Terbaik")
plt.show()
```


```
# Cek Nilai SSE setiap k
for idx, sse_val in enumerate(sse, start=1):
    print(f'k={idx}; SSE={sse_val}')
```

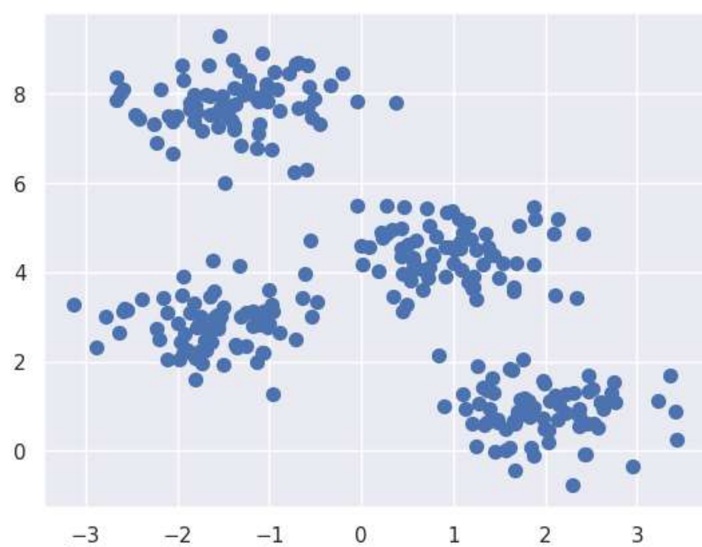
```
k=1; SSE=680.8244000000001
k=2; SSE=152.36870647733906
k=3; SSE=78.940841426146
k=4; SSE=57.34540931571814
k=5; SSE=46.53558205128205
k=6; SSE=39.49834884135471
k=7; SSE=34.299985543844244
k=8; SSE=30.085448259233434
k=9; SSE=27.766706937799043
```

Praktikum 2

Konsep K-Means untuk klasterisasi data

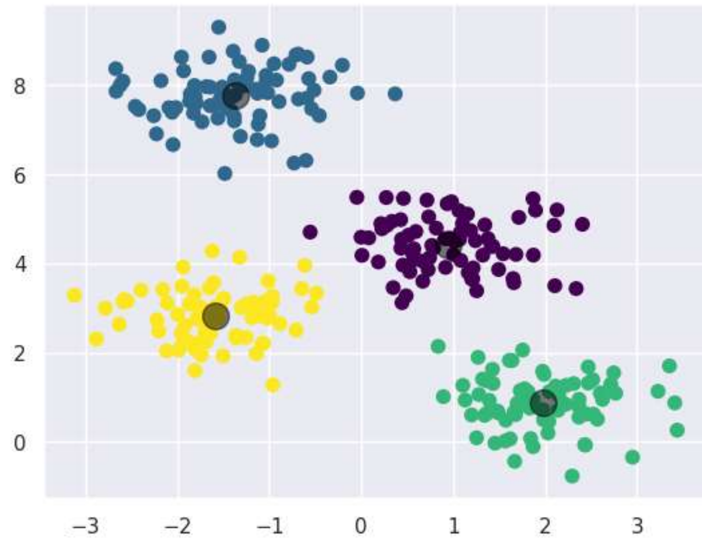
```
#import library
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import numpy as np
```

```
#pengantar kmeans
from sklearn.datasets import make_blobs
X, y_true = make_blobs(n_samples=300, centers=4,
                       cluster_std=0.60, random_state=0)
plt.scatter(X[:, 0], X[:, 1], s=50);
```



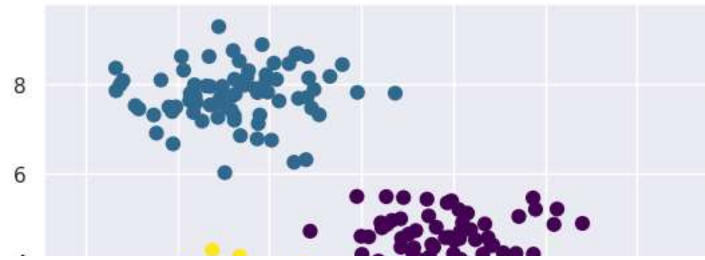
```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)


plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=50, cmap='viridis')

centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='black', s=200, alpha=0.5)
```

```
<matplotlib.collections.PathCollection at 0x7ce93051e8c0>
```



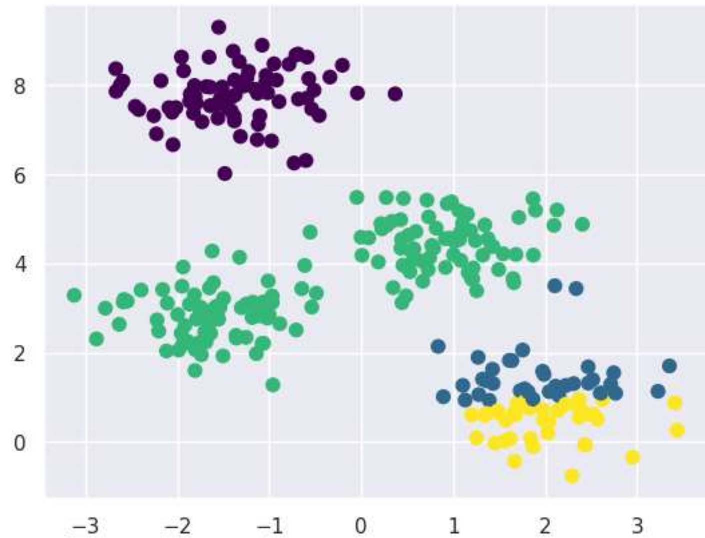
Algoritma Expectation-Maximization

```
from sklearn.metrics import pairwise_distances_argmin

def find_clusters(X, n_clusters, rseed=2):
    # 1. Randomly choose clusters
    rng = np.random.RandomState(rseed)
    i = rng.permutation(X.shape[0])[:n_clusters]
    centers = X[i]

    while True:
        # 2a. input label center yang baru
        labels = pairwise_distances_argmin(X, centers)

        # 2b. update center dari titik baru
        new_centers = np.array([X[labels == i].mean(0)
                                for i in range(n_clusters)])

        # 2c. cek konvergensi
        if np.all(centers == new_centers):
            break
        centers = new_centers

    return centers, labels

centers, labels = find_clusters(X, 4)
plt.scatter(X[:, 0], X[:, 1], c=labels,s=50, cmap='viridis');
```



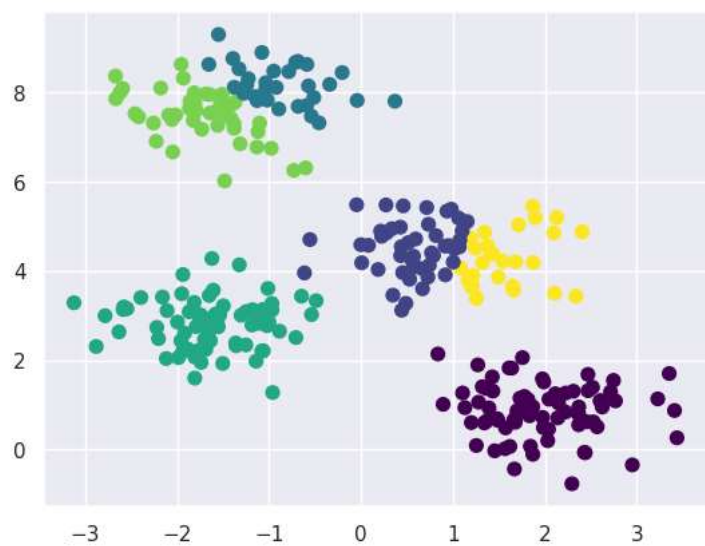
Perubahan random

```
centers, labels = find_clusters(X, 4, rseed=0)
plt.scatter(X[:, 0], X[:, 1], c=labels,s=50, cmap='viridis');
```



Optimalisasi Jumlah Klaster

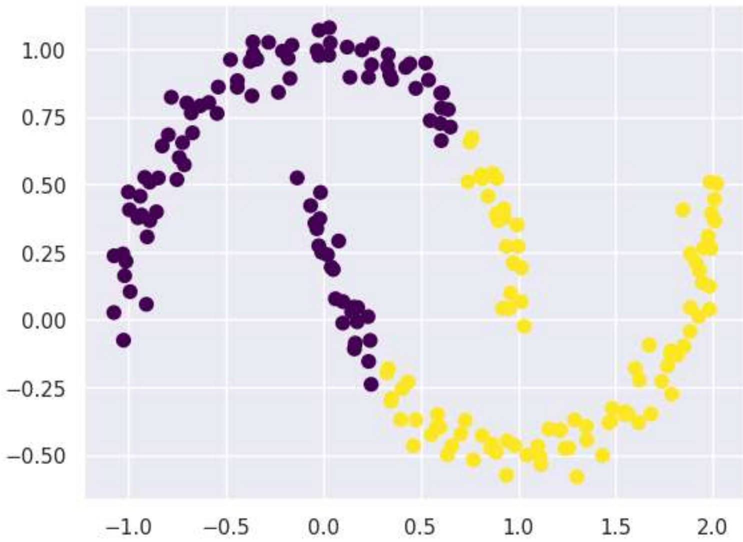
```
labels = KMeans(6, random_state=0).fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels, s=50, cmap='viridis');
```



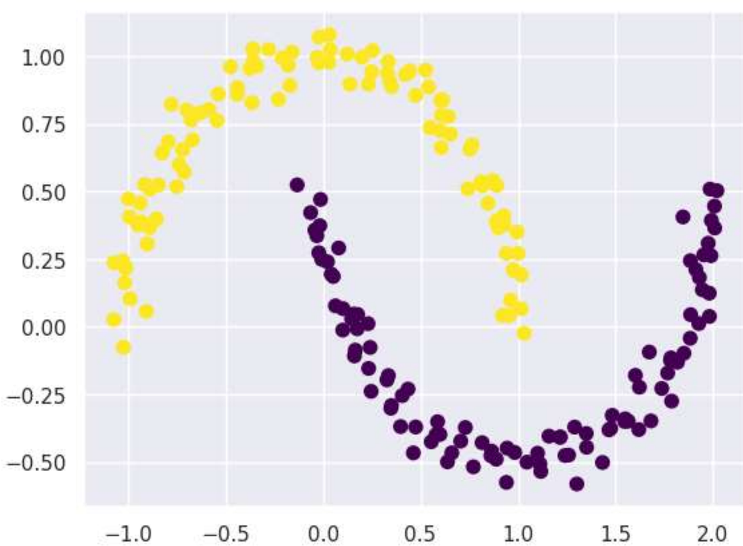
Batas Klaster yang Tidak Selalu Linier

```
from sklearn.datasets import make_moons
X, y = make_moons(200, noise=.05, random_state=0)
```

```
labels = KMeans(2, random_state=0).fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels,s=50, cmap='viridis');
```




```
from sklearn.cluster import SpectralClustering
model = SpectralClustering(n_clusters=2, affinity='nearest_neighbors',
                           assign_labels='kmeans')
labels = model.fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=labels, s=50, cmap='viridis');
```



Contoh Kasus 1: Karakter Angka

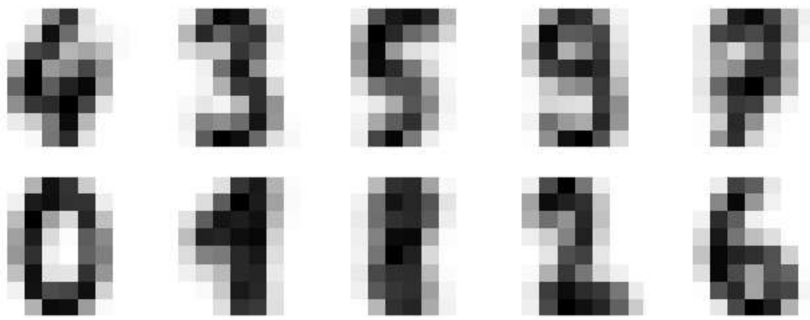
```
from sklearn.datasets import load_digits
digits = load_digits()
digits.data.shape
```

```
(1797, 64)
```

```
# terapkan K-Means
kmeans = KMeans(n_clusters=10, random_state=0)
clusters = kmeans.fit_predict(digits.data)
kmeans.cluster_centers_.shape
```

```
(10, 64)
```

```
fig, ax = plt.subplots(2, 5, figsize=(8, 3))
centers = kmeans.cluster_centers_.reshape(10, 8, 8)
for axi, center in zip(ax.flat, centers):
    axi.set(xticks=[], yticks=[])
    axi.imshow(center, interpolation='nearest', cmap=plt.cm.binary)
```

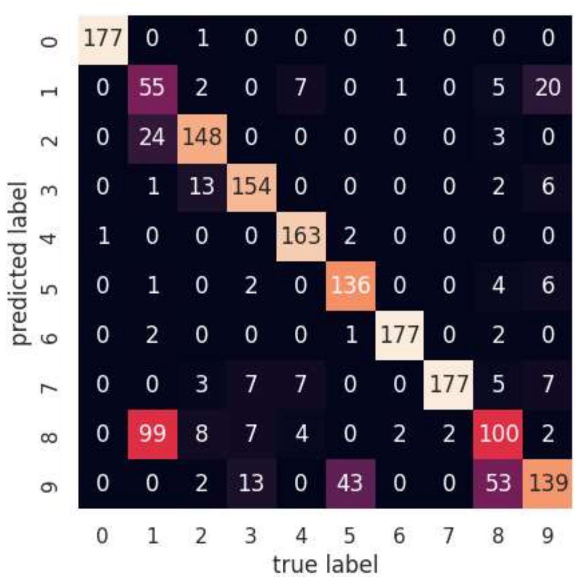


```
from scipy.stats import mode

labels = np.zeros_like(clusters)
for i in range(10):
    mask = (clusters == i)
    labels[mask] = mode(digits.target[mask])[0]
```

```
from sklearn.metrics import accuracy_score
accuracy_score(digits.target, labels)
```

```
0.7935447968836951
```

```
from sklearn.metrics import confusion_matrix
mat = confusion_matrix(digits.target, labels)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=digits.target_names,
            yticklabels=digits.target_names)
plt.xlabel('true label')
plt.ylabel('predicted label');
```



```
from sklearn.manifold import TSNE


tsne = TSNE(n_components=2, init='random', random_state=0)
digits_proj = tsne.fit_transform(digits.data)

# hitung klaster
kmeans = KMeans(n_clusters=10, random_state=0)
clusters = kmeans.fit_predict(digits_proj)

# permutasi label
labels = np.zeros_like(clusters)
for i in range(10):
    mask = (clusters == i)
    labels[mask] = mode(digits.target[mask])[0]

# hitung akurasi
accuracy_score(digits.target, labels)
```

```
0.9415692821368948
```

Studi Kasus 2: Kompresi Citra

```
from sklearn.datasets import load_sample_image
flower = load_sample_image("flower.jpg")
ax = plt.axes(xticks=[], yticks=[])
ax.imshow(flower);
```

```
flower.shape
```

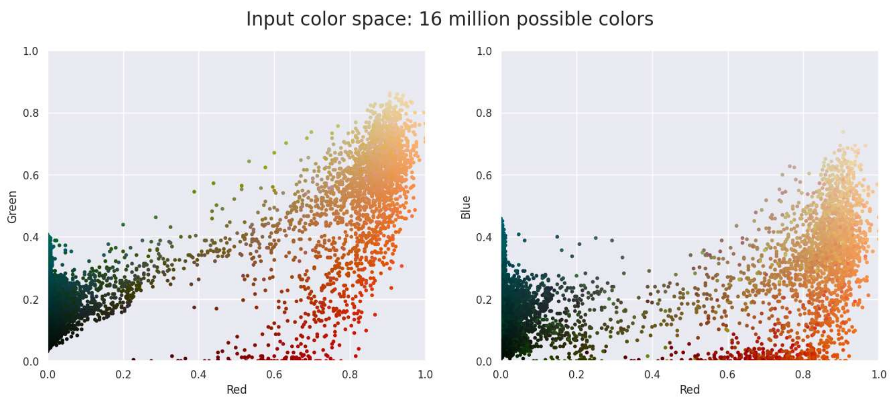
```
(427, 640, 3)
```

```
data = flower / 255.0
data = data.reshape(427 * 640, 3)
data.shape
```

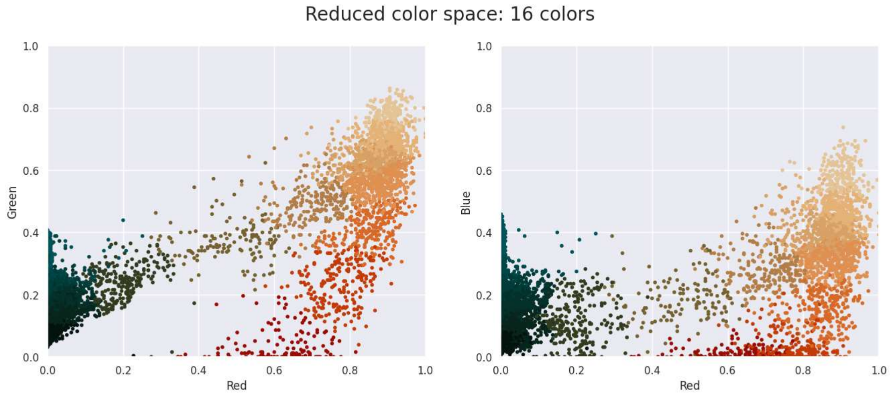
```
(273280, 3)
```

```
def plot_pixels(data, title, colors=None, N=10000):
    if colors is None:
        colors = data

    # choose a random subset
    rng = np.random.RandomState(0)
    i = rng.permutation(data.shape[0])[:N]
    colors = colors[i]
    R, G, B = data[i].T

    fig, ax = plt.subplots(1, 2, figsize=(16, 6))
    ax[0].scatter(R, G, color=colors, marker='.')
    ax[0].set(xlabel='Red', ylabel='Green', xlim=(0, 1), ylim=(0, 1))

    ax[1].scatter(R, B, color=colors, marker='.')
    ax[1].set(xlabel='Red', ylabel='Blue', xlim=(0, 1), ylim=(0, 1))

    fig.suptitle(title, size=20);
```

```
plot_pixels(data, title='Input color space: 16 million possible colors')
```




```
import warnings; warnings.simplefilter('ignore')  # Fix NumPy issues.

from sklearn.cluster import MiniBatchKMeans
kmeans = MiniBatchKMeans(16)
kmeans.fit(data)
new_colors = kmeans.cluster_centers_[kmeans.predict(data)]

plot_pixels(data, colors=new_colors,title="Reduced color space: 16 colors")
```




```
flower_recolored = new_colors.reshape(flower.shape)

fig, ax = plt.subplots(1, 2, figsize=(16, 6),
                       subplot_kw=dict(xticks=[], yticks=[]))
fig.subplots_adjust(wspace=0.05)
ax[0].imshow(flower)
ax[0].set_title('Original Image', size=16)
ax[1].imshow(flower_recolored)
ax[1].set_title('16-color Image', size=16);
```

Praktikum 3

Self-optimizing Map (SOM)

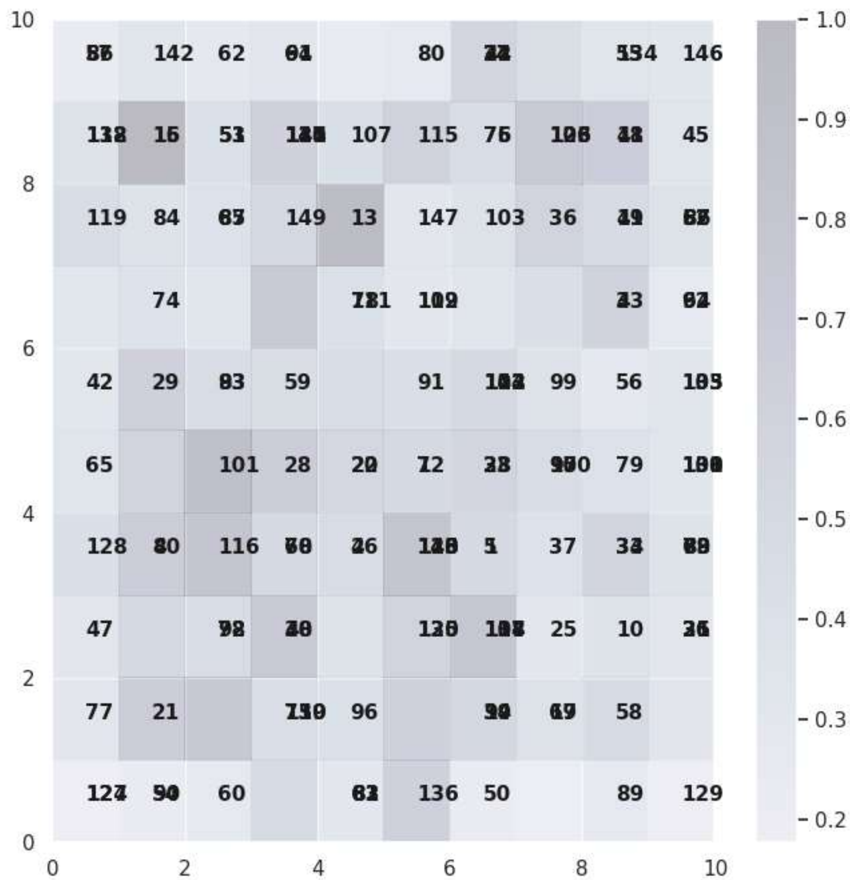
```
pip install minisom
```

```
Requirement already satisfied: minisom in /usr/local/lib/python3.10/dist-packages (2.3.1)
```

```
from minisom import MiniSom
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
```

```
# Load dataset
iris = datasets.load_iris()
data = iris.data
```

```
# Normalisasi data
data = data / data.max(axis=0)


# Inisialisasi SOM
map_size = (10, 10)
som = MiniSom(map_size[0], map_size[1], data.shape[1], sigma=0.5, learning_rate=0.5)


# Inisialisasi bobot secara acak
som.random_weights_init(data)


# Pelatihan SOM
num_epochs = 100
som.train_random(data, num_epochs)


# Visualisasi hasil SOM
plt.figure(figsize=(8, 8))
for i, x in enumerate(data):
    w = som.winner(x)  # Pemenang untuk sampel x
    plt.text(w[0]+.5, w[1]+.5, str(i+1), color='k', fontdict={'weight': 'bold', 'size': 11})
plt.pcolor(som.distance_map().T, cmap='bone_r', alpha=.2)
plt.colorbar()

plt.show()
```



Praktikum 4

Penerapan metode Self-Organizing Map (SOM) untuk segmentasi citra Lenna.

```
pip install minisom
```

```
Requirement already satisfied: minisom in /usr/local/lib/python3.10/dist-packages (2.3.1)
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
from skimage import io


# Fungsi untuk menginisialisasi bobot SOM
def initialize_weights(input_shape, output_shape):
    return np.random.rand(output_shape[0], output_shape[1], input_shape[2])


# Fungsi untuk menghitung jarak antara vektor input dan bobot SOM
def calculate_distance(input_vector, weights):
    return np.linalg.norm(input_vector - weights, axis=2)


# Fungsi untuk menemukan indeks unit pemenang (unit dengan bobot terdekat)
def find_winner_unit_in_image(input_vector, weights):
    distances = calculate_distance(input_vector, weights)
    return np.unravel_index(np.argmin(distances), distances.shape)


import numpy as np

def initialize_weights(input_shape, som_shape):
    # Implementasi inisialisasi bobot
    return np.random.rand(*som_shape)

def find_winner_unit_in_image(input_vector, weights):
    # Implementasi pencarian unit pemenang
    return (0, 0, 0)  # Contoh hasil, sesuaikan dengan logika pencarian sebenarnya

def update_weights(input_vector, weights, winner, learning_rate, neighborhood_radius):
    # Implementasi pembaruan bobot
    pass  # Ganti dengan logika pembaruan bobot yang sesuai

# Fungsi untuk melatih SOM
def train_som(image, num_epochs, initial_learning_rate, initial_neighborhood_radius):
    input_shape = image.shape
    som_shape = (10, 10, input_shape[2])  # Ukuran SOM sesuai dengan jumlah saluran warna
    weights = initialize_weights(input_shape, som_shape)

    for epoch in range(num_epochs):
        # Update parameter pembelajaran dan radius tetangga
        learning_rate = initial_learning_rate * np.exp(-epoch / num_epochs)
        neighborhood_radius = initial_neighborhood_radius * np.exp(-epoch / num_epochs)
        # Pemrosesan SOM
        for i in range(input_shape[0]):
            for j in range(input_shape[1]):
                input_vector = image[i, j, :]
                winner = find_winner_unit_in_image(input_vector, weights)
                update_weights(input_vector, weights, winner, learning_rate, neighborhood_radius)

    return weights



# Load citra Lenna (Anda bisa mengganti ini dengan citra lain jika diperlukan)
Lenna_path = "Lenna.jpg"
Lenna = io.imread(Lenna_path) / 255.0
# Normalisasi intensitas piksel menjadi rentang [0, 1]


# Latih SOM
num_epochs = 100
initial_learning_rate = 0.1
initial_neighborhood_radius = 5
trained_weights = train_som(Lenna, num_epochs, initial_learning_rate, initial_neighborhood_radius)


# Visualisasi bobot SOM
plt.imshow(trained_weights)
plt.title('Trained SOM Weights for Lena')
plt.show()
```


Trained SOM Weights for Lena
0