# LAB No 11

# Implementation of Fuzzy C means Clustering

Fuzzy C-Means (FCM) clustering is an unsupervised soft-clustering technique that assigns data points to multiple clusters with varying degrees of membership, making it ideal for handling overlapping or uncertain data. In this practice program, students implement FCM in Python to generate clusters, analyze membership values, visualize results, and compare its performance with traditional hard-clustering methods like K-means.

**Install Required libraries**

```
pip install scikit-fuzzy
```

**Question No. 1**

**Task:**

Generate a synthetic 2-dimensional dataset consisting of three clusters. Apply **Fuzzy C-Means clustering** and analyze the results.

**Questions:**

1. Generate a 2D dataset with three groups of points using Gaussian noise.
2. Apply Fuzzy C-Means (FCM) clustering using **skfuzzy** with 3 clusters.
3. Plot the clustered data points and cluster centers.
4. Display the **membership values** for any 5 randomly selected points.
5. Compute and interpret the **Fuzzy Partition Coefficient (FPC)**.
6. Compare the results with K-means clustering.

Generate + Code + Markdown

```python
import numpy as np
import matplotlib.pyplot as plt
```

✓ 0.0s Python

```python
np.random.seed(42)

# Generate 3 clusters
cluster1 = np.random.randn(100, 2) + np.array([2, 2])
cluster2 = np.random.randn(100, 2) + np.array([-2, -2])
cluster3 = np.random.randn(100, 2) + np.array([2, -2])

# Combine data
data = np.vstack((cluster1, cluster2, cluster3))
```

✓ 0.0s Python

```python
import skfuzzy as fuzz

# Transpose data for skfuzzy (features × samples)
data_T = data.T

cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    data_T,
    c=3,
    m=2,
    error=0.005,
    maxiter=1000,
    init=None
)
```

✓ 0.0s Python

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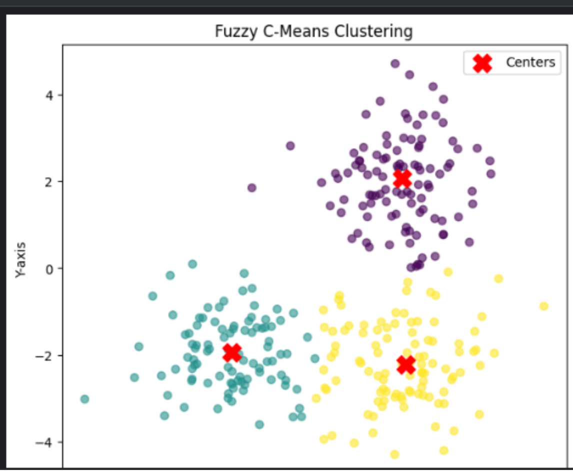
```python
cluster_labels = np.argmax(u, axis=0)

plt.figure(figsize=(7, 6))
plt.scatter(data[:, 0], data[:, 1], c=cluster_labels, cmap='viridis', alpha=0.6)
plt.scatter(cntr[:, 0], cntr[:, 1], c='red', marker='X', s=200, label='Centers')
plt.title("Fuzzy C-Means Clustering")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.legend()
plt.show()
```

[19] ✓ 0.2s Python



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```python
for idx in random_indices:
    print(f"Point {data[idx]} → Memberships: {u[:, idx]}")
```

[20] ✓ 0.0s Python

```
Point [2.06023021 4.46324211] → Memberships: [0.81270686 0.08240736 0.10488578]
Point [-4.12389572 -2.52575502] → Memberships: [0.07282993 0.81510859 0.11206148]
Point [ 0.6955305  -1.33032745] → Memberships: [0.12346628 0.21791258 0.65862114]
Point [ 1.89296964 -3.03524232] → Memberships: [0.02334563 0.03824475 0.93840962]
Point [2.25049285 2.34644821] → Memberships: [0.98405561 0.00588575 0.01005864]
```

```python
print("Fuzzy Partition Coefficient (FPC):", fpc)
```

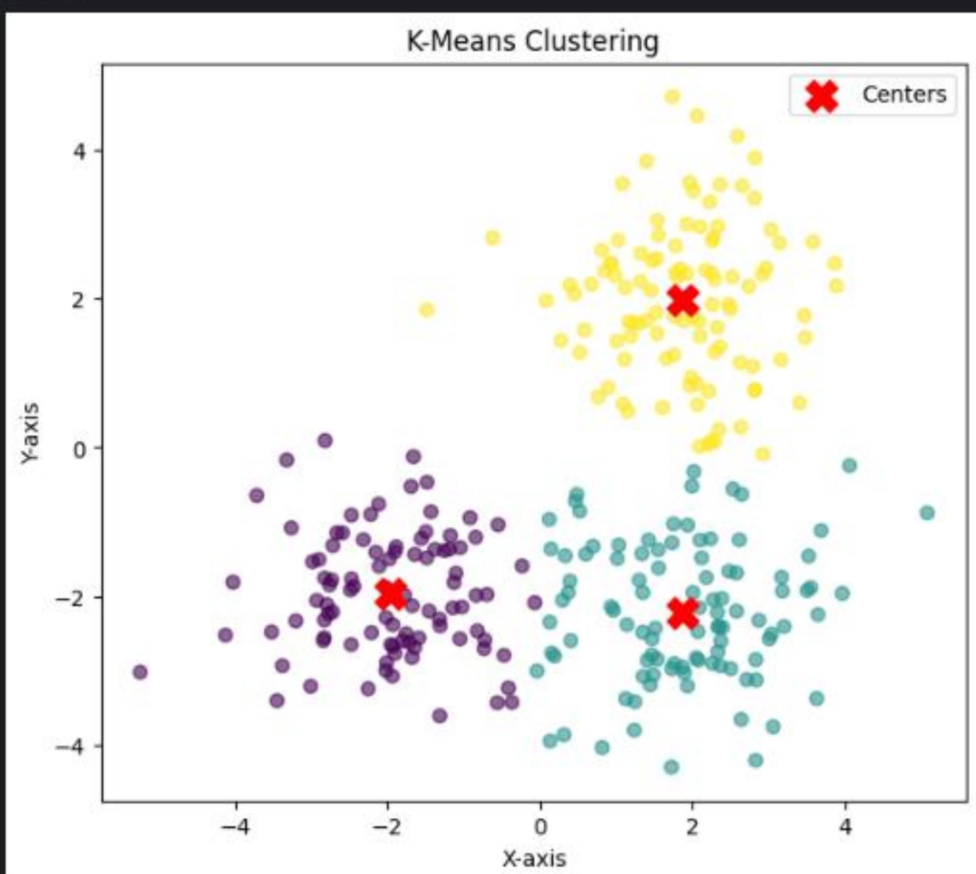
[21] ✓ 0.0s Python

```
Fuzzy Partition Coefficient (FPC): 0.763676789438928
```

```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_labels = kmeans.fit_predict(data)

plt.figure(figsize=(7, 6))
plt.scatter(data[:, 0], data[:, 1], c=kmeans_labels, cmap='viridis', alpha=0.6)
plt.scatter(kmeans.cluster_centers_[:, 0],
            kmeans.cluster_centers_[:, 1],
            c='red', marker='X', s=200, label='Centers')
plt.title("K-Means Clustering")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.legend()
plt.show()
```

[22] ✓ 23.8s Python

✓ 23.8s



7. Explain why FCM is more suitable for overlapping clusters than K-means.

Answer:

Fuzzy C-Means (FCM) is more suitable for overlapping clusters because it uses **soft clustering**, where each data point is assigned a **degree of membership** to all clusters rather than being assigned to only one cluster. This allows FCM to effectively handle uncertainty and overlap between clusters by representing partial belonging.

In contrast, K-Means uses **hard clustering**, where each data point belongs to exactly one cluster. This rigid assignment can lead to incorrect clustering when cluster boundaries overlap, as points near the boundaries are forced into a single cluster.

Therefore, FCM provides a more flexible and realistic clustering approach for overlapping data, making it superior to K-Means in scenarios involving ambiguous or uncertain cluster boundaries.

**Question No. 2**

**Task:**

Use the Iris dataset to cluster samples into 3 fuzzy classes and compare them with the actual species labels.

**Questions:**

1. Load the Iris dataset from sklearn.
2. Apply normalization and then use **FCM** to form 3 clusters.
3. Identify the predicted cluster for the first 20 samples.
4. Compare the predicted clusters with the actual labels.
5. Compute the **accuracy of FCM** (use majority-mapping method).
6. Report the **FPC value** and explain what it indicates about cluster quality.
7. Compare FCM results with K-means clustering on the same dataset.

```python
from sklearn.datasets import load_iris
import numpy as np

iris = load_iris()
X = iris.data          # features
y = iris.target        # actual labels
```

```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_norm = scaler.fit_transform(X)
```

```python
import skfuzzy as fuzz

# Transpose data for skfuzzy
X_T = X_norm.T

cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    X_T,
    c=3,
    m=2,
    error=0.005,
    maxiter=1000,
    init=None
)
```

```python
predicted_clusters = np.argmax(u, axis=0)

print("First 20 Predicted Clusters:")
print(predicted_clusters[:20])
```

```
First 20 Predicted Clusters:
[2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2]
```

```python
print("Actual Labels (first 20):")
print(y[:20])
```

```
Actual Labels (first 20):
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
```

```python
from scipy.stats import mode

cluster_labels = predicted_clusters
mapped_labels = np.zeros_like(cluster_labels)

for i in range(3):
    mask = cluster_labels == i
    mapped_labels[mask] = mode(y[mask])[0]
```

```python
accuracy = np.mean(mapped_labels == y)
print("FCM Accuracy:", accuracy)
```

```
FCM Accuracy: 0.84
```

```python
print("Fuzzy Partition Coefficient (FPC):", fpc)
```

```
Fuzzy Partition Coefficient (FPC): 0.7064976545705912
```

```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
kmeans_labels = kmeans.fit_predict(X_norm)
```

```python
mapped_kmeans = np.zeros_like(kmeans_labels)

for i in range(3):
    mask = kmeans_labels == i
    mapped_kmeans[mask] = mode(y[mask])[0]

kmeans_accuracy = np.mean(mapped_kmeans == y)
print("K-Means Accuracy:", kmeans_accuracy)
```

```
K-Means Accuracy: 0.6666666666666666
```

## Question No. 3

### Task:

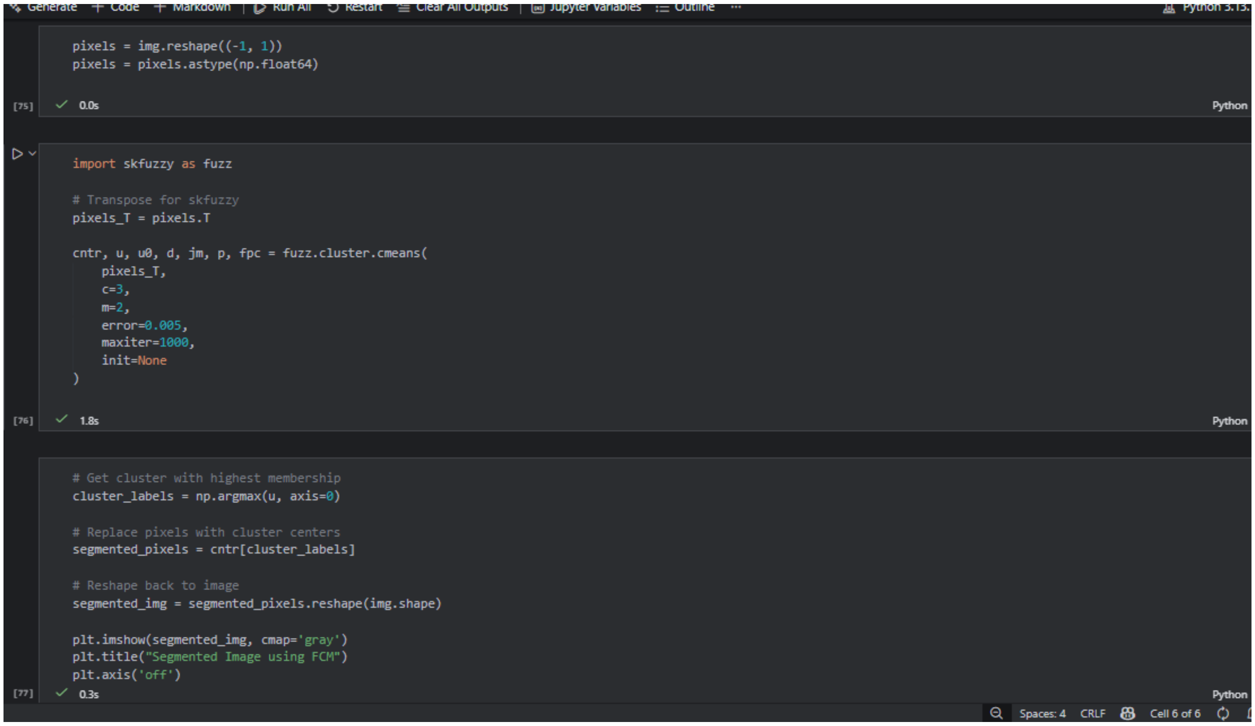
Segment a grayscale image into meaningful regions using fuzzy clustering.

### Questions:

1. Load any grayscale image (or the one provided by the teacher).
2. Convert the image into a 1D pixel array.
3. Apply Fuzzy C-Means clustering to segment the image into **three clusters**.
4. Reconstruct the segmented image and display it.

```python
import numpy as np
import matplotlib.pyplot as plt
```

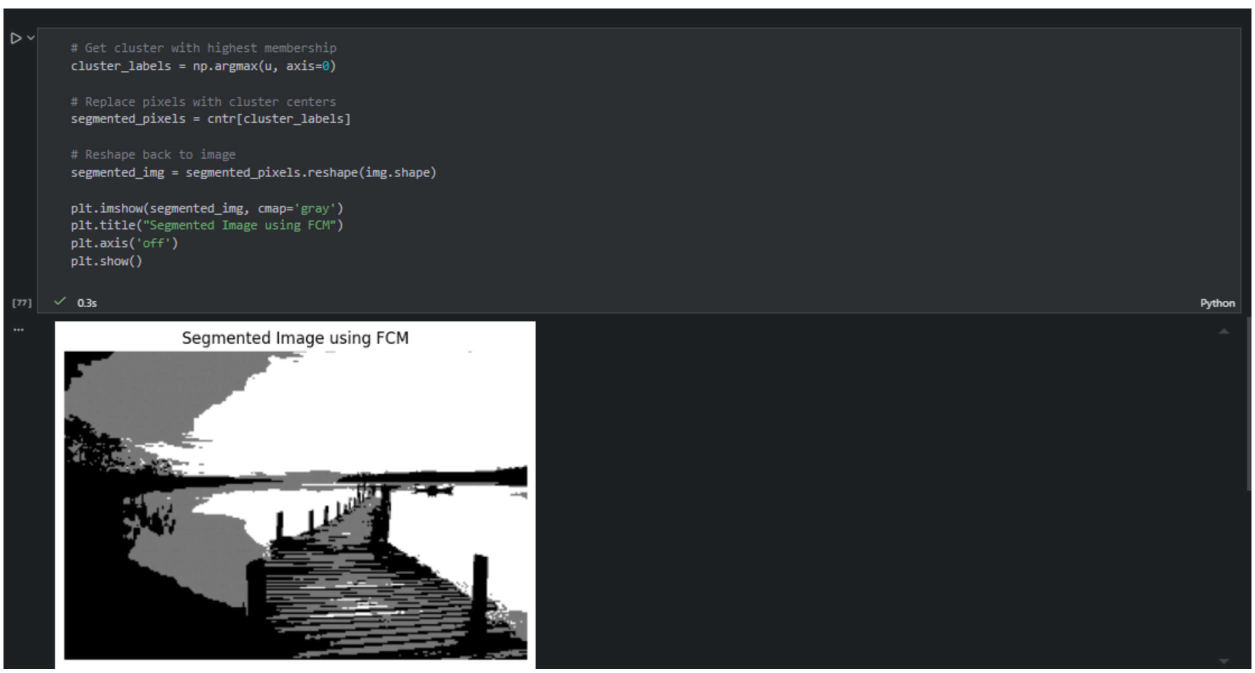
```python
import cv2
import numpy as np
import matplotlib.pyplot as plt

# Load grayscale image
img = cv2.imread('image.png', cv2.IMREAD_GRAYSCALE)

plt.imshow(img, cmap='gray')
plt.title("Original Grayscale Image")
plt.axis('off')
plt.show()
```



```python
pixels = img.reshape((-1, 1))
pixels = pixels.astype(np.float64)
```

```python
import skfuzzy as fuzz

# Transpose for skfuzzy
pixels_T = pixels.T

cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    pixels_T,
    c=3,
    m=2,
    error=0.005,
    maxiter=1000,
    init=None
)
```

```python
# Get cluster with highest membership
cluster_labels = np.argmax(u, axis=0)

# Replace pixels with cluster centers
segmented_pixels = cntr[cluster_labels]

# Reshape back to image
segmented_img = segmented_pixels.reshape(img.shape)

plt.imshow(segmented_img, cmap='gray')
plt.title("Segmented Image using FCM")
plt.axis('off')
```



```python
# Get cluster with highest membership
cluster_labels = np.argmax(u, axis=0)

# Replace pixels with cluster centers
segmented_pixels = cntr[cluster_labels]

# Reshape back to image
segmented_img = segmented_pixels.reshape(img.shape)

plt.imshow(segmented_img, cmap='gray')
plt.title("Segmented Image using FCM")
plt.axis('off')
plt.show()
```



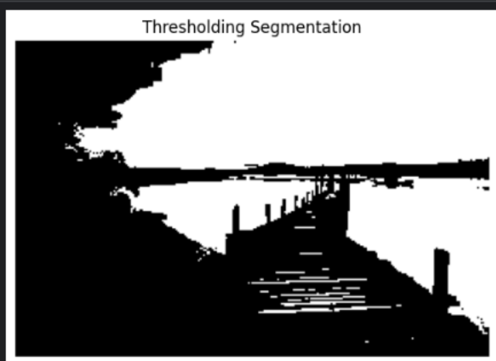
5. Explain how pixel membership values differ across regions.

Answer:

In Fuzzy C-Means segmentation, each pixel is assigned a **membership value** for every cluster instead of a hard label. Pixels in **homogeneous regions** (clear dark or bright areas) show high membership for a single cluster. However, pixels near **edges or boundaries** exhibit distributed membership values across multiple clusters, representing uncertainty. This allows FCM to produce smoother transitions between regions compared to hard segmentation methods.

6. Compare your segmented image with segmentation from **thresholding** or **K-means**.

```python
_, thresh_img = cv2.threshold(img, 127, 255, cv2.THRESH_BINARY)

plt.imshow(thresh_img, cmap='gray')
plt.title("Thresholding Segmentation")
plt.axis('off')
plt.show()
```




7. Discuss how changing the number of clusters (c = 2, 4, 5) affects segmentation quality.

Answer:

Effect of changing number of clusters (c = 2, 4, 5)

- **c = 2:**
  Image is over-simplified; important details may be lost.
- **c = 3:**
  Balanced segmentation; main regions clearly separated.
- **c = 4 or 5:**
  Finer segmentation; captures subtle intensity variations but may introduce noise and over-segmentation.

Optimal number of clusters depends on image complexity and application requirements.

**Question No. 4**

**Task:**

Perform market segmentation on a small customer dataset using Fuzzy C-Means clustering.

**Dataset Fields:**

- Age
- Income
- Spending Score

**Questions:**

1. Create or load the given dataset of 10–20 customers.
2. Normalize the features using MinMaxScaler.
3. Apply FCM to generate **3 customer clusters**.
4. Assign each customer to the cluster with maximum membership.
5. Display the membership matrix and cluster centers.
6. Interpret each cluster (e.g., high income–low spending).
7. Compare the results with K-means segmentation and justify whether FCM is better.

```python
import pandas as pd
import numpy as np

# Create dataset
data = {
    "Age": [22, 25, 47, 52, 46, 56, 23, 24, 45, 53, 35, 40],
    "Income": [15000, 18000, 52000, 58000, 50000, 62000,
               16000, 17000, 48000, 60000, 40000, 45000],
    "SpendingScore": [80, 75, 20, 15, 25, 10, 85, 78, 30, 12, 55, 45]
}

df = pd.DataFrame(data)
df
```

0.0s

Python

| | Age | Income | SpendingScore |
|---|---|---|---|
| 0 | 22 | 15000 | 80 |
| 1 | 25 | 18000 | 75 |
| 2 | 47 | 52000 | 20 |
| 3 | 52 | 58000 | 15 |
| 4 | 46 | 50000 | 25 |
| 5 | 56 | 62000 | 10 |
| 6 | 23 | 16000 | 85 |
| 7 | 24 | 17000 | 78 |
| 8 | 45 | 48000 | 30 |
| 9 | 53 | 60000 | 12 |
| 10 | 35 | 40000 | 55 |
| 11 | 40 | 45000 | 45 |

```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_scaled = scaler.fit_transform(df)

X_scaled
```

✓ 0.0s Python

```
array([[0.        , 0.        , 0.93333333],
       [0.08823529, 0.06382979, 0.86666667],
       [0.73529412, 0.78723404, 0.13333333],
       [0.88235294, 0.91489362, 0.06666667],
       [0.70588235, 0.74468085, 0.2       ],
       [1.        , 1.        , 0.        ],
       [0.02941176, 0.0212766 , 1.        ],
       [0.05882353, 0.04255319, 0.90666667],
       [0.67647059, 0.70212766, 0.26666667],
       [0.91176471, 0.95744681, 0.02666667],
       [0.38235294, 0.53191489, 0.6       ],
       [0.52941176, 0.63829787, 0.46666667]])
```

```python
import skfuzzy as fuzz

# Transpose for skfuzzy
X_T = X_scaled.T

cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    X_T,
    c=3,
    m=2,
    error=0.005,
    maxiter=1000,
    init=None
```

✓ 0.0s Python

```python
cluster_labels = np.argmax(u, axis=0)
df["FCM_Cluster"] = cluster_labels
df
```

✓ 0.0s Python

| | Age | Income | SpendingScore | FCM_Cluster |
|---|---|---|---|---|
| 0 | 22 | 15000 | 80 | 0 |
| 1 | 25 | 18000 | 75 | 0 |
| 2 | 47 | 52000 | 20 | 2 |
| 3 | 52 | 58000 | 15 | 2 |
| 4 | 46 | 50000 | 25 | 2 |
| 5 | 56 | 62000 | 10 | 2 |
| 6 | 23 | 16000 | 85 | 0 |
| 7 | 24 | 17000 | 78 | 0 |
| 8 | 45 | 48000 | 30 | 1 |
| 9 | 53 | 60000 | 12 | 2 |
| 10 | 35 | 40000 | 55 | 1 |
| 11 | 40 | 45000 | 45 | 1 |

```python
membership_df = pd.DataFrame(
    u.T,
    columns=["Cluster 0", "Cluster 1", "Cluster 2"]
)

membership_df
```

✓ 0.0s Python

| | | | |
|---|---|---|---|
| 1 | 0.987044 | 0.009686 | 0.003270 |
| 2 | 0.015472 | 0.135916 | 0.848612 |
| 3 | 0.000439 | 0.002515 | 0.997046 |
| 4 | 0.027351 | 0.320428 | 0.652221 |
| 5 | 0.012514 | 0.056079 | 0.931407 |
| 6 | 0.990792 | 0.006682 | 0.002526 |
| 7 | 0.998788 | 0.000895 | 0.000317 |
| 8 | 0.033207 | 0.569343 | 0.397451 |
| 9 | 0.003675 | 0.018878 | 0.977447 |
| 10 | 0.076770 | 0.866461 | 0.056769 |
| 11 | 0.000929 | 0.996767 | 0.002304 |

```python
cluster_centers = pd.DataFrame(
    scaler.inverse_transform(cntr),
    columns=["Age", "Income", "SpendingScore"]
)

cluster_centers
```

0.1s Python

| | Age | Income | SpendingScore |
|---|---|---|---|
| 0 | 23.526018 | 16549.805837 | 79.436745 |
| 1 | 39.375992 | 44037.137192 | 45.047362 |
| 2 | 51.290666 | 57022.805103 | 15.778898 |

```python
from sklearn.cluster import KMeans
```

0.0s Python

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```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
df["KMeans_Cluster"] = kmeans.fit_predict(X_scaled)

df
```

[85] 0.0s Python

| | Age | Income | SpendingScore | FCM_Cluster | KMeans_Cluster |
|---|---|---|---|---|---|
| 0 | 22 | 15000 | 80 | 0 | 1 |
| 1 | 25 | 18000 | 75 | 0 | 1 |
| 2 | 47 | 52000 | 20 | 2 | 0 |
| 3 | 52 | 58000 | 15 | 2 | 2 |
| 4 | 46 | 50000 | 25 | 2 | 0 |
| 5 | 56 | 62000 | 10 | 2 | 2 |
| 6 | 23 | 16000 | 85 | 0 | 1 |
| 7 | 24 | 17000 | 78 | 0 | 1 |
| 8 | 45 | 48000 | 30 | 1 | 0 |
| 9 | 53 | 60000 | 12 | 2 | 2 |
| 10 | 35 | 40000 | 55 | 1 | 0 |
| 11 | 40 | 45000 | 45 | 1 | 0 |

```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
df["KMeans_Cluster"] = kmeans.fit_predict(X_scaled)

df
```

[86] 0.0s Python

```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3, random_state=42)
df["KMeans_Cluster"] = kmeans.fit_predict(X_scaled)

df
```

✓ 0.0s Python

| | Age | Income | SpendingScore | FCM_Cluster | KMeans_Cluster |
|---|---|---|---|---|---|
| 0 | 22 | 15000 | 80 | 0 | 1 |
| 1 | 25 | 18000 | 75 | 0 | 1 |
| 2 | 47 | 52000 | 20 | 2 | 0 |
| 3 | 52 | 58000 | 15 | 2 | 2 |
| 4 | 46 | 50000 | 25 | 2 | 0 |
| 5 | 56 | 62000 | 10 | 2 | 2 |
| 6 | 23 | 16000 | 85 | 0 | 1 |
| 7 | 24 | 17000 | 78 | 0 | 1 |
| 8 | 45 | 48000 | 30 | 1 | 0 |
| 9 | 53 | 60000 | 12 | 2 | 2 |
| 10 | 35 | 40000 | 55 | 1 | 0 |
| 11 | 40 | 45000 | 45 | 1 | 0 |

**Question No. 5**

*(Dataset: Kaggle → "COVID-19 World Dataset")*

**Task:**

Cluster Pakistan and its neighboring countries based on COVID-19 indicators.

**Questions:**

1. Select the countries:
   - Pakistan
   - India
   - China
   - Iran
   - Afghanistan
2. Extract the following variables from the dataset:
   - Total Cases
   - Total Deaths
   - Population

3. Normalize the selected features.
4. Apply FCM with **2 clusters** and report the cluster membership values.
5. Show the final clusters for each country.
6. Interpret results (e.g., high-impact vs. low-impact countries).
7. Compute the **FPC** and discuss cluster quality.
8. Compare FCM-based clustering with K-means clustering and comment on differences.

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```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import MinMaxScaler
from sklearn.cluster import KMeans
import skfuzzy as fuzz
```

[94] 0.0s Python

```python
df = pd.read_csv("COVID19_world_dataset.csv", encoding="ISO-8859-1")
df.head()
```

[98] 0.0s Python

| | Country | Total Cases | New Cases | Total Deaths | New Deaths | Total Recovered | Active Cases | Serious, Critical | Tot Cases/1M pop | Deaths/1M pop | Total Tests | Tests/1M pop |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | USA | 5,02,876 | 33,752 | 18,747 | 2,035 | 27,314 | 4,56,815 | 10,917 | 1,519 | 57.0 | 25,38,888 | 7,670 |
| 1 | Spain | 1,58,273 | 5,051 | 16,081 | 634 | 55,668 | 86,524 | 7,371 | 3,385 | 344.0 | 3,55,000 | 7,593 |
| 2 | Italy | 1,47,577 | 3,951 | 18,849 | 570 | 30,455 | 98,273 | 3,497 | 2,441 | 312.0 | 9,06,864 | 14,999 |
| 3 | France | 1,24,869 | 7,120 | 13,197 | 987 | 24,932 | 86,740 | 7,004 | 1,913 | 202.0 | 3,33,807 | 5,114 |
| 4 | Germany | 1,22,171 | 3,936 | 2,736 | 129 | 53,913 | 65,522 | 4,895 | 1,458 | 33.0 | 13,17,887 | 15,730 |

```python
countries = ['Pakistan', 'India', 'China', 'Iran', 'Afghanistan']

df_selected = df[df['Country'].isin(countries)]
```

[99] 0.0s Python

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```python
df.columns
```

[101] ✓ 0.0s Python

```
Index(['Country', 'Total Cases', 'New Cases', 'Total Deaths', 'New Deaths',
       'Total Recovered', 'Active Cases', 'Serious, Critical',
       'Tot Cases/1M pop', 'Deaths/1M pop', 'Total Tests', 'Tests/1M pop'],
      dtype='object')
```

```python
countries = ['Pakistan', 'India', 'China', 'Iran', 'Afghanistan']

df_selected = df[df['Country'].isin(countries)]
df_selected
```

[102] ✓ 0.1s Python

| | Country | Total Cases | New Cases | Total Deaths | New Deaths | Total Recovered | Active Cases | Serious, Critical | Tot Cases/1M pop | Deaths/1M pop | Total Tests | Tests/1M pop |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | China | 81,907 | 42 | 3,336 | 1 | 77,455 | 1,116 | 144 | 57 | 2.0 | NaN | NaN |
| 7 | Iran | 68,192 | 1,972 | 4,232 | 122 | 35,465 | 28,495 | 3,969 | 812 | 50.0 | 2,42,568 | 2,888 |
| 21 | India | 7,600 | 875 | 249 | 22 | 774 | 6,577 | NaN | 6 | 0.2 | 1,89,111 | 137 |
| 32 | Pakistan | 4,695 | 206 | 66 | 1 | 727 | 3,902 | 45 | 21 | 0.3 | 54,706 | 248 |
| 85 | Afghanistan | 521 | 37 | 15 | NaN | 32 | 474 | NaN | 13 | 0.4 | NaN | NaN |

```python
features = df_selected[['Total Cases', 'Total Deaths']]
features.index = df_selected['Country']
features
```

[103] ✓ 0.1s Python

Generate + Code + Markdown | Run All Restart Clear All Outputs | Jupyter Variables Outline ··· Python 3.13.7

```python
features = df_selected[['Total Cases', 'Total Deaths']]
features.index = df_selected['Country']
features
```

[103] ✓ 0.1s Python

| Country | Total Cases | Total Deaths |
|---|---|---|
| China | 81,907 | 3,336 |
| Iran | 68,192 | 4,232 |
| India | 7,600 | 249 |
| Pakistan | 4,695 | 66 |
| Afghanistan | 521 | 15 |

```python
countries = ['Pakistan', 'India', 'China', 'Iran', 'Afghanistan']
df_selected = df[df['Country'].isin(countries)]
df_selected
```

[107] ✓ 0.0s Python

| | Country | Total Cases | New Cases | Total Deaths | New Deaths | Total Recovered | Active Cases | Serious, Critical | Tot Cases/1M pop | Deaths/1M pop | Total Tests | Tests/1M pop |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | China | 81,907 | 42 | 3,336 | 1 | 77,455 | 1,116 | 144 | 57 | 2.0 | NaN | NaN |
| 7 | Iran | 68,192 | 1,972 | 4,232 | 122 | 35,465 | 28,495 | 3,969 | 812 | 50.0 | 2,42,568 | 2,888 |
| 21 | India | 7,600 | 875 | 249 | 22 | 774 | 6,577 | NaN | 6 | 0.2 | 1,89,111 | 137 |
| 32 | Pakistan | 4,695 | 206 | 66 | 1 | 727 | 3,902 | 45 | 21 | 0.3 | 54,706 | 248 |
| 85 | Afghanistan | 521 | 37 | 15 | NaN | 32 | 474 | NaN | 13 | 0.4 | NaN | NaN |

```python
features = df_selected[['Total Cases', 'Total Deaths']]
features.index = df_selected['Country']
features
```

✓ 0.0s Python

| | Total Cases | Total Deaths |
|---|---|---|
| **Country** | | |
| China | 81,907 | 3,336 |
| Iran | 68,192 | 4,232 |
| India | 7,600 | 249 |
| Pakistan | 4,695 | 66 |
| Afghanistan | 521 | 15 |

```python
features = features.replace(',', '', regex=True)
```

✓ 0.0s Python

```python
features = features.apply(pd.to_numeric)
```

✓ 0.0s Python

```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
features_norm = scaler.fit_transform(features)
```

✓ 0.0s Python

```python
features.dtypes
```

✓ 0.0s Python

```
Total Cases     int64
Total Deaths    int64
dtype: object
```

```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
features_norm = scaler.fit_transform(features)
```

✓ 0.0s Python

```python
import skfuzzy as fuzz
import numpy as np

data = features_norm.T

cntr, u, u0, d, jm, p, fpc = fuzz.cluster.cmeans(
    data,
    c=2,
    m=2,
    error=0.005,
    maxiter=1000,
    init=None
)
```

✓ 0.0s Python

```python
membership = pd.DataFrame(
    u.T,
    index=features.index,
    columns=['Cluster 1', 'Cluster 2']
)

membership
```

✓ 0.0s Python

| | Cluster 1 | Cluster 2 |
|---|---|---|
| **Country** | | |
| China | 0.987858 | 0.012142 |
| Iran | 0.988430 | 0.011570 |
| India | 0.001968 | 0.998032 |
| Pakistan | 0.000090 | 0.999910 |
| Afghanistan | 0.001616 | 0.998384 |

```python
final_clusters = membership.idxmax(axis=1)
final_clusters
```

✓ 0.0s Python

```
Country
China          Cluster 1
Iran           Cluster 1
India          Cluster 2
Pakistan       Cluster 2
Afghanistan    Cluster 2
dtype: object
```

```python
fpc
```

✓ 0.0s Python

```
np.float64(0.9891609836079184)
```

```python
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=2, random_state=42)
kmeans_labels = kmeans.fit_predict(features_norm)

kmeans_result = pd.Series(
    kmeans_labels,
    index=features.index,
    name='KMeans Cluster'
)

kmeans_result
```

✓ 0.1s Python

```
Country
China          0
Iran           0
India          1
Pakistan       1
Afghanistan    1
Name: KMeans Cluster, dtype: int32
```