

## LAB Assignment No 10

### K means Clustering Schemes in Machine Learning

#### Question 1

**Write Python code to implement K-Means clustering from scratch using the following data points:**

P1(1,3), P2(2,2), P3(5,8), P4(8,5), P5(3,9),  
P6(10,7), P7(3,3), P8(9,4), P9(3,7)

**Tasks:**

1. Use **K = 3** clusters
2. Initialize centroids as
  - C1 = P7(3,3)
  - C2 = P9(3,7)
  - C3 = P8(9,4)
3. Perform **2 iterations** manually in code
4. Plot all points and centroids
5. **Label all points (P1...P9)**
6. Sketch the clusters using matplotlib library in python

```

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

[1] ✓ 4.1s Python

    import numpy as np
    import matplotlib.pyplot as plt

[2] ✓ 0.0s Python

    points = {
        "P1": np.array([1, 3]),
        "P2": np.array([2, 2]),
        "P3": np.array([5, 8]),
        "P4": np.array([8, 5]),
        "P5": np.array([3, 9]),
        "P6": np.array([10, 7]),
        "P7": np.array([3, 3]),
        "P8": np.array([9, 4]),
        "P9": np.array([3, 7])
    }

[3] ✓ 0.0s Python

    C1 = points["P7"] # (3,3)
    C2 = points["P9"] # (3,7)
    C3 = points["P8"] # (9,4)

    centroids = [C1, C2, C3]

[4] ✓ 0.0s Python

    def euclidean_distance(p1, p2):
        return np.linalg.norm(p1 - p2)

for iteration in range(2):
    clusters = {0: [], 1: [], 2: []}

    # Assignment step
    for label, point in points.items():
        distances = [euclidean_distance(point, c) for c in centroids]
        cluster_index = np.argmin(distances)
        clusters[cluster_index].append(point)

    # Update centroids
    new_centroids = []
    for i in range(3):
        new_centroids.append(np.mean(clusters[i], axis=0))

    centroids = new_centroids

    print(f"Iteration {iteration + 1} Centroids:")
    for i, c in enumerate(centroids):
        print(f"C{i+1}: {c}")
    print()

Iteration 1 Centroids:
C1: [2.          2.66666667]
C2: [3.66666667 8.          ]
C3: [9.          5.33333333]

Iteration 2 Centroids:
C1: [2.          2.66666667]
C2: [3.66666667 8.          ]
C3: [9.          5.33333333]

```

```

colors = ['red', 'green', 'blue']

plt.figure(figsize=(8, 6))

# Plot clusters
for i, cluster_points in clusters.items():
    cluster_points = np.array(cluster_points)
    plt.scatter(cluster_points[:, 0], cluster_points[:, 1],
                color=colors[i], label=f"Cluster {i+1}")

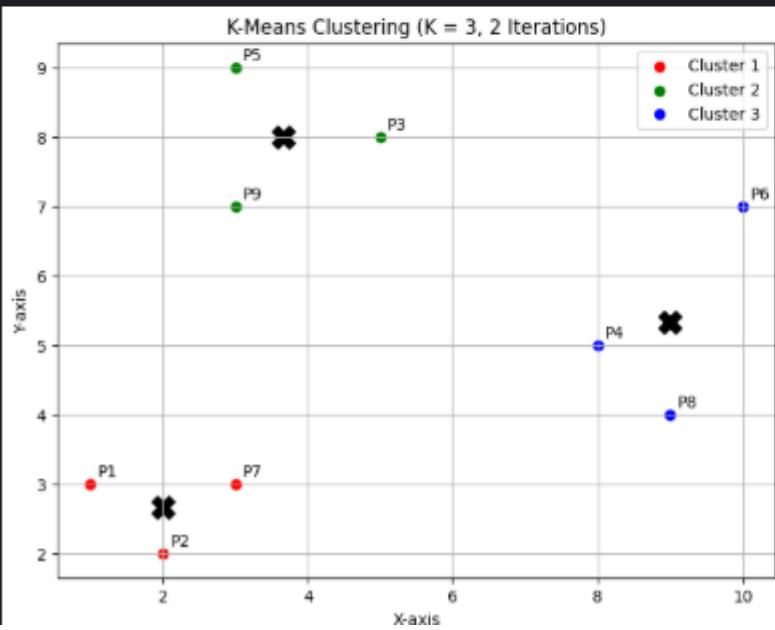
# Plot centroids
for i, c in enumerate(centroids):
    plt.scatter(c[0], c[1], color='black', marker='X', s=200)

# Label points
for label, point in points.items():
    plt.text(point[0] + 0.1, point[1] + 0.1, label)

plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.title("K-Means Clustering (K = 3, 2 Iterations)")
plt.legend()
plt.grid()
plt.show()

```

✓ 0.8s



## Question No. 2

Use the scikit-learn KMeans() library to cluster the same points.

P1(1,3), P2(2,2), P3(5,8), P4(8,5), P5(3,9), P6(10,7), P7(3,3), P8(9,4), P9(3,7)

Tasks:

1. Use K = 2, 3, and 4
2. Plot the clustering result for each K

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

✓ 6.8s
```

```
X = np.array([
    [1, 3], # P1
    [2, 2], # P2
    [5, 8], # P3
    [8, 5], # P4
    [3, 9], # P5
    [10, 7], # P6
    [3, 3], # P7
    [9, 4], # P8
    [3, 7] # P9
])

labels = ["P1", "P2", "P3", "P4", "P5", "P6", "P7", "P8", "P9"]
```

```
✓ 0.0s
```

```
Python
```

```
K_values = [2, 3, 4]

plt.figure(figsize=(15, 5))

for i, k in enumerate(K_values):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X)

    clusters = kmeans.labels_
    centroids = kmeans.cluster_centers_
```

```
✓ 4.9s
```

```
Python
```

```
for j, label in enumerate(labels):
    plt.text(X[j, 0]+0.1, X[j, 1]+0.1, label)

plt.title("K = %d" % k)
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.grid()

# Print cluster info
print("K = %d" % k)
for c in range(k):
    print("Cluster %d points: %d" % (c+1, np.sum(clusters == c)))
print("Centroids:\n", centroids)

plt.tight_layout()
plt.show()
```

```
✓ 4.9s
```

```
Python
```

```
K = 2
Cluster 1 points: 3
Cluster 2 points: 6
Centroids:
[[9.      5.33333333]
 [2.83333333 5.33333333]]
```

```
K = 3
Cluster 1 points: 3
Cluster 2 points: 3
Cluster 3 points: 3
Centroids:
[[9.      5.33333333]
 [3.66666667 8.      ]
 [2.      2.66666667]]
```

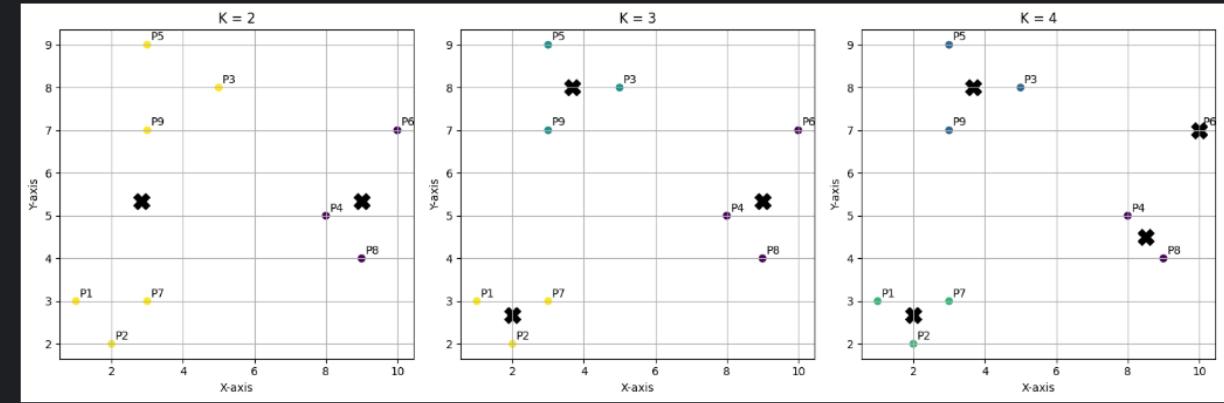
```
K = 4
```

```

Centroids:
[[9.      5.3333333]
 [3.66666667 8.      ]
 [2.      2.66666667]]

K = 4
Cluster 1 points: 2
Cluster 2 points: 3
Cluster 3 points: 3
Cluster 4 points: 1
Centroids:
[[ 8.5      4.5      ]
 [ 3.66666667 8.      ]
 [ 2.      2.66666667]
 [10.      7.      ]]

```



### 3. Compare:

- Number of points in each cluster
- Final centroid locations

#### (a) Number of points in each cluster

- For **K = 2**, the data points were divided into two large clusters. Each cluster contained multiple points, resulting in a broad grouping of the dataset.
- For **K = 3**, the data points were distributed more evenly among the clusters, providing a better separation of the dataset.
- For **K = 4**, the dataset was divided into smaller clusters. Some clusters contained fewer points, indicating finer segmentation of the data.

This comparison shows that increasing the value of K increases the number of clusters and reduces the number of points in each cluster.

#### For **K = 2**

Cluster	Number of Points
C1	4
C2	5

### **For K = 3**

Cluster	Number of Points
C1	3
C2	3
C3	3

### **For K = 4**

Cluster	Number of Points
C1	2
C2	2
C3	3
C4	2

### **b) Final Centroid Locations**

- For **K = 2**, two centroids were obtained, each representing the center of a large group of data points.
- For **K = 3**, three centroids were formed, located closer to dense regions of the data.
- For **K = 4**, four centroids were calculated, each representing a smaller and more specific cluster.

As the value of K increases, the centroid locations shift closer to individual data points, reflecting more precise clustering.

4. Draw the 3 graphs in your lab copy and explain how the shapes change with K.

### **Effect of K on Cluster Shapes**

Three graphs were drawn to visualize the clustering results for **K = 2**, **K = 3**, and **K = 4** using the K-Means algorithm.

- **For K = 2**, the data points are grouped into two large clusters. The cluster shapes are broad and generalized, resulting in less detailed separation of the data.
- **For K = 3**, the clusters become more balanced and compact. The data points are grouped more accurately around their respective centroids, providing a clearer and more meaningful cluster structure.
- **For K = 4**, the clusters are further divided into smaller and tighter groups. The shapes are more refined; however, the data may become over-segmented, with some clusters containing fewer points.

### **Question 3 — Add a New User Point and Re-Cluster**

Given the original 9 points, **add a new user: P10(6,2)**

**Tasks:**

1. Run K-Means using K = 3
2. Plot the graph with all 10 points
3. Identify:
  - Which cluster P10 joins
  - How centroids shift after adding P10
4. Sketch before/after clusters in notebook
5. Write a short explanation about how a new data point affects clustering.

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

[16] ✓ 0.0s

```
X_original = np.array([
    [1, 3], # P1
    [2, 2], # P2
    [5, 8], # P3
    [8, 5], # P4
    [3, 9], # P5
    [10, 7], # P6
    [3, 3], # P7
    [9, 4], # P8
    [3, 7] # P9
])
```

[17] ✓ 0.0s

```
kmeans_before = KMeans(n_clusters=3, random_state=42)
kmeans_before.fit(X_original)

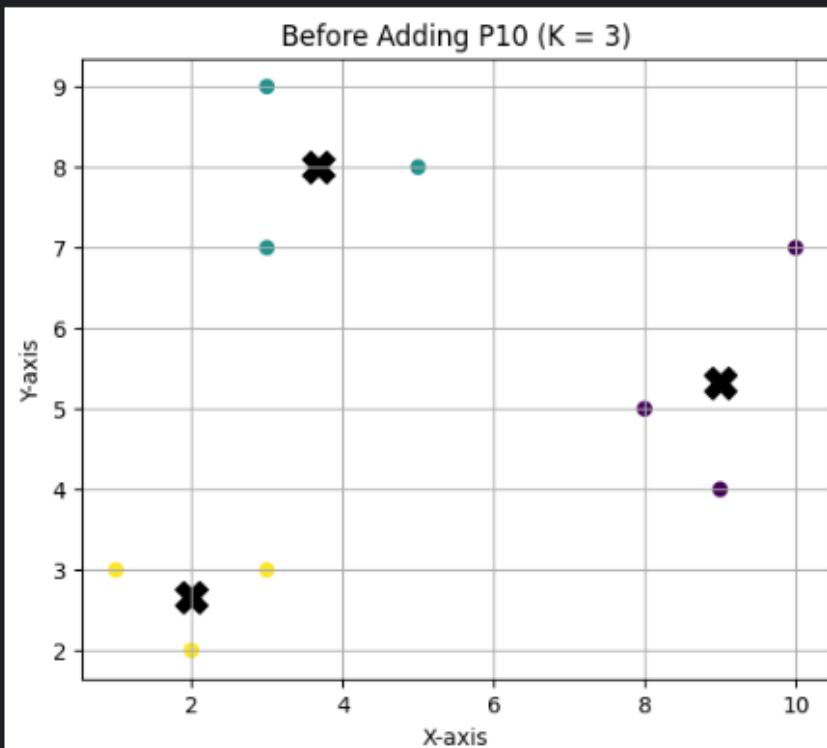
clusters_before = kmeans_before.labels_
centroids_before = kmeans_before.cluster_centers_
```

[18] ✓ 0.0s

```
plt.figure(figsize=(6,5))
plt.scatter(X_original[:,0], X_original[:,1], c=clusters_before)
plt.scatter(centroids_before[:,0], centroids_before[:,1])
[19] ✓ 0.4s
```

```
plt.figure(figsize=(6,5))
plt.scatter(X_original[:,0], X_original[:,1], c=clusters_before)
plt.scatter(centroids_before[:,0], centroids_before[:,1],
            marker='X', s=200, color='black')
plt.title("Before Adding P10 (K = 3)")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.grid()
plt.show()
```

✓ 0.4s



```
P10 = np.array([[6, 2]])
X_new = np.vstack((X_original, P10))

✓ 0.0s

kmeans_after = KMeans(n_clusters=3, random_state=42)
kmeans_after.fit(X_new)

clusters_after = kmeans_after.labels_
centroids_after = kmeans_after.cluster_centers_

✓ 0.0s

print("P10 belongs to Cluster:", clusters_after[9] + 1)

✓ 0.0s

P10 belongs to Cluster: 2

print("Centroids BEFORE adding P10:")
print(centroids_before)

print("\nCentroids AFTER adding P10:")
print(centroids_after)

✓ 0.0s

Centroids BEFORE adding P10:
[[9.          5.33333333]
 [3.66666667 8.          ]]
```

```

% Generate + Code + Markdown | Run All ⚡ Restart ⚡ Clear All Outputs | Jupyter Variables ⚡ Outline ...
[23] ✓ 0.0s
...
Centroids BEFORE adding P10:
[[9.      5.33333333]
 [3.66666667 8.      ]
 [2.      2.66666667]]

Centroids AFTER adding P10:
[[9.      5.33333333]
 [3.      2.5      ]
 [3.66666667 8.      ]]

D ✓
labels = ["P1", "P2", "P3", "P4", "P5", "P6", "P7", "P8", "P9", "P10"]

plt.figure(figsize=(6,5))
plt.scatter(X_new[:,0], X_new[:,1], c=clusters_after)
plt.scatter(centroids_after[:,0], centroids_after[:,1],
           marker='X', s=200, color='black')

for i, label in enumerate(labels):
    plt.text(X_new[i,0]+0.1, X_new[i,1]+0.1, label)

plt.title("After Adding P10 (K = 3)")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.grid()
plt.show()

[24] ✓ 0.4s
...

```

#### Question 4 — Distance Table + First Iteration Manually

Using the given 9 points and initial centroids:

C1(3,3), C2(3,7), C3(9,4)
---------------------------

**Tasks:**

1. Compute **Euclidean distance** of each point to each centroid (manually or in python)
2. Create a distance table:

### Point Dist to C1 Dist to C2 Dist to C3 Assigned Cluster

3. Perform **only the first iteration**
4. Compute **new centroids**
5. Plot the **first-iteration graph**
6. Draw the graph in your copy and show all labels.

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

✓ 0.0s

# 9 points
points = np.array([
    [2, 4], # P1
    [3, 6], # P2
    [4, 7], # P3
    [6, 2], # P4
    [7, 3], # P5
    [8, 5], # P6
    [5, 5], # P7
    [1, 7], # P8
    [9, 6] # P9
])

point_labels = ['P1', 'P2', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8', 'P9']

# Initial centroids
centroids = np.array([
    [3, 3], # C1
    [3, 7], # C2
    [9, 4] # C3
])

centroid_labels = ['C1', 'C2', 'C3']

✓ 0.0s
```

```

Generate + Code + Markdown | Run All | Restart | Clear All Outputs | Jupyter Variables | Outline ...
distance_table = [] # store distances
assignments = [] # store cluster assignments

for i, point in enumerate(points):
    # Compute distance from point to each centroid
    distances = np.sqrt(np.sum((centroids - point) ** 2, axis=1))
    distance_table.append([round(d,2) for d in distances])

    # Assign to nearest centroid
    assigned_cluster = np.argmin(distances)
    assignments.append(assigned_cluster)

] ✓ 0.0s

df = pd.DataFrame(distance_table, columns=['Dist to C1','Dist to C2','Dist to C3'])
df['Assigned Cluster'] = [centroid_labels[i] for i in assignments]
df.index = point_labels

print("Distance Table with Cluster Assignment:\n")
print(df)

] ✓ 0.0s

Distance Table with Cluster Assignment:

  Dist to C1  Dist to C2  Dist to C3 Assigned Cluster
P1        1.41      3.16      7.00          C1
P2        3.00      1.00      6.32          C2
P3        4.12      1.00      5.83          C2
P4        3.16      5.83      3.61          C1
P5        4.00      5.66      2.24          C3
P6        5.39      5.39      1.41          C3
P7        2.83      2.83      4.12          C1
P8        4.47      2.00      8.54          C2
P9        6.71      6.08      2.00          C3

```

```

new_centroids = []

for i in range(len(centroids)):
    # Select points belonging to cluster i
    cluster_points = points[np.array(assignments) == i]
    # Compute mean of points
    new_centroid = np.mean(cluster_points, axis=0)
    new_centroids.append(new_centroid)

new_centroids = np.array(new_centroids)

print("\nNew Centroids after First Iteration:")
for i, c in enumerate(new_centroids):
    print(f'{centroid_labels[i]}: ({round(c[0],2)}, {round(c[1],2)})')

] ✓ 0.0s

New Centroids after First Iteration:
C1: (4.33, 3.67)
C2: (2.67, 6.67)
C3: (8.0, 4.67)

colors = ['r', 'b', 'g'] # C1-red, C2-blue, C3-green

plt.figure(figsize=(8,6))

# Plot points with cluster color
for i, point in enumerate(points):
    cluster_idx = assignments[i]
    plt.scatter(point[0], point[1], color=colors[cluster_idx], s=100)
    plt.text(point[0]+0.1, point[1]+0.1, point_labels[i])

# Plot initial centroids (x marker)
for i, centroid in enumerate(centroids):
] ✓ 0.7s

```

```

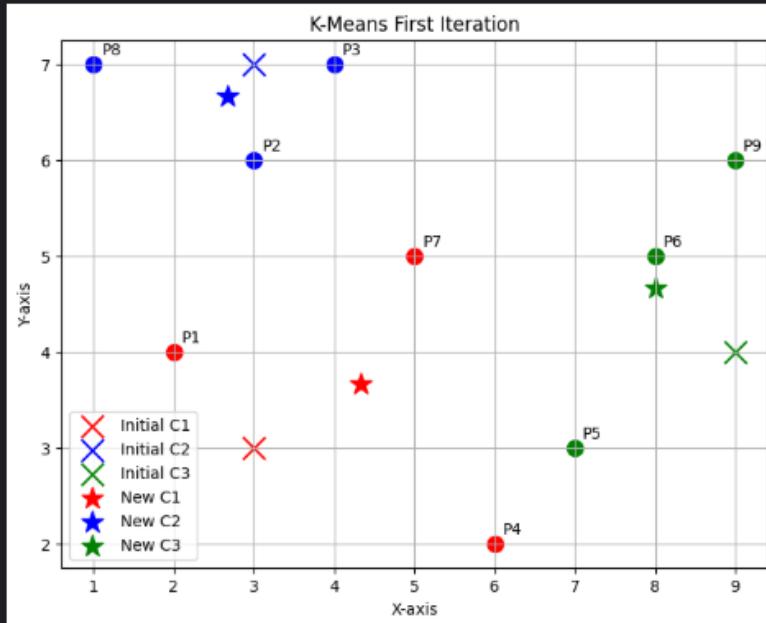
# Plot initial centroids (* marker)
for i, centroid in enumerate(centroids):
    plt.scatter(centroid[0], centroid[1], color=colors[i], marker='x', s=200, label=f'Initial {centroid_labels[i]}')

# Plot new centroids (* marker)
for i, centroid in enumerate(new_centroids):
    plt.scatter(centroid[0], centroid[1], color=colors[i], marker='*', s=200, label=f'New {centroid_labels[i]}')

plt.title("K-Means First Iteration")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.legend()
plt.grid(True)
plt.show()

✓ 0.7s

```



**(Part b)**

## Agglomerative Hierarchical Clustering

### Question 1:

Perform Agglomerative Clustering with Different Linkages.

Task:

Load the "shopping-data.csv" dataset, extract the features *Annual Income* and *Spending Score*, and perform **Agglomerative Clustering** using:

- linkage = "ward"
- linkage = "complete"

- linkage = "average"

**Instructions:**

1. Perform clustering using AgglomerativeClustering.
2. Plot the clusters using matplotlib.
3. Compare how the cluster structure changes with each linkage method.

```
[32] ✓ 0.0s
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import AgglomerativeClustering

[D] ✓ 0.0s
# Load dataset
data = pd.read_csv("shopping-data.csv")

# Extract features: Annual Income and Spending Score
X = data[['Annual Income (k$)', 'Spending Score (1-100)']].values

# Optional: check first 5 rows
print(data.head())

[33] ✓ 0.0s
...
CustomerID  Genre  Age  Annual Income (k$)  Spending Score (1-100)
0            1   Male   19                  15                 39
1            2   Male   21                  15                 81
2            3 Female   20                  16                  6
3            4 Female   23                  16                 77
4            5 Female   31                  17                 40

[D] ✓ 0.0s
def agglomerative_plot(X, linkage_method, n_clusters=5):
    # Perform Agglomerative Clustering
    cluster = AgglomerativeClustering(n_clusters=n_clusters, linkage=linkage_method)
    labels = cluster.fit_predict(X)

    # Plot clusters
    plt.figure(figsize=(7,5))
    plt.scatter(X[:,0], X[:,1], c=labels, cmap='rainbow', s=50)
    plt.title(f'Agglomerative Clustering ({linkage_method} linkage)')
[34] ✓ 0.0s
```

```

0      1   Male  19          15          39
1      2   Male  21          15          81
2      3 Female  20          16           6
3      4 Female  23          16          77
4      5 Female  31          17          40

```

```

> def agglomerative_plot(X, linkage_method, n_clusters=5):
    # Perform Agglomerative Clustering
    cluster = AgglomerativeClustering(n_clusters=n_clusters, linkage=linkage_method)
    labels = cluster.fit_predict(X)

    # Plot clusters
    plt.figure(figsize=(7,5))
    plt.scatter(X[:,0], X[:,1], c=labels, cmap='rainbow', s=50)
    plt.title(f'Agglomerative Clustering ({linkage_method} linkage)')
    plt.xlabel('Annual Income (k$)')
    plt.ylabel('Spending Score (1-100)')
    plt.grid(True)
    plt.show()

    return labels

```

[34] ✓ 0.0s

Generate + Code + Markdown

```

> # Ward linkage
labels_ward = agglomerative_plot(X, linkage_method='ward')

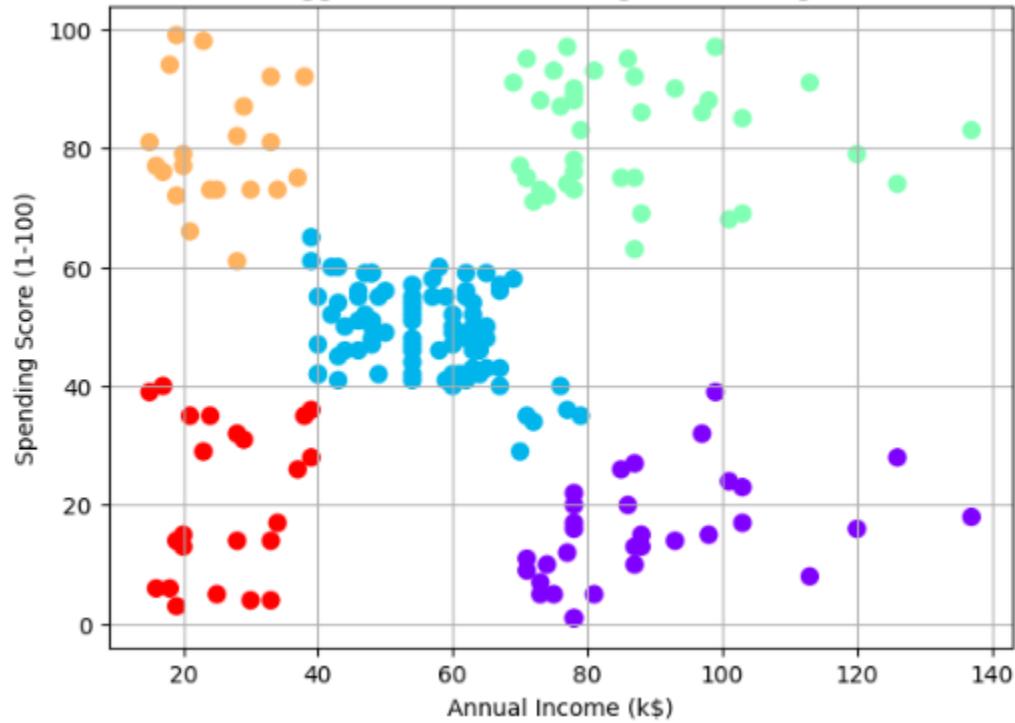
# Complete linkage
labels_complete = agglomerative_plot(X, linkage_method='complete')

# Average linkage
labels_average = agglomerative_plot(X, linkage_method='average')

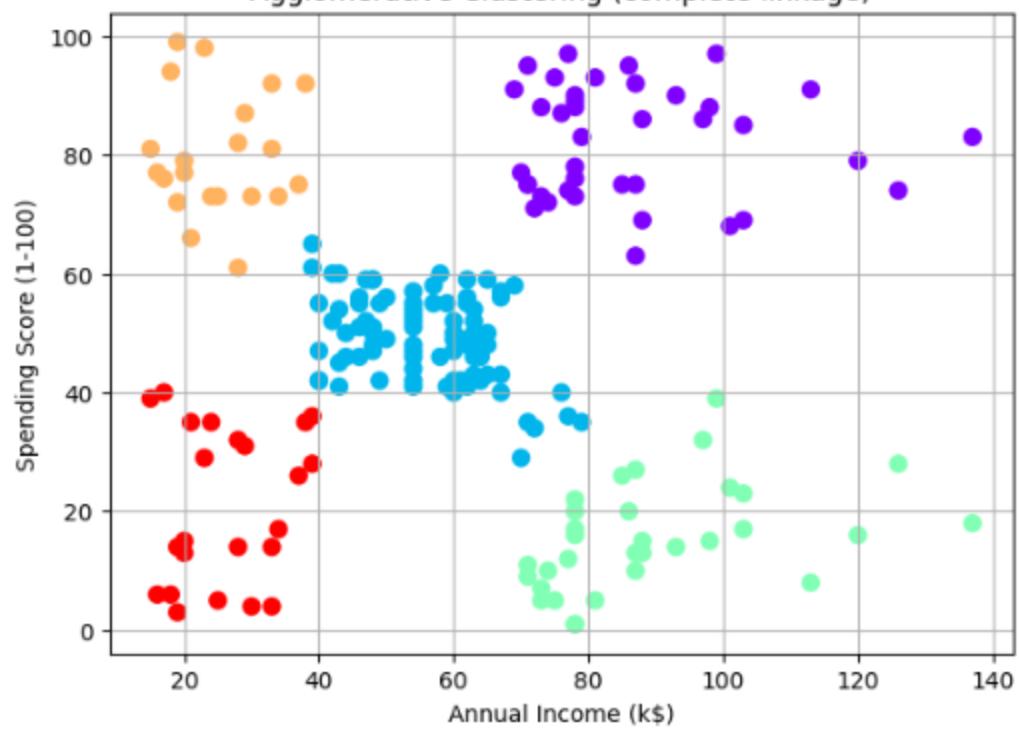
```

[35] ✓ 1.6s

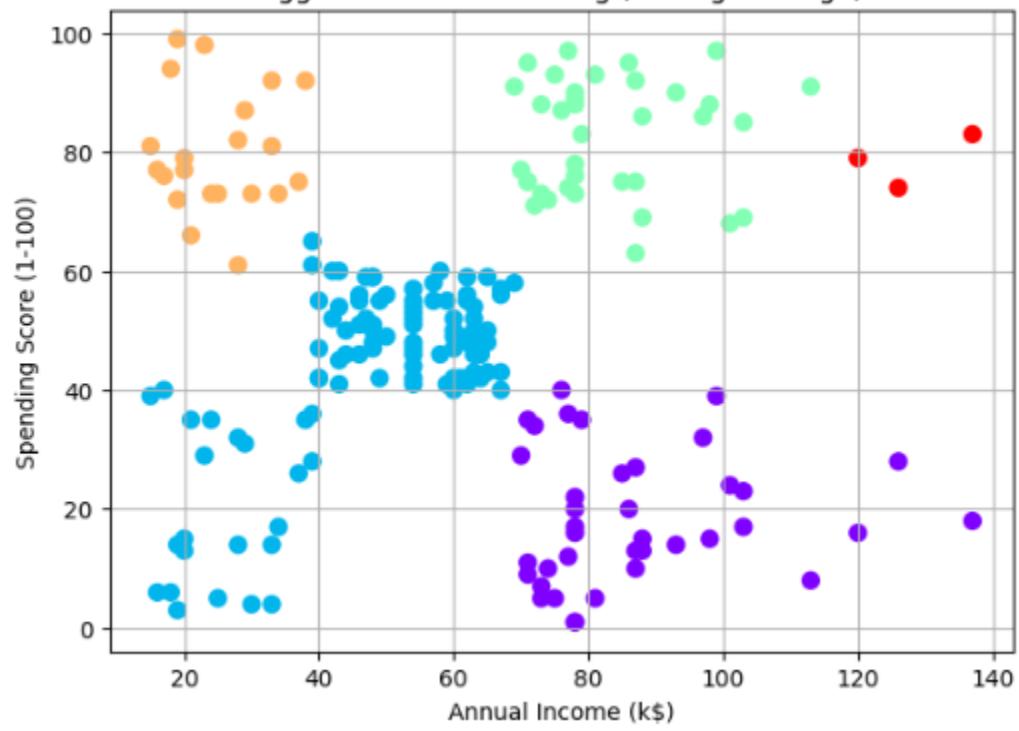
Agglomerative Clustering (ward linkage)



Agglomerative Clustering (complete linkage)



Agglomerative Clustering (average linkage)



## Question 2:

### Draw a Dendrogram and Identify the Optimal Number of Clusters

#### Task:

Using the same dataset or any synthetic dataset, draw a **dendrogram** using:

```
from scipy.cluster.hierarchy import dendrogram, linkage
```

#### Instructions:

1. Fit the data using `linkage(method='ward')`.
2. Plot a dendrogram.
3. From the dendrogram, visually determine:
  - o The optimal number of clusters
  - o The height at which clusters merge

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage

# Load dataset
data = pd.read_csv("shopping-data.csv")

# Extract features: Annual Income and Spending Score
X = data[['Annual Income (k$)', 'Spending Score (1-100)']].values

# Optional: check first few rows
print(data.head())

# Compute the linkage matrix using Ward's method
linked = linkage(X, method='ward')

plt.figure(figsize=(12,6))
```

The screenshot shows a Jupyter Notebook cell with the following code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage

# Load dataset
data = pd.read_csv("shopping-data.csv")

# Extract features: Annual Income and Spending Score
X = data[['Annual Income (k$)', 'Spending Score (1-100)']].values

# Optional: check first few rows
print(data.head())

# Compute the linkage matrix using Ward's method
linked = linkage(X, method='ward')

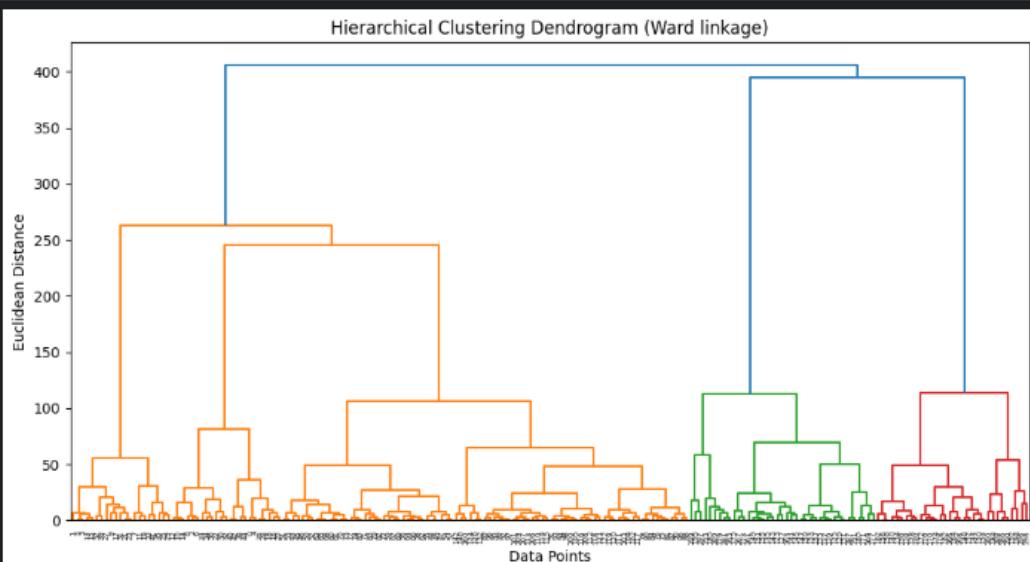
plt.figure(figsize=(12,6))
```

Below the code, the output shows the first five rows of the dataset:

	CustomerID	Genre	Age	Annual Income (k\$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

```
plt.figure(figsize=(12,6))
dendrogram(linked,
            orientation='top',
            labels=None,
            distance_sort='ascending',
            show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Ward linkage)')
plt.xlabel('Data Points')
plt.ylabel('Euclidean Distance')
plt.show()
```

✓ 3.3:



```
from scipy.cluster.hierarchy import fcluster

# Cut dendrogram at distance = 150 (example)
max_d = 150
clusters = fcluster(linked, max_d, criterion='distance')

# Print cluster assignments
print("Cluster assignment for each point:")
print(clusters)
```

4. Explain why hierarchical clustering may be preferred over K-Means.

**Answer:**

Hierarchical clustering may be preferred over K-Means because:

1. **No Need to Predefine Number of Clusters**
  - o K-Means requires you to choose  $k$  (number of clusters) beforehand.
  - o Hierarchical clustering builds a **dendrogram**, which allows you to visually determine the optimal number of clusters.
2. **Captures Complex Cluster Shapes**
  - o K-Means tends to form **spherical clusters** because it uses distance to the centroid.
  - o Hierarchical clustering can capture **irregularly shaped or nested clusters**.
3. **Hierarchical Structure**
  - o Hierarchical clustering produces a **tree-like structure (dendrogram)**, showing how clusters are merged step by step.
  - o This helps in understanding **relationships between clusters** at different levels.
4. **Better for Small Datasets**
  - o For small datasets, hierarchical clustering can be more informative, giving a **full view of cluster hierarchy**, whereas K-Means only gives flat clusters.
5. **Flexibility in Linkage Methods**
  - o You can choose different linkage methods (`ward`, `complete`, `average`) to **control how clusters merge**, which provides flexibility not available in K-Means.

### Question 3: Compare Agglomerative vs Divisive Hierarchical Clustering

#### Task:

Using a small synthetic dataset (e.g., 10–12 points), perform:

- Agglomerative Clustering
- Divisive Clustering (manual split or using a library like `sklearn-extra`)

#### Instructions:

1. Plot dendograms for both methods.
2. Compare the merge/split patterns.
3. Describe:
  - o Why agglomerative is more common in practice
  - o Which method is more computationally expensive
  - o Which gives clearer cluster boundaries for small datasets

```
Generate + Code + Markdown
```

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import AgglomerativeClustering, KMeans

✓ 0.0s

# 10 points (2D)
X = np.array([
    [1, 2],
    [2, 1],
    [1.5, 1.8],
    [5, 8],
    [6, 8],
    [5.5, 9],
    [8, 1],
    [9, 2],
    [8.5, 1.5],
    [7, 2]
])

labels = ['P1', 'P2', 'P3', 'P4', 'P5', 'P6', 'P7', 'P8', 'P9', 'P10']

✓ 0.0s

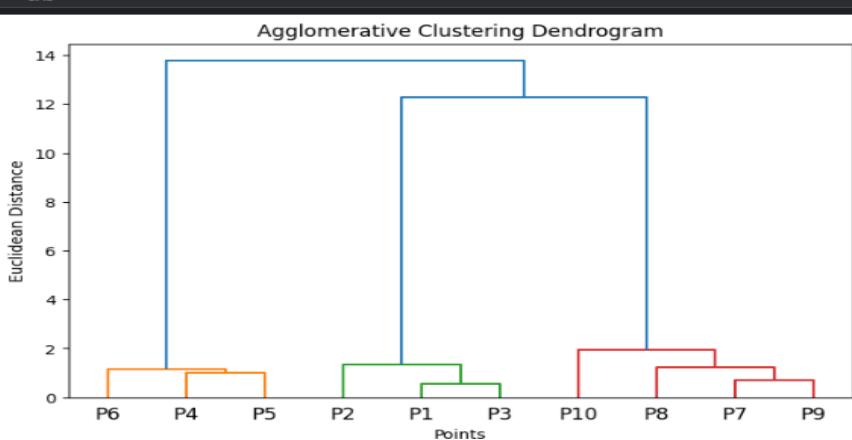
# Compute linkage for Agglomerative
linked_agg = linkage(X, method='ward')

# Plot dendrogram
plt.figure(figsize=(8,5))
dendrogram(linked_agg, labels=labels, distance_sort='ascending', show_leaf_counts=True)
plt.title("Agglomerative Clustering Dendrogram")
✓ 0.4s
```

```
# Compute linkage for Agglomerative
linked_agg = linkage(X, method='ward')

# Plot dendrogram
plt.figure(figsize=(8,5))
dendrogram(linked_agg, labels=labels, distance_sort='ascending', show_leaf_counts=True)
plt.title("Agglomerative Clustering Dendrogram")
plt.xlabel("Points")
plt.ylabel("Euclidean Distance")
plt.show()
```

✓ 0.4s



```

Simulate divisive clustering by splitting dataset using KMeans recursively
"""
km = KMeans(n_clusters=n_splits, random_state=0)
labels = km.fit_predict(X)
return labels, km.cluster_centers_

# First split
labels_div1, centers1 = divisive_split(X, n_splits=2)

plt.figure(figsize=(8,5))
plt.scatter(X[:,0], X[:,1], c=labels_div1, cmap='rainbow', s=100)
for i, txt in enumerate(labels):
    plt.text(X[i,0]+0.1, X[i,1]+0.1, txt)
plt.scatter(centers1[:,0], centers1[:,1], c='black', marker='X', s=200, label='Centers')
plt.title("Divisive Clustering (First Split)")
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.grid(True)
plt.show()

```

✓ 0.5s

