lab 11

October 23, 2024

```
[1]: import numpy as np
     def euclidean_distance(a, b):
         return np.sqrt(np.sum((a - b) ** 2))
     def single linkage(clusters):
         min_distance = float('inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distance = np.min([euclidean_distance(p1, p2) for p1 in clusters[i]_

¬for p2 in clusters[j]])

                 if distance < min_distance:</pre>
                     min_distance = distance
                     pair_to_merge = (i, j)
         return pair_to_merge
     def complete_linkage(clusters):
         max_distance = float('-inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distance = np.max([euclidean distance(p1, p2) for p1 in clusters[i]_

¬for p2 in clusters[j]])
                 if distance > max_distance:
                     max_distance = distance
                     pair_to_merge = (i, j)
         return pair_to_merge
     def average_linkage(clusters):
         avg distance = float('inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distances = [euclidean_distance(p1, p2) for p1 in clusters[i] for_
      →p2 in clusters[j]]
                 distance = np.mean(distances)
```

```
if distance < avg_distance:</pre>
                avg_distance = distance
                pair_to_merge = (i, j)
    return pair_to_merge
def centroid_linkage(clusters):
    centroids = [np.mean(cluster, axis=0) for cluster in clusters]
    min_distance = float('inf')
    pair to merge = None
    for i in range(len(centroids)):
        for j in range(i + 1, len(centroids)):
            distance = euclidean_distance(centroids[i], centroids[j])
            if distance < min distance:</pre>
                min_distance = distance
                pair_to_merge = (i, j)
    return pair_to_merge
def ward_linkage(clusters):
    min_increase = float('inf')
    pair_to_merge = None
    total_variance = lambda cluster: np.sum((cluster - np.mean(cluster, __
 ⇒axis=0)) ** 2)
    for i in range(len(clusters)):
        for j in range(i + 1, len(clusters)):
            combined_cluster = np.vstack((clusters[i], clusters[j]))
            increase = total_variance(combined_cluster) -__
 stotal_variance(clusters[i]) - total_variance(clusters[j])
            if increase < min_increase:</pre>
                min_increase = increase
                pair_to_merge = (i, j)
    return pair_to_merge
# Example usage
data_points = np.array([[1, 1], [3, 2], [9, 1], [3, 7], [7, 2], [9, 7], [4, 8], __
 \hookrightarrow [8, 3], [1, 4]])
clusters = [[point] for point in data_points]
# Run the linkage methods
print("Single Linkage Pair:", single_linkage(clusters))
print("Complete Linkage Pair:", complete_linkage(clusters))
print("Average Linkage Pair:", average_linkage(clusters))
print("Centroid Linkage Pair:", centroid_linkage(clusters))
print("Ward Linkage Pair:", ward_linkage(clusters))
```

Single Linkage Pair: (3, 6)
Complete Linkage Pair: (0, 5)

```
Average Linkage Pair: (3, 6)
Centroid Linkage Pair: (3, 6)
Ward Linkage Pair: (3, 6)
```

```
[2]: import numpy as np
     # Function to calculate Euclidean distance
     def euclidean_distance(a, b):
         return np.sqrt(np.sum((a - b) ** 2))
     # Function to find the closest pairs based on Single Linkage
     def single linkage(clusters):
         min distance = float('inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distance = np.min([euclidean_distance(p1, p2) for p1 in clusters[i]_

¬for p2 in clusters[j]])
                 if distance < min distance:</pre>
                     min_distance = distance
                     pair_to_merge = (i, j)
         return pair_to_merge
     # Function for Complete Linkage
     def complete_linkage(clusters):
         max_distance = float('-inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distance = np.max([euclidean distance(p1, p2) for p1 in clusters[i]_

¬for p2 in clusters[j]])
                 if distance > max_distance:
                     max_distance = distance
                     pair_to_merge = (i, j)
         return pair_to_merge
     # Function for Average Linkage
     def average_linkage(clusters):
         avg_distance = float('inf')
         pair_to_merge = None
         for i in range(len(clusters)):
             for j in range(i + 1, len(clusters)):
                 distances = [euclidean_distance(p1, p2) for p1 in clusters[i] for
      ⇒p2 in clusters[j]]
                 distance = np.mean(distances)
                 if distance < avg_distance:</pre>
                     avg_distance = distance
```

```
pair_to_merge = (i, j)
    return pair_to_merge
# Function for Centroid Linkage
def centroid_linkage(clusters):
    centroids = [np.mean(cluster, axis=0) for cluster in clusters]
    min distance = float('inf')
    pair_to_merge = None
    for i in range(len(centroids)):
        for j in range(i + 1, len(centroids)):
            distance = euclidean distance(centroids[i], centroids[j])
            if distance < min_distance:</pre>
                min distance = distance
                pair_to_merge = (i, j)
    return pair_to_merge
# Function for Ward's Method
def ward_linkage(clusters):
    min_increase = float('inf')
    pair_to_merge = None
    total_variance = lambda cluster: np.sum((cluster - np.mean(cluster, __
 ⇒axis=0)) ** 2)
    for i in range(len(clusters)):
        for j in range(i + 1, len(clusters)):
            combined_cluster = np.vstack((clusters[i], clusters[j]))
            increase = total_variance(combined_cluster) -__
 stotal_variance(clusters[i]) - total_variance(clusters[j])
            if increase < min_increase:</pre>
                min increase = increase
                pair_to_merge = (i, j)
    return pair_to_merge
# Hierarchical Clustering Function
def hierarchical_clustering(data, linkage_method):
    clusters = [[point] for point in data]
    while len(clusters) > 1:
        if linkage_method == 'single':
            pair_to_merge = single_linkage(clusters)
        elif linkage_method == 'complete':
            pair_to_merge = complete_linkage(clusters)
        elif linkage_method == 'average':
            pair_to_merge = average_linkage(clusters)
        elif linkage_method == 'centroid':
            pair_to_merge = centroid_linkage(clusters)
        elif linkage_method == 'ward':
            pair_to_merge = ward_linkage(clusters)
```

```
# Merge the clusters
             new_cluster = clusters[pair_to_merge[0]] + clusters[pair_to_merge[1]]
             clusters.append(new_cluster)
             # Remove the merged clusters
             clusters.pop(max(pair_to_merge))
             clusters.pop(min(pair_to_merge))
         return clusters[0]
     # Example Data Points
     data_points = np.array([[1, 1], [3, 2], [9, 1], [3, 7], [7, 2], [9, 7], [4, 8], __
      \hookrightarrow [8, 3], [1, 4]])
     # Run hierarchical clustering for each linkage method
     for method in ['single', 'complete', 'average', 'centroid', 'ward']:
         clustered_data = hierarchical_clustering(data_points, method)
         clustered_data_list = [cluster.tolist() for cluster in clustered_data]
         print(f"Clusters using {method.capitalize()} Linkage:
      →{clustered data list}")
    Clusters using Single Linkage: [[9, 7], [9, 1], [7, 2], [8, 3], [3, 7], [4, 8],
    [1, 4], [1, 1], [3, 2]]
    Clusters using Complete Linkage: [[7, 2], [8, 3], [3, 2], [3, 7], [9, 1], [4,
    8], [1, 4], [1, 1], [9, 7]]
    Clusters using Average Linkage: [[9, 7], [9, 1], [7, 2], [8, 3], [3, 7], [4, 8],
    [1, 4], [1, 1], [3, 2]]
    Clusters using Centroid Linkage: [[9, 7], [9, 1], [7, 2], [8, 3], [3, 7], [4,
    8], [1, 4], [1, 1], [3, 2]]
    Clusters using Ward Linkage: [[9, 7], [9, 1], [7, 2], [8, 3], [3, 7], [4, 8],
    [1, 4], [1, 1], [3, 2]]
[3]: import numpy as np
     import matplotlib.pyplot as plt
     from scipy.cluster.hierarchy import dendrogram, linkage, fcluster # Import_{\sqcup}
     from scipy.spatial.distance import pdist, squareform
     # Define distance functions
     def euclidean distance(a, b):
         return np.sqrt(np.sum((a - b) ** 2))
     def manhattan_distance(a, b):
         return np.sum(np.abs(a - b))
     def minkowski_distance(a, b, p=3):
```

```
return np.power(np.sum(np.abs(a - b) ** p), 1/p)
# Calculate proximity matrix
def proximity_matrix(data, metric='euclidean'):
   n = data.shape[0]
   matrix = np.zeros((n, n))
   for i in range(n):
        for j in range(n):
            if metric == 'euclidean':
                matrix[i, j] = euclidean_distance(data[i], data[j])
            elif metric == 'manhattan':
                matrix[i, j] = manhattan_distance(data[i], data[j])
            elif metric == 'minkowski':
                matrix[i, j] = minkowski_distance(data[i], data[j])
   return matrix
# Function to calculate SSE
def calculate_sse(data, cluster_assignments):
   for cluster in np.unique(cluster_assignments):
        cluster_points = data[cluster_assignments == cluster]
        cluster center = np.mean(cluster points, axis=0)
        sse += np.sum((cluster_points - cluster_center) ** 2)
   return sse
# Plot SSE against number of clusters
def plot_sse(data):
   sse_values = []
   max_k = 10 # Maximum number of clusters to consider
   for k in range(1, max_k + 1):
        # Use hierarchical clustering to assign clusters
        Z = linkage(data, method='ward')
        cluster_assignments = fcluster(Z, k, criterion='maxclust')
        sse = calculate_sse(data, cluster_assignments)
        sse_values.append(sse)
   plt.figure(figsize=(10, 5))
   plt.plot(range(1, max_k + 1), sse_values, marker='o')
   plt.title('SSE vs Number of Clusters')
   plt.xlabel('Number of Clusters')
   plt.ylabel('Sum of Squared Errors (SSE)')
   plt.xticks(range(1, max_k + 1))
   plt.grid()
   plt.show()
```

```
# Plot dendrogram for different linkage methods
def plot_dendrograms(data):
    methods = ['single', 'complete', 'average', 'centroid', 'ward']
    plt.figure(figsize=(15, 10))
    for i, method in enumerate(methods):
        plt.subplot(3, 2, i + 1)
        Z = linkage(data, method=method)
        dendrogram(Z)
        plt.title(f'Dendrogram ({method.capitalize()} Linkage)')
    plt.tight_layout()
    plt.show()
# Main code
data_points = np.array([[1, 1], [3, 2], [9, 1], [3, 7], [7, 2], [9, 7], [4, 8],
 \rightarrow [8, 3], [1, 4]])
# Calculate and display proximity matrices
print("Proximity Matrix (Euclidean):")
print(proximity_matrix(data_points, metric='euclidean'))
print("\nProximity Matrix (Manhattan):")
print(proximity_matrix(data_points, metric='manhattan'))
print("\nProximity Matrix (Minkowski):")
print(proximity_matrix(data_points, metric='minkowski'))
# Plot SSE
plot_sse(data_points)
# Plot Dendrograms
plot_dendrograms(data_points)
Proximity Matrix (Euclidean):
              2.23606798 8.
                                      6.32455532 6.08276253 10.
  7.61577311 7.28010989 3.
                                    ]
 [ 2.23606798 0.
                          6.08276253 5.
                                                              7.81024968
  6.08276253 5.09901951 2.82842712]
                                      8.48528137 2.23606798 6.
 [ 8.
              6.08276253 0.
  8.60232527 2.23606798 8.54400375]
 [ 6.32455532 5.
                          8.48528137 0.
                                                  6.40312424 6.
   1.41421356 6.40312424 3.60555128]
 Γ 6.08276253 4.
                   2.23606798 6.40312424 0.
                                                              5.38516481
  6.70820393 1.41421356 6.32455532]
 Γ10.
             7.81024968 6.
                                      6.
                                              5.38516481 0.
```

```
5.09901951 4.12310563 8.54400375]
[\ 7.61577311 \ \ 6.08276253 \ \ 8.60232527 \ \ 1.41421356 \ \ 6.70820393 \ \ 5.09901951
          6.40312424 5.
[ 7.28010989   5.09901951   2.23606798   6.40312424   1.41421356   4.12310563
 6.40312424 0.
                     7.071067817
          2.82842712 8.54400375 3.60555128 6.32455532 8.54400375
Г3.
        7.07106781 0. ]]
  5.
Proximity Matrix (Manhattan):
[[ 0. 3. 8. 8. 7. 14. 10. 9. 3.]
[3. 0. 7. 5. 4. 11. 7. 6. 4.]
[8. 7. 0. 12. 3. 6. 12. 3. 11.]
[8. 5. 12. 0. 9. 6. 2. 9. 5.]
[7. 4. 3. 9. 0. 7. 9. 2. 8.]
[14. 11. 6. 6. 7. 0. 6. 5. 11.]
[10. 7. 12. 2. 9. 6. 0. 9. 7.]
[9. 6. 3. 9. 2. 5. 9. 0. 8.]
[ 3. 4. 11. 5. 8. 11. 7. 8. 0.]]
[2.08008382 0. 6.00924501 5. 4. 6.98636803
 6.00924501 5.01329793 2.5198421 ]
[8. 6.00924501 0. 7.5595263 2.08008382 6.
 7.76393608 2.08008382 8.13822304]
 [6.07317794 5. 7.5595263 0. 5.73879355 6.
 1.25992105 5.73879355 3.27106631]
 [6.00924501 4. 2.08008382 5.73879355 0. 5.10446872
 6.24025147 1.25992105 6.07317794]
 [8.99588289 6.98636803 6. 6. 5.10446872 0.
 5.01329793 4.02072576 8.13822304]
 [7.17905435 6.00924501 7.76393608 1.25992105 6.24025147 5.01329793
 0. 5.73879355 4.49794145]
 [7.05400406 5.01329793 2.08008382 5.73879355 1.25992105 4.02072576
 5.73879355 0. 7.00679612]
 [3. 2.5198421 8.13822304 3.27106631 6.07317794 8.13822304
```

4.49794145 7.00679612 0.



