

# 220962050\_Arhaan\_Lab11

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## 0.1 Question

Consider the mentioned dataset and apply the hierarchical data-clustering algorithm, to identify the clusters. Write a Python function (without using the scikit-learn library) to do the following:-

- Plot a graph that displays the number of clusters on the x-axis and the Sum of Squared Errors (SSE) on the y-axis.
- Display the proximity matrix using Euclidean distance, Manhattan distance, and Minkowski distance.
- Plot the dendrogram for single, complete, average, centroid, and ward linkage methods.

```
[8]: import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import scipy.cluster.hierarchy as sch
import scipy.spatial.distance as dist

data = np.array([
    [1, 1], # p1
    [3, 2], # p2
    [9, 1], # p3
    [3, 7], # p4
    [7, 2], # p5
    [9, 7], # p6
    [4, 8], # p7
    [8, 3], # p8
    [1, 4]  # p9
])
```

### 0.1.1 ( B )

```
[9]: def proximity_matrices(data):
    euclidean_dist = dist.squareform(dist.pdist(data, metric='euclidean'))
    manhattan_dist = dist.squareform(dist.pdist(data, metric='cityblock'))
    minkowski_dist = dist.squareform(dist.pdist(data, metric='minkowski', p=3))

    euclidean_df = pd.DataFrame(euclidean_dist, columns=[f'p{i+1}' for i in
    ↪range(len(data))],
                                index=[f'p{i+1}' for i in range(len(data))])
```

```

    manhattan_df = pd.DataFrame(manhattan_dist, columns=[f'p{i+1}' for i in
↪range(len(data))],
                                index=[f'p{i+1}' for i in range(len(data))])
    minkowski_df = pd.DataFrame(minkowski_dist, columns=[f'p{i+1}' for i in
↪range(len(data))],
                                index=[f'p{i+1}' for i in range(len(data))])

    return euclidean_df, manhattan_df, minkowski_df

euclidean_df, manhattan_df, minkowski_df = proximity_matrices(data)

print("Euclidean Distance Matrix:\n", euclidean_df)
print("\nManhattan Distance Matrix:\n", manhattan_df)
print("\nMinkowski Distance Matrix:\n", minkowski_df)

```

Euclidean Distance Matrix:

	p1	p2	p3	p4	p5	p6	p7	\
p1	0.000000	2.236068	8.000000	6.324555	6.082763	10.000000	7.615773	
p2	2.236068	0.000000	6.082763	5.000000	4.000000	7.810250	6.082763	
p3	8.000000	6.082763	0.000000	8.485281	2.236068	6.000000	8.602325	
p4	6.324555	5.000000	8.485281	0.000000	6.403124	6.000000	1.414214	
p5	6.082763	4.000000	2.236068	6.403124	0.000000	5.385165	6.708204	
p6	10.000000	7.810250	6.000000	6.000000	5.385165	0.000000	5.099020	
p7	7.615773	6.082763	8.602325	1.414214	6.708204	5.099020	0.000000	
p8	7.280110	5.099020	2.236068	6.403124	1.414214	4.123106	6.403124	
p9	3.000000	2.828427	8.544004	3.605551	6.324555	8.544004	5.000000	

	p8	p9
p1	7.280110	3.000000
p2	5.099020	2.828427
p3	2.236068	8.544004
p4	6.403124	3.605551
p5	1.414214	6.324555
p6	4.123106	8.544004
p7	6.403124	5.000000
p8	0.000000	7.071068
p9	7.071068	0.000000

Manhattan Distance Matrix:

	p1	p2	p3	p4	p5	p6	p7	p8	p9
p1	0.0	3.0	8.0	8.0	7.0	14.0	10.0	9.0	3.0
p2	3.0	0.0	7.0	5.0	4.0	11.0	7.0	6.0	4.0
p3	8.0	7.0	0.0	12.0	3.0	6.0	12.0	3.0	11.0
p4	8.0	5.0	12.0	0.0	9.0	6.0	2.0	9.0	5.0
p5	7.0	4.0	3.0	9.0	0.0	7.0	9.0	2.0	8.0
p6	14.0	11.0	6.0	6.0	7.0	0.0	6.0	5.0	11.0
p7	10.0	7.0	12.0	2.0	9.0	6.0	0.0	9.0	7.0

```
p8  9.0  6.0  3.0  9.0  2.0  5.0  9.0  0.0  8.0
p9  3.0  4.0 11.0  5.0  8.0 11.0  7.0  8.0  0.0
```

Minkowski Distance Matrix:

	p1	p2	p3	p4	p5	p6	p7 \
p1	0.000000	2.080084	8.000000	6.073178	6.009245	8.995883	7.179054
p2	2.080084	0.000000	6.009245	5.000000	4.000000	6.986368	6.009245
p3	8.000000	6.009245	0.000000	7.559526	2.080084	6.000000	7.763936
p4	6.073178	5.000000	7.559526	0.000000	5.738794	6.000000	1.259921
p5	6.009245	4.000000	2.080084	5.738794	0.000000	5.104469	6.240251
p6	8.995883	6.986368	6.000000	6.000000	5.104469	0.000000	5.013298
p7	7.179054	6.009245	7.763936	1.259921	6.240251	5.013298	0.000000
p8	7.054004	5.013298	2.080084	5.738794	1.259921	4.020726	5.738794
p9	3.000000	2.519842	8.138223	3.271066	6.073178	8.138223	4.497941

	p8	p9
p1	7.054004	3.000000
p2	5.013298	2.519842
p3	2.080084	8.138223
p4	5.738794	3.271066
p5	1.259921	6.073178
p6	4.020726	8.138223
p7	5.738794	4.497941
p8	0.000000	7.006796
p9	7.006796	0.000000

### 0.1.2 ( A )

```
[10]: def calculate_sse(data, clusters):
    sse = 0
    for cluster in clusters:
        cluster_points = data[cluster]
        cluster_center = np.mean(cluster_points, axis=0)
        sse += np.sum((cluster_points - cluster_center) ** 2)
    return sse

def plot_sse(data):
    sse_values = []
    for k in range(1, len(data) + 1):
        linkage_matrix = sch.linkage(data, method='ward')
        clusters = sch.fcluster(linkage_matrix, k, criterion='maxclust')
        sse = calculate_sse(data, [np.where(clusters == i)[0] for i in range(1,
↪k + 1)])
        sse_values.append(sse)

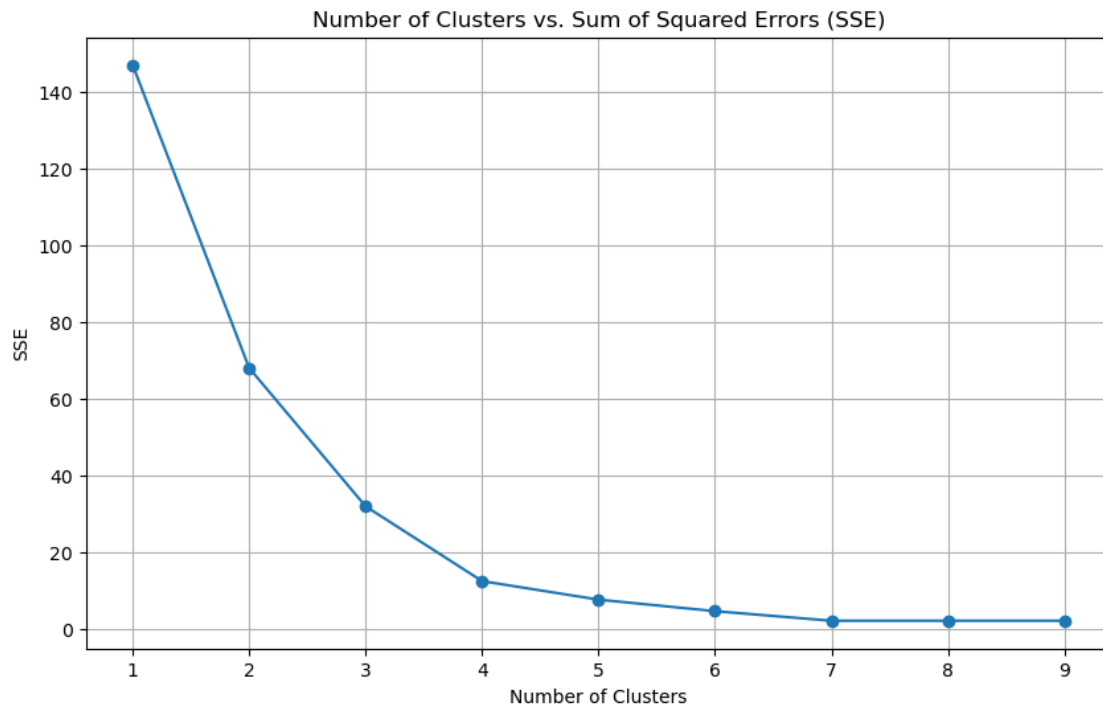
    plt.figure(figsize=(10, 6))
    plt.plot(range(1, len(data) + 1), sse_values, marker='o')
```

```
plt.title('Number of Clusters vs. Sum of Squared Errors (SSE)')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.grid(True)
plt.show()
```

```
plot_sse(data)
```

/usr/lib/python3/dist-packages/numpy/core/fromnumeric.py:3504: RuntimeWarning: Mean of empty slice.

```
return _methods._mean(a, axis=axis, dtype=dtype,
/usr/lib/python3/dist-packages/numpy/core/_methods.py:121: RuntimeWarning:
invalid value encountered in divide
ret = um.true_divide(
```



### 0.1.3 ( C )

```
[11]: def plot_dendrogram(data):
    methods = ['single', 'complete', 'average', 'centroid', 'ward']

    plt.figure(figsize=(15, 10))
    for i, method in enumerate(methods):
        plt.subplot(3, 2, i + 1)
        linkage_matrix = sch.linkage(data, method=method)
```

```
sch.dendrogram(linkage_matrix)
plt.title(f'Dendrogram ({method.capitalize()} Linkage)')
plt.xlabel('Sample Index')
plt.ylabel('Distance')
```

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

```
plot_dendrogram(data)
```

