Aim-: Implement K-Means clustering/ hierarchical clustering on sales_data_sample.csv dataset. Determine the number of clusters using the elbow method.

INPUT

```
import pandas as pd

import matplotlib.pyplot as plt from sklearn.cluster

import KMeans from sklearn.preprocessing

import StandardScaler from scipy.cluster.hierarchy

import dendrogram, linkage from sklearn.cluster i

mport AgglomerativeClustering

import numpy as np

import seaborn as sns


# Load the dataset

# Load the dataset with a specified encoding
data = pd.read_csv('sales_data_sample.csv', encoding='ISO-8859-1')


# Preprocess the dataset (choose relevant features)
# Replace 'SALES', 'QUANTITYORDERED', 'PRICEEACH' with actual column names in
your dataset
features = data[['SALES', 'QUANTITYORDERED', 'PRICEEACH']]


# Standardize the features

scaler =StandardScaler()

scaled_features=scaler.fit_transform(features)


# Elbow method to determine the optimal number of clusters for K-Means
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wcss = []
# within-cluster sum of squares
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, random_state=42)
    kmeans.fit(scaled_features)
    wcss.append(kmeans.inertia_)

# Plot the elbow curve
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal K (K-Means)')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()

# Automatically determine the optimal number of clusters from the elbow #
This function calculates the "elbow" as the point with the maximum curvature
def optimal_k_elbow(wcss):
x1, y1 = 1, wcss[0]
x2, y2 = 10, wcss[-1]
distances = []
for i in range(10):
x0 = i + 1
y0 = wcss[i]
numerator = abs((y2 - y1) * x0 - (x2 - x1) * y0 + x2 * y1 - y2 * x1)
denominator = np.sqrt((y2 - y1) ** 2 + (x2 - x1) ** 2)
distances.append(numerator / denominator)
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return distances.index(max(distances)) + 1

optimal_k = optimal_k_elbow(wcss)

# Apply K-Means clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
kmeans_labels = kmeans.fit_predict(scaled_features)

# Print the number of clusters for K-Means
print(f'Number of clusters determined by K-Means (Elbow Method): {optimal_k}')

# Plot K-Means clusters with colored datapoints
plt.figure(figsize=(8, 6))
sns.scatterplot(x=scaled_features[:, 0], y=scaled_features[:, 1], hue=kmeans_labels,
palette='Set1', s=100)
plt.title(f'K-Means Clustering with {optimal_k} Clusters')
plt.xlabel('Feature 1 (e.g., SALES)')
plt.ylabel('Feature 2 (e.g., QUANTITYORDERED)')
plt.show()

# Perform hierarchical clustering using 'ward' linkage method
linked = linkage(scaled_features, method='ward')

# Plot the dendrogram showing the first 4 levels (truncate_mode='level', p=4)
plt.figure(figsize=(10, 7))
dendrogram(linked, orientation='top', distance_sort='descending', show_leaf_counts=True,
truncate_mode='level', p=4)
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plt.title('Dendrogram for Hierarchical Clustering (Truncated to 4 Levels)')

plt.xlabel('Sample Index')

plt.ylabel('Euclidean Distance')

plt.show()


# Automatically determine the number of clusters from the dendrogram
# You can determine this by visually inspecting where the largest gap in the dendrogram
appears
def get_optimal_clusters_from_dendrogram(linked, threshold=0.7):
    dendrogram_data = dendrogram(linked, no_plot=True)

distances = np.diff(dendrogram_data['dcoord'], axis=1).ravel()

threshold_distance = np.percentile(distances, threshold * 100)

num_clusters = np.sum(distances > threshold_distance) + 1

return num_clusters


optimal_hc = get_optimal_clusters_from_dendrogram(linked)


# Apply hierarchical clustering with the chosen number of clusters

hc = AgglomerativeClustering(n_clusters=optimal_hc, metric='euclidean', linkage='ward')

hierarchical_labels = hc.fit_predict(scaled_features)


# Print the number of clusters for hierarchical clustering

print(f'Number of clusters determined by Hierarchical Clustering: {optimal_hc}')
```
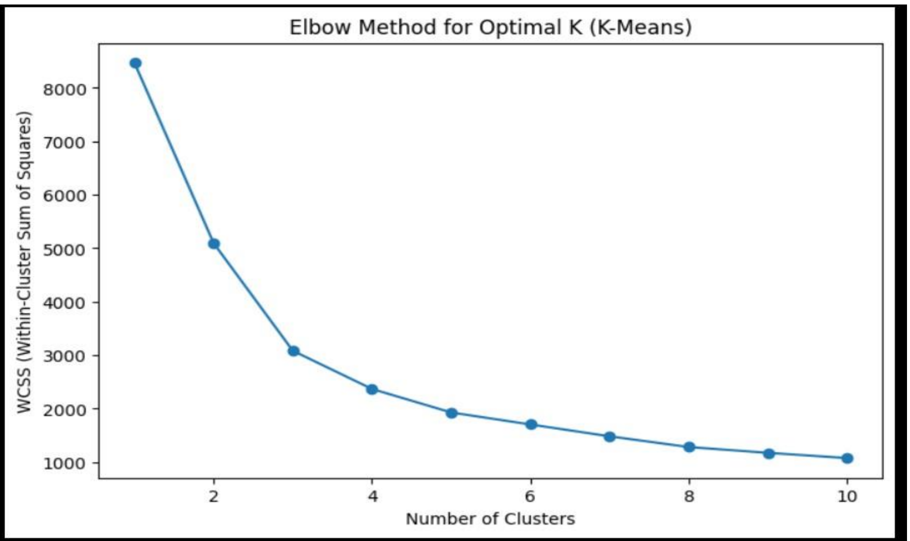
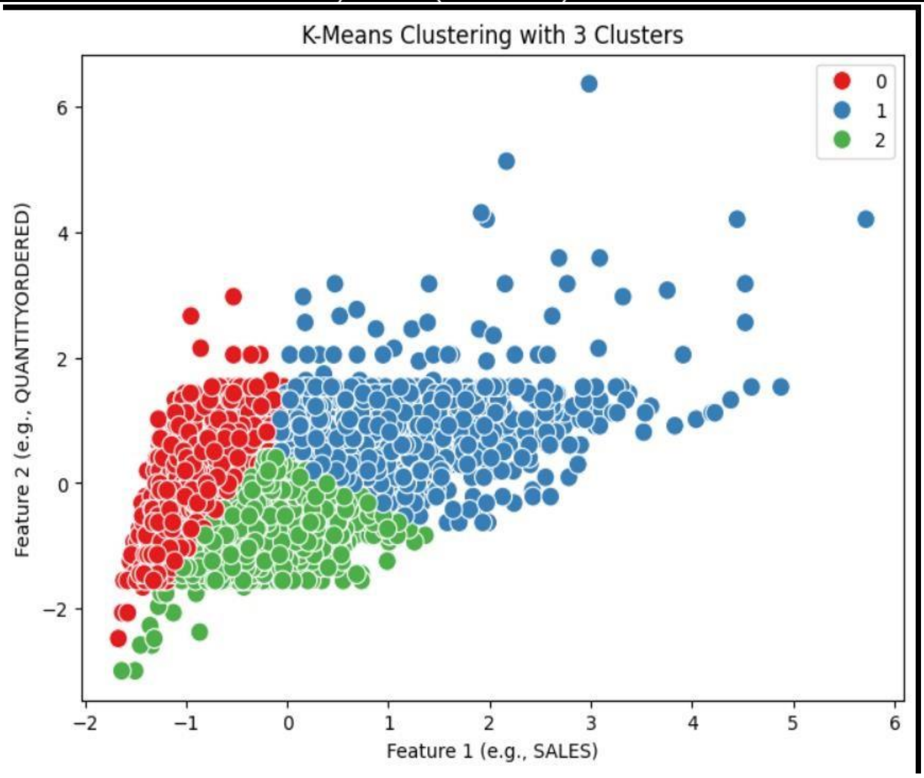
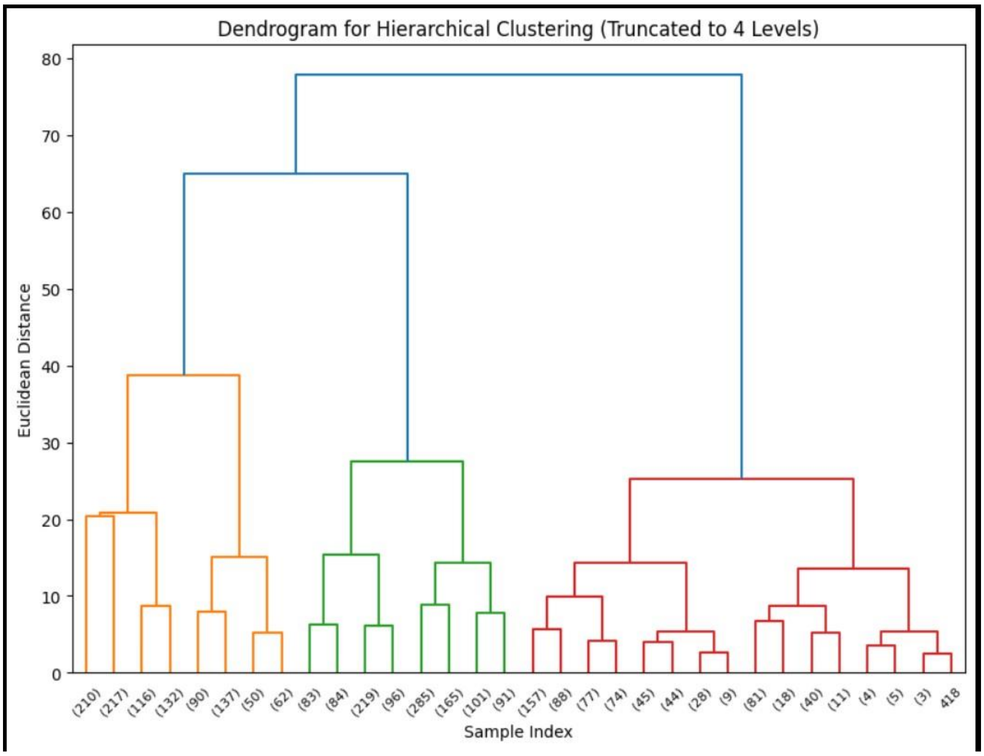




```
... Number of clusters determined by K-Means (Elbow Method): 3
```





Number of clusters determined by Hierarchical Clustering: 2541