```
import pandas as pd
```

```
df = pd.read_csv('mcdonalds.csv')
```

```
print("Variable Names:")
print(df.columns)
```

```
Variable Names:
Index(['yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap',
       'tasty', 'expensive', 'healthy', 'disgusting', 'Like', 'Age',
       'VisitFrequency', 'Gender'],
      dtype='object')
```

```
print("\nSample Size:")
print(len(df))
```

```
Sample Size:
1453
```

```
print("\nFirst Three Rows:")
print(df.head(3))
```

```
First Three Rows:
  yummy convenient spicy fattening greasy fast cheap tasty expensive healthy  \
0    No        Yes    No       Yes     No  Yes   Yes    No       Yes      No
1   Yes        Yes    No       Yes    Yes  Yes   Yes   Yes       Yes      No
2    No        Yes   Yes       Yes    Yes  Yes    No   Yes       Yes     Yes

  disgusting Like  Age      VisitFrequency  Gender
0         No   -3   61  Every three months  Female
1         No   +2   51  Every three months  Female
2         No   +1   62  Every three months  Female
```

```
segmentation_data = df.iloc[:, :11]
```

```
numeric_segmentation_data = segmentation_data.apply(lambda x: x.eq('Yes').astype(int))
```

```
print("Average Value of Transformed Segmentation Variables:")
print(numeric_segmentation_data.mean())
```

```
Average Value of Transformed Segmentation Variables:
yummy         0.552650
convenient    0.907777
spicy         0.093599
fattening     0.867171
greasy        0.526497
fast          0.900206
cheap         0.598761
tasty         0.644184
expensive     0.357880
healthy       0.198899
disgusting    0.242946
dtype: float64
```

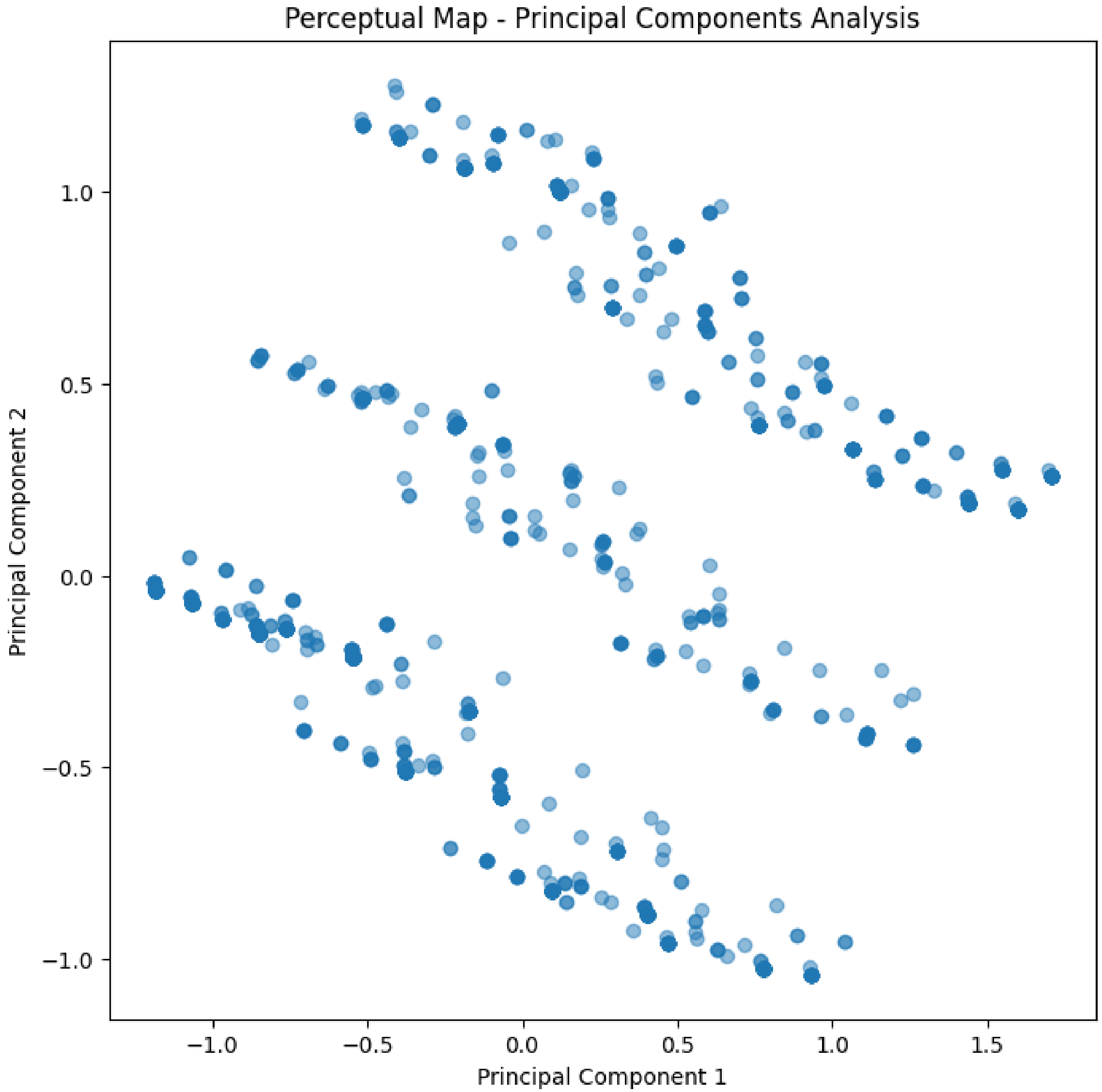
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
```

```
pca = PCA(n_components=2)
principal_components = pca.fit_transform(numeric_segmentation_data)
```

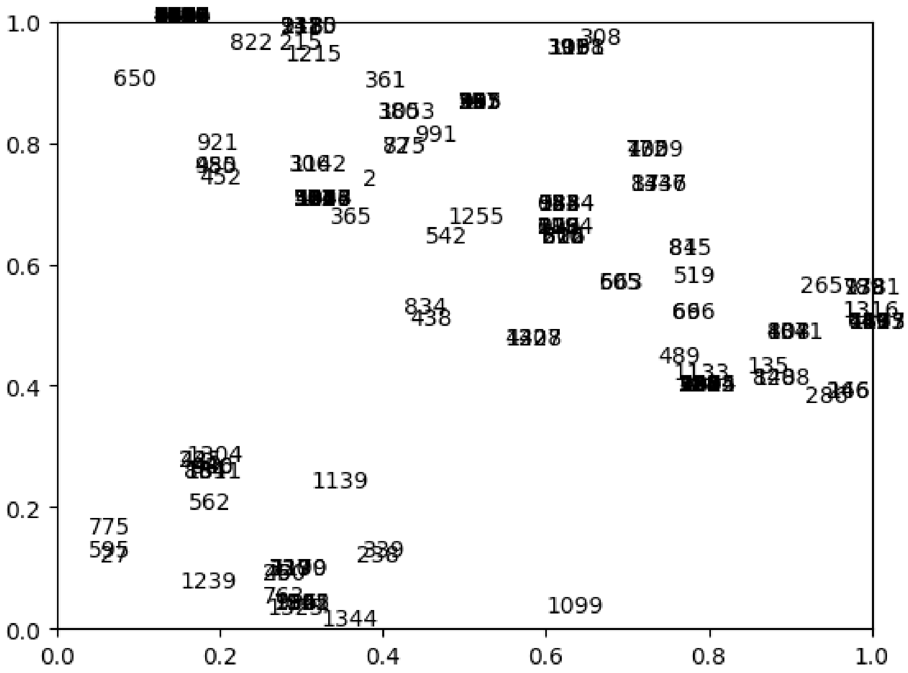
```
pc_df = pd.DataFrame(data=principal_components, columns=['PC1', 'PC2'])
```

```
plt.figure(figsize=(8, 8))
plt.scatter(pc_df['PC1'], pc_df['PC2'], alpha=0.5)
plt.title('Perceptual Map - Principal Components Analysis')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
```

```
Text(0, 0.5, 'Principal Component 2')
```




```
for i, txt in enumerate(df.index):
    plt.annotate(txt, (pc_df['PC1'][i], pc_df['PC2'][i]))

plt.show()
```




```
explained_variance_ratio = pca.explained_variance_ratio_
print(f'Explained Variance Ratio - PC1: {explained_variance_ratio[0]:.2f}')
print(f'Explained Variance Ratio - PC2: {explained_variance_ratio[1]:.2f}')
```

```
Explained Variance Ratio - PC1: 0.30
Explained Variance Ratio - PC2: 0.19
```

```
factor_loadings = pca.components_.T
```

```
print("Factor Loadings:")
print(factor_loadings)
```

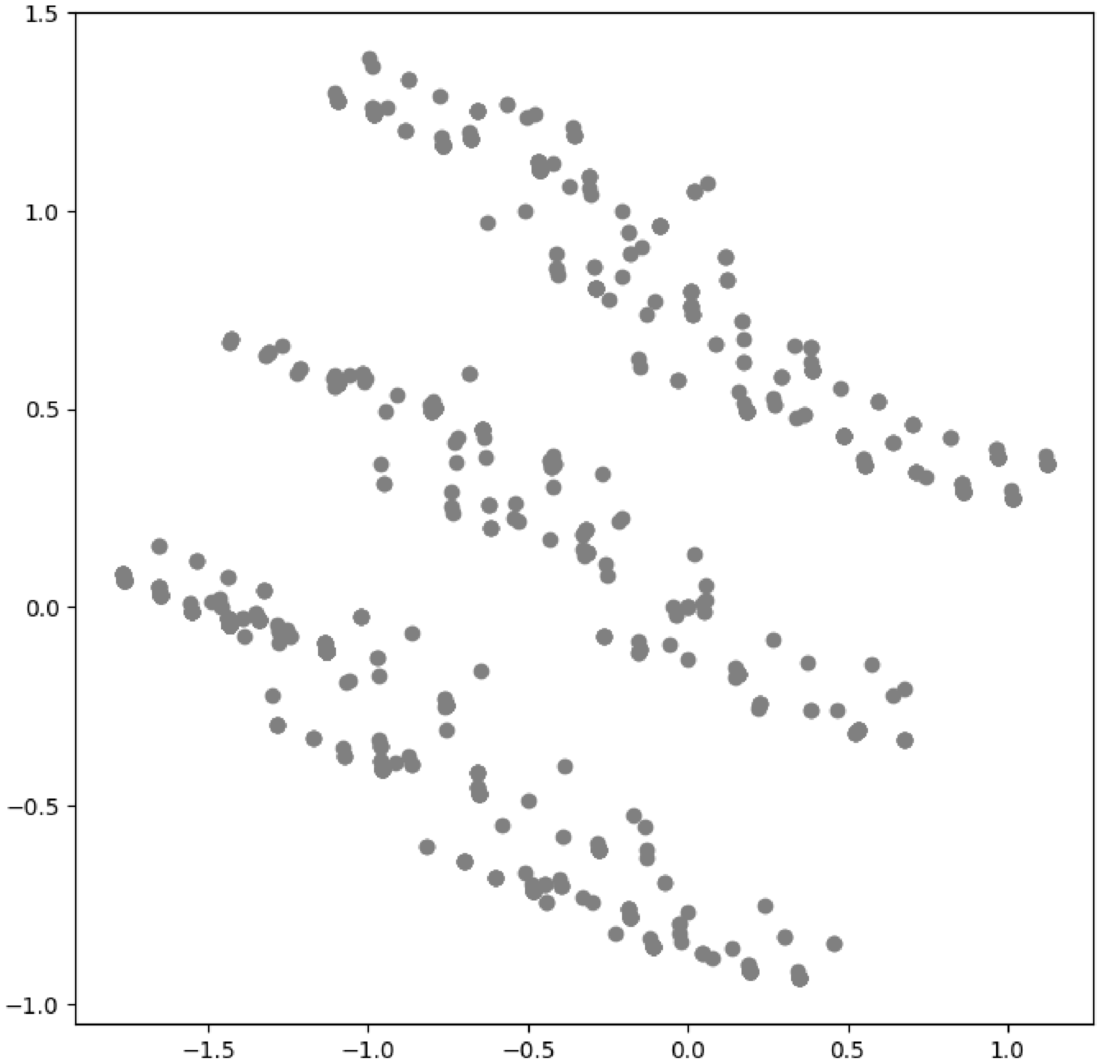
```
Factor Loadings:
[[-0.47693349  0.36378978]
 [-0.15533159  0.016414  ]
 [-0.00635636  0.01880869]
 [ 0.11623168 -0.03409395]
 [ 0.3044427  -0.06383884]
 [-0.10849325 -0.0869722 ]
 [-0.33718593 -0.61063276]
 [-0.47151394  0.3073178 ]
```

```
 [ 0.32904173  0.60128596]
 [-0.21371062  0.07659344]
 [ 0.37475293 -0.13965633]]
```

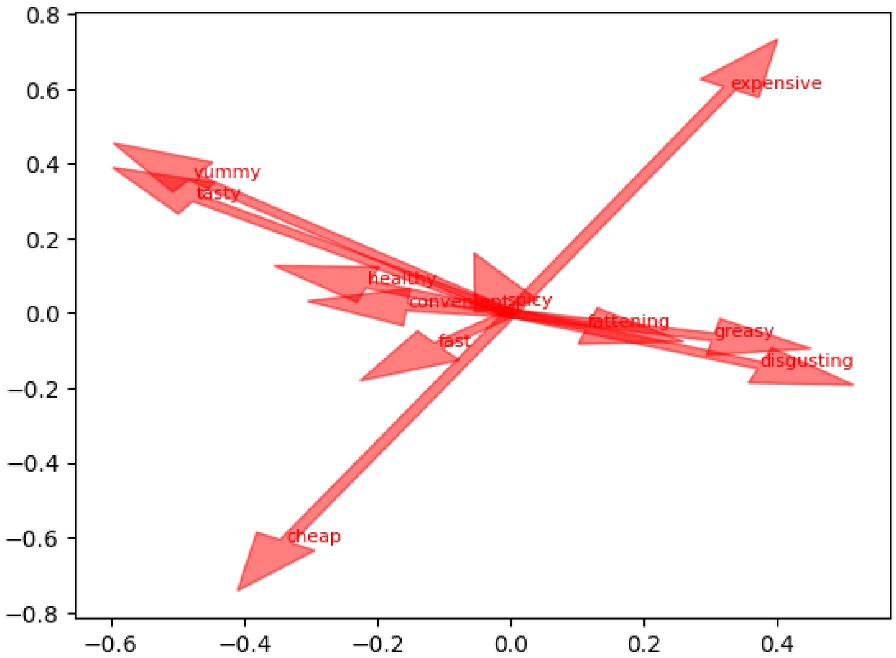
```
rotated_vars = np.dot(numeric_segmentation_data.values, factor_loadings)
```

```
plt.figure(figsize=(8, 8))
plt.scatter(rotated_vars[:, 0], rotated_vars[:, 1], color='grey', label='Consumers')
```

```
<matplotlib.collections.PathCollection at 0x7bdab2e92920>
```

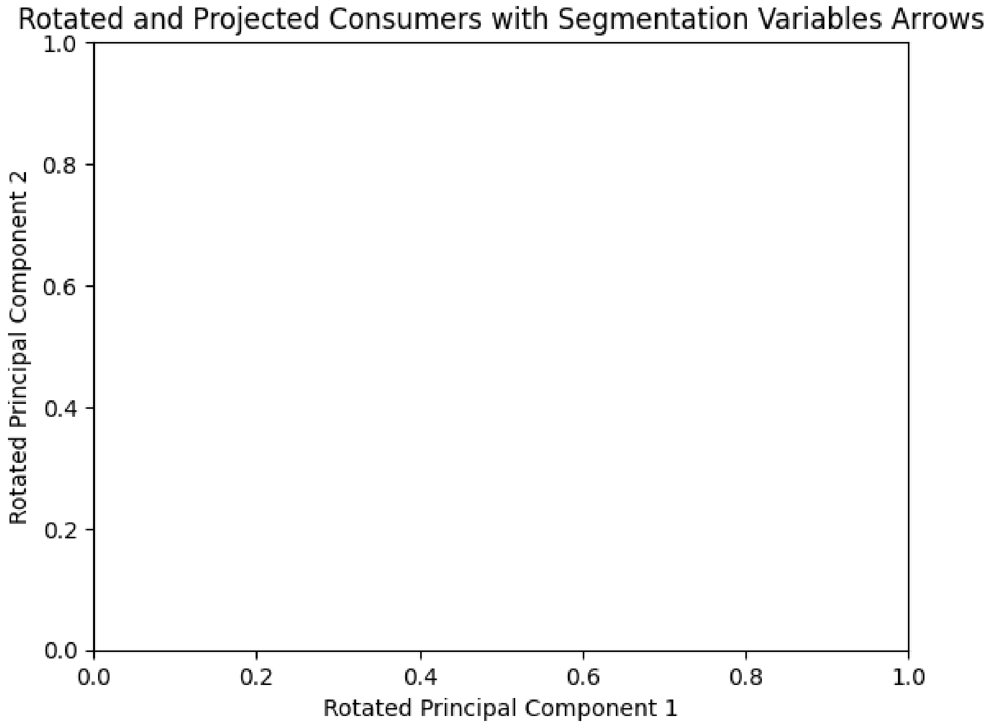



```
for i in range(len(factor_loadings)):
    plt.arrow(0, 0, factor_loadings[i, 0], factor_loadings[i, 1], color='red', alpha=0.5, width=0.02, head_width=0.1)
    plt.text(factor_loadings[i, 0], factor_loadings[i, 1], segmentation_data.columns[i], color='red', fontsize=8)
```




```
plt.xlabel('Rotated Principal Component 1')
plt.ylabel('Rotated Principal Component 2')
plt.title('Rotated and Projected Consumers with Segmentation Variables Arrows')
```

```
Text(0.5, 1.0, 'Rotated and Projected Consumers with Segmentation Variables Arrows')
```




```
plt.show()
```

```
#Using k-Means
```

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

```
num_segments = 4
```

```
kmeans = KMeans(n_clusters=num_segments, random_state=42)
segment_labels = kmeans.fit_predict(rotated_vars)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Se
  warnings.warn(
```

```
pc_df['Segment'] = segment_labels
```

```
print(pc_df.head())
```

```
        PC1       PC2  Segment
0  0.425367 -0.219079        0
1 -0.218638  0.388190        1
2  0.375415  0.730435        1
3 -0.172926 -0.352752        2
4  0.187057 -0.807610        0
```

```
!pip install scikit-learn
```

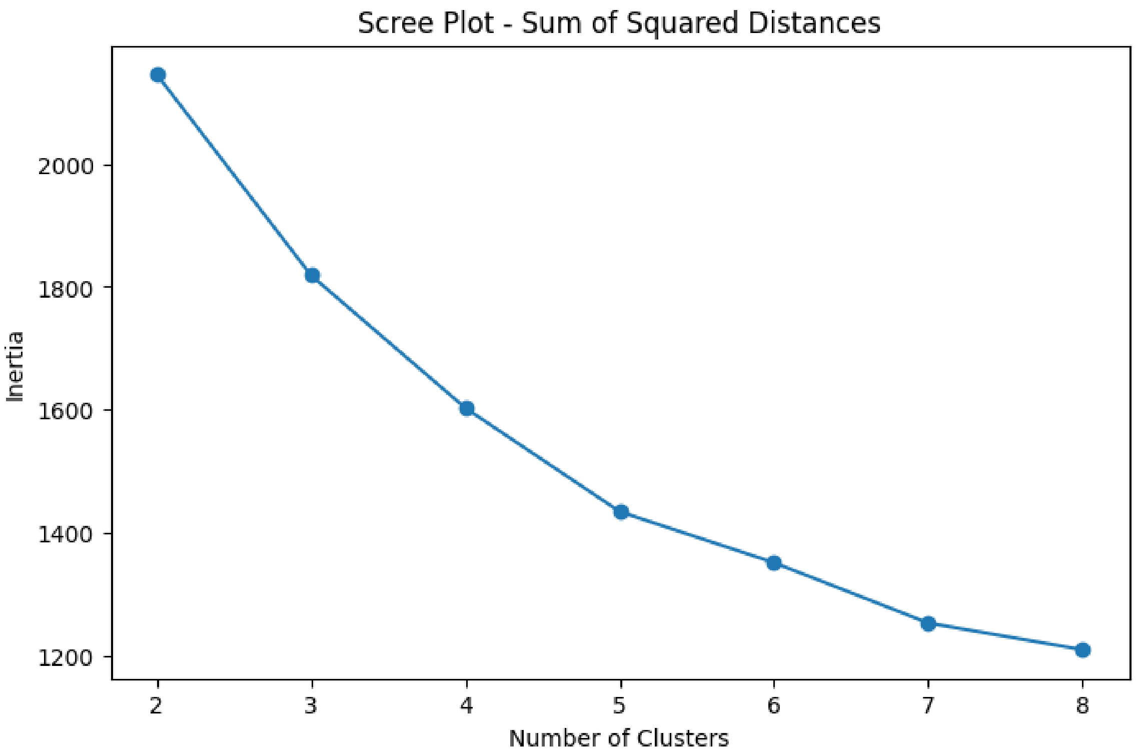
```
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.2.2)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.23.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.4)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.2.0)
```

```
from sklearn.metrics import silhouette_score
```

```
inertia_values = []
```

```
min_clusters = 2
max_clusters = 8

for num_clusters in range(min_clusters, max_clusters + 1):
    kmeans = KMeans(n_clusters=num_clusters, n_init=10, random_state=42)
    kmeans.fit(numeric_segmentation_data)

    # Calculate sum of squared distances (inertia) for the current clustering
    inertia_values.append(kmeans.inertia_)
```

```
plt.figure(figsize=(8, 5))
plt.plot(range(min_clusters, max_clusters + 1), inertia_values, marker='o')
plt.title('Scree Plot - Sum of Squared Distances')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.show()
```




```
from sklearn.utils import resample
```

```
n_bootstraps = 200
```

```
n_init = 10
```

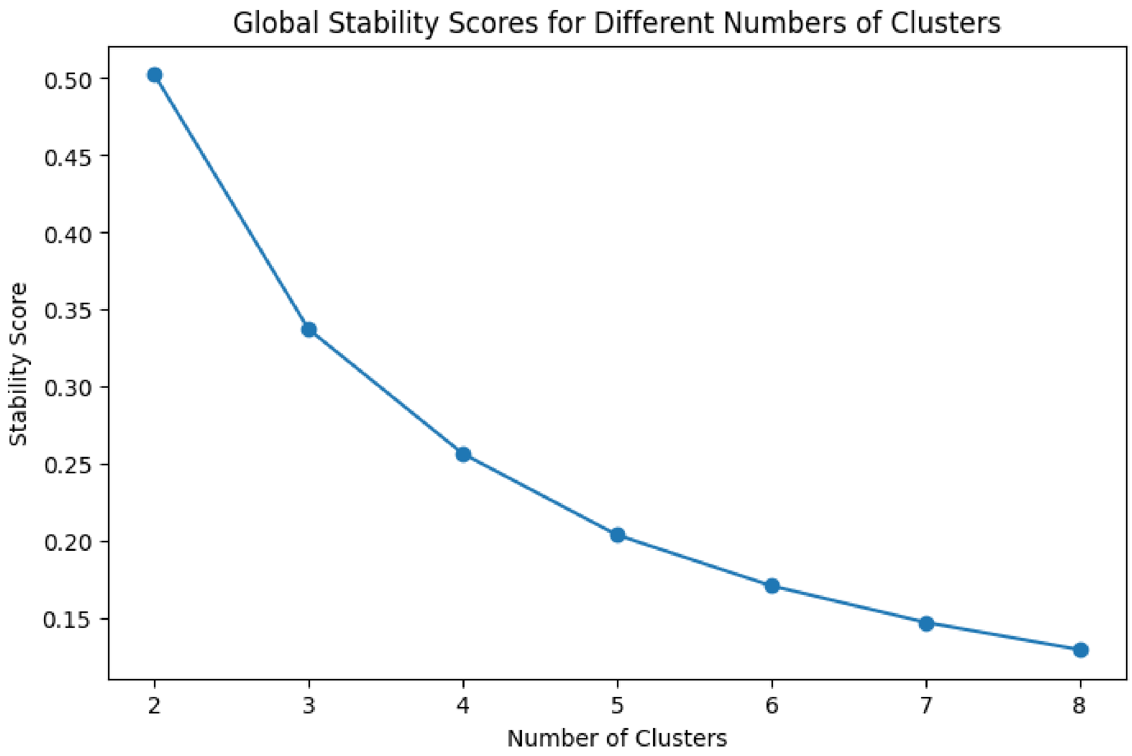
```
min_clusters = 2
max_clusters = 8
```

```
cluster_labels_bootstrap = np.zeros((n_bootstraps, max_clusters - min_clusters + 1, len(numeric_segmentation_data)))
```

```
for i in range(n_bootstraps):
    # Generate a bootstrap sample
    bootstrap_sample = resample(numeric_segmentation_data, replace=True, random_state=i)

    for num_clusters in range(min_clusters, max_clusters + 1):
        kmeans = KMeans(n_clusters=num_clusters, n_init=n_init, random_state=i)
        kmeans.fit(bootstrap_sample)

        # Store cluster labels
        cluster_labels_bootstrap[i, num_clusters - min_clusters, :] = kmeans.labels_
```

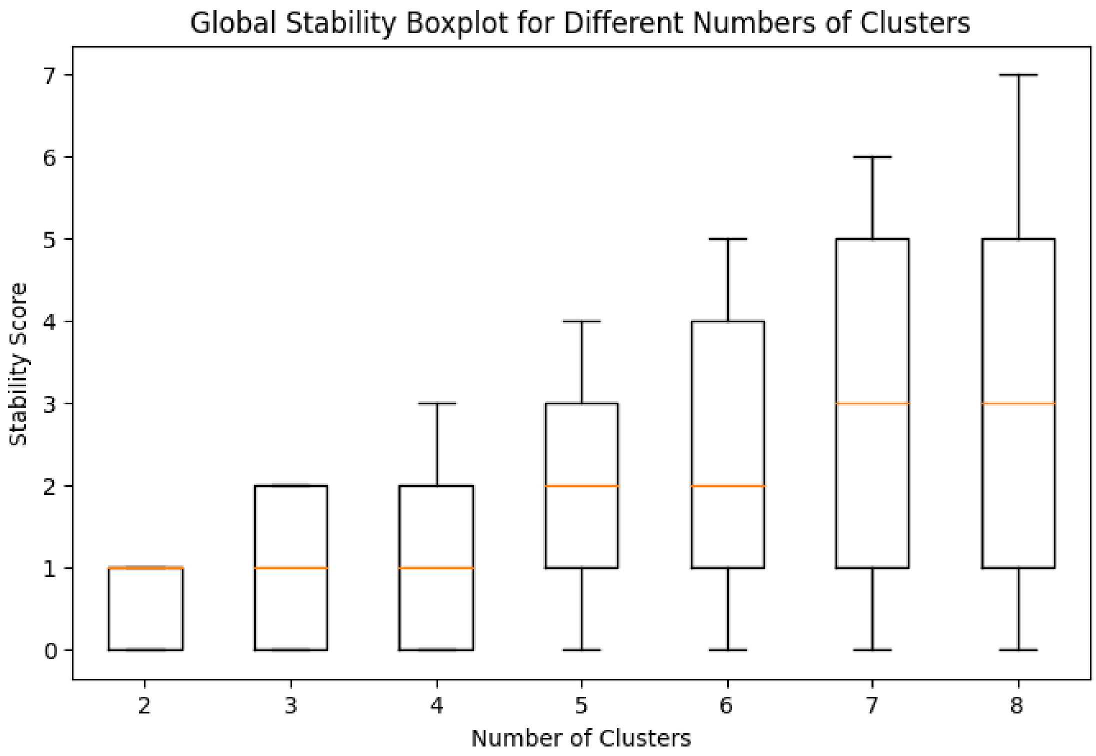
```
stability_scores = np.zeros((max_clusters - min_clusters + 1,))
for num_clusters in range(min_clusters, max_clusters + 1):
    # Calculate the proportion of times each pair of observations is clustered together across bootstrap samples
    pair_agreement = np.sum(cluster_labels_bootstrap[:, num_clusters - min_clusters, :] == cluster_labels_bootstrap[:, num_clusters - min_clusters, None, :], axi

    # Calculate the stability score for the current number of clusters
    stability_scores[num_clusters - min_clusters] = np.mean(pair_agreement)
```

```
plt.figure(figsize=(8, 5))
plt.plot(range(min_clusters, max_clusters + 1), stability_scores, marker='o')
plt.title('Global Stability Scores for Different Numbers of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Stability Score')
plt.show()
```




```
stability_scores = cluster_labels_bootstrap[:, :, 0]
```

```
plt.figure(figsize=(8, 5))
plt.boxplot(stability_scores, labels=range(min_clusters, max_clusters + 1))
plt.title('Global Stability Boxplot for Different Numbers of Clusters')
plt.xlabel('Number of Clusters')
plt.ylabel('Stability Score')
plt.show()
```




```
pip install seaborn
```

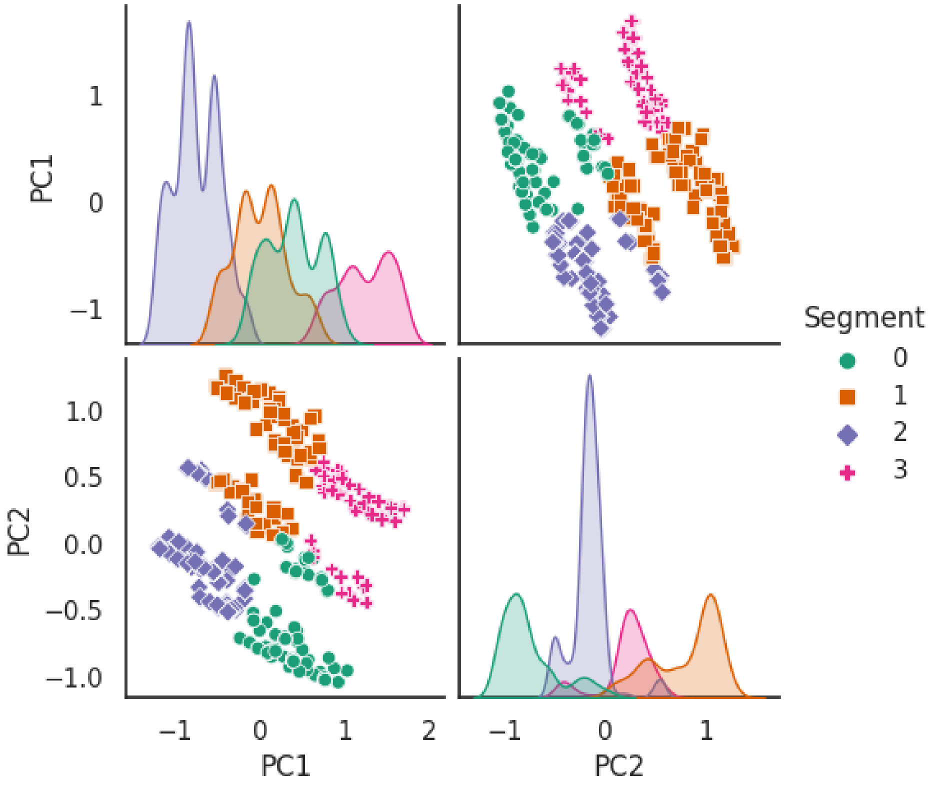
```
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.12.2)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.23.5)
Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.5.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.1 in /usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (4.47.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.1->seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->seaborn) (2023.3.post1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>=3.1->seaborn) (1.16.0)
```

```
import seaborn as sns
```

```
sns.set(style="white")
```

```
sns.pairplot(pc_df, hue='Segment', palette='Dark2', markers=["o", "s", "D", "P"], diag_kind="kde")
```

```
<seaborn.axisgrid.PairGrid at 0x7bdab0f838e0>
```




```
plt.show()
```

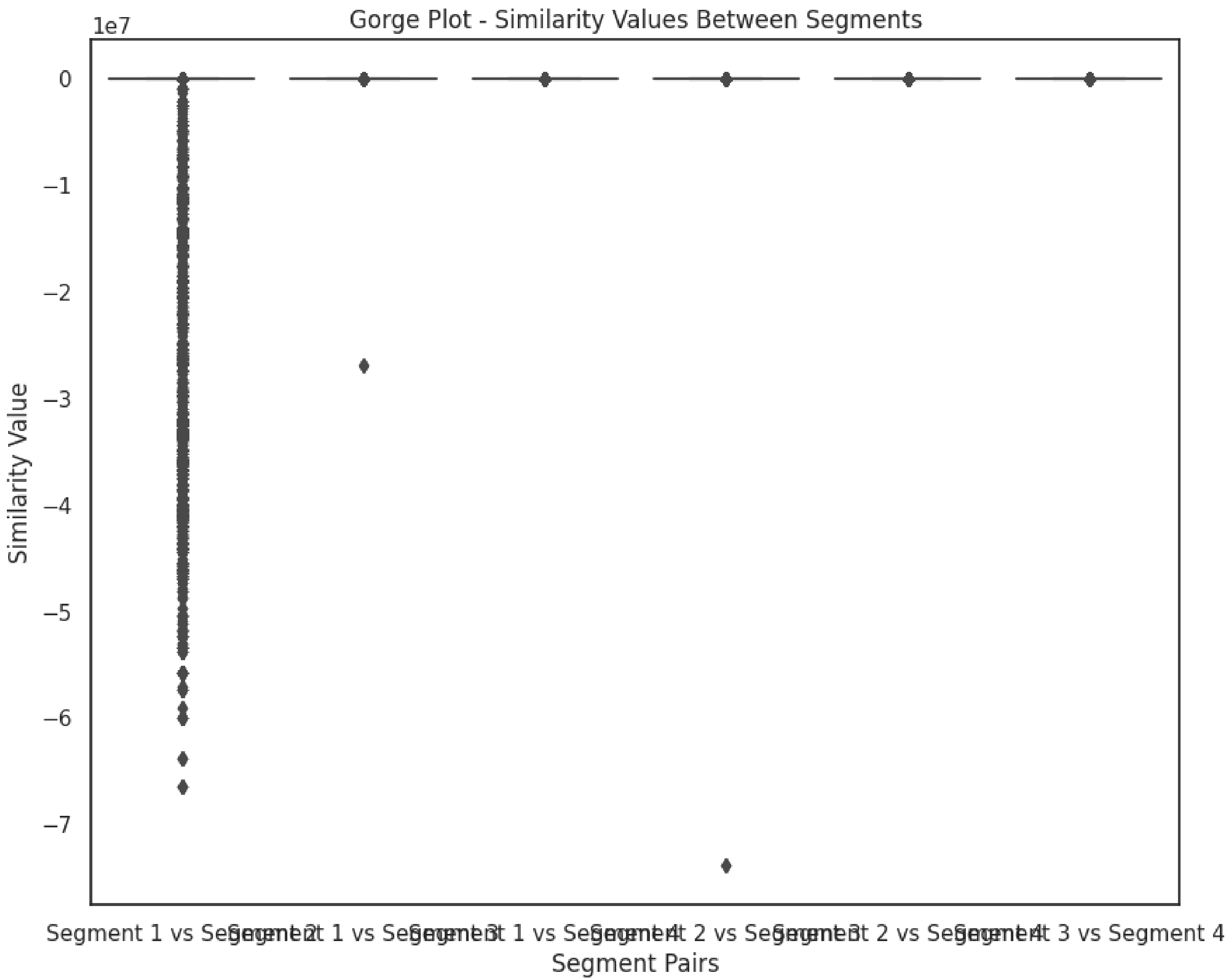
```
from sklearn.metrics import pairwise_distances
```

```
pairwise_distances_within_segments = []
for segment in range(num_segments):
    segment_data = rotated_vars[segment_labels == segment]
    pairwise_distances_within_segments.append(pairwise_distances(segment_data))
```

```
similarity_values = []
segment_pairs = []

for i in range(num_segments):
    for j in range(i + 1, num_segments):
        min_data_points = min(pairwise_distances_within_segments[i].shape[0], pairwise_distances_within_segments[j].shape[0])
        similarity = 1 - pairwise_distances_within_segments[i][:min_data_points, :min_data_points] / pairwise_distances_within_segments[j][:min_data_points, :min

        # Flatten the similarity matrix and store values and corresponding segment pairs
        similarity_values.extend(similarity.flatten())
        segment_pairs.extend([f'Segment {i+1} vs Segment {j+1}' for _ in range(min_data_points**2)])
```

```
<ipython-input-66-2ca3ec738031>:7: RuntimeWarning: divide by zero encountered in divide
  similarity = 1 - pairwise_distances_within_segments[i][:min_data_points, :min_data_points] / pairwise_distances_within_segments[j][:min_data_points, :min_d
<ipython-input-66-2ca3ec738031>:7: RuntimeWarning: invalid value encountered in divide
  similarity = 1 - pairwise_distances_within_segments[i][:min_data_points, :min_data_points] / pairwise_distances_within_segments[j][:min_data_points, :min_d
```

```
data = pd.DataFrame({'Segment Pairs': segment_pairs, 'Similarity Values': similarity_values})

plt.figure(figsize=(10, 8))
sns.boxplot(x='Segment Pairs', y='Similarity Values', data=data)

plt.title('Gorge Plot - Similarity Values Between Segments')
plt.xlabel('Segment Pairs')
plt.ylabel('Similarity Value')

plt.show()
```




```
pip install scikit-learn-extra
```

```
Collecting scikit-learn-extra
  Downloading scikit_learn_extra-0.3.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2.0 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.0/2.0 MB 8.4 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib/python3.10/dist-packages (from scikit-learn-extra) (1.23.5)
Requirement already satisfied: scipy>=0.19.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn-extra) (1.11.4)
```

```
Requirement already satisfied: scikit-learn>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn-extra) (1.2.2)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.23.0->scikit-learn-extra) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.23.0->scikit-learn-extra) (3.2.0)
Installing collected packages: scikit-learn-extra
Successfully installed scikit-learn-extra-0.3.0
```

```
pip install segmentation-models
```

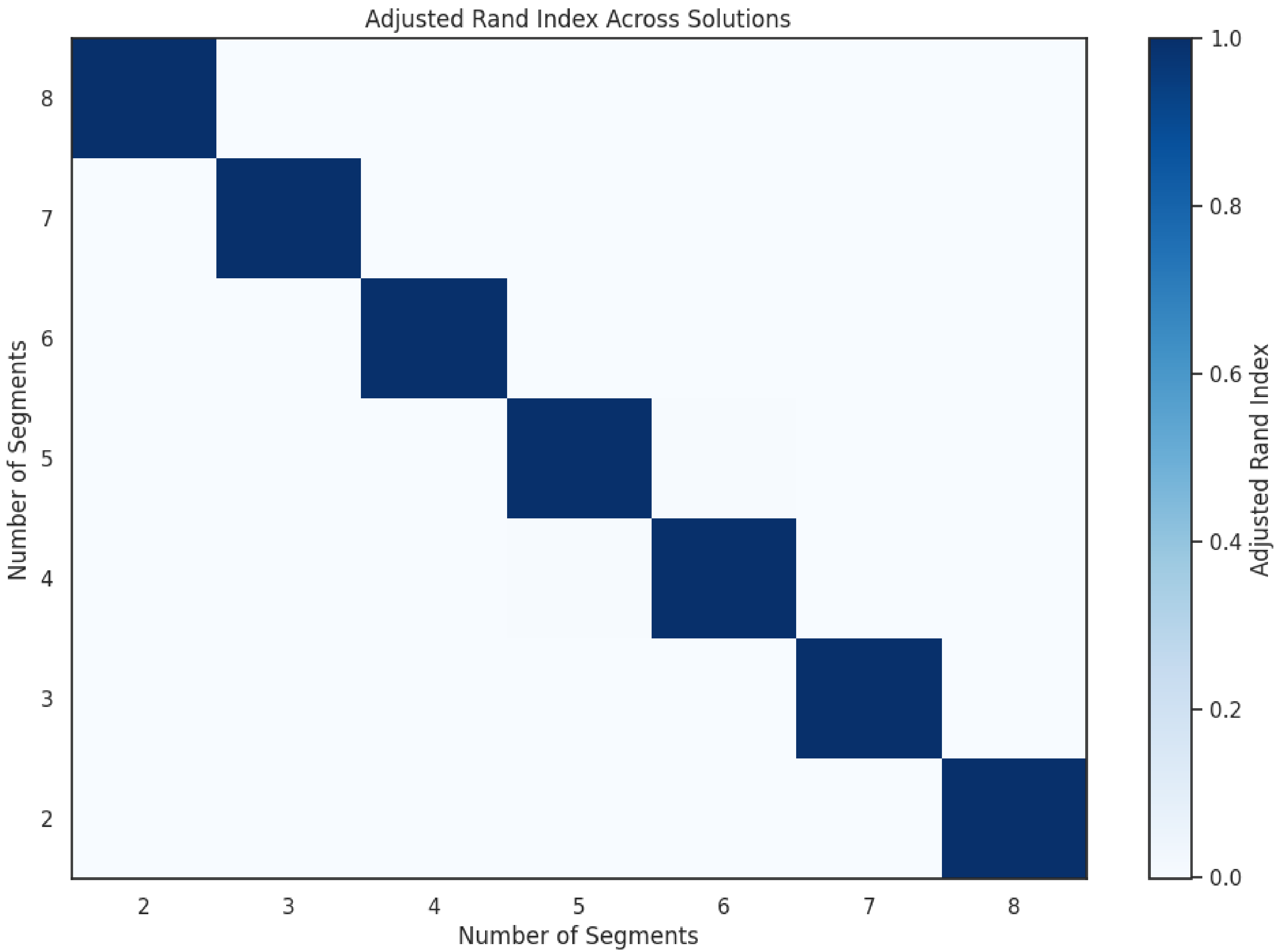
```
Collecting segmentation-models
  Downloading segmentation_models-1.0.1-py3-none-any.whl (33 kB)
Collecting keras-applications<=1.0.8,>=1.0.7 (from segmentation-models)
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 50.7/50.7 kB 3.8 MB/s eta 0:00:00
Collecting image-classifiers==1.0.0 (from segmentation-models)
  Downloading image_classifiers-1.0.0-py3-none-any.whl (19 kB)
Collecting efficientnet==1.0.0 (from segmentation-models)
  Downloading efficientnet-1.0.0-py3-none-any.whl (17 kB)
Requirement already satisfied: scikit-image in /usr/local/lib/python3.10/dist-packages (from efficientnet==1.0.0->segmentation-models) (0.19.3)
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.10/dist-packages (from keras-applications<=1.0.8,>=1.0.7->segmentation-models) (1.23.5)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages (from keras-applications<=1.0.8,>=1.0.7->segmentation-models) (3.9.0)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (1.11.4)
Requirement already satisfied: networkx>=2.2 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (3.2.1)
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,!=8.3.0,>=6.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segm
Requirement already satisfied: imageio>=2.4.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (2.31.
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (1.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from scikit-image->efficientnet==1.0.0->segmentation-models) (23.2
Installing collected packages: keras-applications, image-classifiers, efficientnet, segmentation-models
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 keras-applications-1.0.8 segmentation-models-1.0.1
```

```
from sklearn.metrics import adjusted_rand_score
```

```
num_segments_range = range(min_clusters, max_clusters + 1)
```

```
adj_rand_indices = np.zeros((len(num_segments_range), len(num_segments_range)))
for i, num_segments_i in enumerate(num_segments_range):
    for j, num_segments_j in enumerate(num_segments_range):
        if i <= j:
            labels_i = cluster_labels_bootstrap[i, num_segments_i - min_clusters, :]
            labels_j = cluster_labels_bootstrap[j, num_segments_j - min_clusters, :]
            adj_rand_indices[i, j] = adjusted_rand_score(labels_i, labels_j)
            adj_rand_indices[j, i] = adj_rand_indices[i, j]
```

```
plt.figure(figsize=(12, 8))
plt.imshow(adj_rand_indices, cmap='Blues', aspect='auto', extent=[min_clusters-0.5, max_clusters+0.5, min_clusters-0.5, max_clusters+0.5])

plt.title('Adjusted Rand Index Across Solutions')
plt.xlabel('Number of Segments')
plt.ylabel('Number of Segments')

plt.colorbar(label='Adjusted Rand Index')
plt.show()
```



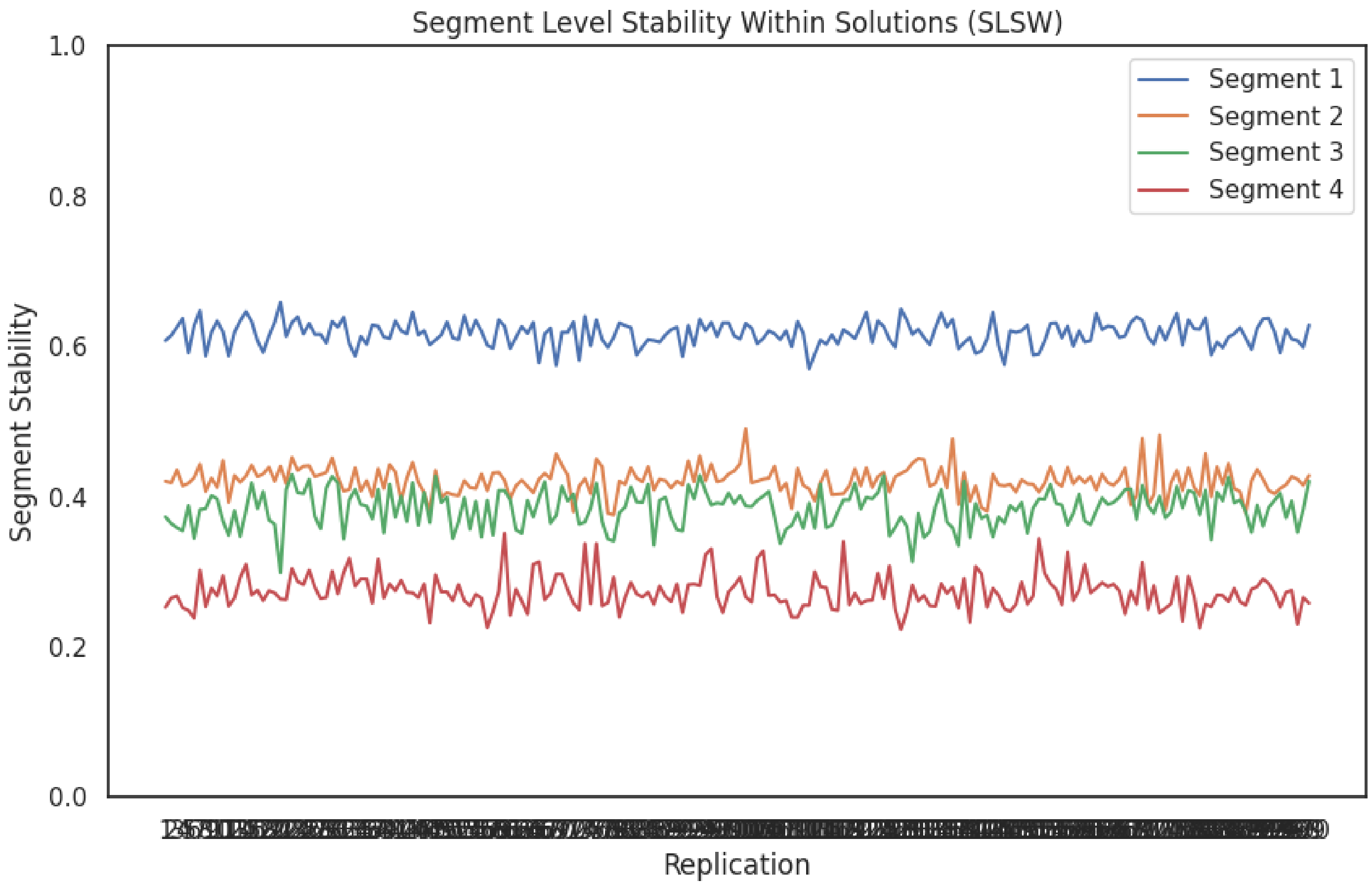

```
from scipy.stats import mode
```

```
segment_stabilities = np.zeros((num_segments, len(cluster_labels_bootstrap)))
```

```

```

```
for i in range(num_segments):
    for j in range(len(cluster_labels_bootstrap)):
        labels_i = cluster_labels_bootstrap[j, i, :]
        segment_stabilities[i, j] = np.mean(labels_i == mode(labels_i)[0])
```

```
plt.figure(figsize=(10, 6))
for i in range(num_segments):
    plt.plot(segment_stabilities[i, :], label=f'Segment {i+1}')

plt.title('Segment Level Stability Within Solutions (SLSW)')
plt.xlabel('Replication')
plt.ylabel('Segment Stability')
plt.ylim(0, 1)
plt.xticks(range(len(cluster_labels_bootstrap)), range(1, len(cluster_labels_bootstrap)+1))
plt.legend()
plt.show()
```




```
# Using Mixtures of Distributions
```

```
pip install mixmod
```

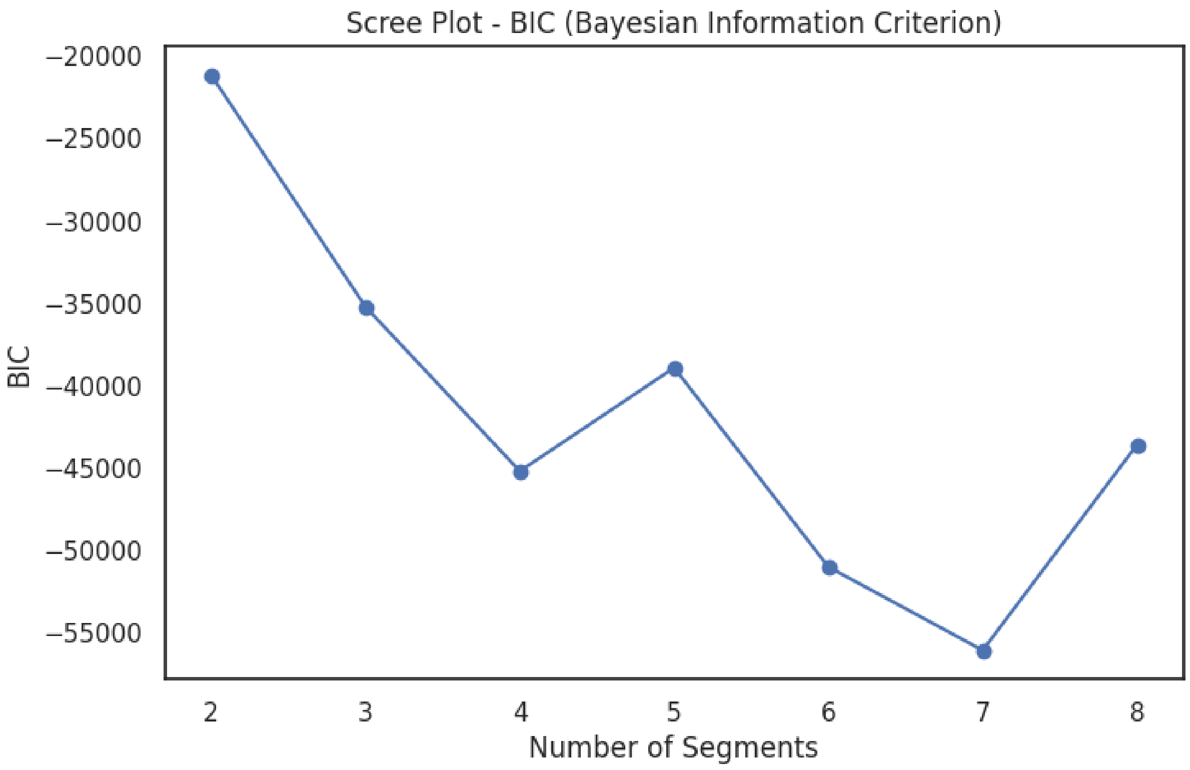
```
Collecting mixmod
  Downloading mixmod-0.2.0-py3-none-any.whl (9.0 kB)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from mixmod) (1.23.5)
Requirement already satisfied: scipy>=1.8 in /usr/local/lib/python3.10/dist-packages (from mixmod) (1.11.4)
Installing collected packages: mixmod
Successfully installed mixmod-0.2.0
```

```
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
from sklearn.utils import resample
```

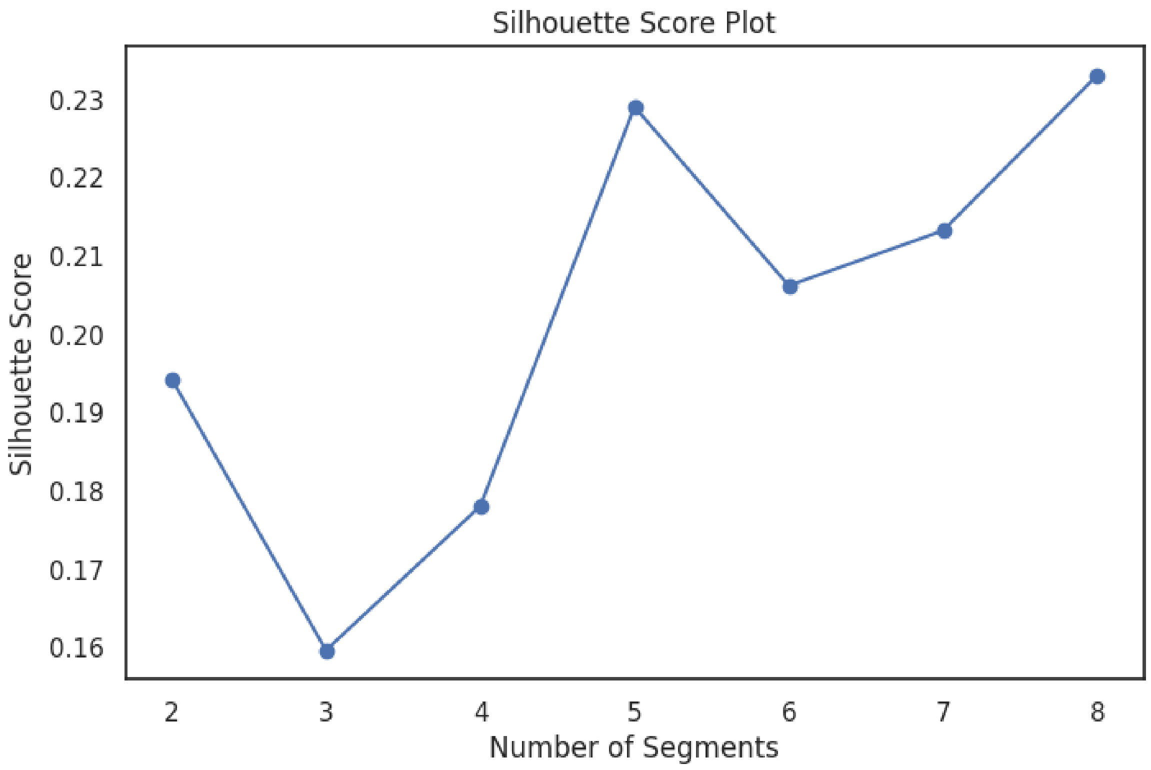
```
min_segments = 2
max_segments = 8
n_init = 10
n_bootstraps = 200

inertia_values = []
silhouette_scores = []
cluster_labels_bootstrap = np.zeros((n_bootstraps, max_segments - min_segments + 1, len(numeric_segmentation_data)))
```

```
for num_segments in range(min_segments, max_segments + 1):
    model = GaussianMixture(n_components=num_segments, n_init=n_init)
    model.fit(numeric_segmentation_data)

    inertia_values.append(model.bic(numeric_segmentation_data))

    silhouette_scores.append(silhouette_score(numeric_segmentation_data, model.predict(numeric_segmentation_data)))

    # Bootstrap stability analysis
    for i in range(n_bootstraps):

        bootstrap_sample = resample(numeric_segmentation_data, replace=True, random_state=i)

        bootstrap_model = GaussianMixture(n_components=num_segments, n_init=n_init)
        bootstrap_model.fit(bootstrap_sample)

        cluster_labels_bootstrap[i, num_segments - min_segments, :] = bootstrap_model.predict(bootstrap_sample)
```

```
plt.figure(figsize=(8, 5))
plt.plot(range(min_segments, max_segments + 1), inertia_values, marker='o')
plt.title('Scree Plot - BIC (Bayesian Information Criterion)')
plt.xlabel('Number of Segments')
plt.ylabel('BIC')
plt.show()
```

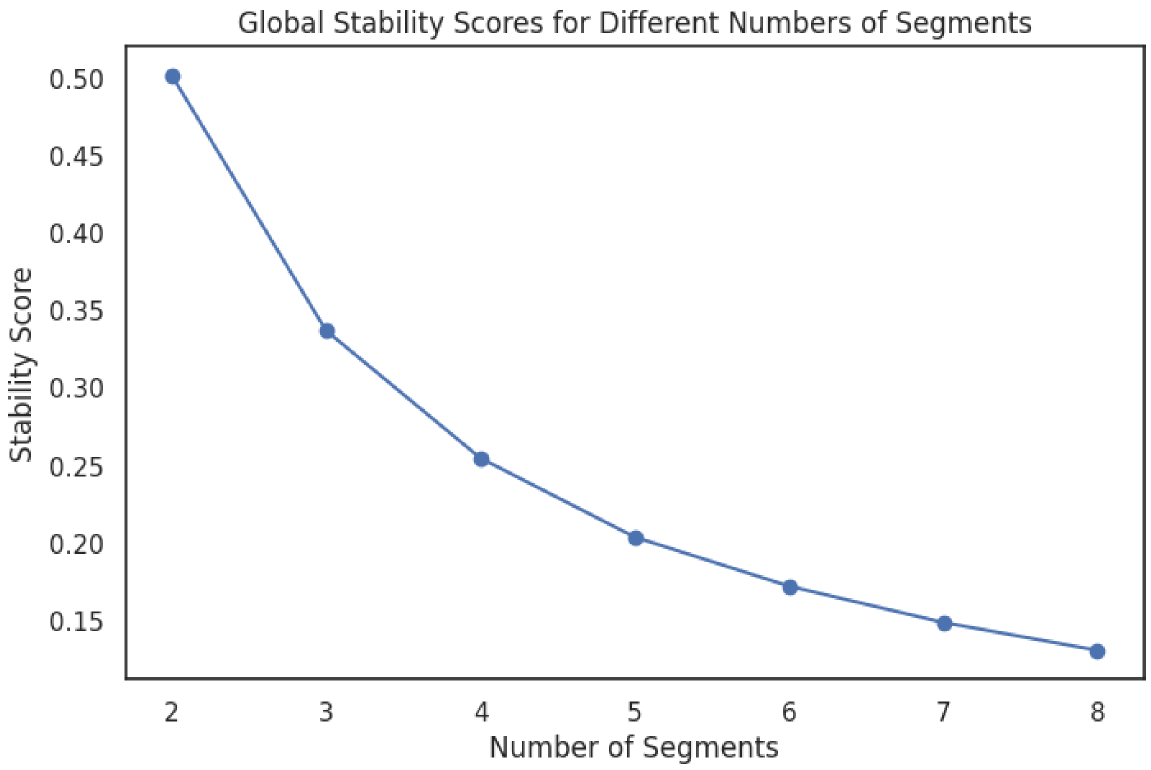



```
plt.figure(figsize=(8, 5))
plt.plot(range(min_segments, max_segments + 1), silhouette_scores, marker='o')
plt.title('Silhouette Score Plot')
plt.xlabel('Number of Segments')
plt.ylabel('Silhouette Score')
plt.show()
```




```
stability_scores = np.zeros((max_segments - min_segments + 1,))
for num_segments in range(min_segments, max_segments + 1):
    pair_agreement = np.sum(cluster_labels_bootstrap[:, num_segments - min_segments, :] == cluster_labels_bootstrap[:, num_segments - min_segments, None, :], axi
    stability_scores[num_segments - min_segments] = np.mean(pair_agreement)
```

```
plt.figure(figsize=(8, 5))
plt.plot(range(min_segments, max_segments + 1), stability_scores, marker='o')
plt.title('Global Stability Scores for Different Numbers of Segments')
plt.xlabel('Number of Segments')
plt.ylabel('Stability Score')
plt.show()
```



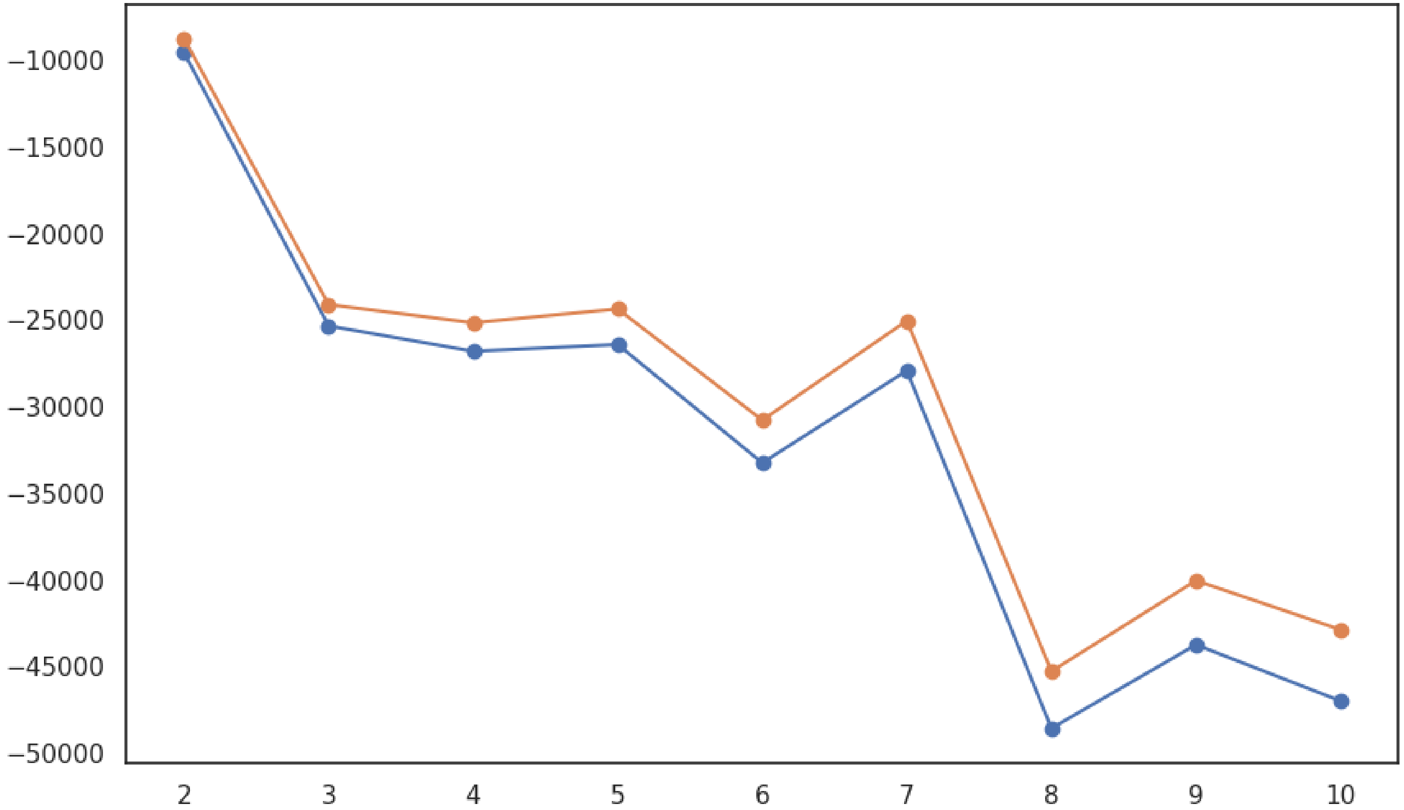

```
from sklearn.mixture import GaussianMixture
```

```
min_components = 2
max_components = 10  # Adjust as needed

aic_values = []
bic_values = []
icl_values = []
```

```
for num_components in range(min_components, max_components + 1):
    model = GaussianMixture(n_components=num_components, random_state=42)
    model.fit(numeric_segmentation_data)

    aic_values.append(model.aic(numeric_segmentation_data))
    bic_values.append(model.bic(numeric_segmentation_data))
```

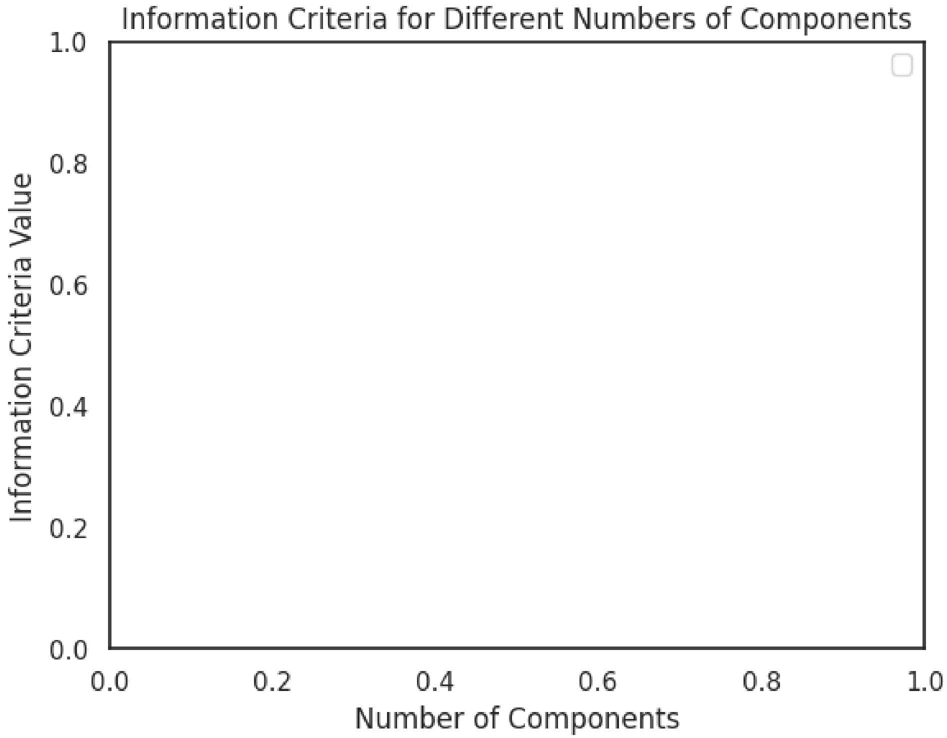
```
plt.figure(figsize=(10, 6))
plt.plot(range(min_components, max_components + 1), aic_values, label='AIC', marker='o')
plt.plot(range(min_components, max_components + 1), bic_values, label='BIC', marker='o')
```

```
[<matplotlib.lines.Line2D at 0x7bda553547f0>]
```




```
plt.title('Information Criteria for Different Numbers of Components')
plt.xlabel('Number of Components')
plt.ylabel('Information Criteria Value')
plt.legend()
plt.show()
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that artists whose label start with an underscore
```




```
from sklearn.mixture import GaussianMixture
```

```
num_clusters_kmeans = 4  # Adjust as needed
kmeans = KMeans(n_clusters=num_clusters_kmeans, random_state=42)
cluster_labels_kmeans = kmeans.fit_predict(numeric_segmentation_data)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Se
  warnings.warn(
```

```
num_components_gmm = 4  # Adjust as needed
gmm = GaussianMixture(n_components=num_components_gmm, random_state=42)
gmm.fit(numeric_segmentation_data)
component_memberships_gmm = gmm.predict_proba(numeric_segmentation_data)
```

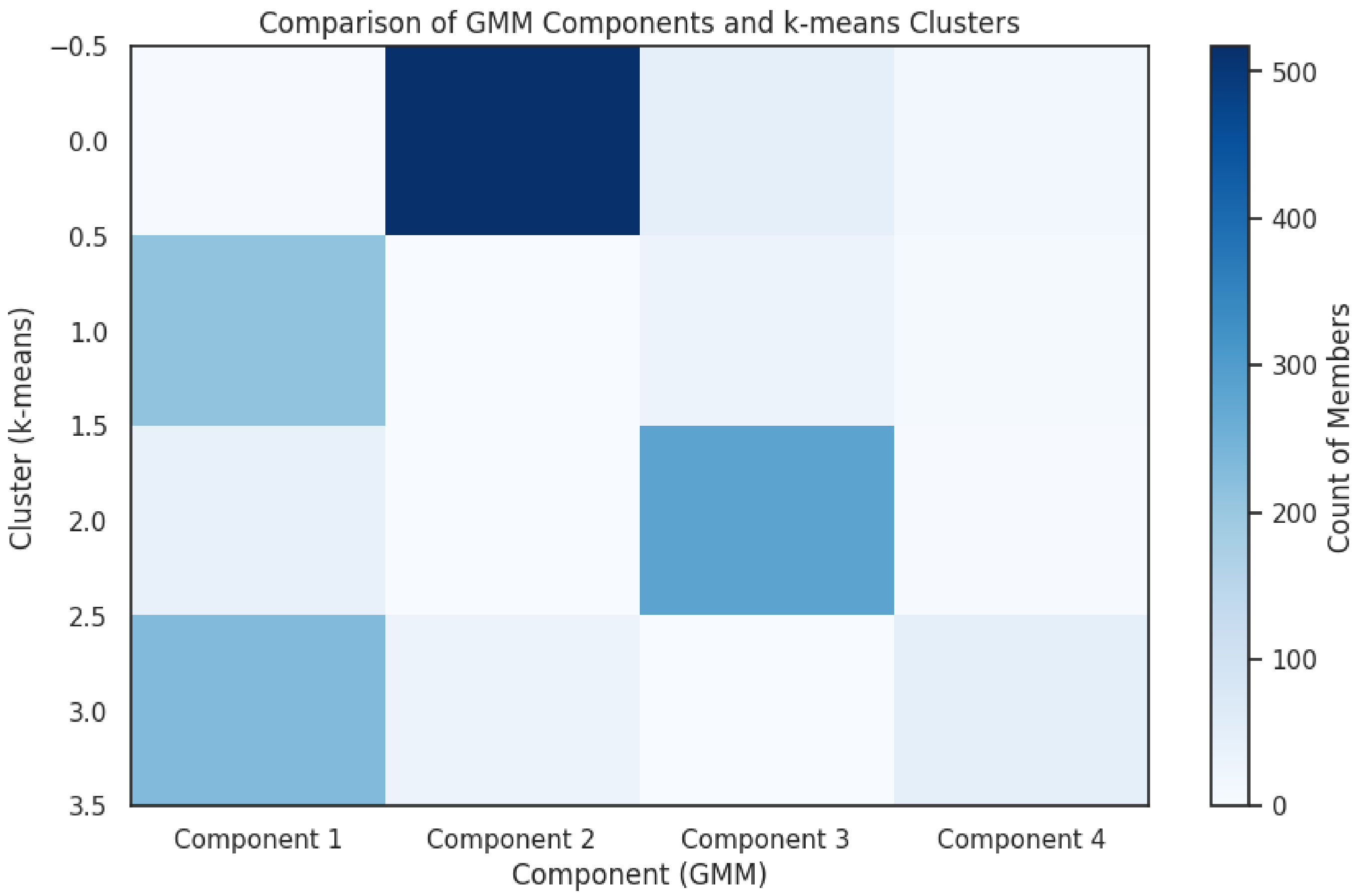
```
comparison_df = pd.DataFrame(component_memberships_gmm, columns=[f'Component {i+1}' for i in range(num_components_gmm)])
comparison_df['Cluster Membership (k-means)'] = cluster_labels_kmeans
```

```
crosstab_df = pd.crosstab(comparison_df['Cluster Membership (k-means)'], columns=comparison_df.iloc[:, :-1].idxmax(axis=1))
```

```
print(crosstab_df)
```

```
col_0                         Component 1  Component 2  Component 3  \
Cluster Membership (k-means)
0                                       4          517           46
1                                     209            0           29
2                                      37            0          282
3                                     229           29            0

col_0                         Component 4
Cluster Membership (k-means)
0                                      13
1                                       8
2                                       4
3                                      46
```

```
plt.figure(figsize=(10, 6))
plt.imshow(crosstab_df.values, cmap='Blues', aspect='auto', interpolation='none')
plt.colorbar(label='Count of Members')
plt.xlabel('Component (GMM)')
plt.ylabel('Cluster (k-means)')
plt.title('Comparison of GMM Components and k-means Clusters')
plt.xticks(np.arange(num_components_gmm), labels=[f'Component {i+1}' for i in range(num_components_gmm)])
plt.show()
```




```
#Using Mixtures of Regression Models
```

```
from sklearn.linear_model import LinearRegression
```

```
independent_variables = df[['yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap', 'tasty', 'expensive', 'healthy', 'disgusting']]
```

```
print(df.head())
```

```
  yummy convenient spicy fattening greasy fast cheap tasty expensive healthy  \
0    No        Yes    No       Yes     No  Yes   Yes    No       Yes      No
1   Yes        Yes    No       Yes    Yes  Yes   Yes   Yes       Yes      No
2    No        Yes   Yes       Yes    Yes  Yes    No   Yes       Yes     Yes
3   Yes        Yes    No       Yes    Yes  Yes   Yes   Yes        No      No
```

```
4    No        Yes    No       Yes    Yes  Yes   Yes    No        No     Yes

  disgusting  Like  Age      VisitFrequency  Gender  Numeric_LIKE  \
0         No  -3.0   61  Every three months  Female           9.0
1         No   2.0   51  Every three months  Female           4.0
2         No   1.0   62  Every three months  Female           5.0
3        Yes   4.0   69        Once a week  Female           2.0
4         No   2.0   49       Once a month    Male           4.0

   NumericLike  Like.n
0            9       9
1            4       4
2            5       5
3            2       2
4            4       4
```

```
original_like_counts = df['Like'].value_counts(sort=False)
print(original_like_counts)
```

```
-3.0     73
 2.0    187
 1.0    152
 4.0    160
 0.0    464
-2.0     59
 3.0    229
-4.0     71
-1.0     58
Name: Like, dtype: int64
```

```
df['Like.n'] = 6 - df['Like'].astype(int)
```

```
new_like_counts = df['Like.n'].value_counts(sort=False)
print(new_like_counts)
```

```
9      73
4     187
5     152
2     160
6     464
8      59
3     229
10     71
7      58
Name: Like.n, dtype: int64
```

```
import statsmodels.api as sm
```

```
categorical_columns = ['Gender']
```

```
numeric_columns = ['Age', 'VisitFrequency']
```

```
print(df.dtypes)
```

```
yummy              object
convenient         object
spicy              object
fattening          object
greasy             object
fast               object
cheap              object
tasty              object
expensive          object
healthy            object
disgusting         object
Like              float64
Age                 int64
VisitFrequency     object
Gender             object
Numeric_LIKE      float64
NumericLike         int64
Like.n              int64
dtype: object
```

```
df['VisitFrequency'] = pd.to_numeric(df['VisitFrequency'], errors='coerce')
```

```
print(df.dtypes)
```

```
yummy              object
convenient         object
spicy              object
fattening          object
greasy             object
fast               object
cheap              object
tasty              object
expensive          object
healthy            object
disgusting         object
Like              float64
Age                 int64
```

```
VisitFrequency    float64
Gender             object
Numeric_LIKE      float64
NumericLike         int64
Like.n              int64
dtype: object
```

```
from sklearn.impute import SimpleImputer
```

```
num_components = 2
```

```
imputer = SimpleImputer(strategy='mean')  # You can choose a different strategy if needed
independent_variables_imputed = imputer.fit_transform(independent_variables)
```

```
gmm = GaussianMixture(n_components=num_components, random_state=42)
gmm.fit(independent_variables_imputed)
```

```
▾                GaussianMixture
GaussianMixture(n_components=2, random_state=42)
```

```
pip install pymer4
```

```
Collecting pymer4
  Downloading pymer4-0.8.1-py2.py3-none-any.whl (136 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 136.9/136.9 kB 3.3 MB/s eta 0:00:00
Requirement already satisfied: pandas>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from pymer4) (1.5.3)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.10/dist-packages (from pymer4) (1.23.5)
Collecting rpy2>=3.5.3 (from pymer4)
  Downloading rpy2-3.5.15.tar.gz (219 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 219.8/219.8 kB 10.0 MB/s eta 0:00:00
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
  Preparing metadata (pyproject.toml) ... done
Requirement already satisfied: seaborn>=0.11.0 in /usr/local/lib/python3.10/dist-packages (from pymer4) (0.12.2)
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.10/dist-packages (from pymer4) (3.7.1)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.10/dist-packages (from pymer4) (0.5.6)
Requirement already satisfied: joblib>=0.14 in /usr/local/lib/python3.10/dist-packages (from pymer4) (1.3.2)
Requirement already satisfied: scipy>=1.4.0 in /usr/local/lib/python3.10/dist-packages (from pymer4) (1.11.4)
Requirement already satisfied: scikit-learn>=1.0 in /usr/local/lib/python3.10/dist-packages (from pymer4) (1.2.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (4.47.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (23.2)
```

```
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->pymer4) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.1.0->pymer4) (2023.3.post1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.1->pymer4) (1.16.0)
Requirement already satisfied: cffi>=1.10.0 in /usr/local/lib/python3.10/dist-packages (from rpy2>=3.5.3->pymer4) (1.16.0)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages (from rpy2>=3.5.3->pymer4) (3.1.2)
Requirement already satisfied: tzlocal in /usr/local/lib/python3.10/dist-packages (from rpy2>=3.5.3->pymer4) (5.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.0->pymer4) (3.2.0)
Requirement already satisfied: pycparser in /usr/local/lib/python3.10/dist-packages (from cffi>=1.10.0->rpy2>=3.5.3->pymer4) (2.21)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->rpy2>=3.5.3->pymer4) (2.1.3)
Building wheels for collected packages: rpy2
  Building wheel for rpy2 (pyproject.toml) ... done
  Created wheel for rpy2: filename=rpy2-3.5.15-cp310-cp310-linux_x86_64.whl size=329862 sha256=c11395a8ad92eeeeafb1c2d5c2ad1069eedd2db48507b2aa0e19064dfe05a1
  Stored in directory: /root/.cache/pip/wheels/af/93/69/c4904a387a34629ae40162ce1e61479cdd4ae3fd40078a9db3
Successfully built rpy2
Installing collected packages: rpy2, pymer4
  Attempting uninstall: rpy2
    Found existing installation: rpy2 3.4.2
    Uninstalling rpy2-3.4.2:
      Successfully uninstalled rpy2-3.4.2
Successfully installed pymer4-0.8.1 rpy2-3.5.15
```

```
import pymer4
```

```
pip install seaborn matplotlib
```

```
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (0.12.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: numpy!=1.24.0,>=1.17 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.23.5)
Requirement already satisfied: pandas>=0.25 in /usr/local/lib/python3.10/dist-packages (from seaborn) (1.5.3)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (4.47.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.25->seaborn) (2023.3.post1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```

```
import seaborn as sns
```

```
from sklearn.mixture import GaussianMixture
from sklearn.linear_model import LinearRegression
```

```
num_components = 2
gmm = GaussianMixture(n_components=num_components, random_state=42)
gmm.fit(independent_variables_imputed)
```

```
▾                 GaussianMixture
GaussianMixture(n_components=2, random_state=42)
```

```
cluster_labels = gmm.predict(independent_variables_imputed)
```

```
dependent_variable = df['Like']

# Fit linear regression models for each cluster
regression_models = {}
for cluster in range(num_components):
    cluster_data = independent_variables_imputed[cluster_labels == cluster]
    dependent_variable_cluster = dependent_variable[cluster_labels == cluster]

    model = LinearRegression().fit(cluster_data, dependent_variable_cluster)
    regression_models[cluster] = model

    print(f"\nRegression Coefficients for Cluster {cluster + 1}:")
    for feature, coef in zip(independent_variables.columns, model.coef_):
        print(f"{feature}: {coef:.4f}")
```

```
Regression Coefficients for Cluster 1:
Like: 0.2500
Age: 0.0000
VisitFrequency: -0.2500
Numeric_LIKE: -0.2500
NumericLike: -0.2500
Like.n: -0.0000
yummy_Yes: -0.0000
convenient_Yes: -0.0000
spicy_Yes: 0.0000
fattening_Yes: 0.0000
greasy_Yes: -0.0000
fast_Yes: 0.0000
cheap_Yes: -0.0000
tasty_Yes: 0.0000
```

```
expensive_Yes: -0.0000
healthy_Yes: 0.0000
disgusting_Yes: 0.0000

Regression Coefficients for Cluster 2:
Like: 0.2500
Age: 0.0000
VisitFrequency: -0.2500
Numeric_LIKE: -0.2500
NumericLike: -0.2500
Like.n: -0.0000
yummy_Yes: 0.0000
convenient_Yes: 0.0000
spicy_Yes: 0.0000
fattening_Yes: -0.0000
greasy_Yes: 0.0000
fast_Yes: 0.0000
cheap_Yes: -0.0000
tasty_Yes: 0.0000
expensive_Yes: -0.0000
healthy_Yes: -0.0000
disgusting_Yes: -0.0000
```

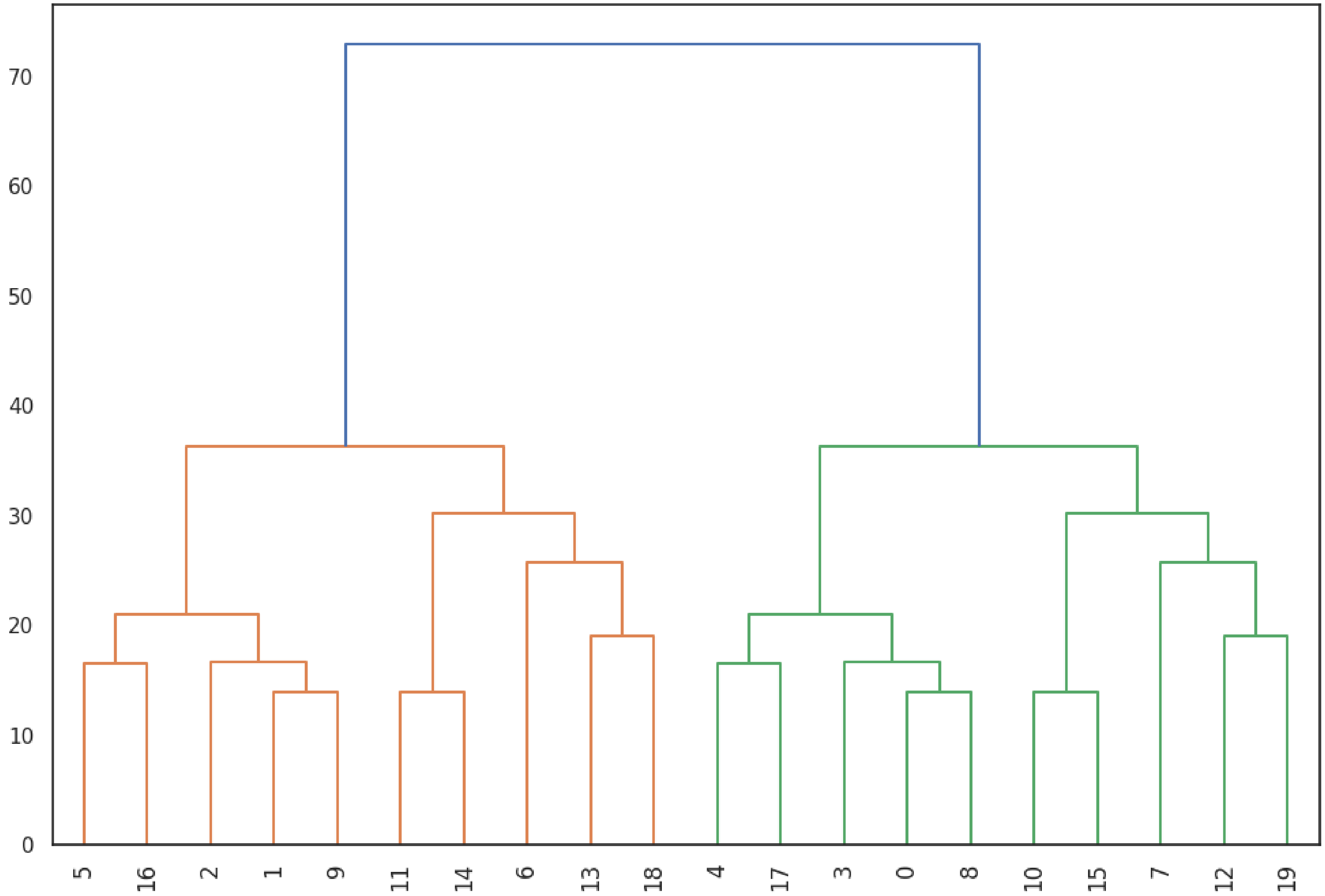
```
from sklearn.cluster import AgglomerativeClustering
from scipy.cluster import hierarchy
```

```
attributes_data = segmentation_data.iloc[:, 1:]
```

```
attributes_data_encoded = pd.get_dummies(attributes_data, columns=attributes_data.select_dtypes(include=['object']).columns)
```

```
linkage_matrix = hierarchy.linkage(attributes_data_encoded.T, method='ward')
```

```
plt.figure(figsize=(12, 8))
dendrogram = hierarchy.dendrogram(linkage_matrix, orientation='top', leaf_rotation=90)
```




```
num_clusters = 4
cluster_labels = AgglomerativeClustering(n_clusters=num_clusters, affinity='euclidean', linkage='ward').fit_predict(attributes_data_encoded.T)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983: FutureWarning: Attribute `affinity` was deprecated in version 1.2 and will be
  warnings.warn(
```

```
if len(cluster_labels) == len(attributes_data_encoded.columns):

    attributes_data_encoded.columns = [f'{col}_Cluster{cluster}' for col, cluster in zip(attributes_data_encoded.columns, cluster_labels)]

    numeric_cluster_labels = [int(label.split('Cluster')[-1]) for label in attributes_data_encoded.columns]

    plt.figure(figsize=(12, 8))
    sns.heatmap(attributes_data_encoded.groupby(numeric_cluster_labels, axis=1).mean().T, cmap='coolwarm', annot=True, fmt=".2f", linewidths=.5)
    plt.title('Segment Profile Plot')
    plt.show()
else:
    print("Error: Length of cluster labels does not match the number of attributes.")
```


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

```
MD_x_transposed = df.T
```

```
```

```
MD_x_encoded = pd.get_dummies(MD_x_transposed)

linkage_matrix = linkage(MD_x_encoded, method='average')
```

```
plt.figure(figsize=(12, 8))
dendrogram(linkage_matrix, orientation='top', labels=MD_x_transposed.index, leaf_rotation=90)
plt.title('Hierarchical Clustering Dendrogram')
plt.show()
```