part_1_orange

January 23, 2025

1 Imports

[34]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from scipy.stats import zscore
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN,␣
↪SpectralClustering
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score, davies_bouldin_score,␣
↪calinski_harabasz_score
from sklearn.neighbors import kneighbors_graph
from sklearn.decomposition import PCA
```

2 Load Data

[35]:
```
# Load the data
file_path = "fic_epita_kantar_codes.csv"
data_codes = pd.read_csv(file_path, sep=';')
```

[36]:
```
# Select relevant columns
columns_of_interest = [
    "A9_1_slice", "A9_2_slice", "A9_3_slice", "A9_4_slice", "A9_5_slice",
    "A9_6_slice", "A9_7_slice", "A9_8_slice", "A9_9_slice", "A9_10_slice",
    "A9_11_slice", "A9_12_slice", "A9_13_slice", "A9_14_slice", "A9_15_slice",
    "A9_16_slice", "A10_1_slice", "A10_2_slice", "A10_3_slice", "A10_4_slice",
    "A10_5_slice", "A10_6_slice", "A10_7_slice", "A10_8_slice",
    "A11_1_slice", "A11_2_slice", "A11_3_slice", "A11_4_slice", "A11_5_slice",
    "A11_6_slice", "A11_7_slice", "A11_8_slice", "A11_9_slice", "A11_10_slice",
    "A11_11_slice", "A11_12_slice", "A11_13_slice"
]
subset_data = data_codes[columns_of_interest]
```

[37]:

```python
# Check for missing values
missing_values = subset_data.isnull().sum()
print("Missing Values:\n", missing_values)

# Data type analysis
data_types = subset_data.dtypes
print("\nData Types:\n", data_types)

# Summary statistics
summary_stats = subset_data.describe()
print("\nSummary Statistics:\n", summary_stats)

# Check for outliers
outliers = subset_data.apply(zscore).abs() > 3
print("\nOutliers:\n", outliers)
```

```
Missing Values:
 A9_1_slice     0
A9_2_slice     0
A9_3_slice     0
A9_4_slice     0
A9_5_slice     0
A9_6_slice     0
A9_7_slice     0
A9_8_slice     0
A9_9_slice     0
A9_10_slice    0
A9_11_slice    0
A9_12_slice    0
A9_13_slice    0
A9_14_slice    0
A9_15_slice    0
A9_16_slice    0
A10_1_slice    0
A10_2_slice    0
A10_3_slice    0
A10_4_slice    0
A10_5_slice    0
A10_6_slice    0
A10_7_slice    0
A10_8_slice    0
A11_1_slice    0
A11_2_slice    0
A11_3_slice    0
A11_4_slice    0
A11_5_slice    0
A11_6_slice    0
A11_7_slice    0
```

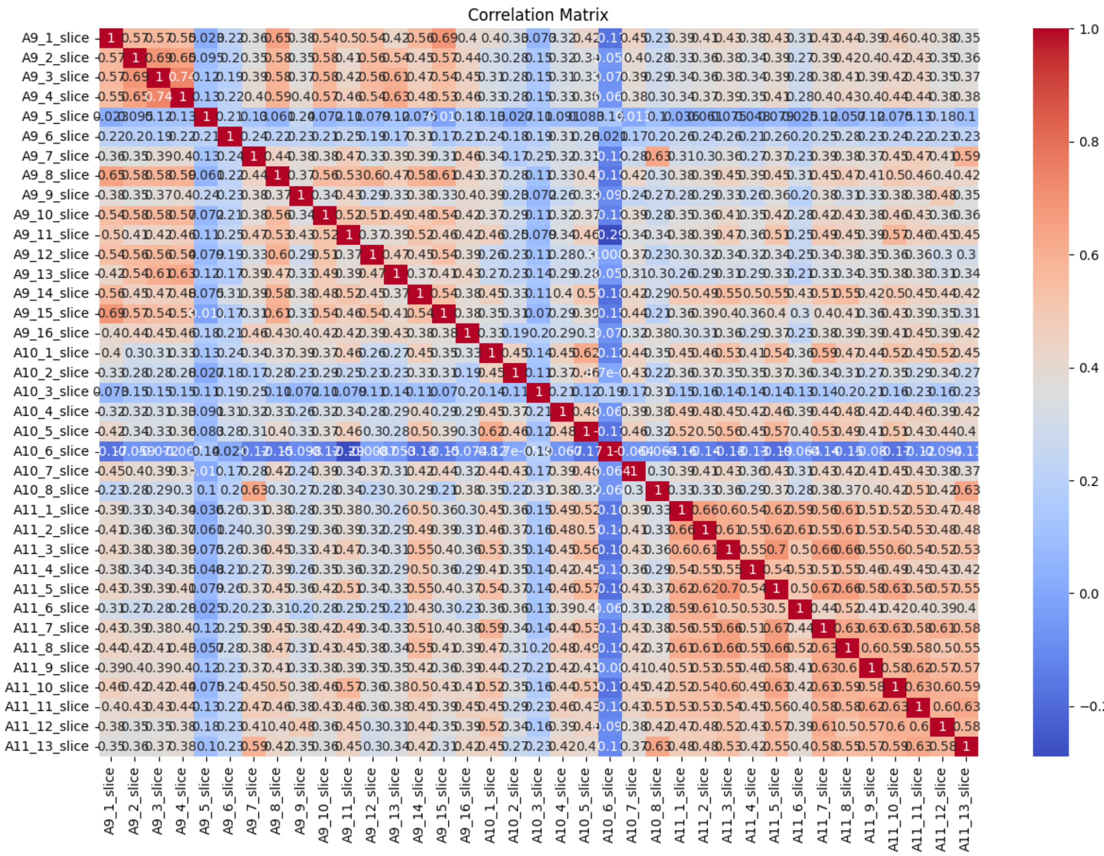
```
A11_8_slice     0
A11_9_slice     0
A11_10_slice    0
A11_11_slice    0
A11_12_slice    0
A11_13_slice    0
dtype: int64

Data Types:
 A9_1_slice      int64
A9_2_slice      int64
A9_3_slice      int64
A9_4_slice      int64
A9_5_slice      int64
A9_6_slice      int64
A9_7_slice      int64
A9_8_slice      int64
A9_9_slice      int64
A9_10_slice     int64
A9_11_slice     int64
A9_12_slice     int64
A9_13_slice     int64
A9_14_slice     int64
A9_15_slice     int64
A9_16_slice     int64
A10_1_slice     int64
A10_2_slice     int64
A10_3_slice     int64
A10_4_slice     int64
A10_5_slice     int64
A10_6_slice     int64
A10_7_slice     int64
A10_8_slice     int64
A11_1_slice     int64
A11_2_slice     int64
A11_3_slice     int64
A11_4_slice     int64
A11_5_slice     int64
A11_6_slice     int64
A11_7_slice     int64
A11_8_slice     int64
A11_9_slice     int64
A11_10_slice    int64
A11_11_slice    int64
A11_12_slice    int64
A11_13_slice    int64
dtype: object
```

```
Summary Statistics:
         A9_1_slice   A9_2_slice   A9_3_slice   A9_4_slice  A9_5_slice  \
count  5000.000000  5000.000000  5000.000000  5000.000000   5000.0000
mean      2.209800     2.698800     2.662000     2.602800      2.6838
std       0.794676     0.843458     0.865047     0.870163      0.8328
min       1.000000     1.000000     1.000000     1.000000      1.0000
25%       2.000000     2.000000     2.000000     2.000000      2.0000
50%       2.000000     3.000000     3.000000     3.000000      3.0000
75%       3.000000     3.000000     3.000000     3.000000      3.0000
max       4.000000     4.000000     4.000000     4.000000      4.0000

        A9_6_slice   A9_7_slice   A9_8_slice   A9_9_slice  A9_10_slice  …  \
count  5000.000000  5000.000000  5000.000000  5000.000000  5000.000000  …
mean      2.208000     2.488800     2.424400     2.090400     2.398800  …
std       0.752628     1.048663     0.852778     0.837358     0.829154  …
min       1.000000     1.000000     1.000000     1.000000     1.000000  …
25%       2.000000     2.000000     2.000000     2.000000     2.000000  …
50%       2.000000     2.000000     2.000000     2.000000     2.000000  …
75%       3.000000     3.000000     3.000000     3.000000     3.000000  …
max       4.000000     4.000000     4.000000     4.000000     4.000000  …

       A11_4_slice  A11_5_slice  A11_6_slice  A11_7_slice  A11_8_slice  \
count  5000.000000  5000.000000  5000.000000  5000.000000  5000.000000
mean      2.023200     1.897000     1.862800     1.935000     2.109800
std       0.786629     0.724221     0.738434     0.742755     0.792635
min       1.000000     1.000000     1.000000     1.000000     1.000000
25%       1.000000     1.000000     1.000000     1.000000     2.000000
50%       2.000000     2.000000     2.000000     2.000000     2.000000
75%       2.000000     2.000000     2.000000     2.000000     3.000000
max       4.000000     4.000000     4.000000     4.000000     4.000000

       A11_9_slice  A11_10_slice  A11_11_slice  A11_12_slice  A11_13_slice
count    5000.0000    5000.00000   5000.000000   5000.000000   5000.000000
mean        2.2690       1.97540      2.242400      1.976400      2.159800
std         0.7889       0.75426      0.803101      0.776379      0.877962
min         1.0000       1.00000      1.000000      1.000000      1.000000
25%         2.0000       1.00000      2.000000      1.000000      2.000000
50%         2.0000       2.00000      2.000000      2.000000      2.000000
75%         3.0000       2.00000      3.000000      2.000000      3.000000
max         4.0000       4.00000      4.000000      4.000000      4.000000

[8 rows x 37 columns]

Outliers:
       A9_1_slice  A9_2_slice  A9_3_slice  A9_4_slice  A9_5_slice  A9_6_slice  \
0           False       False       False       False       False       False
1           False       False       False       False       False       False
2           False       False       False       False       False       False
```

```
3          False       False       False       False       False       False
4          False       False       False       False       False       False
…          …         …         …         …         …         …
4995       False       False       False       False       False       False
4996       False       False       False       False       False       False
4997       False       False       False       False       False       False
4998       False       False       False       False       False       False
4999       False       False       False       False       False       False

      A9_7_slice  A9_8_slice  A9_9_slice  A9_10_slice  …  A11_4_slice  \
0          False       False       False        False  …        False
1          False       False       False        False  …        False
2          False       False       False        False  …        False
3          False       False       False        False  …        False
4          False       False       False        False  …        False
…          …         …         …          …  …          …
4995       False       False       False        False  …        False
4996       False       False       False        False  …        False
4997       False       False       False        False  …        False
4998       False       False       False        False  …        False
4999       False       False       False        False  …        False

      A11_5_slice  A11_6_slice  A11_7_slice  A11_8_slice  A11_9_slice  \
0           False        False        False        False        False
1           False        False        False        False        False
2           False        False        False        False        False
3           False        False        False        False        False
4           False        False        False        False        False
…           …          …          …          …          …
4995        False        False        False        False        False
4996        False        False        False        False        False
4997        False        False        False        False        False
4998        False        False        False        False        False
4999        False        False        False        False        False

      A11_10_slice  A11_11_slice  A11_12_slice  A11_13_slice
0            False         False         False         False
1            False         False         False         False
2            False         False         False         False
3            False         False         False         False
4            False         False         False         False
…            …           …           …           …
4995         False         False         False         False
4996         False         False         False         False
4997         False         False         False         False
4998         False         False         False         False
4999         False         False         False         False
```

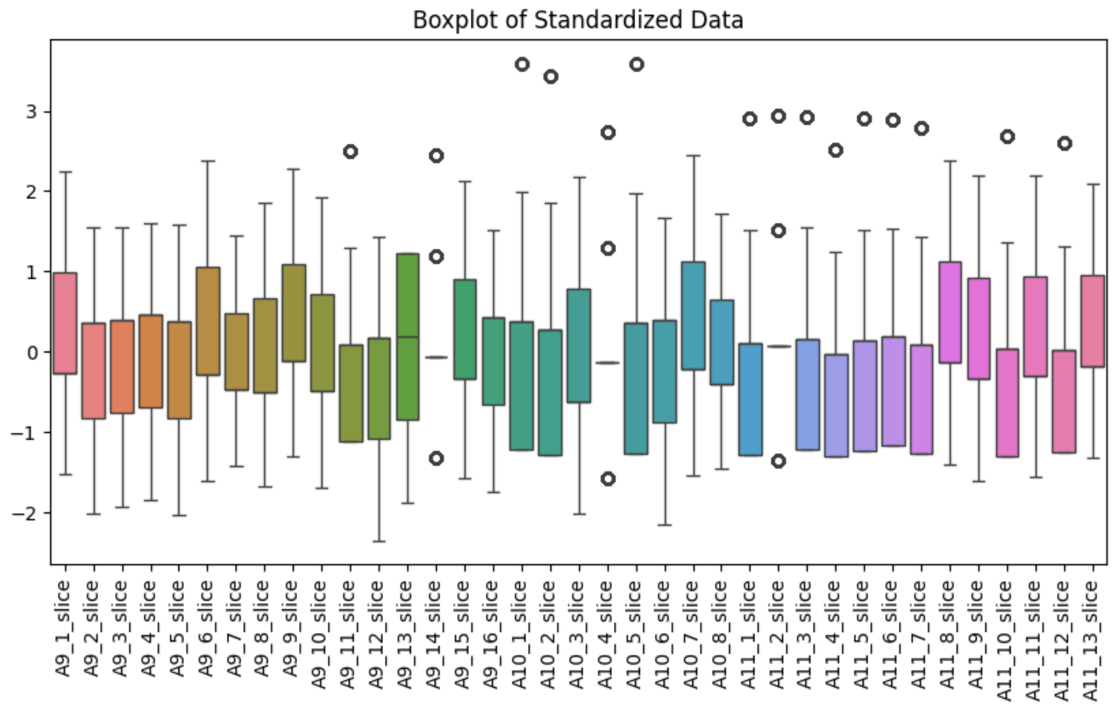
```
[5000 rows x 37 columns]
```

[38]:
```python
# Correlation heatmap
plt.figure(figsize=(15, 10))
sns.heatmap(subset_data.corr(), annot=True, cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()
```



[39]:
```python
# Standardize data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(subset_data)
```

[40]:
```python
# Check if clustering is appropriate (variance and distribution)
plt.figure(figsize=(10, 5))
sns.boxplot(data=pd.DataFrame(scaled_data, columns=columns_of_interest))
plt.xticks(rotation=90)
plt.title("Boxplot of Standardized Data")
plt.show()
```



3 Clustering

[41]:
```
# Function to evaluate clustering
def evaluate_clustering(labels, data):
    if len(set(labels)) > 1:  # At least 2 clusters
        silhouette = silhouette_score(data, labels)
        davies_bouldin = davies_bouldin_score(data, labels)
        calinski_harabasz = calinski_harabasz_score(data, labels)
    else:
        silhouette, davies_bouldin, calinski_harabasz = None, None, None
    return silhouette, davies_bouldin, calinski_harabasz

results = {}
```

3.1 Kmeans

[42]:
```
from sklearn.model_selection import ParameterGrid
from sklearn.decomposition import PCA

def grid_search_kmeans(data, param_grid):
    results = []
    for params in ParameterGrid(param_grid):
        kmeans = KMeans(**params, random_state=42)
```

```
        kmeans_labels = kmeans.fit_predict(data)
        score = evaluate_clustering(kmeans_labels, data)
        results.append({'params': params, 'score': score})
    return results

# Try multiple values of PCA components
pca_results = {}
pca_components = [2, 3, 4, 5]  # List of PCA components to try

for n_components in pca_components:
    pca = PCA(n_components=n_components)
    reduced_data = pca.fit_transform(scaled_data)

    # Define the parameter grid for KMeans
    param_grid = {
        'n_clusters': [3, 4, 5, 6, 7, 8, 9],
        'init': ['k-means++', 'random'],
        'max_iter': [100, 300],
        'n_init': [10, 20]
    }

    pca_results[n_components] = grid_search_kmeans(reduced_data, param_grid)

results['K-Means'] = pca_results
```

3.2 Hierarchical Clustering

[43]:

```
from sklearn.model_selection import ParameterGrid
from sklearn.decomposition import PCA

def grid_search_agglo(data, param_grid):
    results = []
    for params in ParameterGrid(param_grid):
        agglo = AgglomerativeClustering(**params)
        agglo_labels = agglo.fit_predict(data)
        score = evaluate_clustering(agglo_labels, data)
        results.append({'params': params, 'score': score})
    return results

# Try multiple values of PCA components
pca_results = {}
pca_components = [2, 3, 4, 5]  # List of PCA components to try

for n_components in pca_components:
    pca = PCA(n_components=n_components)
    reduced_data = pca.fit_transform(scaled_data)
```

```
    # Define the parameter grid for Agglomerative Clustering
    param_grid = {
        'n_clusters': [3, 4, 5, 6, 7, 8, 9],
        'linkage': ['ward', 'complete', 'average', 'single']
    }

    pca_results[n_components] = grid_search_agglo(reduced_data, param_grid)

results['Agglomerative'] = pca_results
```

3.3 DBSCAN

[44]:
```
from sklearn.model_selection import ParameterGrid

def grid_search_dbscan(data, param_grid):
    results = []
    for params in ParameterGrid(param_grid):
        dbscan = DBSCAN(**params)
        dbscan_labels = dbscan.fit_predict(data)
        score = evaluate_clustering(dbscan_labels, data)
        results.append({'params': params, 'score': score})
    return results

# Try multiple values of PCA components
pca_results = {}
pca_components = [2, 3, 4, 5]  # List of PCA components to try

for n_components in pca_components:
    pca = PCA(n_components=n_components)
    reduced_data = pca.fit_transform(scaled_data)

    # Define the parameter grid for Agglomerative Clustering
    param_grid = {
        'eps': [0.5, 1.0, 1.5, 2.0],
        'min_samples': [3, 5, 10, 15],
    }

    pca_results[n_components] = grid_search_dbscan(reduced_data, param_grid)

results['DBSCAN'] = pca_results
```

3.4 Gaussian Mixture Model

[45]:
```
from sklearn.model_selection import ParameterGrid

def grid_search_gmm(data, param_grid):
    results = []
```

```
    for params in ParameterGrid(param_grid):
        gmm = GaussianMixture(**params)
        gmm_labels = gmm.fit_predict(data)
        score = evaluate_clustering(gmm_labels, data)
        results.append({'params': params, 'score': score})
    return results

# Try multiple values of PCA components
pca_results = {}
pca_components = [2, 3, 4, 5]  # List of PCA components to try

for n_components in pca_components:
    pca = PCA(n_components=n_components)
    reduced_data = pca.fit_transform(scaled_data)

    # Define the parameter grid for Agglomerative Clustering
    param_grid = {
        'n_components': [3, 4, 5, 6, 7, 8, 9],
        'covariance_type': ['full', 'tied', 'diag', 'spherical'],
        'random_state': [42]
    }

    pca_results[n_components] = grid_search_gmm(reduced_data, param_grid)

results['GMM'] = pca_results
```

3.5 Spectral Clustering

[46]:
```
from sklearn.model_selection import ParameterGrid

def grid_search_spectral(data, param_grid):
    results = []
    for params in ParameterGrid(param_grid):
        spectral = SpectralClustering(**params)
        spectral_labels = spectral.fit_predict(data)
        score = evaluate_clustering(spectral_labels, data)
        results.append({'params': params, 'score': score})
    return results

# Try multiple values of PCA components
pca_results = {}
pca_components = [2, 3, 4, 5]  # List of PCA components to try

for n_components in pca_components:
    pca = PCA(n_components=n_components)
    reduced_data = pca.fit_transform(scaled_data)
```

```
    # Define the parameter grid for Agglomerative Clustering
    param_grid = {
        'n_clusters': [3, 4, 5, 6, 7, 8, 9],
        'affinity': ['nearest_neighbors'],
        'random_state': [42]
    }

    pca_results[n_components] = grid_search_spectral(reduced_data, param_grid)

results['Spectral'] = pca_results
```

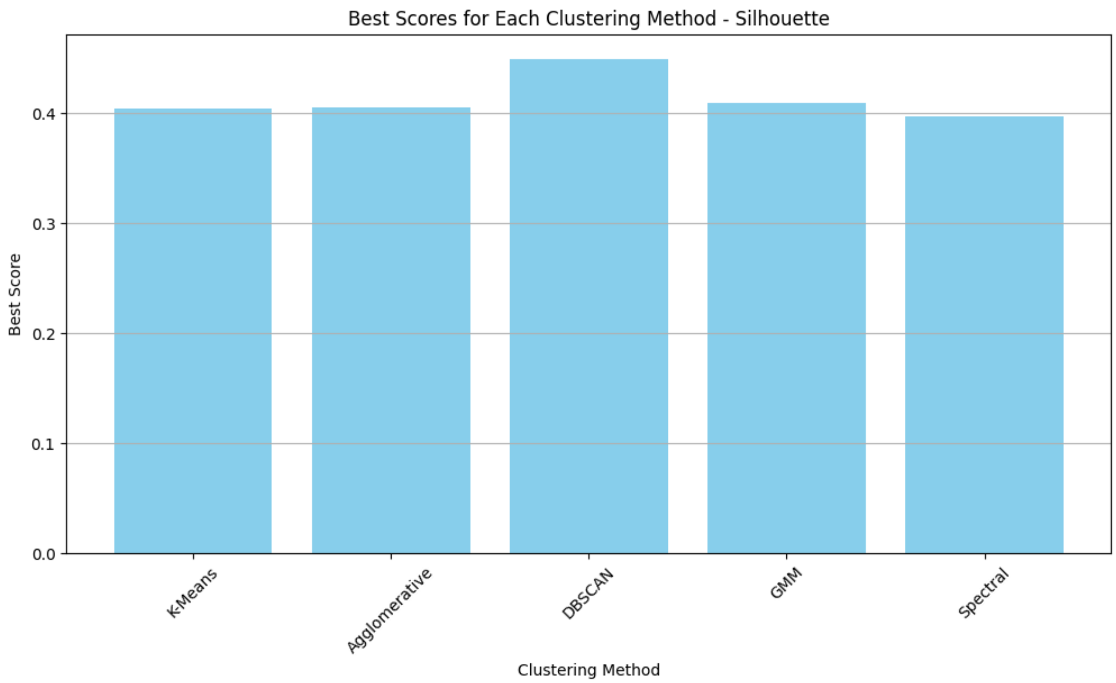
3.6 Results

[47]:
```
# Display best score and hyperparameters for each method
best_hyperparameters = {}
for method, pca_comps in results.items():
    for pca in pca_comps:
        best_score = max(pca_comps[pca], key=lambda x: x['score'][0])  # Get␣
 ↪the score with the highest first value
        if method not in best_hyperparameters:
            best_hyperparameters[method] = {'pca': pca, 'params':␣
 ↪best_score['params'], 'score': best_score['score']}
        else:
            current_best_score = best_hyperparameters[method]['score']
            if best_score['score'] > current_best_score:
                best_hyperparameters[method] = {'pca': pca, 'params':␣
 ↪best_score['params'], 'score': best_score['score']}

print("Best Hyperparameters:")
for method, params in best_hyperparameters.items():
    print(f"Method: {method}, PCA Components: {params['pca']}, Parameters:␣
 ↪{params['params']}, Score: {params['score']}")
```

```
Best Hyperparameters:
Method: K-Means, PCA Components: 2, Parameters: {'init': 'k-means++',
'max_iter': 100, 'n_clusters': 3, 'n_init': 10}, Score: (0.40443286145861834,
0.8298231240610466, 5212.267717603587)
Method: Agglomerative, PCA Components: 2, Parameters: {'linkage': 'average',
'n_clusters': 3}, Score: (0.4057401636000236, 0.5352545178441465,
841.8433707196778)
Method: DBSCAN, PCA Components: 2, Parameters: {'eps': 1.0, 'min_samples': 5},
Score: (0.4496954069972326, 4.554114205204604, 1.4256395627023446)
Method: GMM, PCA Components: 2, Parameters: {'covariance_type': 'spherical',
'n_components': 3, 'random_state': 42}, Score: (0.4091182669177925,
0.8263318291705856, 4963.319464247499)
Method: Spectral, PCA Components: 2, Parameters: {'affinity':
'nearest_neighbors', 'n_clusters': 3, 'random_state': 42}, Score:
```

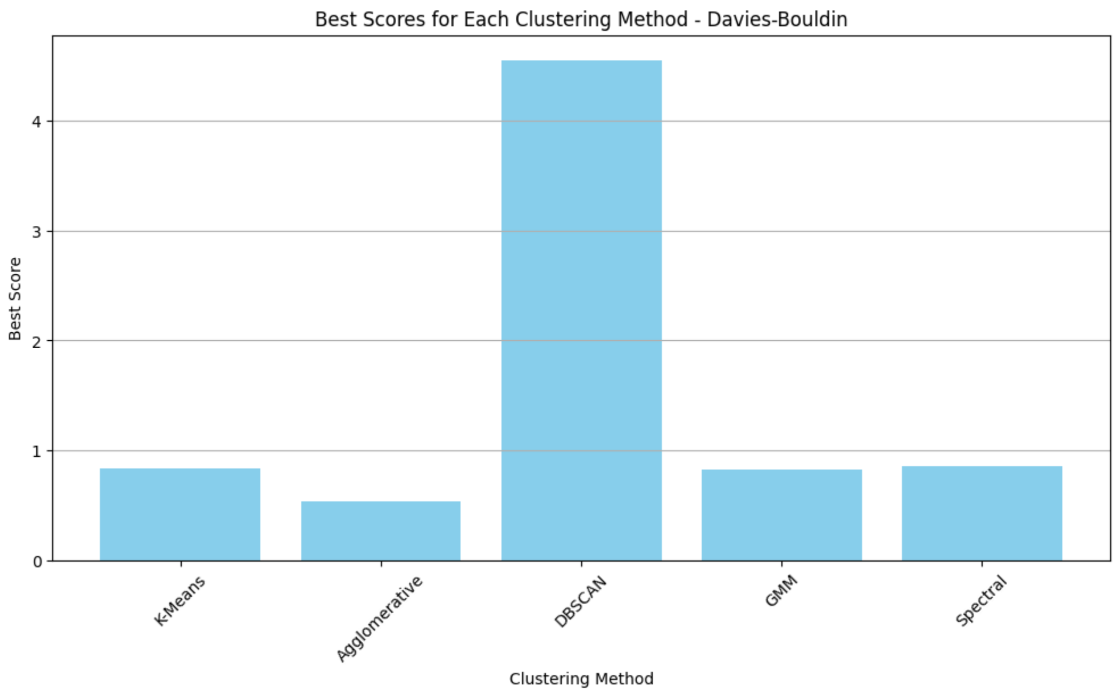
(0.3972480352144417, 0.85240793427272, 5115.223573515349)

[48]:
```
import matplotlib.pyplot as plt

# Data to plot
methods = list(best_hyperparameters.keys())
pca_components = [best_hyperparameters[method]['pca'] for method in methods]
scores = [best_hyperparameters[method]['score'][0] for method in methods]  #␣
↪Using the first score for plotting

# Create a bar plot
plt.figure(figsize=(12, 6))
plt.bar(methods, scores, color='skyblue')
plt.title('Best Scores for Each Clustering Method - Silhouette')
plt.xlabel('Clustering Method')
plt.ylabel('Best Score')
plt.xticks(rotation=45)
plt.grid(axis='y')

# Show the plot
plt.show()
```



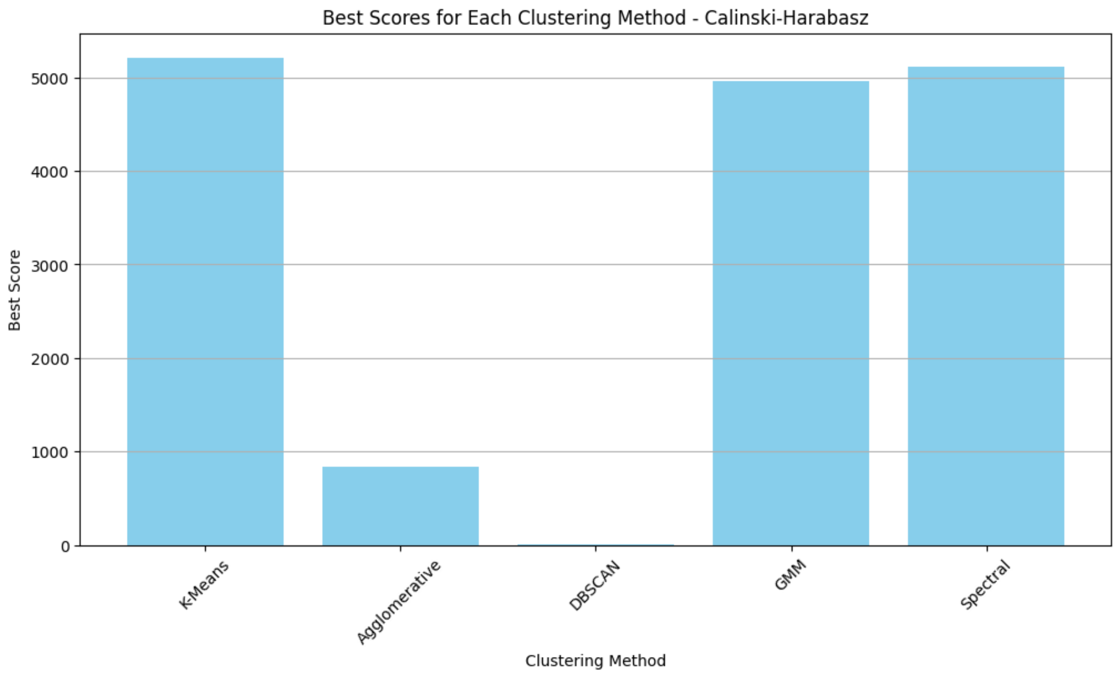
[49]:
```
import matplotlib.pyplot as plt

# Data to plot
```

```
methods = list(best_hyperparameters.keys())
pca_components = [best_hyperparameters[method]['pca'] for method in methods]
scores = [best_hyperparameters[method]['score'][1] for method in methods]  #␣
 ↪Using the first score for plotting

# Create a bar plot
plt.figure(figsize=(12, 6))
plt.bar(methods, scores, color='skyblue')
plt.title('Best Scores for Each Clustering Method - Davies-Bouldin')
plt.xlabel('Clustering Method')
plt.ylabel('Best Score')
plt.xticks(rotation=45)
plt.grid(axis='y')

# Show the plot
plt.show()
```



[50]:
```
import matplotlib.pyplot as plt

# Data to plot
methods = list(best_hyperparameters.keys())
pca_components = [best_hyperparameters[method]['pca'] for method in methods]
scores = [best_hyperparameters[method]['score'][2] for method in methods]  #␣
 ↪Using the first score for plotting
```

```
# Create a bar plot
plt.figure(figsize=(12, 6))
plt.bar(methods, scores, color='skyblue')
plt.title('Best Scores for Each Clustering Method - Calinski-Harabasz')
plt.xlabel('Clustering Method')
plt.ylabel('Best Score')
plt.xticks(rotation=45)
plt.grid(axis='y')

# Show the plot
plt.show()
```



[51]:
```
# Best clustering method: K-Means
best_method = "K-Means"
best_pca_components = 2
best_parameters = {'init': 'k-means++', 'max_iter': 100, 'n_clusters': 3,␣
 ↪'n_init': 10}
best_score = (0.40443286145861834, 0.8298231240610466, 5212.267717603587)

# Apply K-Means with the best parameters
kmeans = KMeans(init=best_parameters['init'],␣
 ↪max_iter=best_parameters['max_iter'],
                n_clusters=best_parameters['n_clusters'],␣
 ↪n_init=best_parameters['n_init'], random_state=42)
```

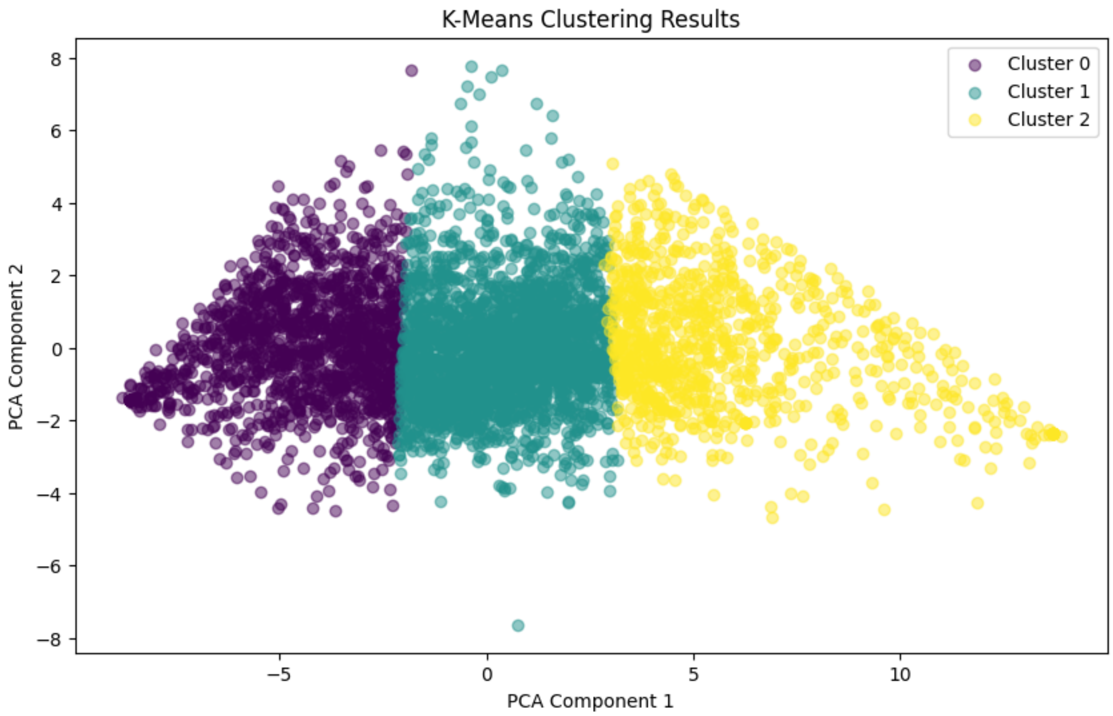
```
labels = kmeans.fit_predict(reduced_data)

# Calculate intra-cluster variances
intra_variances = []
n_clusters = best_parameters['n_clusters']  # Use the number of clusters from␣
↪parameters
for k in range(n_clusters):
    cluster_data = reduced_data[labels == k]
    intra_variance = np.var(cluster_data, axis=0).mean()  # Mean variance of␣
↪features
    intra_variances.append(intra_variance)

# Intra-group variance
variance_intra = np.mean(intra_variances)

# Calculate cluster centers
centers = kmeans.cluster_centers_

# Inter-group variance
mean_center = np.mean(centers, axis=0)
variance_inter = np.var(centers, axis=0).mean()  # Mean variance of centers

# Calculate the ratio
ratio = variance_inter / variance_intra

print(f"Variance Intra-Groupes: {variance_intra}")
print(f"Variance Inter-Groupes: {variance_inter}")
print(f"Ratio: {ratio}")
```

```
Variance Intra-Groupes: 2.239027214294898
Variance Inter-Groupes: 3.47646804372618
Ratio: 1.5526689544150851
```

[52]:

```
import matplotlib.pyplot as plt

# Plot the reduced data with cluster labels
plt.figure(figsize=(10, 6))
unique_labels = set(labels)
colors = plt.cm.viridis(np.linspace(0, 1, len(unique_labels)))  # Updated to␣
↪use viridis directly

for i, label in enumerate(unique_labels):
    if label == -1:  # Noise points
        color = 'k'  # Black for noise
    else:
        color = colors[i]  # Use the index to get the color
```

```
    plt.scatter(reduced_data[labels == label, 0], reduced_data[labels == label,␣
↪1],
                color=color, label=f'Cluster {label}' if label != -1 else␣
↪'Noise', alpha=0.5)

plt.title('K-Means Clustering Results')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.legend()
plt.show()
```



[55]:
```
# Assuming 'data' is your DataFrame and 'labels' are the cluster labels
subset_data['Cluster'] = labels  # Convert labels to a list before adding to␣
↪the DataFrame

# Group by cluster and calculate summary statistics
cluster_summary = subset_data.groupby('Cluster').agg(['mean', 'std', 'count'])

# Display the summary statistics for each cluster
print(cluster_summary)

# Calculate the importance of each feature for each cluster
importance_summary = {}
```

```python
for label in unique_labels:
    if label != -1:  # Skip noise points
        cluster_data = subset_data[subset_data['Cluster'] == label]
        importance = cluster_data.drop(columns=['Cluster']).mean()  # Calculate mean for each feature
        importance_summary[label] = importance

# Convert the summary to a DataFrame for better visualization
importance_df = pd.DataFrame(importance_summary).T

# Create a summary of the most important features for each cluster
importance_summary_str = {}

for label in unique_labels:
    if label != -1:  # Skip noise points
        # Get the importance of features for the current cluster
        importance = importance_df.loc[label]
        # Sort features by importance
        sorted_importance = importance.sort_values(ascending=False)
        # Create a summary string for the top features
        summary = ', '.join([f'{feature} : {value:.1f}' for feature, value in sorted_importance.items()])
        importance_summary_str[label] = summary

# Display the importance summary for each cluster
print("Importance Summary for Each Cluster:")
for label in importance_summary_str.keys():
    # Get the top 5 features for the current cluster
    top_features = importance_df.loc[label].nlargest(5)
    # Check the most common value for these features in the cluster
    most_common_values = {feature: subset_data[subset_data['Cluster'] == label][feature].mode()[0] for feature in top_features.index}
    print(f'Cluster {label}: {top_features.index.tolist()} with most common values: {most_common_values}')
```

```
        A9_1_slice                      A9_2_slice                      A9_3_slice  \
              mean       std count         mean       std count         mean
Cluster
0         1.600424  0.593215  1414     2.062942  0.758718  1414     2.016973
1         2.236713  0.598308  2653     2.751979  0.676251  2653     2.699962
2         3.056806  0.742624   933     3.511254  0.599653   933     3.531618

                      A9_4_slice  … A11_10_slice A11_11_slice           \
              std count       mean  …        count         mean       std
Cluster                             …
0        0.779965  1414   1.942008  …         1414     1.553748  0.582485
```

```
1        0.698298  2653   2.636261  …         2653     2.290991  0.573206
2        0.558121   933   3.509110  …          933     3.147910  0.680498

              A11_12_slice                A11_13_slice
        count          mean       std count          mean       std count
Cluster
0        1414     1.363508  0.544650  1414     1.429986  0.626479  1414
1        2653     2.016585  0.565895  2653     2.220882  0.666637  2653
2         933     2.790997  0.795807   933     3.092176  0.765451   933

[3 rows x 111 columns]
Importance Summary for Each Cluster:
Cluster 0: ['A10_6_slice', 'A9_5_slice', 'A9_12_slice', 'A10_3_slice',
'A9_13_slice'] with most common values: {'A10_6_slice': 3, 'A9_5_slice': 3,
'A9_12_slice': 2, 'A10_3_slice': 2, 'A9_13_slice': 2}
Cluster 1: ['A9_12_slice', 'A9_13_slice', 'A9_2_slice', 'A9_5_slice',
'A9_3_slice'] with most common values: {'A9_12_slice': 3, 'A9_13_slice': 3,
'A9_2_slice': 3, 'A9_5_slice': 3, 'A9_3_slice': 3}
Cluster 2: ['A9_13_slice', 'A9_12_slice', 'A9_3_slice', 'A9_2_slice',
'A9_4_slice'] with most common values: {'A9_13_slice': 4, 'A9_12_slice': 4,
'A9_3_slice': 4, 'A9_2_slice': 4, 'A9_4_slice': 4}
```

```
/tmp/ipykernel_19443/2211454646.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  subset_data['Cluster'] = labels  # Convert labels to a list before adding to
the DataFrame
```

3.6.1 Cluster 0 :

Features principales

- **A10_6_slice** (Les espaces extérieurs sont surtout des sources de contraintes) : *Plutôt pas d'accord* (3)

- **A9_5_slice** (Je préfère que les espaces extérieurs soient plutôt sauvages que très entretenus) : *Plutôt pas d'accord* (3)

- **A9_12_slice** (J'investis beaucoup d'argent dans l'aménagement et l'entretien de mes espaces extérieurs) : *Plutôt d'accord* (2)

- **A10_3_slice** (Les espaces extérieurs sont avant tout des espaces utilitaires) : *Plutôt d'accord* (2)

- **A9_13_slice** (Il m'arrive de regarder des vidéos, des tutoriels de jardinage sur Internet) : *Plutôt d'accord* (2)

Description Ce cluster regroupe des individus qui :
- Ne perçoivent pas les espaces extérieurs comme étant des sources de contraintes.
- Préfèrent un entretien modéré des espaces extérieurs, plutôt que des espaces totalement sauvages.
- Investissent raisonnablement dans l'aménagement de leurs espaces extérieurs.
- Considèrent les espaces extérieurs comme utilitaires et recherchent parfois des informations en ligne pour les entretenir ou les aménager.

3.6.2 Cluster 1 :

Features principales

- **A9_12_slice** (J'investis beaucoup d'argent dans l'aménagement et l'entretien de mes espaces extérieurs) : *Plutôt pas d'accord* (3)

- **A9_13_slice** (Il m'arrive de regarder des vidéos, des tutoriels de jardinage sur Internet) : *Plutôt pas d'accord* (3)

- **A9_2_slice** (Je m'intéresse beaucoup aux nouveautés concernant l'aménagement des espaces extérieurs) : *Plutôt pas d'accord* (3)

- **A9_5_slice** (Je préfère que les espaces extérieurs soient plutôt sauvages que très entretenus) : *Plutôt pas d'accord* (3)

- **A9_3_slice** (Je recherche souvent des informations sur l'aménagement des espaces extérieurs) : *Plutôt pas d'accord* (3)

Description Ce cluster regroupe des individus qui :
- Investissent peu dans l'aménagement et l'entretien de leurs espaces extérieurs.
- Sont peu intéressés par les nouveautés liées à l'aménagement des espaces extérieurs ou par la recherche d'informations sur le sujet.
- Ne préfèrent pas particulièrement des espaces extérieurs sauvages ni trop entretenus.
- Ne consomment pas de contenus numériques (vidéos, tutoriels) en rapport avec le jardinage ou l'aménagement des espaces extérieurs.

3.6.3 Cluster 2 :

Features principales

- **A9_13_slice** (Il m'arrive de regarder des vidéos, des tutoriels de jardinage sur Internet) : *Pas du tout d'accord* (4)

- **A9_12_slice** (J'investis beaucoup d'argent dans l'aménagement et l'entretien de mes espaces extérieurs) : *Pas du tout d'accord* (4)

- **A9_3_slice** (Je recherche souvent des informations sur l'aménagement des espaces extérieurs) : *Pas du tout d'accord* (4)

- **A9_2_slice** (Je m'intéresse beaucoup aux nouveautés concernant l'aménagement des espaces extérieurs) : *Pas du tout d'accord* (4)

- **A9_4_slice** (Je recherche souvent des informations sur l'entretien des espaces extérieurs) : *Pas du tout d'accord* (4)

Description Ce cluster regroupe des individus qui :
- Ont un désintérêt marqué pour les espaces extérieurs, ne s'impliquant pas dans leur aménagement ou leur entretien.
- N'investissent pas financièrement dans leurs espaces extérieurs.
- Ne recherchent ni d'informations ni de tutoriels concernant le jardinage ou l'entretien des espaces extérieurs.
- Ne s'intéressent pas aux nouveautés liées aux espaces extérieurs.

3.6.4 Résumé global

- **Cluster 0 :** Approche modérée envers les espaces extérieurs, perçus comme utilitaires, avec un intérêt occasionnel pour leur entretien.

- **Cluster 1 :** Désintérêt global pour l'aménagement et l'entretien des espaces extérieurs, sans rejet total mais avec un faible investissement personnel et financier.

- **Cluster 2 :** Rejet complet de l'investissement, de l'entretien et de l'intérêt pour les espaces extérieurs.

4 Conclusion

Dans le cadre de notre analyse de clustering, nous avons réalisé un benchmark en utilisant plusieurs métriques de performance : Silhouette, Davies-Bouldin et Calinski-Harabasz. Nous avons appliqué différentes méthodes de clustering, notamment KMeans, Agglomerative Clustering, DBSCAN, Gaussian Mixture Model et Spectral Clustering.
Les résultats de cette évaluation ont montré que le Kmeans offrait les meilleures performances globales selon les métriques analysées (surtout pour 3 clusters). En conséquence, nous avons décidé de nous concentrer sur cette méthode.

En termes de variance, nous avons obtenu les résultats suivants : - Variance Intra-Groupes: 2.239 - Variance Inter-Groupes: 3.476 - Ratio: 1.553

Ces résultats soulignent l'efficacité du KMeans dans notre analyse.