swiggy-clustering

April 19, 2023

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.compose import ColumnTransformer
import matplotlib.pyplot as plt
import prince
```

[2]:
```
plots_path = './plots/'
```

[3]:
```
df = pd.read_csv('swiggy-preprocessed.csv', index_col=[0])
```

[4]:
```
df.head()
```

[4]:

id	name	city	rating	rating_count	cost	lic_no	link	address	menu
567335	AB FOODS POINT	Abohar	0.0	Too Few Ratings	200.0	22122652000138	https://www.swiggy.com/restaurants/ab-foods-po…	AB FOODS POINT, NEAR RISHI NARANG DENTAL CLINI…	Menu/567335.json
531342	Janta Sweet House	Abohar	4.4	50+ ratings	200.0	12117201000112	https://www.swiggy.com/restaurants/janta-sweet…	Janta Sweet House, Bazar No.9, Circullar Road,…	Menu/531342.json
158203	theka coffee desi	Abohar	3.8	100+ ratings	100.0	22121652000190	https://www.swiggy.com/restaurants/theka-coffe…	theka coffee desi, sahtiya sadan road city	Menu/158203.json
187912	Singh Hut	Abohar	3.7	20+ ratings	250.0	22119652000167	https://www.swiggy.com/restaurants/singh-hut-n…	Singh Hut, CIRCULAR ROAD NEAR NEHRU PARK ABOHAR	Menu/187912.json
543530	GRILL MASTERS	Abohar	0.0	Too Few Ratings	250.0	12122201000053	https://www.swiggy.com/restaurants/grill-maste…		

```
543530  GRILL MASTERS, ADA Heights, Abohar - Hanumanga…  Menu/543530.json
```

id	sub_area	area	cuisine1	cuisine2
567335	Abohar	Abohar	Beverages	Pizzas
531342	Abohar	Abohar	Sweets	Bakery
158203	Abohar	Abohar	Beverages	Beverages
187912	Abohar	Abohar	Fast Food	Indian
543530	Abohar	Abohar	Italian-American	Fast Food

[5]:
```
cat_vars = ['sub_area', 'area', 'cuisine1', 'cuisine2', 'rating_count', 'city']
num_vars = ['rating', 'cost']

df = df[cat_vars + num_vars]
```

[6]:
```
# Calculate the mean rating for each combination of 'sub_area', 'area', 'city',␣
 ↪'cuisine1', 'cuisine2'
mean_ratings = df.groupby(['sub_area', 'area', 'city', 'cuisine1',␣
 ↪'cuisine2'])['rating'].mean()

# Define a function to replace 0 rating with the mean for its corresponding␣
 ↪combination of 'sub_area', 'area', 'city', 'cuisine1', 'cuisine2'
def replace_rating(row):
    if row['rating'] == 0:
        return mean_ratings.loc[row['sub_area'], row['area'], row['city'],␣
 ↪row['cuisine1'], row['cuisine2']]
    else:
        return row['rating']

# Apply the function to the 'rating' column
df['rating'] = df.apply(replace_rating, axis=1)
```

[7]:
```
le = LabelEncoder()
```

[8]:
```
# Encode the categorical variables using LabelEncoder
for col in cat_vars:
    df[col] = le.fit_transform(df[col])
```

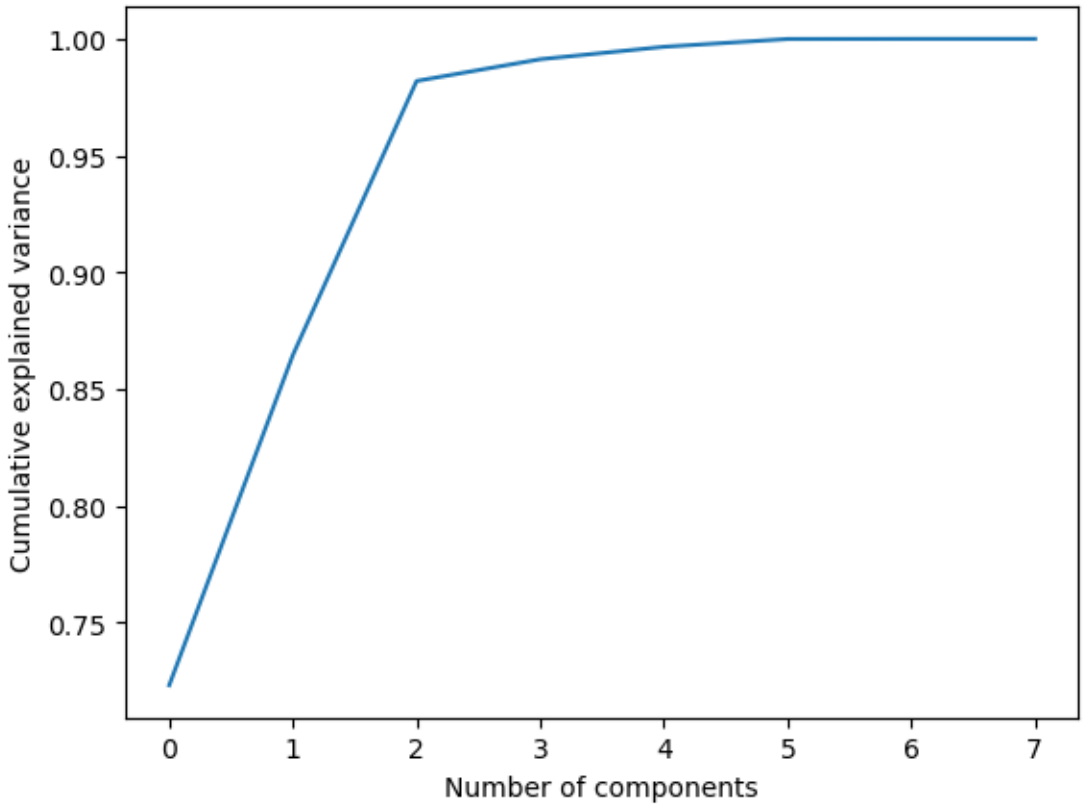
[9]:
```
df
```

[9]:

id	sub_area	area	cuisine1	cuisine2	rating_count	city	rating	cost
567335	1	3	12	72	7	0	0.0	200.0
531342	1	3	88	8	4	0	4.4	200.0
158203	1	3	12	11	0	0	3.8	100.0
187912	1	3	27	39	3	0	3.7	250.0
543530	1	3	43	26	7	0	0.0	250.0

```
…          …   …       …       …            …   …      …    …
553122       815   815        27        81              7   551     0.0  200.0
562647       815   815        73        72              7   551     1.4  300.0
559435       815   815        27        81              7   551     0.0  300.0
418989       815   815        24        23              7   551     0.0  250.0
447770       815   815        73        72              7   551     1.4  200.0

[145814 rows x 8 columns]
```

[10]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA

# your data
X = df.values

# fit PCA
pca = PCA().fit(X)

# scree plot
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of components')
plt.ylabel('Cumulative explained variance')
plt.savefig(plots_path + 'number-of-comp.png', bbox_inches='tight')
plt.show()
```



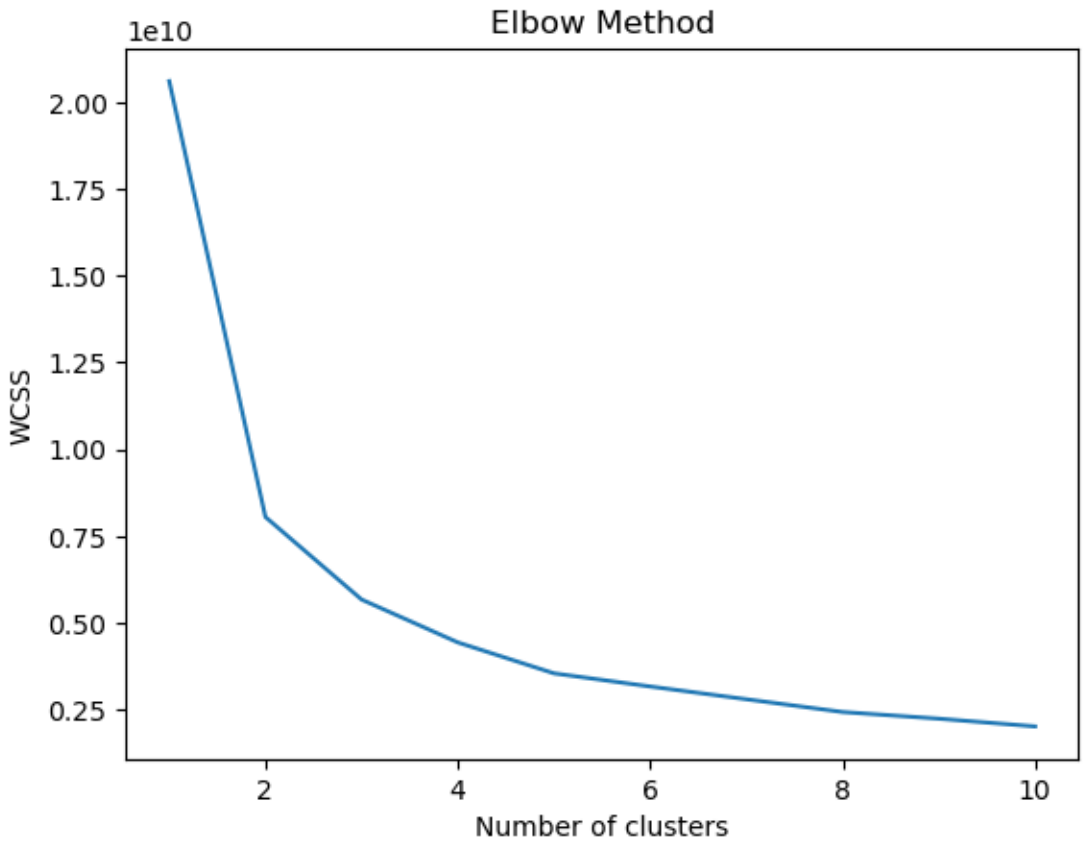
[11]:
```
mca = prince.MCA(n_components=2)
mca.fit(df)
```

[11]: <prince.mca.MCA at 0x16a68eb30>

[12]:
```
def elbow_kmeans(df):
    # Determine optimal number of clusters using WCSS
    wcss = []
    for i in range(1, 11):
        kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42,␣
 ↪n_init='auto')
        kmeans.fit(df)
        wcss.append(kmeans.inertia_)
    plt.plot(range(1, 11), wcss)
    plt.title('Elbow Method')
    plt.xlabel('Number of clusters')
    plt.ylabel('WCSS')
    plt.savefig(plots_path + 'elbow-method.png', bbox_inches='tight')
    plt.show()
```

[13]:
```
reduced_df = df[['sub_area', 'area' , 'cuisine1' , 'rating', 'cost']]
```

[14]:
```
elbow_kmeans(reduced_df)
```



[15]:
```
mca.__dict__
```

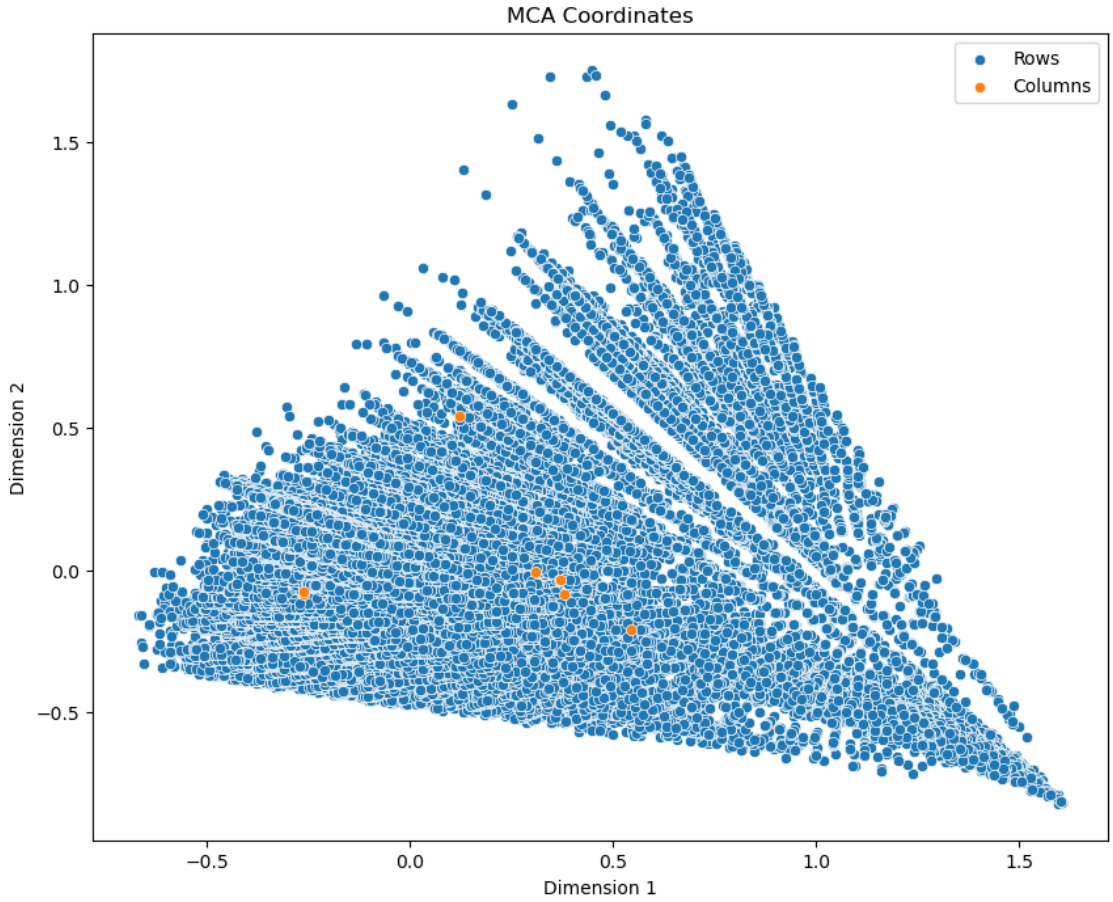
[15]:
```
{'n_components': 2,
 'n_iter': 10,
 'copy': True,
 'check_input': True,
 'random_state': None,
 'engine': 'sklearn',
 'K_': 8,
 'J_': 8,
 'row_masses_': 567335    1.405308e-06
531342    1.469142e-06
158203    6.230993e-07
187912    1.556319e-06
543530    1.572039e-06
             ...
553122    1.189033e-05
562647    1.254964e-05
```

```
 559435    1.236671e-05
 418989    1.183793e-05
 447770    1.207326e-05
 Length: 145814, dtype: float64,
 'col_masses_': sub_area        0.289151
 area            0.287300
 cuisine1        0.029025
 cuisine2        0.029180
 rating_count    0.003514
 city            0.164372
 rating          0.001427
 cost            0.196030
 dtype: float64,
 'active_rows_': Int64Index([567335, 531342, 158203, 187912, 543530, 158204,
156588, 244866,
             156602, 158193,
             …
             378059, 529034, 185296, 561381, 214210, 553122, 562647, 559435,
             418989, 447770],
            dtype='int64', length=145814),
 'active_cols_': Index(['sub_area', 'area', 'cuisine1', 'cuisine2',
'rating_count', 'city',
        'rating', 'cost'],
       dtype='object'),
 'svd_': SVD(U=array([[ 0.00525257, -0.0029841 ],
        [ 0.00531044, -0.00296487],
        [ 0.00353762, -0.00221788],
        …,
        [-0.00189259,  0.00228076],
        [-0.00257419,  0.00261881],
        [-0.0024279 ,  0.00274767]]), s=array([0.32840166, 0.24629496]),
V=array([[-0.42554824, -0.4248765 ,  0.18986789,  0.19346214,  0.05605982,
          0.15261665,  0.04375899,  0.73250382],
        [-0.18283895, -0.16577415, -0.02413657, -0.0248435 , -0.00176146,
          0.89293284, -0.01315489, -0.37467835]])),
 'total_inertia_': 0.2117542910200209,
 'row_contributions_':                0         1
 567335  0.000028  0.000009
 531342  0.000028  0.000009
 158203  0.000013  0.000005
 187912  0.000033  0.000012
 543530  0.000033  0.000012
 …          …         …
 553122  0.000007  0.000008
 562647  0.000003  0.000005
 559435  0.000004  0.000005
 418989  0.000007  0.000007
```

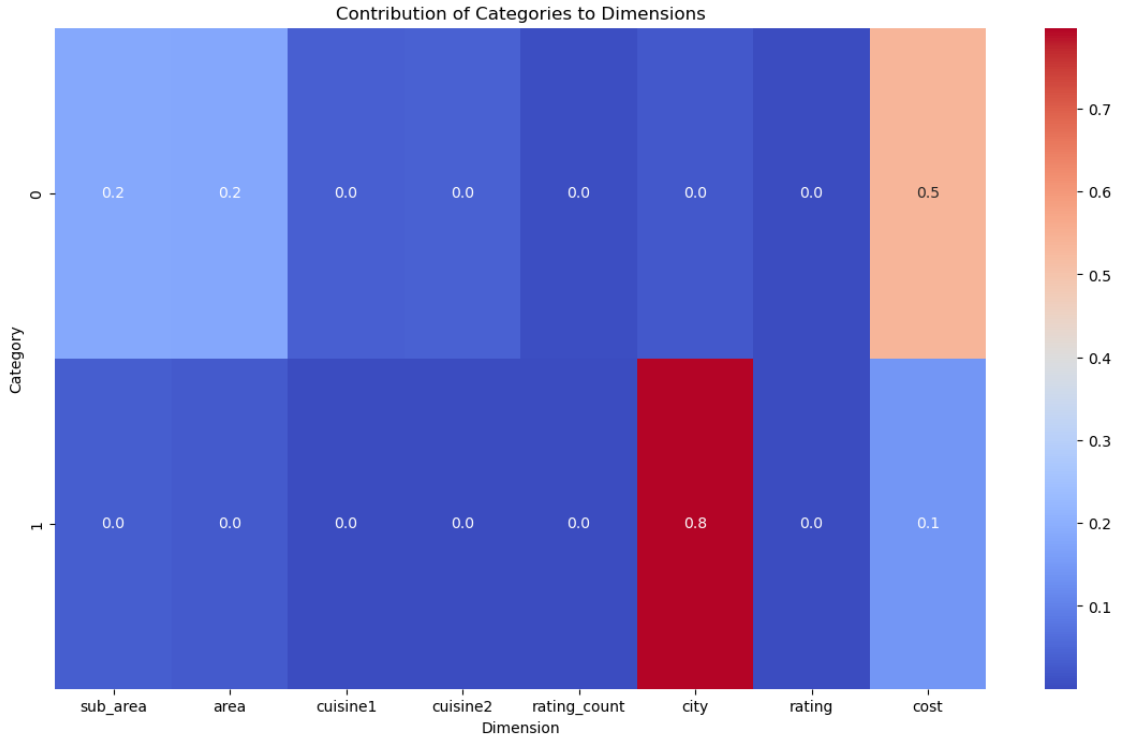
```
447770  0.000006  0.000008

[145814 rows x 2 columns],
'column_contributions_':                        0         1
sub_area      0.181091  0.033430
area          0.180520  0.027481
cuisine1      0.036050  0.000583
cuisine2      0.037428  0.000617
rating_count  0.003143  0.000003
city          0.023292  0.797329
rating        0.001915  0.000173
cost          0.536562  0.140384}
```

[16]:
```
# Get the row and column coordinates
row_coords = mca.row_coordinates(df)
col_coords = mca.column_coordinates(df)
```

[17]:
```
# Plot the row and column coordinates
fig, ax = plt.subplots(figsize=(10, 8))
sns.scatterplot(x=row_coords[0], y=row_coords[1], ax=ax)
sns.scatterplot(x=col_coords[0], y=col_coords[1], ax=ax)
ax.set_xlabel('Dimension 1')
ax.set_ylabel('Dimension 2')
ax.legend(['Rows', 'Columns'])
ax.set_title('MCA Coordinates')
plt.savefig(plots_path + 'mca-cordinates.png', bbox_inches='tight')
plt.show()
```

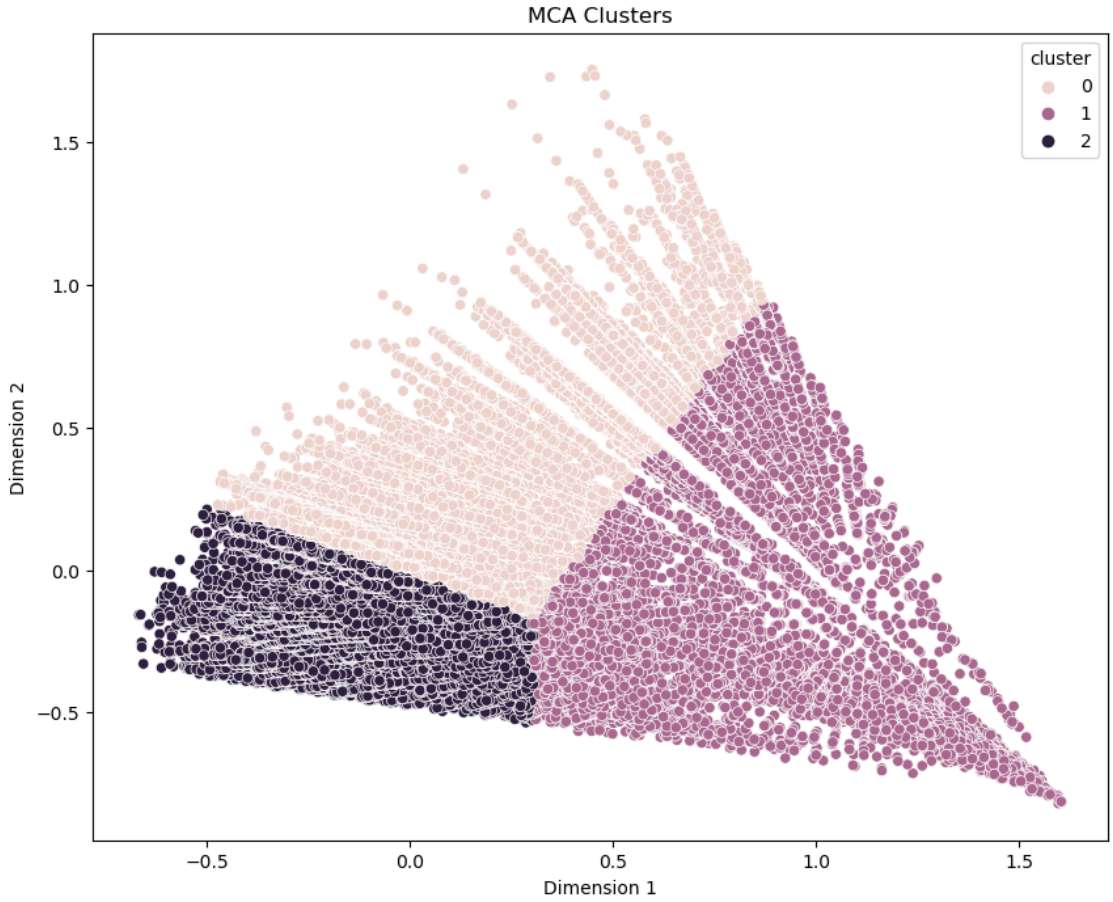


[18]:
```
fig, ax = plt.subplots(figsize=(14, 8))
sns.heatmap(mca.column_contributions_.T, cmap='coolwarm', ax=ax, annot=True,␣
↪fmt='.1f')
ax.set_xlabel('Dimension')
ax.set_ylabel('Category')
ax.set_xticklabels(df.columns)
ax.set_title('Contribution of Categories to Dimensions')
plt.savefig(plots_path + 'contribution-of-cat.png', bbox_inches='tight')
plt.show()
```



[19]:
```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3, n_init='auto')
kmeans.fit(row_coords)
df['cluster'] = kmeans.labels_
```

[20]:
```
fig, ax = plt.subplots(figsize=(10, 8))
sns.scatterplot(x=row_coords[0], y=row_coords[1], hue=df['cluster'], ax=ax)
ax.set_xlabel('Dimension 1')
ax.set_ylabel('Dimension 2')
ax.set_title('MCA Clusters')
plt.savefig(plots_path + 'mca-clusters.png', bbox_inches='tight')
plt.show()
```

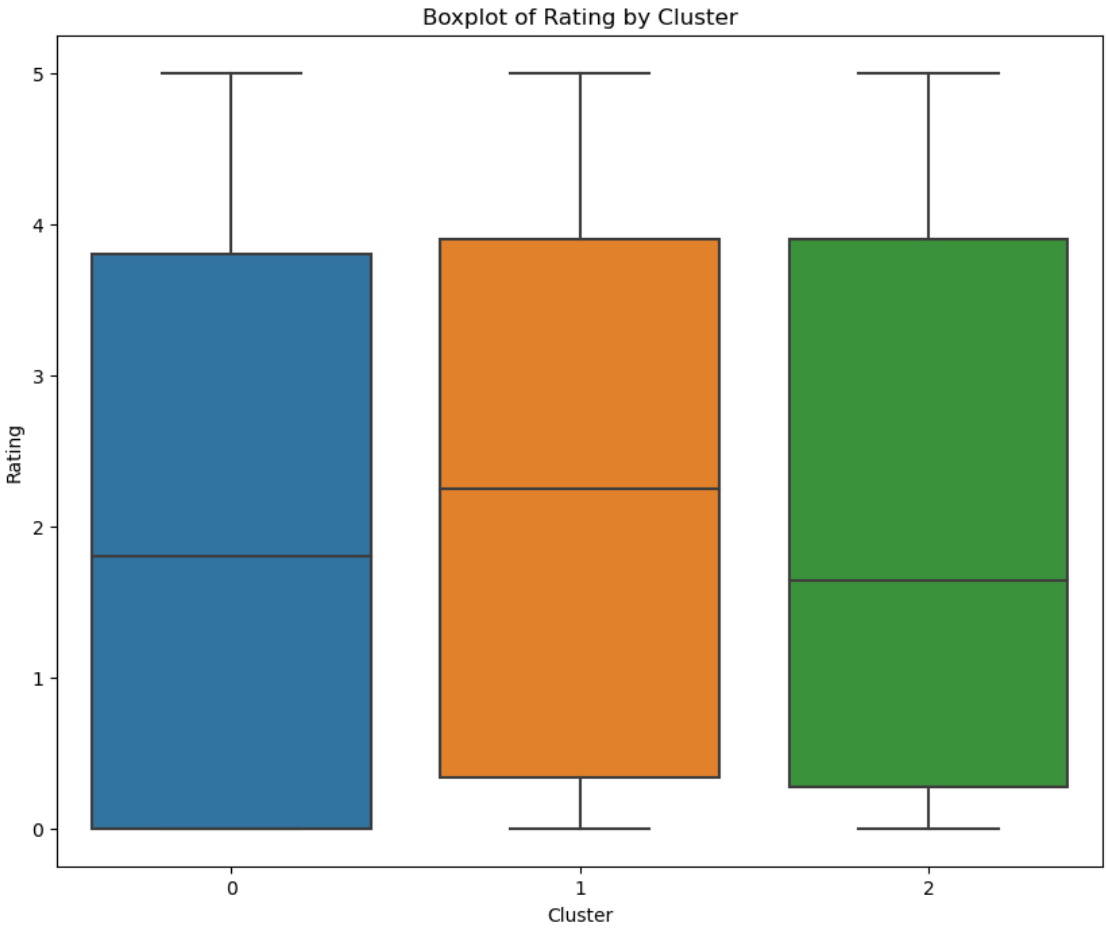


[21]:
```
cluster_means = df.groupby('cluster').mean()
print(cluster_means)
```

```
           sub_area        area   cuisine1   cuisine2  rating_count  \
cluster
0        421.198369  418.587938  42.001692  41.971998      5.058635
1        119.039367  119.875027  43.136712  43.632059      4.858314
2        567.280576  562.701647  40.803487  41.194262      5.166386

                city    rating        cost
cluster
0         345.384507  2.004475  246.375413
1         126.862358  2.234188  373.084604
2         160.972048  2.021925  278.240085
```

[22]:
```
# Example: Boxplot of rating by cluster
fig, ax = plt.subplots(figsize=(10, 8))
sns.boxplot(x='cluster', y='rating', data=df, ax=ax)
ax.set_xlabel('Cluster')
```

```
ax.set_ylabel('Rating')
ax.set_title('Boxplot of Rating by Cluster')
plt.savefig(plots_path + 'rating-by-cluster.png', bbox_inches='tight')
plt.show()
```



[23]:
```
from sklearn.metrics import silhouette_score
silhouette_score(row_coords, df['cluster'])
```

[23]: 0.32317602711857785

The silhouette score measures the goodness of clustering based on the distance between points within the same cluster compared to the distance between points in different clusters. It ranges from -1 to 1, where a score close to 1 indicates that the clustering is good, while a score close to -1 indicates that the clustering is poor. Therefore, a higher silhouette score means better clustering.

In summary, silhouette score provide a measure of how well the data points are clustered. Higher scores indicate better clustering.