Question 1

March 4, 2023

0.1 Question 1

[ ]:
```
%load_ext autoreload
%autoreload 2
```

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pylab as plt
from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import dendrogram
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans, AgglomerativeClustering
from utils import styled_print, plot_scatter_plot
```

0.1.1 Part B - Clustering With Python

Part 1 - Use non hierarchical k-means (k=3) and show clusters' memberships of the above dataset.

[ ]:
```
# Initialize the dataset
data = np.array(
    [[8, 4], [5, 4], [2, 4], [2, 6], [2, 8], [8, 6]]
)

# Dataframe of the dataset
data_df = pd.DataFrame.from_dict({
    "RID": [1, 2, 3, 4, 5, 6],
    "Dimension 1": [8, 5, 2, 2, 2, 8],
    "Dimension 2": [4, 4, 4, 6, 8, 6]
})

# Setting RID as Index Column
# data_df = data_df.set_index('RID')

data_df.head(10)
```

[ ]:

	RID	Dimension 1	Dimension 2
0	1	8	4
1	2	5	4

```
2    3            2            4
3    4            2            6
4    5            2            8
5    6            8            6
```

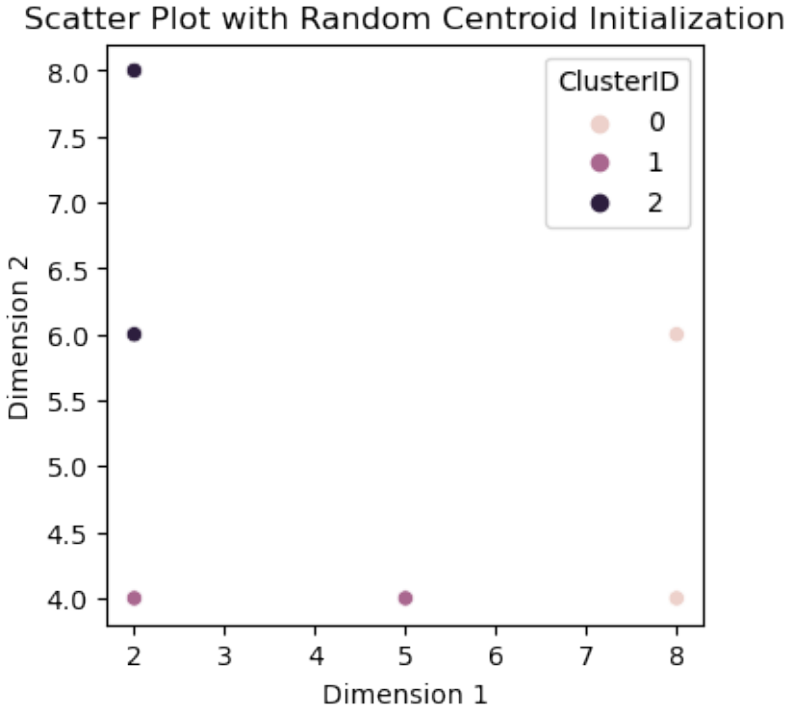
[ ]:
```python
# Function to create Cluster Map for Better Visualization and Filtering
def create_cluster_map(data, model):
    cluster_map = pd.DataFrame()
    cluster_map['ClusterID'] = model.labels_
    cluster_map = pd.concat([data, cluster_map], axis=1)
    return cluster_map

def get_centroid(data, kmeans):
    centroids = pd.DataFrame(kmeans.cluster_centers_, columns=data.columns)
    return centroids
```

[ ]:
```python
kmeans = KMeans(n_clusters=3, random_state=0, init='random', n_init='auto').
 ↪fit(data_df.drop('RID', axis=1))
cluster_map = create_cluster_map(data_df, kmeans)

styled_print(f"Cluster Map from Kmeans with Random Cluster Initialization",␣
 ↪header=True)
print(cluster_map.head(10))

styled_print(f"Cluster Centroid from Kmeans with Random Cluster␣
 ↪Initialization", header=True)
print(get_centroid(data_df.drop('RID', axis=1), kmeans).head(10))
```

```
> Cluster Map from Kmeans with Random Cluster Initialization
   RID  Dimension 1  Dimension 2  ClusterID
0    1            8            4          0
1    2            5            4          1
2    3            2            4          1
3    4            2            6          2
4    5            2            8          2
5    6            8            6          0
> Cluster Centroid from Kmeans with Random Cluster Initialization
   Dimension 1  Dimension 2
0          8.0          5.0
1          3.5          4.0
2          2.0          7.0
```

[ ]:
```python
plot_scatter_plot(
    df=cluster_map,
    x="Dimension 1",
    y="Dimension 2",
    hue='ClusterID',
```

```
    title="Scatter Plot with Random Centroid Initialization",
    figsize=(4, 4),
    dpi=100)
```



As we can see from the above table that it is not matching the table we got from the manual clustering in Part A. The reason is that in Part A we selected RID 1, 3 and 5 as initial centroid while here we are selecting random samples as initial centroid. Let's try selecting RID 1, 3 and 5 as initial centroids to verify our manual clustering in Part A.

[ ]:
```
init_centroids = [[8, 4], [2, 4], [2, 8]]
kmeans = KMeans(n_clusters=3, random_state=0, init=init_centroids, n_init=1).
 ↪fit(data_df.drop('RID', axis=1))
cluster_map = create_cluster_map(data_df, kmeans)

styled_print(f"Cluster Map from Kmeans with Proposed Centroid Initialization",␣
 ↪header=True)
print(cluster_map.head(10))

styled_print(f"Cluster Centroid from Kmeans with Proposed Centroid␣
 ↪Initialization", header=True)
print(get_centroid(data_df.drop('RID', axis=1), kmeans).head(10))
```

› **Cluster Map from Kmeans with Proposed Centroid Initialization**

RID	Dimension 1	Dimension 2	ClusterID

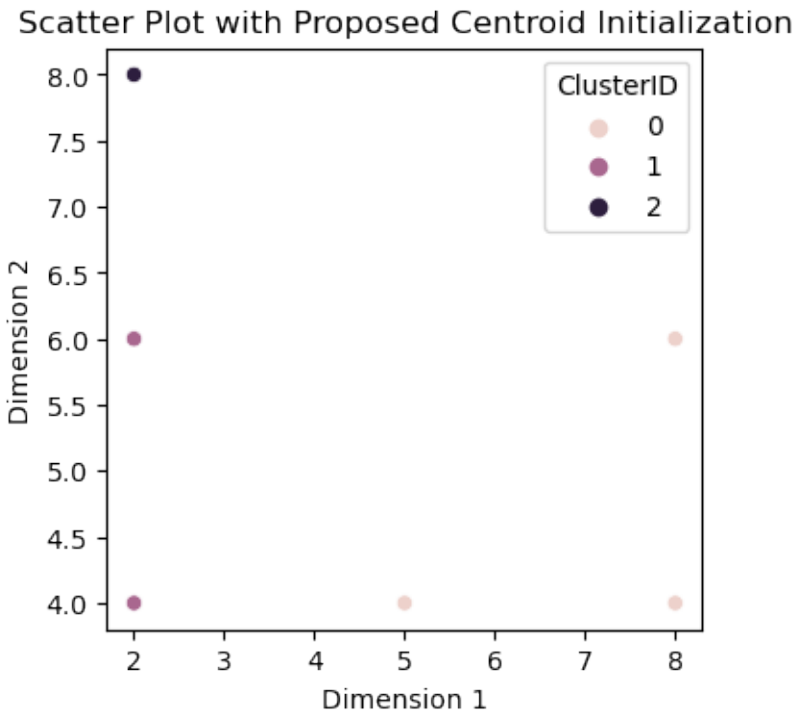
```
0    1            8            4          0
1    2            5            4          0
2    3            2            4          1
3    4            2            6          1
4    5            2            8          2
5    6            8            6          0
```

> Cluster Centroid from Kmeans with Proposed Centroid Initialization

```
   Dimension 1  Dimension 2
0          7.0     4.666667
1          2.0     5.000000
2          2.0     8.000000
```

Again here the results are almost same apart from one case. In our manual clustering sample with RID 4 was part of the same cluster as RID 5 i.e. Cluster ID 2. Here RID 3 and RID 4 are part of same cluster with Cluster ID 1. If you remember the shortest distance of sample with RID 4 was same for Cluster ID 1 and Cluster ID 2. In the manual calculation we randomly selected Cluster ID 2 and that is why sample with RID 4 landed in the same cluster as the sample with RID 5. If we have selected Cluster ID 1 at that stage, we would have got the same result as mentioned in this table.

[ ]:
```
plot_scatter_plot(
    df=cluster_map,
    x="Dimension 1",
    y="Dimension 2",
    hue='ClusterID',
    title="Scatter Plot with Proposed Centroid Initialization",
    figsize=(4, 4),
    dpi=100)
```



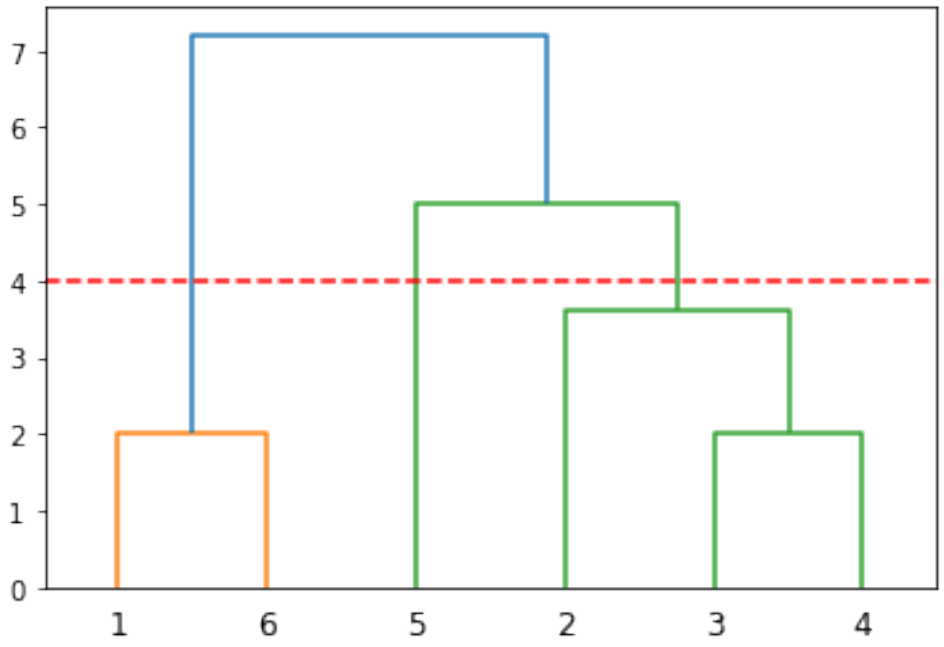
Part 2 - Use Hierarchical Clustering - Agglomerative Clustering.

[ ]:
```
agglomerative = AgglomerativeClustering(n_clusters=None, distance_threshold=0,␣
↪metric='euclidean', linkage = 'complete').fit(data_df.drop('RID', axis=1))
```

[ ]:
```
# Source of the function is https://scikit-learn.org/stable/auto_examples/
↪cluster/plot_agglomerative_dendrogram.html
def plot_dendrogram(model, **kwargs):
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count
    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)
    dendrogram(linkage_matrix, **kwargs)
```

```
plot_dendrogram(agglomerative, truncate_mode="level", p=5, labels=[1, 2, 3, 4,␣
↪5, 6])
plt.axhline(y = 4, color = 'r', linestyle = '--')
```

[ ]: <matplotlib.lines.Line2D at 0x7fba2879ab50>



As we can see that heirarchical clustering creates 6 clusters at the beginning and gradually converges to 1 cluster. Based on different threshold we can have different number of clusters. For example if we choose distance threshold to be 4 (indicated with red line), we have total 3 clusters where data samples with RID 1 and 6 are part of one cluster. Data samples with RID 2, 3, and 4 are part of second cluster. The data sample with RID 5 is part of third cluster.

Clustering on Restaurants Table from Assignment 1 (For Bonus Marks)

[ ]:
```
csv_path = "../Assignment - 1 - Database Design/data/restaurants.csv"
df = pd.read_csv(csv_path)
df.head(5)
```

[ ]:

	id	position	name	score	\
0	1	19	PJ Fresh (224 Daniel Payne Drive)	NaN	
1	2	9	J' ti`'z Smoothie-N-Coffee Bar	NaN	
2	3	6	Philly Fresh Cheesesteaks (541-B Graymont Ave)	NaN	
3	4	17	Papa Murphy's (1580 Montgomery Highway)	NaN	
4	5	162	Nelson Brothers Cafe (17th St N)	4.7	

	ratings	category	price_range	\

```
0      NaN                     Burgers, American, Sandwiches           $
1      NaN  Coffee and Tea, Breakfast and Brunch, Bubble Tea         NaN
2      NaN        American, Cheesesteak, Sandwiches, Alcohol           $
3      NaN                                              Pizza          $
4     22.0         Breakfast and Brunch, Burgers, Sandwiches         NaN

                                      full_address zip_code        lat  \
0      224 Daniel Payne Drive, Birmingham, AL, 35207    35207  33.562365
1  1521 Pinson Valley Parkway, Birmingham, AL, 35217    35217  33.583640
2          541-B Graymont Ave, Birmingham, AL, 35204    35204  33.509800
3         1580 Montgomery Highway, Hoover, AL, 35226    35226  33.404439
4               314 17th St N, Birmingham, AL, 35203    35203  33.514730

          lng
0 -86.830703
1 -86.773330
2 -86.854640
3 -86.806614
4 -86.811700
```

First let's try to cluster restaurants based on `score` and `ratings` features. Let's remove the Null values.

[ ]:
```
data_df = df.dropna(axis=0, subset=["score", "ratings"])
data_df.head()
```

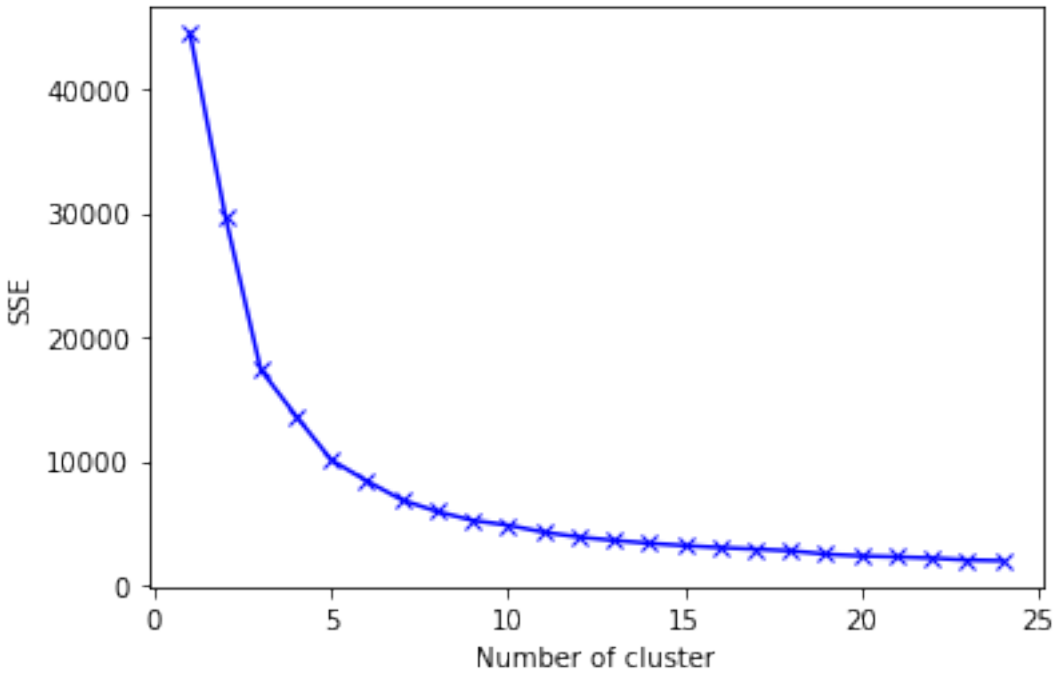
[ ]:
```
    id  position                                    name  score  ratings  \
4    5       162          Nelson Brothers Cafe (17th St N)    4.7     22.0
6    7        27                             Jinsei Sushi    4.7     63.0
13  14        51               Panera (521 Fieldstown Road)    4.6     44.0
15  16        88  Jeni's Splendid Ice Cream (Pepper Place)    5.0     20.0
18  19        30                             Falafel Cafe    4.9     48.0

                                          category price_range  \
4          Breakfast and Brunch, Burgers, Sandwiches         NaN
6                           Sushi, Asian, Japanese           $
13  Breakfast and Brunch, salad, Sandwich, Family …           $
15  Ice Cream &amp;amp; Frozen Yogurt, Comfort Food, D…       $$$
18  Middle Eastern, Mediterranean, Vegetarian, Gre…           $

                                full_address zip_code        lat        lng
4        314 17th St N, Birmingham, AL, 35203    35203  33.514730 -86.811700
6       1830 29th Ave S, Birmingham, AL, 35209    35209  33.480440 -86.790440
13  521 Fieldstown Road, Gardendale, AL, 35071    35071  33.651407 -86.819247
15       219 29th St S, Birmingham, AL, 35233    35233  33.516600 -86.789950
18       401 19th St S, Birmingham, AL, 35233    35233  33.508353 -86.803170
```

[ ]:
```
scaler = StandardScaler()
data_scaled = pd.DataFrame(scaler.fit_transform(data_df[["score", "ratings"]]),␣
↪columns = data_df[["score", "ratings"]].columns)
data_scaled.head()
```

[ ]:

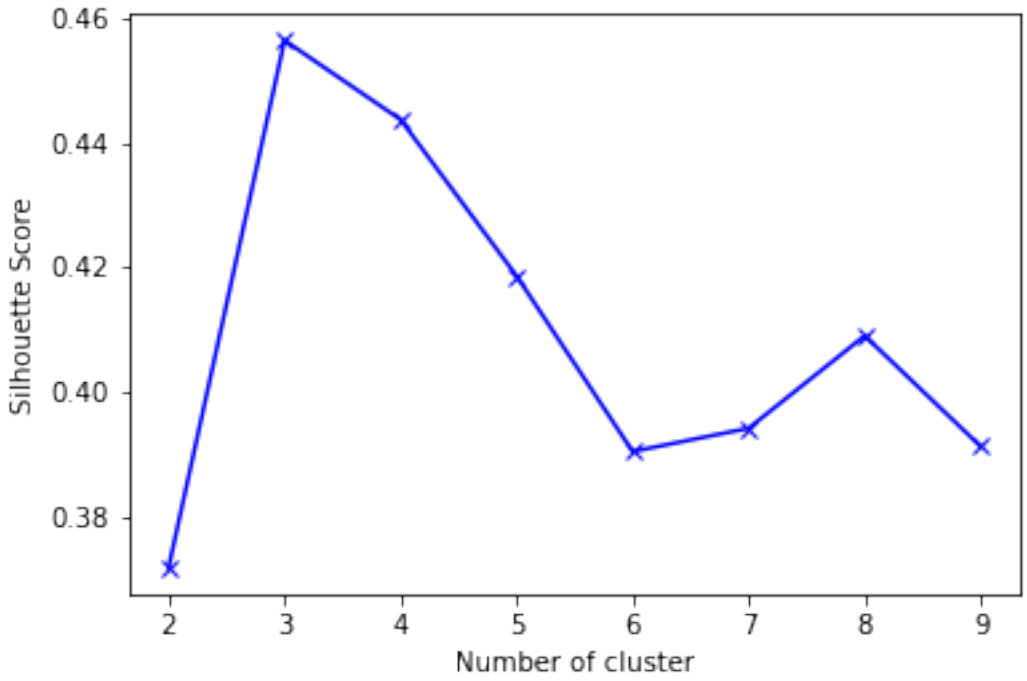
	score	ratings
0	0.466403	-0.730465
1	0.466403	-0.164009
2	0.130871	-0.426513
3	1.472997	-0.758097
4	1.137466	-0.371249

[ ]:
```
sse = {}
for k in range(1, 25):
    kmeans = KMeans(n_init='auto', n_clusters=k, init='random', random_state=0).
↪fit(data_scaled)
    sse[k] = kmeans.inertia_

# Elbow plot
plt.figure()
plt.plot(list(sse.keys()), list(sse.values()), 'bx-')
plt.xlabel("Number of cluster")
plt.ylabel("SSE")
plt.show()
```



From Elbow Plot we are getting k = 3. Let's verify same for Silhouette Score.

[ ]:
```
sc = {}
for k in range(2, 10):
    kmeans = KMeans(n_init='auto', n_clusters=k, init='random', random_state=0).
 ↪fit(data_scaled)
    labels = kmeans.predict(data_scaled)
    sc[k] = silhouette_score(data_scaled, labels)

# Elbow plot
plt.figure()
plt.plot(list(sc.keys()), list(sc.values()), 'bx-')
plt.xlabel("Number of cluster")
plt.ylabel("Silhouette Score")
plt.show()
```



As we can see that the Silhouette Score bumps up at k = 3. We will use k = 3 for our model development.

[ ]:
```
kmeans = KMeans(n_init='auto', n_clusters = 3, random_state = 1).
 ↪fit(data_scaled)

data_df['KMeans_Labels'] = kmeans.predict(data_scaled)
data_scaled['KMeans_Labels'] = kmeans.predict(data_scaled)
```

```
<ipython-input-16-99eca3b3d76b>:3: 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
  data_df['KMeans_Labels'] = kmeans.predict(data_scaled)
```

[ ]:
```
data_df.head(10)
```

[ ]:

	id	position	name	score	\
4	5	162	Nelson Brothers Cafe (17th St N)	4.7	
6	7	27	Jinsei Sushi	4.7	
13	14	51	Panera (521 Fieldstown Road)	4.6	
15	16	88	Jeni's Splendid Ice Cream (Pepper Place)	5.0	
18	19	30	Falafel Cafe	4.9	
19	20	40	MrBeast Burger (838 Odum Road)	3.7	
26	27	113	Ruscelli's Food Truck at Mojo Pub	4.7	
34	35	80	Starbucks (Hwy 11 and Avenue W)	4.6	
35	36	77	Moe's Southwest Grill (655 Fieldstown Road, Su…	4.8	
36	37	66	La Tia Paisa Taco Shop	4.3	

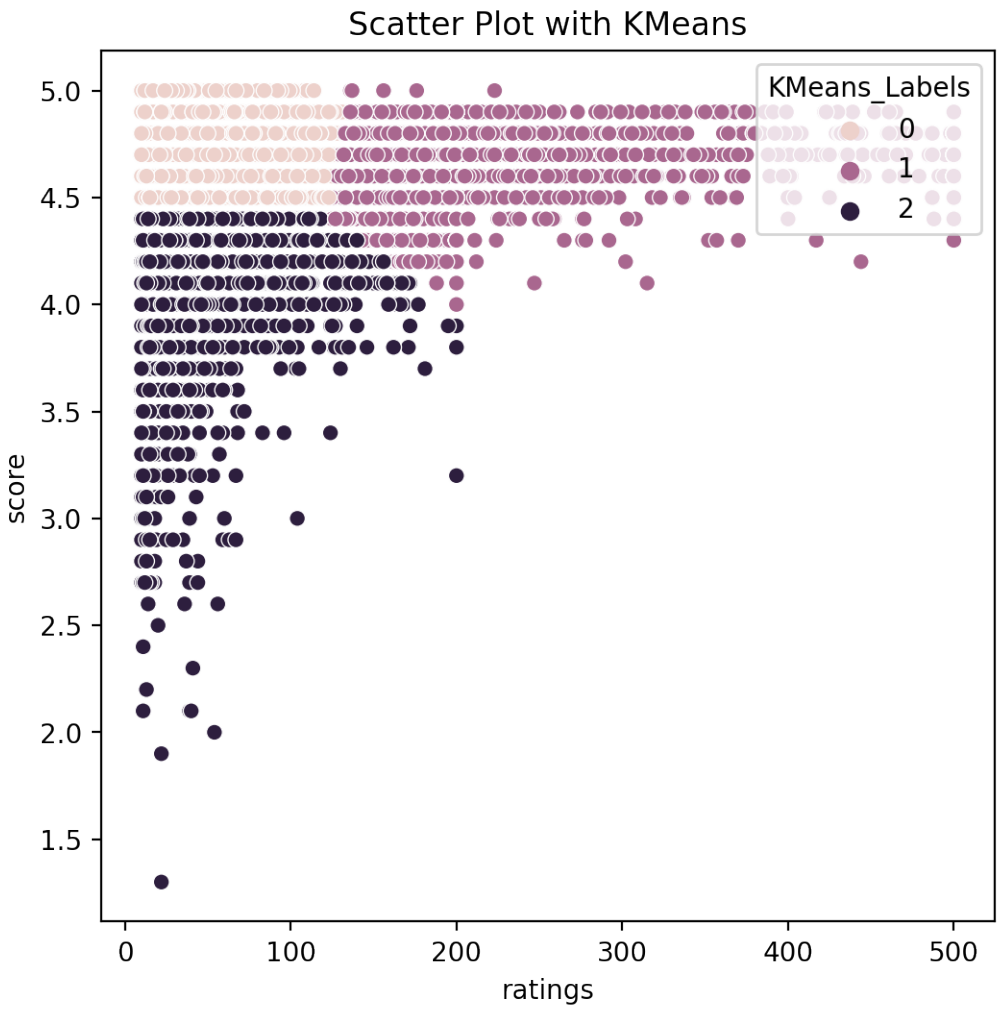
	ratings	category	price_range	\
4	22.0	Breakfast and Brunch, Burgers, Sandwiches	NaN	
6	63.0	Sushi, Asian, Japanese	$	
13	44.0	Breakfast and Brunch, salad, Sandwich, Family …	$	
15	20.0	Ice Cream & Frozen Yogurt, Comfort Food, D…	$$$	
18	48.0	Middle Eastern, Mediterranean, Vegetarian, Gre…	$	
19	19.0	American, Burgers, Sandwich	$$	
26	100.0	Italian, Exclusive to Eats	$	
34	21.0	Bakery, Breakfast and Brunch, Cafe, Coffee &am…	$	
35	24.0	Mexican, Fast Food, Salads, Healthy	$	
36	24.0	Mexican, Breakfast and Brunch, Burritos	$$	

	full_address	zip_code	lat	\
4	314 17th St N, Birmingham, AL, 35203	35203	33.514730	
6	1830 29th Ave S, Birmingham, AL, 35209	35209	33.480440	
13	521 Fieldstown Road, Gardendale, AL, 35071	35071	33.651407	
15	219 29th St S, Birmingham, AL, 35233	35233	33.516600	
18	401 19th St S, Birmingham, AL, 35233	35233	33.508353	
19	838 Odum Road, Gardendale, AL, 35071	35071	33.645480	
26	2801 7th Ave S, Birmingham, AL, 35233	35233	33.511130	
34	2401 Crossplex Boulevard 101, Birmingham, AL, …	35208	33.497944	
35	655 Fieldstown Road, Gardendale, AL, 35071	35071	33.649758	
36	406 W Valley Ave, Homewood, AL, 35209	35209	33.470750	

	lng	KMeans_Labels

```
4  -86.811700              0
6  -86.790440              0
13 -86.819247              0
15 -86.789950              0
18 -86.803170              0
19 -86.826260              2
26 -86.788388              0
34 -86.874391              0
35 -86.823942              0
36 -86.826140              2
```

[ ]:
```
plot_scatter_plot(
    df=data_df,
    x="ratings",
    y="score",
    hue='KMeans_Labels',
    title="Scatter Plot with KMeans",
    figsize=(6, 6),
    dpi=200)
```



As we can see the Kmeans is able to group reastaurant in three groups: 1. Restaurants with Higher Score and Higher Number of Ratings are part of Cluster 1. 2. Restaurant with Lower Score and Lower Number of Ratings are part of Cluster 2. 3. Restaurats with Higher Score but Lower Number of Ratings are part of Cluster 0.

This is so interesting information because cluster 0 highlights the restaurants which might be new in area but serve really good food and people might be liking them a lot. It would be great for UberEats to recommend those restaurants to customers.