Level 2: Restaurant Data Analytics | Data Analysis

- **Task 1: Restaurant Ratings**
- **Task 2: Cuisine Combination**
- **Task 3: Geographic Analysis**
- **Task 4: Restaurant Chains**

Step 1: Import necessary Python libraries.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tabulate import tabulate
import itertools
import plotly.express as px
from sklearn.cluster import KMeans
```

Step 2: Load the dataset into a DataFrame.

In [2]:
```
# Read the csv file using pandas read_csv
resto_df = pd.read_csv(r"Dataset .csv")
resto_df
```

Out[2]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currenc
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Botswan Pula(P
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Botswan Pula(P
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian	...	Botswan Pula(P
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japanese, Sushi	...	Botswan Pula(P
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japanese, Korean	...	Botswan Pula(P
...	...	...	...	...	...	...	...	...	...	...	...	.
9546	5915730	Naml Gurme	208	��stanbul	Kemanke�� Karamustafa Pa��a Mahallesi, Rhtm ...	Karak�_y	Karak�_y, ��stanbul	28.977392	41.022793	Turkish	...	Turkis Lira(TL
9547	5908749	Ceviz A��ac	208	��stanbul	Ko��uyolu Mahallesi, Muhittin ��st�_nda�� Cadd...	Ko��uyolu	Ko��uyolu, ��stanbul	29.041297	41.009847	World Cuisine, Patisserie, Cafe	...	Turkis Lira(TL
9548	5915807	Huqqa	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.034640	41.055817	Italian, World Cuisine	...	Turkis Lira(TL
9549	5916112	A���k Kahve	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.036019	41.057979	Restaurant Cafe	...	Turkis Lira(TL
9550	5927402	Walter's Coffee Roastery	208	��stanbul	Cafea��a Mahallesi, Bademalt Sokak, No 21/B, ...	Moda	Moda, ��stanbul	29.026016	40.984776	Cafe	...	Turkis Lira(TL

9551 rows × 21 columns

Step 3: Basic Inspection on given dataset

- **Top 5 rows - using head**

In [3]:
```
resto_df.head()
```

Out[3]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency	Has Table booking	C de
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Botswana Pula(P)	Yes	
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Botswana Pula(P)	Yes	
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian	...	Botswana Pula(P)	Yes	
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japanese, Sushi	...	Botswana Pula(P)	No	
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japanese, Korean	...	Botswana Pula(P)	Yes	

5 rows × 21 columns

- **bottom 5 rows using tail**

In [4]:

```
resto_df.tail()
```

Out[4]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency
9546	5915730	Namlı Gurme	208	��stanbul	Kemanke�� Karamustafa Pa��a Mahallesi, Rıhtım ...	Karak�_y	Karak�_y, ��stanbul	28.977392	41.022793	Turkish	...	Turkish Lira(TL)
9547	5908749	Ceviz A��acı	208	��stanbul	Ko��uyolu Mahallesi, Muhittin ��st�_nda�� Cadd...	Ko��uyolu	Ko��uyolu, ��stanbul	29.041297	41.009847	World Cuisine, Patisserie, Cafe	...	Turkish Lira(TL)
9548	5915807	Huqqa	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.034640	41.055817	Italian, World Cuisine	...	Turkish Lira(TL)
9549	5916112	A���k Kahve	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.036019	41.057979	Restaurant Cafe	...	Turkish Lira(TL)
9550	5927402	Walter's Coffee Roastery	208	��stanbul	Cafea��a Mahallesi, Bademaltı Sokak, No 21/B, ...	Moda	Moda, ��stanbul	29.026016	40.984776	Cafe	...	Turkish Lira(TL)

5 rows × 21 columns

- **Inspecting Column Names and Data Types**

In [5]:
```
resto_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9551 entries, 0 to 9550
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant ID         9551 non-null   int64  
 1   Restaurant Name       9551 non-null   object 
 2   Country Code          9551 non-null   int64  
 3   City                  9551 non-null   object 
 4   Address               9551 non-null   object 
 5   Locality              9551 non-null   object 
 6   Locality Verbose      9551 non-null   object 
 7   Longitude             9551 non-null   float64
 8   Latitude              9551 non-null   float64
 9   Cuisines              9542 non-null   object 
 10  Average Cost for two  9551 non-null   int64  
 11  Currency              9551 non-null   object 
 12  Has Table booking     9551 non-null   object 
 13  Has Online delivery   9551 non-null   object 
 14  Is delivering now     9551 non-null   object 
 15  Switch to order menu  9551 non-null   object 
 16  Price range           9551 non-null   int64  
 17  Aggregate rating      9551 non-null   float64
 18  Rating color          9551 non-null   object 
 19  Rating text           9551 non-null   object 
 20  Votes                 9551 non-null   int64  
dtypes: float64(3), int64(5), object(13)
memory usage: 1.5+ MB
```

- **Checking for Missing Values**

In [6]:
```
resto_df.isnull().sum()
```

Out[6]:
```
Restaurant ID           0
Restaurant Name         0
Country Code            0
City                    0
Address                 0
Locality                0
Locality Verbose        0
Longitude               0
Latitude                0
Cuisines                9
Average Cost for two    0
Currency                0
Has Table booking       0
Has Online delivery     0
Is delivering now       0
Switch to order menu    0
Price range             0
Aggregate rating        0
Rating color            0
Rating text             0
Votes                   0
dtype: int64
```

In [7]:
```
cuisines = resto_df['Cuisines'].dropna().str.split(", ").explode()
```

- **Basic Statistical Summary**

In [8]:
```
resto_df.describe()
```

Out[8]:

	Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Aggregate rating	Votes
count	9.551000e+03	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000
mean	9.051128e+06	18.365616	64.126574	25.854381	1199.210763	1.804837	2.666370	156.909748
std	8.791521e+06	56.750546	41.467058	11.007935	16121.183073	0.905609	1.516378	430.169145
min	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0.000000	0.000000
25%	3.019625e+05	1.000000	77.081343	28.478713	250.000000	1.000000	2.500000	5.000000
50%	6.004089e+06	1.000000	77.191964	28.570469	400.000000	2.000000	3.200000	31.000000
75%	1.835229e+07	1.000000	77.282006	28.642758	700.000000	2.000000	3.700000	131.000000
max	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4.900000	10934.000000

- **Checking Unique Values**

In [9]:
```
resto_df.nunique()
```

Out[9]:
```
Restaurant ID           9551
Restaurant Name         7446
Country Code              15
City                     141
Address                 8918
Locality                1208
Locality Verbose        1265
Longitude               8120
Latitude                8677
Cuisines                1825
Average Cost for two     140
Currency                  12
Has Table booking          2
Has Online delivery        2
Is delivering now          2
Switch to order menu       1
Price range                4
Aggregate rating          33
Rating color               6
Rating text                6
Votes                   1012
dtype: int64
```

- **Checking Shape**

In [10]:
```
resto_df.shape
```

Out[10]:
```
(9551, 21)
```

Task 1: Restaurant Ratings

- **Analyze the distribution of aggregate ratings and determine the most common rating range.**

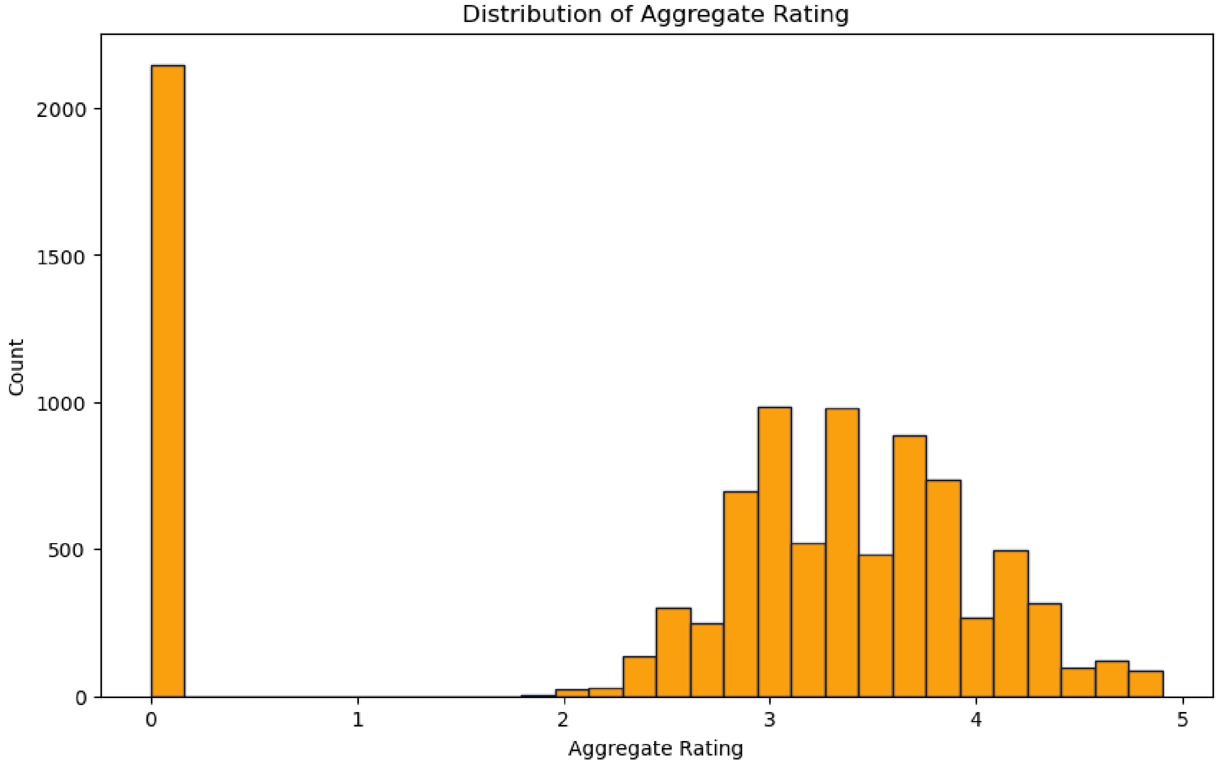
In [11]:
```
agg_val_count = resto_df['Aggregate rating'].value_counts()
agg_val_count
```

Out[11]:
```
Aggregate rating
0.0    2148
3.2     522
3.1     519
3.4     498
3.3     483
3.5     480
3.0     468
3.6     458
3.7     427
3.8     400
2.9     381
3.9     335
2.8     315
4.1     274
4.0     266
2.7     250
4.2     221
2.6     191
4.3     174
4.4     144
2.5     110
4.5      95
2.4      87
4.6      78
4.9      61
2.3      47
4.7      42
2.2      27
4.8      25
2.1      15
2.0       7
1.9       2
1.8       1
Name: count, dtype: int64
```

In [24]:
```
rating_most_common = agg_val_count.idxmax()
print(f'The Most Common rating range is: {rating_most_common}')
```

```
The Most Common rating range is: 0.0
```

In [12]:
```
plt.figure(figsize=(10, 6))
plt.hist(resto_df['Aggregate rating'], bins=30, color='#fca311', edgecolor='#14213d')
plt.xlabel('Aggregate Rating')
plt.ylabel('Count')
plt.title('Distribution of Aggregate Rating')
plt.show()
```



- **Calculate the average number of votes received by restaurants.**

In [13]:
```
avg_vote = round(resto_df['Votes'].mean(), 2)
print(f'The Average number of Votes received by restaurants : {avg_vote}')
```

```
The Average number of Votes received by restaurants : 156.91
```

Task 2: Cuisine Combination

- **Identify the most common combinations of

cuisines in the dataset.**

In [14]:
```
common_cuisines_combinations = resto_df.groupby('Cuisines')['Aggregate rating'].mean().sort_values(ascending=False)
top_10_combinations = common_cuisines_combinations.head(10)
print(f'The Top 10 most common combinations are : {top_10_combinations}')
```

```
The Top 10 most common combinations are : Cuisines
Italian, Deli               4.9
Hawaiian, Seafood           4.9
American, Sandwich, Tea     4.9
Continental, Indian         4.9
European, Asian, Indian     4.9
European, Contemporary      4.9
European, German            4.9
BBQ, Breakfast, Southern    4.9
American, Coffee and Tea    4.9
Sunda, Indonesian           4.9
Name: Aggregate rating, dtype: float64
```

- **Determine if certain cuisine combinations

tend to have higher ratings.**

In [15]:
```
max_rating = common_cuisines_combinations.iloc[0]
print(f'The Max Rating is: {max_rating}')
```

```
The Max Rating is: 4.9
```

In [16]:
```
max_rated_rest = resto_df.loc[resto_df['Aggregate rating'] == max_rating]
print('Restorents having the Maximum Ratings: ')
max_rated_rest['Restaurant Name']
```

```
Restorents having the Maximum Ratings:
```

Out[16]:
```
3                                             Ooma
8        Spiral - Sofitel Philippine Plaza Manila
10                               Silantro Fil-Mex
39                                     Coco Bambu
48                              Braseiro da G��vea
                          ...
9484               Restaurant Mosaic @ The Orient
9514                             Ministry of Crab
9524                                 Gaga Manjero
9538                                    Starbucks
9540                             Draft Gastro Pub
Name: Restaurant Name, Length: 61, dtype: object
```

Task 3: Geographic Analysis

- **Plot the locations of restaurants on a

map using longitude and latitude coordinates.**

In [17]:
```
resto_df[['Latitude', 'Longitude']]
```

Out[17]:

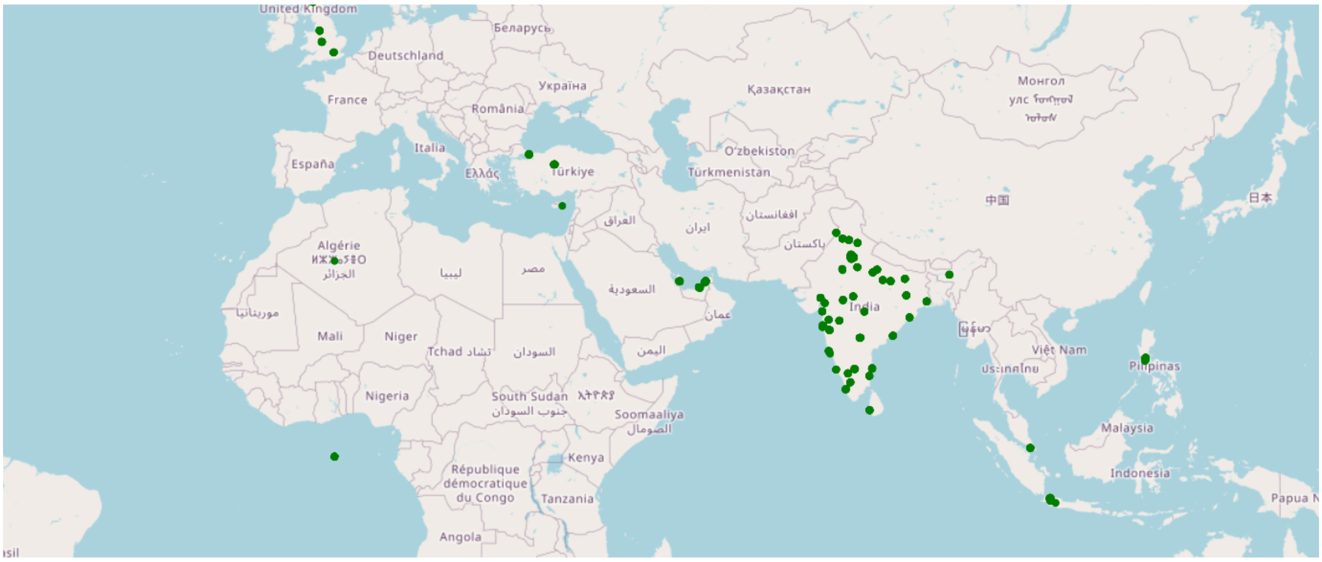
	Latitude	Longitude
0	14.565443	121.027535
1	14.553708	121.014101
2	14.581404	121.056831
3	14.585318	121.056475
4	14.584450	121.057508
...	...	...
9546	41.022793	28.977392
9547	41.009847	29.041297
9548	41.055817	29.034640
9549	41.057979	29.036019
9550	40.984776	29.026016

9551 rows × 2 columns

In [5]:
```
print(resto_df["Longitude"].isnull().sum())
print(resto_df["Latitude"].isnull().sum())
```

```
0
0
```

In [18]:
```
# plot the restaurents on the map
fig = px.scatter_mapbox(resto_df,lat='Latitude',  lon='Longitude',
     hover_name='Restaurant Name',       color_discrete_sequence=['green'],
     zoom=2,
)
fig.update_layout(
    mapbox_style="open-street-map",
)
```



- **Identify any patterns or clusters of restaurants in specific areas.**

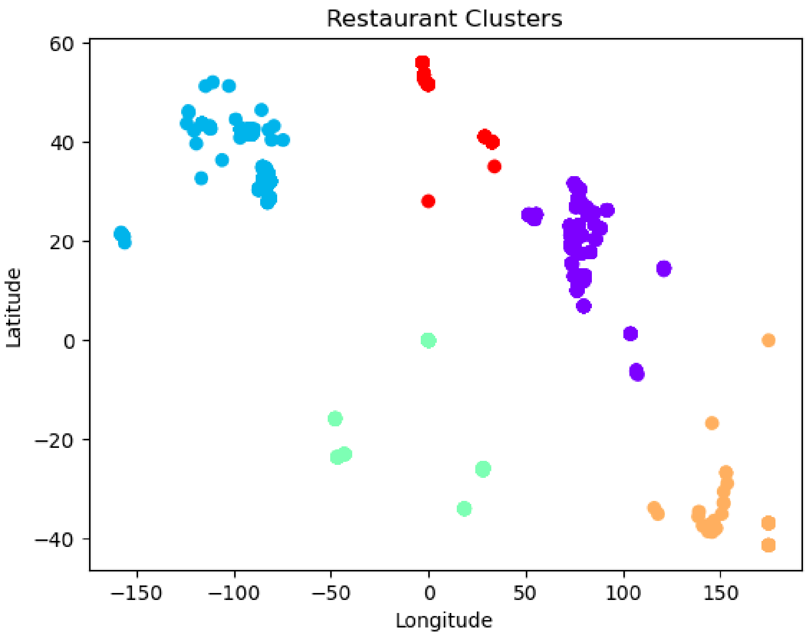
In [19]:
```
X=resto_df[['Latitude','Longitude']]
num_cluster=5
# k mean clustering
kmeans=KMeans(n_clusters=num_cluster,n_init=10,random_state=42)
resto_df['Cluster']=kmeans.fit_predict(X)
```

In [20]:
```
# plot on the map
fig=px.scatter_mapbox(resto_df,lat='Latitude',lon='Longitude',
    hover_name='Restaurant Name', hover_data=['Cuisines','Country Code'],
    color='Cluster',    color_continuous_scale='reds',
    zoom=2,
)
```

```
fig.update_layout(
    mapbox_style="open-street-map",
)
```

In [21]:

```
# Plotting the clusters
plt.scatter(resto_df['Longitude'], resto_df['Latitude'], c=resto_df['Cluster'], cmap='rainbow')
plt.title('Restaurant Clusters')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```



Task 4: Restaurant Chains

- **Identify if there are any restaurant chains present in the dataset**

In [22]:

```
resto_df.head(2)
```

Out[22]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Yes	No	No	No
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Yes	No	No	No

2 rows × 22 columns

In [23]:
```
res_count=resto_df['Restaurant Name'].value_counts()
potential_chains=res_count[res_count > 10].index
print("Potential restaurant chains:")
for chain in potential_chains:
    print(f"--{chain}")
```

```
Potential restaurant chains:
--Cafe Coffee Day
--Domino's Pizza
--Subway
--Green Chick Chop
--McDonald's
--Keventers
--Pizza Hut
--Giani
--Baskin Robbins
--Barbeque Nation
--Giani's
--Barista
--Dunkin' Donuts
--Costa Coffee
--Pind Balluchi
--Wah Ji Wah
--Twenty Four Seven
--Pizza Hut Delivery
--Sagar Ratna
--Republic of Chicken
--KFC
--Starbucks
--Chaayos
--Burger King
--Haldiram's
--Shree Rathnam
--Frontier
--Moti Mahal Delux
--Bikanervala
--Aggarwal Sweets
--Behrouz Biryani
--Karim's
--Bikaner Sweets
--Chicago Pizza
--Apni Rasoi
--34, Chowringhee Lane
--Wow! Momo
--Madras Cafe
--Burger Point
```

- **Analyze the ratings and popularity of different restaurant chains.**

In [24]:
```
restaurant_chain_stats=resto_df.groupby('Restaurant Name').agg({
    'Aggregate rating':'mean',
    'Votes':'sum',
}).reset_index()

restaurant_chain_stats.columns=['Restaurant Name','Average rating','Total Votes']
restaurant_chain_stats=restaurant_chain_stats.sort_values(by='Total Votes',ascending=False)
print("Restaurant Chain Rating and Popularity Analysis (Sorted by Total Votes):")
print(restaurant_chain_stats.head(20))
```

```
Restaurant Chain Rating and Popularity Analysis (Sorted by Total Votes):
                Restaurant Name  Average rating  Total Votes
663              Barbeque Nation        4.353846        28142
101   AB's - Absolute Barbecues        4.825000        13400
6943                        Toit        4.800000        10934
785                    Big Chill        4.475000        10853
2297                  Farzi Cafe        4.366667        10098
6988                    Truffles        3.950000         9682
1510                     Chili's        4.580000         8156
2879            Hauz Khas Social        4.300000         7931
3261                 Joey's Pizza        4.250000         7807
4902                   Peter Cat        4.300000         7574
796              Big Yellow Door        4.266667         7511
5571              Saravana Bhavan        4.133333         7238
6080                   Starbucks        3.805556         7139
4941            Pirates of Grill        4.025000         7091
3405                     Karim's        3.030769         6878
2098              Domino's Pizza        2.740506         6643
6106                      Subway        2.907937         6124
2145              Dunkin' Donuts        3.136364         5974
783                  Big Brewsky        4.500000         5705
4924               Pind Balluchi        2.630000         5582
```

Observations

- Restaurant Chain Rating and Popularity Analysis (Sorted by Total Votes)
    - Barbeque Nation
    - AB's - Absolute Barbecues
    - Toit
    - Big Chill
    - Farzi Cafe