LEVEL 2 : TASK 1 : RESTAURANT RATING

IMPORT LIBRARIES

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

DATA COLLECTION

In [2]:
```
df=pd.read_csv('Dataset .csv',encoding='unicode_escape')
```

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

Out[3]:

	ï»¿Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	C
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	...	B
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	...	B
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	...	B
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	...	B
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	...	B

5 rows × 21 columns

In [4]:
```
df.shape
```

Out[4]:
```
(9551, 21)
```

TO CHECK NULL VALUES

In [5]:
```
pd.isnull(df).sum()
```

Out[5]:
```
ï»¿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
```

TO DELETE NULL VALUES

In [6]:
```
df.dropna(inplace=True)
```

In [7]:
```
df.shape
```

Out[7]:
```
(9542, 21)
```

In [8]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9542 entries, 0 to 9550
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   ï»¿Restaurant ID      9542 non-null   int64  
 1   Restaurant Name       9542 non-null   object 
 2   Country Code          9542 non-null   int64  
 3   City                  9542 non-null   object 
 4   Address               9542 non-null   object 
 5   Locality              9542 non-null   object 
 6   Locality Verbose      9542 non-null   object 
 7   Longitude             9542 non-null   float64
 8   Latitude              9542 non-null   float64
 9   Cuisines              9542 non-null   object 
 10  Average Cost for two  9542 non-null   int64  
 11  Currency              9542 non-null   object 
 12  Has Table booking     9542 non-null   object 
 13  Has Online delivery   9542 non-null   object 
 14  Is delivering now     9542 non-null   object 
 15  Switch to order menu  9542 non-null   object 
 16  Price range           9542 non-null   int64  
 17  Aggregate rating      9542 non-null   float64
 18  Rating color          9542 non-null   object 
 19  Rating text           9542 non-null   object 
 20  Votes                 9542 non-null   int64  
dtypes: float64(3), int64(5), object(13)
memory usage: 1.6+ MB
```

In [9]:
```
df.describe()
```

Out[9]:

	ï»¿Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Aggregate rating	Votes
count	9.542000e+03	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000
mean	9.043301e+06	18.179208	64.274997	25.848532	1200.326137	1.804968	2.665238	156.772060
std	8.791967e+06	56.451600	41.197602	11.010094	16128.743876	0.905563	1.516588	430.203324
min	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0.000000	0.000000
25%	3.019312e+05	1.000000	77.081565	28.478658	250.000000	1.000000	2.500000	5.000000
50%	6.002726e+06	1.000000	77.192031	28.570444	400.000000	2.000000	3.200000	31.000000
75%	1.835260e+07	1.000000	77.282043	28.642711	700.000000	2.000000	3.700000	130.000000
max	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4.900000	10934.000000

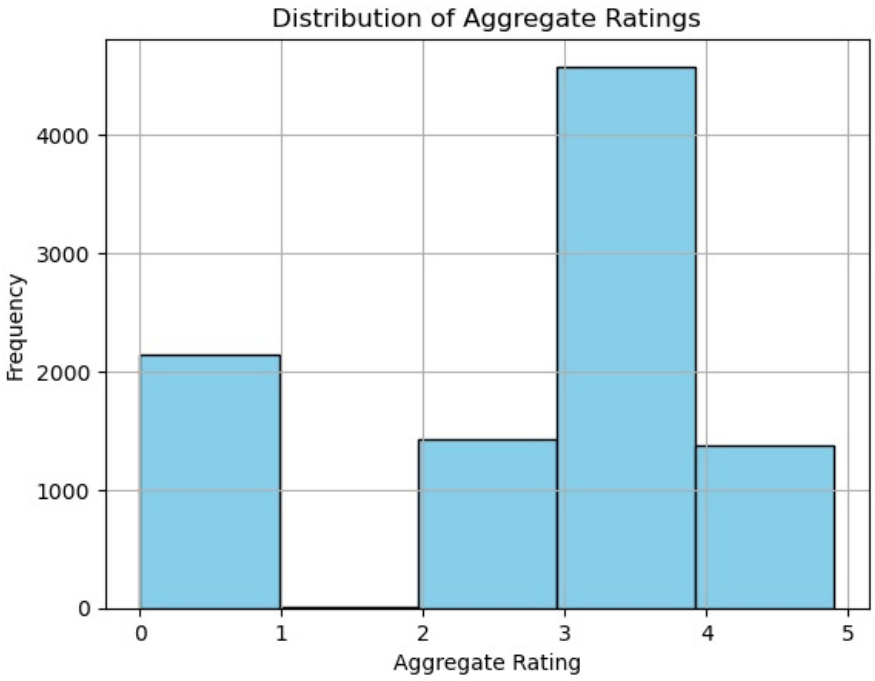
ANALYZE THE DISTRIBUTION OF AGGREGATE RATINGS AND DETERMINE THE MOST COMMON

RATING RANGE.

In [10]:
```
df.columns
```

Out[10]:
```
Index(['ï»¿Restaurant ID', 'Restaurant Name', 'Country Code', 'City',
       'Address', 'Locality', 'Locality Verbose', 'Longitude', 'Latitude',
       'Cuisines', 'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes'],
      dtype='object')
```

In [11]:
```
# Plotting the distribution of aggregate ratings
plt.hist(df['Aggregate rating'], bins=5, color='skyblue', edgecolor='black')
plt.title('Distribution of Aggregate Ratings')
plt.xlabel('Aggregate Rating')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



In [12]:
```
# Determine the most common rating range
rating_counts = df['Aggregate rating'].value_counts()
most_common_rating = rating_counts.idxmax()
most_common_rating_count = rating_counts.max()
```

In [13]:
```
print(f"The most common rating range is {most_common_rating} with {most_common_rating_count} restaurants.")
```

```
The most common rating range is 0.0 with 2148 restaurants.
```

CALCULATE THE AVERAGE NUMBER OF VOTES RECEIVED BY RESTAURANTS.

In [14]:
```
# Calculate the average number of votes received by restaurants
average_votes = df['Votes'].mean()

print("Average number of votes received by restaurants:", average_votes)
```

```
Average number of votes received by restaurants: 156.7720603647034
```

LEVEL 2 : TASK 2 :CUISINE COMBINATION

IDENTIFY THE MOST COMMON COMBINATIONS OF CUISINES IN THE DATASET.

In [15]:
```
# Splitting cuisines and counting combinations
cuisine_combinations = df['Cuisines'].str.split(', ')
cuisine_counts = {}

for combination in cuisine_combinations:
    combination.sort()  # Sorting to ensure we count combinations regardless of order
    key = ', '.join(combination)
    cuisine_counts[key] = cuisine_counts.get(key, 0) + 1
```

In [16]:
```
# Finding the most common combination
most_common_combination = max(cuisine_counts, key=cuisine_counts.get)
```

```
frequency = cuisine_counts[most_common_combination]

print("Most common combination of cuisines:", most_common_combination)
print("Frequency:", frequency)
```

```
Most common combination of cuisines: North Indian
Frequency: 936
```

DETERMINE IF CERTAIN CUISINE COMBINATIONS TEND TO HAVE HIGHER RATINGS.

In [24]:
```
average_rating_by_combination = df.groupby(['Cuisines'])['Aggregate rating'].mean().reset_index().max()

print("Average ratings for cuisine combinations:")
print(average_rating_by_combination)
```

```
Average ratings for cuisine combinations:
Cuisines            World Cuisine, Patisserie, Cafe
Aggregate rating                                4.9
dtype: object
```

In [25]:
```
# Calculate the average rating for each cuisine combination
average_rating_by_combination = df.groupby(['Cuisines'])['Aggregate rating'].mean().reset_index()

print("Average ratings for cuisine combinations:")
print(average_rating_by_combination)
```

```
Average ratings for cuisine combinations:
                                      Cuisines  Aggregate rating
0                                      Afghani             0.725
1                        Afghani, Mughlai, Chinese             0.000
2                            Afghani, North Indian             0.000
3     Afghani, North Indian, Pakistani, Arabian             0.000
4                                      African             4.700
...                                        ...               ...
1820                     Western, Asian, Cafe             4.200
1821                 Western, Fusion, Fast Food             3.200
1822                              World Cuisine             4.900
1823            World Cuisine, Mexican, Italian             4.400
1824            World Cuisine, Patisserie, Cafe             4.200

[1825 rows x 2 columns]
```

LEVEL 2 : TASK 3 : GEOGRAPHIC ANALYSIS

PLOT THE LOCATIONS OF RESTAURANTS ON A MAP USING LONGITUDE AND LATITUDE COORDINATES.

In [30]:
```
!pip install folium
```

```
Defaulting to user installation because normal site-packages is not writeable
Collecting folium
  Obtaining dependency information for folium from https://files.pythonhosted.org/packages/18/09/8569904c8ce5679
cc02826d98de633c07abcd2443a23181e5f71ff9dacbc/folium-0.15.1-py2.py3-none-any.whl.metadata
  Downloading folium-0.15.1-py2.py3-none-any.whl.metadata (3.4 kB)
Collecting branca>=0.6.0 (from folium)
  Obtaining dependency information for branca>=0.6.0 from https://files.pythonhosted.org/packages/17/ce/14166d0e
273d12065516625fb02426350298e7b4ba59198b5fe454b46202/branca-0.7.1-py3-none-any.whl.metadata
  Downloading branca-0.7.1-py3-none-any.whl.metadata (1.5 kB)
Requirement already satisfied: jinja2>=2.9 in c:\anaconda\lib\site-packages (from folium) (3.1.2)
Requirement already satisfied: numpy in c:\anaconda\lib\site-packages (from folium) (1.24.3)
Requirement already satisfied: requests in c:\anaconda\lib\site-packages (from folium) (2.31.0)
Requirement already satisfied: xyzservices in c:\anaconda\lib\site-packages (from folium) (2022.9.0)
Requirement already satisfied: MarkupSafe>=2.0 in c:\anaconda\lib\site-packages (from jinja2>=2.9->folium) (2.1.
1)
Requirement already satisfied: charset-normalizer<4,>=2 in c:\anaconda\lib\site-packages (from requests->folium)
(2.0.4)
Requirement already satisfied: idna<4,>=2.5 in c:\anaconda\lib\site-packages (from requests->folium) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in c:\anaconda\lib\site-packages (from requests->folium) (1.26
.16)
Requirement already satisfied: certifi>=2017.4.17 in c:\anaconda\lib\site-packages (from requests->folium) (2024
.2.2)
Downloading folium-0.15.1-py2.py3-none-any.whl (97 kB)
   ---------------------------------------- 0.0/97.0 kB ? eta -:--:--
   ---- ----------------------------------- 10.2/97.0 kB ? eta -:--:--
   ---------------------------------------- 97.0/97.0 kB 1.8 MB/s eta 0:00:00
Downloading branca-0.7.1-py3-none-any.whl (25 kB)
Installing collected packages: branca, folium
Successfully installed branca-0.7.1 folium-0.15.1
```

In [31]:
```
import folium as fl
```

In [32]:
```
df.columns
```

Out[32]:
```
Index(['ï»¿Restaurant ID', 'Restaurant Name', 'Country Code', 'City',
       'Address', 'Locality', 'Locality Verbose', 'Longitude', 'Latitude',
       'Cuisines', 'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes'],
      dtype='object')
```

In [33]:
```
# Create a map centered on the mean latitude and longitude
map_restaurants = fl.Map(location=[df['Latitude'].mean(), df['Longitude'].mean()], zoom_start=5)
```

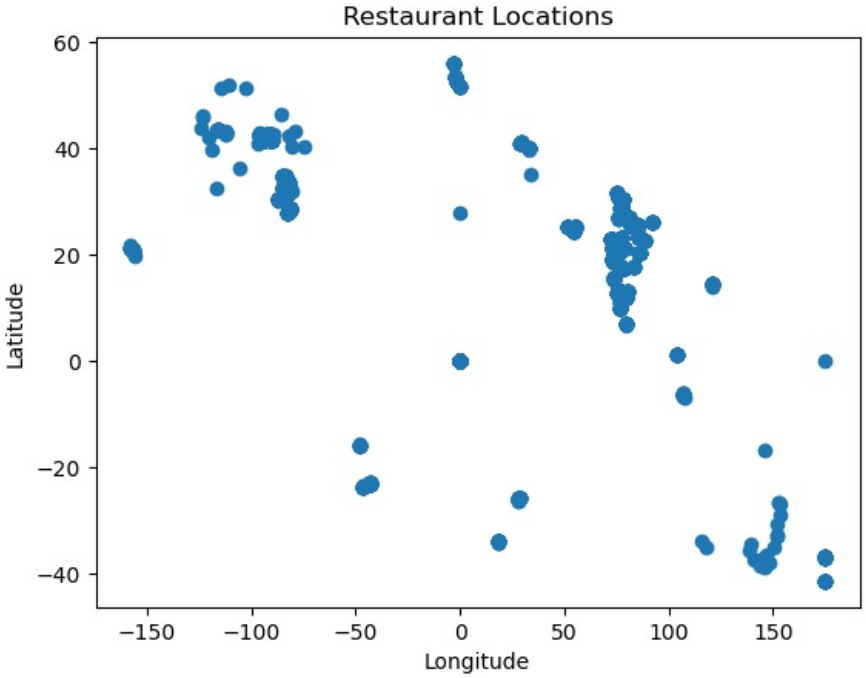
In [38]:
```
# Add markers for each restaurant
for i, row in df.iterrows():
    fl.Marker(location=[row['Latitude'], row['Longitude']], popup=row['Restaurant Name']).add_to(map_restaurants

# Display the map
map_restaurants.save('restaurants_map.html')
```

IDENTIFY ANY PATTERNS OR CLUSTERS OF RESTAURANTS IN SPECIFIC AREA.

In [39]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [41]:
```
# Visualize the data
plt.scatter(df['Longitude'], df['Latitude'])
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Restaurant Locations')
plt.show()
```



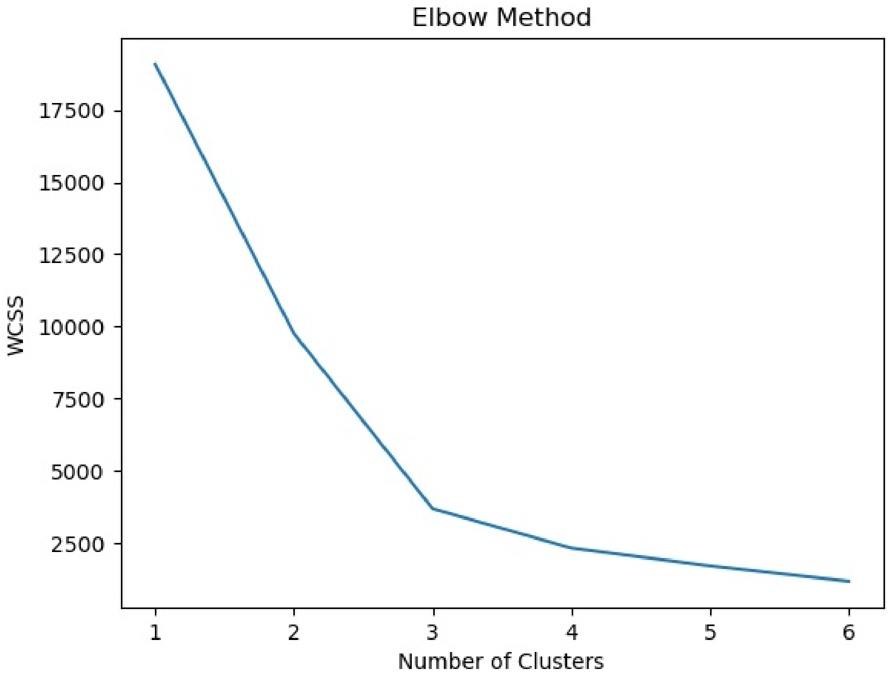
In [45]:
```
# Exclude non-numeric columns
numeric_columns = df[['Latitude', 'Longitude']]

# Standardize the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(numeric_columns)
```

In [46]:
```
# Determine the optimal number of clusters using the elbow method
wcss = []
for i in range(1, 7):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(scaled_data)
    wcss.append(kmeans.inertia_)

# Plot the elbow method
plt.plot(range(1, 7), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```

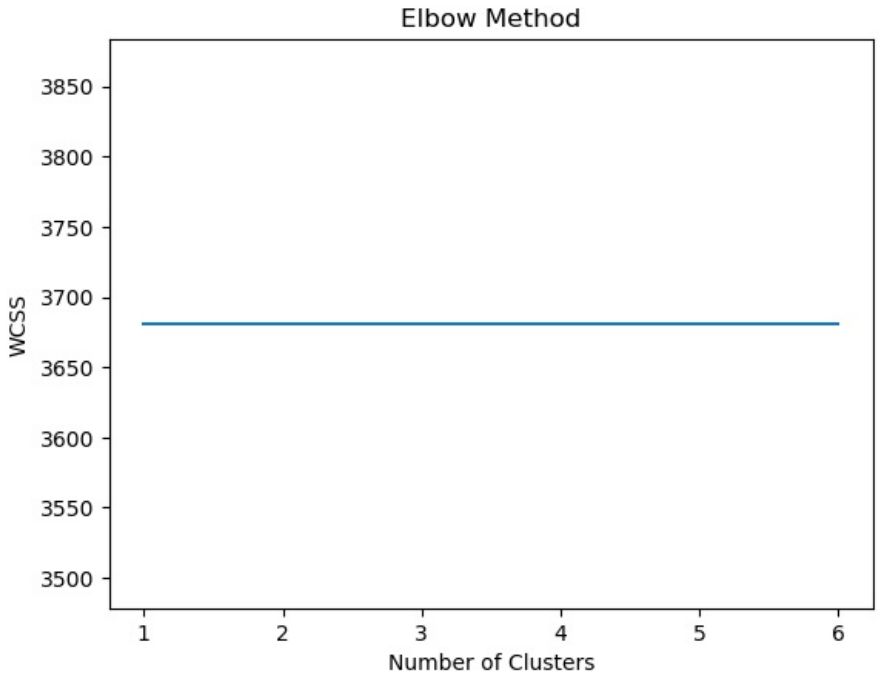
```
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
C:\Anaconda\Lib\site-packages\sklearn\cluster\_kmeans.py:1412: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```



In [47]:

```
# Determine the optimal number of clusters using the elbow method
wcss = []
for i in range(1, 7):
    kmeans = KMeans(n_clusters=3, init='k-means++', random_state=42, n_init=10)
    kmeans.fit(scaled_data)
    wcss.append(kmeans.inertia_)

# Plot the elbow method
plt.plot(range(1, 7), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



LEVEL 2 : TASK 4 : RESTAURANT CHAINS

IDENTIFY IF THERE ARE ANY RESTAURANT CHAINS PRESENT IN THE DATASET.

In [48]:
```
# Count the occurrences of each restaurant name
restaurant_counts = df['Restaurant Name'].value_counts()

# Find restaurant chains (those with more than one location)
restaurant_chains = restaurant_counts[restaurant_counts > 1]

# Print the list of restaurant chains
if len(restaurant_chains) > 0:
    print("Restaurant chains present in the dataset:")
    print(restaurant_chains)
else:
    print("No restaurant chains found in the dataset.")
```

```
Restaurant chains present in the dataset:
Restaurant Name
Cafe Coffee Day                   83
Domino's Pizza                    79
Subway                            63
Green Chick Chop                  51
McDonald's                        48
                                  ..
Zaika Kathi Rolls                  2
The Night Owl                      2
The Cheesecake Factory             2
New Kadimi                         2
Ceviche Tapas Bar & Restaurant     2
Name: count, Length: 734, dtype: int64
```

ANALYZE THE RATINGS AND POPULARITY OF DIFFERENT RESTAURANT CHAINS.

In [49]:
```
df.columns
```

Out[49]:
```
Index(['ï»¿Restaurant ID', 'Restaurant Name', 'Country Code', 'City',
       'Address', 'Locality', 'Locality Verbose', 'Longitude', 'Latitude',
       'Cuisines', 'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes'],
      dtype='object')
```

In [51]:
```
# Define a mapping of textual ratings to numeric values
rating_mapping = {
    'Good': 3,
    'Very Good': 4,
    'Excellent': 5,
    # Add more mappings as needed
}

# Map textual ratings to numeric values
```

```
df['Rating text'] = df['Rating text'].map(rating_mapping)

# Now calculate the mean rating and sum of num_ratings
chain_stats = df.groupby('Restaurant Name').agg({'Rating text': 'mean', 'Aggregate rating': 'sum'})
```

In [52]:
```
# Group by restaurant name and calculate average rating and total number of ratings
chain_stats = df.groupby('Restaurant Name').agg({'Rating text': 'mean', 'Aggregate rating': 'sum'})

# Sort the chains by total number of ratings to find the most popular ones
sorted_chains_by_popularity = chain_stats.sort_values(by='Aggregate rating', ascending=False)

# Sort the chains by average rating to find the highest-rated ones
sorted_chains_by_rating = chain_stats.sort_values(by='Rating text', ascending=False)

# Print the top 10 chains by popularity
print("Top 10 restaurant chains by popularity:")
print(sorted_chains_by_popularity.head(10))

# Print the top 10 highest-rated chains
print("\nTop 10 highest-rated restaurant chains:")
print(sorted_chains_by_rating.head(10))
```

```
Top 10 restaurant chains by popularity:
                  Rating text  Aggregate rating
Restaurant Name
Domino's Pizza       3.000000             216.5
Cafe Coffee Day      3.000000             200.8
Subway               3.000000             183.2
McDonald's           3.000000             160.3
Green Chick Chop     3.000000             136.3
Barbeque Nation      4.307692             113.2
Pizza Hut            3.666667              99.6
Keventers            3.000000              97.6
Giani                3.000000              78.0
Dunkin' Donuts       3.000000              69.0

Top 10 highest-rated restaurant chains:
                             Rating text  Aggregate rating
Restaurant Name
Licorish Bistro                      5.0               4.6
Sushi Leblon                         5.0               4.6
Sr. Sol 1                            5.0               4.6
La Plage                             5.0               4.6
Conï¿½_u                              5.0               4.8
Stacks And Racks                     5.0               4.6
Star Noodle                          5.0               4.6
La Favorita                          5.0               4.5
Kuremal Mohan Lal Kulfi Wale         5.0               4.5
Kuchi n Kream                        5.0               4.6
```

THANKYOU

CONNECT WITH ME:

LinkedIn: https://www.linkedin.com/in/harshita-sharma-b68154220/

GitHub: https://github.com/DATAPREDICTS

Instagram: https://www.instagram.com/datapredicts?utm_source=qr&igsh=czVzc2k5c3oxOWQ4

YouTube: https://youtube.com/@Datapredicts?si=eDKAqVciVxg23zab