EDA on Zomato dataset

In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
#checking version of libraries
pd.__version__
```

Out[4]: '2.1.4'

In [5]:
```
np.__version__
```

Out[5]: '1.26.4'

In [6]:
```
sns.__version__
```

Out[6]: '0.12.2'

In [172…
```
# read files
df_zomato=pd.read_csv('zomato.csv',encoding='latin1')
df_zomato2=pd.read_csv('zomato.csv',encoding='latin1')
df_countrycode=pd.read_excel('Country-Code.xlsx')
```

In [8]:
```
df_zomato.head()
```

Out[8]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency
0	6317637	Le Petit Souffle	162	Makati City	Third Floor,	Century City Mall,	Century City Mall,	121.027535	14.565443	French, Japanese,	...	Botswana Pula(P)

					Century City Mall, Kalayaan Avenu...	Poblacion, Makati City	Poblacion, Makati City, Mak...			Desserts		
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)
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)
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)
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong	121.057508	14.584450	Japanese, Korean	...	Botswana Pula(P)

Megamall, Ortigas...		City, Mandal...

5 rows × 21 columns

In [9]:
```
df_countrycode.head()
```

Out[9]:

	Country Code	Country
0	1	India
1	14	Australia
2	30	Brazil
3	37	Canada
4	94	Indonesia

In [10]:
```
#viewing name of all columns
df_zomato.columns
```

Out[10]:
```
Index(['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]:
```
df_zomato.shape
```

Out[11]:
```
(9551, 21)
```

In [12]:
```
df_zomato.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
```

In [13]:
```
#removing some unwanted columns
df_zomato.drop(columns=['Longitude','Latitude','Restaurant ID','Address','Locality Verbose'],axis=1,inplace=True)
```

In [14]:
```
df_zomato
```

Out[14]:

	Restaurant Name	Country Code	City	Locality	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregat ratin
0	Le Petit Souffle	162	Makati City	Century City Mall,	French, Japanese,	1100	Botswana Pula(P)	Yes	No	No	No	3	4.

				Poblacion, Makati City	Desserts								
1	Izakaya Kikufuji	162	Makati City	Little Tokyo, Legaspi Village, Makati City	Japanese	1200	Botswana Pula(P)	Yes	No	No	No	3	4.
2	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	Yes	No	No	No	4	4.
3	Ooma	162	Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	No	No	No	No	4	4.
4	Sambo Kojin	162	Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	Yes	No	No	No	4	4.
...	...	...	...	...	...	...	...	...	...	...	...	...	.
9546	NamlÛ± Gurme	208	ÛÁstanbul	Karakí_y	Turkish	80	Turkish Lira(TL)	No	No	No	No	3	4.
9547	Ceviz AÛôacÛ±	208	ÛÁstanbul	Ko^ôuyolu	World Cuisine, Patisserie, Cafe	105	Turkish Lira(TL)	No	No	No	No	3	4.

9548	Huqqa	208	ÛÁstanbul	Kuruí_e^ôme	Italian, World Cuisine	170	Turkish Lira(TL)	No	No	No	No	4	3.
9549	A^ô^ôk Kahve	208	ÛÁstanbul	Kuruí_e^ôme	Restaurant Cafe	120	Turkish Lira(TL)	No	No	No	No	4	4.
9550	Walter's Coffee Roastery	208	ÛÁstanbul	Moda	Cafe	55	Turkish Lira(TL)	No	No	No	No	2	4.

9551 rows × 16 columns

In [15]:
```
df_zomato.columns
```

Out[15]:
```
Index(['Restaurant Name', 'Country Code', 'City', 'Locality', '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 [16]:
```
df_zomato.describe()
```

Out[16]:

	Country Code	Average Cost for two	Price range	Aggregate rating	Votes
count	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000
mean	18.365616	1199.210763	1.804837	2.666370	156.909748
std	56.750546	16121.183073	0.905609	1.516378	430.169145
min	1.000000	0.000000	1.000000	0.000000	0.000000
25%	1.000000	250.000000	1.000000	2.500000	5.000000
50%	1.000000	400.000000	2.000000	3.200000	31.000000

75%	1.000000	700.000000	2.000000	3.700000	131.000000
max	216.000000	800000.000000	4.000000	4.900000	10934.000000

In [17]:

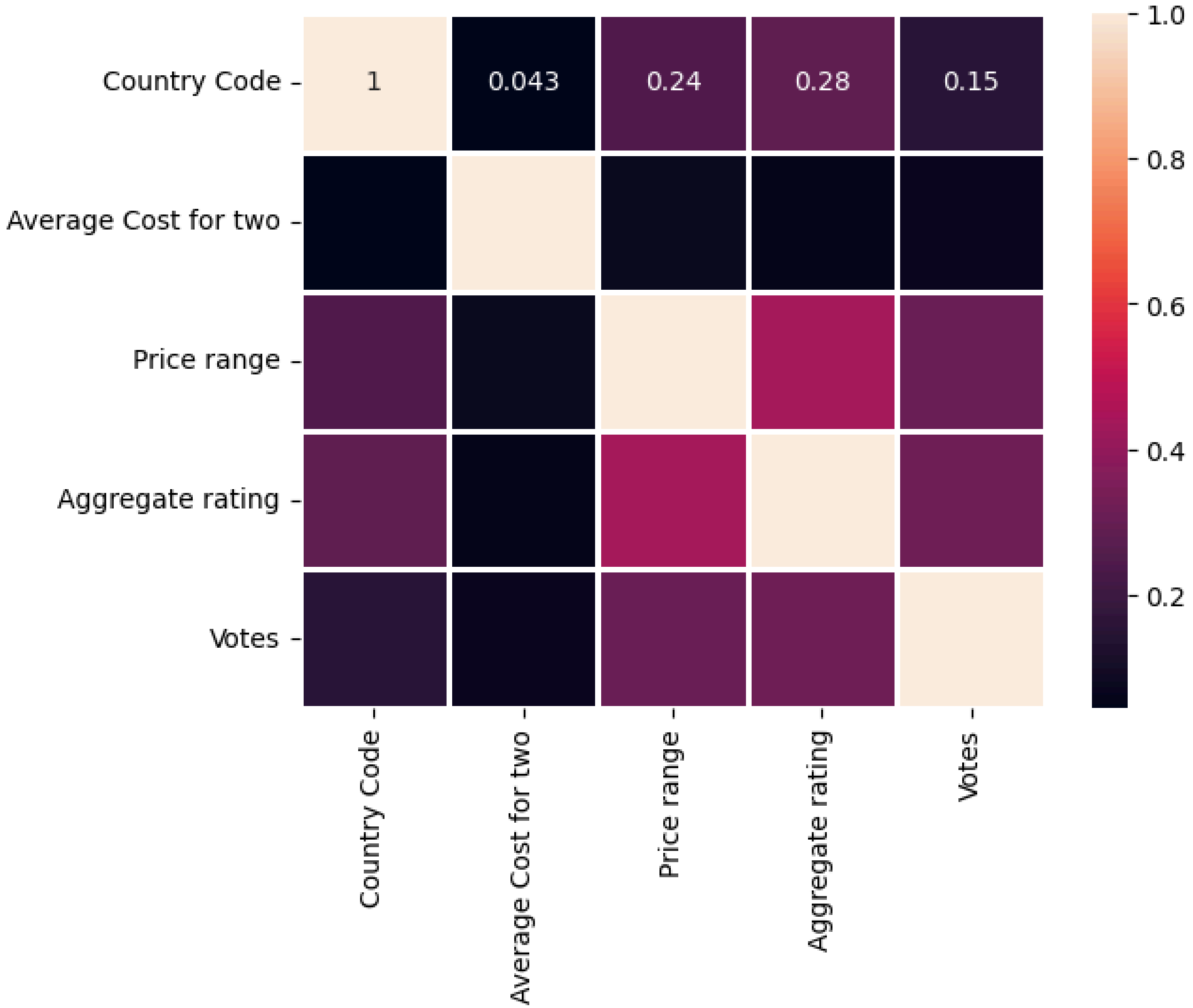
```python
#seperationg out int and float type numeric data
numeric_df = df_zomato.select_dtypes(include=['int64', 'float64'])
```

In [195…

```python
#plotting a correlation heatmap for numeric data
sns.heatmap(numeric_df.corr(),
            annot=True,
            linewidths=1)
```

Out[195…

```
<Axes: >
```



In [19]:

```
#checking missing values
df_zomato.isnull().sum()
```

Out[19]:

```
Restaurant Name         0
Country Code            0
City                    0
Locality                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 [20]:
```
#missing values in terms of percentage
perc_missingdata=df_zomato.isnull().sum()*100/len(df_zomato)
perc_missingdata
```

Out[20]:
```
Restaurant Name         0.000000
Country Code            0.000000
City                    0.000000
Locality                0.000000
Cuisines                0.094231
Average Cost for two    0.000000
Currency                0.000000
Has Table booking       0.000000
Has Online delivery     0.000000
Is delivering now       0.000000
Switch to order menu    0.000000
Price range             0.000000
Aggregate rating        0.000000
Rating color            0.000000
Rating text             0.000000
Votes                   0.000000
dtype: float64
```

In [21]:
```
missing_df=pd.DataFrame({'variables':df_zomato.columns,
                        'Percent_Missing':perc_missingdata})
missing_df.sort_values('Percent_Missing',inplace=True)
```

```
In [22]: missing_df
```

Out[22]:

	variables	Percent_Missing
Restaurant Name	Restaurant Name	0.000000
Country Code	Country Code	0.000000
City	City	0.000000
Locality	Locality	0.000000
Average Cost for two	Average Cost for two	0.000000
Currency	Currency	0.000000
Has Table booking	Has Table booking	0.000000
Has Online delivery	Has Online delivery	0.000000
Is delivering now	Is delivering now	0.000000
Switch to order menu	Switch to order menu	0.000000
Price range	Price range	0.000000
Aggregate rating	Aggregate rating	0.000000
Rating color	Rating color	0.000000
Rating text	Rating text	0.000000
Votes	Votes	0.000000
Cuisines	Cuisines	0.094231

```
In [23]: #checking missing value for a particular column
df_zomato['Cuisines'].isnull().sum()
```

Out [23]: 9

In [24]:
```
subset_df=df_zomato[['Aggregate rating','Rating color','Rating text','Votes']]
subset_df
```

Out [24]:

	Aggregate rating	Rating color	Rating text	Votes
0	4.8	Dark Green	Excellent	314
1	4.5	Dark Green	Excellent	591
2	4.4	Green	Very Good	270
3	4.9	Dark Green	Excellent	365
4	4.8	Dark Green	Excellent	229
...	...	...	...	...
9546	4.1	Green	Very Good	788
9547	4.2	Green	Very Good	1034
9548	3.7	Yellow	Good	661
9549	4.0	Green	Very Good	901
9550	4.0	Green	Very Good	591

9551 rows × 4 columns

In [25]:
```
subset_df['Rating color'].value_counts()
```

Out [25]:
```
Rating color
Orange        3737
White         2148
Yellow        2100
Green         1079
```

```
Dark Green     301
Red            186
Name: count, dtype: int64
```

In [26]:
```
subset_df['Rating text'].value_counts()
```

Out[26]:
```
Rating text
Average      3737
Not rated    2148
Good         2100
Very Good    1079
Excellent     301
Poor          186
Name: count, dtype: int64
```

In [27]:
```
df_zomato['Has Table booking'].value_counts()
```

Out[27]:
```
Has Table booking
No     8393
Yes    1158
Name: count, dtype: int64
```

In [28]:
```
result_rating = subset_df.groupby('Rating color')[['Aggregate rating', 'Rating text']].aggregate(['min', 'max'])
```

In [29]:
```
result_rating
```

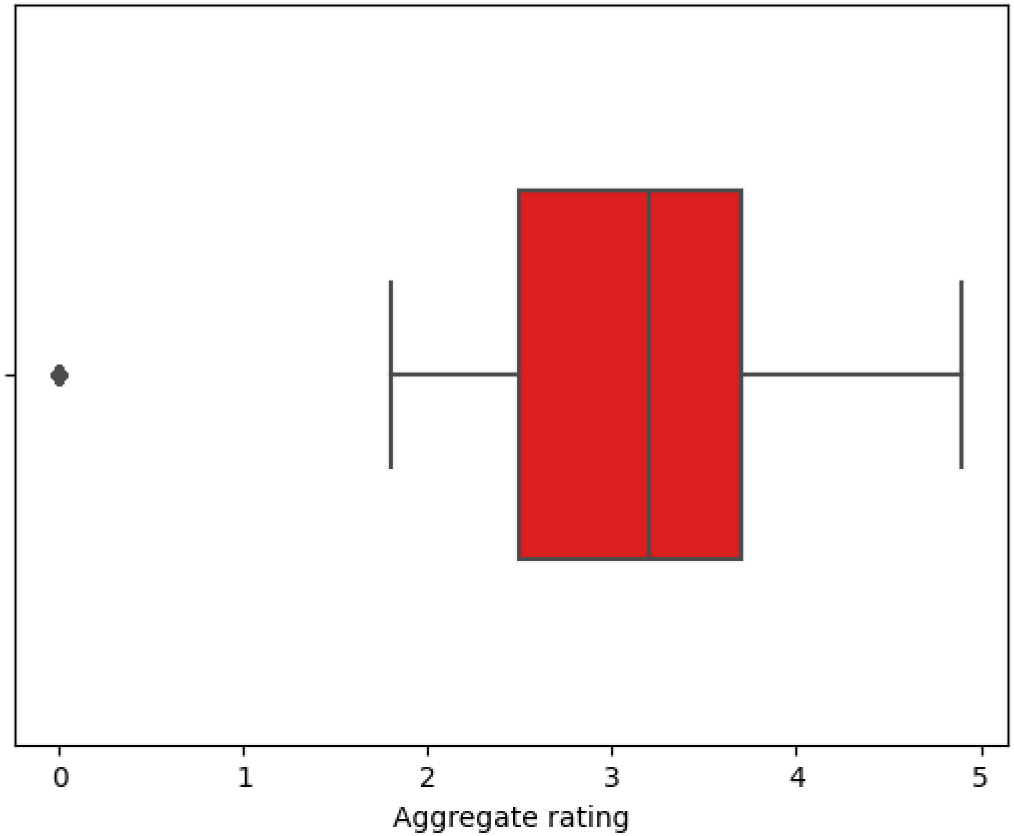
Out[29]:

	Aggregate rating		Rating text	
	min	max	min	max
Rating color				
Dark Green	4.5	4.9	Excellent	Excellent
Green	4.0	4.4	Very Good	Very Good
Orange	2.5	3.4	Average	Average
Red	1.8	2.4	Poor	Poor

White	0.0	0.0	Not rated	Not rated
Yellow	3.5	3.9	Good	Good

In [30]:
```
#boxplot
sns.boxplot(data=df_zomato,
            x='Aggregate rating',
            color='Red',
            width=0.5)
```

Out[30]: <Axes: xlabel='Aggregate rating'>



In [31]:
```
#75% of aggerate rating lie between 2.5 to 3.5
```

In [32]:
```python
join_df=pd.merge(left=df_zomato,
                right=df_countrycode,
                left_on='Country Code',
                right_on='Country Code',
                how='inner')
```

In [33]:
```python
join_df.head()
```

Out[33]:

	Restaurant Name	Country Code	City	Locality	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating
0	Le Petit Souffle	162	Makati City	Century City Mall, Poblacion, Makati City	French, Japanese, Desserts	1100	Botswana Pula(P)	Yes	No	No	No	3	4.8
1	Izakaya Kikufuji	162	Makati City	Little Tokyo, Legaspi Village, Makati City	Japanese	1200	Botswana Pula(P)	Yes	No	No	No	3	4.5
2	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	Yes	No	No	No	4	4.4
3	Ooma	162	Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	No	No	No	No	4	4.9

4	Sambo Kojin	162	Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	Yes	No	No	No	4	4.8

In [34]:
```
df_countrycode.head()
```

Out[34]:

	Country Code	Country
0	1	India
1	14	Australia
2	30	Brazil
3	37	Canada
4	94	Indonesia

In [35]:
```
join_df.shape
```

Out[35]:
```
(9551, 17)
```

In [36]:
```
currency_df=join_df.loc[:,['Country Code','Currency']]
currency_df.value_counts()
```

Out[36]:
```
Country Code  Currency
1             Indian Rupees(Rs.)        8652
216           Dollar($)                  434
215           Pounds(£)                   80
30            Brazilian Real(R$)          60
189           Rand(R)                     60
214           Emirati Diram(AED)          60
148           NewZealand($)               40
208           Turkish Lira(TL)            34
14            Dollar($)                   24
```

```
162          Botswana Pula(P)          22
94           Indonesian Rupiah(IDR)    21
166          Qatari Rial(QR)           20
184          Dollar($)                 20
191          Sri Lankan Rupee(LKR)     20
37           Dollar($)                  4
Name: count, dtype: int64
```

In [37]:
```python
join_df['Has Online delivery'].value_counts()
```

Out[37]:
```
Has Online delivery
No     7100
Yes    2451
Name: count, dtype: int64
```

In [38]:
```python
#penetration percentage countrywise
perc_penetration=join_df.Country.value_counts()*100/len(join_df['Country'])
```

In [39]:
```python
perc_penetration
```

Out[39]:
```
Country
India              90.587373
United States       4.544027
United Kingdom      0.837609
Brazil              0.628206
UAE                 0.628206
South Africa        0.628206
New Zealand         0.418804
Turkey              0.355984
Australia           0.251283
Phillipines         0.230342
Indonesia           0.219872
Singapore           0.209402
Qatar               0.209402
Sri Lanka           0.209402
Canada              0.041880
Name: count, dtype: float64
```

In [40]:
```python
country_values=join_df.Country.value_counts().values
country_values
```

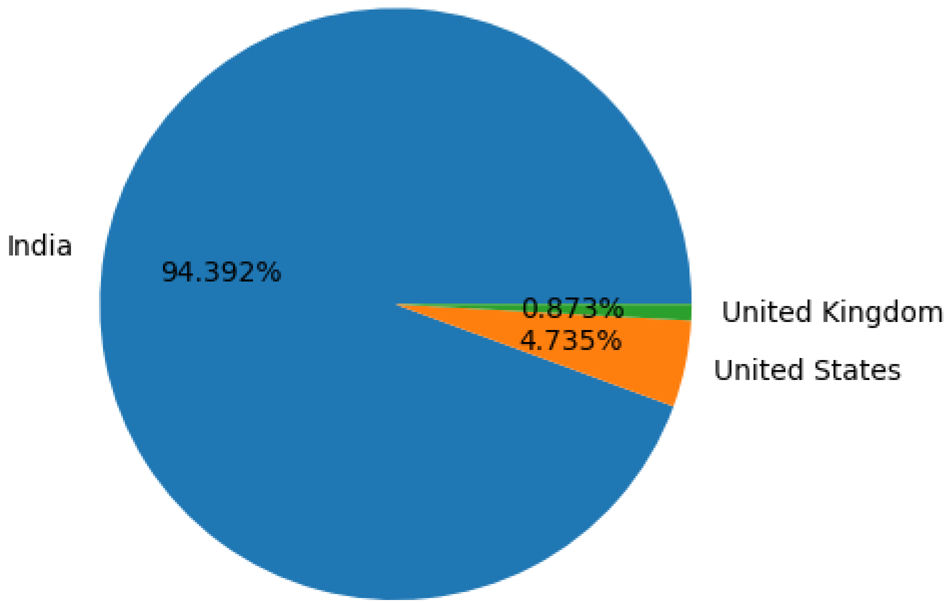
Out[40]:
```
array([8652,  434,   80,   60,   60,   60,   40,   34,   24,   22,   21,
         20,   20,   20,    4], dtype=int64)
```

In [41]:
```
country_names=join_df.Country.value_counts().index
country_names
```

Out[41]:
```
Index(['India', 'United States', 'United Kingdom', 'Brazil', 'UAE',
       'South Africa', 'New Zealand', 'Turkey', 'Australia', 'Phillipines',
       'Indonesia', 'Singapore', 'Qatar', 'Sri Lanka', 'Canada'],
      dtype='object', name='Country')
```

In [42]:
```
plt.pie(country_values[:3],labels=country_names[:3],autopct='%1.3f%%')
```

Out[42]:
```
([<matplotlib.patches.Wedge at 0x22a5c57d410>,
  <matplotlib.patches.Wedge at 0x22a5c5f6f10>,
  <matplotlib.patches.Wedge at 0x22a5c604d10>],
 [Text(-1.0829742700952103, 0.19278674827836725, 'India'),
  Text(1.077281715838356, -0.22240527134123297, 'United States'),
  Text(1.0995865153823035, -0.03015783794312073, 'United Kingdom')],
 [Text(-0.590713238233751, 0.10515640815183668, '94.392%'),
  Text(0.5876082086391032, -0.12131196618612707, '4.735%'),
  Text(0.5997744629358018, -0.01644972978715676, '0.873%')])
```



In [43]:
```
#country and online delivery
join_df.groupby(['Country','Has Online delivery']).size().reset_index()
```

Out[43]:

	Country	Has Online delivery	0
0	Australia	No	24
1	Brazil	No	60
2	Canada	No	4
3	India	No	6229
4	India	Yes	2423
5	Indonesia	No	21

6	New Zealand	No	40
7	Phillipines	No	22
8	Qatar	No	20
9	Singapore	No	20
10	South Africa	No	60
11	Sri Lanka	No	20
12	Turkey	No	34
13	UAE	No	32
14	UAE	Yes	28
15	United Kingdom	No	80
16	United States	No	434

In [44]:
```
#which country has online delivery option in zomato
join_df[join_df['Has Online delivery']=='Yes'].Country.value_counts()
```

Out[44]:
```
Country
India    2423
UAE        28
Name: count, dtype: int64
```

In [45]:
```
join_df[join_df['Has Online delivery']=='No'].Country.value_counts()
```

Out[45]:
```
Country
India             6229
United States      434
United Kingdom      80
Brazil              60
South Africa        60
New Zealand         40
```

```
Turkey                34
UAE                   32
Australia             24
Phillipines           22
Indonesia             21
Singapore             20
Qatar                 20
Sri Lanka             20
Canada                 4
Name: count, dtype: int64
```

In [46]:
```
join_df.loc[join_df['Has Online delivery']=='Yes',['Country','Currency']].value_counts()
```

Out[46]:
```
Country  Currency
India    Indian Rupees(Rs.)    2423
UAE      Emirati Diram(AED)      28
Name: count, dtype: int64
```

In [47]:
```
join_df.loc[join_df['Has Online delivery']=='No',['Country','Currency']].value_counts()
```

Out[47]:
```
Country         Currency
India           Indian Rupees(Rs.)        6229
United States   Dollar($)                  434
United Kingdom  Pounds(� £)                 80
Brazil          Brazilian Real(R$)          60
South Africa    Rand(R)                     60
New Zealand     NewZealand($)               40
Turkey          Turkish Lira(TL)            34
UAE             Emirati Diram(AED)          32
Australia       Dollar($)                   24
Phillipines     Botswana Pula(P)            22
Indonesia       Indonesian Rupiah(IDR)      21
Qatar           Qatari Rial(QR)             20
Singapore       Dollar($)                   20
Sri Lanka       Sri Lankan Rupee(LKR)       20
Canada          Dollar($)                    4
Name: count, dtype: int64
```

In [95]:
```
#data of indian restaurants
indian_cities=join_df[join_df['Country']=='India']
```

In [97]:

```
indian_cities
```

Out[97]:

	Restaurant Name	Country Code	City	Locality	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Ra c
624	Jahanpanah	1	Agra	Agra Cantt	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	No	3	3.9	Yel
625	Rangrezz Restaurant	1	Agra	Agra Cantt	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	No	2	3.5	Yel
626	Time2Eat - Mama Chicken	1	Agra	Agra Cantt	North Indian	500	Indian Rupees(Rs.)	No	No	No	No	2	3.6	Yel
627	Chokho Jeeman Marwari Jain Bhojanalya	1	Agra	Civil Lines	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	No	2	4.0	Gr
628	Pinch Of Spice	1	Agra	Civil Lines	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	No	3	4.2	Gr
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
9271	D Cabana	1	Vizag	Sagar Nagar	Continental, Seafood, Chinese,	600	Indian Rupees(Rs.)	No	No	No	No	2	3.6	Yel

					North Indian, B...									
9272	Kaloreez	1	Vizag	Siripuram	Cafe, North Indian, Chinese	400	Indian Rupees(Rs.)	No	No	No	No	2	3.7	Yel
9273	Plot 17	1	Vizag	Siripuram	Burger, Pizza, Biryani	600	Indian Rupees(Rs.)	No	No	No	No	2	4.3	Gr
9274	Vista - The Park	1	Vizag	The Park, Lawsons Bay	American, North Indian, Thai, Continental	1500	Indian Rupees(Rs.)	No	No	No	No	4	3.8	Yel
9275	Flying Spaghetti Monster	1	Vizag	Waltair Uplands	Italian	1400	Indian Rupees(Rs.)	No	No	No	No	3	4.4	Gr

8652 rows × 17 columns

In [99]:
```
indian_cities.shape
```

Out[99]:
```
(8652, 17)
```

In [101…
```
#viewing cities count
city_count=indian_cities['City'].value_counts()
```

In [103…
```
city_count
```

Out[103…
```
City
New Delhi       5473
Gurgaon         1118
Noida           1080
```

```
Faridabad        251
Ghaziabad         25
Ahmedabad         21
Guwahati          21
Lucknow           21
Bhubaneshwar      21
Amritsar          21
Pune              20
Puducherry        20
Patna             20
Ludhiana          20
Ranchi            20
Surat             20
Vadodara          20
Nashik            20
Nagpur            20
Mysore            20
Mumbai            20
Varanasi          20
Mangalore         20
Agra              20
Kochi             20
Kolkata           20
Dehradun          20
Allahabad         20
Aurangabad        20
Bangalore         20
Bhopal            20
Chennai           20
Coimbatore        20
Goa               20
Indore            20
Jaipur            20
Kanpur            20
Vizag             20
Chandigarh        18
Hyderabad         18
Secunderabad       2
Panchkula          1
Mohali             1
Name: count, dtype: int64
```

In [105…

```
#selecting first 5 cities from sorted city
city_count[:5]
```

Out[105…

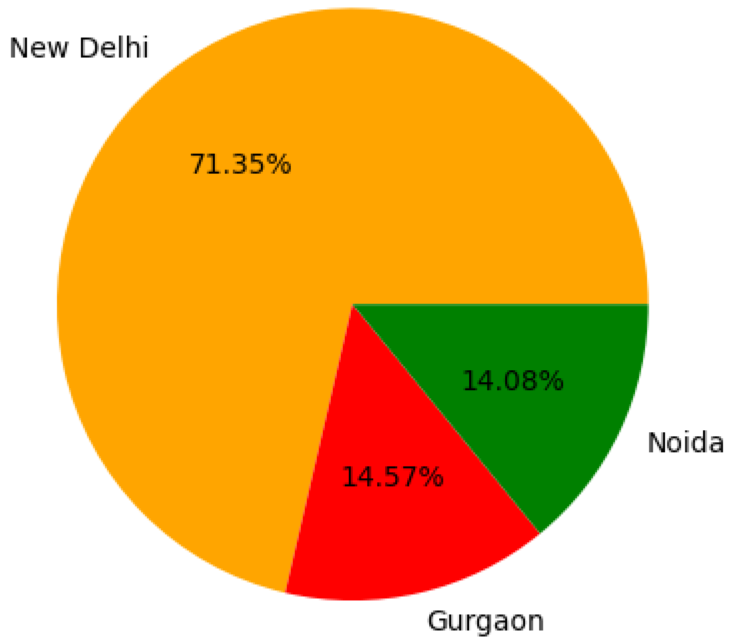
```
City
New Delhi    5473
Gurgaon      1118
Noida        1080
Faridabad     251
Ghaziabad      25
Name: count, dtype: int64
```

In [111…

```
#plotting a pie chart for top 5 cities
plt.pie(city_count.values[:3],
       labels=city_count.index[:3],
       autopct='%1.2f%%',
       colors=['orange','red','green'])
```

Out[111…

```
([<matplotlib.patches.Wedge at 0x22a5f282790>,
  <matplotlib.patches.Wedge at 0x22a5f276d10>,
  <matplotlib.patches.Wedge at 0x22a5f28fa90>],
 [Text(-0.6836225695617262, 0.8617773392157762, 'New Delhi'),
  Text(0.24897482286810813, -1.0714530029720364, 'Gurgaon'),
  Text(0.9941442744692855, -0.47082604169686504, 'Noida')],
 [Text(-0.37288503794275973, 0.47006036684496877, '71.35%'),
  Text(0.13580444883714987, -0.5844289107120197, '14.57%'),
  Text(0.542260513346883, -0.25681420456192633, '14.08%')])
```



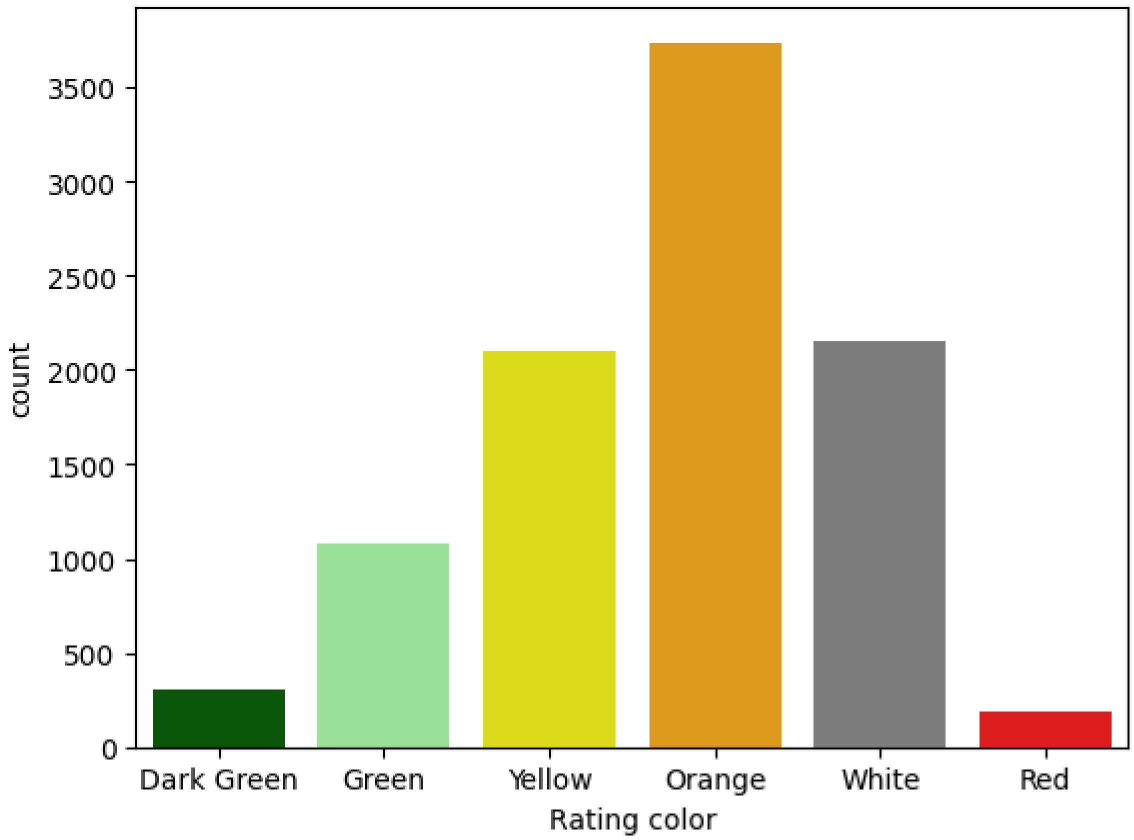
In [125…

```
sns.countplot(
    data=join_df,
    x='Rating color',
    palette=palette,
    order=['Dark Green', 'Green', 'Yellow', 'Orange', 'White', 'Red']
)
```

```
C:\Users\Aditya\anaconda3\Lib\site-packages\seaborn\categorical.py:641: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  grouped_vals = vals.groupby(grouper)
```

Out[125…

```
<Axes: xlabel='Rating color', ylabel='count'>
```



In [127…
```
result_rating
```

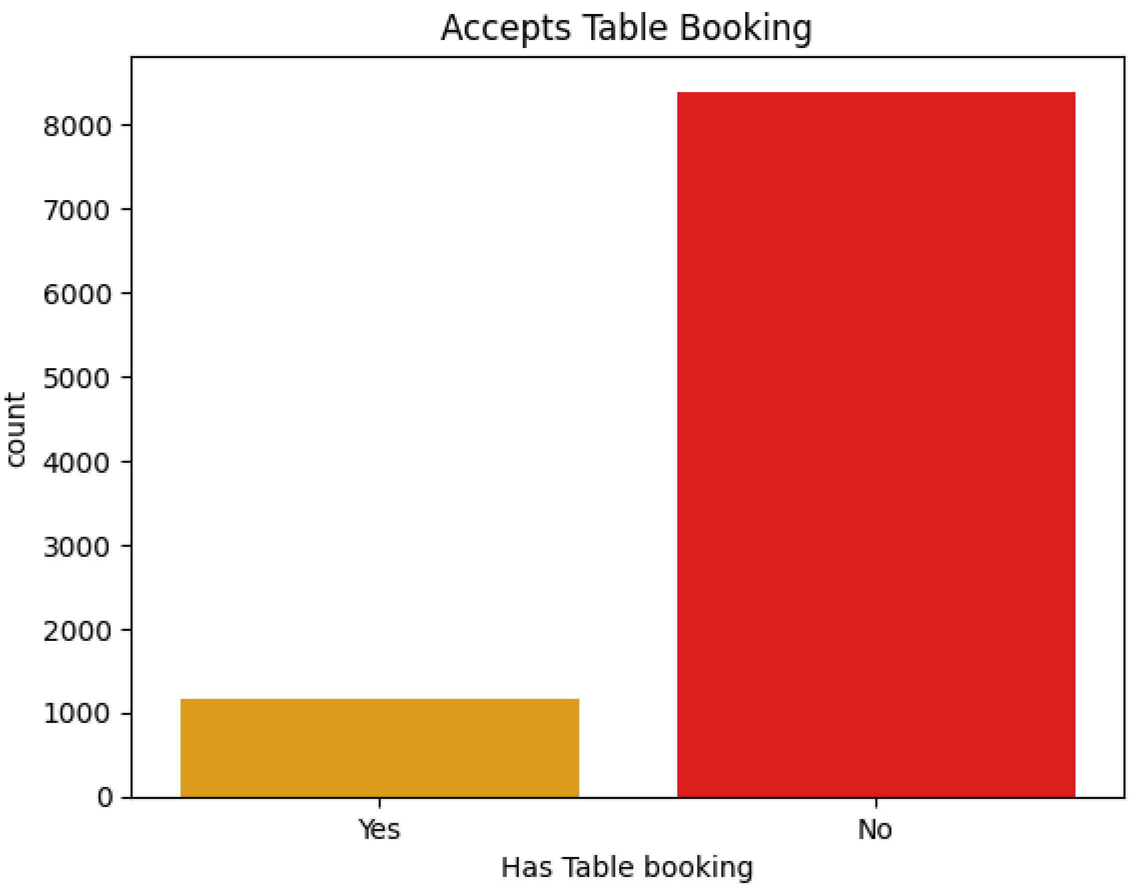
Out[127…

	Aggregate rating		Rating text	
	min	max	min	max
Rating color				
Dark Green	4.5	4.9	Excellent	Excellent
Green	4.0	4.4	Very Good	Very Good
Orange	2.5	3.4	Average	Average

Red	1.8	2.4	Poor	Poor
White	0.0	0.0	Not rated	Not rated
Yellow	3.5	3.9	Good	Good

In [131…

```
sns.countplot(data=join_df, x='Has Table booking', palette=['orange', 'red'])
plt.title('Accepts Table Booking')
plt.show()
```



In [141…

```
#what is the avg cost for two as per country
```

```
join_df.groupby('Country')['Average Cost for two'].mean().sort_values(ascending=False).round(1)
```

Out[141…

```
Country
Indonesia         281190.5
Sri Lanka           2375.0
Phillipines         1606.8
India                623.4
South Africa         419.7
Qatar                223.8
UAE                  166.4
Singapore            155.8
Brazil               134.7
Turkey                84.9
New Zealand           69.8
United Kingdom        47.8
Canada                36.2
United States         26.2
Australia             24.1
Name: Average Cost for two, dtype: float64
```

In [145…

```
#highest avg cost in indian cities

indian_cities.groupby('City')['Average Cost for two'].mean().sort_values(ascending=False)
```

Out[145…

```
City
Panchkula      2000.000000
Hyderabad      1361.111111
Pune           1337.500000
Jaipur         1310.000000
Kolkata        1272.500000
Bangalore      1232.500000
Goa            1175.000000
Ludhiana       1160.000000
Chennai        1085.000000
Mumbai         1072.500000
Chandigarh     1072.222222
Agra           1065.000000
Indore          960.000000
Kanpur          915.000000
Lucknow         859.523810
Ahmedabad       857.142857
```

```
Puducherry        842.500000
Secunderabad      825.000000
Guwahati          821.428571
Vadodara          820.000000
Mysore            814.500000
Surat             812.500000
Patna             797.500000
Mangalore         782.500000
Coimbatore        782.500000
Vizag             780.000000
Ranchi            735.000000
Kochi             730.000000
Dehradun          727.500000
Nagpur            715.000000
Gurgaon           714.016100
Bhubaneshwar      678.571429
Nashik            662.500000
Aurangabad        622.500000
Bhopal            620.000000
Ghaziabad         602.000000
New Delhi         596.088069
Mohali            550.000000
Noida             539.490741
Allahabad         517.500000
Varanasi          505.000000
Amritsar          480.952381
Faridabad         447.609562
Name: Average Cost for two, dtype: float64
```

In [147…

```
#lowest 3 avg cost in indian cities

indian_cities.groupby('City')['Average Cost for two'].mean().sort_values(ascending=False)[-3:]
```

Out[147…

```
City
Varanasi     505.000000
Amritsar     480.952381
Faridabad    447.609562
Name: Average Cost for two, dtype: float64
```

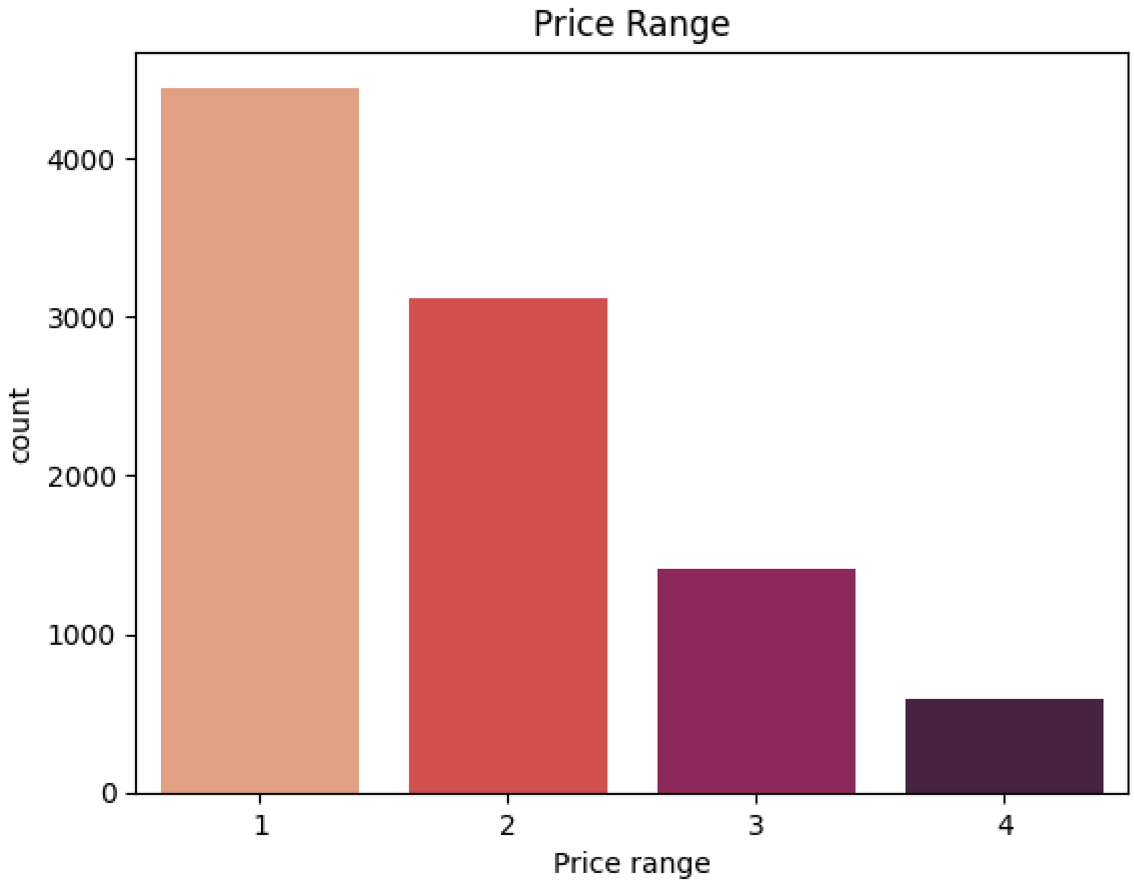
In [155…

```
join_df['Price range'] = join_df['Price range'].astype('category')
```

In [157…

```
#viewing price range of restaurants, where 1 means less expensive and 4 means highly expensive
sns.countplot(data=join_df, x='Price range', palette='rocket_r', order=sorted(join_df['Price range'].unique()))
plt.title('Price Range')
plt.show()
```

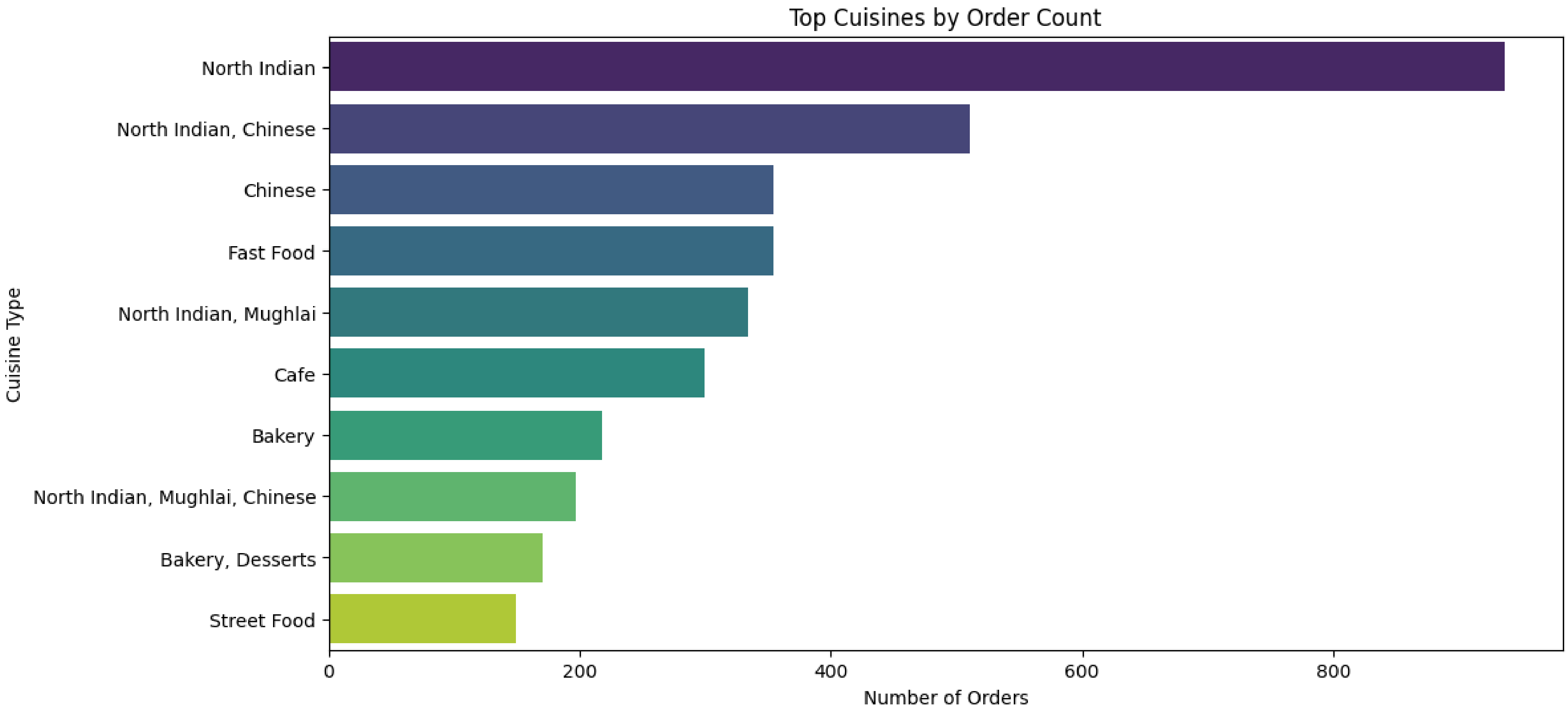
```
C:\Users\Aditya\anaconda3\Lib\site-packages\seaborn\categorical.py:641: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behav
ior or observed=True to adopt the future default and silence this warning.
  grouped_vals = vals.groupby(grouper)
```



In [159…

```
# Count the occurrences of each cuisine type
cuisine_counts = df_zomato['Cuisines'].value_counts().head(10)  # Displaying top 10 cuisines for clarity
```

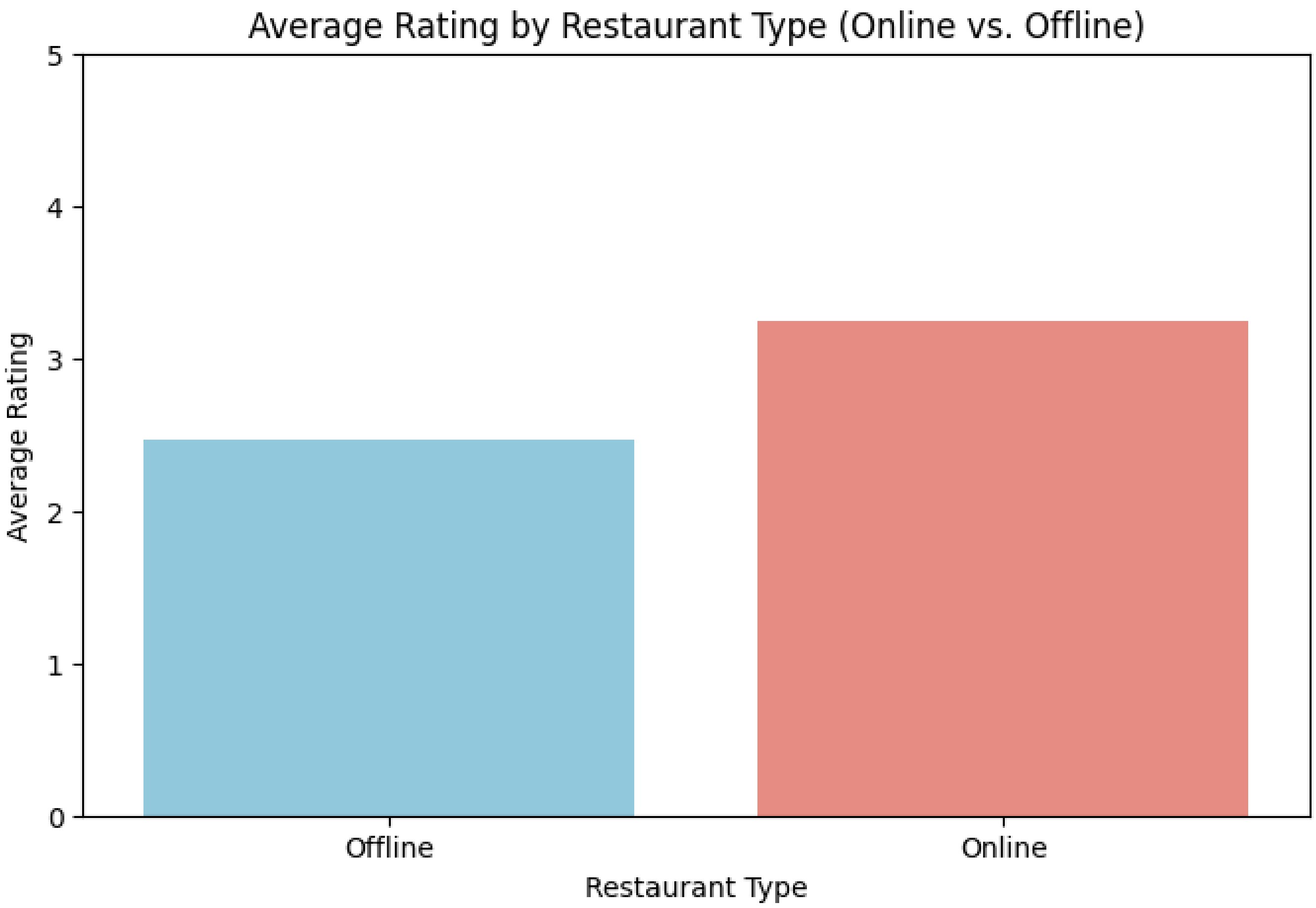
```python
# Plotting the data
plt.figure(figsize=(12, 6))
sns.barplot(x=cuisine_counts.values, y=cuisine_counts.index, palette='viridis')
plt.title('Top Cuisines by Order Count')
plt.xlabel('Number of Orders')
plt.ylabel('Cuisine Type')
plt.show()
```



In [161…

```python
df_zomato['Has Online delivery'] = df_zomato['Has Online delivery'].replace({'Yes': 'Online', 'No': 'Offline'})

# Calculate average rating for online and offline restaurants
rating_by_type = df_zomato.groupby('Has Online delivery')['Aggregate rating'].mean()

# Plotting the data
plt.figure(figsize=(8, 5))
```

```
sns.barplot(x=rating_by_type.index, y=rating_by_type.values, palette=['skyblue', 'salmon'])
plt.title('Average Rating by Restaurant Type (Online vs. Offline)')
plt.xlabel('Restaurant Type')
plt.ylabel('Average Rating')
plt.ylim(0, 5)  # Assuming the rating scale is from 0 to 5
plt.show()
```

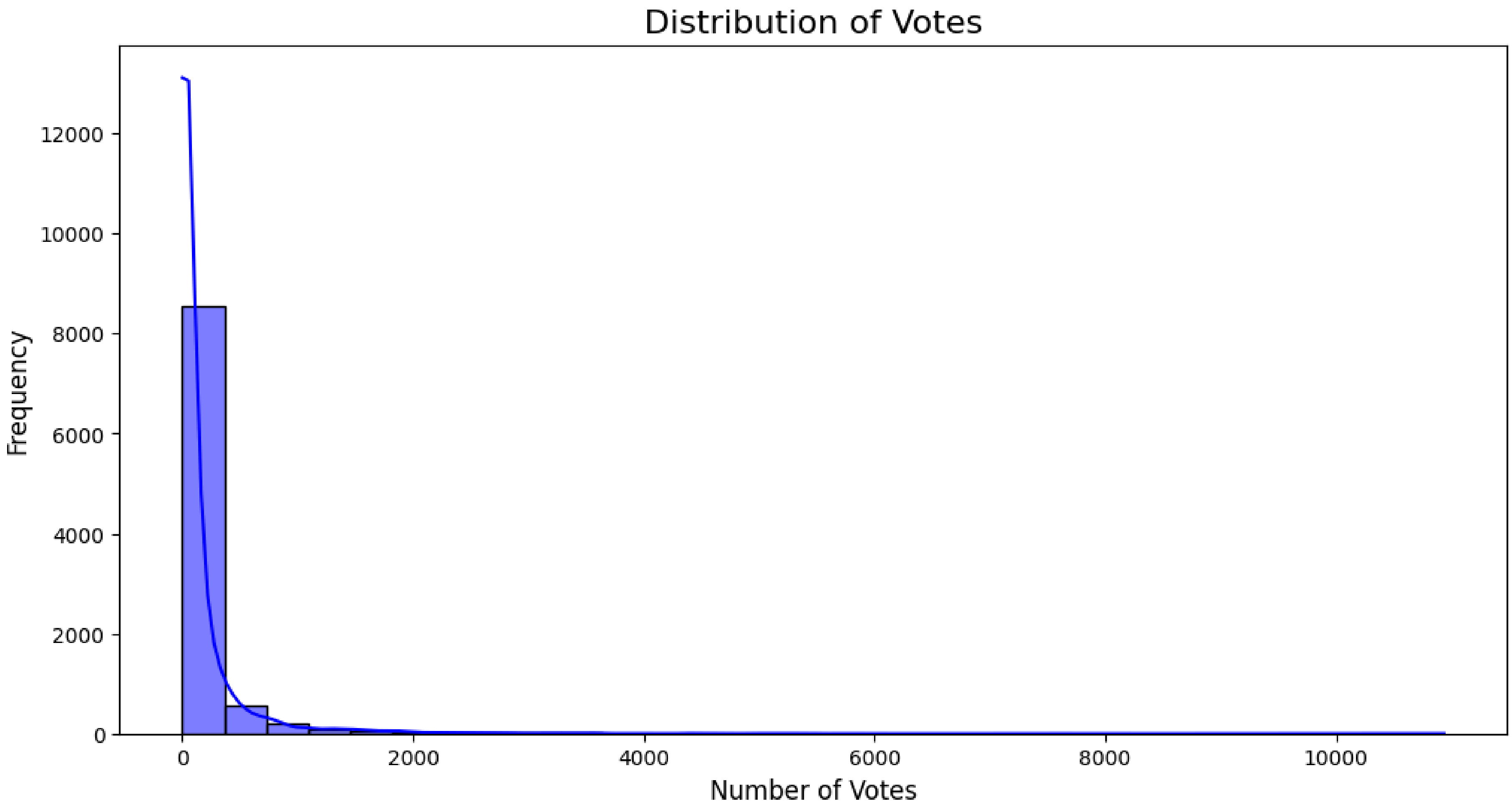


In [199…

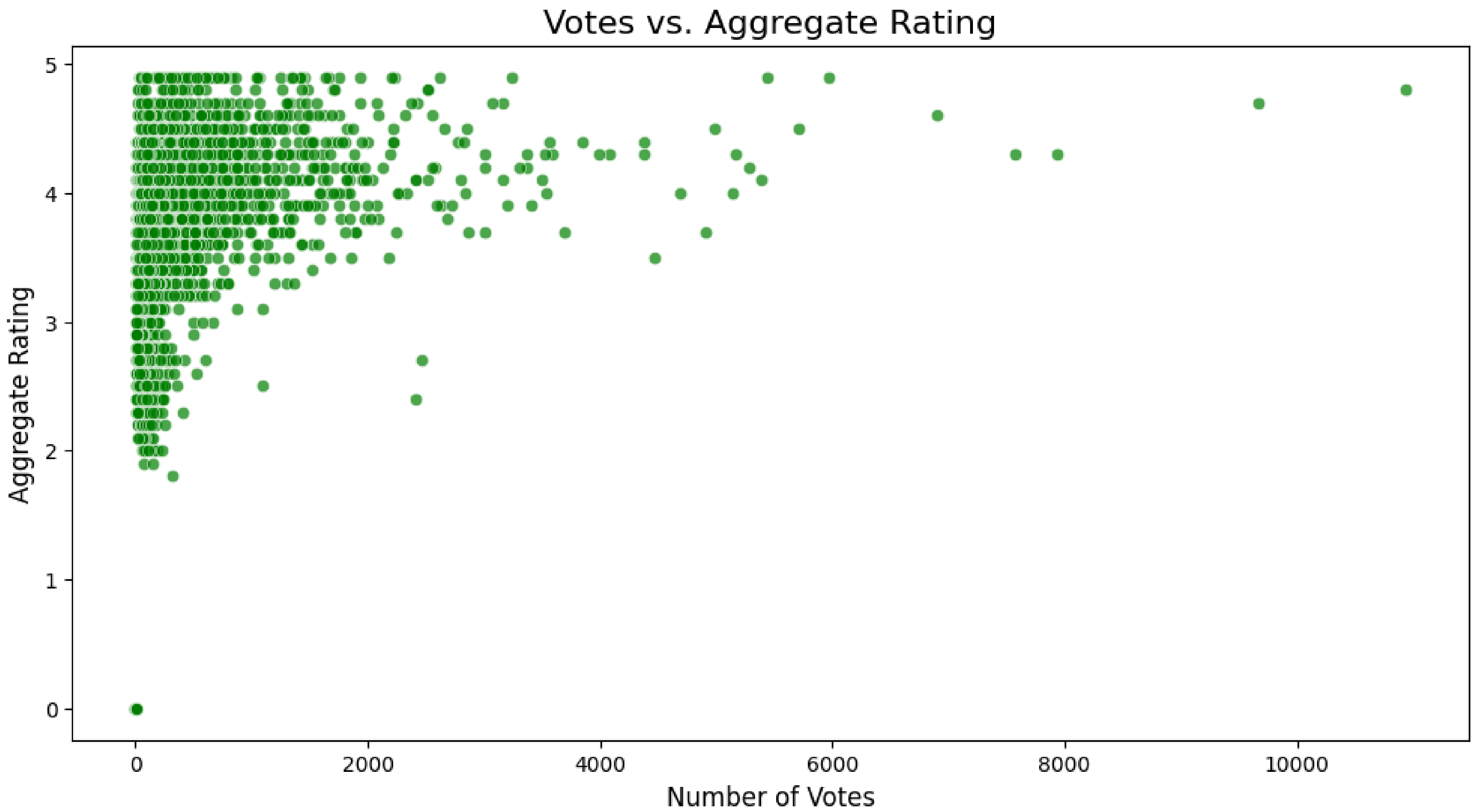
```
# 1. Distribution of Votes
plt.figure(figsize=(12, 6))
sns.histplot(df_zomato['Votes'], bins=30, kde=True, color='blue')
plt.title('Distribution of Votes', fontsize=16)
plt.xlabel('Number of Votes', fontsize=12)
```

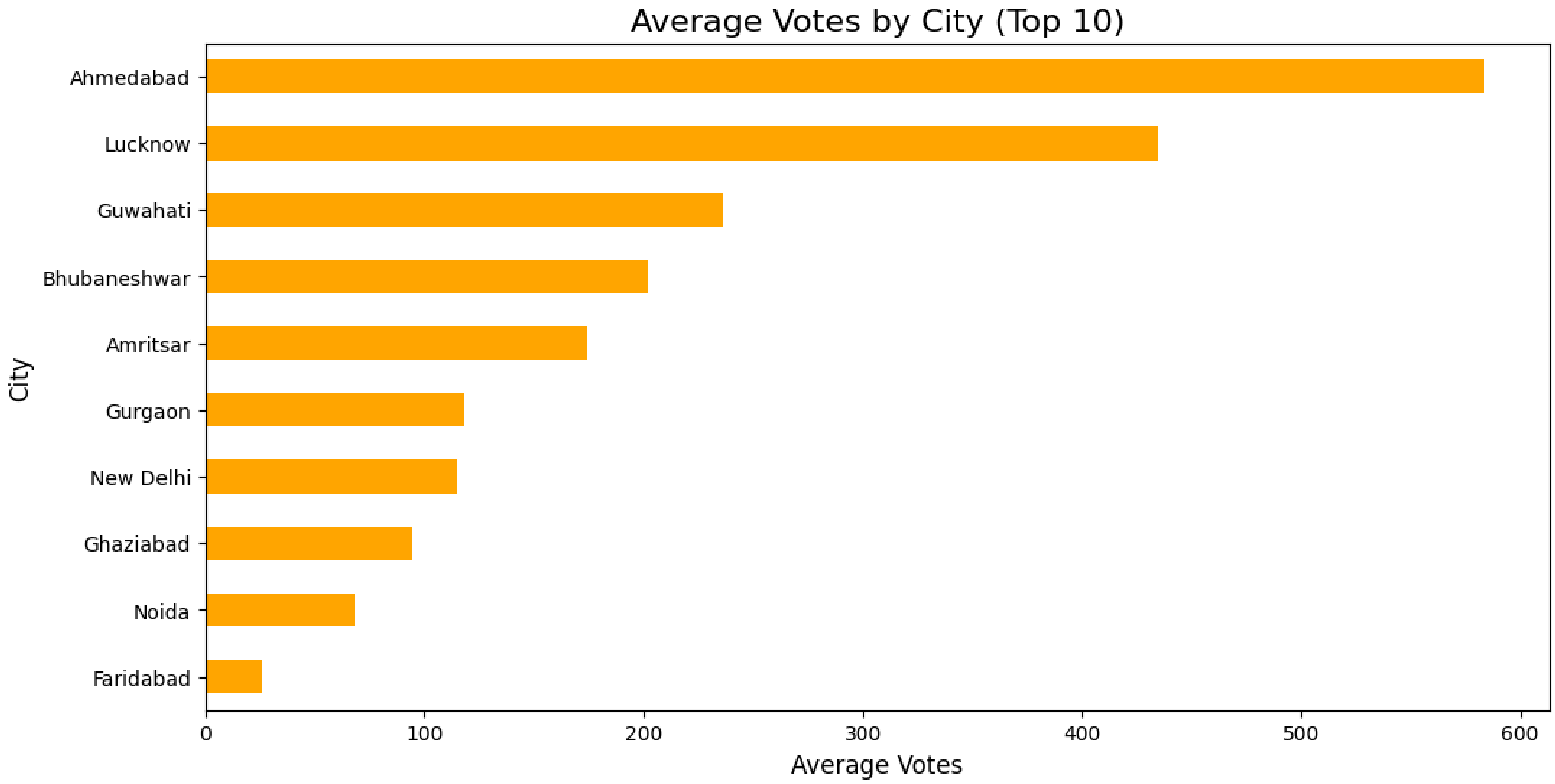
```python
plt.ylabel('Frequency', fontsize=12)
plt.show()

# 2. Votes vs. Aggregate Rating
plt.figure(figsize=(12, 6))
sns.scatterplot(x='Votes', y='Aggregate rating', data=df_zomato, alpha=0.7, color='green')
plt.title('Votes vs. Aggregate Rating', fontsize=16)
plt.xlabel('Number of Votes', fontsize=12)
plt.ylabel('Aggregate Rating', fontsize=12)
plt.show()

# 3. Average Votes by City
top_cities = df_zomato['City'].value_counts().nlargest(10).index  # Top 10 cities with most restaurants
city_votes = df_zomato[df_zomato['City'].isin(top_cities)].groupby('City')['Votes'].mean().sort_values()

plt.figure(figsize=(12, 6))
city_votes.plot(kind='barh', color='orange')
plt.title('Average Votes by City (Top 10)', fontsize=16)
plt.xlabel('Average Votes', fontsize=12)
plt.ylabel('City', fontsize=12)
plt.show()

# 4. Votes by Rating Categories
rating_category_votes = df_zomato.groupby('Rating text')['Votes'].mean().sort_values()

plt.figure(figsize=(12, 6))
rating_category_votes.plot(kind='bar', color='purple')
plt.title('Average Votes by Rating Category', fontsize=16)
plt.xlabel('Rating Category', fontsize=12)
plt.ylabel('Average Votes', fontsize=12)
plt.xticks(rotation=45)
plt.show()
```

```
C:\Users\Aditya\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is depreca
ted and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

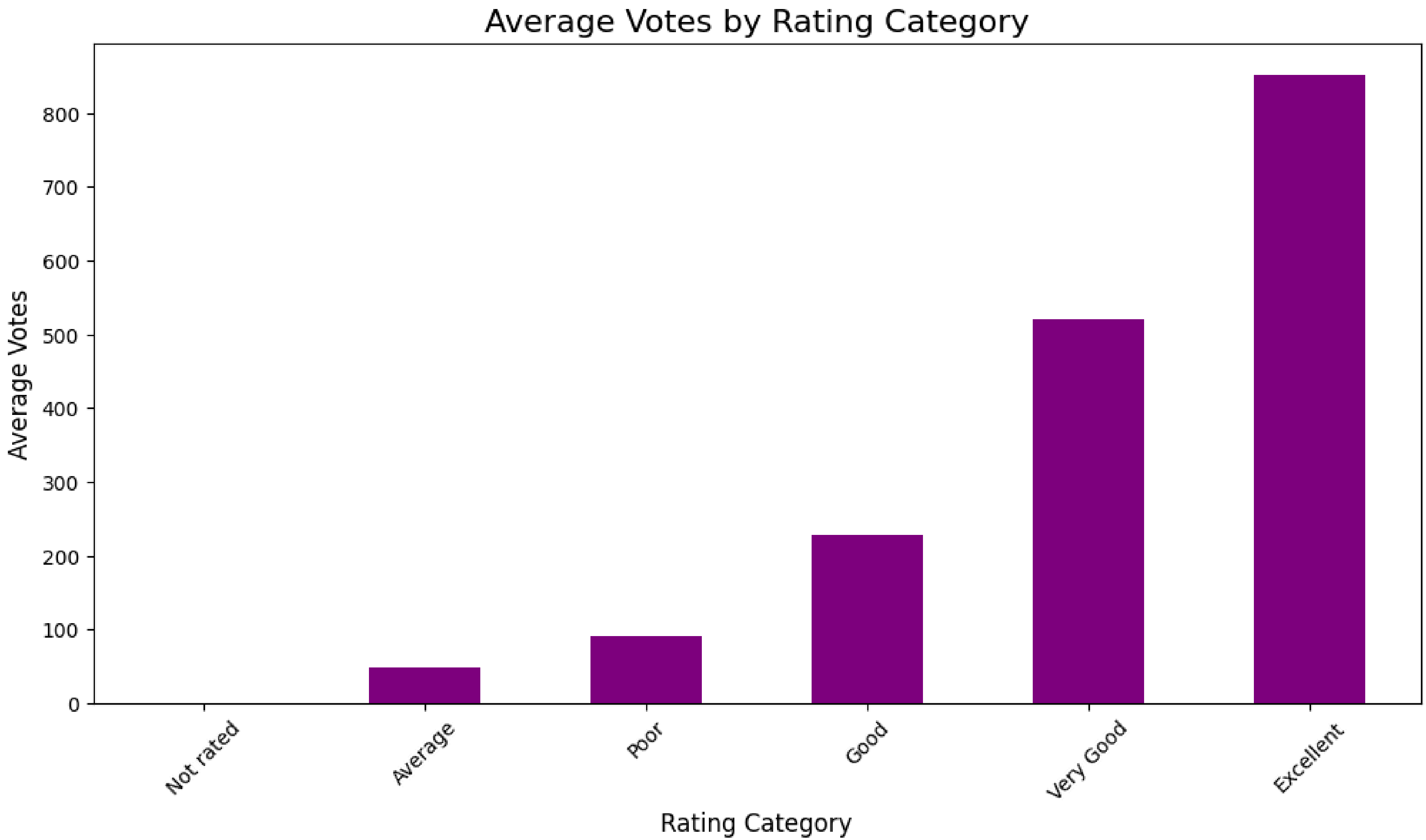


Distribution of Votes
Frequency
Number of Votes
0
2000
4000
6000
8000
10000
12000
0
2000
4000
6000
8000
10000


Votes vs. Aggregate Rating
Aggregate Rating
Number of Votes
0
1
2
3
4
5
0
2000
4000
6000
8000
10000



Average Votes by City (Top 10)
Ahmedabad
Lucknow
Guwahati
Bhubaneshwar
Amritsar
Gurgaon
New Delhi
Ghaziabad
Noida
Faridabad
City
0
100
200
300
400
500
600
Average Votes

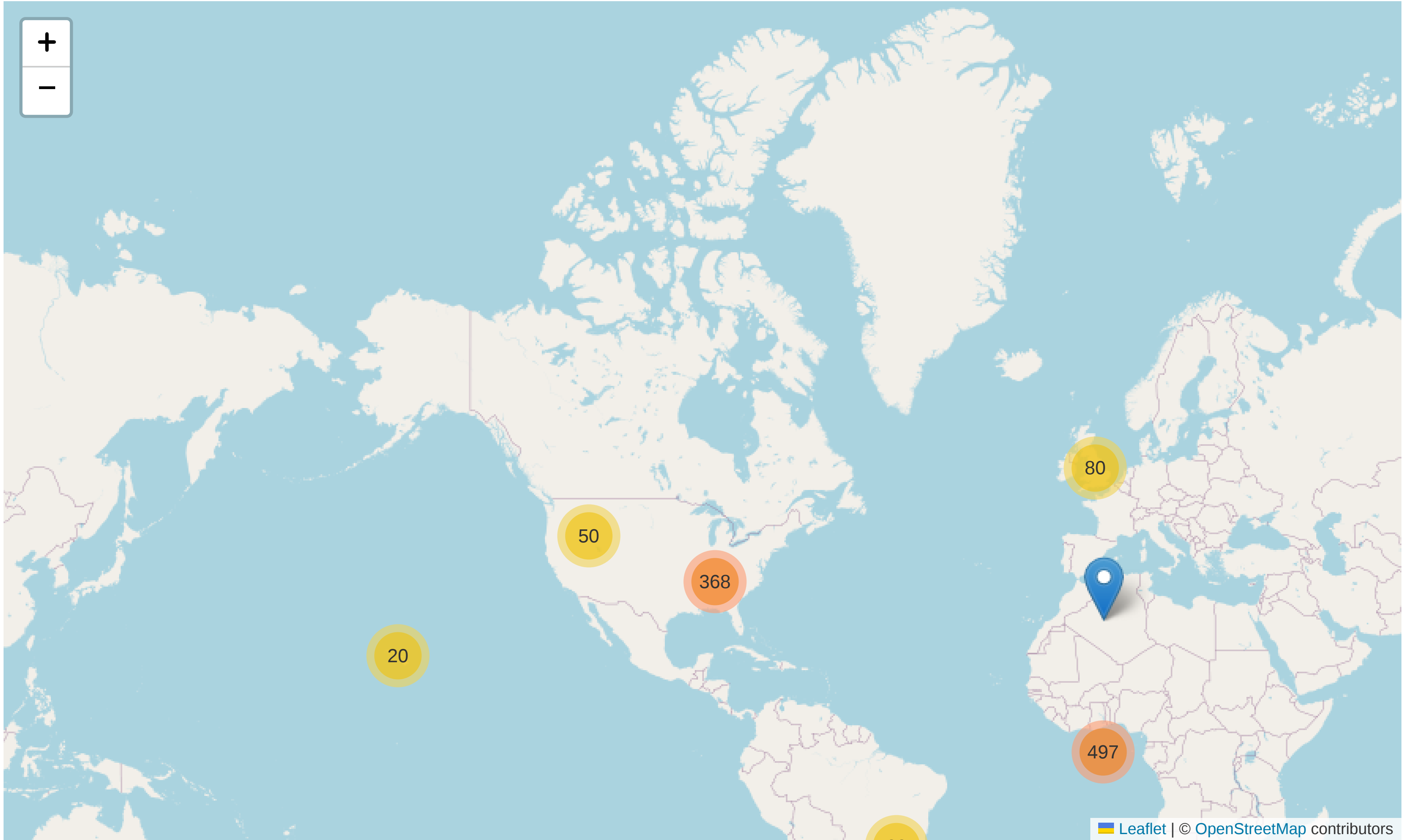


In [176…

```
# Initialize a map
cluster_map = folium.Map(location=[20, 0], zoom_start=2)

# Add clustered markers
marker_cluster = MarkerCluster().add_to(cluster_map)

for _, row in geo_data.iterrows():
```

```
    folium.Marker(
        location=[row['Latitude'], row['Longitude']],
        popup=f"Restaurant: {row['Restaurant Name']}<br>City: {row['City']}<br>Rating: {row['Aggregate rating']}",
    ).add_to(marker_cluster)

# Save or display map
cluster_map.save('clustered_restaurants_map.html')
cluster_map
```

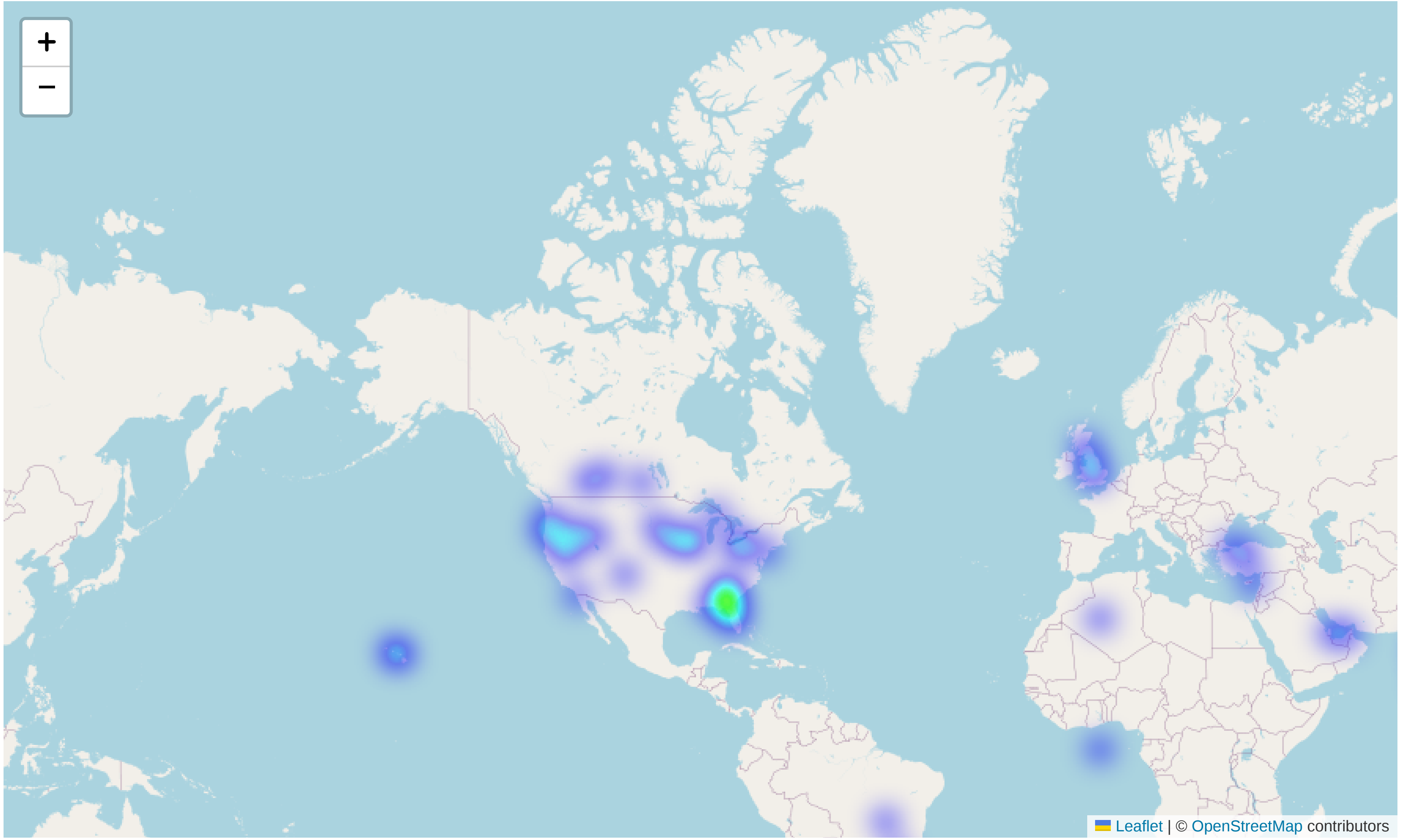
Out[176…



In [201…

```python
from folium.plugins import HeatMap

# Create heatmap data
heat_data = geo_data[['Latitude', 'Longitude']].values.tolist()

# Initialize a heatmap
heat_map = folium.Map(location=[20, 0], zoom_start=2)

# Add heatmap layer
HeatMap(heat_data, radius=10).add_to(heat_map)

# Save or display map
heat_map.save('heatmap_restaurants.html')
heat_map
```

Out [201…



In [182…

```
# Top 10 Restaurants by Aggregate Rating
top_rated_restaurants = df_zomato[['Restaurant Name', 'City', 'Aggregate rating', 'Votes']].sort_values(
    by='Aggregate rating', ascending=False).head(10)

print("Top 10 Highly Rated Restaurants")
print(top_rated_restaurants)

# Top 10 Restaurants by Votes
```

```python
most_voted_restaurants = df_zomato[['Restaurant Name', 'City', 'Aggregate rating', 'Votes']].sort_values(
    by='Votes', ascending=False).head(10)

print("Top 10 Most Voted Restaurants")
print(most_voted_restaurants)
```

```
Top 10 Highly Rated Restaurants
                    Restaurant Name             City  Aggregate rating  Votes
1381                    Caterspoint          Gurgaon               4.9    223
589        AB's Absolute Barbecues             Dubai               4.9    641
374   McGuire's Irish Pub & Brewery        Pensacola               4.9   2238
9303                          Miann         Auckland               4.9    281
9299                          Milse         Auckland               4.9    754
9296               Talaga Sampireun        Tangerang               4.9   2212
50                Garota de Ipanema   Rio de Janeiro               4.9     49
9291               Talaga Sampireun          Jakarta               4.9   1640
48               Braseiro da Gíçvea   Rio de Janeiro               4.9     40
428               Mama's Fish House   Rest of Hawaii               4.9   1343
Top 10 Most Voted Restaurants
                Restaurant Name       City  Aggregate rating  Votes
728                        Toit  Bangalore               4.8  10934
735                    Truffles  Bangalore               4.7   9667
3994          Hauz Khas Social  New Delhi               4.3   7931
2412                 Peter Cat    Kolkata               4.3   7574
739   AB's - Absolute Barbecues  Bangalore               4.6   6907
2414            Barbeque Nation    Kolkata               4.9   5966
743                 Big Brewsky  Bangalore               4.5   5705
2307  AB's - Absolute Barbecues  Hyderabad               4.9   5434
736              The Black Pearl  Bangalore               4.1   5385
2411                      BarBQ    Kolkata               4.2   5288
```

In [185…

```python
# Restaurants with the Lowest Ratings
low_rated_restaurants = df_zomato[['Restaurant Name', 'City', 'Aggregate rating', 'Votes']].sort_values(
    by='Aggregate rating', ascending=True).head(10)

print("Restaurants with the Lowest Ratings")
print(low_rated_restaurants)

# Restaurants with Low Ratings and Votes
low_performance = df_zomato[(df_zomato['Aggregate rating'] < 2.5) & (df_zomato['Votes'] < 50)]
```

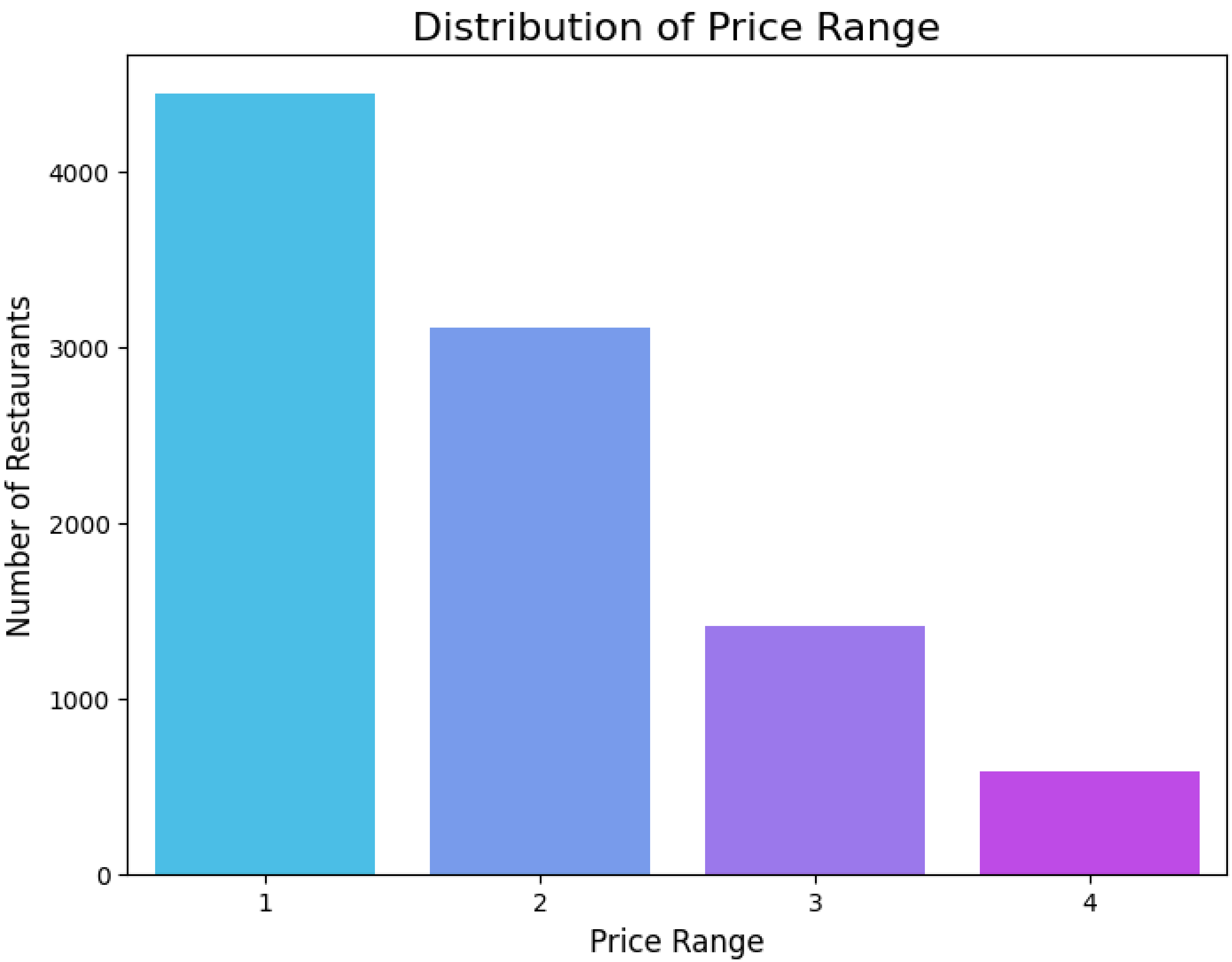
```python
print("Underperforming Restaurants")
print(low_performance[['Restaurant Name', 'City', 'Aggregate rating', 'Votes']])
```

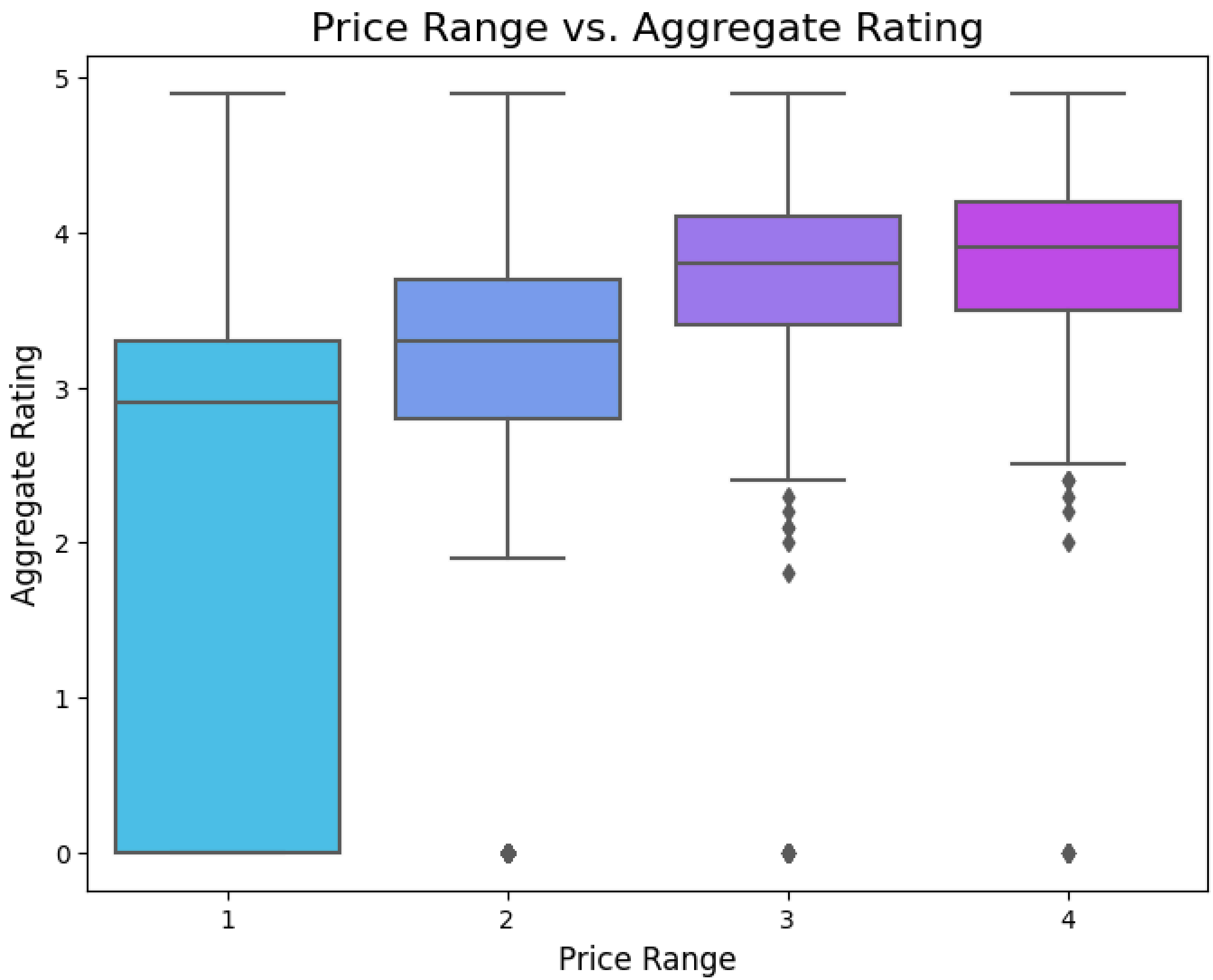
```
Restaurants with the Lowest Ratings
           Restaurant Name       City  Aggregate rating  Votes
6615           LSK Express  New Delhi               0.0      1
1994           Apni Rasoi    Gurgaon               0.0      0
1995  Bala Ji Sweets Corner   Gurgaon               0.0      0
1996               Barista    Gurgaon               0.0      0
1997       Biryani Express    Gurgaon               0.0      1
1998         Cafe #22hours    Gurgaon               0.0      0
1999       Cake Innovation    Gurgaon               0.0      1
2000           Chawla's□_    Gurgaon               0.0      1
2001       China Gathering    Gurgaon               0.0      1
2002    Chinese Hot Express    Gurgaon               0.0      0
Underperforming Restaurants
            Restaurant Name            City  Aggregate rating  Votes
30            Sandubas Cafí©       Brasí_lia               0.0      2
58      Quiosque Chopp Brahma  Rio de Janeiro               0.0      1
69          Cantinho da Gula      Sí£o Paulo               0.0      0
77             Divino Fogí£o      Sí£o Paulo               0.0      2
78               Super Grill      Sí£o Paulo               0.0      2
...                      ...             ...               ...    ...
9109            Bread & Pasta           Noida               0.0      1
9110            Chillies Cafe           Noida               0.0      3
9111                 Platters           Noida               0.0      0
9112                The Grand           Noida               0.0      1
9351  Damascena Coffee House      Birmingham               0.0      3

[2224 rows x 4 columns]
```

In [187…

```python
import seaborn as sns
import matplotlib.pyplot as plt

# Distribution of Price Range
plt.figure(figsize=(8, 6))
sns.countplot(x='Price range', data=df_zomato, palette='cool')
plt.title('Distribution of Price Range', fontsize=16)
plt.xlabel('Price Range', fontsize=12)
plt.ylabel('Number of Restaurants', fontsize=12)
plt.show()
```

```python
# Price Range vs. Aggregate Rating
plt.figure(figsize=(8, 6))
sns.boxplot(x='Price range', y='Aggregate rating', data=df_zomato, palette='cool')
plt.title('Price Range vs. Aggregate Rating', fontsize=16)
plt.xlabel('Price Range', fontsize=12)
plt.ylabel('Aggregate Rating', fontsize=12)
plt.show()
```


Distribution of Price Range
Number of Restaurants
4000
3000
2000
1000
0
1
2
3
4
Price Range



In [189…

```
# Impact of Table Booking on Ratings
table_booking = df_zomato.groupby('Has Table booking')['Aggregate rating'].mean()

print("Average Rating Based on Table Booking")
print(table_booking)

# Impact of Online Delivery on Ratings
```

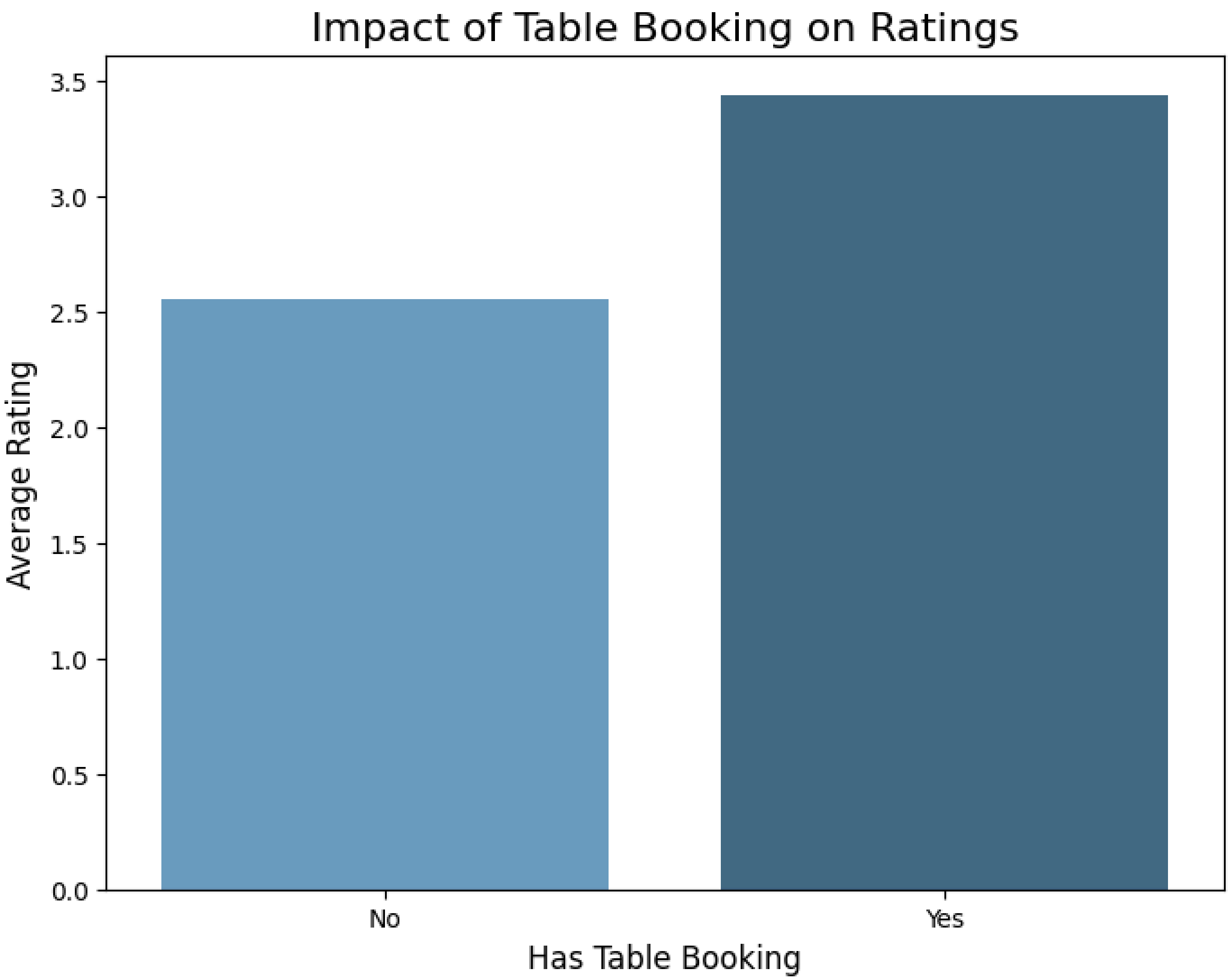
```python
online_delivery = df_zomato.groupby('Has Online delivery')['Aggregate rating'].mean()

print("Average Rating Based on Online Delivery")
print(online_delivery)

# Visualization
plt.figure(figsize=(8, 6))
sns.barplot(x=table_booking.index, y=table_booking.values, palette='Blues_d')
plt.title('Impact of Table Booking on Ratings', fontsize=16)
plt.xlabel('Has Table Booking', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.show()

plt.figure(figsize=(8, 6))
sns.barplot(x=online_delivery.index, y=online_delivery.values, palette='Greens_d')
plt.title('Impact of Online Delivery on Ratings', fontsize=16)
plt.xlabel('Has Online Delivery', fontsize=12)
plt.ylabel('Average Rating', fontsize=12)
plt.show()
```

```
Average Rating Based on Table Booking
Has Table booking
No     2.559359
Yes    3.441969
Name: Aggregate rating, dtype: float64
Average Rating Based on Online Delivery
Has Online delivery
No     2.465296
Yes    3.248837
Name: Aggregate rating, dtype: float64
```

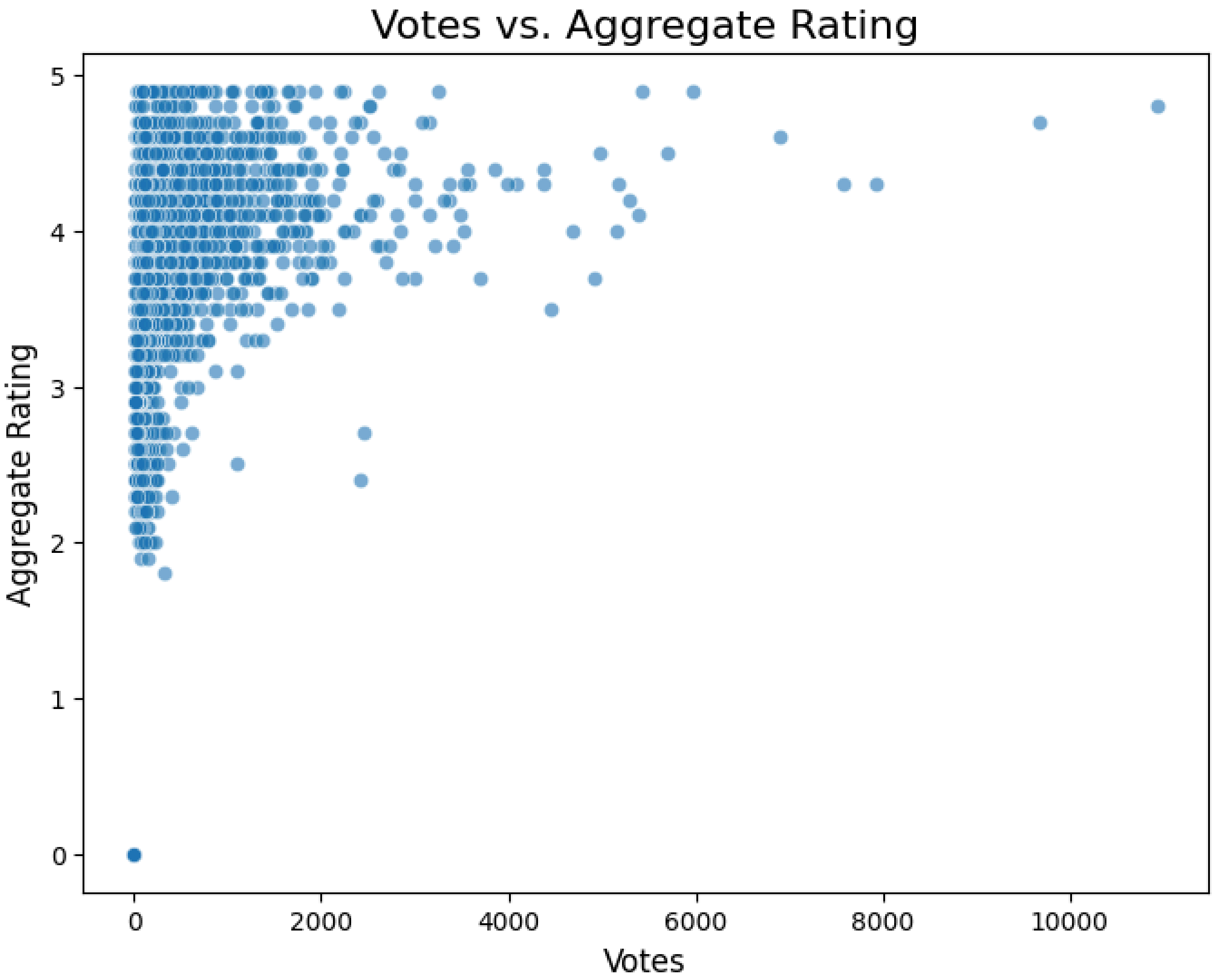

Impact of Table Booking on Ratings
Average Rating
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
No
Yes
Has Table Booking

In [191…

```
# Relationship between Votes and Ratings
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Votes', y='Aggregate rating', data=df_zomato, alpha=0.6)
plt.title('Votes vs. Aggregate Rating', fontsize=16)
plt.xlabel('Votes', fontsize=12)
plt.ylabel('Aggregate Rating', fontsize=12)
plt.show()
```

```
# Average Votes by Price Range
avg_votes_by_price = df_zomato.groupby('Price range')['Votes'].mean()

print("Average Votes by Price Range")
print(avg_votes_by_price)
```



```
Average Votes by Price Range
Price range
1     44.597435
2    147.607131
3    443.860795
4    368.595563
Name: Votes, dtype: float64
```

Insights

```
In [ ]:
-majority (3737) ratings lie in 'Average /Orange' category

-94% restaurants are from india in this data set

-majority(6229) of restaurants in india do NOT offer online delivery

-very less restaurants offer table booking

-top 5 indian cities having highest number of restaurants are
New Delhi    5473
Gurgaon      1118
Noida        1080
Faridabad     251
Ghaziabad      25

-Top 3 countries with highest avg cost for 2 people are
Indonesia         281190.5
Sri Lanka           2375.0
Phillipines         1606.8

-top 3 countries with least cost avg for 2 people are
Canada                36.2
United States         26.2
Australia             24.1


-top 3 indian cities with highest avg cost for 2 people are
Panchkula       2000.000000
Hyderabad       1361.111111
```

```
Pune             1337.500000

- top 3 indian cities with lowest avg cost for 2 people are
Varanasi          505.000000
Amritsar          480.952381
Faridabad         447.609562

-high number of restaurants (>4000) lie in expensive category-1( i.e very less expensive), very less number of resta

-most popular cusines are north indian followed by chinese

-average rating of restaurants having online delivery is higher(appx 3) as compared to those who does not offer onli

-average rating of restaurants offering table booking is higher as compared to those who does not offer table bookin

- meaning the majority of restaurants receive very few votes.
A small number of restaurants have a significantly high number of votes.


-There is a general trend that restaurants with a higher number of votes tend to have better aggregate ratings.Most

-top 3 voted cities are Ahemdabad,Lucknow,Guwahati


-excellent rated restaurants have highest number of votes

-Top 3 Highly Rated Restaurants

                    Restaurant Name     |      City  |Aggregate rating  |Votes
1381                     Caterspoint     |   Gurgaon  |             4.9  |  223
589          AB's Absolute Barbecues     |      Dubai |              4.9 |   641
374   McGuire's Irish Pub & Brewery     |  Pensacola |             4.9  | 2238


-Top 3 Most Voted Restaurants

                Restaurant Name|       City | Aggregate rating | Votes
728                        Toit|  Bangalore |             4.8 | 10934
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735              Truffles|  Bangalore |            4.7 |  9667
3994     Hauz Khas Social|  New Delhi |            4.3 |  7931
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