

\*\*\* **\*SECTION-2\*** \*\*\*

\*\*\* **\*ZOMATO DATA SET\*** \*\*\*

\*\*\* **\*Exploratory Data Analysis (EDA)\***  
\*\*\*

### **\*Step 1: Import necessary libraries\***

- Pandas
- Matplotlib
- Seaborn

In [221...

```
# Pandas is a powerful, open-source library in Python for data manipulation and analysis
import pandas as pd

# Matplotlib is a popular, open-source plotting library for Python, providing a variety of data visualization options
import matplotlib.pyplot as plt

# Seaborn is a Python data visualization library built on top of Matplotlib, providing a high-level interface for creating attractive and informative statistical plots
import seaborn as sns
```

### **\*Step 2: Load Zomato data & Basic Information\***

In [224...

```
zomato_data = pd.read_csv('zomato_data.csv') # Replace 'zomato_data.csv' with the path to your Zomato data file
print('\nLoading Zomato Data Set:\n')
zomato_data
```

Loading Zomato Data Set:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Centi Pc Mal
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Littl Mal
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa S La, Mand C
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	Me Mand N
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	Me Mand N
...	...	...	...	...	...	...	
9546	5915730	NamlÛ± Gurme	208	ÛÁstanbul	Kemanke±ô Karamustafa Pa±ôa Mahallesi, RÛ±htÛ±...	Karakí_y	I ÛÁ
9547	5908749	Ceviz AÛôacÛ±	208	ÛÁstanbul	Ko±ôuyolu Mahallesi, Muhittin îstí_ndaÛô Cadd...	Ko±ôuyolu	Ko± ÛÁ
9548	5915807	Huqqa	208	ÛÁstanbul	Kuruí_e±ôme Mahallesi, Muallim Naci Caddesi, N...	Kuruí_e±ôme	Kuruí_ ÛÁ
9549	5916112	A±ô±ôk Kahve	208	ÛÁstanbul	Kuruí_e±ôme Mahallesi, Muallim Naci Caddesi, N...	Kuruí_e±ôme	Kuruí_ ÛÁ

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	
9550	5927402	Walter's Coffee Roastery	208	ÜÁstanbul	CafeaÜôa Mahallesi, BademaltÜ± Sokak, No 21/B,...	Moda	Üj

9551 rows × 21 columns

In [226...

```
print('\nBasic Information About Zomato Data Set:\n')
zomato_data.info()
# Provides information about dataset shape, column data types, and missing va
```

Basic Information About Zomato Data Set:

```
<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
```

## \*Step 3: Identify & Counting of missing values\*

In [229...

```
# Create a Boolean DataFrame with isnull()
missing_bool = zomato_data.isnull()
missing_bool
```

Out[229...

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	L
0	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	
9546	False	False	False	False	False	False	False	False	
9547	False	False	False	False	False	False	False	False	
9548	False	False	False	False	False	False	False	False	
9549	False	False	False	False	False	False	False	False	
9550	False	False	False	False	False	False	False	False	

9551 rows × 21 columns



In [231...

```
# Count missing values for each column using sum()
missing_counts = missing_bool.sum()
missing_counts
```

Out[231...

```
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
```

## \*Step 4: Summary Statistics For Numerical Columns\*

```
In [234... # Get summary statistics
summary_stats = zomato_data.describe()
summary_stats
```

```
Out[234...
      Restaurant ID Country Code Longitude Latitude Average Cost for two Price range
count 9.551000e+03 9551.000000 9551.000000 9551.000000 9551.000000 9551.000000
mean 9.051128e+06 18.365616 64.126574 25.854381 1199.210763 1.804837
std 8.791521e+06 56.750546 41.467058 11.007935 16121.183073 0.905609
min 5.300000e+01 1.000000 -157.948486 -41.330428 0.000000 1.000000
25% 3.019625e+05 1.000000 77.081343 28.478713 250.000000 1.000000
50% 6.004089e+06 1.000000 77.191964 28.570469 400.000000 2.000000
75% 1.835229e+07 1.000000 77.282006 28.642758 700.000000 2.000000
max 1.850065e+07 216.000000 174.832089 55.976980 800000.000000 4.000000
```



```
In [ ]: # 1. Restaurant ID:
        # Range: IDs range from 53 to 18,500,650 (min to max), showing a wide vari
        # No insights can be directly drawn here other than confirming t

# 2. Country Code:
        # Mean: 18.37 indicates that the dataset predominantly consists of restaur
        # Min: 25%, 50%, and 75%: Country code is 1 (likely India) for at least
        # Max: 216 indicates the dataset includes global restaurants.

# 3. Longitude & Latitude:
        # Range: Longitude ranges from -157.95 to 174.83 and Latitude from -41.33
        # Mean Latitude: ~25.85 and Longitude: ~64.13 suggest that most restaurant

# 4. Average Cost for Two:
        # Mean: ₹1,199 suggests that meals are moderately priced, but...
        # Standard Deviation (std): 16,121 shows high variability—some restaurants
        # Min: ₹0 indicates free meals (possibly promotional or missing data).
        # 75% Quartile: 75% of the restaurants have prices below ₹700, sugg
        # Max: ₹800,000 indicates extreme outliers, probably representing luxury d

# 5. Price Range (1-4):
        # Mean: ~1.8 suggests that most restaurants fall between cheap to moderate
        # 75% Quartile: 75% of restaurants are within the price range of
        # Max of 4: Some high-end restaurants exist, but they are a minority.

# 6. Aggregate Rating:
        # Mean: 2.67 is on the lower side, suggesting that restaurants may general
        # Median (50%): 3.2 shows that half the restaurants score above this ratin
        # Max: 4.9 is near-perfect, meaning at least a few restaurants have excell

# 7. Votes:
        # Mean: ~157 votes suggest that most restaurants attract moderate engageme
# Standard Deviation: 430 shows high variability—some restaurants are far more p
        # Quartile: 75% of restaurants have 131 votes or fewer, indicating that th
        # Max: One restaurant has 10,934 votes, suggesting it is extremely popular

# Key Insights:
# Geographic Concentration:
        # Most restaurants are likely located in India (Country Code = 1). However,

# Pricing Distribution:
        # The majority of restaurants offer meals for less than ₹700, indicating a f
```

```

# Customer Engagement:
    # While the average number of votes is 157, some restaurants receive thousand votes

# Ratings:
    # The overall average rating of 2.67 is relatively low, possibly indicating low customer satisfaction
# Price Range and Ratings Correlation:
    # With most restaurants having a price range of 1-2, it seems affordable despite the low ratings

# Outliers and Data Quality Issues:
    # Extreme values like a cost of ₹800,000 for two people or a restaurant with no reviews

```

## \*Step 5: Identify & Iterating of Categorical Columns\*

```

In [237... # Identify Categorical Columns:
categorical_columns = zomato_data.select_dtypes(include=['object', 'category']).
categorical_columns

Out[237... Index(['Restaurant Name', 'City', 'Address', 'Locality', 'Locality Verbose',
      'Cuisines', 'Currency', 'Has Table booking', 'Has Online delivery',
      'Is delivering now', 'Switch to order menu', 'Rating color',
      'Rating text'],
      dtype='object')

In [239... for col in categorical_columns:
    print(f"{col}: {zomato_data[col].nunique()} unique values")
    print(zomato_data[col].unique()[:3], "\n") # Display first 5 unique values

```

Restaurant Name: 7446 unique values  
 ['Le Petit Souffle' 'Izakaya Kikufuji' 'Heat - Edsa Shangri-La']

City: 141 unique values  
 ['Makati City' 'Mandaluyong City' 'Pasay City']

Address: 8918 unique values  
 ['Third Floor, Century City Mall, Kalayaan Avenue, Poblacion, Makati City'  
 'Little Tokyo, 2277 Chino Roces Avenue, Legaspi Village, Makati City'  
 'Edsa Shangri-La, 1 Garden Way, Ortigas, Mandaluyong City']

Locality: 1208 unique values  
 ['Century City Mall, Poblacion, Makati City'  
 'Little Tokyo, Legaspi Village, Makati City'  
 'Edsa Shangri-La, Ortigas, Mandaluyong City']

Locality Verbose: 1265 unique values  
 ['Century City Mall, Poblacion, Makati City, Makati City'  
 'Little Tokyo, Legaspi Village, Makati City, Makati City'  
 'Edsa Shangri-La, Ortigas, Mandaluyong City, Mandaluyong City']

Cuisines: 1825 unique values  
 ['French, Japanese, Desserts' 'Japanese'  
 'Seafood, Asian, Filipino, Indian']

Currency: 12 unique values  
 ['Botswana Pula(P)' 'Brazilian Real(R\$)' 'Dollar(\$)']

Has Table booking: 2 unique values  
 ['Yes' 'No']

Has Online delivery: 2 unique values  
 ['No' 'Yes']

Is delivering now: 2 unique values  
 ['No' 'Yes']

Switch to order menu: 1 unique values  
 ['No']

Rating color: 6 unique values  
 ['Dark Green' 'Green' 'Yellow']

Rating text: 6 unique values  
 ['Excellent' 'Very Good' 'Good']

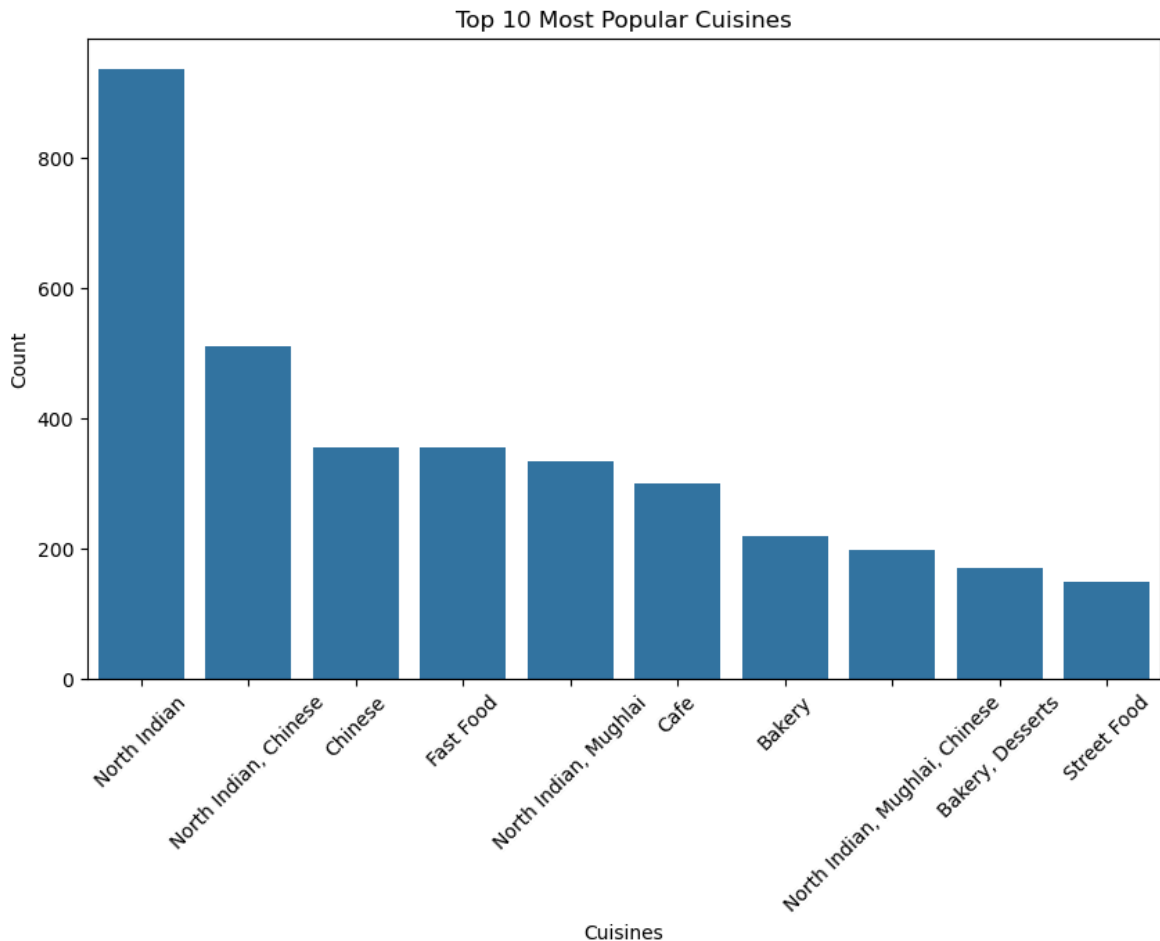
## \*Step 6: Seaborn Plot to Visualizing the Distribution of Cuisine Types.\*

In [242...]

```
# Assuming 'zomato_data' is our DataFrame with a column named 'Cuisines'
cuisine_counts = zomato_data['Cuisines'].value_counts()

# Visualize the top 10 most frequent and popular cuisines
plt.figure(figsize=(10, 6))
sns.barplot(x=cuisine_counts.index[:10], y=cuisine_counts.values[:10])
plt.xlabel('Cuisines')
plt.ylabel('Count')
```

```
plt.title('Top 10 Most Popular Cuisines')
plt.xticks(rotation=45)
plt.show()
# Observations
# Most Popular Cuisines: The cuisines with the tallest bars are the most frequent
# Comparative Popularity: This bar plot also allows a quick comparison, showing
# Trends: The types of cuisines in the top ranks can suggest culinary trends
# This plot helps you quickly identify which cuisines are most popular and in
```

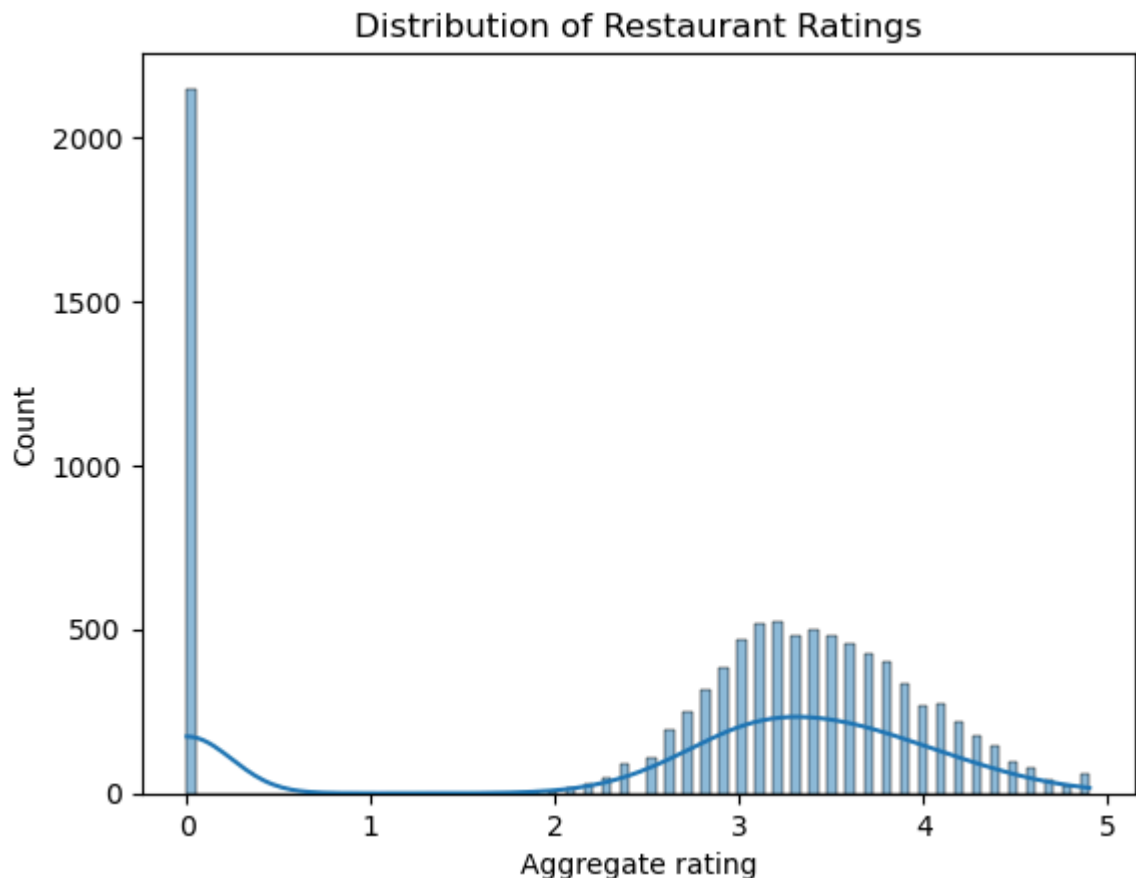


## \*Step 7: Distribution of Restaurant Ratings using a Seaborn plot.\*

In [253...

```
# Assuming 'zomato_data' is your DataFrame with a column named 'Aggregate rating'
rating = zomato_data['Aggregate rating']
sns.histplot(rating, bins=100, kde=True) # Adjust the number of bins as needed
plt.title('Distribution of Restaurant Ratings')
plt.xlabel('Aggregate rating')
plt.ylabel('Count')
plt.show()
# Observations
# Spread of Ratings: The histogram reveals how ratings are spread across different
# Frequency Peaks: Peaks indicate where ratings are most frequent. For instance
# Skewness: If the plot skews toward higher or lower ratings, this suggests a
# The KDE curve in this plot adds a smooth line, showing the underlying distribution
```





## \*Step 8: Relationship Between Two Numerical Columns\*

In [247...

```
df = pd.DataFrame(zomato_data)
# Plotting the scatter plot
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Votes', y='Aggregate rating', data=df, color='g', s=10, edgecolor='b')
plt.xlabel("Number of Votes")
plt.ylabel("Aggregate Rating")
plt.title("Relationship between Number of Votes and Aggregate Rating")
plt.show()

# Observations
# Positive or Negative Correlation: If data points form an upward trend from left to right, it indicates a positive correlation.
# Cluster Patterns: Clusters of points around certain values may reveal segments or groups within the data.
# Outliers: Points far from the main cluster may indicate unique cases, such as restaurants with very high votes but low ratings.

# Interpretation
# A scatter plot like this provides a visual representation of any relationship between the two numerical variables.
```

Relationship between Number of Votes and Aggregate Rating

