# **Zomato Restaurants Ratings Analysis**



#### **Problem Statement**

**Company:** Zomato, a leading food delivery and restaurant discovery platform.

**Background:** Zomato is planning to expand its business on a global scale and aims to provide a seamless dining experience to its users. To achieve this, they need to gain a comprehensive understanding of the restaurant landscape and customer preferences worldwide. Specifically, they want to analyze their ratings data to uncover valuable insights about restaurants, services, cuisines, and customer sentiments in various countries and cities.

**Objective:** As a data scientist, your task is to analyze the Zomato ratings data and provide insights into the following key aspects:

#### 1. Country-Level Analysis:

- Identify the top-performing countries in terms of restaurant ratings.
- Analyze the overall customer satisfaction levels by country.

#### 2. City-Level Analysis:

- Explore customer ratings and reviews across different cities.
- Determine the most popular and highly-rated cities for dining.

#### 3. Rating Distributions:

• Examine the distribution of customer ratings and identify any trends or patterns.

#### 4. Restaurant Insights:

- Uncover insights about the highest and lowest-rated restaurants.
- Evaluate the correlation between restaurant attributes and ratings.

#### 5. Service Quality:

• Investigate customer feedback on restaurant services and identify areas for improvement.

#### 6. Cuisine Analysis:

- Determine the popularity of different cuisines in various regions.
- Analyze the relationship between cuisines and customer ratings.

**Deliverables:** Your findings and insights will be presented in a comprehensive report, which will guide Zomato in making data-driven decisions to enhance their global business expansion strategy.

**Success Criteria:** Successful completion of this project will provide Zomato with actionable insights to make informed decisions for their global expansion, improve customer satisfaction, and optimize their platform's restaurant offerings.

# **Dataset Description:**

#### **Columns**

- Restaurant Id: Unique identifier for each restaurant.
- Restaurant Name: The name of the restaurant.
- Country Code: The country in which the restaurant is located.
- City: The city in which the restaurant is located.
- Address: The street address of the restaurant.
- Locality: The specific location within the city.
- Locality Verbose: A detailed description of the locality.
- **Longitude**: The longitude coordinate of the restaurant's location.
- Latitude: The latitude coordinate of the restaurant's location.
- Cuisines: The types of cuisines offered by the restaurant.
- Average Cost for Two: The cost for two people in different currencies (local currency).
- Currency: The currency used in the country.
- Has Table Booking: Whether the restaurant offers table booking (yes/no).
- Has Online Delivery: Whether the restaurant offers online delivery (yes/no).
- **Is Delivering**: Whether the restaurant is currently delivering (yes/no).
- **Switch to Order Menu**: Whether the restaurant allows switching to an order menu (yes/no).
- **Price Range**: The range of prices for food.
- Aggregate Rating: The average rating out of 5.
- Rating Color: The color representation of the average rating.
- Rating Text: Textual representation of the rating.
- Votes: The number of ratings given by customers.

## **Data Source**

[https://www.kaggle.com/datasets/shrutimehta/zomato-restaurants-data? select=zomato.csv] (https://www.kaggle.com/datasets/shrutimehta/zomato-restaurants-data?select=zomato.csv%5D)

# Importing the necessary libraries (pandas, numpy, matplotlib, seaborn, warnings)

```
In [921]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from pandas import Series
%matplotlib inline
warnings.filterwarnings('ignore')
```

## Reading the dataset

```
In [689]: data = pd.read_csv("Data/zomato.csv", encoding = "latin-1")
In [690]: original_data = data.copy()
```

# Viewing the top five records

In [691]: data.head()

Out[691]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	L
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	12
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	12
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	12
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	12
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	12

5 rows × 21 columns

# viewing the last five records

In [692]: data.tail()

#### Out [692]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose
9546	5915730	NamlÛ± Gurme	208	ÛÁstanbul	Kemanke⊡ô Karamustafa Pa⊡ôa Mahallesi, RÛ±htÛ±	Karakí_y	Karakí_y, ÛÁstanbul
9547	5908749	Ceviz AÛôacÛ±	208	ÛÁstanbul	Ko⊡ôuyolu Mahallesi, Muhittin îîstí_ndaÛô Cadd	Ko⊡ôuyolu	Ko⊡ôuyolu, ÛÁstanbul
9548	5915807	Huqqa	208	ÛÁstanbul	Kuruí_e⊡ôme Mahallesi, Muallim Naci Caddesi, N	Kuruí_e⊡ôme	Kuruí_e⊡ôme, ÛÁstanbul
9549	5916112	A⊡ô⊡ôk Kahve	208	ÛÁstanbul	Kuruí_e⊡ôme Mahallesi, Muallim Naci Caddesi, N	Kuruí_e⊡ôme	Kuruí_e⊡ôme, ÛÁstanbul
9550	5927402	Walter's Coffee Roastery	208	ÛÁstanbul	CafeaÛôa Mahallesi, BademaltÛ± Sokak, No 21/B,	Moda	Moda, ÛÁstanbul

5 rows × 21 columns

## **Exploring the features in a dataset**

## **Exploring the shape of the dataset**

```
In [694]: data.shape
Out[694]: (9551, 21)
```

## **Checking for null values**

```
In [695]: data.isna().sum()
Out[695]: Restaurant ID
                                    0
          Restaurant Name
                                    0
          Country Code
                                    0
                                    0
          City
          Address
                                    0
                                    0
          Locality
          Locality Verbose
                                    0
          Longitude
                                    0
          Latitude
                                    0
                                    9
          Cuisines
          Average Cost for two
                                    0
                                    0
          Currency
          Has Table booking
                                    0
          Has Online delivery
                                    0
           Is delivering now
                                    0
           Switch to order menu
                                    0
          Price range
                                    0
                                    0
          Aggregate rating
          Rating color
                                    0
          Rating text
                                    0
          Votes
                                    0
          dtype: int64
```

## Insights:

• Out of 21 features 1 feature named (Cuisines) has a missing values of (9)

## **Checking for datatypes**

In [696]: |data.dtypes Out[696]: Restaurant ID int64 Restaurant Name object Country Code int64 City object Address object Locality object Locality Verbose object Longitude float64 Latitude float64 Cuisines object Average Cost for two int64 Currency object Has Table booking object Has Online delivery object Is delivering now object Switch to order menu object Price range int64 Aggregate rating float64 Rating color object Rating text object Votes int64 dtype: object

#### **Exploring the unique features**

In [697]:	data.nunique()		
Out[697]:	Restaurant ID Restaurant Name	9551 7446	
		7440 15	
	Country Code	141	
	City Address	8918	
	Locality	1208	
	-	1265	
	Locality Verbose	8120	
	Longitude Latitude	8677	
	Cuisines	1825	
		140	
	Average Cost for two	140	
	Currency	2	
	Has Table booking		
	Has Online delivery	2 2	
	Is delivering now	1	
	Switch to order menu		
	Price range	4	
	Aggregate rating	33	
	Rating color	6	
	Rating text	6	
	Votes	1012	
	dtype: int64		

## Checking for duplicated values in the features

```
In [698]: data.duplicated().sum()
Out[698]: 0
```

## **Insights:**

• There are no duplicated features (0)

## Adding new feature (Country)

```
In [699]: country_map = {
    1: "India",
    14: "Australia",
    30: "Brazil",
    37: "Canada",
    94: "Indonesia",
    148: "NewZealand",
    162: "Philippines",
    166: "Quatar",
    184: "Singapore",
    189: "South Africa",
    191: "Sri Lanka",
    208: "Turkey",
    214: "Abu Dhabi",
    215: "UK",
    216: "USA"
}
```

```
In [700]: data["Country"] = data["Country Code"].map(country_map)
```

In [701]: data.head()

#### Out [701]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	L
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	12
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	12
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	12
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	12
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	12

5 rows × 22 columns

## Checking for duplicated records after adding Country feature

In [702]: data.duplicated().sum()

Out[702]: 0

# dropping the unwanted features

In [703]: features\_to\_drop = ["Restaurant ID","Longitude","Latitude","Localit
data.drop(columns=features\_to\_drop, axis=1, inplace=True)

```
In [704]: data.drop(columns=["Address"], axis=1, inplace=True)
In [705]: data.drop(columns=["Country Code"], axis=1, inplace=True)
In [706]: | data.head()
```

Out [706]:

Restaurant Name	City	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	ls delivering now	מ
0 Le Petit Souffle	Makati City	French, Japanese, Desserts	1100	Botswana Pula(P)	Yes	No	No	
<b>1</b> Izakaya Kikufuji	Makati City	Japanese	1200	Botswana Pula(P)	Yes	No	No	
Heat - <b>2</b> Edsa Shangri-La	Mandaluyong City	Seafood, Asian, Filipino, Indian	4000	Botswana Pula(P)	Yes	No	No	
3 Ooma	Mandaluyong City	Japanese, Sushi	1500	Botswana Pula(P)	No	No	No	
4 Sambo Kojin	Mandaluyong City	Japanese, Korean	1500	Botswana Pula(P)	Yes	No	No	

In [707]: data.shape

Out[707]: (9551, 15)

#### Checking for duplicated records after dropping unwanted features from the dataset

```
In [708]: res = data.duplicated().reset_index()
```

In [709]: res[res[0] == True].sum()

Out[709]: index 289479 43

dtype: int64

#### Insights:

• There are 43 duplicated records

## **Dropping duplicated records**

```
In [710]: data = data.drop_duplicates()
```

```
In [711]: data.duplicated().sum()
Out[711]: 0
```

#### **Exploring numerical and categorical features**

```
In [712]: numerical_features = [feature for feature in data.columns if data[f
In [713]: |numerical_features
Out[713]: ['Average Cost for two', 'Price range', 'Aggregate rating', 'Vote
In [714]: categorical_features = [feature for feature in data.columns if data
In [715]: | categorical_features
Out[715]: ['Restaurant Name',
           'City',
           'Cuisines',
           'Currency',
           'Has Table booking',
           'Has Online delivery',
           'Is delivering now',
           'Switch to order menu',
           'Rating color',
           'Rating text',
           'Country']
In [716]: print(f"Number of numerical features : {len(numerical_features)}")
          print(f"Number of categorical features : {len(categorical_features)
          Number of numerical features: 4
          Number of categorical features: 11
```

## Insights:

 Out of 15 features - 4 features are numerical features and 11 features are categorical features

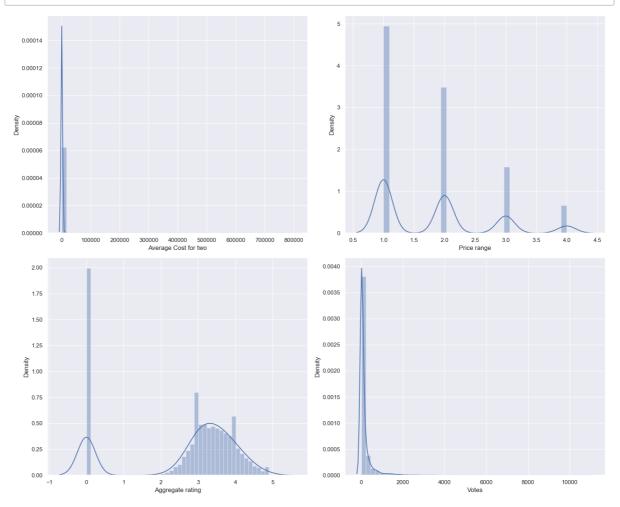
## Removing Missing values using mode

```
In [717]: mode_value = data["Cuisines"].mode()[0]
data["Cuisines"].fillna(mode_value,inplace=True)
```

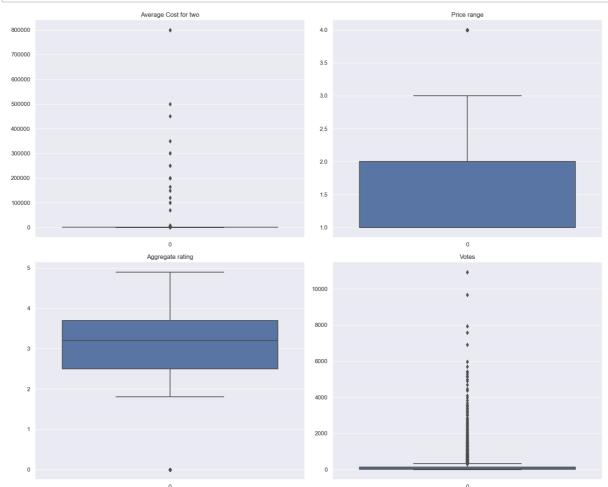
In [718]:	<pre>data.isnull().sum()</pre>	
Out[718]:	Restaurant Name	0
	City	0
	Cuisines	0
	Average Cost for two	0
	Currency	0
	Has Table booking	0
	Has Online delivery	0
	Is delivering now	0
	Switch to order menu	0
	Price range	0
	Aggregate rating	0
	Rating color	0
	Rating text	0
	Votes	0
	Country	0
	dtype: int64	

## **Outlier Detection**

```
In [719]: count = 1
plt.figure(figsize=(16,13))
for feature in numerical_features:
    plt.subplot(2,2,count)
    sns.distplot(data[feature])
    count+=1
plt.tight_layout()
plt.show()
```



```
In [720]: count = 1
   plt.figure(figsize=(16,13))
   for feature in numerical_features:
        plt.subplot(2,2,count)
        sns.boxplot(data[feature])
        plt.title(f"{feature}")
        count+=1
        plt.title(f'{feature}')
   plt.tight_layout()
   plt.show()
```



# **EDA(Exploratory Data Analysis)**

#### Distribution of restaurants across countries and cities

```
In [721]: country_rank_list = data.groupby("Country")["Votes"].sum().reset_in
```

```
In [722]: country_rank_list
```

#### Out[722]:

	Country	Votes
0	Abu Dhabi	29611
1	Australia	2674
2	Brazil	1177
3	Canada	412
4	India	1187070
5	Indonesia	16214
6	NewZealand	9721
7	Philippines	8963
8	Quatar	3276
9	Singapore	638
10	South Africa	18910
11	Sri Lanka	2929
12	Turkey	14670
13	UK	16439
14	USA	185848

In [724]: country\_rank\_list

#### Out[724]:

	Country	Votes
4	India	1187070
14	USA	185848
0	Abu Dhabi	29611
10	South Africa	18910
13	UK	16439
5	Indonesia	16214
12	Turkey	14670
6	NewZealand	9721
7	Philippines	8963
8	Quatar	3276
11	Sri Lanka	2929
1	Australia	2674
2	Brazil	1177
9	Singapore	638
3	Canada	412

In [725]: top\_five\_voted\_countries = country\_rank\_list.head(5)

In [726]: |top\_five\_voted\_countries

## Out[726]:

	Country	Votes
4	India	1187070
14	USA	185848
0	Abu Dhabi	29611
10	South Africa	18910
13	UK	16439

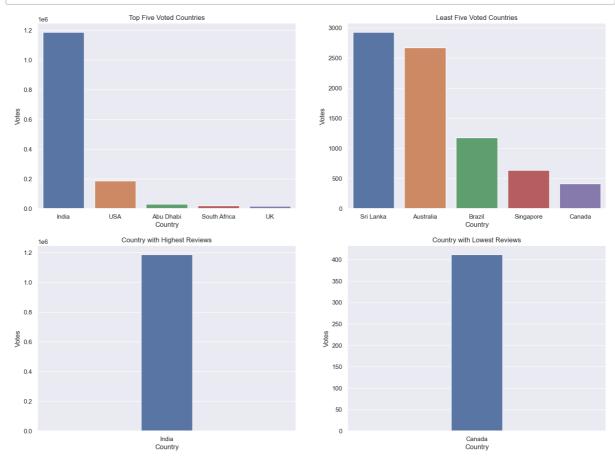
In [727]: least\_five\_voted\_countries = country\_rank\_list.tail(5)

```
least_five_voted_countries
In [728]:
Out[728]:
                Country Votes
                Sri Lanka
                        2929
            11
             1
                Australia
                        2674
             2
                  Brazil
                        1177
               Singapore
                         638
             3
                 Canada
                         412
In [729]: maximum_voted_country = country_rank_list.head(1)
In [730]: maximum_voted_country
Out [730]:
                        Votes
              Country
                 India 1187070
           minimum_voted_country = country_rank_list.sort_values(by="Votes").
In [731]:
In [732]: minimum_voted_country
Out[732]:
              Country Votes
```

Canada

412

```
In [733]: sns.set(style="darkgrid")
    plt.figure(figsize=(18,13))
    plt.subplot(2,2,1)
    axis_1 = sns.barplot(x='Country', y='Votes', data=top_five_voted_co
    plt.title("Top Five Voted Countries")
    plt.subplot(2,2,2)
    axis_2 = sns.barplot(x='Country', y='Votes', data=least_five_voted_
    plt.title("Least Five Voted Countries")
    plt.subplot(2,2,3)
    axis_3 = sns.barplot(x='Country', y='Votes', data=maximum_voted_couplt.title("Country with Highest Reviews")
    plt.subplot(2,2,4)
    axis_4 = sns.barplot(x='Country', y='Votes', data=minimum_voted_couplt.title("Country with Lowest Reviews")
    plt.show()
```



#### **Observation:**

- From the above observations, India and the USA have the maximum number of customers across the globe.
- The country with the maximum number of customers is **India**.
- The country with the minimum number of customers is **Canada**.

#### Cities with maximum reviews from India

```
In [734]: grouped_data = data.groupby("Country")
```

In [735]: reviews\_from\_india = grouped\_data.get\_group("India")

In [736]: reviews\_from\_india

Out [736]:

	Restaurant Name	City	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	ls delivering now	S
624	Jahanpanah	Agra	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	
626	Time2Eat - Mama Chicken	Agra	North Indian	500	Indian Rupees(Rs.)	No	No	No	
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	
•••									
9271	D Cabana	Vizag	Continental, Seafood, Chinese, North Indian, B	600	Indian Rupees(Rs.)	No	No	No	
9272	Kaloreez	Vizag	Cafe, North Indian, Chinese	400	Indian Rupees(Rs.)	No	No	No	
9273	Plot 17	Vizag	Burger, Pizza, Biryani	600	Indian Rupees(Rs.)	No	No	No	
9274	Vista - The Park	Vizag	American, North Indian, Thai, Continental	1500	Indian Rupees(Rs.)	No	No	No	
9275	Flying Spaghetti Monster	Vizag	Italian	1400	Indian Rupees(Rs.)	No	No	No	

8609 rows × 15 columns

In [737]: reviews\_from\_indian\_cities = reviews\_from\_india.groupby("City")

In [738]: votings\_from\_indian\_cities = reviews\_from\_indian\_cities["Votes"].su

```
In [739]: votings_from_indian_cities = votings_from_indian_cities.reset_index
In [740]: votings_from_indian_cities.sort_values(
               by="Votes",
               ascending = False,
               inplace = True
           )
In [741]: votings_from_indian_cities.head()
Out [741]:
                   City
                         Votes
            31 New Delhi
                        628262
            15
                Gurgaon 132155
            32
                  Noida
                         73478
             5 Bangalore
                         56115
            22
                 Kolkata
                         44593
In [742]: |top_five_voted_indian_cities = votings_from_indian_cities.head(5)
In [743]:
          top_five_voted_indian_cities
Out [743]:
                   City
                         Votes
            31 New Delhi
                        628262
            15
                Gurgaon
                        132155
            32
                  Noida
                         73478
             5 Bangalore
                         56115
            22
                 Kolkata
                         44593
```

#### Out[744]:

	Restaurant Name	City	Cuisines	Average Cost for two	Currency	Has Table booking	Has Online delivery	ls delivering now	S
624	Jahanpanah	Agra	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	
626	Time2Eat - Mama Chicken	Agra	North Indian	500	Indian Rupees(Rs.)	No	No	No	
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	
9271	D Cabana	Vizag	Continental, Seafood, Chinese, North Indian, B	600	Indian Rupees(Rs.)	No	No	No	
9272	Kaloreez	Vizag	Cafe, North Indian, Chinese	400	Indian Rupees(Rs.)	No	No	No	
9273	Plot 17	Vizag	Burger, Pizza, Biryani	600	Indian Rupees(Rs.)	No	No	No	
9274	Vista - The Park	Vizag	American, North Indian, Thai, Continental	1500	Indian Rupees(Rs.)	No	No	No	
9275	Flying Spaghetti Monster	Vizag	Italian	1400	Indian Rupees(Rs.)	No	No	No	

8609 rows × 15 columns

# **Overall Rating Categories in india**

In [745]: reviews\_from\_india.head()

**Average** 

Out [745]:

	Restaurant Name	City	Cuisines	Cost for two	Currency	Table booking	Online delivery	delivering now	ord mei
624	Jahanpanah	Agra	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	1
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	1
626	Time2Eat - Mama Chicken	Agra	North Indian	500	Indian Rupees(Rs.)	No	No	No	1
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	1
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	1

Has

Has

Is Swite

# Cities With Zero Poor Ratings, Zero Not Rated Ratings And Excellent Ratings

In [746]: rating = reviews\_from\_india[["City","Aggregate rating","Rating colo

```
In [747]: excellent_rating = rating[(rating["Aggregate rating"]>=4.7) & (rati
In [748]: excellent_rating = rating[(rating["Rating text"] != "Poor") & (rati
In [749]: excellent_rating.head()
```

Out[749]:

	City	Aggregate rating	Rating color	Rating text	
637	Agra	4.9	Dark Green	Excellent	
646	Ahmedabad	4.5	Dark Green	Excellent	
653	Ahmedabad	4.6	Dark Green	Excellent	
660	Ahmedabad	4.5	Dark Green	Excellent	
727	Bangalore	4.7	Dark Green	Excellent	

```
In [750]: excellent_rating_cities = excellent_rating[["City","Rating text"]]
```

```
In [751]: excellent_rating_cities
Out [751]:
                         City Rating text
             637
                         Agra
                                Excellent
             646
                   Ahmedabad
                                Excellent
             653
                   Ahmedabad
                                Excellent
                   Ahmedabad
                                Excellent
             660
             727
                     Bangalore
                                Excellent
            9195 Secunderabad
                                Excellent
            9216
                     Vadodara
                                Excellent
            9228
                     Vadodara
                                Excellent
                         Vizag
                                Excellent
            9256
            9262
                         Vizag
                                Excellent
            116 rows × 2 columns
In [752]: | excellent_rating_cities = excellent_rating_cities.groupby("City").c
In [753]:
           excellent_rating_cities = excellent_rating_cities.sort_values(
                by="Rating text",
                ascending = False
            )
           Top Cities With Excellent Ratings
          top_five_excellent_rating_cities = excellent_rating_cities.head(5)
In [755]: top_five_excellent_rating_cities = top_five_excellent_rating_cities
In [756]:
          top_five_excellent_rating_cities
Out [756]:
                   City
                       Rating text
            0 New Delhi
                               28
                               12
                Gurgaon
            2 Bangalore
                                9
                                6
            3
                Chennai
```

Goa

6

# Cities With Zero Poor Ratings, Zero Not Rated Very And Good Ratings

#### **Top Cities With Very Good Rating**

```
In [761]: | very_good_rating = very_good_rating.head()
In [762]: very_good_rating = very_good_rating.reset_index()
In [763]: |very_good_rating
Out[763]:
                   City Rating text
            0 New Delhi
                             300
               Gurgaon
                              83
            2
                 Noida
                              27
               Guwahati
                              15
                  Pune
                              14
            4
```

# Cities With Zero Poor Ratings, Zero Not Rated And Good Ratings

```
In [764]: good_rating = rating[(rating["Rating text"] != "Poor") & (rating["R
In [765]: good_rating.reset_index(inplace=True)
    good_rating = good_rating[["City","Rating text"]]
In [766]: good_rating = good_rating.groupby("City").count()
```

#### **Top Cities With Good Ratings**

```
In [768]:
           good_rating = good_rating.head()
In [769]:
           good_rating = good_rating.reset_index()
In [770]:
           good_rating
Out [770]:
                   City Rating text
               New Delhi
                             1128
            0
                Gurgaon
                              257
            2
                  Noida
                              173
            3 Faridabad
                               22
            4 Mangalore
                               18
```

# Cities With Zero Poor Ratings, Zero Not Rated And Average Ratings

## **Top Cities With Average Ratings**

```
In [775]: average_rating = average_rating.head()
In [776]: average_rating = average_rating.reset_index()
```

```
In [777]: average_rating

Out[777]:

City Rating text

0 New Delhi 2489

1 Gurgaon 504

2 Noida 448

3 Faridabad 123

4 Ghaziabad 18

Cities With Poor Ratings
```

## **Top Cities With Poor Ratings**

	City	Rating text
0	New Delhi	97
1	Noida	45
2	Gurgaon	34
3	Faridabad	2
4	Ghaziabad	1

## Cities With Not Ratings

#### **Top Not Rated Cities**

```
In [789]: |not_rated_rating = not_rated_rating.head()
In [790]: not_rated_rating = not_rated_rating.reset_index()
In [791]: |not_rated_rating
Out[791]:
                   City Rating text
              New Delhi
                             1408
            0
                  Noida
                             370
            2
                Gurgaon
                             224
               Faridabad
                              99
            4 Ghaziabad
                               2
```

## **Ratings Categories**

```
In [792]: category = {
    "Dark Green":"Excellent",
    "Green":"Very Good",
    "Yellow":"Good",
    "Orange":"Average",
    "Red":"Poor",
    "White":"Not rated"
}

In [793]: rating_group = rating.groupby("Rating color").count()

In [794]: rating_group = rating_group.reset_index()

In [795]: rating_group["Rating category"] = rating_group["Rating color"].map()
```

```
In [796]: | overall_ratings = rating_group
In [797]:
            overall_ratings
Out [797]:
                             City Aggregate rating Rating text Rating category
                Rating color
             0
                  Dark Green
                              116
                                              116
                                                         116
                                                                     Excellent
              1
                                              692
                                                         692
                                                                    Very Good
                      Green
                              692
             2
                            3671
                                             3671
                                                        3671
                                                                     Average
                     Orange
                                                                        Poor
             3
                       Red
                              180
                                              180
                                                         180
                      White 2103
                                             2103
                                                        2103
                                                                    Not rated
                      Yellow 1847
                                             1847
                                                        1847
                                                                       Good
             5
In [798]:
            overall_rating = overall_ratings[["Rating category","Aggregate rati
In [799]:
            overall_rating
Out [799]:
                Rating category Aggregate rating
             0
                       Excellent
                                           116
              1
                     Very Good
                                           692
             2
                                          3671
                       Average
                          Poor
                                           180
              3
                      Not rated
                                          2103
              4
                                           1847
                          Good
  In [ ]:
```

## **Ranking Cities Across India with Rating Categories**

## Cities With Rankings

```
In [803]: ranked_cities_by_ratings
```

Out[803]:	Rating text	City	Average	Excellent	Good	Not rated	Poor	Very Good
	31	New Delhi	2489	28	1128	1408	97	300
	15	Gurgaon	504	12	257	224	34	83
	5	Bangalore	0	9	2	0	0	9
	9	Chennai	0	6	2	0	0	12
	17	Hyderabad	0	6	2	0	0	10
	14	Goa	0	6	5	0	0	9
	22	Kolkata	0	5	4	0	0	11
	36	Pune	0	4	2	0	0	14
	23	Lucknow	0	4	4	0	0	13
	27	Mumbai	1	4	7	0	0	8
	16	Guwahati	0	3	3	0	0	15
	1	Ahmedabad	0	3	5	0	0	13
	19	Jaipur	1	3	4	0	0	12
	10	Coimbatore	0	3	6	0	0	11
	32	Noida	448	2	173	370	45	27
	21	Kochi	0	2	6	0	0	12
	8	Chandigarh	2	2	2	0	0	12
	29	Nagpur	1	2	6	0	1	10
	7	Bhubaneshwar	0	2	10	0	0	9
	40	Vadodara	0	2	9	0	0	9
	42	Vizag	0	2	10	0	0	8
	11	Dehradun	0	1	9	0	0	10
	0	Agra	1	1	9	0	0	9
	6	Bhopal	2	1	8	0	0	9
	24	Ludhiana	0	1	11	0	0	8
	12	Faridabad	123	1	22	99	2	3
	38	Secunderabad	0	1	0	0	0	1
	18	Indore	1	0	7	0	0	12
	39	Surat	1	0	9	0	0	10
	20	Kanpur	3	0	10	0	0	7
	3	Amritsar	5	0	12	0	0	4
	28	Mysore	2	0	15	0	0	3
	35	Puducherry	2	0	15	0	0	3
	25	Mangalore	0	0	18	0	0	2
	41	Varanasi	8	0	11	0	0	1

37	Ranchi	11	0	8	0	0	1
26	Mohali	0	0	0	0	0	1
33	Panchkula	0	0	0	0	0	1
30	Nashik	8	0	12	0	0	0
34	Patna	9	0	11	0	0	0
2	Allahabad	15	0	5	0	0	0
13	Ghaziabad	18	0	4	2	1	0
4	Aurangabad	16	0	4	0	0	0

#### Cities With above average ratings

```
In [804]: cities_with_good_ratings = ranked_cities_by_ratings[["City","Good",
```

#### **Top Five Cities With Above Average Ratings**

```
In [805]: cities_with_good_ratings["Total"] = cities_with_good_ratings.sum(ax
In [806]:
          cities_with_good_ratings = cities_with_good_ratings.head(5)
           cities_with_good_ratings["Total"] = cities_with_good_ratings.sum(ax
           cities with good ratings["Average"] = cities with good ratings.medi
In [807]: cities_with_good_ratings = cities_with_good_ratings.head()
In [808]:
          cities_with_good_ratings
Out[808]:
           Rating text
                         City Good Very Good Excellent Total Average
                  31
                     New Delhi
                              1128
                                        300
                                                 28
                                                    2912
                                                            714.0
                  15
                      Gurgaon
                               257
                                         83
                                                 12
                                                      704
                                                            170.0
```

9

12

10

9

6

6

40

40

36

9.0

9.0

8.0

## **Cities with Zero Poor Ratings**

Bangalore

Chennai

17 Hyderabad

2

2

5

9

```
In [809]: cities_with_poor_ratings = ranked_cities_by_ratings[["City","Poor"]
In [810]: cities_with_poor_ratings
Out[810]:
```

Rating text	City	Poor
31	New Delhi	97

15	Gurgaon	34
5	Bangalore	0
9	Chennai	0
17	Hyderabad	0
14	Goa	0
22	Kolkata	0
36	Pune	0
23	Lucknow	0
27	Mumbai	0
16	Guwahati	0
1	Ahmedabad	0
19	Jaipur	0
10	Coimbatore	0
32	Noida	45
21	Kochi	0
8	Chandigarh	0
29	Nagpur	1
7	Bhubaneshwar	0
40	Vadodara	0
42	Vizag	0
11	Dehradun	0
0	Agra	0
6	Bhopal	0
24	Ludhiana	0
12	Faridabad	2
38	Secunderabad	0
18	Indore	0
39	Surat	0
20	Kanpur	0
3	Amritsar	0
28	Mysore	0
35	Puducherry	0
25	Mangalore	0
41	Varanasi	0
37	Ranchi	0
26	Mohali	0

```
2
                        Allahabad
                       Ghaziabad
                                   1
                 13
                      Aurangabad
                                   0
                  4
In [811]:
          zero_ratings = cities_with_poor_ratings[cities_with_poor_ratings["P
In [812]:
          zero_ratings = zero_ratings.sort_values(
               by="Poor",
               ascending = True
           )
In [813]: zero_ratings = zero_ratings.groupby("City").count().reset_index()
In [911]: zero_ratings = zero_ratings.head(5)
```

## **Top Not Rated Cities**

Panchkula

Nashik

Patna

0

0

33

30

34

```
In [815]: cities_with_not_rated_ratings = ranked_cities_by_ratings[["City","N
In [816]: cities_with_not_rated_ratings
```

Out[816]:

Rating text	City	Not rated
31	New Delhi	1408
15	Gurgaon	224
5	Bangalore	0
9	Chennai	0
17	Hyderabad	0
14	Goa	0
22	Kolkata	0
36	Pune	0
23	Lucknow	0
27	Mumbai	0
16	Guwahati	0
1	Ahmedabad	0
19	Jaipur	0
10	Coimbatore	0

```
0
21
            Kochi
 8
       Chandigarh
                            0
29
           Nagpur
                            0
                            0
 7
    Bhubaneshwar
         Vadodara
                            0
40
                            0
42
             Vizag
11
         Dehradun
                            0
                            0
 0
             Agra
                            0
 6
           Bhopal
                            0
         Ludhiana
24
12
        Faridabad
                           99
38
    Secunderabad
                            0
            Indore
                            0
18
                            0
39
             Surat
20
           Kanpur
                            0
                            0
 3
          Amritsar
                            0
28
           Mysore
       Puducherry
                            0
35
25
        Mangalore
                            0
                            0
41
          Varanasi
                            0
           Ranchi
37
           Mohali
                            0
26
        Panchkula
                            0
33
                            0
30
           Nashik
                            0
34
            Patna
        Allahabad
                            0
 2
                            2
13
        Ghaziabad
 4
      Aurangabad
                            0
```

Noida

```
In [818]: not_rated_cities.head()
Out[818]:
            Rating text
                           City Not rated
                                    1408
                   31
                       New Delhi
                                    370
                   32
                          Noida
                   15
                        Gurgaon
                                    224
                   12
                       Faridabad
                                     99
                      Ghaziabad
                                      2
                   13
In [819]: | not_rated_cities = not_rated_cities.head(5)
In [820]: not_rated_cities
Out[820]:
            Rating text
                           City Not rated
                       New Delhi
                                    1408
                   31
                   32
                          Noida
                                    370
                        Gurgaon
                                    224
                   15
                       Faridabad
                                     99
                   12
                   13 Ghaziabad
           Cities With Zero Not Rated Cities
           zero_not_rated = ranked_cities_by_ratings[["City","Not rated"]]
In [821]:
In [822]:
           zero_not_rated = zero_not_rated[zero_not_rated["Not rated"] == 0]
In [823]:
           zero_not_rated
```

City Not rated

0

0

0

0

0

0

0

0

0

Bangalore

Hyderabad

Chennai

Goa

Kolkata

Lucknow

Mumbai

Guwahati

Pune

Out [823]:

Rating text

5

9

17

14

22

36

23

27

16

1	Ahmedabad	0
19	Jaipur	0
10	Coimbatore	0
21	Kochi	0
8	Chandigarh	0
29	Nagpur	0
7	Bhubaneshwar	0
40	Vadodara	0
42	Vizag	0
11	Dehradun	0
0	Agra	0
6	Bhopal	0
24	Ludhiana	0
38	Secunderabad	0
18	Indore	0
39	Surat	0
20	Kanpur	0
3	Amritsar	0
28	Mysore	0
35	Puducherry	0
25	Mangalore	0
41	Varanasi	0
37	Ranchi	0
26	Mohali	0
33	Panchkula	0
30	Nashik	0
34	Patna	0
2	Allahabad	0
4	Aurangabad	0

```
In [824]: top_zero_not_rated_cities = zero_not_rated.head(5)
```

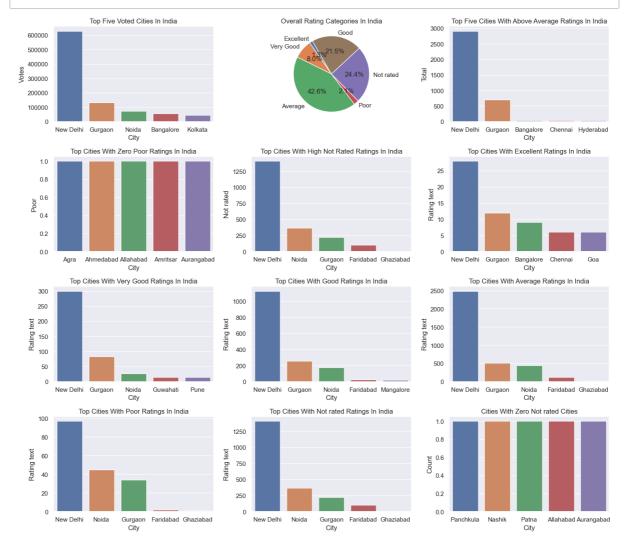
```
In [825]: top_zero_not_rated_cities
```

#### Out[825]:

Rating text	City	Not rated
5	Bangalore	0
9	Chennai	0
17	Hyderabad	0
14	Goa	0
22	Kolkata	0

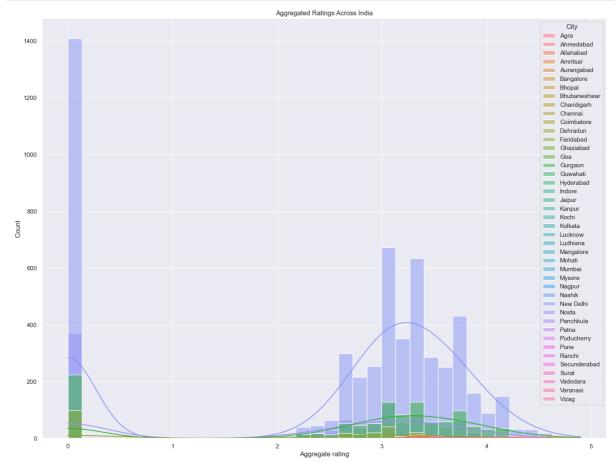
```
In [912]: |sns.set(style="darkgrid")
          plt.figure(figsize=(15,13))
          plt.subplot(4,3,1)
          sns.barplot(x="City", y="Votes", data=top_five_voted_indian_cities)
          plt.title("Top Five Voted Cities In India")
          plt.subplot(4,3,2)
          plt.pie(
              overall_rating['Aggregate rating'],
              labels=overall rating['Rating category'],
              autopct='%1.1f%%',
              startangle=120
          )
          plt.title("Overall Rating Categories In India")
          plt.subplot(4,3,3)
          sns.barplot(x="City", y="Total", data=cities_with_good_ratings)
          plt.title("Top Five Cities With Above Average Ratings In India")
          plt.subplot(4,3,4)
          sns.barplot(x="City", y="Poor", data=zero_ratings)
          plt.title("Top Cities With Zero Poor Ratings In India")
          plt.subplot(4,3,5)
          sns.barplot(x="City", y="Not rated", data=not_rated_cities)
          plt.title("Top Cities With High Not Rated Ratings In India")
          plt.subplot(4,3,6)
          sns.barplot(x="City", y="Rating text", data=top_five_excellent_rati
          plt.title("Top Cities With Excellent Ratings In India")
          plt.subplot(4,3,7)
          sns.barplot(x="City", y="Rating text", data=very_good_rating)
          plt.title("Top Cities With Very Good Ratings In India")
          plt.subplot(4,3,8)
          sns.barplot(x="City", y="Rating text", data=good_rating)
          plt.title("Top Cities With Good Ratings In India")
          plt.subplot(4,3,9)
          sns.barplot(x="City", y="Rating text", data=average_rating)
          plt.title("Top Cities With Average Ratings In India")
          plt.subplot(4,3,10)
          sns.barplot(x="City", y="Rating text", data=poor_rating)
          plt.title("Top Cities With Poor Ratings In India")
          plt.subplot(4,3,11)
          sns.barplot(x="City", y="Rating text", data=not_rated_rating)
          plt.title("Top Cities With Not rated Ratings In India")
          plt.subplot(4,3,12)
          sns.countplot(x='City', data=zero_not_rated.tail())
          plt.xlabel("City")
```

```
plt.ylabel("Count")
plt.title("Cities With Zero Not rated Cities")
plt.tight_layout()
plt.show()
```



### **Observation**

- The Overall performance of indian restaurants are Average (42%)
- Top five cities with highest votings from the customers are New Delhi,Gurgaon,Noida,Guwahati,Pune
- Top five above average rating cities are New Delhi,Gurgoan,Banglore,Chennai,Hyderabad
- Top five excellent rating cities are New Delhi, Gurgoan, Banglore, Chennai, Goa
- Top five very good rating cities are New Delhi, Gurgoan, Noida, Guwahati, Pune
- Top five good rating cities are New Delhi, Gurgoan, Noida, Faridabad, Manglore
- Top five average rating cities are New Delhi, Gurgoan, Noida, Faridabad, Ghaziabad
- Top five poor rated cities are New Delhi, Noida, Gurgoan, Faridabad, Ghaziabad
- Top five not rated cities are New Delhi, Noida, Gurgoan, Faridabad, Ghaziabad
- Top five cities with zero poor ratings are Banglore,Indore,Kanpur,Secunderabad,Surat
- Top five cities with zero not rated are Panchkula, Nashik, Patna, Allahabad, Aurangabad



**Ratings Across Restaurants, Cusines and cities** 

In [828]: reviews\_from\_india.head()

Out[828]:

	Destaurant			Average		Has	Has	Is	Swite
	Restaurant Name	City	Cuisines	Cost for two	Currency	Table booking	Online delivery	delivering now	ord mei
624	Jahanpanah	Agra	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	1
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	1
626	Time2Eat - Mama Chicken	Agra	North Indian	500	Indian Rupees(Rs.)	No	No	No	1
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	1
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	1

In [829]: indian\_restaurants\_data = reviews\_from\_india[["Restaurant Name","Ci

In [830]: indian\_restaurants\_data.head()

Out[830]:

	Restaurant Name	City	Cuisines	Average Cost for two	Price range	Has Table booking	Has Online delivery	ls delivering now	Switch to order menu	F
624	Jahanpanah	Agra	North Indian, Mughlai	850	3	No	No	No	No	
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	2	No	No	No	No	
626	Time2Eat - Mama Chicken	Agra	North Indian	500	2	No	No	No	No	
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	2	No	No	No	No	
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	3	No	No	No	No	

# How many Restaurants has Online Delivery in India?

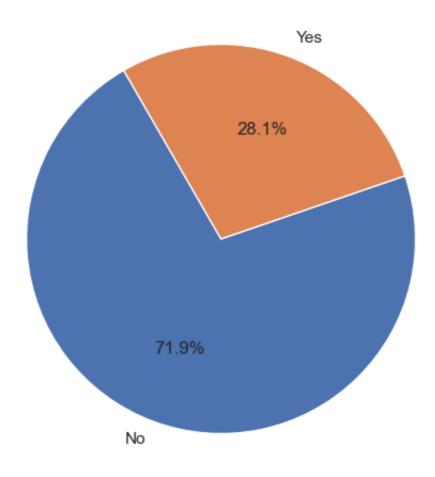
1

Yes

2417

```
In [834]: plt.figure(figsize=(16,13))
   plt.subplot(2,2,1)
   plt.pie(
        online_delivery["Counts"],
        labels = online_delivery["Online Delivery"],
        autopct='%1.1f%%',
        startangle=120
   )
   plt.title("Online Delivery")
   plt.show()
```

### Online Delivery



### **Observation**

• In India, only 28.1% of the restaurants offer online delivery, while the remaining 71.9% do not provide this service.

## How many Restaurants has table booking in india?

```
In [835]: table_booking = indian_restaurants_data["Has Table booking"].value_
```

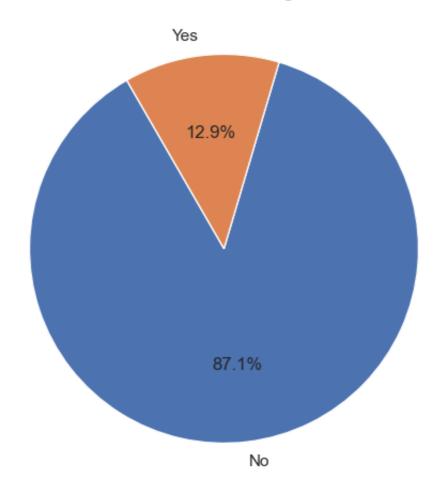
## In [837]: table\_booking

#### Out[837]:

	lable Booking	Counts
0	No	7498
1	Yes	1111

```
In [838]: plt.figure(figsize=(16,13))
   plt.subplot(2,2,1)
   plt.pie(
        table_booking["Counts"],
        labels = table_booking["Table Booking"],
        autopct='%1.1f%%',
        startangle=120
   )
   plt.title("Has Table Bookings")
   plt.show()
```

### Has Table Bookings



### **Observation:**

• In India, only **12.9**% of the restaurants has a table bookings, while the remaining 87.1% do not provide this service.

# How many restaurants are delivering right now

```
In [841]: plt.figure(figsize=(16,13))
  plt.subplot(2,2,1)
  plt.pie(
          delivering["Counts"],
          labels = delivering["Delivering"],
          autopct='%1.1f%%',
          startangle=120
    )
  plt.title("Is Delivering Rightnow")
  plt.show()
```

Is Delivering Rightnow



### **Observation:**

• In india, only **0.4**% of the restaurants are delivering right now, while the rest **99.6**% of the restaurants are not delivering right now

## **Cuisines Ratings In India**

```
In [842]: cuisines_count_india = indian_restaurants_data["Cuisines"].value_co
```

# **Top Rated Cuisines Distribution**

In [843]: top\_10\_rated\_cuisines\_in\_india = cuisines\_count\_india.head(10)

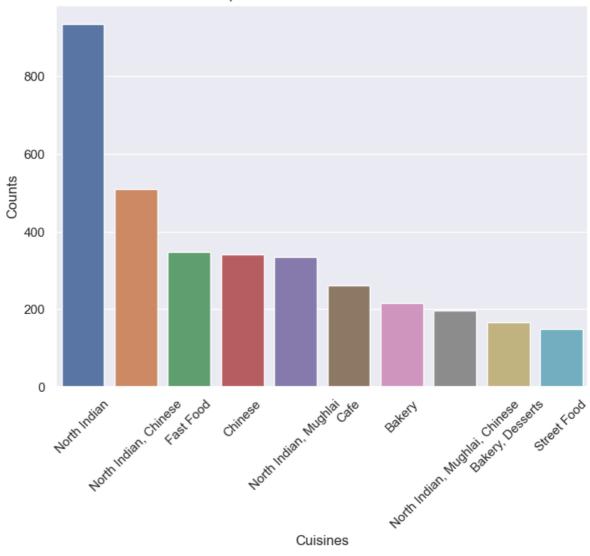
In [844]: top\_10\_rated\_cuisines\_in\_india

Out[844]:

	index	Cuisines
0	North Indian	935
1	North Indian, Chinese	510
2	Fast Food	347
3	Chinese	340
4	North Indian, Mughlai	334
5	Cafe	262
6	Bakery	216
7	North Indian, Mughlai, Chinese	197
8	Bakery, Desserts	167
9	Street Food	149

```
In [845]: plt.figure(figsize=(18,13))
    plt.subplot(2,2,1)
    cs = sns.barplot(
        x = top_10_rated_cuisines_in_india["index"],
        y = top_10_rated_cuisines_in_india["Cuisines"]
)
    cs.set_xticklabels(cs.get_xticklabels(),rotation=45);
    plt.xlabel("Cuisines")
    plt.ylabel("Counts")
    plt.title("Top 10 Rated Cuisines Distribution")
    plt.show()
```





# **Excellent Rating Restaurants**

```
In [846]: restaurants_with_excellent_ratings = indian_restaurants_data[indian]
```

In [847]: | restaurants\_with\_excellent\_ratings

#### Out[847]:

	Restaurant Name	City	Cuisines	Average Cost for two	Price range	Has Table booking	Has Online delivery	delive
637	Sheroes Hangout	Agra	Cafe, North Indian, Chinese	0	1	No	No	
646	Huber & Holly	Ahmedabad	Ice Cream, Desserts, Continental	300	1	No	Yes	
653	Cryo Lab	Ahmedabad	Desserts, Ice Cream	350	2	No	No	
660	Nini's Kitchen	Ahmedabad	North Indian, Continental, Beverages, Italian,	950	3	No	Yes	
727	The Fatty Bao - Asian Gastro Bar	Bangalore	Asian	2400	4	Yes	Yes	
					•••			
9195	Coffee Cup	Secunderabad	Cafe, Continental	800	2	Yes	No	
9216	22nd Parallel	Vadodara	South Indian	400	2	No	No	
9228	La Quello - Mediterranean Kitchen	Vadodara	Mediterranean, Italian	1300	3	No	No	
9256	Pizza Hut	Vizag	Pizza, Fast Food	600	2	No	No	
9262	Barbeque Nation	Vizag	North Indian, Chinese, Mediterranean	1600	4	No	No	
116 ro	116 rows × 10 columns							
excel	excellent_rating_restaurants = restaurants_with_excellent_ratings.g							

```
In [848]:
In [849]: excellent_rating_restaurants = excellent_rating_restaurants.reset_i
In [850]: excellent_rating_restaurants = excellent_rating_restaurants.sort_va
              by="Rating text",
              ascending = False
```

# **Top Excellent Rating Restaurants**

```
In [851]: top_excellent_rating_restaurants = excellent_rating_restaurants.hea
```

```
In [852]: top_excellent_rating_restaurants

Out[852]:

Restaurant Name Rating text

6 Barbeque Nation 10
```

	Restaurant Name	Rating text
6	Barbeque Nation	10
1	AB's - Absolute Barbecues	4
20	Chili's	4
88	Twigly	2
61	Onesta	2

## **Top Excellent Rating Cuisines**

### Out [856]:

	Cuisines	Counts
0	North Indian	7
1	Ice Cream	5
2	North Indian, Mughlai	4
3	Modern Indian	3
4	Bakery, Desserts	3
5	Cafe	3
6	Mexican, American, Tex-Mex, Burger	3
7	European, Mediterranean, North Indian	3
8	North Indian, Chinese	3
9	Fast Food	2

## **Very Good Rating Restaurants**

```
In [857]: restaurants_with_very_good_ratings = indian_restaurants_data[indian]
In [858]: very_good_rating_restaurants = restaurants_with_very_good_ratings.g
```

## **Top Very Good Ratings**

```
In [861]: top_very_good_rating_restaurants = very_good_rating_restaurants.hea
```

In [862]: top\_very\_good\_rating\_restaurants

Out[862]:

	Restaurant Name	Rating text
41	Barbeque Nation	12
409	Pizza Hut	6
201	Farzi Cafe	5
340	Mocha	4
414	Punjab Grill	4

### **Top Very Good Rating Cuisines**

```
In [863]: very_good_rating_cuisines = restaurants_with_very_good_ratings["Cui
```

In [864]: very\_good\_rating\_cuisines = very\_good\_rating\_cuisines.head()

In [865]: very\_good\_rating\_cuisines

Out[865]:

	index	Cuisines
0	North Indian, Mughlai	25
1	North Indian, Chinese	19
2	Cafe	18
3	North Indian	16
4	Chinese	14

```
In [867]:
          very_good_rating_cuisines
Out [867]:
                       Cuisines Counts
           0 North Indian, Mughlai
                                  25
              North Indian, Chinese
                                  19
           2
                          Cafe
                                  18
           3
                    North Indian
                                  16
                       Chinese
                                  14
  In [ ]:
  In [ ]:
           Good Rating Restaurants
In [868]:
           restaurants_with_good_ratings = indian_restaurants_data[indian_rest
In [869]: |good_restaurant_count = restaurants_with_good_ratings.shape[0]
In [870]:
          good_restaurant_count
Out[870]: 1847
In [871]:
          good_rating_restaurants = restaurants_with_good_ratings.groupby("Re
In [872]:
          good_rating_restaurants = good_rating_restaurants.reset_index()
```

# **Top Good Ratings**

by="Rating text",
ascending = False

In [873]:

)

```
In [874]: top_good_rating_restaurants = good_rating_restaurants.head()
```

good\_rating\_restaurants = good\_rating\_restaurants.sort\_values(

```
In [875]: top_good_rating_restaurants
```

#### Out [875]:

_		Restaurant Name	Rating text
	806	McDonald's	20
	433	Dunkin' Donuts	16
	556	Haldiram's	15
	1184	Starbucks	15
	682	Keventers	13

## **Top Good Rating Cuisines**

#### Out [879]:

	Cuisines	Counts
0	North Indian	92
1	Cafe	75
2	North Indian, Mughlai	71
3	Fast Food	56
4	North Indian, Chinese	55
5	Street Food	39
6	Chinese	38
7	Bakery, Desserts	31
8	Bakery, Desserts, Fast Food	31
9	North Indian, Mughlai, Chinese	29

# **Average Rating Restaurants**

```
In [880]: restaurants_with_average_ratings = indian_restaurants_data[indian_r
In [881]: average_restaurant_count = restaurants_with_average_ratings.shape[0]
```

## **Top Average Ratings Restaurants**

```
In [886]: top_average_rating_restaurants = average_rating_restaurants.head()
In [887]: top_average_rating_restaurants
```

Out [887]:

	Restaurant Name	Rating text
430	Cafe Coffee Day	56
816	Domino's Pizza	53
2399	Subway	43
1030	Green Chick Chop	38
1543	McDonald's	27

# **Top Average Rating Cuisines**

```
average_rating_cuisines
In [891]:
Out [891]:
                                     Cuisines Counts
               0
                                  North Indian
                                                   366
               1
                          North Indian, Chinese
                                                   303
               2
                          North Indian, Mughlai
                                                  185
               3
                                      Chinese
                                                  150
                                    Fast Food
               4
                                                  150
               5
                                                  129
                                         Cafe
               6 North Indian, Mughlai, Chinese
                                                  122
               7
                                       Bakery
                                                   96
                                                   77
                              Pizza, Fast Food
               8
               9
                              Bakery, Desserts
                                                   72
```

## **Poor Rating Restaurants**

```
In [892]:
          restaurants_with_poor_ratings = indian_restaurants_data[indian_rest
In [893]:
          poor_restaurant_count = restaurants_with_poor_ratings.shape[0]
In [894]:
          poor_restaurant_count
Out[894]: 180
In [895]:
          poor_rating_restaurants = restaurants_with_poor_ratings.groupby("Re
In [896]:
          poor_rating_restaurants = poor_rating_restaurants.reset_index()
In [897]:
          poor_rating_restaurants = poor_rating_restaurants.sort_values(
              by="Rating text",
              ascending = False
          )
```

# **Top Poor Rating Restaurants**

```
In [898]: top_poor_rating_restaurants = poor_rating_restaurants.head()
```

```
In [899]: top_poor_rating_restaurants
```

#### Out[899]:

	Restaurant Name	Rating text
39	Domino's Pizza	12
121	Wah Ji Wah	7
102	Subway	7
86	Pizza Hut Delivery	5
94	Sagar Ratna	4

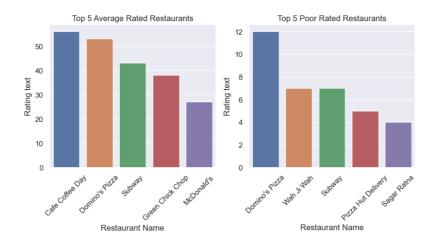
# **Top Poor Rating Cuisines**

### Out [903]:

	Cuisines	Counts
0	North Indian, Chinese	17
1	Pizza, Fast Food	13
2	North Indian	11
3	North Indian, Mughlai, Chinese	9
4	North Indian, Mughlai	9
5	Chinese	8
6	American, Fast Food, Salad, Healthy Food	7
7	South Indian, North Indian, Chinese	5
8	Chinese, Fast Food	5
9	Biryani, North Indian	4

```
In [904]: | sns.set_style("darkgrid")
          plt.figure(figsize=(15,13))
          plt.subplot(3,3,1)
          er = sns.barplot(x="Restaurant Name",y="Rating text",data=top_excel
          plt.title("Top 5 Excellent Rated Restaurants")
          er.set_xticklabels(er.get_xticklabels(),rotation=45);
          plt.subplot(3,3,2)
          vg = sns.barplot(x="Restaurant Name",y="Rating text",data=top_very_
          plt.title("Top 5 Very Good Rated Restaurants")
          vg.set_xticklabels(vg.get_xticklabels(),rotation=45);
          plt.subplot(3,3,3)
          g = sns.barplot(x="Restaurant Name",y="Rating text",data=top_good_r
          plt.title("Top 5 Good Rated Restaurants")
          g.set_xticklabels(g.get_xticklabels(),rotation=45);
          plt.subplot(3,3,7)
          av = sns.barplot(x="Restaurant Name",y="Rating text",data=top_avera
          plt.title("Top 5 Average Rated Restaurants")
          av.set_xticklabels(av.get_xticklabels(),rotation=45);
          plt.subplot(3,3,8)
          av = sns.barplot(x="Restaurant Name",y="Rating text",data=top_poor_
          plt.title("Top 5 Poor Rated Restaurants")
          av.set_xticklabels(av.get_xticklabels(),rotation=45);
          plt.show()
```

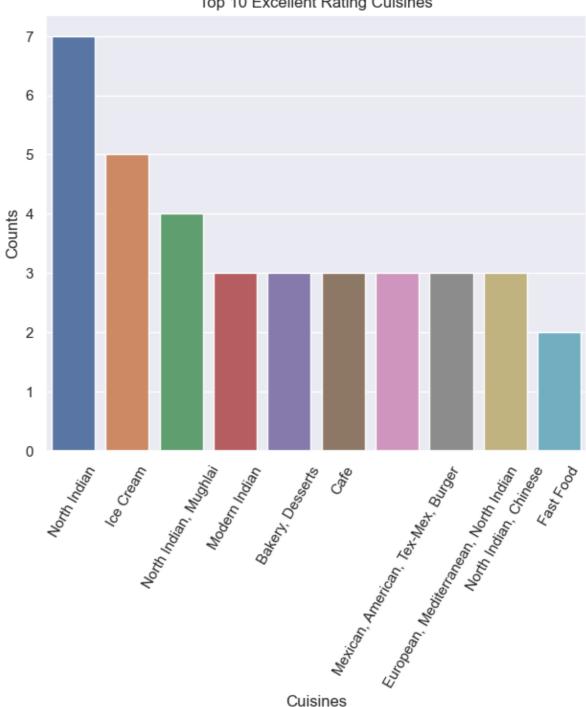




```
In [905]: sns.set_style("darkgrid")
          plt.figure(figsize=(16,13))
          plt.subplot(2,2,1)
          exc = sns.barplot(
              x = "Cuisines",
              y = "Counts",
              data = excellent_rating_cuisines
          exc.set_xticklabels(exc.get_xticklabels(),rotation=60);
          plt.title("Top 10 Excellent Rating Cuisines")
```

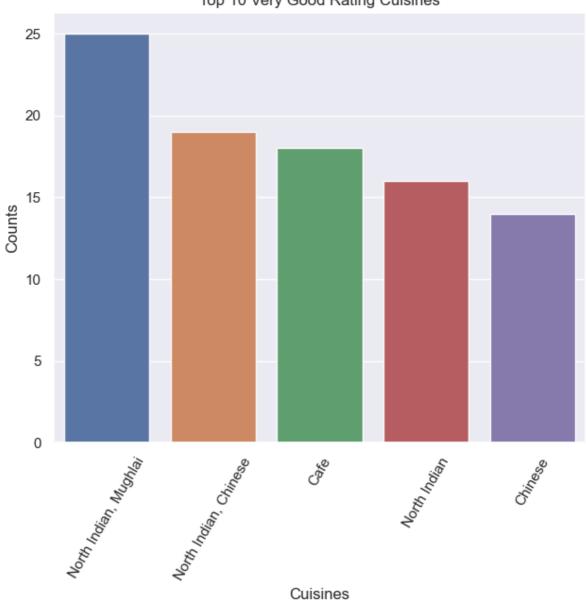
Out[905]: Text(0.5, 1.0, 'Top 10 Excellent Rating Cuisines')





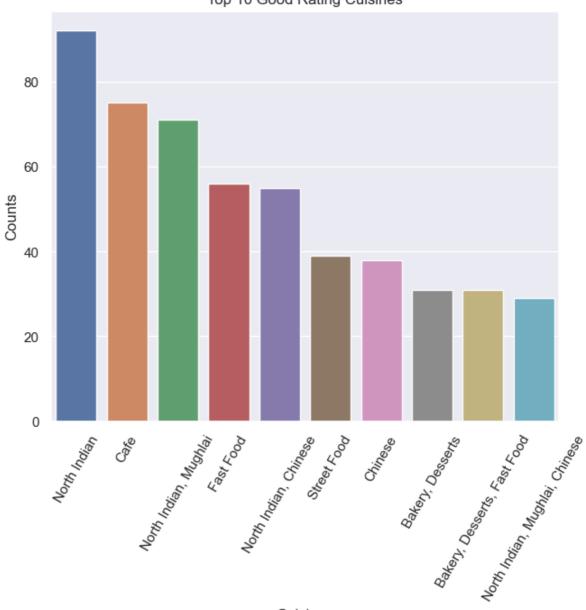
Out[906]: Text(0.5, 1.0, 'Top 10 Very Good Rating Cuisines')





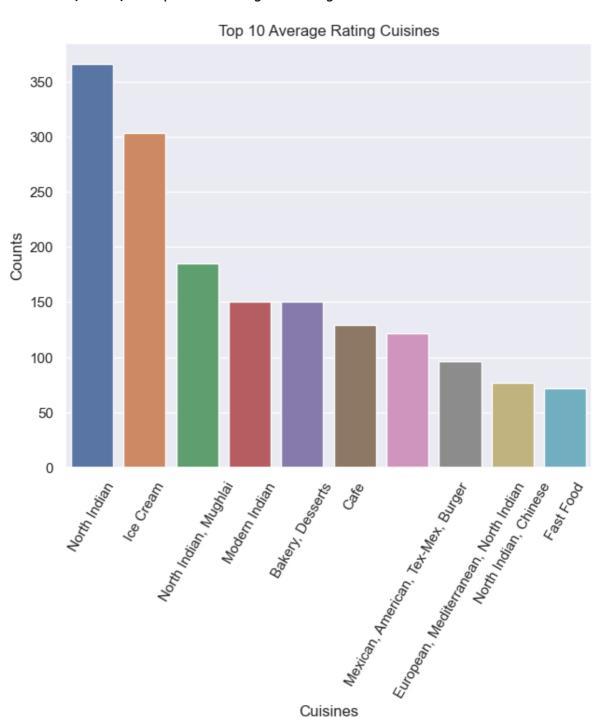
Out[907]: Text(0.5, 1.0, 'Top 10 Good Rating Cuisines')



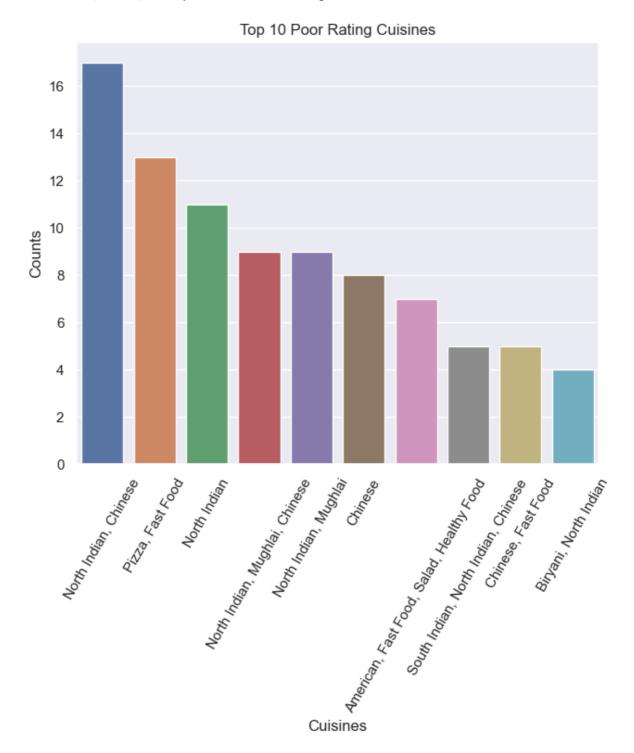


Cuisines

Out[908]: Text(0.5, 1.0, 'Top 10 Average Rating Cuisines')



Out[909]: Text(0.5, 1.0, 'Top 10 Poor Rating Cuisines')



Average Cost for two people in India

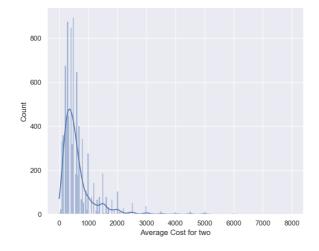
```
In [913]: cost_for_two = reviews_from_india
```

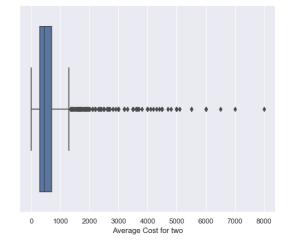
In [914]: cost\_for\_two.head()

#### Out [914]:

	Destaurant			Average		Has	Has	Is	Swite
	Restaurant Name	City	Cuisines	Cuisines Cost for Currency Ta		Table booking	Online delivery	delivering now	ord mei
624	Jahanpanah	Agra	North Indian, Mughlai	850	Indian Rupees(Rs.)	No	No	No	1
625	Rangrezz Restaurant	Agra	North Indian, Mughlai	700	Indian Rupees(Rs.)	No	No	No	1
626	Time2Eat - Mama Chicken	Agra	North Indian	500	Indian Rupees(Rs.)	No	No	No	1
627	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Rajasthani	400	Indian Rupees(Rs.)	No	No	No	1
628	Pinch Of Spice	Agra	North Indian, Chinese, Mughlai	1000	Indian Rupees(Rs.)	No	No	No	1

```
In [916]: plt.figure(figsize=(16,13))
   plt.subplot(2,2,1)
   sns.histplot(
        x=cost_for_two["Average Cost for two"],
        kde = True
)
   plt.subplot(2,2,2)
   sns.boxplot(
        x=cost_for_two["Average Cost for two"]
)
   plt.show()
```





#### **Observation**

- From the above observation it is clearly visible that the distribution of the Average
   Cost for two people is right skewed so to estimate the centeral value median is the
   best measure to go with beacause mean is more sensitive to outliers, so it is not the
   best measure to go with
- Median and Mode are the best measures to go with in estimating centeral values in case of outliers.

```
In [940]:

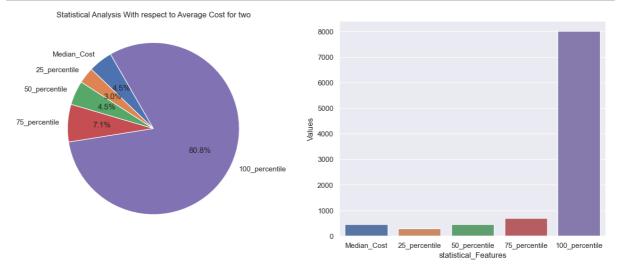
def percentile_analysis(data : Series):
    columns = ["Median_Cost","25_percentile","50_percentile","75_pe
    P25 = data.quantile(0.25)
    P50 = data.quantile(0.50)
    P75 = data.quantile(0.75)
    P100 = data.quantile(1.0)
    values = [P50,P25,P50,P75,P100]
    stats_data = {
        "statistical_Features":columns,
        "Values":values
    }
    stats_data = pd.DataFrame(stats_data)
    return stats_data
```

```
In [943]: result = percentile_analysis(cost_for_two["Average Cost for two"])
    result.head()
```

#### Out[943]:

	statistical_Features	Values
0	Median_Cost	450.0
1	25_percentile	300.0
2	50_percentile	450.0
3	75_percentile	700.0
4	100_percentile	8000.0

```
In [945]: plt.figure(figsize=(16,13))
   plt.subplot(2,2,1)
   plt.pie(
        result["Values"],
        labels = result["statistical_Features"],
        autopct='%1.1f%',
        startangle=120
   )
   plt.title("Statistical Analysis With respect to Average Cost for tw
   plt.subplot(2,2,2)
   sns.barplot(
        x = result["statistical_Features"],
        y = result["Values"]
   )
   plt.show()
```



#### **Observation**

Median value with respect to Average Cost for two people is Rs.450

```
In [ ]:
```