Zomato India Case Study EDA

Part A: Data Analysis and Missing Values

This part answers the following questions for data:

1. Identify and handle missing values.
2. Detect and correct any inconsistencies in the dataset (e.g., data types, mislabeled categories).
3. Feature engineering (if necessary), like extracting useful information from existing data.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
df = pd.read_csv('zomato_restaurants_in_India.csv')
```

```
df.head(1) #getting first row to check the data
```

	res_id	name	establishment	url	address	c
0	3400299	Bikanervala	['Quick Bites']	https://www.zomato.com/agra/bikanervala-khanda...	Kalyani Point, Near Tulsi Cinema, Bypass Road,...	A

1 rows × 26 columns

```
df.tail(1) #similar to above checking last rows further to check the data initially
```

	res_id	name	establishment	url	addr
211943	18879846	Freshco's - The Health Cafe	['Café']	https://www.zomato.com/vadodara/freshcos-the-h...	Sho Gro F Oppo Natu Circ

1 rows × 26 columns

```
df.index
```

```
RangeIndex(start=0, stop=211944, step=1)
```

```
df.shape
```

```
(211944, 26)
```

```
df.columns
```

```
Index(['res_id', 'name', 'establishment', 'url', 'address', 'city', 'city_id',
       'locality', 'latitude', 'longitude', 'zipcode', 'country_id',
       'locality_verbose', 'cuisines', 'timings', 'average_cost_for_two',
       'price_range', 'currency', 'highlights', 'aggregate_rating',
       'rating_text', 'votes', 'photo_count', 'opentable_support', 'delivery',
       'takeaway'],
      dtype='object')
```

```
df.dtypes
```

```
res_id                   int64
name                    object
establishment           object
url                     object
address                 object
city                    object
```

```
city_id                  int64
locality                object
latitude               float64
longitude              float64
zipcode                 object
country_id               int64
locality_verbose        object
cuisines                object
timings                 object
average_cost_for_two     int64
price_range              int64
currency                object
highlights              object
aggregate_rating       float64
rating_text             object
votes                    int64
photo_count              int64
opentable_support      float64
delivery                 int64
takeaway                 int64
dtype: object
```

```
df.info()
#getting the information for each feature (columns). The non null count also shows if there are null values in the column.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 211944 entries, 0 to 211943
Data columns (total 26 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   res_id                211944 non-null  int64
 1   name                  211944 non-null  object
 2   establishment         211944 non-null  object
 3   url                   211944 non-null  object
 4   address               211810 non-null  object
 5   city                  211944 non-null  object
 6   city_id               211944 non-null  int64
 7   locality              211944 non-null  object
 8   latitude              211944 non-null  float64
 9   longitude             211944 non-null  float64
 10  zipcode               48757 non-null   object
 11  country_id            211944 non-null  int64
 12  locality_verbose      211944 non-null  object
 13  cuisines              210553 non-null  object
 14  timings               208070 non-null  object
 15  average_cost_for_two  211944 non-null  int64
 16  price_range           211944 non-null  int64
 17  currency              211944 non-null  object
 18  highlights            211944 non-null  object
 19  aggregate_rating      211944 non-null  float64
 20  rating_text           211944 non-null  object
 21  votes                 211944 non-null  int64
 22  photo_count           211944 non-null  int64
 23  opentable_support     211896 non-null  float64
 24  delivery              211944 non-null  int64
 25  takeaway              211944 non-null  int64
dtypes: float64(4), int64(9), object(13)
memory usage: 42.0+ MB
```

Any column above having number of non-null less than 211944 contains null values. In the next step we will check the unique values in all columns to identify if there are different types of unique values or not.

```
dfcopy = df # creating copy for data in case original data is required afterwards.
#df contains data that will be transformed to cater inconsistencies
```

```
#checking missing values # by this we are getting the count of all the missing values
df.isna().sum()
```

```
res_id                       0
name                         0
establishment                0
url                          0
address                    134
city                         0
city_id                      0
locality                     0
latitude                     0
longitude                    0
zipcode                 163187
country_id                   0
locality_verbose             0
cuisines                  1391
timings                   3874
average_cost_for_two         0
price_range                  0
```

```
currency                  0
highlights                0
aggregate_rating          0
rating_text               0
votes                     0
photo_count               0
opentable_support        48
delivery                  0
takeaway                  0
dtype: int64
```

```
for column in df:
    percentage = (df[column].isnull().sum()/211944*100).round(2)
    print(f" The {column} has {percentage} percent null values")
```

```
 The res_id has 0.0 percent null values
 The name has 0.0 percent null values
 The establishment has 0.0 percent null values
 The url has 0.0 percent null values
 The address has 0.06 percent null values
 The city has 0.0 percent null values
 The city_id has 0.0 percent null values
 The locality has 0.0 percent null values
 The latitude has 0.0 percent null values
 The longitude has 0.0 percent null values
 The zipcode has 77.0 percent null values
 The country_id has 0.0 percent null values
 The locality_verbose has 0.0 percent null values
 The cuisines has 0.66 percent null values
 The timings has 1.83 percent null values
 The average_cost_for_two has 0.0 percent null values
 The price_range has 0.0 percent null values
 The currency has 0.0 percent null values
 The highlights has 0.0 percent null values
 The aggregate_rating has 0.0 percent null values
 The rating_text has 0.0 percent null values
 The votes has 0.0 percent null values
 The photo_count has 0.0 percent null values
 The opentable_support has 0.02 percent null values
 The delivery has 0.0 percent null values
 The takeaway has 0.0 percent null values
```

Considering the results obtained from percentage of missing value, zip code contains 77 percent null values. These are significantly high and will not affect the results afterwards for our predictive model. Therefore, it would be better to drop the column for zip code. However, we can further align with the stakeholders to understand what is use of zip code and how it can be required for any information that representatives of Zomato would like to extract. Being data analyst and considering the data that we have, I am dropping the column to make a better model. Only for the value of Cuisines, we drop restiatnts where there are no values.

```
df = df.dropna(subset=['cuisines']) #dropping null values for cuisines to clean the data
```

```
df = df.drop(columns = ['zipcode']) #dropping the zip code
```

```
df.columns
```

```
Index(['res_id', 'name', 'establishment', 'url', 'address', 'city', 'city_id',
       'locality', 'latitude', 'longitude', 'country_id', 'locality_verbose',
       'cuisines', 'timings', 'average_cost_for_two', 'price_range',
       'currency', 'highlights', 'aggregate_rating', 'rating_text', 'votes',
       'photo_count', 'opentable_support', 'delivery', 'takeaway'],
      dtype='object')
```

The column zipcode is dropped from the data.

```
df.dtypes
```

```
res_id                    int64
name                     object
establishment            object
url                      object
address                  object
city                     object
city_id                   int64
locality                 object
latitude                float64
longitude               float64
country_id                int64
locality_verbose         object
cuisines                 object
timings                  object
average_cost_for_two      int64
price_range               int64
```

```
currency                 object
highlights               object
aggregate_rating        float64
rating_text              object
votes                     int64
photo_count               int64
opentable_support       float64
delivery                  int64
takeaway                  int64
dtype: object
```

Considering the features above, right now it seems data types for the features are correct based on kind of data available to us.

```
df.duplicated().sum()
```

```
150606
```

```
pct_duplicates = (df.duplicated().sum()/df.shape[0]*100).round(2)
print(f"The percentage of the duplicate rows in the data set is {pct_duplicates}")
```

```
The percentage of the duplicate rows in the data set is 71.53
```

There are a lot of rows which are duplicates. To keep the data consist we would need to drop the duplicate values.

```
dfnew = df.drop_duplicates(keep='first', ignore_index=True)
#deleting all the duplicates to get the clean data which can help in getting meaningful analysis
```

```
dfnew.duplicated().sum()
```

```
0
```

The new dataset is being generated named as dfnew which do not have any duplicate values

It is evident that there are many values in res_id which are repeating. This also does not look consistent with data as it is unique for every restuarant. Therefore, data has further duplicate values which needs to be checked.

```
df['res_id'].duplicated() #to confirm the duplication
```

```
0         False
1         False
2         False
3         False
4         False
          ...
211939     True
211940    False
211941     True
211942    False
211943     True
Name: res_id, Length: 210553, dtype: bool
```

```
df2= dfnew.drop_duplicates(subset=['res_id'], keep='first', ignore_index=True)
```

```
df2.shape
```

```
(55098, 25)
```

df2 contains dataframe which is clear of all duplicates to ensure meaningful insights are generated.

Here are many features like URL and other which look like insignificant rightnow for initial analysis required. We will use them as required as the updated dataframe is saved in df2. I am creating a new variable having dataframe only inlcuding columns or features which are significant for analysis. Here discussion with stakeholders is key. However, I am making an assumption based on various industry practices and looking at the data.

```
df2.columns
```

```
Index(['res_id', 'name', 'establishment', 'url', 'address', 'city', 'city_id',
       'locality', 'latitude', 'longitude', 'country_id', 'locality_verbose',
       'cuisines', 'timings', 'average_cost_for_two', 'price_range',
       'currency', 'highlights', 'aggregate_rating', 'rating_text', 'votes',
       'photo_count', 'opentable_support', 'delivery', 'takeaway'],
      dtype='object')
```

```
dfnew1 = df2[['res_id','name', 'establishment', 'city', 'city_id', 'locality', 'locality_verbose', 'cuisines', 'timings', 'average_cost_
```

```
dfnew1.head(2)
```

	res_id	name	establishment	city	city_id	locality	locality_verbose	cuisines	timings	average_cost_for_two	price_ra
0	3400299	Bikanervala	['Quick Bites']	Agra	34	Khandari	Khandari, Agra	North Indian, South Indian, Mithai, Street Foo...	8:30am – 10:30pm (Mon-Sun)	700	
1	3400005	Mama Chicken Mama Franky House	['Quick Bites']	Agra	34	Agra Cantt	Agra Cantt, Agra	North Indian, Mughlai, Rolls, Chinese, Fast Fo...	12:30PM to 12Midnight (Mon, Wed, Thu, Fri, Sat...	600	

```
for column in dfnew1:
    print('column',' ',column,' has unique values ', dfnew1[column].nunique())
    print(dfnew1[column].unique())
    print('------------------------------------')
```

```
column   res_id  has unique values  55098
[ 3400299  3400005  3401013 ... 18019952  3200996  3201138]
------------------------------------
column   name  has unique values  40757
['Bikanervala' 'Mama Chicken Mama Franky House' 'Bhagat Halwai' ...
 'Red China' 'Wah Ustad' 'Geeta lodge']
------------------------------------
column   establishment  has unique values  27
["['Quick Bites']" "['Casual Dining']" "['Bakery']" "['Café']" "['Dhaba']"
 "['Bhojanalya']" "['Bar']" "['Sweet Shop']" "['Fine Dining']"
 "['Food Truck']" "['Dessert Parlour']" "['Lounge']" "['Pub']"
 "['Beverage Shop']" "['Kiosk']" "['Paan Shop']" "['Confectionery']" '[]'
 "['Shack']" "['Club']" "['Food Court']" "['Mess']" "['Butcher Shop']"
 "['Microbrewery']" "['Cocktail Bar']" "['Pop up']" "['Irani Cafe']"]
------------------------------------
column   city  has unique values  99
['Agra' 'Ahmedabad' 'Gandhinagar' 'Ajmer' 'Alappuzha' 'Allahabad'
 'Amravati' 'Amritsar' 'Aurangabad' 'Bangalore' 'Bhopal' 'Bhubaneshwar'
 'Chandigarh' 'Mohali' 'Panchkula' 'Zirakpur' 'Nayagaon' 'Chennai'
 'Coimbatore' 'Cuttack' 'Darjeeling' 'Dehradun' 'New Delhi' 'Gurgaon'
 'Noida' 'Faridabad' 'Ghaziabad' 'Greater Noida' 'Dharamshala' 'Gangtok'
 'Goa' 'Gorakhpur' 'Guntur' 'Guwahati' 'Gwalior' 'Haridwar' 'Hyderabad'
 'Secunderabad' 'Indore' 'Jabalpur' 'Jaipur' 'Jalandhar' 'Jammu'
 'Jamnagar' 'Jamshedpur' 'Jhansi' 'Jodhpur' 'Junagadh' 'Kanpur'
 'Kharagpur' 'Kochi' 'Kolhapur' 'Kolkata' 'Howrah' 'Kota' 'Lucknow'
 'Ludhiana' 'Madurai' 'Manali' 'Mangalore' 'Manipal' 'Udupi' 'Meerut'
 'Mumbai' 'Thane' 'Navi Mumbai' 'Mussoorie' 'Mysore' 'Nagpur' 'Nainital'
 'Nasik' 'Nashik' 'Neemrana' 'Ooty' 'Palakkad' 'Patiala' 'Patna'
 'Puducherry' 'Pune' 'Pushkar' 'Raipur' 'Rajkot' 'Ranchi' 'Rishikesh'
 'Salem' 'Shimla' 'Siliguri' 'Srinagar' 'Surat' 'Thrissur' 'Tirupati'
 'Trichy' 'Trivandrum' 'Udaipur' 'Varanasi' 'Vellore' 'Vijayawada' 'Vizag'
 'Vadodara']
------------------------------------
column   city_id  has unique values  83
[   34    11 11303 11297    24 11335    22    25     4    26    29    12
     7    30 11289 11324    35     1 11309    15    13 11311 11339    21
 11337 11291     6    14 11336    10 11306 11307 11321 11338 11352 11301
 11322    23 11354     9 11334     2 11302     8    20 11295 11308    31
 11299 11329     3 11304    36    33 11328    16 11079    18 11314 11333
    40    37     5 11293 11310 11294    27 11305 11331    19 11327 11076
    38 11298 11323 11332 11290 11054    39 11330 11300    28    32]
------------------------------------
column   locality  has unique values  3727
['Khandari' 'Agra Cantt' 'Shahganj' ... 'Navapura' 'L&T Knowledge City'
 'Danteshwar']
------------------------------------
column   locality_verbose  has unique values  3905
['Khandari, Agra' 'Agra Cantt, Agra' 'Shahganj, Agra' ...
 'Navapura, Vadodara' 'L&T Knowledge City, Vadodara'
 'Danteshwar, Vadodara']
------------------------------------
column   cuisines  has unique values  9382
['North Indian, South Indian, Mithai, Street Food, Desserts'
 'North Indian, Mughlai, Rolls, Chinese, Fast Food, Street Food'
 'Fast Food, Mithai' ...
 'Street Food, Biryani, Chinese, Fast Food, North Indian, Mughlai'
 'North Indian, Chinese, Mexican, Italian, Thai, Continental'
```

```
dfnew1.shape
```

```
(55098, 17)
```

EDA Statistical Analysis

This parapraph provide analysis for following questions:

1. Descriptive Statistics: Summarize the central tendency, dispersion, and shape of the dataset's distribution.
2. Distribution Analysis: Analyze the distribution of key variables (e.g., ratings,price range, cuisines).
3. Correlation Analysis: Examine the relationships between different variables.

```
dfnew1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 55098 entries, 0 to 55097
Data columns (total 17 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   res_id               55098 non-null  int64  
 1   name                 55098 non-null  object 
 2   establishment        55098 non-null  object 
 3   city                 55098 non-null  object 
 4   city_id              55098 non-null  int64  
 5   locality             55098 non-null  object 
 6   locality_verbose     55098 non-null  object 
 7   cuisines             55098 non-null  object 
 8   timings              54230 non-null  object 
 9   average_cost_for_two  55098 non-null  int64  
 10  price_range          55098 non-null  int64  
 11  highlights           55098 non-null  object 
 12  aggregate_rating     55098 non-null  float64
 13  rating_text          55098 non-null  object 
 14  votes                55098 non-null  int64  
 15  photo_count          55098 non-null  int64  
 16  delivery             55098 non-null  int64  
dtypes: float64(1), int64(7), object(9)
memory usage: 7.1+ MB
```

```
dfnew1.describe() #this is the way to get statistical analysis of all the values
```

	res_id	city_id	average_cost_for_two	price_range	aggregate_rating	votes	photo_count	delivery
count	5.509800e+04	55098.000000	55098.000000	55098.000000	55098.000000	55098.000000	55098.000000	55098.000000
mean	1.309156e+07	3354.276997	531.792697	1.719591	2.979478	225.210008	162.336782	-0.345003
std	8.122561e+06	5150.396004	595.916590	0.879407	1.449025	620.517701	589.287353	0.935579
min	5.000000e+01	1.000000	0.000000	1.000000	0.000000	-18.000000	0.000000	-1.000000
25%	3.000944e+06	8.000000	200.000000	1.000000	2.900000	6.000000	1.000000	-1.000000
50%	1.869208e+07	26.000000	350.000000	1.000000	3.500000	36.000000	10.000000	-1.000000
75%	1.887349e+07	11294.000000	600.000000	2.000000	3.900000	177.000000	70.000000	1.000000
max	1.915979e+07	11354.000000	30000.000000	4.000000	4.900000	42539.000000	17702.000000	1.000000

```
dfnew1[['price_range', 'aggregate_rating']].describe()
```

	price_range	aggregate_rating
count	55098.000000	55098.000000
mean	1.719591	2.979478
std	0.879407	1.449025
min	1.000000	0.000000
25%	1.000000	2.900000
50%	1.000000	3.500000
75%	2.000000	3.900000
max	4.000000	4.900000

```
dfnew1.describe(include=['object']) #getting description for all the categorical or descriptive columns
```

	name	establishment	city	locality	locality_verbose	cuisines	timings	highlights	rating_text
count	55098	55098	55098	55098	55098	55098	54230	55098	55098
unique	40757	27	99	3727	3905	9382	7699	31167	33
top	Domino's Pizza	['Quick Bites']	Bangalore	Civil Lines	Gomti Nagar, Lucknow	North Indian	11 AM to 11 PM	['Dinner', 'Takeaway Available', 'Lunch', 'Cas...	Average
freq	399	14000	2247	751	274	4295	6986	860	16256

This is also presents us with some analysis because we can observe

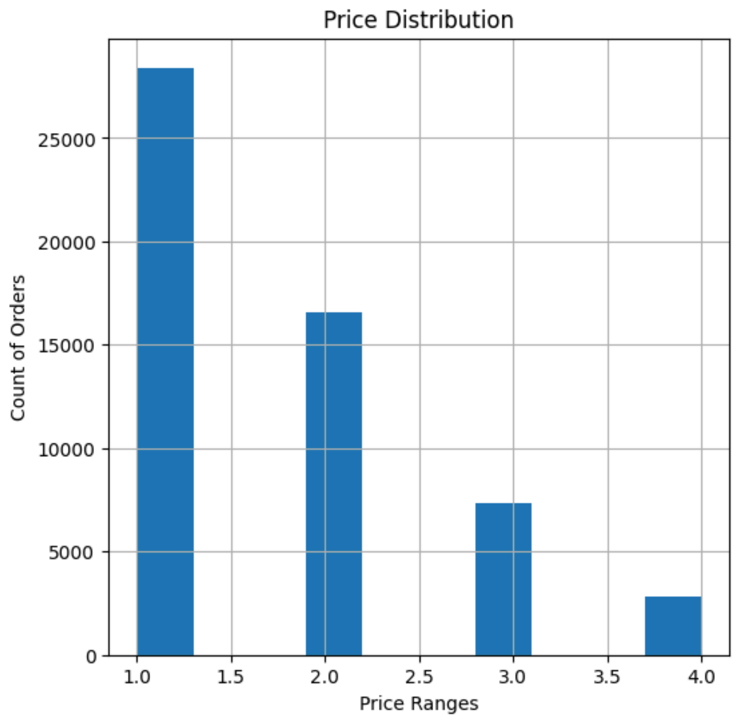
1. The most frequent establishment (type of restuarants) is 'Quick Bytes' on Zomato according to data. There are total 27 different types of establishments.
2. According to this data, we can predict that city having most restuarants is Chennai. Although this might be because of data collection. Therefore, it can be discussed with stakeholders for deriving any analysis further. The data is further for 99 more cities as per analysis above.
3. The most exisitng cusine as per data is North Indian.

This derivation is from the current observation, however there will be further analysis on data to derive more such key insights which can be benficial for the analysis of Zomato.

```
dfnew1.columns
```

```
Index(['res_id', 'name', 'establishment', 'city', 'city_id', 'locality',
       'locality_verbose', 'cuisines', 'timings', 'average_cost_for_two',
       'price_range', 'highlights', 'aggregate_rating', 'rating_text', 'votes',
       'photo_count', 'delivery'],
      dtype='object')
```

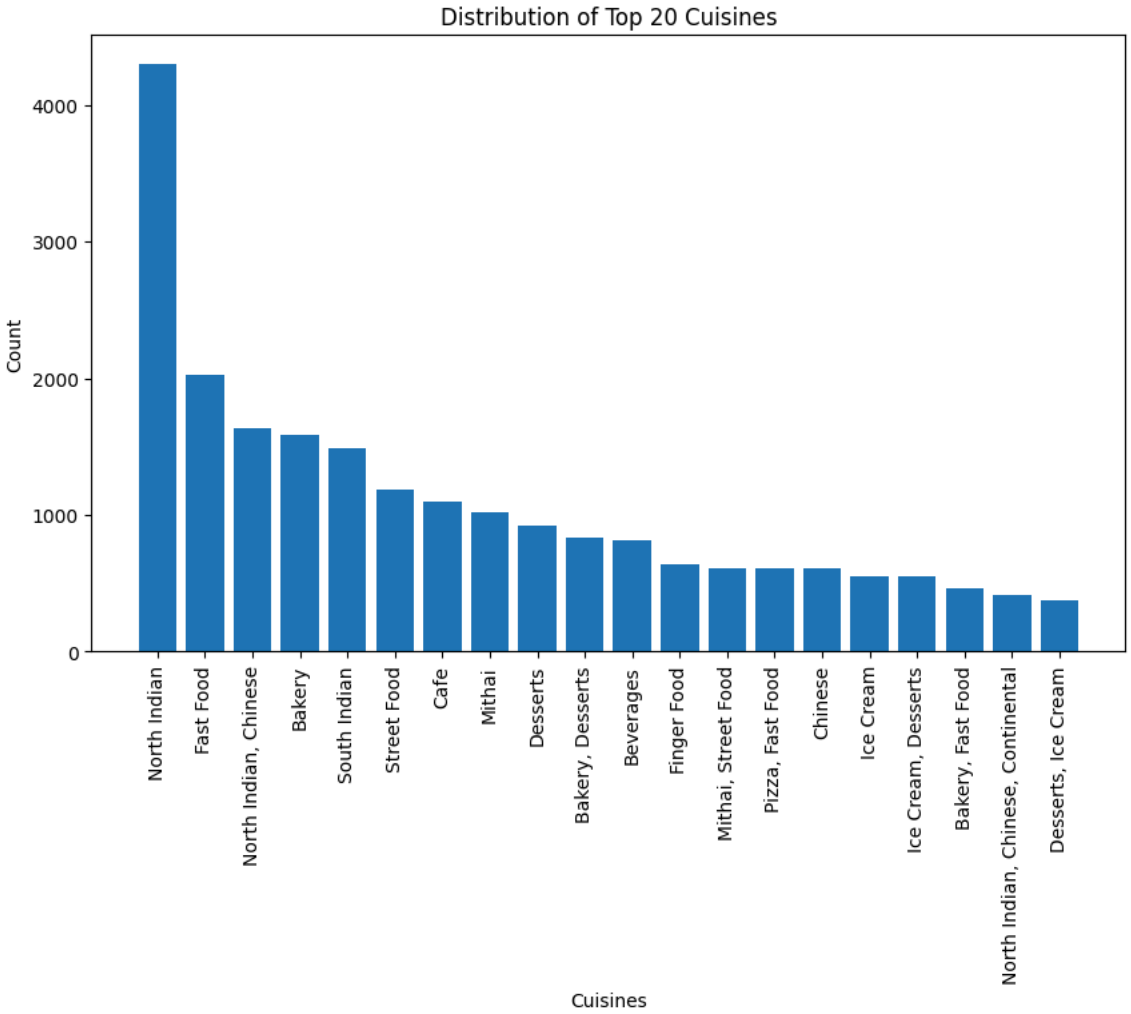
```
fig, ax = plt.subplots(figsize=(6, 6))
dfnew1[['price_range']].hist(ax=ax)
ax.set_xlabel('Price Ranges')
ax.set_ylabel('Count of Orders')
ax.set_title('Price Distribution')
plt.show()
```




```
dfnew1['price_range'].value_counts()
```

```
price_range
1    28401
2    16541
3     7361
4     2795
Name: count, dtype: int64
```

```
cuisines = dfnew1['cuisines'].value_counts()[:20]
plt.figure(figsize=(10, 6))
plot = plt.bar(cuisines.index,cuisines.values)#defining four bins to get the idea of rating
plt.title('Distribution of Top 20 Cuisines')
plt.xticks(rotation=90)
plt.xlabel('Cuisines')
plt.ylabel('Count')
plt.show()
```

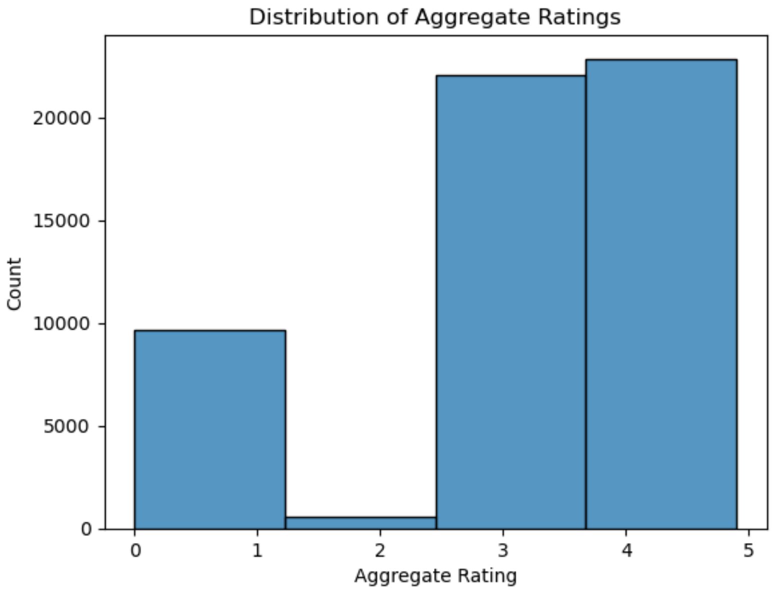



```
cuisines = dfnew1['cuisines'].value_counts()[:20]
cuisines
```

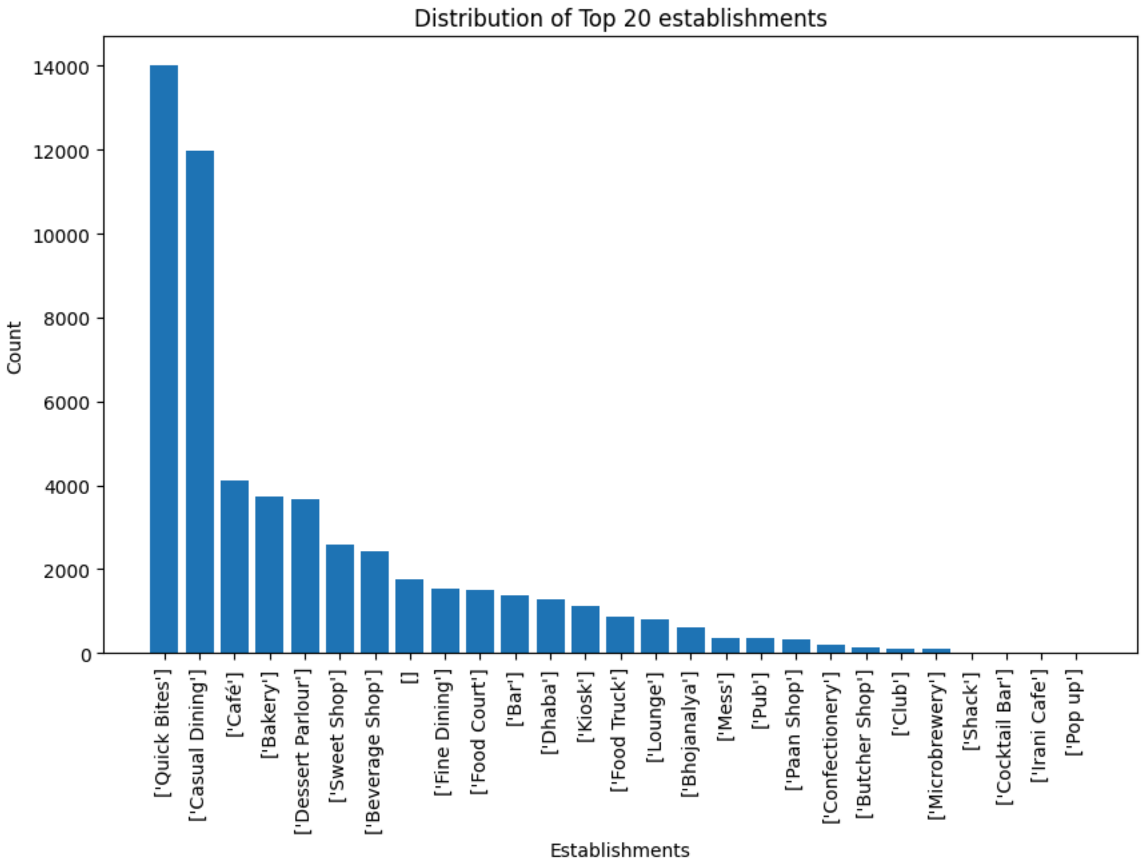
```
cuisines
North Indian                          4295
Fast Food                             2025
North Indian, Chinese                 1636
Bakery                                1585
South Indian                          1489
Street Food                           1187
Cafe                                  1098
Mithai                                1020
Desserts                               922
Bakery, Desserts                       836
Beverages                              817
Finger Food                            642
Mithai, Street Food                    612
Pizza, Fast Food                       608
Chinese                                607
Ice Cream                              552
Ice Cream, Desserts                    551
Bakery, Fast Food                      468
North Indian, Chinese, Continental     414
Desserts, Ice Cream                    373
Name: count, dtype: int64
```

The most listed cuisine on Zomato is North Indian by considerable margin based on data provided to us. The difference from the top second one is 2270 units in count.

```
ratings = dfnew1['aggregate_rating']
plot = sns.histplot(ratings, bins=4) # Using histplot for histogram
plot.set_xlabel("Aggregate Rating")  # Set x-axis label
plot.set_ylabel("Count")  # Set y-axis label
plot.set_title("Distribution of Aggregate Ratings")  # Set title
plt.show()
```




```
estb = dfnew1['establishment'].value_counts()
plt.figure(figsize=(10, 6))
plot = plt.bar(estb.index,estb.values)#defining four bins to get the idea of rating
plt.title('Distribution of Top 20 establishments')
plt.xticks(rotation=90)
plt.xlabel('Establishments')
plt.ylabel('Count')
plt.show()
```



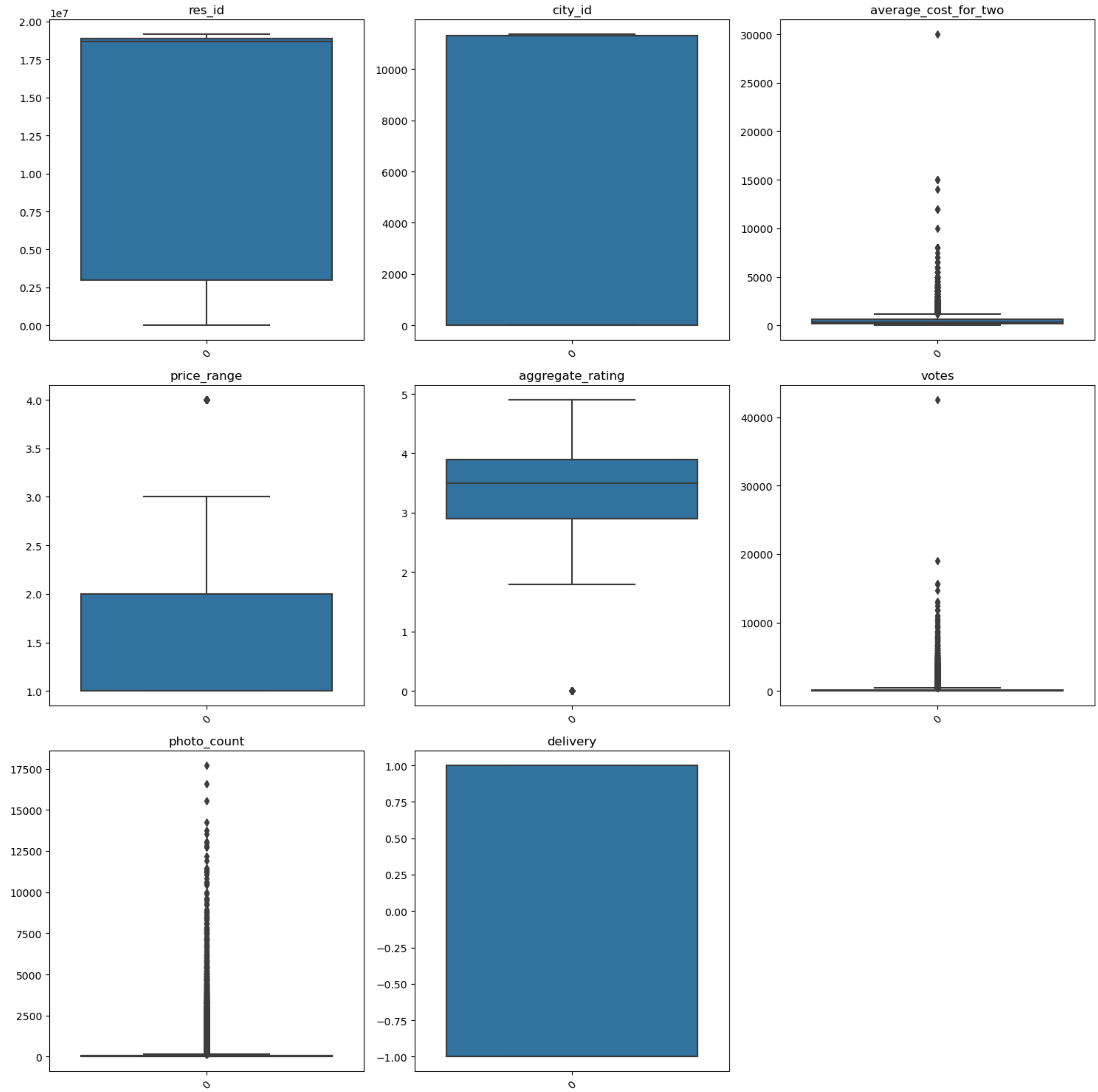

```
estb = dfnew1['establishment'].value_counts()
estb
```

```
establishment
['Quick Bites']        14000
```

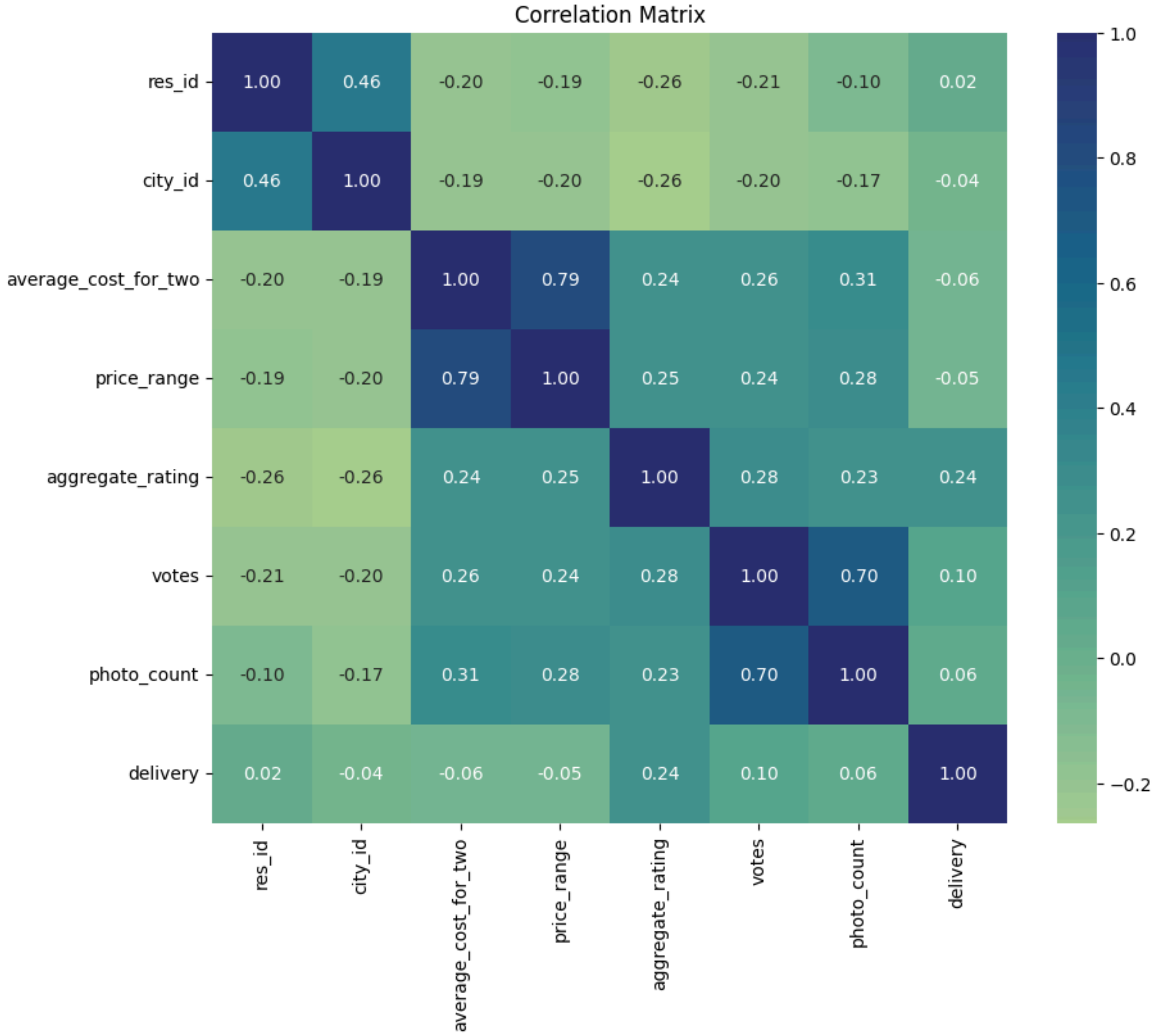
```
['Casual Dining']      11973
['Café']                4114
['Bakery']              3733
['Dessert Parlour']     3668
['Sweet Shop']          2604
['Beverage Shop']       2436
[]                      1766
['Fine Dining']         1534
['Food Court']          1491
['Bar']                 1384
['Dhaba']               1278
['Kiosk']               1126
['Food Truck']           865
['Lounge']               816
['Bhojanalya']           628
['Mess']                 361
['Pub']                  356
['Paan Shop']            320
['Confectionery']        217
['Butcher Shop']         154
['Club']                 112
['Microbrewery']         110
['Shack']                 18
['Cocktail Bar']          16
['Irani Cafe']            14
['Pop up']                 4
Name: count, dtype: int64
```

With this data we have from Zomato, there are 14000 restuarants which are Quick Bytes and there are 11973 which are casual dining places. This is considerably high number based on all data we have. One can make analysis that high number of places that gets registered on Zomato or higher number of restuarants on Zomato as either Quick Bytes or Cansual Dining. However there are others as well but this is considerably high number across India. Further analysis will help in defining how to target the relevant markets but this can also be a good indicator to begin with.

```
dfplot = dfnew1.select_dtypes(include='number')

# Calculate the number of rows needed
num_rows = (len(dfplot.columns) - 1) // 3 + 1

# Create subplots
fig, axes = plt.subplots(num_rows, 3, figsize=(15, 5 * num_rows))

# Flatten the axes array for easy iteration
axes = axes.flatten()

# Create boxplots for each numerical column
for i, column in enumerate(dfplot.columns):
    sns.boxplot(dfplot[column], ax=axes[i])
    axes[i].set_title(column)
    axes[i].tick_params(axis='x', rotation=45)

# Hide empty subplots if necessary
for j in range(len(dfplot.columns), len(axes)):
    axes[j].axis('off')

# Adjust layout
plt.tight_layout()

# Show plot
plt.show()
```




```
correlation = dfnew1.select_dtypes(include=['number']).corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation, annot=True, cmap="crest", fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



It is evident that for there is positive correlation between photo count and votes. It can be infered that all popular restuarants have their photos available. Moreover, price range is also related to costs for two. The higher the costs for two is resturants will fall in the place of high range for price

Regional Analysis

Customer preferances across cities can be defined by aggregate rating across cities. We can see which cuisine across cities has highest ratings.

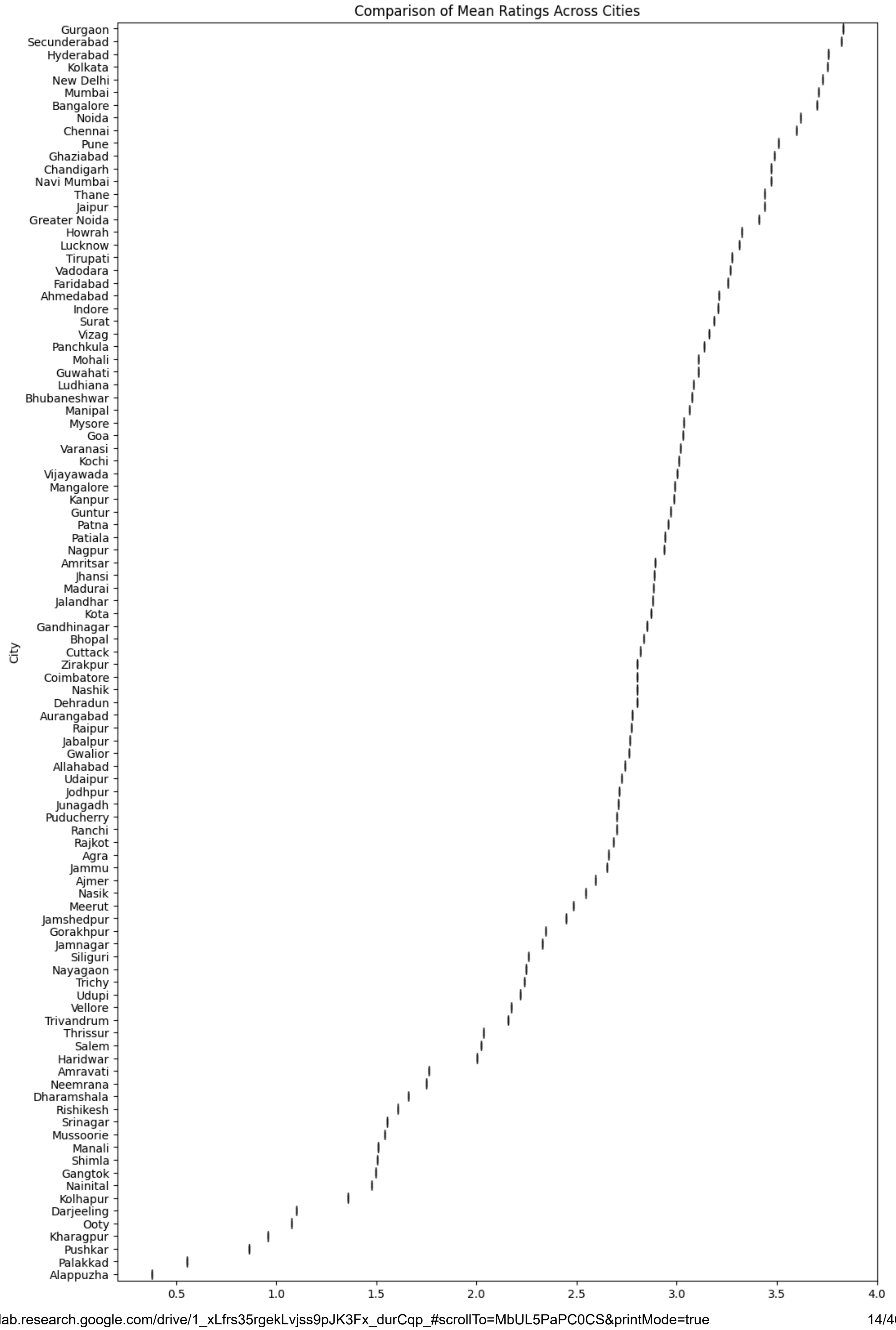
```
regions = dfnew1.groupby(['city', 'cuisines'])['aggregate_rating'].mean().reset_index()
regionsorted = regions.sort_values(by=['city', 'aggregate_rating'], ascending=[True, False])
topcuisinesincity = regionsorted.groupby('city').head(1)
topcuisinesincity
```

	city	cuisines	aggregate_rating
168	Agra	North Indian, Continental, Italian	4.9
303	Ahmedabad	Chinese, Japanese	4.9
586	Ajmer	Continental, Beverages, South Indian, Fast Foo...	4.8
713	Alappuzha	Arabian, Continental	4.0
919	Allahabad	North Indian, Mediterranean	4.7
...	...	...	...
20479	Varanasi	North Indian, Chinese, BBQ	4.9
20647	Vellore	Juices, Italian, Burger	3.8
20853	Vijayawada	North Indian, Andhra	4.9
21058	Vizag	European, Mediterranean, North Indian	4.9
21193	Zirakpur	Andhra, Goan, North Indian, Kerala	4.6

99 rows × 3 columns

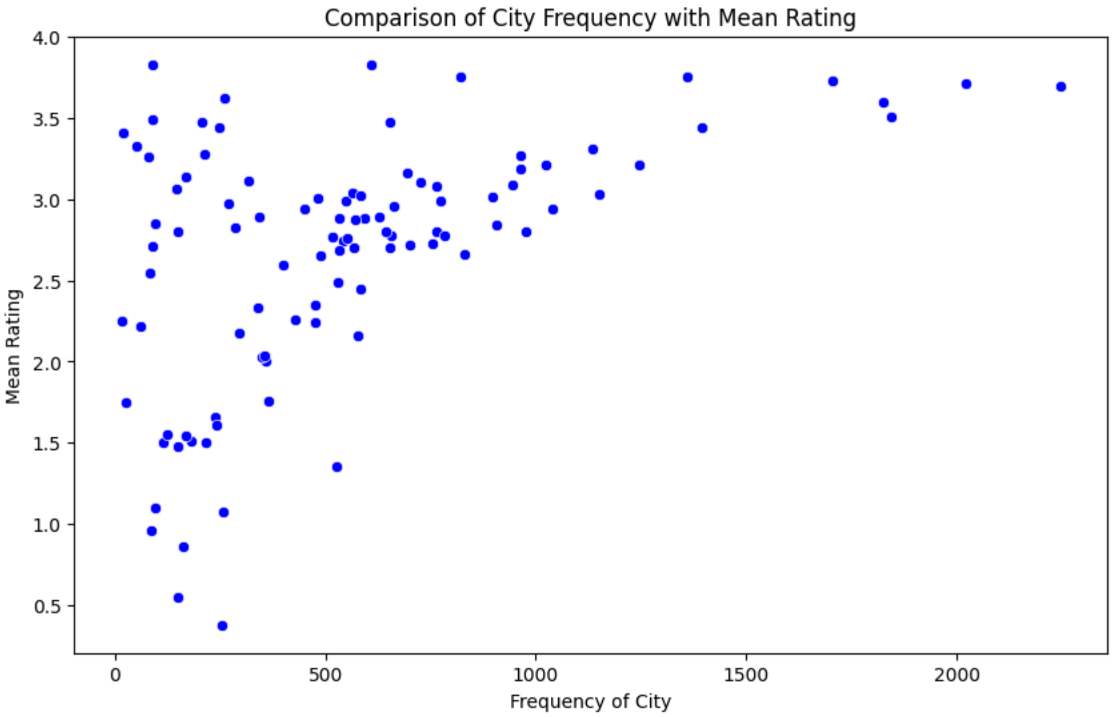
```
# Group the data by city and calculate mean rating
city_stats = dfnew1.groupby('city')['aggregate_rating'].mean().reset_index()

# Sort the cities based on mean rating
city_stats_sorted = city_stats.sort_values(by='aggregate_rating', ascending=False)

# Set up the figure and axes
plt.figure(figsize=(12, 20))

# Create box plot
sns.boxplot(x='aggregate_rating', y='city', data=city_stats_sorted, orient='h', palette='viridis')

# Add labels and title
plt.xlabel('Mean Rating')
plt.ylabel('City')
plt.title('Comparison of Mean Ratings Across Cities')

# Show the plot
plt.show()
```

```
<ipython-input-89-e7368ee8126e>:11: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.boxplot(x='aggregate_rating', y='city', data=city_stats_sorted, orient='h', palette='viridis')
```

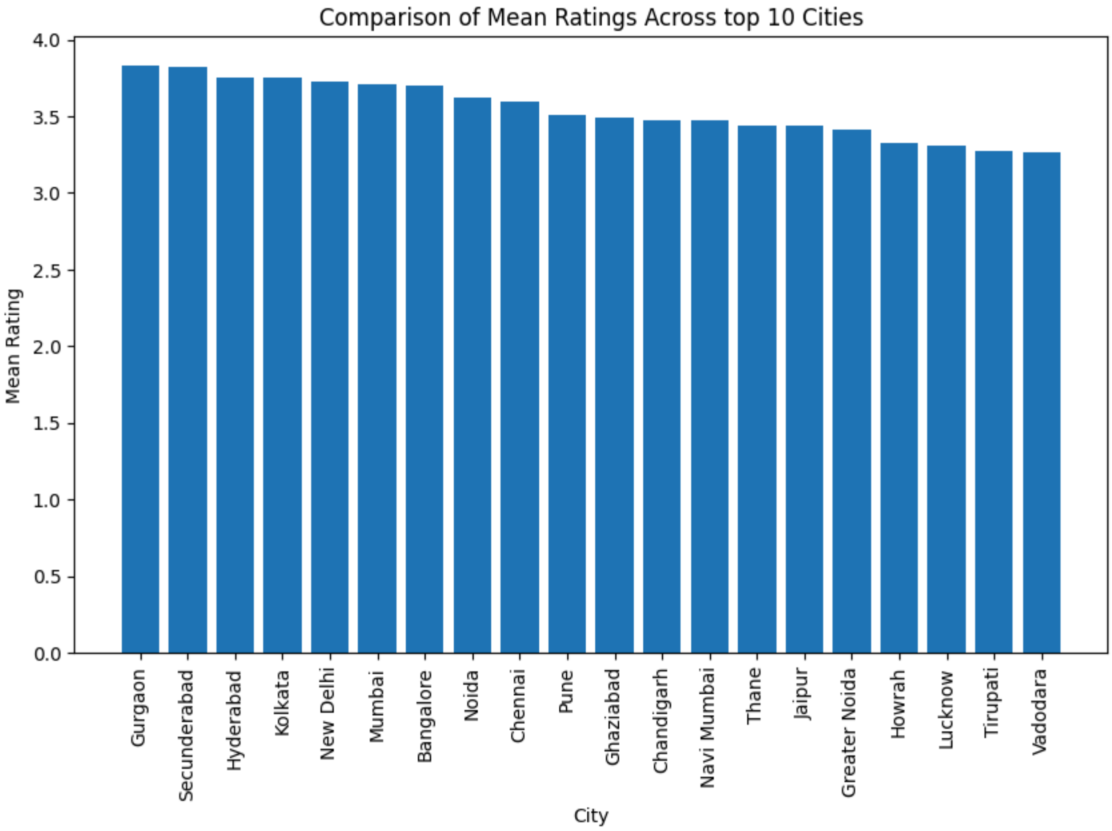


Mean Rating

```
city_stats = dfnew1.groupby('city').agg(mean_rating=('aggregate_rating', 'mean'), frequency=('city', 'size')).reset_index()

# Set up the figure and axes
plt.figure(figsize=(10, 6))

# Create scatter plot
sns.scatterplot(x='frequency', y='mean_rating', data=city_stats, color='blue')

# Add labels and title
plt.xlabel('Frequency of City')
plt.ylabel('Mean Rating')
plt.title('Comparison of City Frequency with Mean Rating')

# Show the plot
plt.show()
```

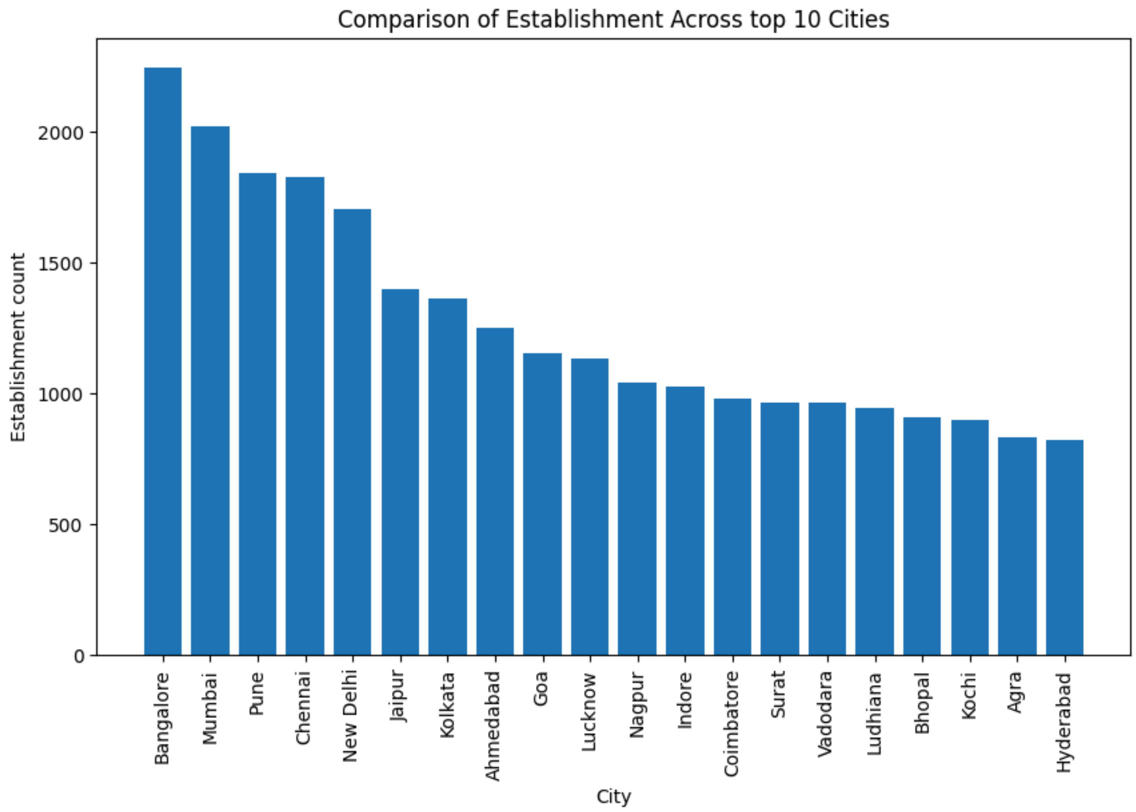



```
# Group the data by city and calculate mean rating
city_num = dfnew1.groupby('city')['aggregate_rating'].mean().reset_index()
city_num1 = city_num.sort_values(by='aggregate_rating', ascending=False)

# Select the top 20 rows
top20city = city_num1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top20city['city'], top20city['aggregate_rating'])
# Add labels and title
plt.xlabel('City')
plt.ylabel('Mean Rating')
plt.title('Comparison of Mean Ratings Across top 10 Cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



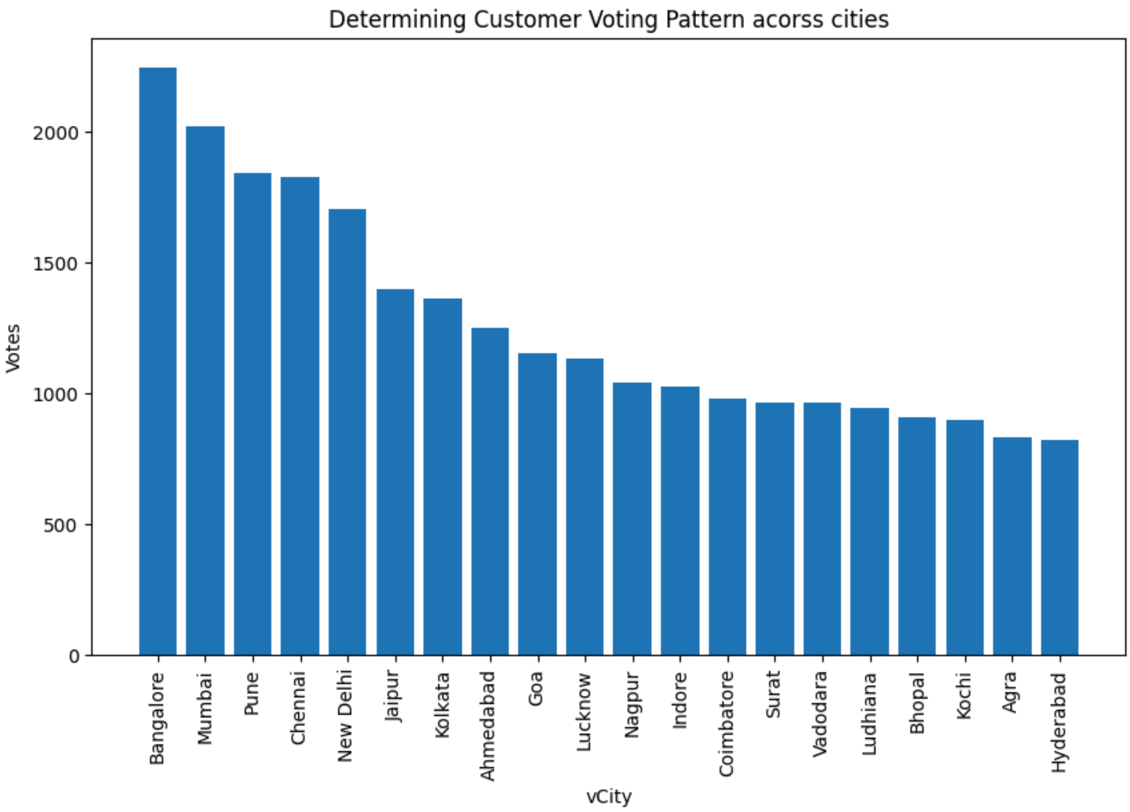
Gurgaon has highest overall mean rating as a place taking ratings for all types of restaurants. It is followed by Secunderabad.

```
# finding overall total establishments to see with respect to cities
estb = dfnew1.groupby('city')['establishment'].size().reset_index()
estb1 = estb.sort_values(by='establishment', ascending=False)

# Select the top 20 rows
top10estb = estb1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top10estb['establishment'])
# Add labels and title
plt.xlabel('City')
plt.ylabel('Establishment count')
plt.title('Comparison of Establishment Across top 10 Cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```

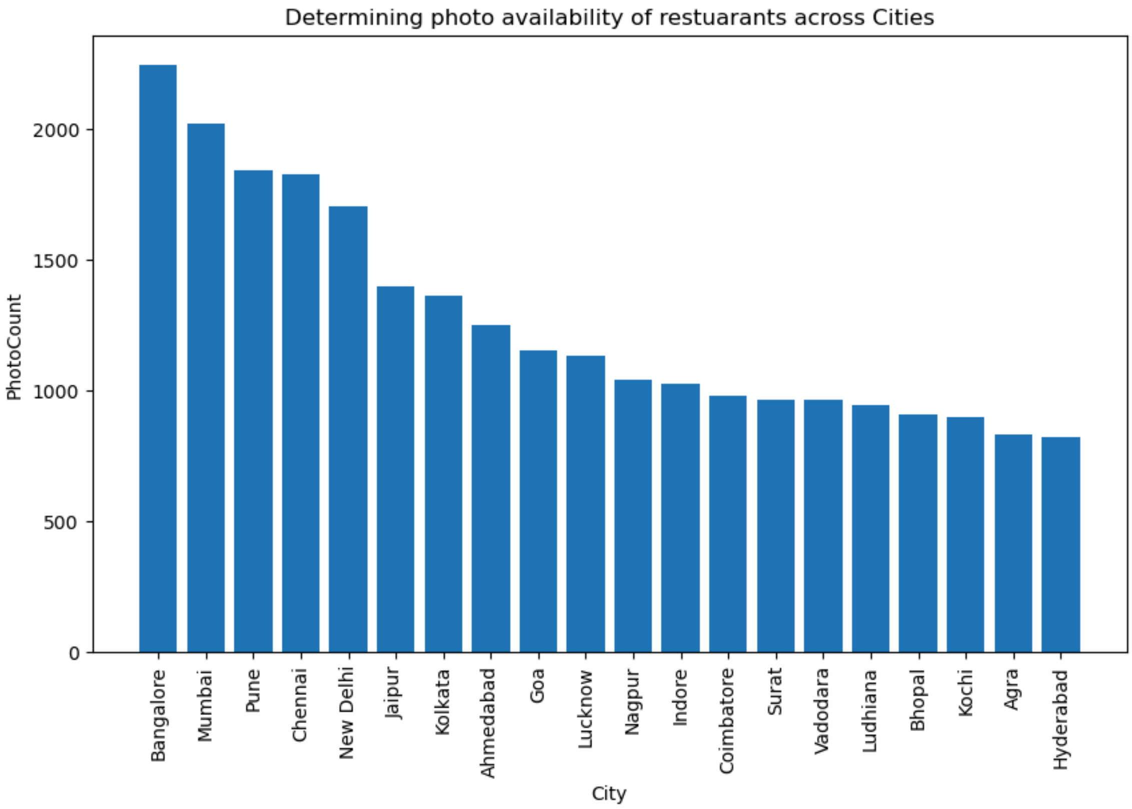


Bangalore has overall most number of establishments or restaurants. It is followed by Mumbai and others as depicted in above visual

```
# finding overall total votes to see with respect to cities
estb = dfnew1.groupby('city')['votes'].size().reset_index()
estb1 = estb.sort_values(by='votes', ascending=False)

# Select the top 20 rows
top10estb = estb1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top10estb['votes'])
# Add labels and title
plt.xlabel('vCity')
plt.ylabel('Votes')
plt.title('Determining Customer Voting Pattern acorss cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```

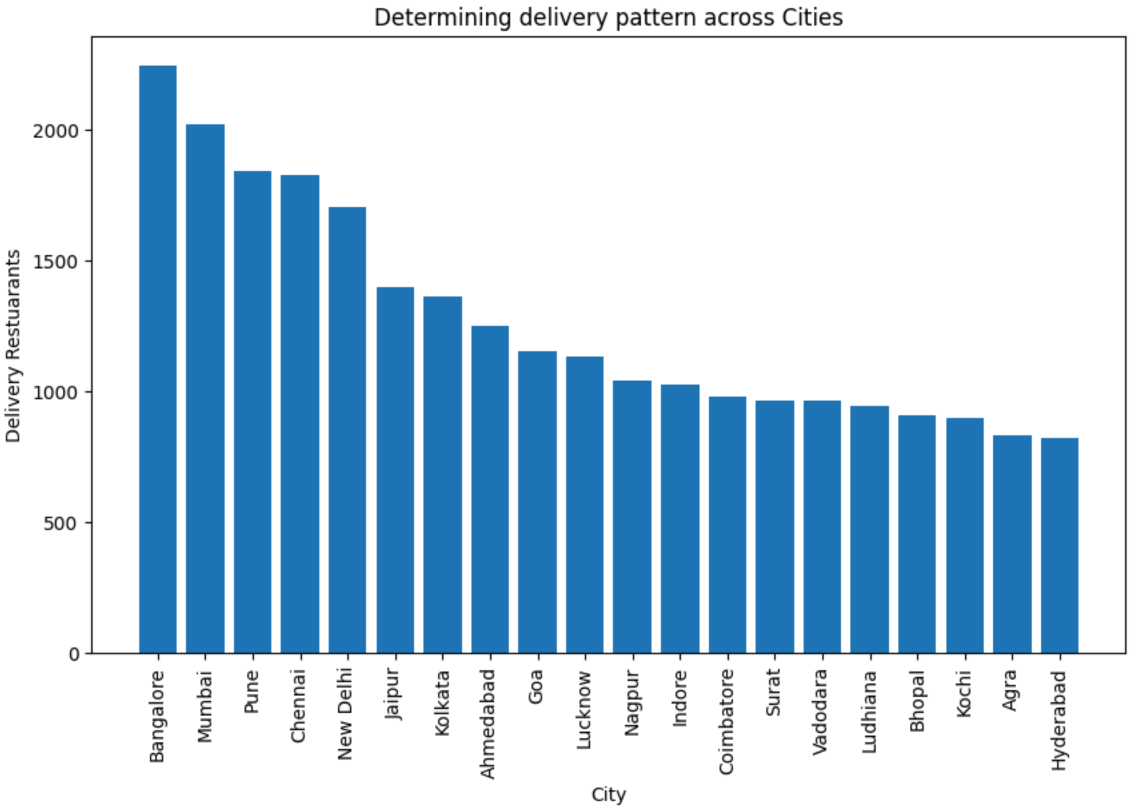



```
# finding overall total establishments to see with respect to cities
estb = dfnew1.groupby('city')['photo_count'].size().reset_index()
estb1 = estb.sort_values(by='photo_count', ascending=False)

# Select the top 20 rows
top10estb = estb1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top10estb['photo_count'])
# Add labels and title
plt.xlabel('City')
plt.ylabel('PhotoCount')
plt.title('Determining photo availability of restuarants across Cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



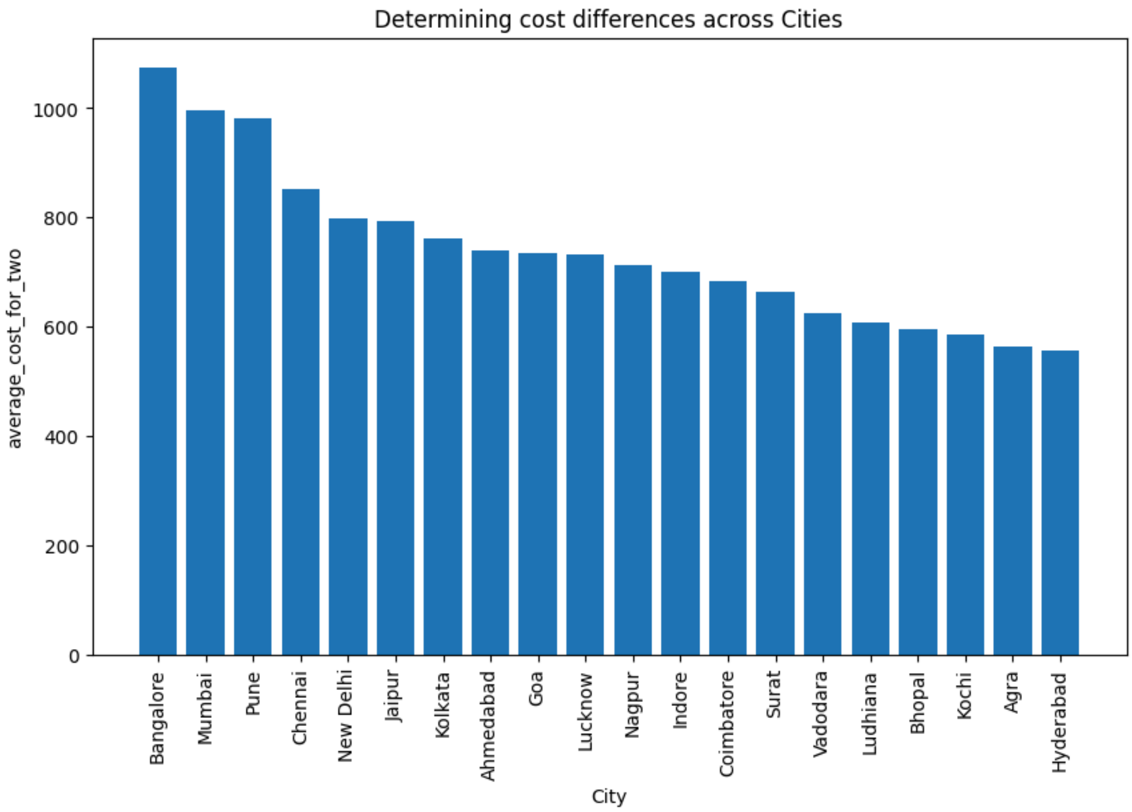
Most number of establishment is also directly counting into popularity of city based on number of votes it has taken.

```
# finding overall total establishments to see with respect to cities
estb = dfnew1.groupby('city')['delivery'].size().reset_index()
estb1 = estb.sort_values(by='delivery', ascending=False)

# Select the top 20 rows
top10estb = estb1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top10estb['delivery'])
# Add labels and title
plt.xlabel('City')
plt.ylabel('Delivery Restuarants')
plt.title('Determining delivery pattern across Cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



The figure indicates the delivery trend across cities

```
# finding overall total establishments to see with respect to cities
cost = dfnew1.groupby('city')['average_cost_for_two'].mean().reset_index()
cost1 = cost.sort_values(by='average_cost_for_two', ascending=False)

# Select the top 20 rows
top20cost = cost1.head(20)


plt.figure(figsize=(10, 6))
plt.bar(top10estb['city'], top20cost['average_cost_for_two'])
# Add labels and title
plt.xlabel('City')
plt.ylabel('average_cost_for_two')
plt.title('Determining cost differences across Cities')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```




```
city_cuisine_ratings = dfnew1.groupby(['city', 'cuisines'])['aggregate_rating'].mean().reset_index()

# Sort the cuisines within each city based on their mean aggregate rating
city_cuisine_ratings_sorted = city_cuisine_ratings.sort_values(by=['city', 'aggregate_rating'], ascending=[True, False])

# Select the top three cuisines for each city
top_cuisines_by_city = city_cuisine_ratings_sorted.groupby('city').head(2)
top_cuisines_by_city
```

	city	cuisines	aggregate_rating
168	Agra	North Indian, Continental, Italian	4.9
45	Agra	Cafe, North Indian, Chinese	4.8
303	Ahmedabad	Chinese, Japanese	4.9
319	Ahmedabad	Continental, Italian, Chinese	4.9
586	Ajmer	Continental, Beverages, South Indian, Fast Foo...	4.8
...	...	...	...
20705	Vijayawada	BBQ	4.6
21058	Vizag	European, Mediterranean, North Indian	4.9
20955	Vizag	Bakery, Cafe	4.7
21193	Zirakpur	Andhra, Goan, North Indian, Kerala	4.6
21212	Zirakpur	Cafe, Continental, Burger, Sandwich, Beverages...	4.4

198 rows × 3 columns

Customer Preference Analysis:

```
regions = dfnew1.groupby(['city', 'cuisines'])['aggregate_rating'].mean().reset_index()
regionsorted = regions.sort_values(by=['city','aggregate_rating'], ascending=[True, False])
topcuisinesincity = regionsorted.groupby('city').head(1)
topcuisinesincity
```

	city	cuisines	aggregate_rating
168	Agra	North Indian, Continental, Italian	4.9
303	Ahmedabad	Chinese, Japanese	4.9
586	Ajmer	Continental, Beverages, South Indian, Fast Foo...	4.8
713	Alappuzha	Arabian, Continental	4.0
919	Allahabad	North Indian, Mediterranean	4.7
...	...	...	...
20479	Varanasi	North Indian, Chinese, BBQ	4.9
20647	Vellore	Juices, Italian, Burger	3.8
20853	Vijayawada	North Indian, Andhra	4.9
21058	Vizag	European, Mediterranean, North Indian	4.9
21193	Zirakpur	Andhra, Goan, North Indian, Kerala	4.6

99 rows × 3 columns

```
from tabulate import tabulate

# Assuming 'topcuisinesincity' DataFrame contains 'city', 'cuisines', and 'aggregate_rating' columns
# You may need to adjust column names based on your actual DataFrame structure

# Extracting data for table
table_data = []
for index, row in topcuisinesincity.iterrows():
    table_data.append([row['city'], row['cuisines'], row['aggregate_rating']])

# Creating table
table_headers = ["City", "Top Cuisine", "Aggregate Rating"]
table = tabulate(table_data, headers=table_headers, tablefmt="grid")

print(table)
```

City	Top Cuisine	Aggregate Rating
Agra	North Indian, Continental, Italian	4.9
Ahmedabad	Chinese, Japanese	4.9
Ajmer	Continental, Beverages, South Indian, Fast Food, Italian, North Indian, Chinese	4.8
Alappuzha	Arabian, Continental	4
Allahabad	North Indian, Mediterranean	4.7
Amravati	Biryani, North Indian, Seafood, Chinese	4.9
Amritsar	Fast Food, Italian	4.9
Aurangabad	North Indian, Seafood, Chinese, Mediterranean	4.8
Bangalore	Asian, Chinese, Thai, Momos	4.9
Bhopal	North Indian, Italian, Beverages	4.7
Bhubaneshwar	Mediterranean, Asian, Continental, North Indian, Arabian	4.9
Chandigarh	Portuguese, Wraps, Burger, Salad	4.9
Chennai	North Indian, Mediterranean, Asian, Arabian, BBQ	4.9
Coimbatore	European, Mediterranean, North Indian, BBQ	4.9
Cuttack	North Indian, Rajasthani	4
Darjeeling	Beverages, Cafe, Chinese, Continental, North Indian, Momos	4.1
Dehradun	North Indian, Mediterranean, BBQ, Chinese	4.9
Dharamshala	Chinese, North Indian, Tibetan, Momos	4
Faridabad	Asian, Chinese, European, North Indian	4.5
Gandhinagar	North Indian, Italian, Chinese	4.3
Gangtok	Italian, Cafe	3.6
Ghaziabad	North Indian, Mughlai	4.9

```
| Goa           | Continental, Seafood, Italian, Mediterranean, North Indian                     |                4.9   |
+---------------+--------------------------------------------------------------------------------+----------------------+
| Gorakhpur     | Cafe, Fast Food                                                                |                4.5   |
+---------------+--------------------------------------------------------------------------------+----------------------+
| Greater Noida | Bakery, Mexican, Italian, Beverages                                            |                4.2   |
+---------------+--------------------------------------------------------------------------------+----------------------+
| Guntur        | BBQ                                                                            |                4.2   |
+---------------+--------------------------------------------------------------------------------+----------------------+
| Gurgaon       | Bar Food, Asian, North Indian, Continental                                     |                4.9   |
+---------------+--------------------------------------------------------------------------------+----------------------+
| Guwahati      | North Indian. Mediterranean                                                    |                4.9   |
```

```
def generate_city_cuisine_table(city_name, dfnew1):

    # Filter DataFrame for the specified city
    city_data = dfnew1[dfnew1['city'] == city_name]

    # If city not found or there's no data for the city, return None
    if city_data.empty:
        return "City not found or no data available."

    # Find the top-rated cuisine for the city
    top_cuisine = city_data.loc[city_data['aggregate_rating'].idxmax()]

    # Extract relevant information for the table
    table_data = [[top_cuisine['city'], top_cuisine['cuisines'], top_cuisine['aggregate_rating']]]

    # Create table headers
    table_headers = ["City", "Top Cuisine", "Aggregate Rating"]

    # Generate table using tabulate
    table = tabulate(table_data, headers=table_headers, tablefmt="outline")

    return table

# Example usage:
# Assuming 'dfnew1' DataFrame contains 'city', 'cuisines', and 'aggregate_rating' columns
# You may need to adjust column names based on your actual DataFrame structure
city_name_input = input("Enter city name: ")
table_output = generate_city_cuisine_table(city_name_input, dfnew1)
print(table_output)
```

```
Enter city name: Mumbai
+--------+---------------------------------------------+--------------------+
| City   | Top Cuisine                                 |   Aggregate Rating |
+========+=============================================+====================+
| Mumbai | Egyptian, Turkish, Lebanese, Moroccan, Greek |               4.9 |
+--------+---------------------------------------------+--------------------+
```

```
establishment_count = dfnew1.groupby(['city', 'establishment']).size().reset_index(name='estblishmentcount')

# Sort the DataFrame by city and count in descending order within each city
establishment_sorted = establishment_count.sort_values(by=['city', 'estblishmentcount'], ascending=[True, False])

# Select the top establishment type for each city
top_establishment = establishment_sorted.groupby('city').first().reset_index()

print(top_establishment)
```

```
          city    establishment  estblishmentcount
0         Agra  ['Quick Bites']                190
1    Ahmedabad  ['Quick Bites']                251
2        Ajmer  ['Quick Bites']                184
3    Alappuzha  ['Quick Bites']                 93
4    Allahabad  ['Quick Bites']                172
..         ...              ...                ...
94    Varanasi  ['Quick Bites']                191
95     Vellore  ['Quick Bites']                113
96  Vijayawada  ['Quick Bites']                165
97       Vizag  ['Quick Bites']                203
98    Zirakpur  ['Quick Bites']                 32

[99 rows x 3 columns]
```

```
table_data = []
for index, row in top_establishment.iterrows():
    table_data.append([row['city'], row['establishment'], row['estblishmentcount']])

# Creating table
table_headers = ["City", "Establishment", "EstablishmentCount"]
table = tabulate(table_data, headers=table_headers, tablefmt="grid")

print(table)
```

```
+---------------+-------------------+----------------------+
| City          | Establishment     |   EstablishmentCount |
+===============+===================+======================+
| Agra          | ['Quick Bites']   |                  190 |
+---------------+-------------------+----------------------+
| Ahmedabad     | ['Quick Bites']   |                  251 |
+---------------+-------------------+----------------------+
| Ajmer         | ['Quick Bites']   |                  184 |
+---------------+-------------------+----------------------+
| Alappuzha     | ['Quick Bites']   |                   93 |
+---------------+-------------------+----------------------+
| Allahabad     | ['Quick Bites']   |                  172 |
+---------------+-------------------+----------------------+
| Amravati      | ['Casual Dining'] |                  155 |
+---------------+-------------------+----------------------+
| Amritsar      | ['Quick Bites']   |                  229 |
+---------------+-------------------+----------------------+
| Aurangabad    | ['Quick Bites']   |                  221 |
+---------------+-------------------+----------------------+
| Bangalore     | ['Casual Dining'] |                  488 |
+---------------+-------------------+----------------------+
| Bhopal        | ['Quick Bites']   |                  253 |
+---------------+-------------------+----------------------+
| Bhubaneshwar  | ['Quick Bites']   |                  278 |
+---------------+-------------------+----------------------+
| Chandigarh    | ['Quick Bites']   |                  131 |
+---------------+-------------------+----------------------+
| Chennai       | ['Casual Dining'] |                  476 |
+---------------+-------------------+----------------------+
| Coimbatore    | ['Quick Bites']   |                  215 |
+---------------+-------------------+----------------------+
| Cuttack       | ['Quick Bites']   |                  131 |
+---------------+-------------------+----------------------+
| Darjeeling    | ['Quick Bites']   |                   50 |
+---------------+-------------------+----------------------+
| Dehradun      | ['Quick Bites']   |                  231 |
+---------------+-------------------+----------------------+
| Dharamshala   | ['Quick Bites']   |                   69 |
+---------------+-------------------+----------------------+
| Faridabad     | ['Quick Bites']   |                   13 |
+---------------+-------------------+----------------------+
| Gandhinagar   | ['Quick Bites']   |                   22 |
+---------------+-------------------+----------------------+
| Gangtok       | ['Quick Bites']   |                   37 |
+---------------+-------------------+----------------------+
| Ghaziabad     | ['Quick Bites']   |                   16 |
+---------------+-------------------+----------------------+
| Goa           | ['Casual Dining'] |                  482 |
+---------------+-------------------+----------------------+
| Gorakhpur     | ['Quick Bites']   |                  167 |
+---------------+-------------------+----------------------+
| Greater Noida | ['Quick Bites']   |                    7 |
+---------------+-------------------+----------------------+
| Guntur        | ['Quick Bites']   |                  119 |
+---------------+-------------------+----------------------+
| Gurgaon       | ['Casual Dining'] |                  105 |
+---------------+-------------------+----------------------+
| Guwahati      | ['Quick Bites']   |                  213 |
```

```
cuisinepopular = dfnew1.groupby(['city', 'cuisines'])['votes'].size().reset_index()
cuisinepopular1 = cuisinepopular.sort_values(by=['city','votes'], ascending=[True, False])
cuisinepopular2 = cuisinepopular1.groupby('city').head(1)
cuisinepopular2
```

	city	cuisines	votes
139	Agra	North Indian	114
532	Ahmedabad	Street Food	80
652	Ajmer	North Indian	73
718	Alappuzha	Bakery	53
896	Allahabad	North Indian	101
...	...	...	...
20475	Varanasi	North Indian	52
20672	Vellore	South Indian	41
20896	Vijayawada	South Indian	38
21160	Vizag	South Indian	57
21242	Zirakpur	North Indian	22

99 rows × 3 columns

```
table_data = []
for index, row in cuisinepopular2.iterrows():
    table_data.append([row['city'], row['cuisines'], row['votes']])

# Creating table
table_headers = ["City", "Cuisine", "Popular Vote Count"]
table = tabulate(table_data, headers=table_headers, tablefmt="grid")

print(table)
```

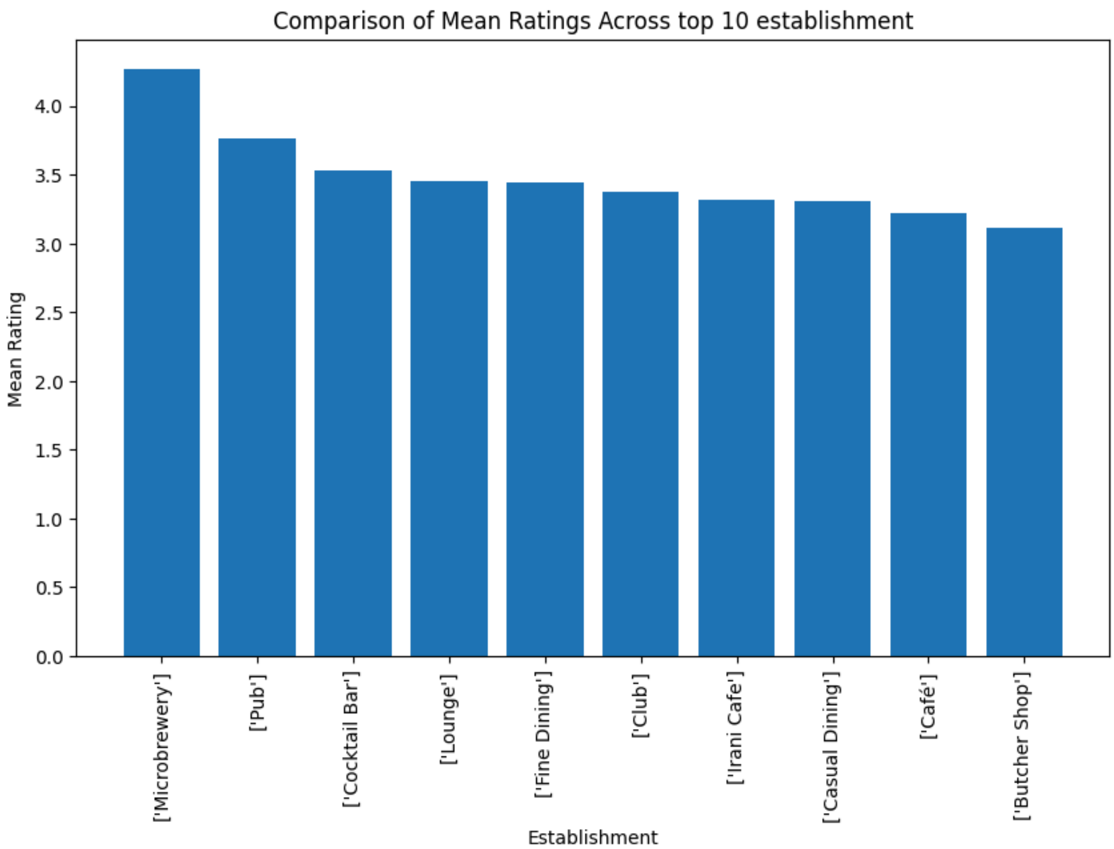
```
+---------------+------------------------------+----------------------+
| Kanpur        | North Indian                 |                   82 |
+---------------+------------------------------+----------------------+
| Kharagpur     | North Indian, Chinese        |                   16 |
+---------------+------------------------------+----------------------+
| Kochi         | Bakery                       |                   38 |
+---------------+------------------------------+----------------------+
| Kolhapur      | Maharashtrian                |                   59 |
+---------------+------------------------------+----------------------+
| Kolkata       | Mishti                       |                   61 |
+---------------+------------------------------+----------------------+
| Kota          | North Indian                 |                  125 |
+---------------+------------------------------+----------------------+
| Lucknow       | North Indian                 |                   94 |
+---------------+------------------------------+----------------------+
| Ludhiana      | North Indian                 |                  102 |
+---------------+------------------------------+----------------------+
| Madurai       | South Indian                 |                  131 |
+---------------+------------------------------+----------------------+
| Manali        | Cafe                         |                   48 |
+---------------+------------------------------+----------------------+
| Mangalore     | South Indian                 |                   34 |
+---------------+------------------------------+----------------------+
| Manipal       | North Indian                 |                    9 |
+---------------+------------------------------+----------------------+
| Meerut        | North Indian                 |                   98 |
+---------------+------------------------------+----------------------+
| Mohali        | North Indian                 |                   45 |
+---------------+------------------------------+----------------------+
| Mumbai        | Bakery, Desserts             |                   57 |
+---------------+------------------------------+----------------------+
| Mussoorie     | North Indian                 |                   30 |
+---------------+------------------------------+----------------------+
| Mysore        | South Indian                 |                   58 |
+---------------+------------------------------+----------------------+
| Nagpur        | North Indian                 |                   84 |
+---------------+------------------------------+----------------------+
| Nainital      | North Indian                 |                   51 |
+---------------+------------------------------+----------------------+
| Nashik        | North Indian                 |                   60 |
+---------------+------------------------------+----------------------+
| Nasik         | Bakery                       |                    9 |
+---------------+------------------------------+----------------------+
| Navi Mumbai   | Chinese                      |                    6 |
+---------------+------------------------------+----------------------+
| Nayagaon      | North Indian                 |                    3 |
+---------------+------------------------------+----------------------+
| Neemrana      | North Indian                 |                    4 |
+---------------+------------------------------+----------------------+
| New Delhi     | North Indian                 |                  128 |
+---------------+------------------------------+----------------------+
| Noida         | North Indian                 |                    9 |
+---------------+------------------------------+----------------------+
| Ooty          | South Indian                 |                   39 |
+---------------+------------------------------+----------------------+
| Palakkad      | Bakery                       |                   27 |
+---------------+------------------------------+----------------------+
| Panchkula     | North Indian                 |                   13 |
+---------------+------------------------------+----------------------+
```

```
cuisinepopular2.sort_values(by=['votes'], ascending=[False])
```

	city	cuisines	votes
8136	Jaipur	North Indian	194
8415	Jalandhar	North Indian	156
11814	Madurai	South Indian	131
15137	New Delhi	North Indian	128
10958	Kota	North Indian	125
...	...	...	...
14546	Navi Mumbai	Chinese	6
14672	Neemrana	North Indian	4
14656	Nayagaon	North Indian	3
6981	Howrah	Fast Food	3
5838	Greater Noida	Burger, Fast Food, Beverages	2

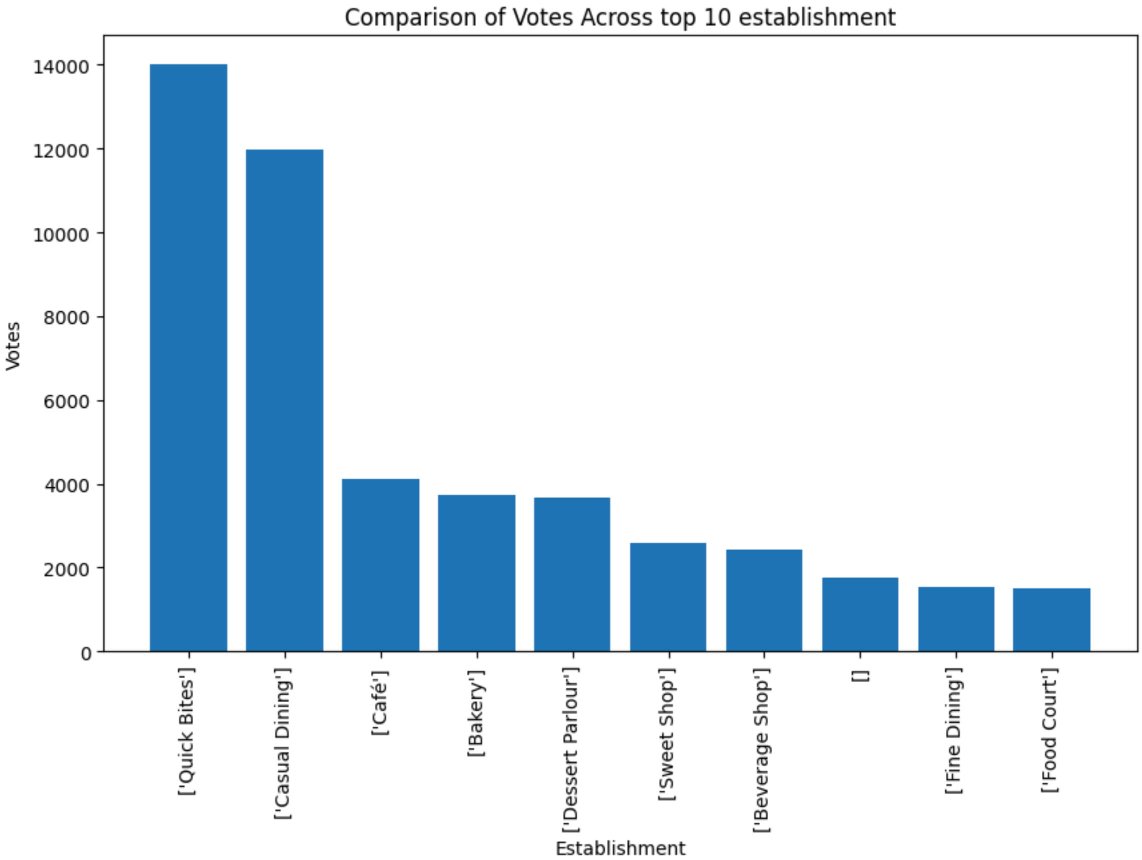
99 rows × 3 columns

```
# Group the data by city and calculate mean rating
est_num = dfnew1.groupby('establishment')['aggregate_rating'].mean().reset_index()
est_num1 = est_num.sort_values(by='aggregate_rating', ascending=False)

# Select the top 20 rows
top20est = est_num1.head(10)


plt.figure(figsize=(10, 6))
plt.bar(top20est['establishment'], top20est['aggregate_rating'])
# Add labels and title
plt.xlabel('Establishment')
plt.ylabel('Mean Rating')
plt.title('Comparison of Mean Ratings Across top 10 establishment')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



In establishments, taking aggregate rating into account top choice for customers are Microbrewery, pubs, cocktails and other as shown in visual above.

```
# Group the data by city and calculate mean rating
est_num = dfnew1.groupby('establishment')['votes'].size().reset_index()
est_num1 = est_num.sort_values(by='votes', ascending=False)

# Select the top 20 rows
top20est = est_num1.head(10)


plt.figure(figsize=(10, 6))
plt.bar(top20est['establishment'], top20est['votes'])
# Add labels and title
plt.xlabel('Establishment')
plt.ylabel('Votes')
plt.title('Comparison of Votes Across top 10 establishment')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```



Quick bytes is highest accross the country and it is followed by casual dining. All others are significantly less than these two based on available data.

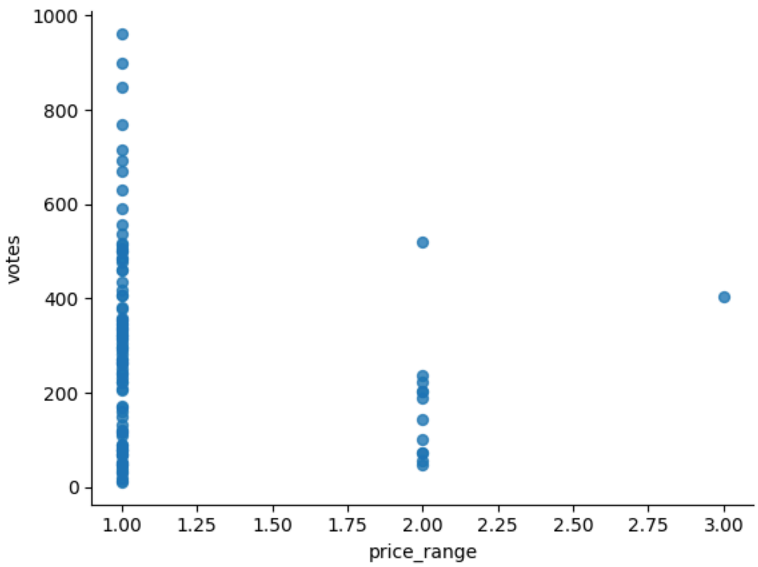
```
pricerange = dfnew1.groupby(['city', 'price_range'])['votes'].size().reset_index()
pricerange1 = pricerange.sort_values(by=['city','votes'], ascending=[True, False])
pricerange2 = pricerange1.groupby('city').head(1)
pricerange2
```

	city	price_range	votes
0	Agra	1	459
5	Ahmedabad	2	521
8	Ajmer	1	272
12	Alappuzha	1	173
16	Allahabad	1	205
...	...	...	...
361	Varanasi	2	204
364	Vellore	1	222
368	Vijayawada	1	239
372	Vizag	1	323
376	Zirakpur	1	85

99 rows × 3 columns

price_range vs votes

```
# @title price_range vs votes

from matplotlib import pyplot as plt
pricerange2.plot(kind='scatter', x='price_range', y='votes', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```



More votes have come acorss price range 1. There are very less for price range 3 and 4 which undermines their popularity

```
table_data = []
for index, row in pricerange2.iterrows():
    table_data.append([row['city'], row['price_range'], row['votes']])

# Creating table
table_headers = ["City", "Price_range", "Popular Vote Count"]
table = tabulate(table_data, headers=table_headers, tablefmt="grid")

print(table)
```

```
+---------------+---------------+----------------------+
| City          |   Price_range |   Popular Vote Count |
+===============+===============+======================+
| Agra          |             1 |                  459 |
+---------------+---------------+----------------------+
| Ahmedabad     |             2 |                  521 |
+---------------+---------------+----------------------+
| Ajmer         |             1 |                  272 |
+---------------+---------------+----------------------+
| Alappuzha     |             1 |                  173 |
+---------------+---------------+----------------------+
| Allahabad     |             1 |                  205 |
+---------------+---------------+----------------------+
| Amravati      |             1 |                  332 |
```

```
+---------------+---------------+---------------------+
| Amritsar      |             1 |                 281 |
+---------------+---------------+---------------------+
| Aurangabad    |             1 |                 336 |
+---------------+---------------+---------------------+
| Bangalore     |             1 |                 962 |
+---------------+---------------+---------------------+
| Bhopal        |             1 |                 500 |
+---------------+---------------+---------------------+
| Bhubaneshwar  |             1 |                 485 |
+---------------+---------------+---------------------+
| Chandigarh    |             1 |                 321 |
+---------------+---------------+---------------------+
| Chennai       |             1 |                 898 |
+---------------+---------------+---------------------+
| Coimbatore    |             1 |                 536 |
+---------------+---------------+---------------------+
| Cuttack       |             1 |                 170 |
+---------------+---------------+---------------------+
| Darjeeling    |             1 |                  51 |
+---------------+---------------+---------------------+
| Dehradun      |             2 |                 237 |
+---------------+---------------+---------------------+
| Dharamshala   |             1 |                 110 |
+---------------+---------------+---------------------+
| Faridabad     |             1 |                  48 |
+---------------+---------------+---------------------+
| Gandhinagar   |             2 |                  46 |
+---------------+---------------+---------------------+
| Gangtok       |             2 |                  55 |
+---------------+---------------+---------------------+
| Ghaziabad     |             1 |                  54 |
+---------------+---------------+---------------------+
| Goa           |             3 |                 403 |
+---------------+---------------+---------------------+
| Gorakhpur     |             1 |                 348 |
+---------------+---------------+---------------------+
| Greater Noida |             1 |                  11 |
+---------------+---------------+---------------------+
| Guntur        |             1 |                 148 |
+---------------+---------------+---------------------+
| Gurgaon       |             2 |                 203 |
+---------------+---------------+---------------------+
| Guwahati      |             1 |                 305 |
```

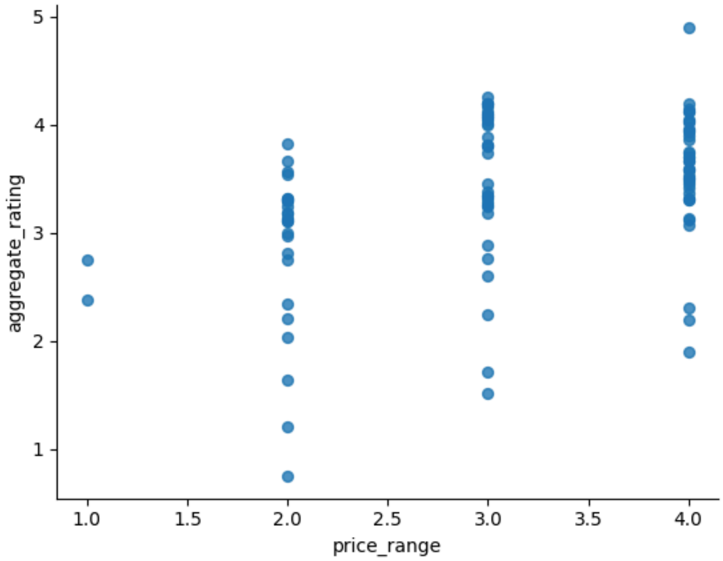
```
pricerange = dfnew1.groupby(['city', 'price_range'])['aggregate_rating'].mean().reset_index()
pricerange1 = pricerange.sort_values(by=['city','aggregate_rating'], ascending=[True, False])
pricerange2 = pricerange1.groupby('city').head(1)
pricerange2
```

	city	price_range	aggregate_rating
1	Agra	2	3.300000
6	Ahmedabad	3	4.040120
11	Ajmer	4	3.500000
13	Alappuzha	2	0.753731
19	Allahabad	4	3.735000
...	...	...	...
362	Varanasi	3	3.342077
367	Vellore	4	3.450000
369	Vijayawada	2	3.316256
374	Vizag	3	3.459211
379	Zirakpur	4	3.528571

99 rows × 3 columns

price_range vs aggregate_rating

```
# @title price_range vs aggregate_rating

from matplotlib import pyplot as plt
pricerange2.plot(kind='scatter', x='price_range', y='aggregate_rating', s=32, alpha=.8)
plt.gca().spines[['top', 'right',]].set_visible(False)
```



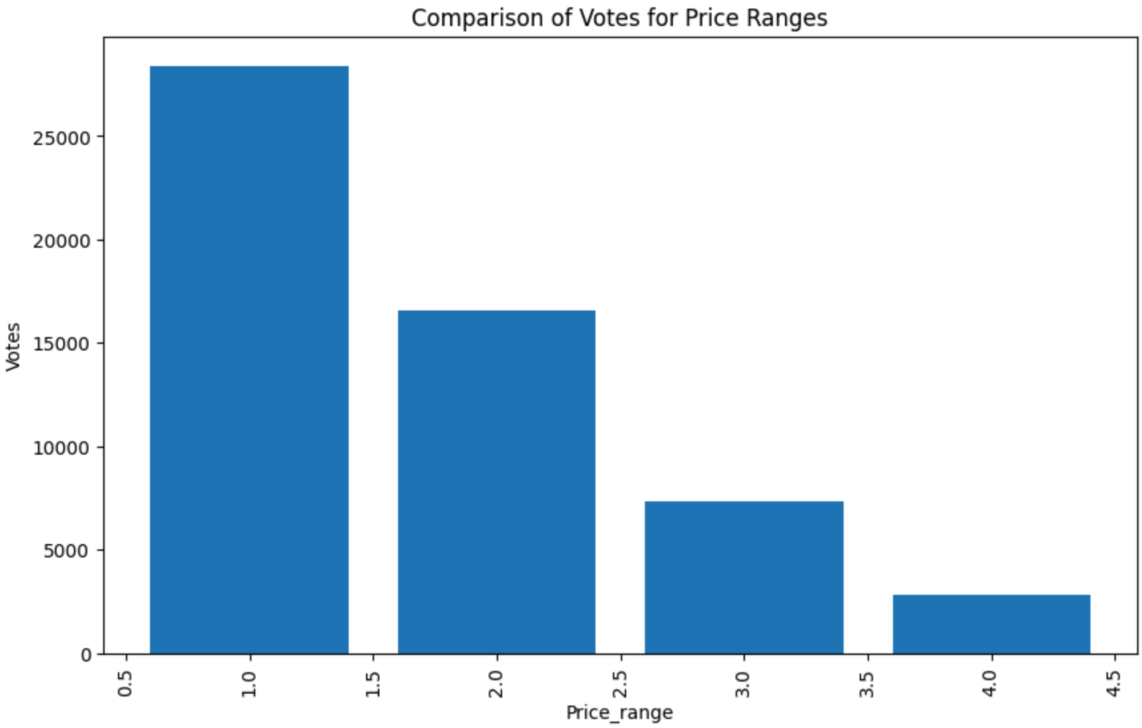
Although we have witnessed that more votes have come for price range 1 but it is evident that more rating is for price range 3 and 4. This is a preferenace analysis which identifies a potential gap in market to be addressed

```
table_data = []
for index, row in pricerange2.iterrows():
    table_data.append([row['city'], row['price_range'], row['aggregate_rating']])

# Creating table
table_headers = ["City", "Price_range", "Aggregate Rating Mean"]
table = tabulate(table_data, headers=table_headers, tablefmt="grid")

print(table)
```

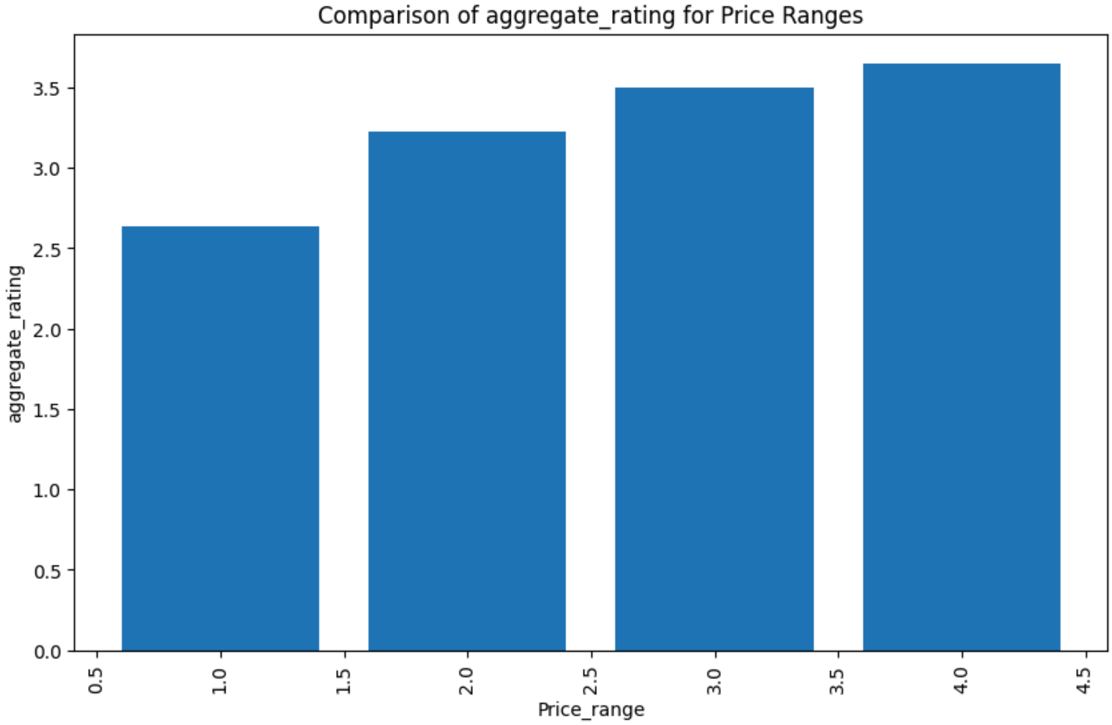
City	Price_range	Aggregate Rating Mean
Agra	2	3.3
Ahmedabad	3	4.04012
Ajmer	4	3.5
Alappuzha	2	0.753731
Allahabad	4	3.735
Amravati	2	2.20312
Amritsar	2	3.18174
Aurangabad	2	3.29241
Bangalore	3	4.19019
Bhopal	4	3.86087
Bhubaneshwar	4	3.9
Chandigarh	3	3.81724
Chennai	3	4.00705
Coimbatore	4	3.65937
Cuttack	4	3.3
Darjeeling	3	1.52143
Dehradun	3	3.33952
Dharamshala	3	2.24286
Faridabad	2	3.82857
Gandhinagar	3	3.81429
Gangtok	3	2.6
Ghaziabad	3	4.25556

```
| Goa           |            4 |                3.42083  |
+---------------+--------------+-------------------------+
| Gorakhpur     |            4 |                4.9      |
+---------------+--------------+-------------------------+
| Greater Noida |            3 |                4.2      |
+---------------+--------------+-------------------------+
| Guntur        |            2 |                3.17838  |
+---------------+--------------+-------------------------+
| Gurgaon       |            4 |                4.12267  |
+---------------+--------------+-------------------------+
```

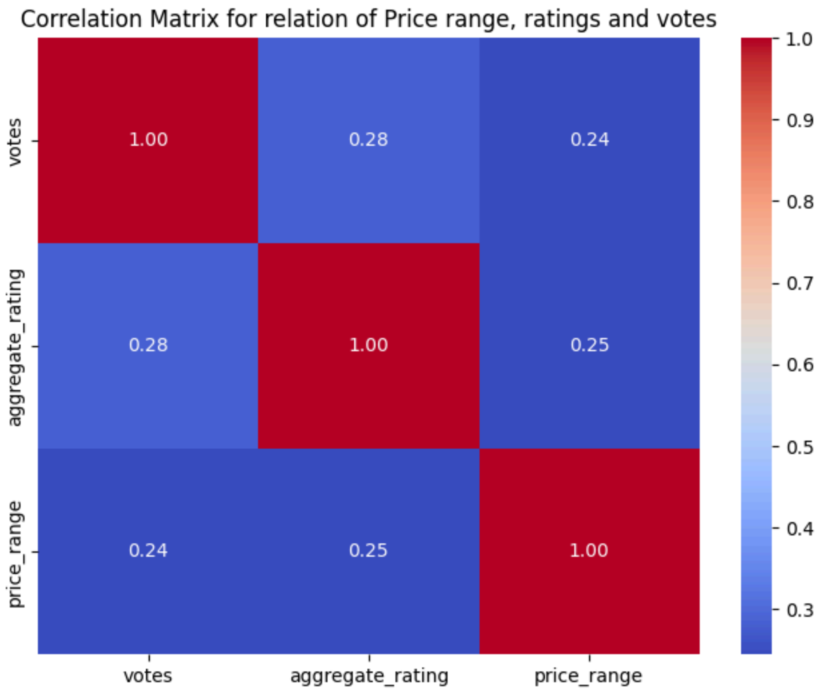
```
# Group the data by city and votes
price = dfnew1.groupby('price_range')['votes'].size().reset_index()


plt.figure(figsize=(10, 6))
plt.bar(price['price_range'], price['votes'])
# Add labels and title
plt.xlabel('Price_range')
plt.ylabel('Votes')
plt.title('Comparison of Votes for Price Ranges')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```




```
# Group the data by city and votes
price = dfnew1.groupby('price_range')['aggregate_rating'].mean().reset_index()


plt.figure(figsize=(10, 6))
plt.bar(price['price_range'], price['aggregate_rating'])
# Add labels and title
plt.xlabel('Price_range')
plt.ylabel('aggregate_rating')
plt.title('Comparison of aggregate_rating for Price Ranges')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```




```
correlation = dfnew1[['votes','aggregate_rating','price_range']].corr()
plt.figure(figsize=(8,6))
sns.heatmap(correlation,annot=True,cmap='coolwarm',fmt='.2f')
plt.title('Correlation Matrix for relation of Price range, ratings and votes')
plt.show()
```




```
dfnew1.columns
```

```
Index(['res_id', 'name', 'establishment', 'city', 'city_id', 'locality',
       'locality_verbose', 'cuisines', 'timings', 'average_cost_for_two',
       'price_range', 'highlights', 'aggregate_rating', 'rating_text', 'votes',
       'photo_count', 'delivery'],
      dtype='object')
```

Competitive Analysis

```
city_profile = dfnew1.groupby('city').agg(
    highest_occuring_name=('name', lambda x: x.mode().iloc[0]),  # Get the mode (most frequent) name in the city
    most_number_of_establishments=('establishment', lambda x: x.mode().iloc[0]),  # Get the mode establishment type in the city
    aggregate_rating=('aggregate_rating', 'mean'),  # Get the mean aggregate rating in the city
    top_cuisine=('cuisines', lambda x: x.mode().iloc[0]), # Get the mode cuisine in the city
    mostoccuringpricerange=('price_range', lambda x: x.mode().iloc[0]) #Get the mode for cuisine
).reset_index()

# Display the city profiles
print(city_profile)
```

```
          city       highest_occuring_name most_number_of_establishments  \
0         Agra  Sri Dauji Mishthan Bhandar               ['Quick Bites']
1    Ahmedabad               Domino's Pizza               ['Quick Bites']
2        Ajmer      Manoj's Kake Di Hatti               ['Quick Bites']
3    Alappuzha                 Best Bakery               ['Quick Bites']
4    Allahabad              Baskin Robbins               ['Quick Bites']
..         ...                         ...                           ...
94    Varanasi                   Chestnuts               ['Quick Bites']
95     Vellore              Domino's Pizza               ['Quick Bites']
96  Vijayawada     Alankar Sweets & Bakers               ['Quick Bites']
97       Vizag          Fresh Choice Bakery               ['Quick Bites']
98    Zirakpur              Baskin Robbins               ['Quick Bites']

    aggregate_rating   top_cuisine  mostoccuringpricerange
0           2.660096  North Indian                       1
1           3.209623   Street Food                       2
2           2.592982  North Indian                       1
3           0.379608        Bakery                       1
4           2.740257  North Indian                       1
..               ...           ...                     ...
94          3.018182  North Indian                       2
95          2.172881  South Indian                       1
96          3.001245  South Indian                       1
97          3.160519  South Indian                       1
98          2.803333  North Indian                       1

[99 rows x 6 columns]
```

```
from tabulate import tabulate

# Initialize an empty list to store city profiles
city_profiles = []

# Iterate over each city
for city in dfnew1['city'].unique():
    # Filter data for the current city
    city_data = dfnew1[dfnew1['city'] == city]

    frequentname = city_data['name'].mode().iloc[0]
    mostestablishments = city_data['establishment'].mode().iloc[0]
    aggregate_rating = city_data['aggregate_rating'].mean()
    top_cuisine = city_data['cuisines'].mode().iloc[0]
    highpricerange =city_data['price_range'].mode().iloc[0]

    # Create a dictionary representing the profile information for the current city
    city_profile = {
        'City': city,
        'FrequentName': frequentname,
        'MostEstablishments': mostestablishments,
        'AggregateRating': aggregate_rating,
        'TopCuisine': top_cuisine,
        'HighPriceRange' : highpricerange
    }

    # Append the city profile to the list of city profiles
    city_profiles.append(city_profile)

city_profiles_df = pd.DataFrame(city_profiles)
city_profiles_df
```

	City	FrequentName	MostEstablishments	AggregateRating	TopCuisine	HighPriceRange
0	Agra	Sri Dauji Mishthan Bhandar	['Quick Bites']	2.660096	North Indian	1
1	Ahmedabad	Domino's Pizza	['Quick Bites']	3.209623	Street Food	2
2	Gandhinagar	Domino's Pizza	['Quick Bites']	2.853125	Pizza, Fast Food	2
3	Ajmer	Manoj's Kake Di Hatti	['Quick Bites']	2.592982	North Indian	1
4	Alappuzha	Best Bakery	['Quick Bites']	0.379608	Bakery	1
...	...	...	...	...	...	...
94	Varanasi	Chestnuts	['Quick Bites']	3.018182	North Indian	2
95	Vellore	Domino's Pizza	['Quick Bites']	2.172881	South Indian	1
96	Vijayawada	Alankar Sweets & Bakers	['Quick Bites']	3.001245	South Indian	1
97	Vizag	Fresh Choice Bakery	['Quick Bites']	3.160519	South Indian	1
98	Vadodara	Tea Post	['Quick Bites']	3.266667	Fast Food	1

99 rows × 6 columns

```
city_profiles_df.set_index('City', inplace=True)
```

```
city_profiles_df
```

	FrequentName	MostEstablishments	AggregateRating	TopCuisine	HighPriceRange
City					
Agra	Sri Dauji Mishthan Bhandar	['Quick Bites']	2.660096	North Indian	1
Ahmedabad	Domino's Pizza	['Quick Bites']	3.209623	Street Food	2
Gandhinagar	Domino's Pizza	['Quick Bites']	2.853125	Pizza, Fast Food	2
Ajmer	Manoj's Kake Di Hatti	['Quick Bites']	2.592982	North Indian	1
Alappuzha	Best Bakery	['Quick Bites']	0.379608	Bakery	1
...	...	...	...	...	...
Varanasi	Chestnuts	['Quick Bites']	3.018182	North Indian	2
Vellore	Domino's Pizza	['Quick Bites']	2.172881	South Indian	1
Vijayawada	Alankar Sweets & Bakers	['Quick Bites']	3.001245	South Indian	1
Vizag	Fresh Choice Bakery	['Quick Bites']	3.160519	South Indian	1
Vadodara	Tea Post	['Quick Bites']	3.266667	Fast Food	1

99 rows × 5 columns

```
for index, row in city_profiles_df.iterrows():
    print([row])
    print('----------------------')
```

```
Name: Varanasi, dtype: object]
----------------------
[FrequentName           Domino's Pizza
MostEstablishments    ['Quick Bites']
AggregateRating              2.172881
TopCuisine               South Indian
HighPriceRange                      1
Name: Vellore, dtype: object]
----------------------
[FrequentName          Alankar Sweets & Bakers
MostEstablishments            ['Quick Bites']
AggregateRating                      3.001245
TopCuisine                       South Indian
HighPriceRange                              1
Name: Vijayawada, dtype: object]
----------------------
[FrequentName          Fresh Choice Bakery
MostEstablishments        ['Quick Bites']
AggregateRating                  3.160519
TopCuisine                   South Indian
HighPriceRange                          1
Name: Vizag, dtype: object]
----------------------
[FrequentName                 Tea Post
MostEstablishments    ['Quick Bites']
AggregateRating              3.266667
TopCuisine                  Fast Food
HighPriceRange                      1
Name: Vadodara, dtype: object]
----------------------
```

```
def get_city_details(city_name):
    # Check if the city name exists in the index
    if city_name in city_profiles_df.index:
        # Retrieve the details of the city
        city_details = city_profiles_df.loc[city_name]
        return city_details
    else:
        print(f"City '{city_name}' not found in the DataFrame.")
        return None
```

```
get_city_details('Chennai')
```

```
FrequentName                      ibaco
MostEstablishments    ['Casual Dining']
AggregateRating                3.597701
TopCuisine                 South Indian
HighPriceRange                        1
Name: Chennai, dtype: object
```

Marketing Campaigns

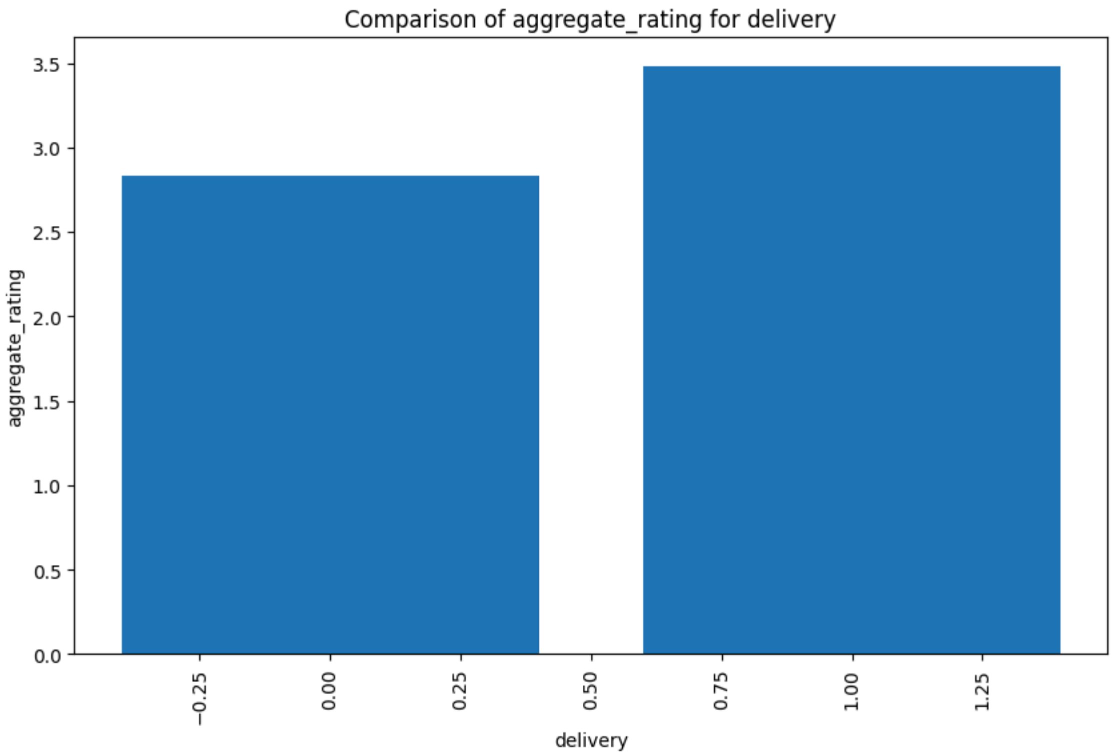
1. The function above provides us with city details. The mean rating is important as it defines how much on average all restaurants are rated. Therefore, all places which are rated below should be analyzed for improvement.
2. The features for all places above the mean rating must be considered to suggest any recommendations for improvements.
3. India is diverse it is also depicted from the analysis of data. Each state or city has their distinct customer base or choice. For example, North Indian cuisine might not be a for Chennai. Therefore, it is also important to determine the cuisine style for the place to be able to suggest cuisine or name of the best place to the customers.
4. For Zomato, the most dominant name in the city is important as it can help them in getting fimilarized and popular medium. Therefore, there should be targeted compaign covering the most popular place of city on platform. It can also be used for getting them on their food delivery platform to deal with customers on that front.
5. Overall for India as well, the most common brands should be picked for inital attention of the customers visiting Zomato platform for information so that it can help customers to recognize Zomato as platform or delivery service. Moreover considering delivery service this appraoch is also beneficial for constant stream of revenue as more orders are taken. Having more popular one on platform will also increase the chances of getting more visits.
6. Considering Zomato as a also delivery providing company, places which do not have delivery in place can also be targeted based on a revenue model that either provide some percentage from their order or monthly sum. This can also help companies which do not have presence to estblish their core presence. Moreover, along with delivery providing partnerships, customers reviews can be used to generate information and a campaign for place on platform. People not fimiliar can reach out and hence can benefit both choices.
7. Since there is a lot of insights from data, there can be criteria established for targeting places to get them on board for delivery service for Zomato. The criteria of rating, price, customer preferences, popularity can help them in providing the quality which is expected and catering to demand. This can reduce the costs that could be incurred to set up resource for delivery for the places which do no get attention from customers.
8. Hence a regional marketing campaign, dealing every region on its distinct qualities is important for Zomato to cater to the preferences of the customers. It is also evident that places which deliver has more rating than the places which do not. Therefore based on delivery,

providing ease to customers who are either at offices or even at work with best quality and timely service is a good campaign to launch. Understanding customers demand everywhere can help in distinguishing from competitors.

9. For each region there can be a dashboard indicating the best cuisine and also indicating most visited based on numbers and data. Pictures can also be published on runtime which will allow visitors at the places which are not regular customers to make more informed decisions.

Market Gap

```
delivery = dfnew1.groupby('delivery')['aggregate_rating'].mean().reset_index()

mindev = 0
delivery = delivery[delivery['delivery'] >= mindev]

plt.figure(figsize=(10, 6))
plt.bar(delivery['delivery'], delivery['aggregate_rating'])
# Add labels and title
plt.xlabel('delivery')
plt.ylabel('aggregate_rating')
plt.title('Comparison of aggregate_rating for delivery')
plt.xticks(rotation=90)

# Show the plot
plt.show()
```

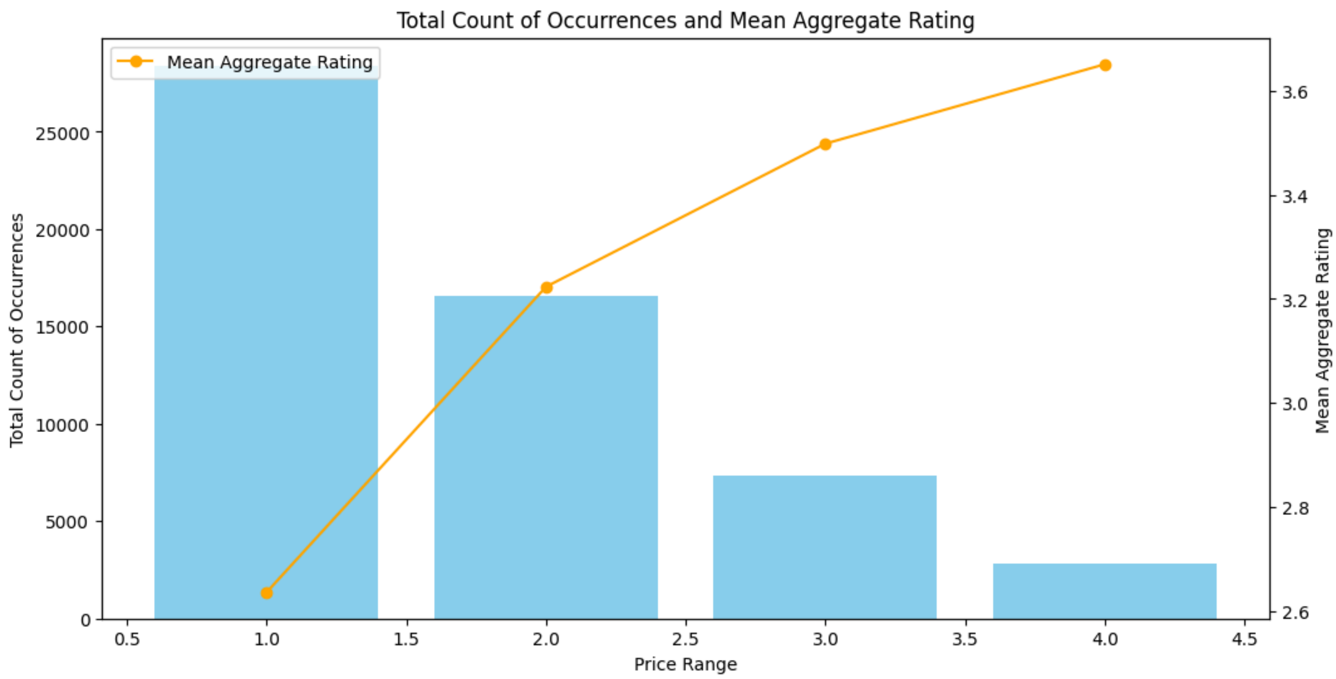


The gap in the market is for restaurant to determine that having delivery option raises the rating. Moreover, all places having rating more than 3 should be targeted by Zomato. For them even Zomato for delivery should be an option to cater to the requirements for the customers.

```
dfnew1['price_range'].value_counts()
```

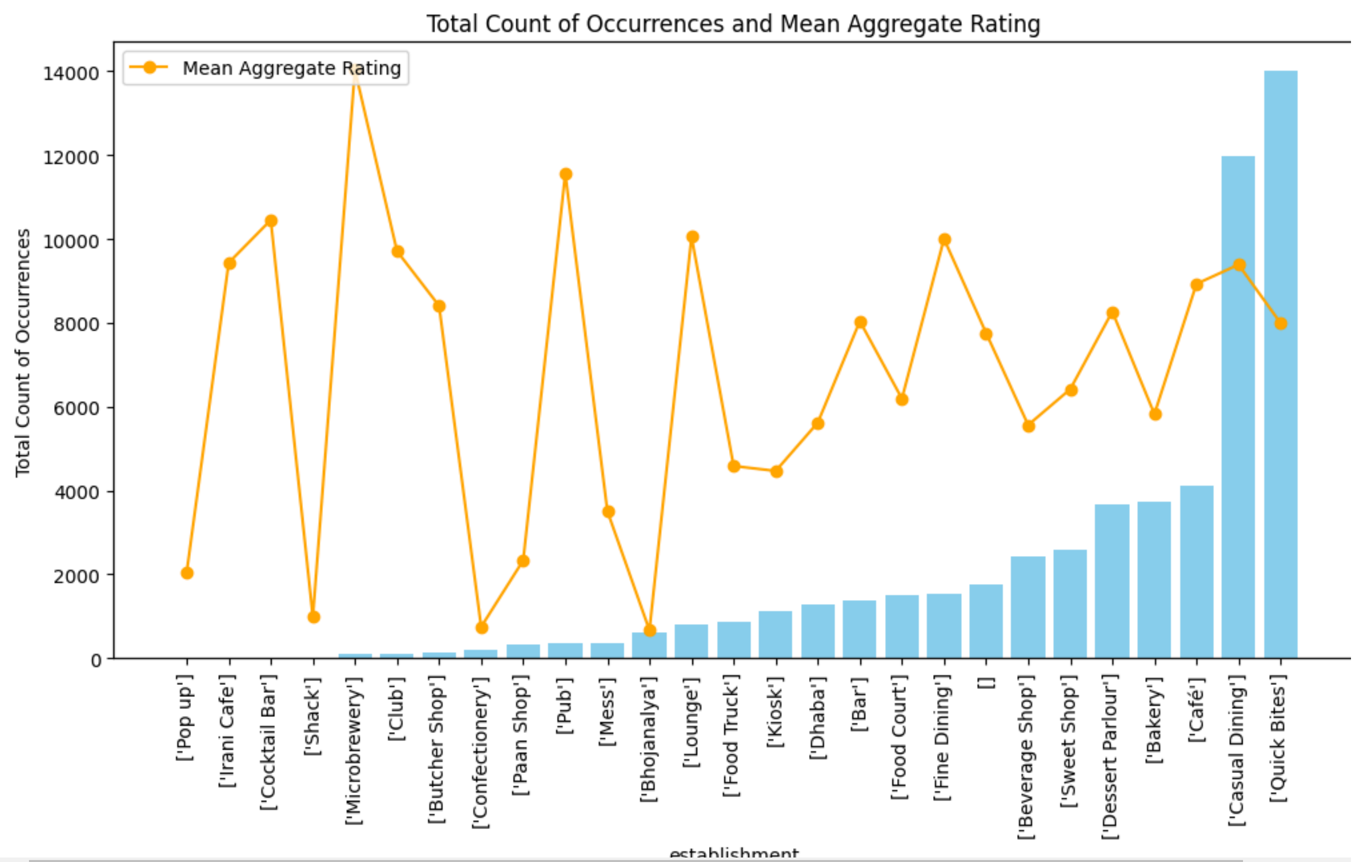
```
price_range
1    28401
2    16541
3     7361
4     2795
Name: count, dtype: int64
```

```
# Group the data by 'price_range' and calculate total count of occurrences and mean aggregate rating
grouped_data = dfnew1.groupby('price_range').agg(count_occurrences=('price_range', 'size'), mean_rating=('aggregate_rating', 'mean')).re

# Plotting the total count of occurrences and mean aggregate rating
plt.figure(figsize=(12, 6))

# Bar plot for total count of occurrences
plt.bar(grouped_data['price_range'], grouped_data['count_occurrences'], color='skyblue', label='Total Count of Occurrences')

# Adding labels and title for the first plot
plt.xlabel('Price Range')
plt.ylabel('Total Count of Occurrences')
plt.title('Total Count of Occurrences and Mean Aggregate Rating')

# Creating a twin axes object for the second plot
plt.twinx()

# Line plot for the mean aggregate rating
plt.plot(grouped_data['price_range'], grouped_data['mean_rating'], color='orange', marker='o', label='Mean Aggregate Rating')

# Adding labels and title for the second plot
plt.ylabel('Mean Aggregate Rating')

# Adding legend for both plots
plt.legend(loc='upper left')

# Show the plot
plt.show()
```



We are witnessing that as price range goes up, rating also go up. However, there are more restuarants at 1 price range. Therefore, this is also one area which can be explored for further targeting customers to reach their satisfaction level.

```
# Group the data by 'establishment' and calculate total count of occurrences and mean aggregate rating
grouped_data = dfnew1.groupby('establishment').agg(count_occurrences=('establishment', 'size'), mean_rating=('aggregate_rating', 'mean')
grouped_data = grouped_data.sort_values(by=['count_occurrences'], ascending=[True])

# Plotting the total count of occurrences and mean aggregate rating
plt.figure(figsize=(12, 6))

# Bar plot for total count of occurrences
plt.bar(grouped_data['establishment'], grouped_data['count_occurrences'], color='skyblue', label='Total Count of Occurrences')

# Adding labels and title for the first plot
plt.xlabel('establishment')
plt.ylabel('Total Count of Occurrences')
plt.xticks(rotation=90)
plt.title('Total Count of Occurrences and Mean Aggregate Rating')

# Creating a twin axes object for the second plot
plt.twinx()

# Line plot for the mean aggregate rating
plt.plot(grouped_data['establishment'], grouped_data['mean_rating'], color='orange', marker='o', label='Mean Aggregate Rating')

# Adding labels and title for the second plot
plt.ylabel('Mean Aggregate Rating')

# Adding legend for both plots
plt.legend(loc='upper left')

# Show the plot
plt.show()
```

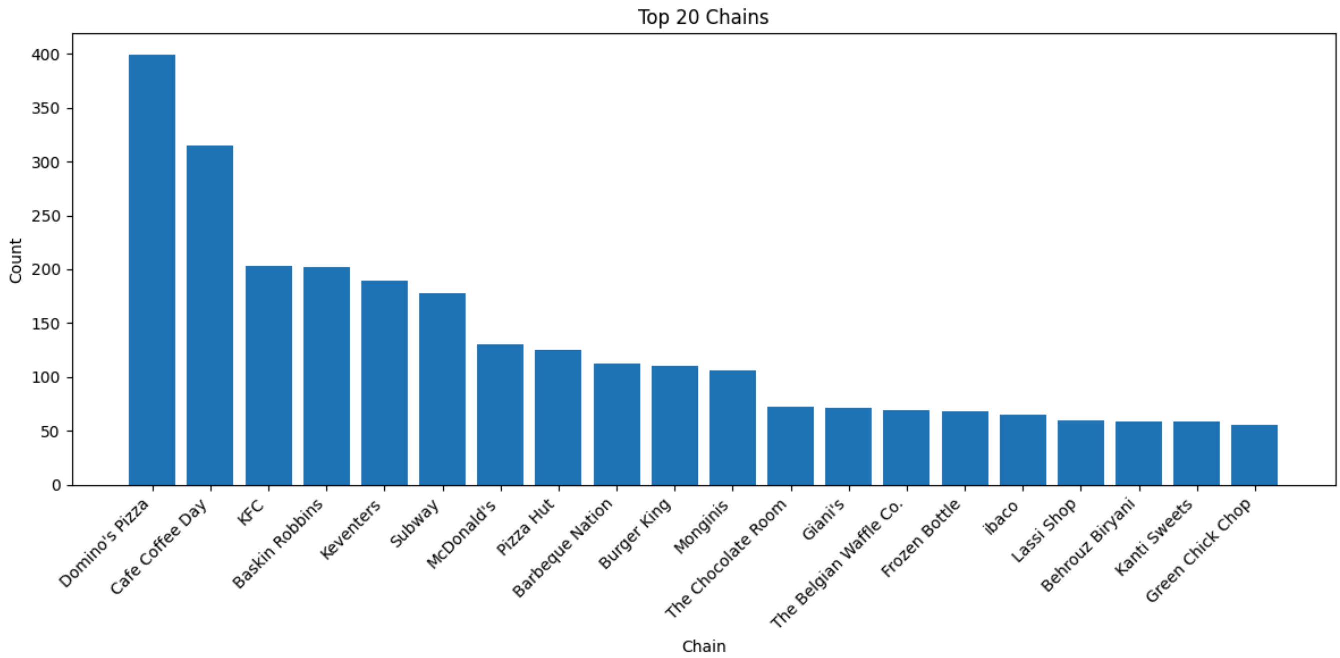


There are some establishments which have higher ratings but are not much in number. These establishments are good for targeting and informing customers based on where there preferences are. Following is a list from picture:

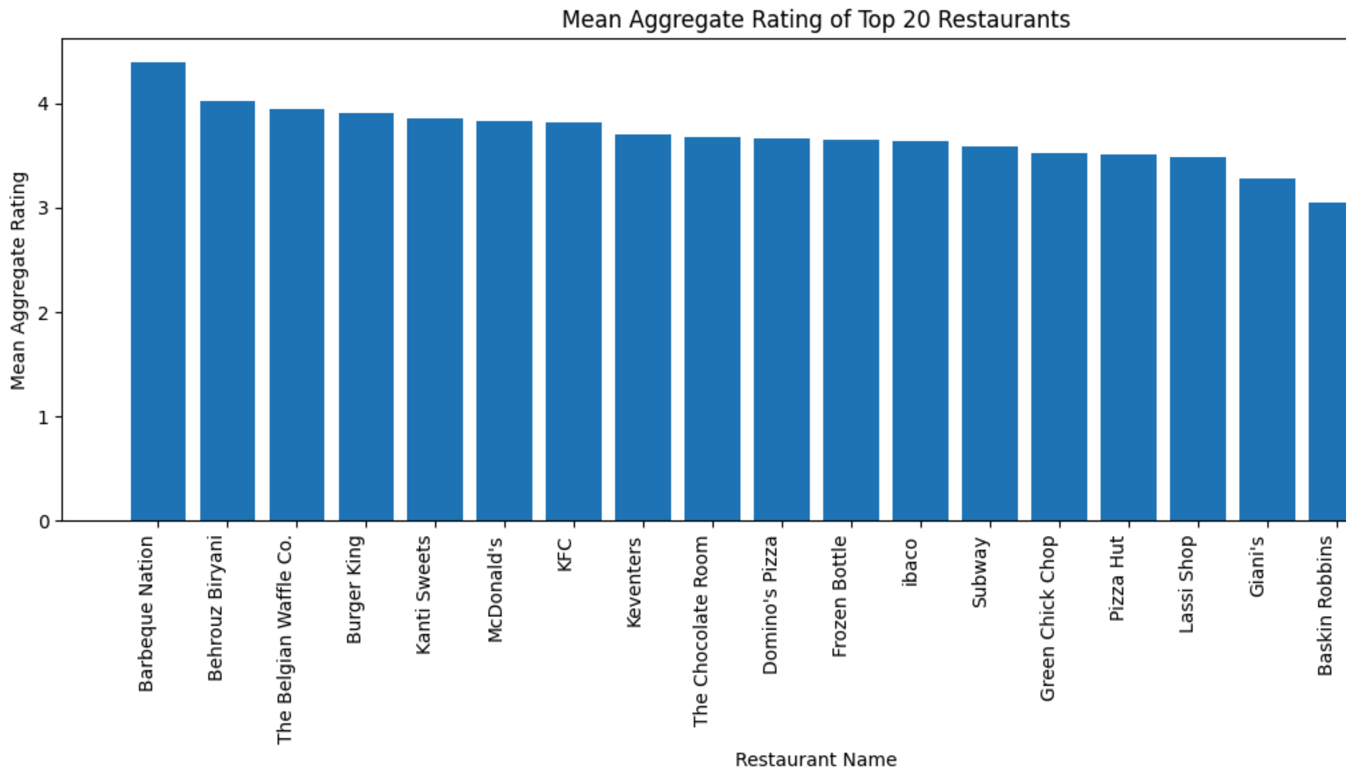
1. Microbrewery
2. Club
3. Butcher Shop
4. Pub
5. Lounge
6. Fine Dining

There are others as well and these can be targeted to provide to ease to customer to further enhance their ratings and increase their popularity

```
chain_counts1 = dfnew1['name'].value_counts()
chain_counts1 = chain_counts1.head(20)

plt.figure(figsize=(12, 6))
plt.bar(chain_counts1.index, chain_counts1.values)

plt.xlabel('Chain')
plt.ylabel('Count')
plt.title('Top 20 Chains')

plt.xticks(rotation=45, ha='right')
plt.tight_layout()

plt.show()
```




```
chain_counts1 = dfnew1['name'].value_counts().head(20)

# Group by restaurant name and calculate the mean aggregate rating
chain_counts = dfnew1.groupby('name')['aggregate_rating'].mean().reset_index()

# Filter chain_counts to include only the top 20 restaurant names
chain_counts = chain_counts[chain_counts['name'].isin(chain_counts1.index)]
chain_counts = chain_counts.sort_values(by= ['aggregate_rating'], ascending=[False])

# Plot the filtered DataFrame
plt.figure(figsize=(12, 6))
plt.bar(chain_counts['name'], chain_counts['aggregate_rating'])

plt.xlabel('Restaurant Name')
plt.ylabel('Mean Aggregate Rating')
plt.title('Mean Aggregate Rating of Top 20 Restaurants')

plt.xticks(rotation=90, ha='right')
plt.tight_layout()

plt.show()
```



Another potential gap could be the restaurant chains. From the above two figures it is depicted that Dominos chain is prevelant across India. However, when it comes to most rated one. the situation is different.Therefore, it is important to targat both lists equally. Most occuring chains are essential in getting more popularity and access for Zomato acorss all regions and in overall country. Moreover, having publications about highest rated ones will help in becoming the ultimate choice of the customers for searching places as it is directly dealing with the customers choices.