Data description:

The collected data has been stored in the Comma Separated Value file **Zomato.csv.** Each restaurant in the dataset is uniquely identified by its Restaurant Id. Every Restaurant contains the following variables:

• **Restaurant Id:** Unique id of every restaurant across various cities of the world

• **Restaurant Name:** Name of the restaurant

• **Country Code:** Country in which restaurant is located

• **City:** City in which restaurant is located

• **Address:** Address of the restaurant

• **Locality:** Location in the city

• **Locality Verbose:** Detailed description of the locality

• **Longitude:** Longitude coordinate of the restaurant's location

• **Latitude:** Latitude coordinate of the restaurant's location

• **Cuisines:** Cuisines offered by the restaurant

• **Average Cost for two:** Cost for two people in different currencies 👫

• **Currency:** Currency of the country

• **Has Table booking:** yes/no

• **Has Online delivery:** yes/ no

• **Is delivering:** yes/ no

• **Switch to order menu:** yes/no

• **Price range:** range of price of food

• **Aggregate Rating:** Average rating out of 5

• **Rating color:** depending upon the average rating color

• **Rating text:** text on the basis of rating of rating

• **Votes:** Number of ratings casted by people

There is another dataset which has the country codes in it

Import required libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
plt.rcParams["figure.figsize"] = (14,8)
sns.set_style('darkgrid')
sns.set(font_scale=1.5)
```

In [2]:

```python
# Load the Zomato dataset into a Pandas DataFrame
df = pd.read_csv('zomato.csv',encoding='latin1')
```

In [3]:

```python
df.head()
```

Out[3]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cui
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	F Japa De
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Jap
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Se Fi
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japa
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japa K

5 rows × 21 columns

In [4]:

```python
df1=pd.read_excel('Country-Code.xlsx')
```

In [5]:

```python
df1.head()
```

Out[5]:

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

Let us merge both datasets. This will help us to understand the dataset country-wise.

In [6]:
```
data=pd.merge(df,df1,on='Country Code',how='left')
```

In [7]:
```
data.head()
```

Out[7]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cui
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	F Japa De
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Jap
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Se Fi
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japa
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japa K

5 rows × 22 columns

In [8]:

```
data.describe()
```

Out[8]:

	Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Aggregate rating	Votes
count	9.551000e+03	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.00000(
mean	9.051128e+06	18.365616	64.126574	25.854381	1199.210763	1.804837	2.666370	156.90974ε
std	8.791521e+06	56.750546	41.467058	11.007935	16121.183073	0.905609	1.516378	430.16914ξ
min	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0.000000	0.00000(
25%	3.019625e+05	1.000000	77.081343	28.478713	250.000000	1.000000	2.500000	5.00000(
50%	6.004089e+06	1.000000	77.191964	28.570469	400.000000	2.000000	3.200000	31.00000(
75%	1.835229e+07	1.000000	77.282006	28.642758	700.000000	2.000000	3.700000	131.00000(
max	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4.900000	10934.00000(

In [9]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9551 entries, 0 to 9550
Data columns (total 22 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant ID         9551 non-null   int64  
 1   Restaurant Name       9551 non-null   object 
 2   Country Code          9551 non-null   int64  
 3   City                  9551 non-null   object 
 4   Address               9551 non-null   object 
 5   Locality              9551 non-null   object 
 6   Locality Verbose      9551 non-null   object 
 7   Longitude             9551 non-null   float64
 8   Latitude              9551 non-null   float64
 9   Cuisines              9542 non-null   object 
 10  Average Cost for two  9551 non-null   int64  
 11  Currency              9551 non-null   object 
 12  Has Table booking     9551 non-null   object 
 13  Has Online delivery   9551 non-null   object 
 14  Is delivering now     9551 non-null   object 
 15  Switch to order menu  9551 non-null   object 
 16  Price range           9551 non-null   int64  
 17  Aggregate rating      9551 non-null   float64
 18  Rating color          9551 non-null   object 
 19  Rating text           9551 non-null   object 
 20  Votes                 9551 non-null   int64  
 21  Country               9551 non-null   object 
dtypes: float64(3), int64(5), object(14)
memory usage: 1.7+ MB
```

Observation:

In the above dataset we can see that most of the columns are categorical

In [10]:
```
data.isnull().sum()
```

Out[10]:
```
Restaurant ID           0
Restaurant Name         0
Country Code            0
City                    0
Address                 0
Locality                0
Locality Verbose        0
Longitude               0
Latitude                0
Cuisines                9
Average Cost for two    0
Currency                0
Has Table booking       0
Has Online delivery     0
Is delivering now       0
Switch to order menu    0
Price range             0
Aggregate rating        0
Rating color            0
Rating text             0
Votes                   0
Country                 0
dtype: int64
```

Observation:

Cuisines column has null value

Fill Null Values

In [11]:
```
data.Cuisines.fillna('Other',inplace=True)
```

In [12]:
```
data.isnull().sum()
```

Out[12]:
```
Restaurant ID           0
Restaurant Name         0
Country Code            0
City                    0
Address                 0
Locality                0
Locality Verbose        0
Longitude               0
Latitude                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
```

Exploratory Analysis and Visualization

In [13]:
```
print('List of counteris the survey is spread accross - ')
for x in pd.unique(data.Country):
    print(x)
print()
print('Total number to country', len(pd.unique(data.Country)))
```

```
List of counteris the survey is spread accross -
Phillipines
Brazil
United States
Australia
Canada
Singapore
UAE
India
Indonesia
New Zealand
United Kingdom
Qatar
South Africa
Sri Lanka
Turkey

Total number to country 15
```

Observation:

The survey seems to have spread across 15 countries. This shows that Zomato is a multinational company having actives business in all those countries.

In [14]:
```
data['Country'].unique()
```

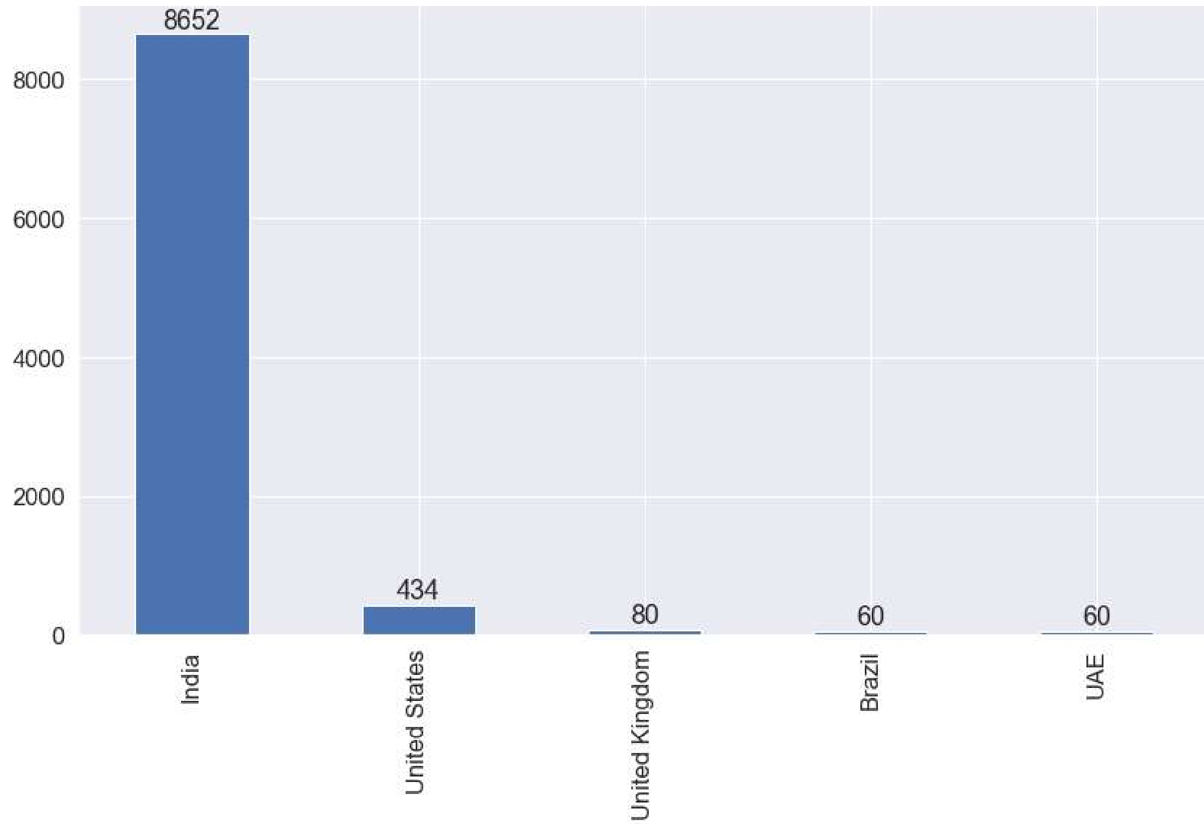
Out[14]:
```
array(['Phillipines', 'Brazil', 'United States', 'Australia', 'Canada',
       'Singapore', 'UAE', 'India', 'Indonesia', 'New Zealand',
       'United Kingdom', 'Qatar', 'South Africa', 'Sri Lanka', 'Turkey'],
      dtype=object)
```

In [15]:
```
country_wise_restr=data['Country'].value_counts()
country_wise_restr
```

Out[15]:
```
India             8652
United States      434
United Kingdom      80
Brazil              60
UAE                 60
South Africa        60
New Zealand         40
Turkey              34
Australia           24
Phillipines         22
Indonesia           21
Singapore           20
Qatar               20
Sri Lanka           20
Canada               4
Name: Country, dtype: int64
```

In [16]:

```
ax=country_wise_restr.head().plot(kind='bar')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



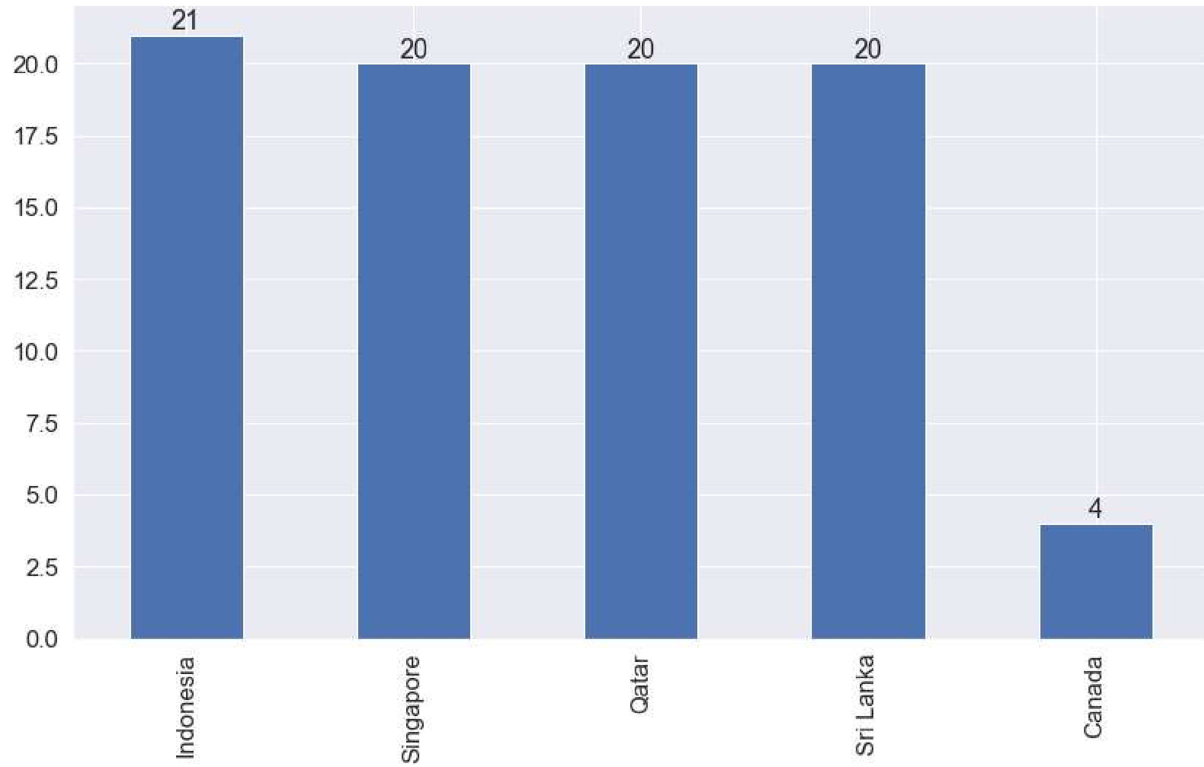
Observation:

1) India has more numbers of zomato restaurent as compared to other countries.

2) Acoording to data india has total 8652 restaurent after that United States has total 434 restaurent.

In [17]:

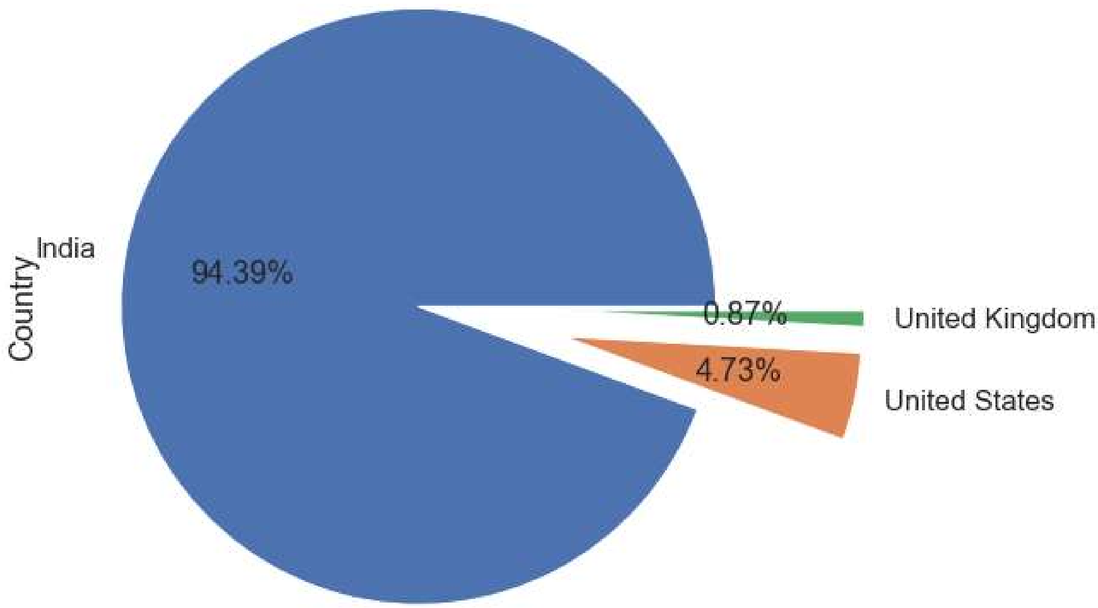
```
ax=country_wise_restr.tail().plot(kind='bar')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Observation:

In above the graph we can see that,Canada has less number of restaurent(According to the data Only 4 restaurent availabe in Canada)

In [18]:
```
data['Country'].value_counts()[:3].plot(kind='pie',autopct='%0.2f%%',explode=[0,0.5,0.5])
plt.show()
```



Observation:

Zomato is the Indian based company so we here see that total 94.39 % of restaurent available in India

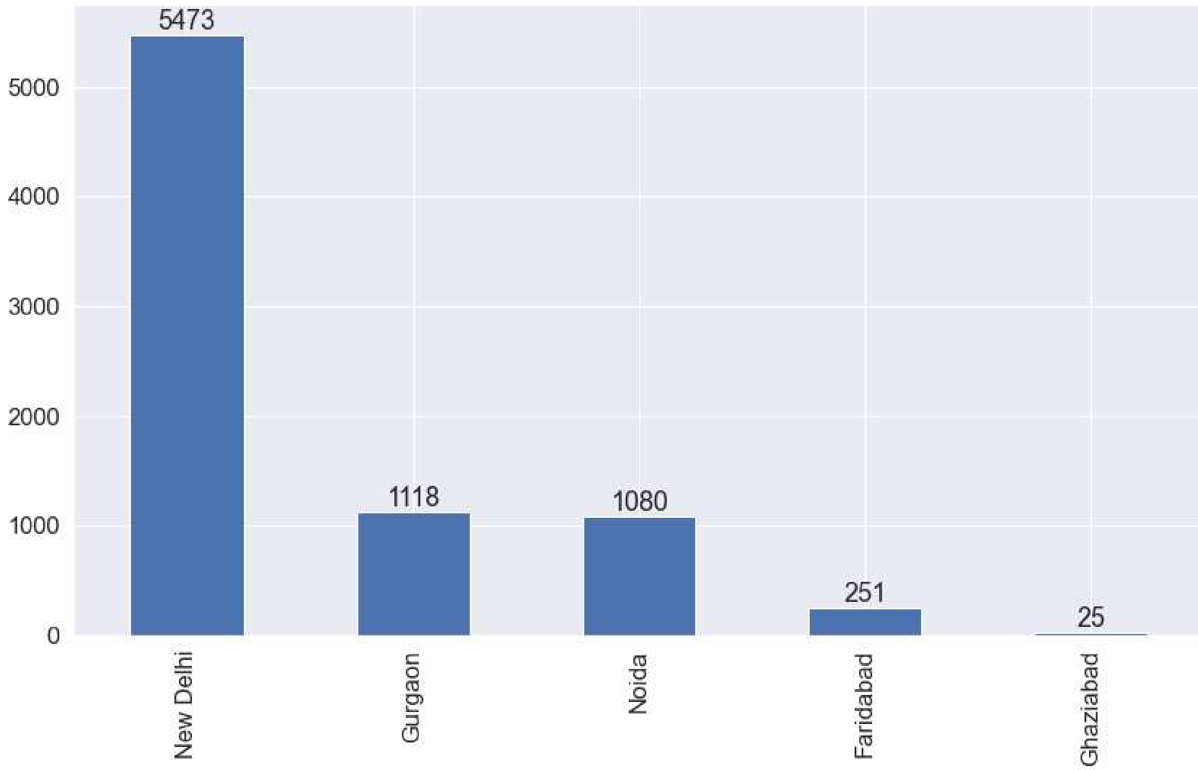
In [19]:

```
indian_cities=data[data['Country']=='India']['City'].value_counts()
indian_cities
```

Out[19]:

```
New Delhi       5473
Gurgaon         1118
Noida           1080
Faridabad        251
Ghaziabad         25
Ahmedabad         21
Guwahati          21
Lucknow           21
Bhubaneshwar      21
Amritsar          21
Pune              20
Puducherry        20
Patna             20
Ludhiana          20
Ranchi            20
Surat             20
Vadodara          20
Nashik            20
Nagpur            20
Mysore            20
Mumbai            20
Varanasi          20
Mangalore         20
Agra              20
Kochi             20
Kolkata           20
Dehradun          20
Allahabad         20
Aurangabad        20
Bangalore         20
Bhopal            20
Chennai           20
Coimbatore        20
Goa               20
Indore            20
Jaipur            20
Kanpur            20
Vizag             20
Chandigarh        18
Hyderabad         18
Secunderabad       2
Panchkula          1
Mohali             1
Name: City, dtype: int64
```

In [20]:
```
ax=indian_cities[:5].plot(kind='bar')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Observation:

New Delhi, Gurgaon & Noida has more no.of zomato restaurents, In New Delhi total 5473 restaurents availabe, this count is more as compared to other city

In [21]:
```
data[data['City']=='New Delhi']['Locality'].count()
```

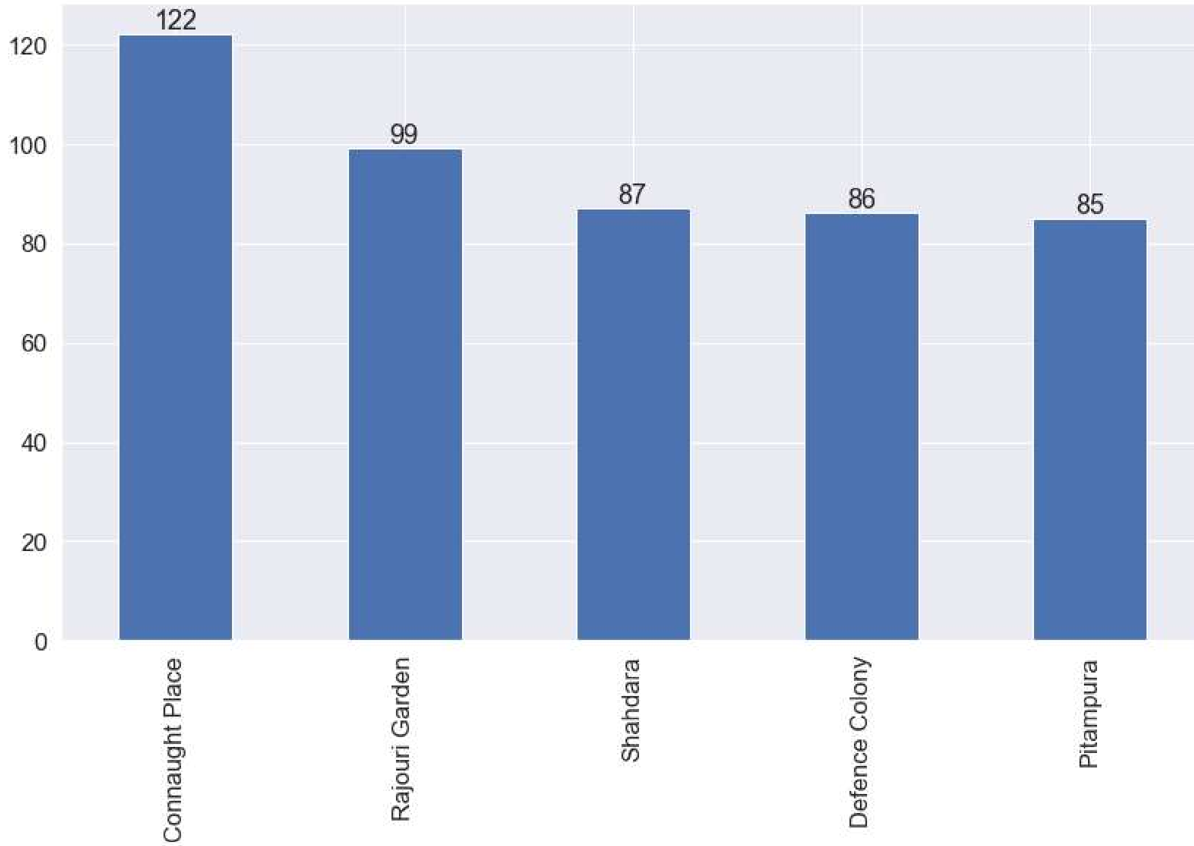
Out[21]:
```
5473
```

Find Restaurent counts with respect to local area

In [22]:
```
Delhi_Locality=data[data['City']=='New Delhi']['Locality'].value_counts().head()
Delhi_Locality
```

Out[22]:
```
Connaught Place    122
Rajouri Garden      99
Shahdara            87
Defence Colony      86
Pitampura           85
Name: Locality, dtype: int64
```

In [23]:
```
ax=Delhi_Locality.plot(kind='bar')
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Observation:

In New Delhi Local area connaught place has more number of restaurents total 122.

Which quisines are more prefer in Connaught Place

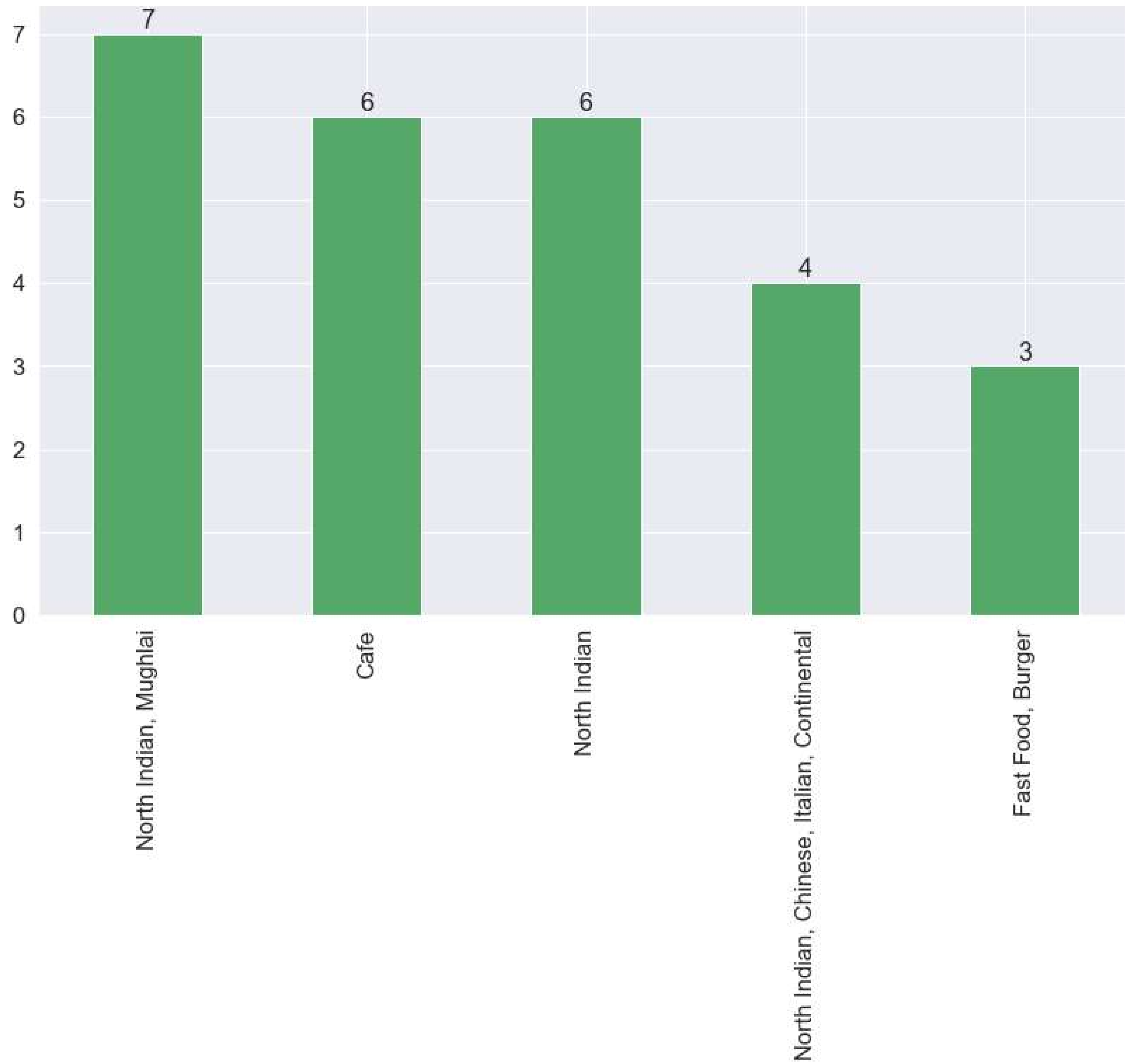
In [24]:
```
Connaught_Place_Cuisines=data[data['Locality']=='Connaught Place']['Cuisines'].value_counts()
Connaught_Place_Cuisines[:5]
```

Out[24]:
```
North Indian, Mughlai                         7
Cafe                                          6
North Indian                                  6
North Indian, Chinese, Italian, Continental   4
Fast Food, Burger                             3
Name: Cuisines, dtype: int64
```

Observation:

Here we see that North Indian Quisines are more prefer in Connaught Place

In [25]:
```python
ax=Connaught_Place_Cuisines[:5].plot(kind='bar',color='g')
for i in ax.containers:
    ax.bar_label(i, label_type='edge')
plt.show()
```



In [26]:
```python
data.columns
```

Out[26]:
```
Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
       'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
       'Average Cost for two', 'Currency', 'Has Table booking',
       'Has Online delivery', 'Is delivering now', 'Switch to order menu',
       'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
       'Votes', 'Country'],
      dtype='object')
```

In [27]:
```python
data[data['Cuisines']=='North Indian']['Country'].value_counts()
```

Out[27]:
```
India    936
Name: Country, dtype: int64
```

Observation:

North Indian cuisine mostly prefered by India

Country wise currency

In [28]:
```
data[['Country','Currency']].value_counts().reset_index().drop(0,axis=1)
```

Out[28]:

	Country	Currency
0	India	Indian Rupees(Rs.)
1	United States	Dollar($)
2	United Kingdom	Pounds(£)
3	Brazil	Brazilian Real(R$)
4	South Africa	Rand(R)
5	UAE	Emirati Diram(AED)
6	New Zealand	NewZealand($)
7	Turkey	Turkish Lira(TL)
8	Australia	Dollar($)
9	Phillipines	Botswana Pula(P)
10	Indonesia	Indonesian Rupiah(IDR)
11	Qatar	Qatari Rial(QR)
12	Singapore	Dollar($)
13	Sri Lanka	Sri Lankan Rupee(LKR)
14	Canada	Dollar($)

In [29]:
```
data[['Restaurant Name','Cuisines','Aggregate rating']].sort_values(by='Aggregate rating',asce
```

Out[29]:

	Restaurant Name	Cuisines	Aggregate rating
1381	Caterspoint	Mexican, American, Healthy Food	4.9
589	AB's Absolute Barbecues	Continental, Indian	4.9
374	McGuire's Irish Pub & Brewery	Burger, Bar Food, Steak	4.9
9303	Miann	Desserts	4.9
9299	Milse	Desserts	4.9
...	...	...	...
4034	Mirch Masala Restaurant	North Indian	0.0
4033	Kashmiri Hills Wazwan	Kashmiri	0.0
4029	New Classic Kitchen	Chinese, Fast Food	0.0
4025	Frugurpop- ibis New Delhi	Ice Cream, Desserts	0.0
5426	Swadist Bhojnalaya	Chinese, North Indian	0.0

9551 rows × 3 columns

In [30]:
```
data['Cuisines'].value_counts().idxmax()
```

Out[30]: 'North Indian'

In [31]:

```
data[['Restaurant Name','Price range']].sort_values(by='Price range',ascending=False)[:10]
```

Out[31]:

	Restaurant Name	Price range
9151	Rendezvous Cafe Restaurant	4
472	Super Loco	4
461	Rhubarb Le Restaurant	4
463	Fratini La Trattoria	4
7427	Basil & Thyme	4
465	The Refinery Singapore	4
468	Colony	4
469	Summer Pavilion	4
470	The Lokal	4
471	I Am	4

In [32]:

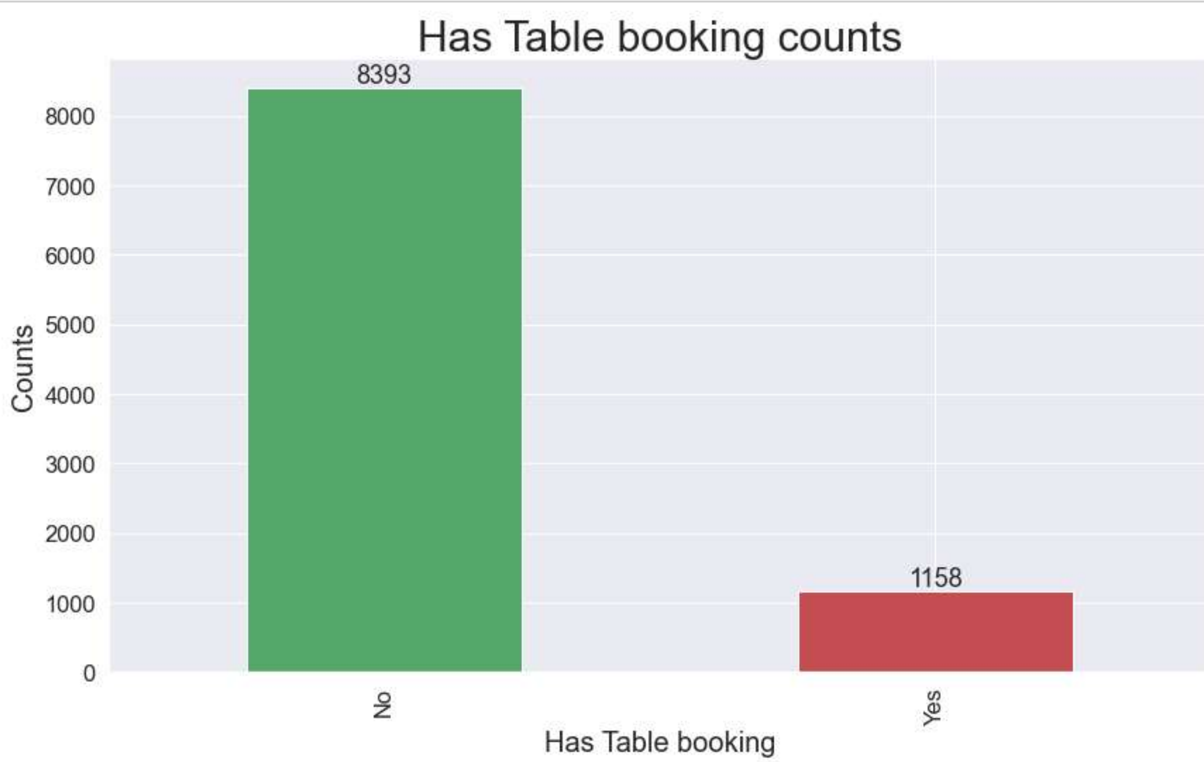
```
df['Has Table booking'].value_counts()
```

Out[32]:

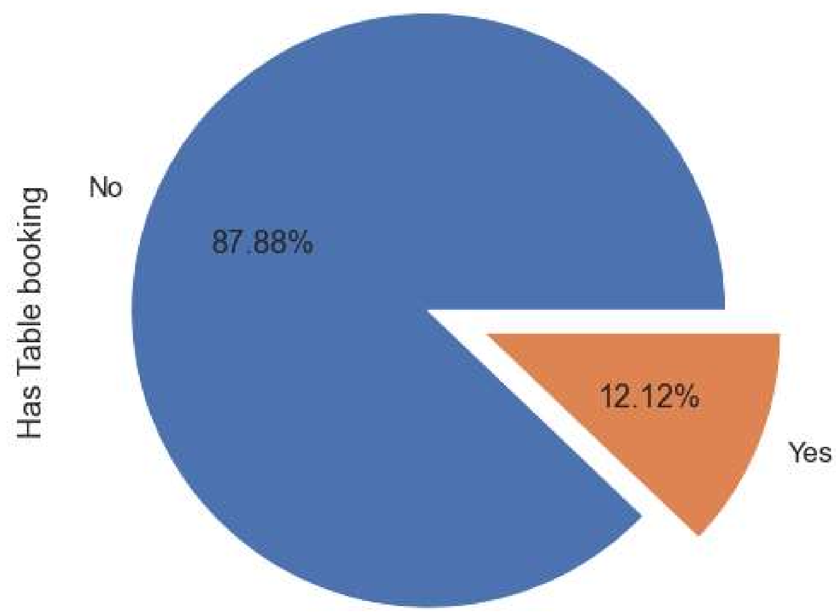
```
No      8393
Yes     1158
Name: Has Table booking, dtype: int64
```

In [33]:

```
ax=df['Has Table booking'].value_counts().plot(kind='bar',color=['g','r'])
plt.title('Has Table booking counts',fontsize=30)
plt.ylabel('Counts',fontsize=20)
plt.xlabel('Has Table booking',fontsize=20)
labels=[]
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```

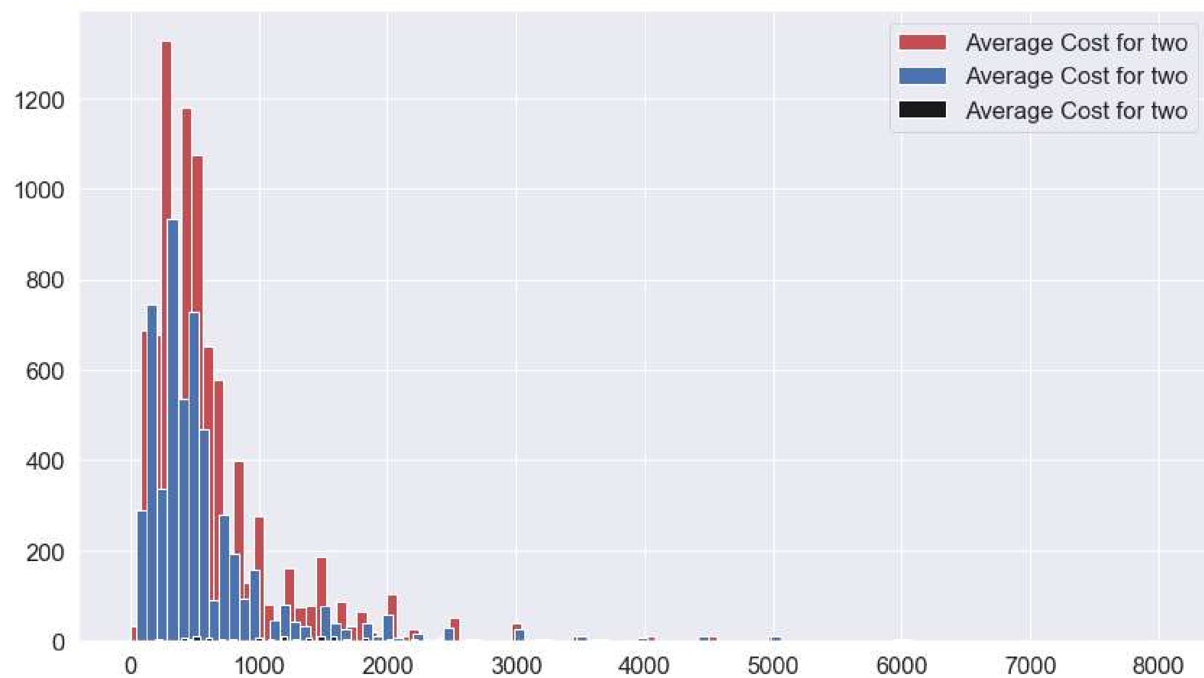


In [34]:
```
df['Has Table booking'].value_counts().plot(kind='pie',autopct='%0.2f%%',explode=[0,0.2])
plt.show()
```

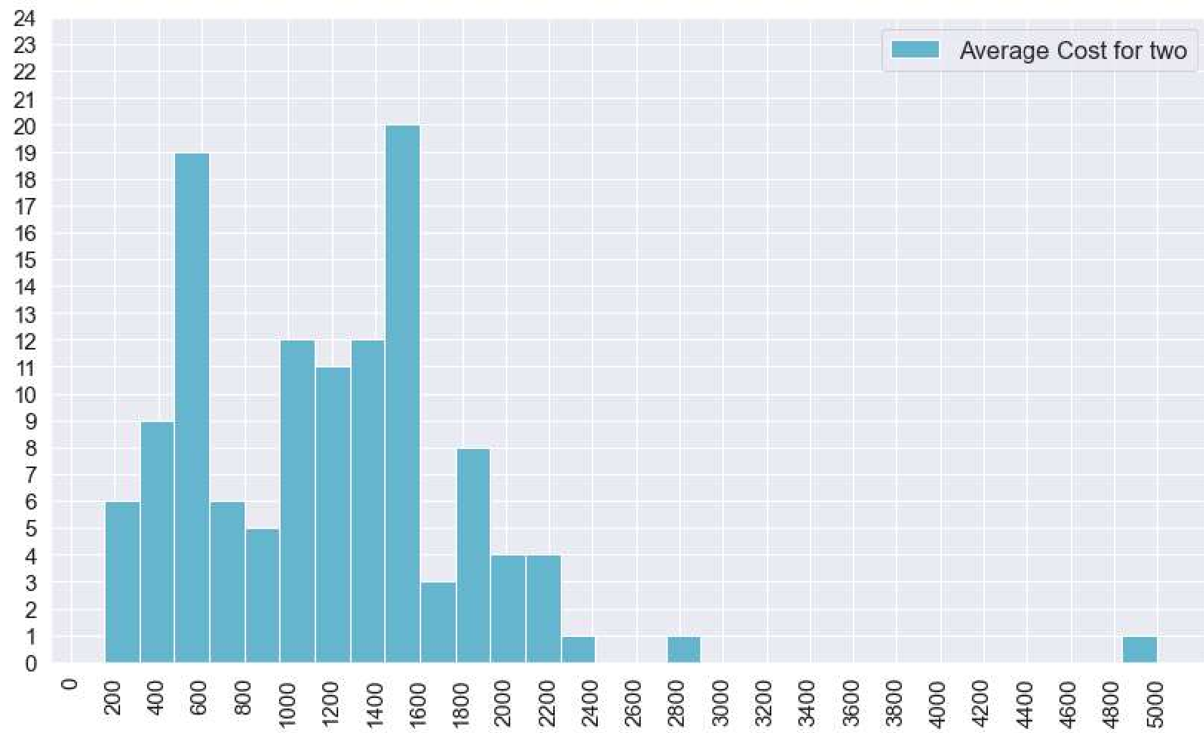


In [35]:
```
data[data['Country']=='India']['Average Cost for two'].hist(bins=100,legend=True,color='r')
data[data['City']=='New Delhi']['Average Cost for two'].hist(bins=100,legend=True)
data[data['Locality']=='Connaught Place']['Average Cost for two'].hist(bins=100,color='k',lege

plt.show()
```

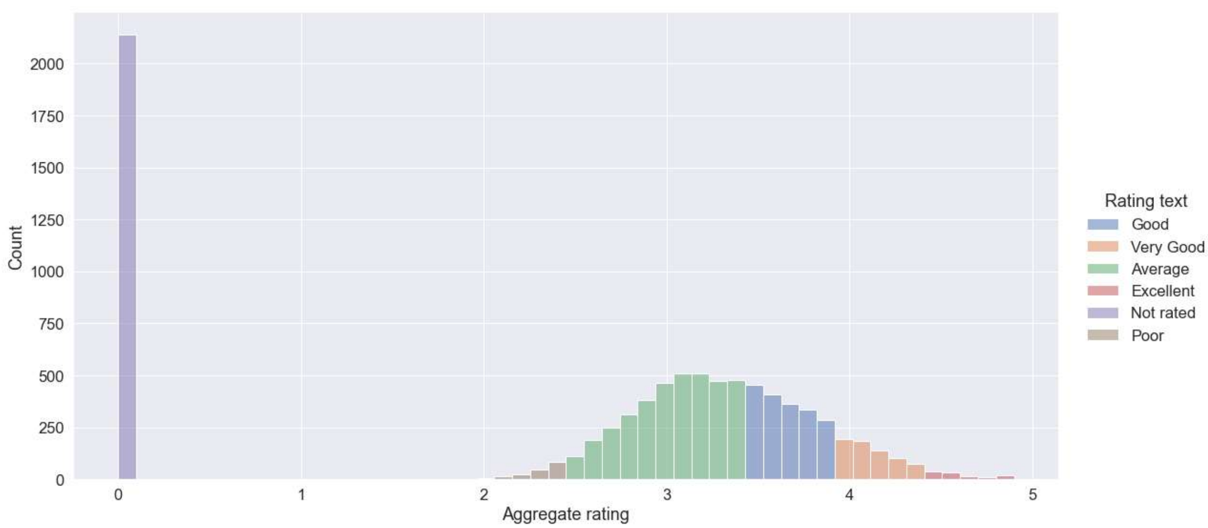


In [36]:
```
data[data['Locality']=='Connaught Place']['Average Cost for two'].hist(bins=30,legend=True, x
                                                                          xrot=90,color='c')
plt.yticks(range(0,25),color='k')
plt.xticks(range(0,5001,200),color='k')
plt.show()
```



In [37]:
```
Zomato_India=data[data['Country']=='India']
```

In [38]:
```
sns.displot(data=Zomato_India,x='Aggregate rating',height=8,aspect=2,bins=50,hue='Rating text
plt.show()
```

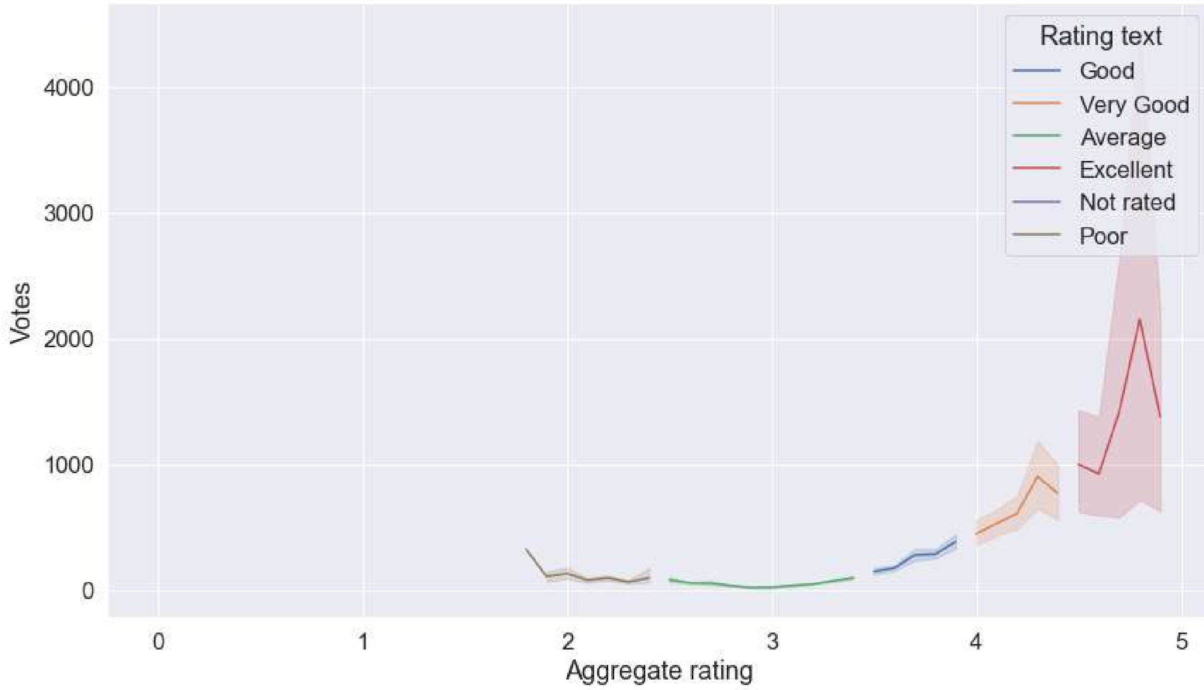


Observation:

- A lot of restaurants are rated **0**. After this most of the restaurants have been rated between **3** and **4**.

In [39]:

```
# Relationship between Aggregate Ratings and Votes
sns.lineplot(data=Zomato_India,x='Aggregate rating', y= 'Votes',hue='Rating text')
plt.show()
```



Observation:

Aggregate Ratings and Votes have an increasing trend.

In [40]:

```
df.head()
```

Out[40]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cui
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	F Japa De
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Jap
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Se Fi
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4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japa K

5 rows × 21 columns

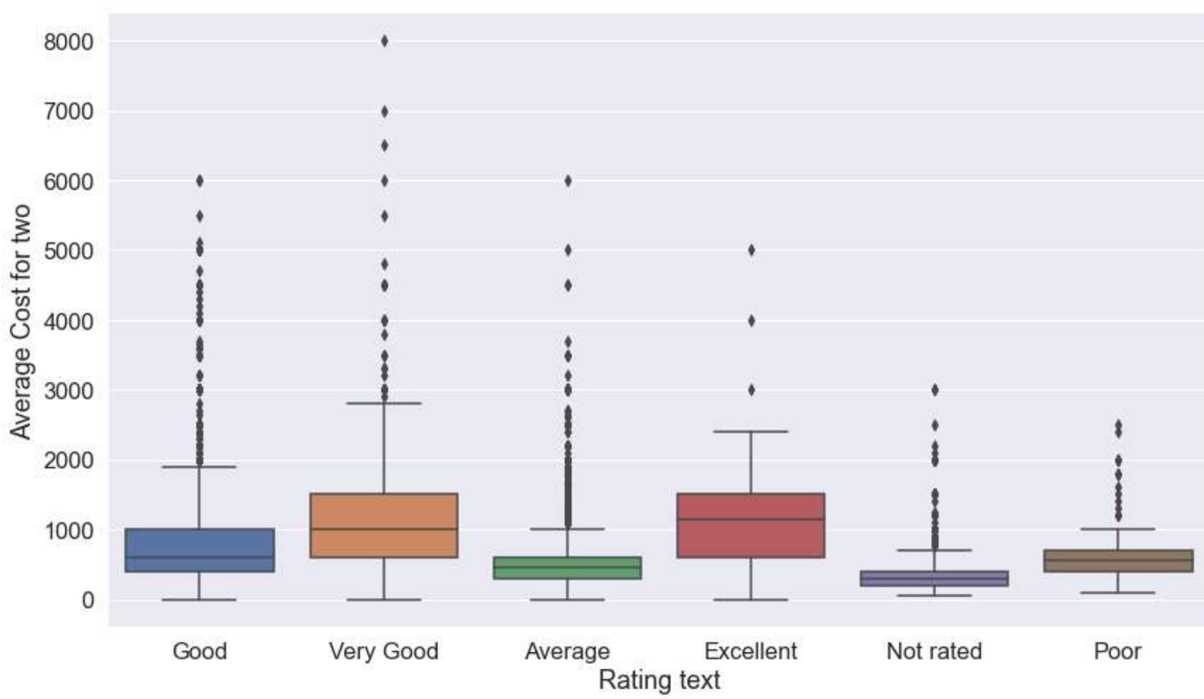
In [41]:

```
sns.heatmap(Zomato_India.corr(),annot=True)
plt.show()
```

In [42]:

```
# Relationship between Average Cost for two and Rating text

sns.boxplot(y = 'Average Cost for two', x = 'Rating text', data = Zomato_India)
plt.show()
```

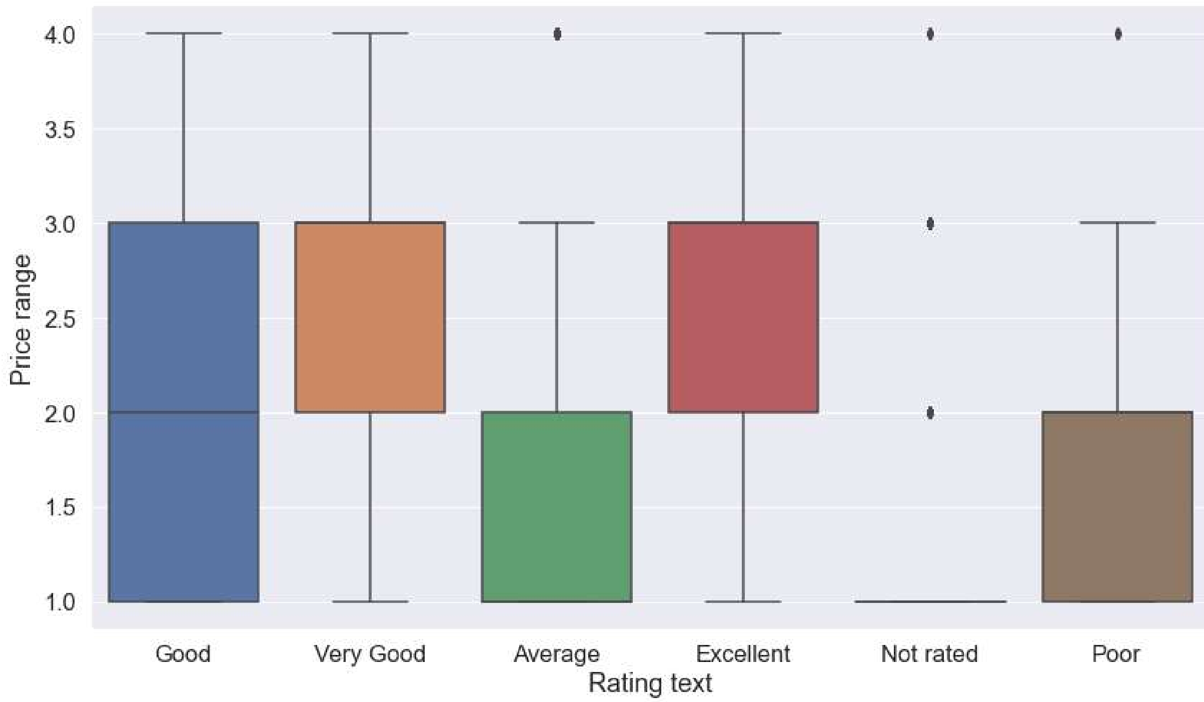


Observation:

Ratings improve as the average cost for two increases.

In [43]:
```
# Relationship between Price range and Rating text

sns.boxplot(y = 'Price range', x = 'Rating text', data = Zomato_India)
plt.show()
```



Observation:

Excellent and Very Good restaurants have very high price.
Average and Poor have the lowest price range.

Lets identify restaurants which have high price range and low ratings

In [44]:
```
Zomato_India['Price range'].value_counts()
```

Out[44]:
```
1    4295
2    2858
3    1111
4     388
Name: Price range, dtype: int64
```

In [45]:
```
exp_india_restaurant = Zomato_India[Zomato_India['Price range'] == 4]
exp_india_restaurant[:5]
```

Out[45]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...
629	3400325	MoMo Cafe	1	Agra	Courtyard by Marriott Agra, Phase 2, Fatehabad...	Courtyard by Marriott Agra, Tajganj	Courtyard by Marriott Agra, Tajganj, Agra	0.000000	0.000000	North Indian, European	...
630	3400059	Peshawri - ITC Mughal	1	Agra	ITC Mughal, Fatehabad Road, Tajganj, Agra	ITC Mughal, Tajganj	ITC Mughal, Tajganj, Agra	78.044095	27.160934	North Indian, Mughlai	...
631	3400060	Taj Bano - ITC Mughal	1	Agra	ITC Mughal, Fatehabad Road, Tajganj, Agra	ITC Mughal, Tajganj	ITC Mughal, Tajganj, Agra	78.044095	27.160934	Mughlai	...
633	3400072	Dawat-e-Nawab - Radisson Blu	1	Agra	Radisson Blu, Taj East Gate Road, Tajganj, Agra	Radisson Blu, Tajganj	Radisson Blu, Tajganj, Agra	78.057044	27.163303	North Indian, Mughlai	...
638	3400350	Bon Barbecue	1	Agra	Parador Hotel, 3A-3B, Phase 1, Fatehabad Road,...	Tajganj	Tajganj, Agra	0.000000	0.000000	North Indian, Chinese, Continental	...

5 rows × 22 columns

In [46]:
```
# Lets check the ratings of these restaurants
exp_india_restaurant['Rating text'].value_counts()
```

Out[46]:
```
Good          167
Very Good      97
Average        88
Excellent      20
Not rated      11
Poor            5
Name: Rating text, dtype: int64
```

Observation:

As the price range is high, most of the ratings are good.
So if price is high, why will be there be 5 poor ratings?

In [47]:
```python
exp_india_restaurant[exp_india_restaurant['Rating text'] == 'Poor']
```

Out[47]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...
1247	306134	The Wine Company	1	Gurgaon	Cyber Hub, DLF Cyber City, Gurgaon	Cyber Hub, DLF Cyber City	Cyber Hub, DLF Cyber City, Gurgaon	77.089048	28.496229	Italian, European	...
8045	718	Americana Kitchen and Bar	1	Noida	Ist Floor, 1-6, Centre Stage Mall, Sector 18, ...	Centre Stage Mall, Sector 18	Centre Stage Mall, Sector 18, Noida	77.322828	28.568343	American, Tex-Mex, Italian, Mexican, North Indian	...
8467	4717	RPM - Zanzi Bar	1	Noida	B-110, Gautam Budh Nagar, Sector 18, Noida	Sector 18	Sector 18, Noida	77.325299	28.570669	Chinese, North Indian	...
9050	3212	Chicane	1	Noida	205-A, 1st Floor, Spice World Mall, Sector 25-...	Spice World Mall, Sector 25	Spice World Mall, Sector 25, Noida	77.341021	28.585493	European, North Indian, Chinese	...
9105	3237	Club Ice Cube	1	Noida	313, 3rd Floor, The Great India Place Mall, Se...	The Great India Place, Sector 38	The Great India Place, Sector 38, Noida	77.326475	28.568067	North Indian, Continental, Chinese	...

5 rows × 22 columns

In [48]:
```python
list_of_cuisines = exp_india_restaurant[exp_india_restaurant['Rating text'] == 'Poor']['Cuisi
list_of_cuisines.values
```

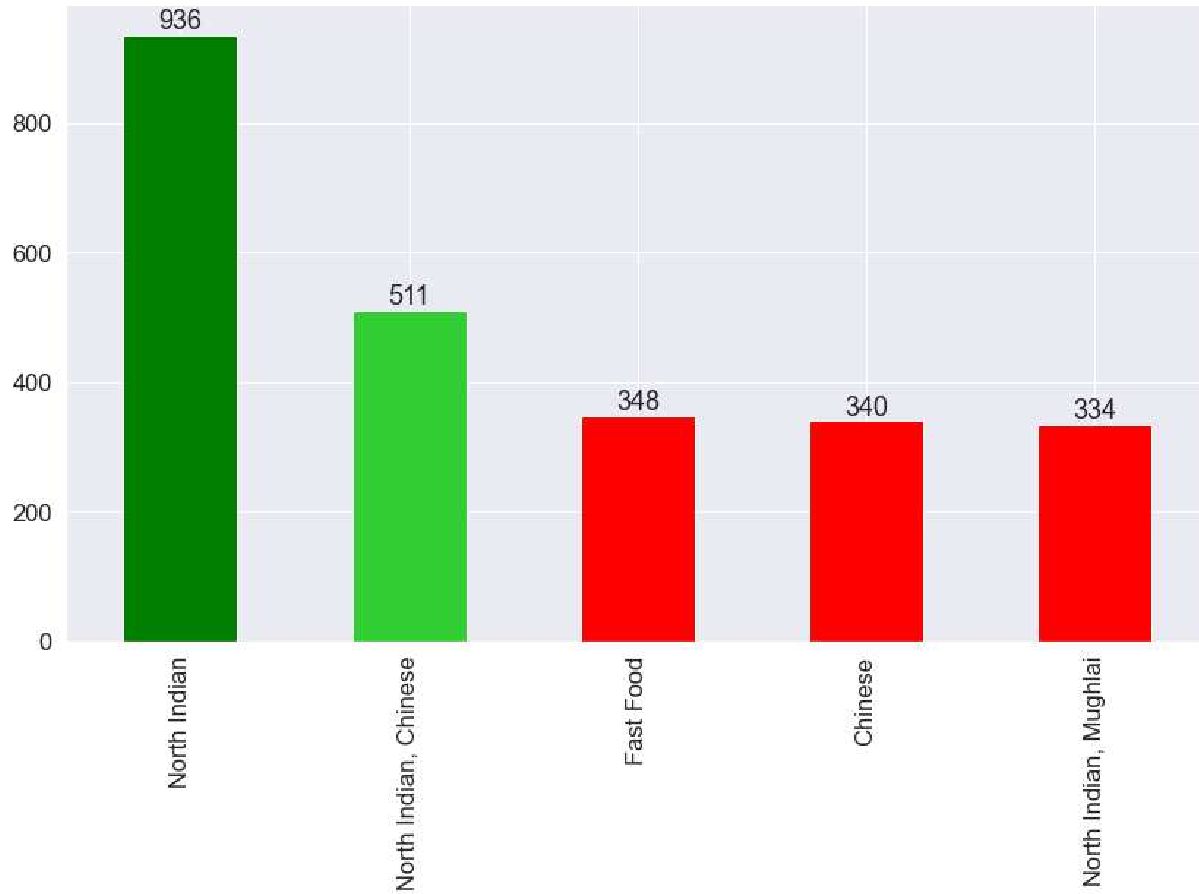
Out[48]:
```
array(['Italian, European',
       'American, Tex-Mex, Italian, Mexican, North Indian',
       'Chinese, North Indian', 'European, North Indian, Chinese',
       'North Indian, Continental, Chinese'], dtype=object)
```

Observation:

These are 5 restaurants which are really expensive but do not have good ratings.
Lets have a look at what is their cuisines.

In [49]:

```
ax=Zomato_India['Cuisines'].value_counts()[:5].plot(kind='bar',color=['green','limegreen','re
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Observation:

"North Indian" is the most popular cuisine. So we can infer that these North Indian restaurants in Gurgaon and Noida which do not provide authentic North Indian dishes and that is why customers are unhappy and rate them poorly.

Lets look at all the restaurants which have poor ratings.

In [50]:

```
bad_rated_restaurants = Zomato_India[Zomato_India['Rating text'] == 'Poor']
bad_rated_restaurants
```

Out[50]:

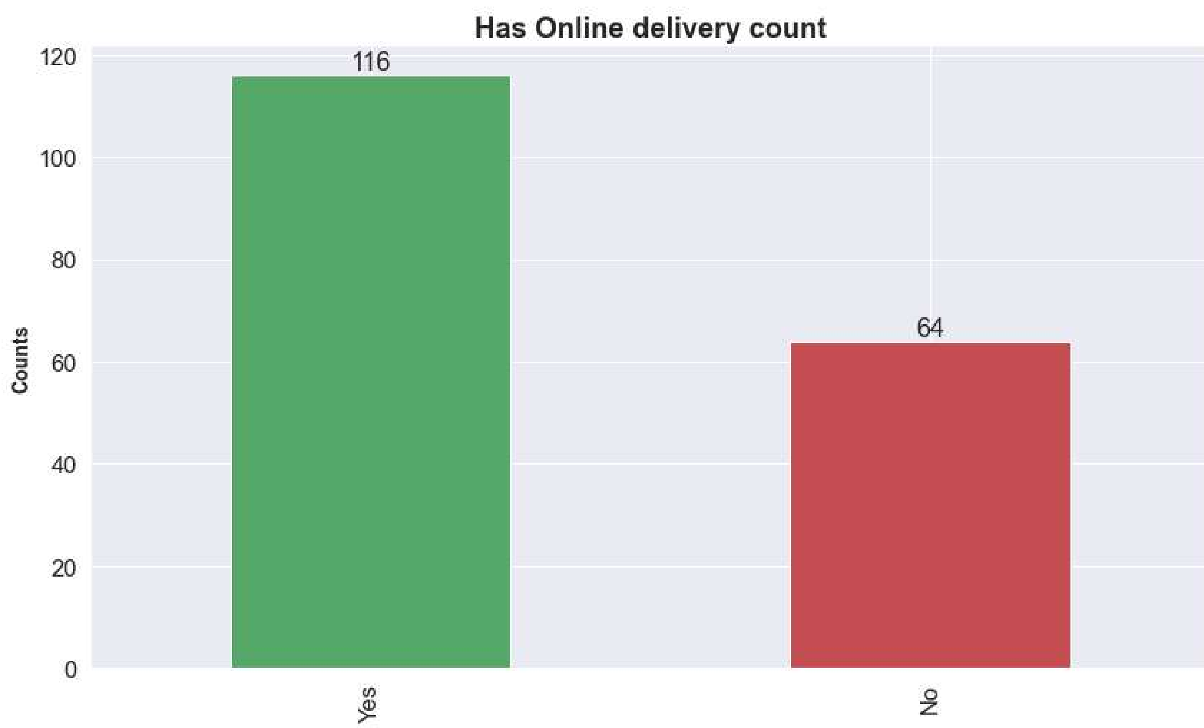
	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuis
890	311051	KFC	1	Faridabad	Shops 21-22, 2nd Floor, Crown Interiorz Mall, ...	Crown Interiorz Mall, Sector 35, Faridabad	Crown Interiorz Mall, Sector 35, Faridabad, Fa...	77.307060	28.469807	Amer Fast F B
896	8128	Mirage Restro Bar	1	Faridabad	2nd Floor, Crown Plaza Mall, Sector 15-A, Sect...	Crown Plaza Mall, Sector 15, Faridabad	Crown Plaza Mall, Sector 15, Faridabad, Faridabad	77.313102	28.397808	In Mu
1138	1683	Pind Balluchi	1	Ghaziabad	Shop 34-40, Level 3, Shipra Mall, Gulmohar Roa...	Shipra Mall, Indirapuram	Shipra Mall, Indirapuram, Ghaziabad	77.370165	28.633970	In Mu
1247	306134	The Wine Company	1	Gurgaon	Cyber Hub, DLF Cyber City, Gurgaon	Cyber Hub, DLF Cyber City	Cyber Hub, DLF Cyber City, Gurgaon	77.089048	28.496229	It Euro
1263	225	Domino's Pizza	1	Gurgaon	UGF/RTC 9, Building 8, Tower C, DLF-2, DLF Cy...	DLF Cyber City	DLF Cyber City, Gurgaon	77.089048	28.494525	Pizza,
...	...	...	...	...	...	...	...	...	...	
9069	428	Sagar Ratna	1	Noida	C-134/B, Supertech Shopprix Mall, Sector 61, N...	Supertech Shopprix Mall, Sector 61	Supertech Shopprix Mall, Sector 61, Noida	77.364833	28.597103	S In In Ch
9070	18070483	Subway	1	Noida	Shop 3, Supertech Shopprix Mall, Sector 61, Noida	Supertech Shopprix Mall, Sector 61	Supertech Shopprix Mall, Sector 61, Noida	77.364981	28.596898	Amer Fast F S He
9104	2979	Chopaal	1	Noida	A-2, 3rd Floor, The Great India Place Mall, Se...	The Great India Place, Sector 38	The Great India Place, Sector 38, Noida	77.325308	28.567150	Chi In S Indian,
9105	3237	Club Ice Cube	1	Noida	313, 3rd Floor, The Great India Place Mall, Se...	The Great India Place, Sector 38	The Great India Place, Sector 38, Noida	77.326475	28.568067	In Contin Ch
9106	2025	Moti Mahal Delux Tandoori Trail	1	Noida	Food Court, The Great India Place Mall, Sector...	The Great India Place, Sector 38	The Great India Place, Sector 38, Noida	77.325445	28.567040	In Mu

180 rows × 22 columns

In [51]:
```
bad_rated_restaurants.shape
```
Out[51]:
```
(180, 22)
```

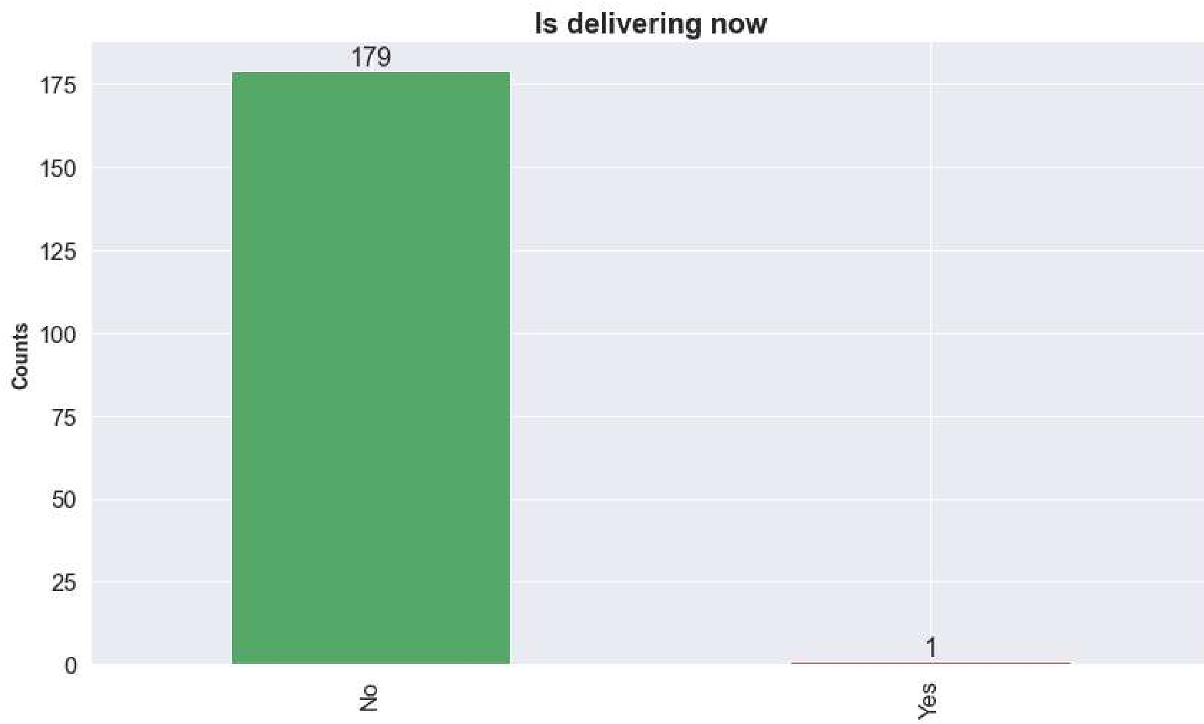
In [52]:
```
bad_rated_restaurants['Has Online delivery'].value_counts()
```
Out[52]:
```
Yes    116
No      64
Name: Has Online delivery, dtype: int64
```

In [53]:
```
ax=bad_rated_restaurants['Has Online delivery'].value_counts().plot(kind='bar',color=['g','r']
for i in ax.containers:
    ax.bar_label(i)
plt.title('Has Online delivery count',fontsize=20,fontweight='bold')
plt.ylabel('Counts',fontsize=14,fontweight='bold')
plt.show()
```



In [54]:
```
bad_rated_restaurants['Is delivering now'].value_counts()
```
Out[54]:
```
No     179
Yes      1
Name: Is delivering now, dtype: int64
```

In [55]:
```
ax=bad_rated_restaurants['Is delivering now'].value_counts().plot(kind='bar',color=['g','r'])
for i in ax.containers:
    ax.bar_label(i)
plt.title('Is delivering now',fontsize=20,fontweight='bold')
plt.ylabel('Counts',fontsize=14,fontweight='bold')
plt.show()
```

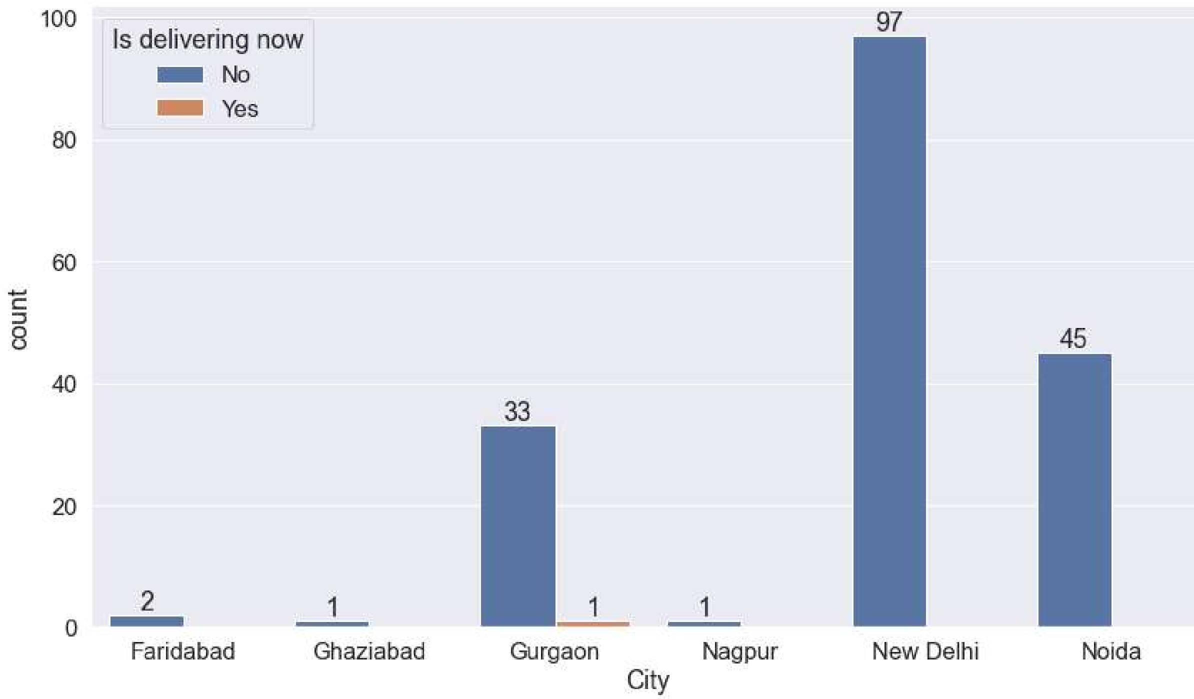


Observation:

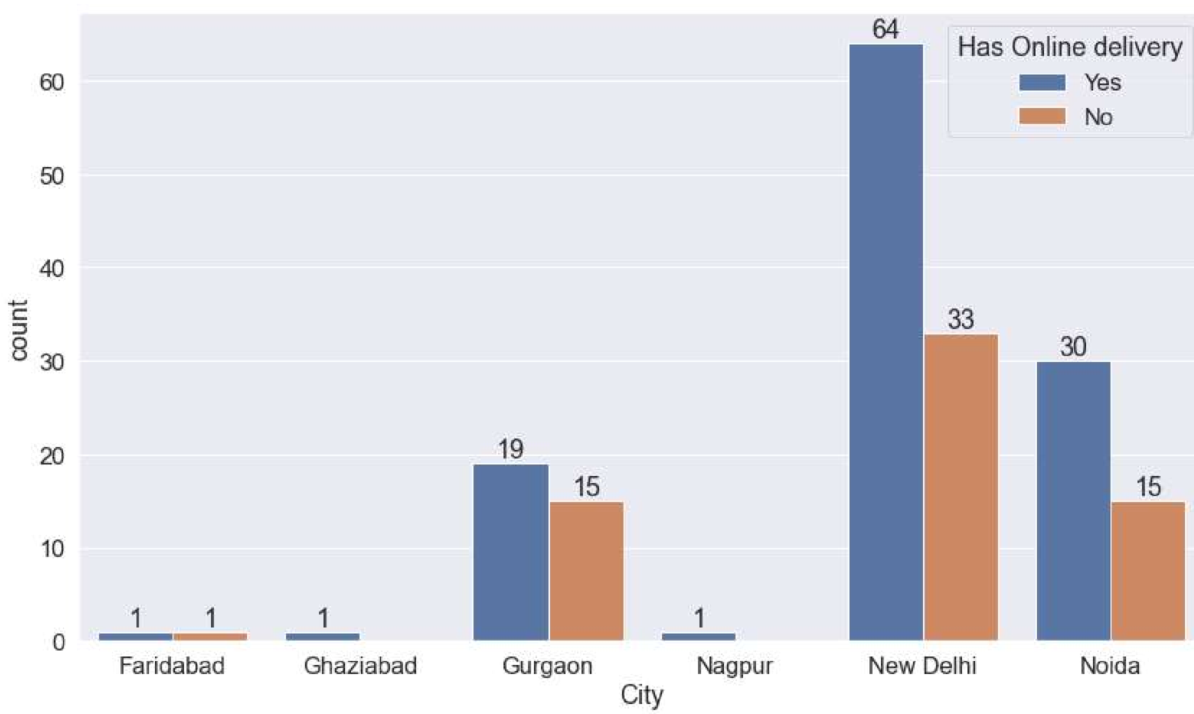
Many of these restaurants are not available for delivery most of the time. Hence people provide poor rating to them.

City wise Analysis of Poor Rated restaurants

In [56]:
```
ax=sns.countplot(x = 'City',hue='Is delivering now', data = bad_rated_restaurants)
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



In [57]:
```
ax=sns.countplot(x = 'City',hue='Has Online delivery', data = bad_rated_restaurants)
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Why are ratings of New Delhi, Noida and Gurgaon bad?

In [58]:
```
# Total no. of bad restaurants

bad_rated_restaurants['City'].value_counts()
```

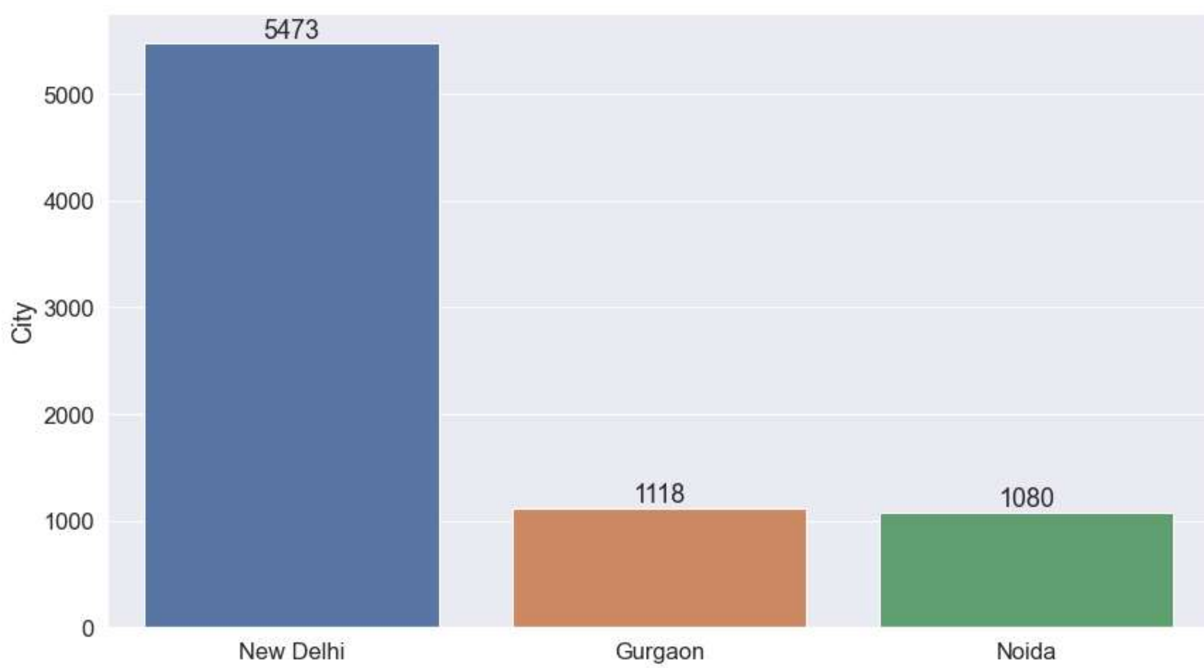
Out[58]:
```
New Delhi    97
Noida        45
Gurgaon      34
Faridabad     2
Ghaziabad     1
Nagpur        1
Name: City, dtype: int64
```

In [59]:
```
# Total number of restaurants

top_3_cities = Zomato_India['City'].value_counts().head(3)
top_3_cities
```

Out[59]:
```
New Delhi    5473
Gurgaon      1118
Noida        1080
Name: City, dtype: int64
```

In [60]:
```
ax=sns.barplot(y = top_3_cities, x = top_3_cities.index)
for i in ax.containers:
    labels+=ax.bar_label(i)
plt.show()
```



Observation:

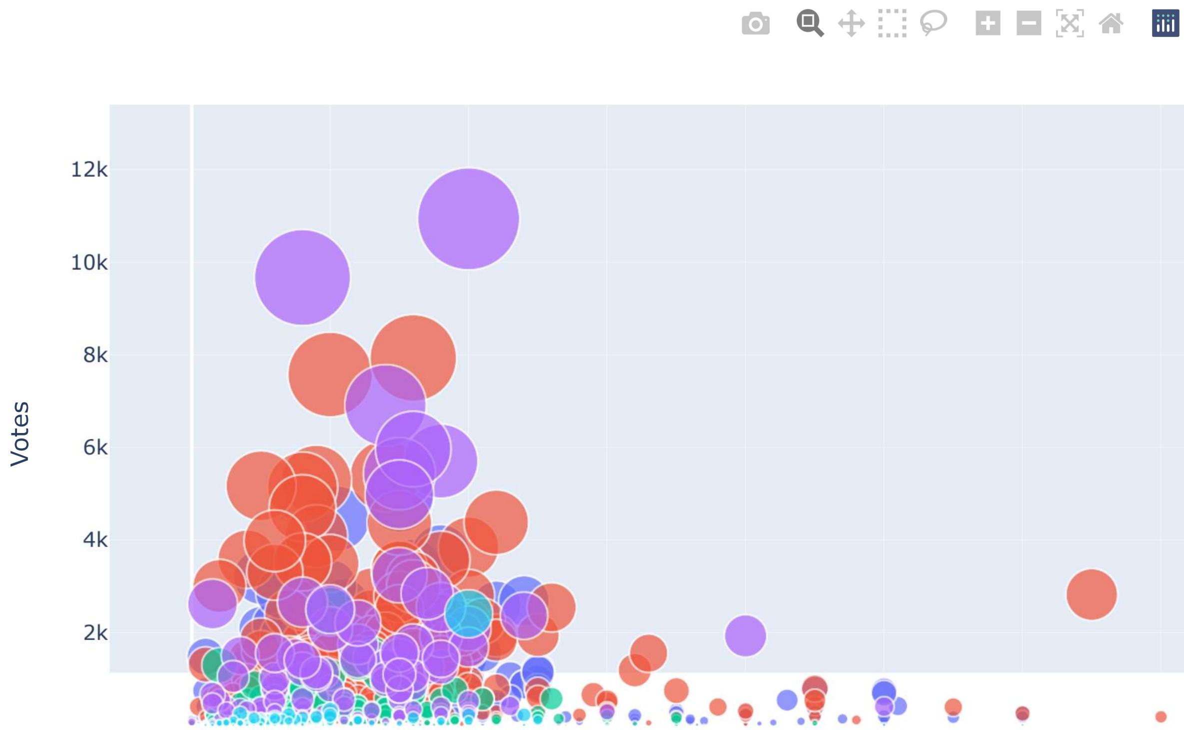
Hence we cannot conclude that these 3 cities have significantly large number of bad restaurants as the total number of restaurants is also high.

Let's make our plots interactive using Plotly-express

In [61]:
```
import plotly_express as px
```

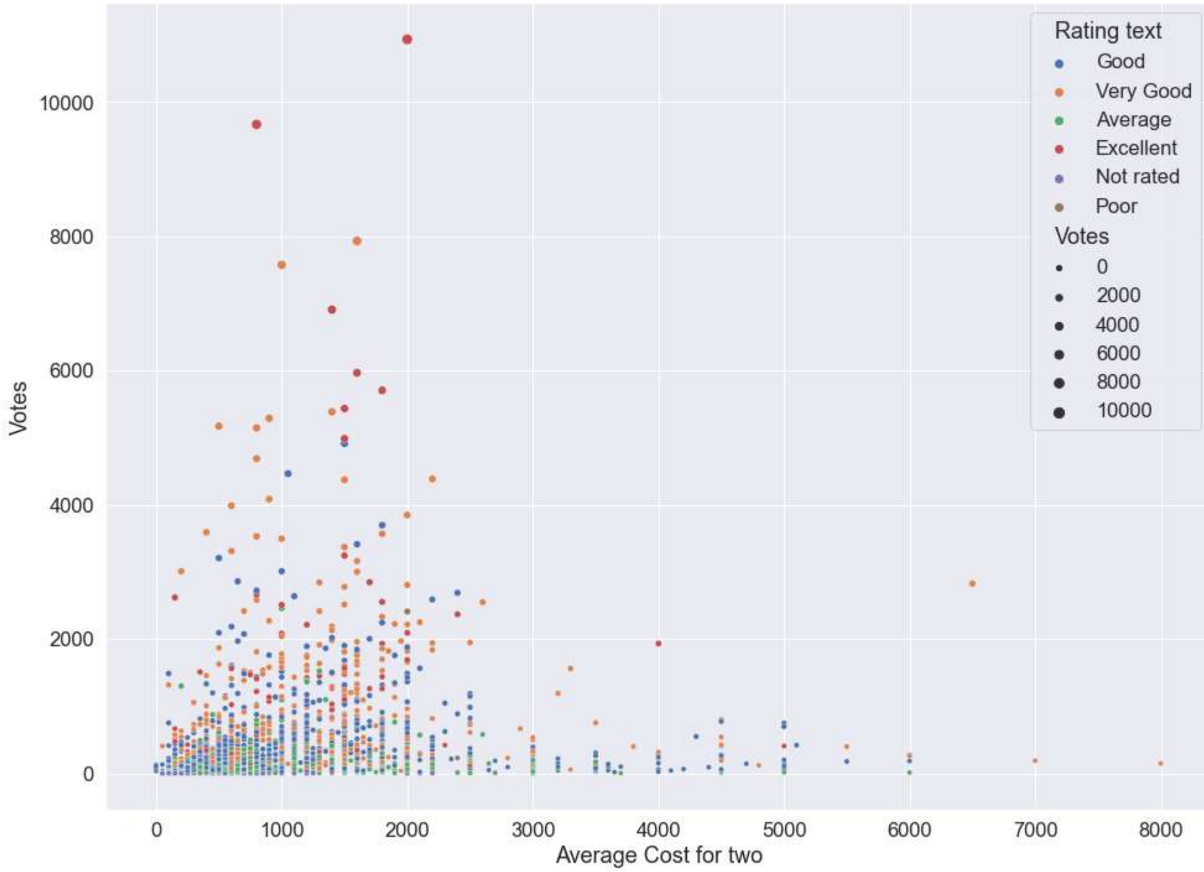
In [62]:
```
# Scatter Plot

px.scatter(Zomato_India, x="Average Cost for two", y="Votes", size="Votes", color="Rating tex
           size_max=60,hover_name='City')
```



In [98]:

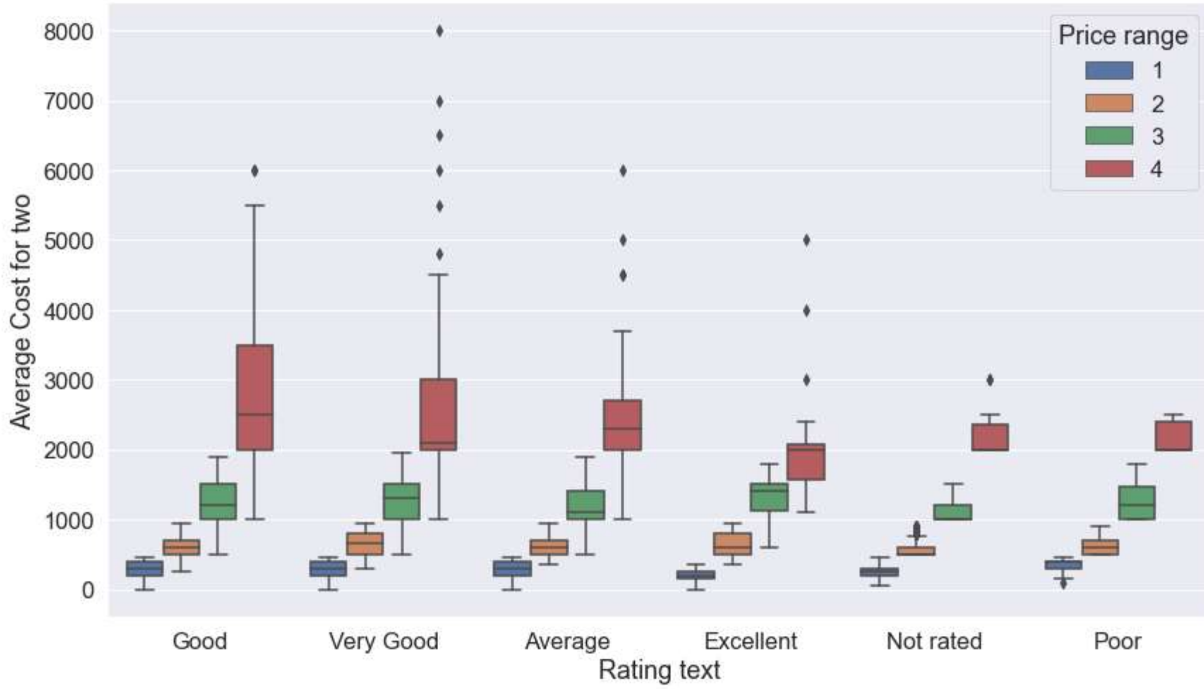
```
plt.figure(figsize=(16,12))
sns.scatterplot(data=Zomato_India,x='Average Cost for two', y="Votes",size='Votes',hue='Ratin
plt.show()
```



Observation:

We can see how the Average Cost for two and the Votes are related and in which cities.

In [70]:
```
sns.boxplot(data=Zomato_India,x='Rating text', y="Average Cost for two",hue="Price range")
plt.show()
```



Observation:

Good and Very Good food have very high cost as compared to excellent and other types of food.

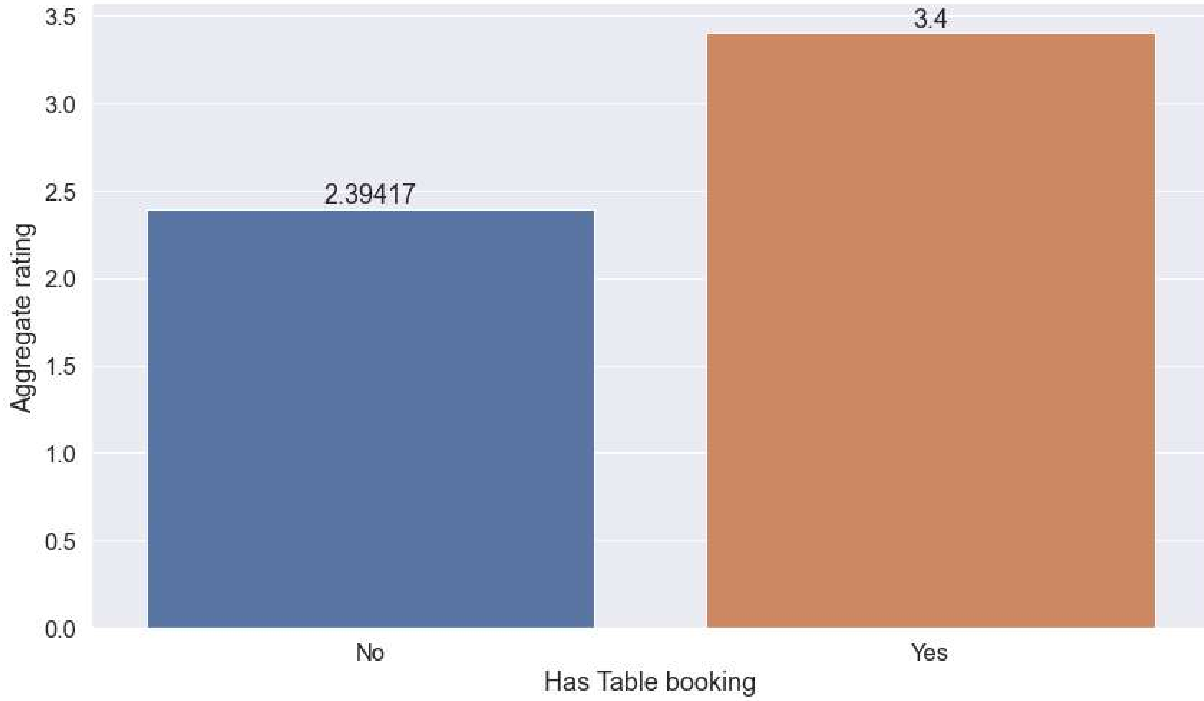
In [64]:
```
# Relationship between Online Delivery and Aggregate rating
ax=sns.barplot(data=Zomato_India, x="Has Online delivery", y="Aggregate rating",ci=None)
for i in ax.containers:
    labels+=ax.bar_label(i)
plt.show()
```

Observation:

Restaurants which have online delivery have better ratings

In [65]:

```
# Relationship between Has Table booking and Aggregate rating
ax=sns.barplot(data=Zomato_India, x="Has Table booking", y="Aggregate rating",ci=None)
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```

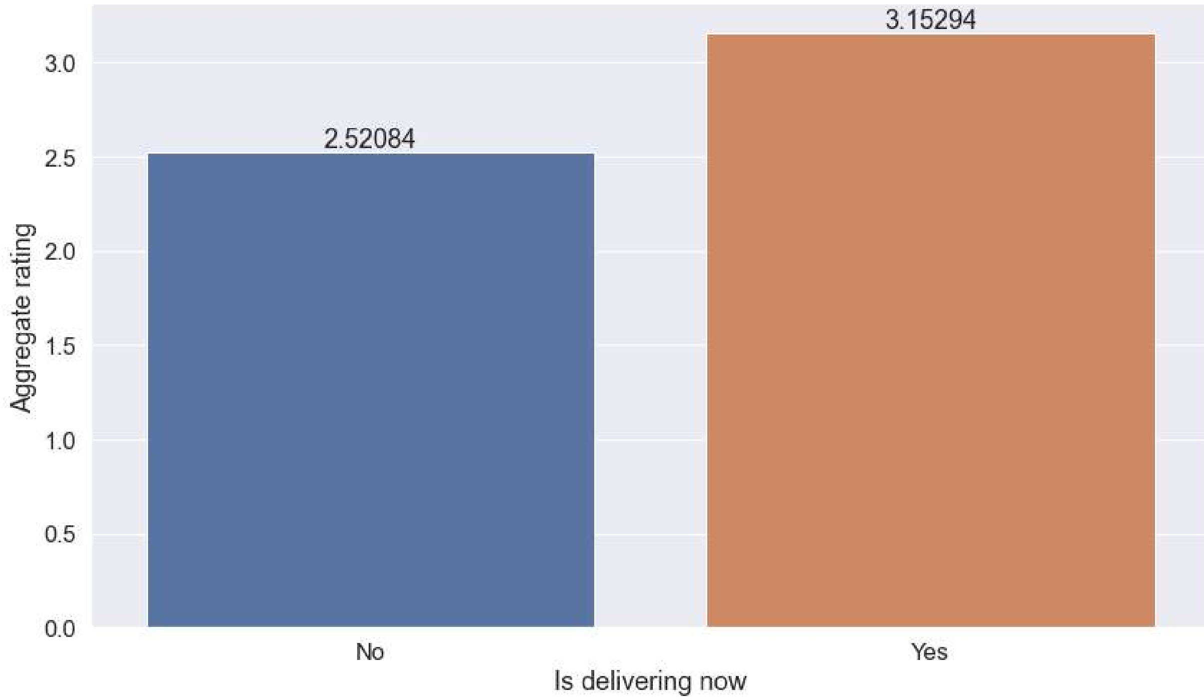


Observation:

Restaurants which have table booking available have more ratings in general.

In [66]:

```
# Relationship between Has Table booking and Aggregate rating
ax=sns.barplot(data=Zomato_India, x="Is delivering now", y="Aggregate rating",ci=None)
for i in ax.containers:
    ax.bar_label(i)
plt.show()
```



Observation:

Restaurants which are delivering now have better ratings than the one which are not.

Inferences and Conclusions

We’ve drawn many inferences from the survey. Here’s a summary of a few of them:

1)The dataset is skewed towards India and doesn't represent the complete data of restaurants worldwide.

2) Restaurants rating is categorized in s categories

1. **Not Rated**
2. **Average**
3. **Good**
4. **Very Good**
5. **Excellent**
6. **Poor**

3) Connaught Palace has maximum restaurants listed on Zomato but in terms of online delivery acceptance Defence colony and Malviya Nagar seems to be doing better.

4)The top-rated restaurants seem to be getting a better rating on the following cuisine

- **North Indian**
- **Chinese**
- **American**
- **Italian**

5)There is no relation between cost and rating. Some of the best-rated restaurants are low on cost and vice versa.