Identifying and Recommending Best Restaurants Project 1

DESCRIPTION

Data Analysis is the process of creating a story using the data for easy and effective communication. It mostly utilizes visualization methods like plots, charts, and tables to convey what the data holds beyond the formal modeling or hypothesis testing task.

Domain: Marketing

Read the information given below and also refer to the data dictionary provided separately in an excel file to build your understanding.

Problem Statement A restaurant consolidator is looking to revamp its B-to-C portal using intelligent automation tech. It is in search of different matrix to identify and recommend restaurants. To make sure an effective model can be achieved it is important to understand the behaviour of the data in hand.

Approach:

1. Data Preliminary analysis:

Perform preliminary data inspection and report the findings as the structure of the data, missing values, duplicates cleaning variable names etc. Based on the findings from the previous questions identify duplicates and remove them. 2. Prepare a preliminary report of the given data by answering following questions. Expressing the results using graphs and plot will make it more appealing.

Explore the geographical distribution of the restaurants, finding out the cities with maximum / minimum number of restaurants. Explore how ratings are distributed overall. Restaurant franchise is a thriving venture. So, it becomes very important to explore the franchise with most national presence. What is the ratio between restaurants that allow table booking vs that do not allow table booking? What is the percentage of restaurants providing online delivery? Is there a difference in no. of votes for the restaurants that deliver and the restaurant that don’t? What are the top 10 cuisines served across cities? What is the maximum and minimum no. of cuisines that a restaurant serves? Also, what is the relationship between No. of cuisines served and Ratings Discuss the cost vs the other variables. Explain the factors in the data that may have an effect on ratings e.g. No. of cuisines, cost, delivery option etc. All the information gathered here will lead to a better understanding of the data and allow for a better implementation of ML models.

Project Task: Week 1

Importing, Understanding, and Inspecting Data :

In [1]:
```
import pandas as pd
import numpy as np
```

Perform preliminary data inspection and report the findings as the structure of the data, missing values, duplicates, etc.

In [2]:
```
data = pd.read_excel('data.xlsx')
```

In [3]:
```
data.shape
```

Out[3]:
```
(9551, 19)
```

In [4]:
```
data.head()
```

Out[4]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	Average Cost for two	Currency	b
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	800000	Indonesian Rupiah(IDR)	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	800000	Indonesian Rupiah(IDR)	
2	7420899	Sushi Masa	94	Jakarta	Jl. Tuna Raya No. 5, Penjaringan	Penjaringan	Penjaringan, Jakarta	106.800144	-6.101298	Sushi, Japanese	500000	Indonesian Rupiah(IDR)	
3	7421967	3 Wise Monkeys	94	Jakarta	Jl. Suryo No. 26, Senopati, Jakarta	Senopati	Senopati, Jakarta	106.813400	-6.235241	Japanese	450000	Indonesian Rupiah(IDR)	
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta	Thamrin	Thamrin, Jakarta	106.821023	-6.196270	French, Western	350000	Indonesian Rupiah(IDR)	

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
Restaurant ID           0
Restaurant Name         1
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
Price range             0
Aggregate rating        0
Rating color            0
Rating text             0
Votes                   0
dtype: int64
```

In [6]:
```
data.duplicated().any()
```

Out[6]:
```
False
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9551 entries, 0 to 9550
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant ID         9551 non-null   int64  
 1   Restaurant Name       9550 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  Price range           9551 non-null   int64  
 15  Aggregate rating      9551 non-null   float64
 16  Rating color          9551 non-null   object 
 17  Rating text           9551 non-null   object 
 18  Votes                 9551 non-null   int64  
dtypes: float64(3), int64(5), object(11)
memory usage: 1.4+ MB
```

In [8]:
```
cd = pd.read_excel('Country-Code.xlsx')
```

In [9]:
```
cd
```

Out[9]:

	Country Code	Country
0	1	India
1	14	Australia
2	30	Brazil
3	37	Canada
4	94	Indonesia
5	148	New Zealand
6	162	Phillipines
7	166	Qatar
8	184	Singapore
9	189	South Africa
10	191	Sri Lanka
11	208	Turkey
12	214	UAE
13	215	United Kingdom
14	216	United States

In [10]:
```
data = pd.merge(data,cd)
```

In [11]:
```
data.duplicated().any()
```
Out[11]: False

In [12]:
```
data.shape
```
Out[12]: (9551, 20)

In [13]:
```
data.columns = ['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', 'Price_range', 'Aggregate_rating',
       'Rating_color', 'Rating_text', 'Votes', 'Country']
```

In [14]:
```
data.head()
```

Out[14]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Ave
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	
2	7420899	Sushi Masa	94	Jakarta	Jl. Tuna Raya No. 5, Penjaringan	Penjaringan	Penjaringan, Jakarta	106.800144	-6.101298	Sushi, Japanese	
3	7421967	3 Wise Monkeys	94	Jakarta	Jl. Suryo No. 26, Senopati, Jakarta	Senopati	Senopati, Jakarta	106.813400	-6.235241	Japanese	
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta	Thamrin	Thamrin, Jakarta	106.821023	-6.196270	French, Western	

In [15]:
```
data.columns.astype('object')
```

Out[15]:
```
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', 'Price_range', 'Aggregate_rating',
       'Rating_color', 'Rating_text', 'Votes', 'Country'],
      dtype='object')
```

In [16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9551 entries, 0 to 9550
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant_ID         9551 non-null   int64  
 1   Restaurant_Name       9550 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  Price_range           9551 non-null   int64  
 15  Aggregate_rating      9551 non-null   float64
 16  Rating_color          9551 non-null   object 
 17  Rating_text           9551 non-null   object 
 18  Votes                 9551 non-null   int64  
 19  Country               9551 non-null   object 
dtypes: float64(3), int64(5), object(12)
memory usage: 1.5+ MB
```

Based on the findings from the previous questions, identify duplicates and remove them

In [17]:
```
data.isnull().sum()
```

Out[17]:
```
Restaurant_ID           0
Restaurant_Name         1
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
Price_range             0
Aggregate_rating        0
Rating_color            0
Rating_text             0
Votes                   0
Country                 0
dtype: int64
```

In [18]:
```
data[data['Restaurant_Name'].isnull()]
```

Out[18]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisine
1603	113702	NaN	1	Ahmedabad	Opposite Sindhu Bhawan, Bodakdev, Ahmedabad	Bodakdev	Bodakdev, Ahmedabad	72.501764	23.040163	Nort Indiar Continenta Mexicar Italia

In [19]:
```
data.dropna(axis=0, subset=['Restaurant_Name'],inplace=True)
```

In [20]:
```
data.reset_index(drop=True,inplace=True)
```

In [21]:
```
data[data['Cuisines'].isnull()]
```

Out[21]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines
9178	17374552	Corkscrew Cafe	216	Gainesville	51 W Main St, Dahlonega, GA 30533	Dahlonega	Dahlonega, Gainesville	-83.985800	34.531800	NaN
9181	17501439	Dovetail	216	Macon	543 Cherry St, Macon, GA 31201	Macon	Macon, Macon	-83.627979	32.836410	NaN
9189	17059060	Hillstone	216	Orlando	215 South Orlando Avenue, Winter Park, FL 32789	Winter Park	Winter Park, Orlando	-81.365260	28.596682	NaN
9415	17284158	Jimmie's Hot Dogs	216	Albany	204 S Jackson St, Albany, GA 31701	Albany	Albany, Albany	-84.153400	31.575100	NaN
9503	17142698	Leonard's Bakery	216	Rest of Hawaii	933 Kapahulu Ave, Honolulu, HI 96816	Kaimuki	Kaimuki, Rest of Hawaii	-157.813432	21.284586	NaN
9513	17616465	Tybee Island Social Club	216	Savannah	1311 Butler Ave, Tybee Island, GA 31328	Tybee Island	Tybee Island, Savannah	-80.848297	31.995810	NaN

9537	17284105	Cookie Shoppe	216	Albany	115 N Jackson St, Albany, GA 31701	Albany	Albany, Albany	-84.154000	31.577200	NaN
9539	17284211	Pearly's Famous Country Cookng	216	Albany	814 N Slappey Blvd, Albany, GA 31701	Albany	Albany, Albany	-84.175900	31.588200	NaN
9543	17606621	HI Lite Bar & Lounge	216	Miller	109 N Broadway Ave, Miller, SD 57362	Miller	Miller, Miller	-98.989100	44.515800	NaN

In [22]:
```
data['Cuisines'].fillna('Others', inplace=True)
```

In [23]:
```
data.isnull().any()
```

Out[23]:
```
Restaurant_ID           False
Restaurant_Name         False
Country_Code            False
City                    False
Address                 False
Locality                False
Locality_Verbose        False
Longitude               False
Latitude                False
Cuisines                False
Average_Cost_for_two    False
Currency                False
Has_Table_booking       False
Has_Online_delivery     False
Price_range             False
Aggregate_rating        False
Rating_color            False
Rating_text             False
Votes                   False
Country                 False
dtype: bool
```

In [24]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9550 entries, 0 to 9549
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant_ID         9550 non-null   int64  
 1   Restaurant_Name       9550 non-null   object 
 2   Country_Code          9550 non-null   int64  
 3   City                  9550 non-null   object 
 4   Address               9550 non-null   object 
 5   Locality              9550 non-null   object 
 6   Locality_Verbose      9550 non-null   object 
 7   Longitude             9550 non-null   float64
 8   Latitude              9550 non-null   float64
 9   Cuisines              9550 non-null   object 
 10  Average_Cost_for_two  9550 non-null   int64  
 11  Currency              9550 non-null   object 
 12  Has_Table_booking     9550 non-null   object 
 13  Has_Online_delivery   9550 non-null   object 
 14  Price_range           9550 non-null   int64  
 15  Aggregate_rating      9550 non-null   float64
 16  Rating_color          9550 non-null   object 
 17  Rating_text           9550 non-null   object 
 18  Votes                 9550 non-null   int64  
 19  Country               9550 non-null   object 
dtypes: float64(3), int64(5), object(12)
memory usage: 1.5+ MB
```

Performing EDA:

Explore the geographical distribution of the restaurants and identify the cities with the maximum and minimum number of restaurants

In [25]:
```
data['City'].value_counts()
```

Out[25]:
```
New Delhi         5473
Gurgaon           1118
Noida             1080
Faridabad          251
Ghaziabad           25
                  ...
Lakes Entrance       1
Paynesville          1
Randburg             1
Princeton            1
Yorkton              1
Name: City, Length: 141, dtype: int64
```

In [26]:
```
data.groupby(['City']).agg(count=('Restaurant_Name','count')).max()
```

Out[26]:
```
count    5473
dtype: int64
```

In [27]:
```
data.groupby(['City']).agg(count=('Restaurant_Name','count')).min()
```

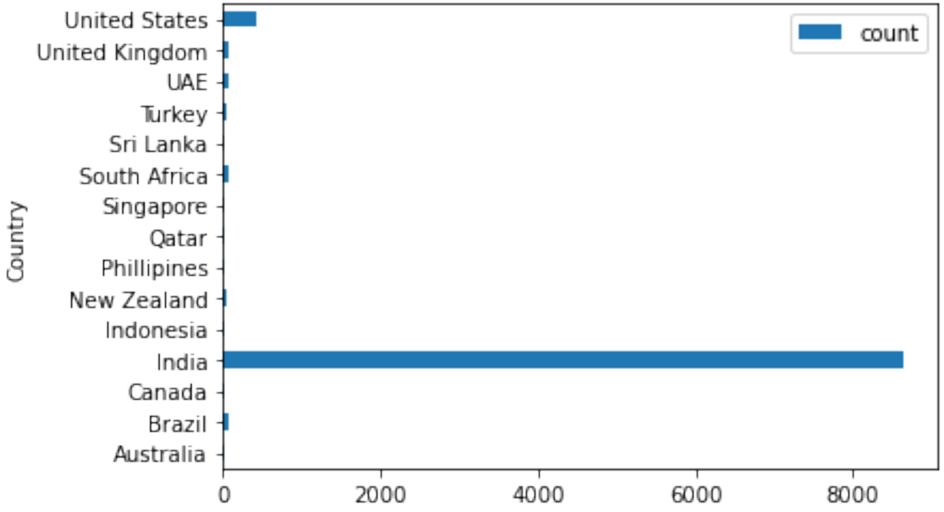
Out[27]:
```
count    1
dtype: int64
```

In [28]:
```
#Country Wise Distribution
geo_country_wise_distr = data.groupby(['Country']).agg(count=('Restaurant_Name','count'))
geo_country_wise_distr.sort_values(by='count',ascending=False)
```

Out[28]:

Country	count
India	8651
United States	434
United Kingdom	80
Brazil	60
South Africa	60
UAE	60
New Zealand	40
Turkey	34
Australia	24
Phillipines	22
Indonesia	21
Qatar	20
Singapore	20
Sri Lanka	20
Canada	4

In [29]:
```
geo_country_wise_distr.plot(kind='barh');
```



In [30]:
```
city_wise_distr = data.groupby(['Country','City']).agg(count=('Restaurant_Name','count'))
city_wise_distr.sort_values(by='count',ascending=False)
```

Out[30]:

		count
Country	**City**	
India	**New Delhi**	5473
	Gurgaon	1118
	Noida	1080
	Faridabad	251
	Ghaziabad	25
	...	...
	Panchkula	1
Australia	**Balingup**	1
Indonesia	**Bandung**	1
Phillipines	**Quezon City**	1
United States	**Winchester Bay**	1

141 rows × 1 columns

NewDelhi has max number of restaurants [5473]

In [31]:

```
#now for min
min_nbr_rest = city_wise_distr[city_wise_distr['count']==1]

#the cities with min number of restaurants
min_nbr_rest
```

Out[31]:

		count
Country	**City**	
Australia	**Armidale**	1
	Balingup	1
	Beechworth	1
	Dicky Beach	1
	East Ballina	1
	Flaxton	1
	Forrest	1
	Huskisson	1
	Inverloch	1
	Lakes Entrance	1
	Lorn	1
	Macedon	1
	Mayfield	1
	Middleton Beach	1
	Montville	1
	Palm Cove	1

	Paynesville	1
	Penola	1
	Phillip Island	1
	Tanunda	1
	Trentham East	1
	Victor Harbor	1
Canada	**Chatham-Kent**	1
	Consort	1
	Vineland Station	1
	Yorkton	1
India	**Mohali**	1
	Panchkula	1
Indonesia	**Bandung**	1
Phillipines	**Quezon City**	1
	Tagaytay City	1
South Africa	**Randburg**	1
	Clatskanie	1
	Cochrane	1
	Fernley	1
	Lakeview	1
	Lincoln	1
	Mc Millan	1
	Miller	1

United States		
	Monroe	1
	Ojo Caliente	1
	Potrero	1
	Princeton	1
	Vernonia	1
	Weirton	1
	Winchester Bay	1

In [32]:
```
min_nbr_rest.count()
```

Out[32]:
```
count    46
dtype: int64
```

46 cities with min number of restaurants [1]

Restaurant franchising is a thriving venture. So, it is very important to explore the franchise with most national presence

In [33]:
```
geo_country_wise_distr = data.groupby(['Country','Restaurant_Name']).agg(count=('Restaurant_Name','c
geo_country_wise_distr.sort_values(by='count',ascending=False)
```

Out[33]:

		count
Country	**Restaurant_Name**	
India	**Cafe Coffee Day**	83
	Domino's Pizza	79
	Subway	63
	Green Chick Chop	51
	McDonald's	48
	...	...
	Hawai Adda	1
	Havemore	1
	Haveliram	1
	Hauz Khas Social	1
United States	**Zunzi's**	1

7472 rows × 1 columns

As India has 8651 the maximum number of restaurant counts, so let's consider the case of India. The franchise with most national presence is Cafe Coffee Day [83] followed by Domino's Pizza [79], Subway [63], Green Chick Chop [51], McDonald's [48] in India.

Find out the ratio between restaurants that allow table booking vs. those that do not allow table booking

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

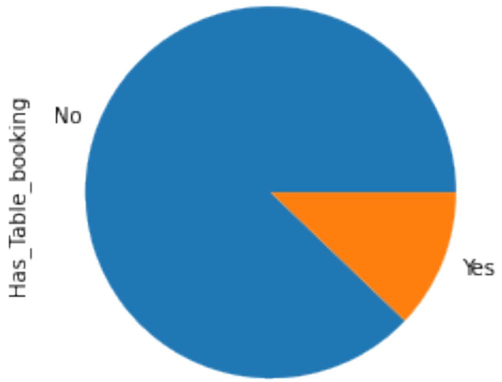
Out[34]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Ave
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	
2	7420899	Sushi Masa	94	Jakarta	Jl. Tuna Raya No. 5, Penjaringan	Penjaringan	Penjaringan, Jakarta	106.800144	-6.101298	Sushi, Japanese	
3	7421967	3 Wise Monkeys	94	Jakarta	Jl. Suryo No. 26, Senopati, Jakarta	Senopati	Senopati, Jakarta	106.813400	-6.235241	Japanese	
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta	Thamrin	Thamrin, Jakarta	106.821023	-6.196270	French, Western	

In [35]:
```
data['Has_Table_booking'].value_counts()
```

Out[35]:
```
No      8392
Yes     1158
Name: Has_Table_booking, dtype: int64
```

In [36]:
```
data['Has_Table_booking'].value_counts().plot(kind='pie');
```



In [37]:
```
do_not_allow_tbl =(data['Has_Table_booking']=='No').sum()
```

In [38]:
```
allow_tbl = (data['Has_Table_booking']=='Yes').sum()
```

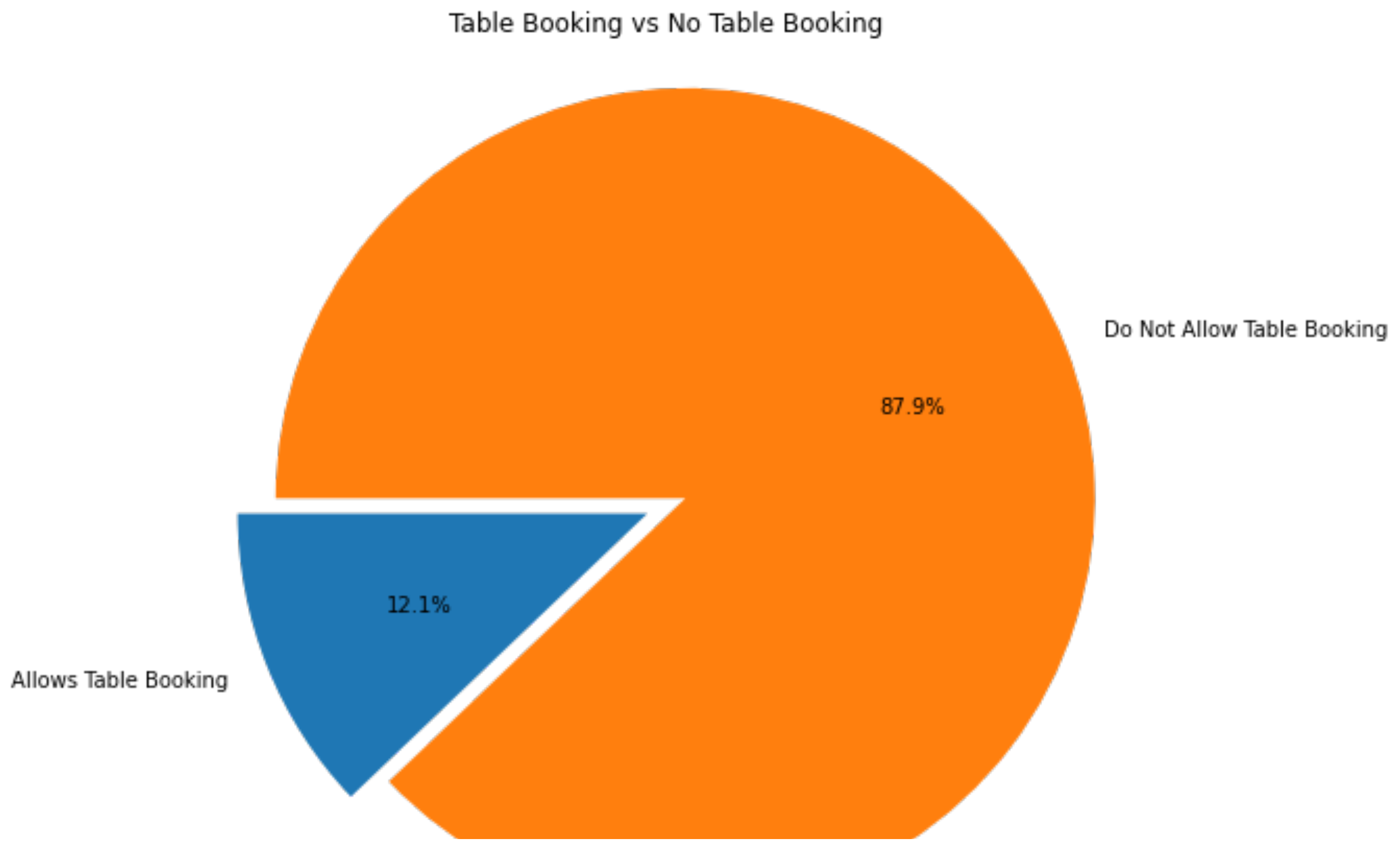
In [39]:
```
ratio =round((allow_tbl/do_not_allow_tbl),2)
```

In [40]:
```
print('The ratio between restaurants that allow table booking vs. those that do not allow table book
```

```
The ratio between restaurants that allow table booking vs. those that do not allow table booking is 0.1
4
```

In [41]:
```

```

```
import matplotlib.pyplot as plt
%matplotlib inline

labels = 'Allows Table Booking', 'Do Not Allow Table Booking'
sizes = [allow_tbl,do_not_allow_tbl]
explode = (0.1, 0)
fig1, ax1 = plt.subplots(figsize=(8,8))
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%', startangle=180)
ax1.set_title("Table Booking vs No Table Booking")
ax1.axis('equal')
plt.show()
```



Find out the percentage of restaurants providing online delivery

In [42]:
```
data['Has_Online_delivery'].value_counts()
```

Out[42]:
```
No     7099
Yes    2451
Name: Has_Online_delivery, dtype: int64
```

In [43]:
```
offline =(data['Has_Online_delivery']=='No').sum()
online = (data['Has_Online_delivery']=='Yes').sum()
```

In [44]:
```
total_ = offline + online
```

In [45]:
```
totalpercent_online = (round(((online/total_)*100),2))
totalpercent_online
```

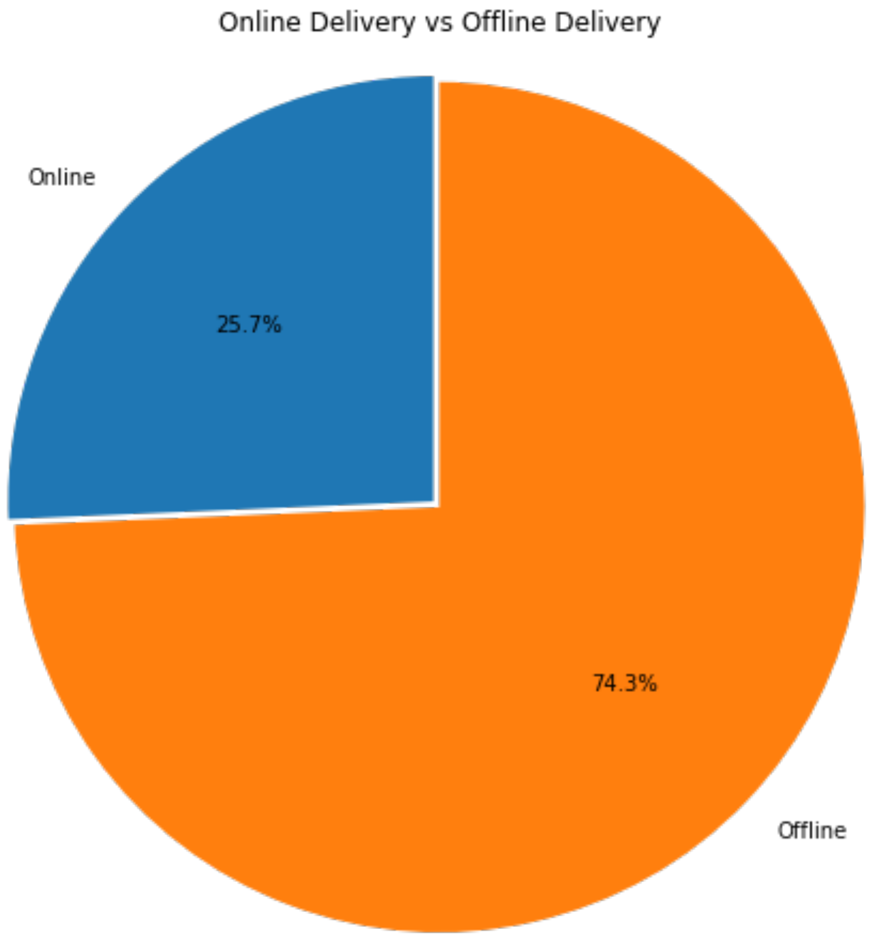
Out[45]:
```
25.66
```

In [46]:
```
print('The percentage of restaurants providing online delivery is',totalpercent_online,'% .')
```

```
The percentage of restaurants providing online delivery is 25.66 % .
```

In [47]:

```
labels = 'Online', 'Offline'
sizes = [online,offline]
explode = (0.02, 0)
fig1, ax1 = plt.subplots(figsize=(8,8))
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%', startangle=90)
ax1.set_title("Online Delivery vs Offline Delivery")
ax1.axis('equal')
plt.show()
```



Calculate the difference in number of votes for the restaurants that deliver and the restaurants that do not deliver

In [48]:
```
data.head()
```

Out[48]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Ave
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	
2	7420899	Sushi Masa	94	Jakarta	Jl. Tuna Raya No. 5, Penjaringan	Penjaringan	Penjaringan, Jakarta	106.800144	-6.101298	Sushi, Japanese	
3	7421967	3 Wise Monkeys	94	Jakarta	Jl. Suryo No. 26, Senopati, Jakarta	Senopati	Senopati, Jakarta	106.813400	-6.235241	Japanese	
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta	Thamrin	Thamrin, Jakarta	106.821023	-6.196270	French, Western	

In [49]:
```
data['Votes'].value_counts().sum()
```

Out[49]:
```
9550
```

In [50]:
```
allow_tbl+online
```

Out[50]:
```
3609
```

In [51]:
```
9550-3609
```

Out[51]:
```
5941
```

In [52]:
```
offline_delv =data[data['Has_Online_delivery']=='No']['Votes'].sum()
online_delv =data[data['Has_Online_delivery']=='Yes']['Votes'].sum()
```

In [53]:
```
print(offline_delv)
print(online_delv)
print(offline_delv-online_delv)
```

```
979962
517914
462048
```

In [54]:
```
#difference in number of votes for the restaurants that deliver and the restaurants that do not deli
print('Difference in number of votes for the restaurants that deliver and the restaurants that do no
```

```
Difference in number of votes for the restaurants that deliver and the restaurants that do not deliver
is 462048
```

Project Task: Week 2

Performing EDA:

What are the top 10 cuisines served across cities?

In [55]:
```
data.head()
```

Out[55]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Ave
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	
2	7420899	Sushi Masa	94	Jakarta	Jl. Tuna Raya No. 5, Penjaringan	Penjaringan	Penjaringan, Jakarta	106.800144	-6.101298	Sushi, Japanese	
3	7421967	3 Wise Monkeys	94	Jakarta	Jl. Suryo No. 26, Senopati, Jakarta	Senopati	Senopati, Jakarta	106.813400	-6.235241	Japanese	
4	7422489	Avec Moi Restaurant and Bar	94	Jakarta	Gedung PIC, Jl. Teluk Betung 43, Thamrin, Jakarta	Thamrin	Thamrin, Jakarta	106.821023	-6.196270	French, Western	

In [56]:
```
#Splitting the 'Cuisines' column
cuisines_all = data['Cuisines'].apply(lambda x:pd.Series(x.split(',')))
```

In [57]:
```
cuisines_all
```

Out[57]:

	0	1	2	3	4	5	6	7
0	Italian	Continental	NaN	NaN	NaN	NaN	NaN	NaN
1	Asian	Indonesian	Western	NaN	NaN	NaN	NaN	NaN
2	Sushi	Japanese	NaN	NaN	NaN	NaN	NaN	NaN
3	Japanese	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	French	Western	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...
9545	Mexican	NaN	NaN	NaN	NaN	NaN	NaN	NaN
9546	Italian	Mediterranean	Pizza	NaN	NaN	NaN	NaN	NaN
9547	Japanese	Sushi	NaN	NaN	NaN	NaN	NaN	NaN
9548	Chinese	Canadian	NaN	NaN	NaN	NaN	NaN	NaN
9549	Asian	NaN	NaN	NaN	NaN	NaN	NaN	NaN

9550 rows × 8 columns

In [58]:
```
cuisines_all.columns=['Cuisine_1','Cuisine_2','Cuisine_3','Cuisine_4','Cuisine_5','Cuisine_6','Cuisi
cuisines_all.head()
```

Out[58]:

	Cuisine_1	Cuisine_2	Cuisine_3	Cuisine_4	Cuisine_5	Cuisine_6	Cuisine_7	Cuisine_8
0	Italian	Continental	NaN	NaN	NaN	NaN	NaN	NaN
1	Asian	Indonesian	Western	NaN	NaN	NaN	NaN	NaN
2	Sushi	Japanese	NaN	NaN	NaN	NaN	NaN	NaN
3	Japanese	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	French	Western	NaN	NaN	NaN	NaN	NaN	NaN

In [59]:
```
cuisine_1_cnt = pd.DataFrame(cuisines_all['Cuisine_1'].value_counts()).reset_index()

cuisine_1_cnt = cuisine_1_cnt.rename(columns={'index':'Cuisines','Cuisine_1':'Counts'})

cuisine_1_cnt.head(10)
```

Out[59]:

	Cuisines	Counts
0	North Indian	2991
1	Chinese	855
2	Fast Food	672
3	Bakery	621
4	Cafe	617
5	American	278
6	South Indian	262
7	Mithai	246
8	Street Food	236
9	Continental	235

In [60]:
```
cuisine_2_cnt = pd.DataFrame(cuisines_all['Cuisine_2'].value_counts()).reset_index()

cuisine_2_cnt = cuisine_2_cnt.rename(columns={'index':'Cuisines','Cuisine_2':'Counts'})

cuisine_2_cnt.head(10)
```

Out[60]:

	Cuisines	Counts
0	Chinese	1156
1	Fast Food	820
2	North Indian	687
3	Mughlai	635
4	Desserts	407
5	Continental	244
6	Italian	240
7	South Indian	219
8	Street Food	216
9	Pizza	110

In [61]:
```
cuisine_3_cnt = pd.DataFrame(cuisines_all['Cuisine_3'].value_counts()).reset_index()

cuisine_3_cnt = cuisine_3_cnt.rename(columns={'index':'Cuisines','Cuisine_3':'Counts'})

cuisine_3_cnt.head(10)
```

Out[61]:

	Cuisines	Counts
0	Chinese	594
1	Fast Food	385
2	Continental	193
3	North Indian	191
4	Italian	189
5	Mughlai	124
6	South Indian	123
7	Salad	70
8	Asian	64
9	Thai	50

In [62]:
```
cuisine_4_cnt = pd.DataFrame(cuisines_all['Cuisine_4'].value_counts()).reset_index()

cuisine_4_cnt = cuisine_4_cnt.rename(columns={'index':'Cuisines','Cuisine_4':'Counts'})

cuisine_4_cnt.head(10)
```

Out[62]:

	Cuisines	Counts
0	Italian	84
1	Chinese	81
2	Fast Food	77
3	Healthy Food	67
4	North Indian	65
5	Street Food	59
6	Continental	50
7	Asian	31
8	Mithai	26
9	South Indian	25

In [63]:
```
cuisine_5_cnt = pd.DataFrame(cuisines_all['Cuisine_5'].value_counts()).reset_index()

cuisine_5_cnt = cuisine_5_cnt.rename(columns={'index':'Cuisines','Cuisine_5':'Counts'})

cuisine_5_cnt.head(10)
```

Out[63]:

	Cuisines	Counts
0	Chinese	41
1	Fast Food	30
2	North Indian	23
3	Thai	20
4	Italian	13
5	Mithai	12
6	Continental	11
7	Mediterranean	11
8	Asian	9
9	Bakery	8

In [64]:

```
cuisine_6_cnt = pd.DataFrame(cuisines_all['Cuisine_6'].value_counts()).reset_index()

cuisine_6_cnt = cuisine_6_cnt.rename(columns={'index':'Cuisines','Cuisine_6':'Counts'})

cuisine_6_cnt.head(10)
```

Out[64]:

	Cuisines	Counts
0	Mithai	23
1	Beverages	12
2	Lebanese	8
3	Chinese	8
4	Thai	5
5	Tea	4
6	Desserts	4
7	Cafe	4
8	Grill	3
9	Italian	3

In [65]:

```
cuisine_7_cnt = pd.DataFrame(cuisines_all['Cuisine_7'].value_counts()).reset_index()

cuisine_7_cnt = cuisine_7_cnt.rename(columns={'index':'Cuisines','Cuisine_7':'Counts'})

cuisine_7_cnt.head(10)
```

Out[65]:

	Cuisines	Counts
0	Desserts	24
1	European	2
2	Mediterranean	2
3	Mithai	2
4	American	1
5	Rajasthani	1
6	Asian	1
7	Pizza	1
8	Lebanese	1
9	Bakery	1

In [66]:
```
cuisine_8_cnt = pd.DataFrame(cuisines_all['Cuisine_8'].value_counts()).reset_index()

cuisine_8_cnt = cuisine_8_cnt.rename(columns={'index':'Cuisines','Cuisine_8':'Counts'})

cuisine_8_cnt.head(10)
```

Out[66]:

	Cuisines	Counts
0	Mithai	8
1	Finger Food	2
2	International	2
3	Mughlai	1
4	Beverages	1

In [67]:
```
Cuisines_app = cuisine_1_cnt.append([cuisine_2_cnt,cuisine_3_cnt,cuisine_4_cnt,cuisine_5_cnt,cuisine
```

In [68]:
```
Cuisines_app['Cuisines']=Cuisines_app.Cuisines.str.replace(' ','')
Cuisines_app
```

Out[68]:

	Cuisines	Counts
0	NorthIndian	2991
1	Chinese	855
2	FastFood	672
3	Bakery	621
4	Cafe	617
...	...	...
0	Mithai	8
1	FingerFood	2
2	International	2
3	Mughlai	1
4	Beverages	1

514 rows × 2 columns

In [69]:
```
grpof_cuisines = Cuisines_app.groupby('Cuisines').sum()
max_cuisines = grpof_cuisines.sort_values(by='Counts',ascending=False)
```

In [70]:
```
max_cuisines
```

Out[70]:

	Counts
Cuisines	
NorthIndian	3959
Chinese	2735
FastFood	1986
Mughlai	995
Italian	763
...	...
Canadian	1
Mineira	1
SoulFood	1
CuisineVaries	1
Peranakan	1

146 rows × 1 columns

In [71]:
```
top_10_cuisines_sac = (max_cuisines.head(10))
top_10_cuisines_sac
```

Out[71]:

Cuisines	Counts
NorthIndian	3959
Chinese	2735
FastFood	1986
Mughlai	995
Italian	763
Bakery	745
Continental	735
Cafe	703
Desserts	653
SouthIndian	636

The top 10 cuisines served across cities are

1. NorthIndian,
2. Chinese,
3. FastFood,
4. Mughlai,
5. Italian,
6. Bakery,
7. Continental,
8. Cafe,
9. Desserts,
10. SouthIndian

What is the maximum and minimum number of cuisines that a restaurant serves? Also, which is the most served cuisine across the restaurant for each city?

In [72]:
```
df = pd.DataFrame(data,columns=['Restaurant_Name','City','Cuisines'])
df
```

Out[72]:

	Restaurant_Name	City	Cuisines
0	Skye	Jakarta	Italian, Continental
1	Satoo - Hotel Shangri-La	Jakarta	Asian, Indonesian, Western
2	Sushi Masa	Jakarta	Sushi, Japanese
3	3 Wise Monkeys	Jakarta	Japanese
4	Avec Moi Restaurant and Bar	Jakarta	French, Western
...	...	...	...
9545	Senor Iguanas	Pocatello	Mexican
9546	Lake House Restaurant	Vineland Station	Italian, Mediterranean, Pizza
9547	Tokyo Sushi	Chatham-Kent	Japanese, Sushi
9548	Consort Restaurant	Consort	Chinese, Canadian
9549	Arigato Sushi	Yorkton	Asian

9550 rows × 3 columns

In [73]:
```
Cuisine_Cnt_by_res=pd.DataFrame(df.groupby('Restaurant_Name').Cuisines.count()).reset_index()
Cuisine_Cnt_by_res.sort_values(by = 'Cuisines', ascending = False)
```

Out[73]:

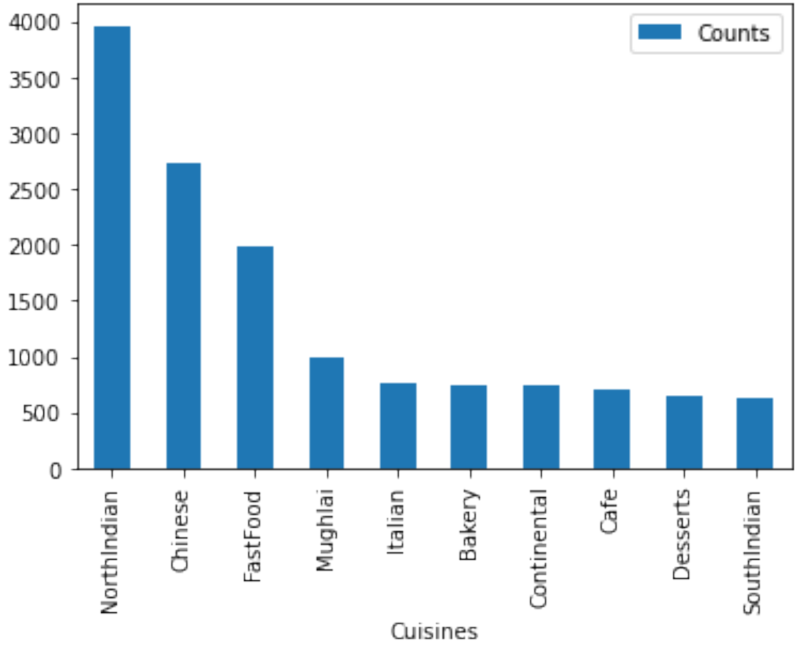
	Restaurant_Name	Cuisines
1098	Cafe Coffee Day	83
2098	Domino's Pizza	79
6105	Subway	63
2716	Green Chick Chop	51
4076	McDonald's	48
...	...	...
2617	Ghungroo Club & Bar - By Gautam Gambhir	1
2616	Ghar Ki Handi	1
2615	Ghar Ka Swad	1
2613	Ghar Bistro Cafe	1
7444	Ìàukura€Ùa Sofras€±	1

7445 rows × 2 columns

The maximum number of cuisines that a restaurant serves is 83 by Cafe Coffee Day, Followed by 79 by Dominos Pizza, 63 by Subway, and minimum is 1.

The most served cuisine across the restaurant for each city

In [74]:
```
top_10_cuisines_sac.plot(kind='bar');
```



In [75]:
```
top_10_cuisines_sac
```

Out[75]:

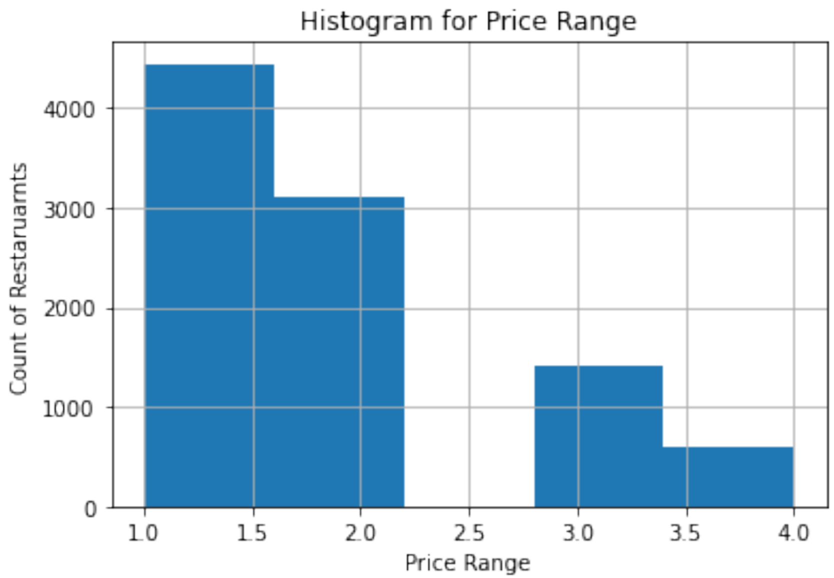
Cuisines	Counts
NorthIndian	3959
Chinese	2735
FastFood	1986
Mughlai	995
Italian	763
Bakery	745
Continental	735
Cafe	703
Desserts	653
SouthIndian	636

The most served cuisine across the restaurant for each city is "NorthIndian" with count as 3959.

What is the distribution cost across the restaurants?

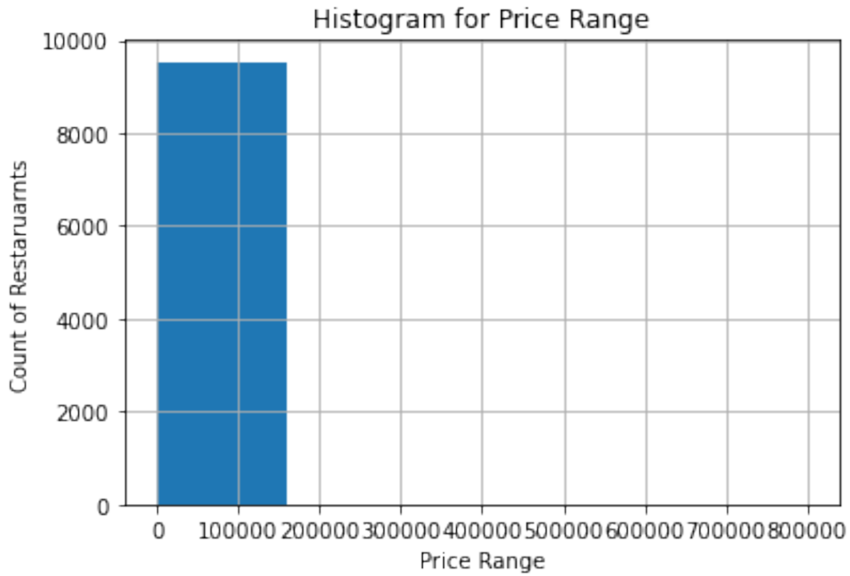
In [76]:
```
import matplotlib.pyplot as plt
%matplotlib inline

hist = data['Price_range'].hist(bins=5)
hist.set_title('Histogram for Price Range')
hist.set_xlabel('Price Range')
hist.set_ylabel('Count of Restaruarnts')
```

Out[76]: Text(0, 0.5, 'Count of Restaruarnts')



In [77]:
```
hist = data['Average_Cost_for_two'].hist(bins=5)
hist.set_title('Histogram for Price Range')
hist.set_xlabel('Price Range')
hist.set_ylabel('Count of Restaruarnts')
```

Out[77]: Text(0, 0.5, 'Count of Restaruarnts')



In [78]:
```
## Distribution cost accross the restaurants
Cost_per_restaurants = pd.DataFrame(data.groupby('Restaurant_Name').Average_Cost_for_two.sum()).rese
Cost_per_restaurants.sort_values(by = 'Average_Cost_for_two', ascending = False)
```

Out[78]:

	Restaurant_Name	Average_Cost_for_two
5897	Skye	800000
5594	Satoo - Hotel Shangri-La	800000
6262	Talaga Sampireun	600000
6170	Sushi Masa	500000
41	3 Wise Monkeys	450000
...	...	...
7096	UrbanCrave	0
486	Atmosphere Grill Cafe Sheesha	0
1746	Cookie Shoppe	0
6691	The Latitude - Radisson Blu	0
522	BMG - All Day Dining	0

7445 rows × 2 columns

In [79]:
```
# Restaurants wise distribution of cost - By Currencies
df=pd.DataFrame(data.groupby(['Currency','Restaurant_Name']).agg(Count = ('Average_Cost_for_two','su
df.sort_values(by='Count', ascending = False)
```

Out[79]:

	Currency	Restaurant_Name	Count
7219	Indonesian Rupiah(IDR)	Satoo - Hotel Shangri-La	800000
7220	Indonesian Rupiah(IDR)	Skye	800000
7222	Indonesian Rupiah(IDR)	Talaga Sampireun	600000
7221	Indonesian Rupiah(IDR)	Sushi Masa	500000
7208	Indonesian Rupiah(IDR)	3 Wise Monkeys	450000
...	...	...	...
418	Dollar($)	Royal Hotel	0
6558	Indian Rupees(Rs.)	The Latitude - Radisson Blu	0
214	Dollar($)	El Vaquero Mexican Restaurant	0
6351	Indian Rupees(Rs.)	The BrewMaster	0
6904	Indian Rupees(Rs.)	UrbanCrave	0

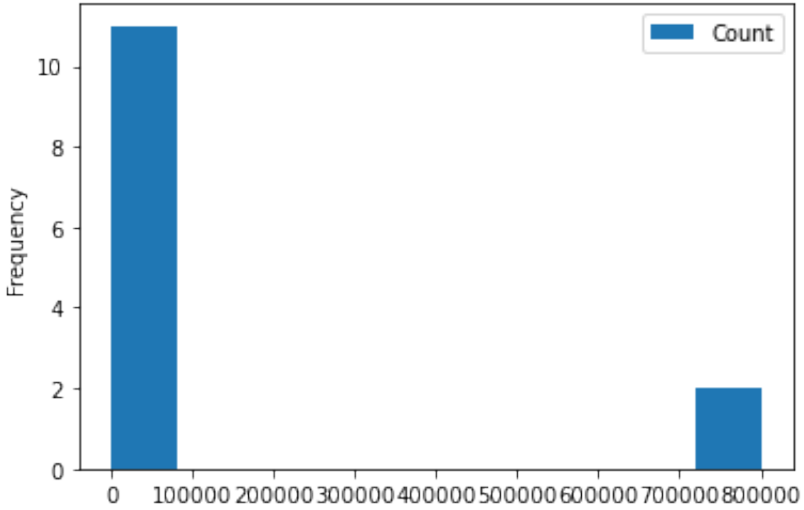
7472 rows × 3 columns

In [80]:
```
df.groupby(['Currency'], sort=False)['Count'].max()
```

Out[80]:
```
Currency
Botswana Pula(P)             6000
Brazilian Real(R$)            460
Dollar($)                     500
Emirati Diram(AED)            750
Indian Rupees(Rs.)          55300
Indonesian Rupiah(IDR)     800000
NewZealand($)                 200
Pounds(å£)                   230
Qatari Rial(QR)               550
Rand(R)                      3210
Sri Lankan Rupee(LKR)        4500
Turkish Lira(TL)              400
Name: Count, dtype: int64
```

In [81]:
```
# Currency wise highest cost accross restaurants
Max_cost=df.groupby('Currency')\
  .apply(lambda group: group[group.Count == group.Count.max()])\
  .reset_index(drop=True)
```

In [82]:
```
(Max_cost).plot(kind='hist');
```



In [83]:
```
Max_cost.sort_values(by='Count', ascending = False)
```

Out[83]:

	Currency	Restaurant_Name	Count
5	Indonesian Rupiah(IDR)	Satoo - Hotel Shangri-La	800000
6	Indonesian Rupiah(IDR)	Skye	800000
4	Indian Rupees(Rs.)	Domino's Pizza	55300
0	Botswana Pula(P)	Spiral - Sofitel Philippine Plaza Manila	6000
11	Sri Lankan Rupee(LKR)	The Manhattan Fish Market	4500
10	Rand(R)	Restaurant Mosaic @ The Orient	3210
3	Emirati Diram(AED)	Applebee's	750
9	Qatari Rial(QR)	Vine - The St. Regis	550
2	Dollar($)	Restaurant Andre	500
1	Brazilian Real(R$)	Coco Bambu	460
12	Turkish Lira(TL)	Nusr-Et	400
8	Pounds(â£)	Restaurant Gordon Ramsay	230
7	NewZealand($)	Hippopotamus - Museum Hotel	200

In [125]:
```
Max_cost.to_excel('Max_cost.xlsx')
```

Above table shows the currency wise distribution of cost across the restaurants

For eg. :

- Satoo - Hotel Shangri-La having avg_cost_for_two 800000 in Indonesian Rupiah(IDR)
- Skye having avg_cost_for_two 800000 in Indonesian Rupiah(IDR)
- Domino's Pizza having avg_cost_for_two 55300 in Indian Rupees(Rs.)

we can also examine further by converting it to specific currency, but this is sufficient for an overview as we just want to know the distribution of cost across the restaurants.

How ratings are distributed among the various factors?

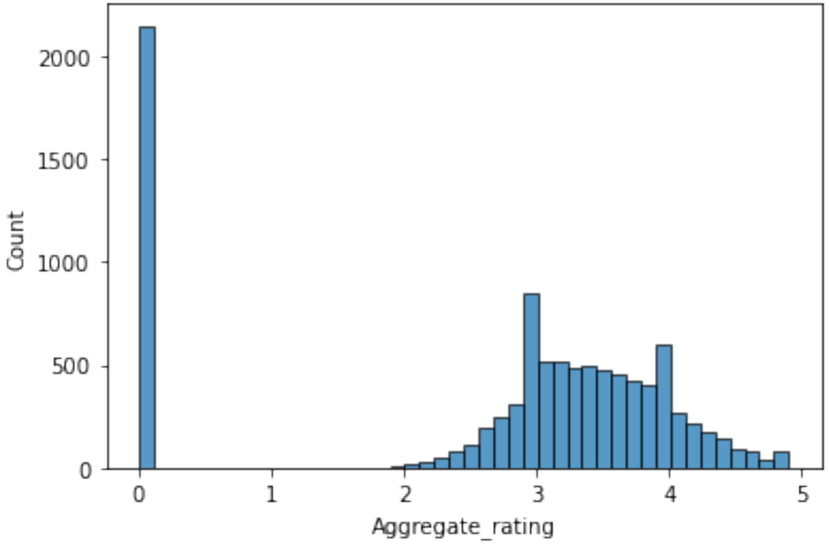
Explain the factors in the data that may have an effect on ratings. For example, number of cuisines, cost, delivery option, etc.

In [84]:
```
data.head(2)
```

Out[84]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Average
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	
1	7410290	Satoo - Hotel Shangri-La	94	Jakarta	Hotel Shangri-La, Jl. Jend. Sudirman	Hotel Shangri-La, Sudirman	Hotel Shangri-La, Sudirman, Jakarta	106.818961	-6.203292	Asian, Indonesian, Western	

In [85]:
```
import seaborn as sns

sns.histplot(data['Aggregate_rating']);
```



In [86]:
```
dest_rating= data.groupby(['Aggregate_rating']).agg(count=("Restaurant_Name","count")).reset_index()
dest_rating.sort_values(by='Aggregate_rating',ascending=False)
```

Out[86]:

	Aggregate_rating	count
32	4.9	61
31	4.8	25
30	4.7	42
29	4.6	78
28	4.5	95
27	4.4	144

26	4.3	174
25	4.2	221
24	4.1	273
23	4.0	266
22	3.9	335
21	3.8	400
20	3.7	427
19	3.6	458
18	3.5	480
17	3.4	498
16	3.3	483
15	3.2	522
14	3.1	519
13	3.0	468
12	2.9	381
11	2.8	315
10	2.7	250
9	2.6	191
8	2.5	110
7	2.4	87
6	2.3	47
5	2.2	27
4	2.1	15

3	2.0	7
2	1.9	2
1	1.8	1
0	0.0	2148

From above graph & table we can see there are 2148 number of restaurants which do not have any ratings also we have 61 number of restaurants which have the highest ratings as 4.9.

In [87]:
```
country_rating= data.groupby(['Country','Aggregate_rating']).agg(count=("Restaurant_Name","count")).
country_rating.sort_values(by='Aggregate_rating',ascending=False)
```

Out[87]:

	Country	Aggregate_rating	count
221	United States	4.9	14
92	New Zealand	4.9	2
139	South Africa	4.9	3
151	Sri Lanka	4.9	1
32	Brazil	4.9	3
...	...	...	...
38	India	1.8	1
200	United States	0.0	3
12	Brazil	0.0	5
180	United Kingdom	0.0	1
37	India	0.0	2139

222 rows × 3 columns

In [127]:
```
country_wise_ratng =country_rating[country_rating.Aggregate_rating >=4.9].reset_index()
country_wise_ratng = country_wise_ratng.sort_values(by='count',ascending=False)
country_wise_ratng
```

Out[127]:

	index	Country	Aggregate_rating	count
1	69	India	4.9	19
11	221	United States	4.9	14
2	79	Indonesia	4.9	4
9	179	UAE	4.9	4
10	199	United Kingdom	4.9	4
0	32	Brazil	4.9	3
4	101	Phillipines	4.9	3
6	139	South Africa	4.9	3
8	163	Turkey	4.9	3
3	92	New Zealand	4.9	2
5	114	Qatar	4.9	1
7	151	Sri Lanka	4.9	1

In [128]:
```
country_wise_ratng.to_excel('country_wise_ratng.xlsx')
```

From the above table we can see that there are 12 countries which have the highest rating values as 4.9,

out of which India & United States, are the top two countries with the highest count [highest number of restaurants with 4.9 rating] as well.

Also Sri Lanka & Qatar, both have same count as 1 which is the minimum .

In [89]:
```
data.Rating_text.value_counts().sum()
```

Out[89]: 9550

In [90]:
```
cntng_rating_Type = data.groupby(['Rating_text']).agg(count=("Restaurant_Name","count"))
cntng_rating_Type
```

Out[90]:

	count
Rating_text	
Average	3737
Excellent	301
Good	2100
Not rated	2148
Poor	186
Very Good	1078

It states that across the countries along with their cities have only 301 restaurants with 'Excellent' rating.

In [91]:
```
country_wise_rating_Type = data.groupby(['Country','Rating_text']).agg(count=("Restaurant_Name","cou
country_wise_rating_Type
```

Out[91]:

	Country	Rating_text	count
0	Australia	Average	4
1	Australia	Excellent	1
2	Australia	Good	13
3	Australia	Poor	1
4	Australia	Very Good	5
...	...	...	...
61	United States	Excellent	68
62	United States	Good	159
63	United States	Not rated	3
64	United States	Poor	2
65	United States	Very Good	179

66 rows × 3 columns

In [92]:
```
country_wise_rating_Type=country_wise_rating_Type[country_wise_rating_Type.Rating_text == 'Excellent
```

In [93]:
```
country_wise_rating_Type.sort_values(by='count',ascending=False)
```

Out[93]:

	index	Country	Rating_text	count
2	14	India	Excellent	116
12	61	United States	Excellent	68
11	56	United Kingdom	Excellent	23
10	51	UAE	Excellent	18
1	6	Brazil	Excellent	16
4	23	New Zealand	Excellent	12
5	27	Phillipines	Excellent	12
7	38	South Africa	Excellent	12
9	47	Turkey	Excellent	10
3	20	Indonesia	Excellent	7
6	31	Qatar	Excellent	4
8	42	Sri Lanka	Excellent	2
0	1	Australia	Excellent	1

In [126]:
```
country_wise_rating_Type.to_excel('country_wise_rating_Type.xlsx')
```

Here we can see India has the highest count of restaurants which are rated as "Excellent".

In [94]:
```
data.head(1)
```

Out[94]:

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	Average_
0	7402935	Skye	94	Jakarta	Menara BCA, Lantai 56, Jl. MH. Thamrin, Thamri...	Grand Indonesia Mall, Thamrin	Grand Indonesia Mall, Thamrin, Jakarta	106.821999	-6.196778	Italian, Continental	

In [95]:
```
data.columns
```

Out[95]:
```
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', 'Price_range', 'Aggregate_rating',
       'Rating_color', 'Rating_text', 'Votes', 'Country'],
      dtype='object')
```

In [96]:
```
f_ratings = data[['Restaurant_ID','Restaurant_Name','Country','City','Aggregate_rating',
                  'Average_Cost_for_two','Votes','Price_range','Has_Table_booking','Has_Online_deliv
```

In [97]:
```
f_ratings.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9550 entries, 0 to 9549
Data columns (total 10 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant_ID         9550 non-null   int64  
 1   Restaurant_Name       9550 non-null   object 
 2   Country               9550 non-null   object 
 3   City                  9550 non-null   object 
 4   Aggregate_rating      9550 non-null   float64
 5   Average_Cost_for_two  9550 non-null   int64  
 6   Votes                 9550 non-null   int64  
 7   Price_range           9550 non-null   int64  
 8   Has_Table_booking     9550 non-null   object 
 9   Has_Online_delivery   9550 non-null   object 
dtypes: float64(1), int64(4), object(5)
memory usage: 746.2+ KB
```

In [98]:
```
dummy = ['Has_Table_booking','Has_Online_delivery']
#0 -no, 1- yes
f_ratings = pd.get_dummies(f_ratings, columns=dummy, drop_first=True)
```

In [99]:
```
f_ratings=f_ratings.merge(Cuisine_Cnt_by_res, left_on='Restaurant_Name',right_on='Restaurant_Name',h
f_ratings.head()
```

Out[99]:

	Restaurant_ID	Restaurant_Name	Country	City	Aggregate_rating	Average_Cost_for_two	Votes	Price_range	Has_Table_booking_Yes
0	7402935	Skye	Indonesia	Jakarta	4.1	800000	1498	3	0
1	7410290	Satoo - Hotel Shangri-La	Indonesia	Jakarta	4.6	800000	873	3	0
2	7420899	Sushi Masa	Indonesia	Jakarta	4.9	500000	605	3	0
3	7421967	3 Wise Monkeys	Indonesia	Jakarta	4.2	450000	395	3	0
4	7422489	Avec Moi Restaurant and Bar	Indonesia	Jakarta	4.3	350000	243	3	0

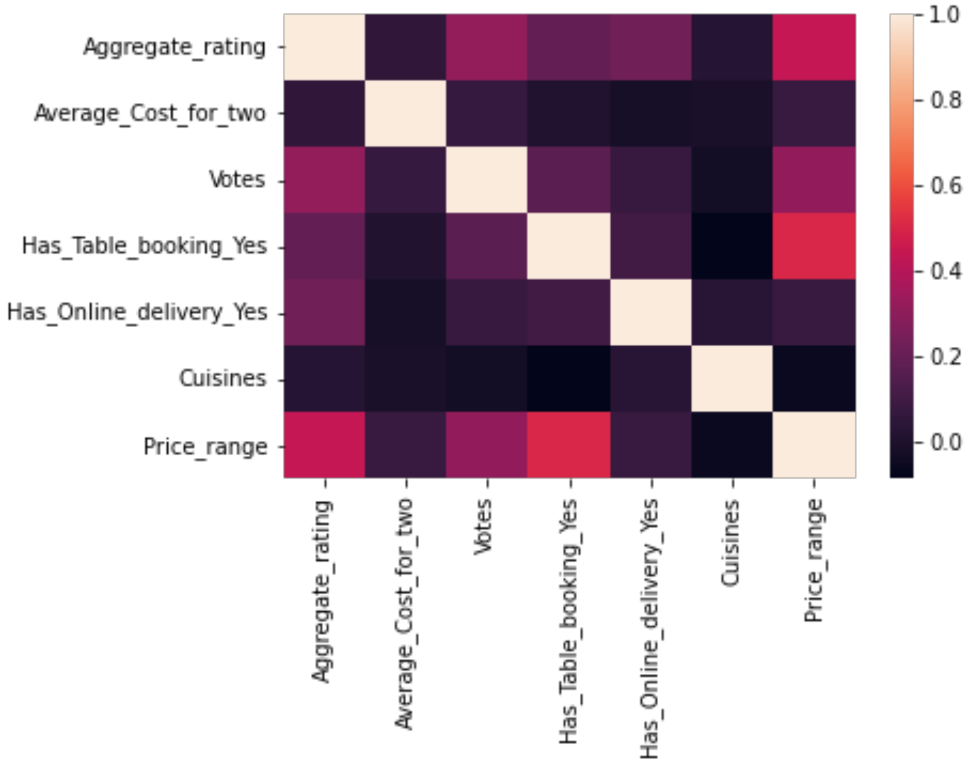
In [100]:
```
f_ratings.corr()
```

Out[100]:

	Restaurant_ID	Aggregate_rating	Average_Cost_for_two	Votes	Price_range	Has_Table_booking_Yes	Has_Online_
Restaurant_ID	1.000000	-0.326144	-0.001696	-0.146895	-0.134419	-0.110118	
Aggregate_rating	-0.326144	1.000000	0.051797	0.313598	0.437874	0.190045	
Average_Cost_for_two	-0.001696	0.051797	1.000000	0.067794	0.075093	0.007757	
Votes	-0.146895	0.313598	0.067794	1.000000	0.309308	0.169497	
Price_range	-0.134419	0.437874	0.075093	0.309308	1.000000	0.502025	
Has_Table_booking_Yes	-0.110118	0.190045	0.007757	0.169497	0.502025	1.000000	
Has_Online_delivery_Yes	-0.085157	0.225772	-0.018976	0.074399	0.078007	0.101204	
Cuisines	-0.143776	0.021097	-0.011641	-0.032142	-0.059862	-0.086821	

In [101]:
```
sns.heatmap(f_ratings[['Aggregate_rating','Average_Cost_for_two','Votes','Has_Table_booking_Yes','Ha
```

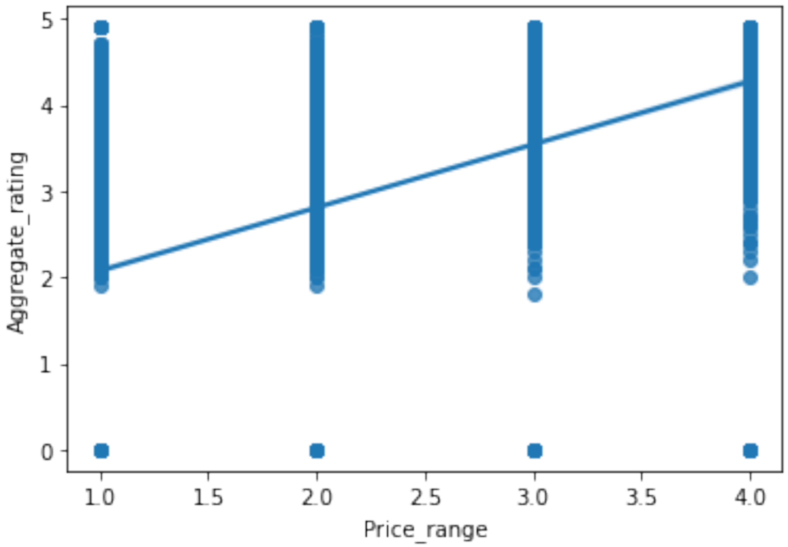
Out[101]: <AxesSubplot:>



In [102]:
```
#corr between rating and price range
sns.regplot(x='Price_range',y='Aggregate_rating',data=f_ratings)
f_ratings[["Price_range", "Aggregate_rating"]].corr()
```

Out[102]:

	Price_range	Aggregate_rating
Price_range	1.000000	0.437874
Aggregate_rating	0.437874	1.000000



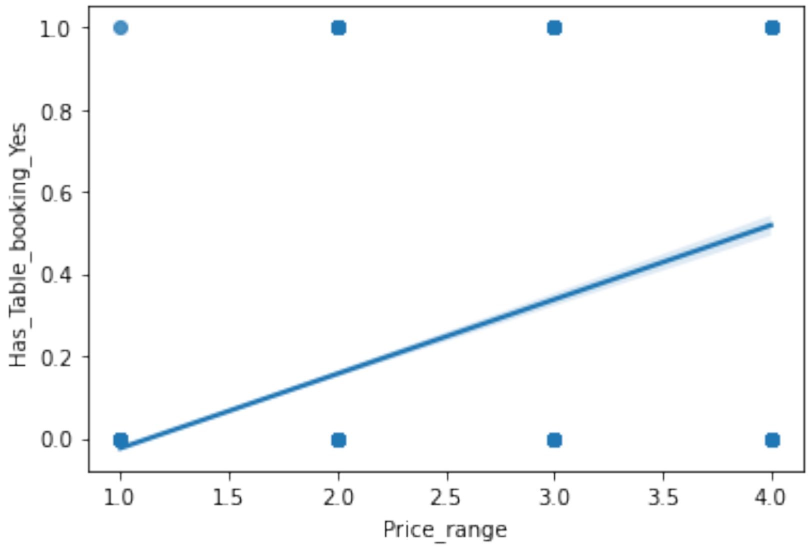
Correlation coefficients whose magnitude are between 0.3 and 0.5 indicate variables which have a low correlation.

But as compared to others it can be consider as factor affecting but it's intensity is low

In [103]:
```
#corr between table booking and price range
sns.regplot(x='Price_range',y='Has_Table_booking_Yes',data=f_ratings)
f_ratings[["Price_range", "Has_Table_booking_Yes"]].corr()
```

Out[103]:

	Price_range	Has_Table_booking_Yes
Price_range	1.000000	0.502025
Has_Table_booking_Yes	0.502025	1.000000



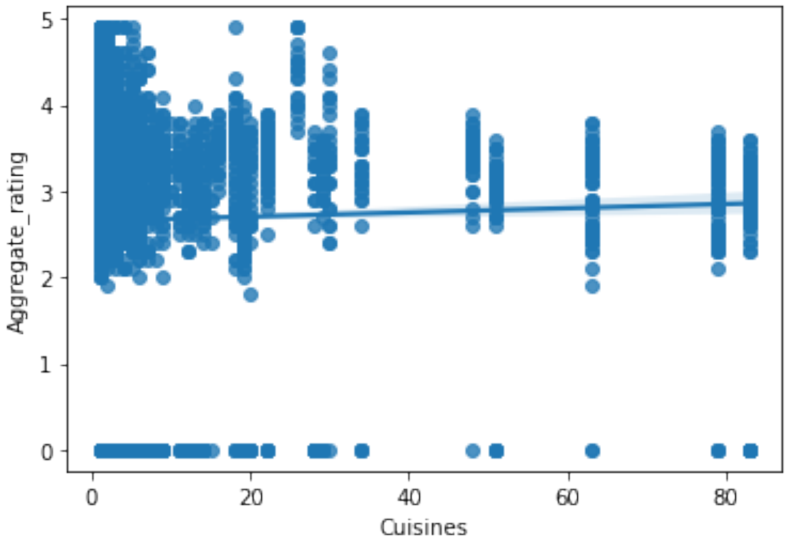
0.5 and 0.7 indicate variables which can be considered moderately correlated.

In [104]:

```
#corr between rating and cuisines
sns.regplot(x='Cuisines',y='Aggregate_rating',data=f_ratings)
f_ratings[['Cuisines','Aggregate_rating']].corr()
```

Out[104]:

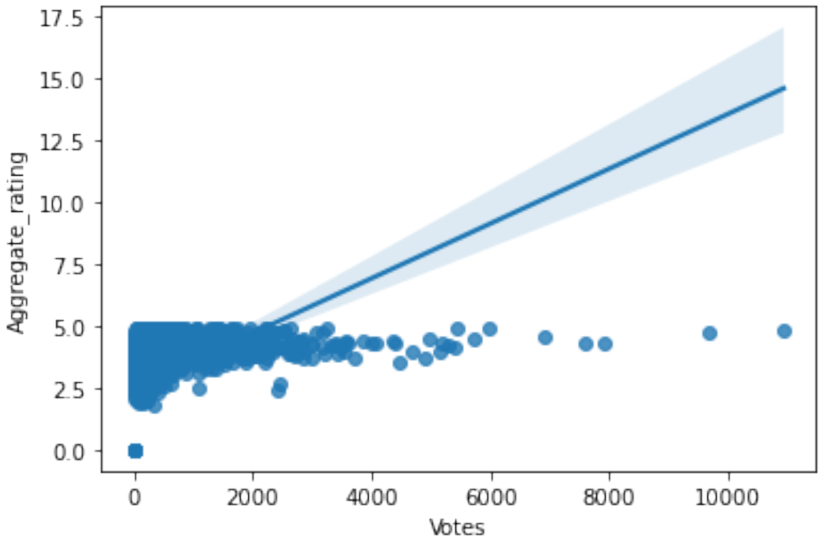
	Cuisines	Aggregate_rating
Cuisines	1.000000	0.021097
Aggregate_rating	0.021097	1.000000



In [105]:
```
#corr between rating and votes
sns.regplot(x='Votes',y='Aggregate_rating',data=f_ratings)
f_ratings[['Votes','Aggregate_rating']].corr()
```

Out[105]:

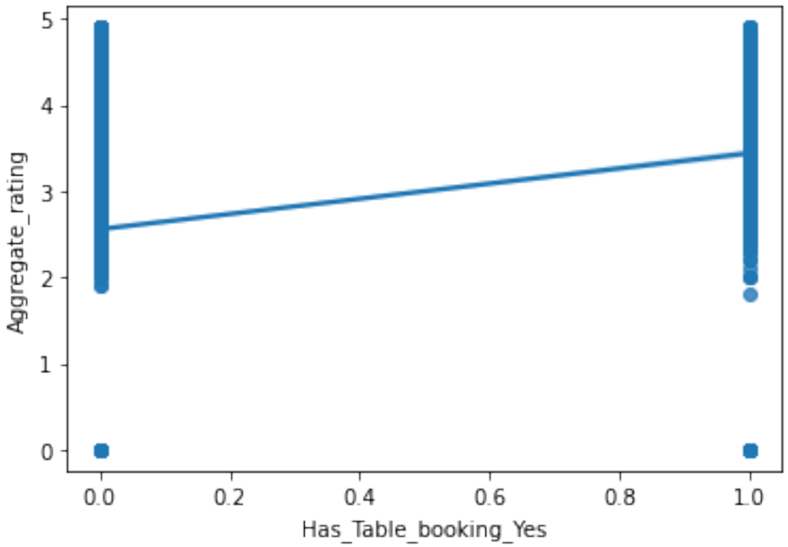
	Votes	Aggregate_rating
Votes	1.000000	0.313598
Aggregate_rating	0.313598	1.000000



In [106]:
```
#corr between rating and table booking
sns.regplot(x='Has_Table_booking_Yes',y='Aggregate_rating',data=f_ratings)
f_ratings[['Has_Table_booking_Yes','Aggregate_rating']].corr()
```

Out[106]:

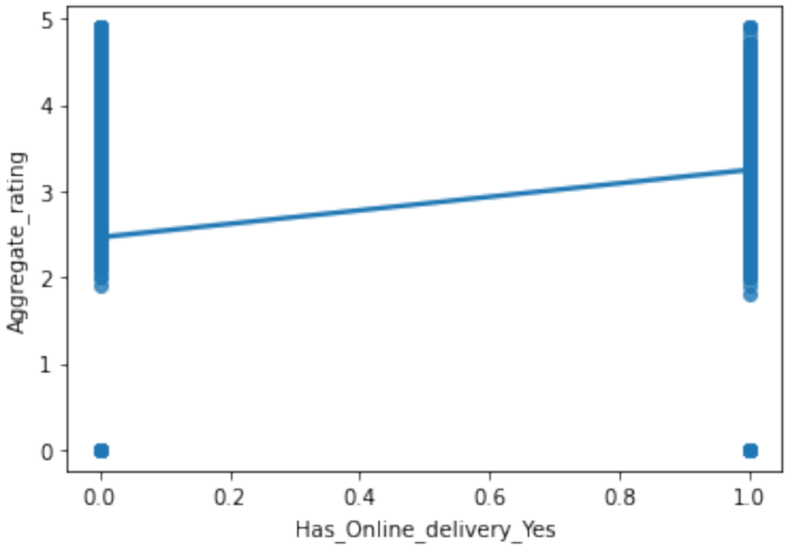
	Has_Table_booking_Yes	Aggregate_rating
Has_Table_booking_Yes	1.000000	0.190045
Aggregate_rating	0.190045	1.000000



In [107]:
```
#corr between rating and online delivery
sns.regplot(x='Has_Online_delivery_Yes',y='Aggregate_rating',data=f_ratings)
f_ratings[['Has_Online_delivery_Yes','Aggregate_rating']].corr()
```

Out[107]:

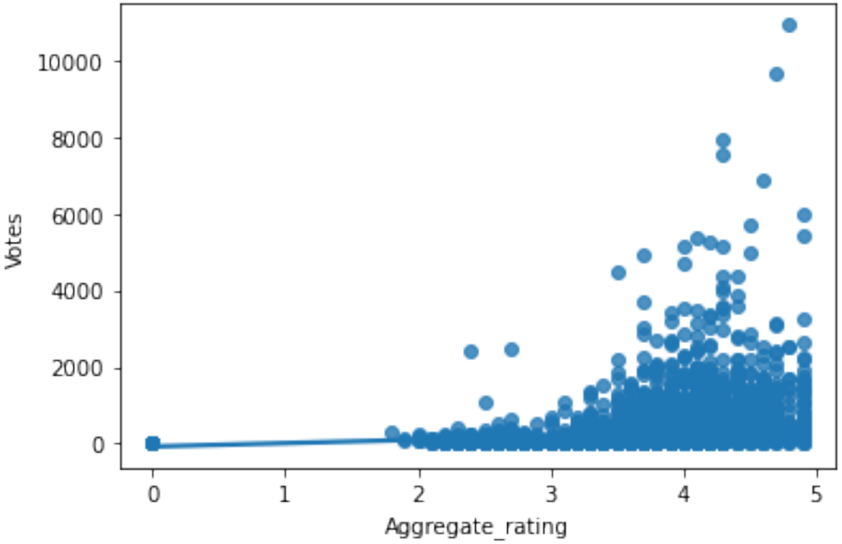
	Has_Online_delivery_Yes	Aggregate_rating
Has_Online_delivery_Yes	1.000000	0.225772
Aggregate_rating	0.225772	1.000000



In [108]:
```
#corr between votes and rating
sns.regplot(x='Aggregate_rating',y='Votes',data=f_ratings)
f_ratings[['Aggregate_rating','Votes']].corr()
```

Out[108]:

	Aggregate_rating	Votes
Aggregate_rating	1.000000	0.313598
Votes	0.313598	1.000000

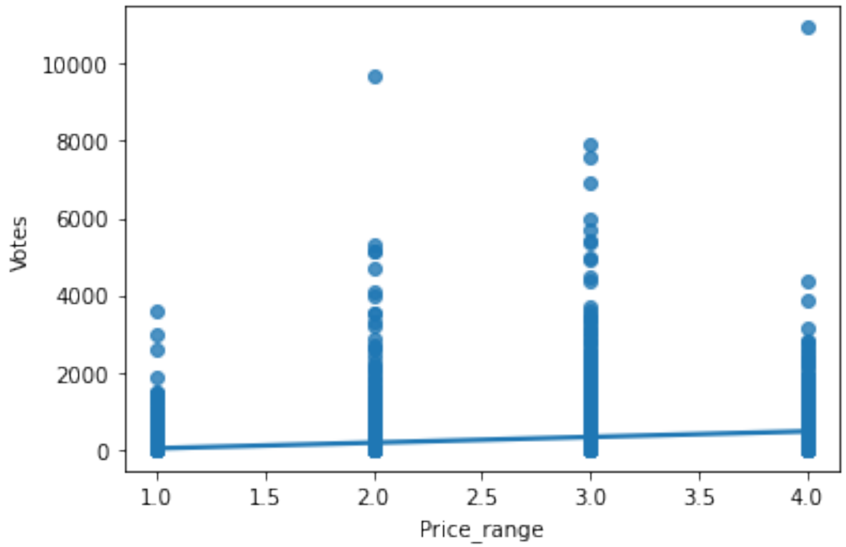


Correlation coefficients whose magnitude are between 0.3 and 0.5 indicate variables which have a low correlation.

In [109]:
```
#corr between votes and price range
sns.regplot(x='Price_range',y='Votes',data=f_ratings)
f_ratings[["Price_range", "Votes"]].corr()
```

Out[109]:

	Price_range	Votes
Price_range	1.000000	0.309308
Votes	0.309308	1.000000



In [110]:
```
f_ratings.to_excel('output.xlsx')
```

In [111]:
```
data.to_excel('uloutput.xlsx')
```

In [116]:
```
Cuisines_app.to_excel('Cuisines_ap.xlsx')
```

In [120]:
```
max_cuisines.to_excel('cumax.xlsx')
```

A correlation coefficient of +1 indicates a perfect positive correlation. As variable x increases, variable y increases. As variable x decreases, variable y decreases. A correlation coefficient of -1 indicates a perfect negative correlation.

Dashboarding:

Visualize the variables using Tableau to help user explore the data and create a better understanding of the restaurants to identify the ‘’star” restaurant

Demonstrate the variables associated with each other and factors to build a dashboard

https://public.tableau.com/app/profile/rushikesh.khankar/viz/Tabprofina22/Dashboard2?publish=yes (https://public.tableau.com/app/profile/rushikesh.khankar/viz/Tabprofina22/Dashboard2?publish=yes)