Project - Identify and Recommend Restaurants to Restaurant Consolidator

Domain: Marketing

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.

Import Liabraries

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

from wordcloud import WordCloud
```

Import Dataset

```
data = pd.read_excel('/content/data.xlsx')
```

```
data.head(5)
```

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	Average Cost for two	Currency	T boo
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)	

Next steps: Generate code with data | View recommended plots | New interactive sheet

1.1 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.

```
data.shape
```

```
(9551, 19)
```

```
data.columns
```

```
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'],
      dtype='object')
```

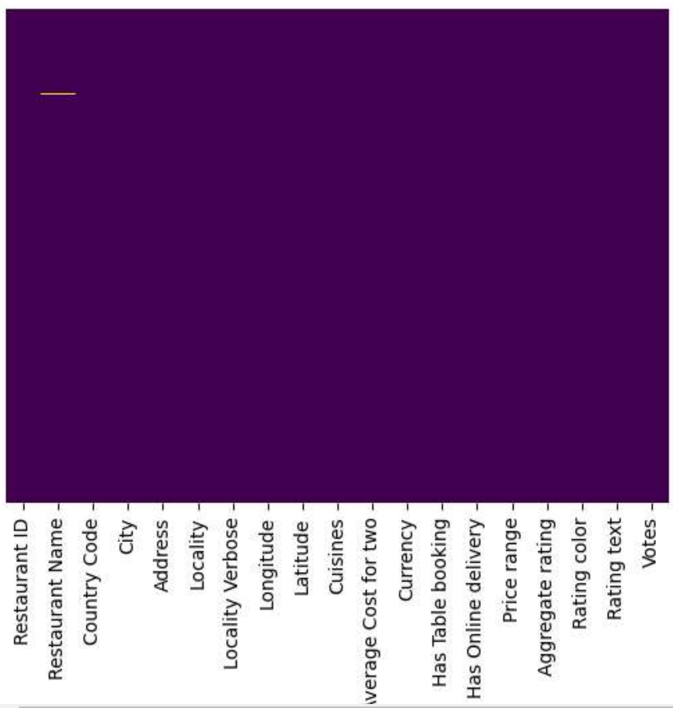
1.2 Based on the findings from the previous questions identify duplicates and remove them.

```
data.isnull().sum().sum()
```

```
10
```

```
sns.heatmap(data.isnull(), yticklabels=False,cbar=False,cmap='viridis')
```

```
<Axes: >
```




```
data1=data.dropna()
```

```
data1.shape
```

```
(9541, 19)
```

> In this dataset we have encountered 10 null values as the number of null values are less we can safely drop them.

```
duplicate=data1[data1.duplicated()]
```

```
duplicate
```

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

> We havent encountered any duplicate values.

Importing Country code file and Merging with existing dataset

```
Country = pd.read_excel('/content/Country_Code.xlsx')
```

```
Country.head(5)
```

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

Next steps: Generate code with Country | View recommended plots | New interactive sheet

Merge the file

```
data2 = pd.merge(data1, Country, on = 'Country Code', how = 'left')
```

```
data2.head(5)
```

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	Average Cost for two	Currency	T boo
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)	

Next steps: Generate code with data2 | View recommended plots | New interactive sheet

After merging the files country name column is added as last column

```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9541 entries, 0 to 9540
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Restaurant ID         9541 non-null   int64
 1   Restaurant Name       9541 non-null   object
 2   Country Code          9541 non-null   int64
 3   City                  9541 non-null   object
 4   Address               9541 non-null   object
 5   Locality              9541 non-null   object
 6   Locality Verbose      9541 non-null   object
 7   Longitude             9541 non-null   float64
 8   Latitude              9541 non-null   float64
```

```
 9   Cuisines              9541 non-null   object
 10  Average Cost for two  9541 non-null   int64
 11  Currency              9541 non-null   object
 12  Has Table booking     9541 non-null   object
 13  Has Online delivery   9541 non-null   object
 14  Price range           9541 non-null   int64
 15  Aggregate rating      9541 non-null   float64
 16  Rating color          9541 non-null   object
 17  Rating text           9541 non-null   object
 18  Votes                 9541 non-null   int64
 19  Country               9541 non-null   object
dtypes: float64(3), int64(5), object(12)
memory usage: 1.5+ MB
```

```
data2.columns = data2.columns.str.replace(' ','_')
data2.columns
```

```
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')
```

```
data2.isnull().sum().sum()
```

```
0
```

2.1 Explore the geographical distribution of the restaurants, finding out the cities with maximum / minimum number of restaurants.

```
data2['Country'].value_counts()
```

Country	count
India	8651
United States	425
United Kingdom	80
South Africa	60
UAE	60
Brazil	60
New Zealand	40
Turkey	34
Australia	24
Phillipines	22
Indonesia	21
Sri Lanka	20
Qatar	20
Singapore	20
Canada	4

```
data2['City'].value_counts()
```

	count
City	
New Delhi	5473
Gurgaon	1118
Noida	1080
Faridabad	251
Ghaziabad	25
...	...
Consort	1
Lincoln	1
Monroe	1
Potrero	1
Lakes Entrance	1

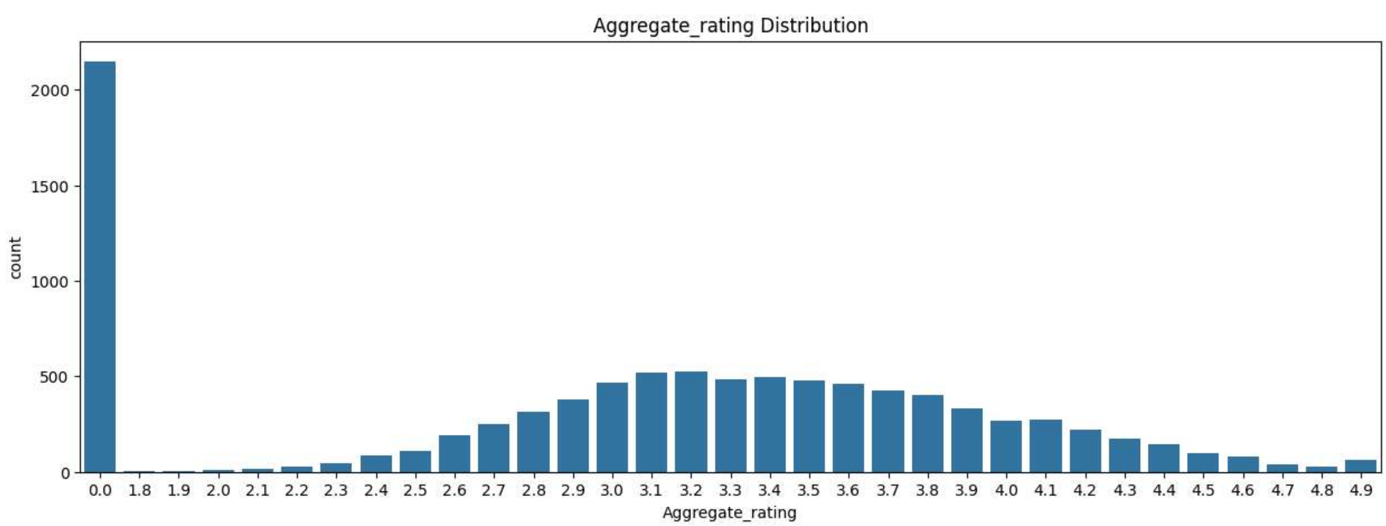
140 rows × 1 columns

> As we can observe that this data set contains high number of restaurants from India and Delhi have the highest number of restaurants.

2.2 Explore how ratings are distributed overall.

```
df = pd.DataFrame(data2)
```

```
plt.figure(figsize=(15, 5))
sns.countplot(x='Aggregate_rating', data=df)
plt.title('Aggregate_rating Distribution')
plt.show()
```



> As we can observe maximum number of customers havent rated restraunts as 0.0 is maximum. Where as per distribution the bell curve peaks at 3.2.

```
Color_counts = df['Rating_color'].value_counts()

# Generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate_from_frequencies(Color_counts)
```

```
# Display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")  # Hide the axis
plt.show()
```

> As per word cloud Orange colour rating is in majority which means average customer isnt very pleased and White is second in rank which means a lot of them havent rated.

```
Text_counts = df['Rating_text'].value_counts()

# Generate the word cloud
wordcloud = WordCloud(width=800, height=400, background_color='white').generate_from_frequencies(Text_counts)

# Display the word cloud
plt.figure(figsize=(10, 5))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")  # Hide the axis
plt.show()
```

> As we can see most of the rating is Average

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

```
Franchise = data2.groupby(['Restaurant_Name']).agg(Count = ('City','count')).reset_index()
Franchise
```

	Restaurant_Name	Count
0	12212	1
1	Let's Burrrp	1
2	#45	1
3	#Dilliwaala6	1
4	#InstaFreeze	1
...	...	...
7431	t Lounge by Dilmah	1
7432	tashas	1
7433	wagamama	1
7434	{Niche} - Cafe & Bar	1
7435	Ìàukura€Ùa Sofras€±	1

7436 rows × 2 columns

Next steps: Generate code with Franchise | View recommended plots | New interactive sheet

```
Franchise_Most = Franchise.sort_values(by = 'Count',ascending=False).reset_index(drop=True)
Franchise_Most
```

	Restaurant_Name	Count
0	Cafe Coffee Day	83
1	Domino's Pizza	79
2	Subway	63
3	Green Chick Chop	51
4	McDonald's	48
...	...	...
7431	Ghar Ki Handi	1
7432	Ghar Ka Swad	1
7433	Ghar Bistro Cafe	1
7434	Ghalib Kabab Corner	1
7435	Ìàukura€Ùa Sofras€±	1

7436 rows × 2 columns

Next steps: Generate code with Franchise_Most | View recommended plots | New interactive sheet

2.4 What is the ratio between restaurants that allow table booking vs that do not allow table booking

```
## Ratio between restaurants that allow table booking vs. those that do not allow table booking
Booking_table=data2.groupby('Has_Table_booking').Restaurant_ID.count()
Booking_table
```

Has_Table_booking	Restaurant_ID
No	8383
Yes	1158

```
print('Ratio between restaurants that allow table booking vs. those that do not allow table booking:',
      round((Booking_table.Yes/Booking_table.No),2))
```

```
Ratio between restaurants that allow table booking vs. those that do not allow table booking: 0.14
```

```
# Graphical representation of above ration - Pie Chart
plt.title('Booking Availability')
plt.pie(Booking_table,labels=('Table Booking Not Allowed','Table Booking Allowed'),explode=(0.1,0),shadow=True,
        autopct='%1.2f%%')
plt.show()
```

We can see in above graph only 12.14% restaurants allow table booking and 87.86 restaurants not allow table booking

2.5 What is the percentage of restaurants providing online delivery

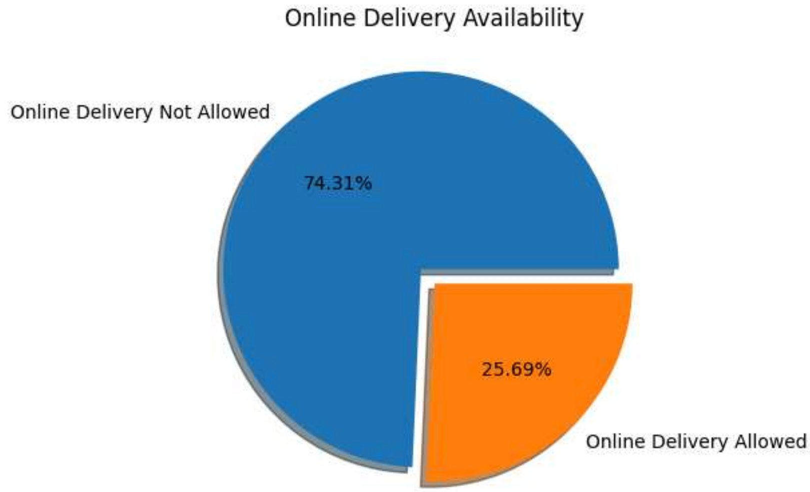
```
online_delivery=data2.groupby('Has_Online_delivery').Restaurant_ID.count()
online_delivery
```

	Restaurant_ID
Has_Online_delivery	
No	7090
Yes	2451

```
print('Percentage of restaurants providing online delivery:', round((online_delivery.Yes/online_delivery.sum()),4)*100)
```

```
Percentage of restaurants providing online delivery: 25.69
```

```
# Graphical representation via Pie Chart
plt.title('Online Delivery Availability')
plt.pie(online_delivery,labels=('Online Delivery Not Allowed','Online Delivery Allowed'),explode=(0.1,0),shadow=True,
        autopct='%1.2f%%')
plt.show()
```



> We can see in above graph only 25.69% restaurants provide online delivery and 74.31 restaurants not provide online delivery

2.6 Is there a difference in no. of votes for the restaurants that deliver and the restaurant that don't

```
Votes = data2.groupby(['Has_Online_delivery']).sum('Votes')
Votes
```

Has_Online_delivery	Restaurant_ID	Country_Code	Longitude	Latitude	Average_Cost_for_two	Price_range	Aggregate_rating	Vot
No	67227164919	165050	425144.965008	177803.058272	9789377	12502	17464.7	9772
Yes	19063894933	8415	188094.559079	68820.590044	1663335	4718	7962.9	5179

Next steps: Generate code with Votes | View recommended plots | New interactive sheet

```
Votes = Votes.drop(['Restaurant_ID','Country_Code','Longitude','Latitude','Average_Cost_for_two',
                                             'Price_range','Aggregate_rating'], axis = 1)
Votes
```

Has_Online_delivery	Votes
No	977236
Yes	517914

Next steps: Generate code with Votes | View recommended plots | New interactive sheet

```
difference_in_votes = Votes.iloc[0]['Votes'] - Votes.iloc[1]['Votes']
print("The difference in number of votes for the restaurants that deliver and the restaurants that do not deliver:= " ,difference_in_votes)
```

```
The difference in number of votes for the restaurants that deliver and the restaurants that do not deliver:=  459322
```

As we can see above there is difference of 459322 votes between Yes and No for online delivery

2.7 What are the top 10 cuisines served across cities

```
data2.groupby("Restaurant_Name")["Cuisines"].max().value_counts().head(10)
```

Cuisines	count
North Indian	818
North Indian, Chinese	438
Chinese	281
Fast Food	263
North Indian, Mughlai	254
Bakery	183
North Indian, Mughlai, Chinese	176
Bakery, Desserts	154
Street Food	137
Cafe	132

Based on above information we can say that North Indian cuisine is at number 1 and and no2. is chinese

2.8 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

```
Max_Min_Cuisines = data2.groupby(['Restaurant_Name','Cuisines']).agg( Count = ('Cuisines','count')).reset_index()
Max_Min_Cuisines = Max_Min_Cuisines.sort_values(by = 'Count', ascending = False).reset_index(drop=True)
Max_Min_Cuisines.rename(columns={'Count':'Restaurant_Count'}, inplace=True)
Max_Min_Cuisines
```

	Restaurant_Name	Cuisines	Restaurant_Count
0	Cafe Coffee Day	Cafe	83
1	Domino's Pizza	Pizza, Fast Food	78
2	Subway	American, Fast Food, Salad, Healthy Food	62
3	Green Chick Chop	Raw Meats, North Indian, Fast Food	47
4	McDonald's	Fast Food, Burger	44
...	...	...	...
7934	Fusilli Reasons	Italian	1
7935	Funkey Monkey	Breakfast, Coffee and Tea	1
7936	Funk House Cafe	Cafe, Italian, Salad	1
7937	Funduz Cafe	Fast Food	1
7938	Ìàukura€Ùa Sofras€±	Kebab, Izgara	1

7939 rows × 3 columns

Next steps: Generate code with Max_Min_Cuisines | View recommended plots | New interactive sheet

```
Max_Min_Cuisines=pd.DataFrame(data2.groupby('Restaurant_Name').Cuisines.count()).reset_index()
Max_Min_Cuisines.sort_values(by = 'Cuisines', ascending = False)
```

	Restaurant_Name	Cuisines
1098	Cafe Coffee Day	83
2096	Domino's Pizza	79
6097	Subway	63
2713	Green Chick Chop	51
4069	McDonald's	48
...	...	...
2613	Ghar Ki Handi	1
2612	Ghar Ka Swad	1
2610	Ghar Bistro Cafe	1
2609	Ghalib Kabab Corner	1
7435	Ìàukura€Ùa Sofras€±	1

7436 rows × 2 columns

> Based on above information we can say that Caffee day is highest cuisines served which is 83 and Least cusines serve by restaurants count is 1

```
data3=data2["Cuisines"].value_counts()
data3
```

	count
Cuisines	
North Indian	936
North Indian, Chinese	511
Chinese	354
Fast Food	354
North Indian, Mughlai	334
...	...
Continental, Mexican, North Indian, Chinese	1
Cafe, Mexican, Italian, Continental	1
Cafe, Continental, Italian, Street Food	1
Cafe, Lebanese, Italian	1
Cafe, Continental, Desserts, Ice Cream, Italian, Beverages	1

1825 rows × 1 columns

```
data2["No_of_cuisines"]=data1["Cuisines"].str.strip().str.split(',').apply(len)
data2.head(5)
```

	Restaurant_ID	Restaurant_Name	Country_Code	City	Address	Locality	Locality_Verbose	Longitude	Latitude	Cuisines	...
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	...

5 rows × 21 columns

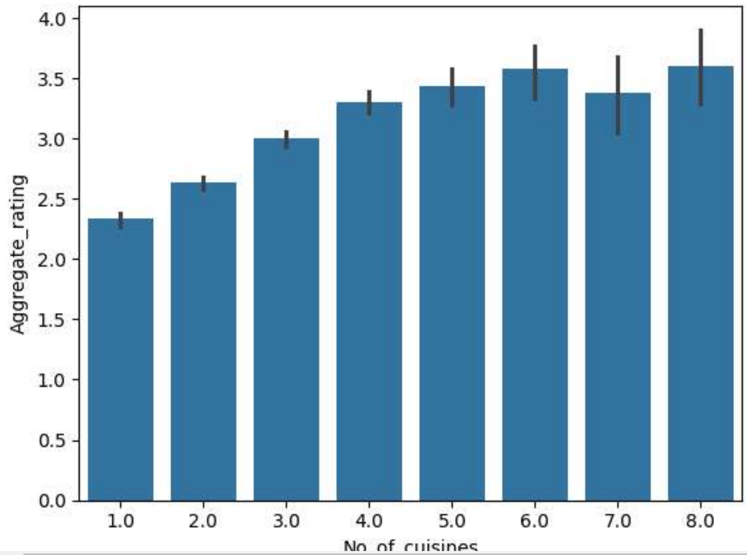
```
data2["No_of_cuisines"]
```

	No_of_cuisines
0	2.0
1	3.0
2	2.0
3	1.0
4	2.0
...	...
9536	2.0
9537	1.0
9538	3.0
9539	NaN
9540	2.0

9541 rows × 1 columns

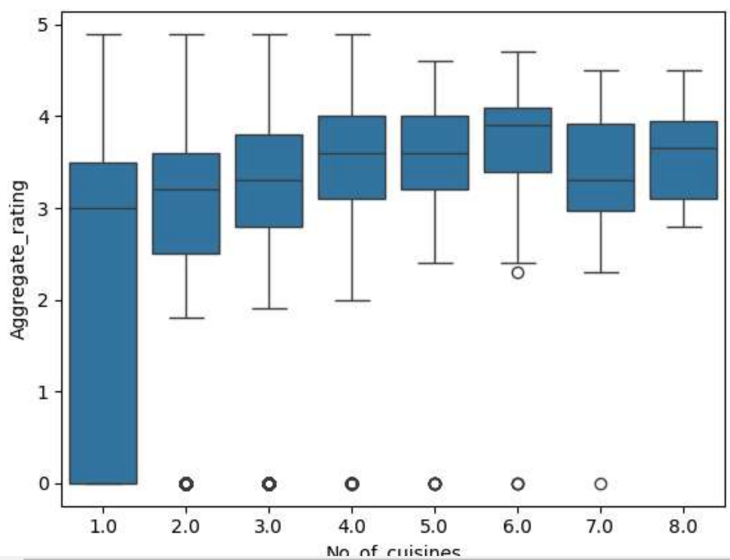
```
sns.barplot(data2, x="No_of_cuisines", y="Aggregate_rating")
```

```
<Axes: xlabel='No_of_cuisines', ylabel='Aggregate_rating'>
```




```
sns.boxplot(data2, x="No_of_cuisines", y="Aggregate_rating")
```

```
<Axes: xlabel='No_of_cuisines', ylabel='Aggregate_rating'>
```



From above chart we can say that restaurant which serve more cuisines they get more ratings

2.9 Discuss the cost vs the other variables

```
# Currency wise distribution of cost
Currency_dis = pd.DataFrame(data2.groupby('Currency').Average_Cost_for_two.count()).reset_index()
Currency_dis.sort_values(by='Average_Cost_for_two', ascending = False)
```

	Currency	Average_Cost_for_two
4	Indian Rupees(Rs.)	8651
2	Dollar($)	473
7	Pounds(â£)	80
1	Brazilian Real(R$)	60
3	Emirati Diram(AED)	60
9	Rand(R)	60
6	NewZealand($)	40
11	Turkish Lira(TL)	34
0	Botswana Pula(P)	22
5	Indonesian Rupiah(IDR)	21
8	Qatari Rial(QR)	20
10	Sri Lankan Rupee(LKR)	20

```
##  Distribution cost accross the restaurants
Cost_per_restaurants = pd.DataFrame(data2.groupby('Restaurant_Name').Average_Cost_for_two.sum()).reset_index()
Cost_per_restaurants.sort_values(by = 'Average_Cost_for_two', ascending = False)
```

	Restaurant_Name	Average_Cost_for_two
5889	Skye	800000
5586	Satoo - Hotel Shangri-La	800000
6254	Talaga Sampireun	600000
6162	Sushi Masa	500000
41	3 Wise Monkeys	450000
...	...	...
1911	Deena Chat Bhandar	0
6683	The Latitude - Radisson Blu	0
7087	UrbanCrave	0
5401	Royal Hotel	0
7103	VNS Live Studio	0

7436 rows × 2 columns

```
# Restaurants wise distribution of cost - by Currencies
data3=pd.DataFrame(data2.groupby(['Currency','Restaurant_Name']).agg(Count = ('Average_Cost_for_two','sum'))).reset_index()
data3.sort_values(by='Count', ascending = False)
```

	Currency	Restaurant_Name	Count
7211	Indonesian Rupiah(IDR)	Skye	800000
7210	Indonesian Rupiah(IDR)	Satoo - Hotel Shangri-La	800000
7213	Indonesian Rupiah(IDR)	Talaga Sampireun	600000
7212	Indonesian Rupiah(IDR)	Sushi Masa	500000
7199	Indonesian Rupiah(IDR)	3 Wise Monkeys	450000
...	...	...	...
5682	Indian Rupees(Rs.)	Sheroes Hangout	0
1046	Indian Rupees(Rs.)	Atmosphere Grill Cafe Sheesha	0
6549	Indian Rupees(Rs.)	The Latitude - Radisson Blu	0
427	Dollar($)	Senor Iguanas	0
1819	Indian Rupees(Rs.)	Chapter 1 Cafe	0

7463 rows × 3 columns

```
data3.groupby(['Currency'], sort=False)['Count'].max()
```

Currency	Count
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(â£)	230
Qatari Rial(QR)	550
Rand(R)	3210
Sri Lankan Rupee(LKR)	4500
Turkish Lira(TL)	400

```
# Currency wise highest cost accross restaurants
Max_cost=data3.groupby('Currency')\
  .apply(lambda group: group[group.Count == group.Count.max()])\
  .reset_index(drop=True)
Max_cost.sort_values(by='Count', ascending = False)
```

```
<ipython-input-126-ecf7dd78b904>:3: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprec
  .apply(lambda group: group[group.Count == group.Count.max()])\
```

	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

> Based on above codes we can say that Satoo and Skye have highest cost across all the restaurants. Satoo restaurant have highest cost in Indonesain currency and Domino's Pizza have highest cost in indian rupees.

2.10 Explain the factors in the data that may have an effect on ratings e.g. No. of cuisines, cost, delivery option etc.

```
## Aggregate_rating vs count
Rating_count=pd.DataFrame(data2.groupby('Aggregate_rating').agg(Count = ('Restaurant_Name','count'))).reset_index()
Rating_count.sort_values(by='Aggregate_rating', ascending = False)
```

	Aggregate_rating	Count
32	4.9	61
31	4.8	25
30	4.7	41
29	4.6	78
28	4.5	95
27	4.4	143
26	4.3	174
25	4.2	221
24	4.1	273
23	4.0	266
22	3.9	332
21	3.8	399
20	3.7	427
19	3.6	458
18	3.5	480
17	3.4	495
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 observation we can say that 61 restaurants have 4.9 ratings and 2148 restaurants have 0 ratings

```
Country_Rating=pd.DataFrame(data2.groupby(['Country','Aggregate_rating']).agg(Count =
                                                                               ('Restaurant_Name','count'))).reset_index()
Country_Rating.sort_values(by='Aggregate_rating', ascending = False)
```

	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
...	...	...	...

```
# Best rated restaurants by country
Country_wise_top_rating=pd.DataFrame(Country_Rating[Country_Rating.Aggregate_rating >= 4.9]).reset_index()
Country_wise_top_rating.sort_values(by='Count', ascending = False)
```

	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

> India have 19 counts for highest rating post that United states have 14 count for highest rating.

```
### Rating Distribution
RatingType_count=pd.DataFrame(data2.groupby('Rating_text').agg(Count = ('Restaurant_Name','count'))).reset_index()
RatingType_count
```

	Rating_text	Count
0	Average	3734
1	Excellent	300
2	Good	2096
3	Not rated	2148
4	Poor	186
5	Very Good	1077

Next steps: Generate code with RatingType_count | View recommended plots | New interactive sheet

> From above observation we can say that Average rating count is higher which is 3734, Not Rated rating count is 2148 and Good Rating count is 2096