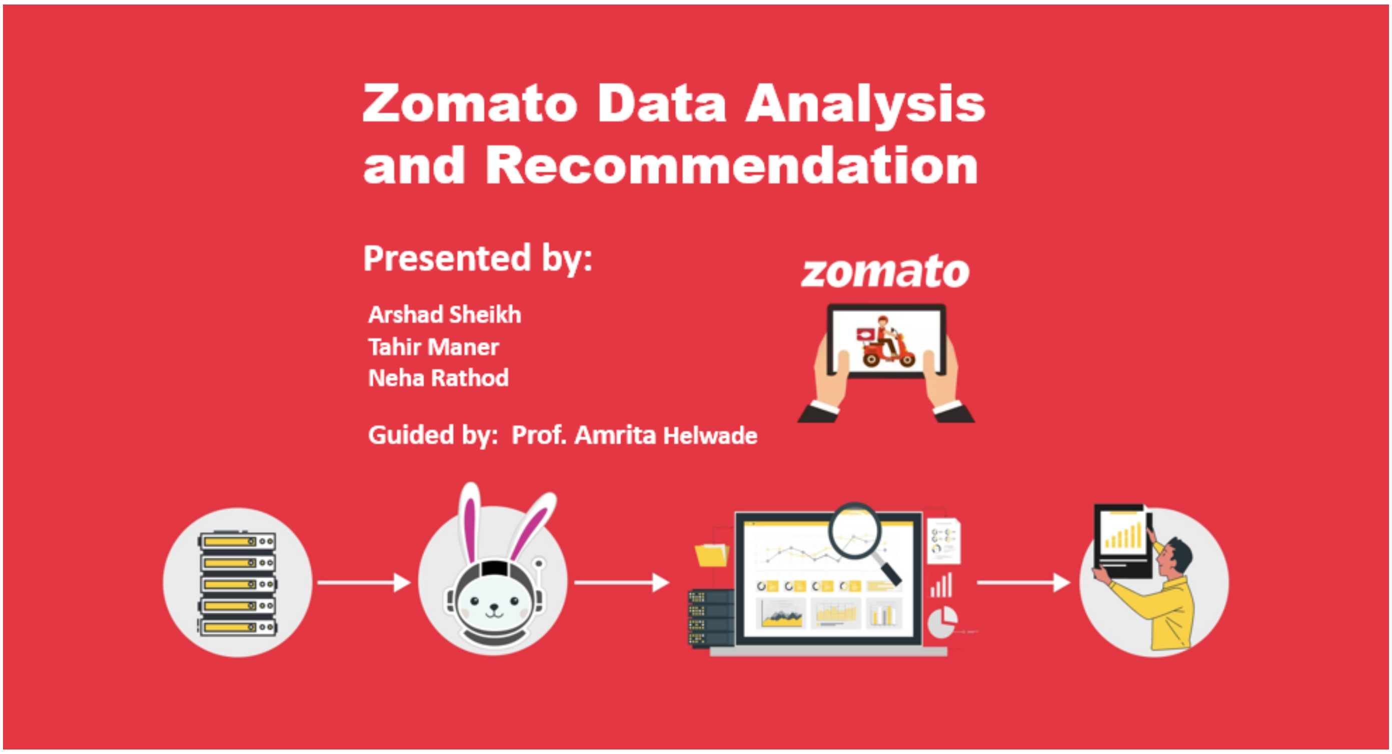


In [1]:

```python
## importing libaries
import sys
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
from matplotlib import style
import pandas as pd
from pandas import Series
import seaborn as sns
from scipy.stats import binom
from scipy.stats import poisson
import scipy.stats as stats
import statsmodels.formula.api as smf
from sklearn import metrics
import plotly.express as px
```

In [3]:

```python
# for Ingoring Warnings
import warnings
warnings.filterwarnings('always')
warnings.filterwarnings('ignore')
```

Reading The Data

In [4]:

```python
df = pd.read_csv(r"C:\Users\TA\Desktop\TA\datasets\zomato.csv")
```

In [5]:

```
df.head() ### for displaying first 5 rows
```

Out[5]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longit
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...	121.027
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...	121.014
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...	121.056
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...	121.056
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...	121.057

5 rows × 21 columns

In [6]:

```
df.columns ### Displaying Columns
```

Out[6]:

```
Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Addres
s',
       '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'],
      dtype='object')
```

Get Info of Data

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9551 entries, 0 to 9550
Data columns (total 21 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  
dtypes: float64(3), int64(5), object(13)
memory usage: 1.5+ MB
```

In [8]:

```
df.describe() ## describing given data
```

Out[8]:

	Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Ag
count	9.551000e+03	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551
mean	9.051128e+06	18.365616	64.126574	25.854381	1199.210763	1.804837	2
std	8.791521e+06	56.750546	41.467058	11.007935	16121.183073	0.905609	1
min	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0
25%	3.019625e+05	1.000000	77.081343	28.478713	250.000000	1.000000	2
50%	6.004089e+06	1.000000	77.191964	28.570469	400.000000	2.000000	3
75%	1.835229e+07	1.000000	77.282006	28.642758	700.000000	2.000000	3
max	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4

Basic statistic details of the dataset is shown using the describe() function-ONLY NUMERICAL VARIABLES displayed

EXPLORATORY DATA ANALYSIS

In [9]:

```
## MISSING VALUES
```

In [10]:

```
# 1. FINDING MISSING VALUES USING FUNCTIONS
df.isnull().sum() ## Checking null Values/finding missing values in our dataset
```

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
dtype: int64
```

Displays all the null values in every column- 'Cuisines' column has 9 missing values hence, feature engineering has to be performed on that column

In [11]:

```
#2. FINDING MISSING VALUES USING QUERY
for columns in df.columns:
    if df[columns].isnull().sum() > 0:
        print(columns)
```

```
Cuisines
```

In [12]:

```
#finding missing values using a simple query
[features for features in df.columns if df[features].isnull().sum() >0]
```

Out[12]:

```
['Cuisines']
```

MERGING 2 FILES

In [13]:

```
#loading excel file using the pd.read_excel function from PANDAS
```

In [14]:

```
df_country = pd.read_excel(r"C:\Users\TA\Desktop\TA\datasets\Country-Code z.xlsx")
df_country.head()
```

Out[14]:

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

Our csv file has 2 columns-'Country Code' and 'Country - As you can recall, we have the 'Country Code' column in our CSV file, so let us combine this excel file and our dataset(csv file) using the pandas merge function on this column

In [15]:

```
#merge function to merge both CSV and XSL files
#displaying our final dataset

final_df = pd.merge(df, df_country, on = "Country Code", how = "left")
final_df.head()
```

Out[15]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longit
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...	121.027
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...	121.014
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...	121.056
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...	121.056
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...	121.057

5 rows × 22 columns

Our final dataset has the 'Country' column added at the end of our new dataset(which is the additonal column) that has been added from excel to our dataset. Creating the final dataset

In [ ]:

```

```

DISPLAYING THE DATATYPES OF FINAL DATASET

In [16]:

```
#checking data types of our final dataset

final_df.dtypes
```

Out[16]:

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

FEATURE SELECTION

Our final dataset has many features , let us a pick a few features & draw insights from our dataset

In [ ]:

```

```

1. TOP 3 CONTRIES WITH MAXIMUM NUMBER OF ORDERS

In [17]:

```
country_name = final_df.Country.value_counts().index
country_name
```

Out[17]:

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

In [18]:

```
country_value = final_df.Country.value_counts().values
country_value
```

Out[18]:

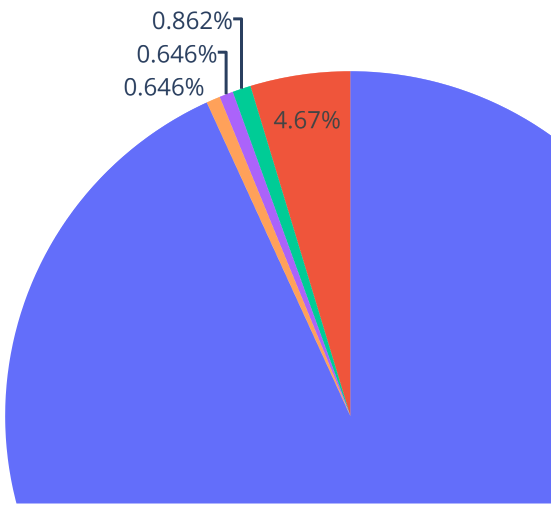
```
array([8652,  434,   80,   60,   60,   60,   40,   34,   24,   22,   21,
         20,   20,   20,    4], dtype=int64)
```

INFERENCE --> From this we can summarize that the maximum number of transactions happen in India

In [ ]:

In [19]:

```
## PIE CHART VISUALIZATION

import plotly.graph_objects as go

labels = country_name
values = country_value

fig = go.Figure(data=[go.Pie(labels=labels[:5], values=values[:5])])
fig.show()
```




```
INFERENCE --> The top 3 countries with maximum number of orders are India (with maximum), USA and then UK.
```

2. COUNTRY WITH MOST RATINGS

In [20]:

```
#displaying the ratings related columns in a dataframe format

final_df.groupby(['Aggregate rating','Rating color','Rating text']).size().reset_index()
```

Out[20]:

	Aggregate rating	Rating color	Rating text	0
0	0.0	White	Not rated	2148
1	1.8	Red	Poor	1
2	1.9	Red	Poor	2
3	2.0	Red	Poor	7
4	2.1	Red	Poor	15
5	2.2	Red	Poor	27
6	2.3	Red	Poor	47
7	2.4	Red	Poor	87
8	2.5	Orange	Average	110
9	2.6	Orange	Average	191
10	2.7	Orange	Average	250
11	2.8	Orange	Average	315
12	2.9	Orange	Average	381
13	3.0	Orange	Average	468
14	3.1	Orange	Average	519
15	3.2	Orange	Average	522
16	3.3	Orange	Average	483
17	3.4	Orange	Average	498
18	3.5	Yellow	Good	480
19	3.6	Yellow	Good	458
20	3.7	Yellow	Good	427
21	3.8	Yellow	Good	400
22	3.9	Yellow	Good	335
23	4.0	Green	Very Good	266
24	4.1	Green	Very Good	274
25	4.2	Green	Very Good	221
26	4.3	Green	Very Good	174
27	4.4	Green	Very Good	144
28	4.5	Dark Green	Excellent	95
29	4.6	Dark Green	Excellent	78
30	4.7	Dark Green	Excellent	42
31	4.8	Dark Green	Excellent	25
32	4.9	Dark Green	Excellent	61

INFERENCE ->

1)Rating color is WHITE when it is NOT RATED
2)Rating color is RED when it is POOR
3)Rating color is ORANGE when it is AVERAGE
4)Rating color is YELLOW when it is GOOD
5)Rating color is GREEN when it is VERY GOOD
6)Rating color is DARK GREEN when it is EXCELLENT

In [21]:

```
#renaming the 0  column to rating count for readability (storing it as a dataset)

ratings = final_df.groupby(['Aggregate rating','Rating color','Rating text']).size().reset_
ratings
```

Out[21]:

	Aggregate rating	Rating color	Rating text	Rating Count
0	0.0	White	Not rated	2148
1	1.8	Red	Poor	1
2	1.9	Red	Poor	2
3	2.0	Red	Poor	7
4	2.1	Red	Poor	15
5	2.2	Red	Poor	27
6	2.3	Red	Poor	47
7	2.4	Red	Poor	87
8	2.5	Orange	Average	110
9	2.6	Orange	Average	191
10	2.7	Orange	Average	250
11	2.8	Orange	Average	315
12	2.9	Orange	Average	381
13	3.0	Orange	Average	468
14	3.1	Orange	Average	519
15	3.2	Orange	Average	522
16	3.3	Orange	Average	483
17	3.4	Orange	Average	498
18	3.5	Yellow	Good	480
19	3.6	Yellow	Good	458
20	3.7	Yellow	Good	427
21	3.8	Yellow	Good	400
22	3.9	Yellow	Good	335
23	4.0	Green	Very Good	266
24	4.1	Green	Very Good	274
25	4.2	Green	Very Good	221
26	4.3	Green	Very Good	174
27	4.4	Green	Very Good	144
28	4.5	Dark Green	Excellent	95
29	4.6	Dark Green	Excellent	78
30	4.7	Dark Green	Excellent	42
31	4.8	Dark Green	Excellent	25

	Aggregate rating	Rating color	Rating text	Rating Count
32	4.9	Dark Green	Excellent	61

```
INFERENCE--> Around 2k ppl have given zero ratings. ratings (4.5-4.9)=excellent. 4.0 to 4.4=v.good. 3.5 to 3.9=good. 2.5 to 3.4 = average & so on
```

In [22]:

```
#displaying first five records in the ratings dataset

ratings.head()
```

Out[22]:

	Aggregate rating	Rating color	Rating text	Rating Count
0	0.0	White	Not rated	2148
1	1.8	Red	Poor	1
2	1.9	Red	Poor	2
3	2.0	Red	Poor	7
4	2.1	Red	Poor	15

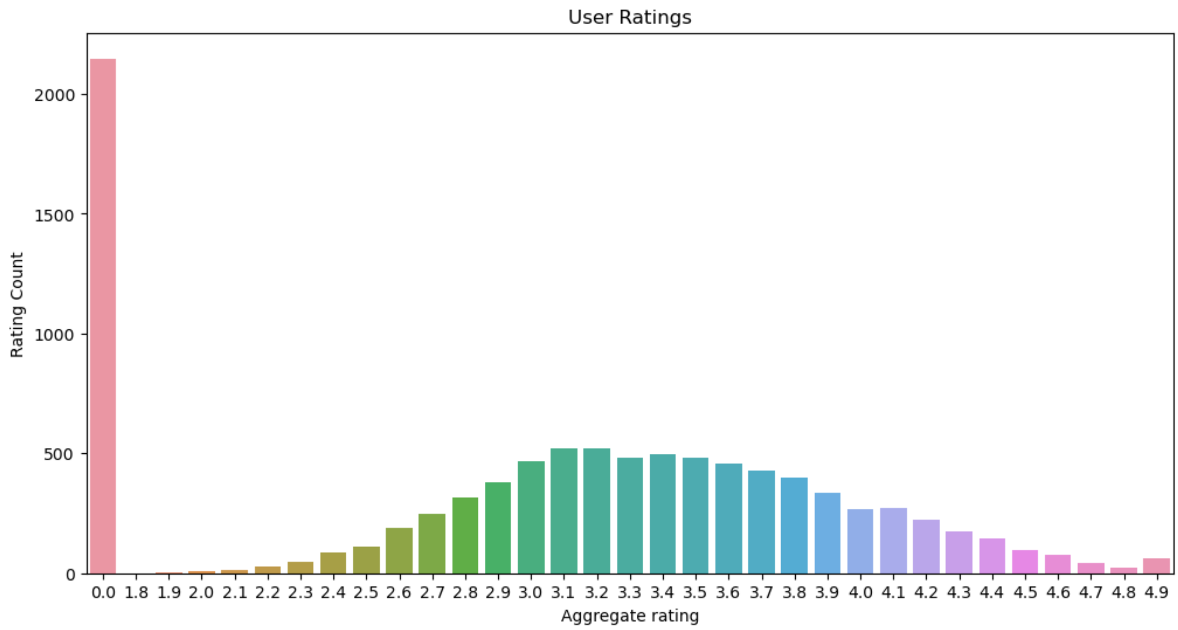
BAR CHART VISUALIZATION

In [23]:

```
#bar plot visualization

plt.rcParams['figure.figsize'] = (12,6)
sns.barplot(x='Aggregate rating',y='Rating Count',data=ratings)
plt.title('User Ratings')
```

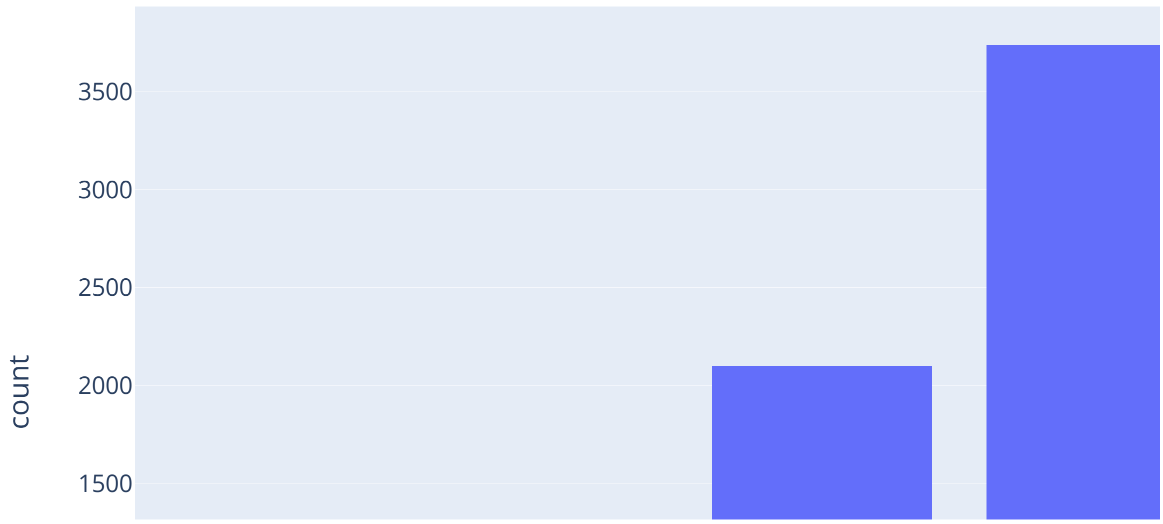
Out[23]:

```
Text(0.5, 1.0, 'User Ratings')
```



In [24]:

```
fig = px.histogram(final_df, "Rating color")
fig.show()
```

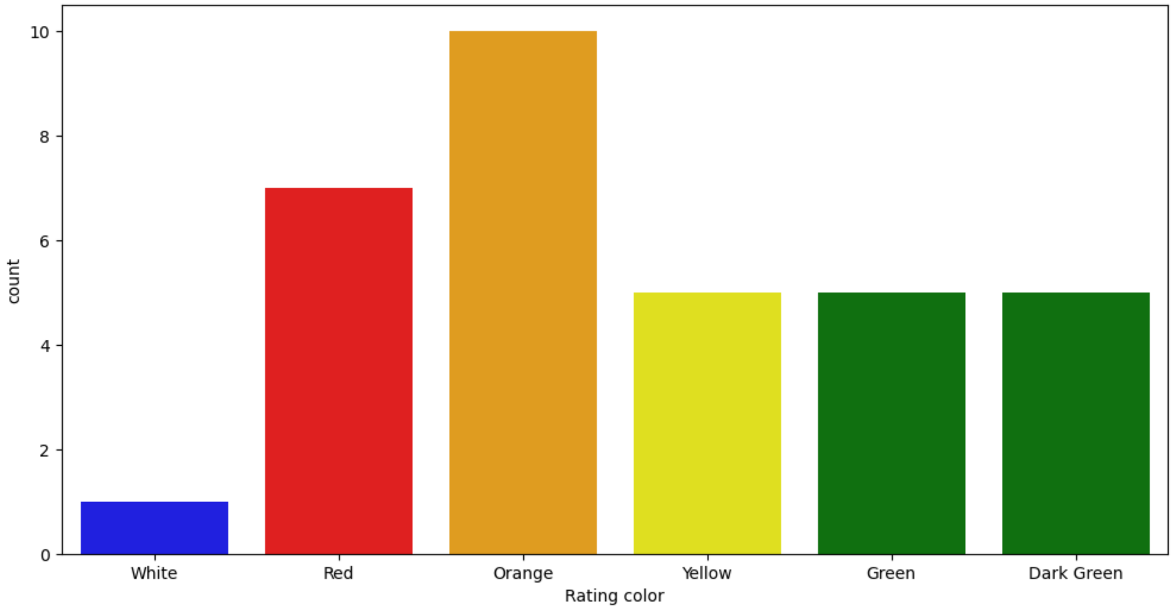


In [25]:

```
#countplot to count the total rating based on color

sns.countplot(x='Rating color',data=ratings,palette=['blue','red','orange','yellow','green'
```

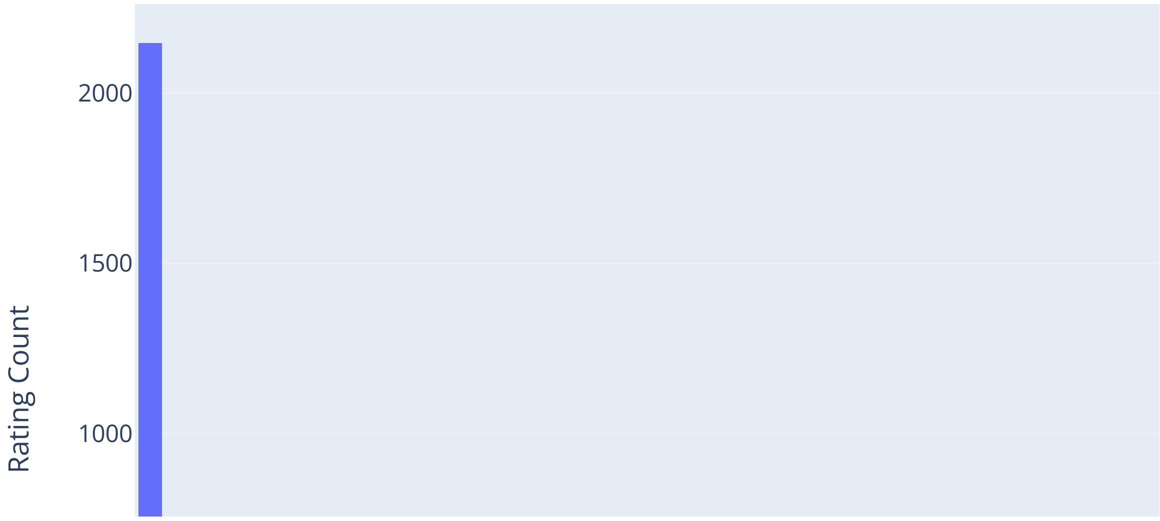
Out[25]:

```
<AxesSubplot:xlabel='Rating color', ylabel='count'>
```



In [26]:

```
fig = px.bar(ratings, x = "Aggregate rating", y = "Rating Count",
             color = "Rating color")
fig.show()
```



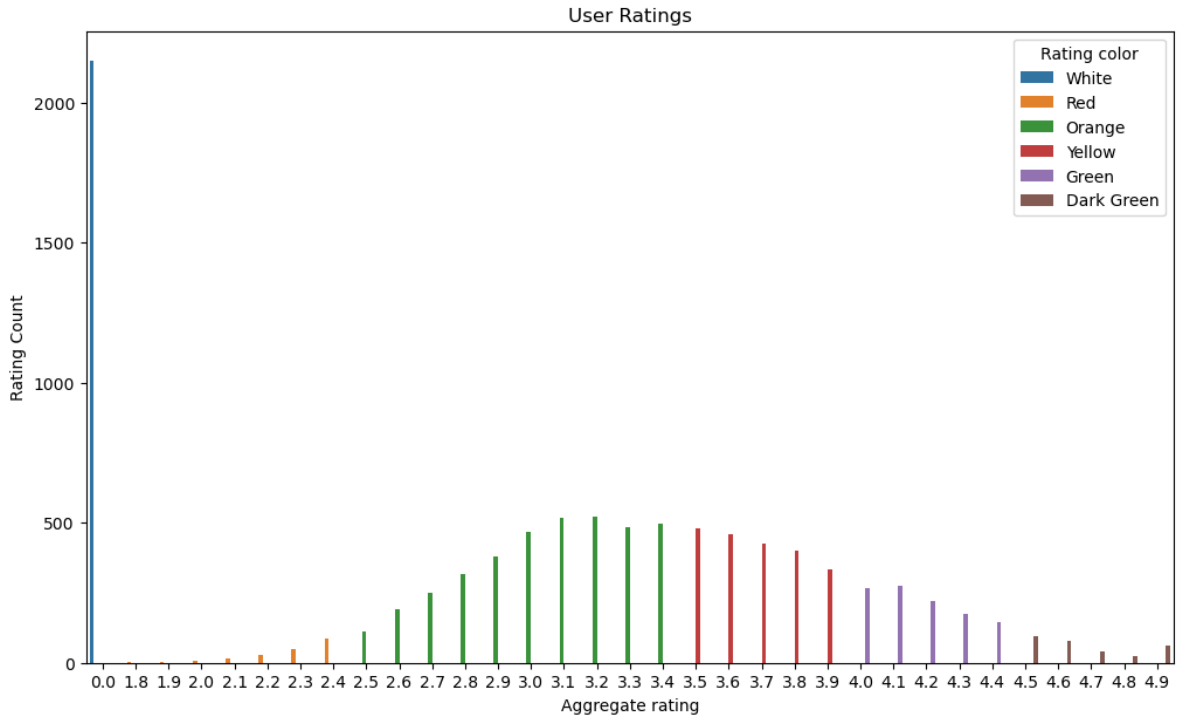

```
Displaying the user rating count in a bar plot. But this would be better if the ratings
are displayed in the same color as that of the rating color. Let us replot with each
rating's own color
```

In [27]:

```
#observing the same  bar plot in the rating colors


plt.rcParams['figure.figsize'] = (12,7)
sns.barplot(x='Aggregate rating',y='Rating Count',hue = 'Rating color',data=ratings)
plt.title('User Ratings')
```

Out[27]:

```
Text(0.5, 1.0, 'User Ratings')
```



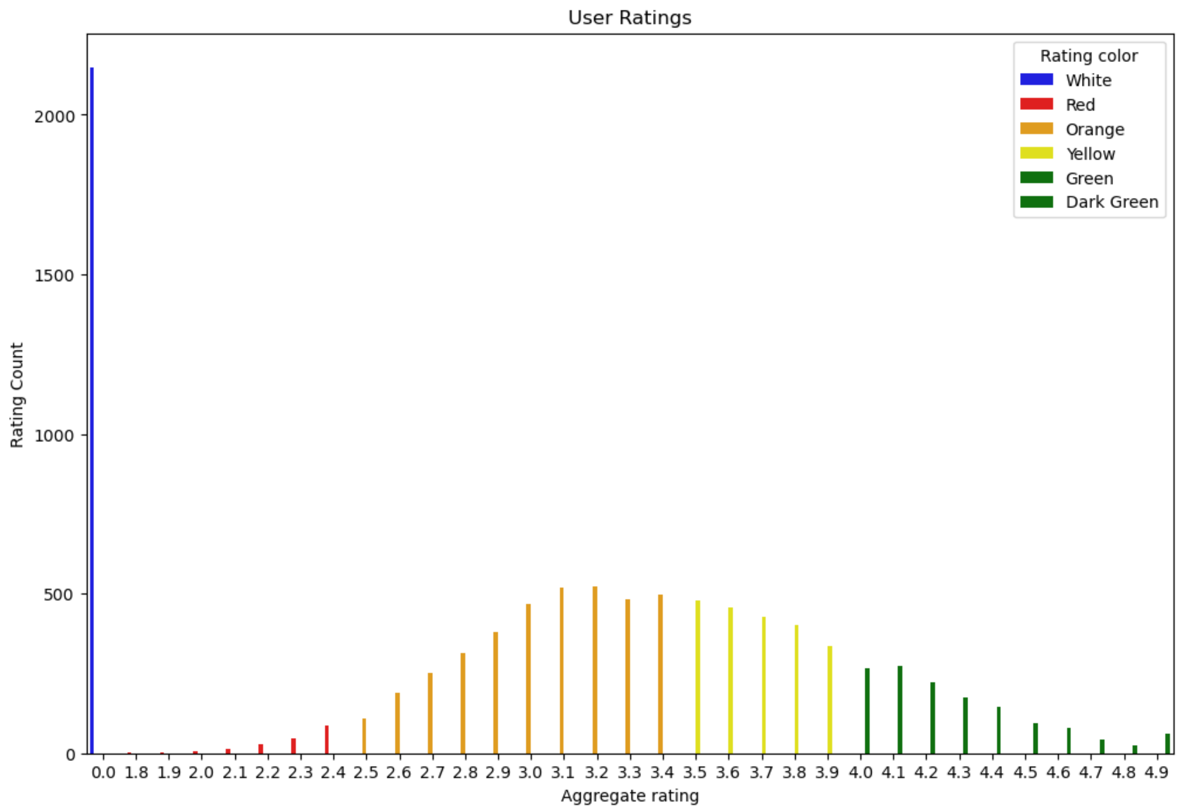
Colors are right but have been mapped wrong. Hence have to map them to the right ratings

In [28]:

```
#observing the same bar plot in the rating colors


plt.rcParams['figure.figsize'] = (12,8)
sns.barplot(x='Aggregate rating',y='Rating Count',hue = 'Rating color',data=ratings,palette
plt.title('User Ratings')
```

Out[28]:

```
Text(0.5, 1.0, 'User Ratings')
```




```
Perfect color mapping is done

INFERENCE- Count of the not rated ones are the highest(white-BLUE for visibility)

    1)Ratings between 4.5 to 4.9 is Excellent (Dark Green)
    2)Ratings between 4.0 to 4.4 is Very Good (Green)
    3)Ratings between 3.5 to 3.9 is Good (Yellow)
    4)Ratings between 2.5 to 3.4 is Average (Orange)
    5)Ratings between 1.8 to 2.4 is Poor (Red)
```

In [ ]:

4. COUNTRIES WITH ZERO RATINGS

In [29]:

```
#finding the names of the countries that has given zero rating

final_df.loc[final_df["Aggregate rating"] == 0].groupby("Country").size().reset_index().ren
    0:"Not Rated"
}).sort_values(by = "Not Rated")
```

Out[29]:

	Country	Not Rated
2	United Kingdom	1
3	United States	3
0	Brazil	5
1	India	2139

In [ ]:

```

```

INFERENCE--> Out of 2148 records , there are 2139 zero ratings which is from India(being the maximum)

5. CURRENCY USED IN EACH COUNTRY

In [30]:

```
#finding which currency is used in which country

final_df[["Currency", "Country"]].groupby("Country").first()
```

Out[30]:

	Currency
Country	
Australia	Dollar($)
Brazil	Brazilian Real(R$)
Canada	Dollar($)
India	Indian Rupees(Rs.)
Indonesia	Indonesian Rupiah(IDR)
New Zealand	NewZealand($)
Phillipines	Botswana Pula(P)
Qatar	Qatari Rial(QR)
Singapore	Dollar($)
South Africa	Rand(R)
Sri Lanka	Sri Lankan Rupee(LKR)
Turkey	Turkish Lira(TL)
UAE	Emirati Diram(AED)
United Kingdom	Pounds(Œ£)
United States	Dollar($)

In [ ]:

```

```

6. COUNTRIES THAT DO NOT HAVE ONLINE DELIVERY OPTION

In [31]:

```
#finding the countries that have online delivery


final_df[["Has Online delivery", "Country"]].groupby(["Has Online delivery", "Country"]).si
```

Out[31]:

	Has Online delivery	Country	0
0	No	Australia	24
1	No	Brazil	60
2	No	Canada	4
3	No	India	6229
4	No	Indonesia	21
5	No	New Zealand	40
6	No	Phillipines	22
7	No	Qatar	20
8	No	Singapore	20
9	No	South Africa	60
10	No	Sri Lanka	20
11	No	Turkey	34
12	No	UAE	32
13	No	United Kingdom	80
14	No	United States	434
15	Yes	India	2423
16	Yes	UAE	28

In [32]:

```
final_df.loc[final_df["Has Online delivery"]=="Yes", "Country"].unique()
```

Out[32]:

```
array(['UAE', 'India'], dtype=object)
```

INFERENCE --> Online deliveries are available in both India and UAE

In [ ]:

```

```

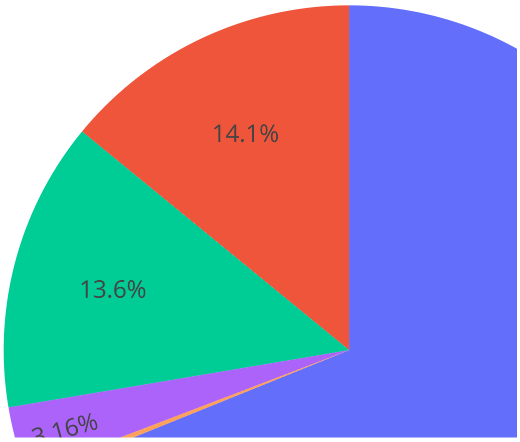
7. CITY DISTRIBUTION OF TOP 5 CITIES

In [33]:

```
city_name = final_df.City.value_counts().index
city_value = final_df.City.value_counts().values
```

In [34]:

```
#pie chart for cities distribution - displaying the top 5 cities

import plotly.graph_objects as go

labels = country_name
values = country_value

fig = go.Figure(data=[go.Pie(labels=city_name[:5], values=city_value[:5])])
fig.show()
```



INFERENCE - Maximum transactions happen in New Delhi of India

In [ ]:

```

```

8. TOP 10 CUISINES

In [ ]:

```

```

In [35]:

```
final_df.Cuisines.value_counts()[:10]
```

Out[35]:

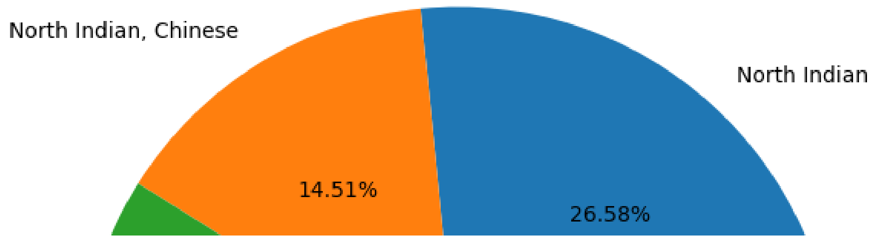
```
North Indian                      936
North Indian, Chinese             511
Chinese                           354
Fast Food                         354
North Indian, Mughlai             334
Cafe                              299
Bakery                            218
North Indian, Mughlai, Chinese    197
Bakery, Desserts                  170
Street Food                       149
Name: Cuisines, dtype: int64
```

In [36]:

```
#pie chart to display the top 10 cuisines

cuisine_val = final_df.Cuisines.value_counts()              #values
cuisine_label = final_df.Cuisines.value_counts().index      #labels

plt.pie(x = cuisine_val[:10],labels = cuisine_label[:10],autopct='%1.2f%%')
```

Out[36]:

```
([<matplotlib.patches.Wedge at 0x23fd907a0d0>,
  <matplotlib.patches.Wedge at 0x23fd907a7f0>,
  <matplotlib.patches.Wedge at 0x23fd907af10>,
  <matplotlib.patches.Wedge at 0x23fd9096670>,
  <matplotlib.patches.Wedge at 0x23fd9096d90>,
  <matplotlib.patches.Wedge at 0x23fd909f4f0>,
  <matplotlib.patches.Wedge at 0x23fd909fc10>,
  <matplotlib.patches.Wedge at 0x23fd8c78370>,
  <matplotlib.patches.Wedge at 0x23fd8c78a90>,
  <matplotlib.patches.Wedge at 0x23fd8c871f0>],
 [Text(0.7383739846958008, 0.8153550507137645, 'North Indian'),
  Text(-0.5794679314239953, 0.9349956772366362, 'North Indian, Chinese'),
  Text(-1.067309479615702, 0.26617752482593154, 'Chinese'),
  Text(-1.0185984499802057, -0.4152796620326146, 'Fast Food'),
  Text(-0.5935788454809928, -0.9261015895664211, 'North Indian, Mughlai'),
  Text(-0.005887079599915552, -1.0999842463843672, 'Cafe'),
  Text(0.4842062514572988, -0.9876964645323336, 'Bakery'),
  Text(0.808736477166136, -0.7456174022251013, 'North Indian, Mughlai, Chine
se'),
  Text(1.0055375294202338, -0.44597564611473206, 'Bakery, Desserts'),
  Text(1.090298995560443, -0.14576728123927227, 'Street Food')],
 [Text(0.4027494461977095, 0.4447391185711442, '26.58%'),
  Text(-0.316073417140361, 0.5099976421290743, '14.51%'),
  Text(-0.5821688070631101, 0.14518774081414446, '10.05%'),
  Text(-0.5555991545346576, -0.22651617929051704, '10.05%'),
  Text(-0.32377027935326874, -0.5051463215816842, '9.48%'),
  Text(-0.003211134327226664, -0.5999914071187457, '8.49%'),
  Text(0.26411250079489024, -0.5387435261085456, '6.19%'),
  Text(0.441128987545165, -0.40670040121369155, '5.59%'),
  Text(0.5484750160474001, -0.24325944333530836, '4.83%'),
  Text(0.5947085430329688, -0.07950942613051214, '4.23%')])
```



Most ordered cuisine is North Indian

In [ ]:

Problems

1)You are in the team incharge of developing the interface for the food app. you are tasked with creating something that enables #user to choose the category of the food. you have no idea what categories to use while designing the app. how can this dataset #help you solve this issue?

2)You are hearing rumors that people in India passionately dislike the restaurants offered in the app. find out whether this #rumor has any substance to it.

3)You are one of the developer working in the food app company. you decide to quit and follow your dreams of opening a restaurant. using this data how will you go about increasing your chances of succeding in this highly competitive business?

In [ ]:

we know that cuisines column has 9 values missing. as the number is not significant we can deal with it later.

Step:

```
1)Missing Values

2)Explore about the numerical variables

3)explore about categorical variables

4)Finding relationship between features.
```

In [ ]:

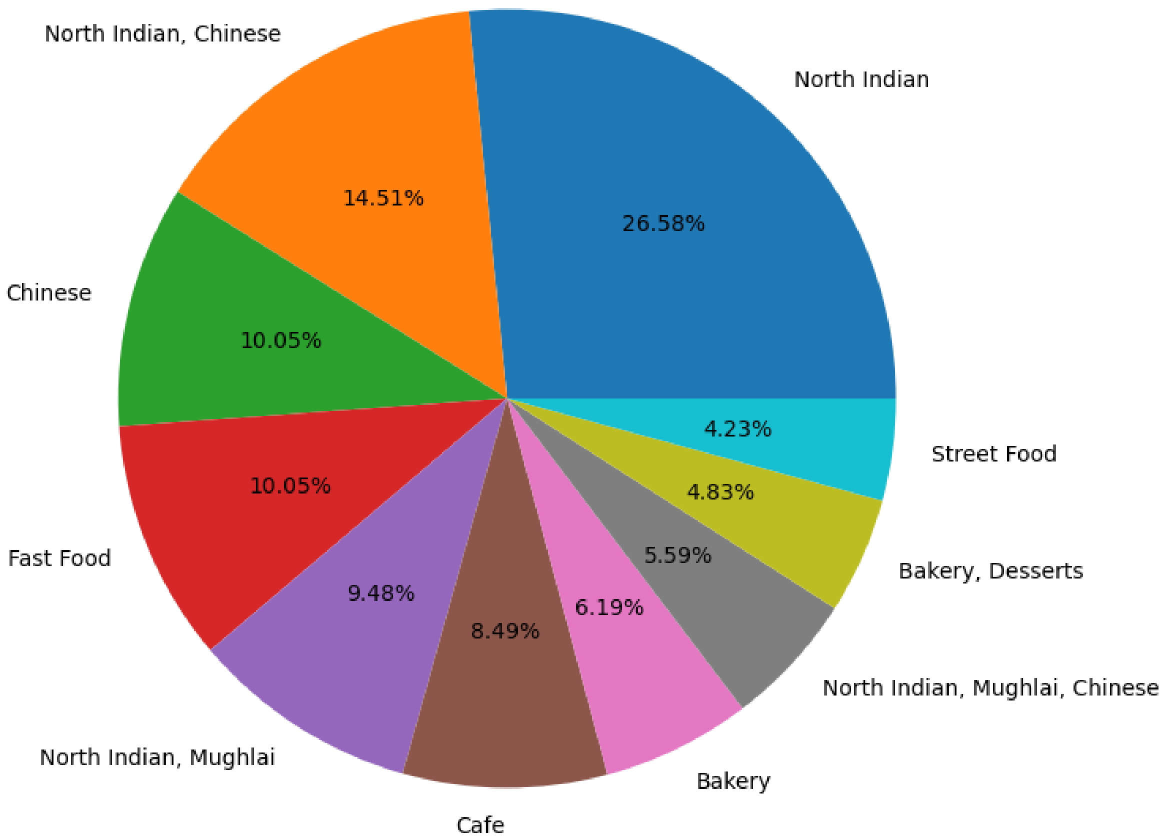
Number of unique cuisines offered? soln: we can use the cusinies column and extract all unique values from it using a simple python script

In [ ]:

```

```

In [37]:

```
#pie chart to display the top 10 cuisines

cuisine_val = final_df.Cuisines.value_counts()           #values
cuisine_label = final_df.Cuisines.value_counts().index      #labels

plt.pie(x = cuisine_val[:10],labels = cuisine_label[:10],autopct='%1.2f%%')
plt.show()
```



In [38]:

```
df['Cuisines'].unique
```

Out[38]:

```
<bound method Series.unique of 0              French, Japanese, Desserts
1                                Japanese
2        Seafood, Asian, Filipino, Indian
3                         Japanese, Sushi
4                        Japanese, Korean
                      ...
9546                              Turkish
9547      World Cuisine, Patisserie, Cafe
9548                Italian, World Cuisine
9549                       Restaurant Cafe
9550                                 Cafe
Name: Cuisines, Length: 9551, dtype: object>
```

In [39]:

```
from pprint import pprint
```

In [40]:

```
cuisines_total = df['Cuisines']
texts = []
hash_map = set()
cuisines_total.dropna(inplace=True)
for i in cuisines_total:
    for j in str(i).split(', '):
        if j not in hash_map:
            texts.append(j.lower())
            hash_map.add(j)
pprint(texts)
```

```
['french',
 'japanese',
 'desserts',
 'seafood',
 'asian',
 'filipino',
 'indian',
 'sushi',
 'korean',
 'chinese',
 'european',
 'mexican',
 'american',
 'ice cream',
 'cafe',
 'italian',
 'pizza',
 'bakery',
 'mediterranean',
 'fast food',
```

Conclusion

North Indian Dish is most Ordered Cuisine.

In [ ]:

```

```

In [ ]:

```

```

let's see how ratings are distributed?

if people are passionately disliking the restaurants on the app there is a good chance they will leave a negative rating. therefore let's see how well the restaurants are faring based on ratings.

First we need to filter out ratings outside of India and separate the columns representing ratings. The country code of India is given to be 1.

In [41]:

```
ratings1 = final_df.groupby(['Aggregate rating','Rating color','Rating text']).size().reset
ratings1
```

Out[41]:

	Aggregate rating	Rating color	Rating text	Rating Count
0	0.0	White	Not rated	2148
1	1.8	Red	Poor	1
2	1.9	Red	Poor	2
3	2.0	Red	Poor	7
4	2.1	Red	Poor	15
5	2.2	Red	Poor	27
6	2.3	Red	Poor	47
7	2.4	Red	Poor	87
8	2.5	Orange	Average	110
9	2.6	Orange	Average	191
10	2.7	Orange	Average	250
11	2.8	Orange	Average	315
12	2.9	Orange	Average	381
13	3.0	Orange	Average	468
14	3.1	Orange	Average	519
15	3.2	Orange	Average	522
16	3.3	Orange	Average	483
17	3.4	Orange	Average	498
18	3.5	Yellow	Good	480
19	3.6	Yellow	Good	458
20	3.7	Yellow	Good	427
21	3.8	Yellow	Good	400
22	3.9	Yellow	Good	335
23	4.0	Green	Very Good	266
24	4.1	Green	Very Good	274
25	4.2	Green	Very Good	221
26	4.3	Green	Very Good	174
27	4.4	Green	Very Good	144
28	4.5	Dark Green	Excellent	95
29	4.6	Dark Green	Excellent	78
30	4.7	Dark Green	Excellent	42
31	4.8	Dark Green	Excellent	25
32	4.9	Dark Green	Excellent	61

In [42]:

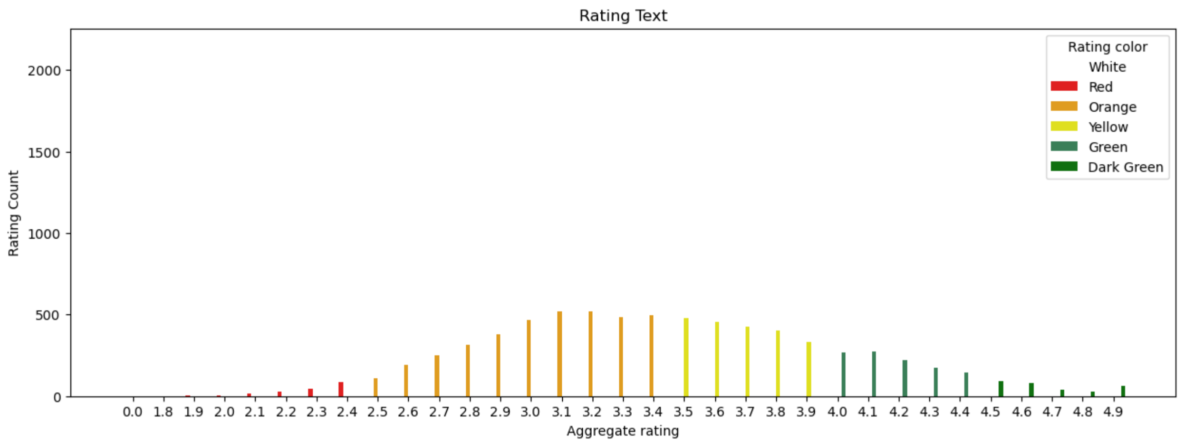
```
from numpy import median
```

In [43]:

```
plt.figure(figsize=(15,5))
sns.barplot(x=ratings1['Aggregate rating'],y=ratings1['Rating Count'],hue=ratings1['Rating
plt.title('Rating Text')
plt.plot()
```

Out[43]:

```
[]
```



In [ ]:

In [44]:

```
# Let's calculate the mean and standard deviation of the data in order to explain it better
```

In [45]:

```
meanrat = ratings1['Aggregate rating'].mean()
stdrat = ratings1['Aggregate rating'].std()
print("Mean rating : ",meanrat, stdrat)
```

```
Mean rating :  3.2484848484848485 1.092051169852291
```

the mean rating is around 3.24 Points and standard deviation is 1.09 Points.

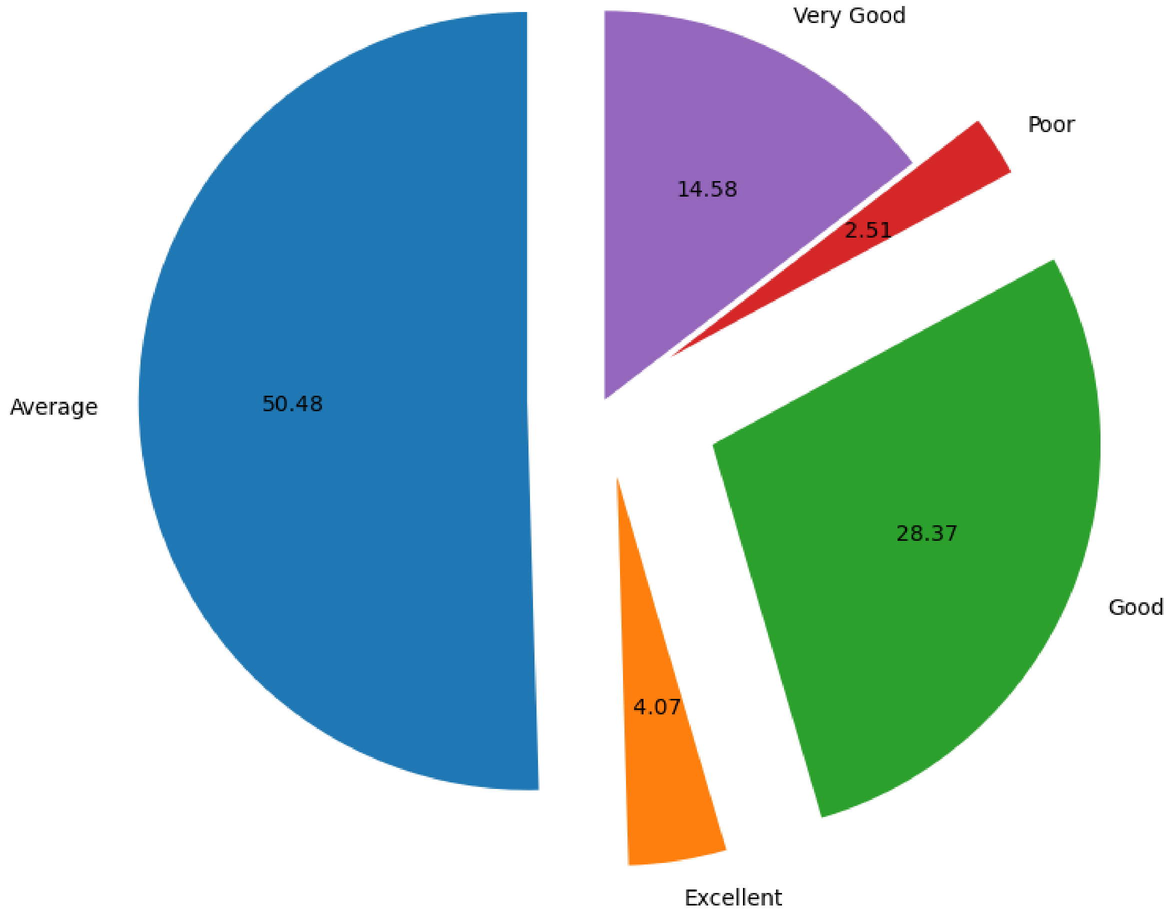
In [ ]:

In [46]:

```
# Pie ploting the data

temp = ratings1[['Rating text', 'Rating Count']].groupby(['Rating text']).sum()
temp.drop('Not rated', axis=0, inplace=True)
```

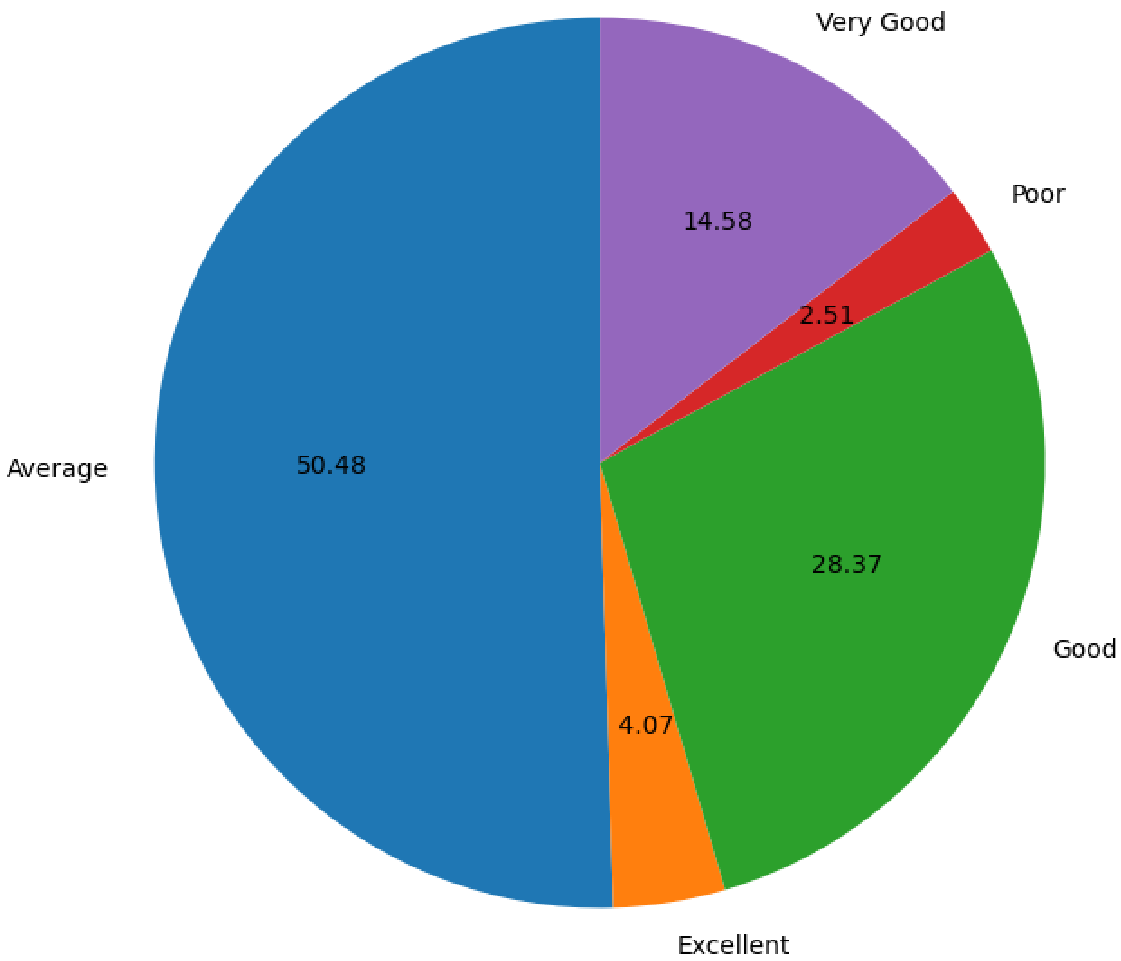
In [47]:

```
plt.figure(figsize=(12,8))
plt.pie(temp['Rating Count'], labels = ['Average', 'Excellent', 'Good', 'Poor', 'Very Good'
plt.show()
```



In [48]:

```
plt.figure(figsize=(12,8))
plt.pie(temp['Rating Count'],
        labels = ['Average', 'Excellent', 'Good', 'Poor', 'Very Good'],
        startangle=90,
        #explode=(0.2,0.2,0.3,0.2,0),
        autopct='%5.2f')
plt.show()
```



In [49]:

```
# importing Libaries
import pylab as pl
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
```

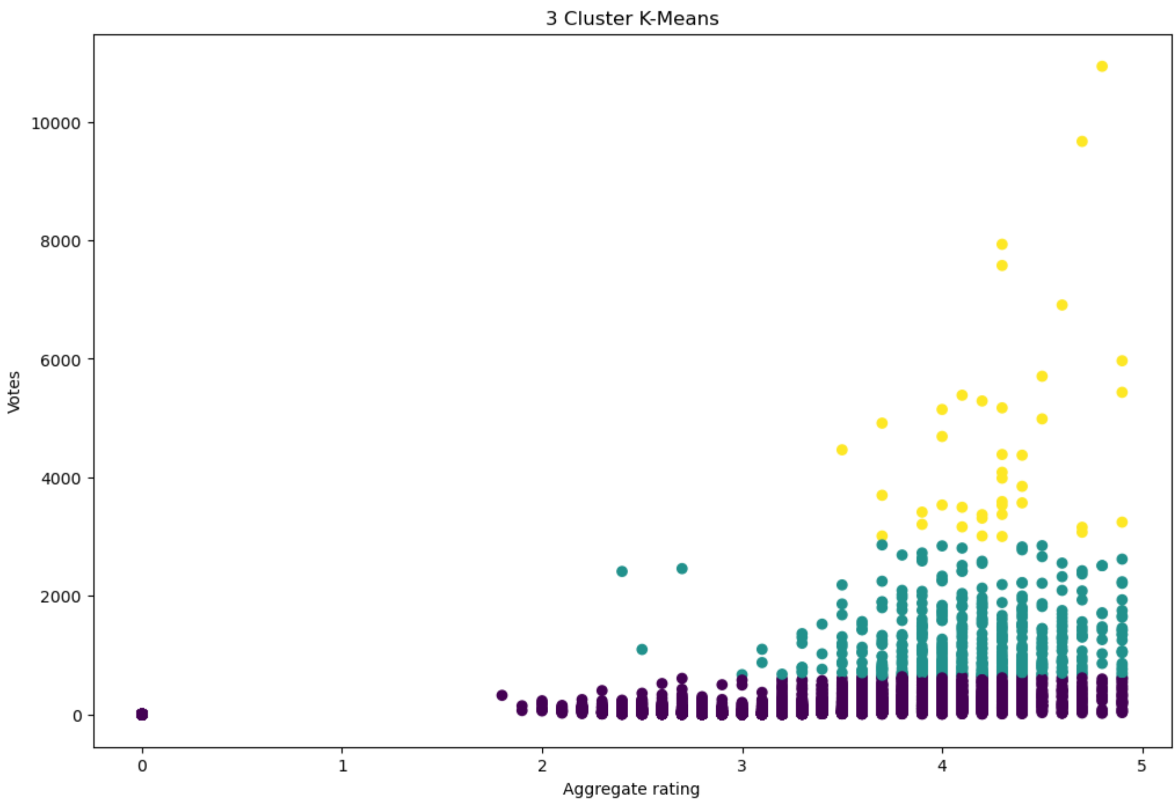
In [50]:

```
X1=df[['Aggregate rating']]
Y1=df[['Votes']]
```

In [51]:

```
kmeans=KMeans(n_clusters=3)

kmeansoutput=kmeans.fit(Y1)

print(kmeansoutput)
pl.figure('3 Cluster K-Means')
pl.scatter(X1, Y1, c=kmeansoutput.labels_)
#pl.scatter(pca_c[:, 0], pca_d[:, 0], c=kmeansoutput.labels_)
pl.xlabel('Aggregate rating')
pl.ylabel('Votes')
pl.title('3 Cluster K-Means')
pl.show()
```

```
KMeans(n_clusters=3)
```



Conclusion

1)The range of ratings for categories are as follows.

```
A] 1.8 - 2.4: poor
B] 2.5 - 3.4: Average
C] 3.5 - 3.9: Good
D] 4.0 - 4.4: Very Good
E] 4.4 - 4.9: Excellent
```

2)The mean rating is 3.24 and 95% of the values lie between 2.15 and 4.34.

```
Due to low number of poor ratings on restaurants it can be concluded that the rumor is
unsubstantiated.
```

In [ ]:

```

```

Finding the relationship between different variables and Ratings.

we can use Data Analysis to check what features are useful to implement in a business to get maximum ratings.

let's start by converting some values into 1 and 0.

In [52]:

```
tt = {'Yes': 1, 'No': 0}
col = ['Has Table booking', 'Has Online delivery', 'Is delivering now', 'Switch to order me
for c in col:
    df.replace({c:tt}, inplace=True)
```

In [53]:

```
sumlist = df[col].sum()
sumlist
```

Out[53]:

```
Has Table booking       1158
Has Online delivery     2451
Is delivering now         34
Switch to order menu       0
dtype: int64
```

Because Switch to order menu is empty we can just drop it.

In [54]:

```
sumlist.drop(['Switch to order menu'], inplace=True)
```

In [55]:

```
df.drop('Switch to order menu', axis = 1, inplace=True)
df.head()
```

Out[55]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longit
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...	121.027
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...	121.014
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...	121.056
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...	121.056
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...	121.057

In [56]:

```
dfrel = df[['Average Cost for two', 'Has Table booking', 'Has Online delivery', 'Is deliver
dfrel
```

Out[56]:

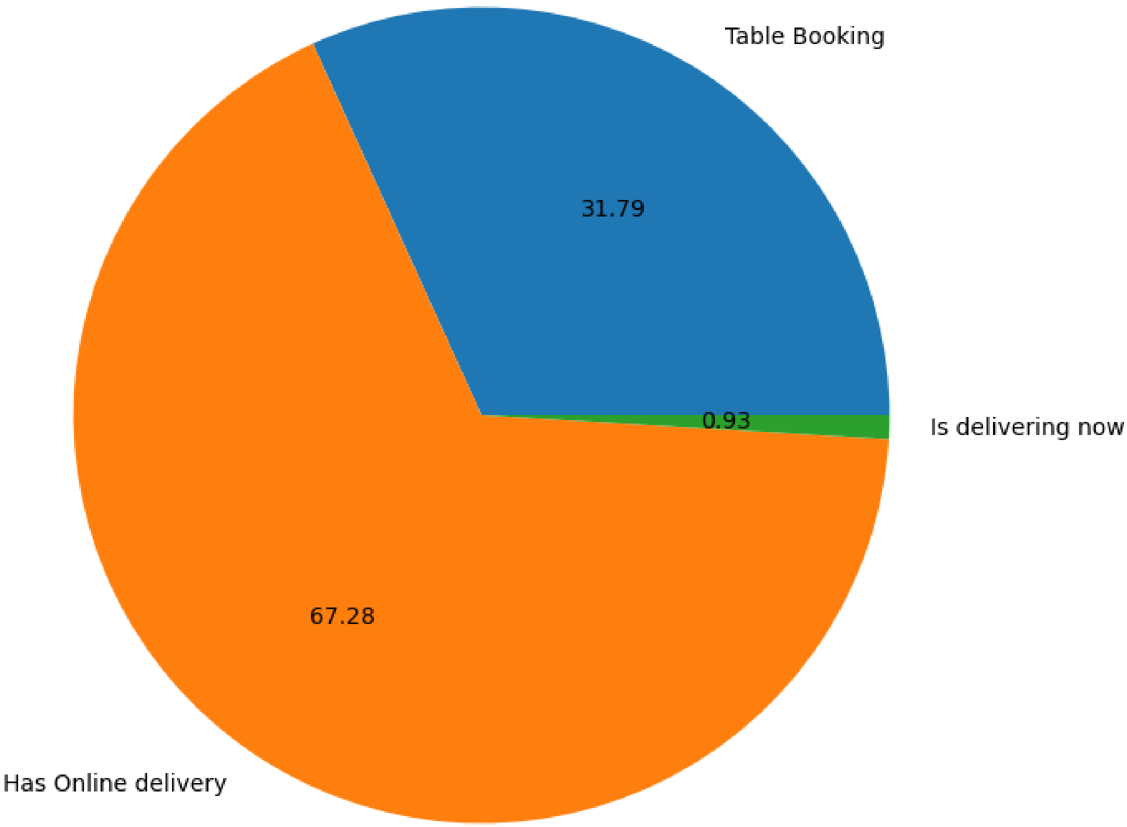
	Average Cost for two	Has Table booking	Has Online delivery	Is delivering now	Price range	Aggregate rating	Votes
0	1100	1	0	0	3	4.8	314
1	1200	1	0	0	3	4.5	591
2	4000	1	0	0	4	4.4	270
3	1500	0	0	0	4	4.9	365
4	1500	1	0	0	4	4.8	229
...	...	...	...	...	...	...	...
9546	80	0	0	0	3	4.1	788
9547	105	0	0	0	3	4.2	1034
9548	170	0	0	0	4	3.7	661
9549	120	0	0	0	4	4.0	901
9550	55	0	0	0	2	4.0	591

9551 rows × 7 columns

Now let's visualize what features are offered.

In [57]:

```
# pie plot to see distribution
plt.pie(sumlist, labels=['Table Booking', 'Has Online delivery', 'Is delivering now'],autop
plt.show()
```



In [58]:

```
dfwozeros = df[df['Aggregate rating'] != 0]
```

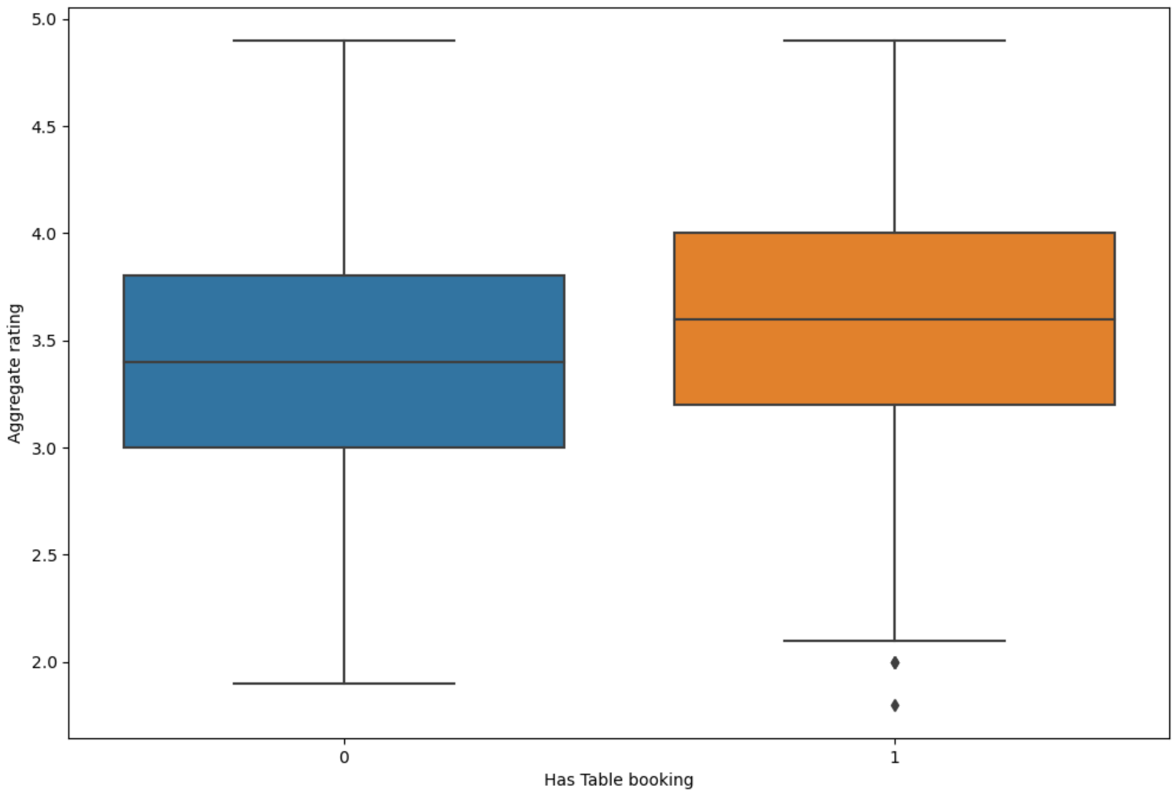
let's see if Online Delivery Affects rating.

In [59]:

```
sns.boxplot(x=col[0], y='Aggregate rating', data=dfwozeros)
```

Out[59]:

```
<AxesSubplot:xlabel='Has Table booking', ylabel='Aggregate rating'>
```

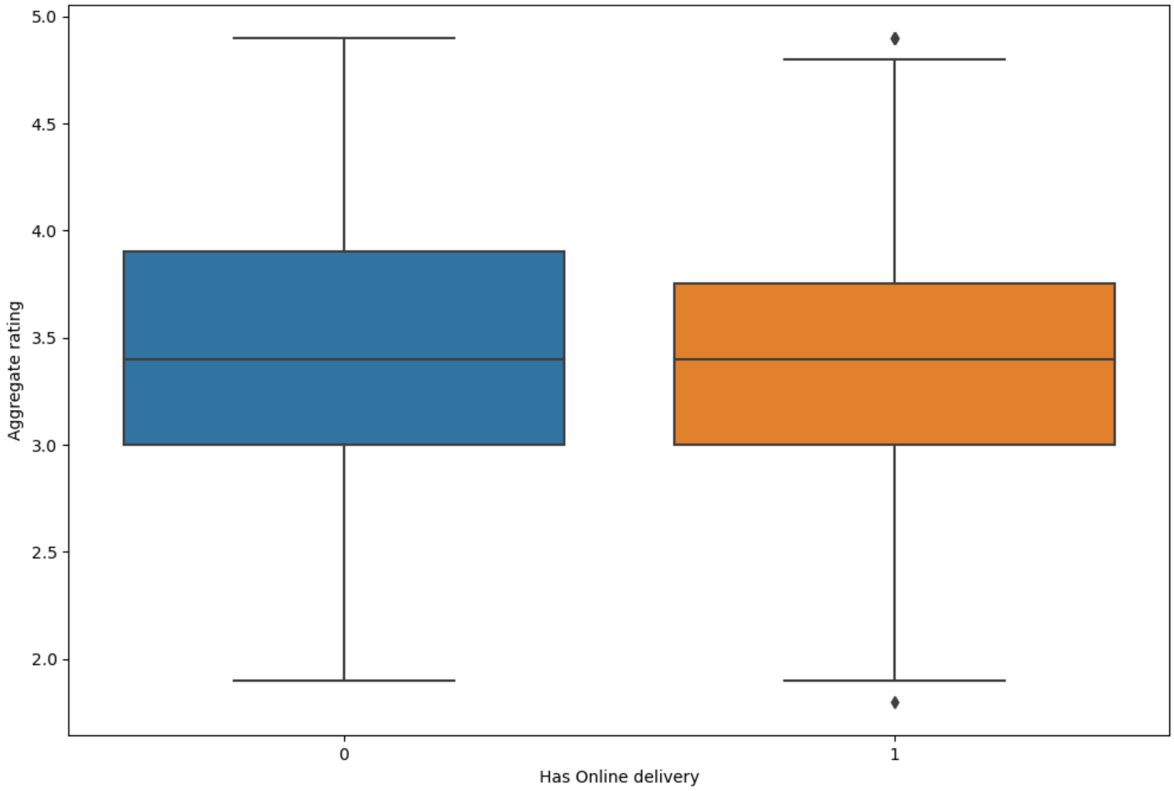


In [60]:

```
sns.boxplot(x=col[1], y='Aggregate rating', data=dfwozeros)
```

Out[60]:

```
<AxesSubplot:xlabel='Has Online delivery', ylabel='Aggregate rating'>
```

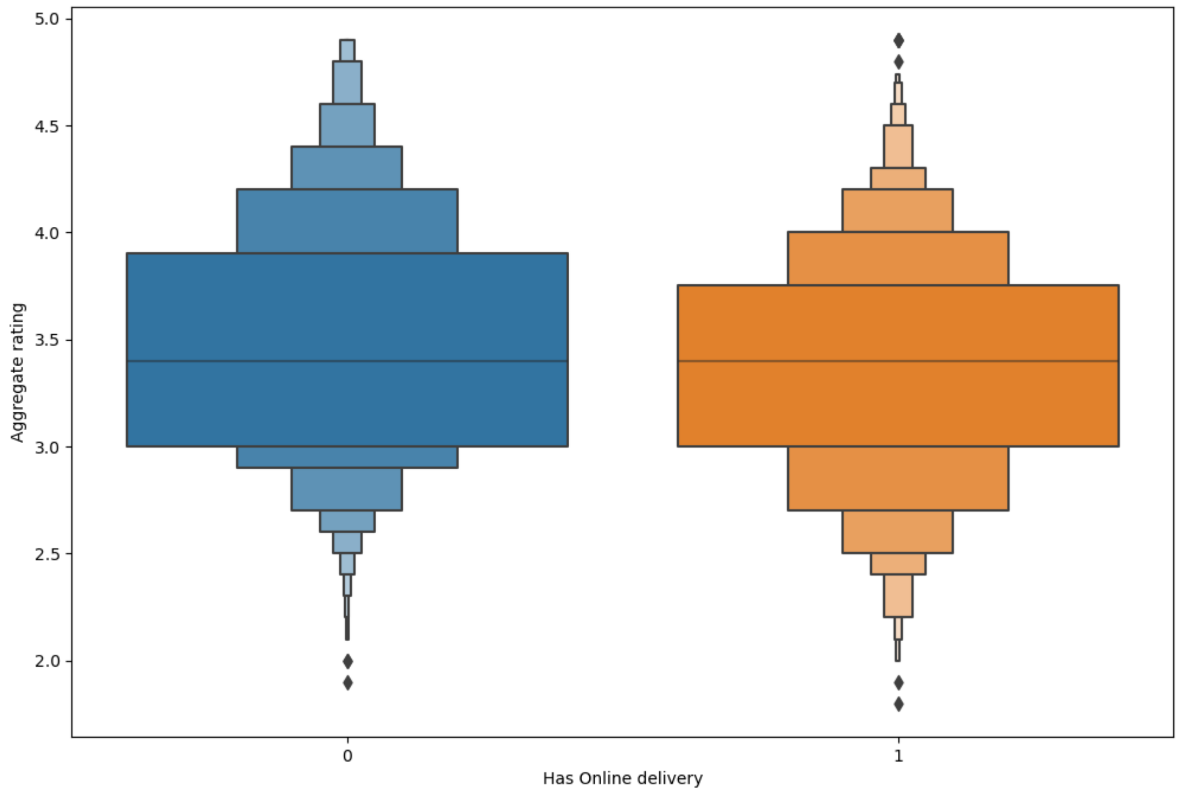


In [61]:

```
sns.boxenplot(x=col[1], y='Aggregate rating', data=dfwozeros)
# Boxenplot is used for better visualisation for data distribution
```

Out[61]:

```
<AxesSubplot:xlabel='Has Online delivery', ylabel='Aggregate rating'>
```

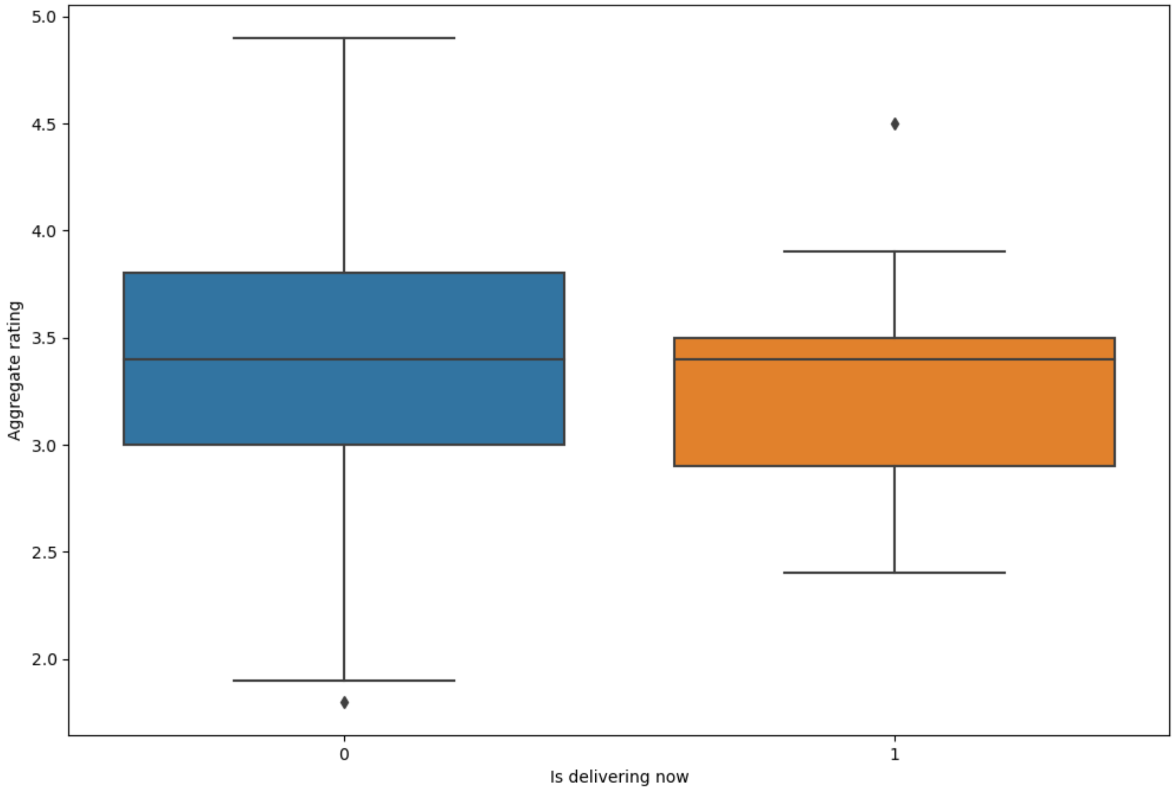


In [62]:

```
sns.boxplot(x=col[2], y='Aggregate rating', data=dfwozeros)
```

Out[62]:

```
<AxesSubplot:xlabel='Is delivering now', ylabel='Aggregate rating'>
```

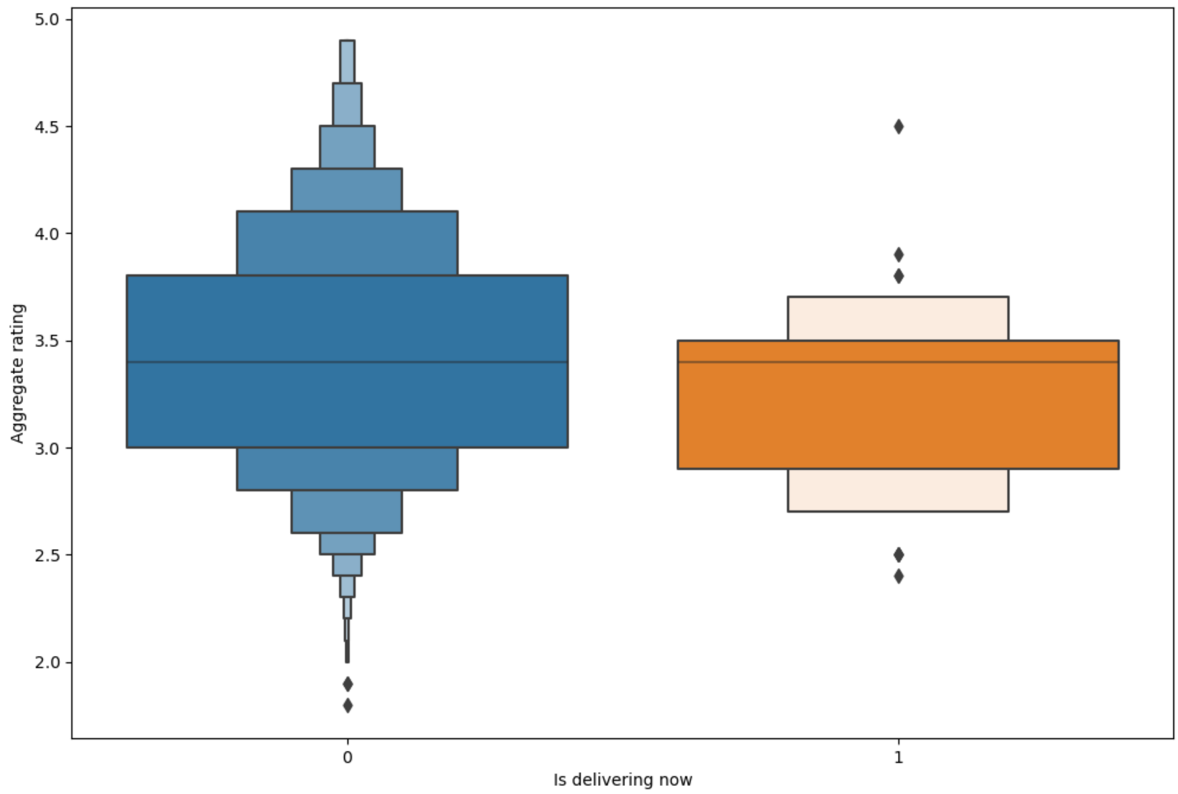


In [63]:

```
sns.boxenplot(x=col[2], y='Aggregate rating', data=dfwozeros)
```

Out[63]:

```
<AxesSubplot:xlabel='Is delivering now', ylabel='Aggregate rating'>
```



Conclusion

1) we can observe that online booking is a common features in restaurants

2) we can observe that these features don't provide any appreciable difference to the aggregate ratings.

3) Implementing these feature doesn't provide a appreciable difference to the rating of the restaurants but online booking is still a good idea to implement

In [ ]:

Let's compare with Price range.

Concentration of Price Range.

In [64]:

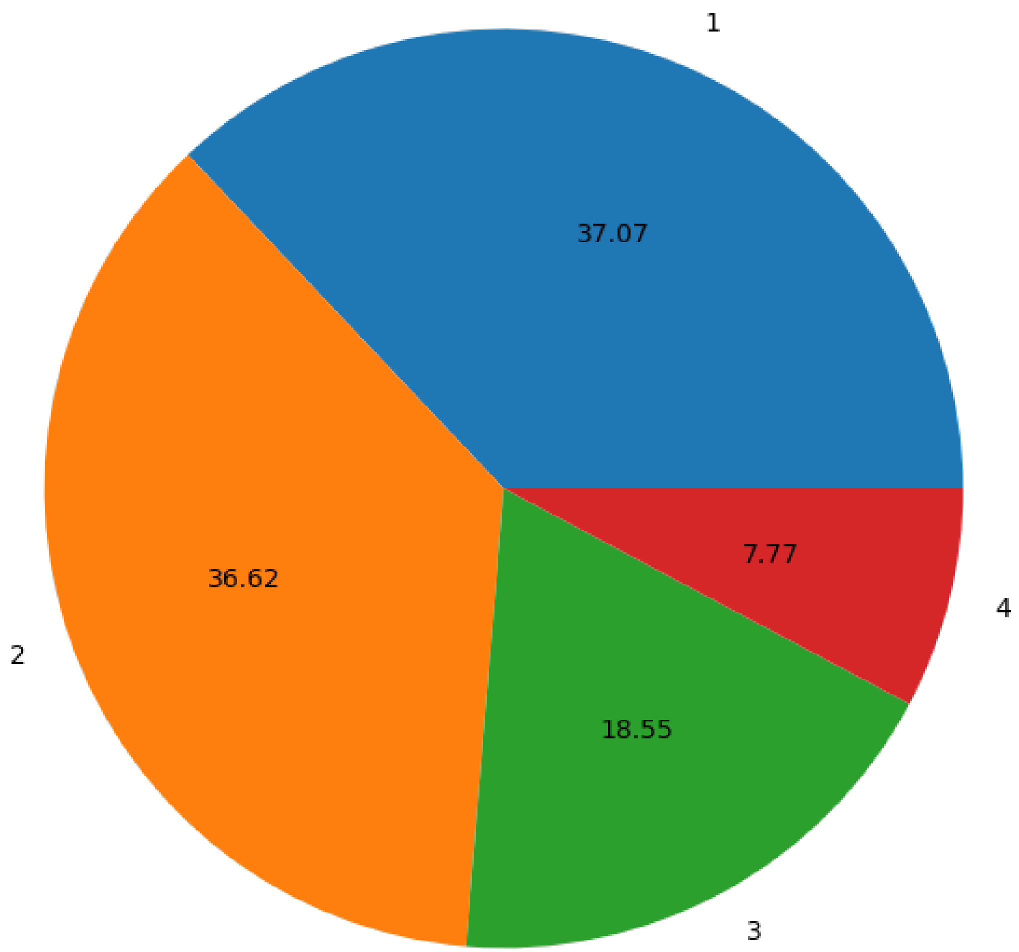
```
sumlist = dfwozeros['Price range'].value_counts()
sumlist
```

Out[64]:

```
1    2744
2    2711
3    1373
4     575
Name: Price range, dtype: int64
```

In [65]:

```
# pie plot for seeing distribution
plt.pie(sumlist, labels=[1, 2, 3, 4], autopct='%1.2f')
plt.show()
```

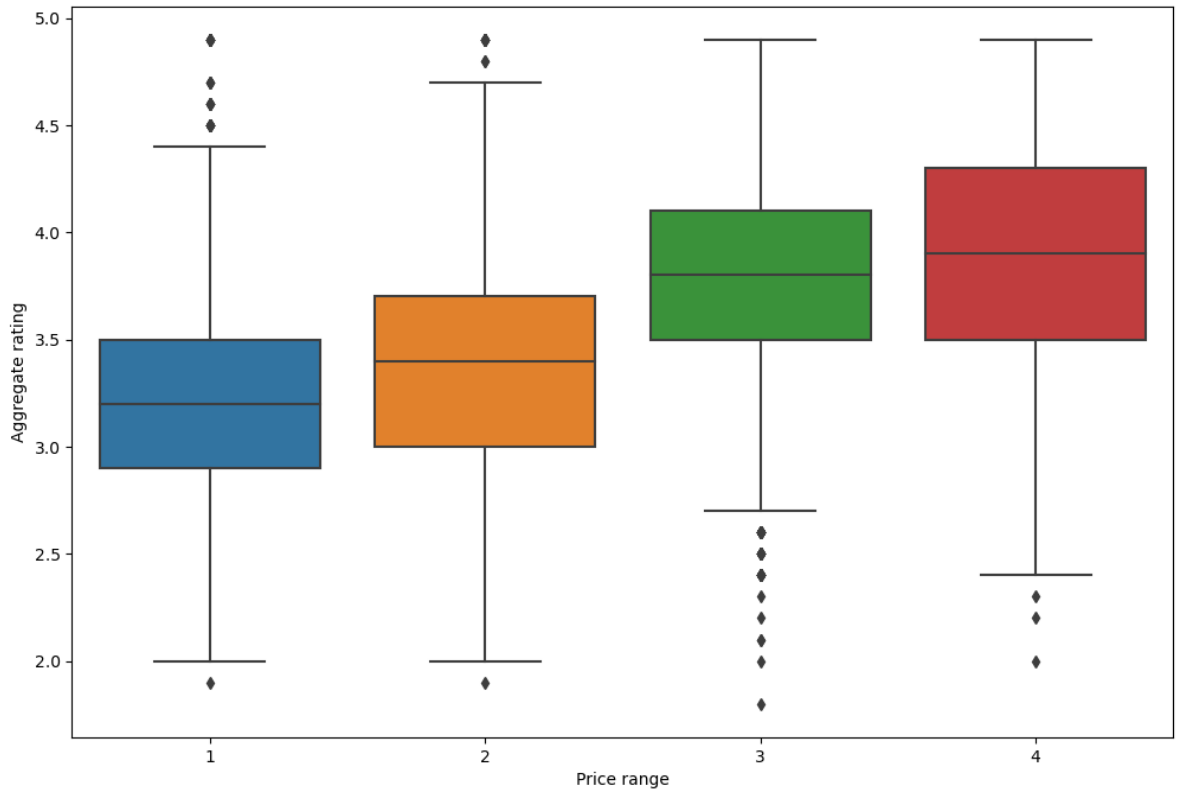


In [66]:

```
sns.boxplot(x='Price range', y='Aggregate rating', data=dfwozeros)
```

Out[66]:

```
<AxesSubplot:xlabel='Price range', ylabel='Aggregate rating'>
```

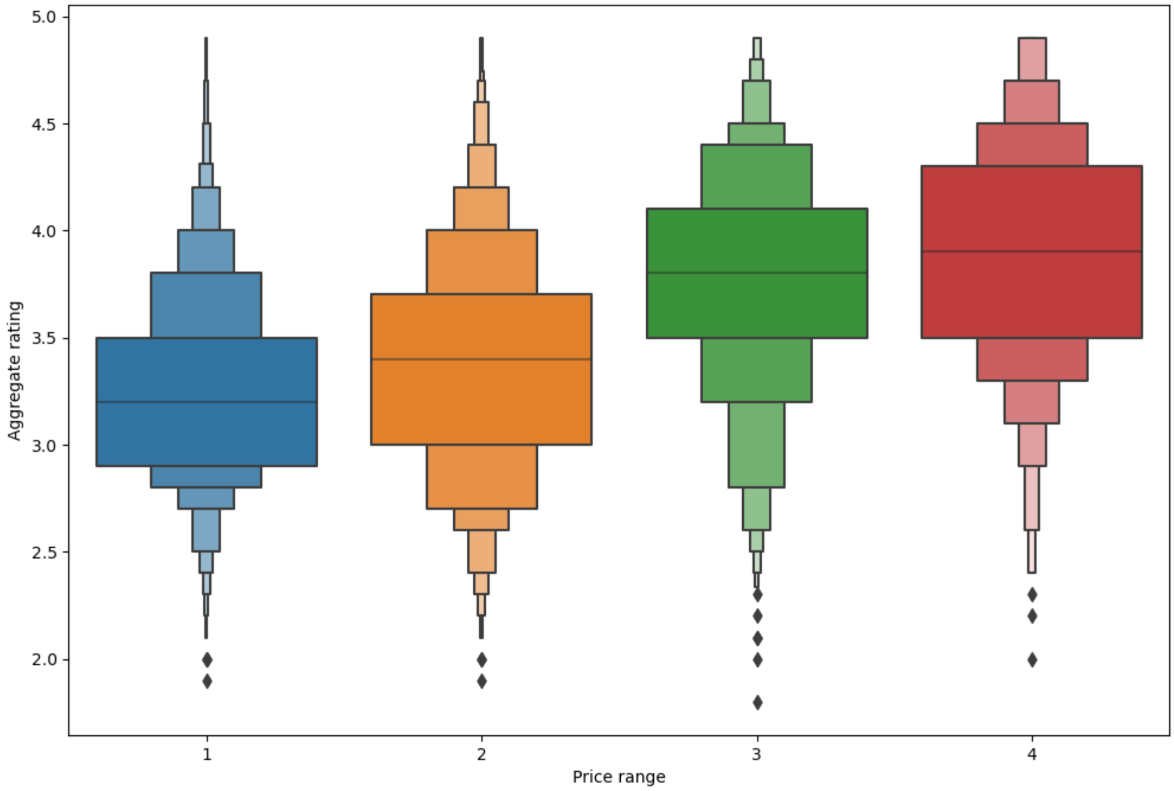


In [67]:

```
sns.boxenplot(x='Price range', y='Aggregate rating', data=dfwozeros)
## it show better distribution and outlier than box plot
```

Out[67]:

```
<AxesSubplot:xlabel='Price range', ylabel='Aggregate rating'>
```



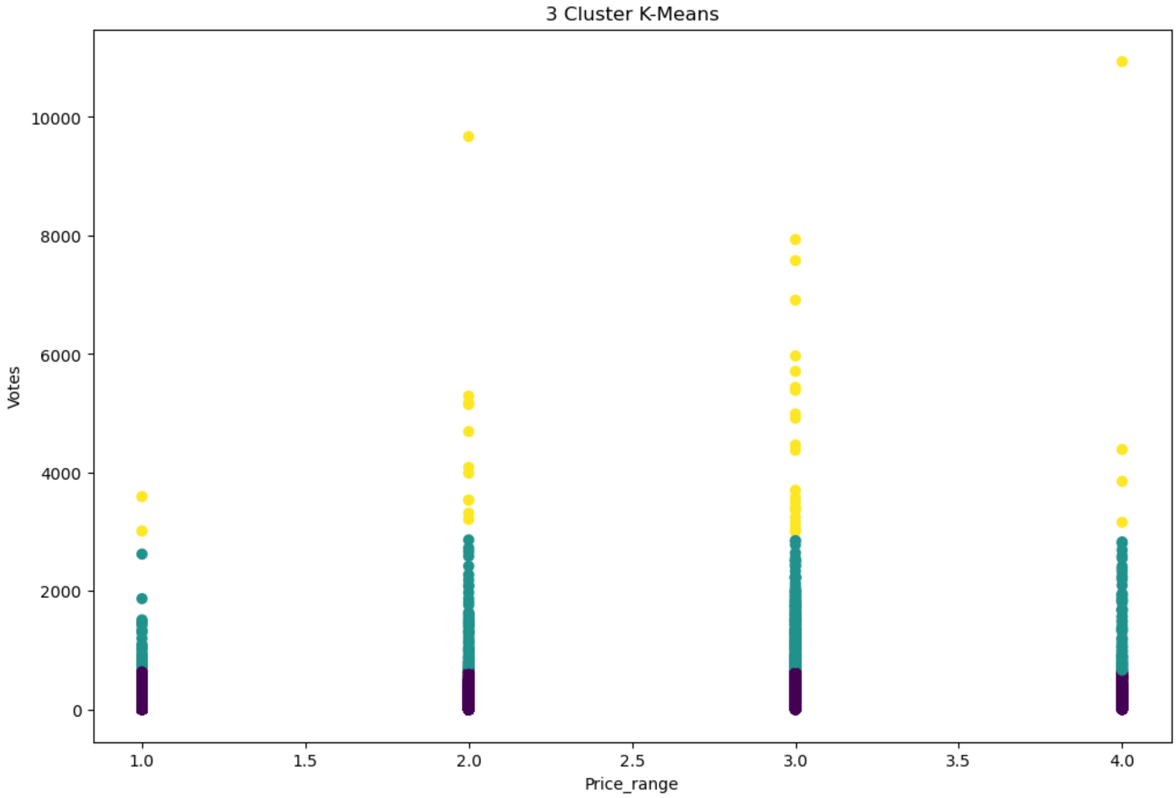
In [68]:

```
X2=df[['Price range']]
Y2=df[['Votes']]
```

In [69]:

```
kmeans=KMeans(n_clusters=3)

kmeansoutput=kmeans.fit(Y2)

print(kmeansoutput)
pl.figure('3 Cluster K-Means')
pl.scatter(X2, Y2, c=kmeansoutput.labels_)
#pl.scatter(pca_c[:, 0], pca_d[:, 0], c=kmeansoutput.labels_)
pl.xlabel('Price_range')
pl.ylabel('Votes')
pl.title('3 Cluster K-Means')
pl.show()
```

```
KMeans(n_clusters=3)
```



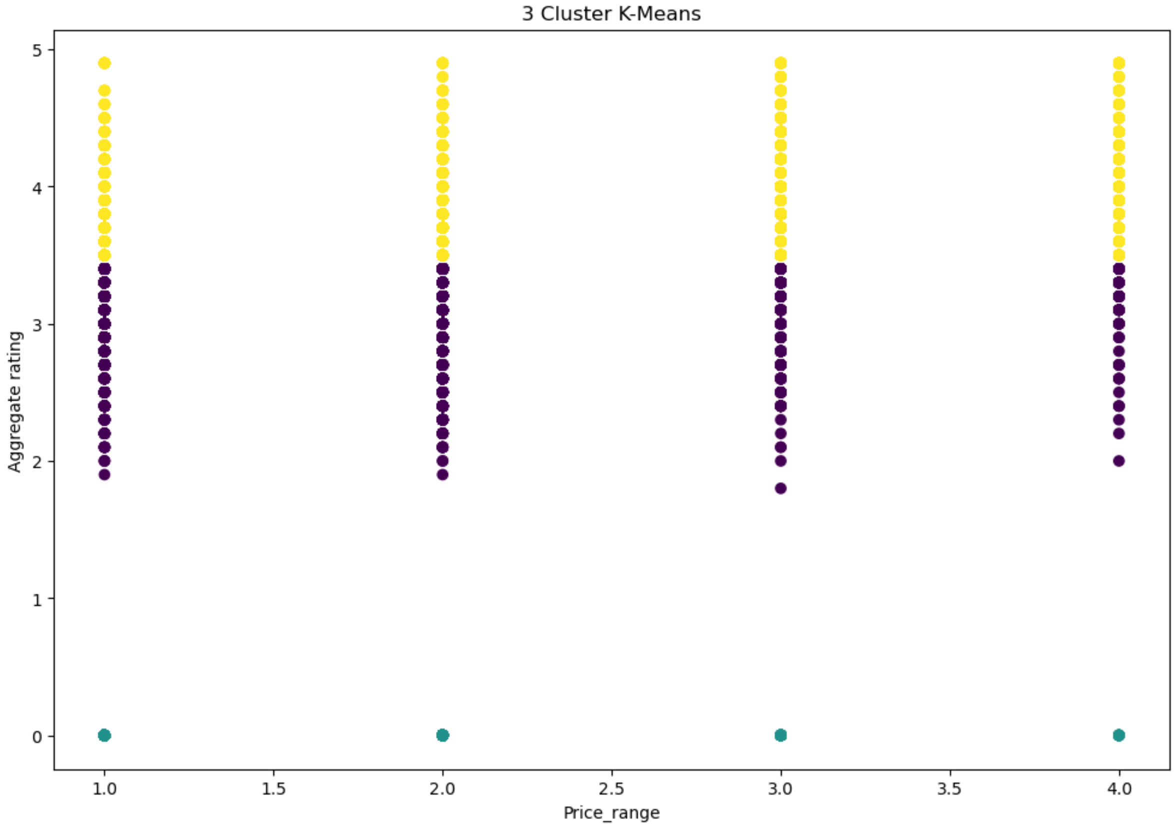
In [70]:

```
X3=df[['Price range']]
Y3=df[['Aggregate rating']]
```

In [71]:

```
kmeans=KMeans(n_clusters=3)

kmeansoutput=kmeans.fit(Y3)

print(kmeansoutput)
pl.figure('3 Cluster K-Means')
pl.scatter(X3, Y3, c=kmeansoutput.labels_)
#pl.scatter(pca_c[:, 0], pca_d[:, 0], c=kmeansoutput.labels_)
pl.xlabel('Price_range')
pl.ylabel('Aggregate rating')
pl.title('3 Cluster K-Means')
pl.show()
```

```
KMeans(n_clusters=3)
```



Conclusion

Price Rating 4 get's the highest average rating and there is an increase in ratings with an increase in Price range.

In [ ]:

One Country Analysis

As We know from above India has Most Order data.

so Let do Some Exploration on that

In [ ]:

```

```

In [72]:

```
# Creating One Country data set
one_selected_country_dataset = final_df[final_df['Country Code']==1]
one_selected_country_dataset.head()
```

Out[72]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude
624	3400025	Jahanpanah	1	Agra	E 23, Shopping Arcade, Sadar Bazaar, Agra Cant...	Agra Cantt	Agra Cantt, Agra	78.011544	27.161661
625	3400341	Rangrezz Restaurant	1	Agra	E-20, Shopping Arcade, Sadar Bazaar, Agra Cant...	Agra Cantt	Agra Cantt, Agra	0.000000	0.000000
626	3400005	Time2Eat - Mama Chicken	1	Agra	Main Market, Sadar Bazaar, Agra Cantt, Agra	Agra Cantt	Agra Cantt, Agra	78.011608	27.160832
627	3400021	Chokho Jeeman Marwari Jain Bhojanalya	1	Agra	1/48, Delhi Gate, Station Road, Raja Mandi, Ci...	Civil Lines	Civil Lines, Agra	77.998092	27.195928
628	3400017	Pinch Of Spice	1	Agra	23/453, Opposite Sanjay Cinema, Wazipura Road,...	Civil Lines	Civil Lines, Agra	78.007553	27.201725

5 rows × 22 columns

In [73]:

```
# Order count Locality vise


one_selected_country_dataset['Locality'].value_counts()
```

Out[73]:

```
Connaught Place                     122
Rajouri Garden                       99
Shahdara                             87
Defence Colony                       86
Malviya Nagar                        85
                                   ... 
Mansingh Road                         1
12th Square Building, Banjara Hills   1
Gachibowli                            1
Holiday Inn Express & Suites          1
Waltair Uplands                       1
Name: Locality, Length: 784, dtype: int64
```

In [74]:

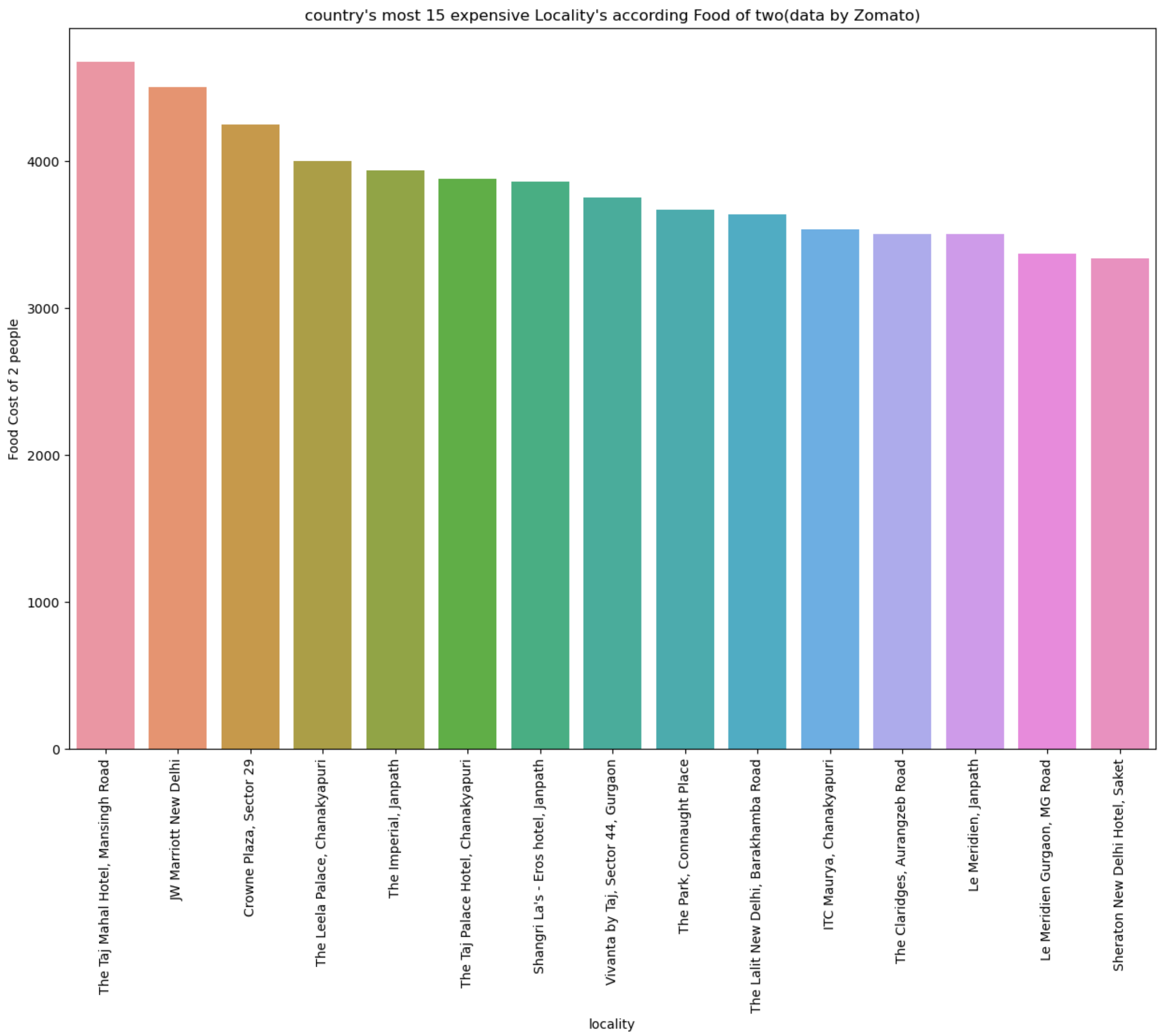
```
one_selected_country_dataset['Average Cost for two'].value_counts()
```

Out[74]:

```
500     893
300     885
400     849
200     677
600     650
       ... 
260       1
7000      1
6500      1
720       1
2350      1
Name: Average Cost for two, Length: 79, dtype: int64
```

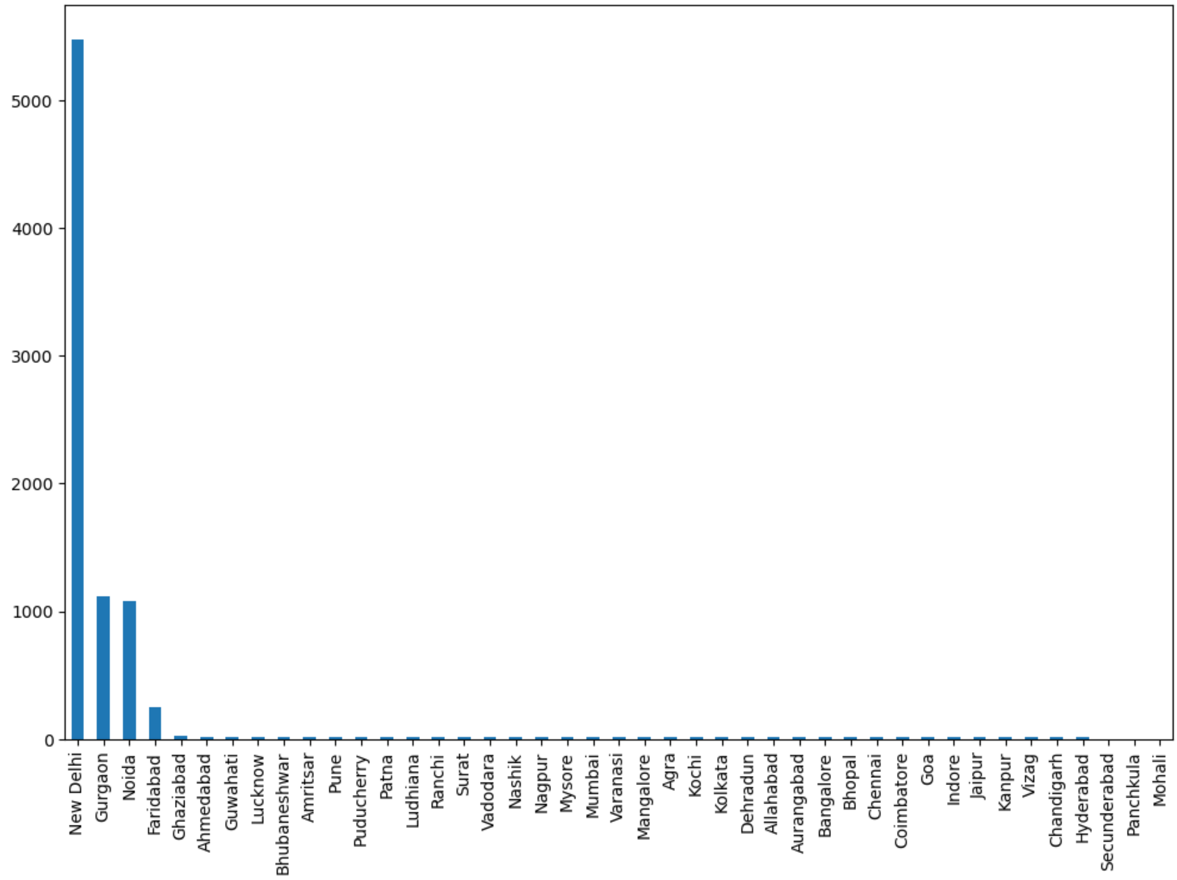
In [75]:

```
## For finding Most Expensive Locality

one_selected_country_dataset['Average Cost for two'] = one_selected_country_dataset['Averag
locality_list = list(one_selected_country_dataset['Locality'].unique())
average_cost_of_2_by_locality=[]
for locality in locality_list:
    x = one_selected_country_dataset[one_selected_country_dataset['Locality']==locality]
    avg_cost = sum(x['Average Cost for two'])/len(x)
    average_cost_of_2_by_locality.append(avg_cost)
data = pd.DataFrame({'locality':locality_list,'Avg_food_cost_of_two':average_cost_of_2_by_l
new_index = (data['Avg_food_cost_of_two'].sort_values(ascending=False)).index.values
sorted_data = data.reindex(new_index)

plt.figure(figsize=(15,10))
sns.barplot(x=sorted_data['locality'][:15],y=sorted_data['Avg_food_cost_of_two'][:15])
plt.xticks(rotation=90)
plt.xlabel("locality")
plt.ylabel("Food Cost of 2 people")
plt.title("country's most 15 expensive Locality's according Food of two(data by Zomato)")
plt.show()
```



In [76]:

```
one_selected_country_dataset["City"].value_counts().plot(kind = 'bar')
plt.show()
```



Conclusion

1) Most of the Order are from New Delhi City in India

2) Most Expensive Locality are also in New Delhi City

In [ ]:

In [77]:

```
df1 = one_selected_country_dataset
```

In [ ]:

```

```

Effect of Average Cost on rating

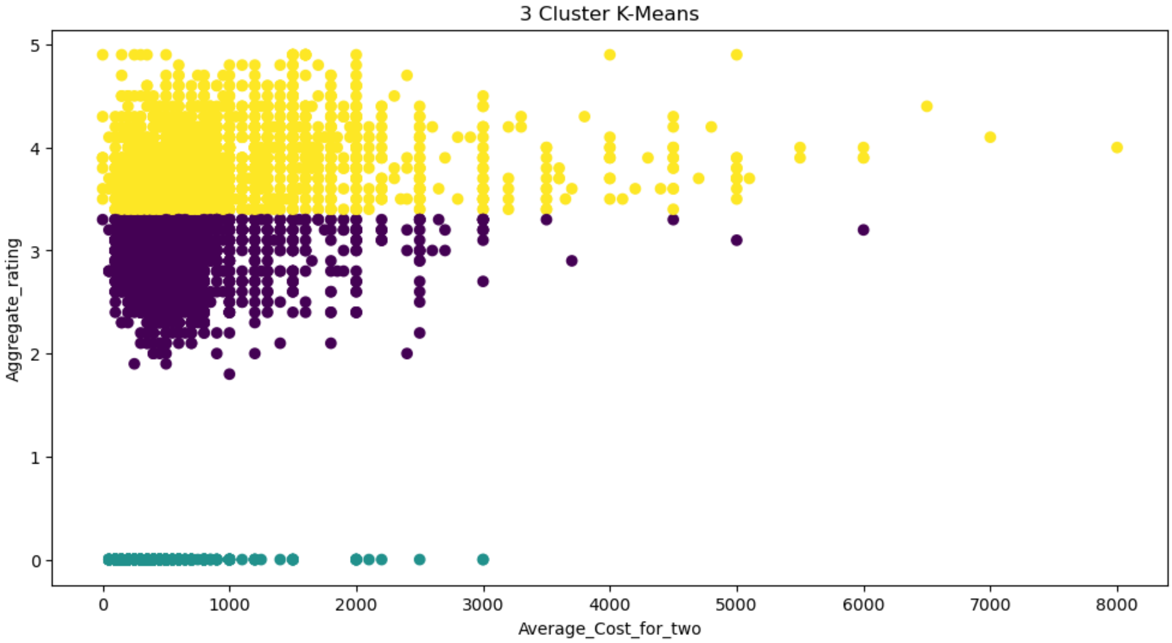
In [78]:

```
X4=df1[['Average Cost for two']]
Y4=df1[['Aggregate rating']]
```

In [79]:

```
kmeans=KMeans(n_clusters=3)

kmeansoutput=kmeans.fit(Y4)

print(kmeansoutput)
plt.rcParams['figure.figsize'] = (12,6)
plt.figure('3 Cluster K-Means')
plt.scatter(X4, Y4, c=kmeansoutput.labels_)
#plt.scatter(pca_c[:, 0], pca_d[:, 0], c=kmeansoutput.labels_)
plt.xlabel('Average_Cost_for_two')
plt.ylabel('Aggregate_rating')
plt.title('3 Cluster K-Means')
plt.show()
```

KMeans(n_clusters=3)



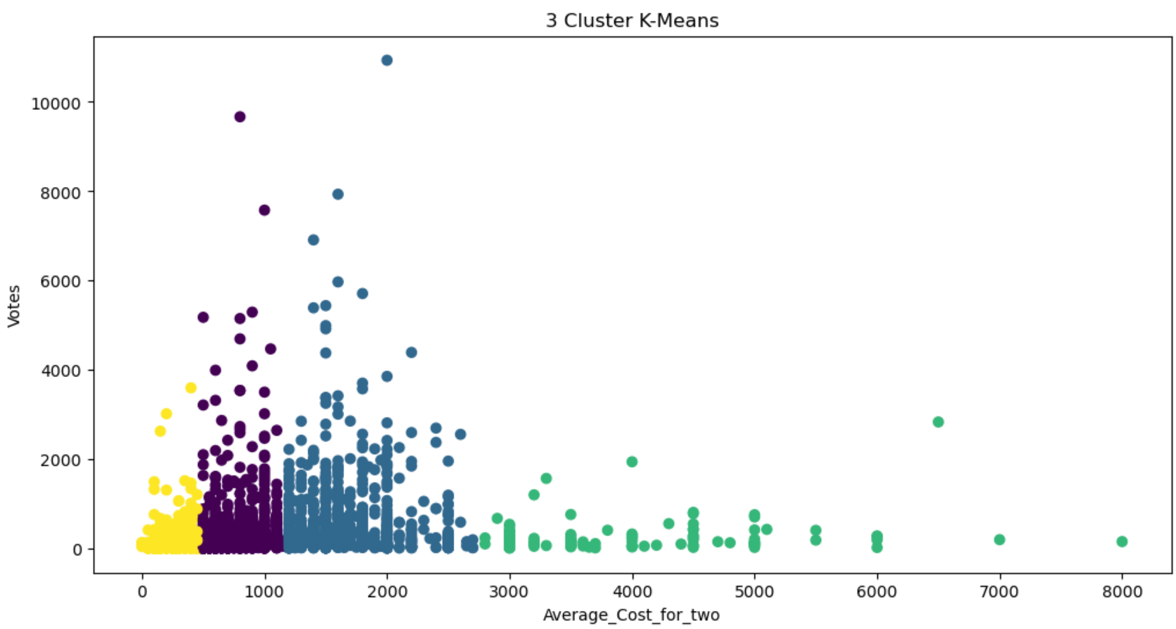
In [80]:

```
X5=df1[['Average Cost for two']]
Y5=df1[['Votes']]
```

In [81]:

```
kmeans=KMeans(n_clusters=4)

kmeansoutput=kmeans.fit(X5)

print(kmeansoutput)
plt.figure('3 Cluster K-Means')
plt.scatter(X5, Y5, c=kmeansoutput.labels_)
#pl.scatter(pca_c[:, 0], pca_d[:, 0], c=kmeansoutput.labels_)
plt.xlabel('Average_Cost_for_two')
plt.ylabel('Votes')
plt.title('3 Cluster K-Means')
plt.show()
```

```
KMeans(n_clusters=4)
```



Conclusion

```
1) The average does affect the rating but indirectly, as people prefer budget-frie
ndly places.
2) As price increases, orders are fewer and votes are fewer, but the rating is hig
her.
3) So we can assume that price is thus affecting the rating.
```

In [ ]:

In [ ]:

Recommandation And Map Plotting.

First Change the data for processing

In [107]:

```
## Drop Unneccessery Columns
zomato=one_selected_country_dataset.drop(['Country Code','Currency','Address', 'Votes'],axi
```

In [108]:

```
#Removing the Duplicates
zomato.duplicated().sum()
zomato.drop_duplicates(inplace=True)
```

In [109]:

```
#Remove the NaN values from the dataset
zomato.isnull().sum()
zomato.dropna(how='any',inplace=True)
```

In [110]:

```
#Changing the column names
zomato = zomato.rename(columns={'Average Cost for two':'cost'})
```

In [111]:

```
zomato['Restaurant'] =zomato['Restaurant Name']
zomato.head()
```

Out[111]:

	Restaurant ID	Restaurant Name	City	Locality	Locality Verbose	Longitude	Latitude	Cuisines	cost
624	3400025	Jahanpanah	Agra	Agra Cantt	Agra Cantt, Agra	78.011544	27.161661	North Indian, Mughlai	850.0
625	3400341	Rangrezz Restaurant	Agra	Agra Cantt	Agra Cantt, Agra	0.000000	0.000000	North Indian, Mughlai	700.0
626	3400005	Time2Eat - Mama Chicken	Agra	Agra Cantt	Agra Cantt, Agra	78.011608	27.160832	North Indian	500.0
627	3400021	Chokho Jeeman Marwari Jain Bhojanalya	Agra	Civil Lines	Civil Lines, Agra	77.998092	27.195928	Rajasthani	400.0
628	3400017	Pinch Of Spice	Agra	Civil Lines	Civil Lines, Agra	78.007553	27.201725	North Indian, Chinese, Mughlai	1000.0

In [112]:

```
#Some Transformations
zomato['cost'] = zomato['cost'].astype(str) #Changing the cost to string
zomato['cost'] = zomato['cost'].apply(lambda x: x.replace(',','.')) #Using lambda function
zomato['cost'] = zomato['cost'].astype(float)
```

In [113]:

```
zomato['Aggregate rating'] = zomato['Aggregate rating'].astype('float')
```

In [114]:

```
# Adjust the column names
zomato['Restaurant Name'] = zomato['Restaurant Name'].apply(lambda x:x.title())
zomato['Has Online delivery'].replace(('Yes','No'),(True, False),inplace=True)
zomato['Has Table booking'].replace(('Yes','No'),(True, False),inplace=True)
```

In [115]:

```
## Computing Mean Rating
restaurants = list(zomato['Restaurant Name'].unique())
zomato['Mean Rating'] = 0
```

As there are many restaurant without rated so we are giving mean rating to those.

In [116]:

```
for i in range(len(restaurants)):
    zomato['Mean Rating'][zomato['Restaurant Name'] == restaurants[i]] = zomato['Aggregate
```

In [117]:

```
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [118]:

```
scaler = MinMaxScaler(feature_range = (1,5))
zomato[['Mean Rating']] = scaler.fit_transform(zomato[['Mean Rating']]).round(2)
```

In [119]:

```
zomato[['Rating text', 'Cuisines']].sample(5)
```

Out[119]:

	Rating text	Cuisines
3825	Very Good	Thai, Chinese
5462	Good	Desserts
8274	Not rated	Chinese, Fast Food
4828	Average	Chinese, North Indian
3928	Average	Bakery, Desserts

In [120]:

```
# RESTAURANT NAMES:
restaurant_names = list(zomato['Restaurant Name'].unique())
def get_top_words(column, top_nu_of_words, nu_of_word):
    vec = CountVectorizer(ngram_range= nu_of_word, stop_words='english')
    bag_of_words = vec.fit_transform(column)
    sum_words = bag_of_words.sum(axis=0)
    words_freq = [(word, sum_words[0, idx]) for word, idx in vec.vocabulary_.items()]
    words_freq =sorted(words_freq, key = lambda x: x[1], reverse=True)
    return words_freq[:top_nu_of_words]
```

In [121]:

```
# Randomly sample 60% of your dataframe
df_percent = zomato.sample(frac=0.5)
```

In [ ]:

```
```

In [122]:

```
## Install neccessery libaries
```

In [123]:

```
#pip install geopy
#pip install folium
```

In [124]:

```
# Import Libaries
```

In [125]:

```
import re
from nltk.corpus import stopwords
import pylab as pl
#To geolocate a query to an address and coordinates:
from geopy.geocoders import ArcGIS
import folium
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics.pairwise import linear_kernel
```

In [126]:

```
df_percent.set_index('Restaurant Name', inplace=True)
indices = pd.Series(df_percent.index)

# Creating tf-idf matrix to Performs the TF-IDF transformation from a provided matrix of co
#TFIDF works by proportionally increasing the number of times a word appears in the documen
#but is counterbalanced by the number of documents in which it is present.

tfidf = TfidfVectorizer(analyzer='word', ngram_range=(1, 2), min_df=0, stop_words='english'
tfidf_matrix = tfidf.fit_transform(df_percent['Rating text'])

cosine_similarities = linear_kernel(tfidf_matrix, tfidf_matrix)
```

Function For Recommandation and Plotting recommanded Restaurant on Map.

In [127]:

```
#geloc = ArcGIS()
#locat = geloc.geocode('Pune')
```

In [128]:

```
zm_list = []
df_new=[]
hotels = folium.Map(location=[20.5937,78.9629],zoom_start=5)
gemaps = folium.FeatureGroup(name='Restaurants')
def recommend(name,city, cosine_similarities = cosine_similarities):

    # Create a list to put top restaurants
    recommend_restaurant = []

    # Find the index of the hotel entered
    idx = indices[indices == name].index[0]

    # Find the restaurants with a similar cosine-sim value and order them from bigges numbe
    score_series = pd.Series(cosine_similarities[idx]).sort_values(ascending=False)

    # Extract top restaurant indexes with a similar cosine-sim value
    top_indexes = list(score_series.iloc[0:200].index)

    # Names of the top restaurants
    for each in top_indexes:
        recommend_restaurant.append(list(df_percent.index)[each])

    # Creating the new data set to show similar restaurants
    df_new = pd.DataFrame(columns=['Restaurant','City','Cuisines', 'Mean Rating','Longitude

    # Create the top similar restaurants with some of their columns
    for each in recommend_restaurant:
        df_new = df_new.append(pd.DataFrame(df_percent[['Restaurant','City','Cuisines','Mea
                                                        'Rating text','cost' ]][df_percent.

    # Drop the same named restaurants and sort only the top 10 by the highest rating
    df_new = df_new.drop_duplicates(subset=['Restaurant','City','Cuisines','Mean Rating','L
                                          'Rating text','cost'], keep=False)
    df_new = df_new[df_new['City']==city]
    df_new = df_new.sort_values(by='Mean Rating', ascending=False).head(10)

    print('TOP %s RESTAURANTS LIKE %s WITH SIMILAR REVIEWS: ' % (str(len(df_new)), name))

    #create a list based on recommation hotels for showing on map
    zm_list=df_new[['Restaurant','City',
                    'Latitude','Longitude','Cuisines',
                    'Mean Rating','Rating text','cost']].values.tolist()

    # in for loop pass the created list for map
    for i in zm_list:
        if i[1]==city:
            #calling map marker for marking location on map
            #for showing restaurant on map pass its map co-ordinates into the location
            gemaps.add_child(folium.Marker(location=[i[2],i[3]],
            #use tooltip to popup or show details realated to marker
                                           tooltip = '<h5><b>'+str(i[0])+"</b></h5><br/>"+s
                                                   '<br/>Rating: <b>'+str(i[5])+'/5</b><br/
                                                   '<br/>Cost for 2: '+str(i[7]),
            #icon use to show pointing the restaurant on map
                                           icon=folium.Icon(color='green')))

    #hotels.add_child(gemaps)
    return df_new
#recommend('Jahanpanah','New Delhi') Example for applying Function
```

```
#df_new
#hotels.add_child(gemaps) For Displaying Map
#hotels.save('map.html') For Saving Map
```

In [129]:

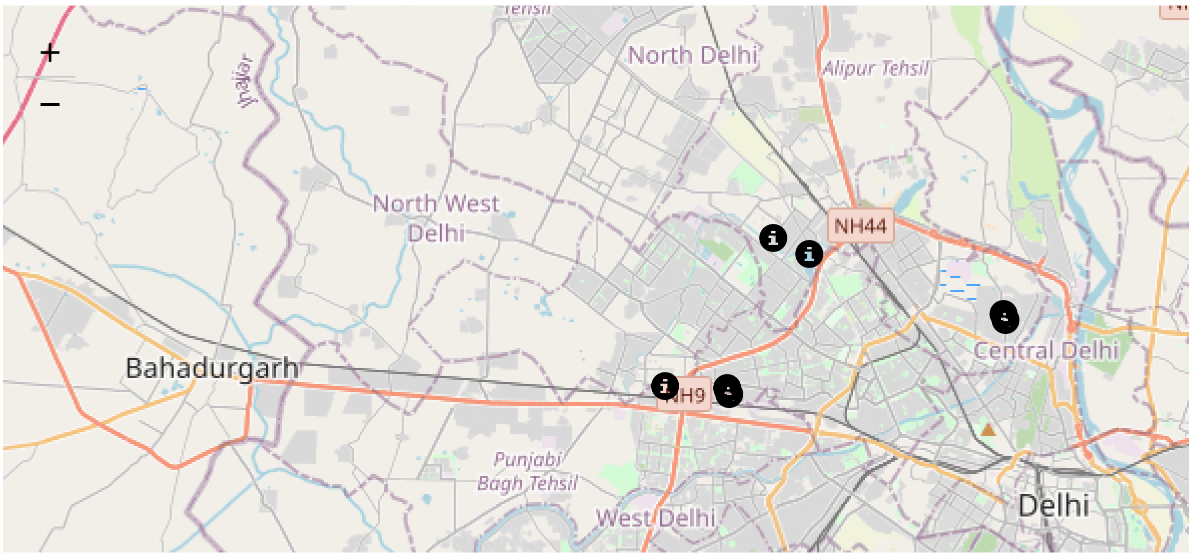
```
def City():
    print("Which Type of Hotels You Like")
    city = input('Enter Your City Name : ')
    # store restaurant name and city name
    zc=zomato[['Restaurant Name','City']][zomato['City']==city]
    print(zc.head(30))
    hotel_name = input("Check list and Enter Type Of Hotels You Like : ")

    recommend(hotel_name,city)
    #hotels.add_child(gemaps)
    return hotel_name,city
```

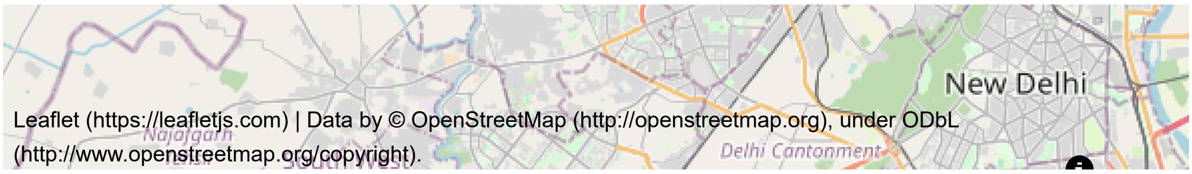
In [130]:

```
# calling city function
City()

# Disaplay map
hotels.add_child(gemaps)
```

```
Which Type of Hotels You Like
Enter Your City Name : New Delhi
                  Restaurant Name       City
2560                   Food Cloud  New Delhi
2561                    Burger.In  New Delhi
2562              Days Of The Raj  New Delhi
2563               Dilli Ka Dhaba  New Delhi
2564                   Govardhan  New Delhi
2565               Mezbaan Grills  New Delhi
2566                   Say Cheese  New Delhi
2567                      Southy  New Delhi
2568                     Monosoz  New Delhi
2569                       Waves  New Delhi
2570                Delhi Darbar  New Delhi
2571                     Chateau  New Delhi
2572                Nariyal Cafe  New Delhi
2573         Rustom'S Parsi Bhonu  New Delhi
2574                    Barshala  New Delhi
2575                    Chawla'Sœ_  New Delhi
2576               Domino'S Pizza  New Delhi
2577                    Sultanat  New Delhi
2578                Bella Italia  New Delhi
2579              Clever Fox Cafe  New Delhi
2580                365 Naturals  New Delhi
2581                        Tpot  New Delhi
2582      4 On 44 Restaurant & Bar  New Delhi
2583                     Rambhog  New Delhi
2584   Selfie Lounge Restro & Bar  New Delhi
2585                         Btw  New Delhi
2586               Chilli Pepper  New Delhi
2587                   Pizza Hut  New Delhi
2588                 Puri Bakers  New Delhi
2589          Jaiveer Naan & Chaap  New Delhi
Check list and Enter Type Of Hotels You Like : Govardhan
TOP 10 RESTAURANTS LIKE Govardhan WITH SIMILAR REVIEWS:
```

Out[130]:





Conclusion

```
1) In this way, we recommended the restaurant based on the liking of the customer
 and which city they are.
2) Recommended restaurants can be viewed on the map.
```

Thank You

In [ ]:

```

```