Zomato Data Analysis

A dataset of Zomato has been provided, named "Zomato_data.csv". Analyze the data and primarily find out the answers of the following questions:

Q1. What type of restaurant do the majority of customers order from?
Q2. How many votes has each type of restaurant received from customers?
Q3. What are the ratings that the majority of restaurants have received?
Q4. Zomato has observed that most couples order most of their foods online. What is their average spending on each other?
Q5. Which mode (online or offline) has received the maximum rating?
Q6. Which type of restaurant received more offline orders, so that Zomato can prefer customers with some good offers?

You can more simplify and analyze the data as required, to find out the answers of more different questions that are not mentioned above.

Later create an AI/ML/DL model of your choice and features.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

In [2]:
```
df = pd.read_csv("Zomato_data.csv") # Reading the CSV file and storing it as a Data
```

Let's look into the data carefully

In [3]:
```
df.head(10) # Looking at the top 10 datas of the dataset, just to have initial and
```

Out[3]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1/5	775	800	Buffet
1	Spice Elephant	Yes	No	4.1/5	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8/5	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7/5	88	300	Buffet
4	Grand Village	No	No	3.8/5	166	600	Buffet
5	Timepass Dinner	Yes	No	3.8/5	286	600	Buffet
6	Rosewood International Hotel - Bar & Restaurant	No	No	3.6/5	8	800	Buffet
7	Onesta	Yes	Yes	4.6/5	2556	600	Cafes
8	Penthouse Cafe	Yes	No	4.0/5	324	700	other
9	Smacznego	Yes	No	4.2/5	504	550	Cafes

Getting a detailed information about the dataset

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148 entries, 0 to 147
Data columns (total 7 columns):
 #   Column                       Non-Null Count  Dtype 
---  ------                       --------------  ----- 
 0   name                         148 non-null    object
 1   online_order                 148 non-null    object
 2   book_table                   148 non-null    object
 3   rate                         148 non-null    object
 4   votes                        148 non-null    int64 
 5   approx_cost(for two people)  148 non-null    int64 
 6   listed_in(type)              148 non-null    object
dtypes: int64(2), object(5)
memory usage: 8.2+ KB
```

From the above given information, it is quite evident that it doesn't include any NaN (Null) values

In [5]:
```python
# Just to make sure the absence of NaN values
df.isnull().sum()
```

Out[5]:
```
name                           0
online_order                   0
book_table                     0
rate                           0
votes                          0
approx_cost(for two people)    0
listed_in(type)                0
dtype: int64
```

Let's check if any duplicate data is present in the dataset or not

In [6]:
```python
df.duplicated().sum()
```

Out[6]:
```
np.int64(0)
```

Since, there are neither any duplicate data or NaN data, let's check the final shape of the dataset.

In [7]:
```python
df.shape
```

Out[7]:
```
(148, 7)
```

Therefore, there are total 148 values in the dataset, with 7 columns

Data Cleaning (For Data Analysis)

Changing the "rate" to float and removing the denominator.

In [8]:
```python
df["rate"] = df["rate"].str.split("/").str[0]
```

In [9]:
```python
df
```

Out[9]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet
...	...	...	...	...	...	...	...
143	Melting Melodies	No	No	3.3	0	100	Dining
144	New Indraprasta	No	No	3.3	0	150	Dining
145	Anna Kuteera	Yes	No	4.0	771	450	Dining
146	Darbar	No	No	3.0	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

148 rows × 7 columns

In [10]:
```
df["rate"] = df["rate"].astype(float)
```

It can be seen that some of the restaurants have 0 votes but still have some rating.

We need those values to be deleted, since they are not desired for data analysis

In [11]:
```
df[df["votes"] == 0]
```

Out[11]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(ty
72	Spicy Tandoor	No	No	4.1	0	150	Dir
75	Om Sri Vinayaka Chats	No	No	3.6	0	500	Dir
84	Chill Out	No	No	3.8	0	100	Dir
90	Me And My Cake	No	No	3.7	0	500	Dir
91	Sunsadm	No	No	3.7	0	400	Dir
92	Annapooraneshwari Mess	No	No	3.7	0	200	Dir
107	Coffee Shopee	No	No	3.4	0	250	Dir
110	Hari Super Sandwich	No	No	3.2	0	200	Dir
113	Dharwad Line Bazaar Mishra Pedha	No	No	3.4	0	150	Dir
114	Cake Bite	No	No	3.4	0	300	Dir
115	Aarush's Food Plaza	No	No	3.4	0	200	Dir
116	Wood Stove	No	No	3.4	0	150	Dir
117	Kulfi & More	No	No	3.4	0	150	Dir
118	Kannadigas Karavali	No	No	3.4	0	250	Dir
125	Soms Kitchen & Bakes	No	No	2.9	0	400	Dir
126	Banashankari Nati Style	No	No	2.9	0	350	Dir
128	Mohitesh Hut Roll	No	No	3.3	0	150	Dir
129	Sri Basaveshwar Jolada Rotti Oota	No	No	3.4	0	150	Dir
130	Roll Magic Fast Food	No	No	3.4	0	200	Dir
131	Foodlieious Multi Cuisine	No	No	3.4	0	100	Dir
132	Thanishka Nati And Karavali Style	No	No	3.1	0	400	Dir
133	Swathi Cool Point	No	No	4.1	0	200	Dir
134	Kaumudis Juoice	No	No	3.3	0	150	Dir
135	Amma - Manae	No	No	3.1	0	400	Dir

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(ty
136	Sri Sai Tiffannies	No	No	3.3	0	150	Dir
137	Hotel Andhra Speices	No	No	2.9	0	250	Dir
138	Sri Murari Family Restaurant	No	No	2.9	0	250	Dir
139	Aramane Donne Biriyani	No	No	2.9	0	150	Dir
140	Darkolates	No	No	3.3	0	200	Dir
141	Swaada Healthy Kitchen	No	No	3.3	0	350	Dir
142	Gawdaru Mane Beriyani	No	No	3.3	0	300	Dir
143	Melting Melodies	No	No	3.3	0	100	Dir
144	New Indraprasta	No	No	3.3	0	150	Dir

In [12]:
```
df.drop(df[df["votes"] == 0].index, inplace=True)
```

In [13]:
```
df
```

Out[13]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet
...	...	...	...	...	...	...	...
124	Kwality Wall's Swirl's Happiness Station	No	No	2.9	25	200	Dining
127	Ruchi Maayaka	No	No	3.3	8	100	Dining
145	Anna Kuteera	Yes	No	4.0	771	450	Dining
146	Darbar	No	No	3.0	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

115 rows × 7 columns

Bayesian Average

The core idea of Bayesian Average is that you "pull" the rating of items with few reviews toward the average rating of all products. This adds "imaginary" or "ghost" reviews that represent the average, which stabilizes the score.

The formula for Bayesian Average is:

$$\text{Adjusted Rating} = \frac{(v \times R) + (m \times C)}{v + m}$$

What the Variables Mean

- R = The item's average rating (e.g., 4.6)
- v = The number of votes (reviews) for that specific item (e.g., 5,000)
- m = The "minimum" number of votes required for confidence. This is the "magic number" you choose. A good starting point is to use the average number of reviews across all products you're comparing. Let's use 100 as an example.

- C = The mean rating across all products (e.g., the average rating of all items on the site, which is often around 3.5 stars)

In [14]:
```
# The variables that can be defined before hand
m = df["votes"].mean().round(0)
C = df["rate"].mean().round(1)

print(f"m = {m} and C = {C}")
```

```
m = 341.0 and C = 3.7
```

In [15]:
```
df["bayesian_average"] = round(((df["votes"] * df["rate"]) + (m * C)) / (df["votes"
```

In [16]:
```
df[df["votes"] <= 341]
```

Out[16]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet
5	Timepass Dinner	Yes	No	3.8	286	600	Buffet
6	Rosewood International Hotel - Bar & Restaurant	No	No	3.6	8	800	Buffet
8	Penthouse Cafe	Yes	No	4.0	324	700	other
...	...	...	...	...	...	...	...
123	Parjanya Chat Zone	No	No	3.3	17	200	Dining
124	Kwality Wall's Swirl's Happiness Station	No	No	2.9	25	200	Dining
127	Ruchi Maayaka	No	No	3.3	8	100	Dining
146	Darbar	No	No	3.0	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

87 rows × 8 columns

The detailed, statistical overview of the dataset

In [17]:
```
df.describe()
```

Out[17]:

	rate	votes	approx_cost(for two people)	bayesian_average
count	115.000000	115.000000	115.000000	115.000000
mean	3.710435	340.800000	469.565217	3.760870
std	0.394563	724.471885	220.415840	0.185763
min	2.600000	4.000000	100.000000	3.200000
25%	3.500000	28.000000	300.000000	3.700000
50%	3.800000	88.000000	450.000000	3.700000
75%	4.000000	311.500000	600.000000	3.800000
max	4.600000	4884.000000	950.000000	4.500000

Therefore, the final dataset for Data Analysis

In [18]:
```
df
```

Out[18]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet
...	...	...	...	...	...	...	...
124	Kwality Wall's Swirl's Happiness Station	No	No	2.9	25	200	Dining
127	Ruchi Maayaka	No	No	3.3	8	100	Dining
145	Anna Kuteera	Yes	No	4.0	771	450	Dining
146	Darbar	No	No	3.0	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

115 rows × 8 columns

Data Cleaning (For ML Model Training)

In [19]:

```
df2 = df.copy()
```

In [20]:

```
df2
```

Out[20]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet
...	...	...	...	...	...	...	...
124	Kwality Wall's Swirl's Happiness Station	No	No	2.9	25	200	Dining
127	Ruchi Maayaka	No	No	3.3	8	100	Dining
145	Anna Kuteera	Yes	No	4.0	771	450	Dining
146	Darbar	No	No	3.0	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

115 rows × 8 columns

Changing the "Yes"s and "No"s of "online_order" and "book_table" columns into 1s and 0s respectively.

Let's first check the unique values of "online_order" and "book_table" columns

In [21]:
```
df2["online_order"].unique()
```

Out[21]:
```
array(['Yes', 'No'], dtype=object)
```

In [22]:
```
df2["book_table"].unique()
```

Out[22]:
```
array(['Yes', 'No'], dtype=object)
```

Since, only two types of labels are available, i.e. "Yes" and "No", we'll be using Label Encoder, a powerful tool from Scikit Learn.

In [23]:
```
label_encoding = LabelEncoder()
```

```
df2["online_order"] = label_encoding.fit_transform(df2["online_order"])
df2["book_table"] = label_encoding.fit_transform(df2["book_table"])
```

Also we need to change "listed_in(type)" column using Label Encoder into 0s, 1s, 2s and 3s

In [24]:
```
df2["listed_in(type)"] = label_encoding.fit_transform(df2["listed_in(type)"])
```

In [25]:
```
df2
```

Out[25]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	1	1	4.1	775	800	0
1	Spice Elephant	1	0	4.1	787	800	0
2	San Churro Cafe	1	0	3.8	918	800	0
3	Addhuri Udupi Bhojana	0	0	3.7	88	300	0
4	Grand Village	0	0	3.8	166	600	0
...	...	...	...	...	...	...	...
124	Kwality Wall's Swirl's Happiness Station	0	0	2.9	25	200	2
127	Ruchi Maayaka	0	0	3.3	8	100	2
145	Anna Kuteera	1	0	4.0	771	450	2
146	Darbar	0	0	3.0	98	800	2
147	Vijayalakshmi	1	0	3.9	47	200	2

115 rows × 8 columns

The "name" and "rate" columns are not required in the ML Model

We need to remove the whole "name" column because it is not required

In [26]:
```
df2.drop("name", axis=1, inplace=True)
```

Also, the "rate" column would lead to "Target Leaking" and wouldn't give any useful insights

In [27]:
```
df2.drop("rate", axis=1, inplace=True)
```

In [28]:
```
df2
```

Out[28]:

	online_order	book_table	votes	approx_cost(for two people)	listed_in(type)	bayesian_average
0	1	1	775	800	0	4.0
1	1	0	787	800	0	4.0
2	1	0	918	800	0	3.8
3	0	0	88	300	0	3.7
4	0	0	166	600	0	3.7
...	...	...	...	...	...	...
124	0	0	25	200	2	3.6
127	0	0	8	100	2	3.7
145	1	0	771	450	2	3.9
146	0	0	98	800	2	3.5
147	1	0	47	200	2	3.7

115 rows × 6 columns

The detailed, statistical overview of the dataset

In [29]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 115 entries, 0 to 147
Data columns (total 6 columns):
 #   Column                     Non-Null Count  Dtype  
---  ------                     --------------  -----  
 0   online_order               115 non-null    int64  
 1   book_table                 115 non-null    int64  
 2   votes                      115 non-null    int64  
 3   approx_cost(for two people) 115 non-null    int64  
 4   listed_in(type)            115 non-null    int64  
 5   bayesian_average           115 non-null    float64
dtypes: float64(1), int64(5)
memory usage: 6.3 KB
```

In [30]:
```
df2.describe()
```

Out[30]:

	online_order	book_table	votes	approx_cost(for two people)	listed_in(type)	bayesian_ave
count	115.000000	115.000000	115.000000	115.000000	115.000000	115.00
mean	0.504348	0.069565	340.800000	469.565217	1.747826	3.76
std	0.502169	0.255526	724.471885	220.415840	0.673346	0.18
min	0.000000	0.000000	4.000000	100.000000	0.000000	3.20
25%	0.000000	0.000000	28.000000	300.000000	1.000000	3.70
50%	1.000000	0.000000	88.000000	450.000000	2.000000	3.70
75%	1.000000	0.000000	311.500000	600.000000	2.000000	3.80
max	1.000000	1.000000	4884.000000	950.000000	3.000000	4.50

Therefore, the final dataset for Data Analysis

In [31]:

```
df2
```

Out[31]:

	online_order	book_table	votes	approx_cost(for two people)	listed_in(type)	bayesian_average
0	1	1	775	800	0	4.0
1	1	0	787	800	0	4.0
2	1	0	918	800	0	3.8
3	0	0	88	300	0	3.7
4	0	0	166	600	0	3.7
...	...	...	...	...	...	...
124	0	0	25	200	2	3.6
127	0	0	8	100	2	3.7
145	1	0	771	450	2	3.9
146	0	0	98	800	2	3.5
147	1	0	47	200	2	3.7

115 rows × 6 columns

Data Analysis

Let's have a look on the types of restaurants that are available on Zomato

In [32]:
```
df["listed_in(type)"].unique()
```

Out[32]:
```
array(['Buffet', 'Cafes', 'other', 'Dining'], dtype=object)
```

In [33]:
```
df["listed_in(type)"].value_counts(sort=False)
```

Out[33]:
```
listed_in(type)
Buffet      7
Cafes      23
other       8
Dining     77
Name: count, dtype: int64
```

It is evident that there are 4 types of restaurants: Dining (77 restaurants), Cafes (23 restaurants), Buffet (7 Restaurants) and Others (8 restaurants)

Q1. What type of restaurant do the majority of customers order from?

In [34]:
```
print(f"There are total {df['votes'].sum()} orders from various restaurants in Zoma
```

```
There are total 39192 orders from various restaurants in Zomato.
```

In [35]:
```
grouped_votes = df.groupby("listed_in(type)")["votes"].sum()
grouped_votes
```

Out[35]:
```
listed_in(type)
Buffet      3028
Cafes       6434
Dining     20363
other       9367
Name: votes, dtype: int64
```

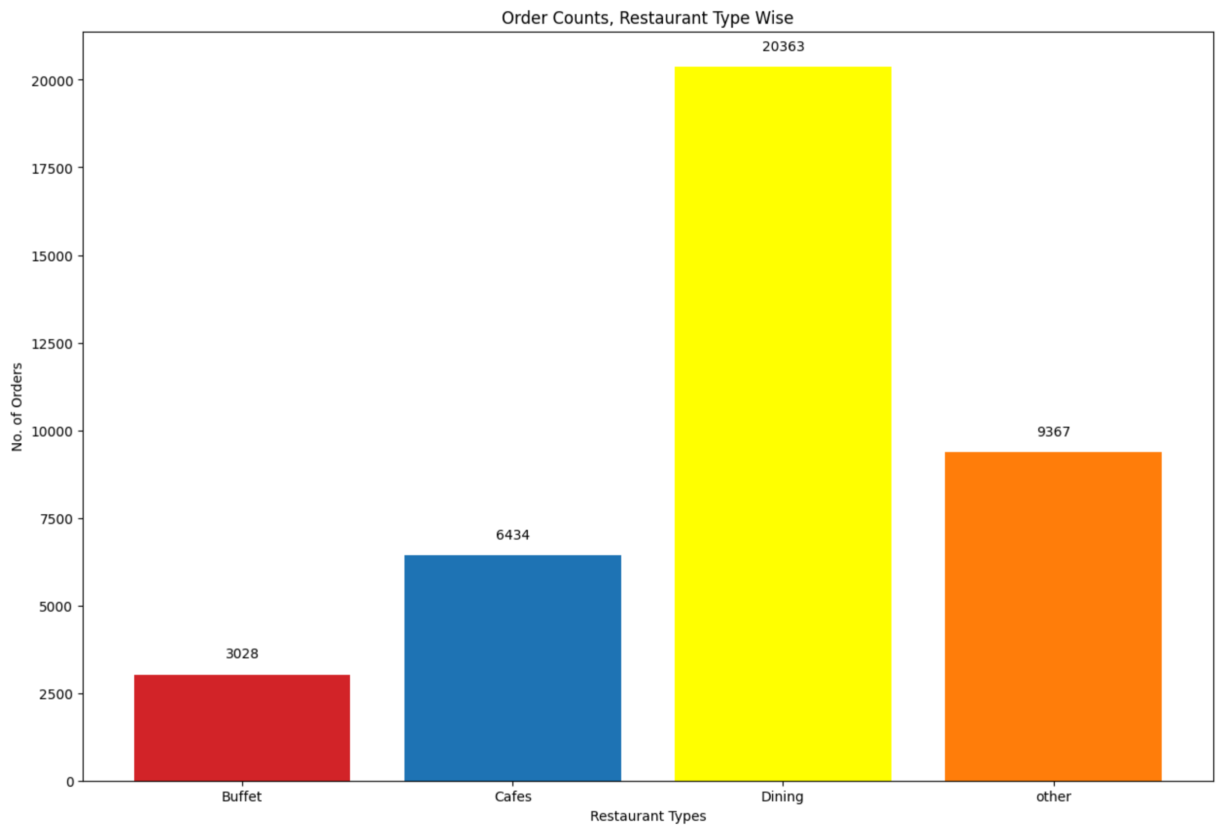
In [36]:
```
fig, ax = plt.subplots(figsize=(15, 10))

res_types = pd.Series(sorted(df["listed_in(type)"].unique()))
res_order_count = pd.Series(df.groupby("listed_in(type)")["votes"].sum())

bar_colors = ['tab:red', 'tab:blue', 'yellow', 'tab:orange']

bars = ax.bar(res_types, res_order_count, color=bar_colors)
ax.bar_label(bars, labels=res_order_count, padding=10)

plt.title("Order Counts, Restaurant Type Wise")
plt.ylabel("No. of Orders")
plt.xlabel("Restaurant Types")
plt.show()
```



Answer 1:

People mostly order their food from "Dining" type of restaurants. According to the dataset, total 20363 out of 39192 orders were from "Dining" type of restaurants.

Q2. How many votes has each type of restaurant received from customers?

In [37]:
```
for i, j in grouped_votes.items():
    print(f"{i} received {j} votes from the customers.")
```

```
Buffet received 3028 votes from the customers.
Cafes received 6434 votes from the customers.
Dining received 20363 votes from the customers.
other received 9367 votes from the customers.
```

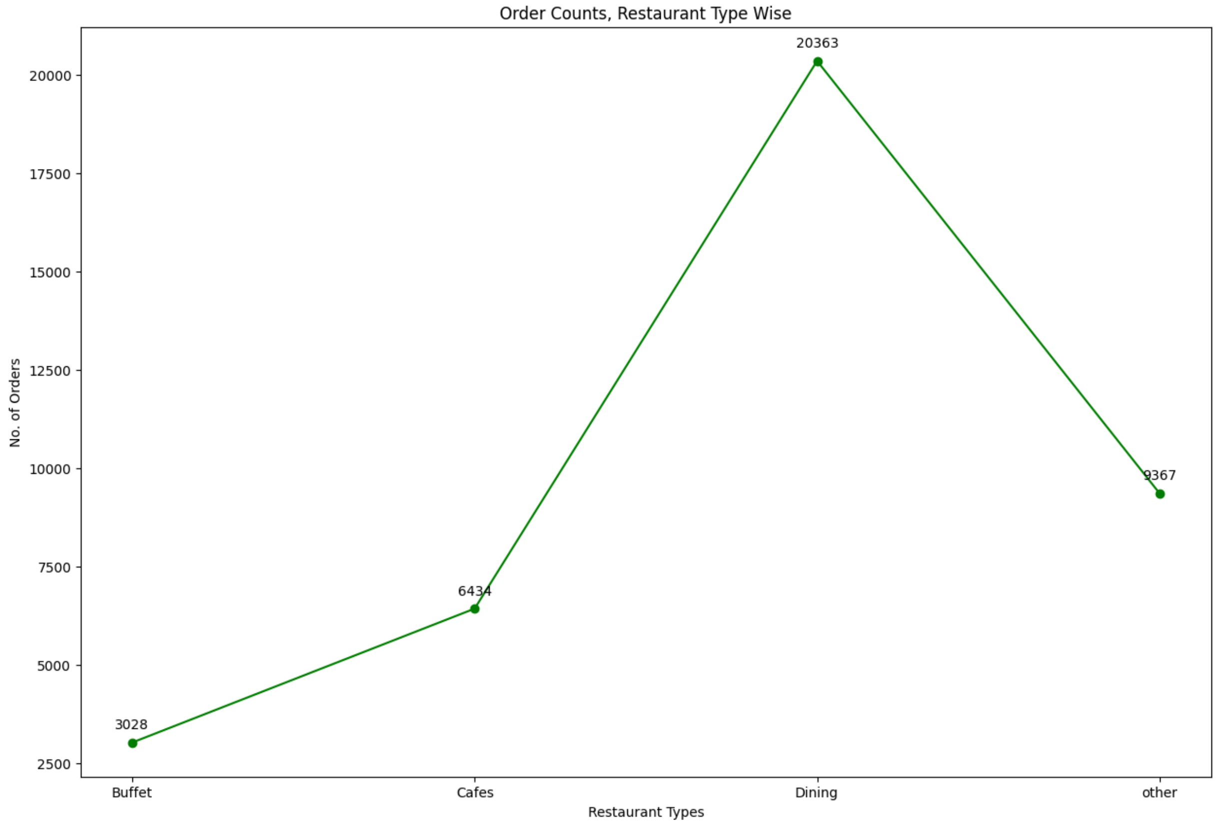
In [38]:
```
fig, ax = plt.subplots(figsize=(15, 10))

plt.plot(res_types, res_order_count, color="green", marker="o")

for i, txt in enumerate(res_order_count):
    plt.annotate(txt, (res_types[i], res_order_count[i]), textcoords="offset points

plt.title("Order Counts, Restaurant Type Wise")
plt.xlabel("Restaurant Types")
plt.ylabel("No. of Orders")
plt.show()
```

```
C:\Users\Kumaresh Basu\AppData\Local\Temp\ipykernel_5688\2849058995.py:6: FutureWarn
ing: Series.__getitem__ treating keys as positions is deprecated. In a future versio
n, integer keys will always be treated as labels (consistent with DataFrame behavio
r). To access a value by position, use `ser.iloc[pos]`
  plt.annotate(txt, (res_types[i], res_order_count[i]), textcoords="offset points",
xytext=(0,10), ha='center')
```



Answer 2:

Buffet received 3028 votes from the customers.

Cafes received 6434 votes from the customers.

Dining received 20363 votes from the customers.

other received 9367 votes from the customers.

Q3. What are the ratings that the majority of restaurants have received?

In [39]:
```
df["rate"].value_counts()
```

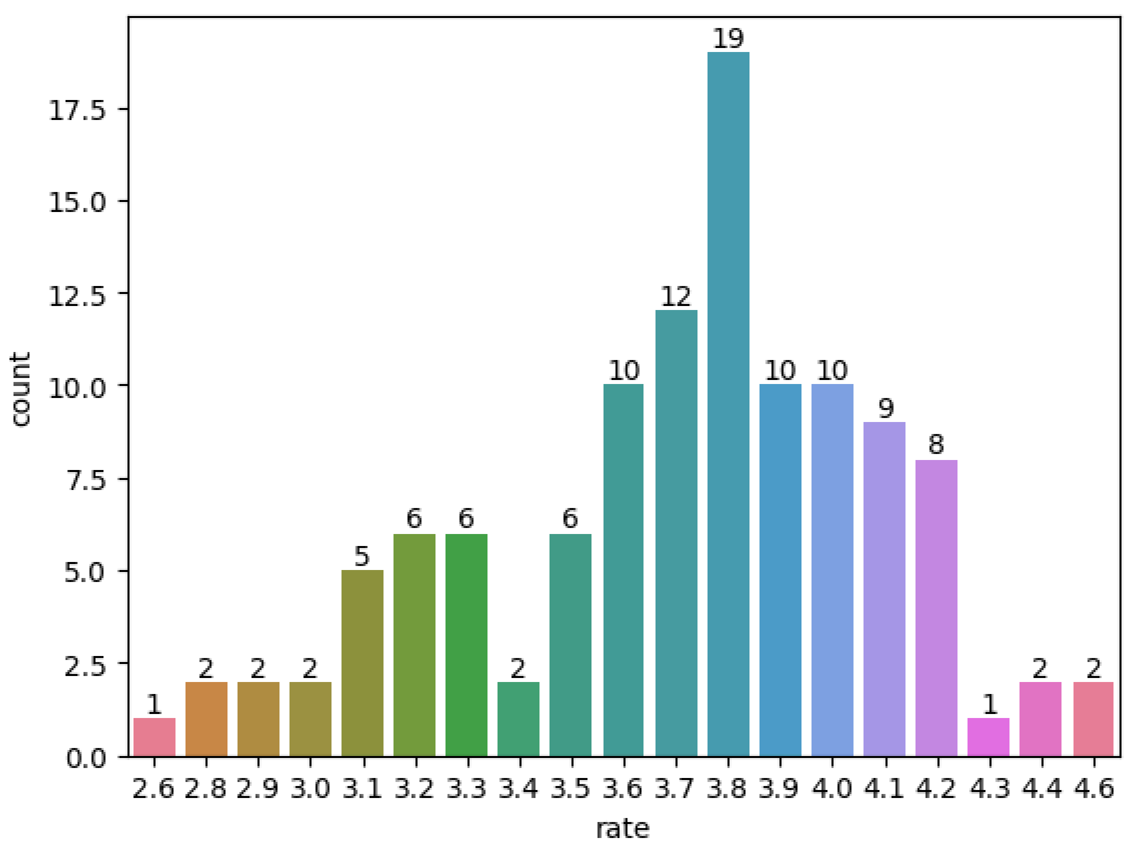
Out[39]:
```
rate
3.8    19
3.7    12
3.6    10
3.9    10
4.0    10
4.1     9
4.2     8
3.2     6
3.3     6
3.5     6
3.1     5
3.0     2
4.6     2
4.4     2
2.8     2
3.4     2
2.9     2
4.3     1
2.6     1
Name: count, dtype: int64
```

In [40]:
```
print(f"A maximum of {df['rate'].value_counts().max()} restaurants have got {df['ra
```

```
A maximum of 19 restaurants have got 3.8/5 ratings
```

In [41]:
```
ax = sns.countplot(x=df["rate"], palette="husl", hue=df["rate"], legend=False)

for container in ax.containers:
    ax.bar_label(container)
```



Answer 3:

A maximum of 19 restaurants have got 3.8/5 ratings

Q4. Zomato has observed that most couples order most of their foods online. What is their average spending on each other?

In [42]:
```
df[df["online_order"] == "Yes"] # Only online orders are listed in the given below
```

Out[42]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
5	Timepass Dinner	Yes	No	3.8	286	600	Buffet
7	Onesta	Yes	Yes	4.6	2556	600	Cafes
8	Penthouse Cafe	Yes	No	4.0	324	700	other
9	Smacznego	Yes	No	4.2	504	550	Cafes
10	Village Café	Yes	No	4.1	402	500	Cafes
11	Cafe Shuffle	Yes	Yes	4.2	150	600	Cafes
12	The Coffee Shack	Yes	Yes	4.2	164	500	Cafes
14	San Churro Cafe	Yes	No	3.8	918	800	Cafes
15	Cafe Vivacity	Yes	No	3.8	90	650	Cafes
16	Catch-up-ino	Yes	No	3.9	133	800	Cafes
17	Kirthi's Biryani	Yes	No	3.8	144	700	Cafes
19	360 Atoms Restaurant And Cafe	Yes	No	3.1	13	400	Cafes
20	The Vintage Cafe	Yes	No	3.0	62	400	Cafes
21	Woodee Pizza	Yes	No	3.7	180	500	Cafes
23	My Tea House	Yes	No	3.6	62	600	Cafes
26	Coffee Tindi	Yes	No	3.8	75	200	Cafes
30	Redberrys	Yes	No	4.0	219	600	Cafes
31	Foodiction	Yes	No	2.8	506	500	other
32	Sweet Truth	Yes	No	3.9	35	500	Dining
33	Ovenstory Pizza	Yes	No	3.9	172	750	Dining
34	Faasos	Yes	No	4.2	415	500	other

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
35	Behrouz Biryani	Yes	No	3.9	230	650	Dining
36	Fast And Fresh	Yes	No	2.8	91	400	Dining
37	Szechuan Dragon	Yes	No	4.2	1647	600	Dining
38	Empire Restaurant	Yes	No	4.4	4884	750	other
39	Maruthi Davangere Benne Dosa	Yes	No	4.0	17	150	Dining
40	Chaatimes	Yes	No	3.8	133	200	Dining
42	McDonald's	Yes	No	3.9	286	500	Dining
43	Domino's Pizza	Yes	No	3.9	540	800	Dining
44	Onesta	Yes	Yes	4.6	2556	600	other
46	Kitchen Garden	Yes	No	3.6	244	300	Dining
47	Recipe	Yes	No	4.0	804	450	Dining
48	Beijing Bites	Yes	No	3.7	679	850	Dining
49	Tasty Bytes	Yes	No	3.1	245	300	Dining
51	Shree Cool Point	Yes	No	4.1	28	150	Dining
53	Biryanis And More	Yes	No	4.0	618	750	Dining
55	FreshMenu	Yes	No	3.9	627	450	Dining
56	Banashankari Donne Biriyani	Yes	No	3.8	104	300	Dining
57	Wamama	Yes	Yes	4.2	354	800	other
59	XO Belgian Waffle	Yes	No	3.7	17	400	Dining
61	Goa 0 Km	Yes	Yes	3.6	163	800	Dining
62	Chinese Kitchen	Yes	No	3.8	58	150	Dining
65	Kabab Magic	Yes	No	4.1	1720	400	Dining

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
66	Namma Brahmin's Idli	Yes	No	3.6	34	100	Dining
69	Burger King	Yes	No	3.2	71	600	Dining
70	The Good Bowl	Yes	No	3.6	6	500	Dining
76	Sri Guru Kottureshwara Davangere Benne Dosa	Yes	No	4.1	558	150	Dining
77	Devanna Dum Biriyani Centre	Yes	No	3.6	28	300	Dining
80	Kadalu Sea Food Restaurant	Yes	No	3.8	153	500	Dining
81	Frozen Bottle	Yes	No	4.2	146	400	Dining
86	Meghana Foods	Yes	No	4.4	4401	600	Dining
99	Polar Bear	Yes	No	3.8	71	400	Dining
120	Bengaluru Coffee House	Yes	No	4.1	201	300	Dining
145	Anna Kuteera	Yes	No	4.0	771	450	Dining
147	Vijayalakshmi	Yes	No	3.9	47	200	Dining

In [43]:

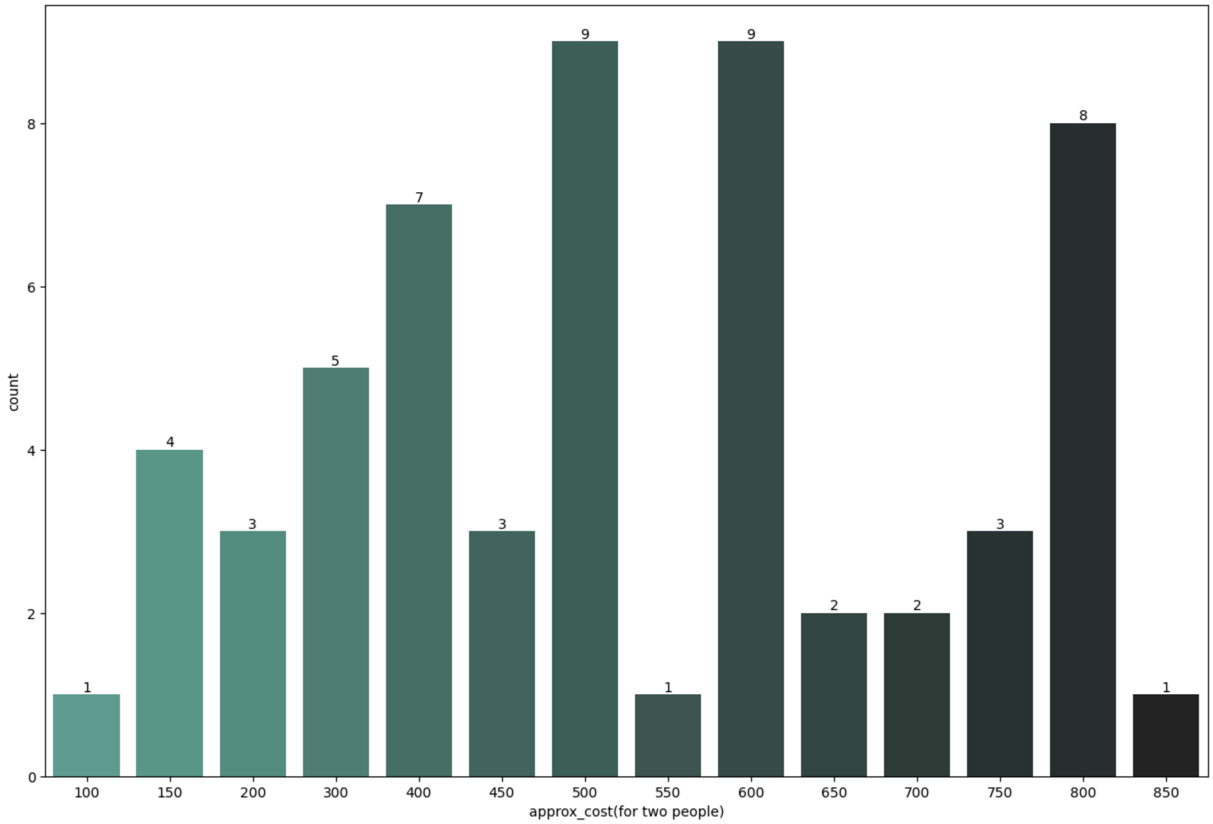
```
costs = df.loc[df["online_order"] == "Yes", "approx_cost(for two people)"]

fig, ax = plt.subplots(figsize=(15, 10))

ax = sns.countplot(x=costs, palette="dark:#5A9_r", hue=costs, legend=False)

for container in ax.containers:
    ax.bar_label(container)

plt.show()
```




```
In [44]: print(f"Most couples, i.e. {costs.value_counts().max()} couples, spend an approxima
```

```
Most couples, i.e. 9 couples, spend an approximate amount of Rs.600 and Rs.500 on ea
ch other.
```

Answer 4:

Most couples, i.e. 9 couples, spend an approximate amount of ₹600 and ₹500 on each other.

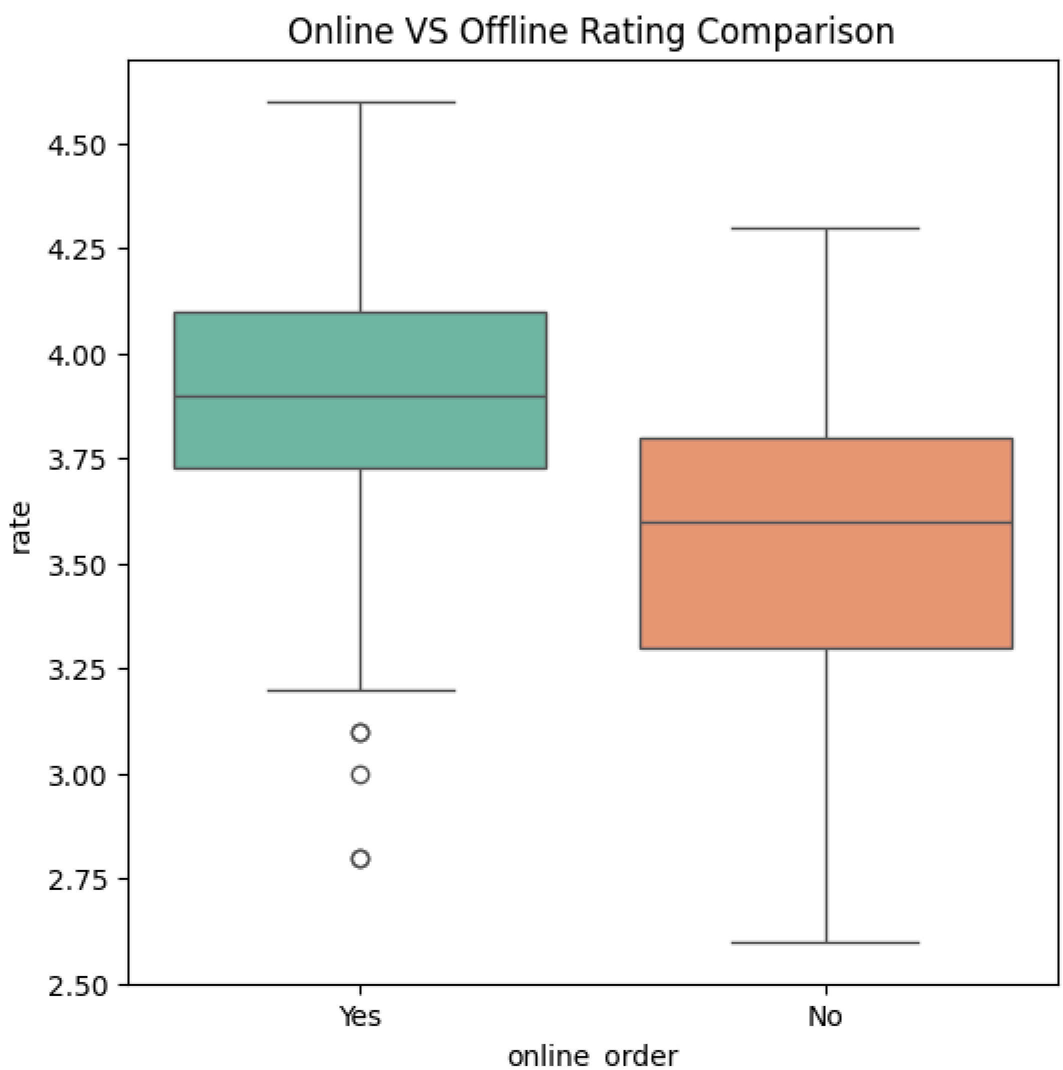
Q5. Which mode (online or offline) has received the maximum rating?

```
In [45]: df.groupby("online_order")["rate"].mean().round(1)
```

```
Out[45]: online_order
         No     3.6
         Yes    3.9
         Name: rate, dtype: float64
```

```
In [46]: plt.figure(figsize=(6, 6))
         plt.title("Online VS Offline Rating Comparison")
         sns.boxplot(x="online_order", y="rate", data=df, palette="Set2", hue=df["online_ord
```

```
Out[46]: <Axes: title={'center': 'Online VS Offline Rating Comparison'}, xlabel='online_ord
         er', ylabel='rate'>
```



Answer 5:

Online orders have better ratings (3.9 out of 5 to be precise) than Offline orders (3.6 out of 5 to be precise).

Q6. Which type of restaurant received more offline orders, so that Zomato can prefer customers with some good offers?

In [47]:
```
offline_res = df.groupby("listed_in(type)")["online_order"].value_counts().unstack(
offline_res
```

Out[47]:

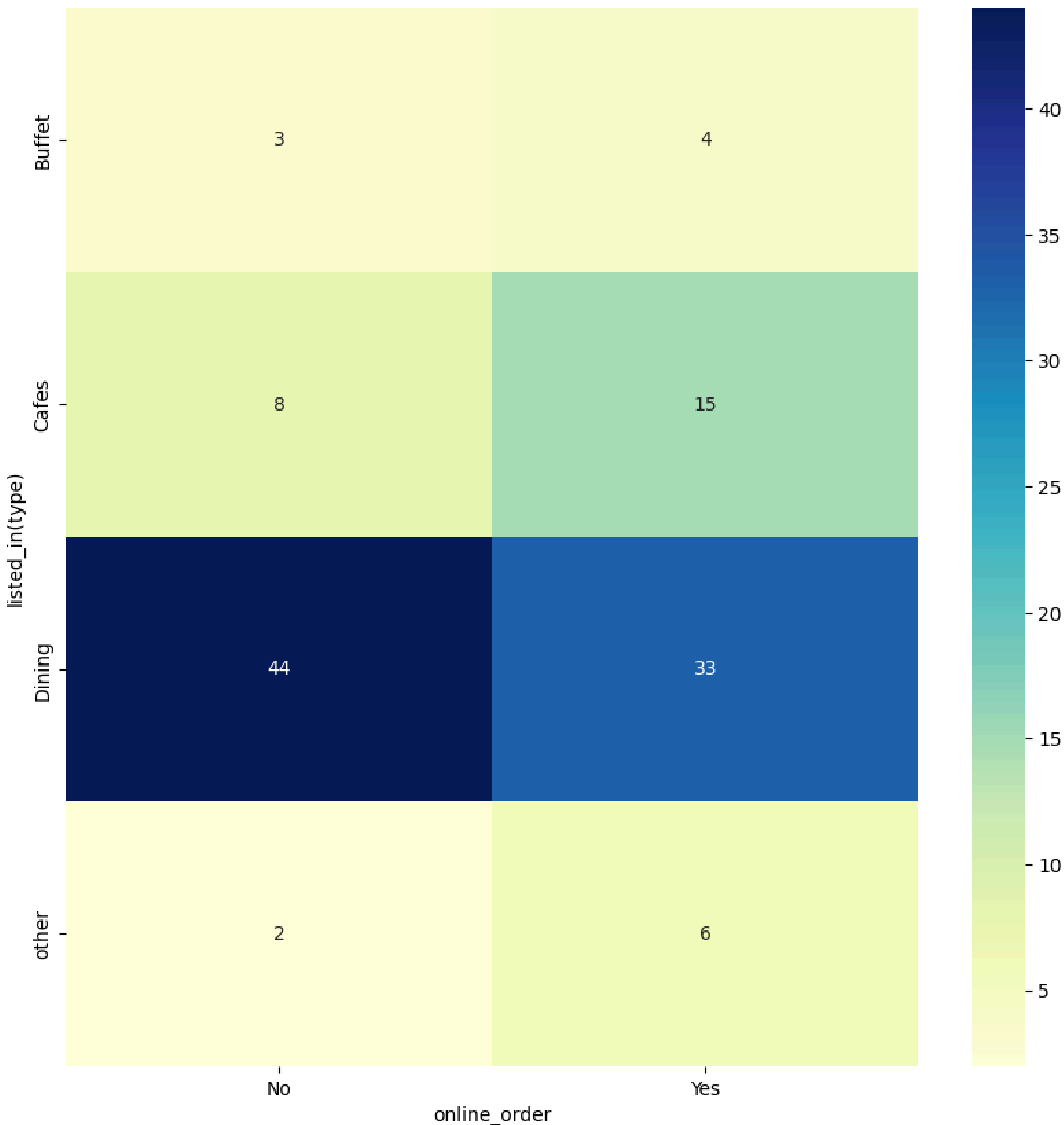
online_order	No	Yes
listed_in(type)		
Buffet	3	4
Cafes	8	15
Dining	44	33
other	2	6

In [48]:

```
plt.figure(figsize=(10,10))

sns.heatmap(data=offline_res, annot=True, fmt="d", cmap="YlGnBu")
```

Out[48]: <Axes: xlabel='online_order', ylabel='listed_in(type)'>



Answer 6:

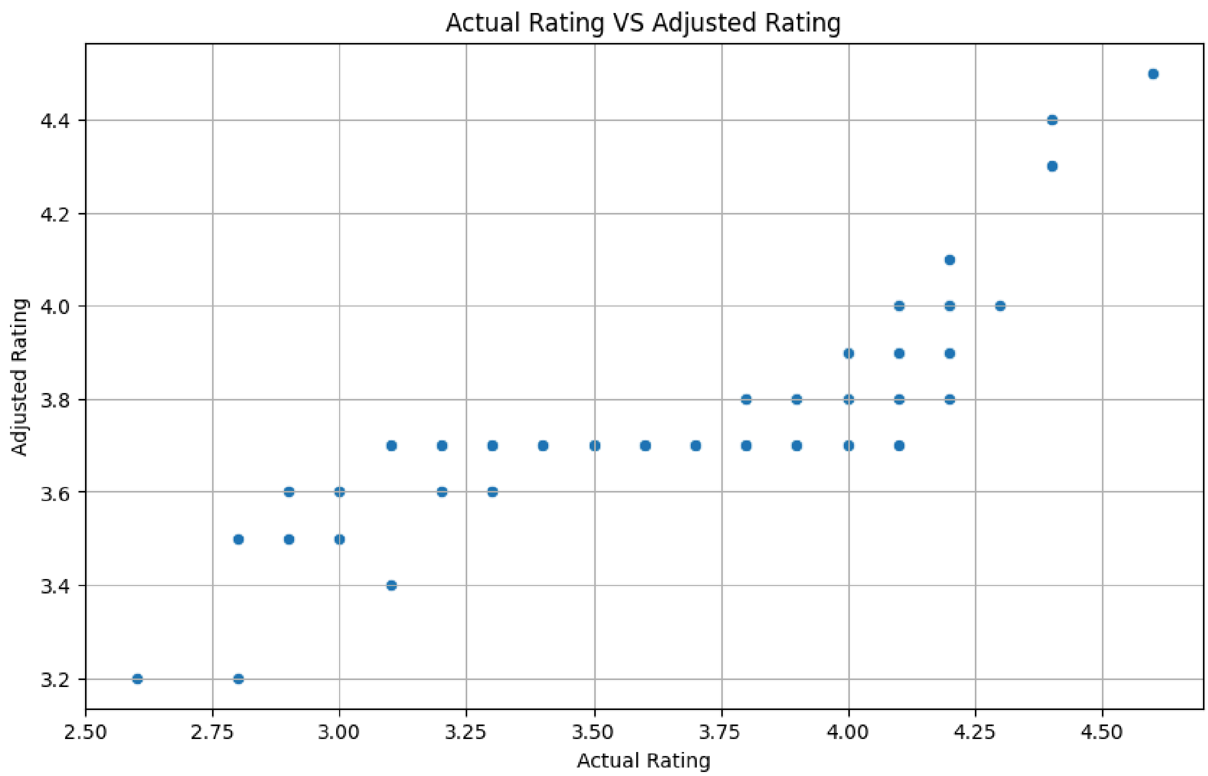
Dining Restaurants receive maximum Offline orders (i.e. 44 orders)

Compare: Actual Rating VS Adjusted Rating

In [49]:
```
plt.figure(figsize=(10, 6))

sns.scatterplot(data=df, x="rate", y="bayesian_average")

plt.title("Actual Rating VS Adjusted Rating")
plt.xlabel("Actual Rating")
plt.ylabel("Adjusted Rating")
plt.grid(True)
plt.show()
```



Model Training

Train-Test Split

Since the data is small, we are going to use 80:20 train-test dataset model. Here 80% of the data will be used to train the model, while 20% of data will be used to test the model (if it is predicting properly or not)

In [50]:
```
input_data = df2.drop(columns=["bayesian_average"])
output_data = df2["bayesian_average"]
```

In [51]:
```
x_train, x_test, y_train, y_test = train_test_split(input_data, output_data, test_s
```

Model Creation, Training and Testing

I will create 2 models, one is Linear Regression and other is Random Forest Regressor

Model Creation

In [52]:
```
model1 = LinearRegression()
model2 = RandomForestRegressor(random_state=42)
```

Model Training

In [53]:
```
model1.fit(x_train, y_train)
```

Out[53]:
```
▾ LinearRegression
▶ Parameters
```

In [54]:
```
model2.fit(x_train, y_train)
```

Out[54]:
```
▾ RandomForestRegressor
▶ Parameters
```

Model Testing

Model Testing for Linear Regression Model

In [55]:
```
log_predict_LR = model1.predict(x_test)
LR_predict = np.exp(log_predict_LR)
```

Model Testing for Random Forest Regressor

In [56]:
```
log_predict_RFR = model2.predict(x_test)
RFR_predict = np.exp(log_predict_RFR)
```

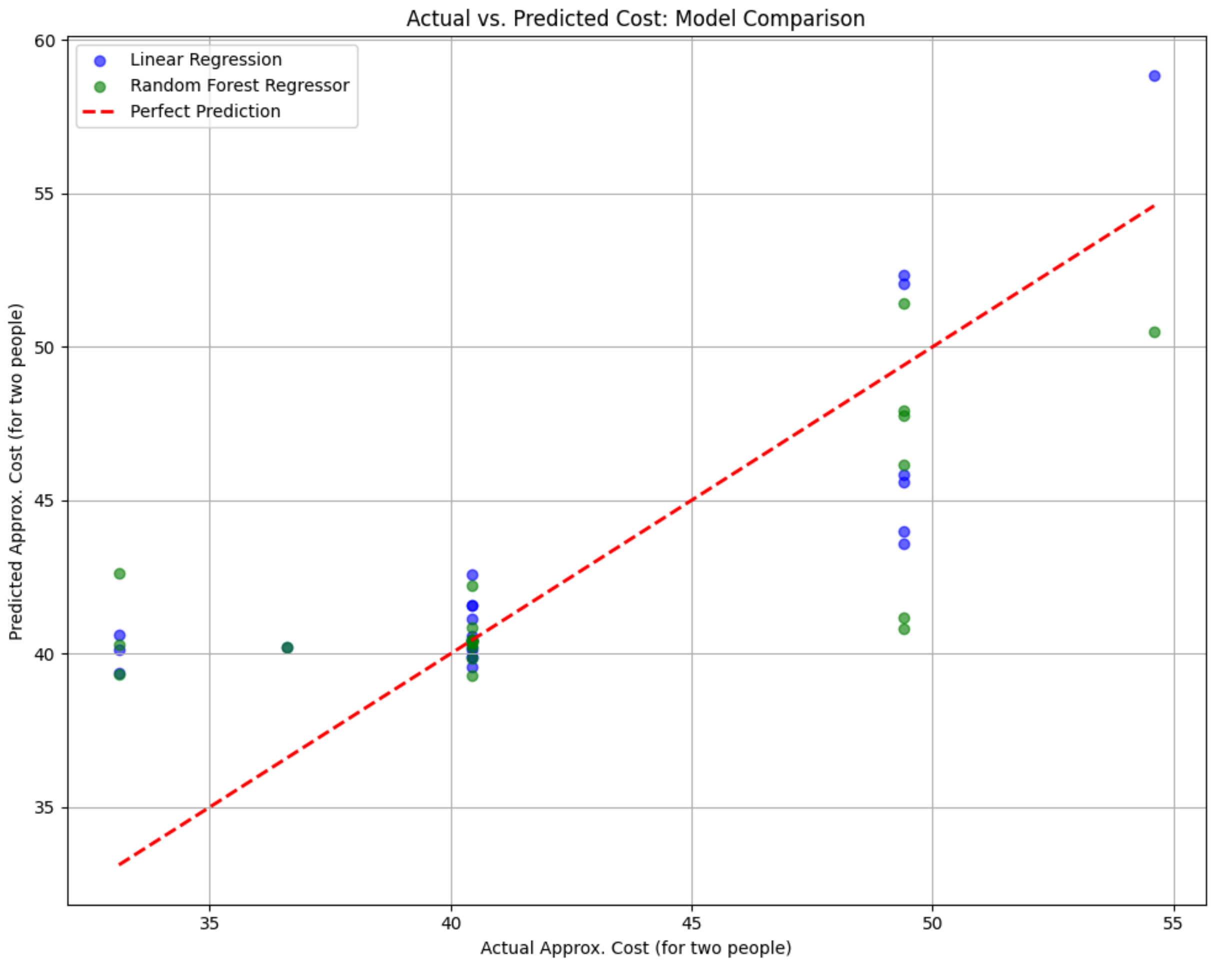
Comparing Models

In [57]:
```
plt.figure(figsize=(10, 8))

plt.scatter(np.exp(y_test), LR_predict, alpha=0.6, color='blue', label=f'Linear Reg
plt.scatter(np.exp(y_test), RFR_predict, alpha=0.6, color='green', label=f'Random F

min_val = np.exp(y_test).min()
max_val = np.exp(y_test).max()
plt.plot([min_val, max_val], [min_val, max_val], color='red', linestyle='--', linew
```

```python
plt.xlabel("Actual Approx. Cost (for two people)")
plt.ylabel("Predicted Approx. Cost (for two people)")
plt.title("Actual vs. Predicted Cost: Model Comparison")
plt.legend()
plt.grid(True)
plt.tight_layout()
```



In [58]:
```python
LR_mae = mean_absolute_error(np.exp(y_test), LR_predict)
LR_mse = mean_squared_error(np.exp(y_test), LR_predict)
LR_rmse = np.sqrt(LR_mse)
LR_r2 = r2_score(np.exp(y_test), LR_predict)

print("Mean Absolute Error (MAE) for Linear Regressing:", LR_mae)
print("Mean Squared Error (MSE) for Linear Regressing:", LR_mse)
print("Root Mean Squared Error (RMSE) for Linear Regressing:", LR_rmse)
print("R² Score for Linear Regressing:", LR_r2)
```

```
Mean Absolute Error (MAE) for Linear Regressing: 2.6366903988494106
Mean Squared Error (MSE) for Linear Regressing: 12.635215719560904
Root Mean Squared Error (RMSE) for Linear Regressing: 3.5546048612413874
R² Score for Linear Regressing: 0.6277412144882519
```

In [59]:
```python
RFR_mae = mean_absolute_error(np.exp(y_test), RFR_predict)
RFR_mse = mean_squared_error(np.exp(y_test), RFR_predict)
RFR_rmse = np.sqrt(RFR_mse)
RFR_r2 = r2_score(np.exp(y_test), RFR_predict)
```

```python
print("Mean Absolute Error (MAE) for Random Forest Regressor:", RFR_mae)
print("Mean Squared Error (MSE) for Random Forest Regressor:", RFR_mse)
print("Root Mean Squared Error (RMSE) for Random Forest Regressor:", RFR_rmse)
print("R² Score for Random Forest Regressor:", RFR_r2)
```

```
Mean Absolute Error (MAE) for Random Forest Regressor: 2.620548892218278
Mean Squared Error (MSE) for Random Forest Regressor: 16.341101214917863
Root Mean Squared Error (RMSE) for Random Forest Regressor: 4.042412796204498
R² Score for Random Forest Regressor: 0.518558398431422
```

Therefore, Linear Regression is better model than Random Forest Regressor

Linear Regression has a precision of 62%, while Random Forest Regressor has a precision of 52%