Zomato Data Analysis Project

Importing Required Libraries

In [1]:
```
import numpy as np                # Used for handling arrays and performing mathematical operations
import pandas as pd               # Used for data manipulation and analysis, especially with tabular data
import matplotlib.pyplot as plt   # Used for creating basic graphs and charts
import seaborn as sns             # Used for making more detailed and beautiful graphs
```

Loading The Zomato Dataset

In [2]:
```
zomato = pd.read_csv("Zomato data .csv")
```

In [3]:
```
zomato
```

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
...	...	...	...	...	...	...	...
143	Melting Melodies	No	No	3.3/5	0	100	Dining
144	New Indraprasta	No	No	3.3/5	0	150	Dining
145	Anna Kuteera	Yes	No	4.0/5	771	450	Dining
146	Darbar	No	No	3.0/5	98	800	Dining
147	Vijayalakshmi	Yes	No	3.9/5	47	200	Dining

148 rows × 7 columns

In [4]:
```
##################################################################################################################
```

Data Cleaning

Removing '/5' From Rate Column

In [5]:
```
def handleRate(value):
    value = str(value).split("/")   # Convert the value to a string and split the string by '/'
    value = value[0]                # keep only the part before the '/'
    return float(value)             # Return the remaining part as a float
```

In [6]:
```
zomato["rate"] = zomato["rate"].apply(handleRate)  # Apply the handleRate function to each value in the 'rate' column
```

In [7]:
```
zomato
```

Out[7]:

	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 [8]:
```
zomato.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    float64
 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: float64(1), int64(2), object(4)
memory usage: 8.2+ KB
```

In [9]:
```
zomato.describe()
```

Out[9]:

	rate	votes	approx_cost(for two people)
count	148.000000	148.000000	148.000000
mean	3.633108	264.810811	418.243243
std	0.402271	653.676951	223.085098
min	2.600000	0.000000	100.000000
25%	3.300000	6.750000	200.000000
50%	3.700000	43.500000	400.000000
75%	3.900000	221.750000	600.000000
max	4.600000	4884.000000	950.000000

In [10]:
```
# Observations from Dataset Information:

# 1. The dataset has a total of 148 rows and 7 columns.
# 2. All columns have non-null values, meaning there are no missing values in the dataset.
# 3. The 'rate' column has been successfully converted to a numeric type (float64) after data cleaning.
# 4. The 'votes' and 'approx_cost(for two people)' columns are integers (int64), representing numeric values.
# 5. The remaining columns ('name', 'online_order', 'book_table', and 'listed_in(type)') are of object type,
#    meaning they contain textual data.
```

In [11]:
```
##########################################################################################################################################################
```

Exploratory Data Analysis (EDA)

In [12]:
```
zomato.head()
```

Out[12]:

	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

Type Of Restaurant

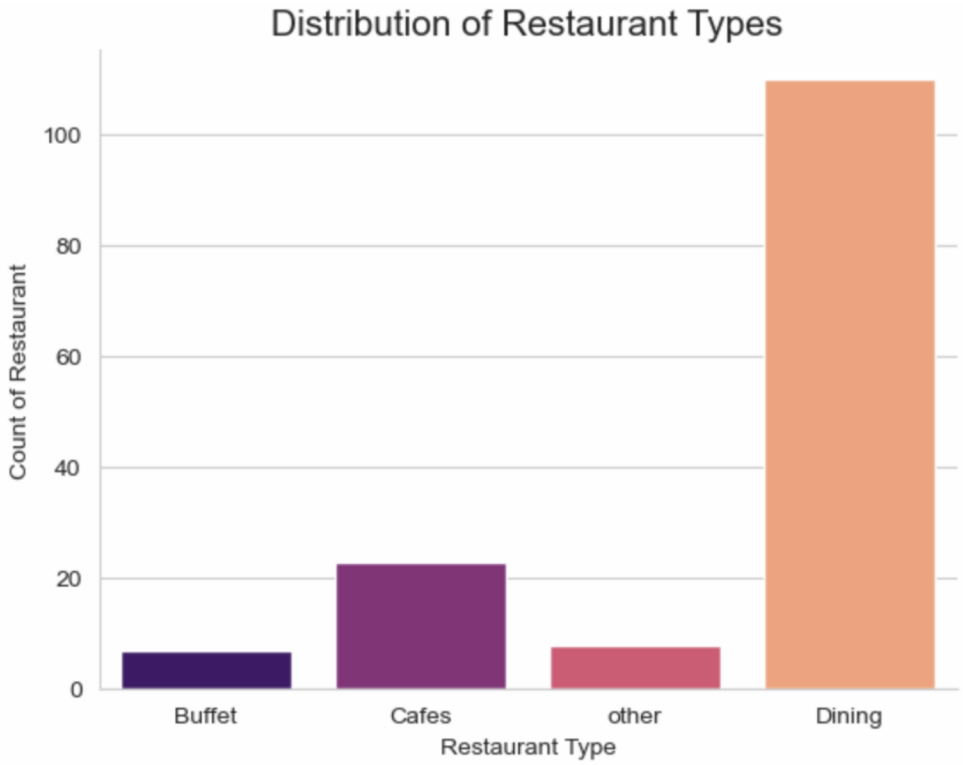
In [13]:
```
sns.set_style("whitegrid")

sns.countplot(x = "listed_in(type)", data = zomato, palette = "magma")

plt.xlabel("Restaurant Type", fontsize = 10)
plt.ylabel("Count of Restaurant", fontsize = 10)
plt.title("Distribution of Restaurant Types", fontsize = 15)

sns.despine()

plt.show()
```



Analysis Of Restaurant Type Distribution:

In [14]:
```
# The count plot shows that 'Dining' restaurants are the most popular among customers,
# followed by 'Cafes' and then 'Buffets'. Other restaurant types have similar lower counts.
# This indicates a strong preference for dining experiences.
```

In [15]:
```
##########################################################################################################################################
```

Total Votes By Restaurant Type

In [16]:
```
grouped_data = zomato.groupby("listed_in(type)")["votes"].sum()

#This line groups the restaurants by type and calculates the total number of votes for each type.
# groupby() is used to group the data by a specific column—in this case, listed_in(type) (restaurant type).
# ['votes'].sum() sums up all the votes for each restaurant type after grouping them.
```

In [17]:
```
vote_sum = pd.DataFrame({"votes": grouped_data})

vote_sum
```

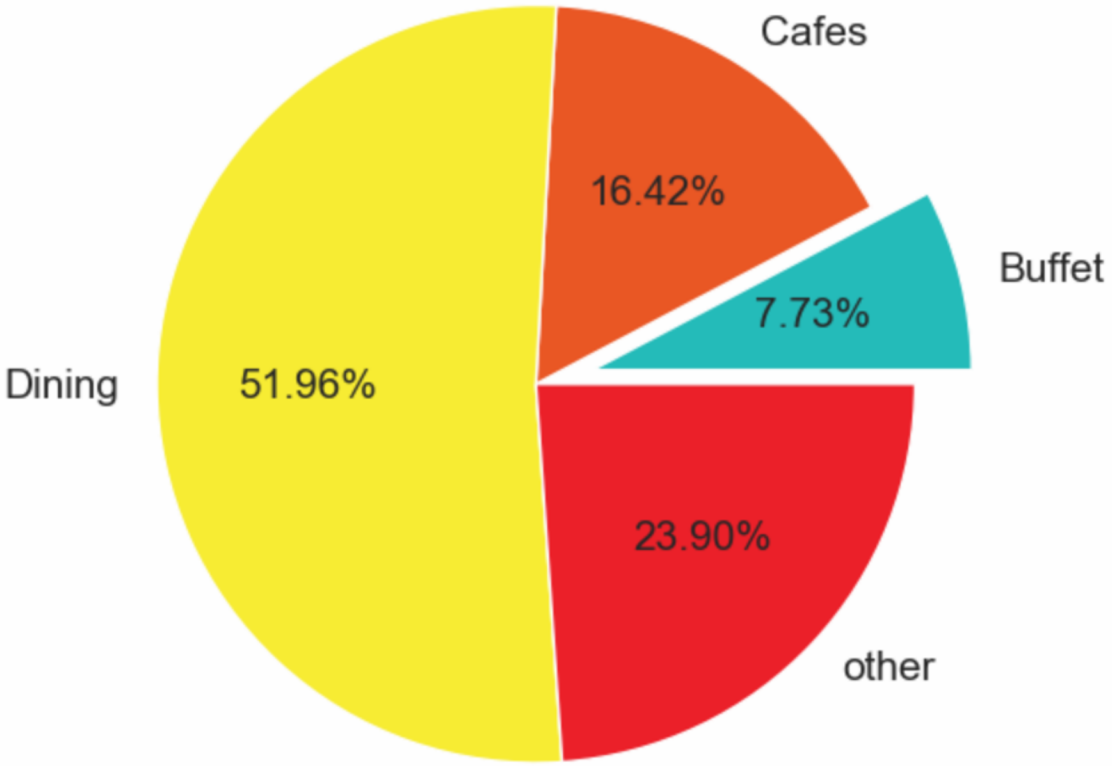
Out[17]:

listed_in(type)	votes
Buffet	3028
Cafes	6434
Dining	20363
other	9367

In [18]:
```
ex1 = [0.2,0.0,0.0,0.0]
color1 = ["#24bcba","#ea5724","#f8ed33","#ec2029"]

plt.pie(vote_sum["votes"], labels = vote_sum.index, autopct = "%0.2f%%", explode = ex1, colors = color1, radius = 1.3,
        textprops = {"fontsize":15})

plt.show()
```



Analysis Of Total Votes By Restaurant Type

In [19]:
```
# The pie chart shows the distribution of total votes by restaurant type.
# Dining restaurants received the most votes, accounting for 51.96% of the total.
# Cafes follow with 16.42% of the votes, showing moderate customer preference.
# Buffet restaurants contributed 7.73% of the votes, indicating a smaller share of customer engagement.
# The "Others" category represents 23.90% of the votes, showing a diverse range of restaurant types receiving a
# notable number of votes.
```

In [20]:
```
##########################################################################################################################################
```

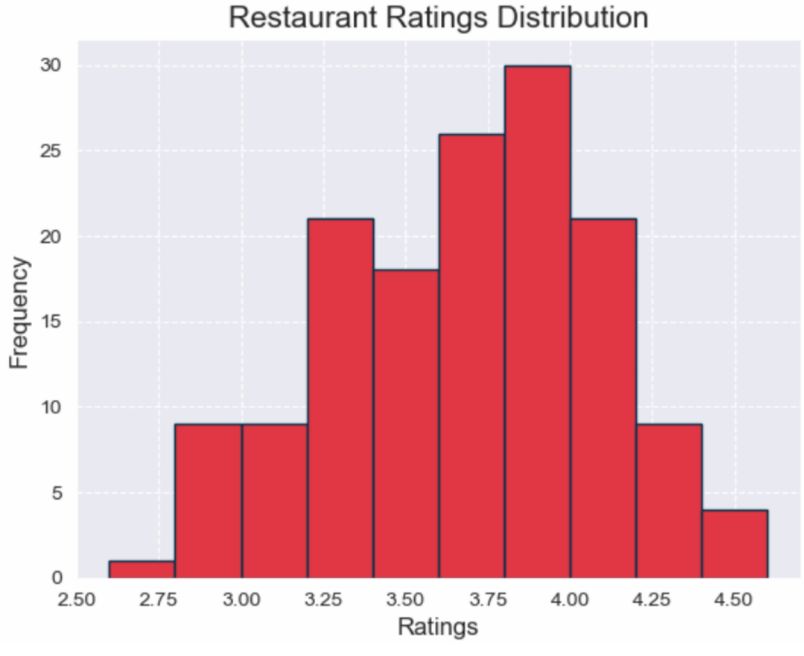
Distribution Of Restaurant Ratings

In [21]:
```
sns.set_style("darkgrid")

plt.hist(zomato["rate"], bins = 10, color = '#E23744', edgecolor = "#003049")

plt.title("Restaurant Ratings Distribution", fontsize = 15)
plt.xlabel("Ratings", fontsize = 12)
plt.ylabel("Frequency", fontsize = 12)
plt.grid(True, linestyle = "--")

plt.show()
```



Analysis Of Distribution Of Restaurant Ratings

In [22]:
```
# Most of the restaurant ratings fall between 3.25 and 4.25,indicating that a majority of restaurants have above-average ratings.
```

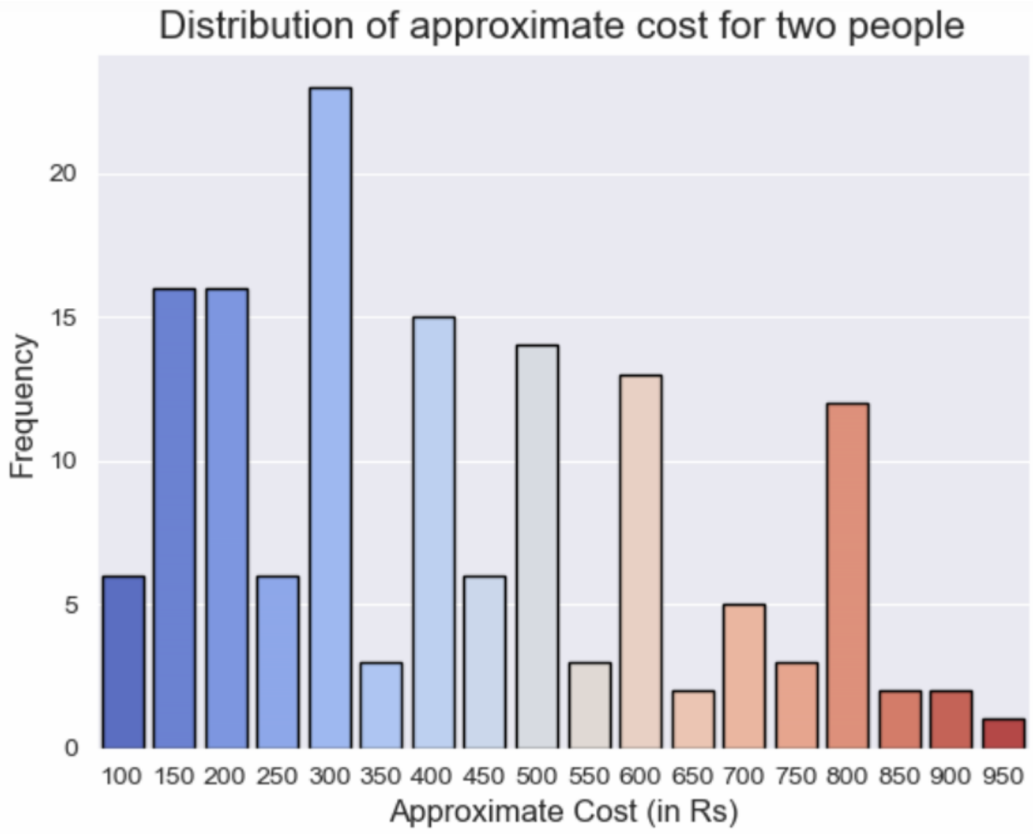
In [23]:
```
##################################################################################################################################################
```

Average Spending on Orders by Couples

In [24]:
```
sns.countplot(x = zomato["approx_cost(for two people)"], palette = "coolwarm", edgecolor = "black")

plt.title("Distribution of approximate cost for two people", fontsize = 15)
plt.xlabel("Approximate Cost (in Rs)", fontsize = 12)
plt.ylabel("Frequency", fontsize = 12)

plt.show()
```



Analysis Of Average Spending On Orders By Couples

In [25]:
```
# The count plot shows that Rs. 300 is the most common amount spent by couples on their orders.
# Following this, Rs. 150 and Rs. 200 are the next most frequent spending amounts.
# The lowest spending value observed is Rs. 950, which occurs less frequently.
```

In [26]:
```
##################################################################################################################################################
```

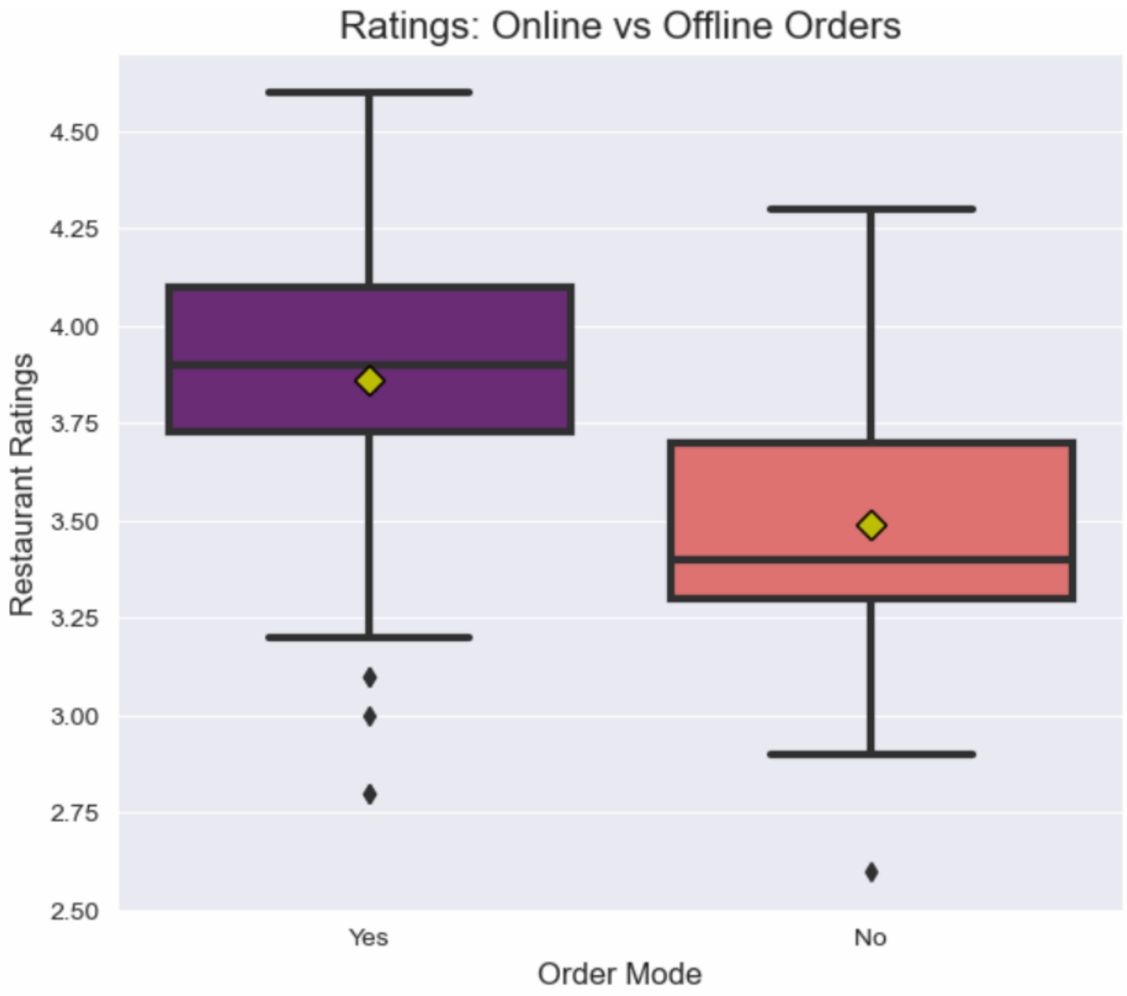
Comparison of Ratings Between Online and Offline Orders

In [27]:
```
plt.figure(figsize = (7,6))

sns.boxplot(x = "online_order", y = "rate", data = zomato, palette = "magma", linewidth = 3, showmeans = True,
            meanprops = {"marker":"D", "markersize":8, "markeredgecolor":"black", "markerfacecolor":"y"})

plt.title("Ratings: Online vs Offline Orders", fontsize = 15)
plt.xlabel("Order Mode", fontsize = 12)
plt.ylabel("Restaurant Ratings", fontsize = 12)

plt.show()
```



Analysis Of Comparison Of Ratings Between Online And Offline Orders

In [28]:
```
# The boxplot shows that restaurants receiving online orders generally have higher ratings compared to those with offline orders.
# The online mode's ratings range between 3.75 and 4.2, while the offline mode's ratings range between 3.25 and 3.75.
# This indicates that customers tend to give higher ratings when ordering online compared to offline.
```

In [29]:
```
##########################################################################################################################################
```

Restaurant Categories with More Offline Orders

In [30]:
```
pivot_table = zomato.pivot_table(index = "listed_in(type)", columns = "online_order", aggfunc = "size", fill_value = 0)

pivot_table
```

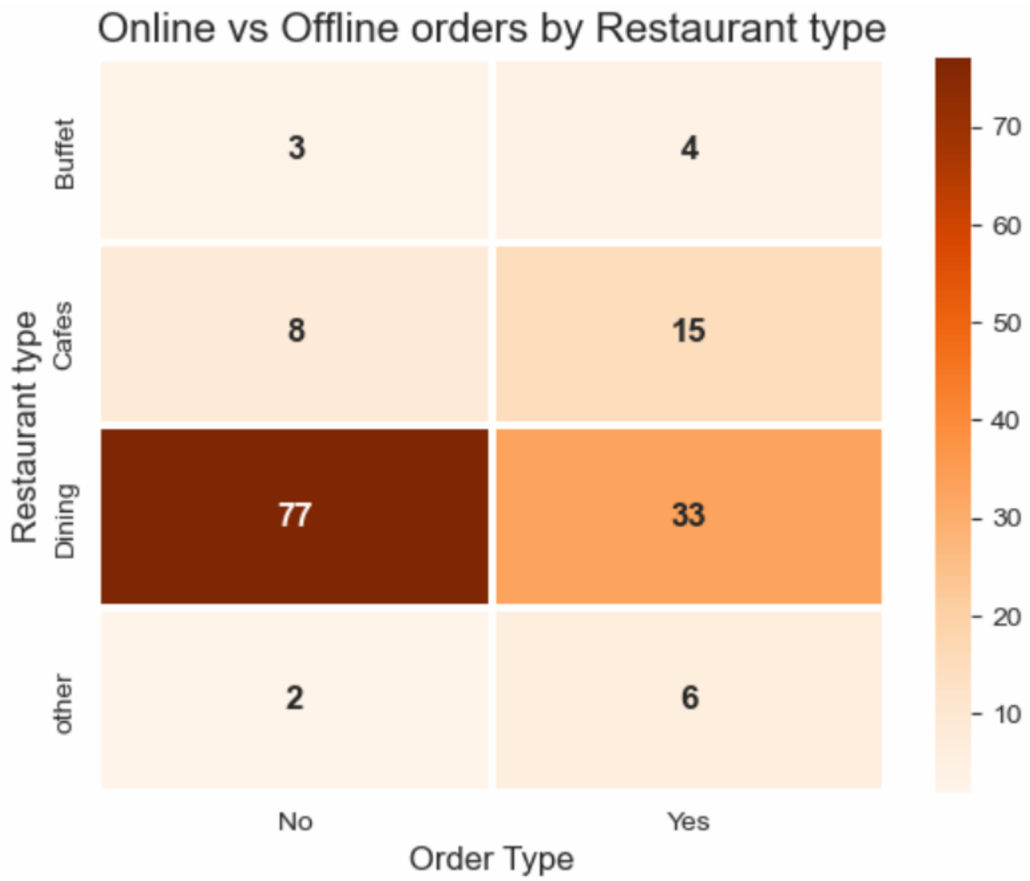
Out[30]:

online_order	No	Yes
listed_in(type)		
Buffet	3	4
Cafes	8	15
Dining	77	33
other	2	6

In [31]:
```
sns.heatmap(pivot_table, annot = True, cmap = "Oranges", linewidth = 1.5, annot_kws = {"size":12, "weight":"bold"})

plt.title("Online vs Offline orders by Restaurant type", fontsize = 15)
plt.xlabel("Order Type", fontsize = 12)
plt.ylabel("Restaurant type", fontsize = 12)

plt.show()
```



Analysis Of Restaurant Categories with More Offline Orders

In [32]:
```
# Most customers prefer to order offline from dining restaurants, with 77 offline orders compared to 33 online orders.
# This suggests that people enjoy the dining experience at these places.

# Cafes receive more online orders (15) than offline (8). This indicates that many customers prefer to order takeout from cafes.

# Buffets have similar numbers for online (4) and offline (3) orders, showing some interest in ordering online, but not a
# strong preference.

# he "Other" category has more online orders (6) than offline (2), suggesting that there are good options available for
# online ordering.
```

In [33]:
```
##########################################################################################################################################
```

Comparing Ratings and Cost for Online and Offline Orders

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

Out[34]:

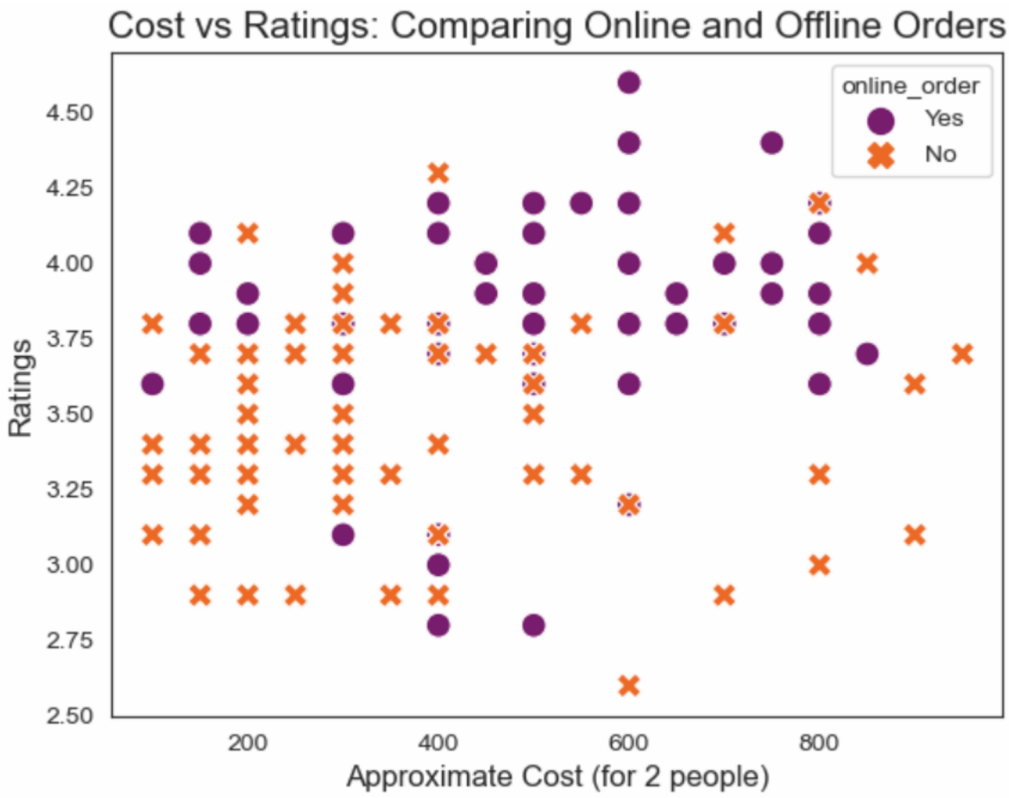
	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
1	Spice Elephant	Yes	No	4.1	787	800	Buffet
2	San Churro Cafe	Yes	No	3.8	918	800	Buffet
3	Addhuri Udupi Bhojana	No	No	3.7	88	300	Buffet
4	Grand Village	No	No	3.8	166	600	Buffet

In [35]:
```
sns.set_style("white")

sns.scatterplot(x = "approx_cost(for two people)", y = "rate", data = zomato, hue = "online_order", size = "online_order",
                sizes = (100,100), style = "online_order", palette = "inferno")

plt.title("Cost vs Ratings: Comparing Online and Offline Orders", fontsize = 15)
plt.xlabel("Approximate Cost (for 2 people)", fontsize = 12)
plt.ylabel("Ratings", fontsize = 12)


plt.show()
```



Analysis Of Comparing Ratings and Cost for Online and Offline Orders

In [36]:
```
# General Trend: There is a slight positive correlation between approximate cost and ratings; as costs increase,
# ratings tend to be higher.

# Online Orders: Restaurants with online orders (purple dots) generally receive better ratings (around 3.5 to 4.5) and
# have a broader range of costs.

# Offline Orders: Offline orders (orange crosses) show more variability in ratings, with many restaurants scoring below 4.0,
# indicating inconsistent quality.

# Cost Distribution: Online orders tend to include higher-cost items that also receive better ratings,
# suggesting that higher-priced restaurants may offer superior quality.
```

In [37]:
```
##########################################################################################################################################
```

How many restaurants offer the option to book a table, and what is their average rating?

In [38]:
```
# How many restaurants offer the option to book a table

sns.set_style("darkgrid")

sns.countplot(x = "book_table", data = zomato, palette = "inferno")

plt.title("Restaurant Offering Table Booking", fontsize = 15)
plt.xlabel("Table Booking Option", fontsize = 12)
plt.ylabel("Count of Restaurants Offering Table Booking", fontsize = 12)

plt.show()
```

In [39]:
```
# The average rating of those restaurants

booking_rest = zomato[zomato["book_table"] == "Yes"]     # Filter restaurants that offer table booking

booking_rest
```

Out[39]:

	name	online_order	book_table	rate	votes	approx_cost(for two people)	listed_in(type)
0	Jalsa	Yes	Yes	4.1	775	800	Buffet
7	Onesta	Yes	Yes	4.6	2556	600	Cafes
11	Cafe Shuffle	Yes	Yes	4.2	150	600	Cafes
12	The Coffee Shack	Yes	Yes	4.2	164	500	Cafes
44	Onesta	Yes	Yes	4.6	2556	600	other
57	Wamama	Yes	Yes	4.2	354	800	other
61	Goa 0 Km	Yes	Yes	3.6	163	800	Dining
63	Jeet Restaurant	No	Yes	4.0	808	850	Dining

In [40]:
```
count_booking = booking_rest.shape[0]    #  Count how many restaurants offer table booking

count_booking
```

Out[40]: 8

In [41]:
```
print(f"The number of Restaurants that offer table booking is : {count_booking}")
```

```
The number of Restaurants that offer table booking is : 8
```

In [42]:
```
# Calculate the average rating of those restaurants

avg_rating_booking = booking_rest["rate"].mean()

avg_rating_booking
```

Out[42]: 4.1875

In [43]:
```
print(f"Average rating of restaurants that offer table booking: {avg_rating_booking:.2f}")
```

```
Average rating of restaurants that offer table booking: 4.19
```

In [44]:
```
##########################################################################################################################
```

Table Booking and Its Effect on Customer Votes

In [45]:
```
plt.figure(figsize = (7,6))
sns.boxplot(x = "book_table", y = "votes", data = zomato, palette = "magma", linewidth = 1.5)

plt.title("Votes Comparison: Table Booking vs No Booking", fontsize=15)
plt.xlabel("Table Booking Option", fontsize = 12)
plt.ylabel("Number of votes", fontsize = 12)

plt.show()
```

Analysis of Relationship Between Table Booking and Votes

In [46]:
```
# Restaurants that offer table booking ("Yes") generally receive more votes compared to those that don't ("No").

# Restaurants with a table booking option typically receive more votes,
# indicating that this feature might help attract more customers.
```

In [47]:
```
##########################################################################################################################################
```

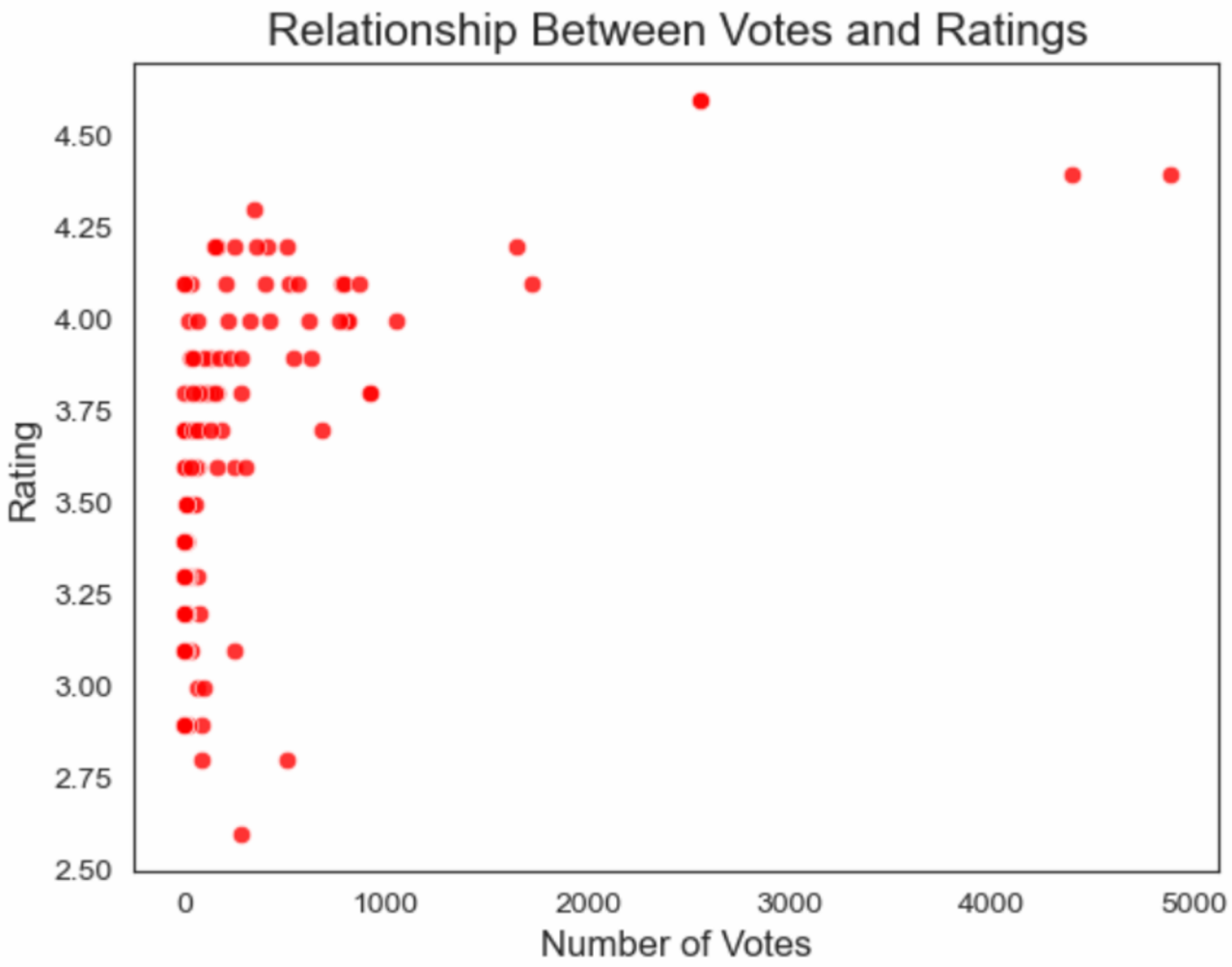
Examining the Relationship Between Customer Votes and Ratings

In [48]:
```
sns.set_style("white")

sns.scatterplot(x = "votes", y = "rate", data = zomato, color = "r", alpha = 0.8)

plt.title("Relationship Between Votes and Ratings", fontsize=15)
plt.xlabel("Number of Votes", fontsize = 12)
plt.ylabel("Rating", fontsize = 12)


plt.show()
```



Analysis of Relationship Between Customer Votes and Ratings

In [49]:
```
# There's a slight positive correlation; as the number of votes increases, ratings generally increase too,
# but it's not very strong.

# Most restaurants have ratings between 3.0 and 4.0, regardless of their vote count.

# Some restaurants with over 2000 votes have ratings above 4.0, indicating that popular restaurants tend to be rated higher,
# though exceptions exist.

# Restaurants with ratings below 3.0 can still receive votes, showing that even less popular restaurants can
# attract some customers.
```

In [50]:
```
##########################################################################################################################################
```

Questions Addressed

In [51]:
```
# 1) What type of restaurant do the majority of customers order from?

# 2) How many votes has each type of restaurant received from customers?

# 3) What are the ratings that the majority of restaurants have received?

# 4)Zomato has observed that most couples order most of their food online. What is their
# average spending on each order?

# 5) Which mode (online or offline) has received the maximum rating?

# 6) Which type of restaurant received more offline orders, so that Zomato can provide those
# customers with some good offers?

# 7) What is the relationship between approximate cost and ratings, and how does it differ between online and offline orders?

# 8) How many restaurants offer the option to book a table, and what is their average rating?

# 9) Does having a table booking option affect the number of votes a restaurant receives?

# 10) What is the relationship between the number of votes and the restaurant ratings?
```