Bangalore Restaurant Success Analysis

Business Persona:

Market Entry Consultant

Business Problem:

- The Bangalore restaurant market is highly competitive with over 51,000 establishments. A new restaurant group wants to enter the market but needs to increase the chances to succeed.

Objective:

- To identify the "Success Recipe" by analyzing the relationship between location, cost, and service features and their impact on restaurant ratings.

This project aims to provide data-driven recommendations on:

1. Where to open.
2. What to offer.
3. How to price.

- I have imported the dataset from kaggle - https://www.kaggle.com/datasets/himanshupoddar/zomato-bangalore-restaurants

In [ ]:
```
# PYTHON LIBRARY
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
# IGNORE WARNINGS
import warnings
warnings.filterwarnings("ignore")
plt.style.use('dark_background')
df = pd.read_csv('zomato.csv')
df.head()
```

Out[ ]:

	url	address	name	online_order	bo
0	https://www.zomato.com/bangalore/jalsa-banasha...	942, 21st Main Road, 2nd Stage, Banashankari, ...	Jalsa	Yes	
1	https://www.zomato.com/bangalore/spice-elephan...	2nd Floor, 80 Feet Road, Near Big Bazaar, 6th ...	Spice Elephant	Yes	
2	https://www.zomato.com/SanchurroBangalore?cont...	1112, Next to KIMS Medical College, 17th Cross...	San Churro Cafe	Yes	
3	https://www.zomato.com/bangalore/addhuri-udupi...	1st Floor, Annakuteera, 3rd Stage, Banashankar...	Addhuri Udupi Bhojana	No	
4	https://www.zomato.com/bangalore/grand-village...	10, 3rd Floor, Lakshmi Associates, Gandhi Baza...	Grand Village	No	

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

Out[ ]:
```
(51717, 17)
```

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['url', 'address', 'name', 'online_order', 'book_table', 'rate', 'votes',
       'phone', 'location', 'rest_type', 'dish_liked', 'cuisines',
       'approx_cost(for two people)', 'reviews_list', 'menu_item',
       'listed_in(type)', 'listed_in(city)'],
      dtype='object')
```

Data Cleaning

In [ ]:
```
df = df.drop(['url','address','phone','menu_item','dish_liked','reviews_list'],a
df.head()
```

Out[ ]:

	name	online_order	book_table	rate	votes	location	rest_type	cuisines
0	Jalsa	Yes	Yes	4.1/5	775	Banashankari	Casual Dining	North Indian, Mughlai, Chinese
1	Spice Elephant	Yes	No	4.1/5	787	Banashankari	Casual Dining	Chinese, North Indian, Thai
2	San Churro Cafe	Yes	No	3.8/5	918	Banashankari	Cafe, Casual Dining	Cafe, Mexican, Italian
3	Addhuri Udupi Bhojana	No	No	3.7/5	88	Banashankari	Quick Bites	South Indian, North Indian
4	Grand Village	No	No	3.8/5	166	Basavanagudi	Casual Dining	North Indian, Rajasthani

In [ ]:
```
def handlerate(value):
    if(value == 'NEW' or value == '-'):
        return np.nan
    else:
        value = str(value).split('/')
        value = value[0]
        return float(value)

df['rate'] = df['rate'].apply(handlerate)
df['rate'].head()
```

Out[ ]:
```
0    4.1
1    4.1
2    3.8
3    3.7
4    3.8
Name: rate, dtype: float64
```

In [ ]:
```
df['rate'].fillna(df['rate'].mean())
print(f"Missing Ratings After Cleaning {df['rate'].isnull().sum()}")
```

```
Missing Ratings After Cleaning 10052
```

In [ ]:
```
location = df['location'].value_counts(ascending=False)
loc_lessthan300 = location[location < 300]

def handle_location(value):
    if value in loc_lessthan300.index:   # use .index (categories)
        return 'others'
    else:
        return value
```

```
df['location'] = df['location'].apply(handle_location)
df['location'].value_counts()
```

Out[ ]:

```
location
BTM                      5124
others                   4707
HSR                      2523
Koramangala 5th Block    2504
JP Nagar                 2235
Whitefield               2144
Indiranagar              2083
Jayanagar                1926
Marathahalli             1846
Bannerghatta Road        1630
Bellandur                1286
Electronic City          1258
Koramangala 1st Block    1238
Brigade Road             1218
Koramangala 7th Block    1181
Koramangala 6th Block    1156
Sarjapur Road            1065
Ulsoor                   1023
Koramangala 4th Block    1017
MG Road                   918
Banashankari              906
Kalyan Nagar              853
Richmond Road             812
Frazer Town               727
Malleshwaram              725
Basavanagudi              684
Residency Road            675
Banaswadi                 664
Brookefield               658
New BEL Road              649
Kammanahalli              648
Rajajinagar               591
Church Street             569
Lavelle Road              529
Shanti Nagar              511
Shivajinagar              499
Domlur                    496
Cunningham Road           491
Old Airport Road          446
Ejipura                   439
Commercial Street         370
St. Marks Road            352
Koramangala 8th Block     320
Name: count, dtype: int64
```

Cleaning approx_cost column (it has commas)

In [ ]:

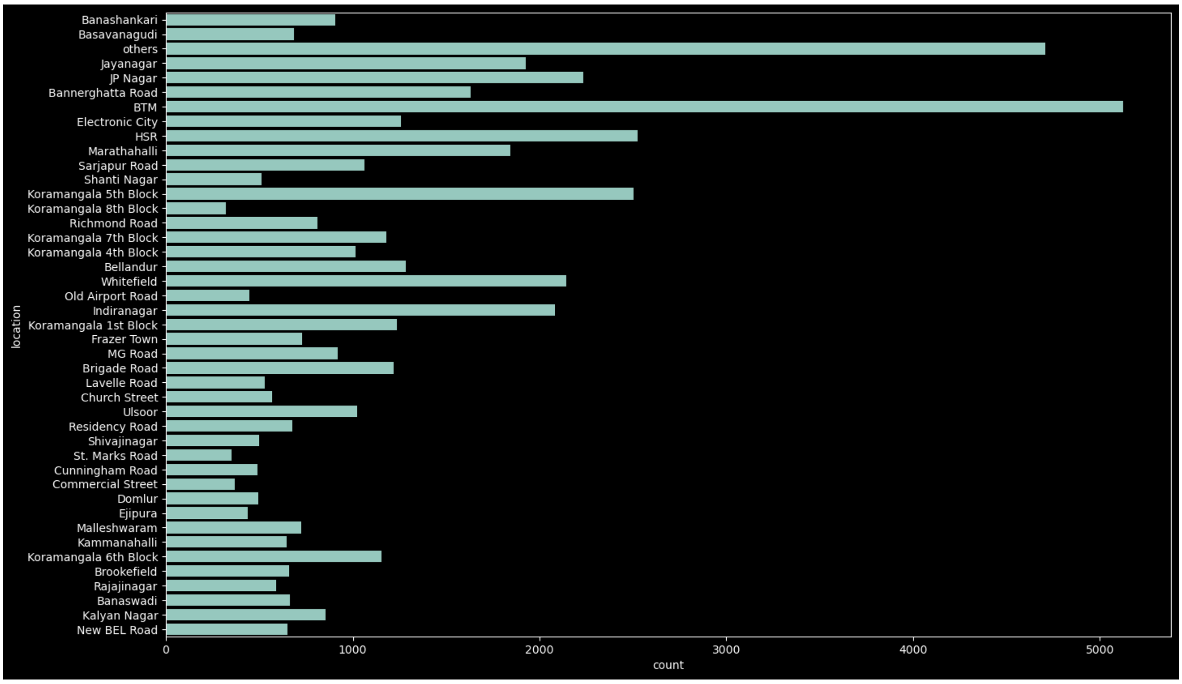
```
df['approx_cost(for two people)'] = df['approx_cost(for two people)'].astype(str
df['approx_cost(for two people)'].astype(float)
```

```
Out[ ]: 0          800.0
        1          800.0
        2          800.0
        3          300.0
        4          600.0
                   ...
        51712     1500.0
        51713      600.0
        51714     2000.0
        51715     2500.0
        51716     1500.0
        Name: approx_cost(for two people), Length: 51717, dtype: float64
```

Univariate Analysis

How many restaurants are there in each location ?

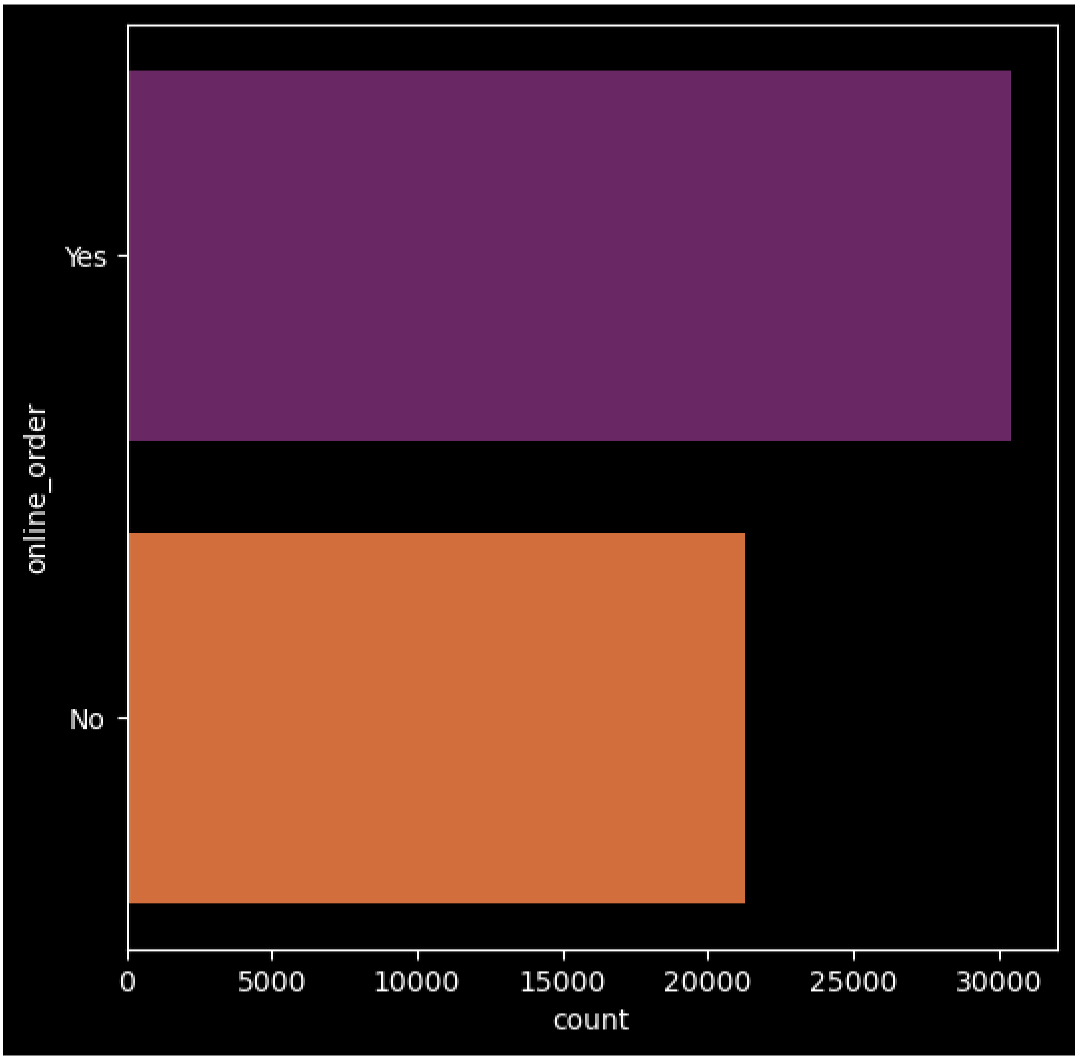
```
In [ ]: plt.figure(figsize = (16,10))
        ax = sns.countplot(df['location'])
```



Insight of count plot: Approximately 60% of restaurants in Bangalore support online ordering, indicating a highly digital-forward market.

```
In [ ]: plt.figure(figsize = (6,6))
        sns.countplot(df['online_order'], palette = 'inferno')
```

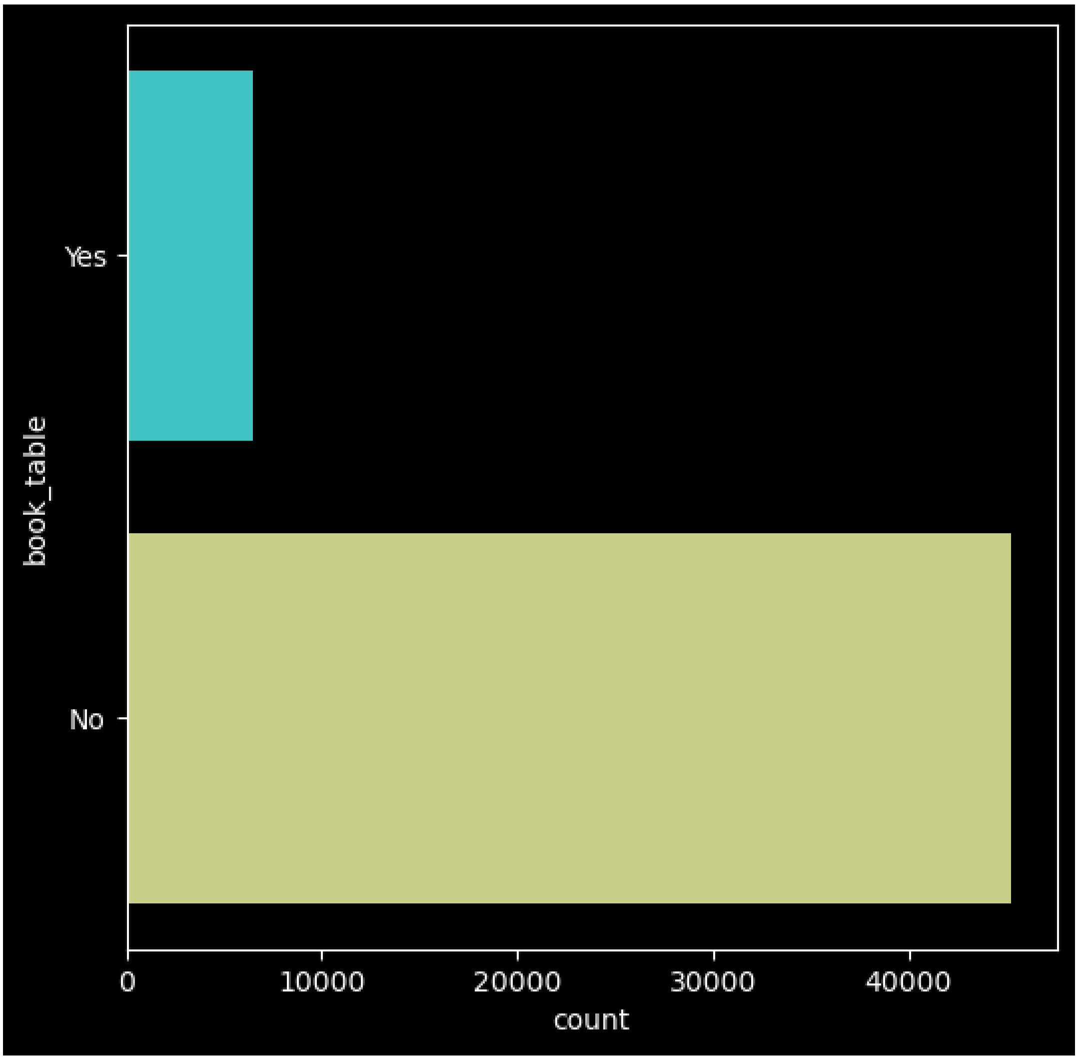
```
Out[ ]: <Axes: xlabel='count', ylabel='online_order'>
```



Insight : Only a small fraction of restarant offer table bookings. Representing focus on quick - service models over fine - dining.

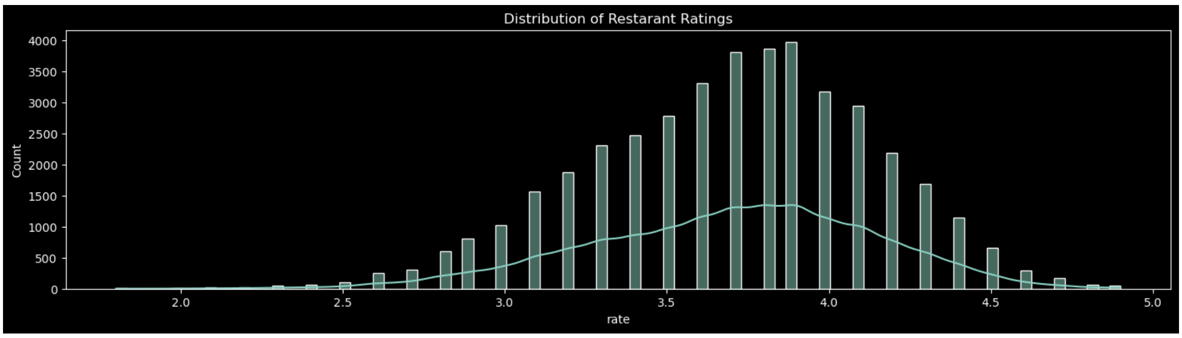
In [ ]:
```
plt.figure(figsize = (6,6))
sns.countplot(df['book_table'], palette = 'rainbow')
```

Out[ ]: <Axes: xlabel='count', ylabel='book_table'>



2. What is the Benchmark for a 'Good' Restaurant in this Market?

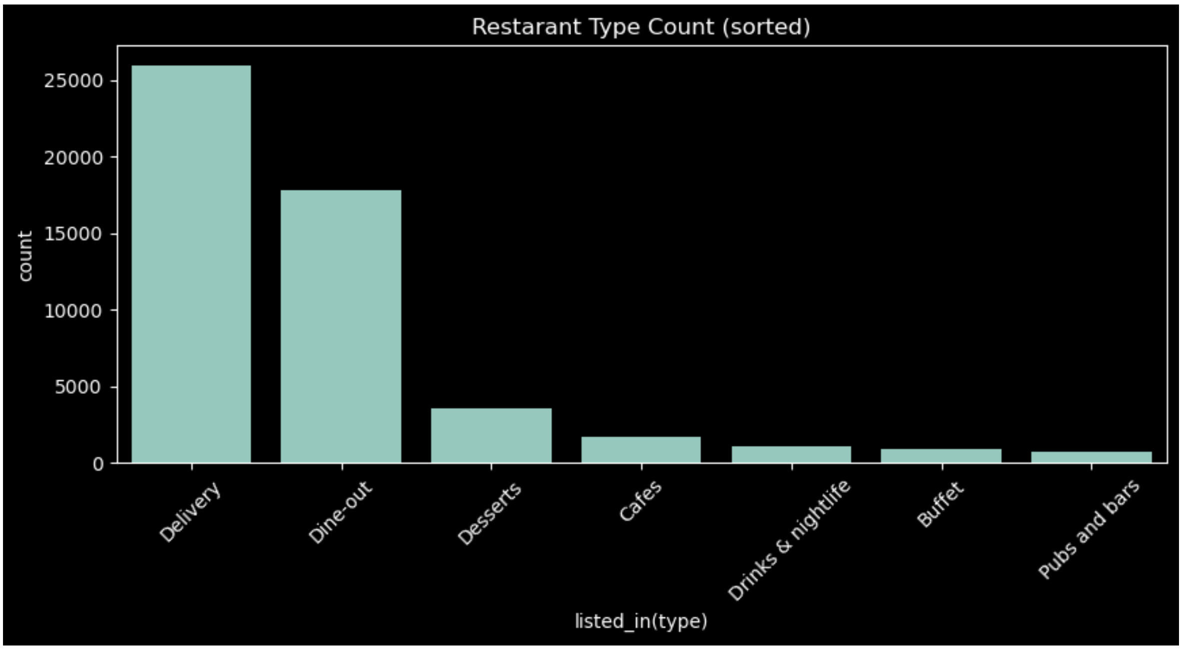
In [ ]:
```
plt.figure(figsize=(17,4))
sns.histplot(df['rate'],kde = True)
plt.title("Distribution of Restarant Ratings")
plt.show()
```



How many restaurants does banglore have as per type ?

In [ ]:
```
plt.figure(figsize=(10,4))

order = df['listed_in(type)'].value_counts().index # sorting by count

sns.countplot(data=df, x = ('listed_in(type)'), order = order)
```

```
plt.title("Restarant Type Count (sorted)")

plt.xticks(rotation = 45)

plt.show()
```



Insight : Delivery and Dine-out has the highest count of restarants in Banglore.

Bivariate Analysis:

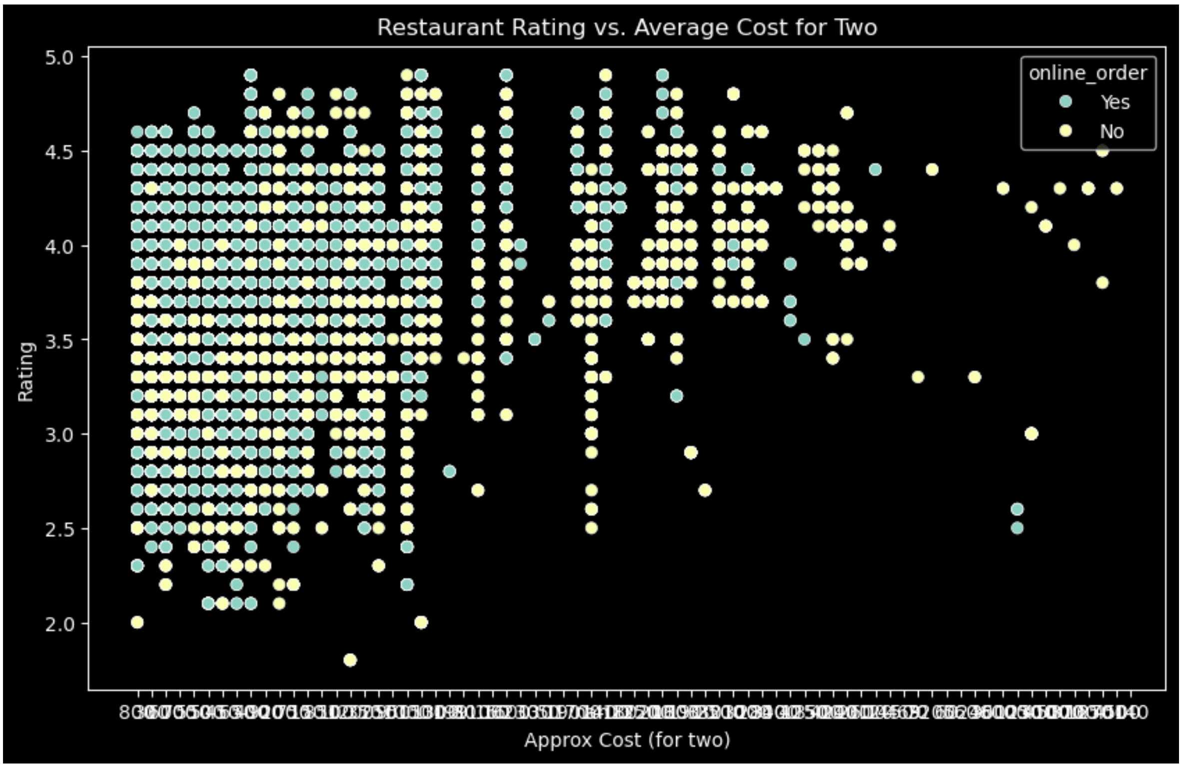
A. Does "Online Ordering" impact the Rating?

In [ ]:
```
plt.figure(figsize=(10,6))
sns.boxplot(x ='online_order', y = 'rate', data=df, palette = 'viridis')
plt.title('Impact of Online Ordering on Restaurant Ratings')
plt.xlabel('Offers Online Order')
plt.ylabel('Rating')
plt.show()
```

As the "No" Boxplot is higher it means that offering online delivery is not correlated with higher customer satisfaction in the banglore market

Does Spending more money guarantee a better experience?

In [ ]:
```
plt.figure(figsize = (10,6))
sns.scatterplot(x='approx_cost(for two people)',y='rate',hue='online_order',data
plt.title('Restaurant Rating vs. Average Cost for Two')
plt.xlabel('Approx Cost (for two)')
plt.ylabel('Rating')
plt.show()
```



Which are the popular location by Ratings in Banglore ?

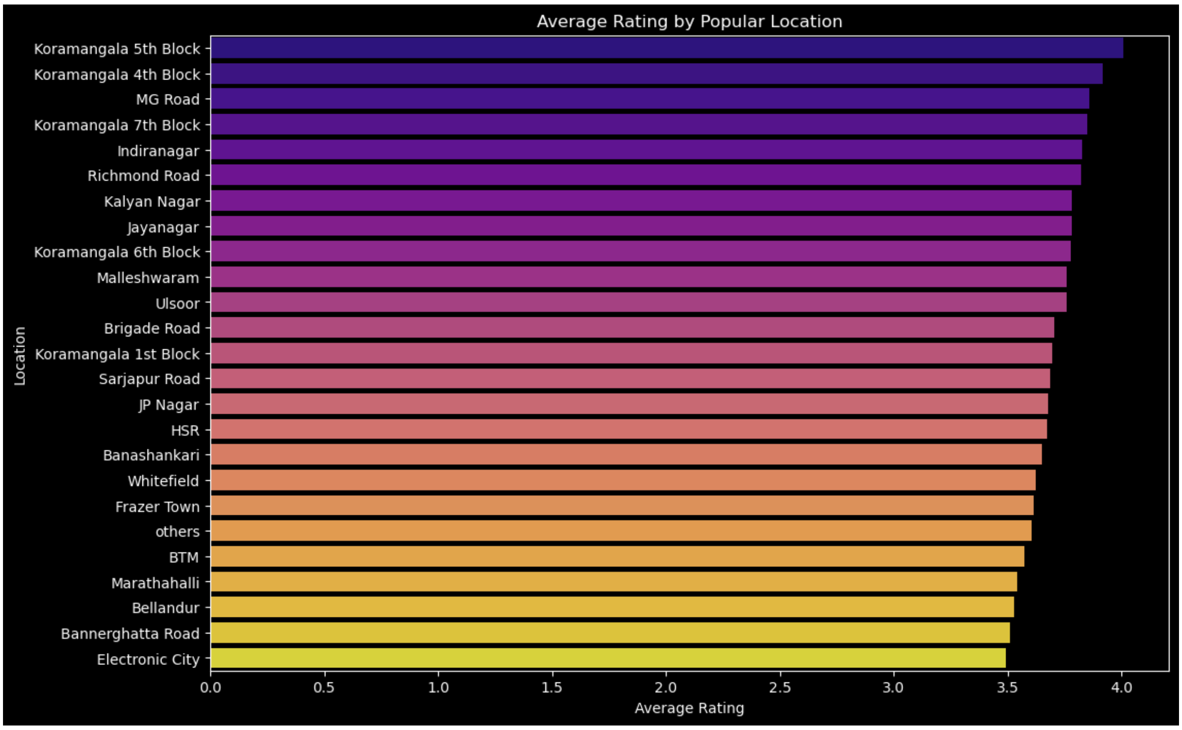
Grouping by location to find average rating and count of restaurants

In [ ]:
```
loc_stats = df.groupby('location').agg({'rate':'mean', 'name':'count'}).rename(c
```

Filtering by location with a significant number of restaurants

In [ ]:
```
popular_locs = loc_stats[loc_stats['count'] > 700].sort_values(by='rate', ascend
```

In [ ]:
```
plt.figure(figsize=(12,8))
sns.barplot(x=popular_locs['rate'], y = popular_locs.index, palette = 'plasma')
plt.title('Average Rating by Popular Location')
plt.xlabel('Average Rating')
plt.ylabel('Location')
plt.show()
```



Insight : The top 3 popular locations are -

- koramangala 4th Block
- koramangala 5th Block
- MG Road

Does Luxury Restaurants have higher ratings?

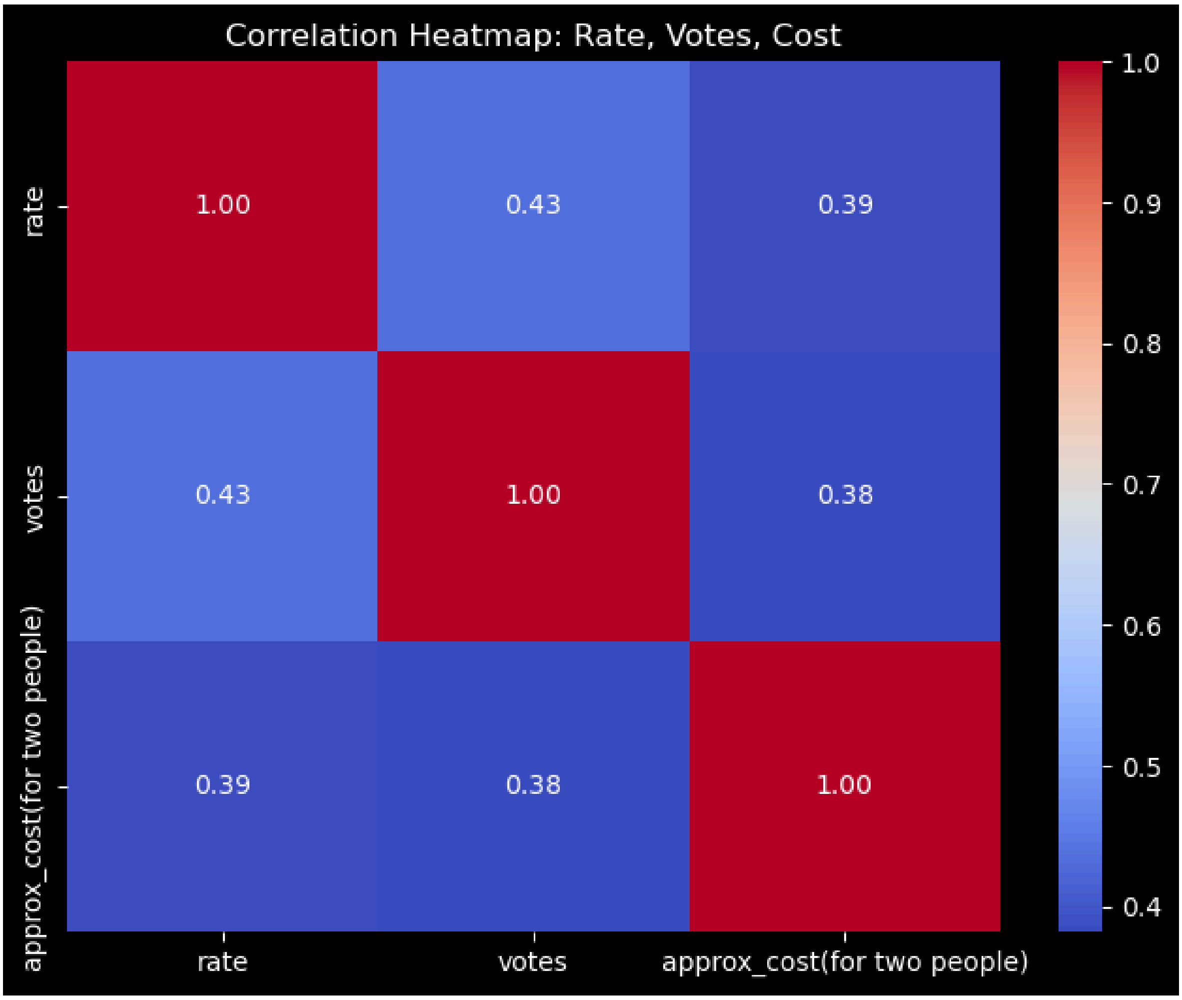
Converting cost to numeric for analysis

In [ ]:
```
df['approx_cost(for two people)'] = df['approx_cost(for two people)'].astype(str
df['approx_cost(for two people)'] = df['approx_cost(for two people)'].astype(flo
```

Selecting numerical columns for correlation

In [ ]:
```
numerical_df = df[['rate','votes','approx_cost(for two people)']]
corr = numerical_df.corr()
```

In [ ]:
```
plt.figure(figsize=(8,6))
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Heatmap: Rate, Votes, Cost")
plt.show()
```



Statistical Insights & Business Interpretations

- Positive Correlation Between Votes and Rating (0.43): There is a moderate positive relationship between the number of votes and the restaurant's rating. This suggests that "popular" restaurants (those with more customer engagement) tend to maintain higher quality standards or better brand perception.

- Cost vs. Rating (0.39): There is a weak-to-moderate positive correlation between the average cost for two and the rating. While more expensive restaurants do trend toward higher ratings, the correlation isn't high enough (0.50) to suggest that price alone guarantees customer satisfaction.

- Price and Popularity (0.38): The correlation between cost and votes is relatively low. This indicates that in Bangalore, high-volume customer traffic (votes) is not exclusive to luxury dining; budget-friendly restaurants can be just as popular as high-end ones.

Strategic Roadmap: Restaurant Market Entry

Final Business Recommendations based on Data Analysis

After cleaning and analyzing **51,717** restaurant records, I have developed a data-driven entry strategy for new investors.

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1. Location Selection Strategy

- **Avoid Saturation:** Areas like **BTM (5,124 restaurants)** are highly saturated; entering here requires a massive marketing budget to stand out.
- **Target High-Value Zones:** Focus on **Indiranagar**, **Koramangala 5th Block**, and **Whitefield**. These locations show a high concentration of restaurants with a significant number of customer votes, indicating an active, high-spending demographic.
- **The "Others" Opportunity:** Locations with fewer than 300 restaurants were grouped as 'others'. These represent "Blue Ocean" opportunities for neighborhood-focused niche dining.

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2. Operational & Service Model

- **The Delivery Standard:** With a vast majority of the market supporting online orders (~30,000 "Yes"), digital integration is a baseline requirement.
- **Service Differentiator:** Data shows a massive gap in **Table Bookings** (only ~6,000 "Yes" vs ~45,000 "No"). Offering high-quality dine-in service with booking capabilities can help a new brand capture the premium segment.
- **Top Performing Category:** Delivery type dominates the market count (25,000), followed by **Dine-out** (17,500). A hybrid model is essential for survival.

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3. Pricing & Positioning

- **The "Mid-Range" Sweet Spot:** The correlation between cost and rating is **0.39**, which is moderate but not absolute.
- **Insight:** You do not need to be the most expensive to be the best-rated. Targeting a mid-range price point allows for high-quality perception without pushing away the mass market.

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4. Customer Engagement (Success Driver)

- **Popularity Breeds Success:** The highest correlation in our study was between **Votes** and **Rating (0.43)**.

- **Actionable Advice:** The business must prioritize customer reviews and engagement. A high volume of votes is a stronger predictor of a high rating than price point alone.

In [ ]:

In [ ]:

In [ ]: