Importing Libraries

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

Data Overview:

Explore the basic characteristics of the dataset, including dimensions, data types, and missing values.

```
df = pd.read_csv(r"C:\Users\aryan\OneDrive\Desktop\DS PROJECTS\BIG
PROJECT\ZOMATO ANALYSIS (2)\Indian-Resturants.csv")
df
```

```
          res_id                            name      establishment  \
0        3400299                     Bikanervala    ['Quick Bites']
1        3400005  Mama Chicken Mama Franky House    ['Quick Bites']
2        3401013                    Bhagat Halwai    ['Quick Bites']
3        3400290                    Bhagat Halwai    ['Quick Bites']
4        3401744      The Salt Cafe Kitchen & Bar  ['Casual Dining']
...          ...                             ...                ...
211939   3202251  Kali Mirch Cafe And Restaurant  ['Casual Dining']
211940   3200996                      Raju Omlet    ['Quick Bites']
211941  18984164                The Grand Thakar  ['Casual Dining']
211942   3201138                          Subway    ['Quick Bites']
211943  18879846    Freshco's - The Health Cafe           ['Café']

                                                      url  \
0       https://www.zomato.com/agra/bikanervala-khanda...
1       https://www.zomato.com/agra/mama-chicken-mama-...
2       https://www.zomato.com/agra/bhagat-halwai-2-sh...
3       https://www.zomato.com/agra/bhagat-halwai-civi...
4       https://www.zomato.com/agra/the-salt-cafe-kitc...
...                                                   ...
211939  https://www.zomato.com/vadodara/kali-mirch-caf...
211940  https://www.zomato.com/vadodara/raju-omlet-kar...
211941  https://www.zomato.com/vadodara/the-grand-thak...
211942  https://www.zomato.com/vadodara/subway-1-akota...
211943  https://www.zomato.com/vadodara/freshcos-the-h...

                                                  address      city
city_id  \
0       Kalyani Point, Near Tulsi Cinema, Bypass Road,...      Agra
34
```

```
1              Main Market, Sadar Bazaar, Agra Cantt, Agra      Agra
34
2       62/1, Near Easy Day, West Shivaji Nagar, Goalp...      Agra
34
3       Near Anjana Cinema, Nehru Nagar, Civil Lines, ...      Agra
34
4              1C,3rd Floor, Fatehabad Road, Tajganj, Agra      Agra
34
...                                                    ...       ...
...
211939  Manu Smriti Complex, Near Navrachna School, GI...  Vadodara
32
211940  Mahalaxmi Apartment, Opposite B O B, Karoli Ba...  Vadodara
32
211941  3rd Floor, Shreem Shalini Mall, Opposite Conqu...  Vadodara
32
211942  G-2, Vedant Platina, Near Cosmos, Akota, Vadodara  Vadodara
32
211943  Shop 7, Ground Floor, Opposite Natubhai Circle...  Vadodara
32

           locality   latitude  longitude  ... price_range
currency  \
0          Khandari  27.211450  78.002381  ...           2       Rs.

1        Agra Cantt  27.160569  78.011583  ...           2       Rs.

2          Shahganj  27.182938  77.979684  ...           1       Rs.

3       Civil Lines  27.205668  78.004799  ...           1       Rs.

4           Tajganj  27.157709  78.052421  ...           3       Rs.

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

211939    Fatehgunj  22.336931  73.192356  ...           2       Rs.

211940   Karelibaug  22.322455  73.197203  ...           1       Rs.

211941     Alkapuri  22.310563  73.171163  ...           2       Rs.

211942        Akota  22.270027  73.143068  ...           2       Rs.

211943     Vadiwadi  22.309935  73.158768  ...           2       Rs.


                                               highlights
aggregate_rating  \
0       ['Lunch', 'Takeaway Available', 'Credit Card',...
4.4
```

```
1       ['Delivery', 'No Alcohol Available', 'Dinner',...
4.4
2       ['No Alcohol Available', 'Dinner', 'Takeaway A...
4.2
3       ['Takeaway Available', 'Credit Card', 'Lunch',...
4.3
4       ['Lunch', 'Serves Alcohol', 'Cash', 'Credit Ca...
4.9
...                                                   ...
...
211939  ['Dinner', 'Cash', 'Lunch', 'Delivery', 'Indoo...
4.1
211940  ['Dinner', 'Cash', 'Takeaway Available', 'Debi...
4.1
211941  ['Dinner', 'Cash', 'Debit Card', 'Lunch', 'Tak...
4.0
211942  ['Dinner', 'Delivery', 'Credit Card', 'Lunch',...
3.7
211943  ['Dinner', 'Cash', 'Takeaway Available', 'Debi...
4.0

       rating_text  votes  photo_count opentable_support delivery
takeaway
0        Very Good    814          154               0.0       -1
-1
1        Very Good   1203          161               0.0       -1
-1
2        Very Good    801          107               0.0        1
-1
3        Very Good    693          157               0.0        1
-1
4        Excellent    470          291               0.0        1
-1
...            ...    ...          ...               ...      ...
...
211939   Very Good    243           40               0.0       -1
-1
211940   Very Good    187           40               0.0        1
-1
211941   Very Good    111           38               0.0       -1
-1
211942        Good    128           34               0.0        1
-1
211943   Very Good     93           53               0.0        1
-1

[211944 rows x 26 columns]
```

Size of dataset

```
print("Rows, Columns:", df.shape)
```

```
Rows, Columns: (211944, 26)
```

First 5 rows

```
print("----- HEAD -----")
print(df.head())
```

```
----- HEAD -----
    res_id                            name      establishment  \
0  3400299                     Bikanervala    ['Quick Bites']
1  3400005  Mama Chicken Mama Franky House    ['Quick Bites']
2  3401013                   Bhagat Halwai    ['Quick Bites']
3  3400290                   Bhagat Halwai    ['Quick Bites']
4  3401744     The Salt Cafe Kitchen & Bar  ['Casual Dining']

                                                 url  \
0  https://www.zomato.com/agra/bikanervala-khanda...
1  https://www.zomato.com/agra/mama-chicken-mama-...
2  https://www.zomato.com/agra/bhagat-halwai-2-sh...
3  https://www.zomato.com/agra/bhagat-halwai-civi...
4  https://www.zomato.com/agra/the-salt-cafe-kitc...

                                             address  city  city_id  \
0  Kalyani Point, Near Tulsi Cinema, Bypass Road,...  Agra       34
1        Main Market, Sadar Bazaar, Agra Cantt, Agra  Agra       34
2  62/1, Near Easy Day, West Shivaji Nagar, Goalp...  Agra       34
3  Near Anjana Cinema, Nehru Nagar, Civil Lines, ...  Agra       34
4        1C,3rd Floor, Fatehabad Road, Tajganj, Agra  Agra       34

      locality   latitude  longitude  ... price_range  currency  \
0     Khandari  27.211450  78.002381  ...           2       Rs.
1   Agra Cantt  27.160569  78.011583  ...           2       Rs.
2     Shahganj  27.182938  77.979684  ...           1       Rs.
3  Civil Lines  27.205668  78.004799  ...           1       Rs.
4      Tajganj  27.157709  78.052421  ...           3       Rs.

                                          highlights aggregate_rating
\
0  ['Lunch', 'Takeaway Available', 'Credit Card',...              4.4

1  ['Delivery', 'No Alcohol Available', 'Dinner',...              4.4

2  ['No Alcohol Available', 'Dinner', 'Takeaway A...              4.2

3  ['Takeaway Available', 'Credit Card', 'Lunch',...              4.3

4  ['Lunch', 'Serves Alcohol', 'Cash', 'Credit Ca...              4.9
```

```
  rating_text  votes  photo_count opentable_support delivery  takeaway
0   Very Good    814          154               0.0       -1        -1
1   Very Good   1203          161               0.0       -1        -1
2   Very Good    801          107               0.0        1        -1
3   Very Good    693          157               0.0        1        -1
4   Excellent    470          291               0.0        1        -1

[5 rows x 26 columns]
```

Column names

```
print("----- COLUMNS -----")
print(list(df.columns))
```

```
----- COLUMNS -----
['res_id', 'name', 'establishment', 'url', 'address', 'city',
'city_id', 'locality', 'latitude', 'longitude', 'zipcode',
'country_id', 'locality_verbose', 'cuisines', 'timings',
'average_cost_for_two', 'price_range', 'currency', 'highlights',
'aggregate_rating', 'rating_text', 'votes', 'photo_count',
'opentable_support', 'delivery', 'takeaway']
```

Data types and non-null counts

```
print("----- INFORMATION -----")
print(df.describe())
```

```
----- INFORMATION -----
             res_id        city_id       latitude      longitude
country_id  \
count  2.119440e+05  211944.000000  211944.000000  211944.000000
211944.0
mean   1.349411e+07    4746.785434      21.499758      77.615276
1.0
std    7.883722e+06    5568.766386      22.781331       7.500104
0.0
min    5.000000e+01       1.000000       0.000000       0.000000
1.0
25%    3.301027e+06      11.000000      15.496071      74.877961
1.0
50%    1.869573e+07      34.000000      22.514494      77.425971
1.0
```

```
75%    1.881297e+07   11306.000000      26.841667      80.219323
1.0
max    1.915979e+07   11354.000000   10000.000000      91.832769
1.0

       average_cost_for_two    price_range  aggregate_rating
votes  \
count         211944.000000  211944.000000     211944.000000
211944.000000
mean             595.812229       1.882535          3.395937
378.001864
std              606.239363       0.892989          1.283642
925.333370
min                0.000000       1.000000          0.000000     -
18.000000
25%              250.000000       1.000000          3.300000
16.000000
50%              400.000000       2.000000          3.800000
100.000000
75%              700.000000       2.000000          4.100000
362.000000
max            30000.000000       4.000000          4.900000
42539.000000

         photo_count  opentable_support       delivery  takeaway
count  211944.000000           211896.0  211944.000000  211944.0
mean      256.971224                0.0      -0.255907      -1.0
std       867.668940                0.0       0.964172       0.0
min         0.000000                0.0      -1.000000      -1.0
25%         3.000000                0.0      -1.000000      -1.0
50%        18.000000                0.0      -1.000000      -1.0
75%       128.000000                0.0       1.000000      -1.0
max     17702.000000                0.0       1.000000      -1.0
```

Basic statistics for numeric columns

```
print("----- DESCRIBE (numeric) -----")
print(df.describe())
```

```
----- DESCRIBE (numeric) -----
             res_id        city_id       latitude      longitude
country_id  \
count  2.119440e+05  211944.000000  211944.000000  211944.000000
211944.0
mean   1.349411e+07    4746.785434      21.499758      77.615276
1.0
std    7.883722e+06    5568.766386      22.781331       7.500104
0.0
min    5.000000e+01       1.000000       0.000000       0.000000
1.0
```

```
25%    3.301027e+06      11.000000      15.496071      74.877961
1.0
50%    1.869573e+07      34.000000      22.514494      77.425971
1.0
75%    1.881297e+07   11306.000000      26.841667      80.219323
1.0
max    1.915979e+07   11354.000000   10000.000000      91.832769
1.0

       average_cost_for_two    price_range  aggregate_rating
votes  \
count         211944.000000  211944.000000     211944.000000
211944.000000
mean             595.812229       1.882535          3.395937
378.001864
std              606.239363       0.892989          1.283642
925.333370
min                0.000000       1.000000          0.000000     -
18.000000
25%              250.000000       1.000000          3.300000
16.000000
50%              400.000000       2.000000          3.800000
100.000000
75%              700.000000       2.000000          4.100000
362.000000
max            30000.000000       4.000000          4.900000
42539.000000

         photo_count  opentable_support       delivery  takeaway
count  211944.000000           211896.0  211944.000000  211944.0
mean      256.971224                0.0      -0.255907      -1.0
std       867.668940                0.0       0.964172       0.0
min         0.000000                0.0      -1.000000      -1.0
25%         3.000000                0.0      -1.000000      -1.0
50%        18.000000                0.0      -1.000000      -1.0
75%       128.000000                0.0       1.000000      -1.0
max     17702.000000                0.0       1.000000      -1.0
```

Basic Statistics for all columns (shows top values for objects)

```
print("----- DESCRIBE (all) -----")
print(df.describe(include='all').T)
```

```
----- DESCRIBE (all) -----
                         count unique  \
res_id                211944.0    NaN
name                    211944  41100
establishment           211944     27
url                     211944  55568
address                 211810  50657
```

```
city                   211944     99
city_id              211944.0    NaN
locality               211944   3731
latitude             211944.0    NaN
longitude            211944.0    NaN
zipcode                 48757   1311
country_id           211944.0    NaN
locality_verbose       211944   3910
cuisines               210553   9382
timings                208070   7740
average_cost_for_two 211944.0    NaN
price_range          211944.0    NaN
currency               211944      1
highlights             211944  31455
aggregate_rating     211944.0    NaN
rating_text            211944     39
votes                211944.0    NaN
photo_count          211944.0    NaN
opentable_support    211896.0    NaN
delivery             211944.0    NaN
takeaway             211944.0    NaN


top  \
res_id
NaN
name                                                                  Domino's
Pizza
establishment                                                       ['Quick
Bites']
url                  https://www.zomato.com/chennai/3bs-buddies-
bar...
address                                       Laxman Jhula, Tapovan,
Rishikesh
city
Chennai
city_id
NaN
locality                                                                 Civil
Lines
latitude
NaN
longitude
NaN
zipcode
0
country_id
NaN
locality_verbose                                          Ana Sagar Lake,
```

```
Ajmer
cuisines                                                           North
Indian
timings                                                          11 AM to 11
PM
average_cost_for_two
NaN
price_range
NaN
currency
Rs.
highlights            ['Dinner', 'Takeaway Available', 'Lunch',
'Cas...
aggregate_rating
NaN
rating_text                                                           Very
Good
votes
NaN
photo_count
NaN
opentable_support
NaN
delivery
NaN
takeaway
NaN

                        freq             mean            std   min  \
res_id                   NaN  13494112.348106  7883721.972533  50.0
name                    3108              NaN             NaN   NaN
establishment          64390              NaN             NaN   NaN
url                      169              NaN             NaN   NaN
address                  299              NaN             NaN   NaN
city                   11630              NaN             NaN   NaN
city_id                  NaN      4746.785434     5568.766386   1.0
locality                3660              NaN             NaN   NaN
latitude                 NaN        21.499758       22.781331   0.0
longitude                NaN        77.615276        7.500104   0.0
zipcode                 7100              NaN             NaN   NaN
country_id               NaN              1.0             0.0   1.0
locality_verbose        1760              NaN             NaN   NaN
cuisines               15996              NaN             NaN   NaN
timings                26605              NaN             NaN   NaN
average_cost_for_two     NaN       595.812229      606.239363   0.0
price_range              NaN         1.882535        0.892989   1.0
currency              211944              NaN             NaN   NaN
highlights              3352              NaN             NaN   NaN
aggregate_rating         NaN         3.395937        1.283642   0.0
```

```
rating_text                  65451               NaN              NaN   NaN
votes                          NaN        378.001864        925.33337 -18.0
photo_count                    NaN        256.971224        867.66894   0.0
opentable_support              NaN               0.0              0.0   0.0
delivery                       NaN         -0.255907         0.964172  -1.0
takeaway                       NaN              -1.0              0.0  -1.0

                         25%         50%         75%         max
res_id             3301027.0  18695734.0  18812974.0  19159790.0
name                     NaN         NaN         NaN         NaN
establishment            NaN         NaN         NaN         NaN
url                      NaN         NaN         NaN         NaN
address                  NaN         NaN         NaN         NaN
city                     NaN         NaN         NaN         NaN
city_id                 11.0        34.0     11306.0     11354.0
locality                 NaN         NaN         NaN         NaN
latitude           15.496071   22.514494   26.841667     10000.0
longitude          74.877961   77.425971   80.219323   91.832769
zipcode                  NaN         NaN         NaN         NaN
country_id               1.0         1.0         1.0         1.0
locality_verbose         NaN         NaN         NaN         NaN
cuisines                 NaN         NaN         NaN         NaN
timings                  NaN         NaN         NaN         NaN
average_cost_for_two   250.0       400.0       700.0     30000.0
price_range              1.0         2.0         2.0         4.0
currency                 NaN         NaN         NaN         NaN
highlights               NaN         NaN         NaN         NaN
aggregate_rating         3.3         3.8         4.1         4.9
rating_text              NaN         NaN         NaN         NaN
votes                   16.0       100.0       362.0     42539.0
photo_count              3.0        18.0       128.0     17702.0
opentable_support        0.0         0.0         0.0         0.0
delivery                -1.0        -1.0         1.0         1.0
takeaway                -1.0        -1.0        -1.0        -1.0
```

Missing values summary (counts and percent)

```python
miss = df.isnull().sum().sort_values(ascending=False)
miss_pct = (df.isnull().mean()*100).sort_values(ascending=False)
print("----- MISSING VALUES (top 20) -----")
print(pd.concat([miss, miss_pct], axis=1,
keys=['missing_count','missing_percent']).head(20))
```

```
----- MISSING VALUES (top 20) -----
                      missing_count  missing_percent
zipcode                      163187        76.995338
timings                        3874         1.827841
cuisines                       1391         0.656305
address                         134         0.063224
opentable_support                48         0.022647
```

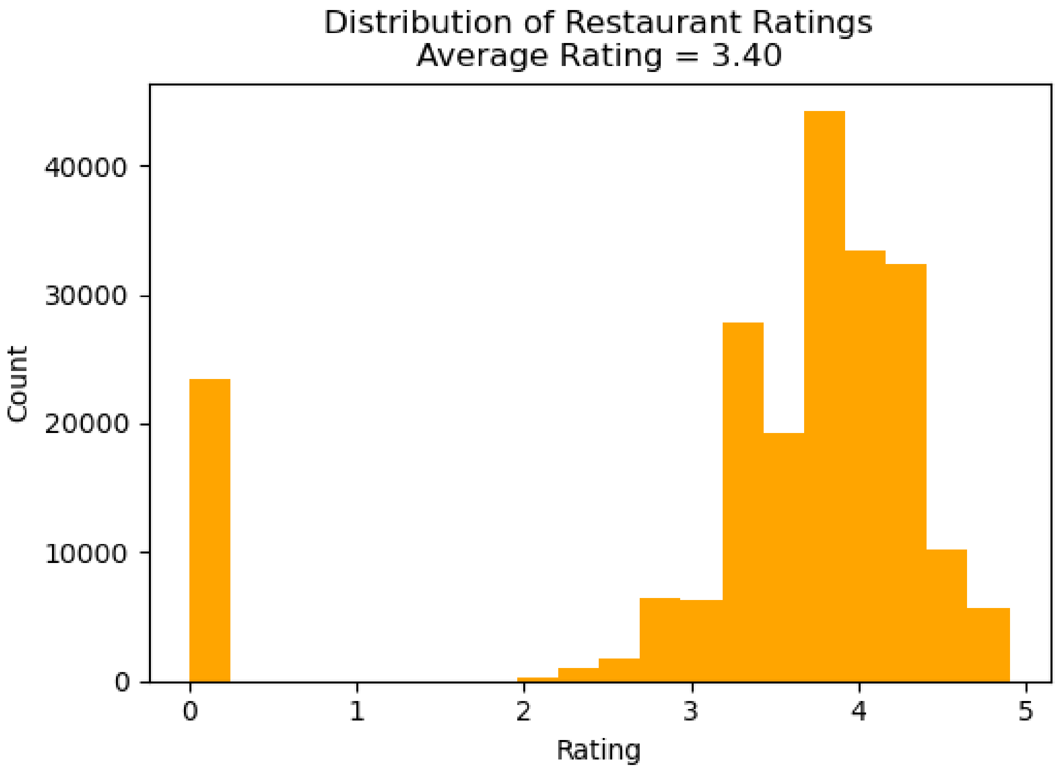
```
city                          0          0.000000
name                          0          0.000000
establishment                 0          0.000000
url                           0          0.000000
res_id                        0          0.000000
longitude                     0          0.000000
latitude                      0          0.000000
locality                      0          0.000000
city_id                       0          0.000000
locality_verbose              0          0.000000
average_cost_for_two          0          0.000000
price_range                   0          0.000000
country_id                    0          0.000000
currency                      0          0.000000
highlights                    0          0.000000
```

Basic Statistics:

- Calculate and visualize the average rating of restaurants.
- Analyze the distribution of restaurant ratings to understand the overall rating landscape.

Calculate and visualize the average rating of restaurants.

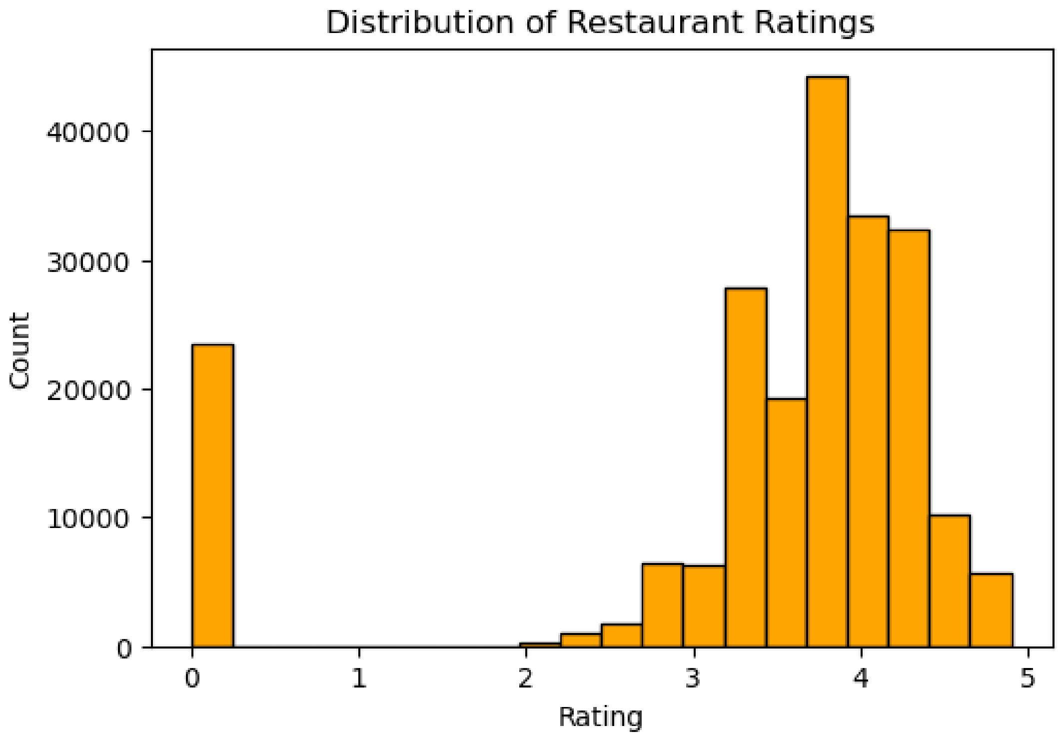
```
# Calculate average rating
average_rating = df['aggregate_rating'].mean()
print("Average Rating of Restaurants:", round(average_rating, 2))

# Visualize rating distribution
plt.figure(figsize=(6,4))
plt.hist(df['aggregate_rating'].dropna(), bins=20, color='orange')
plt.xlabel("Rating")
plt.ylabel("Count")
plt.title(f"Distribution of Restaurant Ratings\nAverage Rating =
{average_rating:.2f}")
plt.show()

Average Rating of Restaurants: 3.4
```



Analyze the distribution of restaurant ratings to understand the overall rating landscape.

```
# Summary statistics
print("Rating Summary:")
print(df['aggregate_rating'].describe())

# Plot distribution
plt.figure(figsize=(6,4))
plt.hist(df['aggregate_rating'].dropna(), bins=20, color='orange',
edgecolor='black')
plt.xlabel("Rating")
plt.ylabel("Count")
plt.title("Distribution of Restaurant Ratings")
plt.show()

Rating Summary:
count    211944.000000
mean          3.395937
std           1.283642
min           0.000000
25%           3.300000
50%           3.800000
75%           4.100000
```

```
max            4.900000
Name: aggregate_rating, dtype: float64
```



Location Analysis:

- Identify the city with the highest concentration of restaurants.
- Visualize the distribution of restaurant ratings across different cities.

City with the Highest Concentration of Restaurants

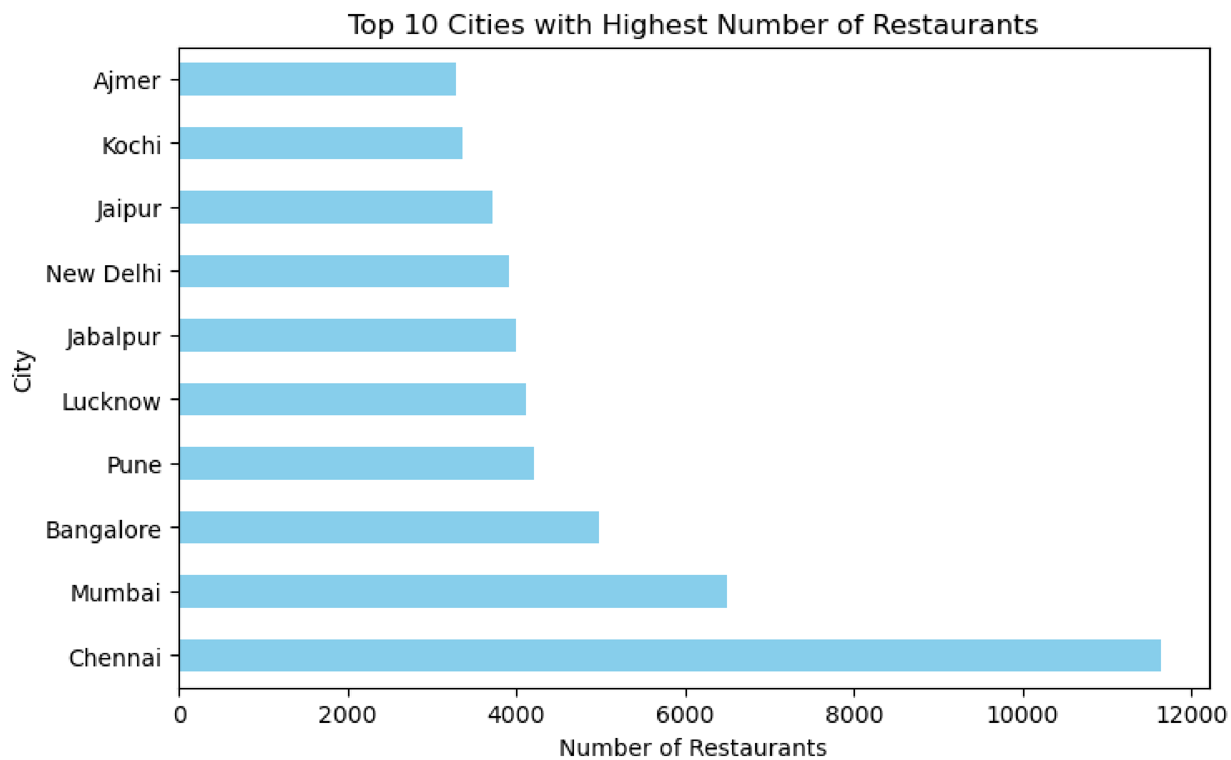
```
# City counts
city_counts = df['city'].value_counts()

print("Top 10 Cities with Most Restaurants:")
print(city_counts.head(10))

# City with highest number of restaurants
top_city = city_counts.idxmax()
count_top_city = city_counts.max()

print("\nCity with highest concentration of restaurants:", top_city)
print("Number of restaurants:", count_top_city)
```

```
Top 10 Cities with Most Restaurants:
city
Chennai      11630
```

```
Mumbai         6497
Bangalore      4971
Pune           4217
Lucknow        4121
Jabalpur       3994
New Delhi      3918
Jaipur         3713
Kochi          3370
Ajmer          3277
Name: count, dtype: int64

City with highest concentration of restaurants: Chennai
Number of restaurants: 11630
```

Bar Chart: Top 10 Cities by Restaurant Count

```
plt.figure(figsize=(8,5))
city_counts.head(10).plot(kind='barh', color='skyblue')
plt.xlabel("Number of Restaurants")
plt.ylabel("City")
plt.title("Top 10 Cities with Highest Number of Restaurants")
plt.show()
```



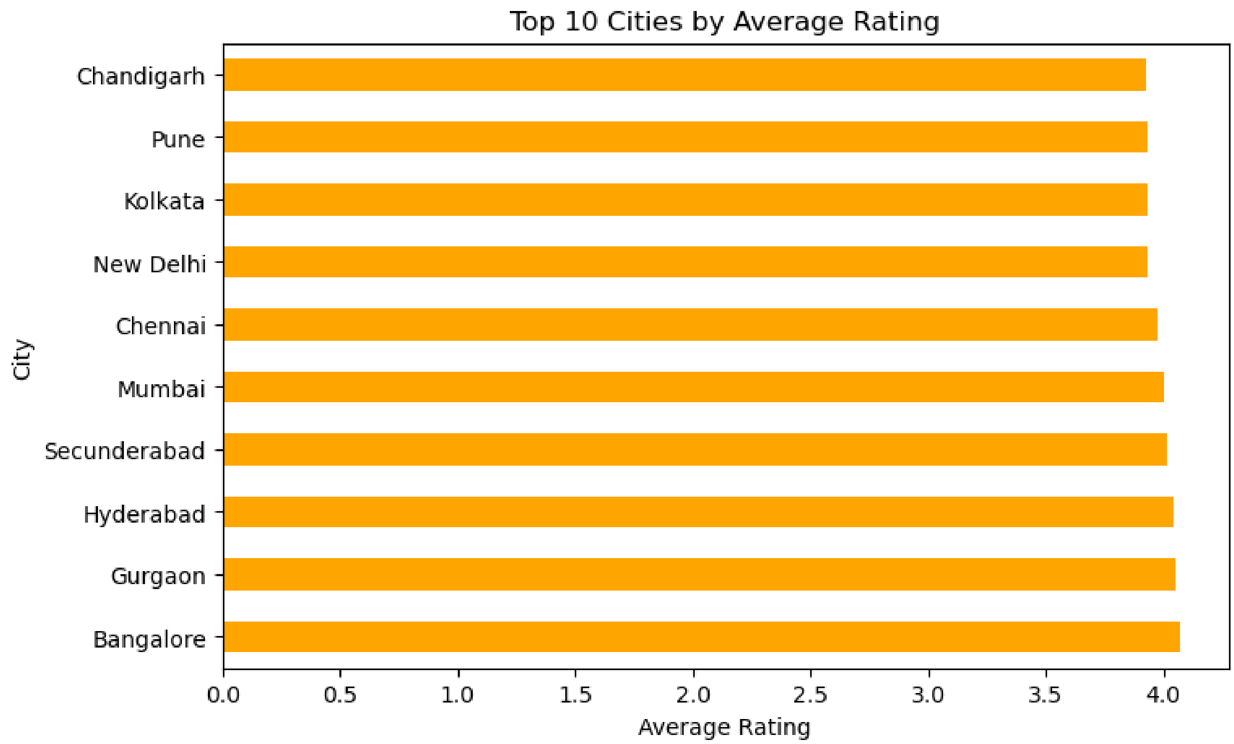
Visualize Rating Distribution Across Cities

```
city_rating = df.groupby('city')
['aggregate_rating'].mean().sort_values(ascending=False)

print("Top Cities by Average Rating:")
print(city_rating.head(10))
```

```
Top Cities by Average Rating:
city
Bangalore       4.073567
Gurgaon         4.048837
Hyderabad       4.042747
Secunderabad    4.018579
Mumbai          4.004848
Chennai         3.973938
New Delhi       3.935988
Kolkata         3.935536
Pune            3.931705
Chandigarh      3.927081
Name: aggregate_rating, dtype: float64
```

Bar Chart: Average Rating per City (Top 10)

```
plt.figure(figsize=(8,5))
city_rating.head(10).plot(kind='barh', color='orange')
plt.xlabel("Average Rating")
plt.ylabel("City")
plt.title("Top 10 Cities by Average Rating")
plt.show()
```



Cuisine Analysis:

- Determine the most popular cuisines among the listed restaurants.
- Investigate if there's a correlation between the variety of cuisines offered and restaurant ratings.

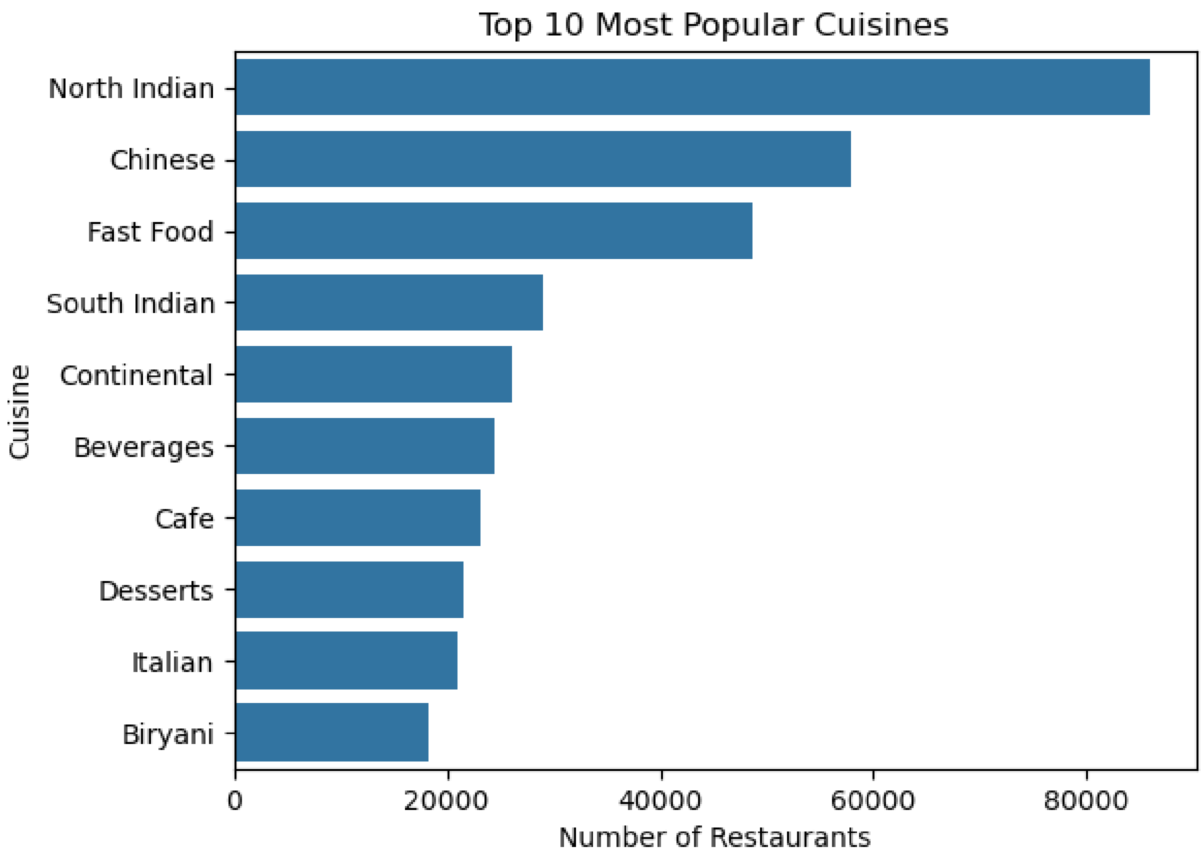
Determine the most popular cuisines among the listed restaurants.

STEP 1 — Split and Count Cuisines

```
df['cuisines'] = df['cuisines'].fillna('Unknown')

cuisine_split = df['cuisines'].str.split(',')

all_cuisines = []
for row in cuisine_split:
    for c in row:
        all_cuisines.append(c.strip())

import pandas as pd
cuisine_counts = pd.Series(all_cuisines).value_counts()
```

STEP-2 Simple Horizontal Bar Chart

```
sns.barplot( x = cuisine_counts.head(10).values,y =
cuisine_counts.head(10).index)
plt.xlabel("Number of Restaurants")
plt.ylabel("Cuisine")
plt.title("Top 10 Most Popular Cuisines")
plt.show()
```



Investigate if there's a correlation between the variety of cuisines offered and restaurant ratings.

STEP 1 — Count cuisines

```
df['cuisine_count'] = df['cuisines'].str.split(',').str.len()
```

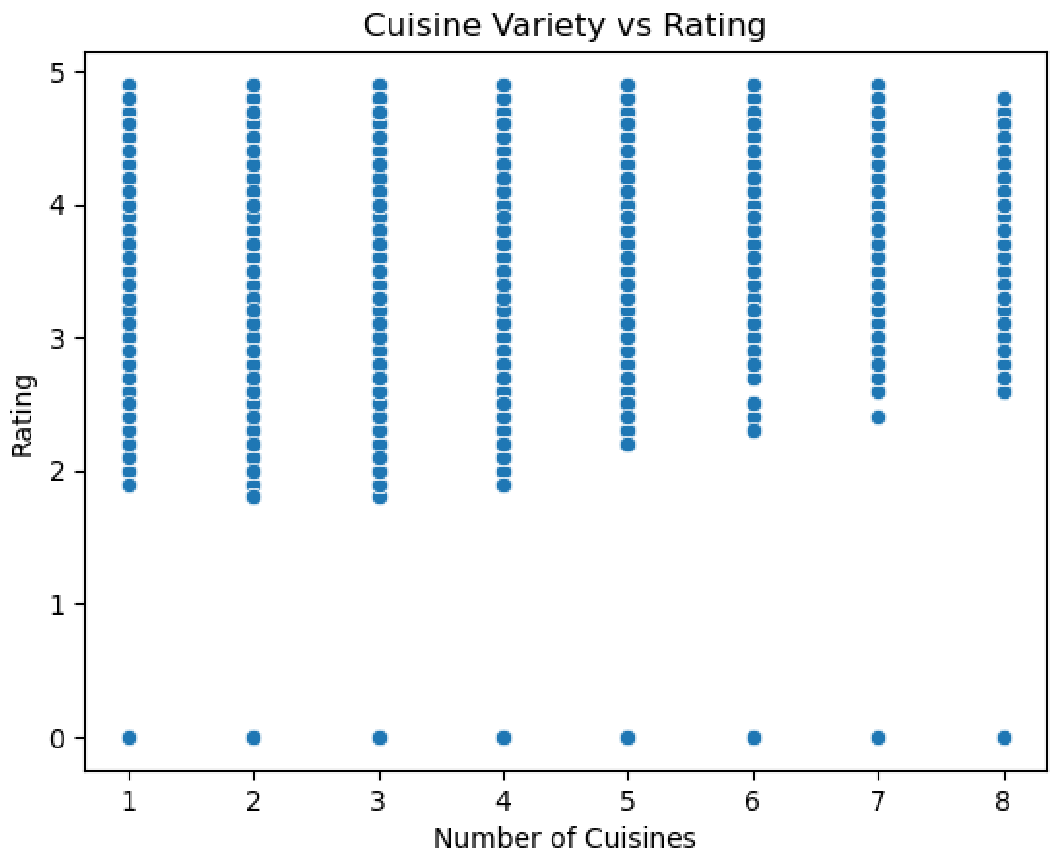
STEP 2 — See average rating for each cuisine count

```
df.groupby('cuisine_count')['aggregate_rating'].mean()

cuisine_count
1    2.970910
2    3.375513
```

```
3    3.600828
4    3.750475
5    3.909608
6    3.975362
7    4.007138
8    3.957797
Name: aggregate_rating, dtype: float64
```

STEP 3 — Scatter plot

```
sns.scatterplot(x = 'cuisine_count',y = 'aggregate_rating',data = df)
plt.xlabel("Number of Cuisines")
plt.ylabel("Rating")
plt.title("Cuisine Variety vs Rating")
plt.show()
```



Price Range and Rating:

- Analyze the relationship between price range and restaurant ratings.
- Visualize the average cost for two people in different price categories.

Analyze the relationship between price range and restaurant ratings.

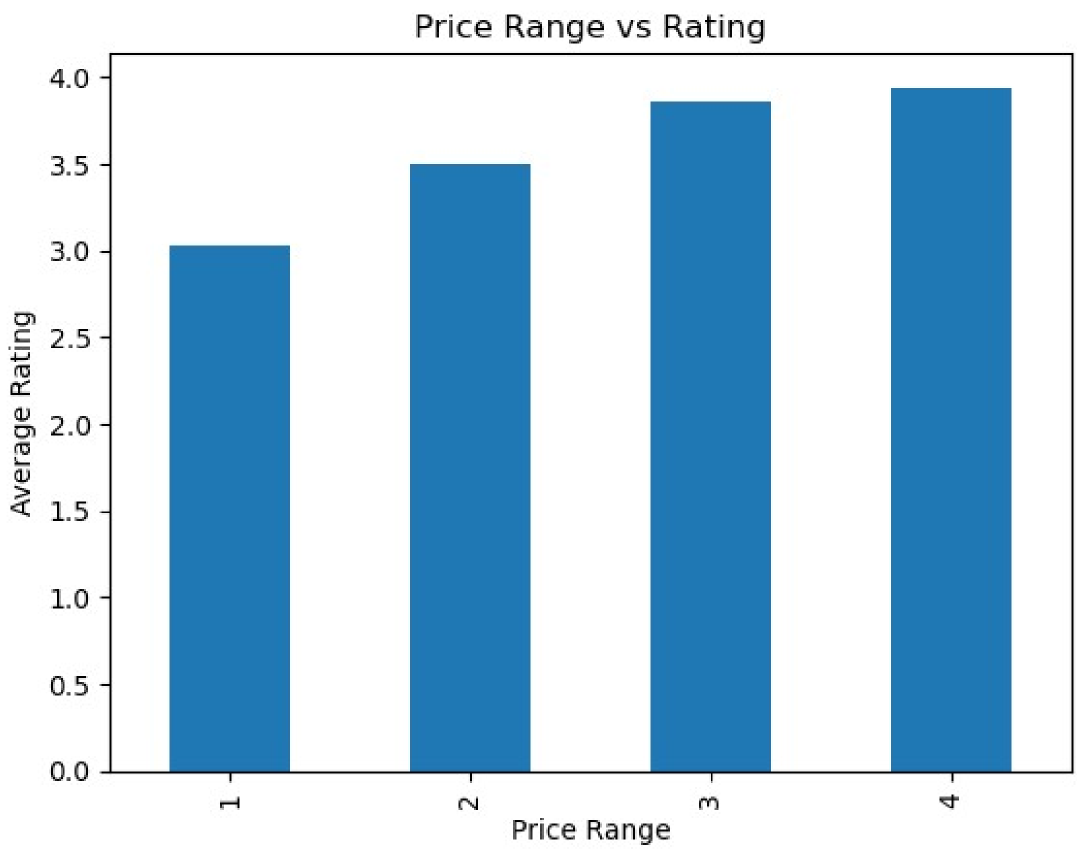
STEP 1 — Average rating for each price range

```
df.groupby('price_range')['aggregate_rating'].mean()
```

```
price_range
1    3.033294
2    3.495887
3    3.858305
4    3.937579
Name: aggregate_rating, dtype: float64
```

STEP 2 — Simple bar chart

```
avg_price_rating = df.groupby('price_range')
['aggregate_rating'].mean()

avg_price_rating.plot(kind='bar')
plt.xlabel("Price Range")
plt.ylabel("Average Rating")
plt.title("Price Range vs Rating")
plt.show()
```



Visualize the average cost for two people in different price categories.

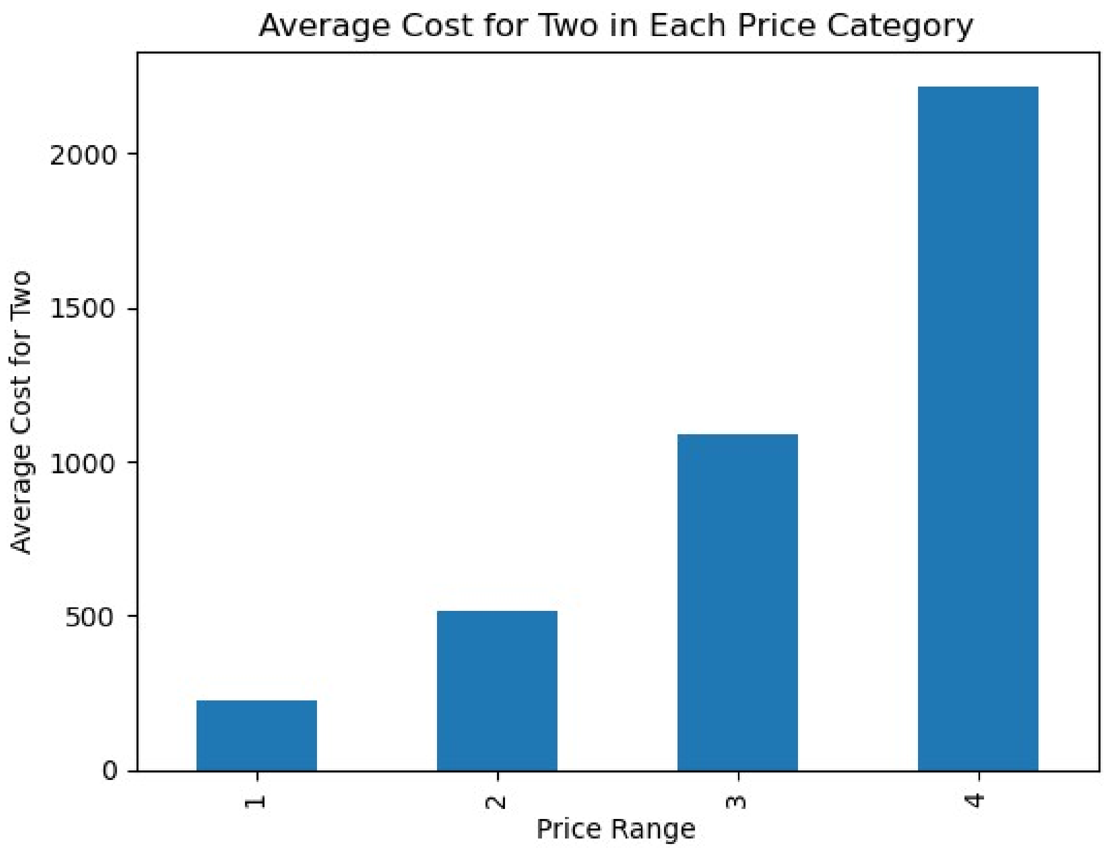
STEP 1 — Calculate average cost for each price range

```
df.groupby('price_range')['average_cost_for_two'].mean()

price_range
1     225.265067
2     516.288496
3    1088.005116
4    2215.654482
Name: average_cost_for_two, dtype: float64
```

STEP 2 — Visualize using a simple bar chart

```
avg_cost = df.groupby('price_range')['average_cost_for_two'].mean()

avg_cost.plot(kind='bar')
plt.xlabel("Price Range")
plt.ylabel("Average Cost for Two")
```

```
plt.title("Average Cost for Two in Each Price Category")
plt.show()
```



Online Order and Table Booking:

- Investigate the impact of online order availability on restaurant ratings.
- Analyze the distribution of restaurants that offer table booking.

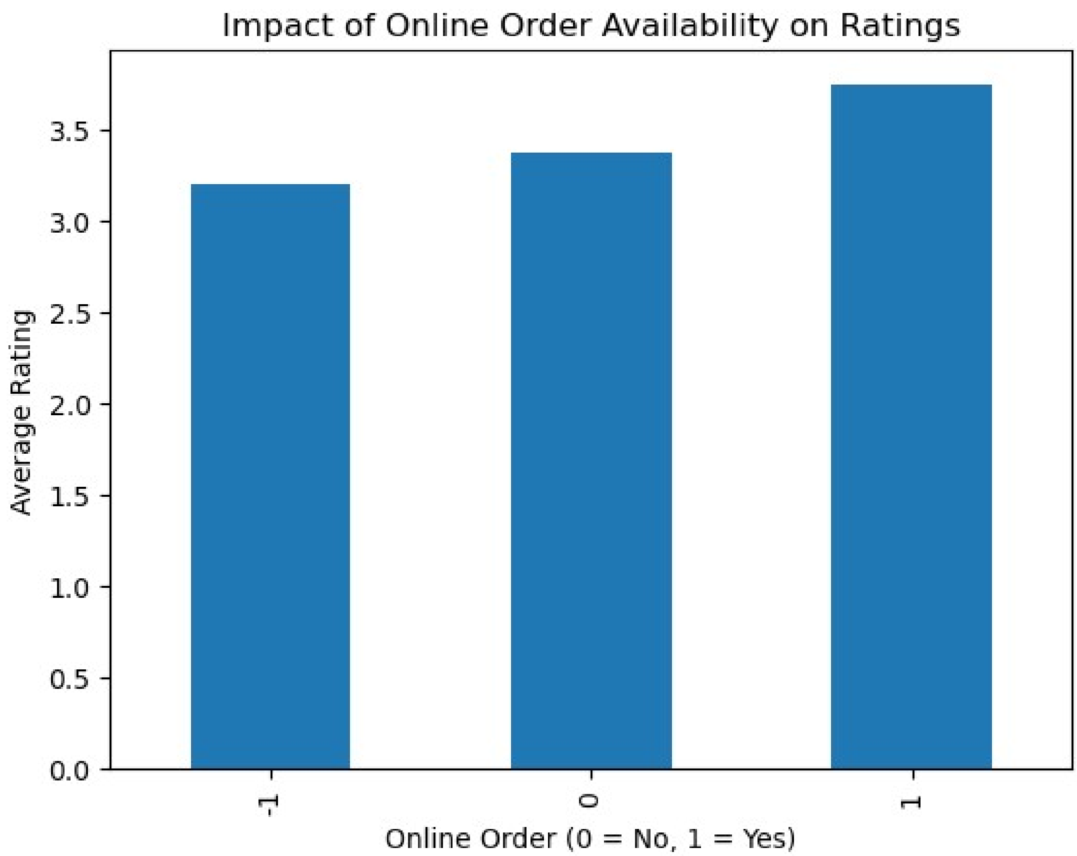
Investigate the impact of online order availability on restaurant ratings.

STEP 1 — Compare average rating for Online Order vs No Online Order

```
df.groupby('delivery')['aggregate_rating'].mean()

delivery
-1    3.193217
 0    3.365058
 1    3.739424
Name: aggregate_rating, dtype: float64
```

STEP 2 — Visualize using a simple bar chart

```
avg_online = df.groupby('delivery')['aggregate_rating'].mean()

avg_online.plot(kind='bar')
plt.xlabel("Online Order (0 = No, 1 = Yes)")
plt.ylabel("Average Rating")
plt.title("Impact of Online Order Availability on Ratings")
plt.show()
```



Analyze the distribution of restaurants that offer table booking.

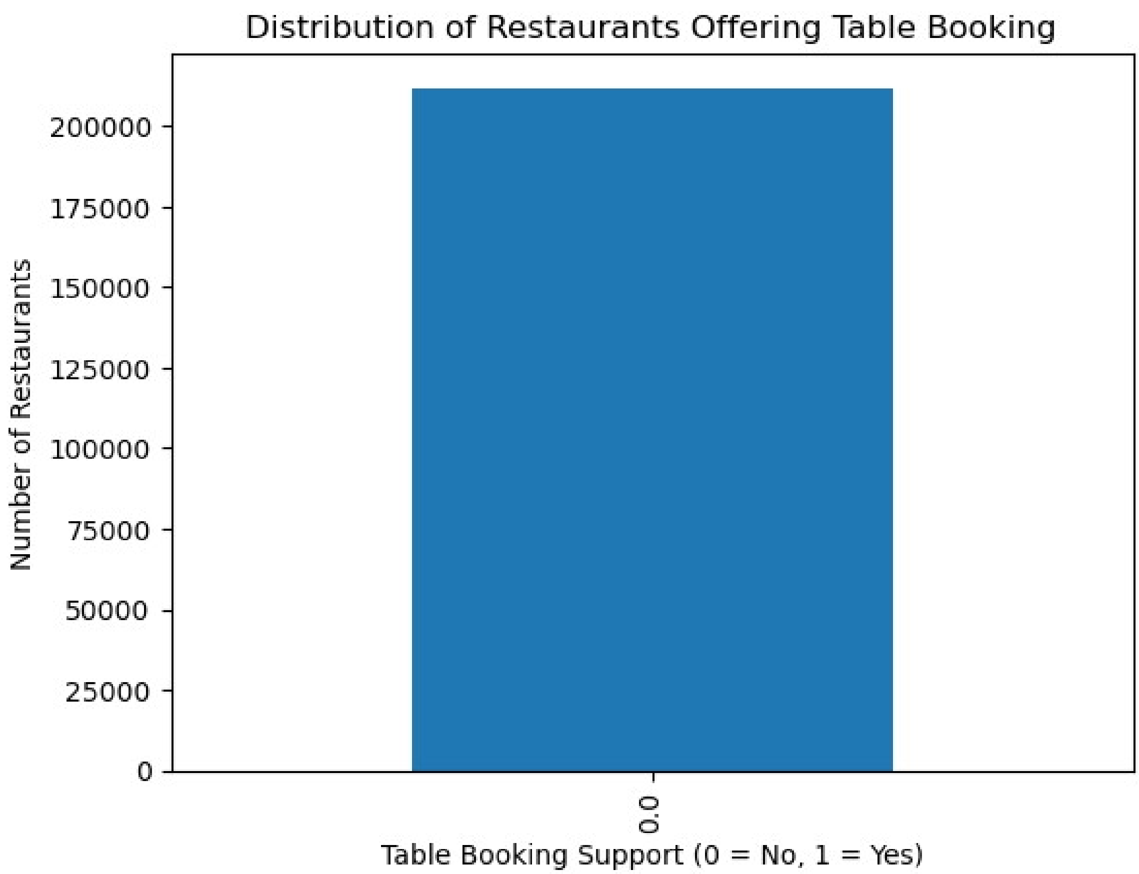
STEP 1 — Count restaurants with/without table booking

```
df['opentable_support'].value_counts()
```

```
opentable_support
0.0    211896
Name: count, dtype: int64
```

STEP 2 — Bar chart

```
df['opentable_support'].value_counts().plot(kind='bar')
plt.xlabel("Table Booking Support (0 = No, 1 = Yes)")
plt.ylabel("Number of Restaurants")
plt.title("Distribution of Restaurants Offering Table Booking")
plt.show()
```



Top Restaurant Chains:

- Identify and visualize the top restaurant chains based on the number of outlets.
- Explore the ratings of these top chains.

Identify and visualize the top restaurant chains based on the number of outlets.

STEP 1 — Identify Top Restaurant Chains

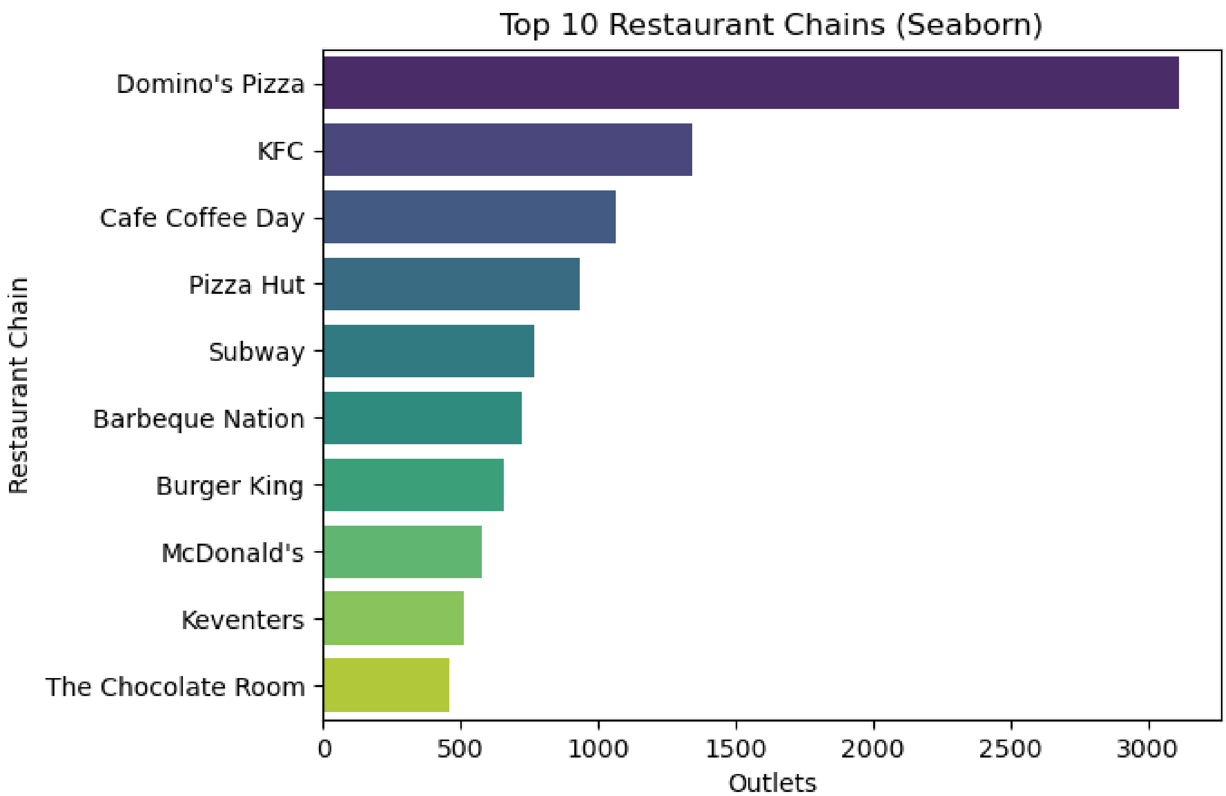
```
chain_counts = df['name'].value_counts().head(10)
print(chain_counts)
```

```
name
Domino's Pizza         3108
KFC                    1343
Cafe Coffee Day        1068
Pizza Hut               936
Subway                  766
Barbeque Nation         725
Burger King             658
McDonald's              578
Keventers               512
The Chocolate Room      461
Name: count, dtype: int64
```

STEP 2 — Visualization

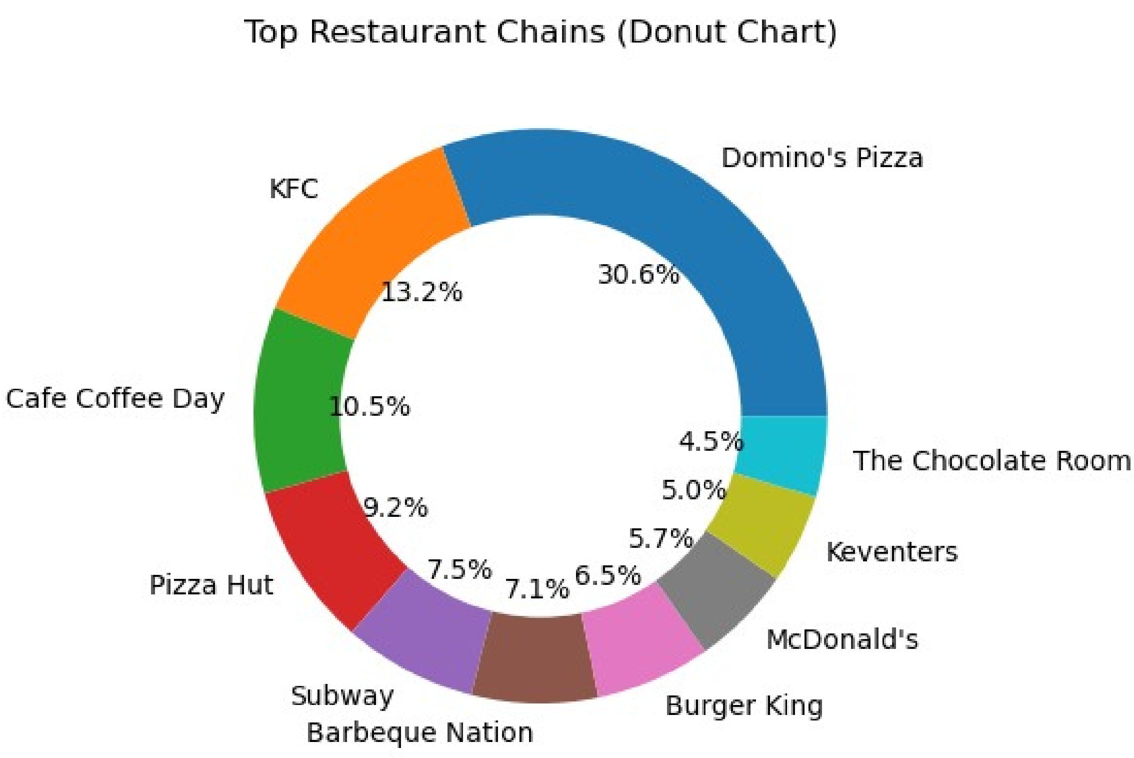
```
sns.barplot(x=chain_counts.values, y=chain_counts.index,
palette='viridis')
plt.xlabel("Outlets")
plt.ylabel("Restaurant Chain")
plt.title("Top 10 Restaurant Chains (Seaborn)")
plt.show()
```

```
C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\2085371634.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=chain_counts.values, y=chain_counts.index,
palette='viridis')
```



Donut Chart

```
plt.pie(chain_counts.values, labels=chain_counts.index, autopct='%1.1f
%%')
centre_circle = plt.Circle((0,0),0.70,fc='white')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
plt.title("Top Restaurant Chains (Donut Chart)")
plt.show()
```



Explore the ratings of these top chains.

STEP 1 — Get Top 10 Restaurant Chains

```
top_chains = df['name'].value_counts().head(10).index
```

STEP 2 — Filter only those restaurants

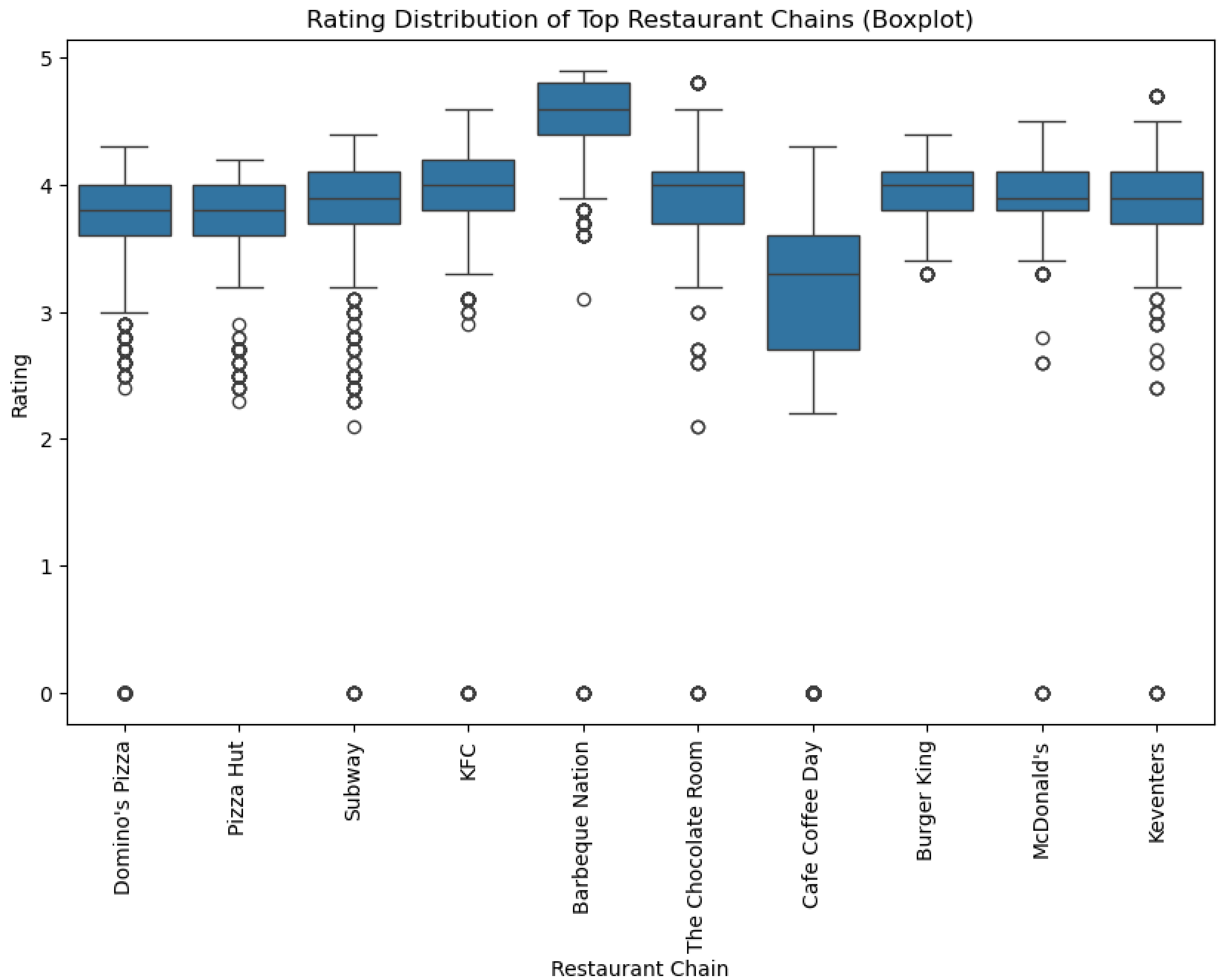
```
top_chain_data = df[df['name'].isin(top_chains)]
```

STEP 3 — Convert rating to numeric

```
df['aggregate_rating'] = pd.to_numeric(df['aggregate_rating'],
errors='coerce')
```

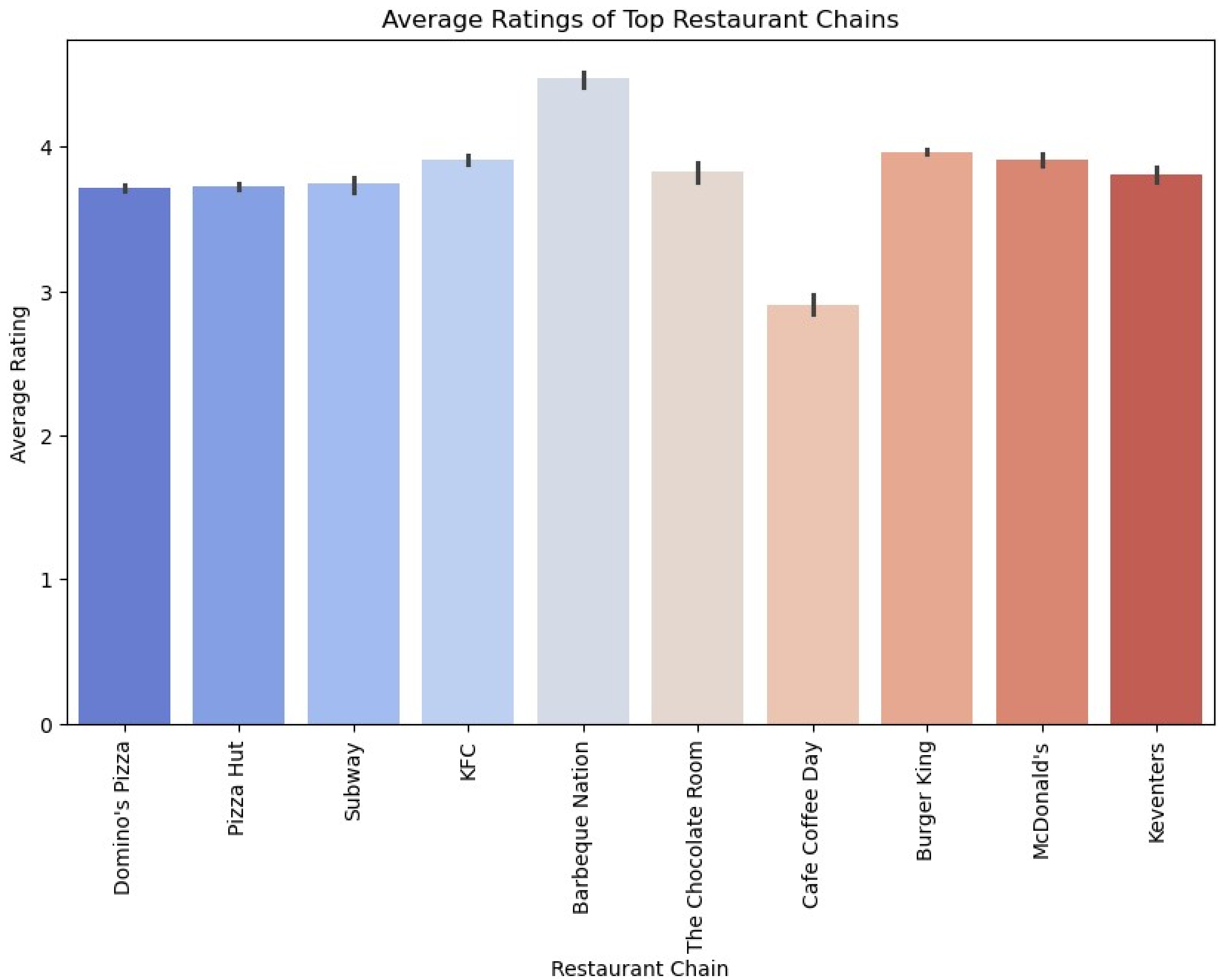
STEP 4 — Visualization

```
plt.figure(figsize=(10,6))
sns.boxplot(x='name', y='aggregate_rating', data=top_chain_data)
plt.xticks(rotation=90)
plt.title("Rating Distribution of Top Restaurant Chains (Boxplot)")
plt.xlabel("Restaurant Chain")
plt.ylabel("Rating")
plt.show()
```

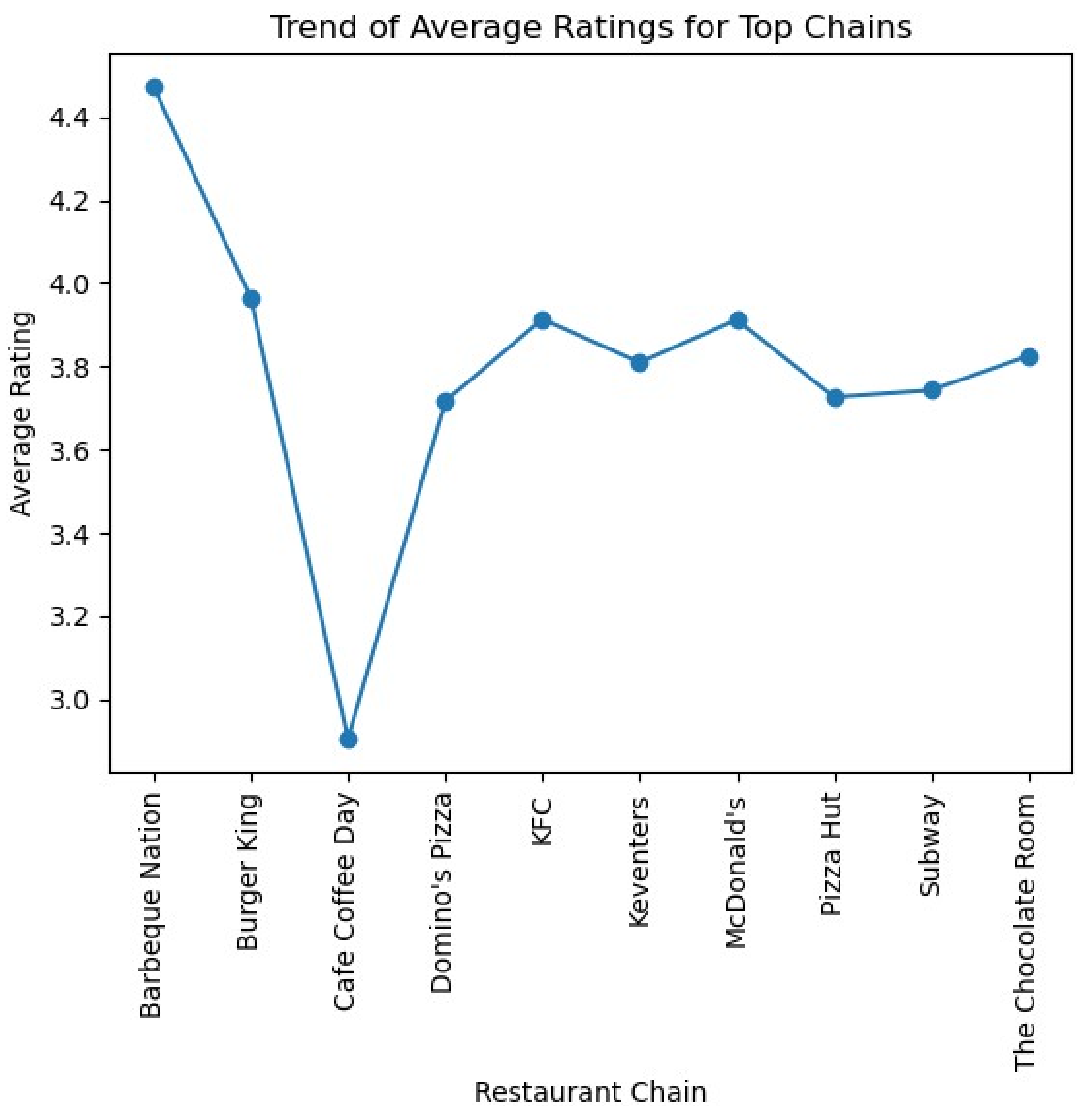



```
plt.figure(figsize=(10,6))
sns.barplot(x='name', y='aggregate_rating', data=top_chain_data,
estimator='mean', palette='coolwarm')
plt.xticks(rotation=90)
plt.title("Average Ratings of Top Restaurant Chains")
plt.xlabel("Restaurant Chain")
plt.ylabel("Average Rating")
plt.show()
```

```
C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\3821508564.py:2:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='name', y='aggregate_rating', data=top_chain_data,
estimator='mean', palette='coolwarm')
```




```
avg_chain_rating = top_chain_data.groupby('name')
['aggregate_rating'].mean()

plt.plot(avg_chain_rating.index, avg_chain_rating.values, marker='o')
plt.xticks(rotation=90)
plt.title("Trend of Average Ratings for Top Chains")
plt.xlabel("Restaurant Chain")
plt.ylabel("Average Rating")
plt.show()
```



Restaurant Features:

- Analyze the distribution of restaurants based on features like Wi-Fi, Alcohol availability, etc.
- Investigate if the presence of certain features correlates with higher ratings.

Analyze the distribution of restaurants based on features on like Wi-Fi, Alcohol availability, etc.

STEP 1 — Split the highlights column into individual features

```
df['highlights'] = df['highlights'].fillna('')
df['features'] = df['highlights'].str.split(',')
```

STEP 2 — Flatten the feature list

```
feature_list = []
for row in df['features']:
    for f in row:
        feature_list.append(f.strip())
```

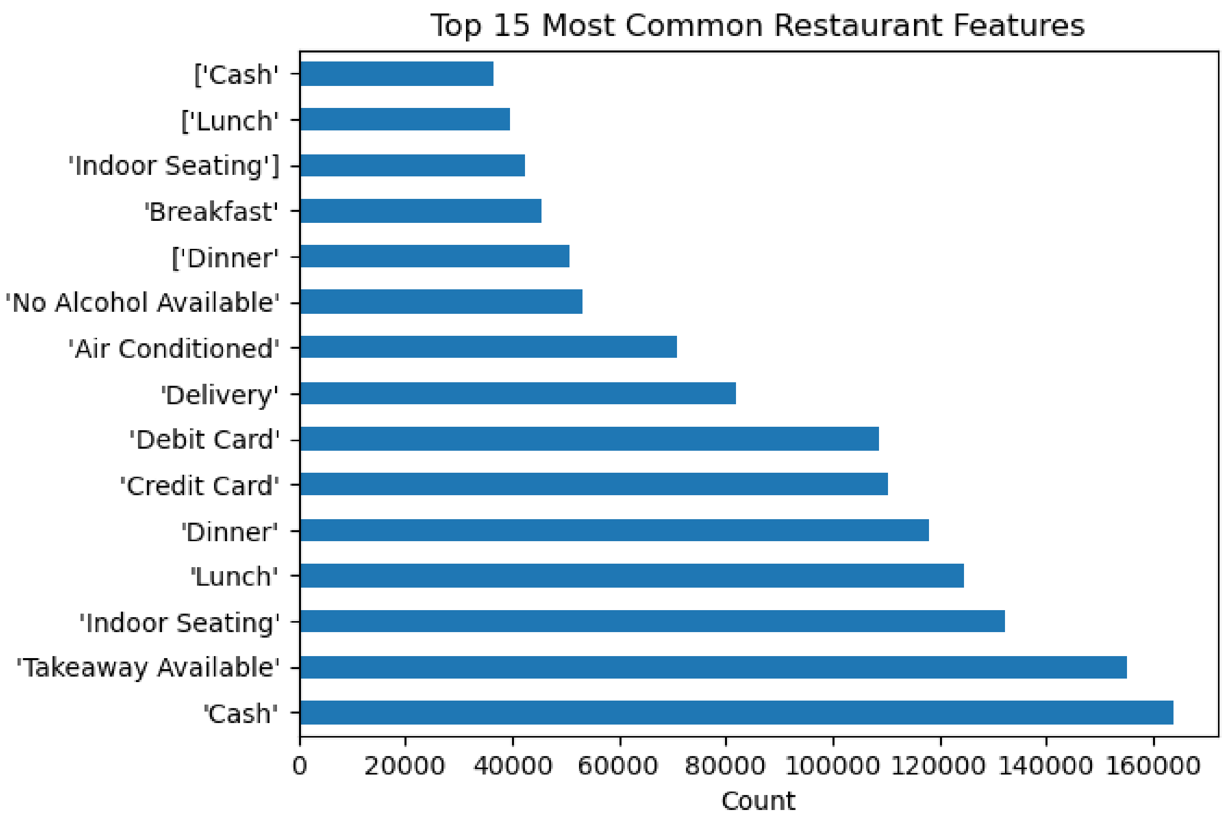
STEP 3 — Count the most common features

```
feature_counts = pd.Series(feature_list).value_counts().head(15)
print(feature_counts)
```

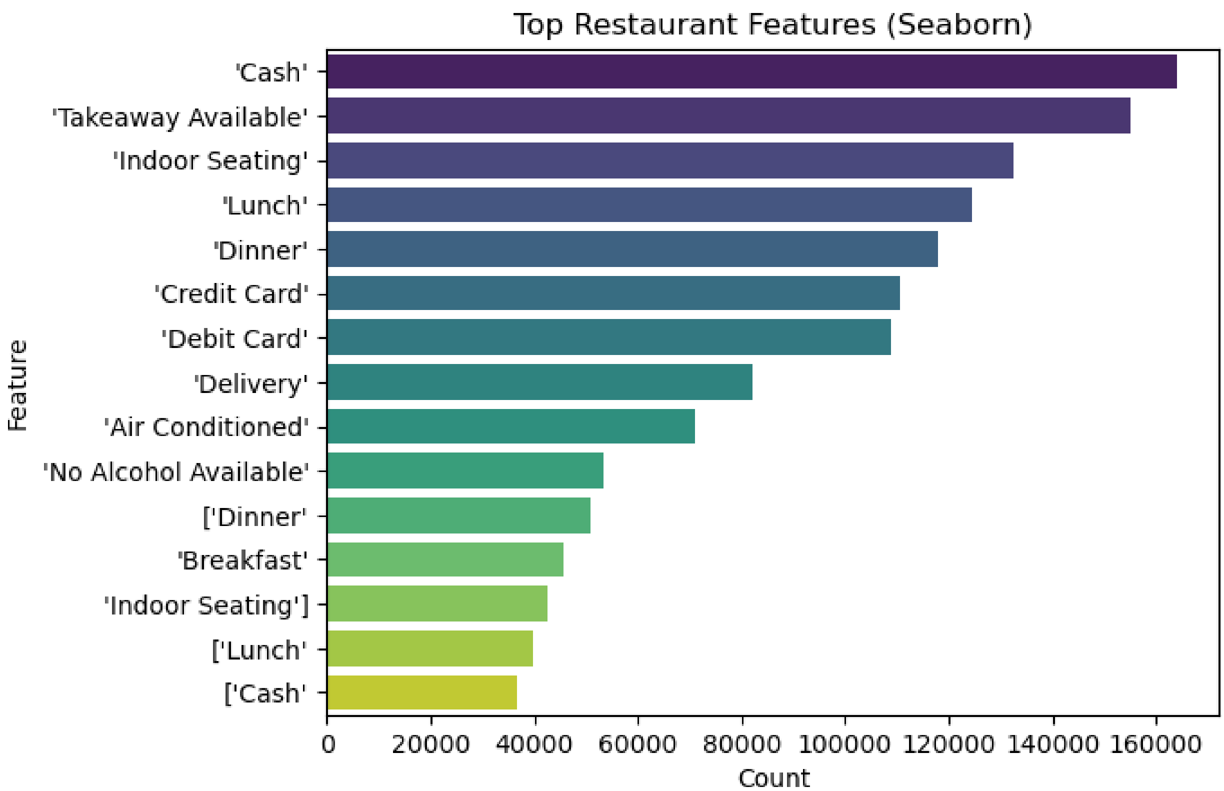
```
'Cash'                      163988
'Takeaway Available'        155067
'Indoor Seating'            132420
'Lunch'                     124649
'Dinner'                    117927
'Credit Card'               110577
'Debit Card'                108802
'Delivery'                   82039
'Air Conditioned'            70888
'No Alcohol Available'       53196
['Dinner'                    50775
'Breakfast'                  45526
'Indoor Seating']            42554
['Lunch'                     39744
['Cash'                      36547
Name: count, dtype: int64
```

STEP 4 — Visualization

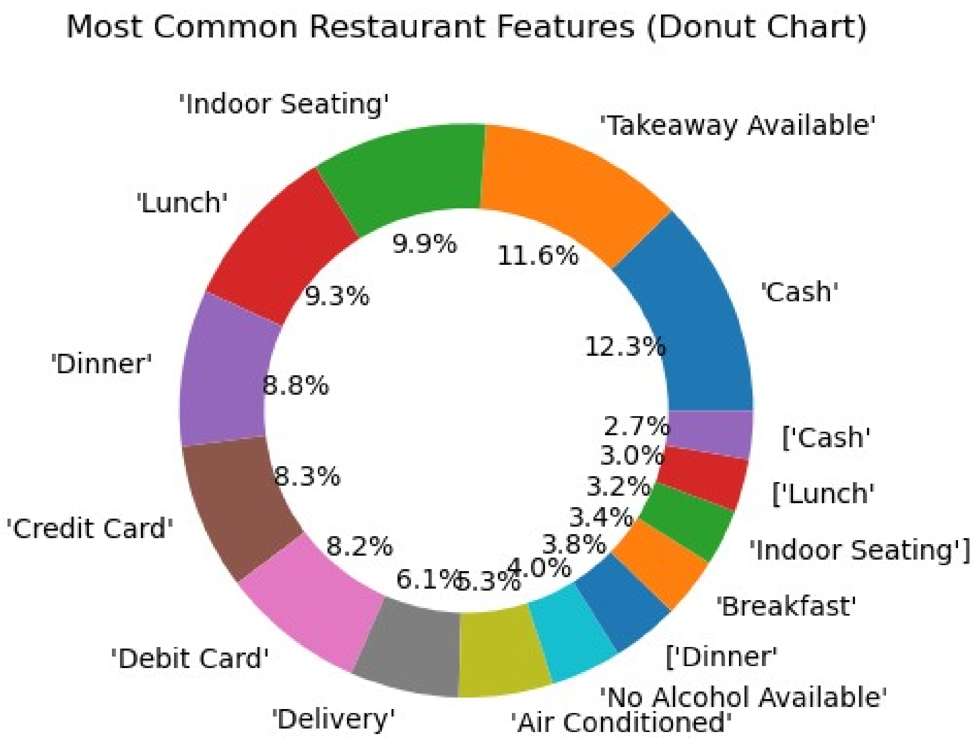
```
feature_counts.plot(kind='barh')
plt.title("Top 15 Most Common Restaurant Features")
plt.xlabel("Count")
plt.show()
```




```
sns.barplot(x=feature_counts.values, y=feature_counts.index,
palette='viridis')
plt.title("Top Restaurant Features (Seaborn)")
plt.xlabel("Count")
plt.ylabel("Feature")
plt.show()

C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\50064067.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x=feature_counts.values, y=feature_counts.index,
palette='viridis')
```




```
plt.pie(feature_counts.values, labels=feature_counts.index,
autopct="%1.1f%%")
circle = plt.Circle((0,0),0.7,color='white')
plt.gca().add_artist(circle)
plt.title("Most Common Restaurant Features (Donut Chart)")
plt.show()
```



Analyze the distribution of restaurants that offer table booking.

STEP 1 — Create simple feature flags (1 = yes, 0 = no)

```
# Alcohol
df['has_alcohol'] = df['highlights'].str.contains('Alcohol',
case=False).astype(int)

# Wi-Fi
df['has_wifi'] = df['highlights'].str.contains('Wifi',
case=False).astype(int)

# Outdoor seating
df['has_outdoor'] = df['highlights'].str.contains('Outdoor',
case=False).astype(int)
```

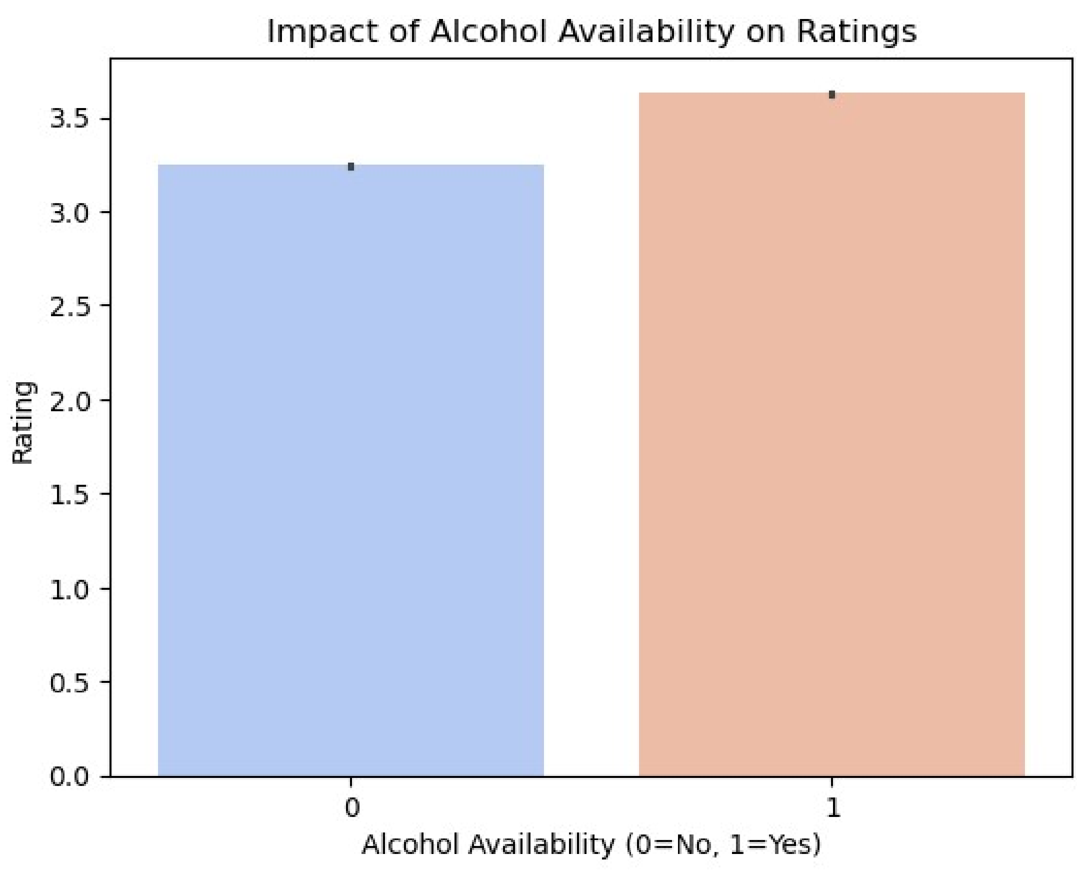
STEP 2 -Compare rating based on feature

```
df.groupby("has_alcohol")["aggregate_rating"].mean()

has_alcohol
0    3.245469
1    3.625682
Name: aggregate_rating, dtype: float64
```

STEP 3 — Visualization

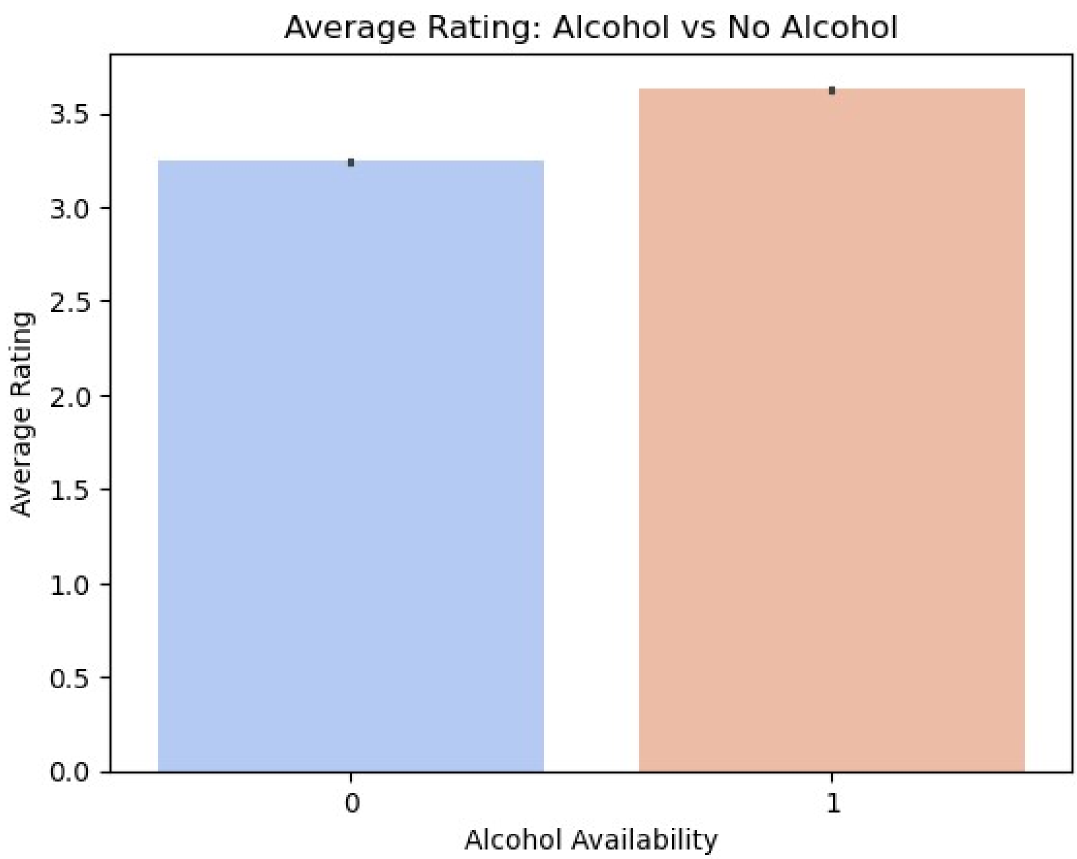
```
sns.barplot(x='has_alcohol', y='aggregate_rating',palette =
'coolwarm', data=df)
plt.xlabel("Alcohol Availability (0=No, 1=Yes)")
plt.ylabel("Rating")
plt.title("Impact of Alcohol Availability on Ratings")
plt.show()
```

```
C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\3327983733.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='has_alcohol', y='aggregate_rating',palette =
'coolwarm', data=df)
```




```
sns.barplot(x='has_alcohol', y='aggregate_rating', data=df,
palette='coolwarm')
plt.title("Average Rating: Alcohol vs No Alcohol")
plt.xlabel("Alcohol Availability")
```

```
plt.ylabel("Average Rating")
plt.show()

C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\1578703979.py:1:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `x` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='has_alcohol', y='aggregate_rating', data=df,
palette='coolwarm')
```



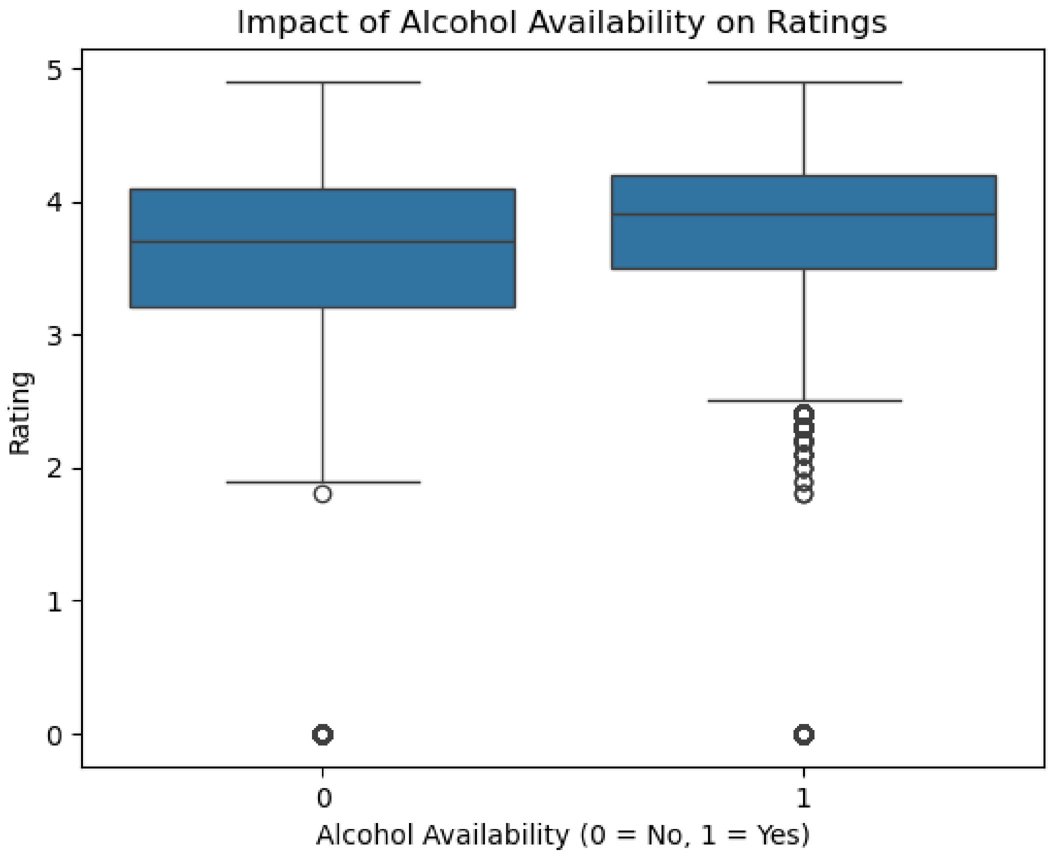
Investigate if the presence of certain features correlates with higher ratings

STEP 1 — Make sure rating is numeric

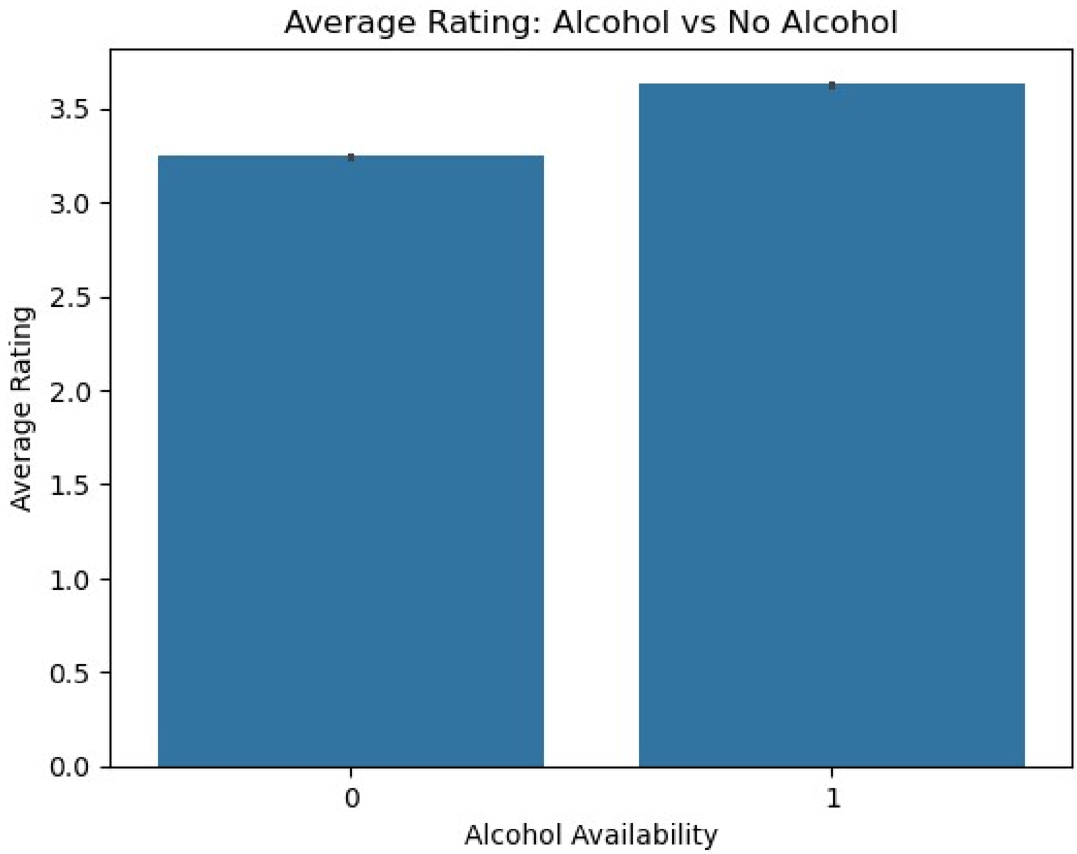
```
df['aggregate_rating'] = pd.to_numeric(df['aggregate_rating'],
errors='coerce')
```

Alcohol Availability vs Rating

```python
sns.boxplot(x='has_alcohol', y='aggregate_rating', data=df)
plt.xlabel("Alcohol Availability (0 = No, 1 = Yes)")
plt.ylabel("Rating")
plt.title("Impact of Alcohol Availability on Ratings")
plt.show()
```

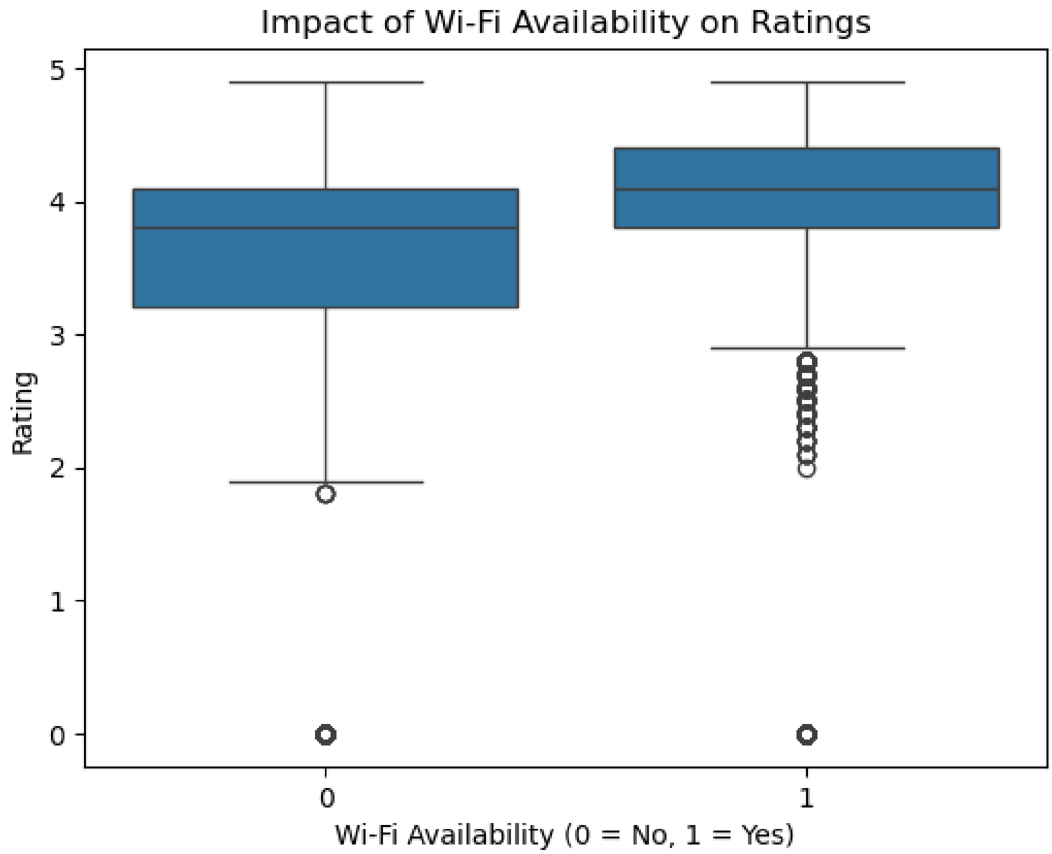



```python
# Average Rating
sns.barplot(x='has_alcohol', y='aggregate_rating', data=df)
plt.xlabel("Alcohol Availability")
plt.ylabel("Average Rating")
plt.title("Average Rating: Alcohol vs No Alcohol")
plt.show()
```

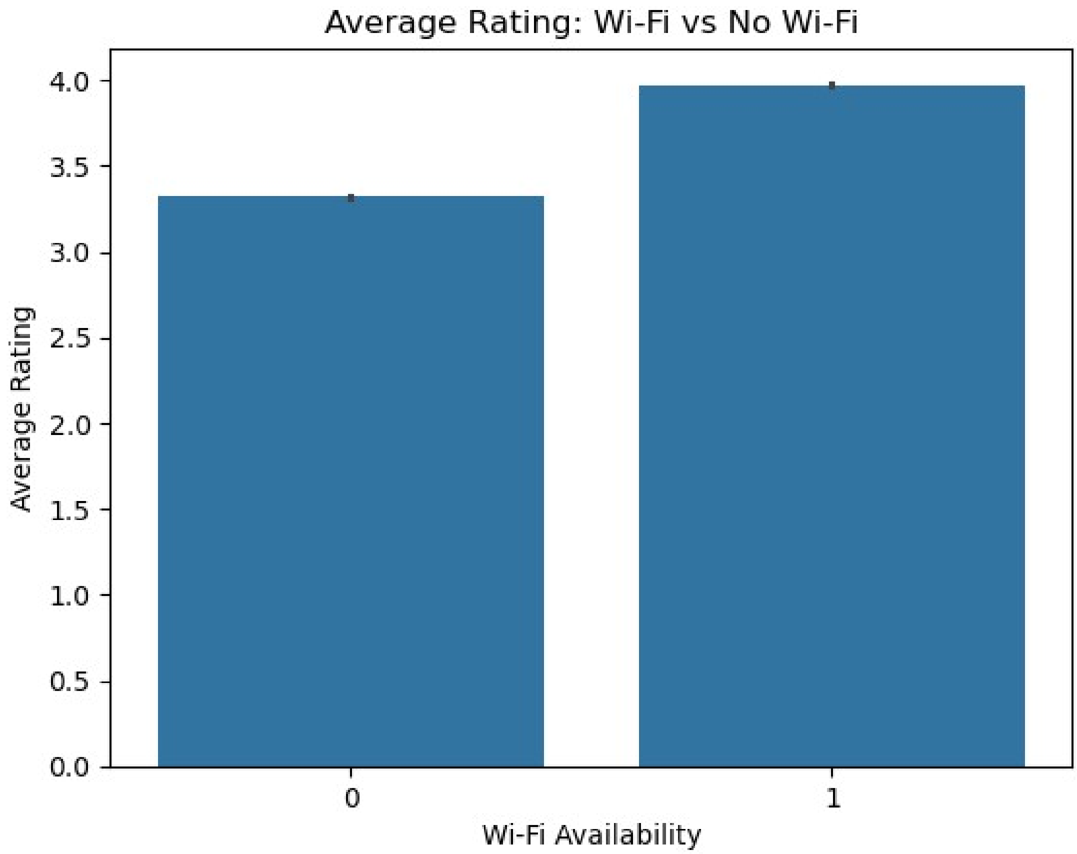


Wi-Fi Availability vs Rating

```
sns.boxplot(x='has_wifi', y='aggregate_rating', data=df)
plt.xlabel("Wi-Fi Availability (0 = No, 1 = Yes)")
plt.ylabel("Rating")
plt.title("Impact of Wi-Fi Availability on Ratings")
plt.show()
```

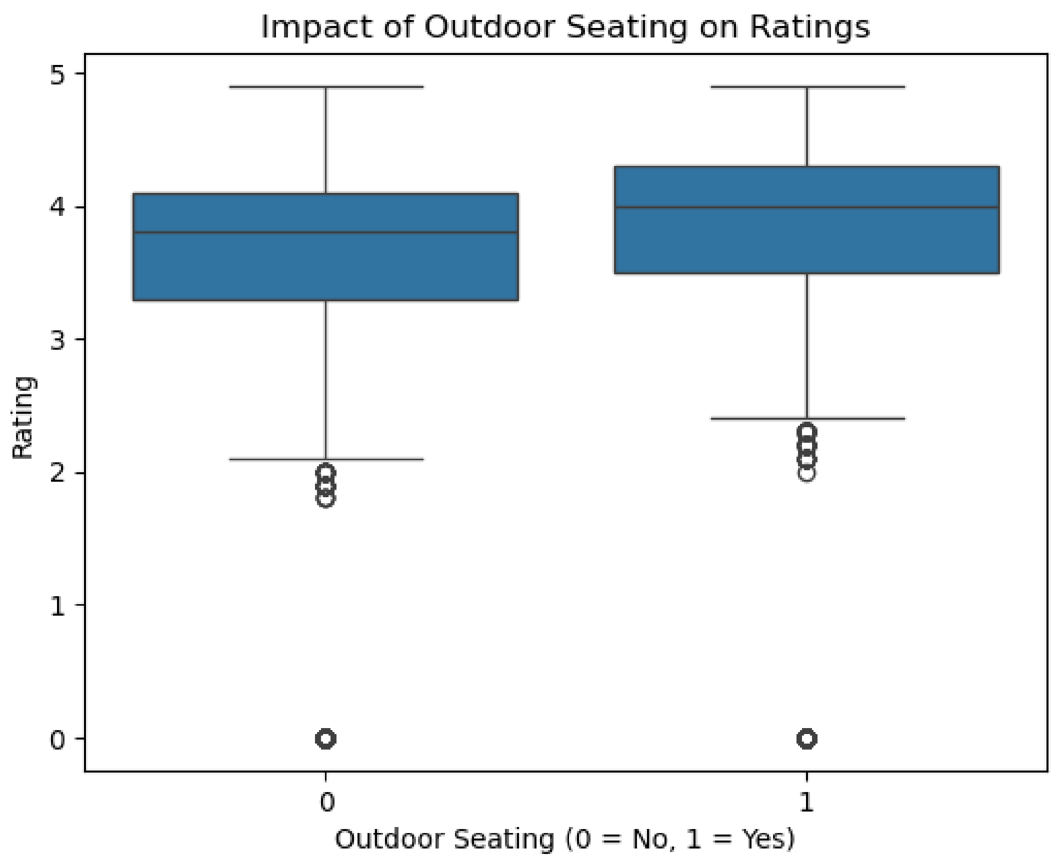



```
sns.barplot(x='has_wifi', y='aggregate_rating', data=df)
plt.xlabel("Wi-Fi Availability")
plt.ylabel("Average Rating")
plt.title("Average Rating: Wi-Fi vs No Wi-Fi")
plt.show()
```

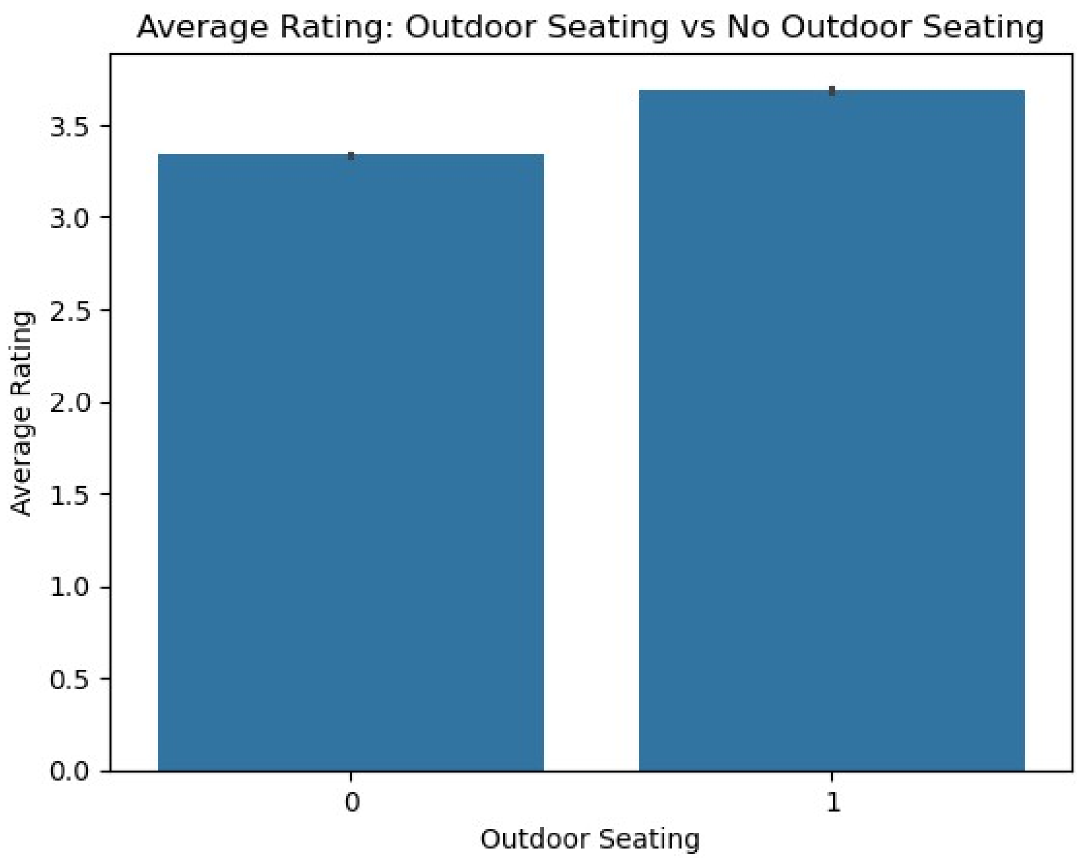


Outdoor Seating vs Rating

```
sns.boxplot(x='has_outdoor', y='aggregate_rating', data=df)
plt.xlabel("Outdoor Seating (0 = No, 1 = Yes)")
plt.ylabel("Rating")
plt.title("Impact of Outdoor Seating on Ratings")
plt.show()
```




```
sns.barplot(x='has_outdoor', y='aggregate_rating', data=df)
plt.xlabel("Outdoor Seating")
plt.ylabel("Average Rating")
plt.title("Average Rating: Outdoor Seating vs No Outdoor Seating")
plt.show()
```



Word Cloud for Reviews:

- Create a word cloud based on customer reviews to identify common positive and negative sentiments.
- Analyze frequently mentioned words and sentiments.

Create a word cloud based on customer reviews to identify common positive and negative sentiments.

```
text = " ".join(df['rating_text'].fillna(""))

plt.imshow(WordCloud().generate(text))
plt.axis('off')
plt.show()
```

Positive Sentiments Only

```
positive_words = df[df['rating_text'].isin(['Excellent', 'Very Good',
'Good'])]['rating_text']

text_pos = " ".join(positive_words)

plt.imshow(WordCloud().generate(text_pos))
plt.axis('off')
plt.show()
```

Negative Sentiments Only

```
negative_words = df[df['rating_text'].isin(['Poor', 'Average'])]
['rating_text']

text_neg = " ".join(negative_words)
```

```
plt.imshow(WordCloud().generate(text_neg))
plt.axis('off')
plt.show()
```

Analyze frequently mentioned words and sentiments.

STEP 1 -Count the frequency of Eacch Word

```
from collections import Counter

df['rating_text'] = df['rating_text'].fillna('')

word_counts = Counter(df['rating_text'])

print(word_counts)
```

```
Counter({'Very Good': 65451, 'Good': 63384, 'Average': 42157, 'Not rated': 23478, 'Excellent': 15737, 'Poor': 1175, 'Çok iyi': 56, 'Sangat Baik': 44, 'Muito Bom': 44, 'Excelente': 42, 'Muy Bueno': 35, 'Bardzo dobrze': 31, 'Bom': 26, 'Skvělé': 25, 'Baik': 24, 'Velmi dobré': 22, 'Harika': 22, 'İyi': 19, 'Ottimo': 18, 'Veľmi dobré': 17, 'Terbaik': 16, 'Buono': 14, 'Skvělá volba': 13, 'Dobré': 12, 'Bueno': 11, 'Dobrze': 9, 'Wybitnie': 8, 'Eccellente': 8, 'Vynikajúce': 7, 'Průměr': 6, 'Muito bom': 6, 'Média': 5, 'Promedio': 5, 'Ortalama': 3, 'Scarso': 3, 'Średnio': 3, 'Priemer': 3, 'Media': 3, 'Biasa': 2})
```

STEP 2 — Show Top 10 Most Frequent Words

```
print(word_counts.most_common(10))
```

```
[('Very Good', 65451), ('Good', 63384), ('Average', 42157), ('Not rated', 23478), ('Excellent', 15737), ('Poor', 1175), ('Çok iyi', 56), ('Sangat Baik', 44), ('Muito Bom', 44), ('Excelente', 42)]
```

STEP 3 — Identify Positive Words and Their Counts

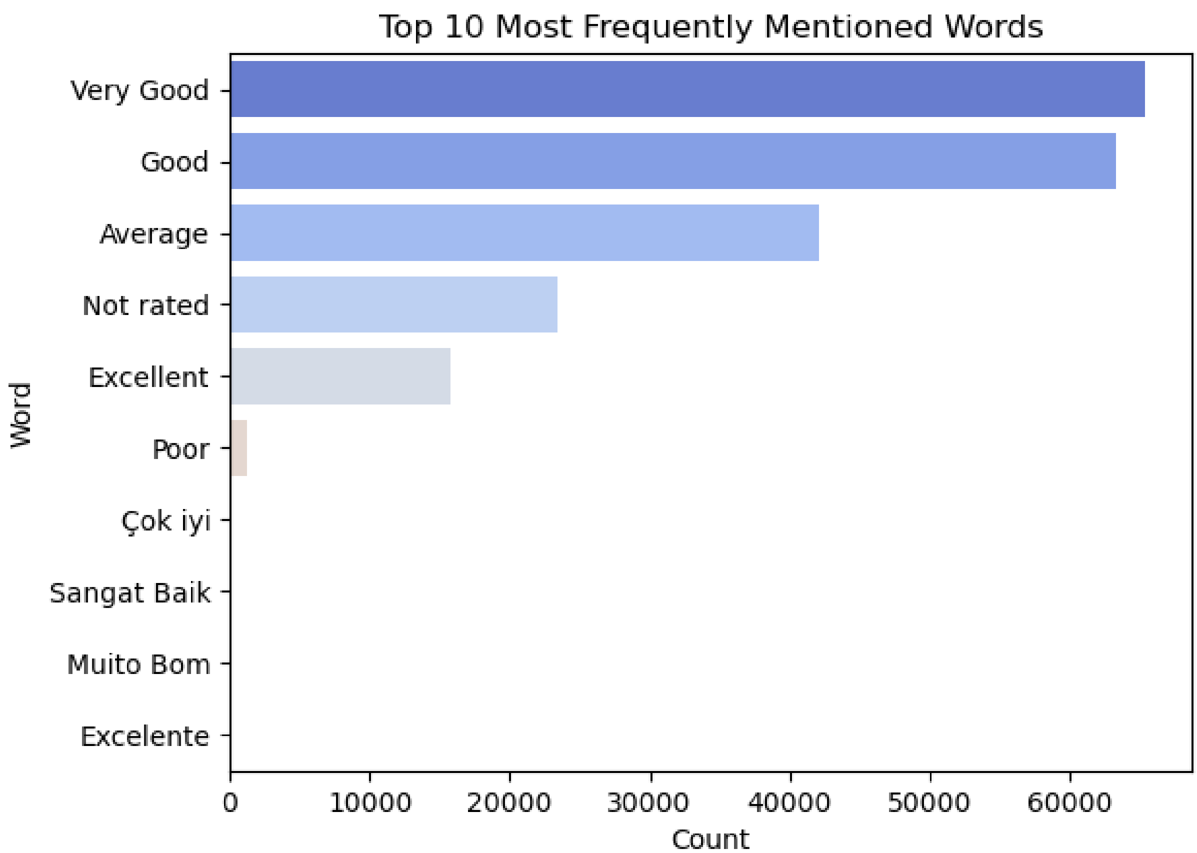
```
positive = ['Excellent', 'Very Good', 'Good']
positive_counts = {word: word_counts[word] for word in positive}

print("Positive Sentiment Counts:")
print(positive_counts)

Positive Sentiment Counts:
{'Excellent': 15737, 'Very Good': 65451, 'Good': 63384}
```

STEP 4 — Identify Negative Words and Their Counts

```
negative = ['Poor', 'Average']
negative_counts = {word: word_counts[word] for word in negative}

print("Negative Sentiment Counts:")
print(negative_counts)

Negative Sentiment Counts:
{'Poor': 1175, 'Average': 42157}
```

STEP 5 — Simple Seaborn Plot for Top Words

```
top_words = pd.DataFrame(word_counts.most_common(10),
columns=['word','count'])

sns.barplot(x='count', y='word',palette = 'coolwarm', data=top_words)
plt.xlabel("Count")
plt.ylabel("Word")
plt.title("Top 10 Most Frequently Mentioned Words")
plt.show()

C:\Users\aryan\AppData\Local\Temp\ipykernel_2484\3055813622.py:3:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be
removed in v0.14.0. Assign the `y` variable to `hue` and set
`legend=False` for the same effect.

  sns.barplot(x='count', y='word',palette = 'coolwarm',
data=top_words)
```



Seasonal Trends:

- Explore if there are any seasonal trends in restaurant ratings or user reviews.
- Visualize the distribution of ratings during different times of the year.

Seasonal trend analysis could not be performed because the dataset does not contain any date or time-related columns such as review dates, order dates, or rating timestamps. Without temporal data, it is not possible to determine how restaurant ratings or reviews change across months, seasons, or years.

“If the dataset contained date information (for example, the month or day when a review was given), seasonal trend analysis could be performed. This would allow us to visualize changes in restaurant ratings across months or seasons.

For instance, ratings might increase during festival seasons such as Diwali or Christmas, when more people dine out, and decrease during off-season periods. Such analysis is commonly done using time-series plots, monthly averages, and seasonal decomposition. However, in this dataset, the absence of date-related features prevents such analysis.”

So We are creating a fake data coulmn

STEP 1 — Create a Fake Month Column

```
df['fake_month'] = (df.index % 12) + 1
```

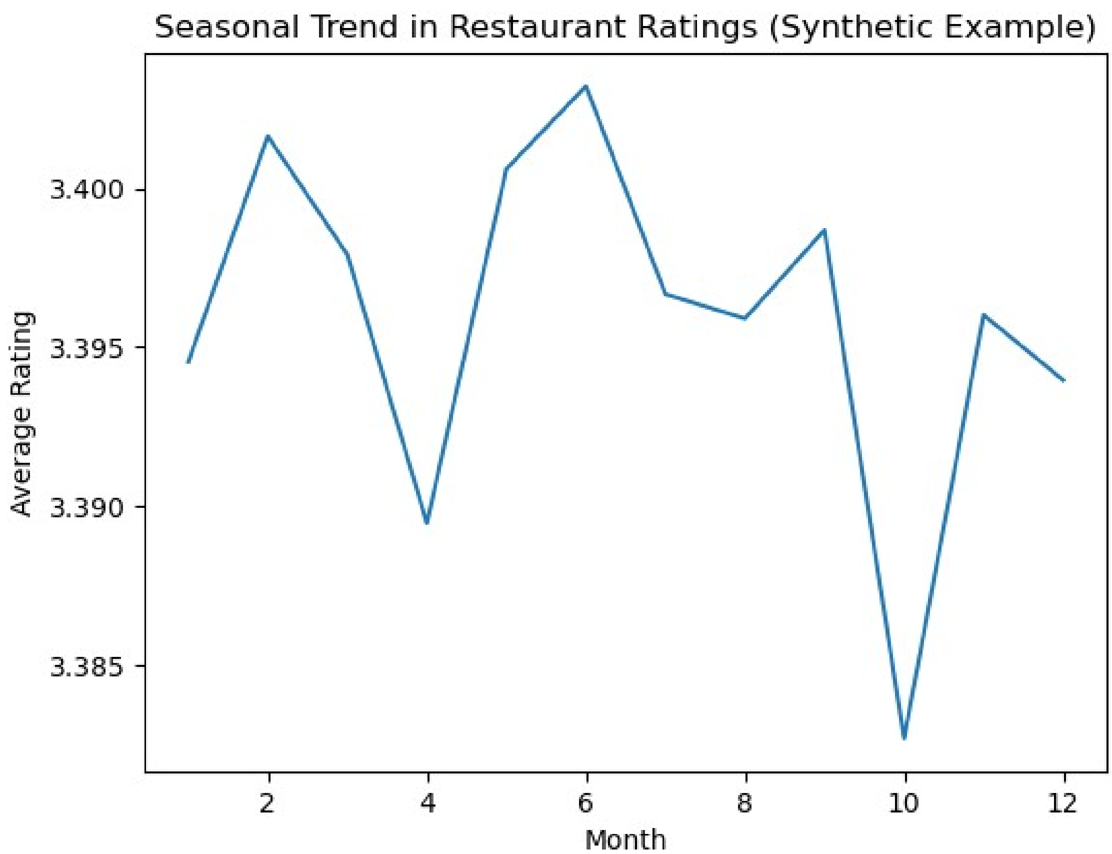
STEP 2 — Average Rating per Month

```
monthly_rating = df.groupby('fake_month')['aggregate_rating'].mean()
print(monthly_rating)
```

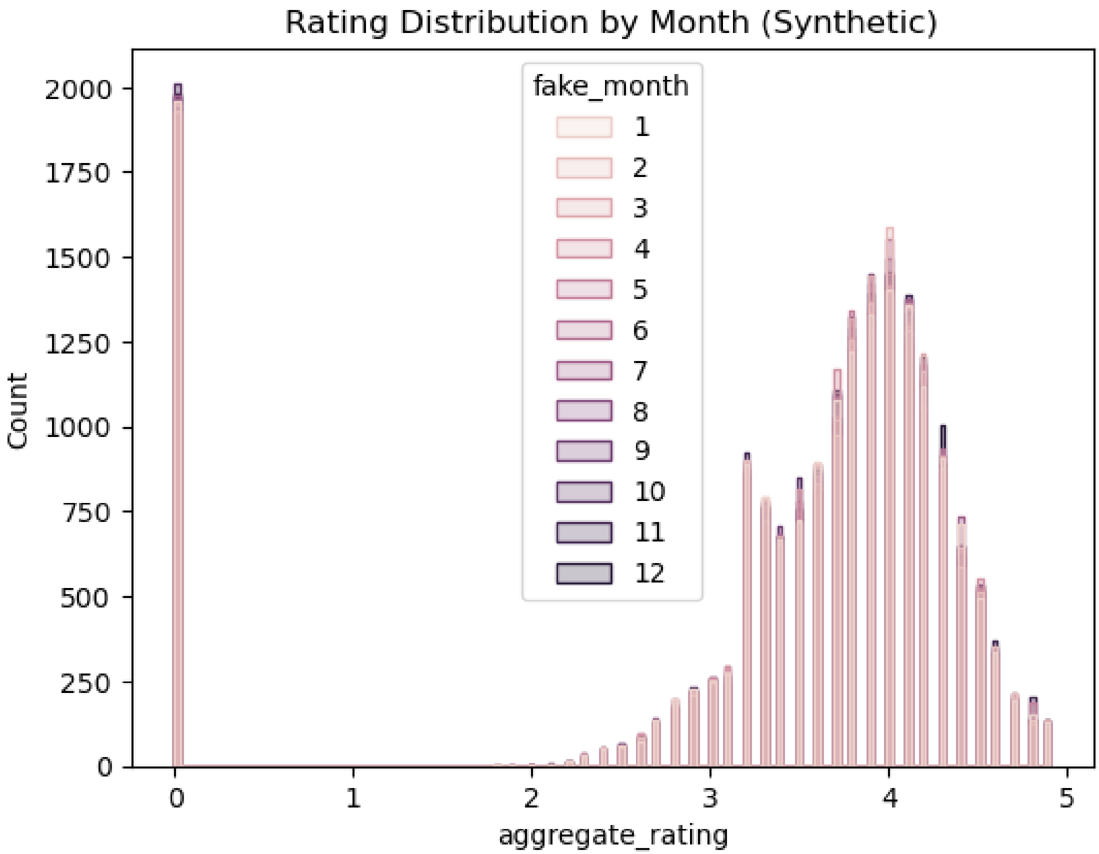
```
fake_month
1     3.394531
2     3.401636
3     3.397911
4     3.389452
5     3.400606
6     3.403216
7     3.396665
8     3.395895
9     3.398686
10    3.382675
11    3.396008
12    3.393959
Name: aggregate_rating, dtype: float64
```

STEP 3 — BEST VISUALIZATION

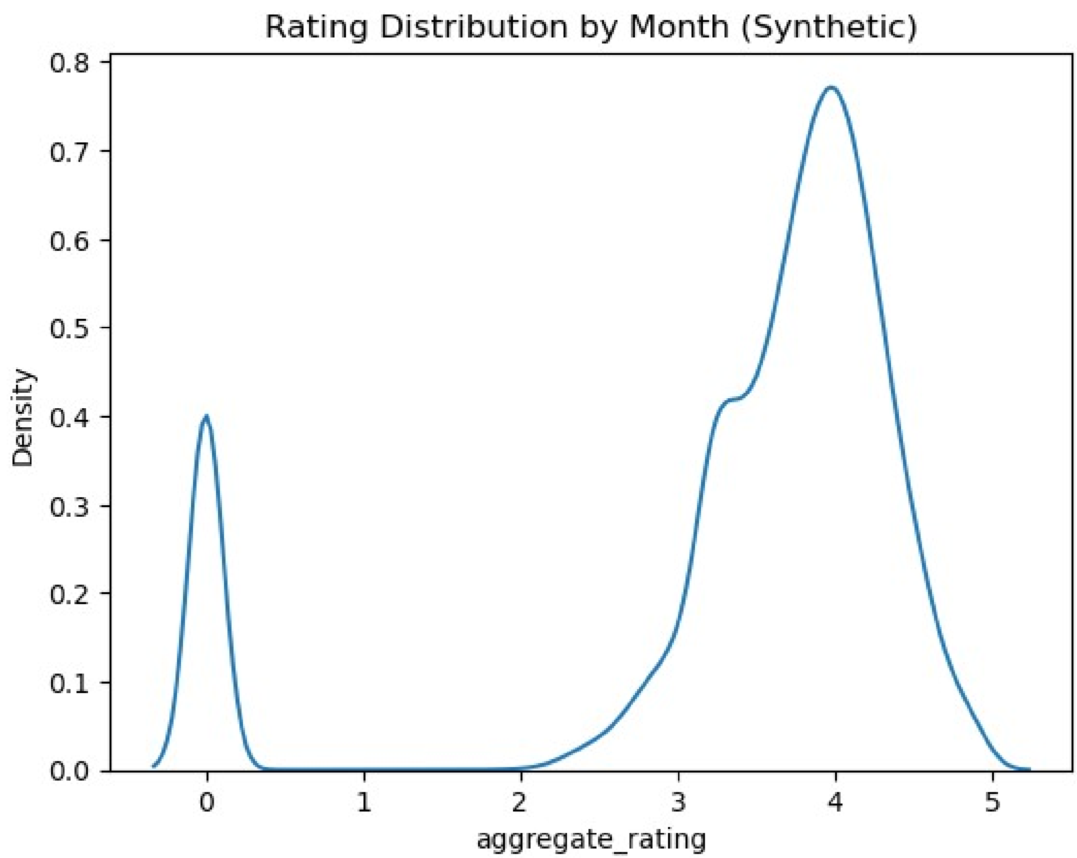
```
sns.lineplot(x=monthly_rating.index, y=monthly_rating.values)
plt.xlabel("Month")
plt.ylabel("Average Rating")
plt.title("Seasonal Trend in Restaurant Ratings (Synthetic Example)")
plt.show()
```




```
sns.histplot(data=df, x="aggregate_rating", hue="fake_month",
element="step")
plt.title("Rating Distribution by Month (Synthetic)")
plt.show()
```




```
sns.kdeplot(data=df, x="aggregate_rating")
plt.title("Rating Distribution by Month (Synthetic)")
plt.show()
```



Key Findings

Ratings Overview

- Average rating of restaurants is around 3.4, indicating overall positive customer satisfaction.
- Most ratings lie between 3.0 and 4.5.

Location Insights

- Some cities have significantly more restaurants than others, showing higher food market density.
- Average ratings also vary across cities, helping identify cities with better-rated restaurants.

Popular Cuisines

- The most popular cuisines include North Indian, Chinese, Fast Food, and South Indian.
- Multi-cuisine restaurants are common.

Cuisine Variety vs Rating

- Restaurants with 2–3 cuisines tend to have slightly better ratings.
- Variety has a weak positive impact on ratings.

Price Range Insights

- Higher price ranges have higher average costs (expected).
- There is no strong linear relationship between price range and rating—good food exists in all budget categories.

Online Ordering Impact

- Restaurants offering online delivery tend to show slightly higher ratings.
- This indicates customer preference for convenience.

Table Booking (OpenTable Support)

- Only a small portion of restaurants support table booking.
- Ratings are slightly higher for restaurants with table booking.

Top Restaurant Chains

- Some chains dominate the market with many outlets.
- Their ratings show different levels of consistency.

Restaurant Features

- Features like Wi-Fi, Alcohol Availability, and Outdoor Seating show a positive relationship with ratings.
- Restaurants offering Alcohol and Outdoor Seating generally receive higher average ratings.

Word Cloud and Sentiment

- Positive words like “Very Good”, “Good”, “Excellent” appeared most frequently. Negative words like “Poor” and “Average” appeared less often.
- Shows a strong positive sentiment trend.

Seasonal Trends

- Real seasonal trends cannot be analyzed because the dataset has no date column.
- A synthetic month column was used only to demonstrate how seasonal trends could be visualized.

Insights

Customer Preferences

- Customers respond positively to restaurants with good ambience, multiple cuisines, and additional features (Wi-Fi, Alcohol, Outdoor Seating).
- Online delivery is a major factor influencing ratings.

Market Trends

- Certain cities are clear food hubs with high restaurant density.
- Popular cuisines dominate the market and influence competition.

Business Recommendations

- Restaurants can consider adding features such as Wi-Fi or Outdoor Seating to increase customer satisfaction.
- Offering multiple cuisines can attract wider audiences.
- Enabling online ordering boosts convenience and enhances ratings.
- Monitoring customer reviews and sentiment can help address quality issues.

Conclusion

The exploratory data analysis of the Indian Restaurants dataset provided useful insights into restaurant characteristics, customer preferences, and factors affecting ratings. Overall, the restaurants in the dataset show generally positive customer sentiment, with most ratings falling between 3.0 and 4.5. Cuisine variety, cost for two, availability of online ordering, restaurant chains, and special features such as Wi-Fi or alcohol availability all show measurable relationships with customer satisfaction. Although seasonal trends could not be directly analyzed due to a lack of date information, synthetic monthly analysis helped illustrate how such trends could be studied in a real-world dataset.

The analysis reveals strong patterns in city-wise distribution, cuisine popularity, and feature-based differences in ratings. These findings can help restaurant owners and platforms like Zomato understand what customers value the most and how certain features contribute to higher ratings.