Level_2&3_(1,2,3,4)_Tasks

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

In [2]:
```
df = pd.read_csv('/Users/bhavesh/Downloads/Dataset .csv')
```

In [3]:
```
df.head()
```

Out[3]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Loc Ver
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century Pobla Makati M
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little T Leg Vil Makati
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Shangr Ort Mandalu City,
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	Mega Ort Mandalu Man
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	Mega Ort Mandalu Man

5 rows × 21 columns

In [4]:
```
print(df.shape)
```

```
(9551, 21)
```

In [5]:
```
print(df.columns.tolist())
```

```
['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address', 'L
ocality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines', 'Averag
e Cost for two', 'Currency', 'Has Table booking', 'Has Online delivery',
'Is delivering now', 'Switch to order menu', 'Price range', 'Aggregate rat
ing', 'Rating color', 'Rating text', 'Votes']
```

In [6]:
```
print(df.dtypes)
```

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

In [7]:
```
print(df.isnull().sum())
```

```
Restaurant ID         0
Restaurant Name       0
Country Code          0
City                  0
Address               0
Locality              0
Locality Verbose      0
Longitude             0
Latitude              0
Cuisines              9
Average Cost for two  0
Currency              0
Has Table booking     0
Has Online delivery   0
Is delivering now     0
Switch to order menu  0
Price range           0
Aggregate rating      0
Rating color          0
Rating text           0
Votes                 0
dtype: int64
```

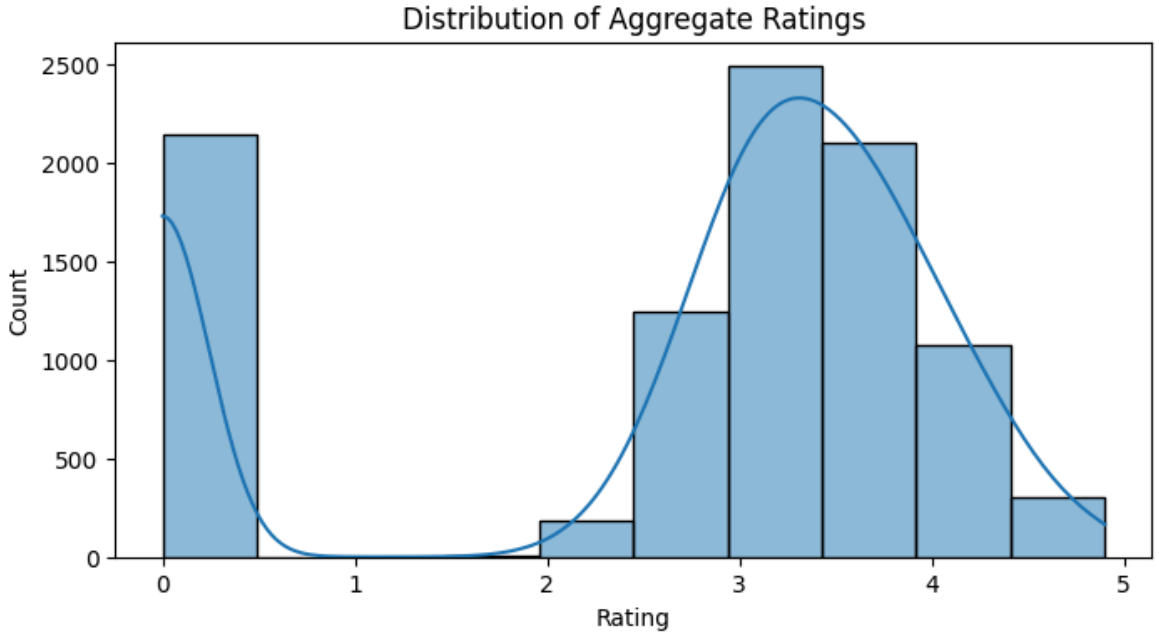
In [8]:
```
duplicates = df.duplicated().sum()
print(duplicates)
```

```
0
```

Task 1 : Restaurant Ratings

1.1 Analyze the distribution of aggregate ratings and determine the most common rating range.

In [9]:
```
plt.figure(figsize=(8,4))
sns.histplot(df['Aggregate rating'], bins=10, kde=True)
plt.title("Distribution of Aggregate Ratings")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.show()
```



In [10]:
```
rating_bins = [0, 1, 2, 3, 4, 5]
rating_labels = ['0–1', '1–2', '2–3', '3–4', '4–5']

df['Rating Range'] = pd.cut(df['Aggregate rating'], bins=rating_bins, lab
```

In [11]:
```
rating_range_counts = df['Rating Range'].value_counts().sort_index()

print("Rating Range Counts:")
print(rating_range_counts)
```

```
Rating Range Counts:
Rating Range
0–1    2148
1–2      10
2–3    1891
3–4    4388
4–5    1114
Name: count, dtype: int64
```

In [12]:
```
most_common_range = rating_range_counts.idxmax()
most_common_count = rating_range_counts.max()

print("Most common rating range:", most_common_range)
print("Number of restaurants in this range:", most_common_count)
```

```
Most common rating range: 3–4
Number of restaurants in this range: 4388
```

- The distribution of aggregate ratings shows that most restaurants fall in the **[3-4]** rating range.

1.2 Calculate the average number of votes received by restaurants.

In [13]:
```
average_votes = df['Votes'].mean()

print("Average Number of Votes Received by Restaurants:", round(average_v
```

```
Average Number of Votes Received by Restaurants: 156.91
```

Task 2 : Cuisine Combination

2.1 Identify the most common combinations of cuisines in the dataset.

In [14]:
```
cuisine_combos = df['Cuisines'].value_counts()
print("Most Common Cuisine Combinations:")
print(cuisine_combos.head(10))
```

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

- The most frequent cuisine combination is **[North Indian]**, appearing **[936]** times in the dataset.

2.2 Determine if certain cuisine combinations tend to have higher ratings.

In [15]:
```
avg_rating_by_combo = (
    df.groupby('Cuisines')['Aggregate rating']
      .mean()
      .round(2)
      .sort_values(ascending=False)
)

print("Average Rating by Cuisine Combination:")
print(avg_rating_by_combo.head(10))
```

```
Average Rating by Cuisine Combination:
Cuisines
American, Sandwich, Tea          4.9
Hawaiian, Seafood                4.9
European, Asian, Indian          4.9
European, Contemporary           4.9
European, German                 4.9
Italian, Deli                    4.9
BBQ, Breakfast, Southern         4.9
American, Coffee and Tea         4.9
Sunda, Indonesian                4.9
American, Caribbean, Seafood     4.9
Name: Aggregate rating, dtype: float64
```

In [16]:
```
print(avg_rating_by_combo.tail(10))
```

```
Cuisines
Italian, Chinese                                0.0
Indian, Persian                                 0.0
Pizza, Burger, Fast Food                        0.0
Continental, Italian, Fast Food                 0.0
Ice Cream, Bakery                               0.0
Hyderabadi, Biryani                             0.0
Pizza, Fast Food, Bakery                        0.0
Pizza, Ice Cream                                0.0
Greek, Mediterranean, Middle Eastern            0.0
Italian, Continental, Fast Food, North Indian   0.0
Name: Aggregate rating, dtype: float64
```

Task 3 : Restaurant Chains

3.1 Identify if there are any restaurant chains present in the dataset.

In [17]:
```
restaurant_counts = df['Restaurant Name'].value_counts()

restaurant_chains = restaurant_counts[restaurant_counts > 1]

restaurant_chains
```

Out[17]:
```
Restaurant Name
Cafe Coffee Day       83
Domino's Pizza        79
Subway                63
Green Chick Chop      51
McDonald's            48
                      ..
Town Hall              2
Halki Aanch            2
Snack Junction         2
Delhi Biryani Hut      2
Beliram Degchiwala     2
Name: count, Length: 734, dtype: int64
```

- Restaurants that appear more than once indicate multiple branches and therefore represent *restaurant chains*.

3.2 Analyze the ratings and popularity ofdifferent restaurant chains.

In [18]:
```
restaurant_counts = df['Restaurant Name'].value_counts()

chains = restaurant_counts[restaurant_counts > 1].index

chains[:10]
```

Out[18]:
```
Index(['Cafe Coffee Day', 'Domino's Pizza', 'Subway', 'Green Chick Cho
p',
       'McDonald's', 'Keventers', 'Pizza Hut', 'Giani', 'Baskin Robbin
s',
       'Barbeque Nation'],
      dtype='object', name='Restaurant Name')
```

In [19]:
```
chain_df = df[df['Restaurant Name'].isin(chains)]
chain_df.head()
```

Out[19]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Lo Ve
5	18189371	Din Tai Fung	162	Mandaluyong City	Ground Floor, Mega Fashion Hall, SM Megamall, ...	SM Megamall, Ortigas, Mandaluyong City	Meg O Manda Ma
10	6309903	Silantro Fil-Mex	162	Pasig City	75 East Capitol Drive, Kapitolyo, Pasig City	Kapitolyo	Kap Pas
12	6318433	Silantro Fil-Mex	162	Quezon City	Second Floor, UP Town Center, Katipunan Avenue...	UP Town Center, Diliman, Quezon City	UP (D Quezo Quezo
35	6601589	Coco Bambu	30	Bras\ufffd_lia	Bras\ufffd_lia Shopping - Piso 2, SCN 5, Bloco A, A...	Bras\ufffd_lia Shopping, Asa Norte	Bras Sho Asa Bras
39	6600427	Coco Bambu	30	Bras\ufffd_lia	SCES, Trecho 2, Conjunto 13/36, Setor de Clube...	Setor De Clubes Esportivos Sul	Se (Espo Bras

5 rows × 22 columns

In [20]:

```
chain_stats = (
    chain_df.groupby("Restaurant Name")
            .agg(
                Avg_Rating=("Aggregate rating", "mean"),
                Total_Votes=("Votes", "sum"),
                Branch_Count=("Restaurant Name", "count")
            )
            .sort_values(by="Avg_Rating", ascending=False)
)

chain_stats.round(2).head(10)
```

Out[20]:

Restaurant Name	Avg_Rating	Total_Votes	Branch_Count
Talaga Sampireun	4.90	5514	3
Silantro Fil-Mex	4.85	1364	2
AB's Absolute Barbecues	4.85	3151	2
AB's - Absolute Barbecues	4.82	13400	4
Naturals Ice Cream	4.80	3094	2
Gymkhana	4.70	328	2
The Cheesecake Factory	4.65	3010	2
Dishoom	4.60	1269	2
Garota de Ipanema	4.60	59	2
Chili's	4.58	8156	5

- The highest-rated chains include **[Talaga Sampireun]**, **[Silantro Fil-Mex]**, and **[AB's Absolute Barbecues]**, all with strong customer satisfaction.

LEVEL 3

TASK 1 : Votes Analysis

1.1 Identify the restaurants with the highest and lowest number of votes.

In [21]:
```
sorted_votes = df.sort_values(by="Votes", ascending=False)

highest_votes = sorted_votes.iloc[0]

lowest_votes = sorted_votes[sorted_votes["Votes"] > 0].iloc[-1]

print(highest_votes)
```

```
Restaurant ID                                                    51705
Restaurant Name                                                   Toit
Country Code                                                         1
City                                                           Bangalore
Address                 298, Namma Metro Pillar 62, 100 Feet Road, Ind...
Locality                                                     Indiranagar
Locality Verbose                                Indiranagar, Bangalore
Longitude                                                    77.640709
Latitude                                                     12.979166
Cuisines                                       Italian, American, Pizza
Average Cost for two                                             2000
Currency                                            Indian Rupees(Rs.)
Has Table booking                                                   No
Has Online delivery                                                 No
Is delivering now                                                   No
Switch to order menu                                                No
Price range                                                          4
Aggregate rating                                                   4.8
Rating color                                                 Dark Green
Rating text                                                   Excellent
Votes                                                             10934
Rating Range                                                        4–5
Name: 728, dtype: object
```

In [22]:
```
print(lowest_votes)
```

```
Restaurant ID                                                 18273067
Restaurant Name                  Curry Capital - Hotel Classic Diplomat
Country Code                                                         1
City                                                         New Delhi
Address                 A-4, NH 8, Near IGI Airport, Mahipalpur, New D...
Locality                              Hotel Classic Diplomat, Mahipalpur
Locality Verbose            Hotel Classic Diplomat, Mahipalpur, New Delhi
Longitude                                                    77.12618
Latitude                                                     28.547656
Cuisines                North Indian, Continental, South Indian, Chinese
Average Cost for two                                             1000
Currency                                            Indian Rupees(Rs.)
Has Table booking                                                  Yes
Has Online delivery                                                 No
Is delivering now                                                   No
Switch to order menu                                                No
Price range                                                          3
Aggregate rating                                                   0.0
Rating color                                                     White
Rating text                                                  Not rated
Votes                                                                1
Rating Range                                                        0–1
Name: 4008, dtype: object
```

- The restaurant with the **highest popularity** (most votes) is **[Toit]** with **[10934] votes**, showing strong customer engagement.
- The restaurant with the **lowest (non-zero) votes** is **[Curry Capital - Hotel Classic Diplomat]** with **[1] votes**, indicating low visibility or limited customer interactions.

1.2 Analyze if there is a correlation between the number of votes and the rating of a restaurant.

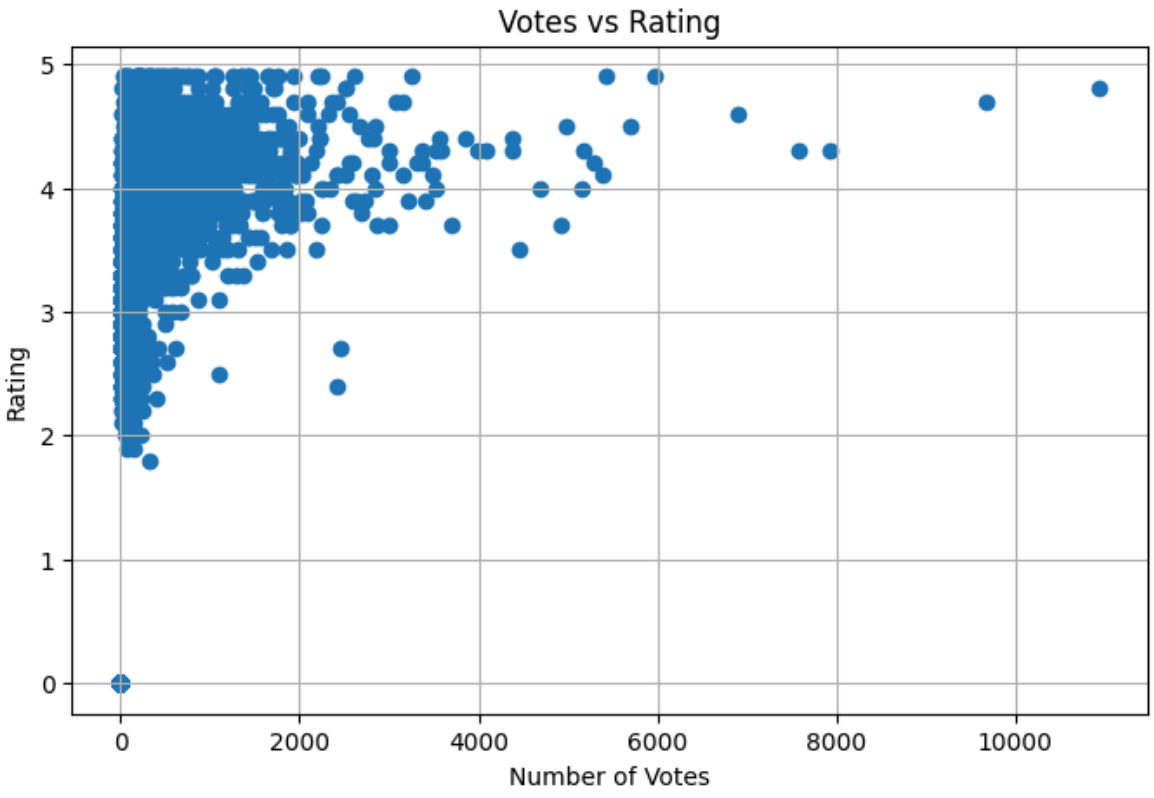
In [23]:
```
correlation = df['Votes'].corr(df['Aggregate rating'])

correlation
```

Out[23]: 0.31369058419541146

- The correlation coefficient between **votes** and **ratings** is **[0.31]**.
- A **positive correlation** suggests that restaurants with more votes tend to have higher ratings, meaning popular restaurants may also be well-rated.

In [24]:
```
plt.figure(figsize=(8,5))
plt.scatter(df['Votes'], df['Aggregate rating'])
plt.title("Votes vs Rating")
plt.xlabel("Number of Votes")
plt.ylabel("Rating")
plt.grid(True)
plt.show()
```



Task 2 : Price Range vs. Online Delivery and Table Booking

2.1 Analyze if there is a relationship between the price range and the availability of online delivery and table booking.

In [25]:
```
df['Online_delivery_binary'] = df['Has Online delivery'].map({'Yes': 1, '
df['Table_booking_binary'] = df['Has Table booking'].map({'Yes': 1, 'No':
```

In [26]:
```
online_by_price = df.groupby('Price range')['Online_delivery_binary'].mea

(online_by_price.round(2))*100
```

Out[26]:
```
Price range
1    16.0
2    41.0
3    29.0
4     9.0
Name: Online_delivery_binary, dtype: float64
```

In [27]:
```
table_by_price = df.groupby('Price range')['Table_booking_binary'].mean()

table_by_price.round(2)*100
```

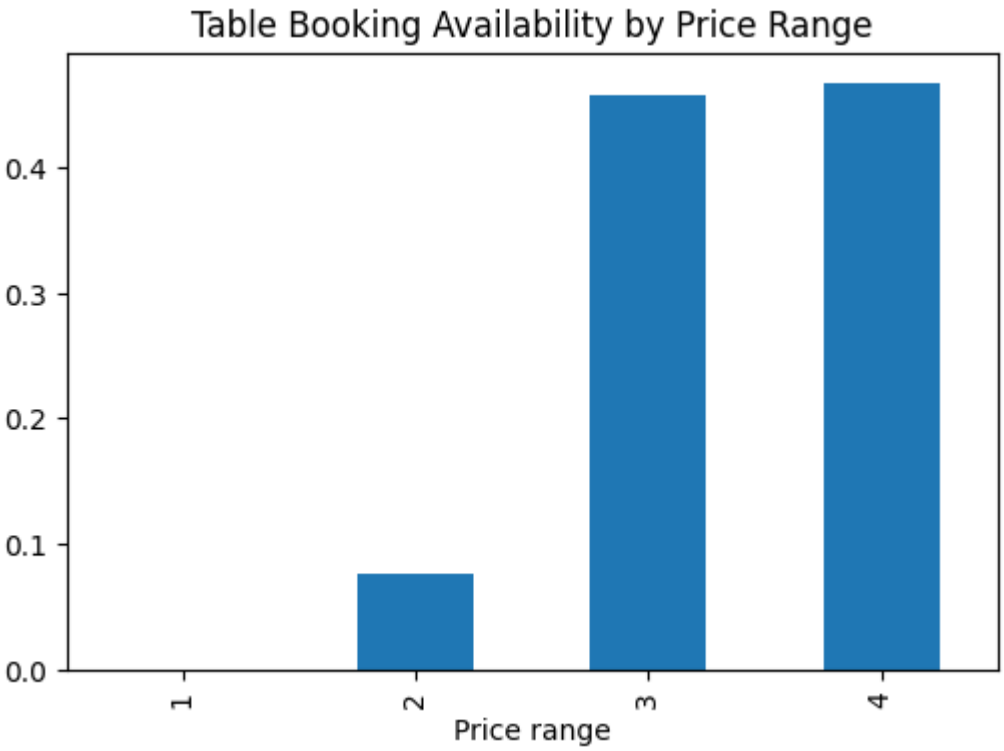
Out[27]:
```
Price range
1     0.0
2     8.0
3    46.0
4    47.0
Name: Table_booking_binary, dtype: float64
```

In [28]:
```
online_by_price.plot(kind='bar', figsize=(6,4), title="Online Delivery Av
```

Out[28]:
```
<Axes: title={'center': 'Online Delivery Availability by Price Range'},
xlabel='Price range'>
```

In [29]:
```
table_by_price.plot(kind='bar', figsize=(6,4), title="Table Booking Avail
```

Out[29]:
```
<Axes: title={'center': 'Table Booking Availability by Price Range'}, xl
abel='Price range'>
```



In [30]:
```
corr_delivery = df['Price range'].corr(df['Online_delivery_binary'])
corr_table = df['Price range'].corr(df['Table_booking_binary'])

corr_delivery, corr_table
```

Out[30]:
```
(0.07791776880448596, 0.5019247250371413)
```

Online Delivery

- Higher price ranges tend to have **[higher]** online delivery availability.
- Price Range **[2]** has the highest percentage of restaurants offering online delivery.

Table Booking

- Table booking shows a **[0.50] correlation** with price range.
- Premium restaurants (higher price range) are **more likely** to offer table booking.

In [31]:
```
df['Online_delivery_binary'] = df['Has Online delivery'].map({'Yes': 1, '
df['Table_booking_binary'] = df['Has Table booking'].map({'Yes': 1, 'No':


online_delivery_rate = df.groupby('Price range')['Online_delivery_binary'
table_booking_rate = df.groupby('Price range')['Table_booking_binary'].me

online_delivery_rate, table_booking_rate
```

Out[31]:
```
(Price range
 1    15.774077
 2    41.310633
 3    29.190341
 4     9.044369
 Name: Online_delivery_binary, dtype: float64,
 Price range
 1     0.022502
 2     7.677482
 3    45.738636
 4    46.757679
 Name: Table_booking_binary, dtype: float64)
```

In [32]:
```
plt.figure(figsize=(8,4))
online_delivery_rate.plot(kind='bar')
plt.title("Online Delivery Availability (%) by Price Range")
plt.ylabel("Percentage %")
plt.show()

plt.figure(figsize=(8,4))
table_booking_rate.plot(kind='bar')
plt.title("Table Booking Availability (%) by Price Range")
plt.ylabel("Percentage %")
plt.show()
```


Online Delivery Availability (%) by Price Range
Percentage %
0
5
10
15
20
25
30
35
40
1
2
3
4
Price range

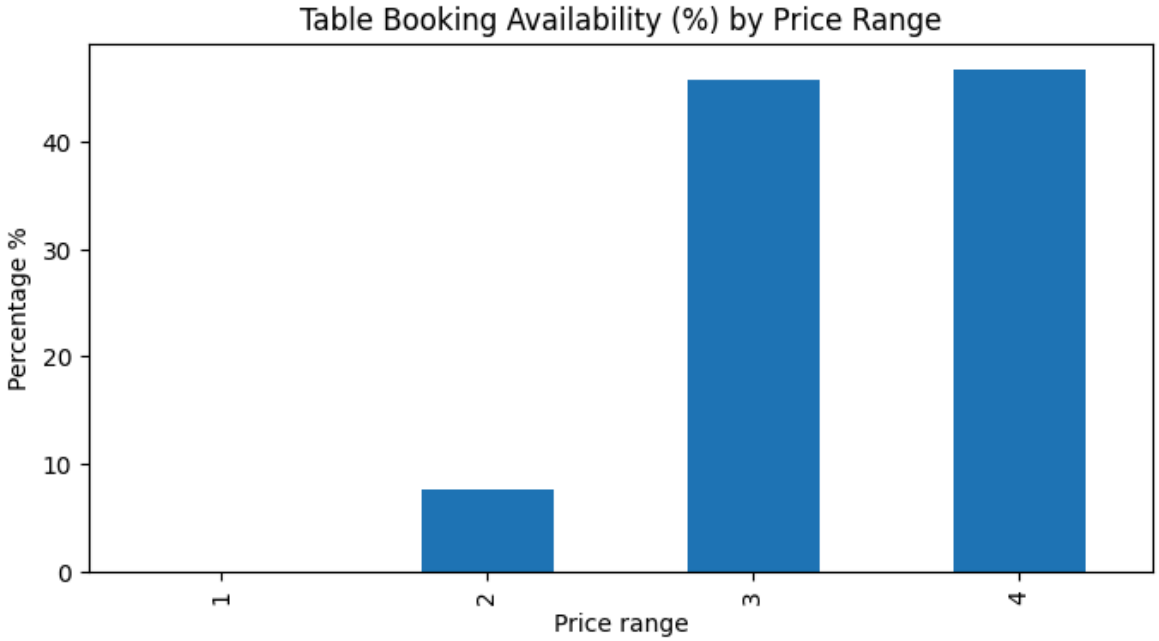


Table Booking Availability (%) by Price Range
Percentage %
0
10
20
30
40
1
2
3
4
Price range