DATA ANALYSIS LEVEL 3

- **Task 1: Restaurant Reviews**
- **Task 2: Votes Analysis**
- **Task 3: Price Range vs. Online Delivery and Table Booking**

Step 1: Import necessary Python libraries.

In [4]:
```
# import python modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [57]:
```
# nltk module
from nltk.sentiment import SentimentIntensityAnalyzer
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from collections import Counter
```

NLTK (Natural Language Toolkit):

- **Purpose**: NLTK is a powerful Python library for working with human language data, making it ideal for text processing and NLP tasks. It includes tools for tokenization, parsing, classification, stemming, tagging, and semantic reasoning, as well as extensive lexical resources like WordNet.

Key Components: - **SentimentIntensityAnalyzer**: Provides a way to assess the sentiment of text data.This analyzer uses a lexicon-based approach to score sentences, making it suitable for understanding the emotional tone in text.

- **word_tokenize**: A function that breaks down sentences into individual words (tokens). This tokenization process is often the first step in analyzing text data at the word level.

- **stopwords**: A list of commonly used words (like "and," "is," and "the") provided by NLTK. These words are usually filtered out to focus on the more meaningful content words in a text.

- **Counter**: A class that counts the frequency of each element in an iterable, which is especially useful for text processing to count word occurrences. By identifying frequently used words, Counter can help in understanding the main themes or focus of a text.

In [59]:
```
import nltk
nltk.download('vader_lexicon')
nltk.download('stopwords')
nltk.download('punkt')
```

```
[nltk_data] Downloading package vader_lexicon to
[nltk_data]     C:\Users\ubade\AppData\Roaming\nltk_data...
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\ubade\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping corpora\stopwords.zip.
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\ubade\AppData\Roaming\nltk_data...
[nltk_data]   Unzipping tokenizers\punkt.zip.
```

Out[59]: True

Step - 2. Read the Dataset from CSV file - Using Pandas

In [62]:
```
restaurant_df = pd.read_csv(r"Dataset .csv")
restaurant_df
```

Out[62]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japanese, Sushi
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.057508	14.584450	Japanese, Korean
...	...	...	...	...	...	...	...	...	...	...
9546	5915730	Namlı Gurme	208	��stanbul	Kemanke�� Karamustafa Pa��a Mahallesi, Rıhtım ...	Karak�_y	Karak�_y, ��stanbul	28.977392	41.022793	Turkish
9547	5908749	Ceviz A��acı	208	��stanbul	Ko��uyolu Mahallesi, Muhittin	Ko��uyolu	Ko��uyolu, ��stanbul	29.041297	41.009847	World Cuisine, Patisserie, Cafe

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines
					��st�_nda�� Cadd...					
9548	5915807	Huqqa	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.034640	41.055817	Italian, World Cuisine
9549	5916112	A���k Kahve	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.036019	41.057979	Restaurant Cafe
9550	5927402	Walter's Coffee Roastery	208	��stanbul	Cafea��a Mahallesi, Bademalt\ Sokak, No 21/B, ...	Moda	Moda, ��stanbul	29.026016	40.984776	Cafe

9551 rows × 21 columns

Step - 3. Basic Inspection on given dataset

- **Top 5 rows - using head**

In [66]:
```
restaurant_df.head()
```

Out[66]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Botswana Pula(P)
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Botswana Pula(P)
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian	...	Botswana Pula(P)
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japanese, Sushi	...	Botswana Pula(P)
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong	121.057508	14.584450	Japanese, Korean	...	Botswana Pula(P)

Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency
				Megamall, Ortigas...		City, Mandal...					

5 rows × 21 columns

- **bottom 5 rows using tail**

In [69]:
```
restaurant_df.tail()
```

Out[69]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...
9546	5915730	Naml\ Gurme	208	��stanbul	Kemanke�� Karamustafa Pa��a Mahallesi, R\ht\m ...	Karak�_y	Karak�_y, ��stanbul	28.977392	41.022793	Turkish	...
9547	5908749	Ceviz A��ac\	208	��stanbul	Ko��uyolu Mahallesi, Muhittin ��st�_nda�� Cadd...	Ko��uyolu	Ko��uyolu, ��stanbul	29.041297	41.009847	World Cuisine, Patisserie, Cafe	...
9548	5915807	Huqqa	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.034640	41.055817	Italian, World Cuisine	...
9549	5916112	A���k Kahve	208	��stanbul	Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...	Kuru�_e��me	Kuru�_e��me, ��stanbul	29.036019	41.057979	Restaurant Cafe	...
9550	5927402	Walter's Coffee Roastery	208	��stanbul	Cafea��a Mahallesi, Bademalt\ Sokak, No 21/B, ...	Moda	Moda, ��stanbul	29.026016	40.984776	Cafe	...

5 rows × 21 columns

- **Inspecting Column Names and Data Types**

In [72]:
```
restaurant_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9551 entries, 0 to 9550
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Restaurant ID         9551 non-null   int64  
 1   Restaurant Name       9551 non-null   object 
 2   Country Code          9551 non-null   int64  
 3   City                  9551 non-null   object 
 4   Address               9551 non-null   object 
 5   Locality              9551 non-null   object 
 6   Locality Verbose      9551 non-null   object 
 7   Longitude             9551 non-null   float64
 8   Latitude              9551 non-null   float64
 9   Cuisines              9542 non-null   object 
 10  Average Cost for two  9551 non-null   int64  
 11  Currency              9551 non-null   object 
 12  Has Table booking     9551 non-null   object 
 13  Has Online delivery   9551 non-null   object 
 14  Is delivering now     9551 non-null   object 
 15  Switch to order menu  9551 non-null   object 
 16  Price range           9551 non-null   int64  
 17  Aggregate rating      9551 non-null   float64
 18  Rating color          9551 non-null   object 
 19  Rating text           9551 non-null   object 
 20  Votes                 9551 non-null   int64  
dtypes: float64(3), int64(5), object(13)
memory usage: 1.5+ MB
```

- **Checking for Missing Values**

In [75]:
```
restaurant_df.isnull().sum()
```

Out[75]:
```
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
```

Handling Missing Values

In [78]:
```
import warnings
warnings.filterwarnings('ignore')
#For a categorical variable, determine the most frequent value, known as the mode.
cuisine_mode = restaurant_df['Cuisines'].mode()[0]
print(cuisine_mode)
# fill the missing value with mode
restaurant_df['Cuisines'].fillna(cuisine_mode,inplace=True)
# check for missing values - for confirmation
restaurant_df.isnull().sum()
```

```
North Indian
```

Out[78]:
```
Restaurant ID           0
Restaurant Name         0
Country Code            0
City                    0
Address                 0
Locality                0
Locality Verbose        0
Longitude               0
Latitude                0
Cuisines                0
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
```

- **Basic Statistical Summary**

In [81]:
```
restaurant_df.describe()
```

Out[81]:

	Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Aggregate rating	Votes
count	9.551000e+03	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000	9551.000000
mean	9.051128e+06	18.365616	64.126574	25.854381	1199.210763	1.804837	2.666370	156.909748
std	8.791521e+06	56.750546	41.467058	11.007935	16121.183073	0.905609	1.516378	430.169145
min	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0.000000	0.000000
25%	3.019625e+05	1.000000	77.081343	28.478713	250.000000	1.000000	2.500000	5.000000
50%	6.004089e+06	1.000000	77.191964	28.570469	400.000000	2.000000	3.200000	31.000000
75%	1.835229e+07	1.000000	77.282006	28.642758	700.000000	2.000000	3.700000	131.000000
max	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4.900000	10934.000000

- **Checking Unique Values**

In [84]:

```
restaurant_df.nunique()
```

Out[84]:
```
Restaurant ID           9551
Restaurant Name         7446
Country Code              15
City                     141
Address                 8918
Locality                1208
Locality Verbose        1265
Longitude               8120
Latitude                8677
Cuisines                1825
Average Cost for two     140
Currency                  12
Has Table booking          2
Has Online delivery        2
Is delivering now          2
Switch to order menu       1
Price range                4
Aggregate rating          33
Rating color               6
Rating text                6
Votes                   1012
dtype: int64
```

- **Checking Shape**

In [87]:
```
restaurant_df.shape
```

Out[87]:
```
(9551, 21)
```

In [89]:
```
restaurant_df.isnull().sum()
```

Out[89]:
```
Restaurant ID           0
Restaurant Name         0
Country Code            0
City                    0
Address                 0
Locality                0
Locality Verbose        0
Longitude               0
Latitude                0
Cuisines                0
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
```

Task 1: Restaurant Reviews

- **Analyze the text reviews to identify the most common positive and negative keywords.**

In [109…
```
rating_text = restaurant_df['Rating text'].value_counts().reset_index()
rating_text
```

Out[109...

	Rating text	count
0	Average	3737
1	Not rated	2148
2	Good	2100
3	Very Good	1079
4	Excellent	301
5	Poor	186

In [111...

```
sia = SentimentIntensityAnalyzer()
stop_words = set(stopwords.words('english'))
positive_review = []
negative_review = []
```

In [113...

```
rating_texts=restaurant_df['Rating text']
```

In [115...

```
for rating_text in rating_texts:
    tokens= word_tokenize(rating_text.lower())
    tokens=[token for token in tokens if token.isalpha() and token not in stop_words]

    sentiment_score=sia.polarity_scores(rating_text)['compound']

    if sentiment_score>=0.05:
        positive_review.extend(tokens)
    elif sentiment_score<0.05:
        negative_review.extend(tokens)
```

In [117...

```
positive_counts=Counter(positive_review)
negative_counts=Counter(negative_review)

num_top_keywords = 10

print('Top positive Review Keywords:')
for keyword, count in positive_counts.most_common(num_top_keywords):
    print(f"{keyword}:{count} times")
```

```
    print()
    print('Top Negative Review Keywords:')
for keyword, count in negative_counts.most_common(num_top_keywords):
    print(f"{keyword}:{count} times")
```

```
Top positive Review Keywords:
good:3179 times

Top Negative Review Keywords:
excellent:301 times

Top Negative Review Keywords:
average:3737 times
rated:2148 times
poor:186 times
```

Observation

- **Positive Keywords - good and excellent**
- **Negative Keywords - average, rated , poor**

- **Calculate the average length of reviews and explore if there is a relationship between review length and rating.**

In [122…

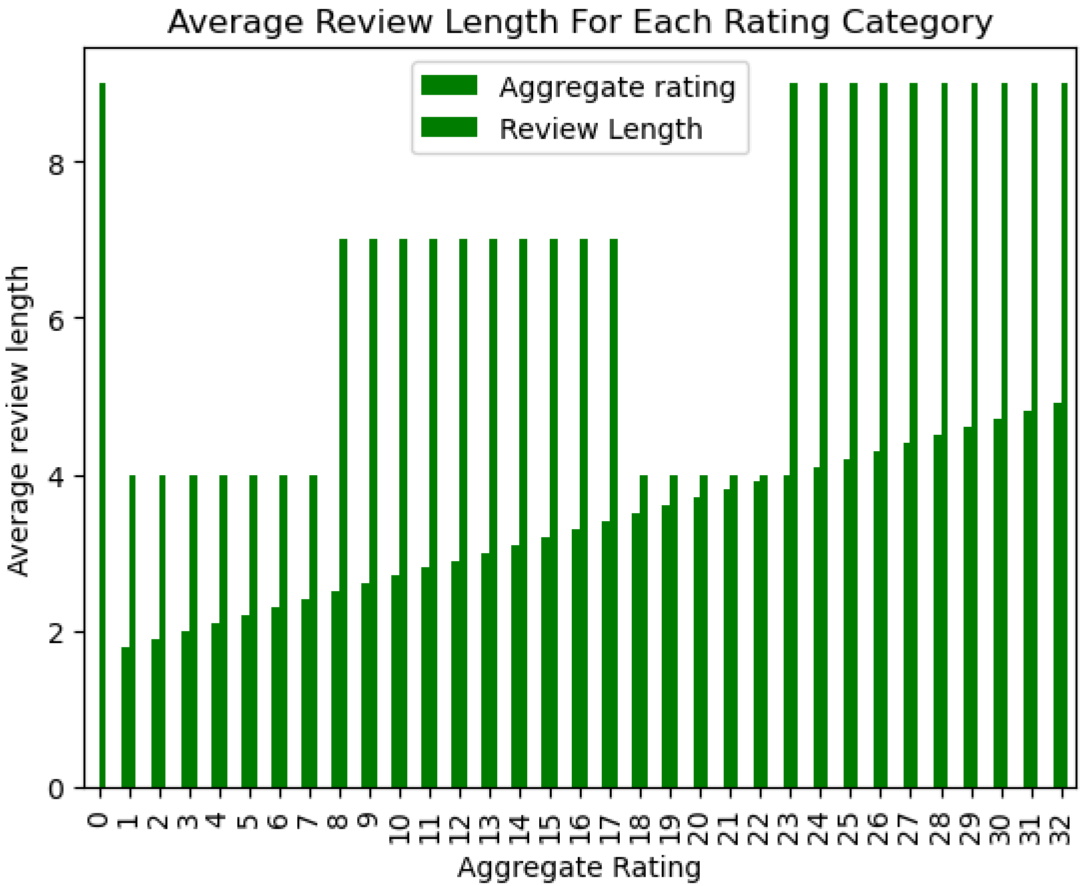
```
restaurant_df['Review Length']=restaurant_df['Rating text'].apply(lambda x: len(str(x)))
avg_rev_len=restaurant_df.groupby('Aggregate rating')['Review Length'].mean()
avg_rev_df = pd.DataFrame(avg_rev_len).reset_index()
```

In [124…

```
plt.figure(figsize=(10,15))
avg_rev_df.plot(kind='bar',color='green')

plt.title('Average Review Length For Each Rating Category')
plt.xlabel('Aggregate Rating')
plt.ylabel('Average review length')
plt.show()
```

```
<Figure size 1000x1500 with 0 Axes>
```



Observation

- Relation between Agg Rating vs Avg Review Text length
    1. Agg Rating 1.8 to 2.4 - Avg Review text length - 4
    2. Avg Rating 2.5 to 3.4 - Avg Review text length - 7
    3. Avg Rating 3.5 to 3.9 - Avg Review text length - 4
    4. Avg Rating 4.0 to 4.9 - Avg Review text length - 9

Task 2 : Votes Analysis

- **Identify the restaurants with the highest and lowest number of votes.**

In [129…

```
cols = ['Votes','Restaurant Name']
df_votes_restaurants=restaurant_df[cols]
print()
print('Restaurant with highest Votes:')
print(df_votes_restaurants.sort_values(by="Votes").tail(1))
print()
print('Restaurant with lowest Votes:')
print(df_votes_restaurants.sort_values(by="Votes").head(90))
```

```
Restaurant with highest Votes:
     Votes Restaurant Name
728  10934            Toit

Restaurant with lowest Votes:
      Votes              Restaurant Name
5799      0          Khalsa Eating Point
7411      0     Radha Swami Chaat Bhandar
7414      0    Ram Ram Ji Kachori Bhandar
7415      0           Rana's Food Corner
7416      0           Sanjay Chicken Shop
...     ...                          ...
1185      0                  Solty Hotel
1183      0                  OMG Tiffinz
1181      0        Narayan Fast Food Home
1178      0          Gopi Sweets & Caters
3621      0               Baweja's Haandi

[90 rows x 2 columns]
```

Observation

- Restaurant with highest Votes
    1. Toit with 10934 Votes

- Restaurant with lowest Votes
    1. Many Restaurants have 0 Votes

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

In [133…
```
cols = ['Votes','Aggregate rating']
df_corr_analysis = restaurant_df[cols]
df_corr_analysis
```

Out[133…

	Votes	Aggregate rating
0	314	4.8
1	591	4.5
2	270	4.4
3	365	4.9
4	229	4.8
...	...	...
9546	788	4.1
9547	1034	4.2
9548	661	3.7
9549	901	4.0
9550	591	4.0

9551 rows × 2 columns

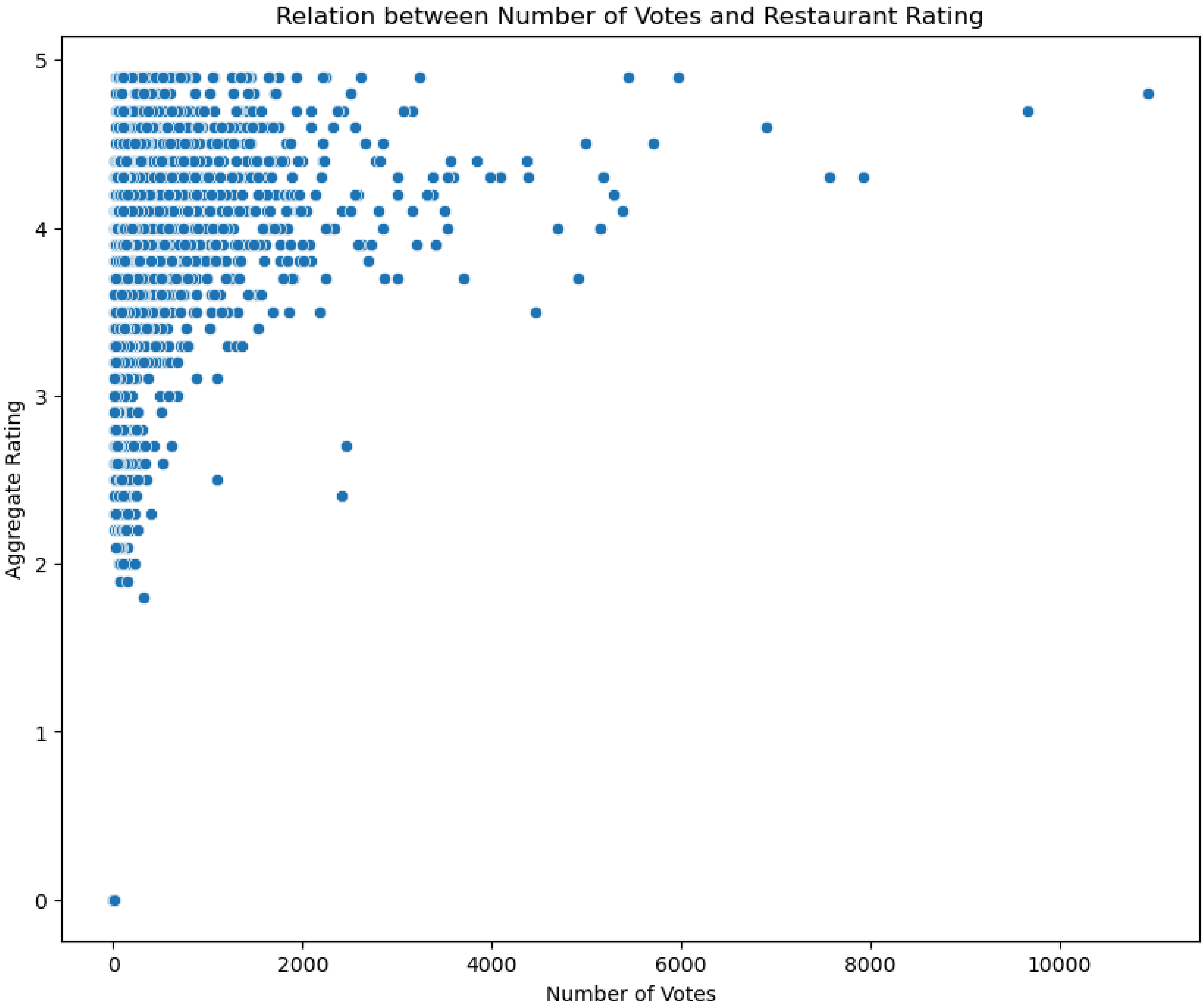
In [135…
```
corr=df_corr_analysis.corr()
corr
```

Out[135…

	Votes	Aggregate rating
Votes	1.000000	0.313691
Aggregate rating	0.313691	1.000000

In [137…

```
plt.figure(figsize=(10,8))
sns.scatterplot(x='Votes',y='Aggregate rating',data=df_corr_analysis)
plt.title('Relation between Number of Votes and Restaurant Rating')
plt.xlabel("Number of Votes")
plt.ylabel('Aggregate Rating')
plt.show()
```


Relation between Number of Votes and Restaurant Rating
Aggregate Rating
Number of Votes
0
1
2
3
4
5
0
2000
4000
6000
8000
10000

Observation

- **Correlation between the number of votes and the rating of a restaurant is 0.31**

Task 3 : Price Range vs. Online Delivery and Table Booking

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

In [142…

```
restaurant_df.head()
```

Out[142…

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Has Table booking
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century City Mall, Poblacion, Makati City, Mak...	121.027535	14.565443	French, Japanese, Desserts	...	Yes
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tokyo, Legaspi Village, Makati City, Ma...	121.014101	14.553708	Japanese	...	Yes
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...	121.056831	14.581404	Seafood, Asian, Filipino, Indian	...	Yes
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong City, Mandal...	121.056475	14.585318	Japanese, Sushi	...	No
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM	SM Megamall, Ortigas, Mandaluyong City	SM Megamall, Ortigas, Mandaluyong	121.057508	14.584450	Japanese, Korean	...	Yes

Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Has Table booking
				Megamall, Ortigas...		City, Mandal...					

5 rows × 22 columns

In [144...

```
cols = ['Price range','Has Online delivery','Has Table booking']
df_analysis=restaurant_df[cols].copy()
df_analysis['Has Online delivery']=df_analysis['Has Online delivery'].map({'Yes':True,'No':False})
df_analysis['Has Table booking']=df_analysis['Has Table booking'].map({'Yes':True,'No':False})
df_analysis
```

Out[144…

	Price range	Has Online delivery	Has Table booking
0	3	False	True
1	3	False	True
2	4	False	True
3	4	False	False
4	4	False	True
...	...	...	...
9546	3	False	False
9547	3	False	False
9548	4	False	False
9549	4	False	False
9550	2	False	False

9551 rows × 3 columns

In [146…

```
summary_table=pd.pivot_table(df_analysis,index='Price range',values=
['Has Online delivery','Has Table booking'],aggfunc=sum)
print('Summary Table:')
summary_table
```

```
Summary Table:
```

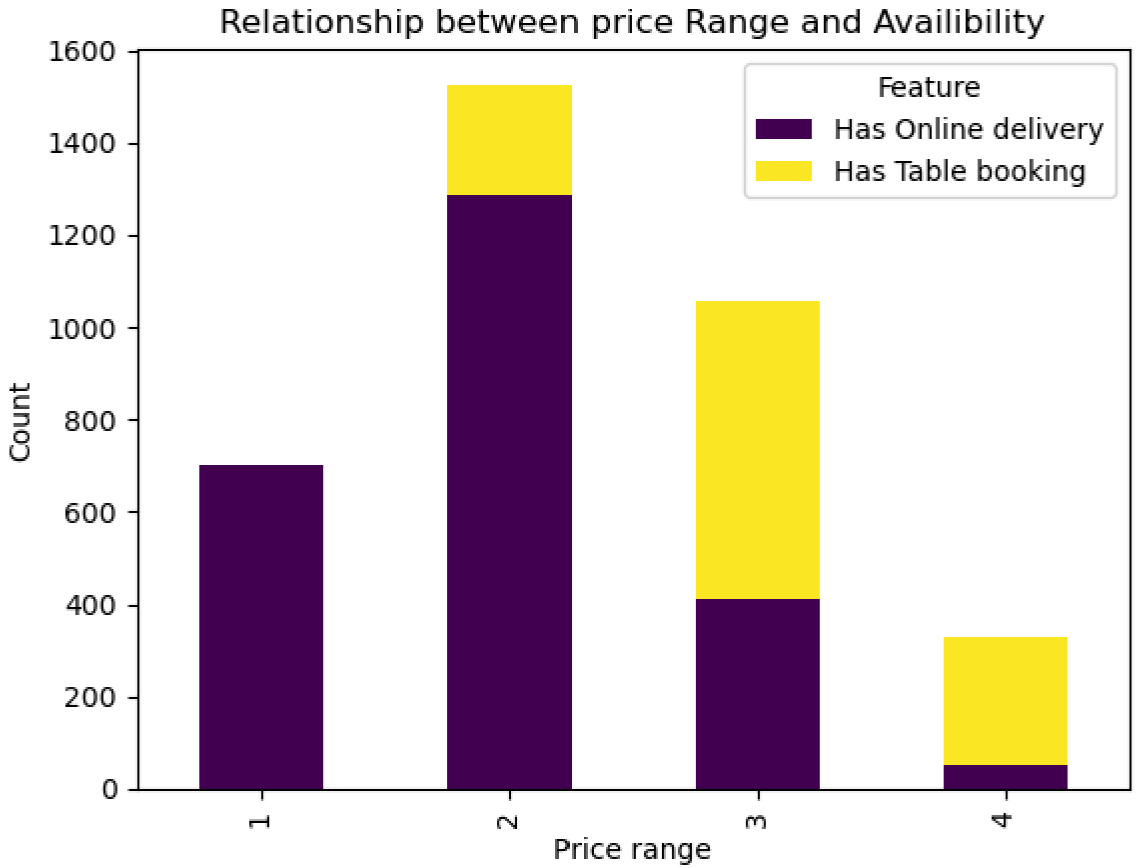
Out[146...

Price range	Has Online delivery	Has Table booking
1	701	1
2	1286	239
3	411	644
4	53	274

In [148...

```
plt.figure(figsize=(10,8))
summary_table.plot(kind='bar',stacked=True,colormap='viridis')
plt.title('Relationship between price Range and Availibility')
plt.xlabel('Price range')
plt.ylabel('Count')
plt.legend(title='Feature',loc='upper right')
plt.show()
```

```
<Figure size 1000x800 with 0 Axes>
```

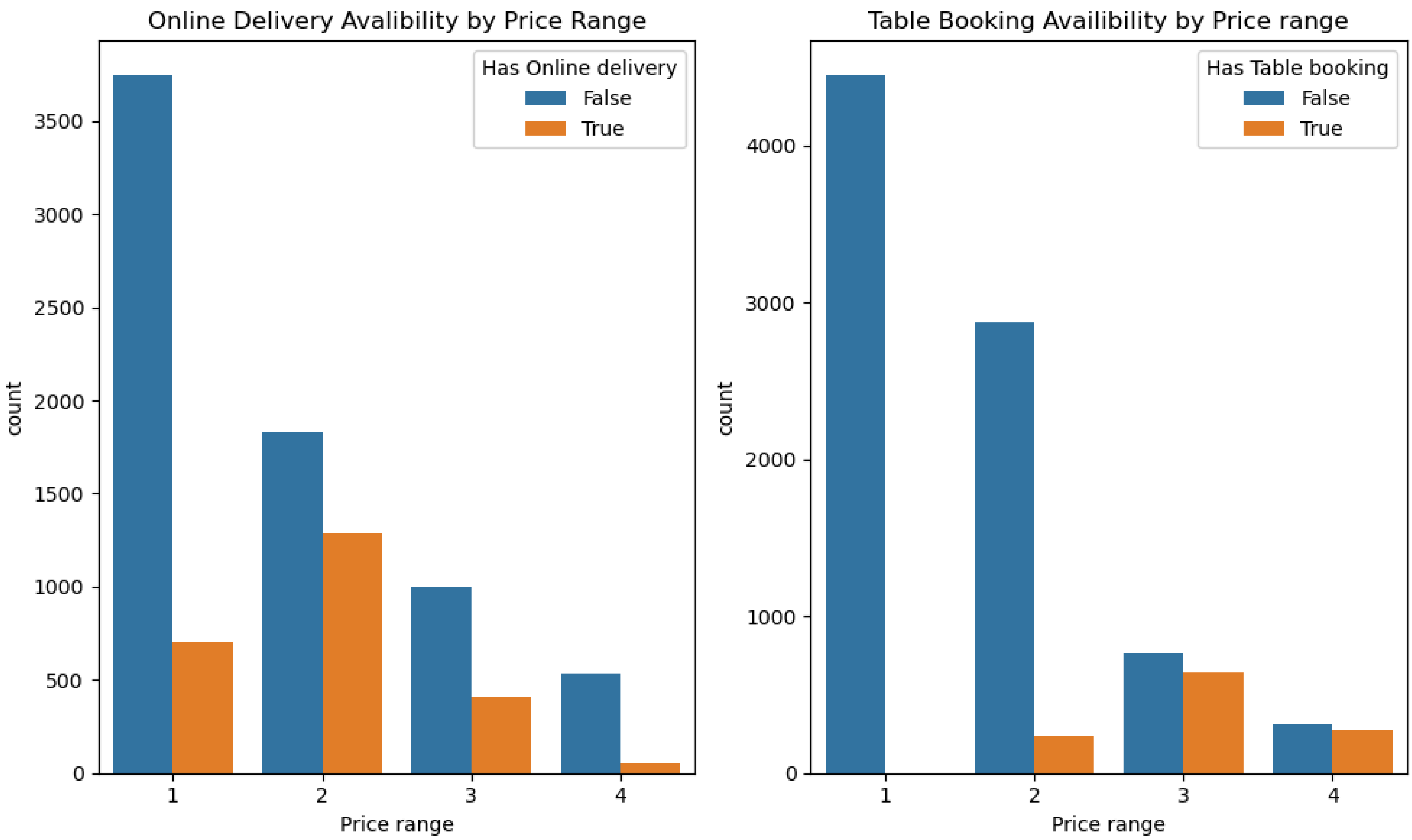


- **Determine if higher-priced restaurants are more likely to offer these services**

In [151…

```
plt.figure(figsize=(10,6))
plt.subplot(1,2,1)
sns.countplot(x='Price range' , hue='Has Online delivery' ,
data=df_analysis)
plt.title('Online Delivery Avalibility by Price Range')
plt.subplot(1,2,2)
sns.countplot(x='Price range', hue='Has Table booking',
data=df_analysis)
plt.title('Table Booking Availibility by Price range')
```

```
plt.tight_layout()
plt.show()
```



Observation

- **The statement "higher-priced restaurants are more likely to offer these services" is not valid**

In [ ]: