Cognifyz
Where data meets intelligence

DATA ANALYSIS

INTERNSHIP TASK

By: Karthikeyan R

RESTAURANT DATA ANALYSIS

This project aims to analyze a dataset containing restaurant information.The analysis focuses on various aspects,such as the distribution of ratings,the relationship between votes and ratings,the availability of online delivery and table booking across different price ranges and identifying common positive and negative keywords in text reviews.

Import Libraries

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("Dataset .csv")
df.head(2)
```

Out[2]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency	Has Table booking	Has Online delivery	de
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)	Yes	No	
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)	Yes	No	

2 rows × 21 columns

In [3]:
```
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
```

In [4]:
```python
# checking for missing values
df.isnull().sum()
```

Out[4]:
```
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 [5]:
```python
# Filling the null values with unknown
df['Cuisines'].fillna('unknown', inplace = True)
```

In [6]:
```python
df.shape
```

Out[6]:
```
(9551, 21)
```

In [7]:
```
#Statistics summary
df.describe()
```

Out[7]:

	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

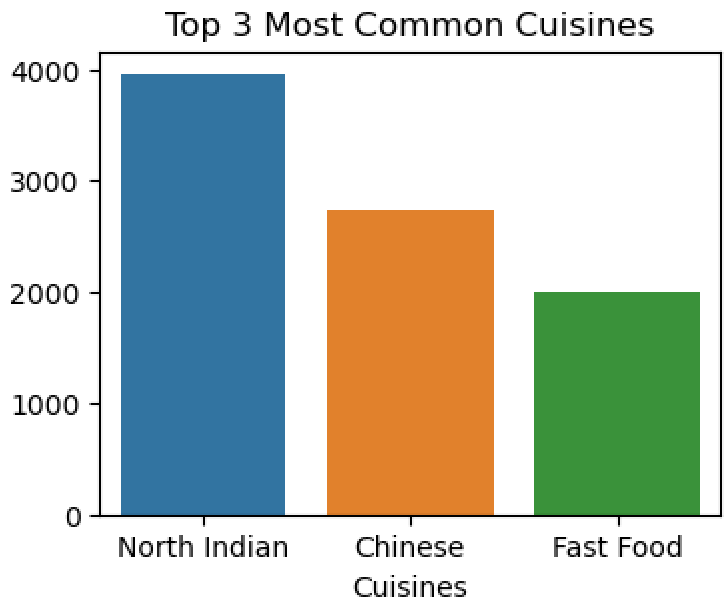
LEVEL 1 - Task 1 : Top Cuisines

Determine the top three most common cuisines in the dataset. Calculate the percentage of restaurants that serve each of the top cuisines

In [8]:
```
cuisines_counts = df['Cuisines'].str.split(', ').explode().value_counts()
Top_3_Cuisines = cuisines_counts.head(3)
Top_3_Cuisines
```

Out[8]:
```
Cuisines
North Indian    3960
Chinese         2735
Fast Food       1986
Name: count, dtype: int64
```

In [9]:
```
plt.figure(figsize = (4,3))
sns.barplot(x = Top_3_Cuisines.index , y = Top_3_Cuisines.values)
plt.title('Top 3 Most Common Cuisines')
plt.show()
```



Calculate the percentage of restaurants that serve each of the top cuisines

In [10]:
```
total_restaurants = len(df)
total_restaurants
```

Out[10]: 9551

In [11]:
```
percentage = (cuisines_counts/total_restaurants) * 100
percentage.head(5)
```

Out[11]:
```
Cuisines
North Indian    41.461627
Chinese         28.635745
Fast Food       20.793634
Mughlai         10.417757
Italian          7.999162
Name: count, dtype: float64
```

LEVEL 1 - Task 2 : City Analysis

Identify the city with the highest number of restaurants in the dataset

In [12]:
```
city = df.groupby('City')['Restaurant ID'].count().sort_values(ascending = False)
city.head(1)
```

Out[12]:
```
City
New Delhi    5473
Name: Restaurant ID, dtype: int64
```

Calculate the average rating for restaurants in each city

In [13]:
```
avg_ratings = df.groupby('City')['Aggregate rating'].mean()
avg_ratings
```

Out[13]:
```
City
Abu Dhabi          4.300000
Agra               3.965000
Ahmedabad          4.161905
Albany             3.555000
Allahabad          3.395000
                     ...
Weirton            3.900000
Wellington City    4.250000
Winchester Bay     3.200000
Yorkton            3.300000
��stanbul           4.292857
Name: Aggregate rating, Length: 141, dtype: float64
```

Determmine the city with the highest average rating

In [14]:
```
city_highest_avg_rating = avg_ratings.sort_values(ascending=False)

city_highest_avg_rating.index[0]

# or

#city_highest_avg_rating = avg_ratings.idxmax()
#city_highest_avg_rating
```

Out[14]:
```
'Inner City'
```

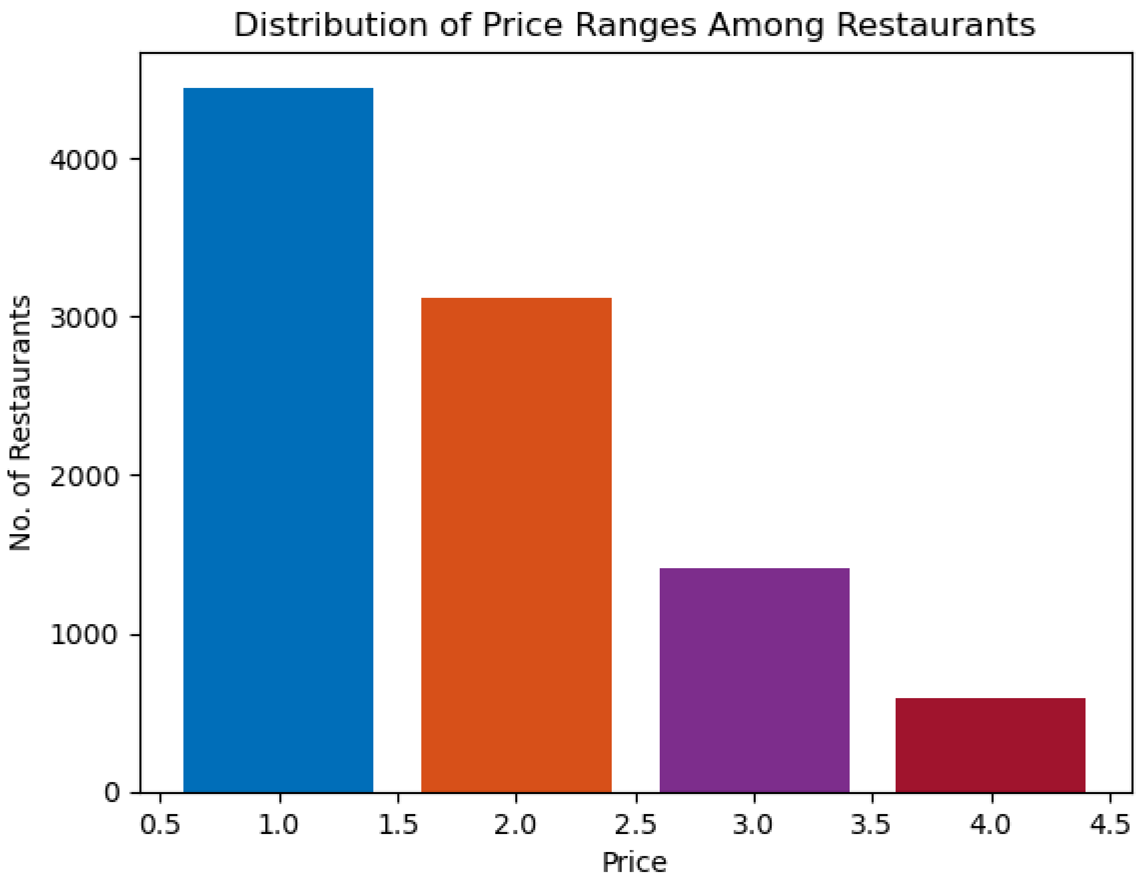
LEVEL 1 - Task 3 : Price Range Prediction

Create a histogram or bar chat to visualize the distribution of price ranges among the restaurants

In [15]:
```
price_range_counts = df['Price range'].value_counts()
price_range_counts
```

Out[15]:
```
Price range
1    4444
2    3113
3    1408
4     586
Name: count, dtype: int64
```

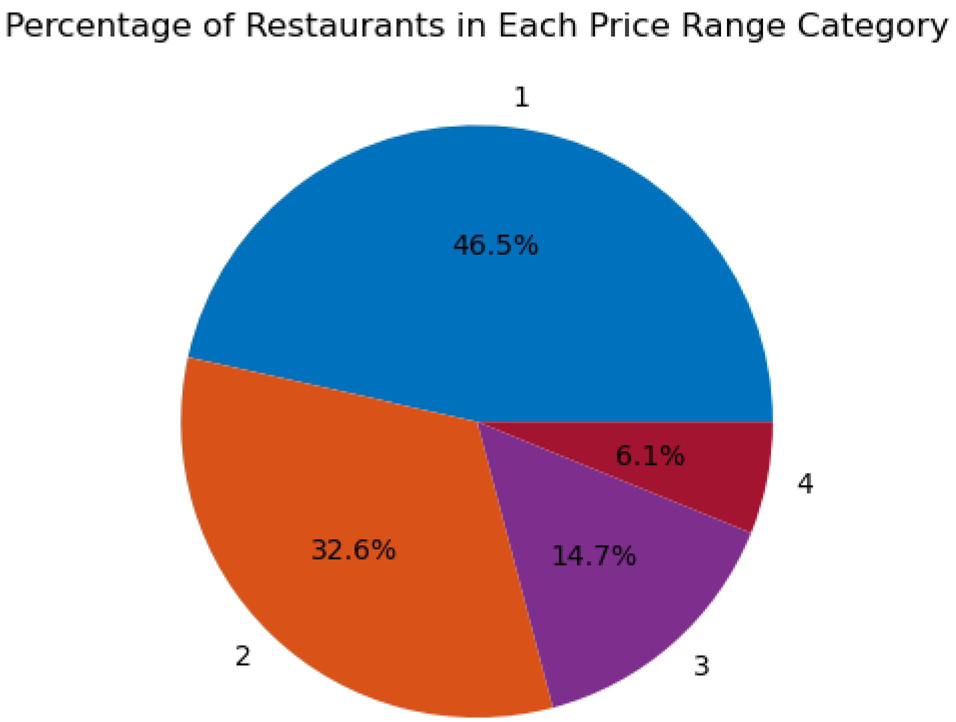
In [16]:
```
plt.figure.figsize = (5, 3)
colors = ['#0072BD','#D95319','#7E2F8E','#A2142F']
plt.bar(price_range_counts.index, price_range_counts.values, color = colors)
plt.xlabel('Price')
plt.ylabel('No. of Restaurants')
plt.title('Distribution of Price Ranges Among Restaurants')
plt.show()
```



Calculate the percentage of restaurants in each price range category

In [17]:
```
total_restaurants = len(df)
total_restaurants
```
Out[17]:
```
9551
```
In [18]:
```
pct_price_range = (price_range_counts/total_restaurants) * 100
pct_price_range
```
Out[18]:
```
Price range
1    46.529159
2    32.593446
3    14.741912
4     6.135483
Name: count, dtype: float64
```

In [19]:
```
plt.figure.figsize = (5, 3)
plt.pie(pct_price_range, labels=pct_price_range.index, autopct='%1.1f%%', colors=colors)
plt.title('Percentage of Restaurants in Each Price Range Category')
plt.show()
```



LEVEL 1 - Task 4 : Online Delivery

Determine the percentage of restaurants that offer online delivery

In [20]:
```python
online_delivery_percentage = (df['Has Online delivery'].map({'Yes': True, 'No': False}).astype(int).sum() / len(df)) *
online_delivery_percentage
```

Out[20]:
```
25.662234321013504
```

Compare the average ratings of restaurants with and without online delivery

In [21]:
```python
avg_rating_with_delivery    = df[df['Has Online delivery'] == 'Yes']['Aggregate rating'].mean()
avg_rating_without_delivery = df[df['Has Online delivery'] == 'No']['Aggregate rating'].mean()

print("Average rating with delivery:", avg_rating_with_delivery)
print("Average rating without delivery:", avg_rating_without_delivery)
```

```
Average rating with delivery: 3.2488372093023257
Average rating without delivery: 2.465295774647887
```

Level 1 - Conclusion

$Task - 1:$

1. North Indian, Chinese and Fast Food are the Top Three Cuisines
2. The Percentage of Top Cuisines serve by the Restaurants are North Indian 41.461627,Chinese 28.635745,Fast Food 20.793634,Mughlai 10.417757 and Italian 7.999162

$Task - 2:$

1. The City of New Delhi has the highest number of Restaurants
2. Compare to all the cities of restaurant the Inner City has the highest average rating

$Task - 3:$

1. The majority of restaurants fall in the lowest price range (1) with 4,444 establishments, while the number decreases significantly as the price range increases, with only 586 in the highest range (4). This trend highlights a strong preference for affordable dining options.
2. Nearly half of the restaurants fall into the lowest price range (1) with 46.53%, while only 6.14% occupy the highest range (4), indicating a strong market preference for more affordable dining options.

$Task - 4:$

1. Only 25.66% of restaurants offer online delivery, suggesting that while the option is available, the majority of establishments still rely on traditional dining or takeaway services.
2. Restaurants offering online delivery have a higher average rating of 3.25 compared to 2.47 for those without, indicating that online delivery may be associated with better customer satisfaction.

LEVEL 2 - Task 1 : Restaurant Ratings

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

In [22]:
```
Avg_rating_common_range = df['Aggregate rating'].value_counts()
print(Avg_rating_common_range)
```

```
Aggregate rating
0.0    2148
3.2     522
3.1     519
3.4     498
3.3     483
3.5     480
3.0     468
3.6     458
3.7     427
3.8     400
2.9     381
3.9     335
2.8     315
4.1     274
4.0     266
2.7     250
4.2     221
2.6     191
4.3     174
4.4     144
2.5     110
4.5      95
2.4      87
4.6      78
4.9      61
2.3      47
4.7      42
2.2      27
4.8      25
2.1      15
2.0       7
1.9       2
1.8       1
Name: count, dtype: int64
```

Calculate the average number of votes received by restaurants

In [23]:
```
average_votes = df['Votes'].mean()
print("Average number of votes:", average_votes)
```

```
Average number of votes: 156.909747670401
```

LEVEL 2 - Task 2 : Cuisine Combination

Identify the most common combinations of cuisines in the dataset

In [24]:
```
most_common_cuisine_comb = df['Cuisines'].value_counts()
most_common_cuisine_comb.head(5)
```

Out[24]:
```
Cuisines
North Indian             936
North Indian, Chinese    511
Chinese                  354
Fast Food                354
North Indian, Mughlai    334
Name: count, dtype: int64
```

Determine if certain cuisine combinations tend to have higher ratings

In [25]:
```
cuisine_higher_ratings = df.groupby('Cuisines')['Aggregate rating'].count().sort_values(ascending = False)
cuisine_higher_ratings.head(5)
```

Out[25]:
```
Cuisines
North Indian             936
North Indian, Chinese    511
Fast Food                354
Chinese                  354
North Indian, Mughlai    334
Name: Aggregate rating, dtype: int64
```

LEVEL 2 - Task 3 : Geographic Analysis

Here there is need of map visualisation. so we cant analyse the question related to this task in python

LEVEL 2 - Task 4 : Restaurant Chains

Identify if there are any restaurant chains present in the dataset

In [26]:
```
restaurant = df['Restaurant Name'].value_counts()
restaurant_chains = restaurant[restaurant > 1]
restaurant_chains
```

Out[26]:
```
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
```

Analyze the ratings and popularity of different restaurant chains

In [27]:
```
## Filter the dataset to include only restaurant chains
chains_data = df[df['Restaurant Name'].isin(restaurant_chains.index)]

## Group by 'Restaurant Name' and calculate average rating and total votes
chains_stats = chains_data.groupby('Restaurant Name').agg({'Aggregate rating': 'mean', 'Votes': 'sum'}).reset_index()

## Sort by average rating and total votes for analysis
chains_stats = chains_stats.sort_values(by=['Aggregate rating', 'Votes'], ascending=[False, False])

## Display the top restaurant chains by rating and popularity
print(chains_stats.head(10))
```

```
                Restaurant Name  Aggregate rating  Votes
629             Talaga Sampireun             4.900   5514
8       AB's Absolute Barbecues             4.850   3151
589            Silantro Fil-Mex             4.850   1364
7     AB's - Absolute Barbecues             4.825  13400
449          Naturals Ice Cream             4.800   3094
293                    Gymkhana             4.700    328
653       The Cheesecake Factory             4.650   3010
218                     Dishoom             4.600   1269
267           Garota de Ipanema             4.600     59
163                     Chili's             4.580   8156
```

Level 2 - Conclusion

$Task - 1:$

1. The most common rating is 0.0, likely indicating unrated restaurants, followed by a concentration in the 3.0 to 3.9 range, suggesting moderate customer satisfaction. Higher ratings above 4.0 are less frequent, indicating fewer standout establishments.
2. On average, restaurants receive approximately 157 votes.

$Task - 2:$

1. The most common cuisines are North Indian, followed by North Indian and Chinese. Fast Food and Chinese cuisines are also popular, each with a significant number of listings.
2. North Indian cuisine and its combinations tend to have higher ratings, with North Indian alone leading, followed by North Indian and Chinese.

$Task - 4:$

1. the dataset includes several restaurant chains, with Cafe Coffee Day, Domino's Pizza, Subway, and McDonald's among the most frequently listed.
2. Restaurant chains like AB's - Absolute Barbecues and Talaga Sampireun have high ratings and significant popularity, with AB's leading in votes and ratings.

LEVEL 3 - Task 1 : Restaurant Reviews

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

In [28]:
```
df['Rating text'].value_counts()
```

Out[28]:
```
Rating text
Average      3737
Not rated    2148
Good         2100
Very Good    1079
Excellent     301
Poor          186
Name: count, dtype: int64
```

In [29]:
```python
from collections import Counter
import re

#Extract and clean the 'Rating text' column
reviews = df['Rating text'].dropna().tolist()

#Define a function to tokenize and clean text
def tokenize(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(r'[^a-z\s]', '', text)  # Remove non-alphabetic characters
    tokens = text.split()  # Split into words
    return tokens

# Tokenize all reviews
all_tokens = []
for review in reviews:
    all_tokens.extend(tokenize(review))

# Step 4: Count the frequency of each token
token_counts = Counter(all_tokens)

# Display the most common tokens
print("Most common tokens:", token_counts.most_common(20))

# Step 5: Define a list of words to ignore
ignore_words = {'rated', 'very'}

# Filter out ignored words
filtered_counts = {word: count for word, count in token_counts.items() if word not in ignore_words}

# Step 6: Separate positive and negative keywords
positive_keywords = {'good', 'excellent'}
negative_keywords = {'poor', 'not'}

# Get the frequency of positive and negative keywords
positive_counts = {word: filtered_counts[word] for word in positive_keywords if word in filtered_counts}
negative_counts = {word: filtered_counts[word] for word in negative_keywords if word in filtered_counts}

# Display the counts of positive and negative keywords
print("Positive Keywords:", positive_counts)
print("Negative Keywords:", negative_counts)
```

```
Most common tokens: [('average', 3737), ('good', 3179), ('not', 2148), ('rated', 2148), ('very', 1079), ('excellen
t', 301), ('poor', 186)]
Positive Keywords: {'good': 3179, 'excellent': 301}
Negative Keywords: {'poor': 186, 'not': 2148}
```

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

In [30]:
```python
df['review_length'] = df['Rating text'].dropna().str.len()  # Add a column for review length
avg_len_review = df['review_length'].mean()
print(f"Average length of reviews: {avg_len_review:.2f} characters")
```

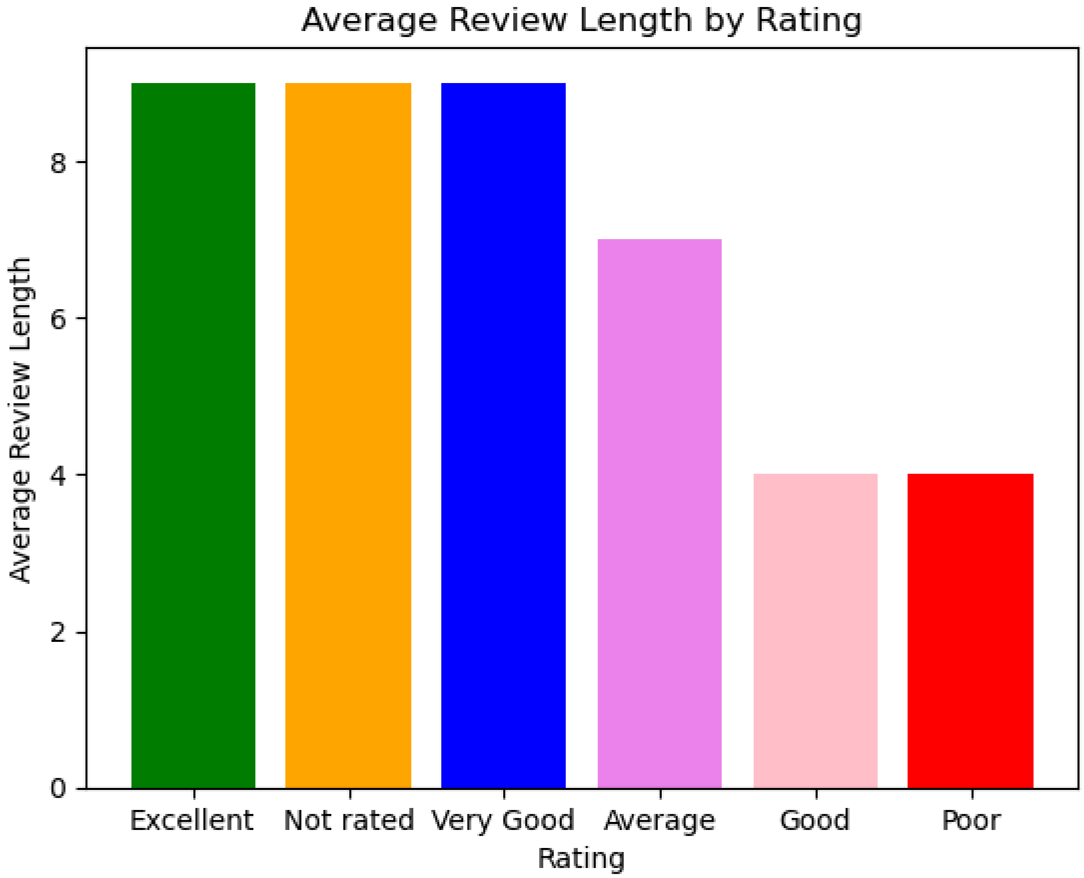
```
Average length of reviews: 7.02 characters
```

In [31]:
```python
rating_length_mean = df.groupby('Rating text')['review_length'].mean().sort_values(ascending = False).reset_index()
rating_length_mean
```

Out[31]:

	Rating text	review_length
0	Excellent	9.0
1	Not rated	9.0
2	Very Good	9.0
3	Average	7.0
4	Good	4.0
5	Poor	4.0

In [32]:
```
plt.figure.figsize=(5,3)
colors = ['green', 'orange', 'blue', 'violet','pink','red']
plt.bar(rating_length_mean['Rating text'], rating_length_mean['review_length'], color = colors)
plt.xlabel('Rating')
plt.ylabel('Average Review Length')
plt.title('Average Review Length by Rating')
plt.show()
```



LEVEL 3 - Task 2 : Vote Analysis

Identify the restaurants with the highest and lowest number of votes

In [33]:
```
highest_votes = df.groupby('Restaurant Name')['Votes'].max().sort_values(ascending = False).reset_index().nlargest(1,'
lowest_votes = df.groupby('Restaurant Name')['Votes'].min().sort_values(ascending = True).reset_index().nsmallest(1,'V
print('\nRestaurants with the highest number of votes :')
print(highest_votes)

print('\n----------------')

print('\nRestaurants with the lowest number of votes :')
print(lowest_votes)
```

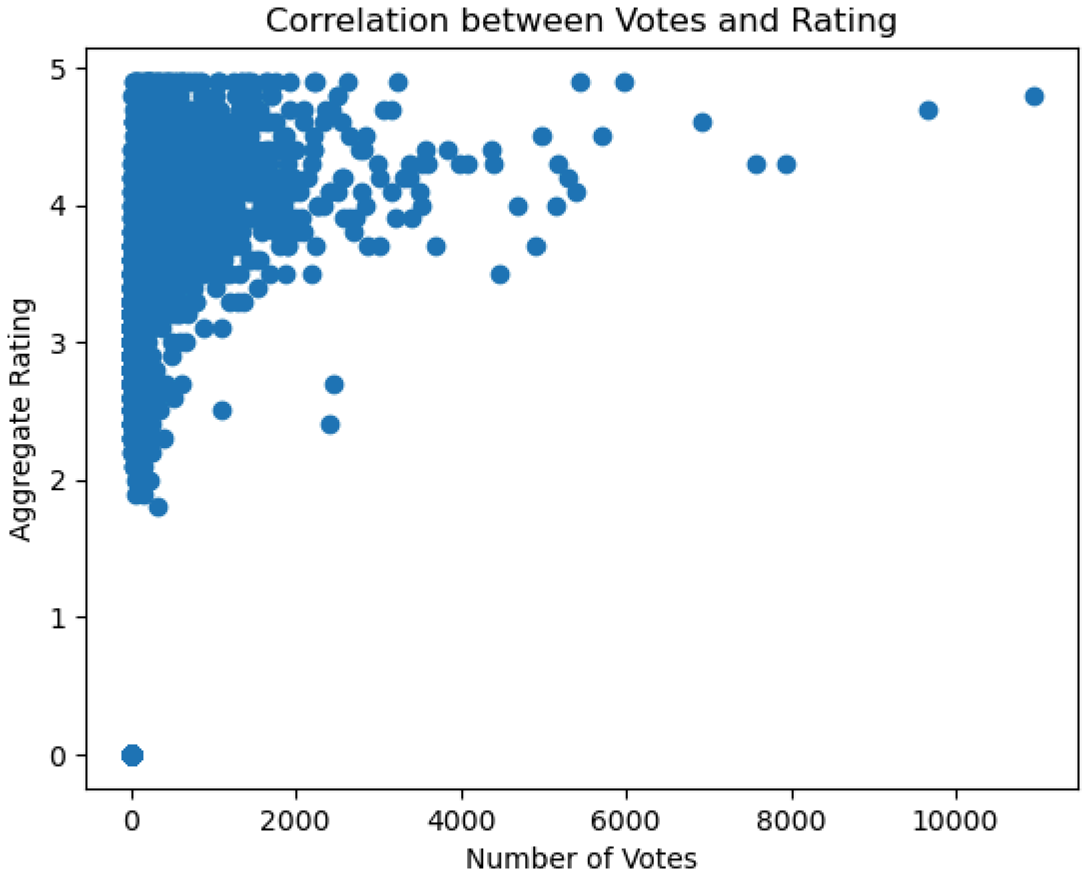
```
Restaurants with the highest number of votes :
  Restaurant Name  Votes
0            Toit  10934

----------------

Restaurants with the lowest number of votes :
     Restaurant Name  Votes
0  Laxmi Food Corner      0
```

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

In [34]:
```
correlation = df['Votes'].corr(df['Aggregate rating'])
print("Correlation between votes and rating:", correlation)
```

```
Correlation between votes and rating: 0.31369058419541035
```

In [35]:
```
plt.scatter(df['Votes'], df['Aggregate rating'])
plt.xlabel('Number of Votes')
plt.ylabel('Aggregate Rating')
plt.title('Correlation between Votes and Rating')
plt.show()
```



LEVEL 3 - Task 3 : Price Range vs Online Delivery & Table Booking

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

In [36]:
```
# checking the unique values in these columns
print(df['Price range'].unique())
print(df['Has Online delivery'].unique())
print(df['Has Table booking'].unique())
```

```
[3 4 2 1]
['No' 'Yes']
['Yes' 'No']
```

In [37]:
```
# replacing string into number because we can't group a string
df['Has Online delivery'] = df['Has Online delivery'].map({'Yes': 1, 'No': 0})
df['Has Table booking'] = df['Has Table booking'].map({'Yes': 1, 'No': 0})
```

In [38]:
```
print(df['Price range'].unique())
print(df['Has Online delivery'].unique())
print(df['Has Table booking'].unique())
```

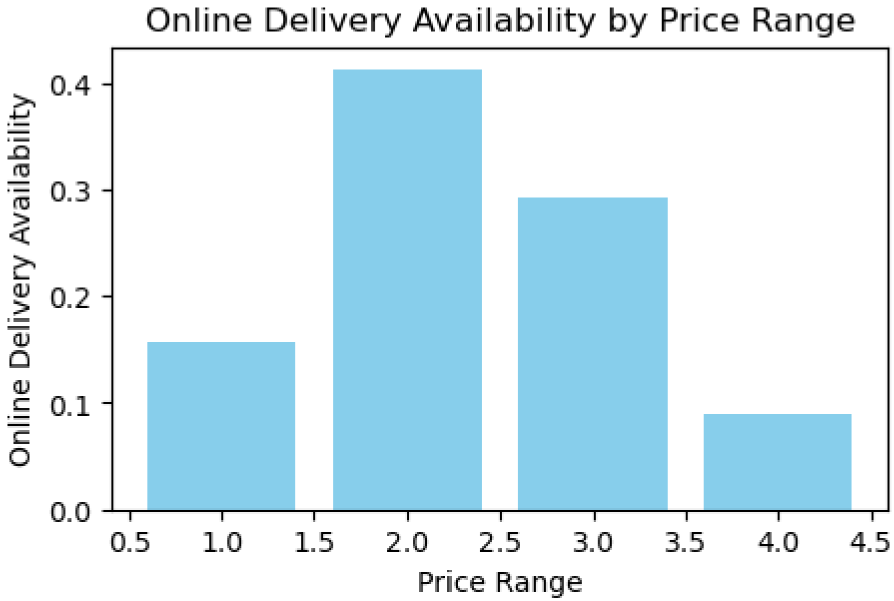
```
[3 4 2 1]
[0 1]
[1 0]
```

In [39]:
```
relationship = df.groupby('Price range')[['Has Online delivery', 'Has Table booking']].mean()
relationship
```

Out[39]:

Price range	Has Online delivery	Has Table booking
1	0.157741	0.000225
2	0.413106	0.076775
3	0.291903	0.457386
4	0.090444	0.467577

In [40]:
```
plt.figure(figsize=(5, 3))
plt.bar(relationship.index, relationship['Has Online delivery'], color='skyblue')
plt.xlabel('Price Range')
plt.ylabel('Online Delivery Availability')
plt.title('Online Delivery Availability by Price Range')
plt.show()
```



In [41]:
```
plt.figure(figsize=(5, 3))
plt.bar(relationship.index, relationship['Has Table booking'], color='violet')
plt.xlabel('Price Range')
plt.ylabel('Table Booking Availability')
plt.title('Table Booking Availability by Price Range')
plt.show()
```

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

In [42]:
```
high_oda = df[df['Price range'] == 4 ]
offer_delivery = high_oda.groupby('Has Online delivery')['Price range'].count()
offer_delivery
```

Out[42]:
```
Has Online delivery
0    533
1     53
Name: Price range, dtype: int64
```

In [43]:
```
high_tba = df[df['Price range'] == 4 ]
offer_booking= high_tba.groupby('Has Table booking')['Price range'].count()
offer_booking
```

Out[43]:
```
Has Table booking
0    312
1    274
Name: Price range, dtype: int64
```

By the Conclusion we know the High Priced Restaurants are mostly offering the Table Bookiing services rather than Online Delivery

Level 3 - Conclusion

$Task - 1:$

1. Common positive keywords in reviews are 'good' and 'excellent,' while 'not' and 'poor' are the most frequent negative keywords.
2. Review length varies by rating, with 'Excellent' and 'Very Good' reviews typically being longer, while 'Good' and 'Poor' reviews tend to be shorter

$Task - 2:$

1. Toit has the highest number of votes with 10,934, while Laxmi Food Corner has the lowest with zero votes.
2. There is a moderate positive correlation of 0.31 between the number of votes and restaurant ratings, suggesting that higher-rated restaurants tend to receive more votes.

$Task - 3:$

1. Price range 2 shows a strong correlation with online delivery (0.41) and a moderate correlation with table booking (0.08), while higher price ranges (3 and 4) are more strongly associated with table booking (0.46) rather than online delivery.
2. The High Priced Restaurants are mostly offering the Table Bookiing services rather than Online Delivery

Final Conclusion

1. City: New Delhi has the highest number of restaurants, with a total of 5,473, followed by Gurgaon with 1118 restarunts. The Ojo Caliente city has the lowest, with just 1 restaurant."
2. Restaurant: To leads with the highest number of votes, accumulating a votes, followed by AB's - Absolute Barbecues 16551 votes, followed by Talaga Sampireun 5514 votes. The resturants with the lowest number of votes a Talaga Sampireun with 5514 votes.
3. Cuisines: North Indian cuisine and its combinations tend to have higher ratings, with North Indian alone leading, followed by North Indian and Chinese. The Least common cuisine combinations, such as French and Japanese or Ice Cream and North Indian, tend to have lower ratings.

In [ ]:

```

```