

```
In [43]: #import necessary library
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```
In [44]: #load and read dataset
df=pd.read_csv('Dataset.csv')
df
```

Out[44]:

	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	Naml\u0027 Gurme	208	\u2615\u2615istanbul	Kemanke\u2615\u2615 Karamustafa Pa\u2615\u2615a Mahallesi, R\u0027ht\u0027m ...	Karak\u2615_y	Karak\u2615_y, \u2615\u2615istanbul	28.977392	41.022793	Turkish
9547	5908749	A\u2615\u2615ac\u0027 Ceviz	208	\u2615\u2615istanbul	Ko\u2615\u2615uyulu Mahallesi, Muhittin \u2615\u2615st\u2615\u2615nda\u2615\u2615 Cadd...	Ko\u2615\u2615uyulu	Ko\u2615\u2615uyulu, \u2615\u2615istanbul	29.041297	41.009847	World Cuisine, Patisserie, Cafe
9548	5915807	Huqqa	208	\u2615\u2615istanbul	Kuru\u2615_e\u2615\u2615me Mahallesi, Muallim Naci Caddesi, N...	Kuru\u2615_e\u2615\u2615me	Kuru\u2615_e\u2615\u2615me, \u2615\u2615istanbul	29.034640	41.055817	Italian, World Cuisine
9549	5916112	A\u2615\u2615\u2615k Kahve	208	\u2615\u2615istanbul	Kuru\u2615_e\u2615\u2615me Mahallesi, Muallim Naci Caddesi, N...	Kuru\u2615_e\u2615\u2615me	Kuru\u2615_e\u2615\u2615me, \u2615\u2615istanbul	29.036019	41.057979	Restaurant Cafe
9550	5927402	Walter's Coffee Roastery	208	\u2615\u2615istanbul	Cafea\u2615\u2615a Mahallesi, Bademalt\u0027 Sokak, No 21/B, ...	Moda	\u2615\u2615istanbul Moda	29.026016	40.984776	Cafe

9551 rows \u00d7 21 columns

```
In [45]: #Check no of rows and column
print("Number of rows =",df.shape[0])
print("Number of column =",df.shape[1])

Number of rows = 9551
Number of column = 21

In [46]: #Checking infomation of all data
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 [47]: #Check null value present in our datasets
df.isnull().sum()

```

```

Out[47]: 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 [48]: #Drop null value in our datasets
df.dropna(inplace=True)

```

```

In [49]: #Again check null value present in our datasets
pd.isnull(df).sum()

```

```

Out[49]: 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

```

```

In [50]: #descriptive stat
df.describe()

```

Out[50]:	Restaurant ID	Country Code	Longitude	Latitude	Average Cost for two	Price range	Aggregate rating	Votes
<b>count</b>	9.542000e+03	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000	9542.000000
<b>mean</b>	9.043301e+06	18.179208	64.274997	25.848532	1200.326137	1.804968	2.665238	156.772060
<b>std</b>	8.791967e+06	56.451600	41.197602	11.010094	16128.743876	0.905563	1.516588	430.203324
<b>min</b>	5.300000e+01	1.000000	-157.948486	-41.330428	0.000000	1.000000	0.000000	0.000000
<b>25%</b>	3.019312e+05	1.000000	77.081565	28.478658	250.000000	1.000000	2.500000	5.000000
<b>50%</b>	6.002726e+06	1.000000	77.192031	28.570444	400.000000	2.000000	3.200000	31.000000
<b>75%</b>	1.835260e+07	1.000000	77.282043	28.642711	700.000000	2.000000	3.700000	130.000000
<b>max</b>	1.850065e+07	216.000000	174.832089	55.976980	800000.000000	4.000000	4.900000	10934.000000

```
In [51]: #Number of unique value in our datasets
df.nunique()
```

```
Out[51]: Restaurant ID      9542
Restaurant Name      7437
Country Code         15
City                 140
Address              8910
Locality             1206
Locality Verbose     1263
Longitude            8111
Latitude             8668
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
```

```
In [52]: #check duplicate value of sum in our datasets
print(df.duplicated().sum())

0
```

```
In [53]: df.columns
```

```
Out[53]: Index(['Restaurant ID', 'Restaurant Name', 'Country Code', 'City', 'Address',
              'Locality', 'Locality Verbose', 'Longitude', 'Latitude', 'Cuisines',
              'Average Cost for two', 'Currency', 'Has Table booking',
              'Has Online delivery', 'Is delivering now', 'Switch to order menu',
              'Price range', 'Aggregate rating', 'Rating color', 'Rating text',
              'Votes'],
              dtype='object')
```

## Identify Categorical & Numerical feature present in our datasets.

```
In [54]: #These are our categorical feature
[feature for feature in df.columns if df[feature].dtype=='O']
```

```
Out[54]: ['Restaurant Name',
          'City',
          'Address',
          'Locality',
          'Locality Verbose',
          'Cuisines',
          'Currency',
          'Has Table booking',
          'Has Online delivery',
          'Is delivering now',
          'Switch to order menu',
          'Rating color',
          'Rating text']
```

```
In [55]: #These are our Numerical feature
[feature for feature in df.columns if df[feature].dtype!='O']
```

```
Out[55]: ['Restaurant ID',
          'Country Code',
          'Longitude',
          'Latitude',
          'Average Cost for two',
          'Price range',
          'Aggregate rating',
          'Votes']
```

# Level 1

## Task 1



### Task: Top Cuisines

Determine the top three most common cuisines in the dataset.

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

### Task: Top Cuisines

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

### Task

1. Determine the top three most common cuisines in the dataset

```
In [56]: df_cuisines=df['Cuisines'].str.split(', ').explode().value_counts()
```

```
In [57]: top_cuisin=df_cuisines.head(3)
top_cuisin
```

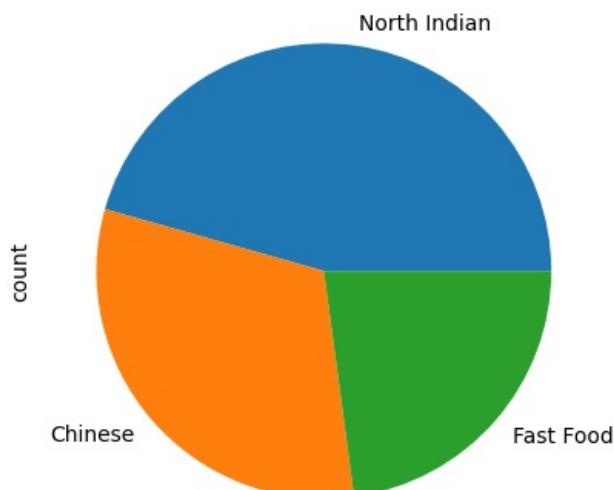
```
Out[57]: Cuisines
North Indian    3960
Chinese         2735
Fast Food       1986
Name: count, dtype: int64
```

### Insights:-

Dominant Cuisines: North Indian cuisine is the most popular in the dataset, followed by Chinese and Fast Food.

```
In [58]: #visualize by using pie chart
top_cuisin.plot(kind='pie')
```

```
Out[58]: <Axes: ylabel='count'>
```



# Task

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

```
In [59]: total_restaurant = len(df)
total_percentage=(top_cuisin/total_restaurant)*100
total_percentage
```

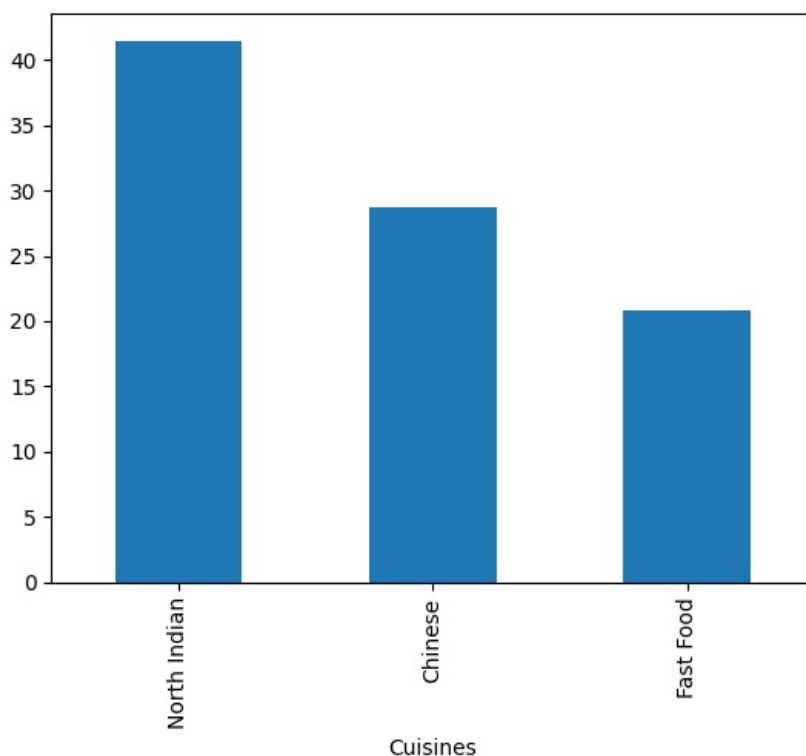
```
Out[59]: Cuisines
North Indian    41.500734
Chinese         28.662754
Fast Food       20.813247
Name: count, dtype: float64
```

## Insights:-

1. Dominance of North Indian Cuisine is a significant portion (41.46%) of restaurants offer North Indian cuisine, indicating its popularity.
2. Chinese and Fast Food cuisines are also widely available, but with lower percentages compared to North Indian.

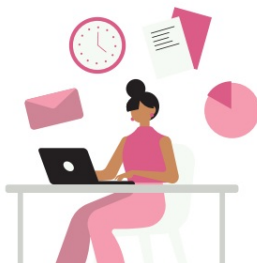
```
In [60]: total_percentage.plot(kind='bar')
```

```
Out[60]: <Axes: xlabel='Cuisines'>
```



## Level 1

### Task 2



#### Task: City Analysis

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

Calculate the average rating for restaurants in each city.

Determine the city with the highest average rating.



# Task

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

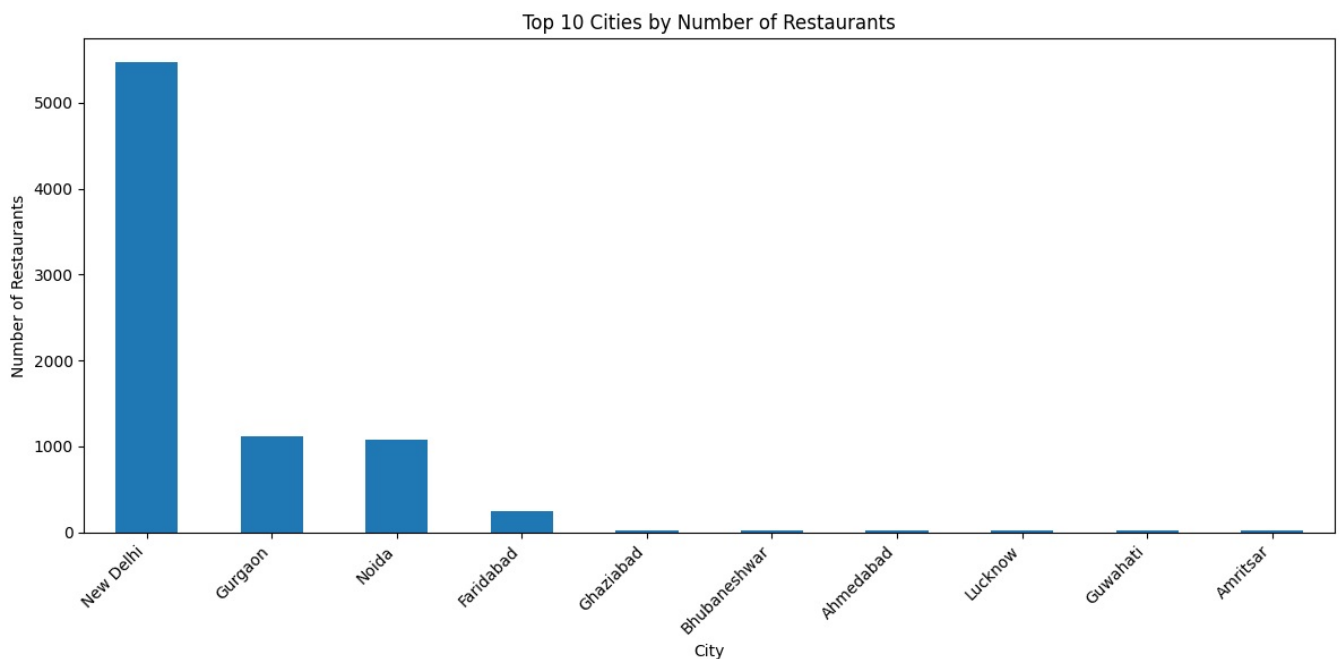
```
In [61]: #count the number of restaurant percity
city_counts = df['City'].value_counts()
city_counts
```

```
Out[61]: City
New Delhi    5473
Gurgaon      1118
Noida        1080
Faridabad    251
Ghaziabad    25
...
Inverloch    1
Mohali        1
Panchkula    1
Bandung       1
Randburg     1
Name: count, Length: 140, dtype: int64
```

```
In [62]: top_city = city_counts.idxmax()
top_city_count = city_counts.max()
print(f"1. The city with the highest number of restaurants is {top_city} with {top_city_count} restaurants.")
```

1. The city with the highest number of restaurants is New Delhi with 5473 restaurants.

```
In [63]: # Visualize the top 10 cities by number of restaurants
plt.figure(figsize=(12, 6))
city_counts.head(10).plot(kind='bar')
plt.title('Top 10 Cities by Number of Restaurants')
plt.xlabel('City')
plt.ylabel('Number of Restaurants')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```



## Insights:-

1. New Delhi has a significantly higher number of restaurants compared to other cities in the dataset.
2. There's a considerable difference between New Delhi and the other cities in terms of restaurant count.

# Task

1. Calculate the average rating for restaurants in each city.

```
In [64]: avg_city_rating=df.groupby('City')['Aggregate rating'].mean().sort_values(ascending=False)
avg_city_rating
```

```
Out[64]: City
Inner City      4.900000
Quezon City     4.800000
Makati City     4.650000
Pasig City      4.633333
Mandaluyong City 4.625000
...
New Delhi       2.438845
Montville       2.400000
Mc Millan       2.400000
Noida           2.036204
Faridabad       1.866932
Name: Aggregate rating, Length: 140, dtype: float64
```

```
In [65]: print("Average ratings for restaurants in each city:")
print(avg_city_rating.head())
```

```
Average ratings for restaurants in each city:
City
Inner City      4.900000
Quezon City     4.800000
Makati City     4.650000
Pasig City      4.633333
Mandaluyong City 4.625000
Name: Aggregate rating, dtype: float64
```

## Insights:

1. City-wise Rating Variation:- There's a significant difference in average ratings across cities, indicating varying restaurant quality standards.
2. Top-rated Cities:- Cities like Inner City, Quezon City, and Makati City have exceptionally high average ratings, suggesting a concentration of high-quality restaurants.
3. Low-rated Cities:- Cities like Noida and Faridabad have relatively lower average ratings, which might indicate areas for improvement in restaurant quality or service.

## Task

1. Determine the city with the highest average rating.

```
In [66]: hight_city_avg_rating = avg_city_rating.index[0]
hight_avg_rating = avg_city_rating.iloc[0]
```

```
In [67]: print(f"The city with the highest average rating is {hight_city_avg_rating} with an average rating of {hight_avg_rating}")
The city with the highest average rating is Inner City with an average rating of 4.90
```

## Insights:-

Inner City has the highest average restaurant rating among all cities in the dataset.

# Level 1

## Task 3



### Task: Price Range Distribution

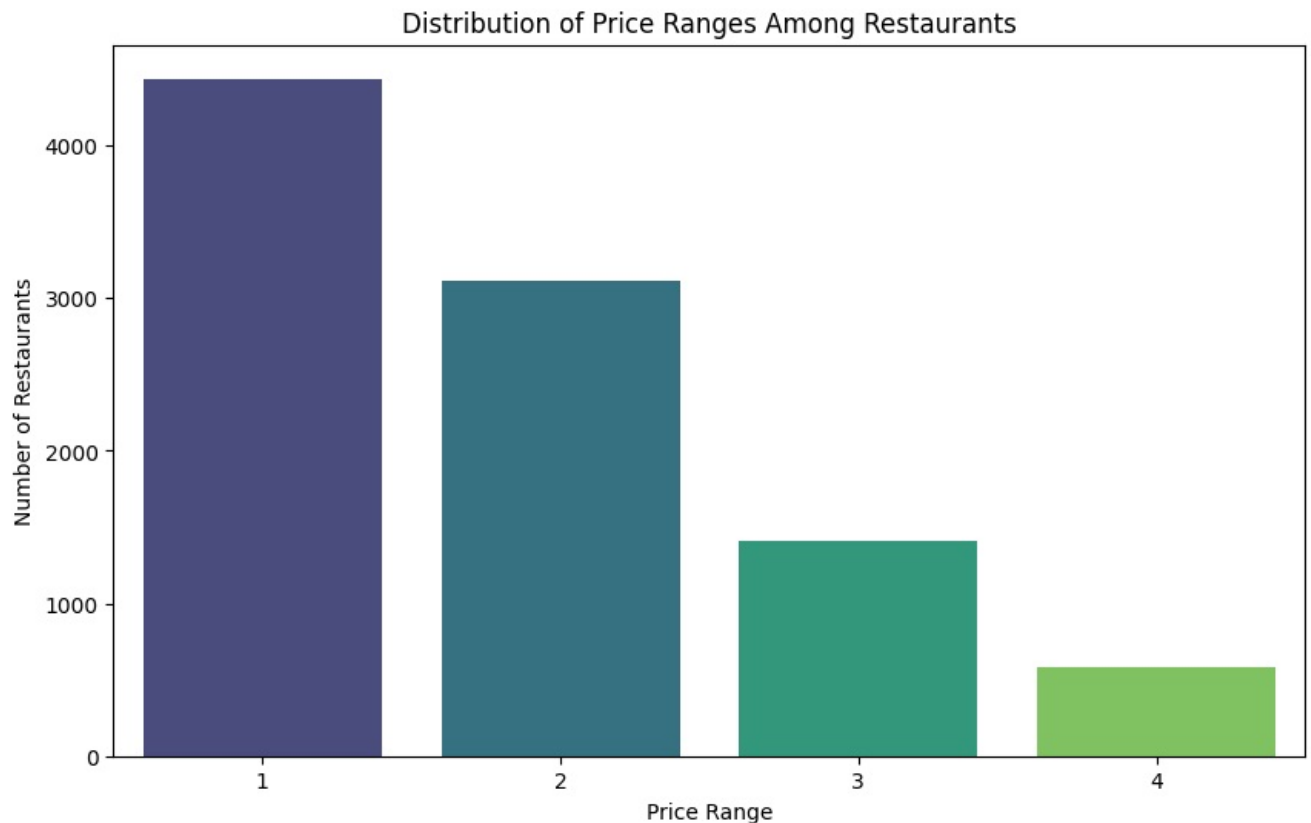
Create a histogram or bar chart to visualize the distribution of price ranges among the restaurants.

Calculate the percentage of restaurants in each price range category.

## Task: Price Range Distribution

1. Create a histogram or bar chart to visualize the distribution of price ranges among the restaurants.

```
In [68]: # Create a bar chart for price range distribution
plt.figure(figsize=(10, 6))
sns.countplot(x='Price range', data=df, palette='viridis')
plt.title('Distribution of Price Ranges Among Restaurants')
plt.xlabel('Price Range')
plt.ylabel('Number of Restaurants')
plt.show()
```



```
In [69]: df['Price range'].value_counts()
```

```
Out[69]: Price range
1      4438
2      3113
3       1405
4         586
Name: count, dtype: int64
```

## Observations:

1. Price Range Distribution: Most restaurants fall in lower price ranges, with fewer in higher tiers.
2. Dominance of Lower Prices: Budget-friendly options dominate the market.

## Task

1. Calculate the percentage of restaurants in each price range category

```
In [70]: # Calculate the percentage of restaurants in each price range category
price_range_counts = df['Price range'].value_counts(normalize=True) * 100
```

```
In [71]: # Convert to a DataFrame for better readability
price_range_percentages = price_range_counts.sort_index().reset_index()
price_range_percentages.columns = ['Price Range', 'Percentage']
price_range_percentages
```

```
Out[71]:
```

	Price Range	Percentage
0	1	46.510166
1	2	32.624188
2	3	14.724376
3	4	6.141270

Insight:



1. The majority of restaurants fall into price range 1, followed by price range 2.
2. As the price range increases, the percentage of restaurants decreases significantly.

# Level 1

## Task 4



### Task: Online Delivery

**Determine the percentage of restaurants that offer online delivery.**

**Compare the average ratings of restaurants with and without online delivery.**

## Task

1. Determine the percentage of restaurants that offer online delivery.

```
In [72]: total_count=df[['Restaurant ID','Restaurant Name','Has Online delivery']].groupby(['Restaurant ID','Restaurant total_count
```

Out[72]:

	Restaurant ID	Restaurant Name	Has Online delivery	total
0	53	Amber	Yes	1
1	55	Berco's	Yes	1
2	60	Colonel's Kababz	No	1
3	64	Diva - The Italian Restaurant	Yes	1
4	65	Drums of Heaven	Yes	1
...	...	...	...	...
9537	18499493	Zombiez	No	1
9538	18500618	Veg. Darbar	No	1
9539	18500628	Grill & Cafe	No	1
9540	18500639	Chandni Chowk 2 China	No	1
9541	18500652	Mahek By Greenz	No	1

9542 rows × 4 columns

```
In [73]: delivery_online_percentage=(df['Has Online delivery']=="Yes").mean()*100
print(f"Percentage of restaurants offering online delivery: {delivery_online_percentage:.2f}%")
```

Percentage of restaurants offering online delivery: 25.69%

## Observation

Percentage of restaurants offering online delivery: 25.66%. This means that about a quarter of the restaurants in the dataset offer online delivery services

## Task

1. Compare the average ratings of restaurants with and without online delivery.

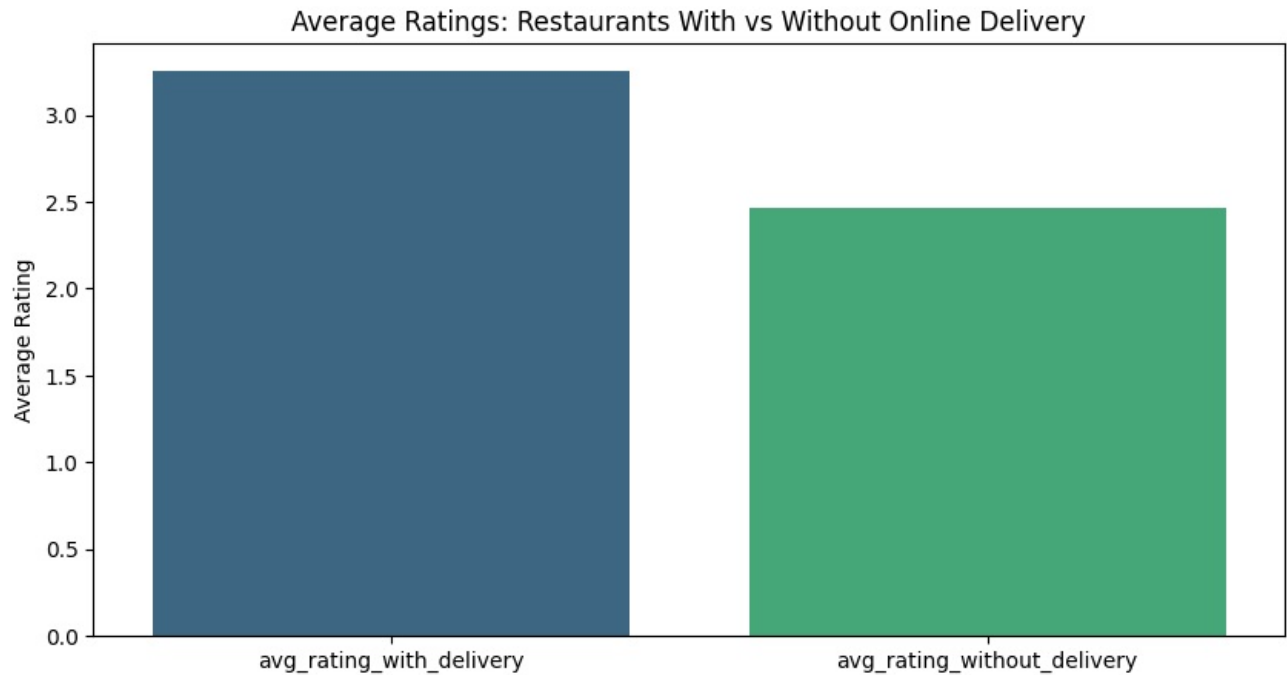
```
In [74]: #Compare rating
avg_rating_with_delivery = df[df['Has Online delivery']=="Yes"]['Aggregate rating'].mean()
avg_rating_without_delivery = df[df['Has Online delivery']=="No"]['Aggregate rating'].mean()
print("Average rating of restaurants with online delivery =",avg_rating_with_delivery)
print("Average rating of restaurants without online delivery =",avg_rating_without_delivery)
```

Average rating of restaurants with online delivery = 3.2488372093023257  
Average rating of restaurants without online delivery = 2.4635171343957127

## Ovservation

1. Average rating of restaurants with online delivery: 3.24
2. Average rating of restaurants without online delivery: 2.46

```
In [75]: # Create a bar plot to visualize the comparison
plt.figure(figsize=(10,5))
sns.barplot(x=['avg_rating_with_delivery','avg_rating_without_delivery'],y=[avg_rating_with_delivery,avg_rating_without_delivery])
plt.title('Average Ratings: Restaurants With vs Without Online Delivery')
plt.ylabel('Average Rating')
plt.show()
```



In [ ]:

In [ ]:

In [ ]:

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js