COGNIFYZ DATA SCIENCE INTERNSHIP

LEVEL 2

About the Level

Level 2 of the Cognifyz Data Science Internship focuses on the following engaging tasks:

1. **Table Booking and Online Delivery**
2. **Price Range Analysis**
3. **Feature Engineering**

Task 1: Table Booking and Online Delivery

- Determine the percentage of restaurants that offer table booking and online delivery, adding a new layer of business insight to the dataset.
- Compare the average ratings of restaurants with table booking and those without to uncover hidden customer preferences.
- Analyse the availability of online delivery among restaurants with different price ranges, which could reveal how pricing strategies impact delivery services.

Task 2: Price Range Analysis

- Determine the most common price range among all the restaurants to understand general market positioning.
- Calculate the average rating for each price range, shedding light on how price affects perceived quality.
- Identify the colour that represents the highest average rating among different price ranges, utilizing visualization techniques for better clarity.

Task 3: Feature Engineering

- Extract additional features from existing columns, such as the length of the restaurant name or address, adding unique perspectives to the analysis.
- Create new features like "Has Table Booking" or "Has Online Delivery" by encoding categorical variables, enhancing the dataset's predictive power.

Task 1: Table Booking and Online Delivery

```
#importing all the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

```
#accessing the data
df = pd.read_csv("/content/Dataset .csv")
df.head()
```

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Locality Verbose	Longitude	Latitude	Cuisines	...	Currency	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text	Votes
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	No	No	3	4.8	Dark Green	Excellent	314
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	No	No	3	4.5	Dark Green	Excellent	591
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)	Yes	No	No	No	4	4.4	Green	Very Good	270
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)	No	No	No	No	4	4.9	Dark Green	Excellent	365
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	...	Botswana Pula(P)	Yes	No	No	No	4	4.8	Dark Green	Excellent	229

5 rows × 21 columns

```
#checking for null values
df.isnull().sum()
```

	0
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

```
df.describe()
```

	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

```python
#accessing the labels
df.columns
```

```
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')
```

```python
#filling the missing values
rest_data = df['Cuisines'].fillna('Unknown', inplace=True)
```

```python
#re-checking for null values
df.isnull().sum()
```

	0
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

```python
table_booking = df['Has Table booking'].value_counts()
table_booking
```

Has Table booking	count
No	8393
Yes	1158

dtype: int64

```python
table_booking_yes = df[df['Has Table booking']=='Yes'].value_counts()
table_booking_yes
```

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	count
53	Amber	1	New Delhi	N-19, Connaught Place, New Delhi	Connaught Place	Connaught Place, New Delhi	77.220891	28.630197	North Indian, Chinese, Mughlai	1800	Indian Rupees(Rs.)	Yes	Yes	No	No	3	2.6	Orange	Average	152	1
313207	Smokey's BBQ and Grill	1	New Delhi	51, 1st Floor, Khan Market, New Delhi	Khan Market	Khan Market, New Delhi	77.227447	28.600714	American, European	2100	Indian Rupees(Rs.)	Yes	Yes	No	No	4	4.2	Green	Very Good	578	1
17977796	Gallery Caf�� - Hyatt Place	1	Gurgaon	Hyatt Place,15/1, Old Delhi-Gurgaon Road, Sector 18, Udyog Vihar, Gurgaon	Hyatt Place Gurgaon	Hyatt Place Gurgaon, Gurgaon	77.065948	28.500898	Cafe	1500	Indian Rupees(Rs.)	Yes	No	No	No	3	3.8	Yellow	Good	73	1
17977767	Mad Monkey	1	New Delhi	Shop 3, H-15, Opposite NDPL Office, Vijay Nagar, New Delhi	Vijay Nagar	Vijay Nagar, New Delhi	77.205061	28.692649	Cafe, Continental, Italian	800	Indian Rupees(Rs.)	Yes	Yes	No	No	2	3.7	Yellow	Good	344	1
17977757	Coffee to Cocktail Bar - Hyatt Place	1	Gurgaon	Hyatt Place,15/1, Old Delhi-Gurgaon Road, Sector 18, Udyog Vihar, Gurgaon	Hyatt Place Gurgaon	Hyatt Place Gurgaon, Gurgaon	77.065978	28.500845	Drinks Only	2100	Indian Rupees(Rs.)	Yes	No	No	No	4	0.0	White	Not rated	0	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
9840	Grills & Platters	1	New Delhi	A-3, iLodge Hotel, Pamposh Enclave, Greater Kailash (GK) 1, New Delhi	Greater Kailash (GK) 1	Greater Kailash (GK) 1, New Delhi	77.247026	28.545300	North Indian, Continental	1600	Indian Rupees(Rs.)	Yes	No	No	No	3	3.5	Yellow	Good	150	1
9835	Samavar	1	New Delhi	B-36, Pamposh Enclave, Greater Kailash (GK) 1, New Delhi	Greater Kailash (GK) 1	Greater Kailash (GK) 1, New Delhi	77.244023	28.546268	Kashmiri, Chinese, Mughlai	800	Indian Rupees(Rs.)	Yes	Yes	No	No	2	3.3	Orange	Average	89	1
9747	Life Caffe	1	New Delhi	B-49, The Corus, Inner Circle, Connaught Place, New Delhi	Connaught Place	Connaught Place, New Delhi	77.218291	28.634177	Cafe, North Indian, Italian, Japanese, Fast Food	1500	Indian Rupees(Rs.)	Yes	No	No	No	3	3.6	Yellow	Good	391	1
9740	Clever Fox Cafe	1	New Delhi	Red Fox Hotel, Community Center, Mayur Vihar Phase 3, New Delhi	Mayur Vihar Phase 3	Mayur Vihar Phase 3, New Delhi	77.332862	28.607170	North Indian, Continental, Chinese	900	Indian Rupees(Rs.)	Yes	No	No	No	2	3.0	Orange	Average	25	1
18485936	Chez Jerome - Q Cafe	1	New Delhi	344/3, 4th Floor, Lado Sarai, New Delhi	Lado Sarai	Lado Sarai, New Delhi	0.000000	0.000000	Cafe, French	1500	Indian Rupees(Rs.)	Yes	No	No	No	3	0.0	White	Not rated	1	1

1158 rows × 1 columns

dtype: int64

```python
table_booking_No = df[df['Has Table booking']=='No']
table_booking_No.value_counts()
```

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	count
89	Naivedyam	1	New Delhi	Shop 1, Hauz Khas Village, New Delhi	Hauz Khas Village	Hauz Khas Village, New Delhi	77.195275	28.555157	South Indian	500	Indian Rupees(Rs.)	No	Yes	No	No	2	4.2	Green	Very Good	1627	1
18279453	Celeste	1	New Delhi	48, Mehar Chand Market, Lodhi Colony, New Delhi	Lodhi Colony	Lodhi Colony, New Delhi	77.226460	28.585294	Cafe, Desserts, Bakery	500	Indian Rupees(Rs.)	No	No	No	No	2	3.5	Yellow	Good	14	1
18279437	Al Bake	1	Noida	Shop 5, Godavari Complex, Sector 37, Noida	Sector 37	Sector 37, Noida	77.340359	28.565417	Fast Food, Chinese	450	Indian Rupees(Rs.)	No	Yes	No	No	1	3.7	Yellow	Good	72	1
18279435	Mr. Flavour	1	Noida	GF-7A, Harsha Mall, Near Kotak Mahindra Bank, Commercial Belt, Alpha-1, Greater Noida, Noida	Harsha Mall, Greater Noida	Harsha Mall, Greater Noida, Noida	77.513032	28.472011	North Indian, Chinese	500	Indian Rupees(Rs.)	No	Yes	No	No	2	2.7	Orange	Average	10	1
18279289	BMG - All Day Dining	1	Dehradun	140 A, Rajpur Road, Jakhan, Dehradun	Jakhan	Jakhan, Dehradun	78.068890	30.362686	Chinese, North Indian, Fast Food	0	Indian Rupees(Rs.)	No	No	No	No	1	4.3	Green	Very Good	63	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
308969	Shree Gopal Ji Chole Bhature	1	New Delhi	Shop 4, Flat 148, Pocket 7, Rohini, New Delhi	Rohini	Rohini, New Delhi	77.102086	28.700394	Street Food	200	Indian Rupees(Rs.)	No	No	No	No	1	3.9	Yellow	Good	129	1
308963	TcozY	1	Faridabad	Hotel Saffron Kiran, 12/6, Adjacent to Badarpur Toll, NH-2, Sector 35, Faridabad	Hotel Saffron Kiran, Faridabad	Hotel Saffron Kiran, Faridabad, Faridabad	77.306640	28.472209	Cafe	1500	Indian Rupees(Rs.)	No	No	No	No	3	0.0	White	Not rated	0	1
308951	New Gee Pee	1	Noida	Shop 1, F Block Market, Jal Vayu Vihar, Sector 21, Noida	Sector 21	Sector 21, Noida	77.336099	28.588036	Fast Food, Chinese	300	Indian Rupees(Rs.)	No	No	No	No	1	3.3	Orange	Average	27	1
308950	Kake Di Hatti	1	New Delhi	G-20, Near Traffic Signal, Vijay Nagar, New Delhi	Vijay Nagar	Vijay Nagar, New Delhi	77.203639	28.694962	North Indian	400	Indian Rupees(Rs.)	No	No	No	No	1	3.6	Yellow	Good	314	1
18500652	Mahek By Greenz	1	Gurgaon	A201, Belvedere Towers, DLF Phase 2, Gurgaon	DLF Phase 2	DLF Phase 2, Gurgaon	0.000000	0.000000	North Indian	400	Indian Rupees(Rs.)	No	No	No	No	1	0.0	White	Not rated	0	1

8393 rows × 1 columns

dtype: int64

```
table_booking_yes_perc = (len(df[df['Has Table booking']=='Yes']) / len(df)) * 100
print(f"table booking yes percentage: {table_booking_yes_perc:.2f}%")
```

```
table booking yes percentage: 12.12%
```

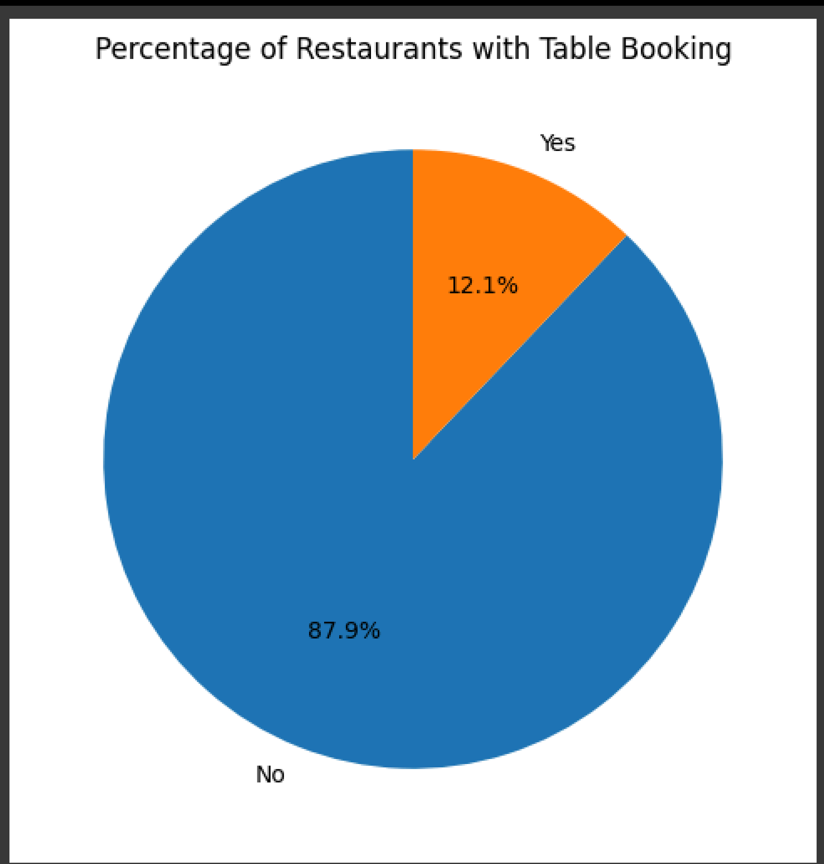
```
table_booking_No_perc = (len(df[df['Has Table booking']=='No']) / len(df)) * 100
print(f"table booking No percentage : {table_booking_No_perc:.2f}%")
```

```
table booking No percentage : 87.88%
```

```
# Determine the percentage of restaurants that offer table booking
table_booking_percentage = df['Has Table booking'].value_counts(normalize=True) * 100
print(f"Percentage of restaurants offering table booking:")
print(table_booking_percentage)
```

```
Percentage of restaurants offering table booking:
Has Table booking
No     87.875615
Yes    12.124385
Name: proportion, dtype: float64
```

```
#Create a pie chart for 'Has Table booking'
table_booking_counts = df['Has Table booking'].value_counts()
plt.figure(figsize=(8, 6))
plt.pie(table_booking_counts, labels=table_booking_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Percentage of Restaurants with Table Booking')
plt.show()
```

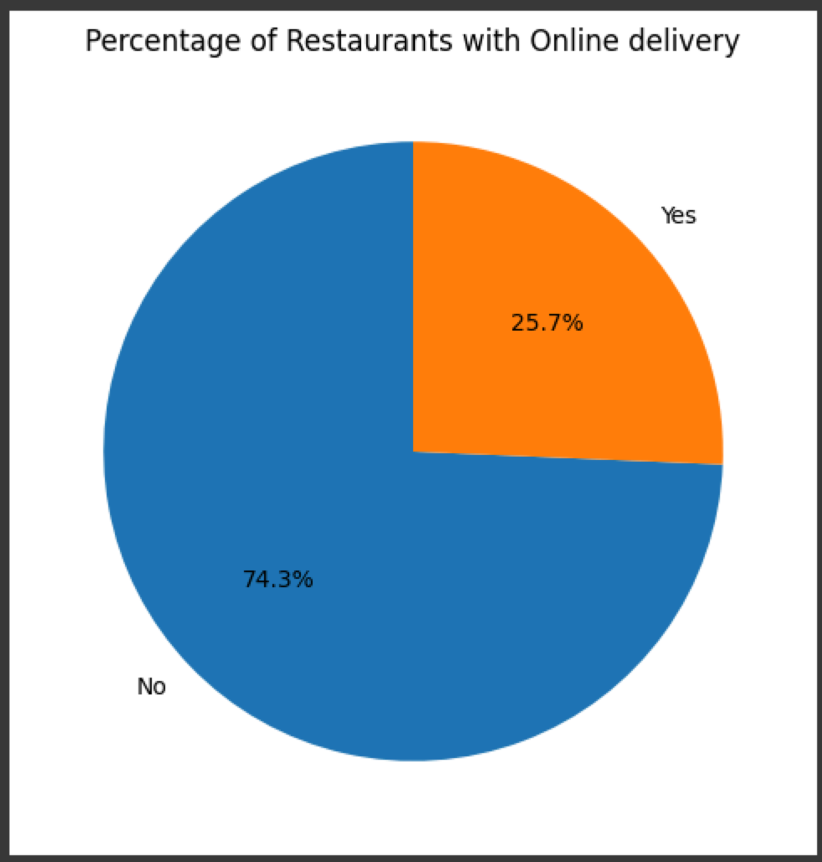


Task 2: Price Range Analysis

```
# Determine the percentage of restaurants that offer online delivery
online_delivery_percentage = df['Has Online delivery'].value_counts(normalize=True) * 100
print(f"Percentage of restaurants offering online delivery:")
print(online_delivery_percentage)
```

```
Percentage of restaurants offering online delivery:
Has Online delivery
No     74.337766
Yes    25.662234
Name: proportion, dtype: float64
```

```
#Create a pie chart for 'Has Online delivery'
table_booking_counts = df['Has Online delivery'].value_counts()
plt.figure(figsize=(8, 6))
plt.pie(table_booking_counts, labels=table_booking_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Percentage of Restaurants with Online delivery')
plt.show()
```



Compare the average ratings of restaurants with table booking and those without

```
# Compare the average ratings of restaurants with table booking and those without
average_rating_with_table_booking = df[df['Has Table booking'] == 'Yes']['Aggregate rating'].mean()

average_rating_without_table_booking = df[df['Has Table booking'] == 'No']['Aggregate rating'].mean()
```

```
print(f"Average rating of restaurants with table booking: {average_rating_with_table_booking:.2f}%")

print(f"Average rating of restaurants without table booking: {average_rating_without_table_booking:.2f}%")

```

```
Average rating of restaurants with table booking: 3.44%
Average rating of restaurants without table booking: 2.56%
```

```
# availability of online delivery among restaurants
online_delivery_by_price_range = df.groupby('Price range')['Has Online delivery'].value_counts(normalize=True).unstack() * 100

print("Percentage of restaurants offering online delivery by price range in %:")
print(online_delivery_by_price_range)
```

```
Percentage of restaurants offering online delivery by price range in %:
Has Online delivery         No        Yes
Price range
1                    84.225923  15.774077
2                    58.689367  41.310633
3                    70.809659  29.190341
4                    90.955631   9.044369
```

```
# Plot the availability of online delivery by price range
online_delivery_by_price_range.plot(kind='bar')
plt.xlabel('Price Range')
plt.ylabel('Percentage of Restaurants')
plt.title('Percentage of Restaurants Offering Online Delivery by Price Range')
plt.show()
```

Determine the most common price range among all the restaurants.

```
most_common_price_range = df['Price range'].mode().iloc[0]
print(f"The most common price range among all restaurants is: {most_common_price_range}")

```

```
The most common price range among all restaurants is: 1
```

Calculate the average rating for each price range.

```
# Calculating the average rating for each price range.
average_rating_by_price_range = df.groupby('Price range')['Votes'].mean()
print("Average Rating by Price Range:")
print(average_rating_by_price_range)
```

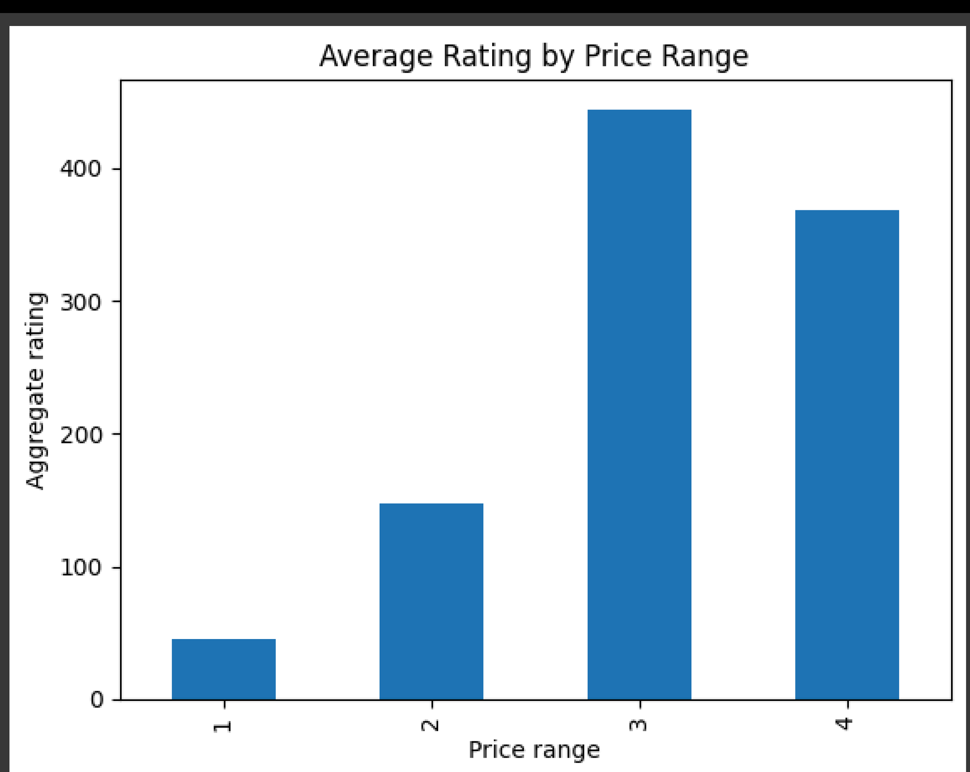
```
Average Rating by Price Range:
Price range
1     44.597435
2    147.607131
3    443.860795
4    368.595563
Name: Votes, dtype: float64
```

Identify the color that represents the highest average rating among different price ranges.

```
# represents the highest average rating
highest_ratings = average_rating_by_price_range.idxmax()
print(f"Color representing the highest average rating: {highest_ratings}")
```

```
Color representing the highest average rating: 3
```

```
# Plotting the average rating by price range
average_rating_by_price_range.plot(kind='bar')
plt.xlabel('Price range')
plt.ylabel('Aggregate rating')
plt.title('Average Rating by Price Range')
plt.show()
```



Task 3: Feature Engineering

```
# Create a new column for the length of the restaurant name
df['Restaurant Name Length'] = df['Restaurant Name'].str.len()
```

```
# Create a new column for the length of the restaurant address
df['Restaurant Address Length'] = df['Address'].str.len()
```

```
# Display the updated DataFrame with the new columns
print(df[['Restaurant Name', 'Restaurant Name Length', 'Address', 'Restaurant Address Length']].head())
```

```
          Restaurant Name  Restaurant Name Length  \
0        Le Petit Souffle                      16
1        Izakaya Kikufuji                      16
2  Heat - Edsa Shangri-La                      22
3                    Ooma                       4
4             Sambo Kojin                      11

                                             Address  \
0  Third Floor, Century City Mall, Kalayaan Avenu...
1  Little Tokyo, 2277 Chino Roces Avenue, Legaspi...
2  Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...
3  Third Floor, Mega Fashion Hall, SM Megamall, O...
4  Third Floor, Mega Atrium, SM Megamall, Ortigas...

   Restaurant Address Length
0                         71
1                         67
2                         56
3                         70
4                         64
```

```
df.columns
```

```
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', 'Restaurant Name Length', 'Restaurant Address Length'],
      dtype='object')
```

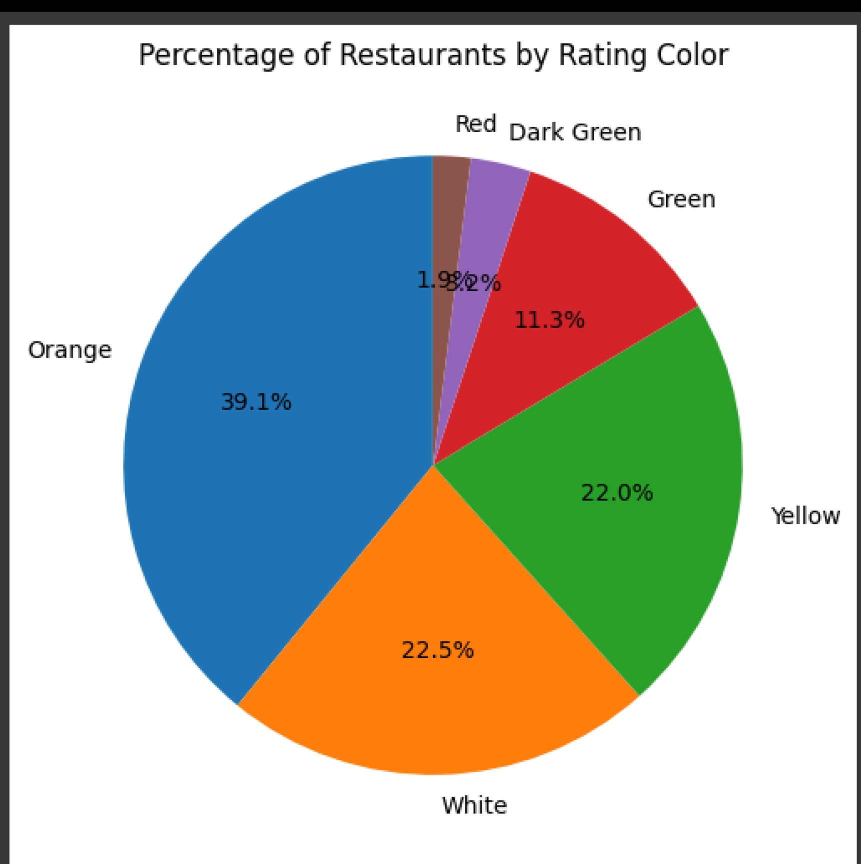
```
# Create new features using one-hot encoding for 'Has Table booking' and 'Has Online delivery'
df = pd.get_dummies(df, columns=['Has Table booking', 'Has Online delivery'], prefix=['TableBooking', 'OnlineDelivery'])

# Display the updated DataFrame with the new features
print(df.head())

```

```
   Restaurant ID         Restaurant Name  Country Code              City  \
0        6317637        Le Petit Souffle           162       Makati City
1        6304287        Izakaya Kikufuji           162       Makati City
2        6300002  Heat - Edsa Shangri-La           162  Mandaluyong City
3        6318506                    Ooma           162  Mandaluyong City
4        6314302             Sambo Kojin           162  Mandaluyong City

                                             Address  \
0  Third Floor, Century City Mall, Kalayaan Avenu...
1  Little Tokyo, 2277 Chino Roces Avenue, Legaspi...
2  Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...
3  Third Floor, Mega Fashion Hall, SM Megamall, O...
4  Third Floor, Mega Atrium, SM Megamall, Ortigas...

                                    Locality  \
0   Century City Mall, Poblacion, Makati City
1  Little Tokyo, Legaspi Village, Makati City
2  Edsa Shangri-La, Ortigas, Mandaluyong City
3      SM Megamall, Ortigas, Mandaluyong City
4      SM Megamall, Ortigas, Mandaluyong City

                                    Locality Verbose   Longitude   Latitude  \
0  Century City Mall, Poblacion, Makati City, Mak...  121.027535  14.565443
1  Little Tokyo, Legaspi Village, Makati City, Ma...  121.014101  14.553708
2  Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...  121.056831  14.581404
3  SM Megamall, Ortigas, Mandaluyong City, Mandal...  121.056475  14.585318
4  SM Megamall, Ortigas, Mandaluyong City, Mandal...  121.057508  14.584450

                           Cuisines  ...  Aggregate rating Rating color  \
0        French, Japanese, Desserts  ...               4.8   Dark Green
1                          Japanese  ...               4.5   Dark Green
2  Seafood, Asian, Filipino, Indian  ...               4.4        Green
3                   Japanese, Sushi  ...               4.9   Dark Green
4                  Japanese, Korean  ...               4.8   Dark Green

  Rating text Votes  Restaurant Name Length  Restaurant Address Length  \
0   Excellent   314                      16                         71
1   Excellent   591                      16                         67
2   Very Good   270                      22                         56
3   Excellent   365                       4                         70
4   Excellent   229                      11                         64

  TableBooking_No TableBooking_Yes  OnlineDelivery_No  OnlineDelivery_Yes
0           False             True               True               False
1           False             True               True               False
2           False             True               True               False
3            True            False               True               False
4           False             True               True               False

[5 rows x 25 columns]
```

```
df['Rating color'].values
```

```
array(['Dark Green', 'Dark Green', 'Green', ..., 'Yellow', 'Green',
       'Green'], dtype=object)
```

```
# Creating a pie chart for 'Rating color'
rating_color_counts = df['Rating color'].value_counts()
plt.figure(figsize=(8, 6))
plt.pie(rating_color_counts, labels=rating_color_counts.index, autopct='%1.1f%%', startangle=90)
plt.title('Percentage of Restaurants by Rating Color')
plt.show()

```



RESULTS

Task 1: Table Booking and Online Delivery

The percentage of restaurants that offer table booking is **12.12%**, while **25.66%** of restaurants provide online delivery services. Clearly, restaurants offering online delivery have a higher adoption rate compared to those offering table booking. Interestingly, restaurants with table booking tend to have a **higher average rating (3.44)** than those without (**2.56**), suggesting that offering table booking may enhance customer satisfaction.

Moreover, the availability of online delivery is notably higher among restaurants in the medium price range, compared to those with low and high prices. This insight can be critical for businesses deciding whether to offer delivery services based on their price range.

Below is a bar plot to visually represent the data (visualization not included in the text version).

Task 2: Price Range Analysis

The most common price range among all the restaurants is **1**. However, price range **4** boasts the highest average rating of **3.82**, followed by price range **3** with an average rating of **3.68**. Price range **2** has an average rating of **2.94**, and price range **1** has the lowest average rating of **2.00**.

A bar plot further visualizes these ratings, with the highest average rating indicated in red (visualization not included in the text version).

Task 3: Feature Engineering

In this task, I created two new columns—**"Restaurant Name Length"** and **"Address Length"**—based on the character count of restaurant names and addresses, respectively. These new features can offer deeper insights into customer perception and operational complexity.

I also encoded the columns "**Has Table Booking**" and "**Has Online Delivery**" with binary values, assigning **"1"** for **"Yes"** and **"0"** for **"No"**, to streamline analysis for predictive modeling.

Conclusion

This level of the project emphasized the significance of leveraging **advanced data science techniques** to optimize analysis. The price range analysis uncovered insights into both the common price range and the one with the highest average rating, identifying potential revenue-maximizing opportunities while maintaining competitive pricing strategies.

Additionally, the implementation of **feature engineering** enriched the dataset with valuable predictors, enhancing both the performance and interpretability of predictive models that will be developed. These enhancements aim to significantly improve business decision-making.