Open in Colab

Project Name - Restaurant_Data_Analysis_Level_1

Project Type - EDA

Industry - Cognifyz Technologies

Contribution - Individual

Member Name - Arindam Paul

Level - 1

Project Summary -

This level 1 tasks of the project focuses on analyzing restaurant data, exploring insights from a dataset consisting of different restaurants name, city, address, locality, rating, price range etc.

The Level 1 tasks undertaken during the Cognifyz Data Science Internship, focusing on data exploration and preprocessing, descriptive analysis, and geospatial analysis of restaurant data. It will be interesting to explore what all other insights can be obtained from the same dataset.

Level 1 Tasks:

Task 1: Data Exploration and Preprocessing

- Explored the restaurant dataset, determining its dimensions.
- Managed missing values across columns, ensuring data integrity.
- Executed data type conversions as needed.
- Analyzed the distribution of the target variable, "Aggregate rating," and addressed class imbalances.

Task 2: Descriptive Analysis

- Calculated fundamental statistical measures (e.g., mean, median, standard deviation) for numerical columns.
- Investigated the distribution of categorical variables like "Country Code," "City," and "Cuisines."
- Identified the top cuisines and cities with the highest restaurant counts.

Task 3: Geospatial Analysis

- Visualized restaurant locations on maps using latitude and longitude data.
- Conducted an analysis of restaurant distribution across different cities and countries.
- Explored potential correlations between restaurant locations and ratings.

So, this notebook consist of all the Level 1 tasks which i completed during the Cognifyz Data Science Internship. The tasks encompass data exploration, data preprocessing, statistical analysis, and geospatial insights within the restaurant industry, demonstrating a foundational understanding of data science principles.

Problem Statement

The Level 1 of the Cognifyz Data Science Internship, focuses on the exploration and analysis of a restaurant dataset. The level comprises three key tasks: Data Exploration and Preprocessing, Descriptive Analysis, and Geospatial Analysis.

Project Objectives:

- Gain proficiency in data exploration and preprocessing.
- Perform descriptive analysis to understand dataset characteristics.
- Apply geospatial analysis techniques to uncover location-based insights.
- Develop foundational data science skills for the restaurant industry.

Key Tasks in Level 1:

Task 1: Data Exploration and Preprocessing

- Explore the dataset to understand its structure, including the number of rows and columns.
- Address missing values in each column, ensuring data integrity.
- Perform data type conversions as necessary.
- Analyze the distribution of the target variable ("Aggregate rating") and identify potential class imbalances.

Task 2: Descriptive Analysis

- Calculate essential statistical measures (e.g., mean, median, standard deviation) for numerical columns.
- Investigate the distribution of categorical variables, such as "Country Code," "City," and "Cuisines."
- Identify the top cuisines and cities with the highest number of restaurants, gaining insights into customer preferences.

Task 3: Geospatial Analysis

- Visualize restaurant locations using latitude and longitude information, providing a spatial perspective.
- Analyze the geographical distribution of restaurants across different cities and countries.
- Explore potential correlations between the restaurant's location and its rating, uncovering location-based patterns.

Let's Begin

Task 1: Data Exploration and Preprocessing

Import Libraries

In [ ]:
```
# Importing Libraries
import pandas as pd
import numpy as np

# Visualization Libraries
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# Ignore all warnings
import warnings

warnings.filterwarnings('ignore')
```

Dataset Loading

In [ ]:
```
# Load Dataset from github repository
df = pd.read_csv("https://raw.githubusercontent.com/Apaulgithub/Restaurant_Data_Ana
```

Dataset First View

In [ ]:
```
# Dataset First Look
# View top 5 rows of the dataset
df.head()
```

Out[ ]:

	Restaurant ID	Restaurant Name	Country Code	City	Address	Locality	Loca Verb
0	6317637	Le Petit Souffle	162	Makati City	Third Floor, Century City Mall, Kalayaan Avenu...	Century City Mall, Poblacion, Makati City	Century (M Poblaci Makati C Ma
1	6304287	Izakaya Kikufuji	162	Makati City	Little Tokyo, 2277 Chino Roces Avenue, Legaspi...	Little Tokyo, Legaspi Village, Makati City	Little Tok Lega Villa Makati C M
2	6300002	Heat - Edsa Shangri-La	162	Mandaluyong City	Edsa Shangri-La, 1 Garden Way, Ortigas, Mandal...	Edsa Shangri-La, Ortigas, Mandaluyong City	Edsa Shan La, Ortig Mandaluy City, M
3	6318506	Ooma	162	Mandaluyong City	Third Floor, Mega Fashion Hall, SM Megamall, O...	SM Megamall, Ortigas, Mandaluyong City	Megam Ortig Mandaluy C Mand
4	6314302	Sambo Kojin	162	Mandaluyong City	Third Floor, Mega Atrium, SM Megamall, Ortigas...	SM Megamall, Ortigas, Mandaluyong City	Megam Ortig Mandaluy C Mand

5 rows × 21 columns

Dataset Rows & Columns count

In [ ]:

```
# Dataset Rows & Columns count
# Checking number of rows and columns of the dataset using shape
```

```
print("Number of rows are: ",df.shape[0])
print("Number of columns are: ",df.shape[1])
```

```
Number of rows are:  9551
Number of columns are:  21
```

Duplicate Values

In [ ]:

```
# Dataset Duplicate Value Count
dup = df.duplicated().sum()
print(f'number of duplicated rows are {dup}')
```

```
number of duplicated rows are 0
```

Missing Values/Null Values

In [ ]:

```
# Missing Values/Null Values Count
df.isnull().sum()
```

Out[ ]:

```
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 [ ]:

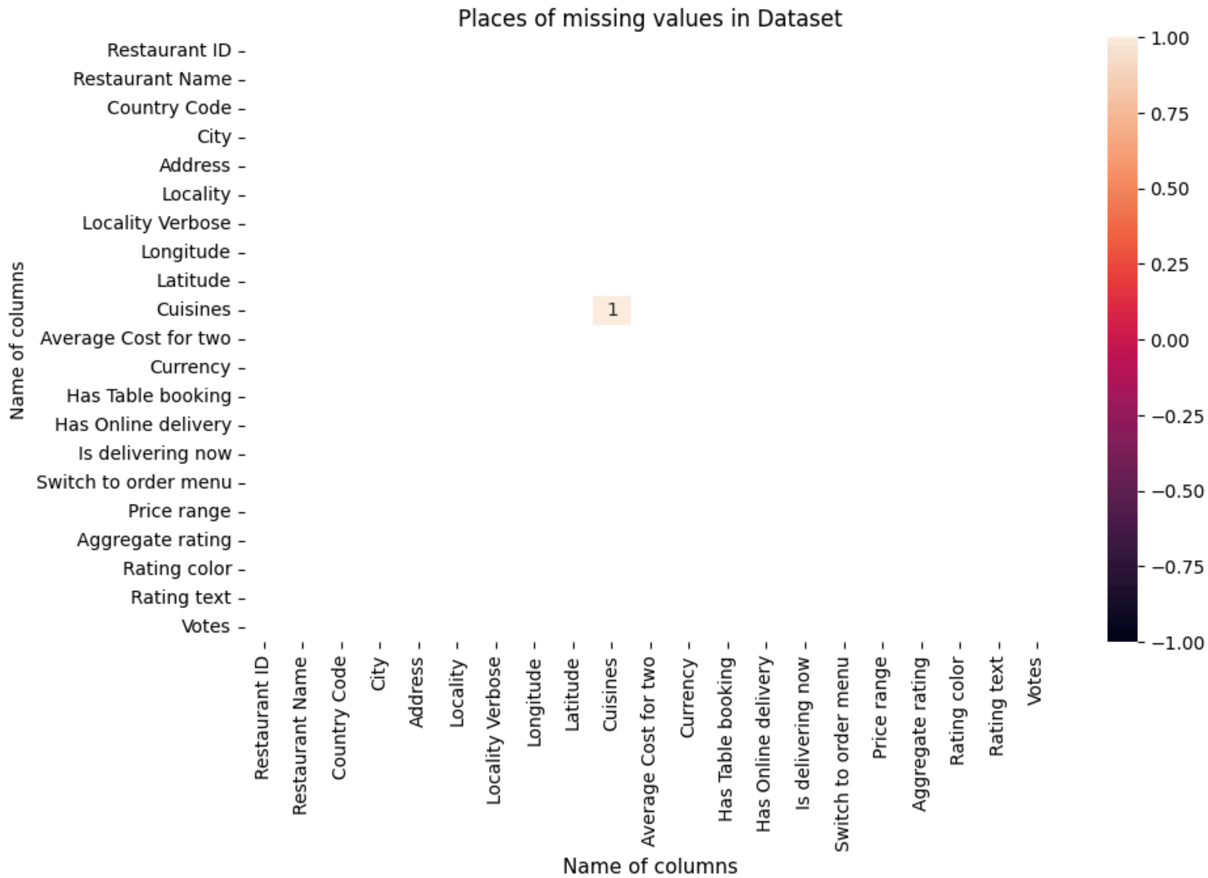
```
# Visualizing the missing values
# Checking Null Value by Plotting Heatmap

# Set the plot size
plt.figure(figsize = (10,6))

# Create the figure object
sns.heatmap(df.isnull().corr(), vmin=-1, annot= True)

# Set labels
plt.xlabel('Name of columns', fontsize=11)
plt.ylabel('Name of columns', fontsize=10)
plt.title('Places of missing values in Dataset', fontsize=12)
```

```python
# To show
plt.show()
```



Handling Missing Values

In [ ]:
```python
# If the null values number will high, then we can replace it with any placeholder
# So, since Cuisines column have low number of missing values, that is only 9, i ha
df = df.dropna(subset=['Cuisines'])
```

In [ ]:
```python
# Checking missing values again for confirmation
print("Missing values/null values count after handling:")
df.isna().sum()
```

```
Missing values/null values count after handling:
```

Out[ ]:
```
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
```

Data Type Conversion

In [ ]:
```
# Dataset Information
# Checking information about the dataset using info
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 9542 entries, 0 to 9550
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Restaurant ID         9542 non-null   int64
 1   Restaurant Name       9542 non-null   object
 2   Country Code          9542 non-null   int64
 3   City                  9542 non-null   object
 4   Address               9542 non-null   object
 5   Locality              9542 non-null   object
 6   Locality Verbose      9542 non-null   object
 7   Longitude             9542 non-null   float64
 8   Latitude              9542 non-null   float64
 9   Cuisines              9542 non-null   object
 10  Average Cost for two  9542 non-null   int64
 11  Currency              9542 non-null   object
 12  Has Table booking     9542 non-null   object
 13  Has Online delivery   9542 non-null   object
 14  Is delivering now     9542 non-null   object
 15  Switch to order menu  9542 non-null   object
 16  Price range           9542 non-null   int64
 17  Aggregate rating      9542 non-null   float64
 18  Rating color          9542 non-null   object
 19  Rating text           9542 non-null   object
 20  Votes                 9542 non-null   int64
dtypes: float64(3), int64(5), object(13)
memory usage: 1.6+ MB
```

Data type conversion is not needed here, everything is looking fine.

Distribution of The Target Variable

In [ ]:

```
# Distribution of the target variable ("Aggregate rating") and identify class imbal
target_counts = df['Aggregate rating'].value_counts()
print("Distribution of target variable:")
print(target_counts)
```

```
Distribution of target variable:
0.0    2148
3.2     522
3.1     519
3.4     495
3.3     483
3.5     480
3.0     468
3.6     458
3.7     427
3.8     399
2.9     381
3.9     332
2.8     315
4.1     274
4.0     266
2.7     250
4.2     221
2.6     191
4.3     174
4.4     143
2.5     110
4.5      95
2.4      87
4.6      78
4.9      61
2.3      47
4.7      41
2.2      27
4.8      25
2.1      15
2.0       7
1.9       2
1.8       1
Name: Aggregate rating, dtype: int64
```

What did i found from the level 1 (task 1)?

- The Restuarant dataset consists of various restuarants information of different cities. Includes information such as restaurant name, city, address, locality, cuisines, rating and price range, among other things.
- There are 9551 rows and 21 columns provided in the data.
- Null values are only present in cuisines; Since there are only few null values present in cuisines (only 9) i will remove them from the data.
- No duplicate values exist.
- Data type conversion not required.
- Distribution of the target variable ("Aggregate rating") well balanced.

Task 2: Descriptive Analysis

Statistical Measures for Numerical Columns

In [ ]:
```
# Basic statistical measures (mean, median, standard deviation, etc.) for numerical
# Select Numerical Columns
numeric_columns = df.select_dtypes(include=['int', 'float'])

# Calculate basic statistical measures using .describe()
summary_stats = numeric_columns.describe()
print(summary_stats)
```

```
       Restaurant ID  Country Code   Longitude    Latitude  \
count   9.542000e+03   9542.000000 9542.000000 9542.000000
mean    9.043301e+06     18.179208   64.274997   25.848532
std     8.791967e+06     56.451600   41.197602   11.010094
min     5.300000e+01      1.000000 -157.948486  -41.330428
25%     3.019312e+05      1.000000   77.081565   28.478658
50%     6.002726e+06      1.000000   77.192031   28.570444
75%     1.835260e+07      1.000000   77.282043   28.642711
max     1.850065e+07    216.000000  174.832089   55.976980

       Average Cost for two  Price range  Aggregate rating        Votes
count           9542.000000  9542.000000       9542.000000  9542.000000
mean            1200.326137     1.804968          2.665238   156.772060
std            16128.743876     0.905563          1.516588   430.203324
min                0.000000     1.000000          0.000000     0.000000
25%              250.000000     1.000000          2.500000     5.000000
50%              400.000000     2.000000          3.200000    31.000000
75%              700.000000     2.000000          3.700000   130.000000
max           800000.000000     4.000000          4.900000 10934.000000
```

In [ ]:
```
# Individual statistics
# Calculate mean for numerical columns
mean = numeric_columns.mean()
print(f"Mean for numerical columns:\n{mean}")
```

```
Mean for numerical columns:
Restaurant ID           9.043301e+06
Country Code            1.817921e+01
Longitude               6.427500e+01
Latitude                2.584853e+01
Average Cost for two    1.200326e+03
Price range             1.804968e+00
Aggregate rating        2.665238e+00
Votes                   1.567721e+02
dtype: float64
```

In [ ]:
```
# Calculate median for numerical columns
median = numeric_columns.median()
print(f"\nMedian for numerical columns:\n{median}")
```

```
Median for numerical columns:
Restaurant ID           6.002726e+06
Country Code            1.000000e+00
Longitude               7.719203e+01
Latitude                2.857044e+01
Average Cost for two    4.000000e+02
Price range             2.000000e+00
Aggregate rating        3.200000e+00
Votes                   3.100000e+01
dtype: float64
```

In [ ]:
```python
# Calculate standard deviation for numerical columns
std_dev = numeric_columns.std()
print(f"\nStandard deviation for numerical columns:\n{std_dev}")
```

```
Standard deviation for numerical columns:
Restaurant ID           8.791967e+06
Country Code            5.645160e+01
Longitude               4.119760e+01
Latitude                1.101009e+01
Average Cost for two    1.612874e+04
Price range             9.055631e-01
Aggregate rating        1.516588e+00
Votes                   4.302033e+02
dtype: float64
```

Distribution of Categorical Variables

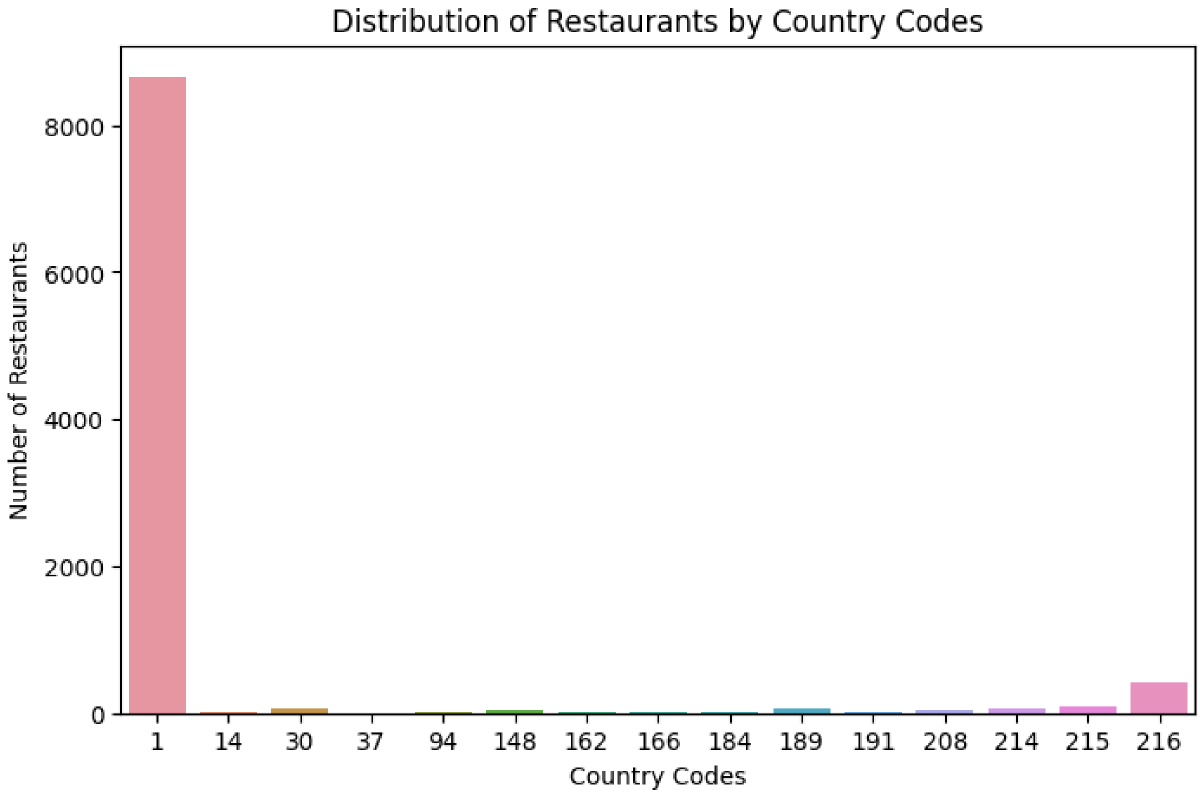
In [ ]:
```python
# Distribution of categorical variables like 'Country Code', 'City', and 'Cuisines'

# Count Plot Visualization Code for Country Codes
# Set plot size
plt.figure(figsize=(8, 5))

# Create the figure object
sns.countplot(x = df['Country Code'])

# Set Labels
plt.xlabel('Country Codes')
plt.ylabel('Number of Restaurants')
plt.title('Distribution of Restaurants by Country Codes')

# Display Chart
plt.show()
```



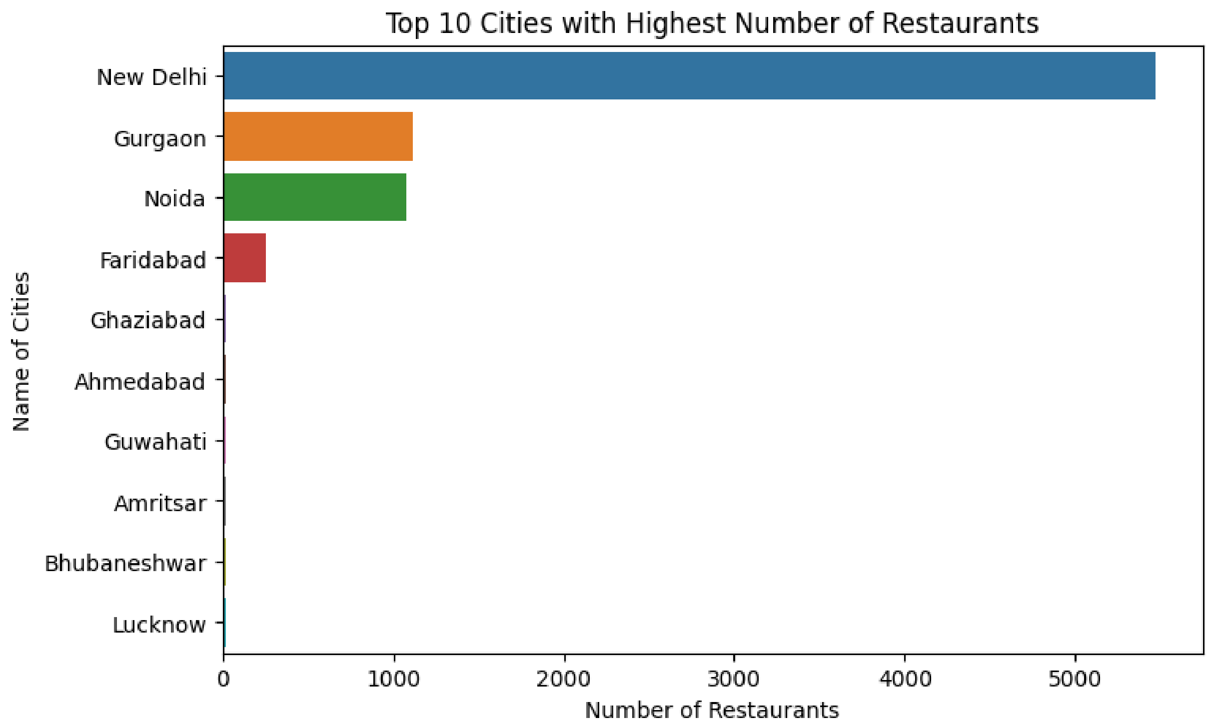
In [ ]:

```
# Count Plot Visualization Code for Cities
# Set plot size
plt.figure(figsize=(8, 5))

# Create the figure object
# There are many cities names present in the data, so i select only the top 10 citi
sns.countplot(y = df['City'], order=df.City.value_counts().iloc[:10].index)

# Set Labels
plt.xlabel('Number of Restaurants')
plt.ylabel('Name of Cities')
plt.title('Top 10 Cities with Highest Number of Restaurants')

# Display Chart
plt.show()
```



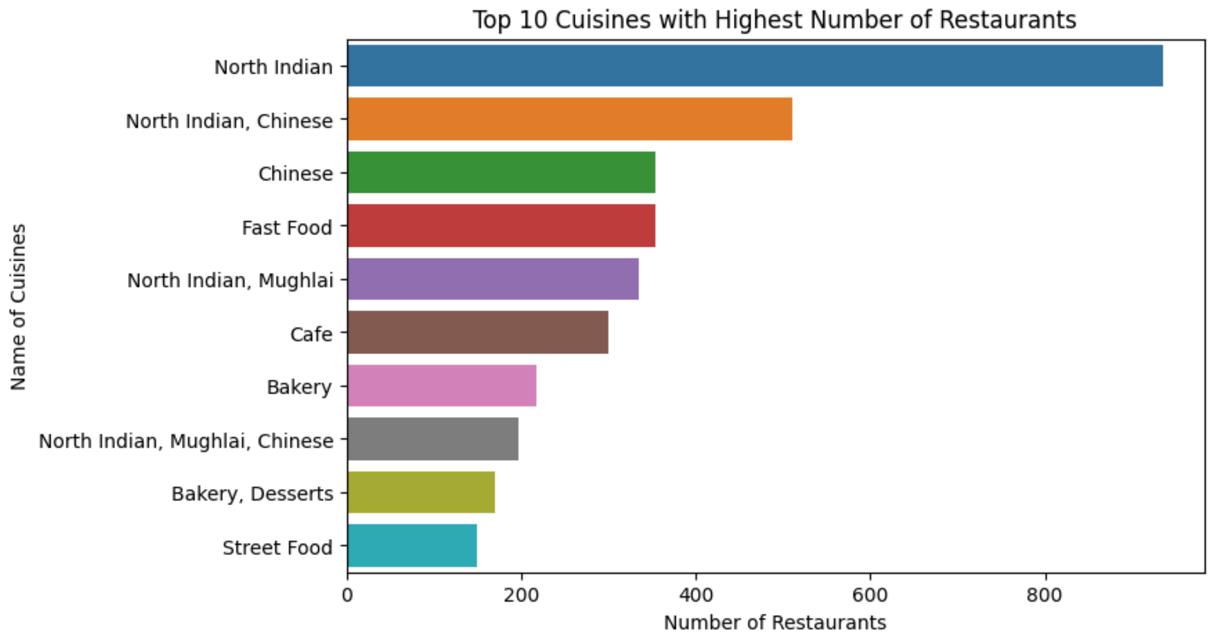
In [ ]:

```python
# Count Plot Visualization Code for Cuisines
# Set plot size
plt.figure(figsize=(8, 5))

# Create the figure object
# There are many cuisine names present in the data, so i select only the top 10 cui
sns.countplot(y = df['Cuisines'], order=df.Cuisines.value_counts().iloc[:10].index)

# Set Labels
plt.xlabel('Number of Restaurants')
plt.ylabel('Name of Cuisines')
plt.title('Top 10 Cuisines with Highest Number of Restaurants')

# Display Chart
plt.show()
```



Top Cuisines and Cities

In [ ]:

```
# Top cuisines and cities with the highest number of restaurants

# Identify the top 10 cuisines
top_cuisines = df['Cuisines'].value_counts().head(10)

# Display the results
print("Top 10 Cuisines with Highest Number of Restaurants:")
print(top_cuisines)
```

```
Top 10 Cuisines with Highest Number of Restaurants:
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: Cuisines, dtype: int64
```

In [ ]:

```
# Identify the top 10 cities
top_cities = df['City'].value_counts().head(10)

# Display the results
print("Top 10 Cities with Highest Number of Restaurants:")
print(top_cities)
```

```
Top 10 Cities with Highest Number of Restaurants:
New Delhi       5473
Gurgaon         1118
Noida           1080
Faridabad        251
Ghaziabad         25
Ahmedabad         21
Guwahati          21
Amritsar          21
Bhubaneshwar      21
Lucknow           21
Name: City, dtype: int64
```

What did i found from the level 1 (task 2)?

- Found the mean, median, mode values and other statistical measures for the numerical columns like 'Restaurant ID', 'Longitude', 'Latitude', 'Price range', etc.
- Country code 1 and 216 are with highest number of restaurants.
- New Delhi, Gurgaon and Noida are in top with highest number of restaurants.
- North Indian and Chinese cuisine are in top with highest number of restaurants.

Task 3: Geospatial Analysis

Visualize Locations of Restaurants

In [ ]:

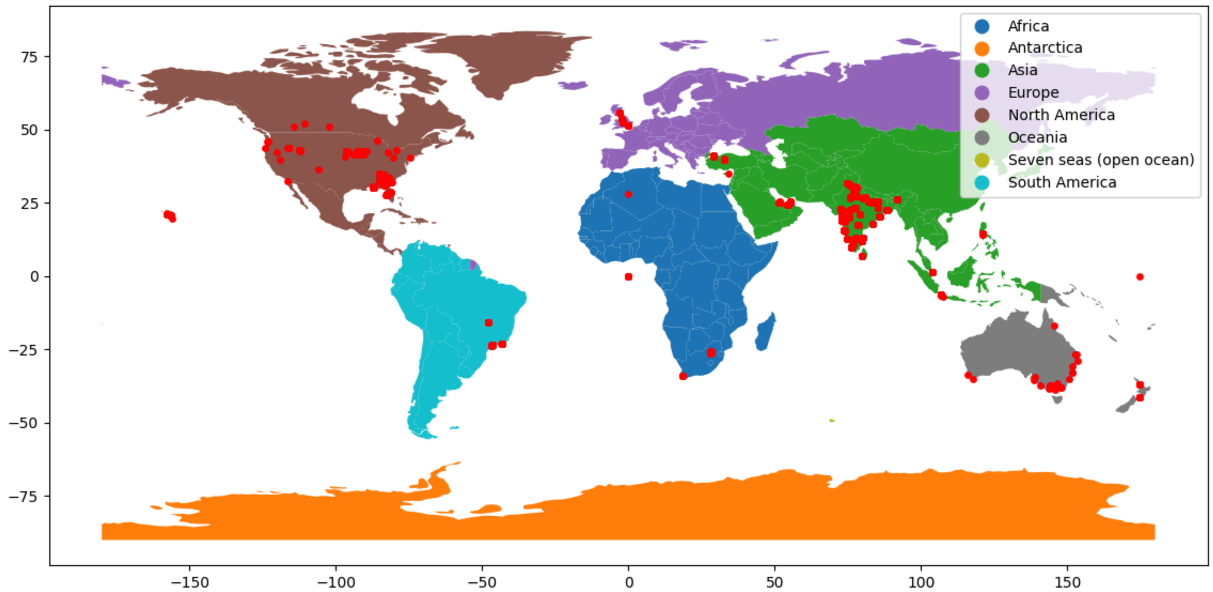
```python
# Locations of restaurants on a map using latitude and longitude information
# Import the necessary libraries
from shapely.geometry import Point
import geopandas as gpd
from geopandas import GeoDataFrame

# Create Point geometry from latitude and longitude using Shapely
gdf = gpd.GeoDataFrame(
    df,
    geometry=gpd.points_from_xy(df.Longitude, df.Latitude)
)

# Create a base map of the world using Geopandas
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))

# Create a map that fits the screen and plots the restaurant locations
# The "continent" column is used for coloring and a legend is displayed
gdf.plot(ax=world.plot("continent", legend = True, figsize=(14, 12)), marker='o', c

# Show the map
plt.show()
```



Distribution of Restaurants by City

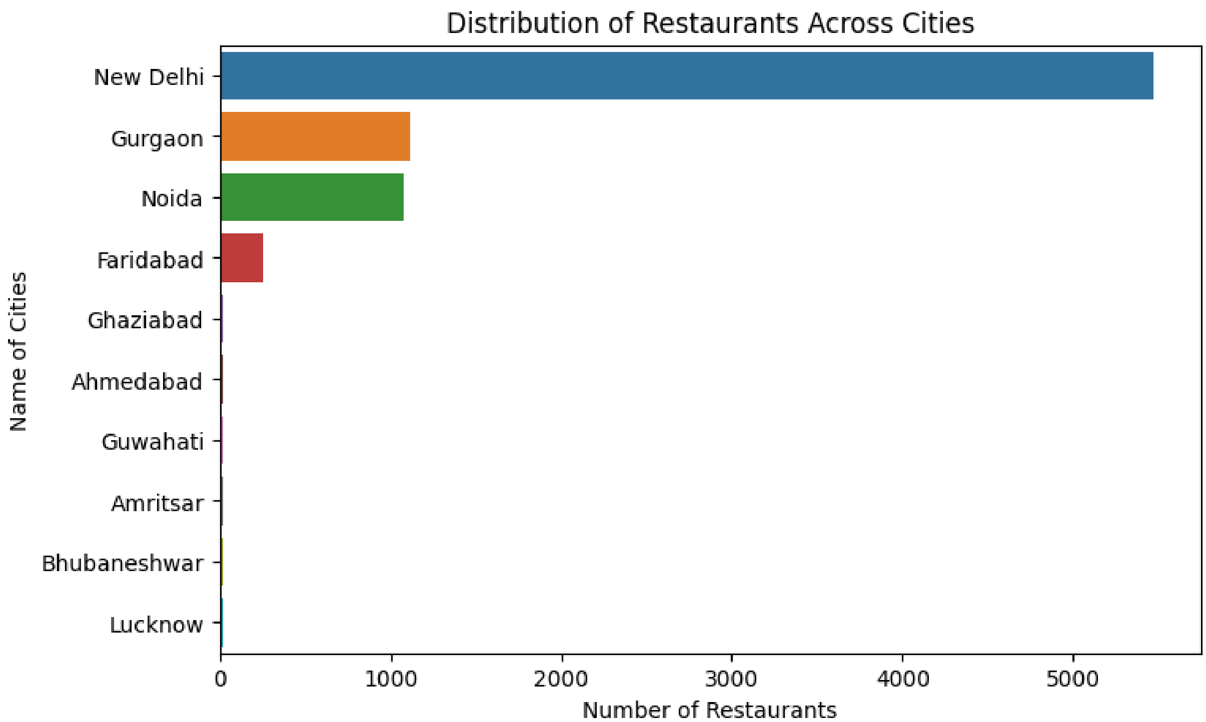
In [ ]:

```
# Distribution of restaurants across different cities or countries
# Set plot size
plt.figure(figsize=(8, 5))

# Create the figure object
# There are many cities names present in the data, so i select only the top 10 citi
sns.countplot(y = df['City'], order=df.City.value_counts().iloc[:10].index)

# Set Labels
plt.xlabel('Number of Restaurants')
plt.ylabel('Name of Cities')
plt.title('Distribution of Restaurants Across Cities')

# Display Chart
plt.show()
```



Correlation Between the Restaurant's Location and its Rating

In [ ]:

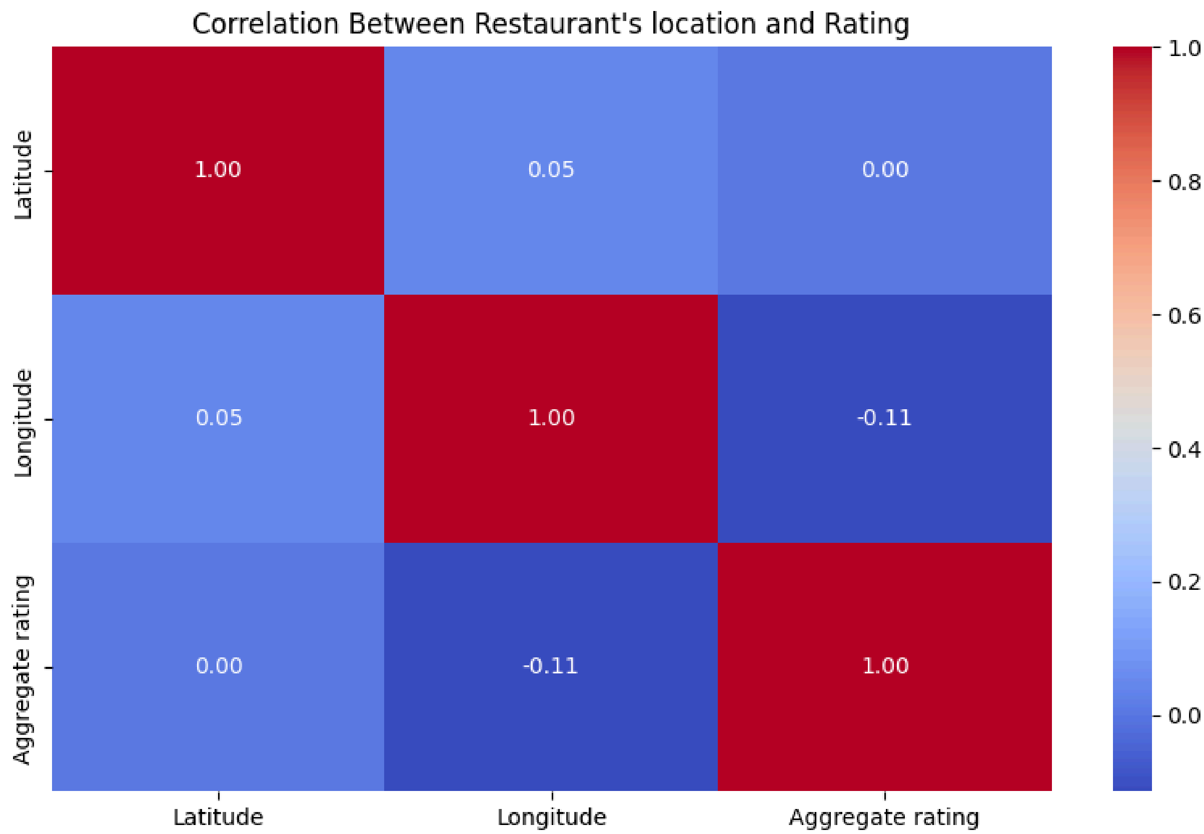
```
# Checking correlation between the restaurant's location and its rating
# Set plot size
plt.figure(figsize=(10, 6))

# Calculate the correlation between latitude, longitude, and ratings
correlation_matrix = df[['Latitude', 'Longitude', 'Aggregate rating']].corr()

# Create a heatmap to visualize the correlation
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")

# Set Title
plt.title("Correlation Between Restaurant's location and Rating")

# Display Chart
plt.show()
```



What did i found from the level 1 (task 3)?

- North America and Asia(mainly India) have the most number of restaurants. Followed by Oceania and others.
- New Delhi have the most number of restaurants. Followed by Gurgaon, Noida and Faridabad.
- There is no correlation between Latitude and Rating. But, Longitude and Rating are negatively correlated.

Conclusion

The insights which i found from the overall level 1 project:

Data Overview:

- The dataset includes restaurant details across various cities with 9,551 rows and 21 columns.
- Minimal null values (9) were found only in the 'Cuisines' column.
- No duplicates exist, and data type conversion wasn't needed.
- The 'Aggregate rating' distribution is well-balanced.

Descriptive Insights:

- Key statistical measures for numerical columns were identified.
- Country codes 1 and 216 have the most restaurants.
- New Delhi, Gurgaon, and Noida are top cities with the highest restaurant counts.
- North Indian and Chinese cuisines are most popular.

Geospatial Analysis:

- North America and Asia (mainly India) have the most number of restaurants.
- New Delhi leads in the number of restaurants, followed by Gurgaon, Noida, and Faridabad.
- Latitude and rating show no correlation, while longitude and rating are negatively correlated.

These insights offer a comprehensive analysis of the restaurant dataset reveals key data characteristics, descriptive insights, and geospatial patterns, informs further analysis.