

ml-project1

August 21, 2024

importing the dependencies

```
[ ]: !pip install nltk
```

```
Requirement already satisfied: nltk in /usr/local/lib/python3.10/dist-packages (3.8.1)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from nltk) (8.1.7)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/dist-packages (from nltk) (1.4.2)
Requirement already satisfied: regex<=2021.8.3 in /usr/local/lib/python3.10/dist-packages (from nltk) (2024.5.15)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from nltk) (4.66.4)
```

```
[ ]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import accuracy_score
```

#Data Preprocessing and Exploration

```
[ ]: #importing the dataset
df=pd.read_csv('/content/drive/MyDrive/Cognifyz/Dataset 2.csv')
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 ...	Currency	Has Table booking \
0	French, Japanese, Desserts ...	Botswana Pula(P)	Yes
1	Japanese ...	Botswana Pula(P)	Yes
2	Seafood, Asian, Filipino, Indian ...	Botswana Pula(P)	Yes
3	Japanese, Sushi ...	Botswana Pula(P)	No
4	Japanese, Korean ...	Botswana Pula(P)	Yes

	Has Online delivery	Is delivering now	Switch to order menu	Price range \
0	No	No	No	3
1	No	No	No	3
2	No	No	No	4
3	No	No	No	4
4	No	No	No	4

	Aggregate rating	Rating color	Rating text	Votes
0	4.8	Dark Green	Excellent	314
1	4.5	Dark Green	Excellent	591
2	4.4	Green	Very Good	270
3	4.9	Dark Green	Excellent	365
4	4.8	Dark Green	Excellent	229

[5 rows x 21 columns]

```
[1]: from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

Checking for the number of rows and columns and also for the presence of null values and dropping them and re-evaluating the number of rows and columns

```
[ ]: #checking for null values and rows and columns
df.describe()
print('num_rows, num_columns= ',df.shape)
df.isnull().sum()
```

```
num_rows, num_columns= (9551, 21)
```

```
[ ]: 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
```

```
[ ]: drop=df.dropna()
print('num_rows, num_columns= ',drop.shape)
```

```
num_rows, num_columns= (9542, 21)
```

Descriptive Analysis

```
[ ]: #Measures of central tendency and dispersion among numerical columns
df.cleaned=df.drop(columns=['Latitude','Longitude','Restaurant ID','Country_
↳Code'])
```

```
df.cleaned.describe()
```

<ipython-input-132-b5746366f825>:2: UserWarning:

Pandas doesn't allow columns to be created via a new attribute name - see <https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access>

```
[ ]:      Average Cost for two  Price range  Aggregate rating      Votes
count      9551.000000    9551.000000    9551.000000    9551.000000
mean       1199.210763      1.804837      2.666370     156.909748
std        16121.183073      0.905609      1.516378     430.169145
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     131.000000
max        800000.000000      4.000000      4.900000    10934.000000
```

Distribution of Categorical Variables

```
[ ]: country_distribution=df['Country Code'].value_counts()
print(country_distribution)
country_distribution=df['Country Code'].value_counts().head(3)
print('top 3 Country Codes with highest number of restaurants:␣
↵',country_distribution)
```

Country Code

1 8652

216 434

215 80

30 60

214 60

189 60

148 40

208 34

14 24

162 22

94 21

184 20

166 20

191 20

37 4

Name: count, dtype: int64

top 3 Country Codes with highest number of restaurants: Country Code

1 8652

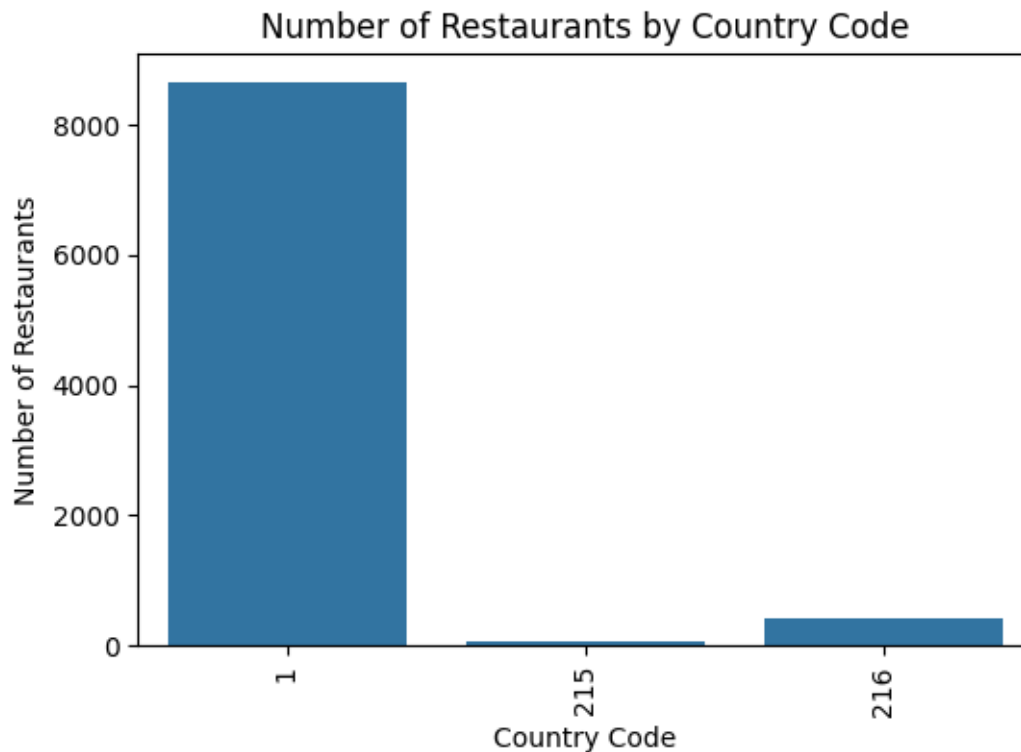
216 434

215 80

Name: count, dtype: int64

```
[ ]: plt.figure(figsize=(6, 4))
sns.barplot(x=country_distribution.index, y=country_distribution.values)
plt.xlabel('Country Code')
plt.ylabel('Number of Restaurants')
plt.title('Number of Restaurants by Country Code')
plt.xticks(rotation=90)
```

```
[ ]: ([0, 1, 2], [Text(0, 0, '1'), Text(1, 0, '215'), Text(2, 0, '216')])
```



```
[ ]: City_Count= df['City'].value_counts()
print('Count_of_Cities', City_Count)
City_Count=df['City'].value_counts().head(3)
print('Top 3 Cities with highest number of restaurants: ',City_Count)
```

```
Count_of_Cities City
New Delhi          5473
Gurgaon            1118
Noida              1080
Faridabad           251
Ghaziabad           25
...
Panchkula           1
Mc Millan           1
```

```

Mayfield          1
Macedon           1
Vineland Station  1
Name: count, Length: 141, dtype: int64
Top 3 Cities with highest number of restaurants: City
New Delhi        5473
Gurgaon          1118
Noida            1080
Name: count, dtype: int64

```

```

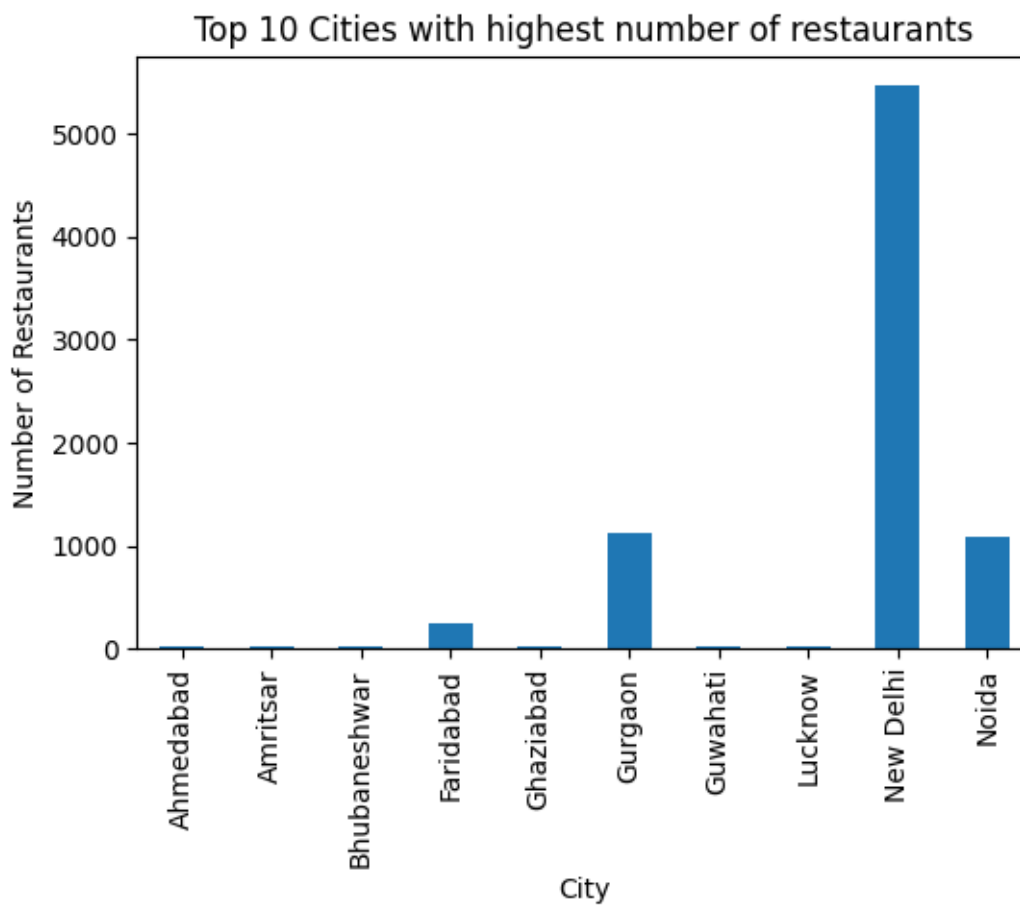
[ ]: City_Count=df['City'].value_counts().head(10).sort_index().
      plot(kind='bar',title='Top 10 Cities with highest number of restaurants',
      figsize=(6,4))
plt.xlabel('City')
plt.ylabel('Number of Restaurants')

```

```

[ ]: Text(0, 0.5, 'Number of Restaurants')

```

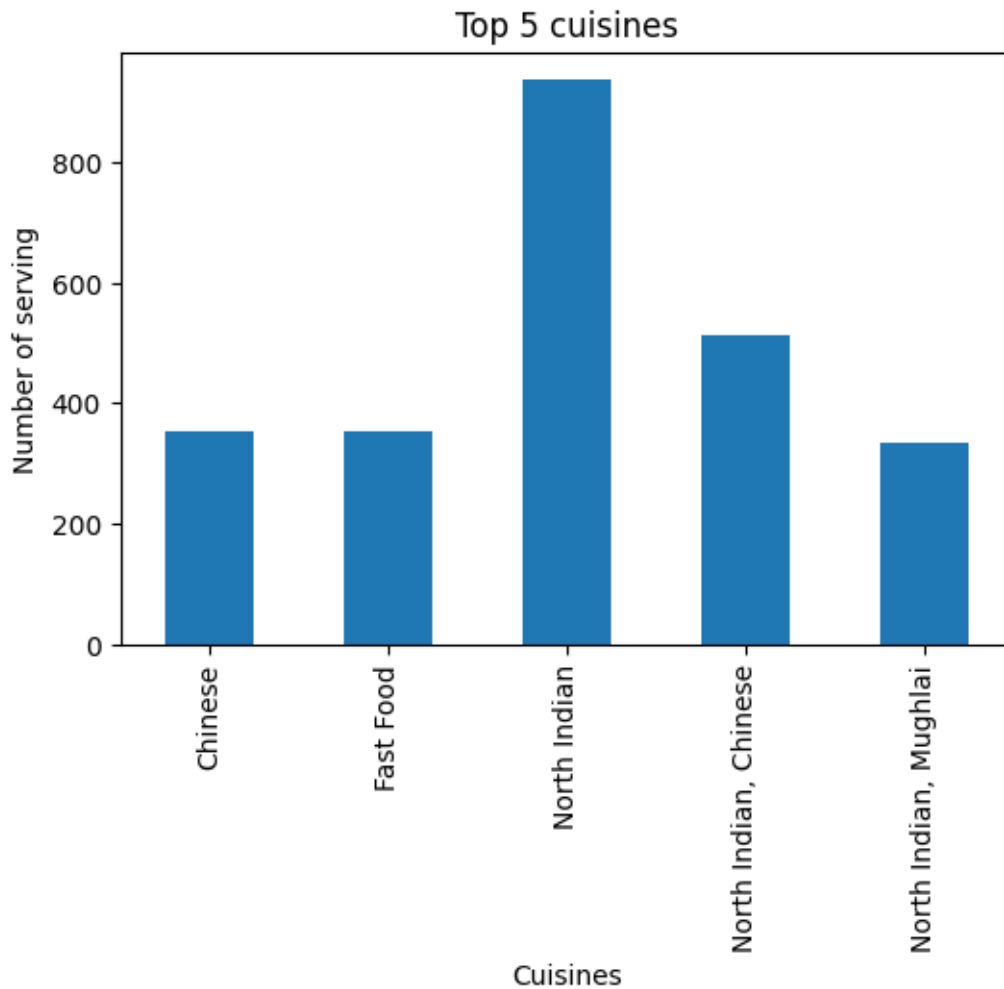


```
[ ]: Cuisines=df['Cuisines'].value_counts()
print(Cuisines)
Cuisines=df['Cuisines'].value_counts().head(5)
print('Top 5 Cuisines that they serve: ',Cuisines)
```

```
Cuisines
North Indian          936
North Indian, Chinese 511
Chinese               354
Fast Food             354
North Indian, Mughlai 334
...
Bengali, Fast Food    1
North Indian, Rajasthani, Asian 1
Chinese, Thai, Malaysian, Indonesian 1
Bakery, Desserts, North Indian, Bengali, South Indian 1
Italian, World Cuisine 1
Name: count, Length: 1825, dtype: int64
Top 5 Cuisines that they serve:  Cuisines
North Indian          936
North Indian, Chinese 511
Chinese               354
Fast Food             354
North Indian, Mughlai 334
Name: count, dtype: int64
```

```
[ ]: Cuisines=df['Cuisines'].value_counts().head(5).sort_index().
      plot(kind='bar',title='Top 5 cuisines', figsize=(6,4))
plt.xlabel('Cuisines')
plt.ylabel('Number of serving')
```

```
[ ]: Text(0, 0.5, 'Number of serving')
```



```
[ ]: df['Rating color'].value_counts()
```

```
[ ]: Rating color
      Orange      3737
      White      2148
      Yellow      2100
      Green       1079
      Dark Green    301
      Red          186
      Name: count, dtype: int64
```

```
[ ]: Rating_Avg=df.groupby('Rating color')['Aggregate rating'].mean()
      print(Rating_Avg)
      Rating_Avg=Rating_Avg.sort_index()
      color_map = {
          'Red': 'red',
```



```

    'Green': 'green',
    'Blue': 'blue',
    'Yellow': 'yellow',
    'Orange': 'orange',
    'White': 'white',
    'Dark Green': 'darkgreen'
}

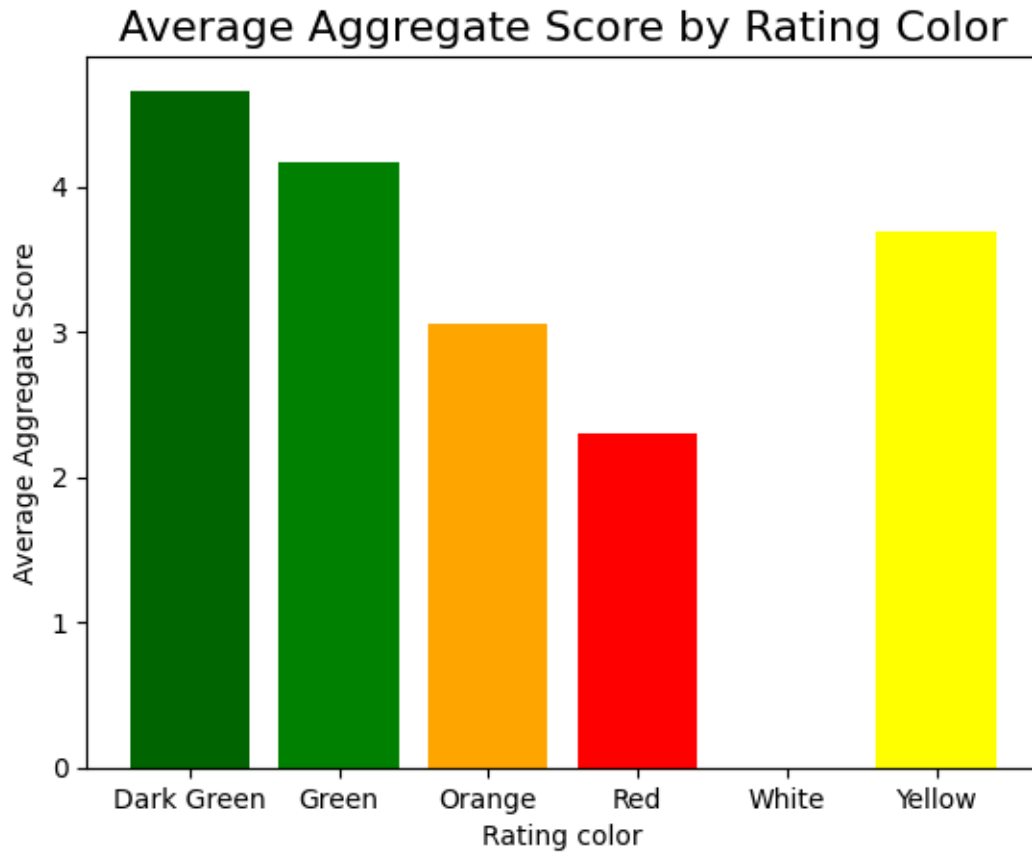
plt.xlabel('Rating color', fontsize=10)
plt.ylabel('Average Aggregate Score', fontsize=10)
plt.title('Average Aggregate Score by Rating Color', fontsize=16)
plt.bar(Rating_Avg.index, Rating_Avg.values, color=[color_map[color] for color_
    ↪in Rating_Avg.index])
plt.show()

```

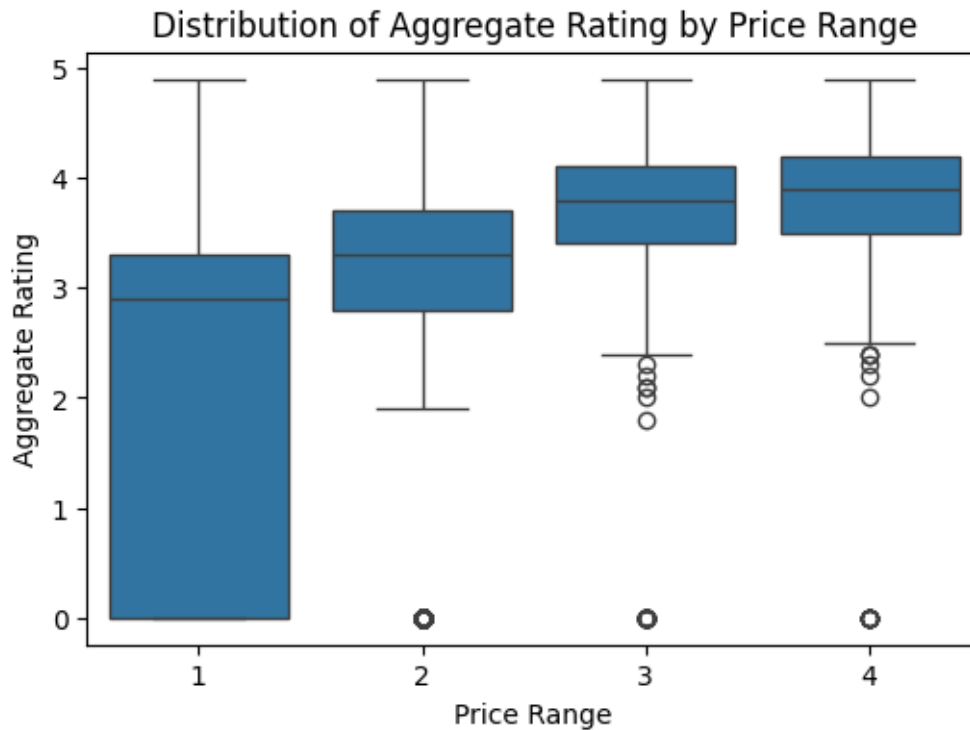
```

Rating color
Dark Green    4.659801
Green         4.168119
Orange        3.051619
Red           2.297849
White         0.000000
Yellow        3.683429
Name: Aggregate rating, dtype: float64

```



```
[ ]: # Visualize the distribution of 'Aggregate rating' for different 'Price range' categories
plt.figure(figsize=(6, 4))
sns.boxplot(x='Price range', y='Aggregate rating', data=df)
plt.title('Distribution of Aggregate Rating by Price Range')
plt.xlabel('Price Range')
plt.ylabel('Aggregate Rating')
plt.show()
```



```
[ ]: # Calculating the correlation coefficient
correlation = df['Votes'].corr(df['Aggregate rating'])

print("Correlation between Votes and Aggregate rating:", correlation)

# Creating a scatter plot to visualize the relationship
fig=px.scatter(df,y='Votes', x='Aggregate rating', trendline='ols')
fig.update_layout(title='Correlation between Votes and Aggregate Rating',
                  width=800, height=600)
fig.update_yaxes(title_text='Number of Votes')
fig.update_xaxes(title_text='Aggregate Rating')
fig.show()
```

Correlation between Votes and Aggregate rating: 0.31369058419541157

```
[ ]: import plotly.express as px
fig=px.scatter_mapbox(
    df,
    lat="Latitude",
    lon="Longitude",
    hover_name="Restaurant Name",
    hover_data=["City", "Country Code", "Aggregate rating"],
    color="Aggregate rating",
```

```

        zoom=3,
        height=400,
        width=800
    )

fig.update_layout(mapbox_style="open-street-map")
fig.update_layout(margin={"r":0,"t":0,"l":0,"b":0})
fig.show()

```

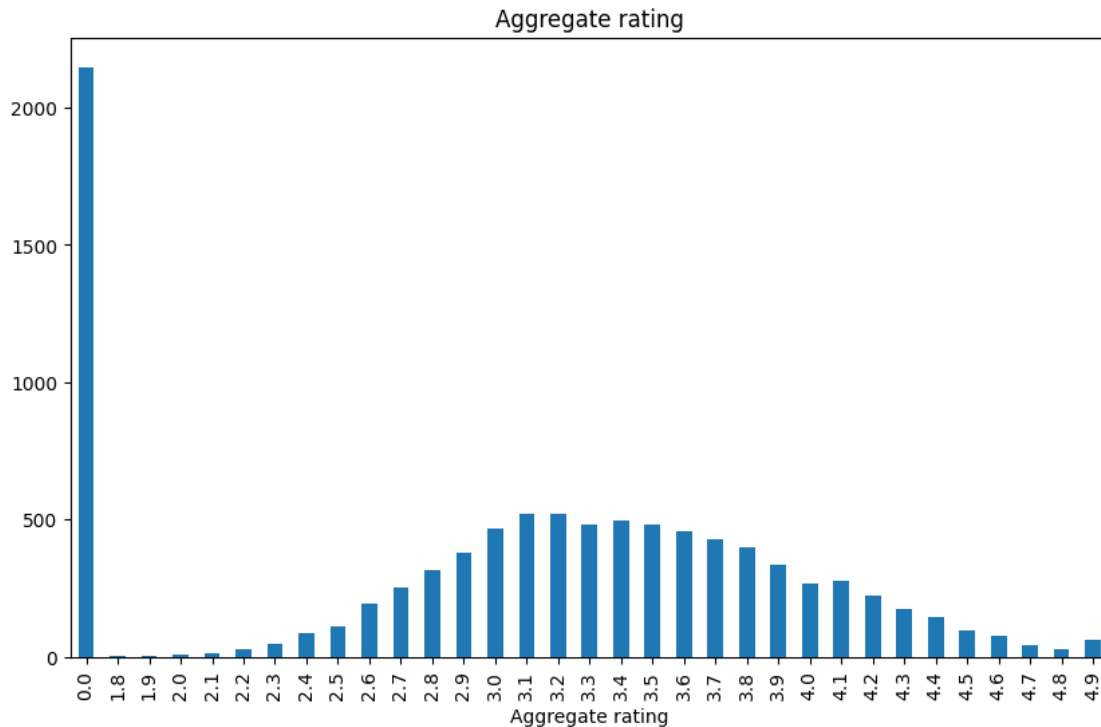
#Sentiment Analysis

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

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

```
[ ]: ax=df['Aggregate rating'].value_counts().sort_index().
      plot(kind='bar',title='Aggregate rating', figsize=(10,6))
plt.xlabel('Aggregate rating')
```

```
[ ]: Text(0.5, 0, 'Aggregate rating')
```



Aggregate Ratings form somewhat of a bell shaped distribution with aratings typically clustering around the range of 3-4

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

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

```
[ ]: ax=df['Rating text'].value_counts().sort_index().plot(kind='bar',title='Rating_
      ↳text      ', figsize=(6,4))
      plt.xlabel('Rating text')
      plt.ylabel('Number of restaurants')
```

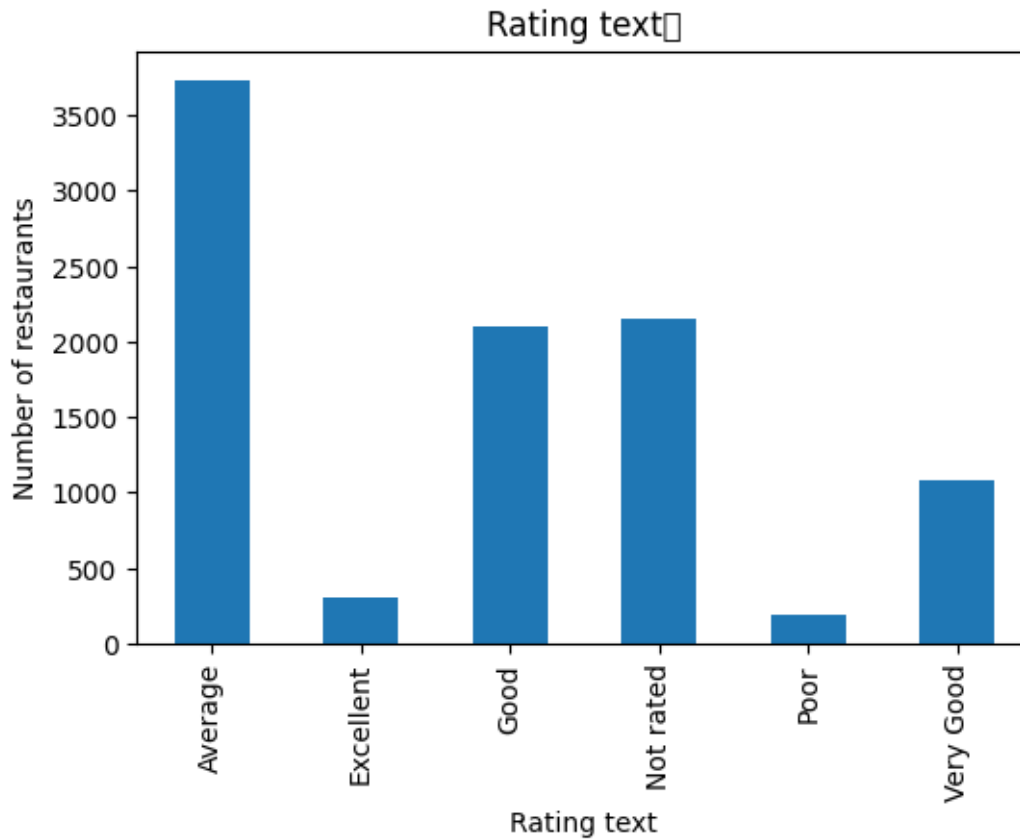
```
[ ]: Text(0, 0.5, 'Number of restaurants')
```

/usr/local/lib/python3.10/dist-packages/IPython/core/events.py:89: UserWarning:

Glyph 9 () missing from current font.

/usr/local/lib/python3.10/dist-packages/IPython/core/pylabtools.py:151:
UserWarning:

Glyph 9 () missing from current font.



```
[ ]: import nltk
      nltk.download('vader_lexicon')
      from nltk.sentiment import SentimentIntensityAnalyzer
      from tqdm.notebook import tqdm
      sia=SentimentIntensityAnalyzer()
```

[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data] Package vader_lexicon is already up-to-date!

```
[ ]: sia.polarity_scores('Excellent')
```

```
[ ]: {'neg': 0.0, 'neu': 0.0, 'pos': 1.0, 'compound': 0.5719}
```

```
[ ]: sia.polarity_scores('Not Rated')
```

```
[ ]: {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

```
[ ]: outcome={}
for i, row in tqdm(df.iterrows(),total=len(df)):
    text=row['Rating text']
    Id=row['Restaurant ID']
    outcome[Id]=sia.polarity_scores(text)
```

```
0%|          | 0/9551 [00:00<?, ?it/s]
```

```
[ ]: Sentiment_Analysis_df=pd.DataFrame(outcome).T
Sentiment_Analysis_df=Sentiment_Analysis_df.reset_index().
    ↪rename(columns={'index':'Restaurant ID'})
Sentiment_Analysis_df=Sentiment_Analysis_df.merge(df,how='left')
```

```
[ ]: Sentiment_Analysis_df.head()
```

```
[ ]: Restaurant ID  neg    neu    pos  compound      Restaurant Name \
0      6317637  0.0  0.000  1.000    0.5719      Le Petit Souffle
1      6304287  0.0  0.000  1.000    0.5719      Izakaya Kikufuji
2      6300002  0.0  0.238  0.762    0.4927  Heat - Edsa Shangri-La
3      6318506  0.0  0.000  1.000    0.5719              Ooma
4      6314302  0.0  0.000  1.000    0.5719      Sambo Kojin
```

```
Country Code      City \
0      162      Makati City
1      162      Makati City
2      162  Mandaluyong City
3      162  Mandaluyong City
4      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 ...      Currency \
0  Century City Mall, Poblacion, Makati City ...  Botswana Pula(P)
1  Little Tokyo, Legaspi Village, Makati City ...  Botswana Pula(P)
2  Edsa Shangri-La, Ortigas, Mandaluyong City ...  Botswana Pula(P)
3  SM Megamall, Ortigas, Mandaluyong City ...  Botswana Pula(P)
4  SM Megamall, Ortigas, Mandaluyong City ...  Botswana Pula(P)
```

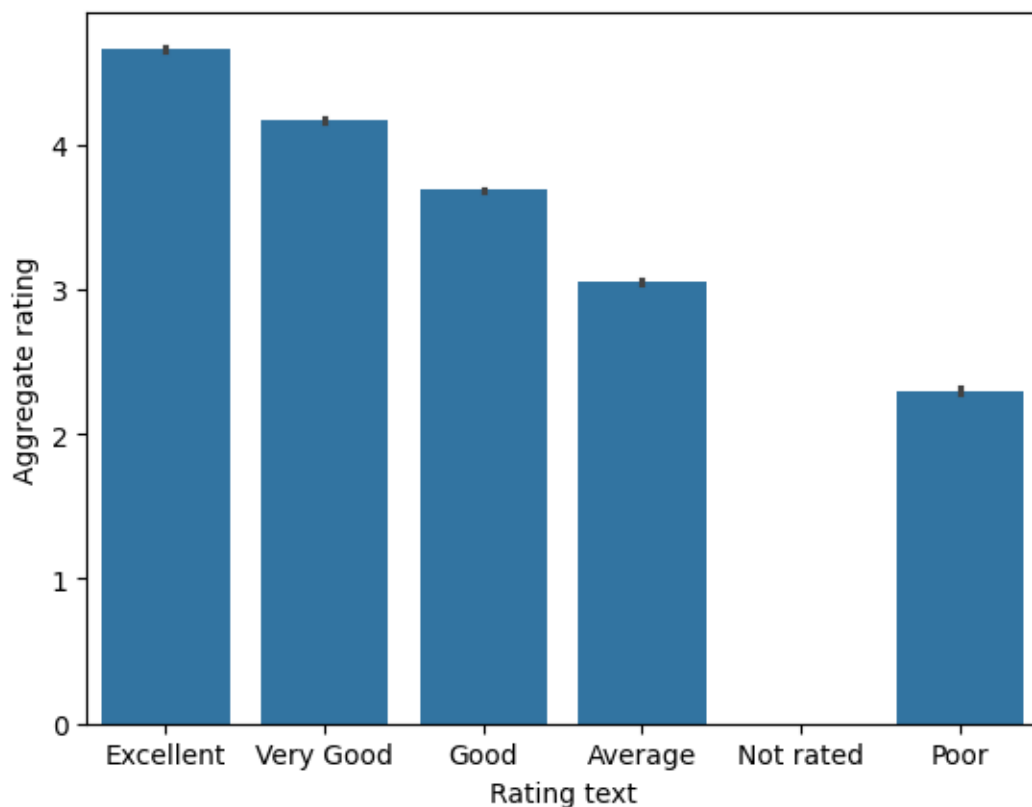
	Has Table booking	Has Online delivery	Is delivering now	\
0	Yes	No	No	
1	Yes	No	No	
2	Yes	No	No	
3	No	No	No	
4	Yes	No	No	

	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text	\
0	No	3	4.8	Dark Green	Excellent	
1	No	3	4.5	Dark Green	Excellent	
2	No	4	4.4	Green	Very Good	
3	No	4	4.9	Dark Green	Excellent	
4	No	4	4.8	Dark Green	Excellent	

	Votes
0	314
1	591
2	270
3	365
4	229

[5 rows x 25 columns]

```
[ ]: px=sns.barplot(data=Sentiment_Analysis_df,x='Rating text',y='Aggregate rating')
```

The reviews with most positive texts are associated with the highest ratings and hence satisfies the virtues of sentiment analysis

```
[ ]: 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	...	Currency	Has Table booking	\
0	French, Japanese, Desserts	...	Botswana Pula(P)	Yes	
1	Japanese	...	Botswana Pula(P)	Yes	
2	Seafood, Asian, Filipino, Indian	...	Botswana Pula(P)	Yes	
3	Japanese, Sushi	...	Botswana Pula(P)	No	
4	Japanese, Korean	...	Botswana Pula(P)	Yes	

	Has Online delivery	Is delivering now	Switch to order menu	Price range	\
0	No	No	No	3	
1	No	No	No	3	
2	No	No	No	4	
3	No	No	No	4	
4	No	No	No	4	

	Aggregate rating	Rating color	Rating text	Votes
0	4.8	Dark Green	Excellent	314
1	4.5	Dark Green	Excellent	591
2	4.4	Green	Very Good	270
3	4.9	Dark Green	Excellent	365
4	4.8	Dark Green	Excellent	229

[5 rows x 21 columns]

```

[ ]: from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from collections import Counter
import re
import nltk
nltk.download('stopwords')
nltk.download('punkt')

```

```

[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data] Package punkt is already up-to-date!

```

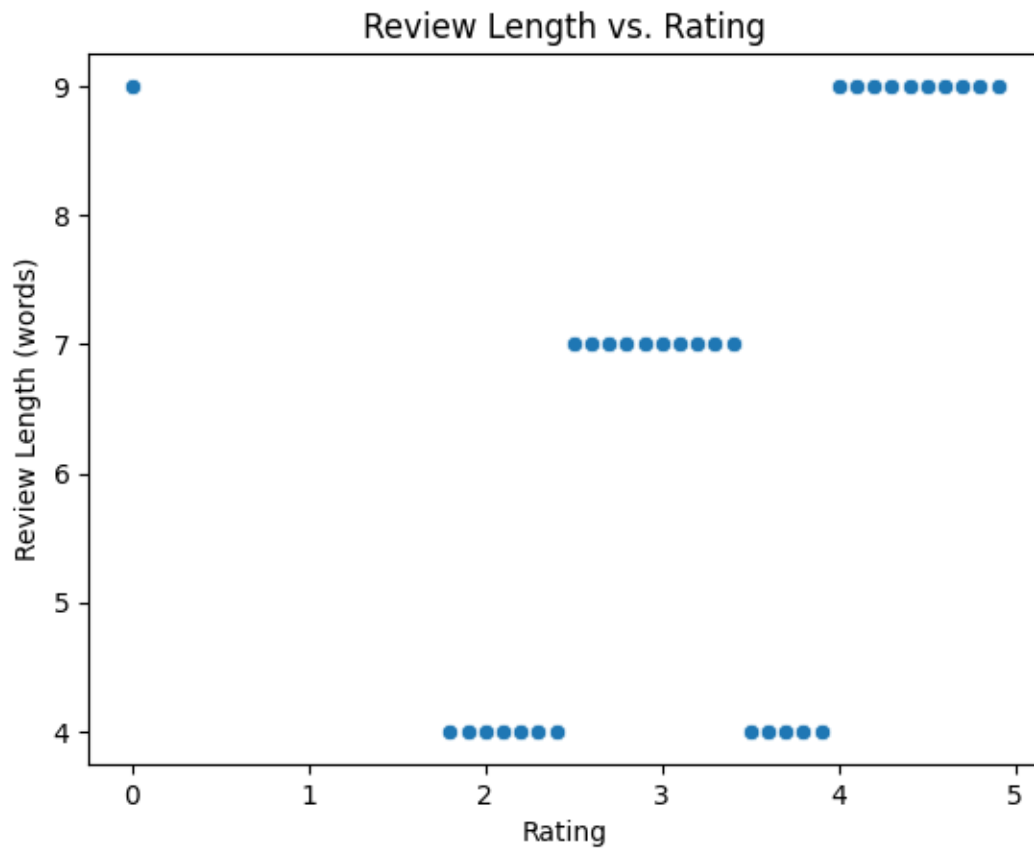
```
[ ]: True
```

```
[ ]: df['rating_length'] = df['Rating text'].apply(len)
```

```
[ ]: average_length = df['rating_length'].mean()
      print(f"Average review length: {average_length:.2f} words")
      correlation = df['Aggregate rating'].corr(df['rating_length'])
      correlation_coefficient=np.corrcoef(df['Aggregate rating'],
      ↪df['rating_length'])[0, 1]
      print(f"Correlation coefficient: {correlation_coefficient:.2f}")
```

Average review length: 7.02 words
Correlation coefficient: -0.48

```
[ ]: sns.scatterplot(data=df, x='Aggregate rating', y='rating_length')
      plt.xlabel('Rating')
      plt.ylabel('Review Length (words)')
      plt.title('Review Length vs. Rating')
      plt.show()
```



Hence there exists a significant negative correlation between review length and the reviews the restaurant receives

#Model Training

```
[ ]:
```

```
[ ]: #feature selection
df.cleaned=df.drop(columns=['Latitude','Longitude','Restaurant ID','Country_
↳Code','Address','Locality','Locality Verbose','Switch to order_
↳menu','Restaurant Name'])
df.cleaned.head()
```

```
[ ]:
```

	City	Cuisines	Average Cost for two \
0	Makati City	French, Japanese, Desserts	1100
1	Makati City	Japanese	1200
2	Mandaluyong City	Seafood, Asian, Filipino, Indian	4000
3	Mandaluyong City	Japanese, Sushi	1500
4	Mandaluyong City	Japanese, Korean	1500

	Currency	Has Table booking	Has Online delivery	Is delivering now \
0	Botswana Pula(P)	Yes	No	No
1	Botswana Pula(P)	Yes	No	No
2	Botswana Pula(P)	Yes	No	No
3	Botswana Pula(P)	No	No	No
4	Botswana Pula(P)	Yes	No	No

	Price range	Aggregate rating	Rating color	Rating text	Votes \
0	3	4.8	Dark Green	Excellent	314
1	3	4.5	Dark Green	Excellent	591
2	4	4.4	Green	Very Good	270
3	4	4.9	Dark Green	Excellent	365
4	4	4.8	Dark Green	Excellent	229

	rating_length
0	9
1	9
2	9
3	9
4	9

```
[ ]: #creating dummies for categorical variables
dummies=pd.get_dummies(df.cleaned,columns=['Cuisines','City','Has Table_
↳booking','Has Online delivery','Is delivering now','Rating color','Rating_
↳text','Price range'])
dummies.head()
```

```

[ ]: Average Cost for two      Currency Aggregate rating Votes \
0      1100 Botswana Pula(P)      4.8      314
1      1200 Botswana Pula(P)      4.5      591
2      4000 Botswana Pula(P)      4.4      270
3      1500 Botswana Pula(P)      4.9      365
4      1500 Botswana Pula(P)      4.8      229

rating_length Cuisines_Afghani Cuisines_Afghani, Mughlai, Chinese \
0      9      False      False
1      9      False      False
2      9      False      False
3      9      False      False
4      9      False      False

Cuisines_Afghani, North Indian \
0      False
1      False
2      False
3      False
4      False

Cuisines_Afghani, North Indian, Pakistani, Arabian Cuisines_African ... \
0      False      False ...
1      False      False ...
2      False      False ...
3      False      False ...
4      False      False ...

Rating text_Average Rating text_Excellent Rating text_Good \
0      False      True      False
1      False      True      False
2      False      False      False
3      False      True      False
4      False      True      False

Rating text_Not rated Rating text_Poor Rating text_Very Good \
0      False      False      False
1      False      False      False
2      False      False      True
3      False      False      False
4      False      False      False

Price range_1 Price range_2 Price range_3 Price range_4
0      False      False      True      False
1      False      False      True      False
2      False      False      False      True
3      False      False      False      True

```

4	False	False	False	True
---	-------	-------	-------	------

[5 rows x 1993 columns]

dropping dummy variables in order to deal with the problem of dummy variable trap

```
[ ]: dummies_drop=dummies.drop(['Currency','Cuisines_Afghani','Rating_
↪text_Average','City_Ankara','Price range_1','Rating color_Yellow'],axis=1)
dummies_drop.head()
```

```
[ ]:
Average Cost for two  Aggregate rating  Votes  rating_length  \
0                1100                4.8    314                9
1                1200                4.5    591                9
2                4000                4.4    270                9
3                1500                4.9    365                9
4                1500                4.8    229                9

Cuisines_Afghani, Mughlai, Chinese  Cuisines_Afghani, North Indian  \
0                                False                                False
1                                False                                False
2                                False                                False
3                                False                                False
4                                False                                False

Cuisines_Afghani, North Indian, Pakistani, Arabian  Cuisines_African  \
0                                False                                False
1                                False                                False
2                                False                                False
3                                False                                False
4                                False                                False

Cuisines_African, Portuguese  Cuisines_American  ...  Rating color_Red  \
0                                False            False  ...            False
1                                False            False  ...            False
2                                False            False  ...            False
3                                False            False  ...            False
4                                False            False  ...            False

Rating color_White  Rating text_Excellent  Rating text_Good  \
0                False                True            False
1                False                True            False
2                False                False           False
3                False                True            False
4                False                True            False

Rating text_Not rated  Rating text_Poor  Rating text_Very Good  \
0                False                False                False
```

1	False	False	False
2	False	False	True
3	False	False	False
4	False	False	False

	Price range_2	Price range_3	Price range_4
0	False	True	False
1	False	True	False
2	False	False	True
3	False	False	True
4	False	False	True

[5 rows x 1987 columns]

Dropping Dummies to solve the problem of Dummy Variable Trap

```
[ ]: #splitting the model into training and test data
model=LinearRegression()
X=dummies_drop.drop(columns=['Aggregate rating'])
Y=dummies_drop['Aggregate rating']
```

```
[ ]: X.head()
```

```
[ ]:
Average Cost for two  Votes  rating_length \
0                1100    314                9
1                1200    591                9
2                4000    270                9
3                1500    365                9
4                1500    229                9
```

	Cuisines_Afghani, Mughlai, Chinese	Cuisines_Afghani, North Indian	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Cuisines_Afghani, North Indian, Pakistani, Arabian	Cuisines_African	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Cuisines_African, Portuguese	Cuisines_American	\
0	False	False	
1	False	False	

2	False	False
3	False	False
4	False	False

	Cuisines_American, Asian, Burger ...	Rating color_Red \
0	False ...	False
1	False ...	False
2	False ...	False
3	False ...	False
4	False ...	False

	Rating color_White	Rating text_Excellent	Rating text_Good \
0	False	True	False
1	False	True	False
2	False	False	False
3	False	True	False
4	False	True	False

	Rating text_Not rated	Rating text_Poor	Rating text_Very Good \
0	False	False	False
1	False	False	False
2	False	False	True
3	False	False	False
4	False	False	False

	Price range_2	Price range_3	Price range_4
0	False	True	False
1	False	True	False
2	False	False	True
3	False	False	True
4	False	False	True

[5 rows x 1986 columns]

```
[ ]: Y.head()
```

```
[ ]: 0    4.8
      1    4.5
      2    4.4
      3    4.9
      4    4.8
      Name: Aggregate rating, dtype: float64
```

```
[ ]: #Dropping the values which have very low frequency in order to perform
      ↳stratified sampling i.e ensuring that our sample is split into homogenous
      ↳group
      class_counts = Y.value_counts()
```



```
print(class_counts)
classes_to_keep = class_counts[class_counts > 7].index
df_filtered= dummies_drop[dummies_drop['Aggregate rating'].
↳isin(classes_to_keep)]
```

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

```
[ ]: model=LinearRegression()
X_filtered=df_filtered.drop(columns=['Aggregate rating'])
Y_filtered=df_filtered['Aggregate rating']
```

```
[ ]: X_train, X_test, Y_train, Y_test = train_test_split(X_filtered,Y_filtered,
↳test_size=0.2, stratify=Y_filtered, random_state=3)
```

```
[ ]: models=[LinearRegression(),DecisionTreeRegressor(),RandomForestRegressor()]
def compare_models_train_test():
    for model in models:
        model.fit(X_train,Y_train)
        test_data_prediction=model.predict(X_test)
        r2=r2_score(Y_test,test_data_prediction)
        print('r2 score of the ',model,' = ',r2)
```

```
[ ]: compare_models_train_test()
```

```
r2 score of the LinearRegression() = 0.9856632694820852
r2 score of the DecisionTreeRegressor() = 0.9763927518471383
r2 score of the RandomForestRegressor() = 0.9860800631110995
```

From the R2 score it can be said that all the models perform significantly well for prediction however the r2 score depends on the values of random state and hence no conclusive result can be made

#K Fold Cross Validation

```
[ ]: cv_lnr=cross_val_score(LinearRegression(),X_filtered,Y_filtered,scoring='r2',
    ↪cv=5)
```

```
[ ]: print(cv_lnr)
mean_r2=sum(cv_lnr)/len(cv_lnr)
mean_r2=round(mean_r2,2)
mean_r2=mean_r2*100
print('mean r2 score: ',mean_r2)
```

```
[-2.01140081e+12  9.81740668e-01  9.84619068e-01 -1.06623296e+09
 -2.32970366e+13]
mean r2 score: -506190072703361.06
```

```
[ ]: cv_dec_tree=cross_val_score(DecisionTreeRegressor(),X_filtered,Y_filtered,scoring='r2',
    ↪cv=5)
```

```
[ ]: print(cv_dec_tree)
print(cv_dec_tree)
mean_r2=sum(cv_dec_tree)/len(cv_dec_tree)
mean_r2=round(mean_r2,2)
mean_r2=mean_r2*100
print('mean r2 score: ',mean_r2)
```

```
[0.97155321 0.97003268 0.97588078 0.97495803 0.978779 ]
[0.97155321 0.97003268 0.97588078 0.97495803 0.978779 ]
mean r2 score: 97.0
```

```
[ ]: cv_random_forest=cross_val_score(RandomForestRegressor(),X_filtered,Y_filtered,scoring='r2',
    ↪cv=5)
print(cv_random_forest)
```

```
[0.9826951  0.98335811 0.98546034 0.98555582 0.9863826 ]
```

```
[ ]: mean_r2=sum(cv_random_forest)/len(cv_random_forest)
mean_r2=round(mean_r2,2)
mean_r2=mean_r2*100
print('mean r2 score: ',mean_r2)
```

```
mean r2 score:  98.0
```

The Random Forrest Regression model is found to be performing the best out of all with it predicting 98% of the variation of data

```
[ ]: rfr=RandomForestRegressor(random_state=10)
rfr.fit(X_train,Y_train)
```

```
[ ]: RandomForestRegressor(random_state=10)
```

```
[ ]: Y_pred=rfr.predict(X_test)
```

```
[ ]: mean_squared_error(Y_test,Y_pred)
```

```
[ ]: 0.03233801408003268
```

```
[ ]: r2_score(Y_test,Y_pred)
```

```
[ ]: 0.9859493502202655
```

```
[ ]: train_rmse = np.sqrt(mean_squared_error(Y_train, y_train_pred))
test_rmse = np.sqrt(mean_squared_error(Y_test, y_test_pred))

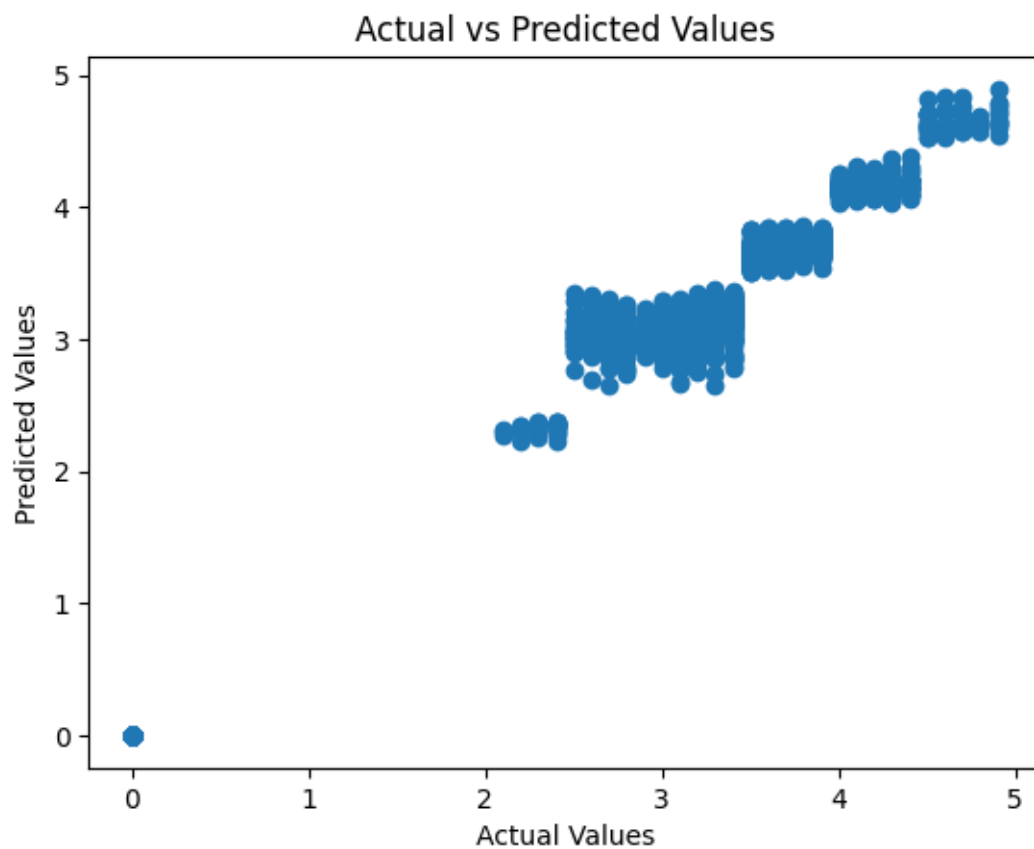
train_r2 = r2_score(Y_train, y_train_pred)
test_r2 = r2_score(Y_test, y_test_pred)

print("Train RMSE:", train_rmse)
print("Test RMSE:", test_rmse)
```

```
Train RMSE: 0.06964499085935906
```

```
Test RMSE: 0.1798277344572652
```

```
[ ]: plt.scatter(Y_test,Y_pred)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')
plt.show()
```



[]: