```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

df = pd.read_csv("Dataset .csv")
df
```

```
      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
...             ...                       ...           ...
...
9546        5915730               Naml\ Gurme           208
��stanbul
9547        5908749              Ceviz A��ac\       208
��stanbul
9548        5915807                     Huqqa           208
��stanbul
9549        5916112               A����k Kahve           208
��stanbul
9550        5927402  Walter's Coffee Roastery           208
��stanbul

                                                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...
...                                                 ...
9546  Kemanke�� Karamustafa Pa��a Mahallesi, R\ht\m ...
9547  Ko��uyolu Mahallesi, Muhittin ��st�_nda�� Cadd...
9548  Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...
9549  Kuru�_e��me Mahallesi, Muallim Naci Caddesi, N...
9550  Cafea��a Mahallesi, Bademalt\ Sokak, No 21/B, ...
```

```
                                        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
...                                          ...
9546                                    Karak�_y
9547                                   Ko��uyolu
9548                                 Kuru�_e��me
9549                                 Kuru�_e��me
9550                                        Moda

                                       Locality Verbose   Longitude  \
0     Century City Mall, Poblacion, Makati City, Mak...  121.027535
1     Little Tokyo, Legaspi Village, Makati City, Ma...  121.014101
2     Edsa Shangri-La, Ortigas, Mandaluyong City, Ma...  121.056831
3     SM Megamall, Ortigas, Mandaluyong City, Mandal...  121.056475
4     SM Megamall, Ortigas, Mandaluyong City, Mandal...  121.057508
...                                                 ...         ...
9546                                Karak�_y, ��stanbul   28.977392
9547                               Ko��uyolu, ��stanbul   29.041297
9548                             Kuru�_e��me, ��stanbul   29.034640
9549                             Kuru�_e��me, ��stanbul   29.036019
9550                                    Moda, ��stanbul   29.026016

       Latitude                          Cuisines  ...
Currency  \
0     14.565443        French, Japanese, Desserts  ...  Botswana
Pula(P)
1     14.553708                          Japanese  ...  Botswana
Pula(P)
2     14.581404  Seafood, Asian, Filipino, Indian  ...  Botswana
Pula(P)
3     14.585318                    Japanese, Sushi  ...  Botswana
Pula(P)
4     14.584450                  Japanese, Korean  ...  Botswana
Pula(P)
...         ...                               ...  ...               .
..
9546  41.022793                           Turkish  ...  Turkish
Lira(TL)
9547  41.009847   World Cuisine, Patisserie, Cafe  ...  Turkish
Lira(TL)
9548  41.055817            Italian, World Cuisine  ...  Turkish
Lira(TL)
9549  41.057979                   Restaurant Cafe  ...  Turkish
Lira(TL)
9550  40.984776                              Cafe  ...  Turkish
```

```
Lira(TL)

     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
...                ...                 ...               ...
9546                No                  No                No
9547                No                  No                No
9548                No                  No                No
9549                No                  No                No
9550                No                  No                No

     Switch to order menu Price range  Aggregate rating  Rating color
\
0                      No            3               4.8    Dark Green

1                      No            3               4.5    Dark Green

2                      No            4               4.4         Green

3                      No            4               4.9    Dark Green

4                      No            4               4.8    Dark Green

...                   ...          ...               ...           ...

9546                   No            3               4.1         Green

9547                   No            3               4.2         Green

9548                   No            4               3.7        Yellow

9549                   No            4               4.0         Green

9550                   No            2               4.0         Green


     Rating text Votes
0      Excellent   314
1      Excellent   591
2      Very Good   270
3      Excellent   365
4      Excellent   229
...          ...   ...
9546   Very Good   788
9547   Very Good  1034
9548        Good   661
9549   Very Good   901
```

```
9550   Very Good   591

[9551 rows x 21 columns]
```

```
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
```

```
#Drop rows with missing values
df.dropna(inplace=True)
```

```
#After handling missing values
df.shape
```

```
(9542, 21)
```

Task 1: Predictive Modeling

```
# Considering some potential features
selected_features = ['Average Cost for two', 'Price range', 'Votes']
```

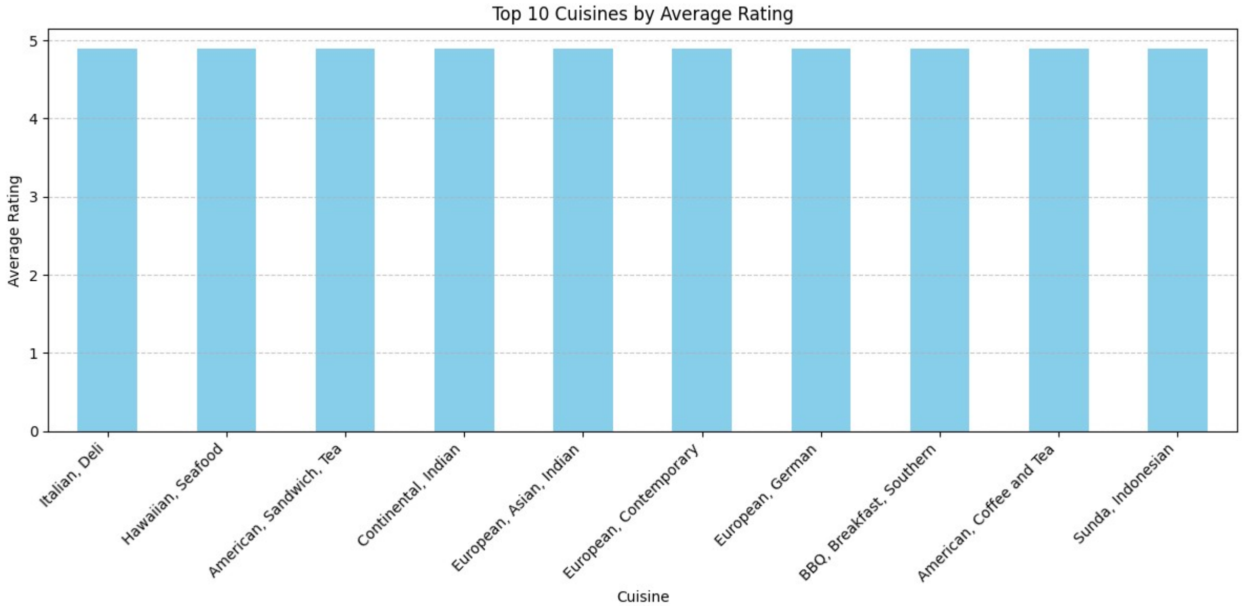
```
X = df[selected_features]
y = df['Aggregate rating']

# Split the dataset into training and testing sets (80% train, 20%
test)
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Build the regression model (Linear Regression as an example)
model = LinearRegression()
model.fit(X_train, y_train)

LinearRegression()

# Predict aggregate ratings on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)

# Mean Squared Error
mse

1.7193421524563215

# Root Mean Squared Error
rmse

1.3112368788500122

# R^2 Score
r2

0.24920612400080278

# Initialize and train different regression models
models = {
    'Linear Regression': LinearRegression(),
    'Decision Tree': DecisionTreeRegressor(random_state=42),
    'Random Forest': RandomForestRegressor(n_estimators=100,
random_state=42)
}

results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    rmse = mean_squared_error(y_test, y_pred, squared=False)
```

```
    r2 = r2_score(y_test, y_pred)
    results[name] = {'MSE': mse, 'RMSE': rmse, 'R^2': r2}

# Print results
print("Regression Model Performance:")
for name, metrics in results.items():
    print(f"Model: {name}")
    print(f"MSE: {metrics['MSE']:.2f}")
    print(f"RMSE: {metrics['RMSE']:.2f}")
    print(f"R^2: {metrics['R^2']:.2f}")
    print("------------------------")
```

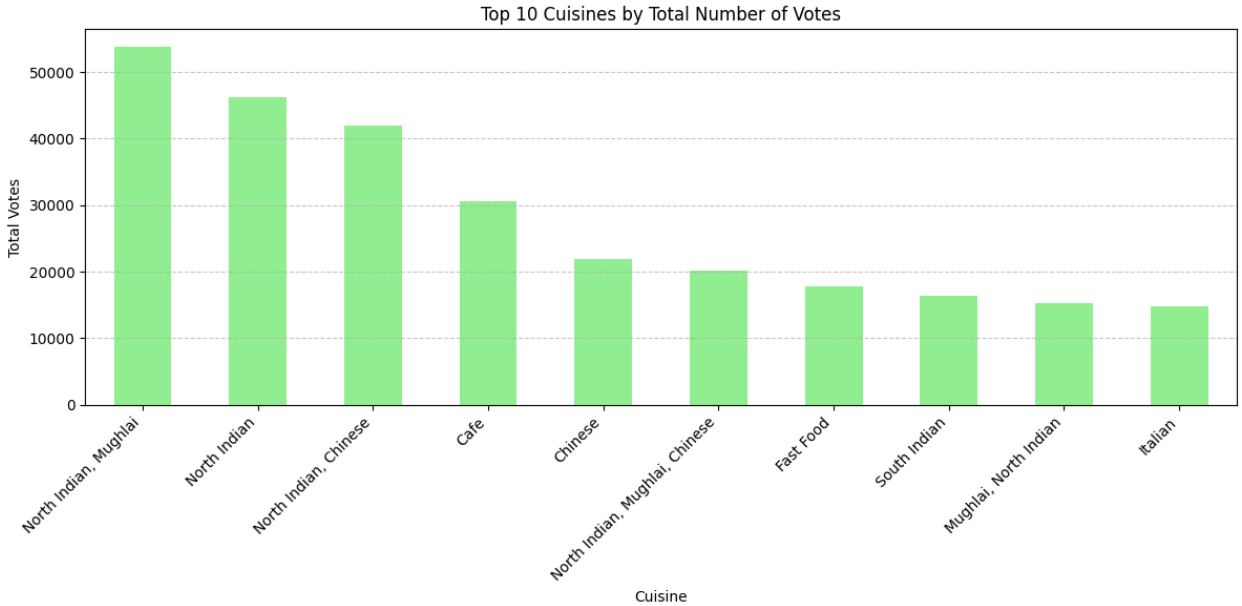
```
Regression Model Performance:
Model: Linear Regression
MSE: 1.72
RMSE: 1.31
R^2: 0.25
------------------------
Model: Decision Tree
MSE: 0.20
RMSE: 0.44
R^2: 0.91
------------------------
Model: Random Forest
MSE: 0.14
RMSE: 0.37
R^2: 0.94
------------------------
```

Task 2: Customer Preference Analysis

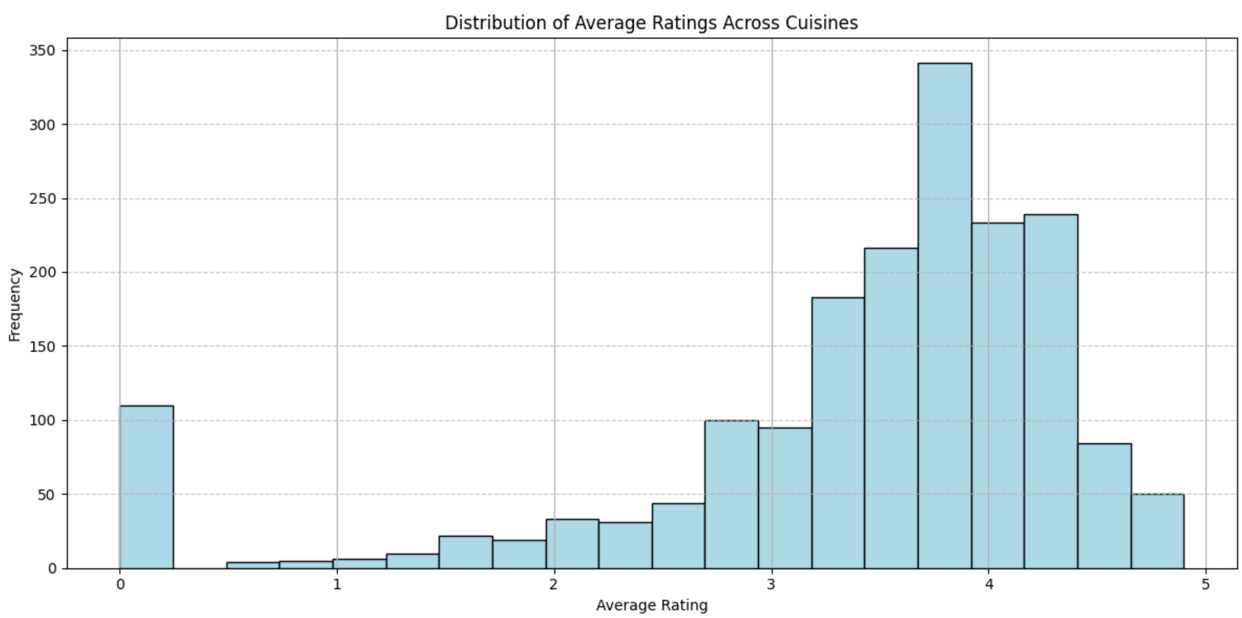
```
# Group the data by cuisine and calculate the average rating for each
cuisine
avg_rating_by_cuisine = df.groupby('Cuisines')['Aggregate
rating'].mean().sort_values(ascending=False)

# Plot the top cuisines by average rating
plt.figure(figsize=(12, 6))
avg_rating_by_cuisine.head(10).plot(kind='bar', color='skyblue')
plt.title('Top 10 Cuisines by Average Rating')
plt.xlabel('Cuisine')
plt.ylabel('Average Rating')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```




```
# Group the data by cuisine and calculate the total number of votes
for each cuisine
total_votes_by_cuisine = df.groupby('Cuisines')
['Votes'].sum().sort_values(ascending=False)

# Plot the top cuisines by total number of votes
plt.figure(figsize=(12, 6))
total_votes_by_cuisine.head(10).plot(kind='bar', color='lightgreen')
plt.title('Top 10 Cuisines by Total Number of Votes')
plt.xlabel('Cuisine')
plt.ylabel('Total Votes')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

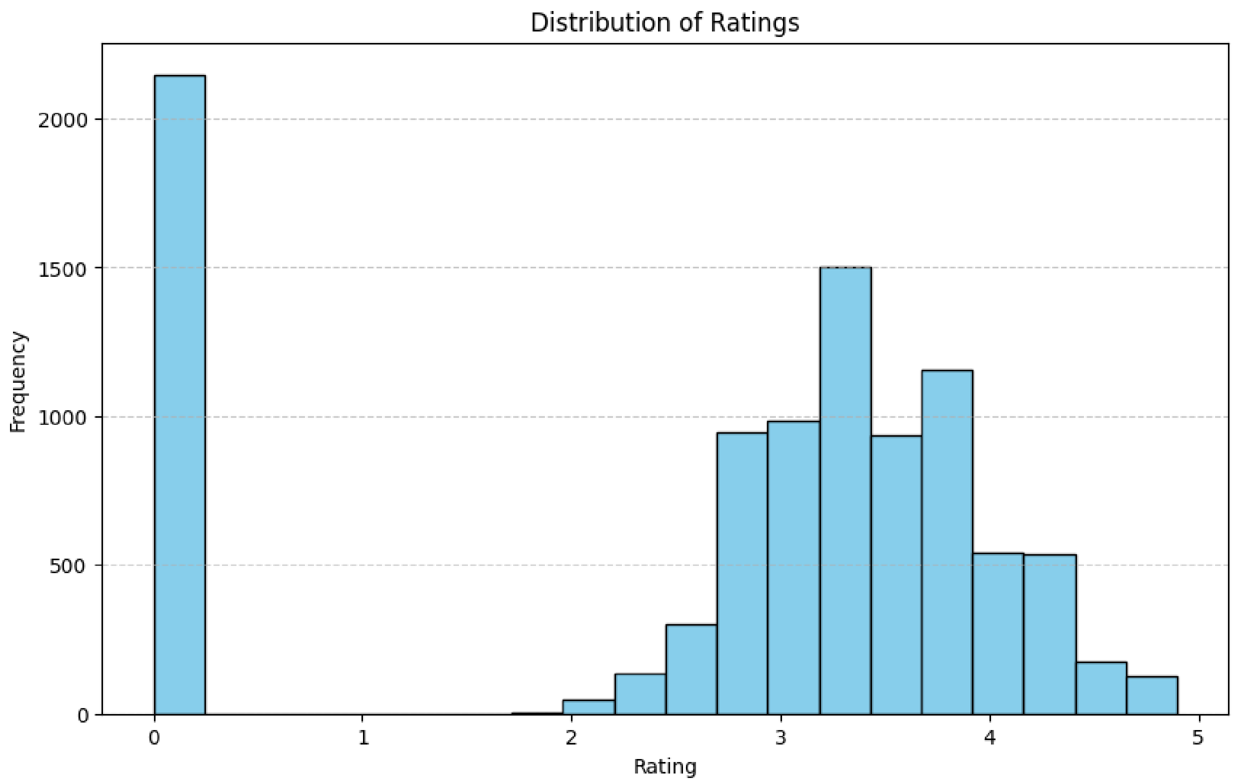



```python
# Plot the distribution of average ratings across cuisines
plt.figure(figsize=(12, 6))
avg_rating_by_cuisine.hist(bins=20, color='lightblue',
edgecolor='black')
plt.title('Distribution of Average Ratings Across Cuisines')
plt.xlabel('Average Rating')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

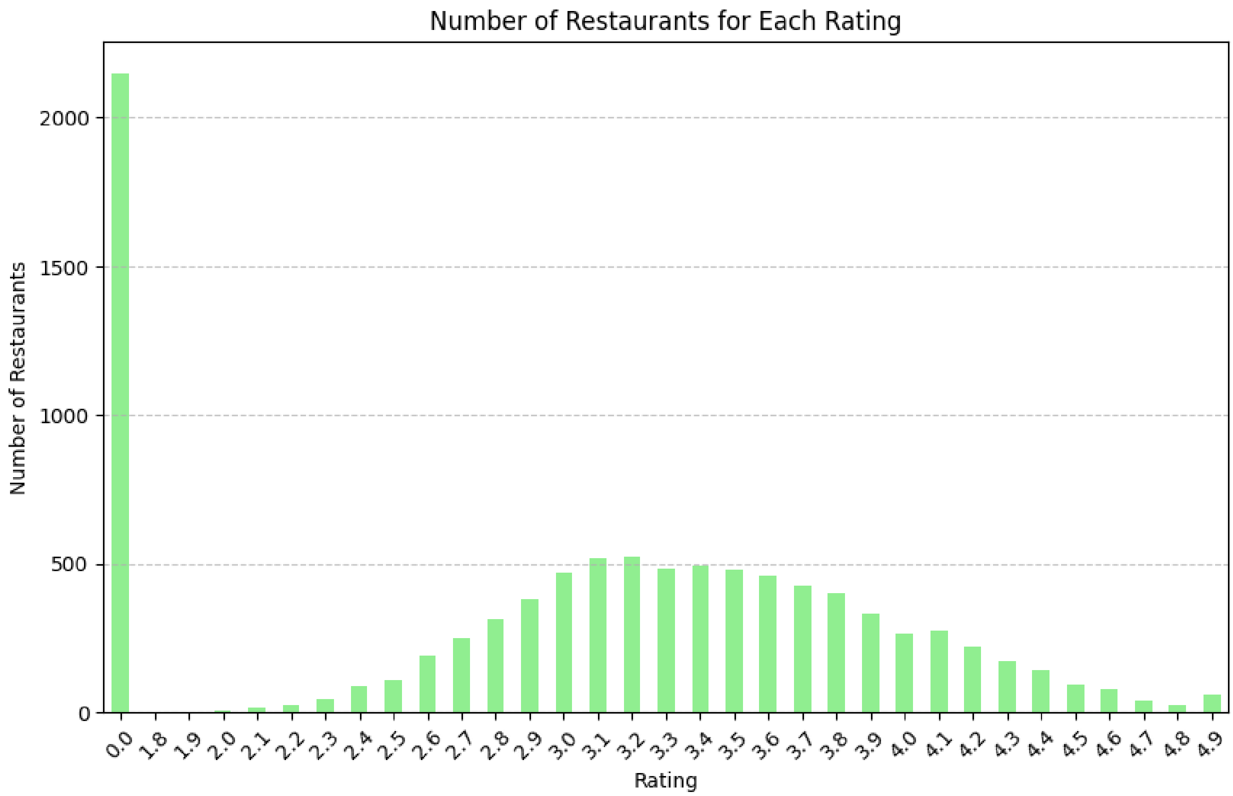


Task 3: Data Visualization

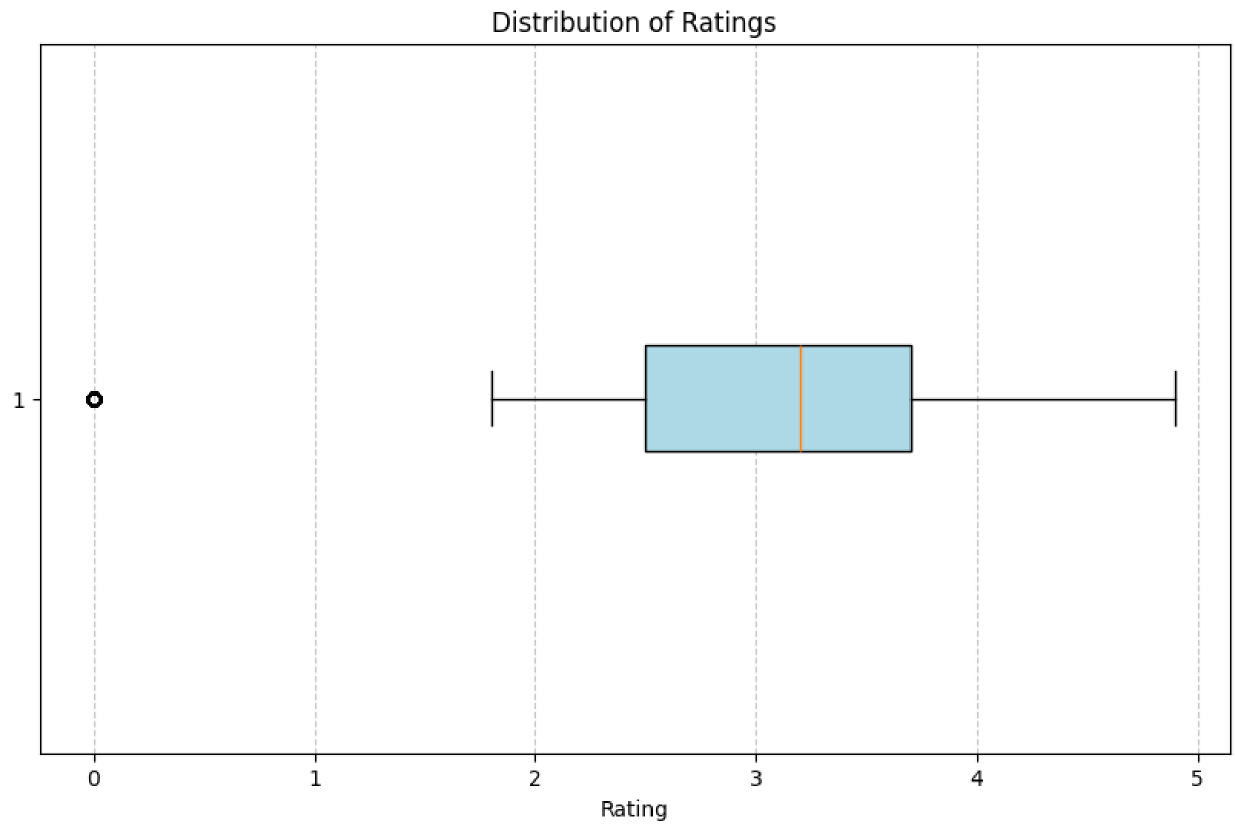
```
# Create a histogram to represent the distribution of ratings
plt.figure(figsize=(10, 6))
plt.hist(df['Aggregate rating'], bins=20, color='skyblue',
edgecolor='black')
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.ylabel('Frequency')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



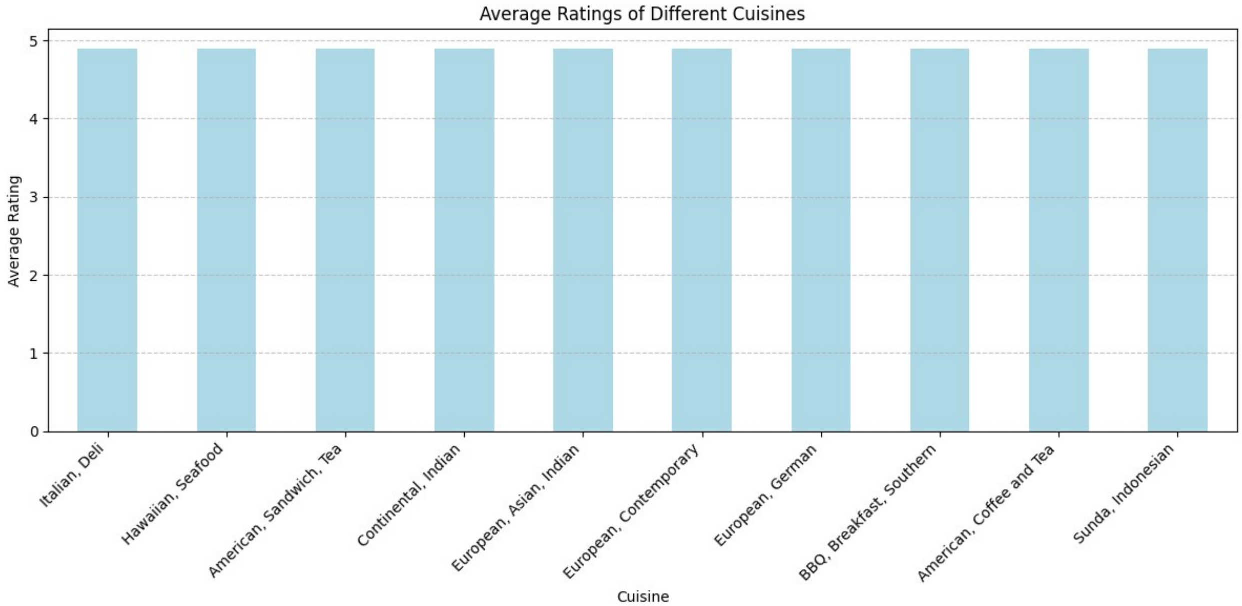

```
# Create a bar plot to represent the number of restaurants for each
rating
plt.figure(figsize=(10, 6))
df['Aggregate rating'].value_counts().sort_index().plot(kind='bar',
color='lightgreen')
plt.title('Number of Restaurants for Each Rating')
plt.xlabel('Rating')
plt.ylabel('Number of Restaurants')
plt.xticks(rotation=45)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



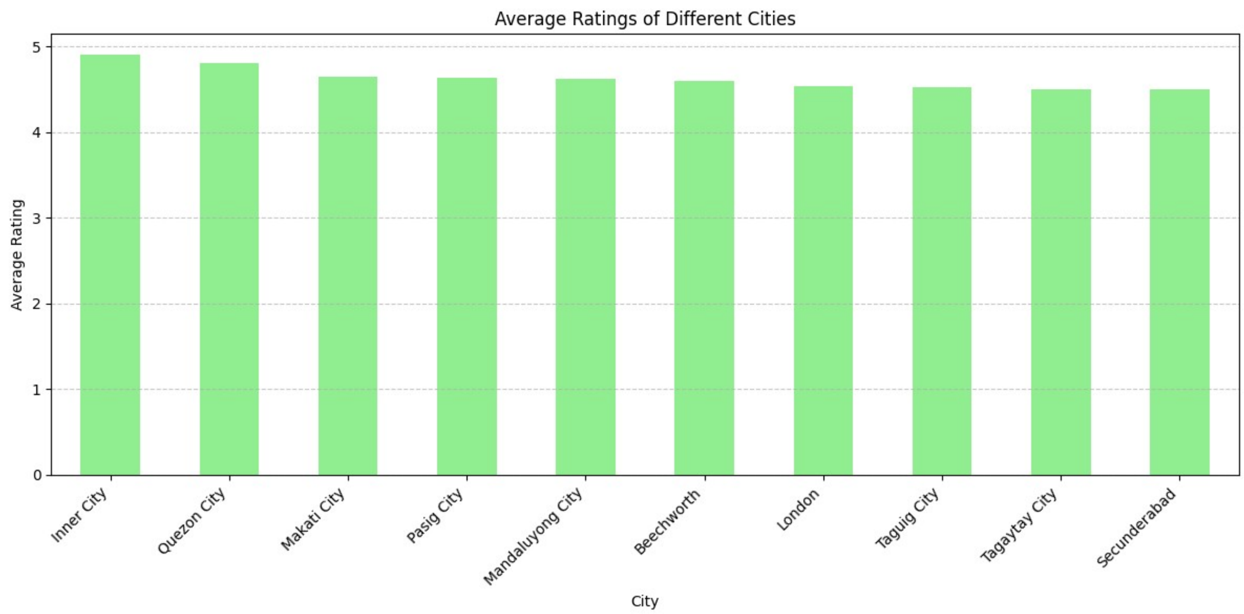

```
# Create a box plot to represent the distribution of ratings
plt.figure(figsize=(10, 6))
plt.boxplot(df['Aggregate rating'], vert=False, patch_artist=True,
boxprops=dict(facecolor='lightblue'))
plt.title('Distribution of Ratings')
plt.xlabel('Rating')
plt.grid(axis='x', linestyle='--', alpha=0.7)
plt.show()
```



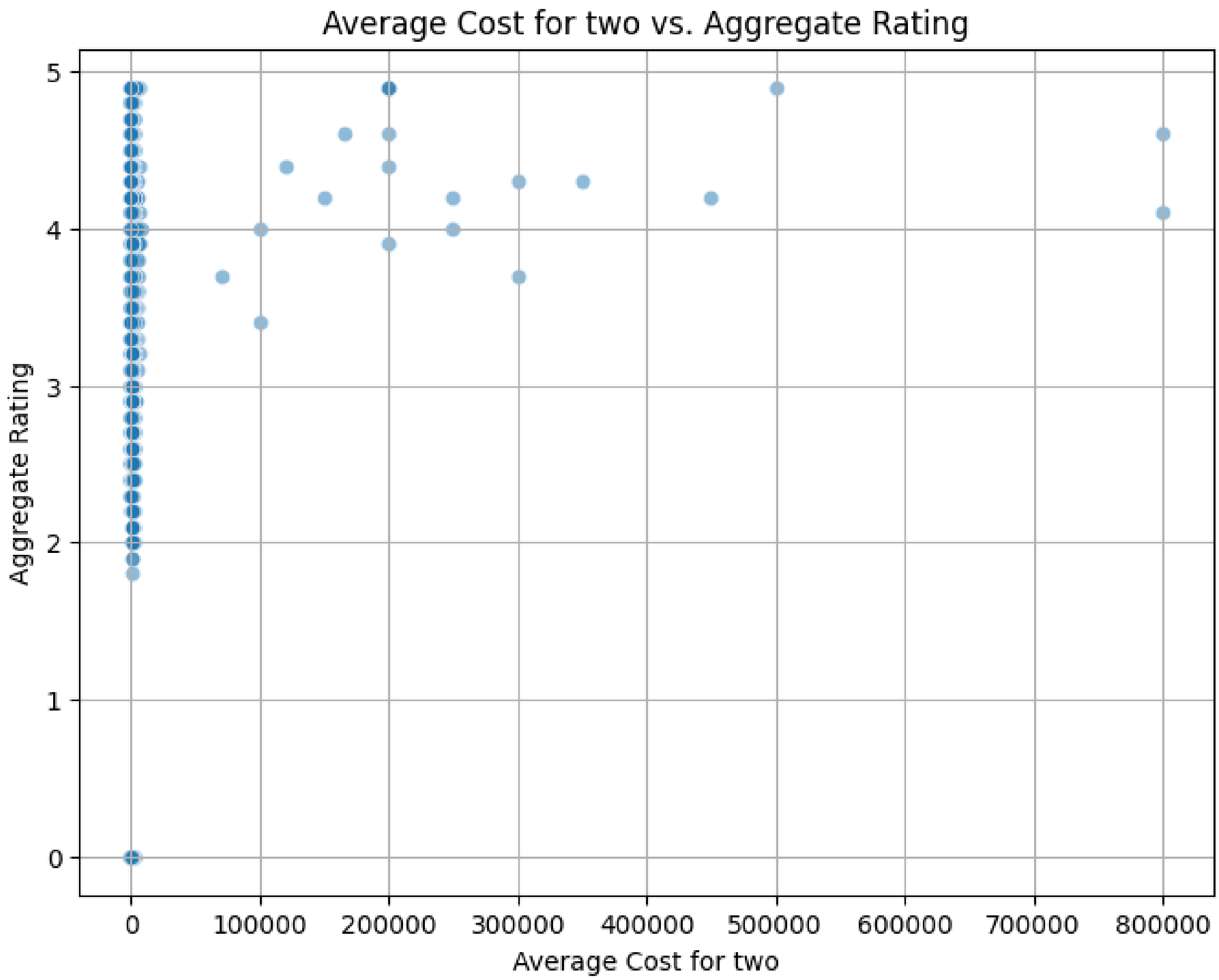

```
# Plot the average ratings of different cuisines
plt.figure(figsize=(12, 6))
avg_rating_by_cuisine.head(10).plot(kind='bar', color='lightblue')
plt.title('Average Ratings of Different Cuisines')
plt.xlabel('Cuisine')
plt.ylabel('Average Rating')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

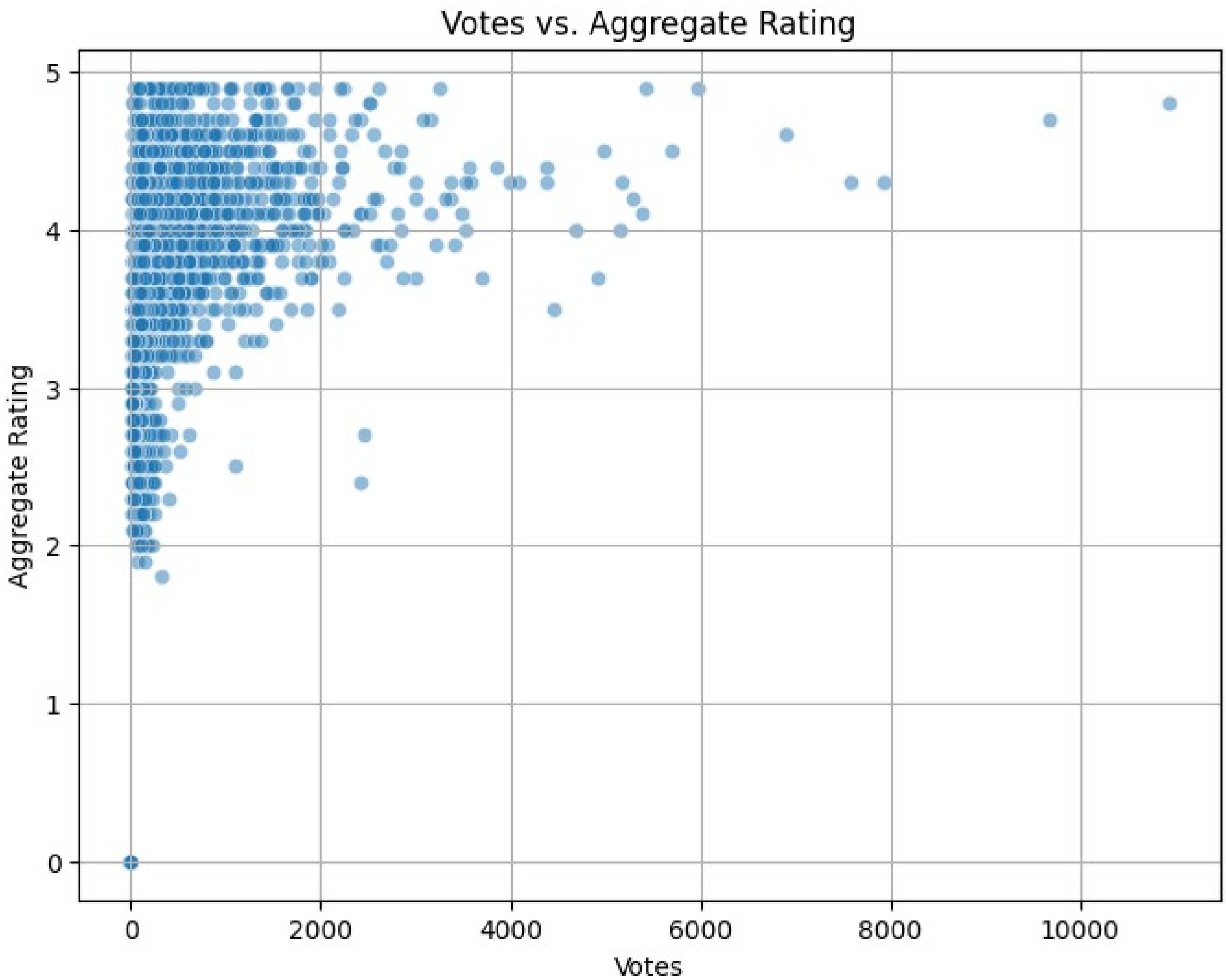



```python
# Calculate the average rating for each city
avg_rating_by_city = df.groupby('City')['Aggregate
rating'].mean().sort_values(ascending=False)

# Plot the average ratings of different cities
plt.figure(figsize=(12, 6))
avg_rating_by_city.head(10).plot(kind='bar', color='lightgreen')
plt.title('Average Ratings of Different Cities')
plt.xlabel('City')
plt.ylabel('Average Rating')
plt.xticks(rotation=45, ha='right')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

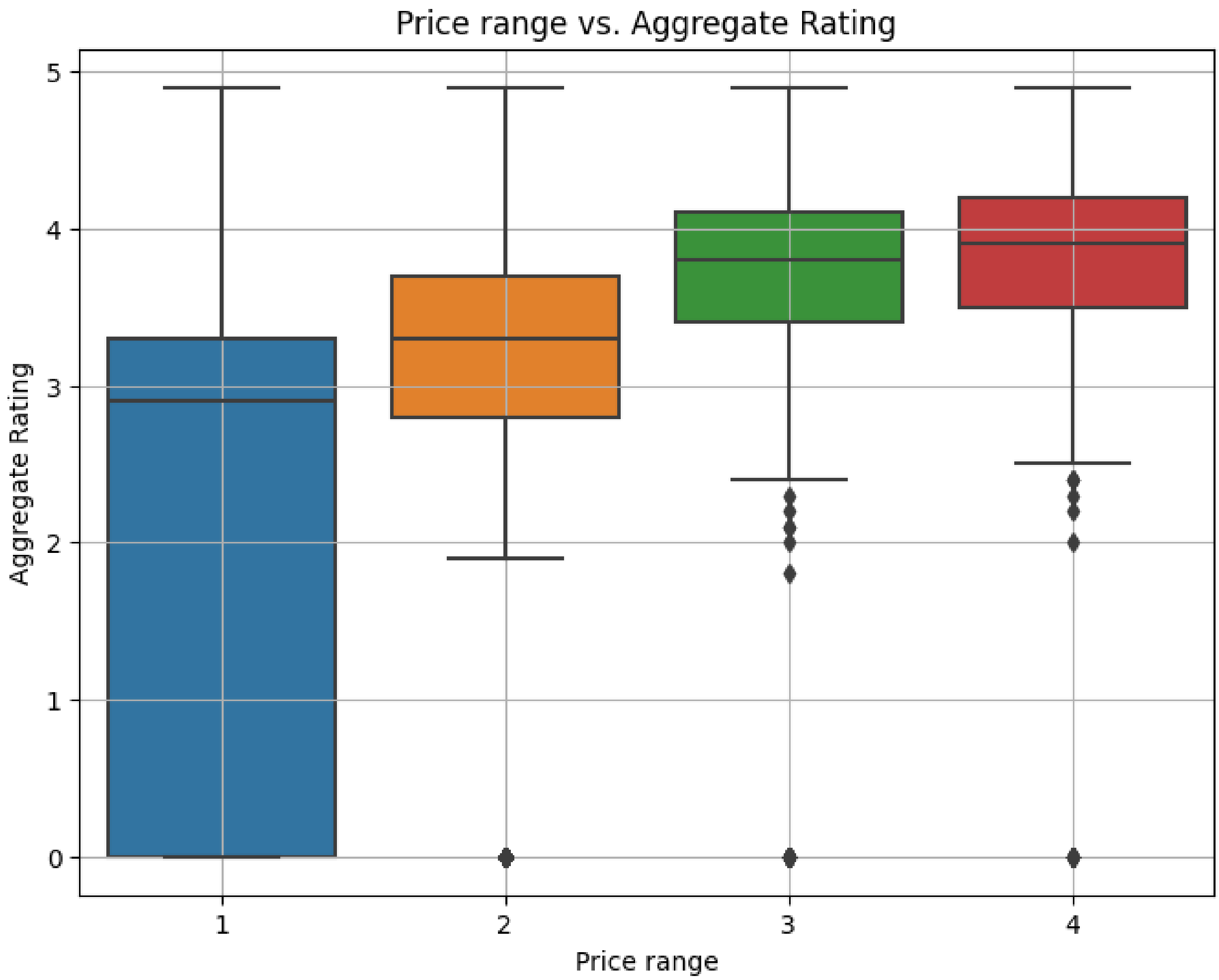


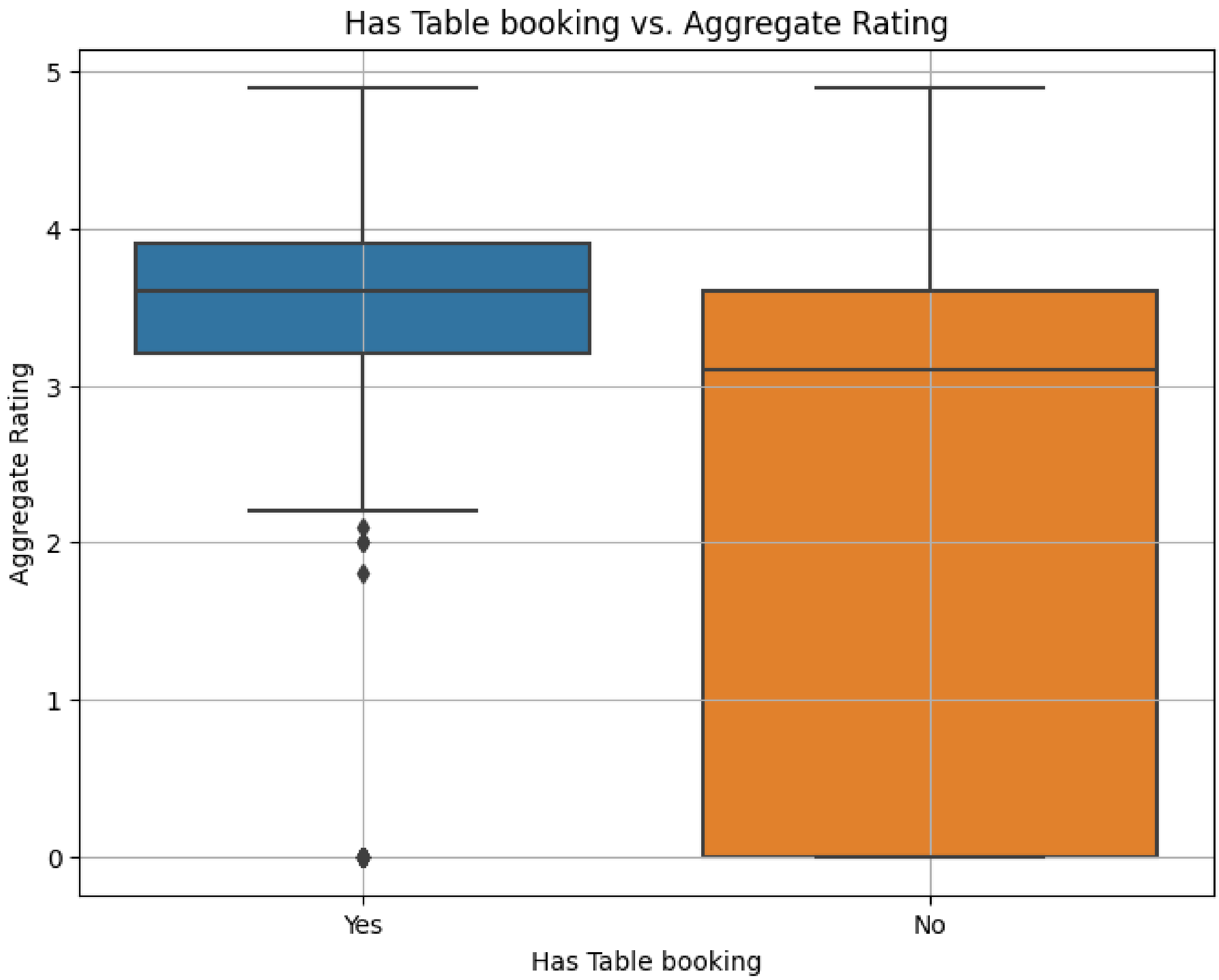

```
# Visualize numerical features vs. target variable (aggregate rating)
num_features = ['Average Cost for two', 'Votes']  # Add more numerical
features if needed

for feature in num_features:
    plt.figure(figsize=(8, 6))
    sns.scatterplot(data=df, x=feature, y='Aggregate rating',
alpha=0.5)
    plt.title(f'{feature} vs. Aggregate Rating')
    plt.xlabel(feature)
    plt.ylabel('Aggregate Rating')
    plt.grid(True)
    plt.show()
```


Average Cost for two vs. Aggregate Rating
Aggregate Rating
Average Cost for two
0
1
2
3
4
5
0
100000
200000
300000
400000
500000
600000
700000
800000




```python
# Visualize categorical features vs. target variable (aggregate
rating)
cat_features = ['Price range', 'Has Table booking', 'Has Online
delivery']  # Add more categorical features if needed

for feature in cat_features:
    plt.figure(figsize=(8, 6))
    sns.boxplot(data=df, x=feature, y='Aggregate rating')
    plt.title(f'{feature} vs. Aggregate Rating')
    plt.xlabel(feature)
    plt.ylabel('Aggregate Rating')
    plt.grid(True)
    plt.show()
```


Price range vs. Aggregate Rating
Aggregate Rating
0
1
2
3
4
5
1
2
3
4
Price range


Has Table booking vs. Aggregate Rating
Aggregate Rating
5
4
3
2
1
0
Yes
No
Has Table booking


Has Online delivery vs. Aggregate Rating
Aggregate Rating
5
4
3
2
1
0
No
Yes
Has Online delivery