Task 1: Predictive Modeling

```
In [42]:
         import pandas as pd
         import numpy as np
         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
         from sklearn.preprocessing import LabelEncoder
In [43]: df = pd.read_csv('Dataset .csv')
In [45]: df = df.drop(columns=['Restaurant ID', 'Restaurant Name', 'Address', 'Locality', 'L
                              'Longitude', 'Latitude', 'Switch to order menu'])
In [46]:
         le = LabelEncoder()
         In [47]: for col in categorical cols:
             df[col] = le.fit_transform(df[col])
In [48]: X = df.drop('Aggregate rating', axis=1)
         y = df['Aggregate rating']
In [49]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
In [50]: linear_reg = LinearRegression()
         decision_tree = DecisionTreeRegressor(random_state=42)
         random_forest = RandomForestRegressor(random_state=42)
In [51]:
         linear reg.fit(X train, y train)
         y_pred_lr = linear_reg.predict(X_test)
In [52]: decision_tree.fit(X_train, y_train)
         y pred dt = decision tree.predict(X test)
In [54]: random_forest.fit(X_train, y_train)
         y_pred_rf = random_forest.predict(X_test)
In [55]: def evaluate_model(y_test, y_pred, model_name):
             print(f"{model_name} Performance:")
             print(f"Mean Squared Error (MSE): {mean_squared_error(y_test, y_pred):.2f}")
             print(f"R-squared (R2): {r2_score(y_test, y_pred):.2f}")
             print("-" * 30)
         evaluate_model(y_test, y_pred_lr, "Linear Regression")
In [56]:
         Linear Regression Performance:
         Mean Squared Error (MSE): 1.30
         R-squared (R2): 0.43
In [57]:
         evaluate model(y test, y pred dt, "Decision Tree")
```

```
Decision Tree Performance:
Mean Squared Error (MSE): 0.06
R-squared (R2): 0.97
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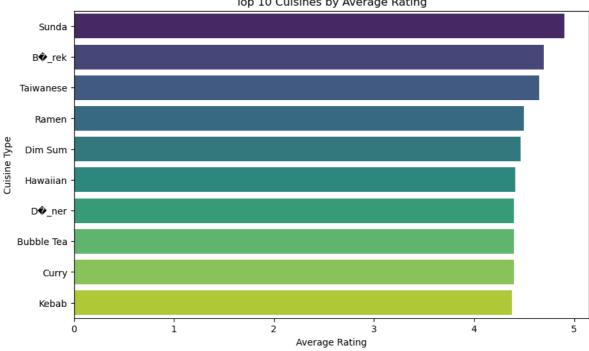
In [58]: evaluate_model(y_test, y_pred_rf, "Random Forest")

Random Forest Performance:
Mean Squared Error (MSE): 0.03
R-squared (R2): 0.99
```

Task 2: Customer Preference Analysis

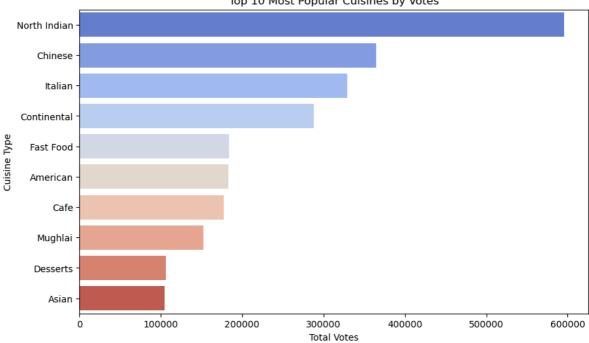
```
import pandas as pd
In [59]:
         import matplotlib.pyplot as plt
         import seaborn as sns
In [60]: df = pd.read_csv('Dataset .csv')
In [61]:
         # 1: Analyze the relationship between the type of cuisine and the restaurant's rat
         df['Cuisines'] = df['Cuisines'].fillna('Unknown')
In [62]:
         df['Cuisines'] = df['Cuisines'].str.split(', ')
         df_cuisine = df.explode('Cuisines')
In [63]:
         cuisine_rating = df_cuisine.groupby('Cuisines')['Aggregate rating'].mean().reset_ir
In [64]:
In [65]: | cuisine_rating = cuisine_rating.sort_values(by='Aggregate rating', ascending=False)
         print("Top 10 cuisines by average rating:")
In [66]:
         print(cuisine_rating.head(10))
         Top 10 cuisines by average rating:
                Cuisines Aggregate rating
         130
                                  4.900000
                   Sunda
         26
                  B� rek
                                   4.700000
         132
              Taiwanese
                                  4.650000
         112
                   Ramen
                                  4.500000
         43
                 Dim Sum
                                  4.466667
         61
                Hawaiian
                                  4,412500
         47
                  D�_ner
                                  4.400000
         23
              Bubble Tea
                                  4.400000
                   Curry
                                  4.400000
         75
                   Kebab
                                  4.380000
In [67]:
         plt.figure(figsize=(10,6))
         sns.barplot(x='Aggregate rating', y='Cuisines', data=cuisine_rating.head(10), palet
         plt.title('Top 10 Cuisines by Average Rating')
         plt.xlabel('Average Rating')
         plt.ylabel('Cuisine Type')
         plt.show()
```

Top 10 Cuisines by Average Rating



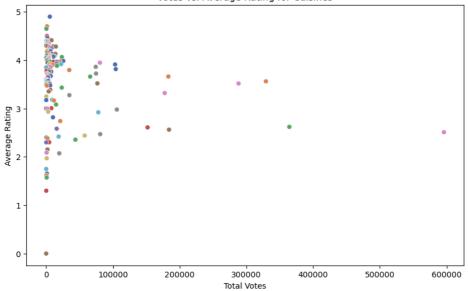
```
# 2: Identify the most popular cuisines based on the number of votes
In [68]:
         cuisine_votes = df_cuisine.groupby('Cuisines')['Votes'].sum().reset_index()
In [69]:
         cuisine_votes = cuisine_votes.sort_values(by='Votes', ascending=False)
In [70]:
In [71]:
         print("Top 10 most popular cuisines by votes:")
         print(cuisine_votes.head(10))
         Top 10 most popular cuisines by votes:
                  Cuisines
                             Votes
              North Indian 595981
         100
                   Chinese 364351
         34
         70
                   Italian 329265
         37
               Continental 288255
         49
                 Fast Food 184058
         2
                  American 183117
         27
                      Cafe 177568
         95
                   Mughlai 151946
         42
                  Desserts 105889
                     Asian 104303
In [72]:
         plt.figure(figsize=(10,6))
         sns.barplot(x='Votes', y='Cuisines', data=cuisine_votes.head(10), palette='coolwarm
         plt.title('Top 10 Most Popular Cuisines by Votes')
         plt.xlabel('Total Votes')
         plt.ylabel('Cuisine Type')
         plt.show()
```

Top 10 Most Popular Cuisines by Votes



```
# 3: Determine if any specific cuisines tend to receive higher ratings
In [73]:
         cuisine_analysis = pd.merge(cuisine_rating, cuisine_votes, on='Cuisines')
In [74]:
         plt.figure(figsize=(10,6))
In [75]:
         sns.scatterplot(x='Votes', y='Aggregate rating', hue='Cuisines', data=cuisine_analy
         plt.title('Votes vs. Average Rating for Cuisines')
         plt.xlabel('Total Votes')
         plt.ylabel('Average Rating')
         plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
         plt.show()
```





- Sunda B**�**_rek Taiwanese • Ramen Dim Sum Hawaiian • D**∲**_ner Bubble Tea . Curry Kebab • Izgara Filipino • Scottish South African • Turkish Pizza World Cuisine • Gourmet Fast Food . Durban Kiwi • Teriyaki Argentine • • Irish Fish and Chips • Contemporary Indonesian Modern Indian • Caribbean International . • Deli • Cajun Southwestern Charcoal Grill Cuban • • Western
- Tapas •
- Southern • • British New American
- Parsi Spanish •
- Vegetarian • Iranian • Sandwich
- Latin American Grill • Belgian
- Burmese • Patisserie . Restaurant Cafe
- Peranakan • Steak
- Sushi • • German • Goan
- Breakfast • • Pub Food
- Mediterranean • Bar Food
- Vietnamese • • Indian
- European • BBQ
- Tex-Mex Andhra
- Diner Unknown
- • French . Seafood
- Asian Fusion Cantonese
- Asian • Japanese
- Coffee and Tea • Australian
- Middle Eastern • Malaysian
- Mangalorean
- Mexican . Pakistani •
- Greek • Chettinad
- American Thai
- Korean Bihari •
- Soul Food Peruvian

```
Sri Lankan
   Fusion
   Maharashtrian
   Brazilian
   Italian
   Modern Australian
   Turkish
   African
   Burger
   Continental
   Hyderabadi
   South American
   Malwani
   Kerala
   Naga
   Lebanese
   Arabian
   Portuguese
   Gujarati
•
   Cafe
   Finger Food
    Oriya
    Rajasthani
   Singaporean
   Salad
   Healthy Food
    Bengali
   Canadian
   Malay
   Juices
   Desserts
   Kashmiri
   Pizza
   Beverages
   Chinese
   Mughlai
   Ice Cream
   Fast Food
   North Indian
   South Indian
   Biryani
   Assamese
   Lucknowi
   Street Food
   Tibetan
   Persian
   Raw Meats
   North Eastern
   Mithai
   Afghani
   Drinks Only
   Nepalese
   Moroccan
   Awadhi
   Armenian
   Cuisine Varies
```

Mineira

```
In [76]: print("Cuisine Analysis DataFrame:")
    print(cuisine_analysis.head(10))
```

Cuisine Analysis DataFrame:

	Cuisines	Aggregate rating	Votes
0	Sunda	4.900000	5514
1	B ∲ _rek	4.700000	1305
2	Taiwanese	4.650000	384
3	Ramen	4.500000	1259
4	Dim Sum	4.466667	1755
5	Hawaiian	4.412500	8012
6	D�_ner	4.400000	72
7	Bubble Tea	4.400000	659
8	Curry	4.400000	2059
9	Kebab	4.380000	1536

Task 3: Data Visualization

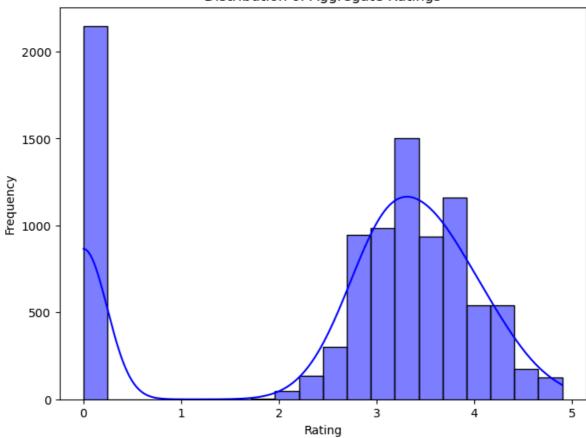
```
In [77]: import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns

In [78]: df = pd.read_csv('Dataset .csv')

In [79]: #1: Visualizing the distribution of ratings

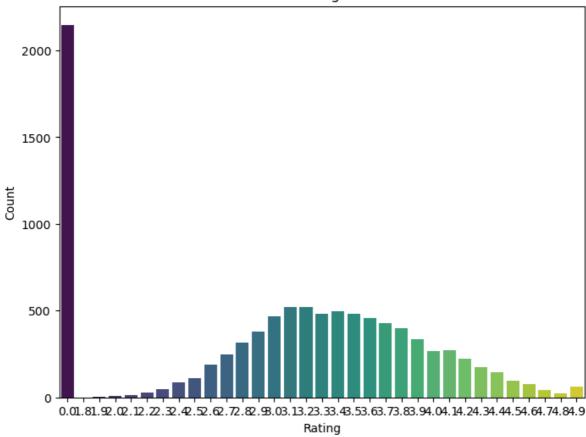
In [80]: plt.figure(figsize=(8,6))
    sns.histplot(df['Aggregate rating'], bins=20, kde=True, color='blue')
    plt.title('Distribution of Aggregate Ratings')
    plt.xlabel('Rating')
    plt.ylabel('Frequency')
    plt.show()
```

Distribution of Aggregate Ratings



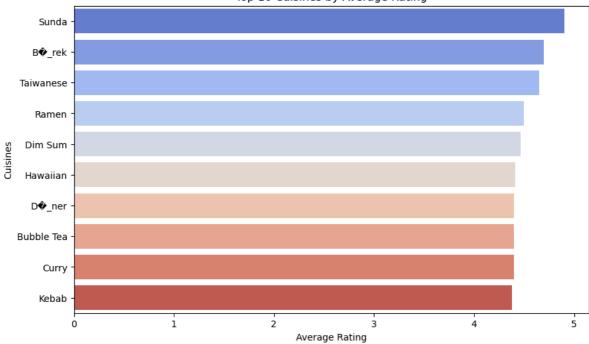
```
In [81]: rating_counts = df['Aggregate rating'].value_counts().sort_index()
    plt.figure(figsize=(8,6))
    sns.barplot(x=rating_counts.index, y=rating_counts.values, palette='viridis')
    plt.title('Bar Plot of Rating Distribution')
    plt.xlabel('Rating')
    plt.ylabel('Count')
    plt.show()
```

Bar Plot of Rating Distribution



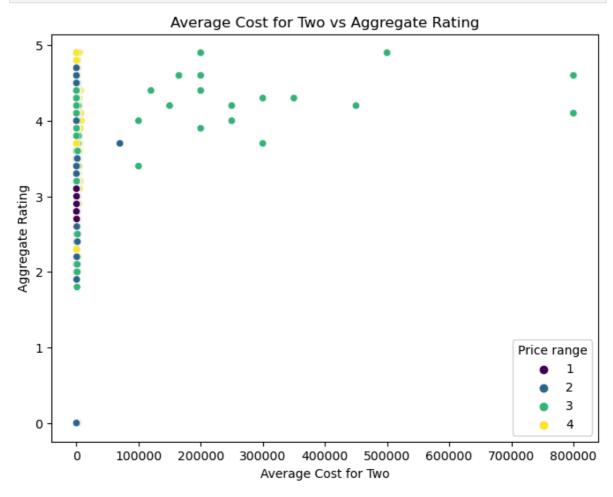
```
# 2: Compare average ratings of different cuisines
In [82]:
         df['Cuisines'] = df['Cuisines'].fillna('Unknown')
In [83]:
         df['Cuisines'] = df['Cuisines'].str.split(', ')
         df_cuisine = df.explode('Cuisines')
In [84]:
         avg_cuisine_rating = df_cuisine.groupby('Cuisines')['Aggregate rating'].mean().rese
In [85]:
         avg_cuisine_rating = avg_cuisine_rating.sort_values(by='Aggregate rating', ascendir
         plt.figure(figsize=(10,6))
In [86]:
         sns.barplot(x='Aggregate rating', y='Cuisines', data=avg_cuisine_rating.head(10), r
         plt.title('Top 10 Cuisines by Average Rating')
         plt.xlabel('Average Rating')
         plt.ylabel('Cuisines')
         plt.show()
```

Top 10 Cuisines by Average Rating

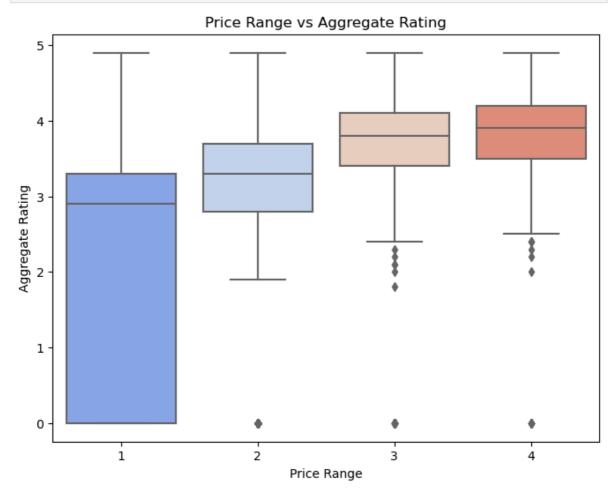


In [87]: # 3: Visualize relationship between various features and aggregate rating

```
In [88]: plt.figure(figsize=(8,6))
    sns.scatterplot(x='Average Cost for two', y='Aggregate rating', data=df, hue='Price
    plt.title('Average Cost for Two vs Aggregate Rating')
    plt.xlabel('Average Cost for Two')
    plt.ylabel('Aggregate Rating')
    plt.show()
```

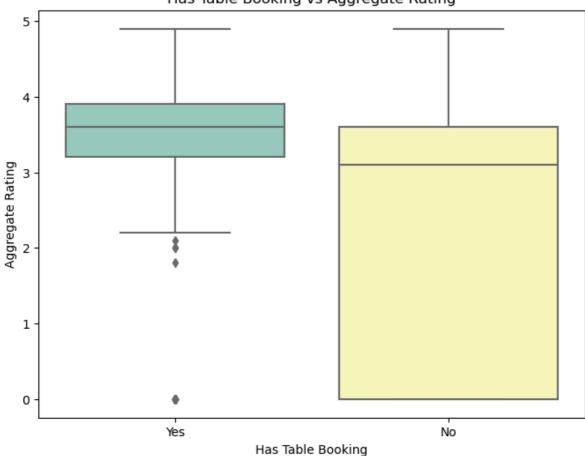


```
In [89]: plt.figure(figsize=(8,6))
    sns.boxplot(x='Price range', y='Aggregate rating', data=df, palette='coolwarm')
    plt.title('Price Range vs Aggregate Rating')
    plt.xlabel('Price Range')
    plt.ylabel('Aggregate Rating')
    plt.show()
```



```
In [90]: plt.figure(figsize=(8,6))
    sns.boxplot(x='Has Table booking', y='Aggregate rating', data=df, palette='Set3')
    plt.title('Has Table Booking vs Aggregate Rating')
    plt.xlabel('Has Table Booking')
    plt.ylabel('Aggregate Rating')
    plt.show()
```

Has Table Booking vs Aggregate Rating



```
In [91]: plt.figure(figsize=(8,6))
    sns.scatterplot(x='Votes', y='Aggregate rating', data=df, color='purple')
    plt.title('Votes vs Aggregate Rating')
    plt.xlabel('Votes')
    plt.ylabel('Aggregate Rating')
    plt.show()
```

Votes vs Aggregate Rating

