Restaurant Rating Prediction

Task :

Predict Restaurent Ratings

Objective :

Build a machine learning model to predict the aggregate rating of a restaurant based on other features.

Importing Libraries

In [1]:
```python
import pandas as pd
import numpy as np
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.metrics import accuracy_score, mean_absolute_error, mean_squared_error, r2_score, confusion_matrix, classification_report
from sklearn.preprocessing import LabelEncoder
```

Loading Dataset and Print 5 Rows of Data

In [2]:
```python
dataset = pd.read_csv('Dataset.csv')
dataset.head()
```

Out[2]:

	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

Data Preprocessing and Splitting

In [3]:
```python
# check for null values
dataset.isna().sum()
# remove null value
dataset= dataset.dropna()
dataset.isna().sum()
```

Out[3]:
```
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
```

In [4]:
```python
dataset.shape
```

Out[4]:
```
(9542, 21)
```

In [5]:
```python
dataset = dataset.drop(['Restaurant ID','Restaurant Name','Country Code','City','Address','Locality','Locality Verbose','Longitude', 'Latitude','Cuisines','Currency'],axis=1)
```

In [6]:
```python
dataset.describe()
```

Out[6]:

	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 [7]:
```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 9542 entries, 0 to 9550
Data columns (total 10 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Average Cost for two  9542 non-null   int64  
 1   Has Table booking     9542 non-null   object 
 2   Has Online delivery   9542 non-null   object 
 3   Is delivering now     9542 non-null   object 
 4   Switch to order menu  9542 non-null   object 
 5   Price range           9542 non-null   int64  
 6   Aggregate rating      9542 non-null   float64
 7   Rating color          9542 non-null   object 
 8   Rating text           9542 non-null   object 
 9   Votes                 9542 non-null   int64  
dtypes: float64(1), int64(3), object(6)
memory usage: 820.0+ KB
```

In [8]:
```python
#Encoding The data
le = LabelEncoder()
dataset['Has Table booking'] = le.fit_transform(dataset['Has Table booking'])
dataset['Has Online delivery'] = le.fit_transform(dataset['Has Online delivery'])
dataset['Is delivering now'] = le.fit_transform(dataset['Is delivering now'])
dataset['Switch to order menu'] = le.fit_transform(dataset['Switch to order menu'])
dataset['Rating color'] = le.fit_transform(dataset['Rating color'])
dataset['Rating text'] = le.fit_transform(dataset['Rating text'])
```

In [9]:
```python
dataset
```

Out[9]:

	Average Cost for two	Has Table booking	Has Online delivery	Is delivering now	Switch to order menu	Price range	Aggregate rating	Rating color	Rating text	Votes
0	1100	1	0	0	0	3	4.8	0	1	314
1	1200	1	0	0	0	3	4.5	0	1	591
2	4000	1	0	0	0	4	4.4	1	5	270
3	1500	0	0	0	0	4	4.9	0	1	365
4	1500	1	0	0	0	4	4.8	0	1	229
...	...	...	...	...	...	...	...	...	...	...
9546	80	0	0	0	0	3	4.1	1	5	788
9547	105	0	0	0	0	3	4.2	1	5	1034
9548	170	0	0	0	0	4	3.7	5	2	661
9549	120	0	0	0	0	4	4.0	1	5	901
9550	55	0	0	0	0	2	4.0	1	5	591

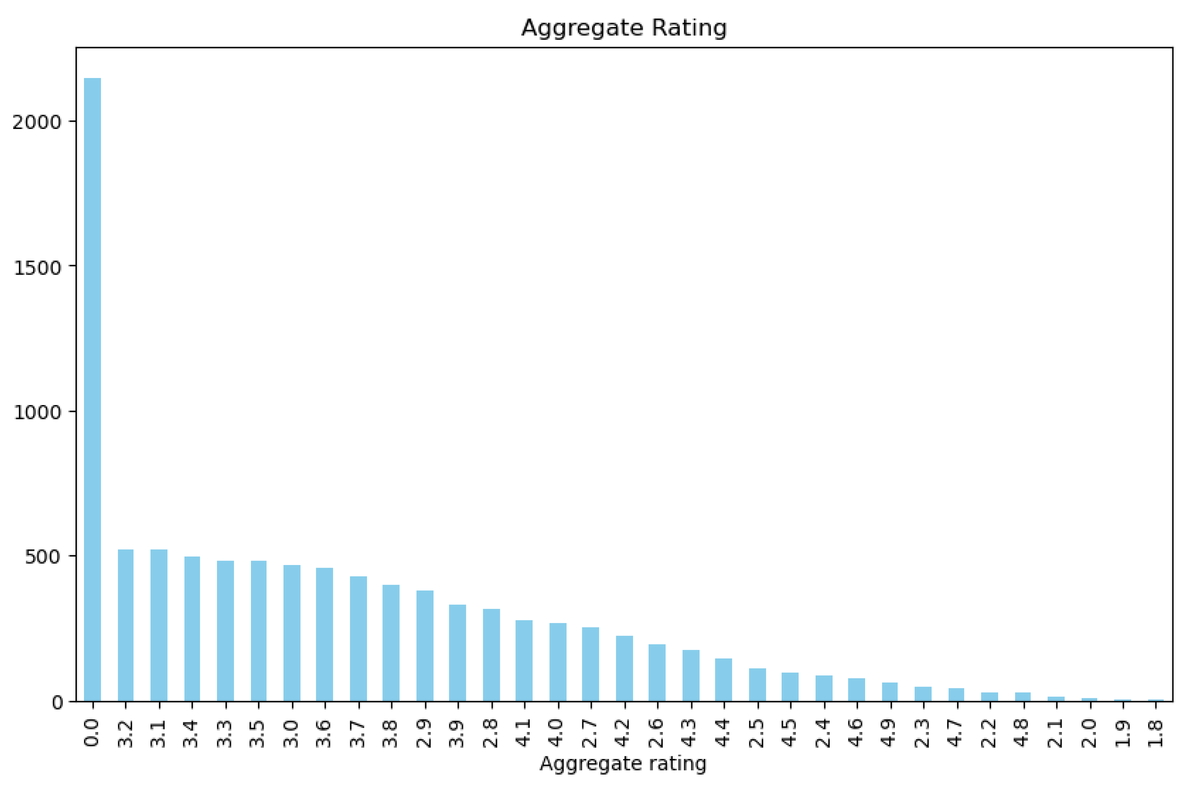
9542 rows × 10 columns

In [10]:
```python
dataset.shape
```

Out[10]:
```
(9542, 10)
```

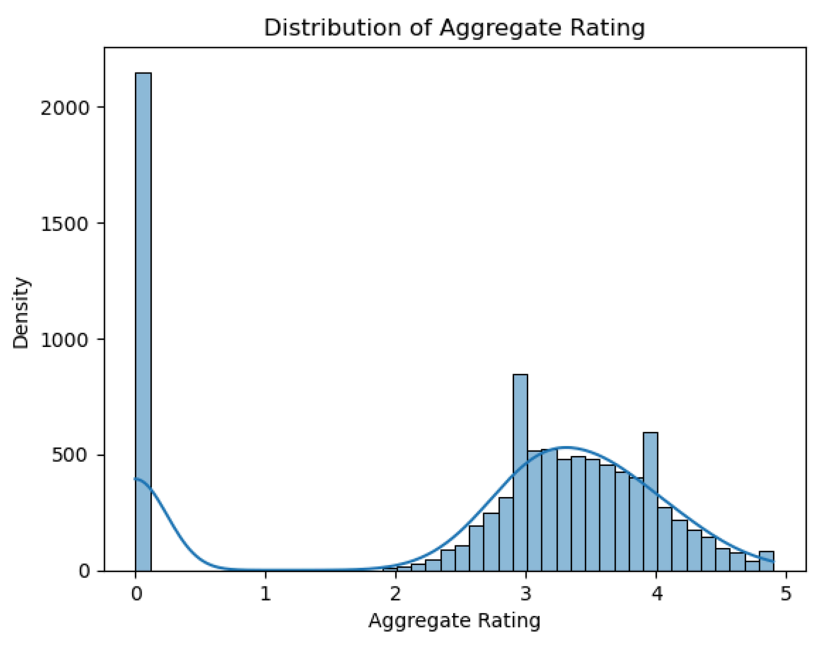
Ploting of Aggregate rating

In [11]:
```python
dataset['Aggregate rating'].value_counts().plot(kind='bar', figsize=(10, 6), color='skyblue')
plt.title('Aggregate Rating')
plt.show()
```



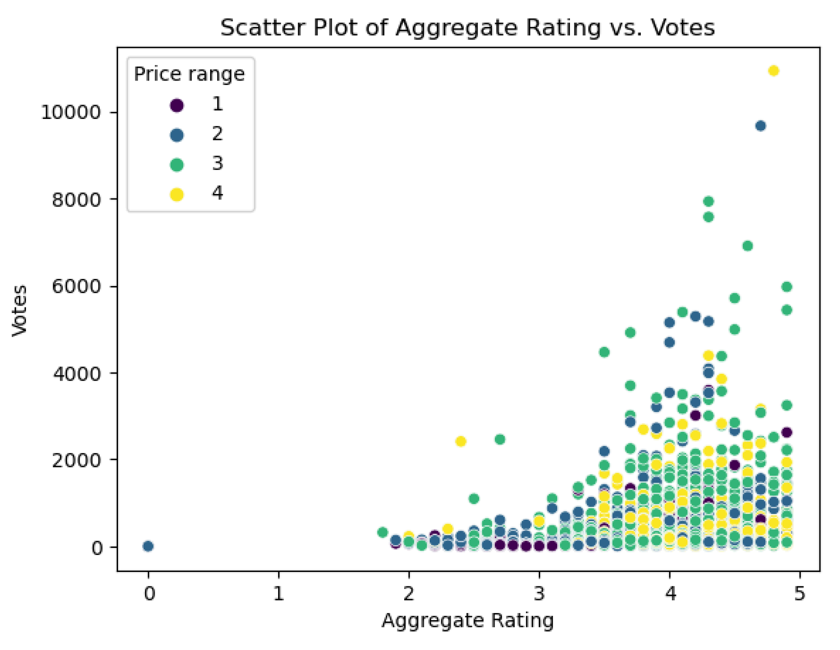
Distribution of Aggregate rating

In [12]:
```python
sns.histplot(dataset['Aggregate rating'], kde=True)
plt.xlabel('Aggregate Rating')
plt.ylabel('Density')
plt.title('Distribution of Aggregate Rating')
plt.show()
```



Scatter Plot of Aggregate Rating Vs Votes

In [13]:
```python
sns.scatterplot(x=dataset["Aggregate rating"], y=dataset["Votes"], hue=dataset["Price range"], palette="viridis")
plt.xlabel('Aggregate Rating')
plt.ylabel('Votes')
plt.title('Scatter Plot of Aggregate Rating vs. Votes')
plt.show()
```



In [14]:
```python
x = dataset.drop('Aggregate rating', axis=1)
y = dataset['Aggregate rating']

# Splitting the data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=250)

x_train.head()
y_train.head()
```

Out[14]:
```
5883    3.8
5470    3.2
5790    0.0
5588    0.0
9283    4.1
Name: Aggregate rating, dtype: float64
```

In [15]:
```python
print("X_Train: ", x_train.shape)
print("X_Test: ",x_test.shape)
print("Y_Train: ",y_train.shape)
print("Y_Test: ",y_test.shape)
```

```
X_Train:  (7633, 9)
X_Test:  (1909, 9)
Y_Train:  (7633,)
Y_Test:  (1909,)
```

Applying Linear Regression Algorithm

In [17]:
```python
linreg = LinearRegression()
linreg.fit(x_train,y_train)
linreg_pred=linreg.predict(x_test)
```

Output After Applying Linear Regression

In [18]:
```python
linreg_mae = mean_absolute_error(y_test, linreg_pred)
linreg_mse = mean_squared_error(y_test, linreg_pred)
linreg_r2 = r2_score(y_test, linreg_pred)
print(f"Mean Absolute Error is: {linreg_mae:.2f}")
print(f"Mean Squared Error is: {linreg_mse:.2f}")
print(f"R2 score is: {linreg_r2:.2f}")
```

```
Mean Absolute Error is: 1.00
Mean Squared Error is: 1.42
R2 score is: 0.39
```

Applying Decision Tree Algorithm

In [19]:
```python
dtree = DecisionTreeRegressor()
dtree.fit(x_train, y_train)
dtree_pred = dtree.predict(x_test)
```

Output After Applying Decision Tree Algorithm

In [20]:
```python
dtree_mae = mean_absolute_error(y_test, dtree_pred)
dtree_mse = mean_squared_error(y_test, dtree_pred)
dtree_r2 = r2_score(y_test, dtree_pred)
print(f"Mean Absolute Error is: {dtree_mae:.2f}")
print(f"Mean Squared Error is: {dtree_mse:.2f}")
print(f"R2 score is: {dtree_r2:.2f}")
```

```
Mean Absolute Error is: 0.15
Mean Squared Error is: 0.05
R2 score is: 0.98
```

Accuracy

The model has achieved an impressive accuracy of 98%, demonstrating its strong predictive power. The Mean Squared Error (MSE) of 0.05 further reinforces this, indicating that the model's predictions are highly precise, with minimal error between the predicted and actual values. Additionally, the R^2 value of 0.98 reveals that the model is extremely effective at capturing the variance in the target variable, making it highly reliable for predicting restaurant ratings. The Decision Tree Regressor model, in particular, is performing exceptionally well when evaluated on the test data, confirming its robustness.

Analysis

In analyzing the factors that influence restaurant ratings, it's observed that the distribution of the target variable, "Aggregate rating," is well balanced, ensuring that the model isn't biased toward any particular rating category. Moreover, there is a clear trend indicating that restaurants with a higher price range tend to receive better ratings. This suggests that customers might associate higher prices with better quality or service, leading to higher ratings for more expensive establishments.

In [ ]: