# Task 1: Predict Restaurant Ratings using Regression

## Objective

Build a regression model to predict the **Aggregate Rating** of a restaurant based on various features like cuisine, location, cost, and other metadata.

```
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.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns
# Mount Google Drive
from google.colab import drive
drive.mount('/content/drive')
# Load Dataset from Google Drive
file_path = '/content/drive/My Drive/ML_Internship/resturant_dataset.csv'
df = pd.read_csv(file_path)
# Preview first few rows
df.head()
```

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

|   | Restaurant<br>ID | Restaurant<br>Name        | Country<br>Code | City                | Address   | Locality   | Locality<br>Verbose   | Longitude  | Latitude  | Cuisines                                  | <br>Currency            | Tal<br>book: |
|---|------------------|---------------------------|-----------------|---------------------|---|--|---|------------|-----------|---|-------------------------|--------------|
| 0 | 6317637          | Le Petit<br>Souffle       | 162             | Makati City         | Third<br>Floor,<br>Century<br>City Mall,<br>Kalayaan<br>Avenu     | Century City<br>Mall,<br>Poblacion,<br>Makati City     | Century City<br>Mall,<br>Poblacion,<br>Makati City,<br>Mak    | 121.027535 | 14.565443 | French,<br>Japanese,<br>Desserts          | <br>Botswana<br>Pula(P) |              |
| 1 | 6304287          | Izakaya<br>Kikufuji       | 162             | Makati City         | Little<br>Tokyo,<br>2277<br>Chino<br>Roces<br>Avenue,<br>Legaspi  | Little Tokyo,<br>Legaspi<br>Village,<br>Makati City    | Little Tokyo,<br>Legaspi<br>Village,<br>Makati City,<br>Ma    | 121.014101 | 14.553708 | Japanese                                  | <br>Botswana<br>Pula(P) |              |
| 2 | 6300002          | Heat - Edsa<br>Shangri-La | 162             | Mandaluyong<br>City | Edsa<br>Shangri-<br>La, 1<br>Garden<br>Way,<br>Ortigas,<br>Mandal | Edsa<br>Shangri-La,<br>Ortigas,<br>Mandaluyong<br>City | Edsa<br>Shangri-La,<br>Ortigas,<br>Mandaluyong<br>City, Ma    | 121.056831 | 14.581404 | Seafood,<br>Asian,<br>Filipino,<br>Indian | <br>Botswana<br>Pula(P) |              |
| 3 | 6318506          | Ooma                      | 162             | Mandaluyong<br>City | Third<br>Floor,<br>Mega<br>Fashion<br>Hall, SM<br>Megamall,<br>O  | SM<br>Megamall,<br>Ortigas,<br>Mandaluyong<br>City     | SM<br>Megamall,<br>Ortigas,<br>Mandaluyong<br>City,<br>Mandal | 121.056475 | 14.585318 | Japanese,<br>Sushi                        | <br>Botswana<br>Pula(P) |              |
| 4 | 6314302          | Sambo<br>Kojin            | 162             | Mandaluyong<br>City | Third<br>Floor,<br>Mega<br>Atrium,<br>SM<br>Megamall,<br>Ortigas  | SM<br>Megamall,<br>Ortigas,<br>Mandaluyong<br>City     | SM<br>Megamall,<br>Ortigas,<br>Mandaluyong<br>City,<br>Mandal | 121.057508 | 14.584450 | Japanese,<br>Korean                       | <br>Botswana<br>Pula(P) |              |

5 rows × 21 columns

#### Step 1: Data Preprocessing

- Handle missing values
- · Encode categorical features
- · Select relevant features for prediction

| <b>→</b> |   | Average<br>Cost<br>for two | Has<br>Table<br>booking | Has<br>Online<br>delivery | Price | Votes | Aggregate<br>rating | Cuisines_Bakery,<br>Desserts | Cuisines_Cafe | Cuisines_Chinese | Cuisines_Fast<br>Food | Cuisines_North<br>Indian |
|----------|---|----------------------------|-------------------------|---------------------------|-------|-------|---------------------|------------------------------|---------------|------------------|-----------------------|--------------------------|
|          | 0 | 1100                       | 1                       | 0                         | 3     | 314   | 4.8                 | False                        | False         | False            | False                 | False                    |
|          | 1 | 1200                       | 1                       | 0                         | 3     | 591   | 4.5                 | False                        | False         | False            | False                 | False                    |
|          | 2 | 4000                       | 1                       | 0                         | 4     | 270   | 4.4                 | False                        | False         | False            | False                 | False                    |
|          | 3 | 1500                       | 0                       | 0                         | 4     | 365   | 4.9                 | False                        | False         | False            | False                 | False                    |
|          | 4 | 1500                       | 1                       | 0                         | 4     | 229   | 4.8                 | False                        | False         | False            | False                 | False                    |

Next steps: Generate code with data View recommended plots New interactive sheet

#### Step 2: Train-Test Split

```
X = data.drop('Aggregate rating', axis=1)
y = data['Aggregate rating']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

### Step 3: Train and Evaluate Models

```
# Linear Regression
lr = LinearRegression()
lr.fit(X_train, y_train)
y_pred_lr = lr.predict(X_test)

print("Linear Regression R2 Score:", r2_score(y_test, y_pred_lr))
print("Linear Regression MSE:", mean_squared_error(y_test, y_pred_lr))

Linear Regression R2 Score: 0.30675107783544675
Linear Regression MSE: 1.5875623551619147

# Decision Tree Regressor
dt = DecisionTreeRegressor(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)

print("Decision Tree R2 Score:", r2_score(y_test, y_pred_dt))
print("Decision Tree MSE:", mean_squared_error(y_test, y_pred_dt))
```

Decision Tree R2 Score: 0.9057745050522386
Decision Tree MSE: 0.21577941759865893

#### Step 4: Feature Importance Analysis

importances = pd.Series(dt.feature\_importances\_, index=X.columns)
importances.sort\_values().plot(kind='barh', figsize=(10,6))
plt.title('Feature Importances from Decision Tree')
plt.show()



