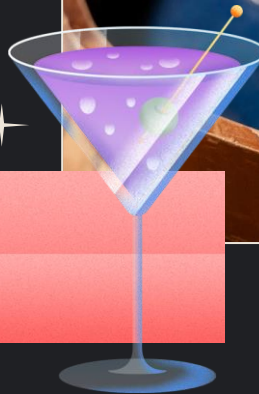


# RESTAURANT RATING PREDICTION USING ML

By-Manav Shah





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OI

PROBLEM STATEMENT



# PROBLEM STATEMENT

Develop a machine learning model to predict the aggregate rating of a restaurant based on various features related to the restaurant's characteristics and operations.

## OBJECTIVE

Predicting Restaurant Ratings




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# DATASET OVERVIEW




# DATASET OVERVIEW

The dataset contains the following columns:

1. Restaurant ID: Unique identifier for each restaurant.
  2. Restaurant Name: Name of the restaurant.
  3. Country Code: Numeric code representing the country where the restaurant is located.
  4. City: Name of the city where the restaurant is situated.
  5. Address: Physical address of the restaurant.
  6. Locality: Locality or neighborhood where the restaurant is located.
  7. Locality Verbose: Detailed description of the locality.
  8. Longitude: Geographical longitude of the restaurant's location.
  9. Latitude: Geographical latitude of the restaurant's location.
  10. Cuisines: Types of cuisines offered by the restaurant.
  11. Average Cost for Two: Average cost for a meal for two people.
  12. Currency: Currency used for transactions in the restaurant.
- 



# DATASET OVERVIEW

- 13. Has Table Booking: Indicator of whether the restaurant accepts table bookings.
  - 14. Has Online Delivery: Indicator of whether the restaurant offers online delivery.
  - 15. Is Delivering Now: Indicator of whether the restaurant is currently delivering.
  - 16. Switch to Order Menu: Indicator of whether the restaurant has switched to an order menu.
  - 17. Price Range: Price range category of the restaurant.
  - 18. Aggregate Rating: Overall rating of the restaurant.
  - 19. Rating Color: Color code representing the rating.
  - 20. Rating Text: Text description of the rating.
  - 21. Votes: Number of votes received by the restaurant.
- 



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IMPORTING DATA



```
✓ [1] import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

```
✓ [2] data = pd.read_csv('/content/Restaurant Rating Dataset.csv')
```

```
0s # Display first few rows
print(data.head())
```

	Restaurant ID	Restaurant Name	Country	Code	
0	6317637	Le Petit Souffle	162		Makat
1	6304287	Izakaya Kikufuji	162		Makat
2	6300002	Heat - Edsa Shangri-La	162		Mandaluyon
3	6318506	Ooma	162		Mandaluyon
4	6314302	Sambo Kojin	162		Mandaluyon





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# DATA PREPROCESSING

# CHECKING FOR NULL VALUES AND HANDELLING :

```
✓ 0s ▶ data['Cuisines'].fillna(data['Cuisines'].mode()[0], inplace=True)
```

✓  
0s



```
# Check for missing values  
print(data.isnull().sum())
```



```
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
```

# LABEL ENCODING FOR CATEGORICAL COLUMNS



```
# Label Encoding for categorical columns
le = LabelEncoder()
data['Cuisines'] = le.fit_transform(data['Cuisines'])
data['City'] = le.fit_transform(data['City'])
data['Currency'] = le.fit_transform(data['Currency'])
```



# REMOVING UNNECESSARY COLUMNS AND FEATURE SCALING

```
✓ [6] # Drop unnecessary columns
      data.drop(['Restaurant ID', 'Restaurant Name', 'Address', 'Locality', 'Locality Verbose'])

✓ #feature scaling
  scaler = StandardScaler()
  numerical_features = ['Average Cost for two', 'Latitude', 'Longitude', 'Votes']
  data[numerical_features] = scaler.fit_transform(data[numerical_features])
```



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# MODEL IMPLEMENTATION

# DEFINING FEATURES AND TARGETS AND SPLIT INTO TRAIN TEST DATA

```
✓ [8] # Define features and target
      X = data.drop('Aggregate rating', axis=1)
      y = data['Aggregate rating']

✓ [9] # Split the data into train and test sets
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

# IMPLEMENTING DECISION TREE REGRESSOR

✓  
0s



```
# Decision Tree Regressor
```

```
dt = DecisionTreeRegressor(random_state=42)  
dt.fit(X_train, y_train)
```

```
# Predictions
```

```
y_pred_dt = dt.predict(X_test)
```

```
# Evaluation
```

```
mse_dt = mean_squared_error(y_test, y_pred_dt)  
r2_dt = r2_score(y_test, y_pred_dt)  
print(f'Decision Tree - MSE: {mse_dt}, R2: {r2_dt}')
```



```
Decision Tree - MSE: 0.17420198848770277, R2: 0.9234650057491243
```



# IMPLEMENTING RANDOM FOREST REGRESSOR

✓  
7s



```
rf = RandomForestRegressor(random_state=42, n_estimators=100)
rf.fit(X_train, y_train)
```

```
# Predictions
```

```
y_pred_rf = rf.predict(X_test)
```

```
# Evaluation
```

```
mse_rf = mean_squared_error(y_test, y_pred_rf)
```

```
r2_rf = r2_score(y_test, y_pred_rf)
```

```
print(f'Random Forest - MSE: {mse_rf}, R2: {r2_rf}')
```



```
Random Forest - MSE: 0.08747064207221349, R2: 0.9615700994791466
```



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CONCLUSION

# CONCLUSION

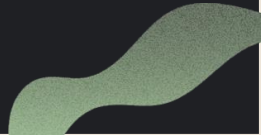

The **Random Forest Regressor** outperforms the **Decision Tree Regressor** in both metrics:

- ❑ The **MSE** is lower for the Random Forest Regressor (0.0875 vs. 0.1742), indicating that the model's predictions are, on average, closer to the actual values.
- ❑ The **R<sup>2</sup>** score is higher for the Random Forest Regressor (0.9616 vs. 0.9235), which means that it explains a larger proportion of the variance in the target variable.

# RECOMMENDATION



Given these results, **the Random Forest Regressor is the better model for predicting restaurant ratings**. It provides higher accuracy and better generalization to the test data, making it the preferred choice for the prediction task.





# THANKS!

**Do you have any questions?**

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