------------------------------Random Forest Regressor------------------------------

Conecting to Drive

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Load the Necessary Libraries

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.feature_selection import chi2
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
```

Data Loading

```
dataset = pd.read_csv('/content/drive/MyDrive/ML Project/Bengaluru_House_Data.csv')
dataset.head()
```

	area_type	availability	location	size	society	total_sqft	bath	balcony	price
0	Super built-up Area	19-Dec	Electronic City Phase II	2 BHK	Coomee	1056	2.0	1.0	39.07
1	Plot Area	Ready To Move	Chikka Tirupathi	4 Bedroom	Theanmp	2600	5.0	3.0	120.00
2	Built-up Area	Ready To Move	Uttarahalli	3 BHK	NaN	1440	2.0	3.0	62.00
3	Super built-up Area	Ready To Move	Lingadheeranahalli	3 BHK	Soiewre	1521	3.0	1.0	95.00
4	Super built-up Area	Ready To Move	Kothanur	2 BHK	NaN	1200	2.0	1.0	51.00

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

Exploratory Data Analysis (EDA)

Data Cleaning

```
dataset.drop_duplicates(inplace=True)
dataset.dropna(subset=['total_sqft', 'size', 'price'], inplace=True)  # Ensure essential columns are not null
```

```
dataset.head()
```

	area_type	availability	location	size	society	total_sqft	bath	balcony	price
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Next steps: Generate code with dataset | View recommended plots | New interactive sheet

Transform the 'size' column in the dataset to extract numeric values

```
dataset['size'] = dataset['size'].apply(lambda x: int(str(x).split(' ')[0]) if isinstance(x, str) else x)
```

```
dataset.head()
```

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

Data Preprocessing

Convert 'total_sqft' to a numeric value

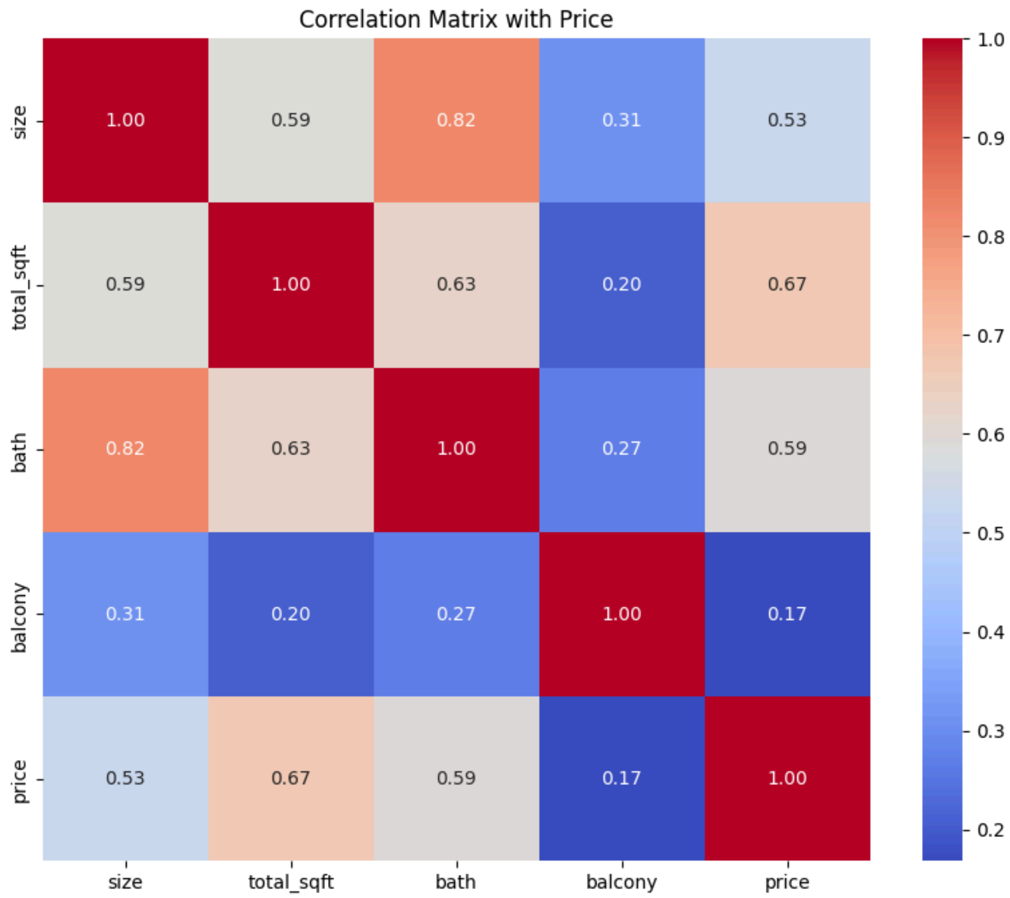
```
def convert_sqft_to_num(x):
    if '-' in str(x):
        tokens = x.split('-')
        return (float(tokens[0]) + float(tokens[1])) / 2
    try:
        return float(x)
    except:
        return None

dataset['total_sqft'] = dataset['total_sqft'].apply(convert_sqft_to_num)
dataset.dropna(inplace=True)
```

Ensure only numeric columns are included for the correlation matrix

```
numeric_data = dataset.select_dtypes(include=[np.number])
```

Correlation Matrix for Numerical Features

```
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Matrix with Price")
plt.show()
```



Ensure only numeric columns are included for the correlation matrix

```
numeric_data = dataset.select_dtypes(include=[np.number])
```

Calculate the correlation matrix for numerical features

```
correlation_matrix = numeric_data.corr()
```

Identify low-correlation columns with 'price' (threshold < 0.1)

```
low_correlation_features = correlation_matrix.index[abs(correlation_matrix['price']) < 0.1]
```

Drop columns with low correlation to 'price' in the main dataset

```
dataset = dataset.drop(columns=low_correlation_features)
```

Handle categorical Data

Encode 'location' as a numerical feature for chi-squared test

```
location_counts = dataset['location'].value_counts()
dataset['location'] = dataset['location'].apply(lambda x: x if location_counts[x] > 10 else 'Other')
label_encoder = LabelEncoder()
dataset['location_encoded'] = label_encoder.fit_transform(dataset['location'])
```

Handle categorical features 'area_type', 'availability', 'location', and 'society'

Encode 'area_type' and 'availability' for chi-squared test

```
label_encoder = LabelEncoder()
dataset['area_type_encoded'] = label_encoder.fit_transform(dataset['area_type'])
dataset['availability_encoded'] = label_encoder.fit_transform(dataset['availability'])
```

Fill NaN values in 'society' and encode it for chi-squared test

```
dataset['society'] = dataset['society'].fillna('Unknown')  # Assign filled values directly
dataset['society_encoded'] = label_encoder.fit_transform(dataset['society'])
```

Convert 'price' to categorical data by binning into price ranges

```
price_bins = pd.qcut(dataset['price'], q=3, labels=['Low', 'Medium', 'High'])
dataset['price_category'] = price_bins
```

Chi-Squared Test

```
# Chi-Squared Test for 'location' and 'society' against the binned 'price_category'
chi_scores_loc, p_values_loc = chi2(dataset[['location_encoded']], dataset['price_category'].cat.codes)
chi_scores_soc, p_values_soc = chi2(dataset[['society_encoded']], dataset['price_category'].cat.codes)

print(f"Chi-Squared Score for Location: {chi_scores_loc[0]}, P-Value: {p_values_loc[0]}")
print(f"Chi-Squared Score for Society: {chi_scores_soc[0]}, P-Value: {p_values_soc[0]}")

# Chi-Squared Test for 'area_type' and 'availability' against the binned 'price_category'
# Convert 'price' to categorical data for chi-squared testing

chi_scores_area, p_values_area = chi2(dataset[['area_type_encoded']], dataset['price_category'].cat.codes)
chi_scores_avail, p_values_avail = chi2(dataset[['availability_encoded']], dataset['price_category'].cat.codes)

print(f"Chi-Squared Score for Area Type: {chi_scores_area[0]}, P-Value: {p_values_area[0]}")
print(f"Chi-Squared Score for Availability: {chi_scores_avail[0]}, P-Value: {p_values_avail[0]}")
```

```
Chi-Squared Score for Location: 556.0604481262152, P-Value: 1.7906383728868622e-121
Chi-Squared Score for Society: 3166.738786217457, P-Value: 0.0
Chi-Squared Score for Area Type: 8.639775290823856, P-Value: 0.013301377929329629
Chi-Squared Score for Availability: 17.6039269945285, P-Value: 0.00015043740148704842
```

Decide to keep or remove

```
# Decide to keep or remove 'location' and 'society' based on chi-squared test results
if p_values_loc[0] >= 0.05:
    dataset = dataset.drop(['location', 'location_encoded'], axis=1)
else:
    dataset = pd.get_dummies(dataset, columns=['location'], drop_first=True)

if p_values_soc[0] >= 0.05:
    dataset = dataset.drop(['society', 'society_encoded'], axis=1)
else:
    dataset = pd.get_dummies(dataset, columns=['society'], drop_first=True)
    # Drop 'area_type' and 'availability' if they have a high p-value (not statistically significant)
if p_values_area[0] >= 0.05:
    dataset = dataset.drop(['area_type', 'area_type_encoded'], axis=1)
else:
    dataset = pd.get_dummies(dataset, columns=['area_type'], drop_first=True)

if p_values_avail[0] >= 0.05:
    dataset = dataset.drop(['availability', 'availability_encoded'], axis=1)
else:
    dataset = pd.get_dummies(dataset, columns=['availability'], drop_first=True)
```

Separate features and target variable

```
X = dataset.drop(['price', 'price_category'], axis=1)
y = dataset['price']

X.head()
```

	size	total_sqft	bath	balcony	location_encoded	area_type_encoded	availability_encoded	society_encoded	location_! Phase Naç
0	2	1056.0	2.0	1.0	44	3	35	441	Fa
1	4	2600.0	5.0	3.0	34	2	73	2351	Fa
3	3	1521.0	3.0	1.0	99	3	73	2107	Fa
5	2	1170.0	2.0	1.0	136	3	73	583	Fa
11	4	2785.0	5.0	3.0	136	2	73	1564	Fa

5 rows × 2812 columns

Split data into training and testing sets

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Model Training with Random Forest

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

```
RandomForestRegressor
RandomForestRegressor(random_state=42)
```

Predict on test set

```
y_pred = model.predict(X_test)
```

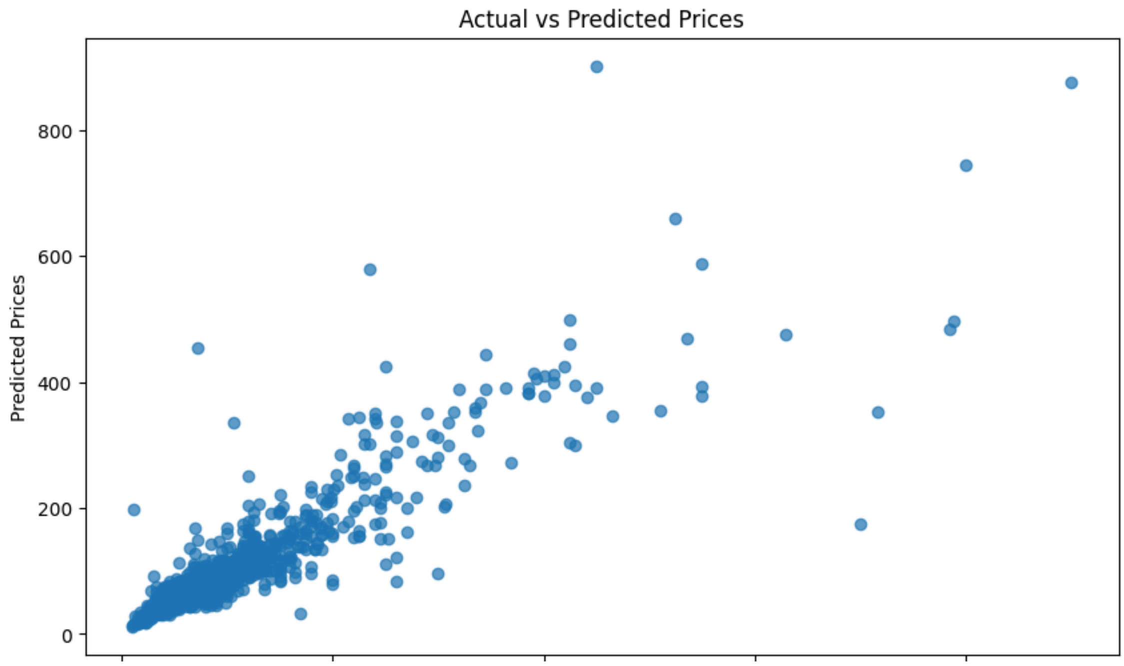
Evaluate the model

```
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f"Mean Absolute Error (MAE): {mae}")
print(f"Root Mean Squared Error (RMSE): {rmse}")
```

```
Mean Absolute Error (MAE): 17.399440586541363
Root Mean Squared Error (RMSE): 39.23284126825341
```

Plot Actual vs Predicted values

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.7)
plt.xlabel("Actual Prices")
plt.ylabel("Predicted Prices")
plt.title("Actual vs Predicted Prices")
plt.show()
```


Actual vs Predicted Prices
Predicted Prices
800
600
400
200
0