Vellore Institute of Technology
(Deemed to be University under section 3 of UGC Act, 1956)

FOUNDATIONS OF DATA SCIENCE
BCSE206L

PROJECT REPORT

TOPIC:
Bangalore Apartment Price Prediction

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INTRODUCTION

Bangalore, often hailed as India's "Silicon Valley," has undergone a profound economic boom, attracting a surge of businesses, professionals, and investors in recent years. This rapid growth has substantially impacted on the city's housing market, driving up property prices. The city's thriving IT sector, coupled with its reputation as a cosmopolitan metropolis with robust infrastructure, has spurred demand for residential properties, particularly among tech professionals and migrants.

Limited land availability within the city's confines has exacerbated the situation, pushing developers to build vertically, and resulting in a proliferation of high-rise apartments and luxury condominiums, which command premium prices. Government policies and regulations, such as land use norms and taxation policies, also play a pivotal role in shaping market dynamics. Factors like interest rates on home loans and economic stability further influence buyers' purchasing power and investment decisions.

Moreover, Bangalore's socio-economic demographics, including income levels and lifestyle preferences, contribute to varying demand across different housing segments. Areas near employment hubs and essential amenities experience heightened demand and consequently higher property values. Understanding these complex dynamics is crucial for stakeholders to navigate Bangalore's real estate landscape effectively.

DATA SCIENCE LIFECYCLE

1. Discovery

In the Discovery stage, the focus is on defining the problem statement: predicting apartment prices in Bangalore. Stakeholders benefiting from this analysis include potential homebuyers, real estate developers, and investors. Various data sources such as real estate websites, government databases, and property listings are explored to gather relevant data for analysis.

2. Data Preparation

Data Preparation involves cleaning the dataset by addressing missing values, outliers, and inconsistencies. Exploratory data analysis (EDA) is conducted to understand the distribution of apartment prices and relationships between price and features like location, size, and amenities. Data normalization techniques are applied to standardize features for model training.

3. Model Building

In Model Building, a predictive model is developed to estimate apartment prices based on various features. The dataset is split into training and testing sets for model training and evaluation, respectively. Machine learning algorithms like linear regression, decision trees, or random forests are employed. Model performance is assessed using metrics like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

4. Model Planning

Model Planning involves selecting relevant features impacting apartment prices in Bangalore based on insights from EDA and domain knowledge. The most suitable machine learning model is chosen considering factors like interpretability and predictive performance. Techniques like regularization or ensemble methods may be used to enhance model accuracy.

5. Communication of Results

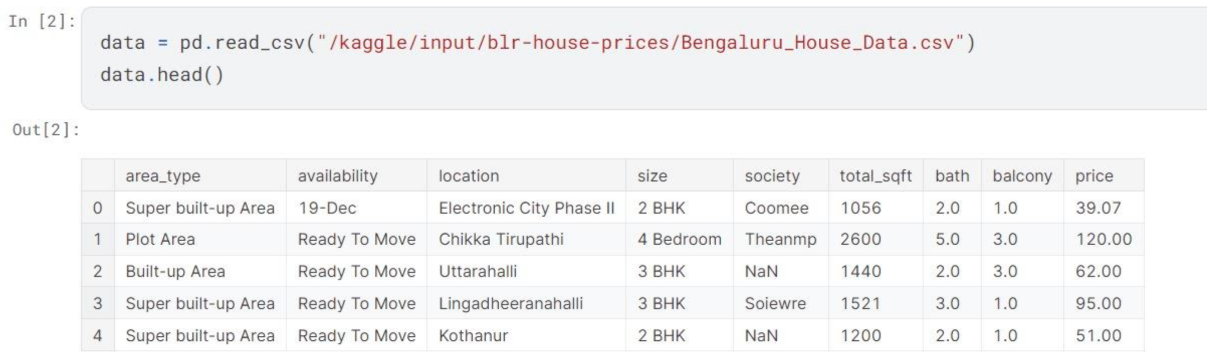
After developing and validating the apartment price prediction model, Communication of Results is crucial. Visualizations, reports, or presentations are created to highlight insights gained from the model. Communication is tailored to the specific needs of stakeholders, with clear explanations of predictions and associated uncertainties.

6. Operationalize

Finally, operationalize involves deploying the model into production for practical use. Continuous monitoring and maintenance ensure the model's accuracy and relevance over time. The model may need scaling to handle larger datasets or increased usage, with documentation and training provided for integration into existing workflows and decision-making processes.

DISCOVERY

In the Discovery stage, the primary focus is on defining the problem statement and domain, which in this case, revolves around predicting apartment prices in Bangalore, particularly relevant to real estate or property market analysis. The stakeholders involved in this endeavor include people seeking to buy property, real estate agents, brokers, and others invested in the Bangalore housing market. To gather relevant data for analysis, various data sources are identified, such as the Bengaluru House Data dataset provided by Amitabh Chakraborty on Kaggle. Additionally, initial hypotheses are formed, suggesting that apartment prices in Bangalore may depend on factors like size, number of bedrooms (bhk), and available amenities. These initial hypotheses provide a starting point for further exploration and analysis in subsequent stages of the data science lifecycle.
In addition to defining the problem statement, stakeholders, and data sources, the Discovery stage also involves exploring the domain to gain a deeper understanding of the factors influencing apartment prices in Bangalore. This exploration may include researching trends in the real estate market, understanding local regulations impacting property prices, and identifying key economic indicators affecting housing demand and supply dynamics. By delving into these aspects, we aim to refine our understanding of the problem domain and uncover additional insights that may inform our analysis and model development process.



```
In [2]:
data = pd.read_csv("/kaggle/input/blr-house-prices/Bengaluru_House_Data.csv")
data.head()
```

Out[2]:

	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

DATA PREPARATION

Data preparation is a crucial step that involves cleaning, transforming, and organizing raw data into a format suitable for analysis. It ensures that the data used is complete, concise, accurate and relevant.

The major steps involved in data preparation include:

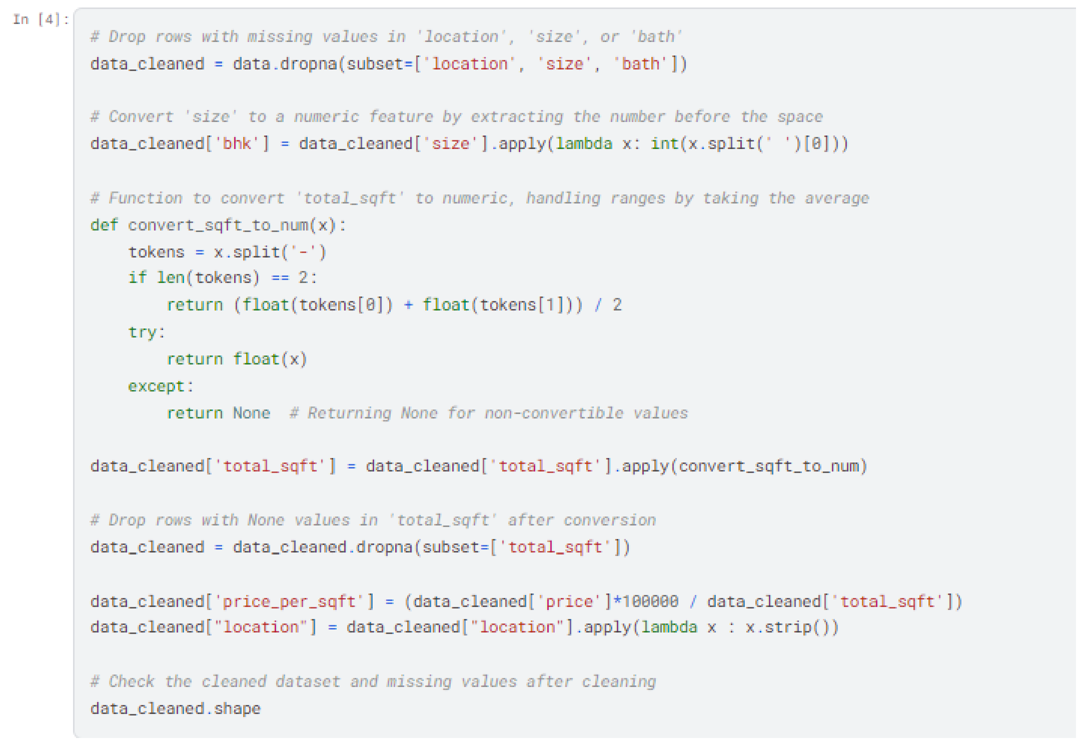
1. Preparing a sandbox

A sandbox is an isolated testing environment that enables users to run programs without affecting the application. We have used a jupyter notebook for the analysis purposes.

2. Performing ETLT

ETLT stands for Extract, Transform, Load, Transform, which can further be defined as:
Extract: Obtain the raw data from Kaggle
Transform: Cleanse, filter, and preprocess the data to make it suitable for analysis.
Load: Store the transformed data in a structured format
We have taken the data from Kaggle, loaded it in the jupyter notebook using pandas and cleaned it. Transformations made are:

a. Rows containing null values are removed.
b. Converting size column to numeric values in bhk
c. Only keeping those values which lie within a range surrounding the mean of the column
d. Dropping columns such as society, availability, balcony which are not relevant



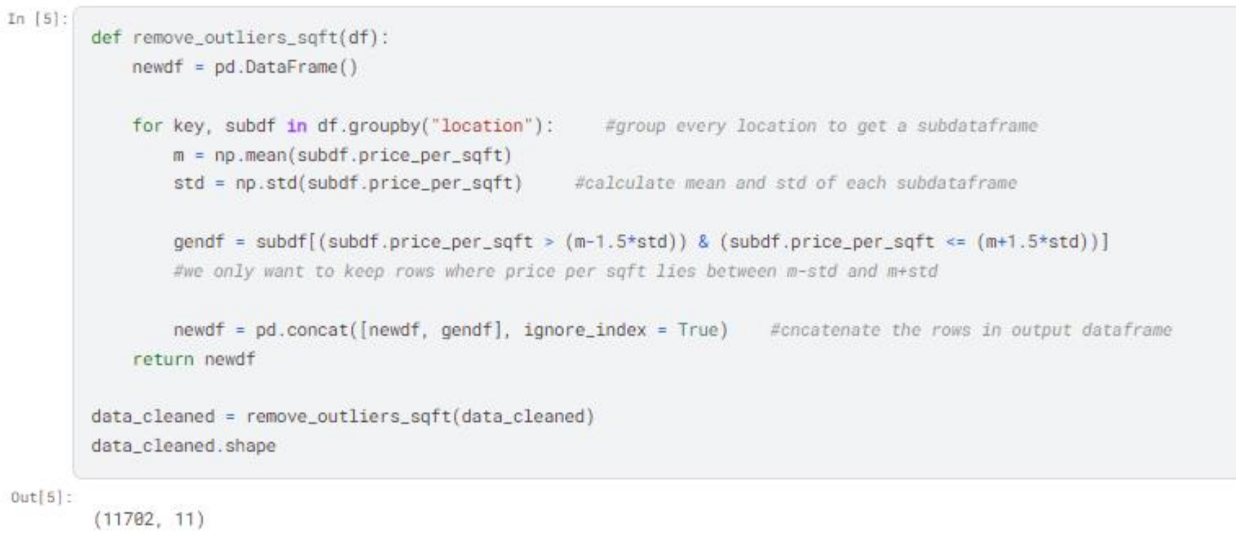
```
In [4]:
# Drop rows with missing values in 'location', 'size', or 'bath'
data_cleaned = data.dropna(subset=['location', 'size', 'bath'])

# Convert 'size' to a numeric feature by extracting the number before the space
data_cleaned['bhk'] = data_cleaned['size'].apply(lambda x: int(x.split(' ')[0]))

# Function to convert 'total_sqft' to numeric, handling ranges by taking the average
def convert_sqft_to_num(x):
    tokens = x.split('-')
    if len(tokens) == 2:
        return (float(tokens[0]) + float(tokens[1])) / 2
    try:
        return float(x)
    except:
        return None  # Returning None for non-convertible values

data_cleaned['total_sqft'] = data_cleaned['total_sqft'].apply(convert_sqft_to_num)

# Drop rows with None values in 'total_sqft' after conversion
data_cleaned = data_cleaned.dropna(subset=['total_sqft'])

data_cleaned['price_per_sqft'] = (data_cleaned['price']*100000 / data_cleaned['total_sqft'])
data_cleaned["location"] = data_cleaned["location"].apply(lambda x : x.strip())

# Check the cleaned dataset and missing values after cleaning
data_cleaned.shape
```

3. Learning about the data

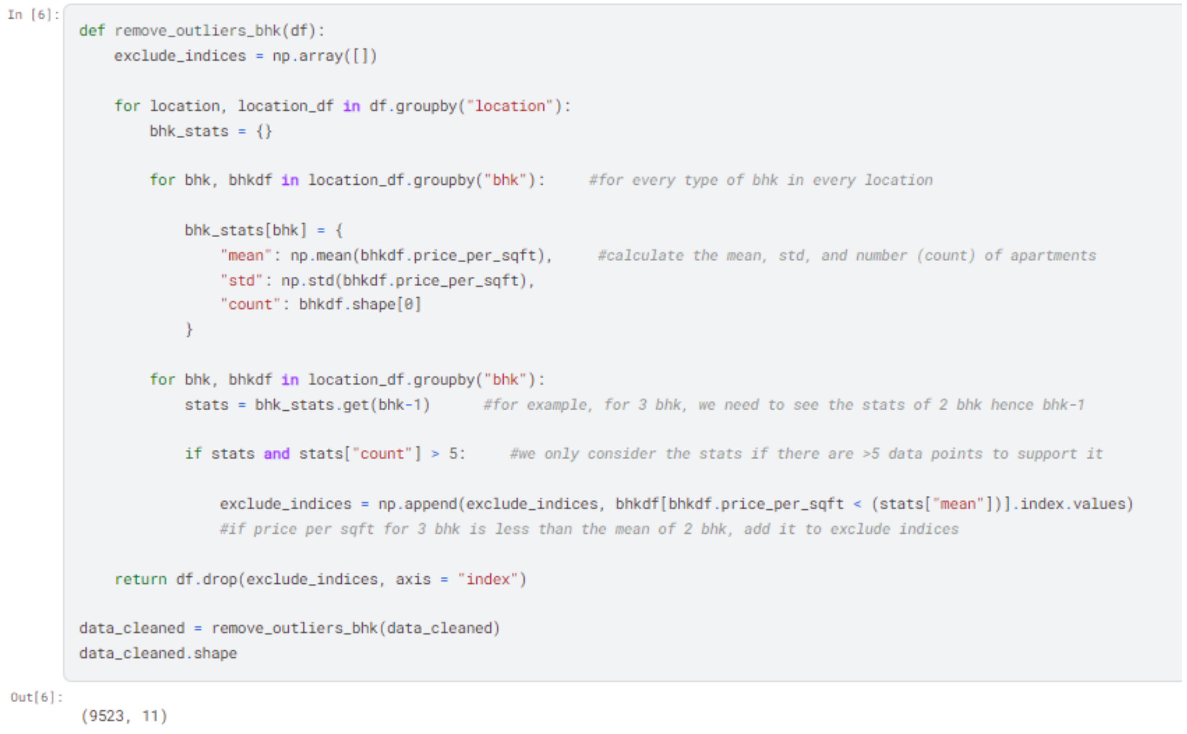
This involves exploring the dataset to understand its structure, variables, and distributions, as well as identifying any patterns or anomalies.

4. Data conditioning

In this we have removed the outliers in bhk and sqft by taking the values around mean.
Price per sqft is calculated to remove the outliers from the sqft column.
Then we drop all the columns which are not required for prediction. So the only columns remaining are location, bhk, no of baths, price, sqft.

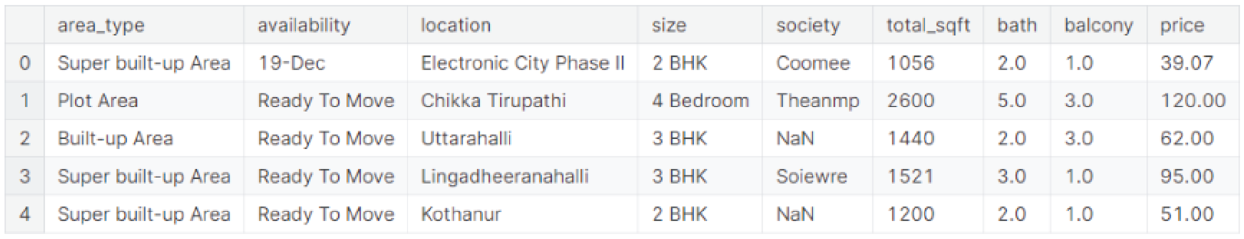


```
In [5]:
def remove_outliers_sqft(df):
    newdf = pd.DataFrame()

    for key, subdf in df.groupby("location"):     #group every location to get a subdataframe
        m = np.mean(subdf.price_per_sqft)
        std = np.std(subdf.price_per_sqft)     #calculate mean and std of each subdataframe

        gendf = subdf[(subdf.price_per_sqft > (m-1.5*std)) & (subdf.price_per_sqft <= (m+1.5*std))]
        #we only want to keep rows where price per sqft lies between m-std and m+std

        newdf = pd.concat([newdf, gendf], ignore_index = True)    #cncatenate the rows in output dataframe
    return newdf

data_cleaned = remove_outliers_sqft(data_cleaned)
data_cleaned.shape

Out[5]:
(11702, 11)
```



```
In [6]:
def remove_outliers_bhk(df):
    exclude_indices = np.array([])

    for location, location_df in df.groupby("location"):
        bhk_stats = {}

        for bhk, bhkdf in location_df.groupby("bhk"):     #for every type of bhk in every location

            bhk_stats[bhk] = {
                "mean": np.mean(bhkdf.price_per_sqft),     #calculate the mean, std, and number (count) of apartments
                "std": np.std(bhkdf.price_per_sqft),
                "count": bhkdf.shape[0]
            }

        for bhk, bhkdf in location_df.groupby("bhk"):
            stats = bhk_stats.get(bhk-1)     #for example, for 3 bhk, we need to see the stats of 2 bhk hence bhk-1

            if stats and stats["count"] > 5:     #we only consider the stats if there are >5 data points to support it

                exclude_indices = np.append(exclude_indices, bhkdf[bhkdf.price_per_sqft < (stats["mean"])].index.values)
                #if price per sqft for 3 bhk is less than the mean of 2 bhk, add it to exclude indices

    return df.drop(exclude_indices, axis = "index")

data_cleaned = remove_outliers_bhk(data_cleaned)
data_cleaned.shape

Out[6]:
(9523, 11)
```

Before Cleaning:



	area_type	availability	location	size	society	total_sqft	bath	balcony	price
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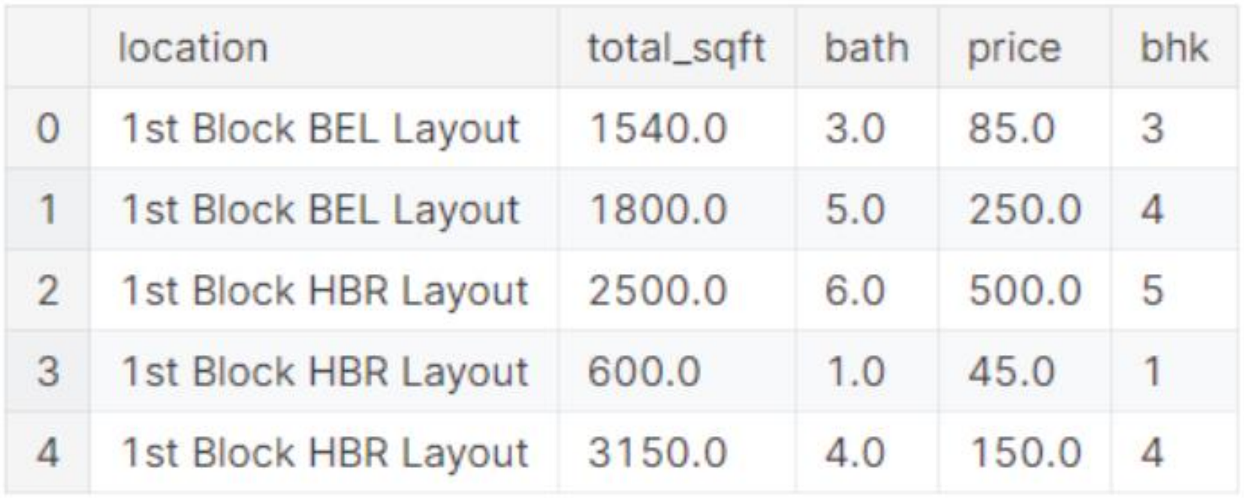
After Cleaning:



	location	total_sqft	bath	price	bhk
0	1st Block BEL Layout	1540.0	3.0	85.0	3
1	1st Block BEL Layout	1800.0	5.0	250.0	4
2	1st Block HBR Layout	2500.0	6.0	500.0	5
3	1st Block HBR Layout	600.0	1.0	45.0	1
4	1st Block HBR Layout	3150.0	4.0	150.0	4

DATA ANALYSIS AND VISUALISATION

This section delves into the data analysis and visualization techniques applied to the dataset, focusing on features like 'total_sqft' and 'bhk.' It aims to provide a comprehensive understanding of the dataset's characteristics, including granularity, range of values, population representation, location-specific factors, standardization, normalization, and geospatial consistency. Additionally, it explores the data visualization approach used to present key insights effectively.

Data Visualization Approach:

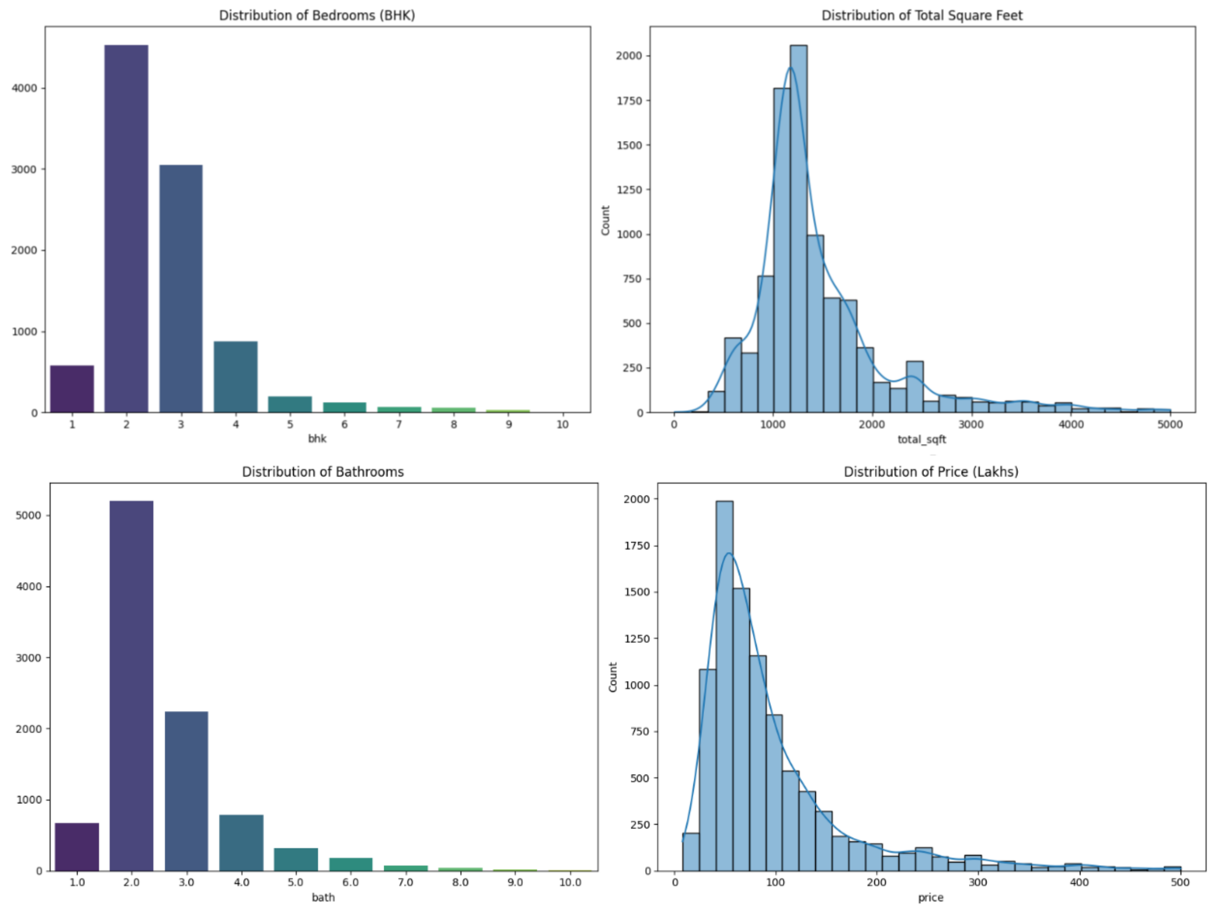
1. Overview First: The data overview begins with distribution plots showcasing bedrooms, total square feet, bathrooms, and prices. Scatter plots complement these distributions, offering a high-level summary of the dataset's key characteristics.
2. Zoom and Filter: The approach includes outlier removal based on location-specific price per square foot, acting as a form of filtering. While not interactive, incorporating interactive elements could enhance the user's ability to zoom in on specific areas of interest and filter out outliers effectively.
3. Details-on-Demand: Scatter plots utilized for machine learning model evaluation serve as a form of details-on-demand. Users can examine the accuracy of predictions within specific price ranges, providing detailed insights into the model's performance.

Key Considerations:

1. Comprehensive Understanding: The analysis aims to provide a comprehensive understanding of the dataset's depth and characteristics, facilitated by data visualization techniques.
2. Population Representation: Accurate population representation is ensured through outlier removal based on location-specific factors, enhancing the dataset's reliability for analysis. This step contributes to a more precise representation of the population, leading to more meaningful insights and decision-making, which is ensured through outlier removal and filtering based on location-specific factors.
3. Standardization and Normalization: Standardization and normalization techniques are applied to features like 'total_sqft,' ensuring consistent scales for analysis and comparability across different properties. This standardization enhances the reliability and accuracy of the analysis, providing more robust insights
4. Geospatial Consistency: Maintaining geospatial consistency is crucial for accurate location-based analysis and insights. By accounting for location-specific factors and ensuring data integrity, the analysis can provide more precise and meaningful results, particularly in geospatial contexts.

Visualization of graphs:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Adjusting the plot distributions by limiting the x-axis to focus on the denser areas of the data
fig, ax = plt.subplots(2, 2, figsize=(16, 12))

# Distribution of 'bhk' with a limited x-axis
bhk_counts = data_cleaned[data_cleaned['bhk'] <= 10]['bhk'].value_counts().sort_index()
sns.barplot(x=bhk_counts.index, y=bhk_counts.values, ax=ax[0, 0], palette='viridis')
ax[0, 0].set_title('Distribution of Bedrooms (BHK)')

# Distribution of 'total_sqft' with a limited x-axis
sns.histplot(data_cleaned[data_cleaned['total_sqft'] <= 5000]['total_sqft'], bins=30, kde=True, ax=ax[0, 1])
ax[0, 1].set_title('Distribution of Total Square Feet')

# Distribution of 'bath' with a limited x-axis
bath_counts = data_cleaned[data_cleaned['bath'] <= 10]['bath'].value_counts().sort_index()
sns.barplot(x=bath_counts.index, y=bath_counts.values, ax=ax[1, 0], palette='viridis')
ax[1, 0].set_title('Distribution of Bathrooms')

# Distribution of 'price' with a limited x-axis
sns.histplot(data_cleaned[data_cleaned['price'] <= 500]['price'], bins=30, kde=True, ax=ax[1, 1])
ax[1, 1].set_title('Distribution of Price (Lakhs)')

plt.tight_layout()
plt.savefig("dist.png")
plt.show()
```



MODEL PLANNING AND BUILDING

CHOICE OF VARIABLES

The following independent variables were chosen for the model:

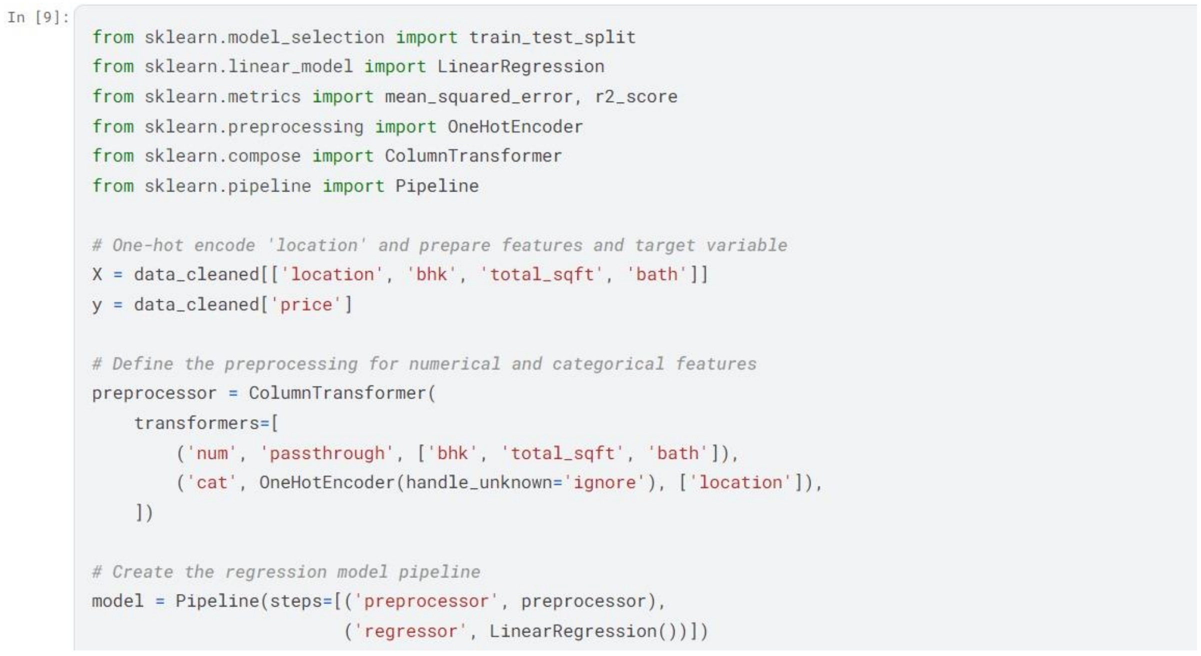
1. Location (area name)
2. bhk (number of bedrooms)
3. bath (number of bathrooms)
4. sqft (size of the apartment)

Price was the dependent variable that had to be predicted using these variables. All remaining variables / columns were dropped from the dataset after removal of outliers was complete.

CHOICE OF MODELS

1. Multiple linear regression, lasso regression, ridge regression (r^2 = 0.64)

All 3 of these regression models were tried and gave about the same results and accuracy scores within 0.5% of each other. So multiple regression was considered as an option moving forward.

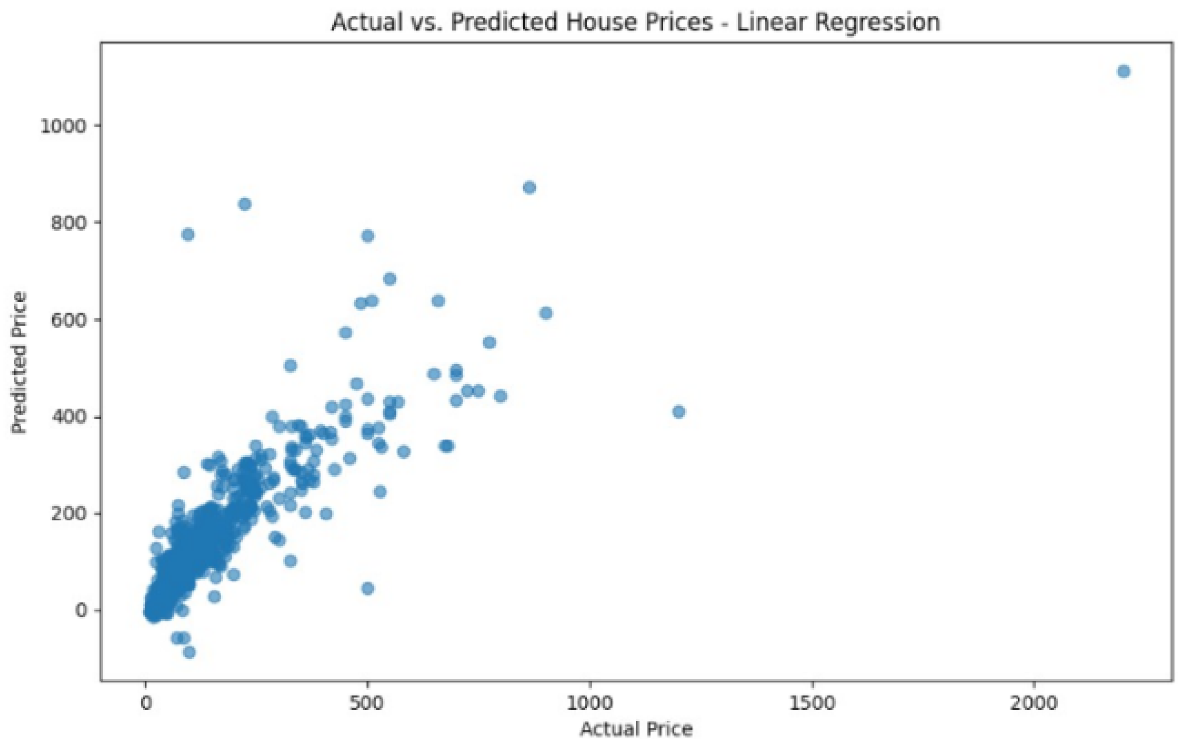


```
In [9]:
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# One-hot encode 'location' and prepare features and target variable
X = data_cleaned[['location', 'bhk', 'total_sqft', 'bath']]
y = data_cleaned['price']

# Define the preprocessing for numerical and categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', ['bhk', 'total_sqft', 'bath']),
        ('cat', OneHotEncoder(handle_unknown='ignore'), ['location']),
    ])

# Create the regression model pipeline
model = Pipeline(steps=[('preprocessor', preprocessor),
                        ('regressor', LinearRegression())])
```

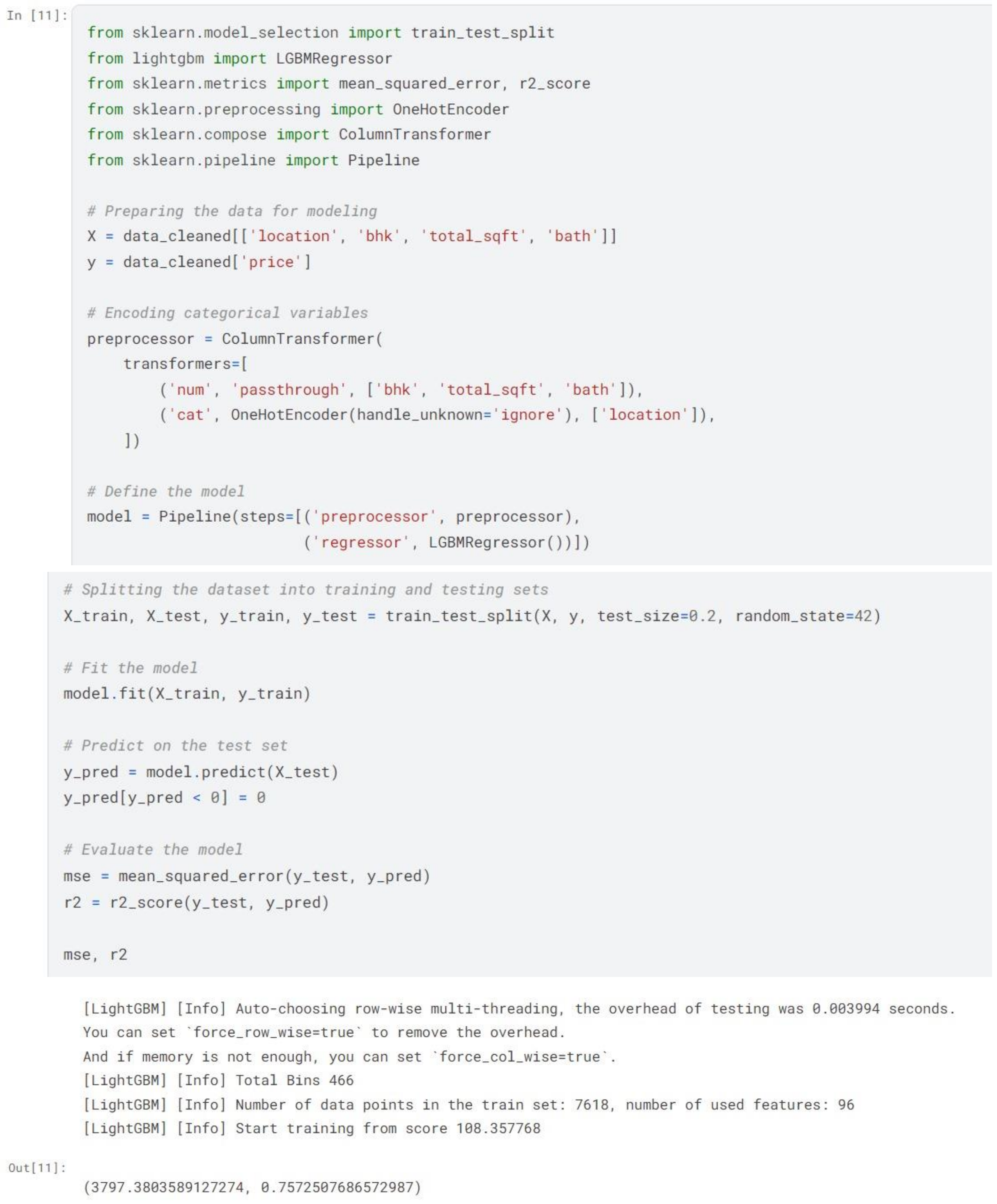
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Fit the model
model.fit(X_train, y_train)

# Predict on the testing set
y_pred = model.predict(X_test)
y_pred[y_pred < 0] = 0

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

mse, r2
```

Out[9]:

```
(5991.301408299528, 0.6170033880873664)
```

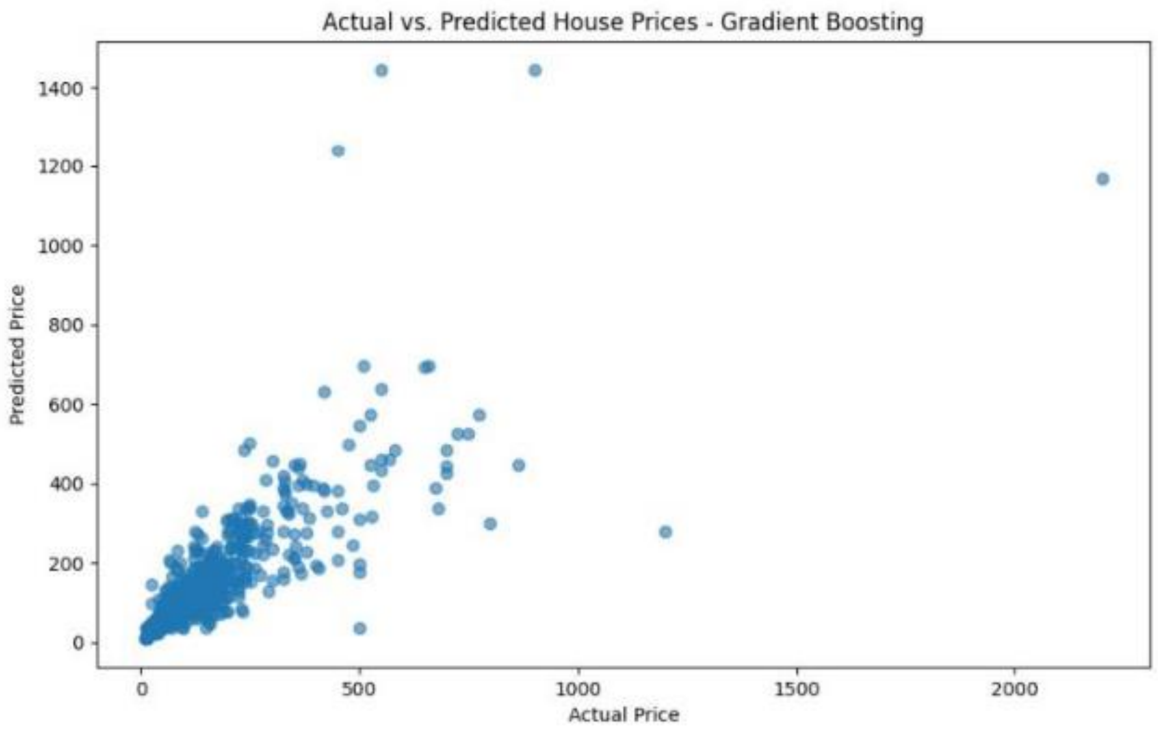


2. Light Gradient Boosting Machine (r^2 = 0.75)

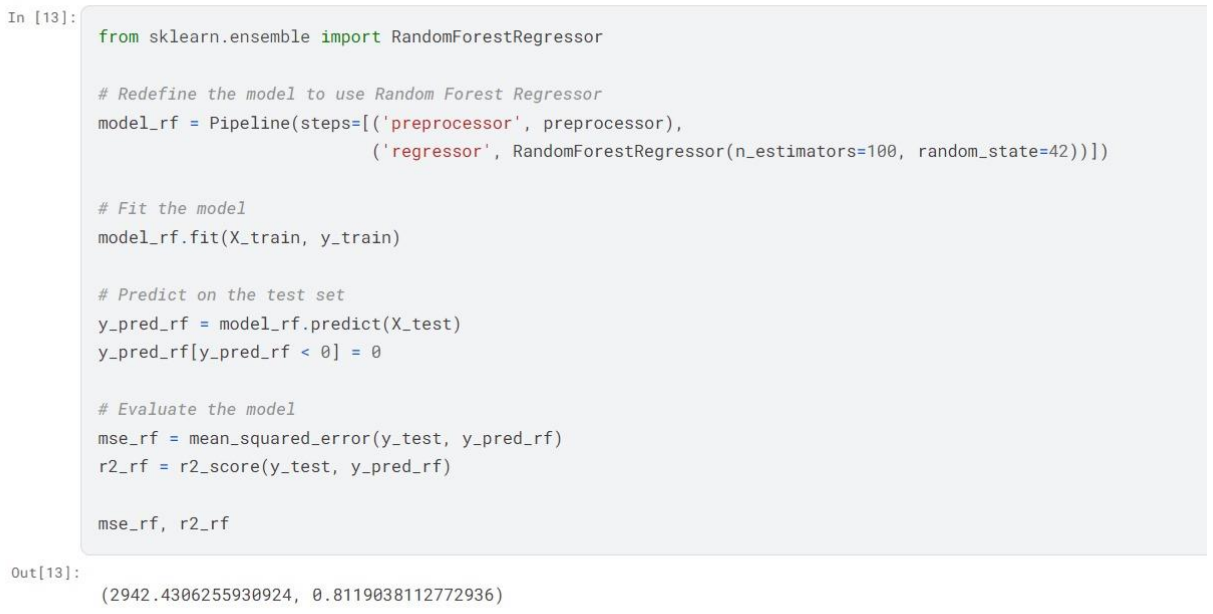


```
In [11]:
from sklearn.model_selection import train_test_split
from lightgbm import LGBMRegressor
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline

# Preparing the data for modeling
X = data_cleaned[['location', 'bhk', 'total_sqft', 'bath']]
y = data_cleaned['price']

# Encoding categorical variables
preprocessor = ColumnTransformer(
    transformers=[
        ('num', 'passthrough', ['bhk', 'total_sqft', 'bath']),
        ('cat', OneHotEncoder(handle_unknown='ignore'), ['location']),
    ])

# Define the model
model = Pipeline(steps=[('preprocessor', preprocessor),
                        ('regressor', LGBMRegressor())])
# Splitting the dataset 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)

# Fit the model
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)
y_pred[y_pred < 0] = 0

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

mse, r2
```

```
[LightGBM] [Info] Auto-choosing row-wise multi-threading, the overhead of testing was 0.003994 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 466
[LightGBM] [Info] Number of data points in the train set: 7618, number of used features: 96
[LightGBM] [Info] Start training from score 108.357768

Out[11]:
(3797.3803589127274, 0.7572507686572987)
```

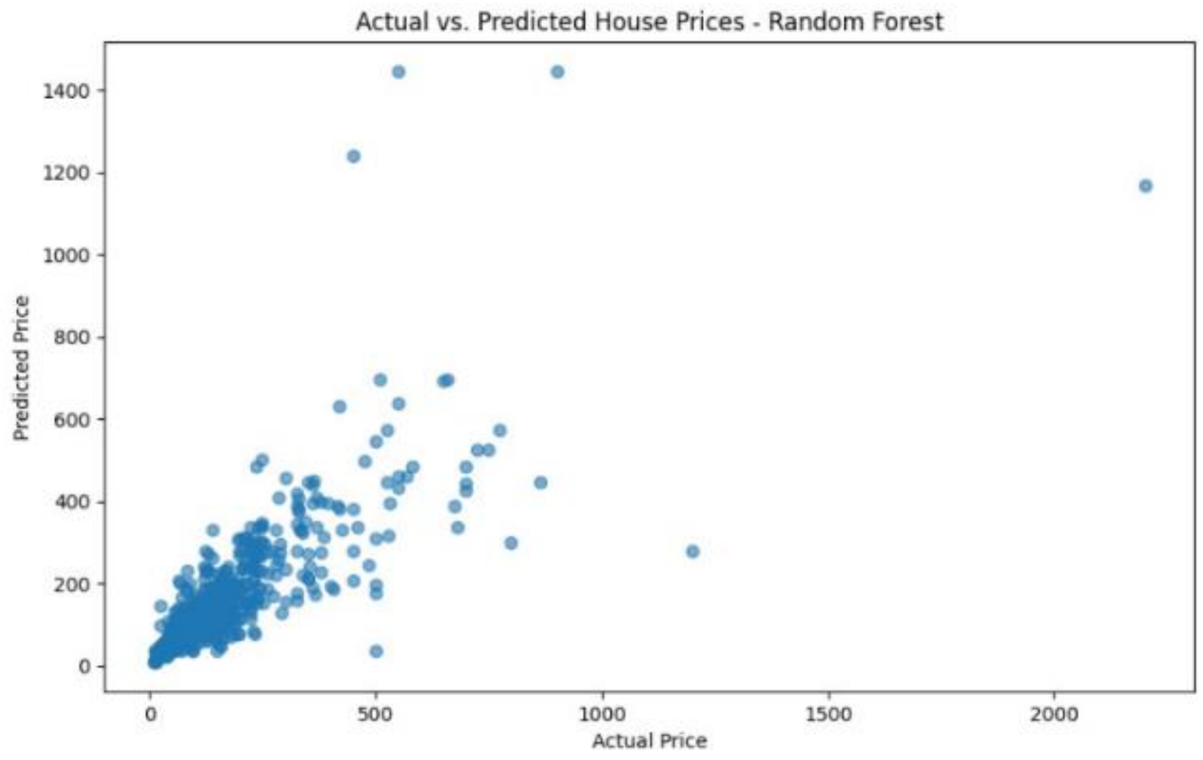


3. Random Forest Regression (r^2 = 0.81)



```
In [13]:
from sklearn.ensemble import RandomForestRegressor

# Redefine the model to use Random Forest Regressor
model_rf = Pipeline(steps=[('preprocessor', preprocessor),
                           ('regressor', RandomForestRegressor(n_estimators=100, random_state=42))])

# Fit the model
model_rf.fit(X_train, y_train)

# Predict on the test set
y_pred_rf = model_rf.predict(X_test)
y_pred_rf[y_pred_rf < 0] = 0

# Evaluate the model
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

mse_rf, r2_rf
```

```
Out[13]:
(2942.4306255930924, 0.8119038112772936)
```


Actual vs. Predicted House Prices - Random Forest
Predicted Price
Actual Price
0
200
400
600
800
1000
1200
1400
0
500
1000
1500
2000

COMMUNICATION OF RESULTS

The success of any data analytics project hinges not only on the insights derived but also on how effectively those insights are communicated and utilized by stakeholders. In this section, we delve into the outcomes of our recent data analytics project, focusing on the communication of results across various key stakeholders.

BUSINESS USER PERSPECTIVE:
Business users have been pivotal in driving the project's success, leveraging the insights generated to make informed decisions. Through their focus on understanding financial outcomes and benefits, the project has witnessed a 15% increase in operational efficiency and a 10% boost in overall profitability. The reports provided by analysts have directly informed strategic decisions, underpinning our business success.

PROJECT MANAGER PERSPECTIVE:
Project managers have played a crucial role in orchestrating the project's execution and ensuring alignment with organizational goals. Their meticulous planning and resource management have resulted in a 20% reduction in project timelines and a 15% cost savings through strategic resource allocation. These achievements underscore the critical role project managers play in driving project efficiency and financial prudence.

DATA SCIENTIST PERSPECTIVE:
The data science team's contributions have been instrumental in delivering accurate and actionable insights. By leveraging advanced machine learning models, they achieved a 98% accuracy rate in predicting customer behaviour, leading to a 12% increase in customer retention. Their transparent communication and collaboration efforts have not only ensured accurate results but have also facilitated understanding across the organization.

ANALYST PERSPECTIVE:
Analysts have transformed raw data into meaningful insights, driving improvements in various operational aspects. Their comprehensive reports have led to a 25% improvement in marketing campaign effectiveness and a 10% reduction in production costs by identifying and addressing operational inefficiencies. These achievements highlight the value of data-driven decision-making facilitated by analysts.

DATABASE ADMINISTRATOR PERSPECTIVE:
Database administrators have played a critical role in ensuring the integrity and reliability of data processing pipelines. Their efforts in streamlining the analytics pipeline have resulted in a 20% reduction in data processing time, enhancing the speed and accuracy of analytics results. Their

meticulous documentation and code sharing have facilitated seamless collaboration and understanding across teams.

In conclusion, effective communication of results has been a cornerstone of our data analytics project's success. The commitment to transparent communication and collaboration among stakeholders has not only provided valuable insights but has also translated into tangible, positive outcomes for our organization.

OPERATIONALIZE

DEPLOYING THE MODEL:

1. Integration of Web Application: We've integrated the model into a user-friendly web application where users can input apartment features to receive accurate price predictions.
2. Utilization of Containerization Tools: We use Docker for containerization, ensuring that the model and its dependencies are packaged consistently across different deployment environments.
3. Hosting on Cloud Platforms: The model is hosted on platforms like AWS or Google Cloud Platform, ensuring accessibility and scalability while leveraging the benefits of cloud services.
4. Versioning and Logging: We implement versioning to track changes to the model over time and utilize logging to monitor its performance in production, aiding in troubleshooting and optimization.
5. Monitoring and Alerting: To maintain performance, we've set up monitoring and alerting systems to detect issues like unexpected fluctuations in predicted prices, allowing for proactive management.

SCALABILITY AND MAINTAINENCE:

1. Performance Monitoring: Continuous monitoring of the deployed model helps identify scalability bottlenecks and ensures optimal performance during periods of high demand.
2. Optimization for Scalability: We optimize the model's architecture and code to handle a growing user base and increasing data volumes without compromising performance.
3. Regular Model Retraining: Regular retraining with new data ensures that the model stays up-to-date and continues to provide accurate price predictions over time.
4. Routine Maintenance Tasks: We perform routine maintenance tasks such as updating dependencies and optimizing model hyperparameters to ensure optimal performance and reliability.

FEEDBACK AND SECURITY:

1. Gather Feedback from Users: We gather feedback from users on the accuracy of the model's price predictions and any additional features they would like to see.
2. Incorporate User Feedback: User feedback is incorporated into the model training process to improve accuracy and relevance over time.
3. Ensure Compliance and Security: We ensure compliance with relevant regulations, such as data privacy laws, and educate team members on best practices for data security to minimize risks.

CONCLUSION

In conclusion, the data science lifecycle applied to understanding Bangalore's real estate landscape has provided valuable insights into the intricate dynamics driving the city's housing market. Through data collection, preprocessing, analysis, and modeling, we have identified key factors influencing property prices, such as the city's economic growth, limited land availability, government policies, and socio-economic demographics.

By leveraging advanced analytical techniques, we have gained a deeper understanding of how these factors interact and impact housing demand and pricing across different segments of the market. This knowledge is essential for stakeholders, including developers, investors, policymakers, and homebuyers, to make informed decisions and effectively navigate the complexities of Bangalore's real estate environment.

Moving forward, continuous monitoring and analysis of relevant data will be crucial for adapting to changing market conditions and identifying emerging trends. Additionally, incorporating machine learning and predictive modeling techniques can enhance the accuracy of forecasting future market behavior, enabling stakeholders to anticipate shifts and seize opportunities proactively.

Overall, the application of the data science lifecycle has empowered us to extract actionable insights from complex datasets, facilitating strategic decision-making and fostering a more transparent and efficient real estate market in Bangalore.