House Price Analysis and Prediction

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1. Introduction

Objectives

- Analyze housing market data to identify key factors influencing house prices.
- Manage data inconsistencies and outliers to ensure data reliability.
- Build a predictive model to accurately forecast house prices.
- Provide insights to help stakeholders make informed decisions about market trends and property valuations.

2. Dataset Description

This dataset contains information about properties, including their attributes and location details.

Dataset Attributes

- **property_id:** Unique identifier for each property.
- **location_id:** Identifier for property location.
- **page_url**: URL link to property details.
- **property_type**: Type of property (e.g., house, apartment).
- **price**: Price of the property.
- **location**: Specific location of the property.
- **city**: City where the property is located.
- **province_name**: Name of the province where the property is located.
- **latitude**: Geographic latitude coordinate of the property.
- **longitude**: Geographic longitude coordinate of the property.
- **baths**: Number of bathrooms in the property.
- **area**: Total area size of the property.
- **purpose**: Purpose of the property (e.g., sale, rent).
- **bedrooms**: Number of bedrooms in the property.
- **date_added**: Date when the property listing was added.
- **agency**: Agency handling the property.
- **agent**: Agent responsible for the property.
- **Area Type:** Type of area where the property is located.
- **Area Size:** Size of the area where the property is located.
- **Area Category:** Category of the area where the property is located.

3. Data Cleaning and Exploration

In [ ]:
```
#imoort libraries
import pandas as pd
import numpy as np
```

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

Basic Info about Dataset

In [ ]:
```python
# Set the display option
pd.options.display.max_columns = None

# check the 5 rows of dataset
df = pd.read_csv('zameen-updated.csv')
df.head()
```

Out[ ]:

	property_id	location_id	page_url	property_type
0	237062	3325	https://www.zameen.com/Property/g_10_g_10_2_gr...	Flat
1	346905	3236	https://www.zameen.com/Property/e_11_2_service...	Flat
2	386513	764	https://www.zameen.com/Property/islamabad_g_15...	House
3	656161	340	https://www.zameen.com/Property/islamabad_bani...	House
4	841645	3226	https://www.zameen.com/Property/dha_valley_dha...	House

In [ ]:
```python
# Check no of columns and rows
df.shape
```

Out[ ]: (168446, 20)

In [ ]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 168446 entries, 0 to 168445
Data columns (total 20 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   property_id     168446 non-null  int64  
 1   location_id     168446 non-null  int64  
 2   page_url        168446 non-null  object 
 3   property_type   168446 non-null  object 
 4   price           168446 non-null  int64  
 5   location        168446 non-null  object 
 6   city            168446 non-null  object 
 7   province_name   168446 non-null  object 
 8   latitude        168446 non-null  float64
 9   longitude       168446 non-null  float64
 10  baths           168446 non-null  int64  
 11  area            168446 non-null  object 
 12  purpose         168446 non-null  object 
 13  bedrooms        168446 non-null  int64  
 14  date_added      168446 non-null  object 
 15  agency          124375 non-null  object 
 16  agent           124374 non-null  object 
 17  Area Type       168446 non-null  object 
 18  Area Size       168446 non-null  float64
 19  Area Category   168446 non-null  object 
dtypes: float64(3), int64(5), object(12)
memory usage: 25.7+ MB
```

In [ ]:
```python
df.describe()
```

Out[ ]:

	property_id	location_id	price	latitude	longitude	
count	1.684460e+05	168446.000000	1.684460e+05	168446.000000	168446.000000	168446.0
mean	1.559626e+07	4375.936395	1.776576e+07	29.859519	71.239804	2.8
std	2.251207e+06	3776.561581	3.531003e+07	3.807870	3.133042	2.4
min	8.657500e+04	1.000000	0.000000e+00	11.052446	25.906027	0.0
25%	1.488320e+07	1058.000000	1.750000e+05	24.948536	67.130363	0.0
50%	1.665851e+07	3286.000000	8.500000e+06	31.459784	73.056182	3.0
75%	1.708662e+07	7220.000000	1.950000e+07	33.560887	73.259870	4.0
max	1.735772e+07	14220.000000	2.000000e+09	73.184088	80.161430	403.0

Identify Missing values

In [ ]:
```python
# Check for missing values
missing_values = df.isnull().sum()
print(missing_values)
```

```
property_id          0
location_id          0
page_url             0
property_type        0
price                0
location             0
city                 0
province_name        0
latitude             0
longitude            0
baths                0
area                 0
purpose              0
bedrooms             0
date_added           0
agency           44071
agent            44072
Area Type            0
Area Size            0
Area Category        0
dtype: int64
```

In [ ]:
```
# Check percentage of missing values
missing_values = df.isnull().sum()/ len(df) *100
print(missing_values)
```

```
property_id       0.000000
location_id       0.000000
page_url          0.000000
property_type     0.000000
price             0.000000
location          0.000000
city              0.000000
province_name     0.000000
latitude          0.000000
longitude         0.000000
baths             0.000000
area              0.000000
purpose           0.000000
bedrooms          0.000000
date_added        0.000000
agency           26.163281
agent            26.163874
Area Type         0.000000
Area Size         0.000000
Area Category     0.000000
dtype: float64
```

Handle the missing values

In [ ]:
```
# Fill missing values in 'agent' and 'agency' columns with 'Unknown'
df['agent'].fillna('Unknown', inplace=True)
df['agency'].fillna('Unknown', inplace=True)
```

Checking Duplicates

```
In [ ]: # Checking for duplicate values
        duplicates = df.duplicated().sum()
        print("Number of Duplicates:" , duplicates)
```

```
Number of Duplicates: 0
```

```
In [ ]: # Check data types
        print(df.dtypes)
```

```
property_id        int64
location_id        int64
page_url          object
property_type     object
price              int64
location          object
city              object
province_name     object
latitude         float64
longitude        float64
baths              int64
area              object
purpose           object
bedrooms           int64
date_added        object
agency            object
agent             object
Area Type         object
Area Size        float64
Area Category     object
dtype: object
```

Handling Inconsistencies

```
In [ ]: # Strip leading/trailing spaces and convert to lowercase for consistency
        categorical_columns = ['page_url', 'property_type', 'location', 'city', 'province_n

        for col in categorical_columns:
            df[col] = df[col].str.strip().str.lower()
```

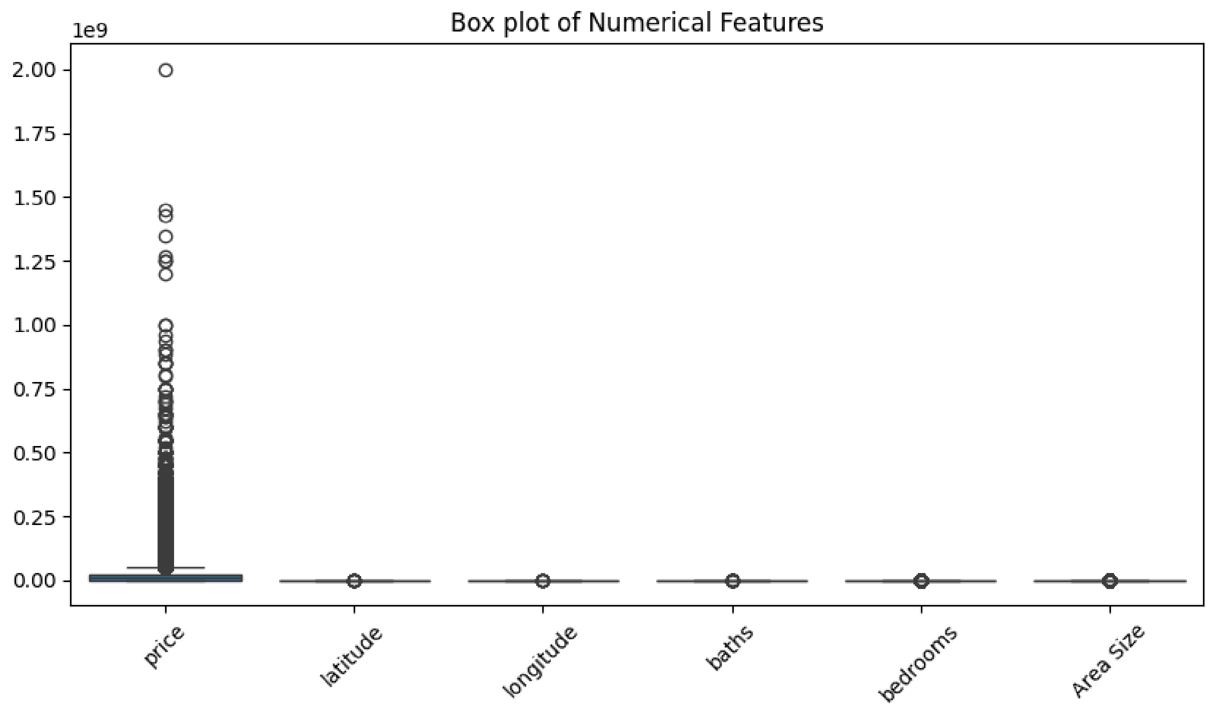
```
In [ ]: # Validate 'price' - it should be positive
        df = df[df['price'] > 0]

        # Validate 'latitude' and 'longitude' - ensure they are within valid ranges
        df = df[(df['latitude'].between(-90, 90)) & (df['longitude'].between(-180, 180))]
```

```
In [ ]: # Validate 'baths' and 'bedrooms' - they should be non-negative integers
        df = df[df['baths'] >= 0]
        df = df[df['bedrooms'] >= 0]
```

Detecting outliers Visually

```
In [ ]: # Numerical columns for outlier detection
        numerical_columns = ['price', 'latitude', 'longitude', 'baths', 'bedrooms', 'Area S
```

```
# Box plot visualization to identify outliers
plt.figure(figsize=(10, 5))
sns.boxplot(data=df[numerical_columns])
plt.title('Box plot of Numerical Features')
plt.xticks(rotation=45)
plt.show()
```



Detecting Outliers using IQR Method

In [ ]:

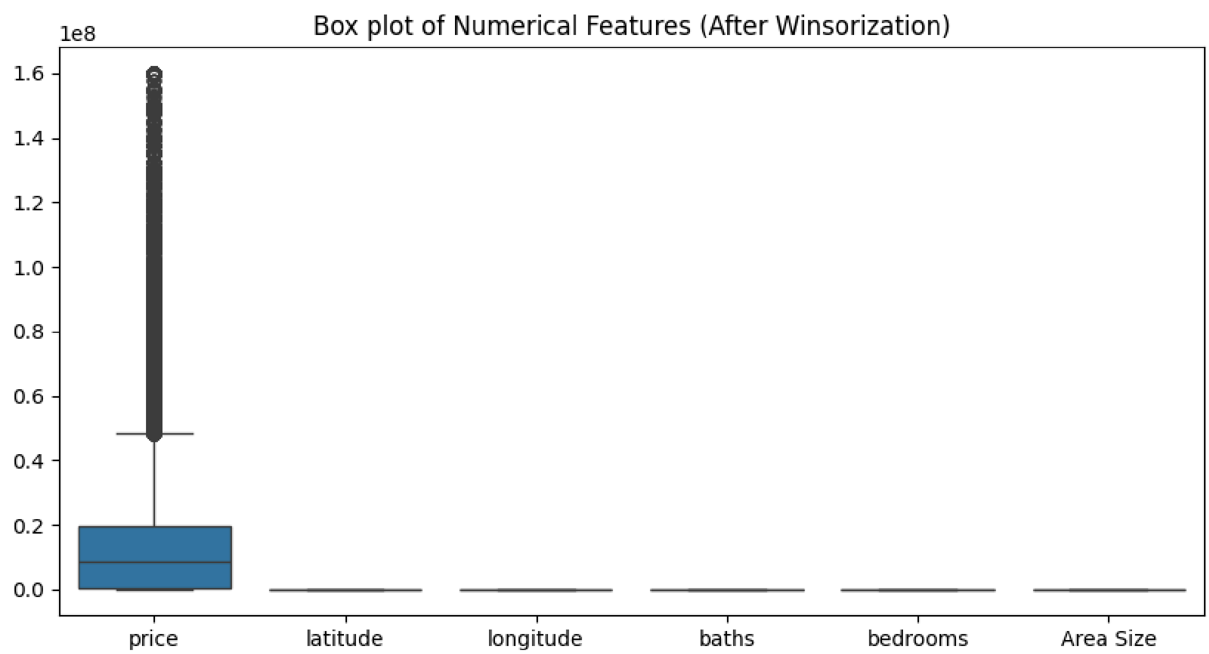
```
# Outlier detection using IQR (Interquartile Range)
Q1 = df[numerical_columns].quantile(0.25)
Q3 = df[numerical_columns].quantile(0.75)
IQR = Q3 - Q1

# Define upper and lower bounds for outlier detection
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Identify outliers
outliers = (df[numerical_columns] < lower_bound) | (df[numerical_columns] > upper_b

# Count outliers for each numerical column
outliers_count = outliers.sum()
print("Number of Outliers:")
print(outliers_count)
```

```
Number of Outliers:
price         13547
latitude          9
longitude         6
baths            22
bedrooms       3319
Area Size      3326
dtype: int64
```

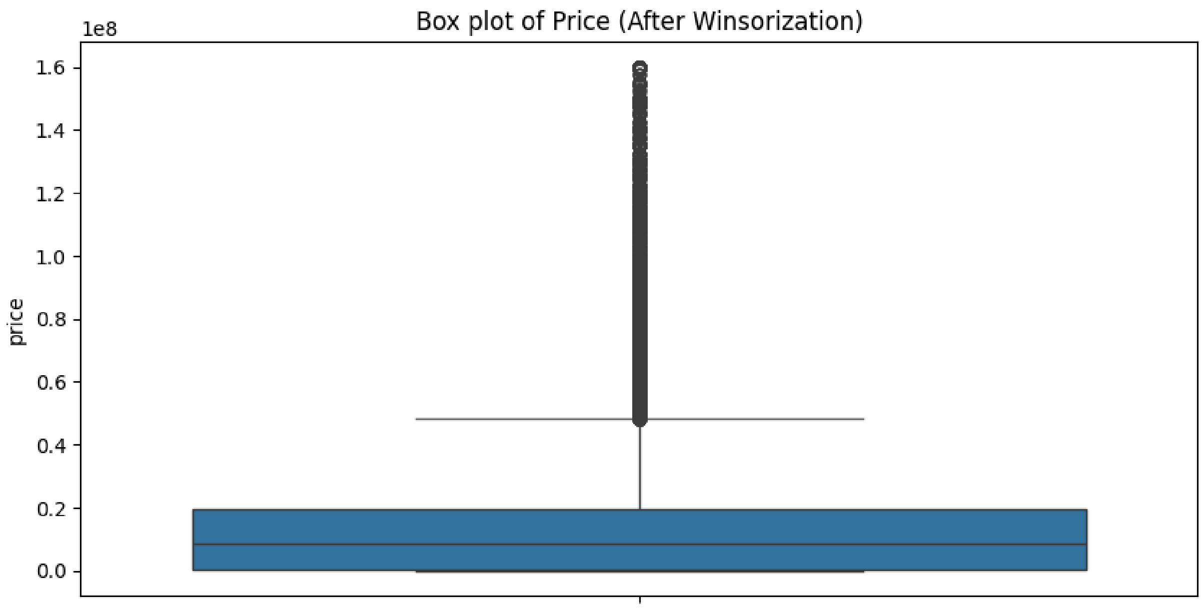
Handling Outliers

In [ ]:
```python
from scipy.stats.mstats import winsorize

# Winsorize numerical columns
df['price'] = winsorize(df['price'], limits=[0.01, 0.01])
df['latitude'] = winsorize(df['latitude'], limits=[0.05, 0.05])
df['longitude'] = winsorize(df['longitude'], limits=[0.05, 0.05])
df['baths'] = winsorize(df['baths'], limits=[0.05, 0.05])
df['bedrooms'] = winsorize(df['bedrooms'], limits=[0.05, 0.05])
df['Area Size'] = winsorize(df['Area Size'], limits=[0.05, 0.05])
```

In [ ]:
```python
# Box plot of numerical columns
plt.figure(figsize=(10, 5))
sns.boxplot(data=df[numerical_columns])
plt.title('Box plot of Numerical Features (After Winsorization)')
plt.show()
```

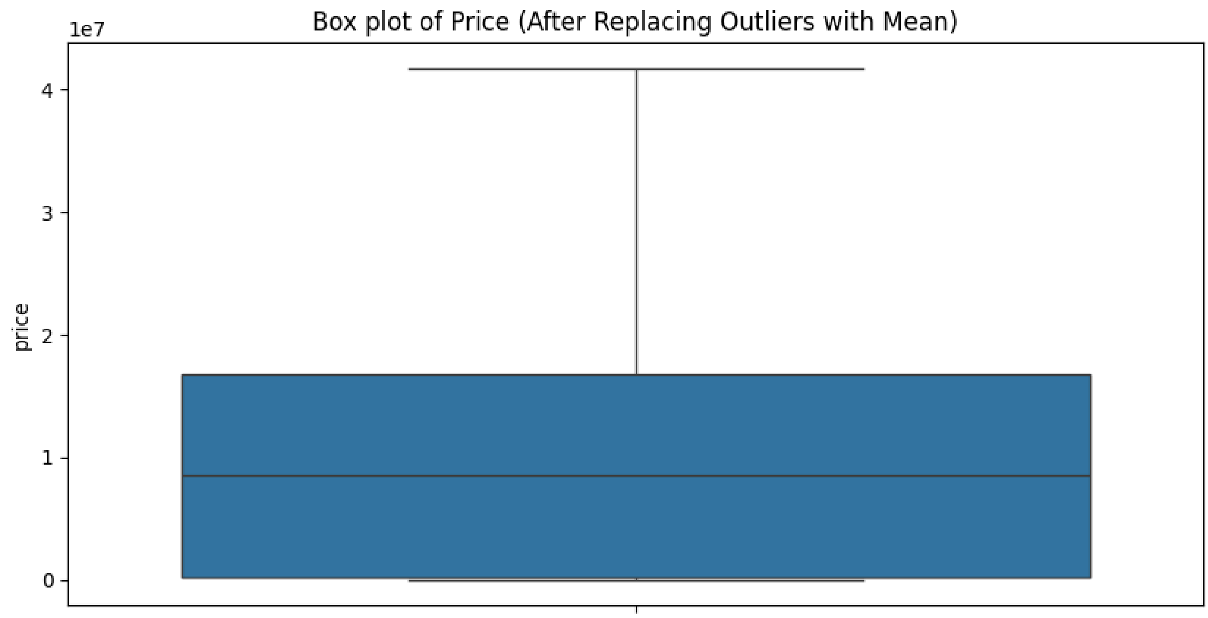


In [ ]:
```python
from scipy.stats.mstats import winsorize

# Visualize the 'price' column after winsorization
plt.figure(figsize=(10, 5))
sns.boxplot(df['price'])
plt.title('Box plot of Price (After Winsorization)')
plt.show()
```



In [ ]:
```python
# Calculate Q1 (25th percentile) and Q3 (75th percentile) for 'price'
Q1_price = df['price'].quantile(0.25)
Q3_price = df['price'].quantile(0.75)
IQR_price = Q3_price - Q1_price

# Define the upper and lower bounds for outlier detection
lower_bound_price = Q1_price - 1.5 * IQR_price
upper_bound_price = Q3_price + 1.5 * IQR_price

# Calculate the mean of 'price'
mean_price = df['price'].mean()

# Replace outliers with the mean
df.loc[df['price'] > upper_bound_price, 'price'] = mean_price
df.loc[df['price'] < lower_bound_price, 'price'] = mean_price
```

In [ ]:
```python
# Visualize the 'price' column after replacing outliers
plt.figure(figsize=(10, 5))
sns.boxplot(df['price'])
plt.title('Box plot of Price (After Replacing Outliers with Mean)')
plt.show()
```



Inspecting Outliers

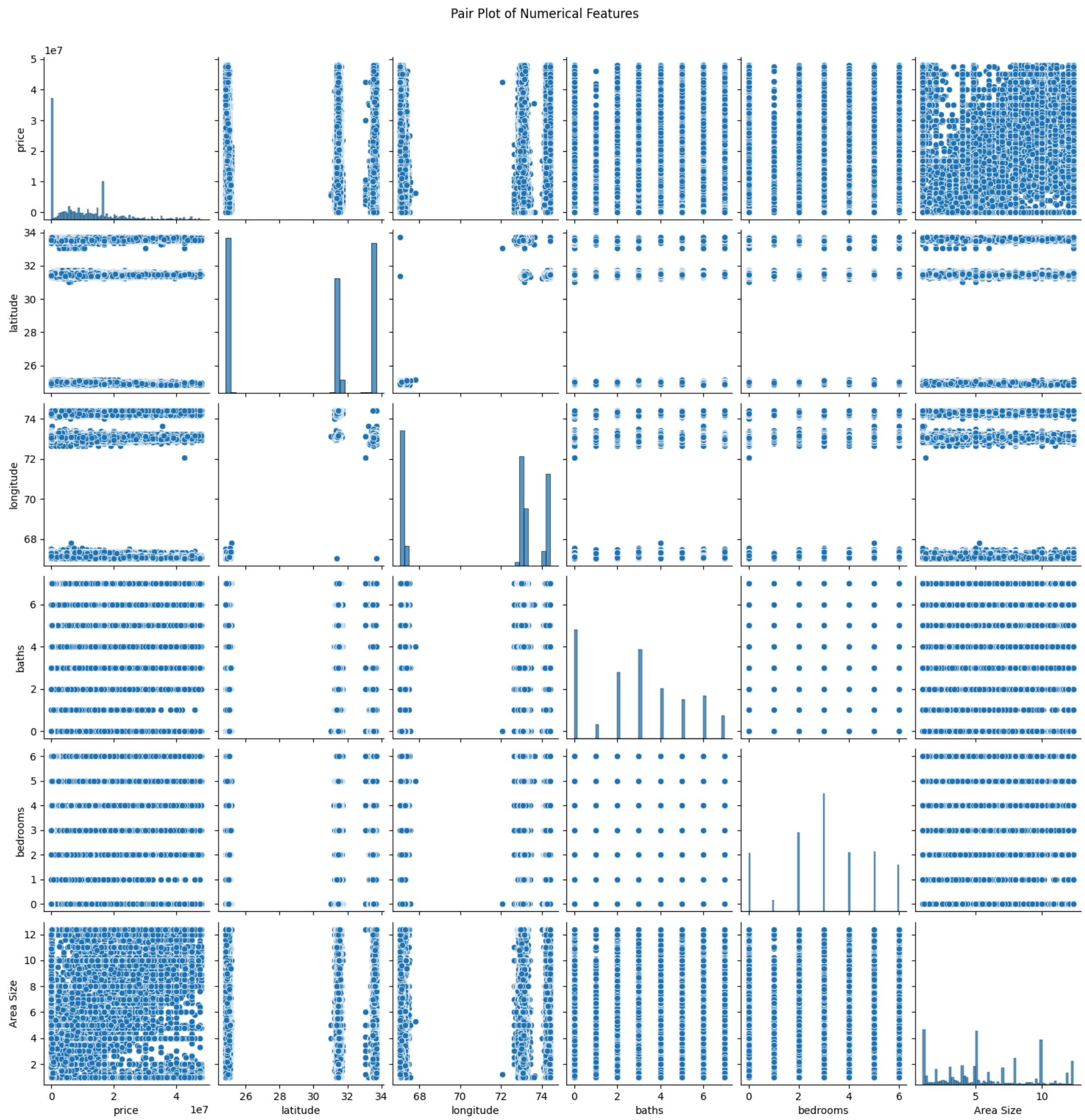
In [ ]:
```
# Create a mask for outliers using NumPy operations
outliers_post = (df[numerical_columns] < lower_bound_price) | (df[numerical_columns

# Count outliers for each numerical column
outliers_count_post = outliers_post.sum()

# Print the number of outliers after handling
print("Number of Outliers After Handling:")
print(outliers_count_post)
```

```
Number of Outliers After Handling:
price        0
latitude     0
longitude    0
baths        0
bedrooms     0
Area Size    0
dtype: int64
```

Analysis of House Price Distribution and Feature Relationships

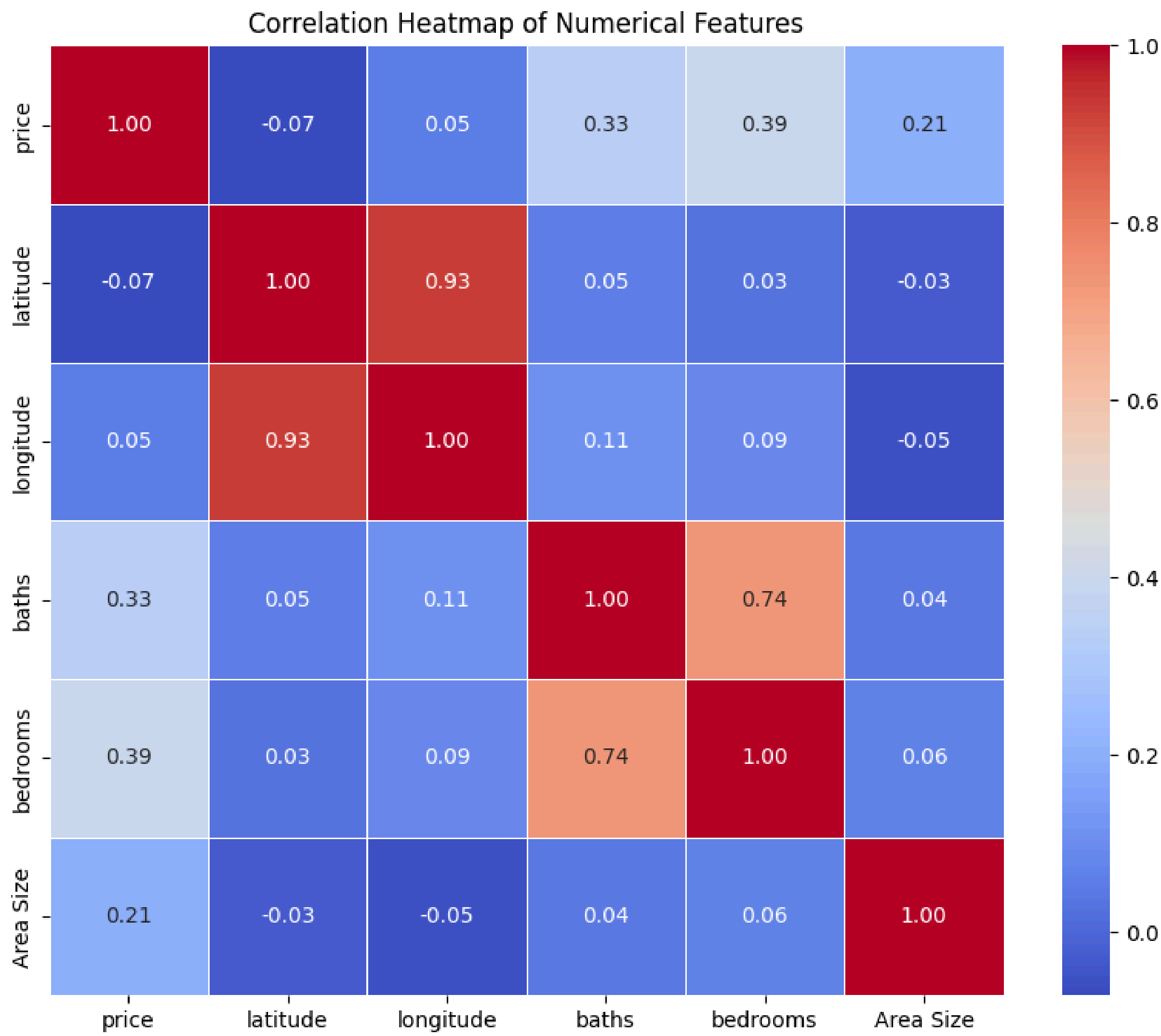
Pair Plot

In [ ]:
```
# Pair plot of numerical columns
sns.pairplot(df[numerical_columns])
plt.suptitle('Pair Plot of Numerical Features', y=1.02)
plt.show()
```



Correlation Heatmap

In [ ]:
```python
# Calculate correlation matrix
corr_matrix = df[numerical_columns].corr()

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewidths=.5)
plt.title('Correlation Heatmap of Numerical Features')
plt.show()
```

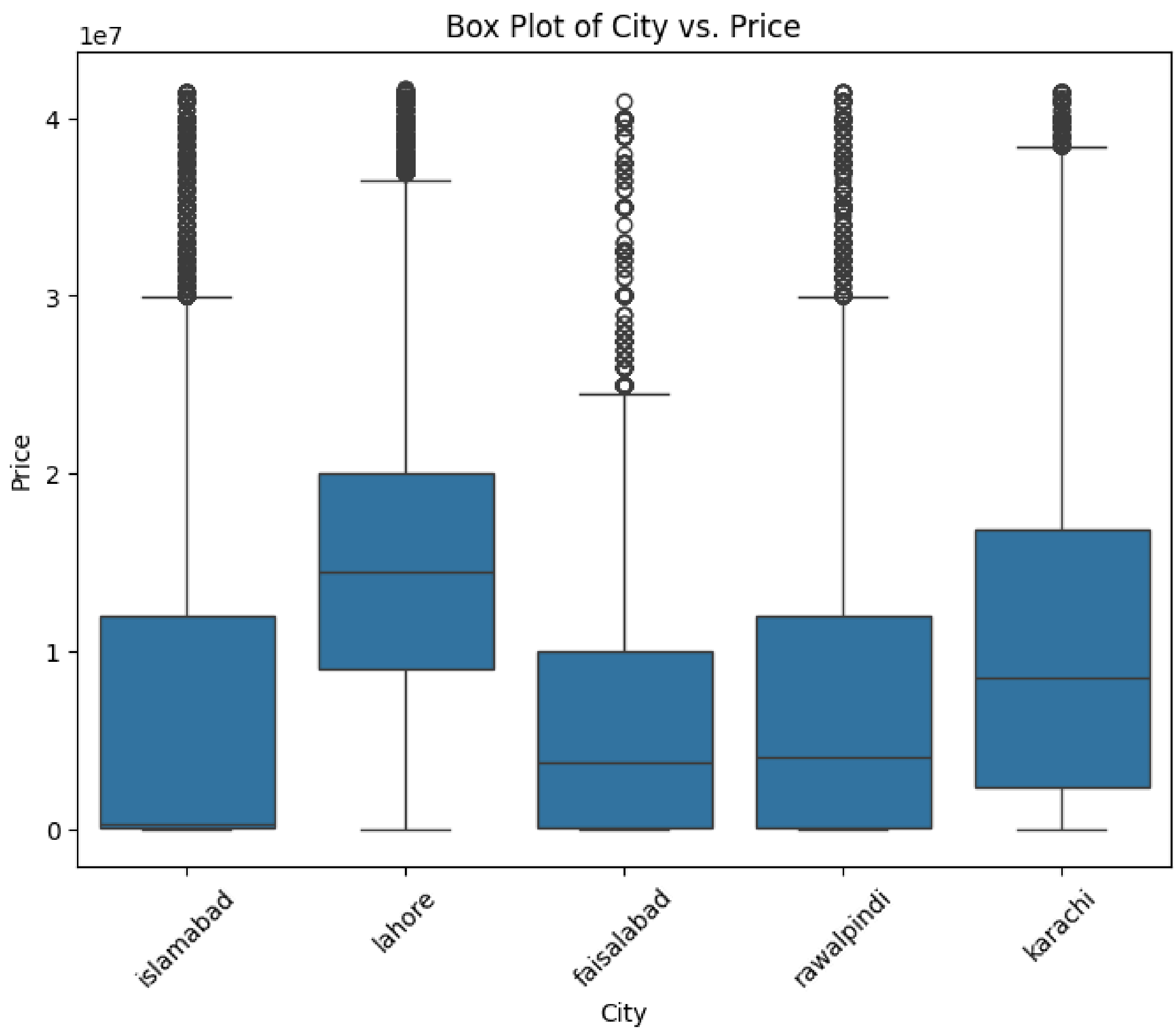


Voilin Plot

In [ ]:
```
# Violin plot of Property Type vs. Price
plt.figure(figsize=(8, 6))
sns.violinplot(x='property_type', y='price', data=df)
plt.title('Violin Plot of Property Type vs. Price')
plt.xlabel('Property Type')
plt.ylabel('Price')
plt.xticks(rotation=45)
plt.show()
```

Box PLot

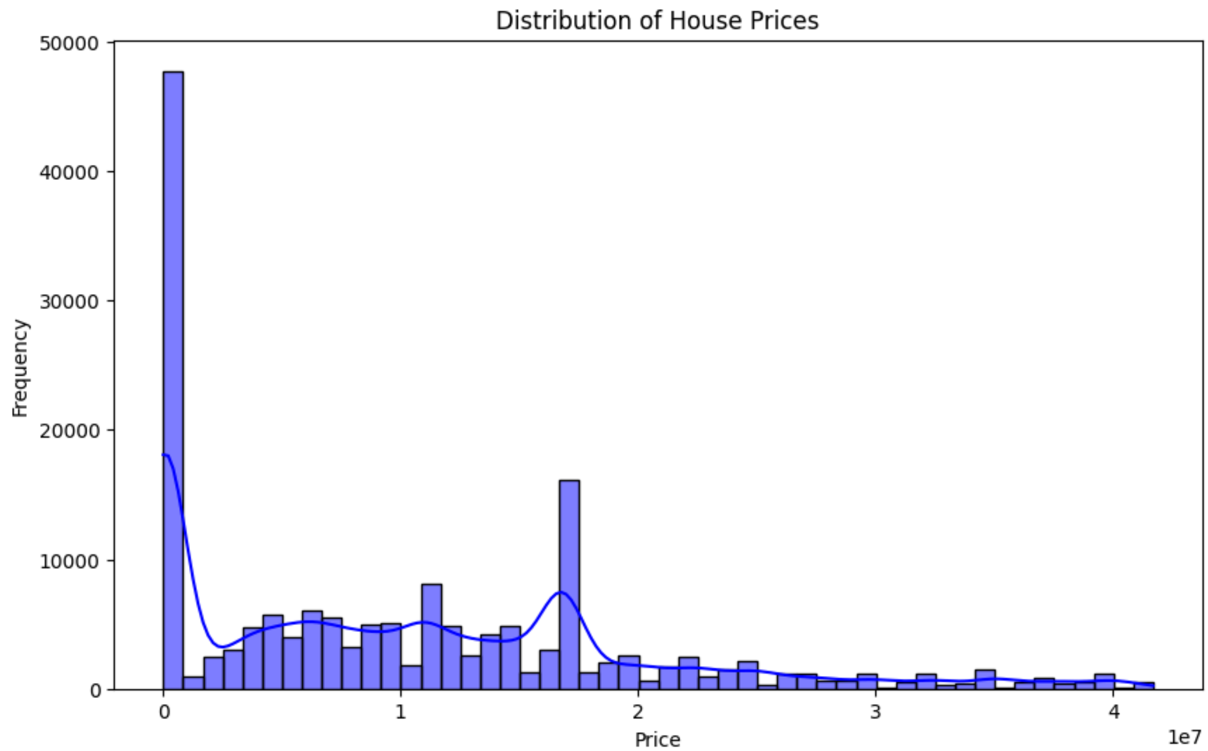
In [ ]:
```
# Box plot: City vs. Price
plt.figure(figsize=(8, 6))
sns.boxplot(x='city', y='price', data=df)
plt.title('Box Plot of City vs. Price')
plt.xlabel('City')
plt.ylabel('Price')
plt.xticks(rotation=45)
plt.show()
```



Histogram

In [ ]:

```
# Histogram with KDE of Price
plt.figure(figsize=(10, 6))
sns.histplot(df['price'], kde=True, bins=50, color='blue')
plt.title('Distribution of House Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



4.Feature Engineering

In [ ]:
```python
import datetime

# Extract the year from 'date_added' and calculate the age
current_year = datetime.datetime.now().year
df['date_added'] = pd.to_datetime(df['date_added'], errors='coerce')
df['house_age'] = current_year - df['date_added'].dt.year
```

In [ ]:
```python
# Handle any possible errors due to 'date_added' conversion by filling NaN with med
df['house_age'].fillna(df['house_age'].median(), inplace=True)
```

In [ ]:
```python
# Create a new feature: number of bathrooms per bedroom
df['baths_per_bedroom'] = df['baths'] / df['bedrooms']

# Handle any possible errors due to division by zero or NaN values
df['baths_per_bedroom'].replace([np.inf, -np.inf], np.nan, inplace=True)
df['baths_per_bedroom'].fillna(df['baths_per_bedroom'].median(), inplace=True)
```

In [ ]:
```python
# Display the new features
print(df[['house_age', 'baths_per_bedroom']].head())
```

```
   house_age  baths_per_bedroom
0          5                1.0
1          5                1.0
2          5                1.2
3          5                1.0
4          5                1.0
```

In [ ]:
```python
df.head()
```

Out[ ]:

	property_id	location_id	page_url	property_type
0	237062	3325	https://www.zameen.com/property/g_10_g_10_2_gr...	flat
1	346905	3236	https://www.zameen.com/property/e_11_2_service...	flat
2	386513	764	https://www.zameen.com/property/islamabad_g_15...	house
3	656161	340	https://www.zameen.com/property/islamabad_bani...	house
4	841645	3226	https://www.zameen.com/property/dha_valley_dha...	house

In [ ]:

```
# Save the dataset with new features
df.to_csv('cleaned_dataset.csv', index=False)
```

Categorical Feature Encoding for Modeling

In [ ]:

```
# List of categorical columns to encode
categorical_columns = [
    'property_type', 'location', 'city',
    'province_name', 'purpose', 'agency',
    'agent', 'Area Type', 'Area Category'
]

# Perform one-hot encoding on the categorical columns
df_encoded = pd.get_dummies(df, columns=categorical_columns, drop_first=True)

# Display the first few rows of the encoded dataset
print(df_encoded.head())
```

5. Outlier Analysis

In [ ]:

```
# Calculate Z-scores for 'price' to identify outliers
from scipy.stats import zscore

df['price_zscore'] = zscore(df['price'])

# Define a threshold for identifying outliers (e.g., z-score greater than 3 or less
outliers_high = df[df['price_zscore'] > 3]
outliers_low = df[df['price_zscore'] < -3]

# Display the number of outliers
```

```
print("Number of High Price Outliers:", len(outliers_high))
print("Number of Low Price Outliers:", len(outliers_low))
```

```
Number of High Price Outliers: 1716
Number of Low Price Outliers: 0
```

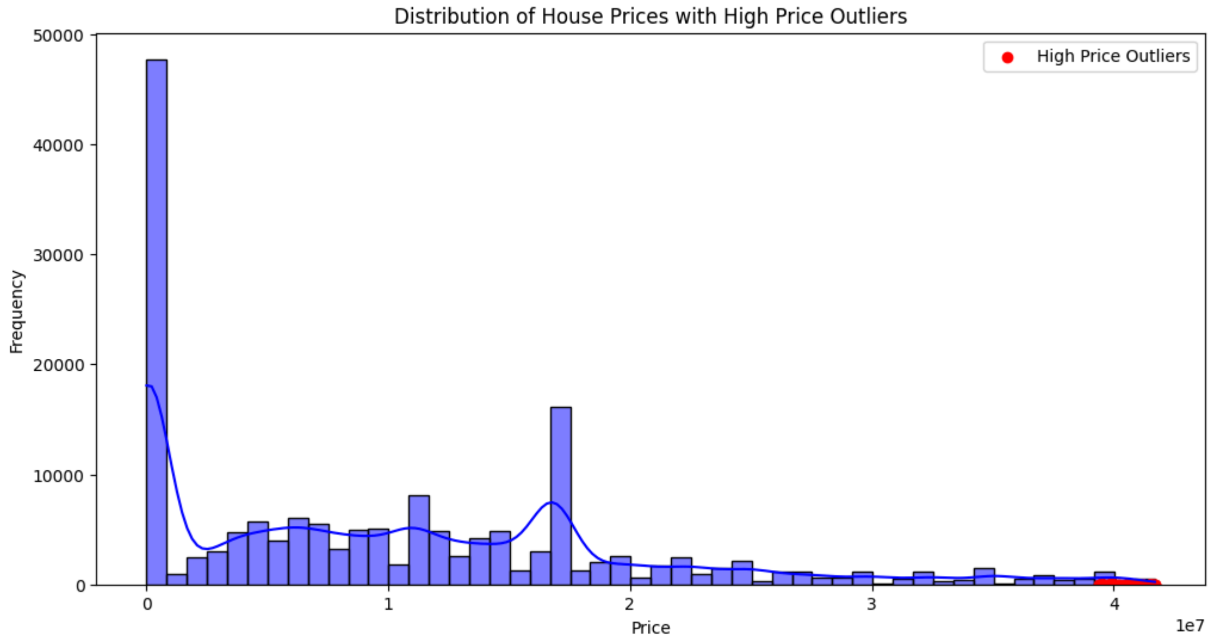
In [ ]:

```
# Print information about high price outliers
print("High Price Outliers:")
print(outliers_high[['property_id', 'price', 'location', 'area', 'bedrooms', 'baths
```

```
High Price Outliers:
        property_id       price      location       area  bedrooms  baths  \
9           1418706  40000000.0          f-11     1 Kanal         5      5
48           482892  40000000.0   multan road     1 Kanal         5      5
56           983075  40000000.0    izmir town   1.6 Kanal         6      0
64          1997947  39500000.0       gulberg    10 Marla         6      6
66          2146098  40000000.0   chaman park    11 Marla         6      3
...             ...         ...           ...         ...       ...    ...
168360     17355128  39500000.0   dha defence     1 Kanal         6      7
168381     17356096  40000000.0   dha defence   1.2 Kanal         5      6
168406     17356560  40000000.0        askari    17 Marla         5      5
168407     17356585  41500000.0   dha defence     1 Kanal         5      5
168415     17357038  41500000.0         nfc 1     1 Kanal         5      6

        house_age
9               5
48              6
56              5
64              5
66              5
...           ...
168360          5
168381          5
168406          5
168407          5
168415          5

[1716 rows x 7 columns]
```

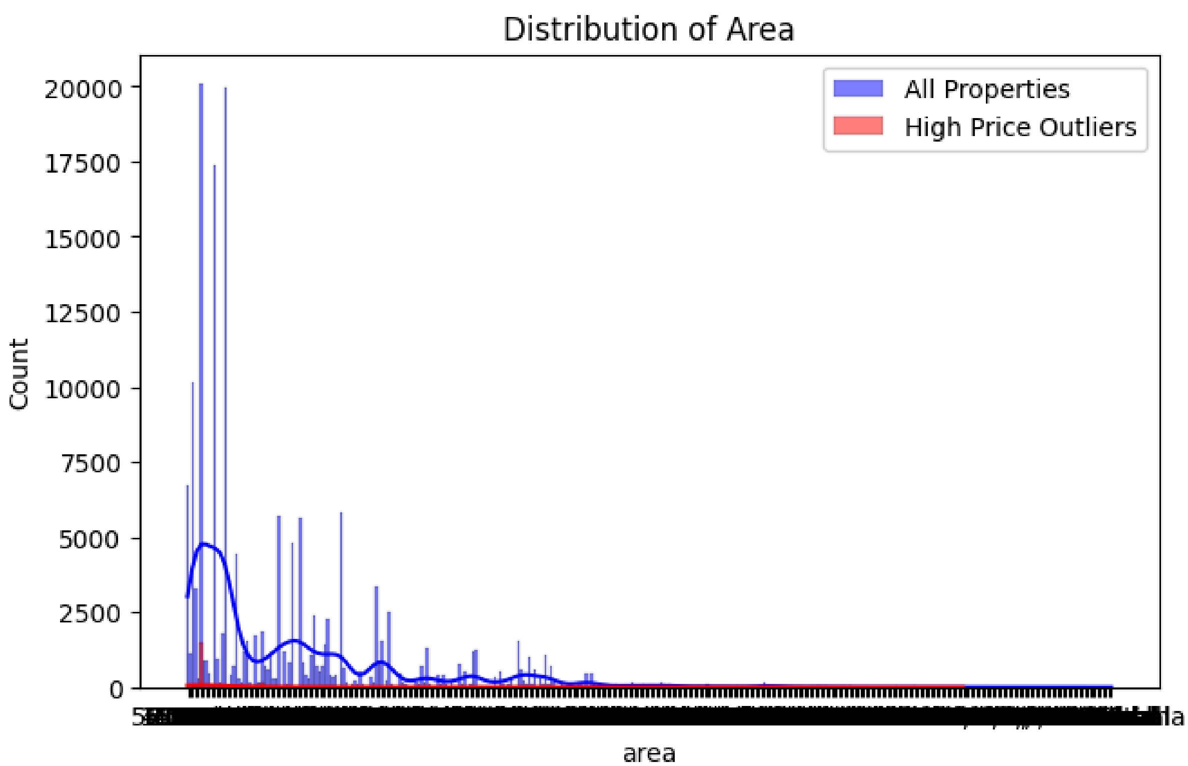
In [ ]:

```
# Visualize the distribution of house prices with outliers highlighted
plt.figure(figsize=(12, 6))
sns.histplot(df['price'], kde=True, bins=50, color='blue')
plt.title('Distribution of House Prices with High Price Outliers')
plt.xlabel('Price')
plt.ylabel('Frequency')

# Highlight high price outliers in the plot
plt.scatter(outliers_high['price'], [0] * len(outliers_high), color='red', label='H
plt.legend()
plt.show()
```



In [ ]:
```
# Visualize distributions of key features for the entire dataset and high price out
plt.figure(figsize=(16, 10))

# Distribution of 'area'
plt.subplot(2, 2, 1)
sns.histplot(df['area'], kde=True, bins=30, color='blue', label='All Properties')
sns.histplot(outliers_high['area'], kde=True, bins=10, color='red', label='High Pri
plt.title('Distribution of Area')
plt.legend()
```

Out[ ]: <matplotlib.legend.Legend at 0x18a541a0560>

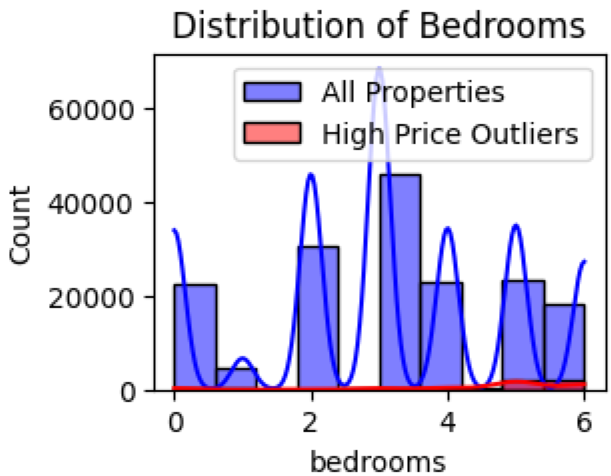


In [ ]:

```python
# Distribution of 'bedrooms'
plt.subplot(2, 2, 2)
sns.histplot(df['bedrooms'], kde=True, bins=10, color='blue', label='All Properties
sns.histplot(outliers_high['bedrooms'], kde=True, bins=5, color='red', label='High
plt.title('Distribution of Bedrooms')
plt.legend()
```

Out[ ]:

```
<matplotlib.legend.Legend at 0x18a52df7e60>
```

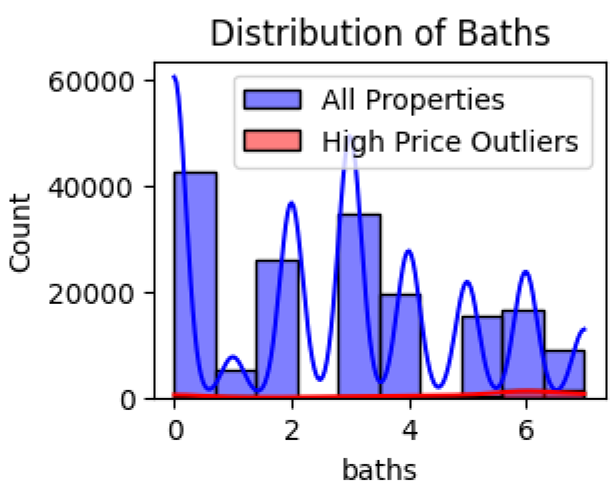


In [ ]:

```python
# Distribution of 'baths'
plt.subplot(2, 2, 3)
sns.histplot(df['baths'], kde=True, bins=10, color='blue', label='All Properties')
sns.histplot(outliers_high['baths'], kde=True, bins=5, color='red', label='High Pri
plt.title('Distribution of Baths')
plt.legend()
```

Out[ ]:

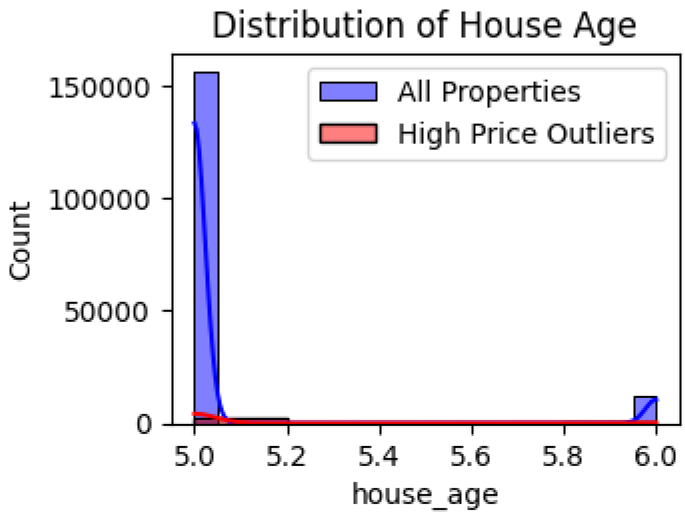
```
<matplotlib.legend.Legend at 0x18a5600c1a0>
```



In [ ]:

```python
# Distribution of 'house_age'
plt.subplot(2, 2, 4)
sns.histplot(df['house_age'], kde=True, bins=20, color='blue', label='All Propertie
sns.histplot(outliers_high['house_age'], kde=True, bins=5, color='red', label='High
plt.title('Distribution of House Age')
plt.legend()
```

```
plt.tight_layout()
plt.show()
```



In [ ]:

```
# Compare summary statistics for key features
summary_stats_all = df[['area', 'bedrooms', 'baths', 'house_age']].describe()
summary_stats_outliers = outliers_high[['area', 'bedrooms', 'baths', 'house_age']].
print("Summary Statistics for All Properties:")
print(summary_stats_all)
print("\nSummary Statistics for High Price Outliers:")
print(summary_stats_outliers)
```

```
Summary Statistics for All Properties:
            bedrooms          baths      house_age
count  168443.000000  168443.000000  168443.000000
mean        3.100224       2.835707       5.072731
std         1.777040       2.177108       0.259695
min         0.000000       0.000000       5.000000
25%         2.000000       0.000000       5.000000
50%         3.000000       3.000000       5.000000
75%         4.000000       4.000000       5.000000
max         6.000000       7.000000       6.000000

Summary Statistics for High Price Outliers:
          bedrooms        baths    house_age
count  1716.000000  1716.000000  1716.000000
mean      4.397436     4.315851     5.049534
std       1.691162     2.428068     0.217043
min       0.000000     0.000000     5.000000
25%       4.000000     3.000000     5.000000
50%       5.000000     5.000000     5.000000
75%       6.000000     6.000000     5.000000
max       6.000000     7.000000     6.000000
```

6. Predictive Modeling

In [ ]:

```
# Function to convert area measurements to square feet
def convert_area(area):
    if isinstance(area, str):
```

```
        area = area.replace(',', '')  # Remove commas from the string
        if 'Marla' in area:
            value = float(area.split()[0])
            return value * 272.25
        elif 'Kanal' in area:
            value = float(area.split()[0])
            return value * 20 * 272.25
        elif 'Square Feet' in area:
            value = float(area.split()[0])
            return value
    return area

# Apply the conversion function to the 'area' column
df['area'] = df['area'].apply(convert_area)
```

Linear Regression

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Select features and target
features = ['area', 'bedrooms', 'baths', 'house_age', 'latitude', 'longitude']
target = 'price'

X = df[features]
y = df[target]

# Split 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_sta

# Train the Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

Out[ ]:
```
LinearRegression

LinearRegression()
```

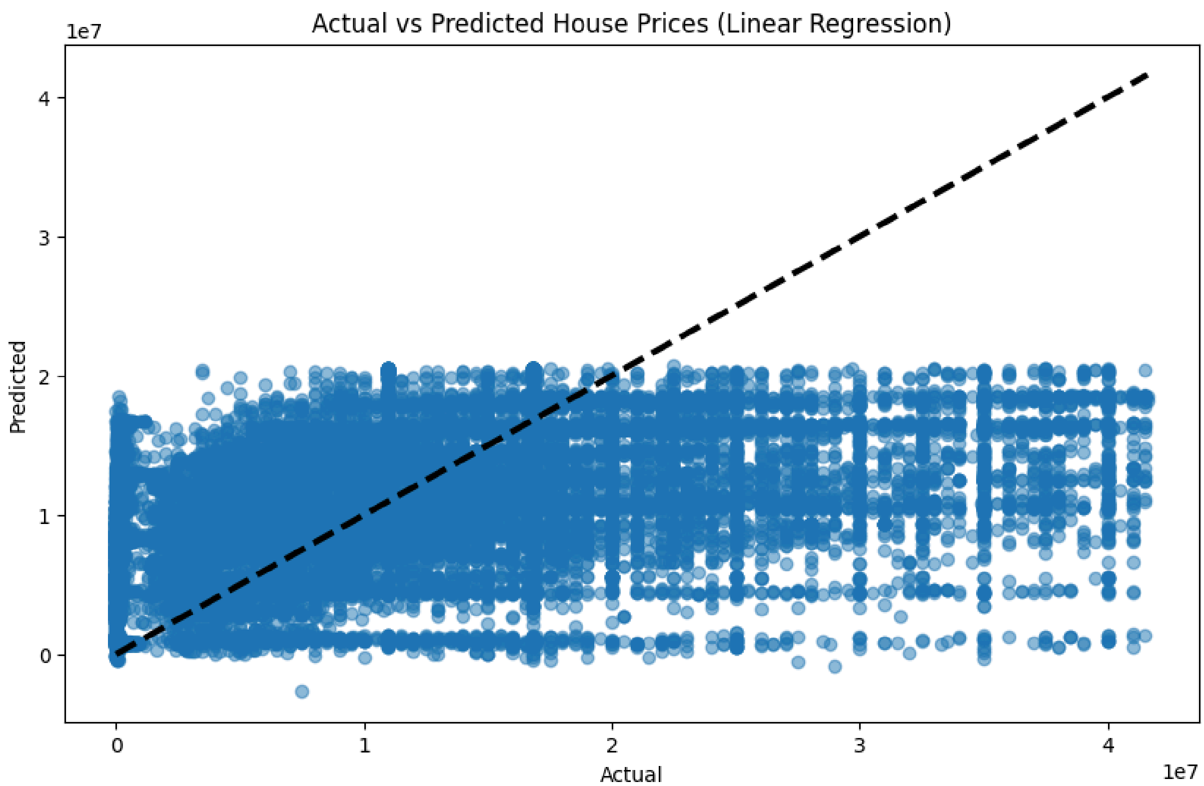
In [ ]:
```
# Make predictions
y_pred_lr = lr_model.predict(X_test)
```

Evaluate the Model Performance

In [ ]:
```
# Evaluate the model
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)

print("Linear Regression Performance:")
print("Mean Absolute Error:", mae_lr)
print("Mean Squared Error:", mse_lr)
print("R-squared:", r2_lr)
```

```
Linear Regression Performance:
Mean Absolute Error: 6411662.5088074645
Mean Squared Error: 71347429312049.25
R-squared: 0.2395611909711216
```

In [ ]:
```
# Plot predictions vs actual prices for Linear Regression
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_lr, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=3)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted House Prices (Linear Regression)')
plt.show()
```



Random forest

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

# Train the Random Forest model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

Out[ ]:
```
▾ RandomForestRegressor
RandomForestRegressor(random_state=42)
```

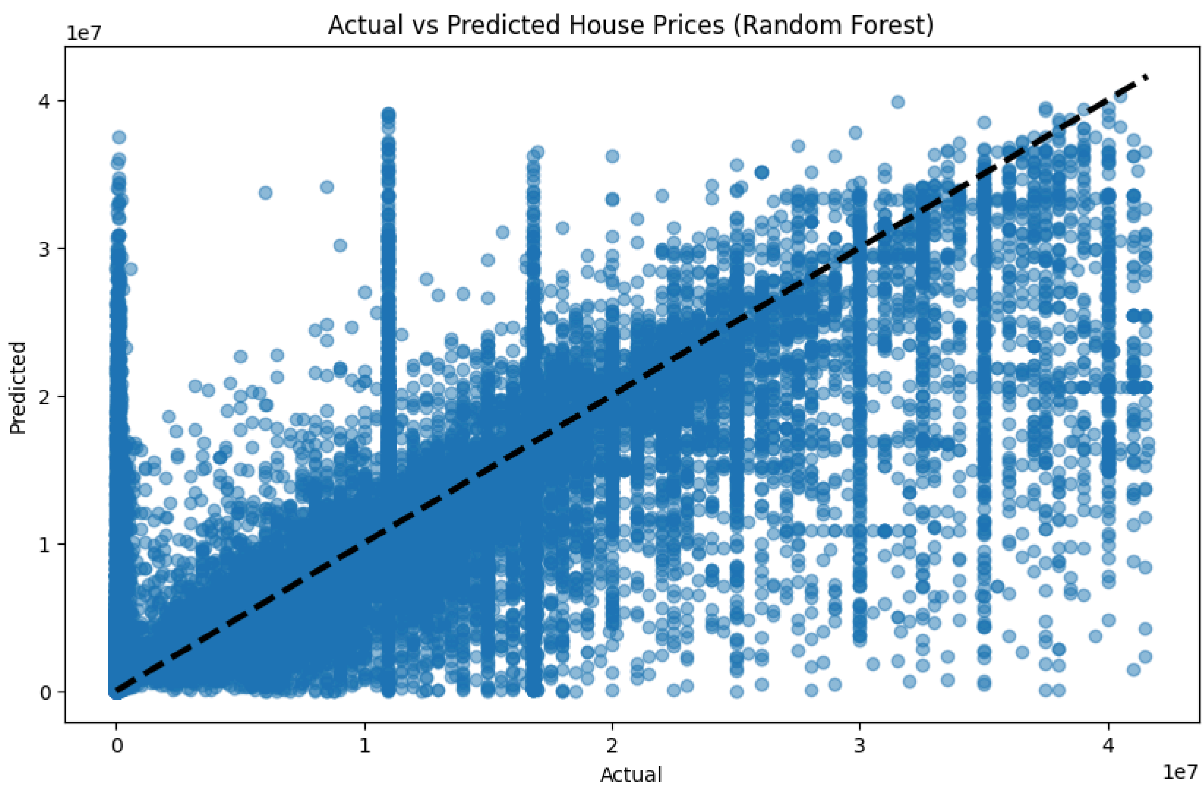
In [ ]:
```
# Make predictions
y_pred_rf = rf_model.predict(X_test)
```

Evaluate the Model Performance

In [ ]:
```
# Evaluate the model
mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)

print("Random Forest Performance:")
print("Mean Absolute Error:", mae_rf)
print("Mean Squared Error:", mse_rf)
print("R-squared:", r2_rf)
```

```
Random Forest Performance:
Mean Absolute Error: 3814927.587887695
Mean Squared Error: 41168477731548.66
R-squared: 0.5612160315014497
```

In [ ]:
```
# Plot predictions vs actual prices for Random Forest
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_rf, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=3)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted House Prices (Random Forest)')
plt.show()
```



Gradient Boosting

In [ ]:
```
from sklearn.ensemble import GradientBoostingRegressor
```

```
# Train the Gradient Boosting model
gb_model = GradientBoostingRegressor(n_estimators=100, random_state=42)
gb_model.fit(X_train, y_train)
```

Out[ ]:

```
▾ GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

In [ ]:

```
# Make predictions
y_pred_gb = gb_model.predict(X_test)
```

Evaluate the Model Performance

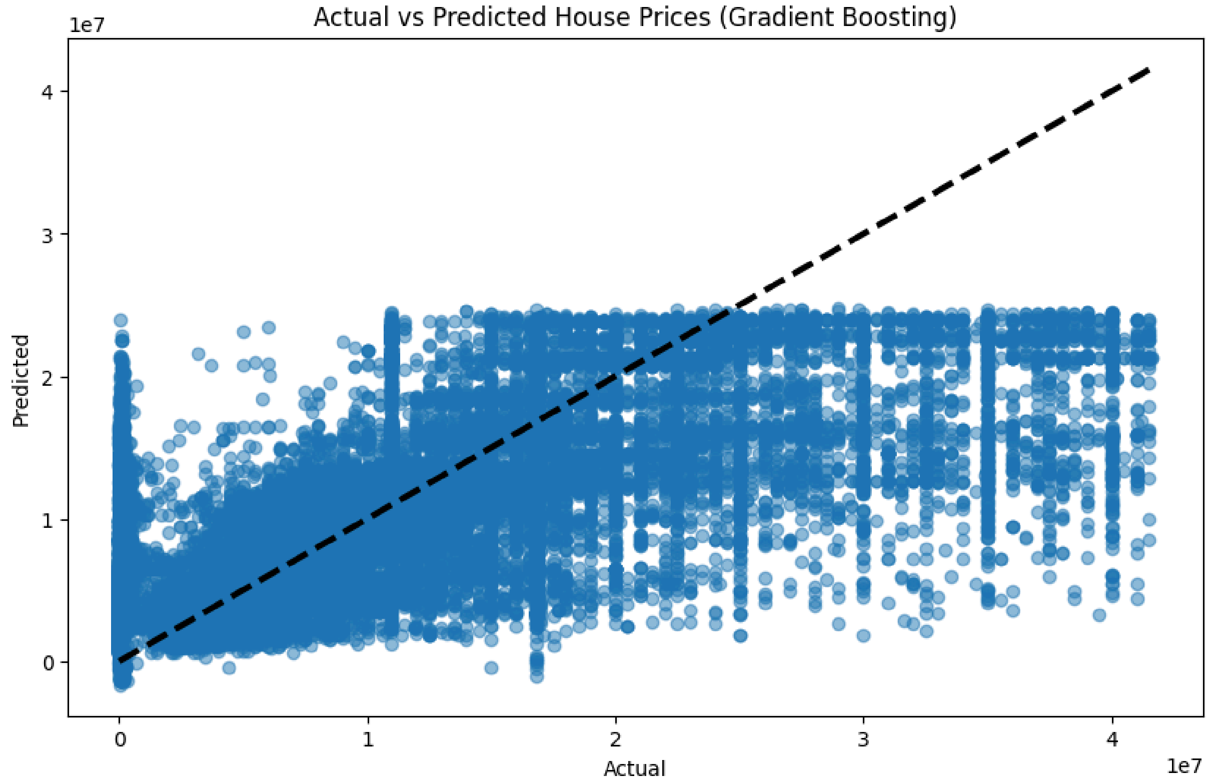
In [ ]:

```
# Evaluate the model
mae_gb = mean_absolute_error(y_test, y_pred_gb)
mse_gb = mean_squared_error(y_test, y_pred_gb)
r2_gb = r2_score(y_test, y_pred_gb)

print("Gradient Boosting Performance:")
print("Mean Absolute Error:", mae_gb)
print("Mean Squared Error:", mse_gb)
print("R-squared:", r2_gb)
```

```
Gradient Boosting Performance:
Mean Absolute Error: 5135581.0343836965
Mean Squared Error: 51133995148997.57
R-squared: 0.4550010456308714
```

In [ ]:

```
# Plot predictions vs actual prices for Gradient Boosting
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_gb, alpha=0.5)
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=3)
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted House Prices (Gradient Boosting)')
plt.show()
```



7.Future price Prediction

In [ ]:
```python
# Define the hypothetical scenarios (adjust as per your data structure)
hypothetical_data = {
    'area': [2500, 1500, 2000],  # in square feet
    'bedrooms': [4, 2, 3],
    'baths': [3, 1, 2],
    'house_age': [10, 5, 8],
    'latitude': [31.5204, 33.6844, 31.4278],
    'longitude': [74.3587, 73.0479, 73.0867]
}

# Create a DataFrame with hypothetical scenarios
df_hypothetical = pd.DataFrame(hypothetical_data)

# Use trained models to predict prices for hypothetical scenarios
predicted_prices_lr = lr_model.predict(df_hypothetical)
predicted_prices_rf = rf_model.predict(df_hypothetical)
predicted_prices_gb = gb_model.predict(df_hypothetical)
```

In [ ]:
```python
# Print the predicted prices for each model
print("Predicted Prices for Hypothetical Scenarios (Linear Regression):")
print(predicted_prices_lr)

print("\nPredicted Prices for Hypothetical Scenarios (Random Forest):")
print(predicted_prices_rf)

# Print the predicted prices for the hypothetical scenarios
```

```python
print("\nPredicted Prices for Hypothetical Scenarios (Gradient Boosting):")
print(predicted_prices_gb)
```

```
Predicted Prices for Hypothetical Scenarios (Linear Regression):
[10081272.47202951  4385032.10518862  7591245.030196  ]

Predicted Prices for Hypothetical Scenarios (Random Forest):
[27841729.24805562  1565870.76190476 13569395.25258376]

Predicted Prices for Hypothetical Scenarios (Gradient Boosting):
[22078417.57633539  3412520.94760612  8819282.0253196 ]
```