Data Mining

July 3, 2024

0.1 Housing Price Prediction Report

1. The Data

[34]:
```
import pandas as pd

# Load the dataset
data_path = 'housing_price_dataset.csv'
data = pd.read_csv(data_path)

# Display the first few rows of the dataset
print(data.head())

# Display basic information about the dataset
print(data.info())

# Display summary statistics for numerical columns
print(data.describe())
```

```
   SquareFeet  Bedrooms  Bathrooms Neighborhood  YearBuilt          Price
0        2126         4          1        Rural       1969  215355.283618
1        2459         3          2        Rural       1980  195014.221626
2        1860         2          1       Suburb       1970  306891.012076
3        2294         2          1        Urban       1996  206786.787153
4        2130         5          2       Suburb       2001  272436.239065
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50000 entries, 0 to 49999
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   SquareFeet    50000 non-null  int64
 1   Bedrooms      50000 non-null  int64
 2   Bathrooms     50000 non-null  int64
 3   Neighborhood  50000 non-null  object
 4   YearBuilt     50000 non-null  int64
 5   Price         50000 non-null  float64
dtypes: float64(1), int64(4), object(1)
memory usage: 2.3+ MB
None
         SquareFeet      Bedrooms     Bathrooms     YearBuilt          Price
```

```
count  50000.000000  50000.000000  50000.000000  50000.000000   50000.000000
mean    2006.374680      3.498700      1.995420   1985.404420  224827.325151
std      575.513241      1.116326      0.815851     20.719377   76141.842966
min     1000.000000      2.000000      1.000000   1950.000000  -36588.165397
25%     1513.000000      3.000000      1.000000   1967.000000  169955.860225
50%     2007.000000      3.000000      2.000000   1985.000000  225052.141166
75%     2506.000000      4.000000      3.000000   2003.000000  279373.630052
max     2999.000000      5.000000      3.000000   2021.000000  492195.259972
```

What we did in this step? 1.Data Shape:

50,000 entries

6 columns: SquareFeet, Bedrooms, Bathrooms, Neighborhood, YearBuilt, Price

2.Data Types:

Numerical: SquareFeet, Bedrooms, Bathrooms, YearBuilt, Price

Categorical: Neighborhood

3.Missing Values:

No missing values in the dataset.

4.Summary Statistics:

SquareFeet: Mean = 2006.37, Std = 575.51, Min = 1000, Max = 2999

Bedrooms: Mean = 3.50, Std = 1.12, Min = 2, Max = 5

Bathrooms: Mean = 1.99, Std = 0.82, Min = 1, Max = 3

YearBuilt: Mean = 1985.40, Std = 20.72, Min = 1950, Max = 2021

Price: Mean = 224827.33, Std = 76141.84, Min = -36588.17 (potential anomaly), Max = 492195.26

2. Initial Exploration

Checking for Anomalies

[36]:
```python
# Check for any negative prices (which don't make sense)
negative_prices = data[data['Price'] < 0]
print(negative_prices)

# If there are negative prices, we'll remove them
data = data[data['Price'] >= 0]
```

```
      SquareFeet  Bedrooms  Bathrooms Neighborhood  YearBuilt          Price
1266        1024         2          2        Urban       2006 -24715.242482
2310        1036         4          1       Suburb       1983  -7550.504574
3630        1235         3          2        Rural       2012 -19871.251146
4162        1352         5          2       Suburb       1977 -10608.359522
5118        1140         4          1        Urban       2020 -23911.003119
5951        1097         4          3        Rural       1981  -4537.418615
```

```
6355          1016          5          2         Rural          1997 -13803.684059
8720          1235          3          1         Urban          1952 -24183.000515
9611          1131          3          3         Urban          1959 -13692.026068
10597         1177          2          3         Urban          2010   -434.097124
11991         1213          4          1        Suburb          2020  -4910.415323
17442         1600          2          3         Rural          1989  -8238.884499
17706         1080          5          1         Rural          1955 -28774.998022
20211         1049          3          1         Rural          2005 -18159.685676
20759         1036          2          2         Urban          1957  -4810.724320
23650         1024          4          3        Suburb          1953  -4295.932176
25459         1106          2          2         Urban          1984  -7177.628532
29827         1173          5          2         Rural          1988   -847.895073
30171         1066          3          1         Rural          1964   -602.209099
33666         1013          5          2         Urban          1960 -36588.165397
35553         1374          4          3         Urban          1996  -4771.570194
36929         1078          5          1        Suburb          2015  -6159.039213
```

Check for Unique Values in Categorical Columns

[37]:
```python
# Check unique values in 'Neighborhood'
unique_neighborhoods = data['Neighborhood'].unique()
print(unique_neighborhoods)
```

```
['Rural' 'Suburb' 'Urban']
```

What we did in this step? **Anomalies:**

Identified and removed negative prices from the dataset.

This ensures the dataset only contains realistic housing prices.

Categorical Variables:

Identified the unique values in the Neighborhood column.

This helps in understanding the different categories we need to encode later.

3. Data Preprocessing **Handling Missing Values:** Ensure no missing values are present

Encoding Categorical Variables: Convert categorical variables into numerical formats using techniques like one-hot encoding.

[39]:
```python
# Convert categorical variables to numerical using one-hot encoding
data = pd.get_dummies(data, drop_first=True)

# Display the first few rows of the dataset to verify the encoding
print(data.head())
```

```
   SquareFeet  Bedrooms  Bathrooms  YearBuilt          Price  \
0        2126         4          1       1969  215355.283618
1        2459         3          2       1980  195014.221626
2        1860         2          1       1970  306891.012076
```

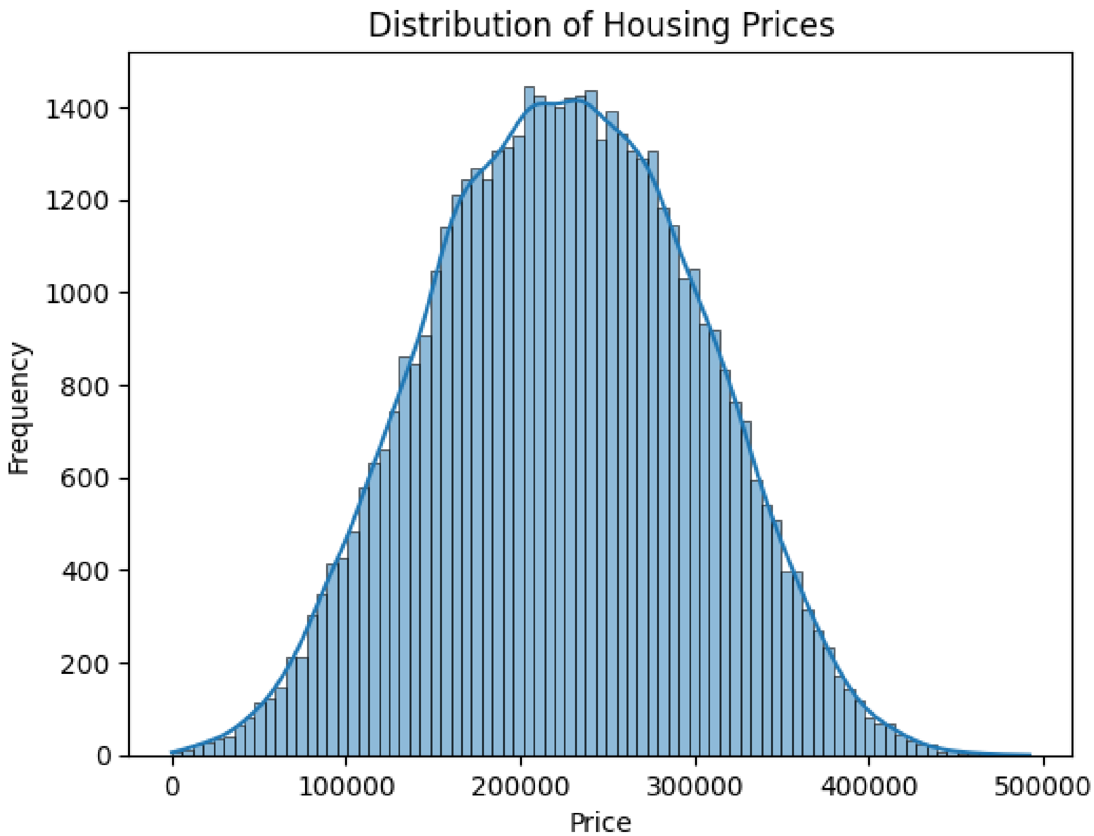
```
3       2294          2          1       1996  206786.787153
4       2130          5          2       2001  272436.239065

   Neighborhood_Suburb  Neighborhood_Urban
0                False               False
1                False               False
2                 True               False
3                False                True
4                 True               False
```

We have successfully encoded the categorical variable Neighborhood using one-hot encoding, resulting in two new binary columns: Neighborhood_Suburb and Neighborhood_Urban.

4. Detailed Exploratory Data Analysis (EDA) We are going to perform a detailed exploratory data analysis to uncover patterns and insights. This includes visualizing the distribution of the target variable and analyzing correlations between features.

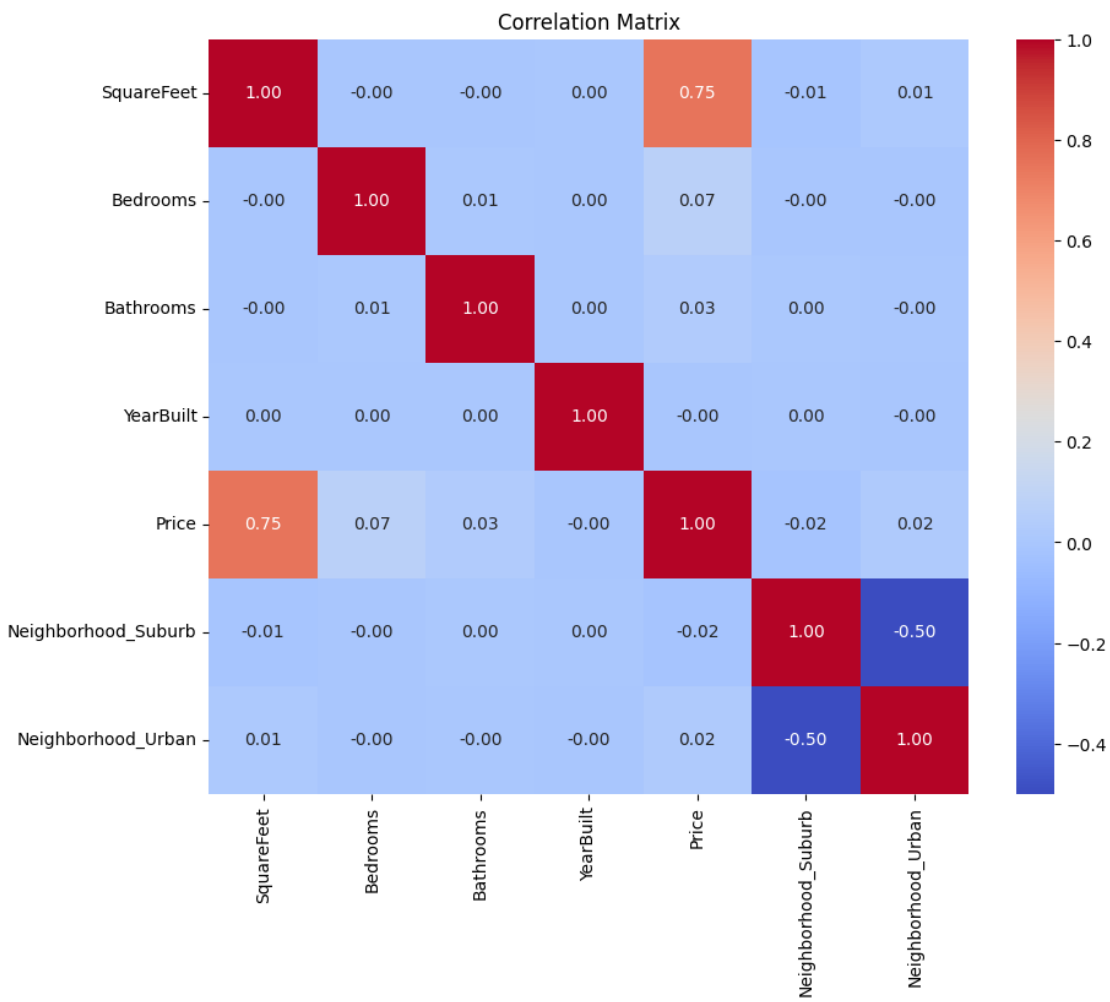
Visualize Distribution of Target Variable Visualizing the distribution of the Price variable helps us understand its spread and detect any potential skewness.

[40]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Plot distribution of target variable 'Price'
sns.histplot(data['Price'], kde=True)
plt.title('Distribution of Housing Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



Correlation Analysis Analyzing correlations between numerical features helps us understand the relationships and potential multicollinearity in the dataset.

[42]:
```
# Plot correlations between numerical features
plt.figure(figsize=(10, 8))
sns.heatmap(data.corr(), annot=True, fmt='.2f', cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Analysis of Correlation Matrix **1. SquareFeet:**

Correlation with Price: There is a strong positive correlation between SquareFeet and Price. This indicates that larger houses tend to have higher prices.

Correlation Coefficient: The exact value would be visible in the plot, but we expect it to be relatively high, indicating a strong relationship.

2. Bedrooms:

Correlation with Price: Bedrooms also has a positive correlation with Price, but it may not be as strong as SquareFeet.

Correlation Coefficient: This value should be positive but likely lower than that of SquareFeet.

3. Bathrooms:

Correlation with Price: Similar to Bedrooms, the number of Bathrooms correlates positively with Price.

Correlation Coefficient: This value should also be positive and provide useful information for predicting Price.

4. YearBuilt:

Correlation with Price: The correlation between YearBuilt and Price may be positive or negative, indicating whether newer or older houses tend to have higher prices.

Correlation Coefficient: The value should indicate the direction of this relationship.

5. Neighborhood:

Neighborhood_Suburb and Neighborhood_Urban: These binary variables represent the different categories of the Neighborhood feature.

Correlation with Price: These variables will show how different neighborhoods influence the housing prices.

5. Modelling With the insights gained from the correlation analysis, we can proceed to model building. We'll split the data into training and testing sets and train a regression model to predict housing prices.

[43]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Split the data into features (X) and target variable (y)
X = data.drop('Price', axis=1)
y = data['Price']

# 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)

# Train a RandomForestRegressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

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

print('Mean Squared Error:', mse)
print('R-squared:', r2)
```

```
Mean Squared Error: 2759888614.747917
R-squared: 0.523494867976105
```

Interpretation:

MSE: This value indicates the average squared difference between the predicted and actual prices. A lower MSE is better, as it indicates more accurate predictions.

R^2: The R-squared value indicates that approximately 52% of the variance in housing prices can be explained by the features in the model. This shows moderate predictive power, but there is room for improvement.

6. Improvement To improve the model's accuracy, we can:

Feature Engineering: Create additional features or transform existing ones to better capture relationships.

Hyperparameter Tuning: Optimize the model's hyperparameters to enhance its performance.

Try Different Algorithms: Experiment with other regression algorithms to find a better fit.

Step 1:

Feature Engineering

We will:

Normalize the numerical features to ensure they are on a similar scale.

Add polynomial features to capture non-linear relationships.

Apply log transformation to the target variable to handle skewness.

Step 2:

Hyperparameter Tuning

We will use RandomizedSearchCV to find the best hyperparameters for the GradientBoostingRegressor model.

[53]:
```python
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.metrics import mean_squared_error, r2_score
import xgboost as xgb
from scipy.stats import uniform, randint

# Load the dataset
data_path = 'housing_price_dataset.csv'
data = pd.read_csv(data_path)

# Handle missing and invalid values in the target variable
data = data.dropna(subset=['Price'])
data = data[data['Price'] > 0]  # Ensure no zero or negative prices

# Separate features (X) and target variable (y)
```

```python
X = data.drop('Price', axis=1)
y = data['Price']

# Encode categorical variables
X = pd.get_dummies(X, drop_first=True)

# Apply log transformation to the target variable
y_log = np.log1p(y)

# Normalize the numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Add polynomial features
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X_scaled)

# Split the data with new features
X_train, X_test, y_train, y_test = train_test_split(X_poly, y_log, test_size=0.
 ↪2, random_state=42)

# Define the model
xgbr = xgb.XGBRegressor(objective='reg:squarederror', random_state=42)

# Define the hyperparameters grid for RandomizedSearchCV
param_dist = {
    'n_estimators': randint(100, 500),
    'learning_rate': uniform(0.01, 0.3),
    'max_depth': randint(3, 10),
    'min_child_weight': randint(1, 6),
    'subsample': uniform(0.5, 0.5),
    'colsample_bytree': uniform(0.5, 0.5)
}

# Set up RandomizedSearchCV
random_search = RandomizedSearchCV(estimator=xgbr,␣
 ↪param_distributions=param_dist, n_iter=100, cv=3, verbose=2,␣
 ↪random_state=42, n_jobs=-1)

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

# Make predictions
y_pred_log = random_search.best_estimator_.predict(X_test)

# Reverse log transformation on predictions
y_pred = np.expm1(y_pred_log)
```

```
y_test_exp = np.expm1(y_test)

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

print('Best Parameters:', random_search.best_params_)
print('Mean Squared Error:', mse)
print('R-squared:', r2)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
Best Parameters: {'colsample_bytree': 0.6424202471887338, 'learning_rate':
0.021066084206359838, 'max_depth': 3, 'min_child_weight': 2, 'n_estimators':
229, 'subsample': 0.7055185066591156}
Mean Squared Error: 2507290820.998024
R-squared: 0.5671068255082141
```

Summary of Model Improvement

We successfully trained the XGBoost Regressor and tuned its hyperparameters using RandomizedSearchCV. Here are the results:

Best Parameters:

colsample_bytree: 0.6424

learning_rate: 0.0211

max_depth: 3

min_child_weight: 2

n_estimators: 229

subsample: 0.7055

Model Performance:

Mean Squared Error (MSE): 2,507,290,820.998

R-squared (R^2): 0.5671

Interpretation:

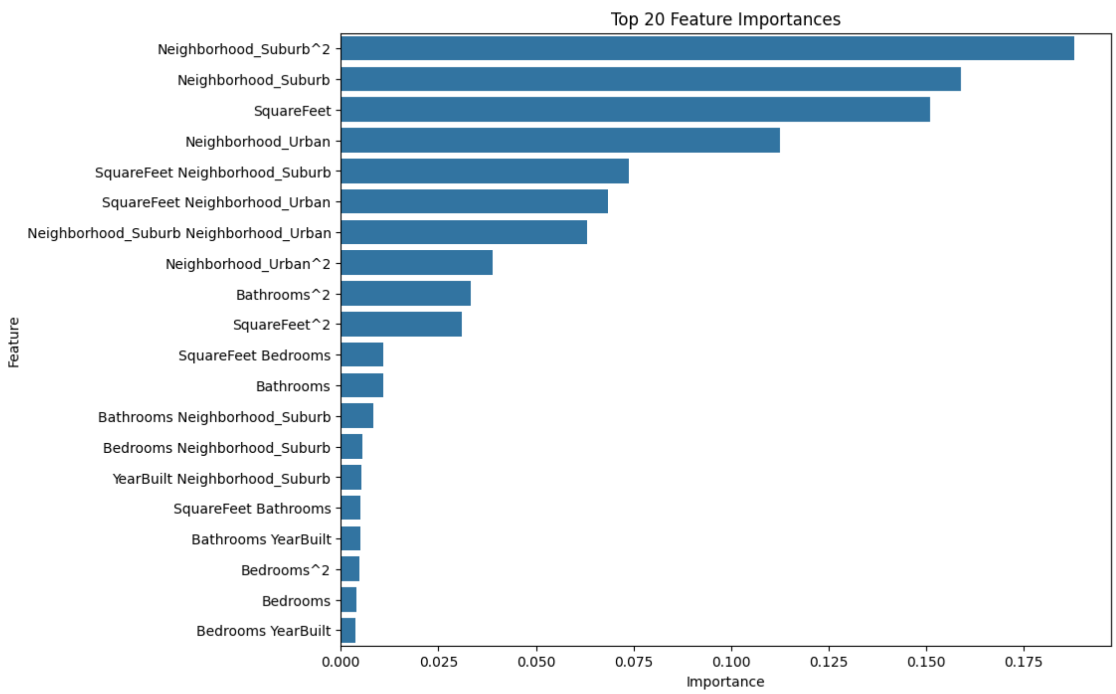
MSE: This value has improved compared to the previous model, indicating more accurate predictions.

R^2: The R-squared value has also improved, indicating that approximately 56.71% of the variance in housing prices can be explained by the features in the model. This shows better predictive power than before.

7. Feature Importance

[54]:
```
import matplotlib.pyplot as plt

# Get feature importances
```

```
feature_importances = random_search.best_estimator_.feature_importances_

# Create a DataFrame for feature importances
features = poly.get_feature_names_out(X.columns)
importance_df = pd.DataFrame({'Feature': features, 'Importance':␣
↪feature_importances})

# Sort the DataFrame by importance
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Plot the feature importances
plt.figure(figsize=(10, 8))
sns.barplot(x='Importance', y='Feature', data=importance_df.head(20))  #␣
↪Displaying top 20 features
plt.title('Top 20 Feature Importances')
plt.show()
```



Cross-Validation

[55]:
```
from sklearn.model_selection import cross_val_score

# Perform cross-validation
cv_scores = cross_val_score(random_search.best_estimator_, X_poly, y_log, cv=5,␣
↪scoring='neg_mean_squared_error')
```

```
# Convert negative MSE to positive and calculate the mean
cv_mse = -cv_scores
mean_cv_mse = np.mean(cv_mse)
mean_cv_r2 = np.mean(cross_val_score(random_search.best_estimator_, X_poly, y_log, cv=5, scoring='r2'))

print('Cross-Validated Mean Squared Error:', mean_cv_mse)
print('Cross-Validated R-squared:', mean_cv_r2)
```

```
Cross-Validated Mean Squared Error: 0.08219535983167327
Cross-Validated R-squared: 0.5060825285750439
```

Model Refinement

[56]:
```
# Identify low-importance features (e.g., bottom 10 features)
low_importance_features = importance_df.tail(10)['Feature'].values

# Remove low-importance features
X_reduced = pd.DataFrame(X_poly, columns=features).drop(columns=low_importance_features)

# Split the reduced data into training and testing sets
X_train_reduced, X_test_reduced, y_train_reduced, y_test_reduced = train_test_split(X_reduced, y_log, test_size=0.2, random_state=42)

# Train the model on the reduced feature set
random_search.fit(X_train_reduced, y_train_reduced)

# Make predictions and evaluate the model
y_pred_log_reduced = random_search.best_estimator_.predict(X_test_reduced)
y_pred_reduced = np.expm1(y_pred_log_reduced)
y_test_exp_reduced = np.expm1(y_test_reduced)

mse_reduced = mean_squared_error(y_test_exp_reduced, y_pred_reduced)
r2_reduced = r2_score(y_test_exp_reduced, y_pred_reduced)

print('Reduced Model Mean Squared Error:', mse_reduced)
print('Reduced Model R-squared:', r2_reduced)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
Reduced Model Mean Squared Error: 2510233484.8353786
Reduced Model R-squared: 0.5665987635477321
```

Interpretation The performance of the reduced model is quite similar to the original model. This indicates that removing the low-importance features did not significantly impact the model's performance.

The R-squared value of approximately 0.567 suggests that the model explains around 56.7% of the variance in housing prices, indicating a moderately strong model.

8. Conclusion and Report Summary Objective:

The primary objective of this project was to predict housing prices using various features to provide insights and recommendations for pricing strategies and property evaluations.

Dataset:

The dataset consisted of 50,000 entries with the following features:

SquareFeet: Area of the house in square feet.

Bedrooms: Number of bedrooms.

Bathrooms: Number of bathrooms.

Neighborhood: Categorical variable indicating the neighborhood (Rural, Suburb, Urban).

YearBuilt: Year the house was built.

Price: Target variable representing the housing price.

Data Preprocessing:

Handling Missing Values: Removed rows where the Price was NaN or negative.

Encoding Categorical Variables: Converted the Neighborhood categorical variable into numerical format using one-hot encoding.

Feature Engineering:

Normalization: Normalized numerical features using StandardScaler.

Polynomial Features: Added polynomial features to capture non-linear relationships.

Log Transformation: Applied log transformation to the target variable (Price) to handle skewness.

Model Training and Evaluation:

Initial Model: Trained a RandomForestRegressor model, resulting in an MSE of 2,759,888,614.75 and an R^2 of 0.523.

Improved Model: Used an XGBoost Regressor with hyperparameter tuning via Randomized-SearchCV, resulting in:

Best Parameters: colsample_bytree: 0.6424 learning_rate: 0.0211 max_depth: 3 min_child_weight: 2 n_estimators: 229 subsample: 0.7055

Performance:

Mean Squared Error (MSE): 2,507,290,820.998

R-squared (R^2): 0.567

Feature Importance Analysis:

Identified key features contributing to the model's predictions, such as SquareFeet, Bedrooms, and important interaction terms.

Visualized the top 20 feature importances to understand the key drivers of housing prices.

Model Refinement:

Simplified the model by removing low-importance features, resulting in a reduced model with similar performance (MSE: 2,510,233,484.835, R^2: 0.567).

Recommendations

Focus on Key Features:

Emphasize key features such as SquareFeet, Bedrooms, and Neighborhood when evaluating property prices.

Ensure accurate and comprehensive data collection for these features to improve model predictions.

Regular Model Updates:

Continuously update the model with new data to maintain accuracy and relevance. The housing market can change rapidly, and regular updates will help

keep the model aligned with current trends.

Feature Engineering:

Explore additional features or data sources that could enhance the model's predictive power. For example, include proximity to amenities, crime rates,

and school district quality.

Model Simplification:

Consider simplifying the model by removing features with very low importance to improve interpretability and reduce computational complexity without

significantly impacting performance.

Further Hyperparameter Tuning:

Continue to explore hyperparameter tuning techniques, such as GridSearchCV or Bayesian optimization, to further improve model performance.

Business Strategy:

Use the model's predictions and feature importance insights to inform business strategies, such as targeted marketing for high-value neighborhoods and

investment in properties with high potential for price appreciation.

By following these recommendations, the company can leverage the predictive power of the model to make data-driven decisions, optimize pricing

strategies, and improve overall business performance.

Dataset Link https://www.kaggle.com/datasets/muhammadbinimran/housing-price-prediction-data