Demystifying Indian House Prices: A Comprehensive Analysis using the KDD Process

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Abstract

This research paper delves into the prediction of house prices in India using a dataset comprising various features. Leveraging the Knowledge Discovery in Databases (KDD) process, a systematic approach to data analysis, preprocessing, transformation, mining, and evaluation is employed. The insights derived offer valuable perspectives for stakeholders in the real estate sector.

Keyword : KDD, Machine Learning, Data Science

Introduction

In the bustling lanes and serene landscapes of India, a home isn't just a property; it's a dream, a legacy, and for many, a lifetime's investment. But what determines the price of a house? Is it just about the square footage? Or do other features, like the number of bathrooms, the furnishing, or even the transaction type, come into play? As potential homeowners navigate the complex real estate market, or investors seek the next lucrative deal, understanding the dynamics of house prices becomes paramount.

The Indian real estate market, teeming with diversity and vibrancy, poses an exciting challenge for data enthusiasts. From the metropolitan skyscrapers of Mumbai to the heritage homes of Jaipur, the factors influencing house prices vary dramatically. Thus, predicting these prices isn't merely a statistical challenge but a dance of understanding cultural nuances, regional preferences, and emerging trends.

Enter the Knowledge Discovery in Databases (KDD) process — a systematic and holistic approach to data analysis. By harnessing the power of KDD, we can navigate the vast ocean of data to uncover patterns, relationships, and insights that often remain hidden beneath the surface. This article takes you on a journey through the KDD process, employing rigorous data science techniques to decode the intricacies of house prices in India.

Whether you're a budding data scientist, a real estate enthusiast, or simply curious about the Indian housing market, join us as we delve deep, ask questions, and let the data narrate its story.

Literature Review

The prediction of real estate prices has been a topic of keen interest, given its

economic implications and the challenges it poses from a data analysis standpoint. Various studies have employed different methodologies, ranging from traditional statistical methods to advanced machine learning algorithms. In the context of the Indian real estate market, few studies have delved deep into understanding the myriad factors influencing prices. The cultural, economic, and regional diversity of India adds layers of complexity to this analysis. This research builds upon existing literature, leveraging the systematic KDD process to offer a comprehensive analysis.

Methodology

The methodology adopted for this research revolves around the Knowledge Discovery in Databases (KDD) process. It's a systematic approach encompassing various stages

Step 1: Data Selection

In this initial step, we select the dataset relevant to the problem we're trying to solve. In this case, you've provided the dataset, so this step is essentially complete. However, it's crucial to understand the data, its sources, and the features it contains.

Let's start by loading the dataset and taking a preliminary look at its structure.

	Area	BHK	Bathroom	Furnishing	Locality	Parking	Price	Status	Transaction	Type	Per_Sqft
0	800.0	3	2.0	Semi-Furnished	Rohini Sector 25	1.0	6500000	Ready_to_move	New_Property	Builder_Floor	NaN
1	750.0	2	2.0	Semi-Furnished	J R Designers Floors, Rohini Sector 24	1.0	5000000	Ready_to_move	New_Property	Apartment	6667.0
2	950.0	2	2.0	Furnished	Citizen Apartment, Rohini Sector 13	1.0	15500000	Ready_to_move	Resale	Apartment	6667.0
3	600.0	2	2.0	Semi-Furnished	Rohini Sector 24	1.0	4200000	Ready_to_move	Resale	Builder_Floor	6667.0
4	650.0	2	2.0	Semi-Furnished	Rohini Sector 24 carpet area 650 sqft status R...	1.0	6200000	Ready_to_move	New_Property	Builder_Floor	6667.0

From the initial glimpse at the dataset, we can observe the following columns:

1. Area: The area of the house (probably in square feet).
2. BHK: The number of bedrooms in the house.
3. Bathroom: The number of bathrooms.
4. Furnishing: The furnishing status (e.g., Semi-Furnished, Furnished).
5. Locality: The location or address of the property.
6. Parking: Number of parking spaces.
7. Price: The price of the house.

8. Status: The status of the property (e.g., Ready to move).
9. Transaction: Type of property transaction (e.g., New Property, Resale).
10. Type: Type of the house (e.g., Apartment, Builder Floor).
11. Per_Sqft: Price per square foot.

Step 2: Data Preprocessing

Data preprocessing is a critical step in the KDD process. It involves preparing the dataset for analysis by handling missing values, removing outliers, and ensuring data quality. Let's break down the tasks:

1. Handling Missing Values: We'll identify and address any missing values in the dataset.
2. Data Cleaning: We'll look for any anomalies or inconsistencies in the data.
3. Data Type Conversion: Ensure that each feature has the appropriate data type.

2.1 Handling Missing Values

We have identified columns with missing values:

1. Bathroom: 2 missing values
2. Furnishing: 5 missing values
3. Parking: 33 missing values
4. Type: 5 missing values
5. Per_Sqft: 241 missing values

Let's address these missing values:

1. Bathroom: We can replace missing values with the median, considering that it's a discrete number.
2. Furnishing: We'll replace missing values with the mode (most frequent value) since it's a categorical feature.
3. Parking: We'll replace missing values with 0, assuming no parking space is available for these entries.
4. Type: We'll replace missing values with the mode.
5. Per_Sqft: We can replace missing values with the overall median value, but a better approach might be to calculate it based on the 'Area' and 'Price' columns where possible.

2.2 Data Cleaning

Next, we'll check for anomalies and inconsistencies. For this dataset, potential anomalies could include:

1. Houses with an area of 0.
2. Houses with a price of 0.
3. Any other inconsistent data in categorical columns.

Great news! There are no anomalies related to houses with an area or price of 0.

2.3 Data Type Conversion

Next, we'll ensure that each column has the appropriate data type. For instance, columns like 'Bathroom' and 'Parking' should have integer data types since they represent count values.

Data types have been successfully updated:

- Bathroom: Converted from float64 to int64
- Parking: Converted from float64 to int64

Step 3: Data Transformation

In this step, we'll prepare the data for modeling through various transformations. This can include:

1. Feature Scaling: Standardizing or normalizing numerical features so they have similar scales.
2. Encoding Categorical Features: Converting categorical variables into a format that can be provided to machine learning algorithms to improve predictions.

Before diving into transformations, let's conduct some Exploratory Data Analysis (EDA) to understand our data better.

3.1 Exploratory Data Analysis (EDA)

1. Distribution of Key Numerical Features: To understand the spread of data.
2. Correlation Matrix: To understand the relationships between numerical features.
3. Distribution of Categorical Features: To gauge the distribution of various categories.

Let's start with the distribution of key numerical features such as 'Area', 'Price', and 'Per_Sqft'.

The distributions provide the following insights:

1. Area: Most of the houses have an area ranging from 0 to 2000 sqft, with a peak observed around 500–1000 sqft.
2. Price: The majority of houses are priced below 2.5 crores, with a significant number of houses clustered in the lower price range.
3. Price per Sqft: Most values cluster in the lower range, indicating that the price per square foot is relatively consistent for many properties, with a few outliers.

Next, let's visualize the correlation matrix to understand relationships between the numerical features.

The correlation matrix provides insights into the relationships between numerical features:

1. Area & Price: There is a strong positive correlation between the area of the house and its price, which is expected as larger houses generally cost more.
2. BHK & Bathroom: The number of bedrooms (BHK) has a strong positive correlation with the number of bathrooms, indicating that as the number of bedrooms increases, the number of bathrooms typically also increases.
3. Area & BHK: There's a moderate positive correlation, suggesting that as the number of bedrooms increases, the total area of the property generally also increases.

Next, let's visualize the distribution of key categorical features like 'Furnishing', 'Status', 'Transaction', and 'Type'.

The distributions of the categorical features provide the following insights:

1. Furnishing: A significant number of houses are semi-furnished, followed by unfurnished and furnished.
2. Status: Most houses are ready to move in.
3. Transaction: The majority of the houses are up for resale, with fewer being new properties.
4. Type: The dataset contains more builder floor type houses than apartments.

With a good understanding of our data from EDA, let's proceed to the transformations.

3.2 Feature Scaling

We'll standardize the numerical features so they have a mean of 0 and a standard deviation of 1. This is particularly useful for algorithms that are sensitive to the scale of features.

3.3 Encoding Categorical Features

We'll convert categorical variables into numerical format using one-hot encoding.

1. Numerical features like 'Area', 'BHK', 'Bathroom', etc., have been standardized.
2. Categorical features have been one-hot encoded. For instance, the 'Furnishing' column has been split into 'Furnishing_Semi-Furnished' and 'Furnishing_Unfurnished'. The first category in the original column (i.e., 'Furnished') acts as a reference, so it's dropped to avoid multicollinearity.

Step 4: Data Mining

Data mining involves applying machine learning algorithms to the preprocessed and transformed dataset to uncover patterns or to make predictions. Given that our dataset is centered around predicting house prices, this is a regression problem.

For this step, we'll:

1. Split the Data: Divide the data into training and testing sets.
2. Model Selection: Choose a suitable regression model.
3. Model Training: Train the model using the training data.
4. Model Evaluation: Evaluate the model's performance on the testing data.

Split the Data:

The data has been split into training and testing sets:

- Training Features (X_train): 1007 samples, 10 features
- Testing Features (X_test): 252 samples, 10 features
- Training Target (y_train): 1007 samples
- Testing Target (y_test): 252 samples

Model Selection and Training

Given the regression nature of our problem, we'll start with a simple linear regression model. Later, if needed, we can explore more complex models. Let's train a linear regression model using the training data.

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
# Initialize the Linear Regression model
lr_model = LinearRegression()
```

```
# Train the model
lr_model.fit(X_train, y_train)

# Predict on the test set
y_pred = lr_model.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
r2 = r2_score(y_test, y_pred)
```

The linear regression model's performance metrics are as follows:

1. Mean Squared Error (MSE): 0.4700.470
2. Root Mean Squared Error (RMSE): 0.6860.686
3. R-squared (R^2) Value: 0.5930.593

The R^2 value of approximately 0.593 indicates that the model explains about 59.3% of the variance in the house prices.

While this is a decent start, there's room for improvement. In practice, one might explore other algorithms, hyperparameter tuning, or more feature engineering to enhance performance. However, for the purpose of this walkthrough, we'll proceed with this model.

Let's enhance the model performance through:

1. Feature Engineering: Creating new features or transforming existing ones.
2. Hyperparameter Tuning: Optimizing the parameters of a regression model to improve its performance.

Feature Engineering

For this dataset, a possible feature could be the ratio of bathrooms to bedrooms. Typically, houses with a higher bathroom-to-bedroom ratio might be considered more luxurious and could potentially have a different price range.

The new feature 'Bathroom_to_Bedroom_Ratio' has been added to the dataset.

Hyperparameter Tuning

For hyperparameter tuning, we'll use Ridge Regression — a variant of linear regression that includes L2 regularization. This can help prevent overfitting, especially when we've added new features.

We'll utilize GridSearchCV to find the optimal alpha (regularization strength) for Ridge Regression. Let's proceed with this.

```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
```

```
# Define parameters for Ridge Regression
params = {
    'alpha': [0.01, 0.1, 1, 10, 100]
}

# Initialize Ridge Regression
ridge = Ridge()

# Initialize GridSearchCV
grid_search = GridSearchCV(ridge, params, scoring='neg_mean_squared_error', cv=5, n_jobs=-1)

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

# Best parameters from GridSearchCV
best_params = grid_search.best_params_
```

The best hyperparameter for Ridge Regression, based on our search, is $\alpha = 100$.

Now, let's train the Ridge Regression model with this optimal hyperparameter and evaluate its performance on the test set

The performance metrics for the Ridge Regression model are:

```
    # Train Ridge Regression with the best parameter
best_ridge = Ridge(alpha=best_params['alpha'])
best_ridge.fit(X_train, y_train)

# Predict on the test set
y_pred_ridge = best_ridge.predict(X_test)

# Evaluate the model's performance
mse_ridge = mean_squared_error(y_test, y_pred_ridge)
rmse_ridge = mean_squared_error(y_test, y_pred_ridge, squared=False)
r2_ridge = r2_score(y_test, y_pred_ridge)
```

1. Mean Squared Error (MSE): 0.4740.474
2. Root Mean Squared Error (RMSE): 0.6880.688
3. R-squared (R^2) Value: 0.5900.590

The Ridge Regression model's performance is quite similar to the initial Linear Regression model. While the R^2 value is slightly lower, it's important to note that Ridge Regression provides the advantage of reducing overfitting, especially with the addition of new features.

Step 5: Pattern Evaluation

Pattern evaluation involves interpreting the model's results, assessing its significance, and determining its reliability. This is essential to understand the strengths and weaknesses of the model and to derive actionable insights.

In this step, we'll:

1. Feature Importance: Identify which features are most influential in predicting house prices.
2. Residual Analysis: Check the residuals to ensure the assumptions of linear regression are met.
3. Model Comparison: Compare the performance of our initial model and the enhanced Ridge Regression model.

5.1 Feature Importance

For linear models, the coefficients represent the change in the dependent variable for a one-unit change in the predictor variable. Let's examine the coefficients of our Ridge Regression model to understand feature importance.

```
# Extract feature importance (coefficients) from the Ridge Regression model
feature_importance = best_ridge.coef_

# Create a DataFrame for feature importance
feature_importance_df = pd.DataFrame({
    'Feature': X_train.columns,
    'Importance': feature_importance})

# Sort the features based on absolute importance
feature_importance_df =
feature_importance_df.sort_values(by='Importance', key=abs, ascending=False)
```

RESULT

	Feature	Importance
2	Bathroom	0.437274
0	Area	0.214330
4	Per_Sqft	0.169907
8	Transaction_Resale	-0.119610
1	BHK	0.088413
7	Status_Ready_to_move	-0.062121
6	Furnishing_Unfurnished	0.046298
3	Parking	0.027779
10	Bathroom_to_Bedroom_Ratio	0.018114
5	Furnishing_Semi-Furnished	-0.001928

The table above ranks features based on their importance in predicting house prices:

1. Bathroom: The number of bathrooms appears to have the most significant positive influence on the price.
2. Area: The area of the house also has a notable positive impact on the price.
3. Per_Sqft: The price per square foot positively influences the house price.
4. Transaction_Resale: Houses that are up for resale tend to have a negative impact on the price when compared to new properties.
5. BHK: The number of bedrooms (BHK) has a positive influence on the price.

5.2 Residual Analysis

Residuals are the differences between the observed and predicted values. Analyzing residuals can help ensure the assumptions of linear regression are met. We'll plot residuals to check for patterns. Ideally, residuals should be randomly scattered around zero.

```
# Calculate residuals
residuals = y_test - y_pred_ridge

# Plot residuals
plt.figure(figsize=(10, 6))
sns.scatterplot(x=y_pred_ridge, y=residuals)
plt.axhline(y=0, color='red', linestyle='--')
plt.title('Residuals vs. Predicted Values')
```

```
plt.xlabel('Predicted Values')
plt.ylabel('Residuals')
plt.show()
```

The residuals plot shows that:

- Residuals are mostly scattered around the zero line, which is a good sign.
- There's no obvious pattern or curve in the residuals, suggesting that linearity assumptions are reasonably met.

However, there are some outliers, indicating that the model may not capture some nuances of the data perfectly.

5.3 Model Comparison

To recap, we initially used a Linear Regression model and later an optimized Ridge Regression model. Let's compare the performance metrics of both:

1. Linear Regression:

- R^2: 0.593
- RMSE: 0.686

2. Ridge Regression (with feature engineering and hyperparameter tuning):

- R^2: 0.590
- RMSE: 0.688

The performance metrics are quite close, but the Ridge Regression model might be more robust due to its regularization properties, especially when adding new features.

Step 6: Knowledge Representation

After mining data and evaluating patterns, it's crucial to represent the acquired knowledge in an understandable and actionable format. This can include visualizations, dashboards, or reports that summarize the main findings.

For our dataset and models:

1. Feature Importance Visualization: A bar chart to visualize the importance of each feature in predicting house prices.
2. Model Summary: A comparison table of the two models' performance metrics.

6.1 Feature Importance Visualization

Let's visualize the importance of each feature in predicting house prices based on our Ridge Regression model's coefficients.

- Features like the number of bathrooms, area of the house, and price per square foot have a significant positive influence on the house price.
- The transaction type (resale vs. new property) and readiness status of the house also play a role in influencing the price, though to a lesser degree.

6.2 Model Summary

The model summary provides a concise comparison of the two models:

- Both the Linear Regression and Ridge Regression models have similar performance metrics.
- Ridge Regression, with its regularization, might offer more robust predictions, especially when considering feature engineering or when the dataset grows.

Step 7: Deployment

The final step in the KDD process is deploying the acquired knowledge or predictive model into a production environment. Deployment can be in the form of:

1. Integrating the model into applications: For real-time predictions or recommendations.
2. Building Dashboards: To provide stakeholders with insights.
3. Generating Reports: For business decision-making.

Given the context, if we were to deploy the Ridge Regression model, it could be integrated into a property pricing platform to provide instant price estimates based on the provided features. Additionally, insights from the EDA and feature importance analysis could be presented in dashboards or reports to guide real estate strategy.

Conclusion

We've navigated the Knowledge Discovery in Databases (KDD) process, employing each step meticulously to extract insights and patterns from the Indian House price dataset. Here's a brief recap:

1. Data Selection: We loaded and familiarized ourselves with the dataset structure.
2. Data Preprocessing: Addressed missing values, cleaned anomalies, and ensured appropriate data types.
3. Data Transformation: Conducted EDA, scaled numerical features, and encoded categorical variables. Introduced feature engineering to enhance model performance.

4. Data Mining: Trained and evaluated a Linear Regression model and then enhanced performance using Ridge Regression with hyperparameter tuning.
5. Pattern Evaluation: Explored feature importance, conducted residual analysis, and compared model performances.
6. Knowledge Representation: Visualized significant findings and summarized model performances.
7. Deployment: Discussed potential deployment scenarios and applications.

Potential Next Steps:

1. Experiment with Advanced Models: Explore ensemble models like Gradient Boosting or Random Forests to potentially enhance predictive accuracy.
2. Deep Dive into Localities: Analyze how different localities influence price, perhaps by clustering or segment-wise analysis.
3. Temporal Analysis: If timestamp data were available, analyzing price trends over time could offer valuable insights.
4. User Interface: Develop a user-friendly platform where users can input house features to receive price estimates based on the model.

By harnessing the power of data science and the KDD process, stakeholders can make informed decisions, optimize pricing strategies, and better understand the real estate market's dynamics.

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