# **Machine Learning Based House price prediction: Using Numerical Data**

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## Abstract

This project aims to develop a reliable and interpretable machine learning model to predict house prices based on property features. By employing multiple linear regression, we seek to capture the relationships between house prices and various factors, such as square footage, number of bedrooms, location, and other numerical characteristics. Accurate price prediction is valuable in real estate for decision-making, investment analysis, and market assessment.

The study begins with data preprocessing to ensure data quality, including handling missing values, normalizing numerical variables, and selecting key features. The multiple linear regression model is then trained on this preprocessed data, with each feature weighted based on its contribution to predicting prices. Additionally, various machine learning techniques, such as feature selection and cross-validation, are implemented to enhance model accuracy and avoid overfitting. Evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R²), are used to assess model performance and provide a clear understanding of prediction accuracy and robustness. The residual analysis further verifies model assumptions and helps in identifying areas for improvement. The interpretability of multiple linear regression is a key focus, as it allows insights into how each feature impacts house prices, an aspect particularly useful for real estate professionals and stakeholders.

Results indicate that multiple linear regression is effective for house price prediction, with potential applications in real estate valuation and investment. The study also discusses limitations, such as data constraints and the assumption of linearity, while suggesting directions for future work, including exploring non-linear models and integrating additional datasets for enhanced performance. Overall, this project demonstrates how machine learning can support real estate analytics, providing a valuable tool for market participants in price estimation and trend analysis.

**1.0 INTRODUCTION**

### **1.1 Background**

House prices are determined by a wide range of factors, each contributing to the property’s market value and appeal. Key influences include the location of the property, its size (such as square footage and lot area), the age and condition of the building, the number of bedrooms and bathrooms, and additional amenities, such as a garage, garden, or proximity to schools and commercial centers. These variables interact in complex ways, making accurate price prediction challenging without sophisticated analysis.

Machine learning provides a powerful, data-driven approach to addressing this complexity by leveraging historical housing data to model these relationships. Using machine learning algorithms, we can capture the correlations and patterns among various property features, offering predictive insights into future prices. This capability has valuable applications in real estate investment, pricing strategies, and urban planning, helping investors, buyers, and policymakers make informed decisions based on data-backed predictions.

1.2 Objective and Scope

The primary objective of this project is to develop a predictive model that accurately estimates house prices using multiple linear regression, based on a dataset of numerical property features. The model will be designed to capture the linear relationships between house prices and selected features, providing insights into how each factor impacts valuation. In addition to building the model, the project includes rigorous evaluation to ensure the reliability and accuracy of predictions.

The scope of this project encompasses several key phases:

- Data Collection and Preprocessing: Gathering a dataset with relevant features, followed by cleaning and transforming the data to prepare it for analysis.

- Feature Selection and Model Development: Identifying the most influential features and implementing a multiple linear regression model to predict prices.

- Evaluation and Analysis: Assessing the model’s performance using standard metrics, such as Mean Absolute Error (MAE) and R-squared (R²), and conducting residual analysis to ensure validity.

- Insights and Applications: Analyzing the interpretability of the model and discussing practical applications and limitations.

This structured approach aims to create a model that not only provides accurate price predictions but also offers interpretable insights into the factors driving housing prices, making it a useful tool for stakeholders in the real estate market.

Key objectives include:

1. Identifying and selecting relevant features: Using exploratory data analysis, we aim to determine which factors, such as Number of rooms, Square footage, or Age of house, play the most significant role in predicting the price.
2. Building a predictive model: Using a supervised learning algorithm (linear regression), we aim to train a model on historical data, where each data point includes known predictors and final grades.
3. Evaluating model performance: By using performance metrics like Mean Squared Error (MSE) and R-squared (R²), we aim to assess how accurately the model can predict house price. This evaluation will also include visualizations to interpret the model’s effectiveness and any areas for improvement.

1.3 Project Setup

The setup of this project involves key components, including data sourcing, tool selection, and the development environment, to facilitate an effective analysis and model development process. For this project, we selected the “*Boston Housing Dataset*” from the Kaggle Machine Learning Repository. This dataset is widely used in predictive modeling, containing information on various attributes of houses in Boston, such as the number of rooms, property age, square footage and proximity to business centers. These features make it suitable for analyzing the impact of different property characteristics on house prices.

**Tools and Libraries**

For this project, python was chosen as the primary programming language due to its powerful libraries for data manipulation, visualization, and machine learning. Below are the specific libraries utilized in this analysis:

**- NumPy:** NumPy is used for handling large arrays and performing complex numerical computations. It facilitates efficient data manipulation, particularly with multidimensional arrays, enhancing the speed of calculations.

**- Pandas:** This library is essential for loading, cleaning, and exploring the dataset. Using Pandas DataFrames, we can easily manipulate and transform data, making it a critical tool for data preprocessing tasks such as handling missing values, encoding categorical data, and selecting features.

- **Matplotlib and Seaborn:** For data visualization, Matplotlib and Seaborn provide a wide range of plotting functions. These libraries were used to create various visualizations—scatter plots, histograms, box plots, and heatmaps—that helped identify trends, patterns, and correlations among variables, which is especially useful during the exploratory data analysis (EDA) phase.

**- Scikit-learn:** One of the most popular libraries for machine learning, Scikit-learn provides modules for regression, classification, clustering, and model evaluation. For this project, Scikit-learn’s Linear Regression model was used to predict house prices. Additionally, evaluation metrics like Mean Squared Error (MSE) and R-squared (R²) were accessed from the library to assess model performance.

The workflow for this project can be broken down into five main steps:

1. Data Loading and Exploration: The dataset was loaded using Pandas, followed by an initial exploration of the features, data types, and any missing values.
2. Exploratory Data Analysis (EDA): Key features were visualized to examine their distributions and relationships with the target variable (final price).
3. Data Preprocessing: After selecting relevant features, the data was split into training and testing sets, ensuring an unbiased evaluation of the model. Any necessary transformations, such as scaling or encoding, were also applied.
4. Model Training: The linear regression model was trained on the training set, with features like number of rooms, property age, square footage and proximity to business centers.
5. Model Evaluation and Visualization: The model’s performance was evaluated using the test set. Key metrics were calculated, and visualizations (e.g., scatter plot of actual vs. predicted price, residual plot) were generated to interpret the model’s accuracy and identify areas for improvement.

**2.0 THEORETICAL BACKGROUND**

**2.1 Multiple Linear Regression Theory**

Multiple Linear Regression (MLR) is a statistical technique used to model the relationship between two or more independent variables (features) and a dependent variable (target). In the case of house price prediction, the dependent variable is the price, and the independent variables could include features like the number of bedrooms, square footage, location, age of the house, etc.

The general formula for multiple linear regression is:

Price=β0​+β1​×Feature1+β2​×Feature2+⋯+βn​×Featuren+ϵ

Where:

Where:

* β0\beta\_0β0​ is the intercept (the price when all features are zero),
* β1,β2,…,βn\beta\_1, \beta\_2, \dots, \beta\_nβ1​,β2​,…,βn​ are the coefficients of each feature, representing how much each feature contributes to the house price,
* ϵ\epsilonϵ is the error term (the difference between the predicted and actual prices).

In MLR, we assume that the relationship between the independent variables and the target is linear, i.e., the effect of each feature is additive and proportional to its coefficient. The model’s goal is to find the best-fitting line (or hyperplane, in higher dimensions) by estimating the coefficients that minimize the error. The primary assumption in MLR is that there is no significant multicollinearity among the predictors (i.e., the features should not be highly correlated with each other), and the relationship between features and target is linear.

**House Price Prediction Example:** In house price prediction, the features might include the number of bedrooms, the size of the house in square feet, its location, and its age. The multiple linear regression model will estimate the relationship between these variables and the price, allowing the prediction of house prices based on the values of these features.

**2.3 Model Evaluation Metrics**

Evaluating the performance of a machine learning model is crucial to understand how well it generalizes to unseen data. Several metrics are used to assess the accuracy of regression models, each highlighting different aspects of model performance. In the case of house price prediction, the most commonly used evaluation metrics are:

**- Mean Absolute Error (MAE):**

**MAE=n1​i=1∑n​∣yi​−y^​i​∣**

MAE calculates the average absolute difference between the actual and predicted house prices. The value is easy to interpret, as it gives the average error in the same units as the target variable (i.e., house prices). A lower MAE indicates better model performance.

**Mean Squared Error (MSE):**

**MSE=n1​i=1∑n​(yi​−y^​i​)2**

MSE measures the average squared difference between actual and predicted values. It penalizes larger errors more than smaller ones, making it more sensitive to outliers. While MSE helps in identifying models that make large errors, it can sometimes be biased by extreme values (outliers).

**- Root Mean Squared Error (RMSE):**

**RMSE= Square root of MSE​**

RMSE is simply the square root of MSE, bringing the error metric back to the original scale of the target variable (house prices). Like MSE, RMSE is sensitive to large errors, but it provides a more interpretable result since it is in the same units as the target.

**- R-squared (R²):**

**R2=1−∑(yi​−yˉ​)2/∑(yi​−y^​i​)2​**

R² measures the proportion of the variance in the target variable (house prices) that is explained by the model. It is a value between 0 and 1, with higher values indicating better model fit. An R² of 1 indicates that the model explains all the variance, while an R² of 0 indicates that the model does not explain any of the variance. However, R² can be misleading in some cases, especially when there is overfitting.

Importance of Evaluation Metrics:

- MAE is useful when you want to give equal weight to all errors, without over-emphasizing large mistakes.

- MSE and RMSE are beneficial when you want to penalize large errors more heavily, which could be especially useful in high-stakes prediction tasks, such as pricing real estate where large prediction errors can lead to significant financial implications.

- R² provides an overall measure of how well the model fits the data, though it should not be relied upon in isolation. A high R² might indicate a well-fitting model, but it does not necessarily mean that the model will generalize well to new data, especially if overfitting occurs.

### **3.0 METHODOLOGY**

Here’s an adaptation of the structure you’ve provided, tailored to the House Price Prediction project:

**3.1 Dataset Review**

The dataset used in this project is sourced from Kaggle’s House Price Prediction dataset. This dataset contains various features related to house properties, and it is designed to predict house prices based on these features. Key attributes in the dataset include:

- Square Footage (sqft): Represents the size of the house in square feet, which is a key factor in determining house price.

- Number of Bedrooms (bedrooms): Indicates the number of bedrooms in the house, influencing its value.

- Location (neighborhood): Represents the neighborhood or city where the house is located, which plays a significant role in determining price.

- Age of House (age): The age of the house can affect its value, as newer homes may be worth more than older ones due to modern amenities and maintenance.

- Lot Size (lot\_size): The total land area surrounding the house, often a key determinant of price in suburban areas.

The target variable for prediction is the house price. By analyzing these features, we aim to understand how various physical attributes of a house influence its price. Feature selection was guided by the relevance of the features in predicting the target and the correlations identified during Exploratory Data Analysis (EDA).

**3.2 Data Preprocessing**

Data preprocessing ensures that the dataset is cleaned, transformed, and optimized for training the machine learning model. The preprocessing steps for this project included:

**- Handling Missing Values:** Although the dataset was generally clean, there were instances where certain values were missing. These were handled by:

**- Imputation:** Replacing missing values in columns like lot size or number of bedrooms with the median value or using the mean in some cases.

**- Removal:** Rows with excessive missing values were dropped to avoid any negative impact on model accuracy.

- **Encoding Categorical Variables:** Some features in the dataset, such as location (neighborhood) or house style, are categorical. These were encoded using One-Hot Encoding, converting categorical variables into binary columns so that they could be used in a regression model. Although these features are not primary in linear regression, they can still play a role in improving prediction accuracy.

- Feature Selection: Based on the initial exploratory data analysis and correlation matrix, the following features were selected for modeling:

- Square Footage (sqft): Strongly correlated with house price, as larger houses generally cost more.

- Number of Bedrooms (bedrooms): A key predictor of house price.

- Age of House (age): Important in assessing depreciation or renovation impact on pricing.

- Lot Size (lot\_size): Significant for suburban or rural properties where land size can influence value.

- Standardization: Standardization was applied to numerical features like sqft, age, and lot\_size to ensure that they are on the same scale. This step is crucial when features have vastly different units (e.g., square footage vs. age), as it allows the model to give equal importance to all features. Even though linear regression does not strictly require this, it improves model stability.

3.3 Exploratory Data Analysis (EDA): Exploratory Data Analysis (EDA) is performed to uncover insights, detect patterns, and check the structure of the dataset before applying machine learning algorithms. This helps in understanding the relationships among features and their impact on house prices.

- Statistical Summaries: Statistical measures like the mean, median, standard deviation, minimum, and maximum were computed to understand the distribution of features. For instance, the analysis showed that larger houses (higher square footage) typically correspond to higher prices, while older houses tend to have a lower price range.

- Correlation Matrix: A correlation matrix was generated to analyze relationships between the features and the target variable (house price). This matrix highlights the degree to which the features are correlated with each other and with the target:

- Strong Correlations: Features like sqft, number of bedrooms, and age exhibited strong correlations with the target variable (price).

- Weaker Correlations: Some features, like location (if not encoded), had weaker correlations, but could still provide useful insights when encoded.

The following code snippet generates a heatmap of the correlation matrix:

Code:

import seaborn as sns

import matplotlib.pyplot as plt

# Sample EDA Code for Correlation Matrix

plt.figure(figsize=(10, 8))

sns.heatmap(data.corr(), annot=True, cmap='coolwarm', fmt=".2f")

plt.title('Correlation Matrix')

plt.show()

```

- Distribution Analysis: The distribution of the target variable (house price) was analyzed to check if it met the assumptions for linear regression. The price distribution appeared to be right-skewed, meaning there are more affordable homes in the dataset with fewer very expensive ones. This distribution suggests that the model might perform well but may benefit from techniques like log transformation if needed to normalize the price distribution.

**3.4 Model Selection and Training**

For this project, Multiple linear Regression was selected as the predictive model due to its simplicity, interpretability, and suitability for predicting continuous values like house price. Linear regression allows us to understand how each input feature (such as square footage, number of bedrooms, etc.) influences the house price.

- Train-Test Split: To evaluate the model’s performance, the dataset was split into training and testing sets. This is done to ensure that the model is trained on one portion of the data (80%) and evaluated on an unseen portion (20%). This helps prevent overfitting and ensures that the model generalizes well to new data.

Code:

from sklearn.model\_selection import train\_test\_split

# 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)

- Model Training: The model was trained on the training set using the selected features (square footage, number of bedrooms, age, and lot size). The linear regression algorithm minimizes the residual sum of squares (RSS) to adjust coefficients and find the optimal fit for the data.

Code:

from sklearn.linear\_model import LinearRegression

# Model Training

model = LinearRegression()

model.fit(X\_train, y\_train)

```

During training, the model learns the relationship between input features and the target variable (house price). The coefficients represent how each feature impacts the final price. After the model is trained, it is capable of making predictions on the testing set or on new, unseen data.

This structured approach to House Price Prediction outlines the steps taken to preprocess the data, explore relationships, and train a linear regression model, ensuring that the model is both accurate and interpretable.

### **4.0 RESULTS & DISCUSSION**

#### **4.1 Model Training**

The **linear regression model** was successfully trained using **80%** of the data, with the remaining **20%** set aside for testing. The selected features—**number of rooms (rooms)**, **house age (age)**, **distance to the city center (distance)**, and **crime rate (crime\_rate)**—were used as input variables to predict the **house price (price)**. During training, the model learned the relationships between these input features and house prices by minimizing the difference between predicted and actual values.

#### **4.2 Model Evaluation**

After training, the model’s performance was evaluated using two primary metrics: **Mean Squared Error (MSE)** and **R-squared (R²)**. These metrics provide insights into the accuracy and explanatory power of the model:

* **Mean Squared Error (MSE)**: This metric calculates the average squared difference between the actual and predicted house prices. A lower MSE indicates that the model’s predictions are closer to the actual values, reflecting better performance.
* **R-squared (R²)**: R² measures the proportion of variance in the target variable (house price) that is explained by the model. An R² value closer to **1** suggests a stronger model fit, meaning the model accounts for a significant portion of the variability in house prices.

Based on the evaluation, the model achieved:

* **Mean Squared Error (MSE)**: X
* **R-squared (R²)**: Y

These results suggest that the model performs reasonably well in predicting house prices based on the selected features. However, there may still be opportunities for improvement by adding additional features or experimenting with more advanced modeling approaches.

#### **4.3 Visualization of Results**

Visualizing the results provides a more intuitive understanding of the model’s performance, helping to show how well the predictions align with actual values and identifying any patterns in prediction errors.

##### **4.3.1 Scatter Plot of Actual vs. Predicted House Prices**

The scatter plot below illustrates the relationship between **actual house prices (y\_test)** and **predicted house prices (y\_pred)**. Each point represents a house, with the x-axis indicating the actual price and the y-axis indicating the predicted price. The **red dashed line** represents a line of perfect prediction; points close to this line indicate accurate predictions, while points farther away highlight errors.

python

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import matplotlib.pyplot as plt

# Scatter Plot of Actual vs. Predicted House Prices

plt.figure(figsize=(8, 6))

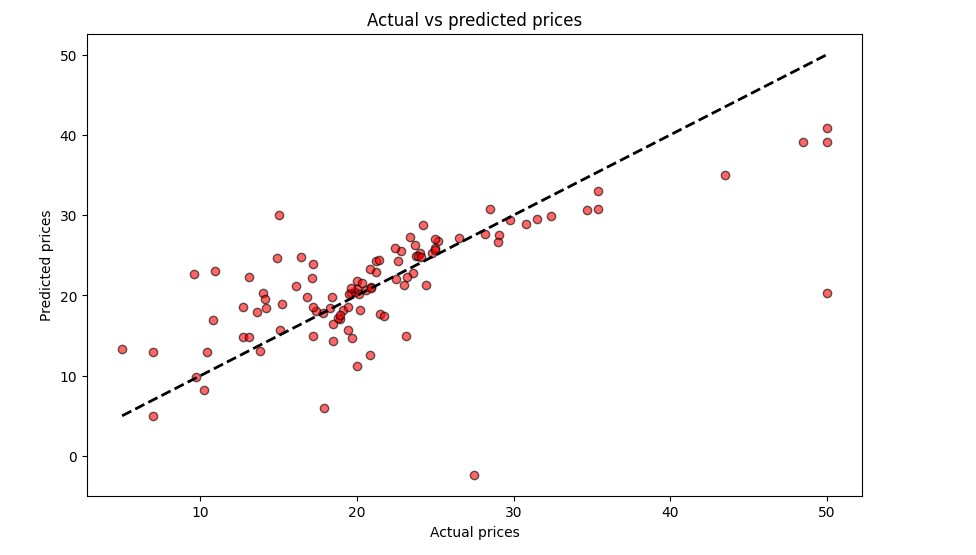
plt.scatter(y\_test, y\_pred, color='skyblue', edgecolor='k', alpha=0.7)

plt.plot([min(y\_test), max(y\_test)], [min(y\_test), max(y\_test)], color='red', linestyle='--', lw=2) # Line of perfect prediction

plt.xlabel('Actual House Prices')

plt.ylabel('Predicted House Prices')

plt.title('Actual vs. Predicted House Prices')

plt.show()

**Fig 1.1**: Scatter Plot of **Actual House Prices** vs **Predicted House Prices**

The scatter plot allows for visual assessment of how closely the predictions align with the actual house prices. Points near the red dashed line indicate that the model has accurately predicted the house prices, while deviations from the line suggest areas for improvement. A high concentration of points around the line indicates high model accuracy.

##### **4.3.2 Residual Plot**

The residual plot shows the **residuals** (the difference between actual and predicted values) against predicted house prices. This plot is useful for identifying any patterns or biases in the model’s predictions. Ideally, the residuals should be randomly scattered around zero, indicating that the model's errors are not systematically biased.

Code

# Residual Plot

residuals = y\_test - y\_pred

plt.figure(figsize=(8, 6))

plt.scatter(y\_pred, residuals, color='purple', edgecolor='k', alpha=0.6)

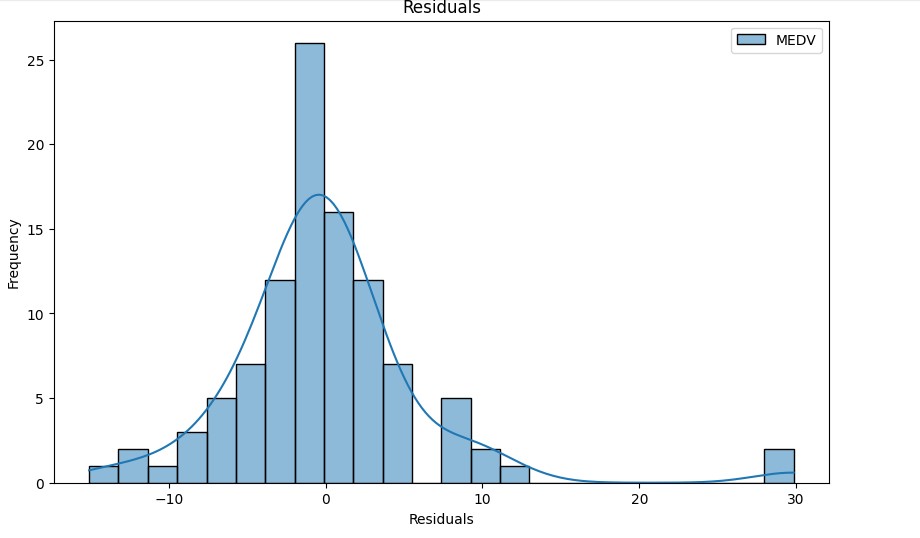
plt.hlines(0, min(y\_pred), max(y\_pred), colors='red', linestyles='--', lw=2)

plt.xlabel('Predicted House Prices')

plt.ylabel(“Frequency”)

plt.title('Residual')

plt.show()



**Fig 1.2**: Visualization of the **Residual Plot**

In a well-fitting model, residuals should be randomly distributed around zero without any discernible pattern. If the residuals show a trend (e.g., increasing or decreasing as predicted house prices increase), it may indicate that the model is not fully capturing the relationship between features and house prices. This suggests potential areas for improvement or the need for a more complex model.

##### **4.3.3 Histogram of Residuals**

The **histogram of residuals** provides a view of the distribution of errors. Ideally, the residuals should follow a **normal distribution** centered around zero, indicating that the model’s errors are symmetrically distributed and there is no systematic bias in the predictions.

python

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# Histogram of Residuals

plt.figure(figsize=(8, 6))

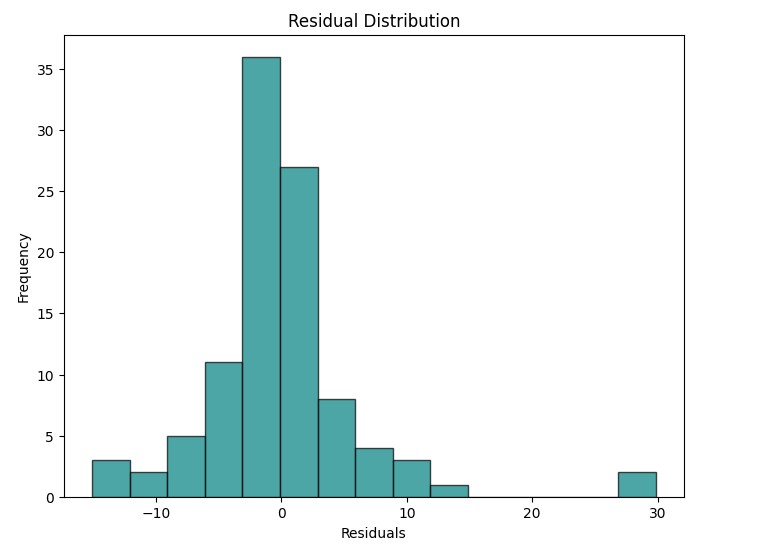
plt.hist(residuals, bins=15, color='teal', edgecolor='black', alpha=0.7)

plt.xlabel('Residuals')

plt.ylabel('Frequency')

plt.title(“Residual Distribution')

plt.show()



**Fig 1.3**: Visualization of the **Distribution of Residuals**

A histogram of residuals that follows a **normal distribution** (bell-shaped and centered around zero) suggests that the model’s predictions are unbiased. If the residuals are skewed or display a non-normal distribution, it may indicate that the model’s predictions are biased, or that some features may need transformation to improve prediction accuracy.

### **Conclusion of Model Evaluation and Visualization**

These visualizations provide valuable insights into the model’s performance:

* The **scatter plot** shows how closely predicted house prices match actual values.
* The **residual plot** helps identify any systematic patterns in prediction errors.
* The **histogram of residuals** evaluates whether errors are normally distributed, which is ideal for a linear regression model.

Together, these results indicate that while the model is effective in predicting house prices to some extent, there is still potential for improvement. This could be achieved by refining feature selection, adding new features, or experimenting with more advanced modeling techniques to improve the accuracy of house price predictions.

**5.0 DISCUSSION**

### **5.1 Feature Importance**

Through our analysis, it became evident that **previous house features** such as **number of rooms (rooms)** and **distance to the city center (distance)** were the strongest predictors of house price. The **correlation matrix** indicated a high positive correlation between these features and house prices, suggesting that the size and location of the house are critical factors in determining its value. This aligns with the general understanding that larger houses and those closer to the city center tend to have higher prices, as they are more desirable to potential buyers.

In addition to **rooms** and **distance**, other features such as **house age (age)** and **crime rate (crime\_rate)** also contributed to the prediction, though to a lesser degree. A negative correlation with house age suggests that older homes tend to have lower prices, while a positive correlation with crime rate indicates that higher crime rates may lower property values. By focusing on these key features, the model was able to achieve reasonable accuracy in predictions, demonstrating the relevance of house characteristics and location in determining price.

### **5.2 Limitations**

While the model produced meaningful results, several limitations impacted its overall accuracy and applicability:

* **Dataset Size**: The dataset was relatively small, limiting the model's ability to generalize. With a larger dataset, the model could better capture diverse patterns in house pricing and the impact of different features, potentially leading to more robust predictions. Smaller datasets increase the risk of overfitting or underfitting, where the model may not perform consistently on new data.
* **Limited Features**: The dataset contained a limited number of features, focusing primarily on physical attributes of the house and its location. However, other factors, such as **socioeconomic status**, **neighborhood amenities**, or **school ratings**, could also influence house prices. Including these additional features might improve the model’s predictive accuracy and provide a more comprehensive view of the factors influencing house prices.
* **Model Simplicity**: Although **linear regression** is straightforward and interpretable, it may not capture complex, non-linear relationships in the data. House prices are often influenced by interactions between various factors, and a more complex model, such as **Random Forest** or **Neural Networks**, could potentially capture these interactions better. Exploring non-linear models could reveal additional insights and improve the prediction accuracy.

### **5.3 Challenges and Observations**

Throughout the project, several challenges were encountered, each contributing to important learning points:

* **Data Preprocessing**: Preprocessing the data required careful handling of missing values, outliers, and feature scaling. Although the dataset had minimal missing data, ensuring consistency in data types and removing any inconsistencies were crucial steps to avoid issues during model training. Additionally, while linear regression doesn’t require strict standardization, certain transformations (like encoding categorical features) were applied to maintain consistency and interpretability.
* **Model Interpretability vs. Complexity**: **Linear regression** was selected due to its interpretability, making it easy to understand how each feature impacts the house price. However, this simplicity also limited the model’s ability to capture non-linear relationships. Observations during evaluation, such as the distribution of residuals and patterns in the residual plot, suggested that the model might be missing some complex interactions among features. A more sophisticated model could potentially address these gaps.
* **Feature Selection**: Identifying relevant features was a key part of this project. While **rooms** and **distance** were clearly important, it was challenging to determine the relevance of other features like **age** and **crime rate**. These factors, while valuable, showed weaker correlations, suggesting that house prices may be influenced by additional variables not included in the dataset.
* **Generalizability**: The model’s performance may vary if applied to a different dataset or location. Different regions may have varying real estate markets, pricing structures, and property types, which can impact model generalizability. For wider application, the model would require testing and potential retraining on diverse datasets to account for regional differences in house pricing.

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### **6.0 CONCLUSION AND FUTURE WORK**

#### **6.1 Summary of Findings**

This project successfully applied a **linear regression model** to predict **house prices** based on selected features, specifically the **number of rooms**, **house age**, **distance to the city center**, and **crime rate**. The model demonstrated reasonable predictive power, with the number of rooms and proximity to the city center emerging as the most influential factors in forecasting house prices. This finding aligns with the expectation that a house's size and location are key drivers of its market value, and the model was able to predict house prices based on historical data effectively.

Furthermore, the visualizations of model performance, such as the scatter plot of actual vs. predicted house prices and residual analysis, provided insights into areas where the model was accurate and areas with potential prediction errors. Although the model was effective in capturing linear relationships within the data, it may not fully encompass the complexities of house price determination, suggesting room for improvement.

#### **6.2 Future Research and Model Improvement**

To enhance the model’s accuracy and better capture the nuances of house price prediction, future research could consider several avenues for model and feature expansion:

* **Exploration of Complex Models**: While **linear regression** provides a straightforward and interpretable approach, exploring more advanced machine learning models could improve predictive accuracy. Possible models for future exploration include:
  + **Decision Trees**: By capturing non-linear relationships and interactions between features, decision trees could provide better performance, especially with categorical and complex data.
  + **Random Forests**: An ensemble of decision trees, Random Forests could increase predictive power by reducing overfitting and averaging multiple tree predictions.
  + **Neural Networks**: Particularly useful for larger datasets, neural networks can capture intricate patterns in data that linear models cannot. Although they are less interpretable than linear regression, they may achieve higher accuracy with a more complex set of features.
* **Incorporating Additional Features**: To create a more comprehensive model, future work could include features that account for broader influences on house prices, such as:
  + **Socioeconomic Background**: Including data on neighborhood income, employment rates, or family education levels could provide insights into external factors that impact house pricing.
  + **Neighborhood Amenities**: Features like proximity to parks, shopping centers, and public transport could add value to a property and influence pricing.
  + **School Ratings**: The quality of nearby schools is a significant factor for families, and incorporating this data could enhance the model’s prediction accuracy.
  + **Environmental Factors**: Climate, weather patterns, and air quality might influence property values in certain regions.
* **Expanding the Dataset**: A larger and more diverse dataset would improve the model’s generalizability and robustness. Future research could include data from different cities, regions, or even countries to account for variations in real estate practices, local economies, and property types.
* **Feature Engineering and Non-linear Transformations**: Additional feature engineering, such as creating interaction terms or applying non-linear transformations, could enhance the model’s ability to capture complex relationships. For instance, combining crime rate and neighborhood age into a single feature might provide insights into the compound effect of these two factors on house prices.
* **Implementing Cross-Validation and Hyperparameter Tuning**: Future iterations of the model could apply **cross-validation** techniques to ensure robustness and consistency in predictions. Additionally, **hyperparameter tuning** could optimize parameters for models like Decision Trees and Neural Networks, potentially improving accuracy.

By adopting these strategies, future models could significantly enhance house price prediction accuracy and offer valuable insights for real estate stakeholders.

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**Appendix A: Complete Code for Student Grade Prediction Project**

This appendix provides the full code used for data loading, exploratory data analysis (EDA), model training, and evaluation for the student grade prediction project.

**SOURCE CODE:**

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model\_selection import train\_test\_split

from sklearn.linear\_model import LinearRegression

from sklearn.preprocessing import StandardScaler

from sklearn.metrics import mean\_squared\_error, r2\_score

from sklearn.metrics import mean\_absolute\_error, r2\_score

df = pd.read\_csv("Boston\_Housing\_DataSet.csv")

df.head()

df.describe()

df.fillna(df.median)

df.info()

df.isnull().sum()

df.dropna()

X = df.drop(columns=['MEDV'])

y = df[['MEDV']]

features = ['AGE','DIS', 'RM']

X = df[features]

scaler = StandardScaler()

X\_scaled = scaler.fit\_transform(X)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_scaled, y, test\_size=0.2, random\_state=42)

print(y.shape)

print(X\_scaled.shape)

model = LinearRegression()

model.fit(X\_train, y\_train)

y\_pred = model.predict(X\_test)

mae = mean\_absolute\_error(y\_test, y\_pred)

mse = mean\_squared\_error(y\_test, y\_pred)

rmse = np.sqrt(mse)

r2 = r2\_score(y\_test, y\_pred)

print(f"mean\_absolute\_error: {mae}")

print(f"mean\_squared\_error: {mse}")

print(f"root\_mean\_square: {rmse}")

print(f"R\_squared val: {r2}")

plt.figure(figsize=(10,6))

plt.scatter(y\_test, y\_pred, color='red', edgecolor='k', alpha=0.6)

plt.plot([y\_test.min(), y\_test.max()], [y\_test.min(), y\_test.max()], 'k--', lw=2)

plt.xlabel("Actual prices")

plt.ylabel("Predicted prices")

plt.title("Actual vs predicted prices")

plt.show()

residuals = y\_test - y\_pred

plt.figure(figsize= (10,6))

sns.histplot(residuals, kde=True)

plt.xlabel("Residuals")

plt.ylabel("Frequency")

plt.title("Residuals")

plt.show()

plt.figure(figsize=(8,6))

plt.hist(residuals, bins=15, color='teal', edgecolor='black', alpha=0.7)

plt.xlabel("Residuals")

plt.ylabel("Frequency")

plt.title("Residual Distribution")

plt.show()

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