Predicting Housing Prices Using Supervised Machine Learning Models

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Abstract: Variations in housing prices exert a profound impact on economic policies and personal financial decisions. This study aims to delve into the factors that affect housing prices and construct a predictive model using machine learning techniques. Machine learning enables computers to acquire knowledge from data and make predictions or decisions. This study forcasts house prices by analyzing the characteristics of data from Seattle, Washington using machine learning multiple linear regression, polynomial regression, and K-nearest neighbors regression (KNN). The findings of this investigation demonstrate that the polynomial regression model is the most accurate in predicting housing prices and can capture nonlinear relationships in the data more effectively than multiple linear regression and K-nearest neighbors regression. The main factors affecting housing prices are interior living space and the construction and design of buildings. These insights hold potential for enhancing government policies, facilitating effective land use decision-making by planners, and enabling investors to make more informed choices.

Keywords: Machine learning models, house price prediction, polynomial regression, K-nearest neighbors regression.

1. Introduction

Housing prices have always been a topic worth discussing. For the government, housing prices are a key issue that needs to be monitored. Governments and planners can make more effective decisions on land use policies. Government regulation can significantly improve housing affordability and availability [1]. emphasized the importance of stabilizing the housing market and suggested that targeted government policies can help regulate housing prices and improve the affordability of low-income families. Housing prices are also closely related to a family. The causal chain between housing price changes and observable changes in outcome variables such as economic behavior and consumption requires that individuals at least be able to perceive the impact of housing price changes on their family wealth and recognize the impact on their financial situation [2]. In addition, buying a house is not only a means of obtaining housing but also a major investment. Especially for risk-averse investors, housing can be a beneficial component of a family portfolio [3]. By analyzing market trends and predicting housing prices, people can determine whether a property in a certain location is suitable for investment.

This paper uses machine learning methods to analyze the house dataset and use these data models to predict housing prices. For large datasets, it is difficult for us to extract useful data and make conclusions from them. However, machine learning can replace the heavy and repetitive work of humans, and it can learn more complex patterns from input data than humans can learn through observation [4]. Machine learning has been widely used in various fields such as biology, medicine, physics, etc. This paper will mainly use supervised learning to explore the relationship between house prices and other factors. In supervised learning, each training example of the input data has its known label, which allows the machine to understand and process similarities and differences when the objects to be classified have many variable attributes within their own categories but still have basic features to identify them [4]. This paper builds regression models based on supervised learning to predict the house prices.

2. Data Description

The dataset studied in this paper is "housing_data," which is a dataset from Seattle, Washington. The dataset contains detailed information such as transaction prices, as well as house features such as the internal living space, land space, longitude and latitude, house condition, and building grade. Analyzing this data can reveal how various factors affect Seattle housing prices.

Before building a model, understanding the meaning and characteristics of the data is necessary. In this section, the charts are created in this study to help understand the distribution and characteristics of the data more clearly and intuitively.

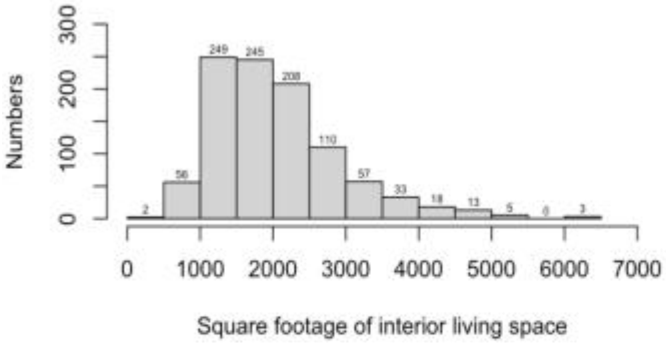

Figure 1: Numbers of interior living space

Figure 1 shows the data distribution, houses with an area of 1000-1500 square footage are the most with 249. There are no houses with space of 5500-6000 square footage. The mean interior living space is 2051.397. The median interior living space is 1900.

Figure 2 describes the construction and design level of the building. Grade is an index from 1 to 13, where 1-3 falls short of building construction and design, 4-6 means below average level, 7 means it has an average level, 8-10 means above-average level, 11-13 means high quality level. According to the Figure 2, it shows that there is no house in a rating of 1-3, 45% of the houses have a rating of 7, and only 2% of the houses have a high-quality level.

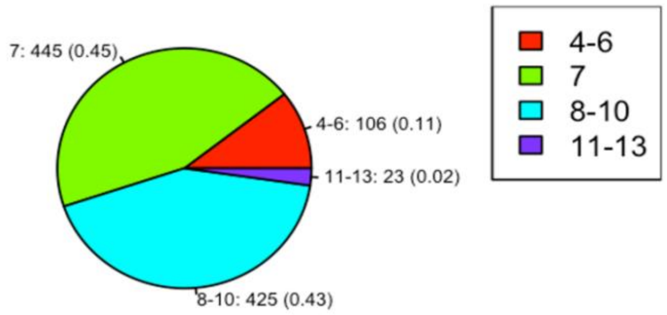

Figure 2: Distribution of Grades

Figure 3 helps readers understand the correlation between the data and the dispersion of the data points. It is worth noting that there is a strong positive correlation between price and the interior living space and grade of houses, which means that as the indoor living area and grade increase, the price also tends to rise. Given these relationships, it is imperative to consider interior living space and grade as influential factors when constructing models of house pricing. Including these variables in the regression models will help to capture the impact of these key factors on price and improve the interpretation of the model based on the data.

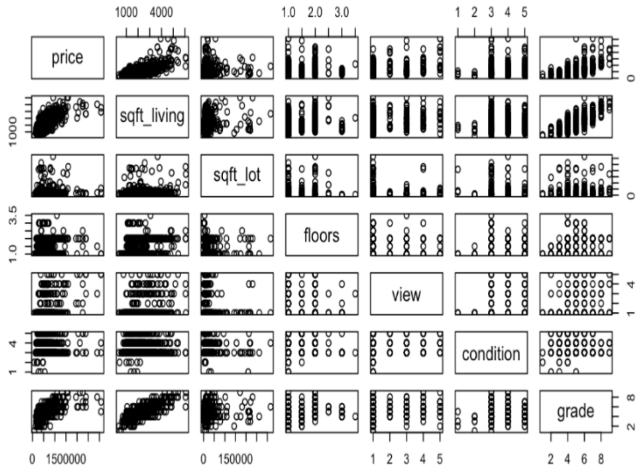

Figure 3: Price and other factors

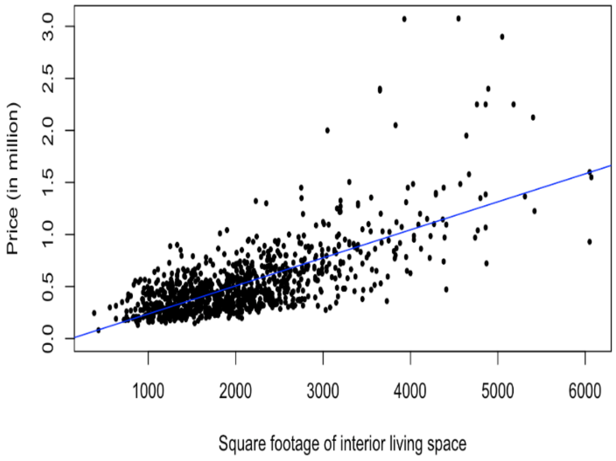

Figure 4: Price and Interior Living Space

Figure 4 is an explanation of the relationship between price and interior space. When interior living space is smaller than 4000, there is a strong linear positive relationship between price and living space. But when the interior living space is larger than 4000, this relationship is less significant. Hence, it is plausible that other factors such as the land space, the condition of houses, and the grade may influence the price. Therefore, a simple linear regression model cannot fully explain the relationship between price and interior living space.

3. Building Models

In this part, the article mainly builds models. By building models to explain the relationship between the variable price and other data, and by training models to predict prices, the article builds three models, multiple linear models, polynomial models, and KNN models. House prices are affected by house structure, plot area, location, etc. At the same time, old and poor quality houses will reduce people's willingness to buy houses, thereby affecting house sales prices [5, 6]. Therefore, when building the model, the research considers the interior living space, land area, grade (building construction and design), and house view as factors which will affect the price of houses.

3.1. Multiple Linear Regression Model

In order to study and predict house prices, this article introduces multiple linear regression:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \ldots + \beta_0 \tag{1}$$

In (1), $\beta_{(1,2,3\ldots n)}$represents the slope coefficient, which represents the change in the dependent variable for each unit change in the corresponding independent variable, and β_0 is the intercept, which is the bias in machine learning [7]. $X_{(1,2,3\ldots n)}$ is the independent variables interior living space, the land space, view, condition, grade.

By training the training set, I get the coefficients and intercept in the model:

$$\text{Price} = 1.58 * 10^2 \text{interiorlivingspace} - 2.639 * 10^{-3} \text{landspace} + 1.158 * 10^5 \text{view} + 3.010 * 10^4 \text{condition} + 8.013 * 10^4 \text{grade} - 5.462 * 10^5 \tag{2}$$

3.2. Polynomial Regression Model

After discussing the multiple linear model, the research explores whether there is a nonlinear relationship in the data. The linear regression model assumes that there is a linear relationship between the predictor variable and the response. If the actual data relationship is nonlinear, the prediction accuracy of the model may greatly reduce [8]. Polynomial regression is used to identify nonlinear relationships within the dataset:

$$Y = \beta_0 + \beta_1 x + \beta_2 x^2 + \beta_3 x^3 + \cdots + \beta_n x^n + \beta_0 \tag{3}$$

In order to determine the degree in polynomial regression, I use the 5-cross validation method to calculate the root mean square error (RMSE). 5-cross validation is a resampling technique widely used in model selection and evaluation. It prevents overfitting and errors in estimating prediction models [9].

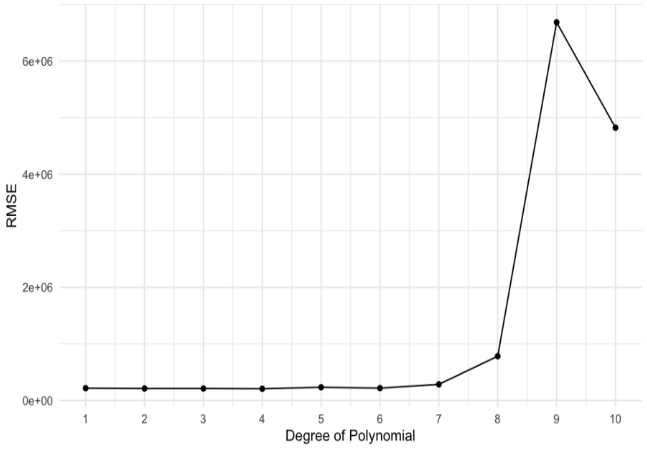

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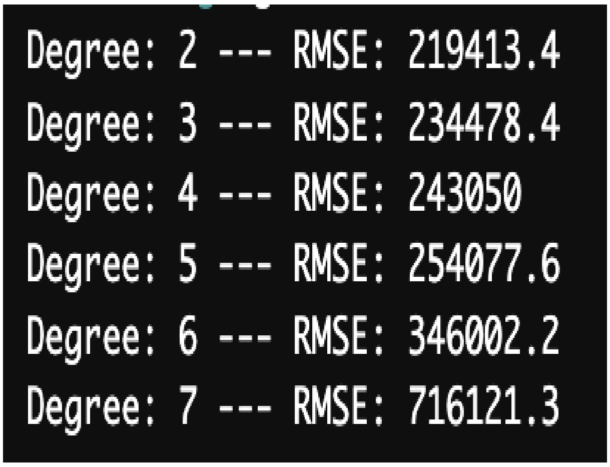
Figure 5: RMSE of different degree of polynomial models



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Degree: 2 --- RMSE: 219413.4
Degree: 3 --- RMSE: 234478.4
Degree: 4 --- RMSE: 243050
Degree: 5 --- RMSE: 254077.6
Degree: 6 --- RMSE: 346002.2
Degree: 7 --- RMSE: 716121.3
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Figure 6: RMSE

Figure 5 shows that RMSE increases significantly when the degree is greater than 7, indicating that the model performs poorly. As shown in Figure 6, when the order is equal to 2, the RMSE is the smallest. Although the polynomial model with high-order terms can reflect more details in the data, in some cases, the high-order terms will capture noise instead of describing the underlying relationship, resulting in overfitting [10]. When the order is 2, the model can explain the data more effectively. A lower RMSE value indicates that the predictions of models are closer to the actual observed values, which means better accuracy and performance [11]. When the order is set to 2, the model can capture the underlying patterns in the data more effectively than higher or lower orders, which may lead to overfitting or underfitting the data, respectively. Therefore, the polynomial regression model with an order of 2 achieves the best balance:

$$\mathrm{price} = 1008565 + 104072 * (\mathrm{interiorlivingspace}) + 28566 * (\mathrm{interiorlivingspace})^{2}23981 * (\mathrm{landspace}) + 2828 * (\mathrm{landspace})^{2} - 27006 * (\mathrm{view}) + 43527 * (\mathrm{view})^{2} - 249362 * (\mathrm{condition}) + 37864 * (\mathrm{condition})^{2} - 119472 * (\mathrm{grade}) + 12816 * (\mathrm{grade})^{2} \tag{4}$$

3.3. K-Nearest Neighbors Model

KNN is a supervised machine learning method that classifies each point by calculating the distance from its k nearest neighbors in the feature space. KNN regression predicts the value of the target variable based on the value of the nearest neighbors.

Euclidean distance is one of the most commonly used distance measurement methods. Using the following formula, it can measure the straight-line distance between a point and another measured point:

$$\mathrm{d}(\mathrm{p},\mathrm{q}) = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{q_i} - \mathrm{p_i})^2} \tag{5}$$

Choosing the right k value in KNN is a point that needs to be studied. Different k values may lead to overfitting or underfitting, and lower k values may fluctuate greatly with different data sets. On the contrary, higher k values may not capture the true patterns in the data. The choice of k depends largely on the input data [12].

In building the polynomial model, this paper uses RMSE to evaluate models of different degrees. Similarly, when building the KNN model, it also can be used to determine the appropriate k value by comparing RMSE.

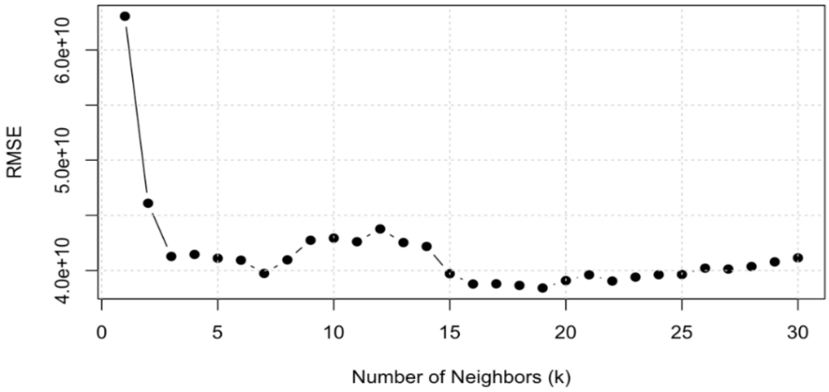

Figure 7: RMSE of different number of neighbors in KNN models

As shown in Figure 7, RMSE is the smallest when k=19, indicating that the KNN model performs best with 19 neighbors. This optimal value allows the model to capture the patterns in the data effectively. Further analysis using a multiple linear regression model including additional variables resulted in an R-squared value of 64.26%, indicating that this multiple linear model can explain more of the data than the linear model. In addition to living spaces, the model also emphasizes the importance of land space, view, condition and grade. The high F-statistic and very low p-value confirm the statistical significance of our model, indicating a strong relationship between the variables and house prices.

While the multiple linear model successfully illustrates the key factors affecting house prices, this paper next builds a polynomial multiple regression model to explain potential nonlinear relationships in the data:

$$\text{price} \sim (\text{sqft\_living})^{\wedge}2 + (\text{sqft\_lot})^{\wedge}2 + \text{view} + \text{condition} + \text{grade} \tag{6}$$

By introducing polynomial terms to capture nonlinear effects and provide a more nuanced understanding of the data. Meanwhile the R-square value is increased to 65.14%, which is higher than the R-squares of linear model and multiple linear model. I think the polynomial is the best model of the three models, because it can explain the complexity of the data.

4. Results

After building and training the model, the next step is to test the performance of the model on the test set. The research uses two statistical measures to evaluate the performance of the model, one is R square:

$$R^2 = 1 - \frac{\text{Residual Variance}}{\text{Total Variance}} \tag{7}$$

The R-squared value ranges from 0 to 1. The larger the R-squared value, the better the model explains the relationship between the dependent variable and the independent variable. Compared with other evaluation parameters, R square is more reliable in regression analysis, so I will use R square as one of the criteria for evaluating the model in this article [13].

Another one is root mean square error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - q_i)^2} \tag{8}$$

Where p_i is the actual value, q_i is the predicted value, and n is the number of the data. For the case where the estimated error distribution is Gaussian, it is more appropriate to use RMSE to evaluate the model's performance [14].

Table 1: R^2, Mean Squared Error and Root Mean Squared Error of the Models

	Multiple Linear Model	Polynomial Model	KNN Model
R^2	0.9932	0.9986	0.9985
MSE	$1.7281 * 10^{11}$	$3.6449 * 10^{10}$	$3.8414 * 10^{10}$
RMSE	$4.1571 * 10^{5}$	$1.9092 * 10^{5}$	$1.9599 * 10^{5}$

The R^2 of the multiple linear model is 0.9932, but it has the largest RMSE among the three models, which is $4.1571 * 10^5$. In comparison, the R^2 of the polynomial regression is 0.9986, and it has the smallest RMSE $1.9092 * 10^5$. The R^2 of the KNN model is 0.9985, and the RMSE is $1.9599 * 10^5$.

Both the polynomial regression model and the KNN model have better performance in predicting house prices, indicating that the data relationships are not only linear but also involve many nonlinear relationships that the multiple linear model cannot capture.

5. Conclusion

In summary, the analysis of the multivariate linear model, polynomial regression model, and KNN model revealed different patterns in the data. Specifically, the polynomial regression model outperformed the other models, capturing the nonlinear relationship in the data and providing the most accurate predictions. The correlation coefficients in the polynomial regression model show that larger living space and higher building grade generally lead to higher housing prices, while other characteristics such as views and conditions also affect the change of housing prices. This analysis can enhance pricing strategies, strengthen market analysis, and ultimately help buyers, sellers, and developers make more informed decisions. Although the polynomial regression model performed best among the three models, it does not determine that the model is always the best model in all similar datasets. The dataset used is specific to Seattle, Washington. Since housing markets in different regions can vary greatly, the study set in this article does not include important factors such as urban economic indicators, the level of amenities, and the safety of the community, which may limit the accuracy and generalizability of the model. The model may not generalize well to other regions without retraining and adjustment. In addition, regularization techniques such as Lasso or Ridge regression can be used to penalize large coefficients to improve the generalization ability of the model. This study demonstrates the potential of machine learning models in predicting housing prices based on various influencing factors. As technology advances, more research can be conducted using more advanced methods such as neural networks and deep learning to develop more extensive and accurate housing price prediction models.

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