Research on Housing Prices Forecasts Based on A Multiple Linear Regression Model

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Abstract: House prices have always been a hotly debated topic. However, the factors affecting them and the extent of their influence have changed over time, so this paper aims to find a simple method of predicting house prices that best fits the recent past. This paper collects a sample of 545 independent samples just updated this quarter. By preprocessing the data and analyzing the multiple linear regression, accurate multiple linear regression equations are obtained for prediction. Meanwhile, the diagnostic illustrates that the samples are independent, there is no multicollinearity between the variables, and the residuals follow a normal distribution. 12 independent variables (Area, Bedroom, Bathroom, Story, Parking, Furnishing status, Guestroom, Basement, Hot water, Air-conditioner, Main road, Preferred area) correspond to a significant positive effect on the variable (Housing prices), with Area, Bathroom’s number, and Air-conditioner’s number being the top three influencing factors. Overall, simple house price predictions can be made using the model developed in this paper.

1 INTRODUCTION

In today's society, housing prices have become one of the focuses of widespread concern. With the acceleration of urbanization and population growth, the development of the real estate market has increasingly attracted widespread attention. Home buyers, renters, investors, and policymakers have taken great interest in the changes in house prices (Li, 2023 & Liao and Anwer, 2022). Especially in some hotspot cities, the dramatic fluctuations of house prices not only directly affect the living standards, psychological health, and investment decisions of residents, but also have a far-reaching impact on the city's social stability and economic development (Chun, 2020 & Kenyon et al., 2024). Against this background, the significance of forecasting home prices becomes more and more prominent. Accurately predicting the future trend of housing prices not only helps home buyers develop a reasonable home purchase plan but also helps investors grasp market opportunities and avoid investment risks. Whereas house prices are influenced by several factors, such as the impact of global factors, advanced economies have a high degree of synchronization in house prices, and structural shocks are one of the main factors driving volatility in house prices (Hirata et al., 2012).

In this paper, the issue of how to effectively predict future housing prices changes will be addressed. Initially, a thorough review of pertinent literature will be conducted to organize existing research findings and methodologies systematically. Ding and Jiang combined the improved lion swarm algorithm with the Backpropagation (BP) neural network model for the housing prices prediction problem. A model called Spiral search Lion Swarm Optimization-BP was proposed by enhancing the lion group algorithm's local search ability and global search ability. The model showed better results in second-hand housing prices prediction and improved the convergence speed and training accuracy of the BP neural network (Ding and Jiang, 2021). Luo et al. discussed the use of multiple linear regression models in housing prices forecasting. The authors used the Python language to process house prices data for selected regions in the U.S. Exploratory data analysis, dummy variable setting, and variance inflation factor correction were used to improve the accuracy and robustness of the model. The conclusion highlights the importance of optimizing the model to improve forecasting accuracy (Luo et al., 2020). Moreover, Zhan et al. integrated Hybrid Bayesian Optimization

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(HBO) with ensemble techniques like Stacking (HBOS), Bagging (HBOB), and Transformers (HBOT) to predict house prices. They leverage Bayesian Optimization for hyperparameter tuning, enhancing prediction accuracy and stability. Using a dataset of 1.89 million Hong Kong real estate transactions from 1996 to 2021, they thoroughly tested their approach (Zhan et al., 2023). By illustrating housing prices predictions for 14,382 observations in 15 urban areas of Oslo, the researchers' simulations validate LitBoost as a tailored tree-boosting model for situations involving data from different known populations with a limited number of observations in each group. By limiting the complexity of the gradient boosting tree, LitBoost can express the final model as a local generalized additive model (GAM), thus improving interpretability while maintaining predictive power (Hjort et al., 2024). They created a statistical model for forecasting individual housing prices and for constructing a house prices index from information on sales prices that includes time, random (ZIP) effects, and autoregression. The model is more effective than S&P/Case-Shiller (Nagaraja, Brown and Zhao, 2011).

In summary, this study analyzes a dataset of 546 samples, each with 13 variables. The prediction method is applied to these variables, and the resulting predictions are analyzed and discussed. The findings are summarized, and recommendations and prospects are presented.

Through the research in this paper, the objective is to provide valuable references for home buyers, investors, policymakers, and participants in the real estate market, to foster the stability and sustainable development of the real estate market. Ultimately, by providing a comprehensive understanding of the drivers of housing prices, this research endeavors to lay the foundation for a more resilient, equitable, and sustainable real estate market that serves the needs of both current and future generations.

2 METHODOLOGY

2.1 Data Sources and Description

This paper's dataset was obtained from the Kaggle website. After examining the dataset with License: CC0 public domain, its availability is 100%, and because this dataset is updated every quarter, it is timely, so this study is not prone to obsolescence. This dataset contains 545 groups of data. Due to the completeness of the data, they were all used as samples for this study. The original CSV dataset was preserved.

2.2 Variable Selection

Each sample was not excluded because there were no missing data or variables inappropriate for analysis. The final selected data contained 12 independent variables (Area, Bedroom, Bathroom, Story, Parking, Furnishing status, Guestroom, Basement, Hot water, Air-conditioner, Main road, Preferred area, Housing prices) and one dependent variable (Housing prices). The specific descriptions are shown in Table 1:

Table 1: List of variables.

Variable	Logogram	Meaning
Area	x_0	Total area of housing
Area_normalized	x_1	Total normalized area of housing
Bedroom	x_2	Total number of bedrooms
Bathroom	x_3	Total number of bathrooms
Story	x_4	Total number of stories
Parking	x_5	Total number of Parking spaces
Furnishing status	x_6	Unfurnished or Semi-furnished or Furnished
Guestroom	x_7	Availability of guest rooms
Basement	x_8	Availability of basement
Hot water	x_9	Availability of heated water function
Air-conditioner	x_{10}	Availability of air-conditioner
Main road	x_{11}	Proximity to main roads
Preferred area	x_{12}	Whether it is a preferred area
Housing prices	Y	The transaction prices of the house

2.3 Method Introduction

Data preprocessing is carried out first. Classify the data, normalize the larger data "Area" in the numerical independent variable to eliminate the influence of the scale, and at the same time accelerate the convergence speed of the model and increase the stability of the model; assign values to the subtypes of variables respectively. Then, the model is established, and the data are imported to obtain the indicators such as the goodness-of-fit R^2 , the influence coefficient B, and so on, as well as the regression equation. In the next step, diagnosis is performed. Assessment is made from three conditional assumptions of regression analysis: sample independence, absence of multicollinearity between independent variables, and normality of residuals.

3 RESULTS AND DISCUSSION

3.1 Pre-Processing

According to the theory of multiple regression analysis, the independent variables affecting house prices are categorized into numerical and subtypes. The categorized statistics of independent variables are shown in Table 2, and the range of values for subtyped variables is shown in Table 3.

Table 2: Categorized statistics of independent variables.

Classifications	Variables
Subtyped independent variables	Main road, Guestroom, Basement, Hot water, Air-conditioner, Preferred area, Furnishing status
Numeric independent variables	Area, Bedroom, Bathroom, Story, Parking

Table 3: Range of values for subtyped independent variables.

Variables	Range
Main road	0,1
Guestroom	0,1
Basement	0,1
Hot water	0,1
Air-conditioner	0,1
Preferred area	0,1
Furnishing status	1,2,3

3.1.1 Preprocessing of Numeric Variables

Since the value of "Area" x_0 in the numerical independent variable is greater than the quadratic of 10, the normalization method is adopted to handle it as x_1. The normalization formula is as follows:

$$x = \frac{x-min}{max-min} \tag{1}$$

The 'min' in the formula represents the value's minimum value in the numeric dependent variable, while the 'max' represents the maximum value. The other numeric variables are not treated because of their small values.

3.1.2 Preprocessing of Subtyped Variables

Since the data content of the independent variables $\mathrm{x}_7, \mathrm{x}_8, \mathrm{x}_9, \mathrm{x}_{10}, \mathrm{x}_{11}, \mathrm{x}_{12}$ are all 'yes' or 'no', which conforms to a 0-1 distribution, then take the values 0 or 1. The range of values for furnishing status is 1 for unfurnished, 2 for semi-furnished, and 3 for furnished, where 1, 2, and 3 are not numerical values, but are simply factors used to represent the three types.

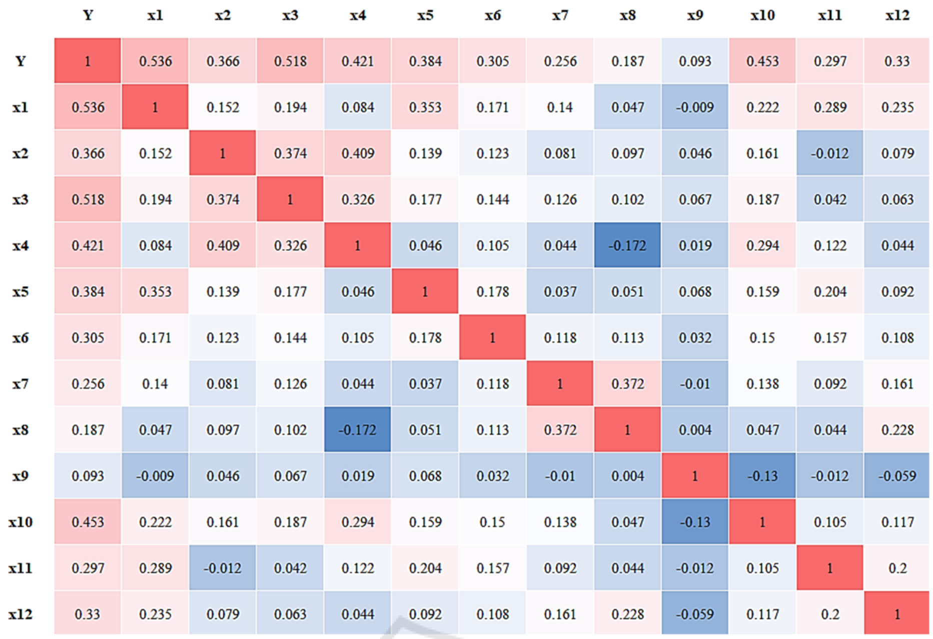
3.2 Modeling of Multiple Linear Regression

By importing the processed data into SPSS, goodness-of-fit R^2 =0.680 can be obtained in the model summary (Table 4), which means that the twelve variables selected in this paper can explain 68% of the dependent variable. This shows that this prediction analysis is significant.

It can also be noted that the value of the statistic F obtained from the analysis of variance is 94.238. A high F-statistic in regression signals that at least one independent variable significantly impacts the dependent variable, suggesting a non-random relationship. It also indicates that the model effectively explains much of the data's variability, implying strong predictive power of the independent variables. Moreover, the p-value is very close to zero, indicating that the regression model is significant.

Table 4: Model summary.

R	R^2	Adjusted R^2	Statistic F	p	DW
0.825	0.680	0.673	94.238	0.000	1.852



	Y	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12
Y	1	0.536	0.366	0.518	0.421	0.384	0.305	0.256	0.187	0.093	0.453	0.297	0.33
x1	0.536	1	0.152	0.194	0.084	0.353	0.171	0.14	0.047	-0.009	0.222	0.289	0.235
x2	0.366	0.152	1	0.374	0.409	0.139	0.123	0.081	0.097	0.046	0.161	-0.012	0.079
x3	0.518	0.194	0.374	1	0.326	0.177	0.144	0.126	0.102	0.067	0.187	0.042	0.063
x4	0.421	0.084	0.409	0.326	1	0.046	0.105	0.044	-0.172	0.019	0.294	0.122	0.044
x5	0.384	0.353	0.139	0.177	0.046	1	0.178	0.037	0.051	0.068	0.159	0.204	0.092
x6	0.305	0.171	0.123	0.144	0.105	0.178	1	0.118	0.113	0.032	0.15	0.157	0.108
x7	0.256	0.14	0.081	0.126	0.044	0.037	0.118	1	0.372	-0.01	0.138	0.092	0.161
x8	0.187	0.047	0.097	0.102	-0.172	0.051	0.113	0.372	1	0.004	0.047	0.044	0.228
x9	0.093	-0.009	0.046	0.067	0.019	0.068	0.032	-0.01	0.004	1	-0.13	-0.012	-0.059
x10	0.453	0.222	0.161	0.187	0.294	0.159	0.15	0.138	0.047	-0.13	1	0.105	0.117
x11	0.297	0.289	-0.012	0.042	0.122	0.204	0.157	0.092	0.044	-0.012	0.105	1	0.2
x12	0.33	0.235	0.079	0.063	0.044	0.092	0.108	0.161	0.228	-0.059	0.117	0.2	1

Figure 1: Pearson correlation.

Table 5: Regression coefficients table.

		Beta	t	significance	tolerances	VIF
	(Constant)		-0.558	0.577		
x_1	Area_normalized	0.283	10.024	0	0.755	1.325
x_2	Bedroom	0.047	1.644	0.101	0.731	1.368
x_3	Bathroom	0.266	9.551	0	0.777	1.287
x_4	Story	0.209	7.006	0	0.677	1.478
x_5	Parking	0.129	4.774	0	0.825	1.212
x_6	Furnishing status	0.087	3.381	0.001	0.913	1.096
x_7	Guestroom	0.061	2.259	0.024	0.825	1.213
x_8	Basement	0.091	3.243	0.001	0.757	1.321
x_9	Hot water	0.098	3.909	0	0.962	1.039
x_{10}	Air-conditioner	0.212	7.879	0	0.828	1.207
x_{11}	Main road	0.079	2.97	0.003	0.853	1.173
x_{12}	Preferred area	0.147	5.585	0	0.871	1.149

According to the given Pearson correlation coefficient matrix, the correlation between the variables can be analyzed initially. The color of Figure 1 shows that the red part is almost distributed in the first column and the first row, except for the diagonal, which indicates that the 12 independent variables have a high degree of influence on Housing prices. Area_normalized, Bathroom, Air-conditioner and Story, all four variables have high correlation (0.536, 0.518, 0.453, 0.421) with Housing prices. The correlation between other variables and prices is weaker but still positive, such as Furnishing status, Main road, and Preferred area.

Moreover, in Table 5, except for the first column, the first row, and the diagonal, the other parts of the table are bluer, which indicates that except for the dependent variable Housing prices, the correlation between the other independent variables is weak. Most of the correlation coefficients are below 0.2, and some of them are even close to zero or less than zero. The correlations between the variables are low except for Area_normalized which is moderately positively correlated with Parking (0.353), and Bedroom and Bathroom which have some degree of positive correlation (0.374). And the weak correlation of independent variables is beneficial for modelling.

Going further, through Table 5, by looking at the "Significance" column, it can be seen that the significance values of x_1 to x_{12} are less than 0.05, so all the independent variables have a significant effect on dependent variable Y. Secondly, by looking at the column of influence coefficient B, it can be found that

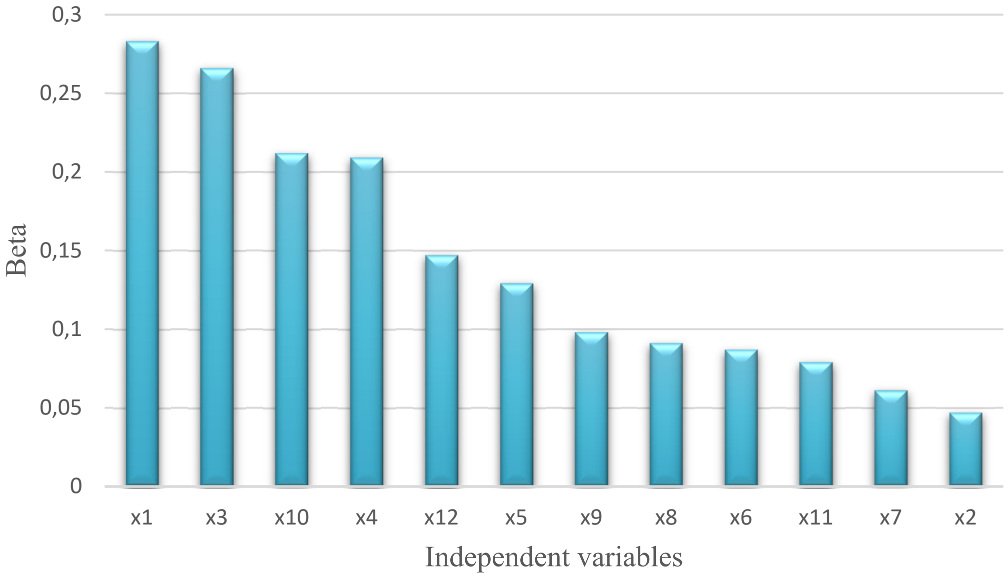


Figure 2: Standardized coefficient of influence of the independent variable on the dependent variable.

the standardized coefficient Beta of all independent variables is greater than 0, so all of these independent variables have a positive influence on the dependent variable Y. And the degree of influence from high to low is: x_1 ,$x_3, x_{10}, x_4, x_{12}, x_5, x_9, x_8, x_6, x_{11}, x_7, x_2$. As shown in Figure 2:

The standardized coefficient Beta value from Table 4 gives the following multiple linear regression equation for the study in this paper:

$$E(Y) = 0.283x_1 + 0.047x_2 + \cdots + 0.147x_{12} \quad (2)$$

3.3 Model Diagnosis

By testing the conditional assumptions of the regression analysis: that the samples are independent of each other, that there is no multicollinearity between the variables, and that the residuals follow a normal distribution, it is possible to diagnose that the multivariate linear regression model used in this paper is reasonably usable.

3.3.1 Sample Independence

The value of the Durbin-Watson statistic can be obtained from Table 4 Model Summary as 1.852, as this value is close to 2, the samples are independent and there is no autocorrelation between the residuals.

3.3.2 No Multicollinearity Between Variables

It can be noticed from the Table 5 coefficients table that the Variance Inflation Factors (VIF) of all the variables are within the range of 0 to 5, so it can be shown that there is no extremely strong correlation between the independent variables involved in this study, i.e., it is proved that these 12 independent variables are not similar and there is no need to delete any of them.

3.3.3 Normality of Residuals

As can be seen from Figure 3, the residuals (the part that does not match the model) follow almost a normal distribution (the black curve in the figure). Although some of them are beyond the highest point of the normal distribution, it is known from the previous section that the variables selected in this paper explain 68% of the dependent variable, i.e., it is still necessary to describe the remaining 32% by looking for other variables that are not in this paper, so it is reasonable to exceed them by a small amount.

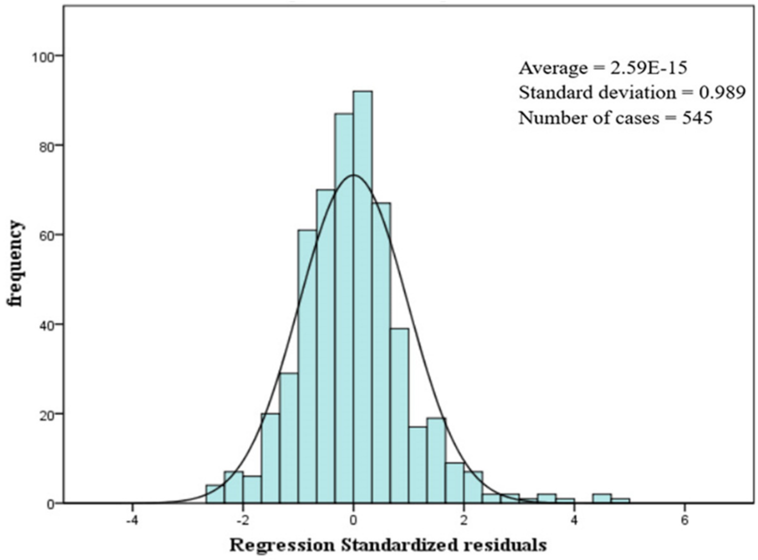


Figure 3: Residual distribution.

4 CONCLUSION

This paper obtained 545 samples updated quarterly from the complete dataset with 12 independent variables and 1 dependent variable. The multiple linear regression model used in this paper was diagnosed (conditional assumptions for regression analysis) and proved to be stable, accurate, and reliable.

The data was pre-processed by taking the normalization of the numerical variables with large values and also assigning labels to the sub-typed variables. Pearson correlation coefficient matrix was analyzed with the aid of SPSS, indicating that the independent variables selected for this paper are weakly correlated with each other and are highly correlated with the dependent variable Y. Then the data was put into a multiple linear regression model. The model fits well with an R-squared value of 0.680, indicating that the model explains 68% of the variation in house prices. Moreover, it was found that all the independent variables positively affect respondent variable Y, which is significant. Their degree of influence in descending order are Area, Bathroom, Air-conditioner, Story, Preferred area, Parking, Hot water, Basement, Furnishing status, Main road, Guestroom, Bedroom ($x_1, x_3, x_{10}, x_4, x_{12}, x_5, x_9, x_8, x_6, x_{11}, x_7, x_2$). The diagnostic test of the model reveals that the samples are independent, there is no multicollinearity between the variables, and the residuals follow a normal distribution, so the model is informative. The final result is a multiple linear standardized regression equation that can be used to accurately predict house prices by simply entering the desired values of each independent variable.

This study will help people to estimate house prices based on their individual needs. It can also help better understand various factors' impact on housing prices and inform analysis and decision-making in the real estate market. In the future, the model can be further improved by considering more factors such as the Age of the house, Layout structure, School district, Market supply and demand, Accessibility, Scenery, Quality of construction, Economic factors, etc. to improve the accuracy and applicability of the forecast.

However, there are some limitations to the study. The independent variable selected in this paper can only explain 68% of Housing prices, so it is not comprehensive enough, and it is necessary to go further to find several variables that can explain the remaining 32% so that it can better assist in forecasting. In addition, the data used in this paper may come from the same geographical area, so the linear regression equation may not be appropriate for all geographical areas. It is better to increase the samples from different places to participate in the prediction modelling.

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