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RESEARCH ARTICLE

HOUSE RECOMMENDATION SYSTEM

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Abstract

Machine learning has been growing exponentially in the last decade and has played a significant role in past years in image detection, spam reorganization, standard speech command, product recommendation, and medical diagnosis. Many applications and algorithms evolve in Machine Learning day to day. One such application found in journals is house price prediction. People are careful when buying a new house with their budgets and market strategies. The paper's objective is to forecast coherent house prices for non-householders based on their financial provisions and aspirations. Predicting housing prices with fundamental factors is the main crux of our research project. Here we aim to make our evaluations based on every essential parameter considered while determining the price. The paper involves predictions using different Regression techniques like Advance linear regression, Decision tree, KNN, and Ada Boost Regression. House price prediction on a data set has been made by using all the techniques mentioned earlier to find thebest among them. The motive of this paper is to help the seller to estimate the selling cost of a house perfectly and to help people to predict the exact time slap to accumulate a house.

Keywords: Machine Learning, House Price, Prediction, LASSO, Decision tree, KNN, Linear Regression, Gradient Boosting

Introduction

Finding the perfect house to buy is an exciting yet challenging endeavor. It requires careful consideration of various factors such as location, size, amenities, and, of course, the price. With the ever-changing real estate market, it can be daunting to determine whether a house is priced fairly or if it will be agood investment in the long run. Fortunately, advancements in technology and data analysis have made it possible to predict house prices with a reasonable level of accuracy. In this paper, we will explore house recommendations along with house price prediction, leveraging the power of artificial intelligence and machinelearning.

House recommendation systems aim to assist potential homebuyers in identifying properties that align with their preferences and requirements. When seeking a house recommendation, it is important to consider various factors such as the desired location, budget, number of bedrooms, amenities, and any specific preferences you may have. By providing this information, the recommendation system can analyze vast amounts of real estate data to suggest properties that meet your criteria.

Objective

The integration of house price prediction with recommendation systems aims to empower homebuyers with valuable insights and information. By providing accurate price estimates and tailored recommendations, these systems assist buyers in making more informed decisions regarding their real estate investments, reducing the risk of making suboptimal choices.

We are selecting the best combination and algorithm to predict the house price, aiming to increase the accuracy and reduce the complexity and also Stating the gaps and discrepancies found in previous related work.

Related work

This section summarises some of the literature's most essential and noteworthy work on house price prediction. A house price prediction system seeks to identify a property's actual value with high accuracy and using an optimized technique. Several concepts and technologies have been utilized to attain specific outcomes. Evaluating them, we learn about the trends in the dataset and optimize our algorithm for maximum accuracy.

We studied several methodologies and concluded that a linear regression model allows us to summarize and study the relationship between two continuous quantitative variables giving an accuracy of 76.15% as shown in Fig. 1. Also, using Lasso Regression did not optimize the solution, as it resulted in an accuracy of 76.14% as shown in Fig 2. In comparison, if we opt for Gradient Boosting Regression, a machine that takes in a strategy to relapse. Also, arrangement problems that produce a prediction model in the structure of a group from claiming powerless prediction models Reported an accuracy of 91.27% as shown in Fig 3. A predictive model's exactness might be helped in two ways: Possibly by grasping characteristic building alternately toward applying boosting calculations straight far. There are a significant number of boosting calculations: Gradient Boosting, XGBoost, AdaBoost, Gentle Boost, and several others. Each boosting algorithm needs its underlying math.

Fig 1. Accuracy achieved by Decision Tree

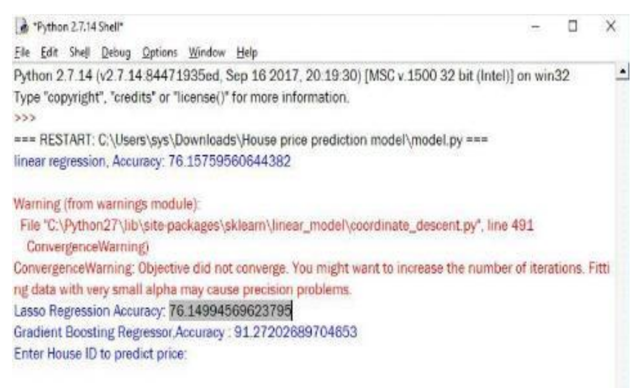

Fig 2. Accuracy achieved by LASSO Regression

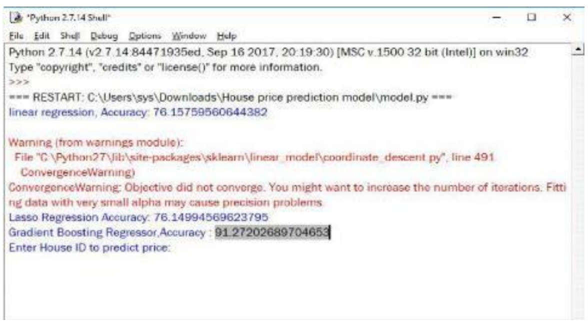

Fig 3. Accuracy achieved by Gradient Boosting Regression

Also, a variety may be watched same time applying them. Boosting calculation will be a standout among those (Agarwal and Chaudhary 2019).

Experimental result

The Predicted house prices using the decision tree regression classifier for the test data are given in Table 1. From the Table, it is clear that five test data record prices are predicted with lesser deviations. For example, record number 25 is predicted accurately, and record numbers 10 and 34 are predicted with less deviation.

Record No.	Actual Price (Lakhs)	Predicted Price (Lakhs)
4	22	24
28	17	20
29	19	14
33	27	24
34	24	23
25	11	11
10	18	17
22	12	10

Table 1. Predicted price values

Comparatively, the performance of multiple linear regression is better than the decision tree regression in predicting house prices. (Varma *et al.*, 2018).

In order to find out the efficient regression technique for prediction, we require specific parameters to perform a comparison among the techniques. The parameters chosen for the comparison are Scores of the algorithm, [MSE] Mean Square Error, and [RMSE] Root Mean Square Error. Table 2 represents the resultant summary of the parameters when the above techniques are implemented practically.

Algorithm	Score	MSE	RMSE
Linear Regression	0.732072	391875744 48.88446	197958 51699
Decision Tree	0.665228	486942930 85.089	197998 46466
K-NN	0.780109 9	32162578 079.96645	179336 22355
LASSO Regression	0.732072	391875537 34.32263	197958 46466
Gradient Boosting Regression	0.917702 2	12037006 088.27804	109713 90390

Table 2. Comparison of algorithms

From the above Table, we can efficiently perform comparisons of different algorithms clearly to find the best among them. Figure 2 below is used to visualize the performance of various techniques in a graphical format based on their scores. In Fig 4, the x-axis represents the various regression techniques considered for the study, and the y-axis represents the score values observed. (Raga Madhuri *et al.*, 2018).

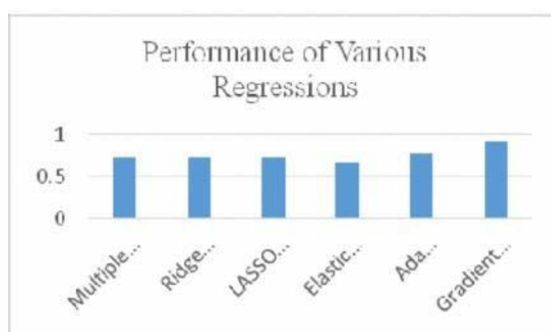

Fig 4. Performance of various regression models

Furthermore, the results are fed as input to the neural network. We use a neural network applied with boosted regression to increase the accuracy of the result. A neural network compares all the predictions and computes them to display the most accurate result. The system makes optimal use of Linear Regression, Forest regression, and Boosted regression. The algorithm's efficiency has been further increased with the use of Neural networks. The system will satisfy customers by providing accurate output and preventing the risk of investing in the wrong house (Chen *et al.*, 2020).

After further study, we came across the ARIMA (Autoregressive Integrated Moving Average) model, a well-known time series forecasting method. The main advantages of the ARIMA model include that it requires data on the time series in question only and it has good short-run forecasting ability. Therefore, the ARIMA model is employed in this paper to predict the house price trend. ARIMA model is the combination of the AR (autoregressive model), MA (moving average model), and ARMA models, where AR uses previous data to predict future change, MA tries to reduce the forecasting errors, AR and MA are mixed to be the ARMA model. P order AR and Q order MA can be denoted in Fig 5.

$$u_t = c + \sum_{i=1}^{p} \phi_i u_{t-i} + \varepsilon_t ,$$

$$u_t = \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t ,$$

Fig 5. ARIMA model's Formulae

Where c and u are two constants, p is the order of the AR model, φi is the AR coefficient, εi is the white noise series with a mean value of zero and a variance of δ^2, q is the order of the MA model, θi is MA coefficient.

The ARIMA and SVR experimental results are shown in Figs. 6 - 7, where the solid and dashed curves denote the ground truth and predict values, respectively.

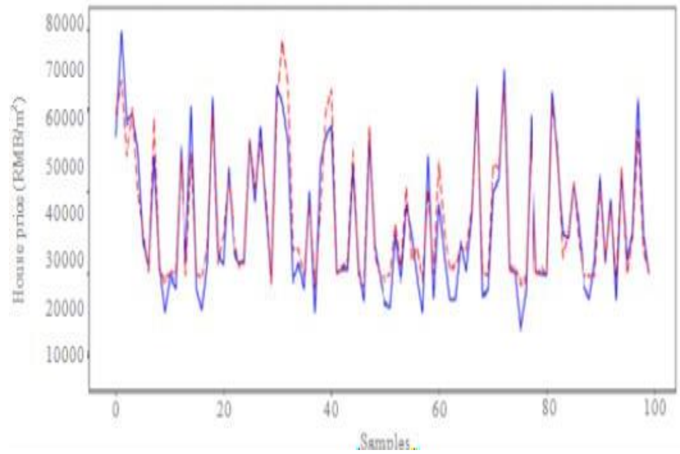

Fig 6. The ground truth and predicted value of the ARIMA model

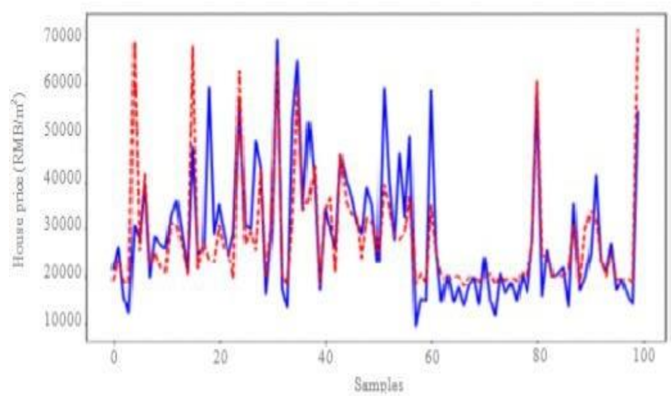

Fig 7. The ground truth and predicted value of the SVR model

The root means square error (RMSE) and mean relative error (MRE) are used to evaluate the prediction performance of the two models. Table 3 shows the performance comparison of the two models on the training and test datasets.

Model	RMSE /Training	RMSE /Test	MRE /Training	MRE /Test
Proposed	5393	7671	0.19	0.22
SVR	9024	10216	0.20	0.28

Table 3. Comparison of algorithms

From Figs. 6 - 7, it can be found that both the proposed model and the SVR model fit the training data well. Moreover, the fitting effects of the two models on the test dataset are inferior to significant deviation between the predicted value and the actual value of some data for the SVR model. As shown in Table I, both the RMSE and MRE indicators of the ARIMA model are smaller than those of the SVR model on the training.

Challenges

Techniques absent in prior implementations include optimal way of stoping the model training at the right instant, a Keras callback that stops training when a monitored measure no longer improves. Others have not employed stacked regression techniques.

Preferences and priorities of homebuyers can be subjective and vary greatly from individual to individual. Incorporating personalized preferences into recommendation systems requires effective techniques for capturing and modeling user preferences, which can be challenging due to the inherent subjectivity and evolving nature of preferences.

Conclusion

House price prediction models and recommendation systems are powerful tools that utilize artificial intelligence and machine learning algorithms to assist homebuyers in finding their dream homes and understanding the potential value of properties. Whether you are a buyer looking for personalized recommendations or a seller seeking to assess the market value of your property, these technologies can provide valuable insights and simplify the decision-making process in the complex world of real estate.

Remember, while these tools can offer useful guidance, it is always advisable to consult with real estate professionals and conduct thorough research before making any major purchasing or selling decisions. Through our experimentation and

the training data, which are consistent with the change curves of training loss and test loss. The predicted value of the ARIMA model is consistent with the actual value. At the same time, there is a

evaluation, we observed that machine learning algorithms are effective in predicting house prices with reasonable accuracy. Among the regression algorithms we examined, gradient boosting consistently outperformed other models, demonstrating its ability to capture complex relationships and provide robust predictions.

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