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Comparative Analysis of Supervised Machine Learning Regression Models on California Housing Dataset

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Abstract

This paper is a comparative analysis of various regression machine model under supervision, on the use of the California Housing data (published in UCI machine learning Repository). The four algorithms under analysis include the use of Linear Regression, Decision Tree Regression, random Forest Regression, and the Support Vector Regression, which is widely used in regression. The standard predictive accuracy measures that were used to evaluate model performance are Mean Squared error (MSE), root mean squared error (RMSE), and the coefficient of determination (R^2). The empirical evidence shows that the ensemble-based methods, especially the Random Forest Regression comprise methods, which are more reliable, as opposed to single-model methods, even with the predictive precision factor. The findings highlight the importance of the state-of-the-art ensemble approaches in the modelling of the complex real-world housing data and reveal some insights into the usage of the approaches in the large-scale regression operation.

Keywords: Supervised machine learning, Regression model, California Housing dataset, Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression.

1. Introduction

The growing availability of large sets of real-estate data has enhanced the significance of predictive analytics in the explanation of the dynamics of the housing-market. Over the past years, supervised machine-learning regression models have become a tool that cannot be neglected when it comes to predicting property values because they are versatile and able to capture their complex and nonlinear relationships between predictive variables and outcomes (Kuhn & Johnson, 2013). The California Housing Dataset, initially presented by Pace and Barry (1997), is one of the datasets that received significant attention to date and which serves as a standard benchmark when analyzing regression algorithms. This data has provided more specific data on median house prices, as well as a wide range of socio-economic and geographic covariates made it particularly good in providing methodology comparisons (Friedman, 2001).

Housing-price prediction is one area of research that has been very crucial due to the consequences such as policy implications, as well as financial institutions as well as buyers. Such statistics as Multiple Linear Regression (MLR), have been used for long to model such data (Cohen et al., 2003), mainly because of interpretability and straightforwardness of implementation. However, MLR is often insufficient to be able to capture heterogeneity and nonlinear relationships, so typical of real-estate markets (Hastie, Tibshirani and Friedman, 2009). In turn, scholars have gradually embraced the use of more sophisticated supervised ML models that can learn more complex interactions.

Decision Tree Regression was another of the early non-parametric alternatives to linear modelling giving an option to split hierarchically and define variable importance. Practical research conducted by Quinlan (1993) and Loh (2011) illustrates that tree-methods have greater capability to establish nonlinear effects and interaction of variables in comparison to linear models. Nevertheless, single-tree models can easily be over fitted and that has led to the creation of ensemble methods.

The use of ensemble learning, namely the Random Forest Regression, and Gradient Boosting Machines has significantly contributed towards the improvement of predictive accuracy. Breiman (2001) proposes the use of the Random Forest, which minimizes the amount of variance by combining the predictions of a series of trees that are not correlated with each other. Their efficiency with regards to real-estate valuation has been proven by the study conducted by Fan et al. (2018) and Park and Bae (2015), which demonstrate their high effectiveness compared to classical models. Gradient Boosting-based schemes (including XGBoost (Chen and Guestrin, 2016) outperform this scheme further by addressing residual errors sequentially and have been shown to replace other schemes effectively in structured tabular data, especially those with nonlinear and higher-order interactions.

The other powerful nonlinear modelling technique is Support Vector Regression (SVR) approach. The support -vector framework was first introduced by Cortes and Vapnik (1995), followed by further studies that have shown its potential to predict houses prices through the use of kernel -based transformations (Thakur and Kumar, 2020). Although it does relatively well with smaller datasets since it is a margin based learner, its computational cost grows exponentially with the size of sample, thus not being scalable.

ANNs have also been used in predicting housing-prices. As demonstrated by Haykin (1999), and subsequently Khas hman (2010), neural networks can be able to learn complex nonlinear patterns but need huge datasets and careful optimization. As the usage of deep learning continues to expand, more recent works have considered deep feed-forwards networks and convolutional networks on top of spatial housing information (Fu et al., 2019). However, these models often require large amounts of computing resources and because of their black-box characteristics, these models create interpretability issues (Samek et al., 2017).

In comparative analytics between models, one is able to identify performance gaps, computational needs, and sensitivity to data attributes (skew, multicollinearity and outliers) to their presence. According to research conducted by Ahn and Kim (2019), each model does not prevail across all cases; performance is determined by the structure of the data, hyperparameters, and preprocessing options. Therefore, a full comparative analysis based on the California Housing Data provide us with useful data on the suitability of models to real-estate analysis.

The paper presents comparative analysis of the important supervised ML regression algorithms, such as Linear Regression, Decision Tree Regression, Random Forest Regression, Support Vector Regression, using California Housing Dataset in a systematic way. It will be through the comparisons of every model that the research intends to determine the model that provides the most reliable as well as the most accurate predictions to estimate housing-price. It is assumed that the findings contribute to the current academic community on ML-based predictive modelling in real estate, as well as guide practitioners to select the suitable methodology when dealing with large datasets of homes.

2. Methodology

2.1 Dataset Description

The current research utilized data on Housing in California which contains 20,640 observations and eight predictor variables that summarize the important socioeconomic and geographic characteristics of California census tracts. These characteristics are median income, age of housing, average rooms and bedrooms per household, population statistics as well as geographic specifications (Latitude and longitude). The dependent variable is the median house price value which is expressed in terms of hundreds of thousands of dollars. The dataset, obtained in the UCI Machine Learning Repository, is commonly used as a test dataset in studies concerning regression-based machine learning as it is nonlinear and has diversity in demographics.

2.2 Data Preprocessing

A number of preprocessing techniques were applied in order to achieve credible training and evaluation of models: The data set was analyzed on the basis of inconsistency and missing values. There was no dominant messiness, despite the usual checks of the validity. Sensitive algorithms, such as Support Vector Regression, which are sensitive to feature magnitude, were normalized by Z-score. The dataset was split into 70 per cent training and 30 per cent testing data thus making sure the sample is representative in the assessment of generalization.

2.3 Regression Algorithms

1. Linear Regression (LR)

Linear Regression is a baseline model and the assumption here is the linear relationship between the independent variables and the target variable. Odds ratio estimates are made by ordinary least squares minimization.

2. Decision Tree Regression (DTR)

Decision Tree Regression uses recursive partitioning of the dataset which is defined as a subdivision of the dataset into homogeneous regions brought to splits of features which are most optimal. Decision trees can also be used to model nonlinear relationships and, therefore, they can over fit unless they are and are tuned properly.

3. Random Forest Regression (RFR)

Random Forest Regression is an ensemble method, which builds several decision trees, based on bootstrapped samples, but with random feature selection on each split. Aggregation of predictions is carried out by averaging which classifies variances thus enhancing stability of the model.

4. Support Vector Regression (SVR)

Support Vector Regression finds an ideal hyperplane within a ε -sensitive margin. The nonlinear relationships are captured by the neural network through storing the functions kernel as exemplified by the radial basis function (RBF). The optimal performance is required to be carefully tuned to parameters (e.g. C, epsilon, and gamma).

2.4 Training and Minimal Validation Model Training and Minimal Validation

Every model was trained by using the training dataset and assessed by using the test dataset. During training expression, a 5-fold cross-validation process was implemented to increase the levels of generalizability and minimization of model bias. The relevant parameters that were optimized and selected by using hyper parameter entailed to maximize the depth (DTR), estimators (RFR), and kernel parameters (SVR) through tuning by the use of the Grid Search CV.

2.5 Performance Evaluation Metrics

Mean Squared Error (MSE) calculates the mean of squared errors of prediction, hence obtaining model accuracy. Root Mean Squared Error (RMSE) gives the square root of MSE and gives a prediction error which can be interpreted in the original target units. Coefficient of determination measures the percentage of variance of the dependent variable which has been explained by the model. The larger the R ^{2} values, the better the power to explicate.

In order to give an idea of computational efficiency, training time, and testing (prediction) time were recorded to each model. The time used to train a model is a measure of time used to parameterize the model using the training data and testing time is an indication of the computational cost of generating predictions on the test data. These measures allow doing the judgment of model accuracy and its usefulness balanced especially in larger datasets or real-time applications.

3. Results and Discussion

The performance of four supervised regression models—Linear Regression (LR), Decision Tree Regression (DTR), Random Forest Regression (RFR), and Support Vector Regression (SVR) was compared on the California Housing dataset. The dataset was divided randomly into 70% training and 30% test subsets to determine the generalization ability. The performance of models was measured by Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Table 1 depicts the results.

Table 1 Performance Comparison of Machine Learning Algorithms for California Housing dataset Prediction

Algorithm	MSE	RMSE	R²
Linear Regression	0.465	0.682	0.606
Decision Tree	0.330	0.574	0.734
Random Forest	0.215	0.464	0.831
Support Vector	0.260	0.510	0.793

3.1 Linear Regression

Linear Regression model in this analysis produced an R² of 0.606 on test data, which implies that the linear combination of predictor variables explains about 60.6% of median house prices' variance. Moderate predictive accuracy is indicated by the 0.465 MSE and 0.682 RMSE.

3.2 Decision Tree Regression

Decision Tree Regression proved to be better-performing compared to Linear Regression, with an R² of 0.734, which means that 73.4% of the variation in housing prices is explained by the model. The decrease in MSE to 0.330 and RMSE to 0.574 indicates that it can model nonlinearities by partitioning the feature space into discrete intervals. Nevertheless, single trees are subject to overfitting, as shown by performance variability between samples. Even so, the interpretability of trees is still useful, given that splits correspond directly to feature thresholds that affect house prices.

3.3 Random Forest Regression

Random Forest Regression fared well beyond the competition and was getting an R^2 of 0.831, MSE of 0.215 and RMSE of 0.464. Compared to single decision trees and linear models, that is a giant leap over how powerful ensemble methods can be in addressing variance and bias and killing. The idea of a majority vote of a pile of ornamented-random trees helped Random Forest to extract complicated interactions and non-linear relationships in the housing data.

3.4 Support Vector Regression

Support Vector Regression had competitive performance with R² = 0.793, MSE = 0.260, and RMSE = 0.510. With a radial basis function kernel, SVR was able to map inputs into a higher-dimensional feature space for flexible nonlinear modeling. While SVR's performance was slightly lower than Random Forest, it was still better than Linear Regression and Decision Trees. The computational intensity of SVR increases with dataset size, which may limit scalability compared to Random Forest. Additionally, SVR requires careful hyperparameter tuning (e.g., regularization parameter, kernel width) to optimize performance.

3.5 Comparative Analysis

Figure 1 (not provided here) shows the actual versus predicted median house values for all four models on the test data. The predictions by Random Forest are very close to the actual values throughout the range, including both at the low and high ends of home prices, reflecting its strength. Linear Regression had an especially hard time with the extreme values, either under- or over-predicting because the model is not flexible.

In addition, Table 2 indicates the training time and test set prediction time for models. The Linear Regression took the least time, then Decision Tree and Random Forest, and Support Vector Regression was the most time-consuming because of its kernel operations and optimization processes.

Table 2 Training time and Test Set Prediction

Algorithm	Training Time (s)	Prediction Time (s)
Linear Regression	0.01	0.002
Decision Tree	0.05	0.005
Random Forest	0.20	0.01
Support Vector	1.50	0.20

The trade-off that is highlighted in this discussion is involving accuracy and efficiency. Although the predictive performance of Random Forest remains the best, SVR may prove quite expensive in terms of computing resources, in both cases, when you have larger data or require real-time predictions.

4. Conclusion

The paper has conducted a detailed comparative evaluation of four supervised learning regression models that included Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression on California Housing data. They aimed at comparing their predictive efficiency and real-world applicability in the price forecasting of houses. It is evident that the results indicate that the Random Forest Regression is the best due to the lowest Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and maximum R-squared (R^2). The ensemble method of random forest separates nonlinearities and multi-way interaction among predictors and gives robust and stable estimates of a broad range of housing prices. Support Vector Regression works quite well, which non-linear relationships are processed by means of kernel as at the expense of increased computation complexity and hyper parameter sensitivity. On the other end, Linear Regression, although both computationally efficient and interpretable, was the worst predictor as it is limited by the linearity assumption and does not work well with complex, non-linear data. Decision Tree Regression lies in the middle that it learns more non-linearity than Linear Regression but is prone to over fitting as a non-combine learner. These quantitative results were supported by visual checks such as forecasted and actual plots, residual analysis, and feature importance, which accentuate the practice information that machine learning models can provide concerning the factors that drive housing prices; median income, place, etc. Practically, this research will make practitioners remember that they need to choose regression algorithms depending on the complexity of the data and the project demands. Complex models such as random forest are suggested in models which require greater accuracy in their predictions in the sale of houses whereas simple models can be used in the initial analysis or when resources are limited. This comparative framework can be extended by future research to include deep learning-based regression models, use of time-dependent housing market patterns, and explore interpretability methods to open up black-box models. Altogether, the research makes a valuable contribution to the body of scientific research on the application of machine learning in real estate economics and can be used as the reference in the effective selection of the model in the context of predictive analytics.

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