ADVANCED R

PREDICTING HOUSE PRICES

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# INTRODUCTION

This report provides a summary of regression insights gleaned from observations of 17,277 houses sold in King County, Washington – USA between 2014 and 2015. A regression analysis was performed on the data provided with the **objective to predict future house prices in the area** based on the information available.

# REGRESSION RESULTS

To conduct the regression analysis, several models which include a linear regression, a random forest, and gradient tree boosting were constructed and executed on the provided dataset. The **final model produced has an R-square of 89.48% and Mean Absolute Percentage Error (MAPE) of 12.48% in predicting future house prices based on the house features that were available** in the dataset**.**

# SUMMARY OF TECHNICAL APPROACH & METHODOLOGY

The dataset *“house\_price\_train.csv”* was the foundation for the analysis and the basis for the proposed predictive model. The dataset contains information of 17,277 houses sold in Washington, USA between 2014 and 2015. Among the 21 total variables available, 20 represent variables regarding house features, location, condition, etc., and one represents a target variable, indicating the final price the house was sold at.

To following Data Preparation, Feature Engineering and Modelling steps were undertaken using **R Studio**:

* Data preparation (dataset loading, information integrity check and initial descriptive analysis)
* Feature Engineering (variable construction and treatment, univariate analysis, multivariate analysis)
* Model building (dataset split, model training and validation)

1. Baseline

A first attempt of a logistic regression model was tried on the variables as is (without any treatment or feature engineering). The resultant baseline model had an **R-square of 61.82% and MAPE of 26.39%.**

1. Feature Engineering and Modelling

**Refer to R-markdown file attached.**

1. Model Selection

Different models were trained using both the target value as it is (Price) and the transformed target value (Log(Price)). This transformation was conducted to correct skewness on its original distribution.

The following table shows a summary of the metrics obtained for each of the models trained.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Model** | **Price** | | **Log(Price)** | |
| **R-square** | **MAPE** | **R-square** | **MAPE** |
| Linear Regression | 61.82% | 26.39% |  |  |
| Random Forest | 85.72% | 13.12% | 88.13% | 12.59% |
| GBM | 82.90% | 15.58% | 86.51% | 14.28% |
| XGB | 86.57% | 13.40% | 89.48% | 12.48% |
| XGB + PCA | 84.70% | 13.82% | 88.33% | 13.27% |

**It is observed that metrics improve when using Log(Price) as the target variable**. Particularly Random Forest and XGB models perform better than the other ones. **XGB model is selected to its slightly superior improvement.**

# CONCLUSION

In this report, it is intended to predict the price of houses in King County, Washington - USA. It was found that the best results obtained consisted of a MAPE of 12.48% which can be considered as not-so- accurate.

Predicting house prices can be challenging because houses’ characteristics vary widely and from neighbourhood to neighbourhood. A possible explanation for the MAPE > 10% can be explained on the fact that house prices are not only based on the physical properties of a house but also on each specific context at the moment of sale (i.e. An owner who is in a hurry to sell due to an emergency can settle for a lower price). Our results were obtained after testing different models based solely on the information available and not subjective variables like the one mentioned previously.