House price prediction using linear regression

Sarthak Shrivastava
Machine learning intern
AI tech systems
sarthak051999@gmail.com
www.ai-techsystems.com

Abstract - Housing prices are an important reflection of the economy, and housing price ranges are of great interest for both buyers and sellers. In this project, house prices will be predicted given explanatory variables that cover many aspects of residential houses. The goal of this project is to create a regression model that are able to accurately estimate the price of the house given the features. The heart of the problem lies within to develop an efficient 3 layer and a 5 layer neural network architecture that can make house prices predictions and to compare there percentage errors.

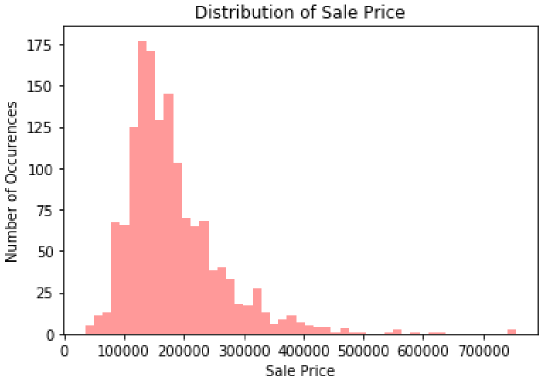
Keywords - exploratory data analysis, data vizualisation, handling missing data, outlier treatment, model training, linear regression, gradient boosting.

I. INTRODUCTION

Housing prices are an important reflection of the economy, and housing price ranges are of great interest for both buyers and sellers. In this project. house prices will be predicted given explanatory variables that cover many aspects of residential houses. As continuous house prices, they can be predicted with various regression techniques including Lasso, Ridge, SVM regression, and Random Forest regression; as individual price ranges, they can be predicted with classification methods including Naive Bayes, logistic regression, SVM classification, and Random Forest classification. We can also perform PCA to improve the prediction accuracy. The goal of this project is to create a linear regression model that is able to accurately estimate the price of the house given the features.

II. METHODOLOGY

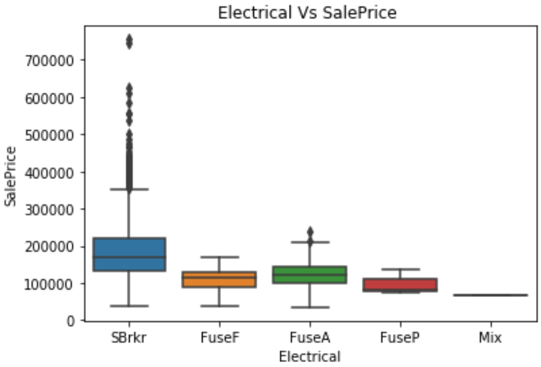
A. Dataset

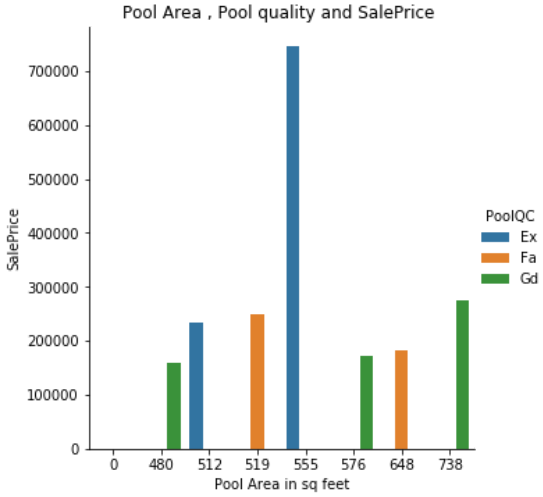


The dataset used in this project is an open-source dataset taken from Kaggle.com. It consists of 3000 records with 80 parameters that have the possibility of affecting the property prices. Some of the parameters are Area in square meters, Overall quality which rates the overall condition and finishing of the house, Location, Year in which house was built, Numbers of Bedrooms and bathrooms, Garage area and number of cars that can fit in garage, swimming pool area, selling year of the house and Price at which house is sold. The SalePrice is the label which we have to predict through regression techniques. Some parameters had numerical values while some had categorical values.We converted categorical columns to numerical columns using pandas get_dummies function because our model can only train on numerical columns.

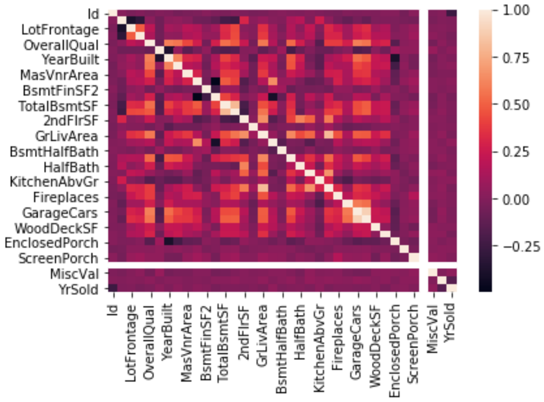
B. Exploratory Data Analysis

Exploratory Data Analysis refers to the critical process of performing initial investigations on data so as to discover patterns,to spot anomalies,to test hypothesis and to check assumptions with the help of summary statistics and graphical representations. We performed some bivariate analysis on the data to get a better overview of the data and to find outliers in our dataset. Outliers can occur due to some kind of errors while collecting the data and need to be removed so that it don't affect the performance of our model.

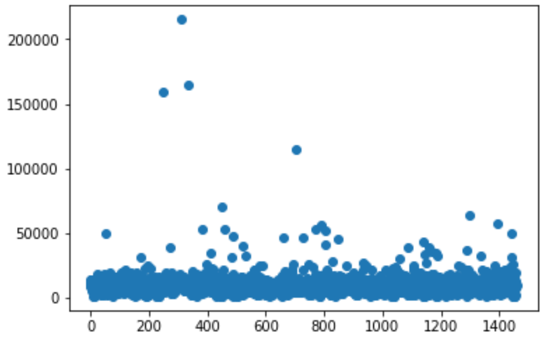




C. Data Preprocessing



The dataset is the prices and features of residential houses sold from 2006 to 2010 in Ames, Iowa, obtained from the Ames Assessor's Office. This dataset consists of 79 house features and 1460 houses with sold prices. Although the dataset is relatively small with only 1460 examples, it contains 79 features such as areas of the houses, types of the floors, and numbers of bathrooms. Such large amounts of features enable us to explore various techniques to predict the house prices. The dataset consists of features in various formats. It has numerical data such as prices and numbers of bathrooms/bedrooms/living rooms, as well as categorical features such as zone classifications for sale, which can be 'Agricultural', 'Residential High Density', 'Residential Low Density', 'Residential Low Density Park', etc. In order to make this data with different format usable for our algorithms, categorical data was converted into separated indicator data, which expands the number of features in this dataset. Besides, there were some features that had values of N/A; we replaced them with the mean/median/0 of their columns so that they don't influence the distribution.



D. Model

We performed supervised learning algorithm 'regression' as it seems more reasonable to perform regression since house prices are continuous.We fitted our model with linear regression algorithm on train data and predicted house prices on the test data. In order to further improve our models, we also performed gradient boosting.We made an instance of gradient boosting regressor and fitted it with our data.For best results and more optimized Model we changed the parameters of gradient boosting regressor.

n_estimators = 15000,
max_depth = 2,
 min_samples_split = 2,
learning_rate = 0.005,
loss = 'huber

III. CONCLUSION

For regression problem, the model performed with an rmse 0.14056 without outlier treatment.After treating outliers the rmse reduced to 0.13729 and after removing three columns that were the most prone to outlies the rmse dropped to 0.13747.Finally,improving parameters of gradient boosting resulted in an rmse of 0.13223 which is the best for now with learning rate = 0.005 and n_estimaters =15000, loss= ‘huber’ instead of ls and depth =2.

IV. REFERENCE

[1] De Cook, Dean. “Ames, Iowa: Alternative to the Boston Housing Data as an End of Semester Regression Project.” Journal of Statistics Education, vol. 19, no. 3, 2011.