

Applied Regression Final Project

Elda Piedade, Thomas Oswald

May 4th, 2020

Introduction

The objective of this project is to find the best linear regression model to predict the median home value for the houses in the Houston neighborhoods. Data was gathered from 96 zip codes in Houston by utilizing python web scrapping resources to collect data from the Texas Hometown Locator website (owned by HTL, Inc.). With the dataset extracted and cleaned, exploratory data analysis and statistical analysis were performed to understand the relationship between the median home value and other variables, such as diversity index, per capita income, and average household size. Based on the analysis, data was modeled with linear regression.

Importance

1. With a good model for prediction and analysis, individuals in Houston will be able to understand how to price their homes for sale. 2. Understanding how the demographic factors relate to median home value is valuable social knowledge.

Data

Response variable : Median Home Value

Predictors:

- * x_1 - Total Population
- * x_2 - Diversity Index
- * x_3 - Median Household Income
- * x_4 - Per Capita Income
- * x_5 - Total Housing Units
- * x_6 - Average Household Size
- * x_7 - Housing affordability Index

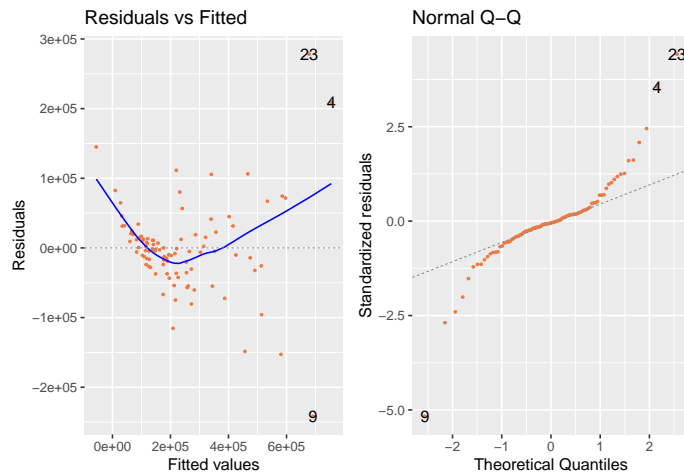
Explained variables:

1. The Diversity Index is a scale of 0 to 100 that represents the likelihood that two persons, chosen at random from the same area, belong to different races or ethnic groups. If an area's entire population belongs to one race and one ethnic group, then the area has zero diversity. An area's diversity index increases to 100 when the population is evenly divided into two or more race/ethnic groups. 2. The Housing Affordability Index base is 100 and represents a balance point where a resident with a median household income can normally qualify to purchase a median price home. Values above 100 indicate increased affordability, while values below 100 indicate decreased affordability. 3. The outcome variable is the median home value (median price home).

Data Loading & Checking full Model Accuracy:

After loading the data and creating a full Linear Regression (LR) model, we found that the model is not adequate. The residuals have a tunnel and bowl shape; the data is heavily-tailed distribution with three possible influential points. To address this problem we will inspect the data and perform a few transformations.

First model - Residual Plots:

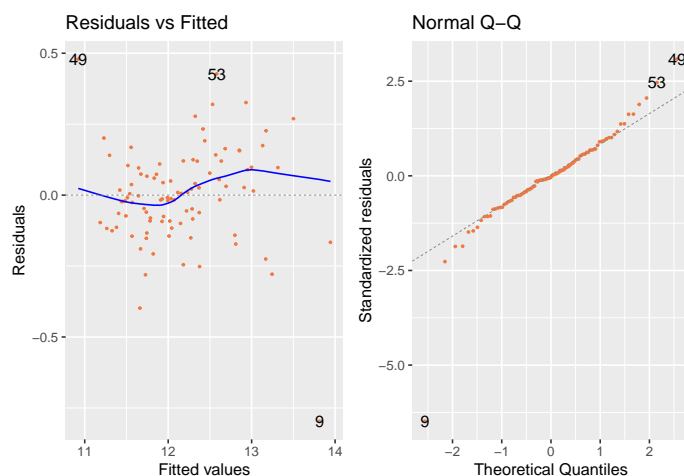


Data Transformation

Constant variance of errors assumptions can often be solved with response variable transformations. The log transformations performed the best compared to other transformations. It has the most appropriate properties for the normality of residuals and constant variance. The residual plot for the other transformation (reciprocal, square root, reciprocal square root and inverse) did not show much improvement from the original model and were very influenced by possible influential points.

In conclusion, our best transformation is the "log" transformation. The residual plot does not appear to have any alarming shape, and the residuals are normally distributed, except for the problematic observations, 9, 49 and 58. Our new transformed model indicates that a linear model provides a decent fit to the data.

Log Transformed model - Residual Plots:



Full Regression Model Significance Test

Our linear regression model is significant given that the p-value for the F-test is smaller than our level of significance 0.05. Looking at the regressor individually, we found that the intercept, total population, median household income, total housing units and housing affordability index are significant for predicting log(median home value). In model detail the F-test is performed to understand if at least one regressor is not equal to zero. The conclusion is supported by the t-test performed for each regressor. This is a first good step in our analysis and important to keep in mind.

```
##
## Call:
## lm(formula = log(Median.Home.Value) ~ ., data = reduce_dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.79685 -0.09169 -0.00563  0.09730  0.47930
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.234e+01  2.922e-01  42.240 < 2e-16 ***
## Total.Population -1.073e-05  4.531e-06  -2.369  0.02003 *
## Diversity.Index1 -2.442e-04  2.137e-03  -0.114  0.90931
## Median.Household.Income  1.481e-05  1.843e-06   8.034 3.95e-12 ***
## Per.Capita.Income -2.328e-06  3.027e-06  -0.769  0.44398
## Total.Housing.Units  3.206e-05  1.135e-05   2.826  0.00584 **
## Average.Household.Size -7.059e-02  7.427e-02  -0.950  0.34446
## Housing.Affordability.Index2 -6.052e-03  5.499e-04 -11.005 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.179 on 88 degrees of freedom
## Multiple R-squared:  0.927, Adjusted R-squared:  0.9212
## F-statistic: 159.6 on 7 and 88 DF, p-value: < 2.2e-16
```

Evaluating all possible subset regression models

In looking for the "best" model, certain criteria must be met in order for proper variable selection of the regressor equation. These criteria help us to be able to explain the data in the simplest way with redundant predictors removed in order to minimize cost and to avoid multi-collinearity in our regression model.

The criteria for our variable selection include: 1) Large R^2 value 2) Maximum Adjusted R^2 value 3) Minimum MSres 4) Minimum Mallows's C_p Statistic value.

Based on the above criteria, the "best" candidate models are:

1) Model 1:

$$\log(\hat{y}) = (1.136e + 01) + (2.438e - 05)x_4$$

2) Model 8:

$$\log(\hat{y}) = (1.232e + 01) + (1.409e - 05)x_3 - (7.258e - 03)x_7$$

3) Model 29:

$$\log(\hat{y}) = (1.267e + 01) + (1.301e - 05)x_3 - (1.547e - 01)x_6 - (6.197e - 03)x_7$$

4) Model 64:

$$\log(y^{hat}) = (1.210e + 01) - (1.258e - 05)x_1 + (1.382e - 05)x_3 + (3.717e - 05)x_5 - (6.015e - 03)x_7$$

5) Model 99:

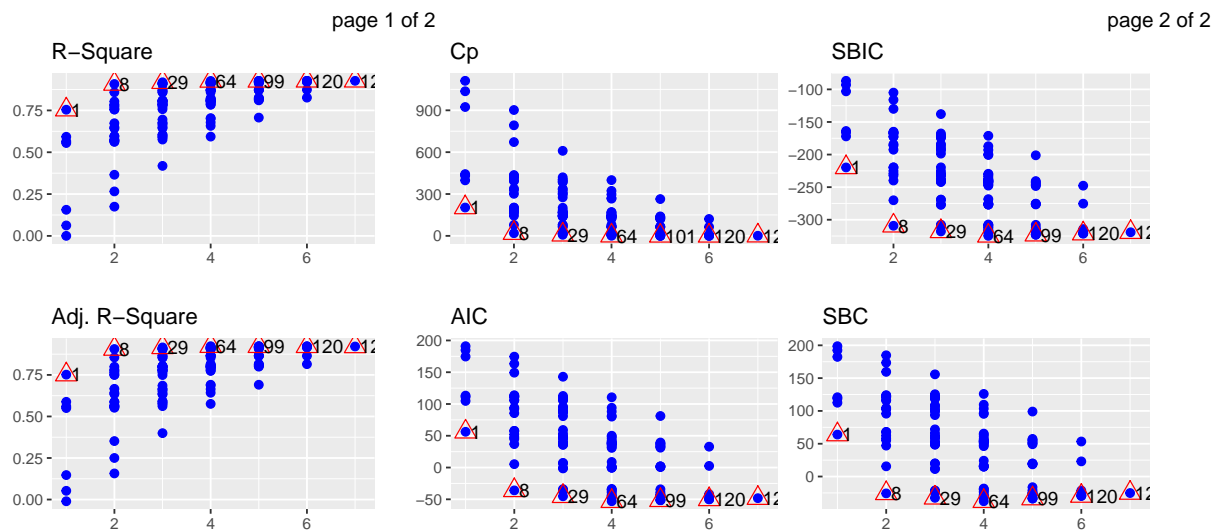
$$\log(y^{hat}) = (1.221e + 01) - (1.036e - 05)x_1 + (1.358e - 05)x_3 + (3.176e - 05)x_5 - (4.477e - 02)x_6 - (5.876e - 03)x_7$$

6) Model 120:

$$\log(y^{hat}) = (1.232e + 01) - (1.084e - 05)x_1 + (1.484e - 05)x_3 - (2.332e - 06)x_4 + (3.223e - 05)x_5 - (7.125e - 02)x_6 - (6.046e - 03)x_7$$

7) Model 127:

$$\log(y^{hat}) = (1.234e + 01) - (1.073e - 05)x_1 - (2.442e - 04)x_2 + (1.481e - 05)x_3 - (2.328e - 06)x_4 + (3.206e - 05)x_5 - (7.059e - 02)x_6 - (6.052e - 03)x_7$$



Evaluation of PRESS and VIF of candidate models:

Once we identified the "best" candidate models, we compare its predicted residual error sum of squares (PRESS) statistic with other candidate models and selected the model with the smallest value. We also compare candidate models by performing a variance inflation factor (VIF) in order to quantify the severity of multicollinearity in the model.

* The model with the lowest PRESS value is Model 64 however there is evidence of multicollinearity.

* The model with the second lowest PRESS value is Model 29 and the same model doesn't show any evidence of multicollinearity in the variance inflation factor test of each regressor.

PRESS Statistic:

```
## [1] "Model 1 PRESS: 10.733"
## [1] "Model 8 PRESS: 4.236"
## [1] "Model 29 PRESS: 3.814"
## [1] "Model 64 PRESS: 3.76"
## [1] "Model 99 PRESS: 3.978"
```

```
## [1] "Model 120 PRESS: 4.97"
## [1] "Model 127 PRESS: 5.792"
```

Multicollinearity Check:

```
## [1] "Variance Inflation Factor"

##          x3          x7
## 1.081888 1.081888

##          x3          x6          x7
## 1.293148 2.136140 1.793435

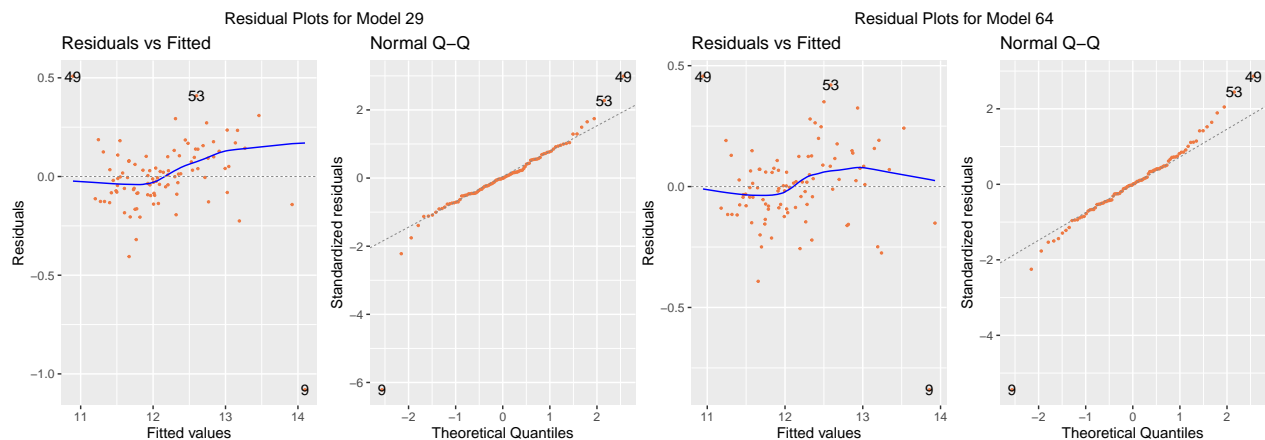
##          x1          x3          x5          x7
## 7.539310 1.107578 8.311564 1.636704

##          x1          x3          x5          x6          x7
## 16.681309 1.388036 16.575790 4.737732 1.960617

##          x1          x3          x4          x5          x6          x7
## 17.011191 7.448650 14.010788 16.626136 6.039030 2.339524

##          x1          x2          x3          x4          x5          x6          x7
## 17.742753 1.550252 7.646411 14.012521 16.921586 6.074919 2.360197
```

Residual Plots of best models:



Cross Validation:

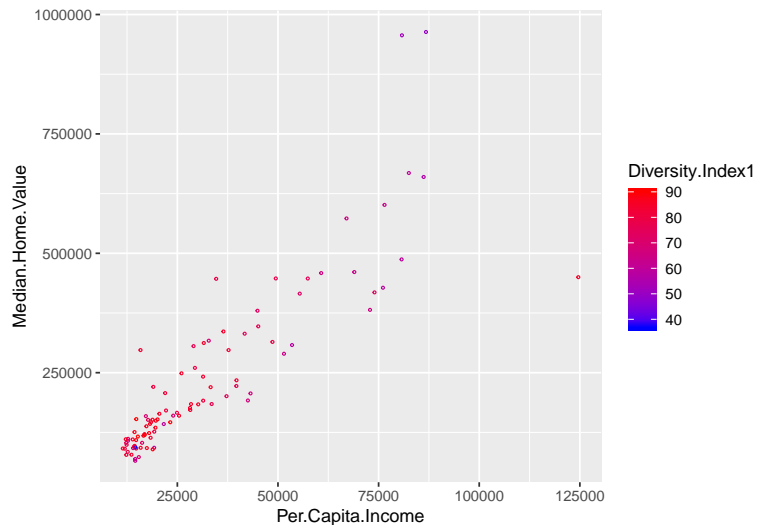
After splitting the data into 4 groups and repeating the fold cross-validation by 12, the best model is Model 64:

$$\log(y^{hat}) = (1.210e + 01) - (1.258e - 05)Total.Population + (1.382e - 05)Median.Household.Income + (3.717e - 05)Total.Housing.Units - (6.015e - 03)Housing.Affordability.Index$$

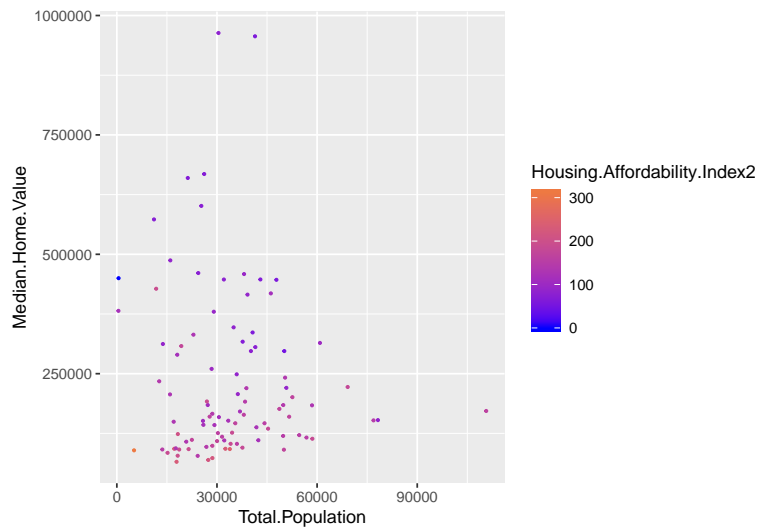
Exploratory Data Analysis:

In houston most zip codes have a diversity index close to 80. However we see that neighborhoods with low diversity index tend to be situated in the extremes. The less diverse areas either have a very large per capita income and median home value, or a very per capita income and median home value. Also we see a positive relationship between both variables.

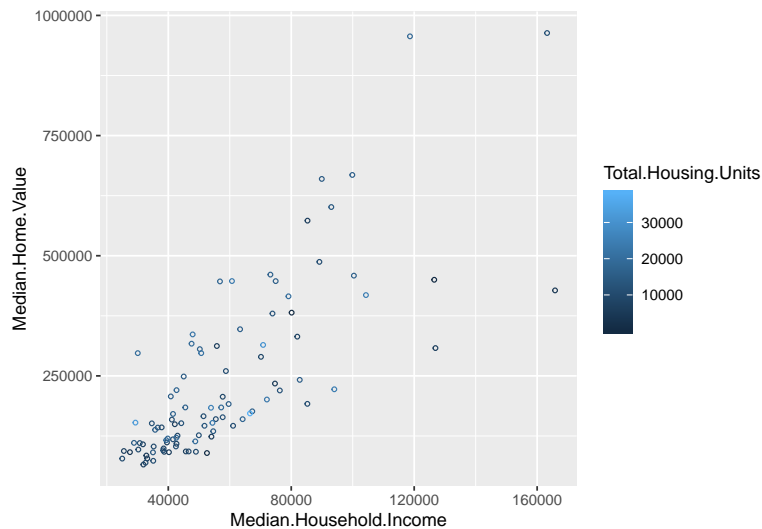
```
## Loading required package: bitops
```



Total population and median home value are not correlated. However we found some interesting insights about how Housing affordability index relates to both variables. The housing affordability index is large for houston areas with median home value below 250,000.00 dollars.



Median Household income is positively correlated to Median home value. However, total housing units does not appear to have any linear relation with median home value.



Exploratory Analysis conclusion

Although we are able to see how the variables used for our best models relate to median home value, we must call attention to the fact that our model predicts a transformed version of the median home value; Therefore, the relationship may be different. Using correlation we can have some insight of how the predictors relate to the logged median home value.

```
## [1] "Logged Median value vs total population -0.016"
## [1] "Logged Median value vs median household income 0.77"
## [1] "Logged Median value vs total housing units 0.25"
## [1] "Logged Median value vs housing affordability index -0.752"
```

It turns out that we have the same results of colleration. Median household income is positively correlated with logged median home value, and housing affordability index is negatively correlatted with median home value. As for total population and total housing units, these are not correlated with median home value. The coeficients of our model agrees with this observation. That is, with all other variables held constant an increase of median household income by 1 dollars results in an increase of $(1.382e-05)$ for logged median home value. In the same manner, an increase of housing affordability index by one unit, results in a decrease of $(6.015e-03)$ for logged median home value.

References