# HARVARD EXTENSION SCHOOL

CSCI E-106 - Data Modeling - Final Project

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**Abstract**

This project, undertaken by a team of students at Harvard Extension School, focuses on developing a comprehensive predictive model for house prices in King County, USA, using the 'KC_House_Sales' dataset. The dataset provides a rich variety of house attributes, allowing for an in-depth analysis of factors influencing property values. The initial phase of the project involves data cleaning and transformation, including the removal of irrelevant variables and conversion of data types. The primary analytical approach combines traditional linear regression models with more complex methods such as neural networks, decision trees, and support vector machines (SVM). The models are trained on a 70% split of the dataset and validated on the remaining 30%, ensuring robustness and accuracy in predictions. In the subsequent stages, the project delves into graphical analysis, revealing key correlations and trends in the data. Techniques such as box plots, scatter plots, and heatmaps provide insights into the relationships between house prices and attributes like square footage, number of bedrooms, and location. The project also explores the impact of categorical variables and property age on pricing. Model performance is thoroughly tested using various metrics, including MSE and R-squared values. The final selection of the primary model, referred to as the "champion" model, is based on its performance on both the training and testing datasets. The project concludes with a discussion on model limitations, assumptions, and an ongoing monitoring plan, ensuring the model's relevance and accuracy over time.

# Contents

## Executive Summary

In this project, our team of data modeling students has meticulously developed a sophisticated model for predicting real estate prices in King County, USA, aiming to inform and guide high-level executives and investment leaders in their strategic decision-making. This model, built from a comprehensive dataset encompassing various property attributes, employs advanced techniques such as linear regression, regression trees, and neural networks, ensuring accuracy and versatility.

The primary objective of the model is to serve as a pivotal tool for investment strategy, market analysis, and policy formulation. It is designed to align with regulatory standards and internal compliance requirements, ensuring ethical and responsible use of data. However, it's important to note that the model's applicability is specific to King County's real estate market, and its predictive accuracy is contingent upon the ongoing integration of current market data.

While our model represents a significant advancement in data-driven real estate analysis, it is essential to recognize its limitations. These include potential biases in historical data and the model's limited generalizability beyond the regional context of King County. Regular updates and adaptations of the model are recommended to maintain its relevance and accuracy in a dynamic market environment.

Overall, this model stands as a testament to the power of data science in enhancing market understanding and investment strategies, offering valuable insights for executive decision-making and organizational growth in the real estate sector.

# I. Introduction

In the ever-evolving landscape of real estate, the ability to accurately predict house prices is invaluable. This project, undertaken by a dedicated team from Harvard Extension School, delves into this realm, focusing on King County, USA. The motivation behind our work is twofold: firstly, to provide a robust predictive tool for potential investors and market analysts, and secondly, to contribute to the academic understanding of real estate market dynamics.

Our approach is grounded in the analysis of the 'KC_House_Sales' dataset, a comprehensive collection of house attributes within King County. The dataset, rich in detail, includes features such as square footage, the number of bedrooms, and geographical location, etc., all of which are pivotal in determining house prices. The initial phase of our project involved a thorough data cleaning process. This step was crucial in ensuring the integrity of our analysis, involving the removal of irrelevant variables, handling missing values, and converting data types for consistency.

Once the data was prepared, we embarked on a methodological journey, exploring various statistical and machine learning techniques. Our primary method, linear regression, served as a foundation model, offering insights into the direct relationships between house features and their prices. However, recognizing the complexity of the real estate market, we expanded our toolkit to include more advanced models like neural networks, decision trees, and support vector machines (SVM). Each of these methods brought a unique perspective and depth to our analysis, enabling us to capture non-linear relationships and complex interactions between variables.

The structure of our project involved splitting the dataset into two parts: 70% for training and 30% for validation. This split was strategically chosen to ensure the robustness of our models against unseen data, a critical aspect of predictive modeling. The training phase was an iterative process, where each model was refined through a series of evaluations and adjustments. In doing so, we aimed to strike a balance between model complexity and predictive accuracy.

Our exploratory data analysis revealed several key insights. We observed that certain features, such as square footage and location, had a significant impact on house prices. This initial observation guided our feature selection and engineering process, where we developed new variables that could potentially enhance the model's performance.

As we progressed, the need for a rigorous evaluation framework became apparent. To this end, we employed various metrics such as MSE, R-squared and Pseudo-R squared values. These metrics were instrumental in assessing the performance of our models, both on the training and validation sets. The final selection of our primary model, which we refer to as the "champion" model, was based on a comprehensive evaluation of these metrics.

In conclusion, this project represents a significant endeavor in the field of predictive analytics for real estate. Through a blend of traditional statistical methods and advanced machine learning techniques, we have developed a model that not only predicts house prices in King County with a high degree of accuracy but also offers insights into the factors that drive these prices. As we move forward, our focus will be on refining the model, exploring new data sources, and adapting to the changing dynamics of the real estate market.

# II. Description of the data and quality

In this section, we meticulously dissect the King County house sales dataset, a crucial foundation for our predictive modeling. This dataset is a rich amalgamation of diverse variables, ranging from basic house attributes like square footage and number of bedrooms, to more nuanced features such as the year of renovation and the presence of a waterfront. The quality of this dataset is paramount, as it directly influences the reliability and precision of our predictive models. We delve into a detailed assessment of the data quality, addressing aspects like completeness, consistency, and potential biases, ensuring that our analysis is built on a robust and accurate foundation.

## Data Overview

The dataset presented for analysis encompasses a range of housing attributes for properties sold in King County, including the sale price, number of bedrooms and bathrooms, square footage of living and lot space, and other characteristics like the presence of a waterfront, views, and the condition and grade of the house. Each entry is timestamped, providing a date of sale, which can be instrumental in understanding market trends over time.

```
# Overview of the King County House Sales Dataset
df_house = read.csv("KC_House_Sales.csv")
cat("Number of NA values in dataframe:", sum(is.na(df_house)))
```

```
## Number of NA values in dataframe: 0
```

```
head(df_house)
```

```
##           id            date           price bedrooms bathrooms sqft_living
## 1 7129300520 20141013T000000    $221,900.00         3      1.00        1180
## 2 6414100192 20141209T000000    $538,000.00         3      2.25        2570
## 3 5631500400 20150225T000000    $180,000.00         2      1.00         770
## 4 2487200875 20141209T000000    $604,000.00         4      3.00        1960
## 5 1954400510 20150218T000000    $510,000.00         3      2.00        1680
## 6 7237550310 20140512T000000  $1,225,000.00         4      4.50        5420
##   sqft_lot floors waterfront view condition grade sqft_above sqft_basement
## 1     5650      1          0    0         3     7       1180             0
## 2     7242      2          0    0         3     7       2170           400
## 3    10000      1          0    0         3     6        770             0
## 4     5000      1          0    0         5     7       1050           910
## 5     8080      1          0    0         3     8       1680             0
## 6   101930      1          0    0         3    11       3890          1530
##   yr_built yr_renovated zipcode     lat     long sqft_living15 sqft_lot15
## 1     1955            0   98178 47.5112 -122.257          1340       5650
## 2     1951         1991   98125 47.7210 -122.319          1690       7639
## 3     1933            0   98028 47.7379 -122.233          2720       8062
## 4     1965            0   98136 47.5208 -122.393          1360       5000
## 5     1987            0   98074 47.6168 -122.045          1800       7503
## 6     2001            0   98053 47.6561 -122.005          4760     101930
```

## Data Types, Categories and Cleaning

Our dataset includes a blend of continuous and categorical data types. Notably, the 'zipcode' and 'waterfront' variables are categorical despite their numeric appearance. 'Zipcode' represents different regions, and 'waterfront' is a binary indicator, thus requiring special attention during preprocessing. These variables, along with others like 'view' and 'condition', will be transformed into dummy variables to facilitate their use in our regression models.

The data cleaning process has involved removing non-informative variables such as IDs, correcting data types (e.g., transforming sale price to a numeric format and parsing dates into a usable format), and creating new variables that could reveal temporal trends (e.g., year, month, day of sale).

```
# The "id" column must be removed
df_house = subset(df_house, select = -id)

# The data in the column "price" must be converted to numeric
df_house$price <- as.numeric(gsub("[\\$,]", "", df_house$price))

# Cleanup of "date" and creation of "year", "month", and "day" columns
df_house$date <- as.POSIXct(df_house$date, format = "%Y%m%d")
df_house$year <- as.numeric(format(df_house$date, "%Y"))
df_house$month <- as.numeric(format(df_house$date, "%m"))
df_house$day <- as.numeric(format(df_house$date, "%d"))

# Collect columns that are numeric only
ndf_house = df_house[sapply(df_house, is.numeric)]
# This action ends up the column "date" from the dataset

head(df_house)
```

```
##         date   price bedrooms bathrooms sqft_living sqft_lot floors waterfront
## 1 2014-10-13  221900        3      1.00        1180     5650      1          0
## 2 2014-12-09  538000        3      2.25        2570     7242      2          0
## 3 2015-02-25  180000        2      1.00         770    10000      1          0
## 4 2014-12-09  604000        4      3.00        1960     5000      1          0
## 5 2015-02-18  510000        3      2.00        1680     8080      1          0
## 6 2014-05-12 1225000        4      4.50        5420   101930      1          0
##   view condition grade sqft_above sqft_basement yr_built yr_renovated zipcode
## 1    0         3     7       1180             0     1955            0   98178
## 2    0         3     7       2170           400     1951         1991   98125
## 3    0         3     6        770             0     1933            0   98028
## 4    0         5     7       1050           910     1965            0   98136
## 5    0         3     8       1680             0     1987            0   98074
## 6    0         3    11       3890          1530     2001            0   98053
##       lat     long sqft_living15 sqft_lot15 year month day
## 1 47.5112 -122.257          1340       5650 2014    10  13
## 2 47.7210 -122.319          1690       7639 2014    12   9
## 3 47.7379 -122.233          2720       8062 2015     2  25
## 4 47.5208 -122.393          1360       5000 2014    12   9
## 5 47.6168 -122.045          1800       7503 2015     2  18
## 6 47.6561 -122.005          4760     101930 2014     5  12
```

## Categorical Variables and Age Analysis

### Renovation Indicator Variable

A binary variable named 'renovated' was introduced to indicate whether a property has undergone renovation. This variable is set to 1 if the 'yr_renovated' field is not zero, signifying that the property has been renovated at least once. Otherwise, it is set to 0, indicating no renovation. This distinction provides a straightforward way to assess the impact of renovations on property values.

```
# Creating a new variable 'renovated'
# 1 if the property has been renovated (yr_renovated != 0), 0 otherwise
df_house$renovated = ifelse(df_house$yr_renovated != 0, 1, 0)
```

### Property Age Calculation

This is a tentative way to consider *"age since last renovation"* and see if there's a correlation between the time a house was last built/renovated on its selling price. A new variable called 'age' was calculated to represent the current age of each property. If a property was renovated, its age is the difference between 2023 and the renovation year ('yr_renovated'). If not renovated, the age is the difference between 2023 and the year the house was built ('yr_built'). This variable helps in understanding the effect of property age and recent renovations on house prices.

```
# Creating 'age' column
df_house$age = ifelse(df_house$renovated == 1,
                      2023 - df_house$yr_renovated,
                      2023 - df_house$yr_built)

head(df_house)
```

```
##         date   price bedrooms bathrooms sqft_living sqft_lot floors waterfront
## 1 2014-10-13  221900        3      1.00        1180     5650      1          0
## 2 2014-12-09  538000        3      2.25        2570     7242      2          0
## 3 2015-02-25  180000        2      1.00         770    10000      1          0
## 4 2014-12-09  604000        4      3.00        1960     5000      1          0
## 5 2015-02-18  510000        3      2.00        1680     8080      1          0
## 6 2014-05-12 1225000        4      4.50        5420   101930      1          0
##   view condition grade sqft_above sqft_basement yr_built yr_renovated zipcode
## 1    0         3     7       1180             0     1955            0   98178
## 2    0         3     7       2170           400     1951         1991   98125
## 3    0         3     6        770             0     1933            0   98028
## 4    0         5     7       1050           910     1965            0   98136
## 5    0         3     8       1680             0     1987            0   98074
## 6    0         3    11       3890          1530     2001            0   98053
##       lat     long sqft_living15 sqft_lot15 year month day renovated age
## 1 47.5112 -122.257          1340       5650 2014    10  13         0  68
## 2 47.7210 -122.319          1690       7639 2014    12   9         1  32
## 3 47.7379 -122.233          2720       8062 2015     2  25         0  90
## 4 47.5208 -122.393          1360       5000 2014    12   9         0  58
## 5 47.6168 -122.045          1800       7503 2015     2  18         0  36
## 6 47.6561 -122.005          4760     101930 2014     5  12         0  22
```

### Reinterpreting Zipcode as a Categorical Variable

Transformation of the 'zipcode' variable from numerical to categorical data. Typically, zip codes are mistakenly treated as numerical values in datasets. However, they are categorical by nature, representing distinct geographical areas rather than possessing any inherent numerical relationship. This conversion is crucial for our analysis, as it allows us to use the zip code as a qualitative variable in our models, acknowledging its role in distinguishing different regions and their unique characteristics in housing prices. The R code snippet demonstrates the simple yet essential process of converting 'zipcode' to a character type, ensuring it is correctly utilized in subsequent analyses.

```
# Convert Zipcode to a Categorical variable (char) instead of number
df_house$zipcode = as.character(df_house$zipcode)
```

## Enhancing Data Integrity: Addressing Redundancies and Correlations

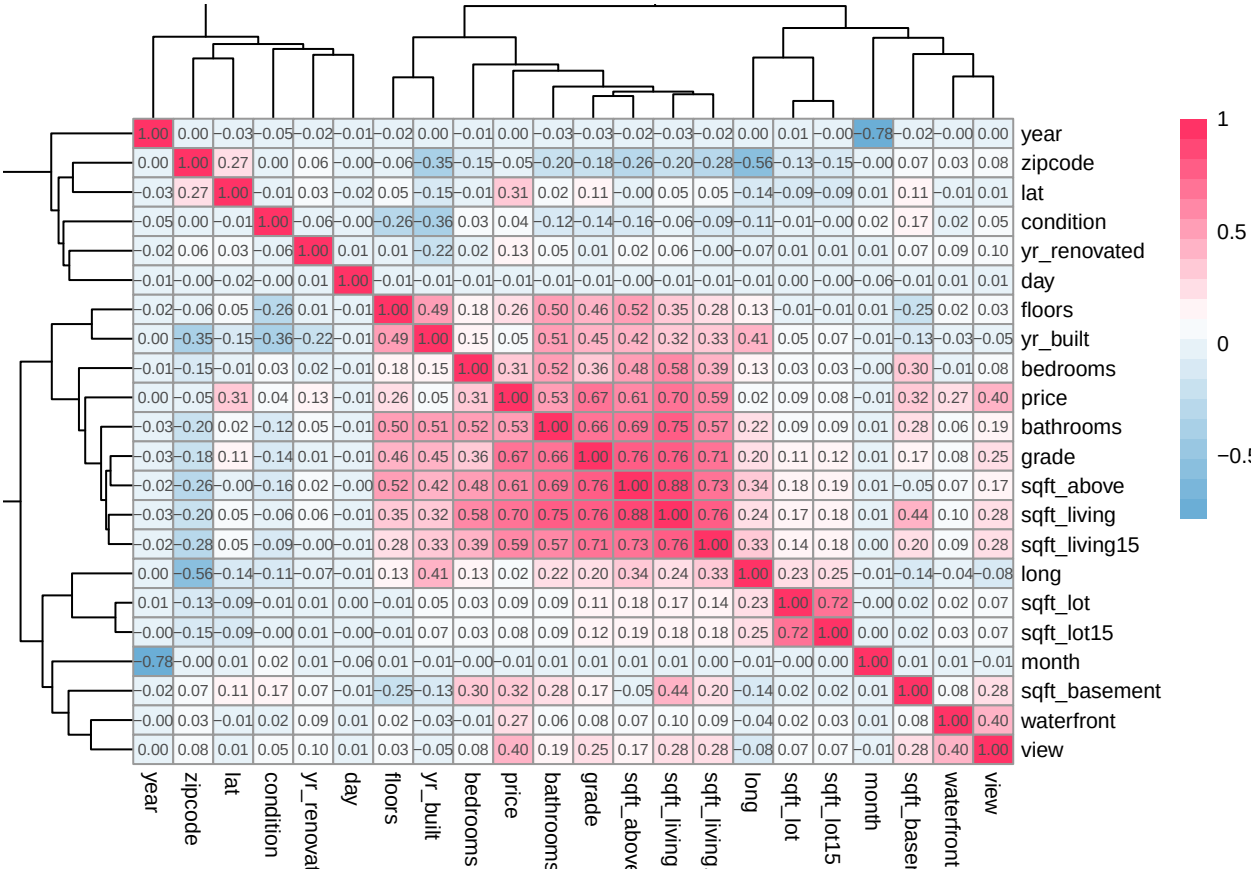
In this pivotal section, we undertake a rigorous data cleaning process, focusing on eliminating unnecessary variables and managing highly correlated variables. This step is vital for enhancing the integrity and validity of our dataset, ensuring that our predictive models are based on the most relevant and independent variables.

By methodically addressing these aspects, we aim to create a more streamlined and efficient dataset, thereby laying a solid foundation for robust and accurate predictive modeling in our real estate analysis.

### Correlation Analysis

In the "Correlation Analysis" section, we delve into examining the relationships between various features of the dataset and the target variable, 'price'. This involves creating a correlation matrix and corresponding plots to visually and statistically identify how different variables are related to each other and to house prices.

```
# Create a correlation Matrix
cor_matrix = cor(ndf_house)
correlation_df = as.data.frame(cor_matrix)

# New dataframe with variables 'highly' (>0.2) correlated with price
x_high = subset(ndf_house,
                select = c(view, waterfront, sqft_basement, sqft_living,
                           sqft_living15, sqft_above, grade, bathrooms,
                           bedrooms, floors, lat))

# Create a Heatmap
pheatmap(cor_matrix,
         color = colorRampPalette(c("#6baed6", "white", "#ff3366"))(20),
         main = "Correlation Matrix Heatmap",
         fontsize = 8,
         cellwidth = 15,
         cellheight = 11,
         display_numbers = TRUE
)
```




**Analysis:** Following the generation of the correlation plot, a thorough analysis is vital. For example, high correlations between 'sqft_living', 'grade', 'sqft_above', and 'price' indicate a strong linear relationship, suggesting that larger homes, built with a high-quality level of construction and design, and more above-ground square footage, tend to be more expensive. These variables could serve as key predictors in a pricing model. We will explore them further int he next model development process. However, it's essential to note that correlation does not imply causation. Variables like 'zipcode', now treated as categorical, will not be represented in this correlation matrix, reminding us to consider geographical influences separately. Additionally, observing any potential multicollinearity between predictors is crucial, as it can affect the reliability of the regression model. Finally, interpreting these correlations within the context of the real estate market in King County provides insights into local housing trends and factors influencing house prices.

### Unraveling High Correlation in Data Variables

This section focuses on identifying highly correlated variables within the King County house sales dataset. Through an R script, we systematically extract numeric variables and construct a correlation matrix, applying a threshold to spotlight significant correlations. We aim to reveal pairs of variables with a correlation coefficient exceeding 0.8, signifying strong linear relationships. This analysis is crucial in understanding interdependencies among variables, guiding us in avoiding multicollinearity in our predictive models and ensuring their statistical integrity and interpretability.

```r
# Identifying highly correlated variables

# Retain only the numeric columns in the dataset
df_house <- df_house[sapply(df_house, is.numeric)]

# use 'complete.obs' to handle missing values
corr_matrix <- cor(df_house, use = "complete.obs")
```

```r
threshold <- 0.8
high_corr <- which(abs(corr_matrix) > threshold, arr.ind = TRUE)
high_corr <- high_corr[high_corr[, 1] < high_corr[, 2], ]

# Find highly correlated predictors
for (pair in 1:nrow(high_corr)) {
    row <- high_corr[pair, "row"]
    col <- high_corr[pair, "col"]
    cat(names(df_house)[row], "and", names(df_house)[col],
        "have a correlation of", corr_matrix[row, col], "\n")
}
```

```
## sqft_living and sqft_above have a correlation of 0.8765966
## yr_renovated and renovated have a correlation of 0.9999685
## yr_built and age have a correlation of -0.9099238
```

### Streamlining the Dataset for Enhanced Analysis

This section of the analysis is dedicated to refining the dataset by removing variables that are redundant or unnecessary for our modeling objectives. Specifically, we remove columns such as 'sqft_living', 'yr_renovated', 'yr_built', 'month', and 'day'. This pruning is an essential step in data preparation, ensuring that our dataset is lean and focused, which helps in improving the efficiency and accuracy of our predictive models. By eliminating these variables, we aim to enhance the clarity and relevancy of our data analysis.

```r
# Remove redundant, unnecessary columns from dataset.
df_house[c("sqft_living", "yr_renovated",
           "yr_built", "month", "day")] <- list(NULL)
```

## Initial Statistical Data Summary

The dataset from King County includes 21,613 observations with 22 variables related to house sales. Variables include continuous data like price, square footage, and lat/long coordinates, and categorical data such as bedrooms, floors, and waterfront status. The price ranges from $75,000 to $7,700,000, with a mean of $540,088. Houses range from 0 to 33 bedrooms, reflecting diverse property types. The dataset also contains binary and ordinal variables, such as view and condition, that require dummy coding for analysis.

```r
str(df_house)
```

```
## 'data.frame':    21613 obs. of  18 variables:
##  $ price        : num  221900 538000 180000 604000 510000 ...
##  $ bedrooms     : int  3 3 2 4 3 4 3 3 3 3 ...
##  $ bathrooms    : num  1 2.25 1 3 2 4.5 2.25 1.5 1 2.5 ...
##  $ sqft_lot     : int  5650 7242 10000 5000 8080 101930 6819 9711 7470 6560 ...
##  $ floors       : num  1 2 1 1 1 1 2 1 1 2 ...
##  $ waterfront   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ view         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ condition    : int  3 3 3 5 3 3 3 3 3 3 ...
##  $ grade        : int  7 7 6 7 8 11 7 7 7 7 ...
##  $ sqft_above   : int  1180 2170 770 1050 1680 3890 1715 1060 1050 1890 ...
##  $ sqft_basement: int  0 400 0 910 0 1530 0 0 730 0 ...
##  $ lat          : num  47.5 47.7 47.7 47.5 47.6 ...
##  $ long         : num  -122 -122 -122 -122 -122 ...
##  $ sqft_living15: int  1340 1690 2720 1360 1800 4760 2238 1650 1780 2390 ...
##  $ sqft_lot15   : int  5650 7639 8062 5000 7503 101930 6819 9711 8113 7570 ...
##  $ year         : num  2014 2014 2015 2014 2015 ...
```

```
##  $ renovated    : num  0 1 0 0 0 0 0 0 0 0 ...
##  $ age          : num  68 32 90 58 36 22 28 60 63 20 ...
```

```
summary(df_house)
```

```
##      price            bedrooms        bathrooms        sqft_lot
##  Min.   :  75000   Min.   : 0.000   Min.   :0.000   Min.   :    520
##  1st Qu.: 321950   1st Qu.: 3.000   1st Qu.:1.750   1st Qu.:   5040
##  Median : 450000   Median : 3.000   Median :2.250   Median :   7618
##  Mean   : 540088   Mean   : 3.371   Mean   :2.115   Mean   :  15107
##  3rd Qu.: 645000   3rd Qu.: 4.000   3rd Qu.:2.500   3rd Qu.:  10688
##  Max.   :7700000   Max.   :33.000   Max.   :8.000   Max.   :1651359
##      floors        waterfront           view          condition
##  Min.   :1.000   Min.   :0.000000   Min.   :0.0000   Min.   :1.000
##  1st Qu.:1.000   1st Qu.:0.000000   1st Qu.:0.0000   1st Qu.:3.000
##  Median :1.500   Median :0.000000   Median :0.0000   Median :3.000
##  Mean   :1.494   Mean   :0.007542   Mean   :0.2343   Mean   :3.409
##  3rd Qu.:2.000   3rd Qu.:0.000000   3rd Qu.:0.0000   3rd Qu.:4.000
##  Max.   :3.500   Max.   :1.000000   Max.   :4.0000   Max.   :5.000
##      grade          sqft_above   sqft_basement         lat
##  Min.   : 1.000   Min.   : 290   Min.   :   0.0   Min.   :47.16
##  1st Qu.: 7.000   1st Qu.:1190   1st Qu.:   0.0   1st Qu.:47.47
##  Median : 7.000   Median :1560   Median :   0.0   Median :47.57
##  Mean   : 7.657   Mean   :1788   Mean   : 291.5   Mean   :47.56
##  3rd Qu.: 8.000   3rd Qu.:2210   3rd Qu.: 560.0   3rd Qu.:47.68
##  Max.   :13.000   Max.   :9410   Max.   :4820.0   Max.   :47.78
##       long        sqft_living15    sqft_lot15          year
##  Min.   :-122.5   Min.   : 399   Min.   :   651   Min.   :2014
##  1st Qu.:-122.3   1st Qu.:1490   1st Qu.:  5100   1st Qu.:2014
##  Median :-122.2   Median :1840   Median :  7620   Median :2014
##  Mean   :-122.2   Mean   :1987   Mean   : 12768   Mean   :2014
##  3rd Qu.:-122.1   3rd Qu.:2360   3rd Qu.: 10083   3rd Qu.:2015
##  Max.   :-121.3   Max.   :6210   Max.   :871200   Max.   :2015
##    renovated            age
##  Min.   :0.00000   Min.   :  8.00
##  1st Qu.:0.00000   1st Qu.: 24.00
##  Median :0.00000   Median : 46.00
##  Mean   :0.04229   Mean   : 49.61
##  3rd Qu.:0.00000   3rd Qu.: 69.00
##  Max.   :1.00000   Max.   :123.00
```

```
# Stat summary of the price
summary(df_house$price)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   75000  321950  450000  540088  645000 7700000
```

## Graphical Analysis

### Exploratory Analysis through Pairwise Scatter Plots

This subsection is dedicated to exploring the relationships between house prices and other key variables using pairwise scatter plots. These visualizations aim to unearth correlations that could indicate influential factors in housing prices within King County. By examining these relationships, we can hypothesize which features may drive property values and warrant further investigation in our predictive modeling.

The Pairwise scatter plot below shows the correlation between highly correlated variables extracted from

heatmap correlation matrix.

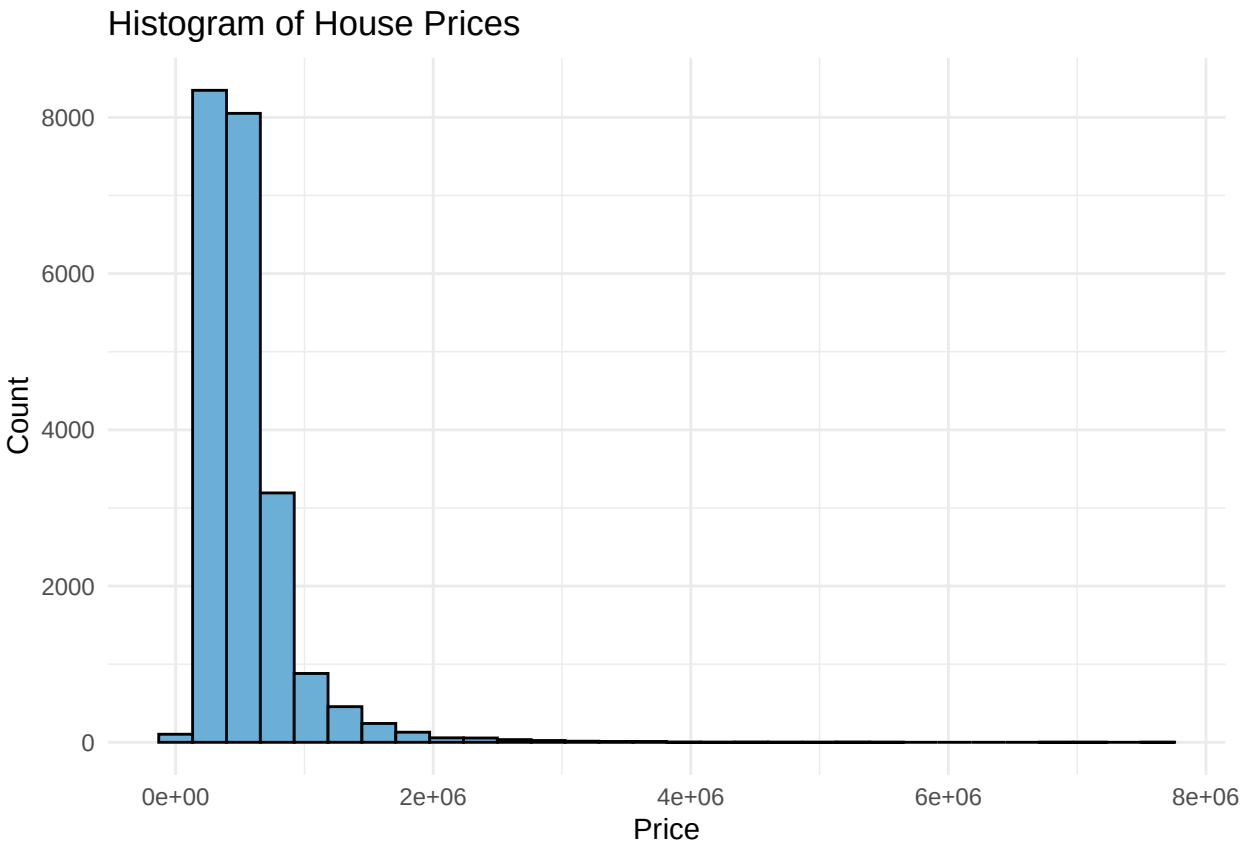
```
# Pairwise scatter plot with correlation coefficients
ggpairs(ndf_house,
        columns = c("price", "sqft_living", "bedrooms", "bathrooms", "grade"),
        title = "Pairwise Scatter Plots with House Price")
```


**Analysis:** The pairwise scatter plots reveal varying degrees of correlation between house prices and selected features. Notably, the square footage of living space (sqft_living) and construction grade (grade) show substantial positive correlations with price, indicating that larger, higher-quality homes tend to command higher prices. Conversely, the number of bedrooms shows a weaker correlation, suggesting that while size matters, the mere number of bedrooms is less predictive of price. These insights are critical for focusing our modeling efforts on the most impactful predictors. Also, notice that each variable's distribution is shown on the diagonal, with price notably skewed towards lower values, indicating most homes are on the more affordable end of the spectrum with fewer high-priced outliers.

### Distribution of Sales Prices

This subsection aims to analyze the distribution of sales prices across the dataset. The histogram provides visual insight into the range and frequency of house prices, highlighting the market's tendencies.

```
# Plot a Histogram of house sales prices
ggplot(df_house, aes(x = price)) +
  geom_histogram(bins = 30, fill = "#6baed6", color = "black") +
  labs(title = "Histogram of House Prices", x = "Price", y = "Count") +
  theme_minimal()
```

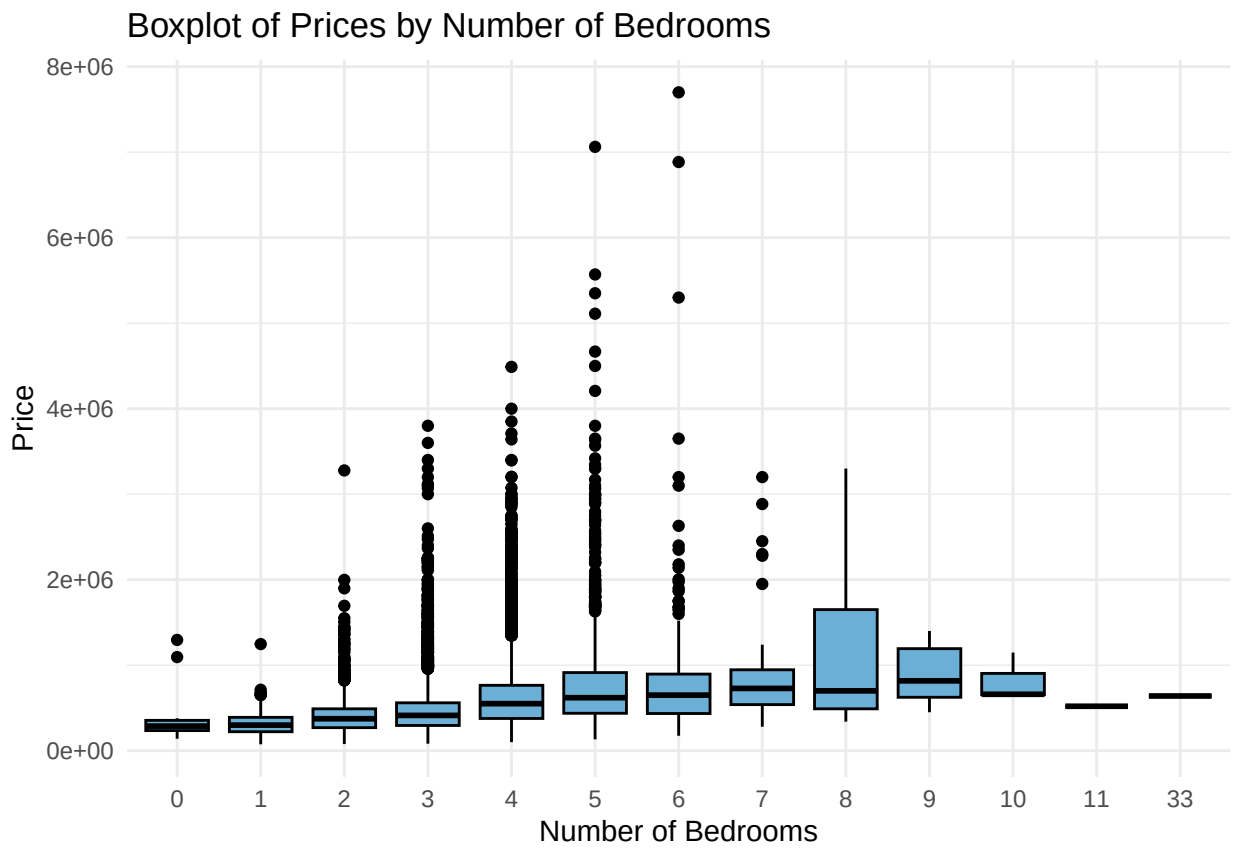



**Analysis:** The histogram below shows the distribution of house prices, revealing that most houses are in the lower price range with a significant decrease in the number of houses as the price increases, indicating a right-skewed distribution with relatively few high-priced houses. This skewness suggests that while the majority of the market consists of moderately priced homes, luxury properties significantly drive up the average price.

### Variability of Housing Prices Across Bedroom Counts

This subsection will analyze the relationship between the number of bedrooms in a property and its market price. By employing a boxplot, we can visually discern the central tendency and dispersion of house prices within each bedroom category, revealing insights into how additional bedrooms could potentially affect property values.

```
# Boxplot for price by number of bedrooms
ggplot(df_house, aes(x = factor(bedrooms), y = price)) +
  geom_boxplot(fill = "#6baed6", color = "black") +
  labs(title = "Boxplot of Prices by Number of Bedrooms",
       x = "Number of Bedrooms", y = "Price") +
  theme_minimal()
```

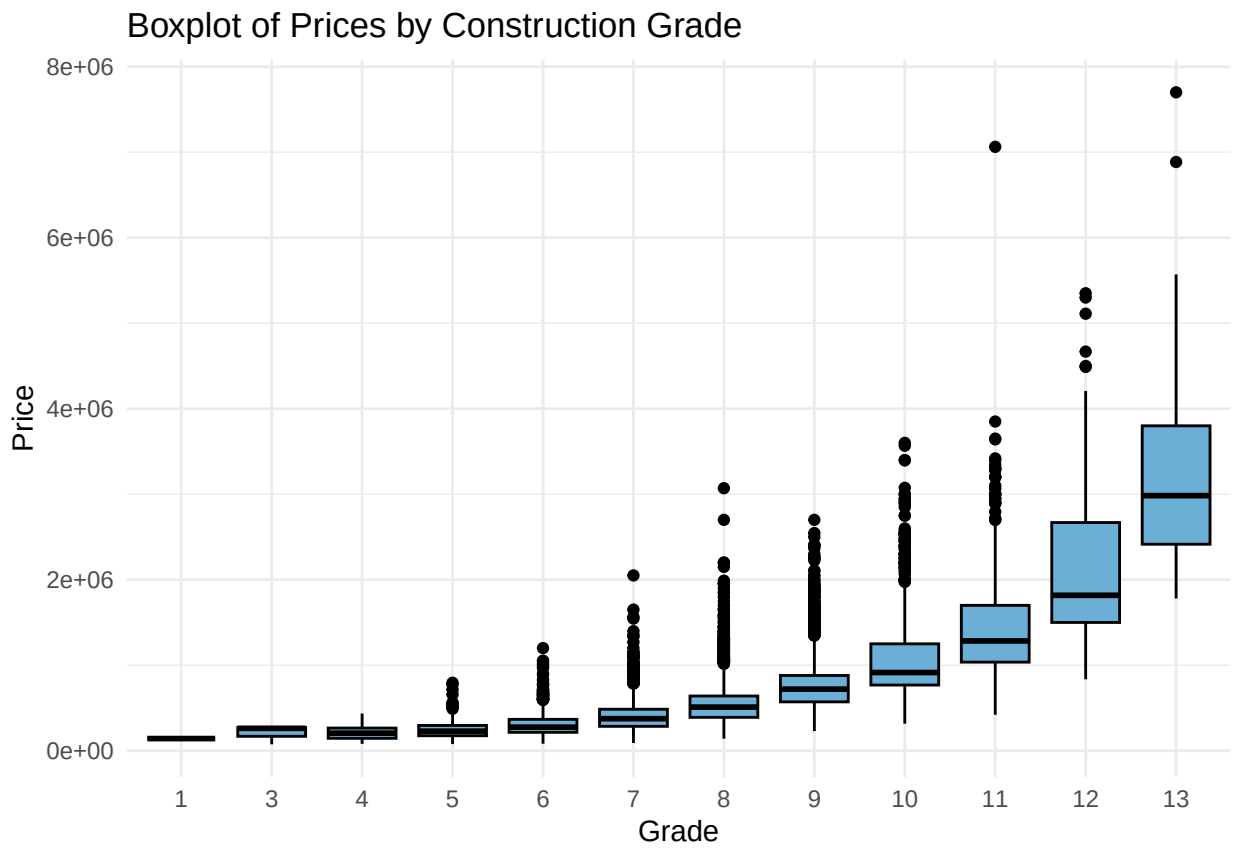



**Analysis:** The provided boxplot depicts the distribution of house prices with respect to the number of bedrooms. It shows a general increase in median price as the number of bedrooms increases up to a certain point, after which the median price plateaus and then fluctuates. Notably, homes with an exceptionally high number of bedrooms (e.g., 11, 33) exhibit significant price variability and outlier presence. This suggests a more complex relationship where factors beyond mere bedroom count may influence the higher pricing tiers. The presence of outliers, especially in categories with fewer bedrooms, indicates exceptions to general trends, possibly due to location, property condition, or other value-adding features.

### Price Variability by Construction Grade

This subsection explores the relationship between house prices and construction grades. Construction grade is an indicator of the quality and design of a building, which can significantly impact its market value. The boxplot visualizes the distribution of house prices within each grade category, revealing how price variability and central tendencies change with the grade.

```
# Boxplot for price by construction grade
ggplot(df_house, aes(x = factor(grade), y = price)) +
  geom_boxplot(fill = "#6baed6", color = "black") +
  labs(title = "Boxplot of Prices by Construction Grade",
       x = "Grade", y = "Price") +
  theme_minimal()
```

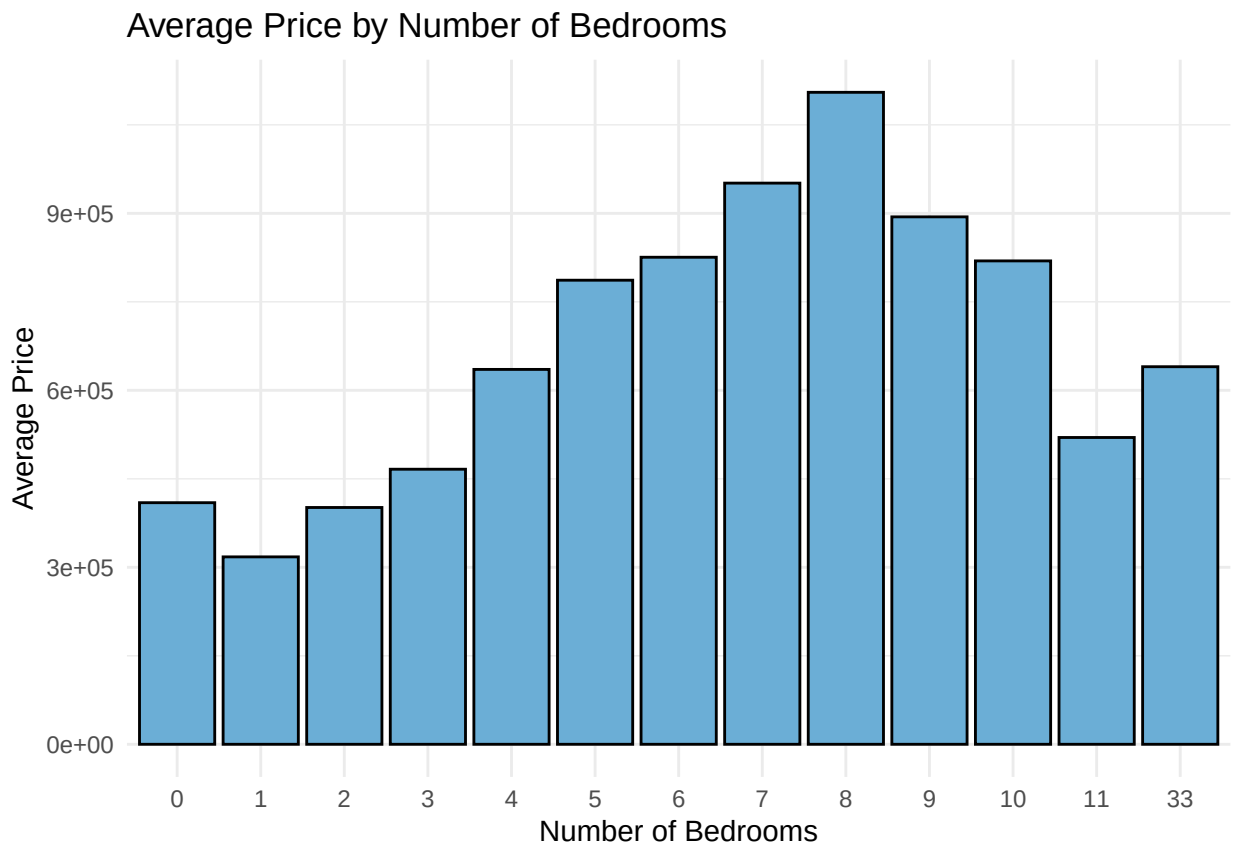



**Analysis:** The boxplot of house prices by construction grade shows that higher-grade homes tend to have a higher median price, indicating a positive correlation between construction quality and house value. Notably, the spread and range of prices increase with the grade, suggesting greater diversity in the higher-end market. Outliers are present across all grades, but are especially pronounced at higher grades, which may indicate a niche market for luxury homes with exceptional features not captured by the grade alone.

### Average Price by Number of Bedrooms

In this subsection, the analysis aims to uncover how the number of bedrooms influences the average house price. This investigation will reveal market trends and preferences, offering insights into the most sought-after property types.

```
# Average Price analysis
average_prices <- aggregate(price ~ bedrooms, data = ndf_house, FUN = mean)
ggplot(average_prices, aes(x = factor(bedrooms), y = price)) +
  geom_bar(stat = "identity", fill = "#6baed6", color = "black") +
  labs(title = "Average Price by Number of Bedrooms",
       x = "Number of Bedrooms",
       y = "Average Price") +
  theme_minimal()
```




**Analysis:** The bar chart depicting "Average Price by Number of Bedrooms" reveals a nuanced view of the housing market. Unlike the variability presented in the "Boxplot of Prices by Number of Bedrooms," which shows a broad price range across different bedroom counts, the bar chart focuses on average values, smoothing out extreme data points. It highlights a peak in average prices for mid-range bedroom counts, suggesting a higher market value for these properties. This pattern may reflect a balance between affordability and space that appeals to a wider demographic, contrasting with the outliers seen in the boxplot. There is a notable outlier at 33 bedrooms with a relatively low average price, which could indicate an atypical property or data error.

### House Prices by Waterfront Presence

Here the analysis examines the impact of a waterfront location on house prices. This visual comparison aims to highlight any premium attached to waterfront properties, which is a common factor in real estate valuation.

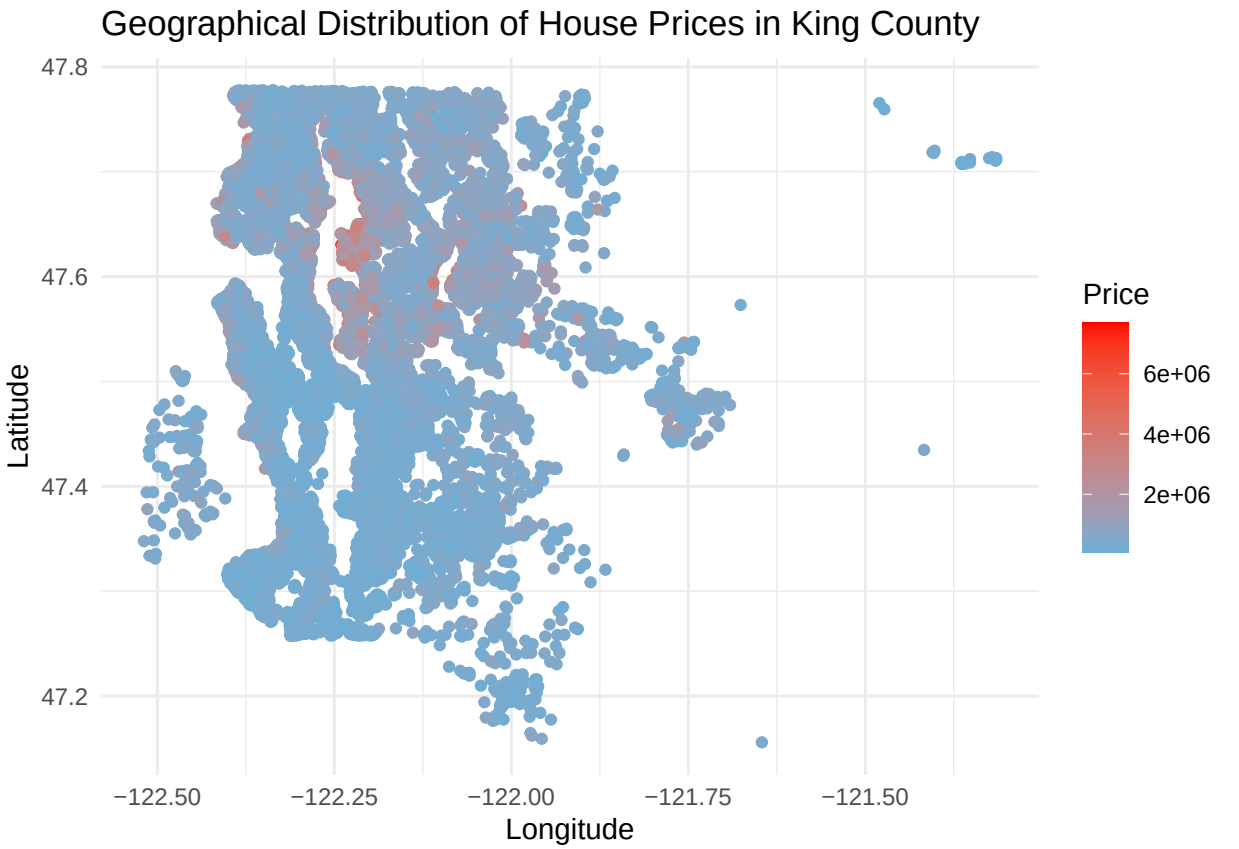
```
# Boxplot for Outlier analysis of Waterfront vs Mountain view
ggplot(df_house, aes(x = factor(waterfront), y = price)) +
  geom_boxplot(fill = "#6baed6", color = "black") +
  labs(title = "Boxplot of House Prices by Waterfront",
       x = "Waterfront", y = "Price") +
  theme_minimal()
```


**Analysis:** The boxplot illustrates a significant difference in the distribution of house prices based on the presence of a waterfront. Non-waterfront properties (denoted by 0) show a dense clustering of prices with fewer outliers, suggesting a more uniform pricing structure within this category. On the other hand, waterfront properties (denoted by 1) exhibit a higher median price and a much wider spread, indicating a greater variance in how much buyers are willing to pay for this luxury feature. The presence of outliers in the waterfront category also suggests that certain premium properties command exceptional prices, which are not as prevalent in non-waterfront real estate. This analysis underscores the value added by waterfront locations, which can significantly increase property values and attract a niche market willing to invest in these desirable features.

### Mapping Price Hotspots: Geospatial Analysis of King County's Real Estate

This geospatial visualization maps the distribution of house prices across King County. By plotting price data against longitude and latitude, we aim to identify regional price trends and potential hotspots of high-value properties. This analysis provides insights into how location within the county correlates with housing prices, supporting a comprehensive understanding of the real estate market dynamics.

```
# Scatter plot of properties with mid-point transition color
ggplot(data = df_house, aes(x = long, y = lat, color = price)) +
  geom_point(alpha = 10) +
  scale_color_gradient(low = "#6baed6", high = "red") +
  labs(title = "Geographical Distribution of House Prices in King County",
       x = "Longitude", y = "Latitude", color = "Price") +
  theme_minimal()
```




**Analysis:** The geographical map scatter plot reveals a concentration of higher-priced properties (indicated by warmer colors) along specific geographic corridors, more specifically situated around the latitude line of 47.6 and longitude between -122.25 and -122.00, which corresponds to the central and northern parts of Seattle, suggesting that certain areas command premium prices. Notably, waterfront locations and urban centers show elevated price levels. The relatively lower-priced properties per square foot, shown in colder colors, are more dispersed and located primarily south of central Seattle, extending towards Tacoma, as well as in the outlying suburban areas. It is also noticeable that along the latitudinal line around 47.4, there are pockets of high-priced properties per square foot, potentially indicating affluent neighborhoods or areas with high-value real estate. This spatial pattern underscores the importance of location in property valuation and can guide potential investments and urban development strategies. The map clearly shows a correlation between location and property value per square foot, with central urban areas exhibiting the highest values. This pattern is typical for urban centers where proximity to amenities, employment opportunities, and other socioeconomic factors drive up real estate prices. The visual representation also highlights outliers, which could be subject to further investigation to understand the factors driving their exceptional market value.

## Summary: Comprehensive Data Assessment and Visual Exploration

In Section II, we dove into the analytical scrutiny of King County's house sales dataset and thoroughly explored it, examining both continuous and categorical variables through statistical tests and extensive graphical analysis, vital for the predictive modeling accuracy. We highlighted the strong correlations between variables like 'sqft_living', 'grade', 'sqft_above', and 'price'. The section progresses through statistical examinations, categorical conversions, and novel variable formulations, all while maintaining a critical eye on data integrity. Extensive graphical analyses elucidate underlying trends, from scatter plots to geospatial mappings, provided nuanced insights into the factors influencing house prices, setting the stage for advanced predictive modeling in subsequent sections, and painting a vivid landscape of the market's intricacies. This foundational work paves the way for sophisticated modeling techniques, poised to capture the essence of the

county's real estate dynamics.

# III. Model Development Process

*Build a regression model to predict price. And of course, create the train data set which contains 70% of the data and use set.seed (1023). The remaining 30% will be your test data set. Investigate the data and combine the level of categorical variables if needed and drop variables. For example, you can drop id, Latitude, Longitude, etc.*

The KC House sales dataset is split into train(70%) and test(30%) datasets, with 15129 observations in the train dataset and 6484 observations in the test dataset.

```
set.seed(1023)
n<-dim(df_house)[1]
IND<-sample(c(1:n),round(n*0.7))
train.dat<-df_house[IND,]
test.dat<-df_house[-c(IND),]

dim(train.dat)
```

```
## [1] 15129    18
```

```
dim(test.dat)
```

```
## [1] 6484   18
```

**Analysis**: The house_lm model to predict price has: - Residual Standard Error of 193,600 - Multiple R-square of 71.38% - p-value of < 2.2e-16 - MSE of 37,494,980,807

Overall, the model appears to be statistically significant overall given the low p-value for the F-statistic. The multiple R-square suggests that 71.38% of the variability in price is explained by the model. Moreover, all most predictors (except sqft_lot) have a statistically significant impact on the house price. Predictions on the test dataset should be done to further validate model usefulness.

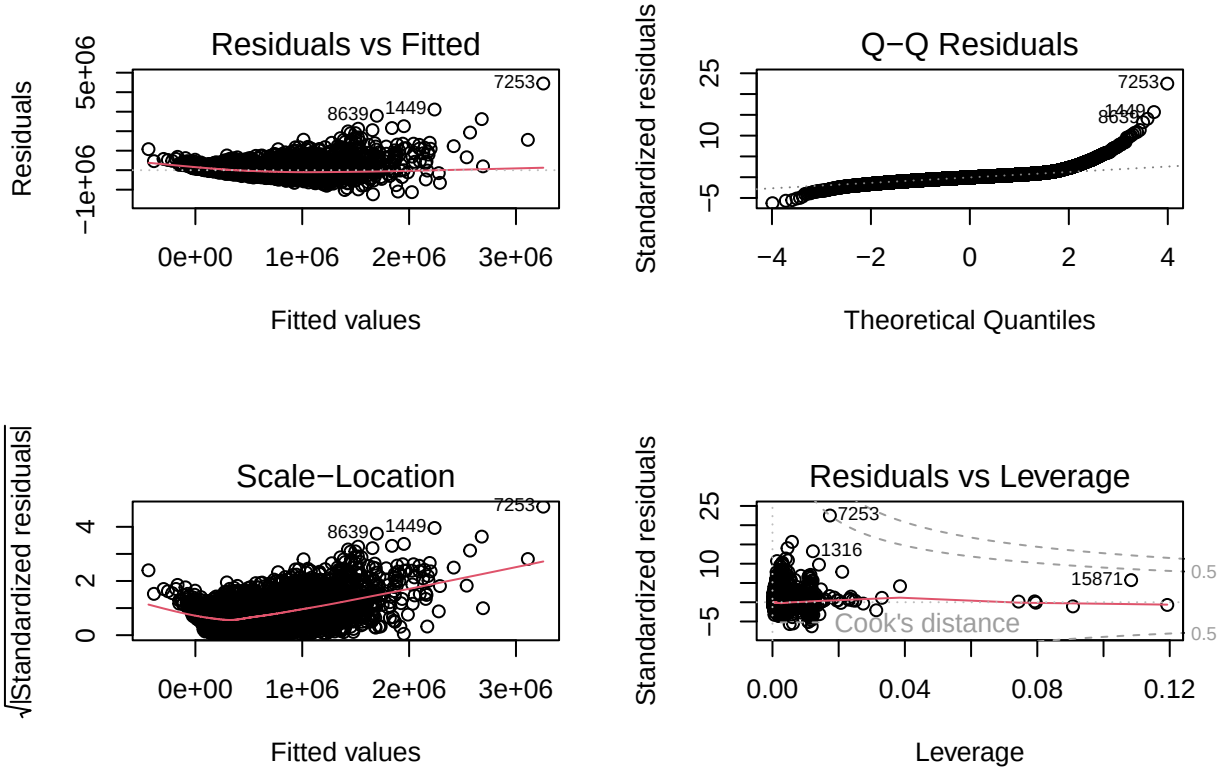
From the model plot we observe the following: - LINEARITY ASSUMPTION: From the Residuals vs Fitted plot, as the residuals seem to be randomly dispersed around the horizontal axis and the line is horizontal, a linear regression model may be appropriate, however we may need to transforming the response variable. - NORMALITY ASSUMPTION: From the Q-Q Residuals plot, as the points are out of the diagonal line on either ends, the residuals do not meet the normality assumption. - CONSTANT VARIANCE ASSUMPTION: The scale location plot points to non constant variance. The HOMOSCEDASTICITY ASSUMPTION is violated. Moreover the line is curvilinear. - The impact of bad data like influential and outlier observations seems to be impactful when inspecting the Residual vs. Leverage graph

```
house_lm<-lm(price ~.,data=train.dat)
summary(house_lm)
```

```
##
## Call:
## lm(formula = price ~ ., data = train.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1236951   -98912    -9119    76684  4444553
##
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.118e+08  7.226e+06 -15.475  < 2e-16 ***
## bedrooms      -3.234e+04  2.197e+03 -14.720  < 2e-16 ***
## bathrooms      3.793e+04  3.821e+03   9.926  < 2e-16 ***
## sqft_lot       1.302e-01  5.979e-02   2.177 0.029494 *
```

```
## floors         1.109e+04  4.261e+03   2.603 0.009242 **
## waterfront     5.261e+05  2.143e+04  24.553  < 2e-16 ***
## view           5.158e+04  2.543e+03  20.285  < 2e-16 ***
## condition      3.320e+04  2.768e+03  11.995  < 2e-16 ***
## grade          9.651e+04  2.546e+03  37.902  < 2e-16 ***
## sqft_above     1.685e+02  4.374e+00  38.523  < 2e-16 ***
## sqft_basement  1.529e+02  5.167e+00  29.583  < 2e-16 ***
## lat            5.673e+05  1.243e+04  45.649  < 2e-16 ***
## long          -1.151e+05  1.410e+04  -8.163 3.52e-16 ***
## sqft_living15  3.578e+01  4.090e+00   8.748  < 2e-16 ***
## sqft_lot15    -3.239e-01  8.632e-02  -3.752 0.000176 ***
## year           3.471e+04  3.473e+03   9.994  < 2e-16 ***
## renovated      1.895e+05  8.381e+03  22.613  < 2e-16 ***
## age            2.397e+03  8.630e+01  27.772  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 199200 on 15111 degrees of freedom
## Multiple R-squared:  0.697,  Adjusted R-squared:  0.6967
## F-statistic:  2045 on 17 and 15111 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,2))
plot(house_lm)
```




```r
MSE <- summary(house_lm)$sigma^2
print(MSE)
```

```
## [1] 39678071311
```

```
vif(house_lm)
```

```
##      bedrooms     bathrooms      sqft_lot        floors    waterfront
##      1.625094      3.301059      2.076177      2.015287      1.183776
##          view     condition         grade    sqft_above sqft_basement
##      1.409452      1.248831      3.399313      4.947021      2.001923
##           lat          long sqft_living15    sqft_lot15          year
##      1.124557      1.512058      3.022717      2.089128      1.006528
##     renovated           age
##      1.093130      2.366014
```

**Analysis**: The R-square values on both training and test data are quite close - 71.38% and 70.86% respectively. This suggests that the model generalizes well to new data, maintaining a similar level of explanatory power. The RMSE of 204,868.3 indicates the average magnitude of errors in predicting house prices on the test data. The SSE of 2.721402e+14 represents the sum of squared differences between predicted and observed values on the test data. A lower RMSE and SSE indicates better model fit, and we will explore furher on how these values can be lowered.

```
# Test data Predictions
house_lm_test_pred <- predict(house_lm, newdata = test.dat)

house_lm_test_mse <- mean((house_lm_test_pred - test.dat$price)^2)
house_lm_test_rmse <- sqrt(house_lm_test_mse)
house_lm_test_residuals <- test.dat$price - house_lm_test_pred
house_lm_test_rsq <- 1 - var(house_lm_test_residuals) / var(test.dat$price)
house_lm_test_sse <- sum((test.dat$price - house_lm_test_pred)^2)

# Add the predictions to the results
results.df <- data.frame(model = "Linear Regression Test Data Predictions",
                         R.Squared.Train = summary(house_lm)$r.square,
                         R.Squared.Test = house_lm_test_rsq,
                         RMSE.test = house_lm_test_rmse,
                         SSE.test = house_lm_test_sse)

print(results.df)
```

```
##                                     model R.Squared.Train R.Squared.Test
## 1 Linear Regression Test Data Predictions       0.6970168      0.6921461
##   RMSE.test     SSE.test
## 1  210589.7 2.875525e+14
```

**Analysis**: The insignificant predictor sqft_lot is dropped and the model is refitted. We observe that the Multiple R-square value remains unchanged at 71.38%. The model is as follows:

Price = -74344803.92767 + -34633.405255bedrooms + 32821.338262bathrooms + 143.671881sqft_living + 8767.015515floors + 531351.549043waterfront + 52065.87946view + 24875.912771condition + 82737.693562grade + 22.301049sqft_above + -896.223982yr_built + 4065.130653yr_renovated + -507.797776zipcode + 473638.095898lat + -206204.537141long + 21.65297sqft_living15 + -0.25171sqft_lot15 + 38482.930296year + 1380.790546month + -331.741298day + -7982223.272107renovated + 1440.530732age + 101303.883852price_binary

```
predictors_to_drop <- c("sqft_lot")

# Update the model by excluding the specified predictors
updated <- as.formula(
```

```
  paste("price ~ .",
        paste0("- `", predictors_to_drop, "`", collapse = "")))

house_lm <- update(house_lm, updated)
summary(house_lm)
```

```
##
## Call:
## lm(formula = price ~ bedrooms + bathrooms + floors + waterfront +
##     view + condition + grade + sqft_above + sqft_basement + lat +
##     long + sqft_living15 + sqft_lot15 + year + renovated + age,
##     data = train.dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1229780   -99024    -9212    76414  4442353
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.116e+08  7.226e+06 -15.442  < 2e-16 ***
## bedrooms      -3.252e+04  2.196e+03 -14.814  < 2e-16 ***
## bathrooms      3.804e+04  3.822e+03   9.953  < 2e-16 ***
## floors         1.079e+04  4.259e+03   2.533  0.01133 *
## waterfront     5.259e+05  2.143e+04  24.542  < 2e-16 ***
## view           5.172e+04  2.543e+03  20.342  < 2e-16 ***
## condition      3.307e+04  2.768e+03  11.947  < 2e-16 ***
## grade          9.661e+04  2.546e+03  37.942  < 2e-16 ***
## sqft_above     1.691e+02  4.365e+00  38.744  < 2e-16 ***
## sqft_basement  1.531e+02  5.167e+00  29.639  < 2e-16 ***
## lat            5.664e+05  1.242e+04  45.597  < 2e-16 ***
## long          -1.123e+05  1.404e+04  -7.996 1.38e-15 ***
## sqft_living15  3.522e+01  4.083e+00   8.627  < 2e-16 ***
## sqft_lot15    -1.960e-01  6.323e-02  -3.099  0.00194 **
## year           3.479e+04  3.474e+03  10.014  < 2e-16 ***
## renovated      1.898e+05  8.381e+03  22.643  < 2e-16 ***
## age            2.405e+03  8.623e+01  27.884  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 199200 on 15112 degrees of freedom
## Multiple R-squared:  0.6969, Adjusted R-squared:  0.6966
## F-statistic:  2172 on 16 and 15112 DF,  p-value: < 2.2e-16
```

```
dispRegFunc(house_lm)
```

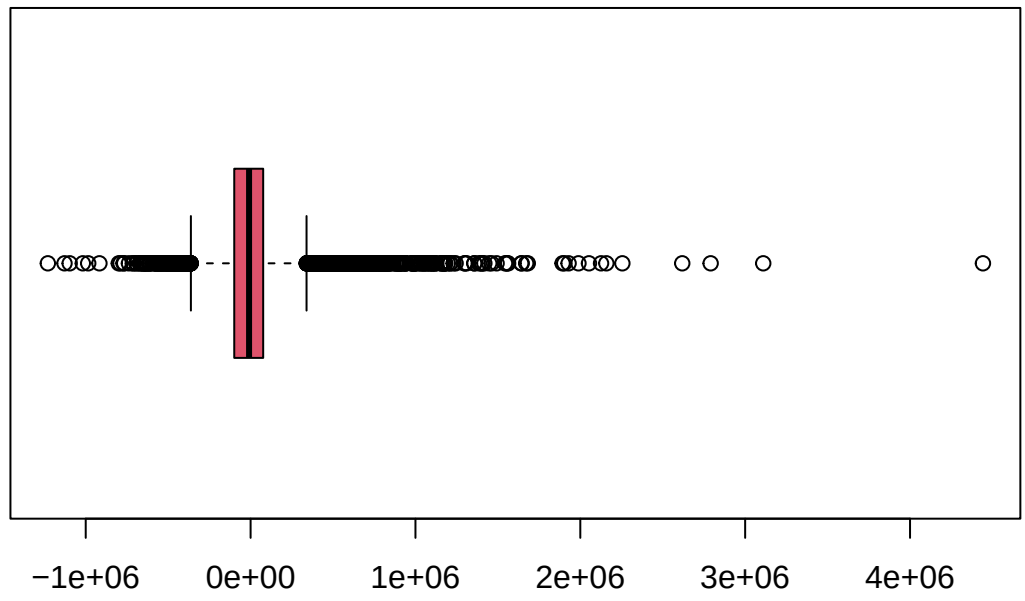
```
## [1] "Y = -111590227.725111 + -32524.766156bedrooms + 38035.229035bathrooms + 10787.175028floors + 525
```

**Analysis**:

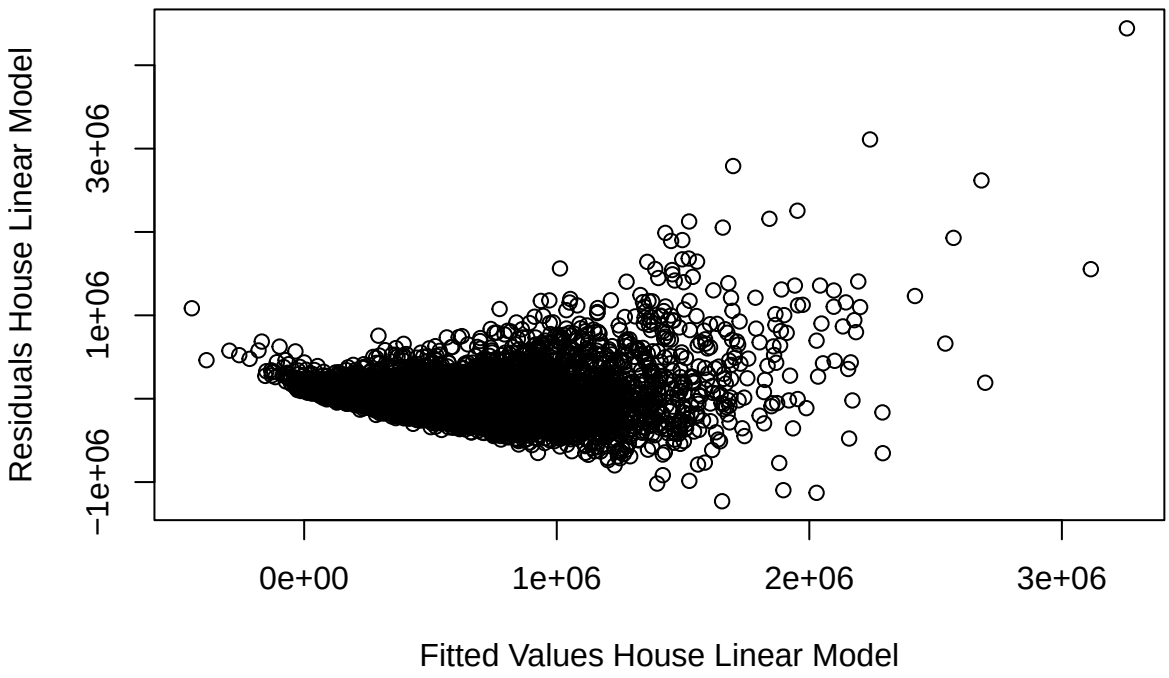
On plotting the boxplot of residuals, we observe multiple outliers on both ends of the whiskers. Moreover, when we plot the residuals against the fitted values, we observe that the residuals spread out with increase in fitted values along x-axis.

```
ei <- house_lm$residuals

boxplot(ei, horizontal=TRUE,
```

```
        staplewex=0.5, col=2, xlab="House Price Regression Residuals")
```




```
plot(house_lm$fitted.values, ei,
     xlab="Fitted Values House Linear Model",
     ylab="Residuals House Linear Model")
```




**Analysis**: Predictors with low p-values of $< 2.2e\text{-}16$ (e.g. bedrooms, bathrooms, sqft_living, etc.) are statistically significant and are important in predicting price. Some predictors that have a have higher p-value (e.g. floors, zipcode, month, day) may not be statistically significant in predicting price.

```
anova(house_lm)
```

```
## Analysis of Variance Table
##
## Response: price
##                  Df     Sum Sq    Mean Sq   F value  Pr(>F)
## bedrooms          1 1.8429e+14 1.8429e+14 4643.4916 < 2e-16 ***
## bathrooms         1 3.5576e+14 3.5576e+14 8963.8807 < 2e-16 ***
## floors            1 3.0574e+09 3.0574e+09    0.0770 0.78136
## waterfront        1 9.2404e+13 9.2404e+13 2328.2653 < 2e-16 ***
## view              1 1.1533e+14 1.1533e+14 2905.9410 < 2e-16 ***
## condition         1 1.6207e+13 1.6207e+13  408.3704 < 2e-16 ***
## grade             1 3.0945e+14 3.0945e+14 7797.1050 < 2e-16 ***
## sqft_above        1 4.0555e+13 4.0555e+13 1021.8607 < 2e-16 ***
## sqft_basement     1 7.8844e+13 7.8844e+13 1986.6033 < 2e-16 ***
## lat               1 1.2513e+14 1.2513e+14 3152.7916 < 2e-16 ***
## long              1 1.2985e+13 1.2985e+13  327.1806 < 2e-16 ***
## sqft_living15     1 2.8011e+12 2.8011e+12   70.5792 < 2e-16 ***
## sqft_lot15        1 2.0893e+11 2.0893e+11    5.2644 0.02178 *
## year              1 3.5173e+12 3.5173e+12   88.6236 < 2e-16 ***
## renovated         1 1.0800e+13 1.0800e+13  272.1317 < 2e-16 ***
## age               1 3.0859e+13 3.0859e+13  777.5446 < 2e-16 ***
## Residuals     15112 5.9976e+14 3.9688e+10
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

**Analysis**:

A two sides t statistical test is used for testing individual coefficients and their significance. The critical t -value applicable given alpha=0.01 and n-2 degrees of freedom is 2.576. H0: intercept =0, HA: intercept is not 0 H0: slope= 0 , HA: slope is not 0 Decision rule: when t > t critical reject null

The model, as indicated by the significant coefficients, suggests that features such as the number of bedrooms, bathrooms, square footage of living space, waterfront status, view, grade, etc, play a statistically significant role in predicting the house price.

```
# We divide by 2 because this is a two tail test
# ... if alpha=0.05, then use .05/2
conf= 0.01/2

# Manually calculate the degrees of freedom
df<-21613-2
value<-formatC(qt(conf,df,lower.tail=FALSE))
print(paste("Critical T values: ",value))
```

```
## [1] "Critical T values:  2.576"
```

```
# Extract coefficients in matrix
matrix_coef <- summary(house_lm)$coefficients
matrix_coef
```

```
##                    Estimate   Std. Error    t value      Pr(>|t|)
## (Intercept)   -1.115902e+08 7.226416e+06 -15.441987  2.184066e-53
## bedrooms      -3.252477e+04 2.195592e+03 -14.813668  2.650259e-49
## bathrooms      3.803523e+04 3.821611e+03   9.952668  2.895154e-23
## floors         1.078718e+04 4.259203e+03   2.532675  1.132963e-02
## waterfront     5.259293e+05 2.143014e+04  24.541568 1.877088e-130
## view           5.171977e+04 2.542536e+03  20.341800  8.982785e-91
## condition      3.306570e+04 2.767776e+03  11.946667  9.490708e-33
## grade          9.660723e+04 2.546148e+03  37.942497 5.462908e-301
## sqft_above     1.691345e+02 4.365482e+00  38.743612 3.730091e-313
## sqft_basement  1.531308e+02 5.166582e+00  29.638698 1.063234e-187
## lat            5.664104e+05 1.242203e+04  45.597256  0.000000e+00
## long          -1.122994e+05 1.404470e+04  -7.995852  1.379457e-15
## sqft_living15  3.522177e+01 4.082684e+00   8.627111  6.910724e-18
## sqft_lot15    -1.959742e-01 6.323252e-02  -3.099262  1.943595e-03
## year           3.478544e+04 3.473546e+03  10.014389  1.560267e-23
## renovated      1.897771e+05 8.381128e+03  22.643383 1.159083e-111
## age            2.404611e+03 8.623474e+01  27.884487 6.689618e-167
```

```
# Matrix manipulation to extract estimates
my_estimates <- matrix_coef[ , 1]

# Step 6: Pr(>|t|) < 0.01 there is sufficient statistical evidence to reject
# null for both parameters. Using a t-test we noted that t-values
# (6.259865 and abs(4.102897) are larger than t-critical that is 2.637
```

$H_o$: Error variances are constant $H_a$: Error variances are not constant Decision Rule is if statistic> critical reject the null or if p-value < alpha (0.01) reject the hull

P value is < 2.2e-16. So we reject $H_o$, Error variances are not constant.

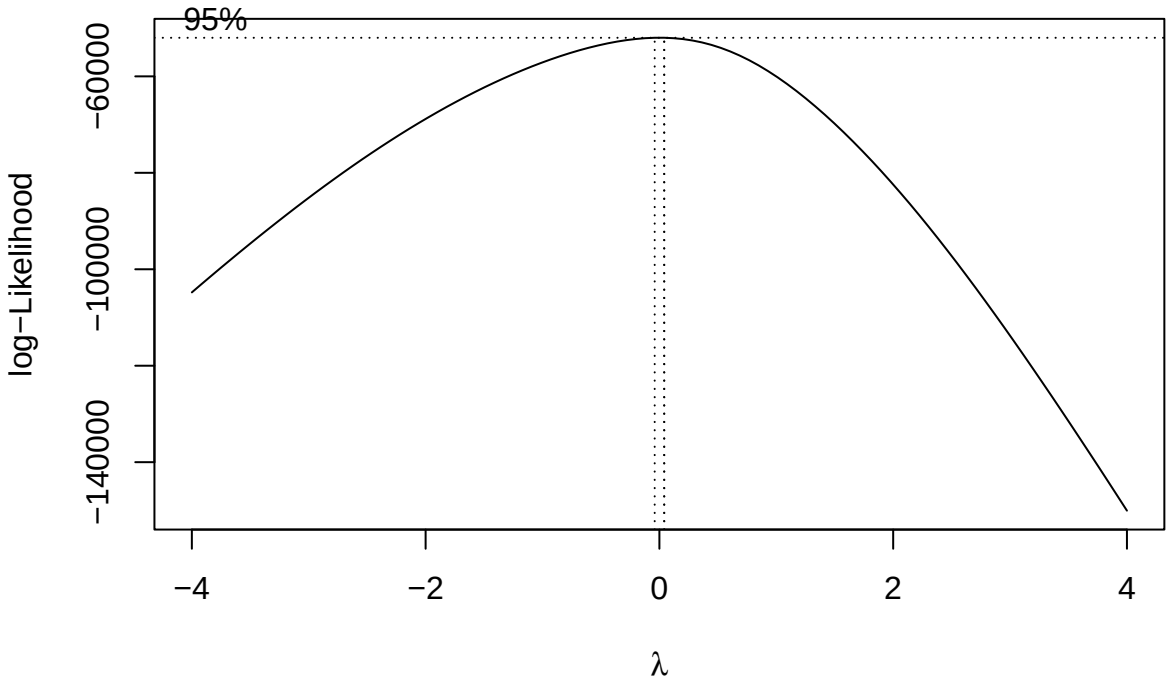
**Analysis**:

```
bptest(house_lm, studentize = FALSE)
```

```
##
##  Breusch-Pagan test
##
## data:  house_lm
## BP = 38445, df = 16, p-value < 2.2e-16
```

**Analysis**: For Boxcox transormation, the optimal lambda is -0.04 with 95% confidence interval range which is close to zero. Although, we can estimate lambda to be zero and apply logarithmic transformation of the data, we have done the boxcox transformation with exact optimal lambda value for better accuracy.

```
bc <- boxcox(house_lm, lambda=seq(-4, 4, by=0.1))
```




```
lambda <- bc$x[which.max(bc$y)]
cat("The optimal lambda is:", lambda, "\n")
```

```
## The optimal lambda is: 0.04040404
```

**Analysis:** After boxcox transformation, we observe that: - Residual Standard Error has reduced significantly to 0.004981 from 193,600 - Multiple R-square has increased to 84.03% from 71.38% - p-value remains same at $<$ 2.2e-16

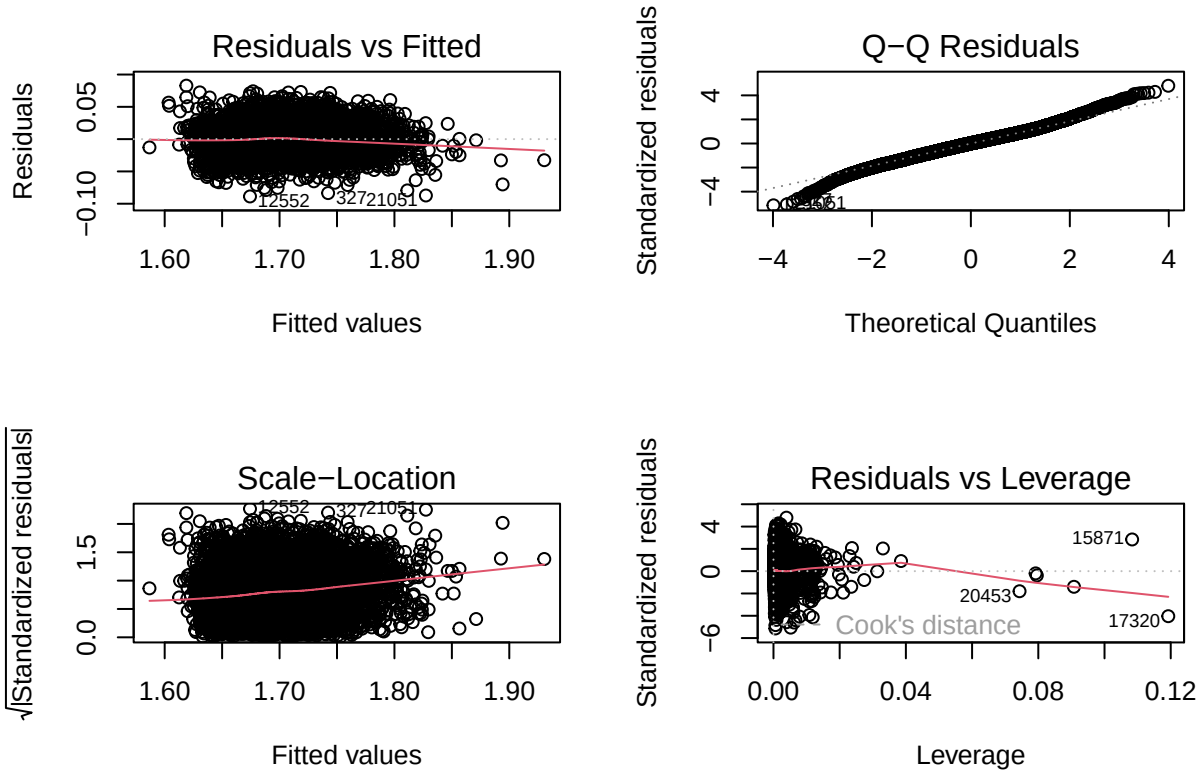
Overall, the model appears to be a much better fit that before. From the model plot we observe the following: - LINEARITY ASSUMPTION: The Residuals vs Fitted plot looks better than before and confirms that a linear regression model is appropriate - NORMALITY ASSUMPTION: The points are much better aligned along the diagonal in the Q-Q Residuals plot, however some tails remain - CONSTANT VARIANCE ASSUMPTION:

The Scale Location plot points to constant variance - There are still some outlier observations which may be to be impactful as seen from the the Residual vs. Leverage graph

```
house_lm1<-lm(price^lambda~.,data=train.dat)
summary(house_lm1)
```

```
##
## Call:
## lm(formula = price^lambda ~ ., data = train.dat)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.088758 -0.010861  0.000204  0.010680  0.082753
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.118e+01  6.270e-01 -17.824  < 2e-16 ***
## bedrooms      -9.122e-04  1.906e-04  -4.785 1.72e-06 ***
## bathrooms      4.468e-03  3.316e-04  13.475  < 2e-16 ***
## sqft_lot       3.371e-08  5.188e-09   6.497 8.48e-11 ***
## floors         4.938e-03  3.697e-04  13.355  < 2e-16 ***
## waterfront     2.446e-02  1.859e-03  13.153  < 2e-16 ***
## view           4.060e-03  2.207e-04  18.402  < 2e-16 ***
## condition      4.852e-03  2.402e-04  20.199  < 2e-16 ***
## grade          1.068e-02  2.209e-04  48.356  < 2e-16 ***
## sqft_above     9.662e-06  3.796e-07  25.455  < 2e-16 ***
## sqft_basement  1.118e-05  4.484e-07  24.926  < 2e-16 ***
## lat            9.337e-02  1.078e-03  86.593  < 2e-16 ***
## long          -4.247e-03  1.224e-03  -3.471  0.00052 ***
## sqft_living15  7.396e-06  3.549e-07  20.838  < 2e-16 ***
## sqft_lot15    -1.222e-08  7.490e-09  -1.631  0.10290
## year           3.848e-03  3.014e-04  12.768  < 2e-16 ***
## renovated      1.789e-02  7.272e-04  24.600  < 2e-16 ***
## age            2.108e-04  7.488e-06  28.148  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01728 on 15111 degrees of freedom
## Multiple R-squared:  0.7706, Adjusted R-squared:  0.7704
## F-statistic:  2986 on 17 and 15111 DF,  p-value: < 2.2e-16
```

```
# Plot
par(mfrow=c(2,2))
plot(house_lm1)
```




```
# Print the output of dispRegFunc wrapped in max 90 char width
output <- capture.output(dispRegFunc(house_lm1))
cat(paste(strwrap(output, width=80), collapse="\n"))
```

```
## [1] "Y = -11.176596 + -0.000912bedrooms + 0.004468bathrooms + 0sqft_lot +
## 0.004938floors + 0.024455waterfront + 0.00406view + 0.004852condition +
## 0.010684grade + 1e-05sqft_above + 1.1e-05sqft_basement + 0.093374lat +
## -0.004247long + 7e-06sqft_living15 + 0sqft_lot15 + 0.003848year +
## 0.01789renovated + 0.000211age"
```

**Analysis:** On predicting the values of the Boxcox transformed model on the test dataset, we observe a R-square test of 75.79% compared to R-square train of 84.03%, from which we conclude that the transformed model generalizes well to new data.

```
# Test data Predictions
pred <- predict(house_lm1,test.dat)^(1/lambda)
act <- test.dat$price

house_lm1_test_mse <- mean((pred - act)^2)
house_lm1_test_rmse <- sqrt(house_lm1_test_mse)
house_lm1_test_residuals <- act - pred
house_lm1_test_rsq <- 1 - var(house_lm1_test_residuals) / var(act)
house_lm1_test_sse <- sum((act - pred)^2)

# Append results
results.df = rbind(results.df,
                   data.frame(model = "Linear Regression Test after Boxcox",
```

```
                              R.Squared.Train = summary(house_lm1)$r.square,
                              R.Squared.Test = house_lm1_test_rsq,
                              RMSE.test = house_lm1_test_rmse,
                              SSE.test = house_lm1_test_sse))

print(results.df)
```

```
##                                    model R.Squared.Train R.Squared.Test
## 1 Linear Regression Test Data Predictions       0.6970168      0.6921461
## 2     Linear Regression Test after Boxcox       0.7706297      0.6609158
##   RMSE.test     SSE.test
## 1  210589.7 2.875525e+14
## 2  221573.0 3.183293e+14
```

# IV. Model Performance Testing

*Use the test data set to assess the model performances. Here, build the best multiple linear models by using the stepwise both ways selection method. Compare the performance of the best two linear models. Make sure that model assumption(s) are checked for the final linear model. Apply remedy measures (transformation, etc.) that helps satisfy the assumptions. In particular you must deeply investigate unequal variances and multicollinearity. If necessary, apply remedial methods (WLS, Ridge, Elastic Net, Lasso, etc.).*

**Analysis:** - add here the analysis of the stepwise model summary outcome.

Graph 1 (Residuals vs Fitted): (linearity assumption) A linear relationship seems appropriate. (The average mean error equal to zero assumption) The average mean seems to be equal to zero.

Graph 2 (Q-Q Residuals): (normality assumption) There is minor departure from a normal distribution at the tails.

Graph 3 (Scale-Location): (constant variance assumption) The residuals do not seem to be equally distributed throughout. (homoscedasticity assumption) The variances do not appear constant and the Breush-Pagan test indicates this with the p-value being lower than alpha.

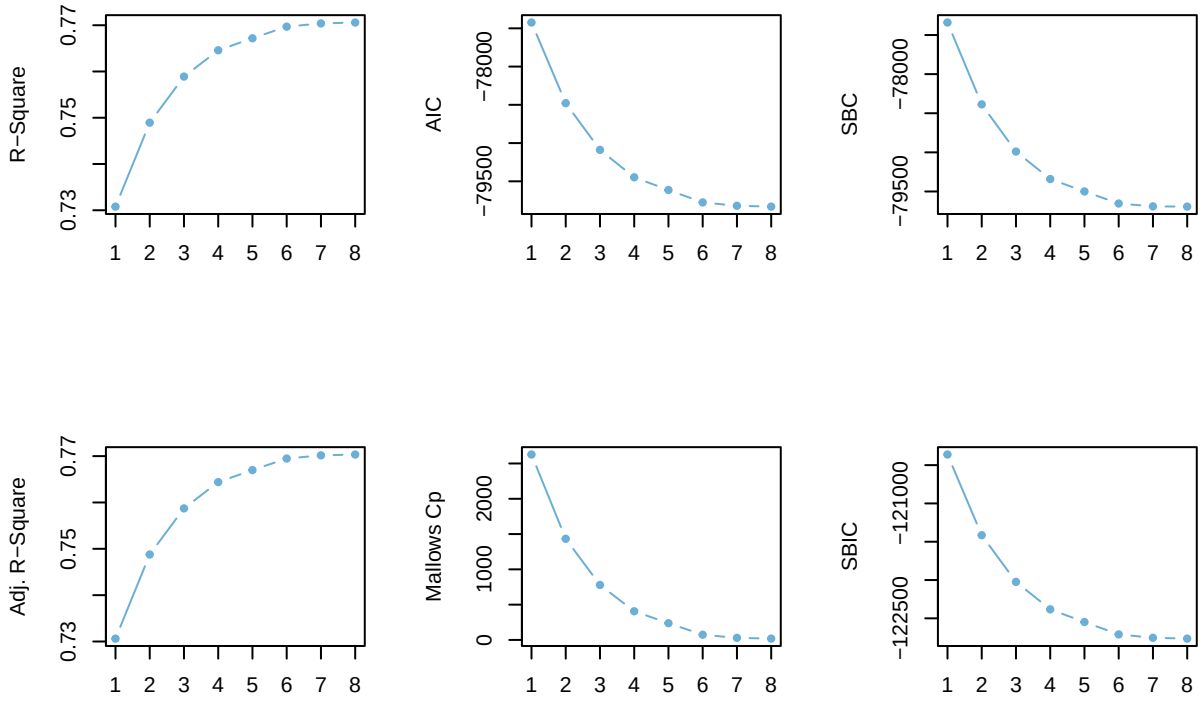
Graph 4 (Residuals vs Leverage): There are no influential outliers.

```
initial_model <- house_lm1

stepwise_model <- ols_step_both_p(initial_model, penter = 0.05, premove = 0.05)

final_model <- lm(formula = stepwise_model$model, data = train.dat)
summary(final_model)
```

```
##
## Call:
## lm(formula = stepwise_model$model, data = train.dat)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.088710 -0.010884  0.000223  0.010686  0.081879
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.120e+01  6.269e-01 -17.865  < 2e-16 ***
## bedrooms      -9.000e-04  1.905e-04  -4.724 2.33e-06 ***
## bathrooms      4.483e-03  3.315e-04  13.525  < 2e-16 ***
## floors         4.958e-03  3.695e-04  13.416  < 2e-16 ***
## view           4.057e-03  2.207e-04  18.385  < 2e-16 ***
## grade          1.069e-02  2.209e-04  48.406  < 2e-16 ***
## sqft_above     9.627e-06  3.790e-07  25.403  < 2e-16 ***
## sqft_basement  1.116e-05  4.483e-07  24.893  < 2e-16 ***
## lat            9.341e-02  1.078e-03  86.639  < 2e-16 ***
## sqft_living15  7.372e-06  3.546e-07  20.787  < 2e-16 ***
## age            2.110e-04  7.488e-06  28.180  < 2e-16 ***
## renovated      1.788e-02  7.272e-04  24.585  < 2e-16 ***
## condition      4.844e-03  2.402e-04  20.171  < 2e-16 ***
## waterfront     2.444e-02  1.859e-03  13.143  < 2e-16 ***
## year           3.850e-03  3.014e-04  12.774  < 2e-16 ***
## sqft_lot       2.794e-08  3.800e-09   7.353 2.03e-13 ***
## long          -4.389e-03  1.221e-03  -3.596 0.000324 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01729 on 15112 degrees of freedom
## Multiple R-squared:  0.7706, Adjusted R-squared:  0.7703
## F-statistic:  3173 on 16 and 15112 DF,  p-value: < 2.2e-16
```

```r
par(mfrow=c(2,3))

# Call the plot function for each plot individually with modified parameters
plot(stepwise_model$rsquare,
     xlab=NA, ylab="R-Square", pch=20, col="#6baed6", type="b")
plot(stepwise_model$aic,
     xlab=NA, ylab="AIC", pch=20, col="#6baed6", type="b")
plot(stepwise_model$sbc,
     xlab=NA, ylab="SBC", pch=20, col="#6baed6", type="b")
plot(stepwise_model$adjr,
     xlab=NA, ylab="Adj. R-Square", pch=20, col="#6baed6", type="b")
plot(stepwise_model$mallows_cp,
     xlab=NA, ylab="Mallows Cp", pch=20, col="#6baed6", type="b")
plot(stepwise_model$sbic,
     xlab=NA, ylab="SBIC", pch=20, col="#6baed6", type="b")
```




**Analysis:** - Please add here your analysis.

```r
# Weighted Least Squares Regression
# We notice from the scale-location graph of the main model
# that the error variances are unequal.
```

```r
# Calculating the weights for the model
ei <- house_lm$residuals
abs.ei <- abs(ei)
g1 <- lm(abs.ei ~ train.dat$price)
summary(g1)
```

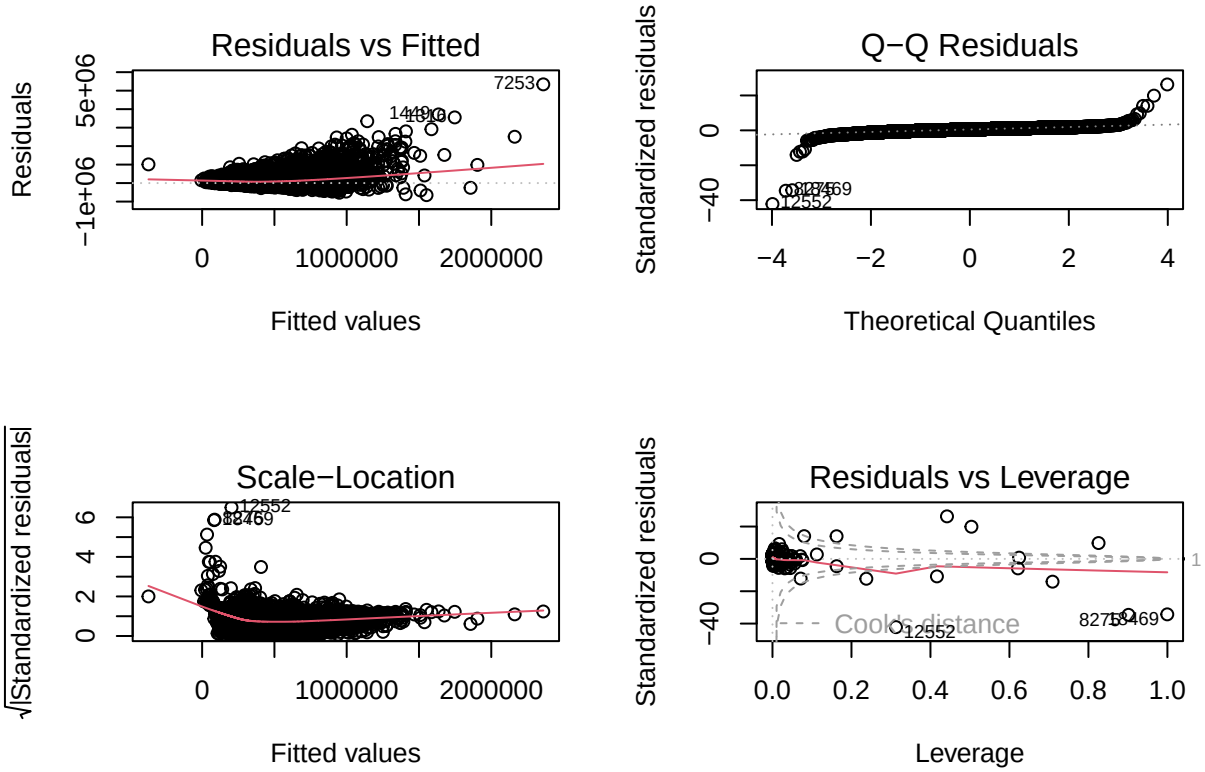
```
##
## Call:
## lm(formula = abs.ei ~ train.dat$price)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -580405  -66049  -12242   52720 2346203
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     -2.282e+04  1.726e+03  -13.22   <2e-16 ***
## train.dat$price  2.752e-01  2.660e-03  103.44   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 118300 on 15127 degrees of freedom
## Multiple R-squared:  0.4143, Adjusted R-squared:  0.4143
## F-statistic: 1.07e+04 on 1 and 15127 DF,  p-value: < 2.2e-16
```

```r
s <- g1$fitted.values
wi = 1/(s^2)

# Weighted-least squares regression
house_lm_wls <- lm(price ~ ., weights = wi, data = train.dat)

summary(house_lm_wls)
```

```
##
## Call:
## lm(formula = price ~ ., data = train.dat, weights = wi)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -57.982   0.043   0.873   1.607  32.558
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -4.453e+07  2.325e+06 -19.154  < 2e-16 ***
## bedrooms      -2.377e+04  9.076e+02 -26.187  < 2e-16 ***
## bathrooms      2.443e+04  1.962e+03  12.449  < 2e-16 ***
## sqft_lot       1.772e-01  3.348e-02   5.295 1.21e-07 ***
## floors         2.923e+04  2.063e+03  14.168  < 2e-16 ***
## waterfront     1.532e+05  3.316e+04   4.621 3.85e-06 ***
## view           4.510e+04  2.634e+03  17.121  < 2e-16 ***
## condition      1.774e+04  7.723e+02  22.968  < 2e-16 ***
## grade          2.919e+04  8.608e+02  33.917  < 2e-16 ***
## sqft_above     1.403e+02  2.918e+00  48.076  < 2e-16 ***
## sqft_basement  1.747e+02  3.414e+00  51.156  < 2e-16 ***
```

```
## lat            2.576e+05  4.289e+03  60.049  < 2e-16 ***
## long           1.099e+05  3.951e+03  27.817  < 2e-16 ***
## sqft_living15 -2.035e+00  1.145e+00  -1.778   0.0755 .
## sqft_lot15     4.182e-01  4.989e-02   8.383  < 2e-16 ***
## year           2.259e+04  1.155e+03  19.554  < 2e-16 ***
## renovated      5.035e+04  5.495e+03   9.163  < 2e-16 ***
## age           -1.613e+01  3.198e+01  -0.504   0.6141
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.657 on 15111 degrees of freedom
## Multiple R-squared:  0.7918, Adjusted R-squared:  0.7915
## F-statistic:  3380 on 17 and 15111 DF,  p-value: < 2.2e-16
```

```
par(mfrow=c(2,2))
suppressWarnings(plot(house_lm_wls))
```




**Analysis:** As of now, there is no multicollinearity issues in the train data set since we have handled the highly correlated variables at the initial section.

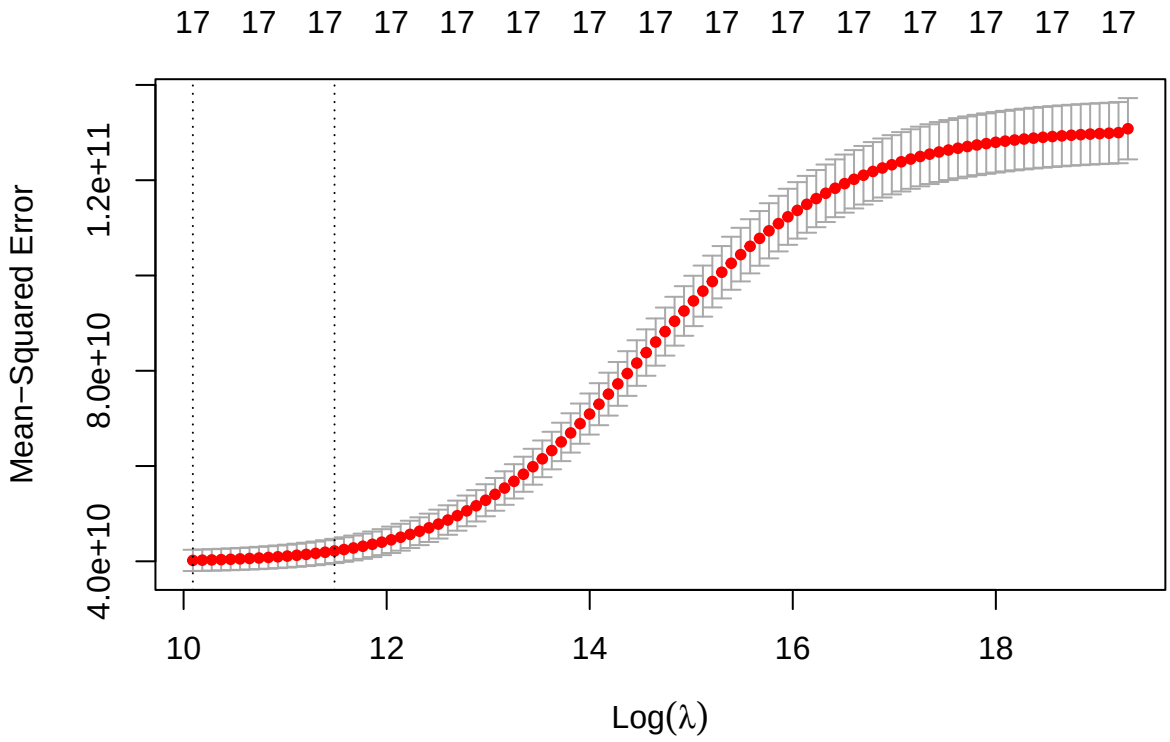
```
# Testing the main (boxcox) model for multicollinearity
vif(house_lm1)
```

```
##      bedrooms     bathrooms      sqft_lot        floors    waterfront
##      1.625094      3.301059      2.076177      2.015287      1.183776
##          view     condition         grade    sqft_above sqft_basement
##      1.409452      1.248831      3.399313      4.947021      2.001923
##           lat          long sqft_living15    sqft_lot15          year
```

```
##      1.124557      1.512058      3.022717      2.089128      1.006528
##     renovated           age
##      1.093130      2.366014
```

**Analysis:** - please add here the analysis of the outcome

```
# Extract 'x' and 'y'
x <- data.matrix(dplyr::select(train.dat, -price))
y <- train.dat$price

# Perform ridge regression
house_lm_ridge <- glmnet::cv.glmnet(x, y, alpha = 0,
                                    nlambda = 100,
                                    lambda.min.ratio = 0.0001)

best.lambda.ridge <- house_lm_ridge$lambda.min
plot(house_lm_ridge)
```



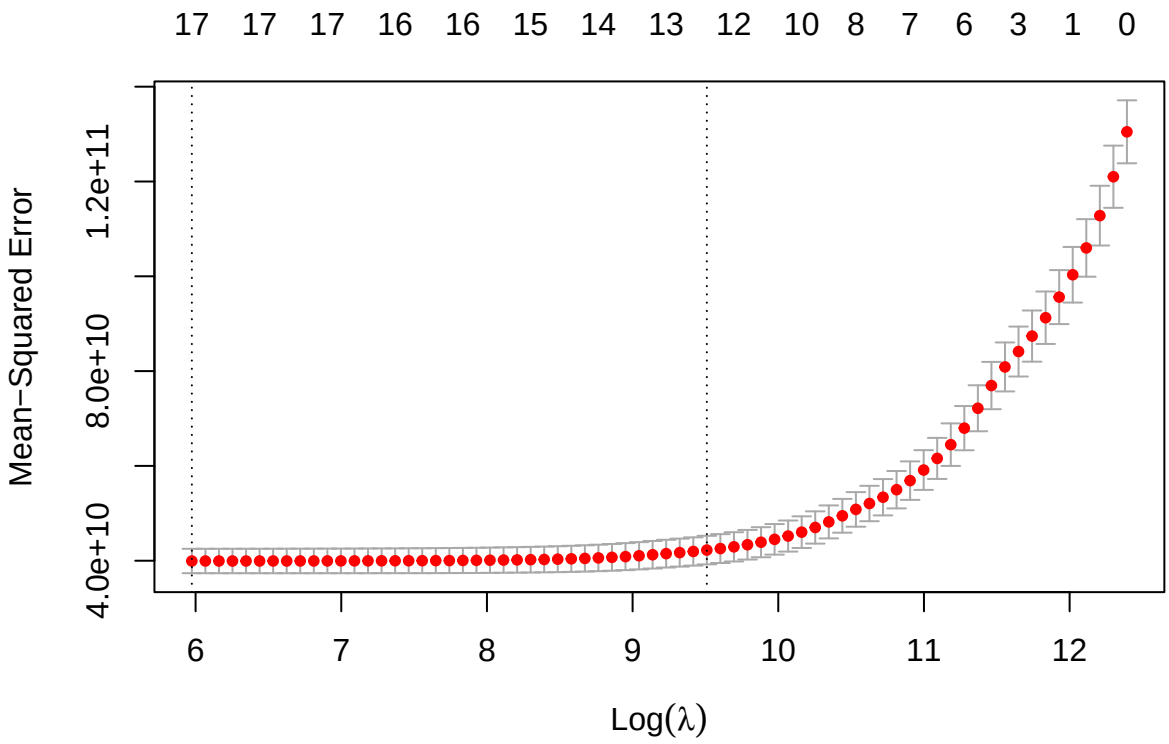

```
print(paste0("Ridge best lambda of ", round(best.lambda.ridge, digits = 3)))
```

```
## [1] "Ridge best lambda of 24125.359"
```

**Analysis:** - please add here the analysis of the outcome

```
house_lm_lasso <- glmnet::cv.glmnet(x, y,
                                    alpha = 1,
                                    nlambda = 100,
                                    lambda.min.ratio = 0.0001)
```

```
best.lambda.lasso <- house_lm_lasso$lambda.min
plot(house_lm_lasso)
```

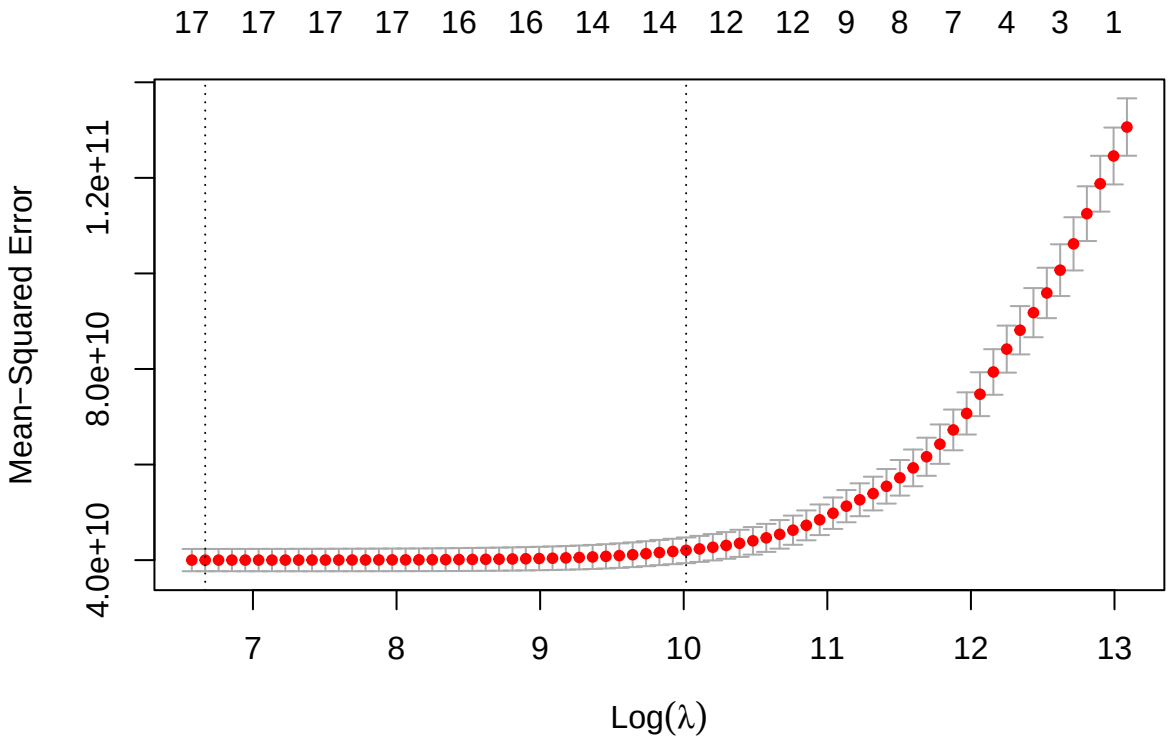



```
print(paste0("Lasso best lambda of ", round(best.lambda.lasso, digits = 3)))
```

```
## [1] "Lasso best lambda of 393.183"
```

**Analysis:** - please add here the analysis of the outcome

```
house_lm_enet <- glmnet::cv.glmnet(
  x, y, alpha = 0.5, nlambda = 100, lambda.min.ratio = 0.0001)

plot(house_lm_enet)
```

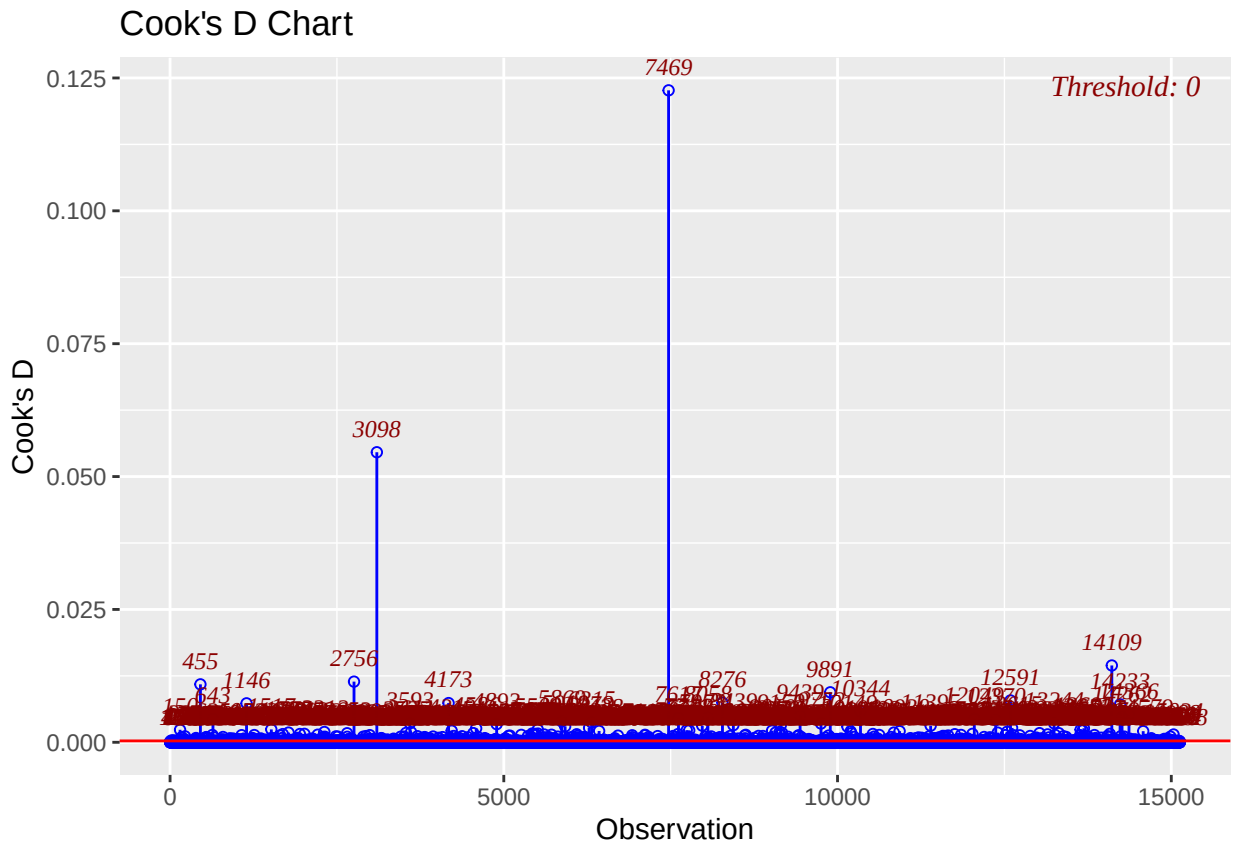



```
best.lambda.enet <- house_lm_enet$lambda.min
print(paste0("ElasticNet best lambda of ",
             round(best.lambda.enet, digits = 3)))
```

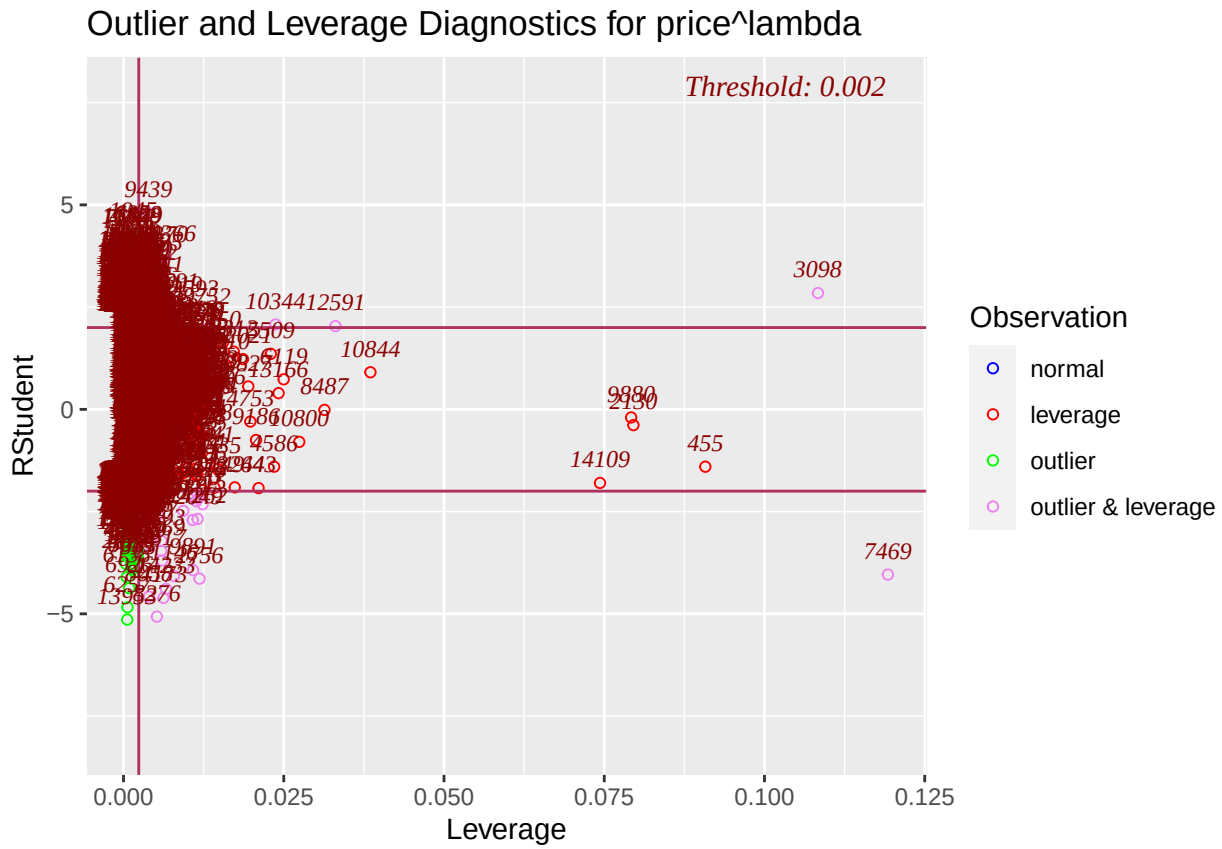
```
## [1] "ElasticNet best lambda of 786.366"
```

**Analysis:** - please add here the analysis of the outcome

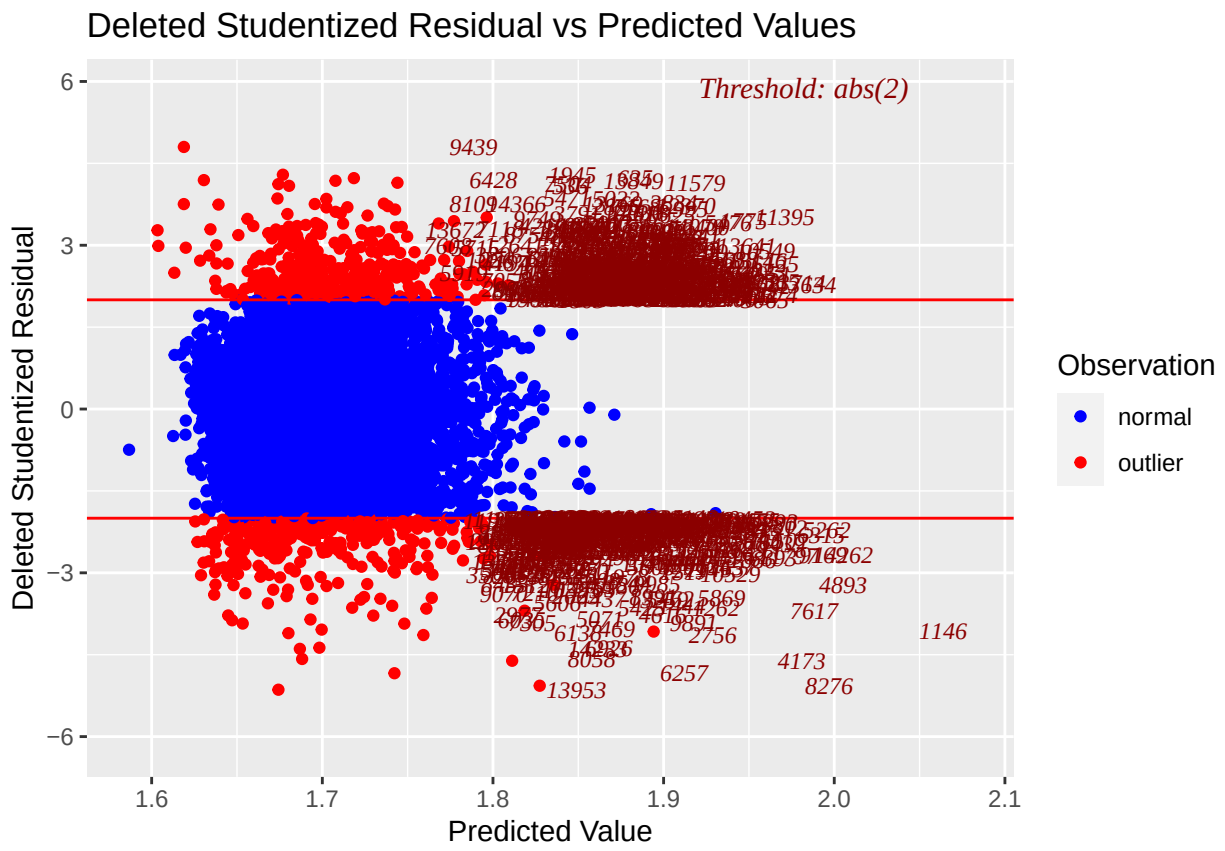
```
# Looking at the residuals using the Cook's distance chart
ols_plot_cooksd_chart(house_lm1)
```




```
# Studentized Residuals vs Leverage Plot
ols_plot_resid_lev(house_lm1)
```




```
# Deleted Studentized Residuals vs Fitted Values Plot
ols_plot_resid_stud_fit(house_lm1)
```



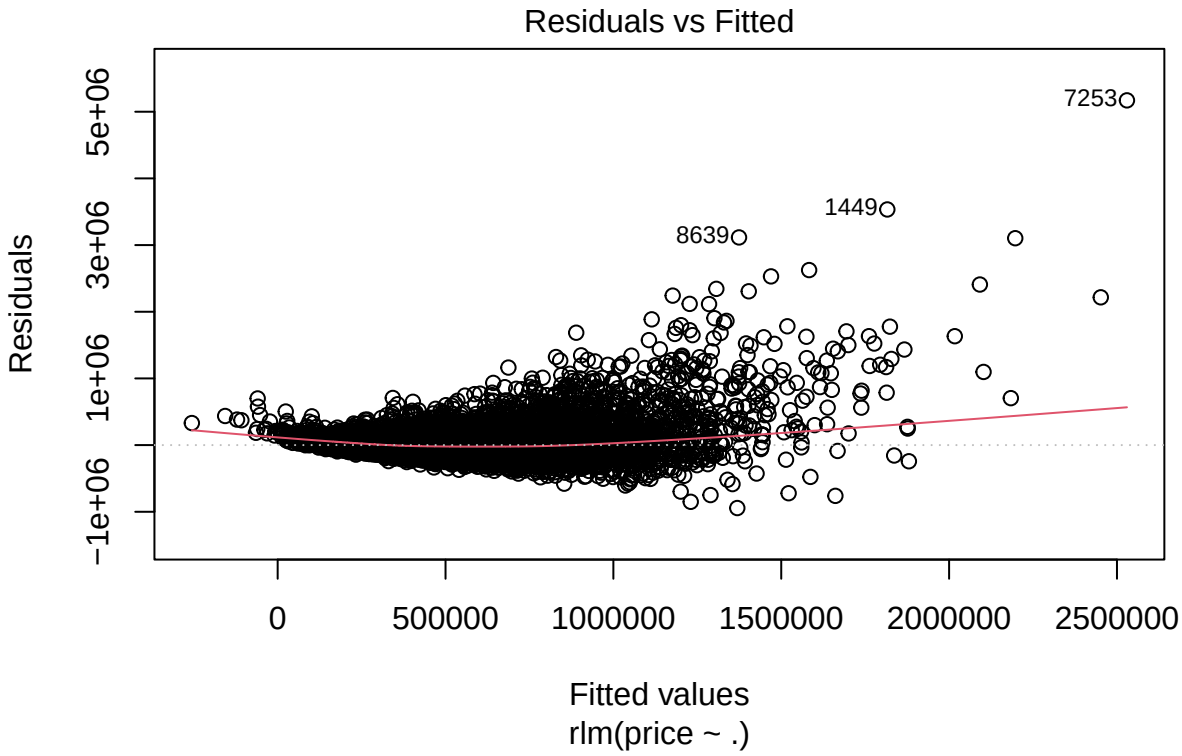

**Analysis:** - please add here the analysis of the outcome

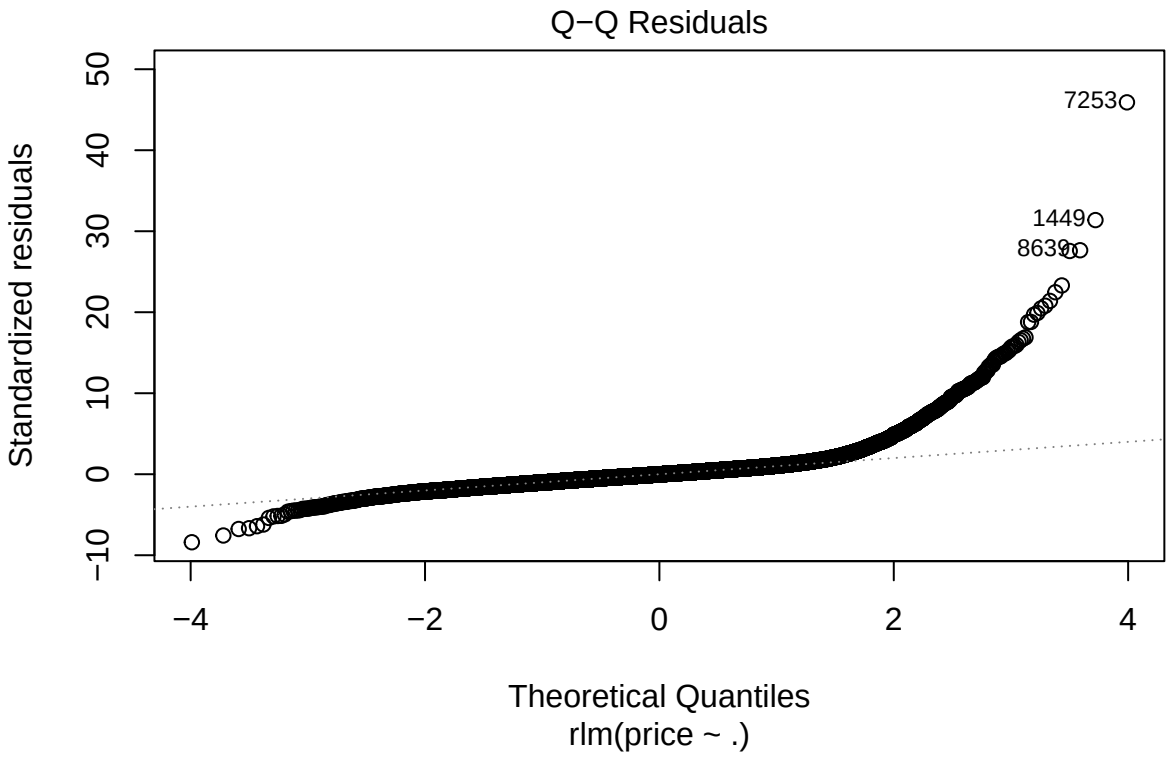
```
# Robust Regression using Huber weights
# There are influential points (see plots above)
house_lm_huber <- MASS::rlm(price ~ ., psi = psi.huber, data = train.dat)
summary(house_lm_huber)
```

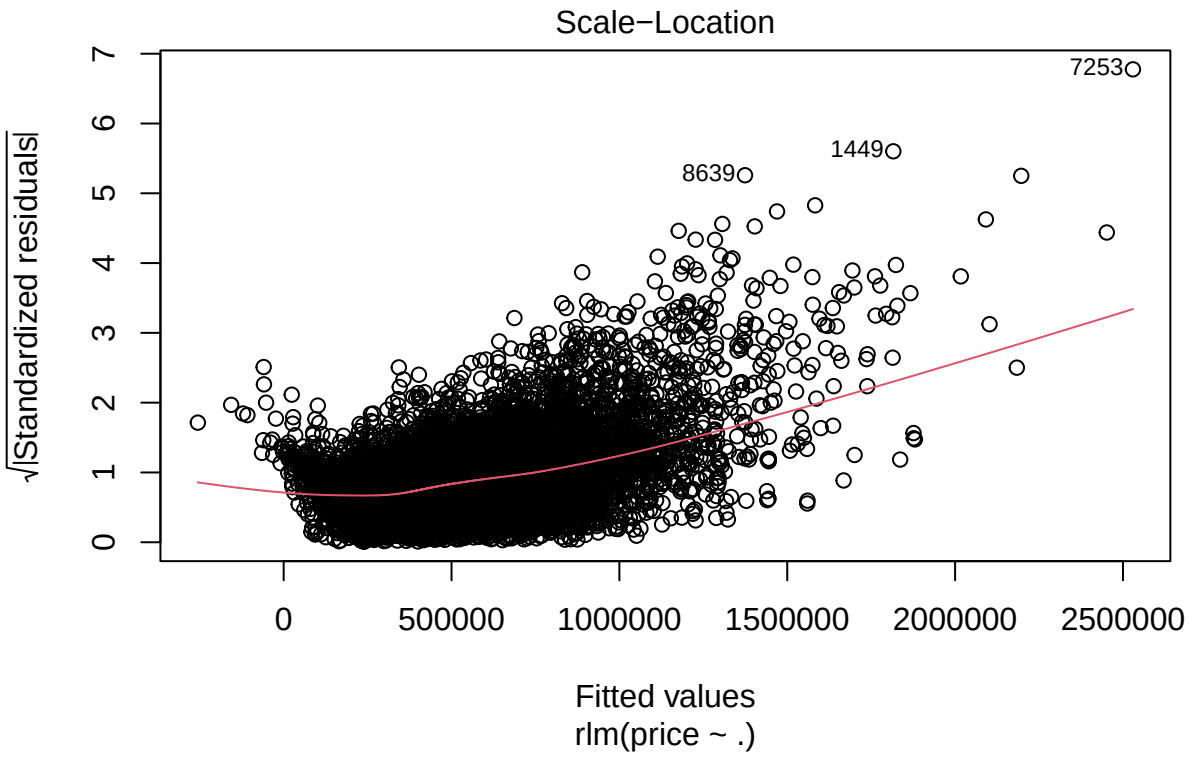
```
##
## Call: rlm(formula = price ~ ., data = train.dat, psi = psi.huber)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -944042  -76206   -1941   75613 5170253
##
## Coefficients:
##                Value         Std. Error    t value
## (Intercept)   -8.156368e+07  4.474412e+06 -1.822890e+01
## bedrooms      -1.901387e+04  1.360324e+03 -1.397750e+01
## bathrooms      2.883477e+04  2.366155e+03  1.218630e+01
## sqft_lot       1.931000e-01  3.700000e-02  5.215800e+00
## floors         2.781035e+04  2.638323e+03  1.054090e+01
## waterfront     4.145041e+05  1.326761e+04  3.124180e+01
## view           4.784910e+04  1.574573e+03  3.038860e+01
## condition      2.986406e+04  1.713990e+03  1.742370e+01
## grade          8.334183e+04  1.576589e+03  5.286210e+01
## sqft_above     1.035569e+02  2.708500e+00  3.823430e+01
## sqft_basement  1.040108e+02  3.199500e+00  3.250810e+01
## lat            5.412197e+05  7.694540e+03  7.033810e+01
```

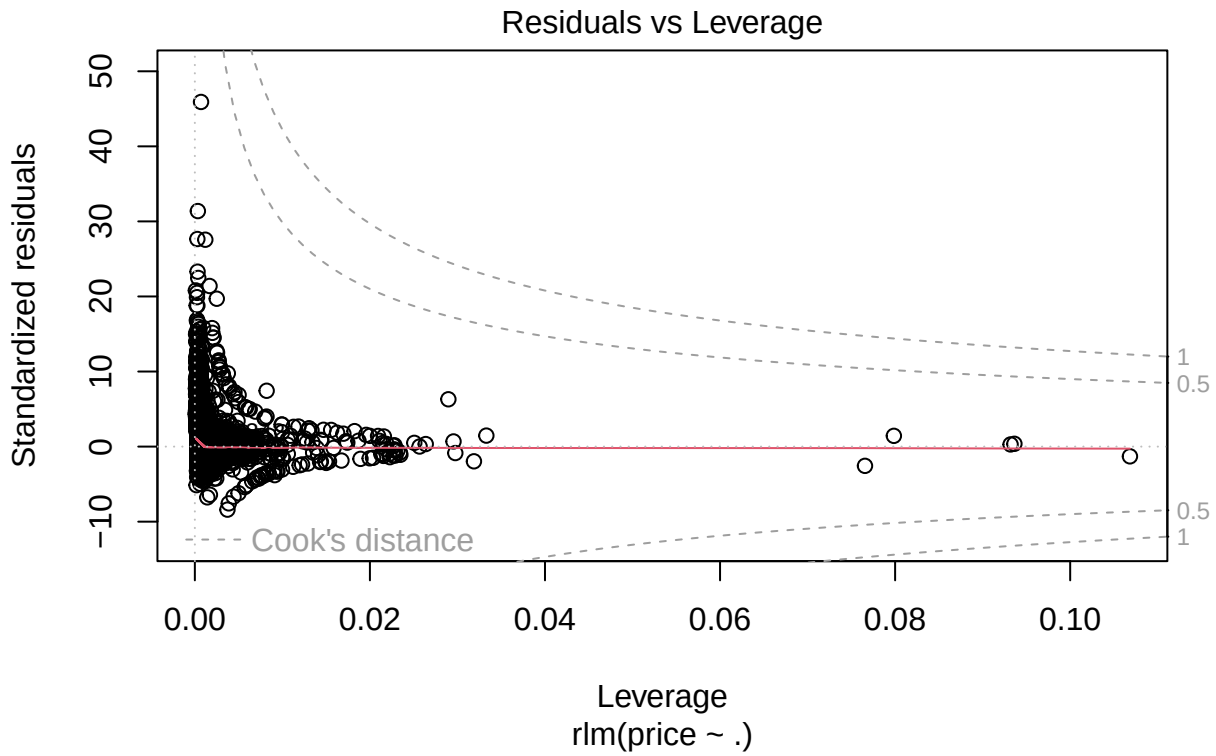
```
## long          -3.764926e+04  8.732129e+03 -4.311600e+00
## sqft_living15  4.455220e+01  2.532600e+00  1.759150e+01
## sqft_lot15    -1.187000e-01  5.340000e-02 -2.221500e+00
## year           2.508902e+04  2.150594e+03  1.166610e+01
## renovated      1.485525e+05  5.189313e+03  2.862660e+01
## age            1.950037e+03  5.343510e+01  3.649360e+01
##
## Residual standard error: 112700 on 15111 degrees of freedom
```

```
plot(house_lm_huber)
```




Q−Q Residuals
Standardized residuals
−10
0
10
20
30
40
50
7253
1449
8639
−4
−2
0
2
4
Theoretical Quantiles
rlm(price ~ .)


Scale−Location
√|Standardized residuals|
0
1
2
3
4
5
6
7
7253
1449
8639
0
500000
1000000
1500000
2000000
2500000
Fitted values
rlm(price ~ .)




```
huber_weights <- data.frame(Observation = 1:nrow(train.dat),
                            Residual = house_lm_huber$resid,
                            Weight = house_lm_huber$w)

a <- huber_weights[order(house_lm_huber$w), ]

head10 <- head(a$Observation,10)
head10
```

```
##  [1] 13244  9986 11395  5127  7807 13634  8814  6125 13714  1775
```

**Analysis:** - please add here the analysis of the outcome

```
# Robust Regression using bisquare weights

house_lm_bisquare <- MASS::rlm(price ~ ., psi = psi.bisquare, data = train.dat)
summary(house_lm_bisquare)
```

```
##
## Call: rlm(formula = price ~ ., data = train.dat, psi = psi.bisquare)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -610680  -65634    2985   80109 5515652
##
## Coefficients:
##               Value         Std. Error    t value
## (Intercept)   -6.813489e+07  4.136702e+06 -1.647080e+01
## bedrooms      -1.345810e+04  1.257652e+03 -1.070100e+01
```

```
## bathrooms      2.595323e+04  2.187567e+03  1.186400e+01
## sqft_lot       2.397000e-01  3.420000e-02  7.004000e+00
## floors         3.095547e+04  2.439193e+03  1.269090e+01
## waterfront     1.851339e+05  1.226622e+04  1.509300e+01
## view           4.059427e+04  1.455731e+03  2.788580e+01
## condition      2.723312e+04  1.584625e+03  1.718580e+01
## grade          7.391210e+04  1.457595e+03  5.070830e+01
## sqft_above     7.877650e+01  2.504100e+00  3.145950e+01
## sqft_basement  8.074940e+01  2.958000e+00  2.729820e+01
## lat            5.341132e+05  7.113788e+03  7.508140e+01
## long          -1.967416e+03  8.073064e+03 -2.437000e-01
## sqft_living15  4.757570e+01  2.341400e+00  2.031890e+01
## sqft_lot15    -7.260000e-02  4.940000e-02 -1.468300e+00
## year           2.080893e+04  1.988276e+03  1.046580e+01
## renovated      1.227366e+05  4.797645e+03  2.558270e+01
## age            1.710056e+03  4.940200e+01  3.461510e+01
##
## Residual standard error: 107200 on 15111 degrees of freedom
```

**Analysis:** - please add here the analysis of the outcome

```r
price.predictors <- colnames(dplyr::select(df_house, -price))

# Predictions for each model using the test dataset
predictions <- data.frame(
  price = test.dat$price,
  price.lm = predict(house_lm1, test.dat),
  price.sw.lm = predict(final_model, test.dat), # Stepwise model = final_model
  price.ridge = predict(house_lm_ridge, s = best.lambda.ridge,
                        newx = data.matrix(test.dat[price.predictors])),
  price.lasso = predict(house_lm_lasso, s = best.lambda.lasso,
                        newx = data.matrix(test.dat[price.predictors])),
  price.en = predict(house_lm_enet, s = best.lambda.enet,
                     newx = data.matrix(test.dat[price.predictors])),
  price.huber = predict(house_lm_huber, test.dat),
  price.bisquare = predict(house_lm_bisquare, test.dat)
)

# Function to calculate SSE, R2, MSE, and RMSE
calc_metrics <- function(actual, predicted) {
  sse <- sum((actual - predicted) ^ 2)
  mse <- sse / length(actual)
  rmse <- sqrt(mse) # Calculate RMSE
  sst <- sum((actual - mean(actual)) ^ 2)
  r2 <- 1 - sse / sst
  #return(c(RMSE = rmse, R2 = r2))
  return(c(SST = sst, SSE = sse, MSE = mse, RMSE = rmse, R2 = r2))
}

# function to each set of predictions
metrics <- data.frame(
  Model = c("Linear", "Stepwise", "Ridge", "Lasso",
            "Elastic Net", "Huber", "Bisquare"),
  do.call(rbind,
          lapply(2:ncol(predictions),
```

```
                function(i) calc_metrics(predictions$price, predictions[,i])))
)

# Display the metrics table with RMSE
metrics %>%
  dplyr::arrange(desc(R2)) %>%
  knitr::kable(caption = "R2, MSE, and RMSE of Different Models")
```

Table 1: R2, MSE, and RMSE of Different Models

| Model | SST | SSE | MSE | RMSE | R2 |
|---|---|---|---|---|---|
| Lasso | 9.339154e+14 | 2.876374e+14 | 44361103219 | 210620.8 | 0.6920092 |
| Elastic Net | 9.339154e+14 | 2.877078e+14 | 44371968147 | 210646.5 | 0.6919337 |
| Ridge | 9.339154e+14 | 2.924757e+14 | 45107292815 | 212384.8 | 0.6868285 |
| Huber | 9.339154e+14 | 3.245680e+14 | 50056756916 | 223733.7 | 0.6524653 |
| Bisquare | 9.339154e+14 | 3.770719e+14 | 58154206866 | 241151.8 | 0.5962462 |
| Linear | 9.339154e+14 | 2.847785e+15 | 439201932857 | 662723.1 | -2.0492969 |
| Stepwise | 9.339154e+14 | 2.847785e+15 | 439201932867 | 662723.1 | -2.0492969 |

```
# This is not working - commenting out temporaryly to improve knit times
#k1<-ols_step_best_subset(house_lm1)
#k1
#plot(k1, guide="none")
```

# V. Challenger Models

In this section, we explore alternative predictive models to challenge our primary regression model. This is crucial for ensuring our final model's robustness by comparing it against these 'challenger' models. Here, we experiment with different modeling techniques such as regression trees, neural networks, or SVMs, evaluating their performance and applicability. This comparative analysis helps in understanding the strengths and weaknesses of various approaches, guiding us to select the most effective model for predicting real estate prices in King County.

## Regression Tree Models

This block is designed to determine the optimal depth for a regression tree model predicting house prices. It iterates over a predefined set of depth values, constructing a model at each depth, and calculating MSE and R-squared values for both the test and training datasets. The loop stores these metrics for each depth, and upon completion, it identifies the depth that yields the highest R-squared value on the test data, suggesting the best generalization performance.

```
depth_values <- c(2, 3, 4, 5, 6, 7, 8)

mse_values = numeric(length(depth_values))
test_rsq_values = numeric(length(depth_values))
train_rsq_values = numeric(length(depth_values))

for (i in seq_along(depth_values)) {
  depth = depth_values[i]

  regression_tree_model = rpart(price ~ .,
                                data = train.dat,
                                method = "anova",
                                control=rpart.control(maxdepth=depth))
  predictions_test <- predict(regression_tree_model, newdata = test.dat)
  predictions_train <- predict(regression_tree_model, newdata = train.dat)

  mse_values[i] <- mean((predictions_test - test.dat$price)^2)
  test_rsq_values[i] = cor(predictions_test,test.dat$price)^2
  train_rsq_values[i] = cor(predictions_train,train.dat$price)^2
}

# Find the maximum R-squared value
max_rsq <- max(test_rsq_values)
# Get the corresponding depth value
best_depth <- depth_values[which.max(test_rsq_values)]

cat("Best depth:", best_depth, "with R-squared:", max_rsq)
```

```
## Best depth: 6 with R-squared: 0.6492524
```

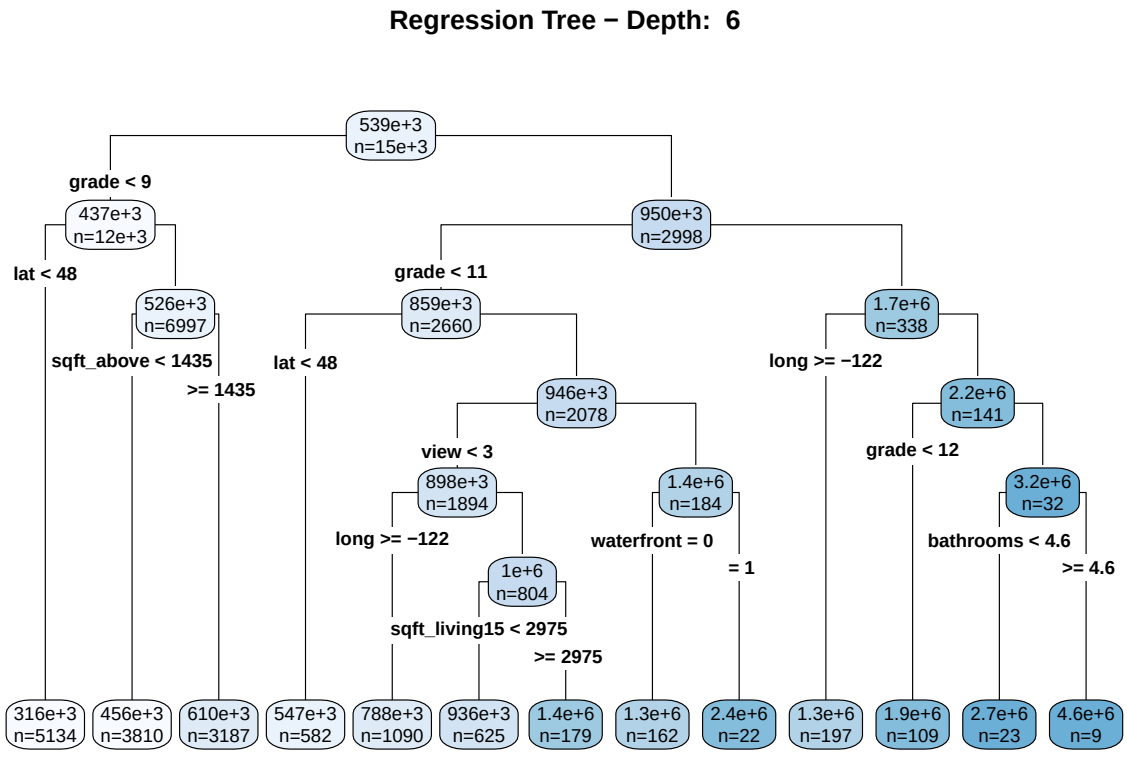
### Optimized Regression Tree Visualization

This subsection presents the visual depiction of the regression tree model at its calculated optimal complexity. By tuning the tree to the 'best_depth', we ensure the model is neither overfitting nor underfitting. The rpart.plot is customized to enhance interpretability, detailing split labels and the count of observations at each node, thereby providing a clear, scaled-up graphical representation of the decision-making process within the model.

Now we use the rpart.plot function to create a detailed plot of the tree, incorporating the optimal tree depth

previously determined (best_depth). The plot is configured to show a type 4 tree, which includes split labels, and extra = 1 to display the number of observations in each node. The main title of the plot reflects the chosen depth for easy reference.

```
# Fitting decision tree with best depth
dtm = rpart(price ~ .,
              data = train.dat,
              method = "anova",
              control=rpart.control(maxdepth=best_depth))

# Plot the tree
rpart.plot(dtm, main=paste("Regression Tree - Depth: ", best_depth),
           type = 4, extra = 1, tweak=1.6)
```

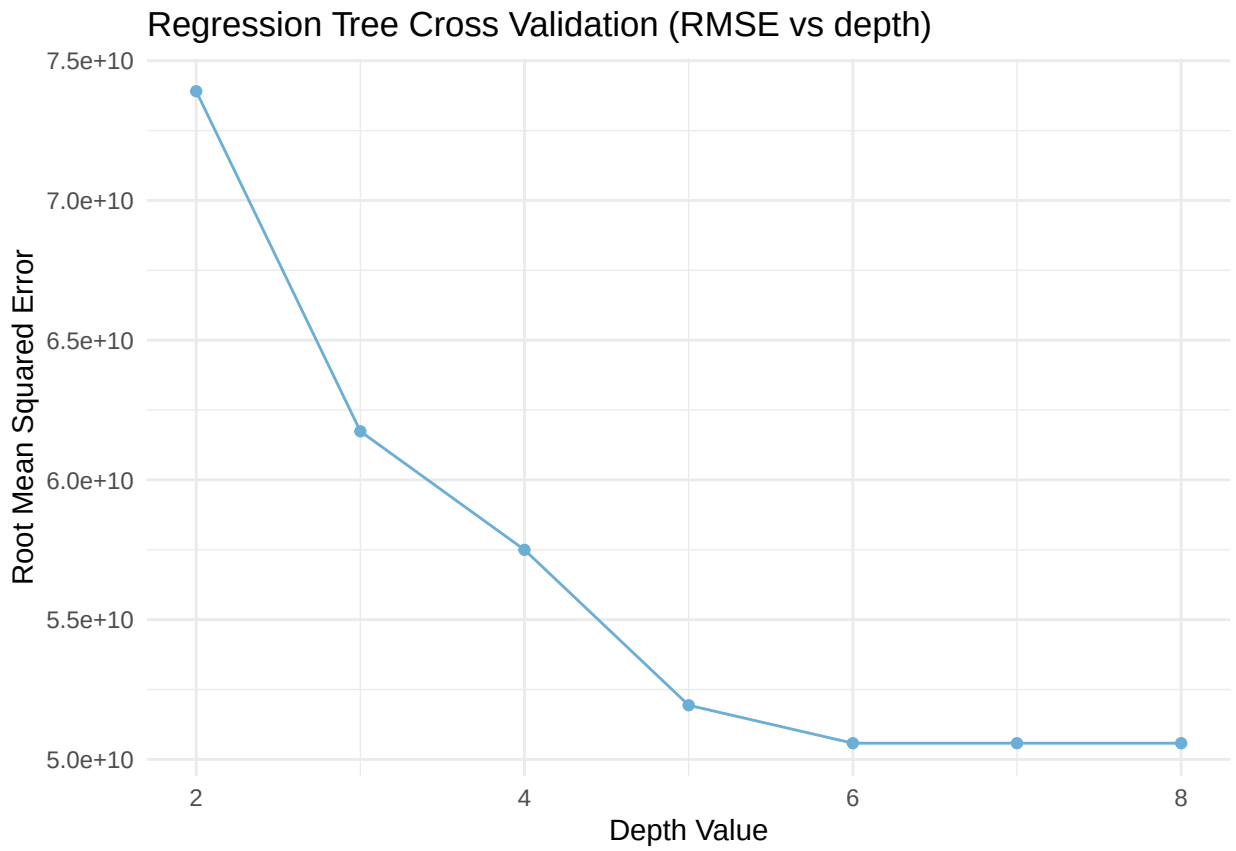



**Analysis:** The regression tree plot depicts a model of depth 6 (best_depth), indicating a sequence of decisions starting from the root node using features such as 'grade', 'lat', 'sqft_above', and others. Each node represents a condition that splits the data, leading to more homogenous subsets. The leaf nodes represent the predicted price, with the number in each leaf node showing the average price for the observations that follow the path to that node. The tree structure suggests that 'grade', 'sqft_living15', location ('waterfront', 'lat' & 'long'), and 'sqft_above' are important predictors, as they appear near the top and on many many different levels of the tree, indicating their significant role in splitting the data and hence in predicting house prices.

### Assessing Regression Tree Model Complexity with RMSE

Analysis of the regression tree model's accuracy across varying depths, utilizing Root Mean Squared Error (RMSE) as the key performance metric.

```r
# Data frame for plotting RMSE results
plot_data <- data.frame(Depth=depth_values, RMSE=mse_values)

# Plot RMSE results vs Depth of the Tree
ggplot(plot_data, aes(x=Depth, y=RMSE)) +
  geom_point(color = "#6baed6") +  # Add points
  geom_line(color = "#6baed6") +   # Connect points with a line
  labs(x = "Depth Value", y = "Root Mean Squared Error",
       title = "Regression Tree Cross Validation (RMSE vs depth)") +
  theme_minimal()  # Use a minimal theme for a clean look
```



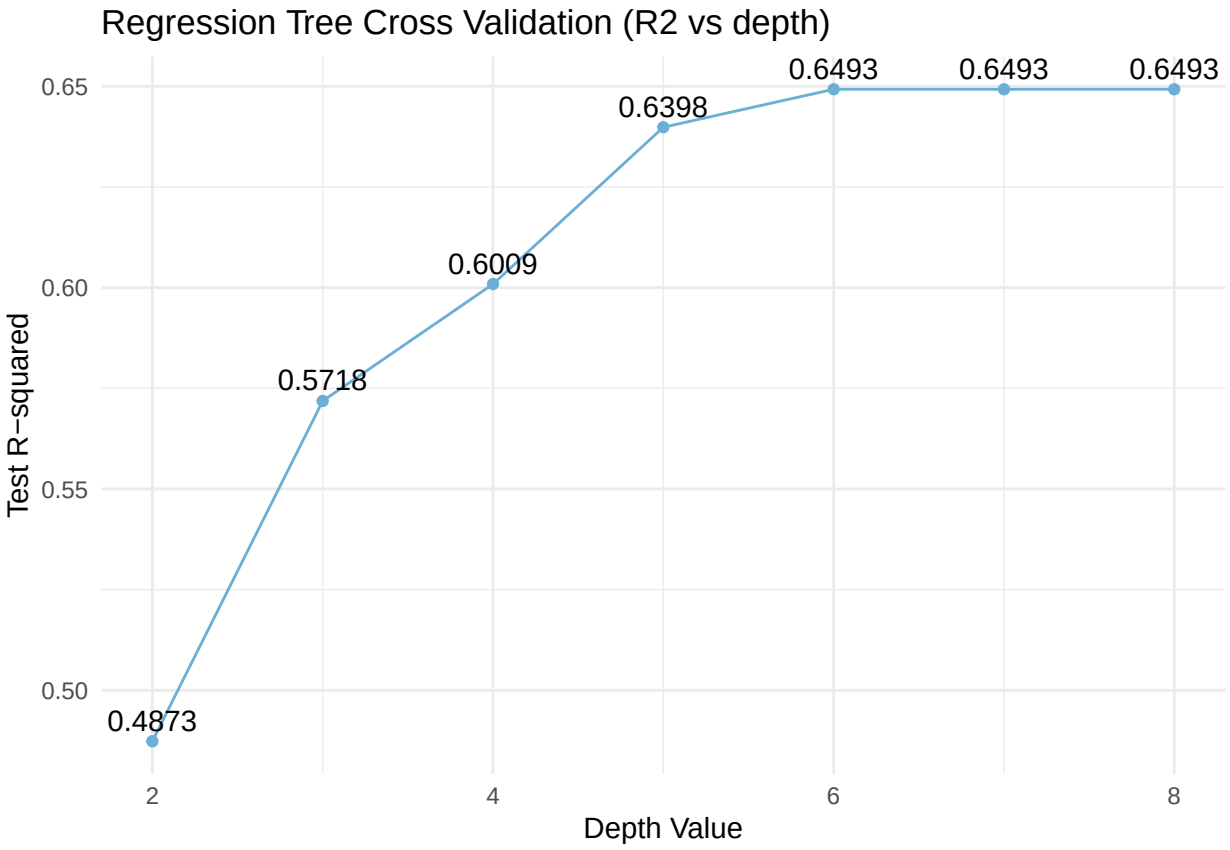

**Analysis:** The plot illustrates how RMSE changes as the depth of the regression tree increases. Initially, RMSE decreases significantly, suggesting improvements in model accuracy with added complexity. However, from a depth of 6 and beyond, the reduction in RMSE plateaus, indicating that increasing the tree depth further provides diminishing returns in terms of model accuracy. This visualization aids in selecting an appropriate model complexity to balance between underfitting and overfitting.

### Regression Tree Model Fit Evaluation with R-squared

Influence of tree depth on the regression tree model's explanatory power, as indicated by the R-squared values.

```r
# Data frame for plotting R-squared results
plot_data <- data.frame(Depth=depth_values, TestR2=test_rsq_values)

# Plot R-squared vs Depth of the Tree
ggplot(plot_data, aes(x=Depth, y=TestR2)) +
```

```
  geom_point(color="#6baed6") +  # Add points with color
  geom_line(color="#6baed6") +   # Connect points with a line of the same color
  geom_text(aes(label=round(TestR2, 4)), vjust=-0.5, color="black") + # Add text labels
  labs(x = "Depth Value", y = "Test R-squared",
       title = "Regression Tree Cross Validation (R2 vs depth)") +
  theme_minimal()  # Use a minimal theme for a clean look
```



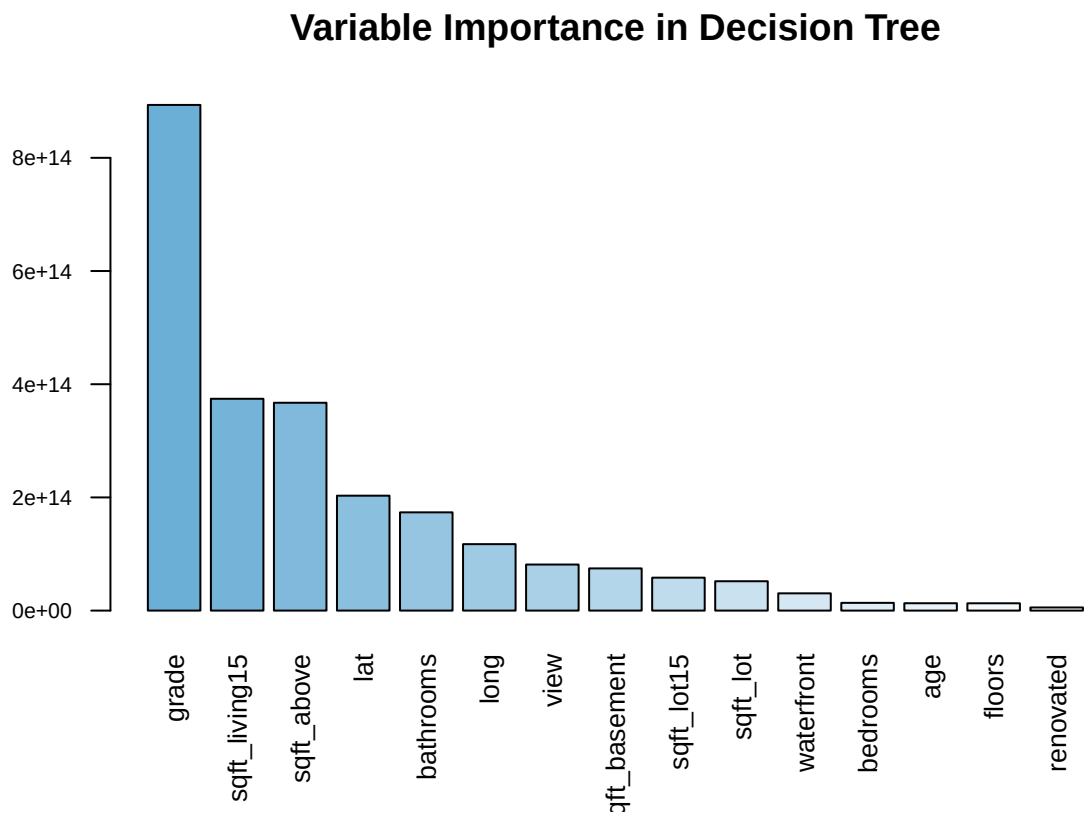

**Analysis:** The plot illustrates the R-squared value at varying tree depths, showing a trend of increasing explanatory power as the depth increases from 2 to 5. The leveling off of R-squared values beyond a depth of 6 suggests that additional depth does not substantially improve the model's ability to explain the variance in the data, indicating an optimal depth for model complexity.

### Prioritizing Features in the Regression Tree Model

This subsection investigates the variable importance derived from the regression tree model, offering a clear depiction of which factors most heavily influence house pricing predictions. The measure of importance is calculated based on the reduction of prediction error attributed to each variable, providing insight into their relative predictive power within the model. This analysis is critical for understanding the key drivers of real estate values and can inform strategic decisions regarding property investments and market evaluations.

```
imp = dtm$variable.importance
dt_test_pred <- predict(dtm, newdata=test.dat)
dt_train_pred <- predict(dtm, newdata=train.dat)
dt_test_results = postResample(pred = dt_test_pred, obs = test.dat$price)
dt_train_results = postResample(pred = dt_train_pred, obs = train.dat$price)
dt_test_sse = sum((dt_test_pred - test.dat$price)^2)
```

```r
# Variable importance may be more reliable
# if considering other values from cross validation
blue_gradient <- colorRampPalette(c("#6baed6", "white"))(length(imp))
barplot(imp, las=2, main="Variable Importance in Decision Tree",
        col=blue_gradient, cex.names=0.8, cex.axis=0.7, cex.lab=0.7)
```




**Analysis:** The bar plot indicates that 'grade' has the most significant impact on the model's decisions, followed by 'sqft_living15', and 'sqft_above'. Variables such as 'age', 'floors', and 'renovated' have minimal impact. This suggests that house quality and living area are the primary drivers of price according to the model, which aligns with real-world expectations of property valuation.

```r
# Append results
results.df = rbind(results.df,data.frame(model = "Decision Tree Regression",
                           R.Squared.Train = unname(dt_train_results[2]),
                           R.Squared.Test = unname(dt_test_results[2]),
                           RMSE.test = unname(dt_test_results[1]),
                           SSE.test = dt_test_sse))
```

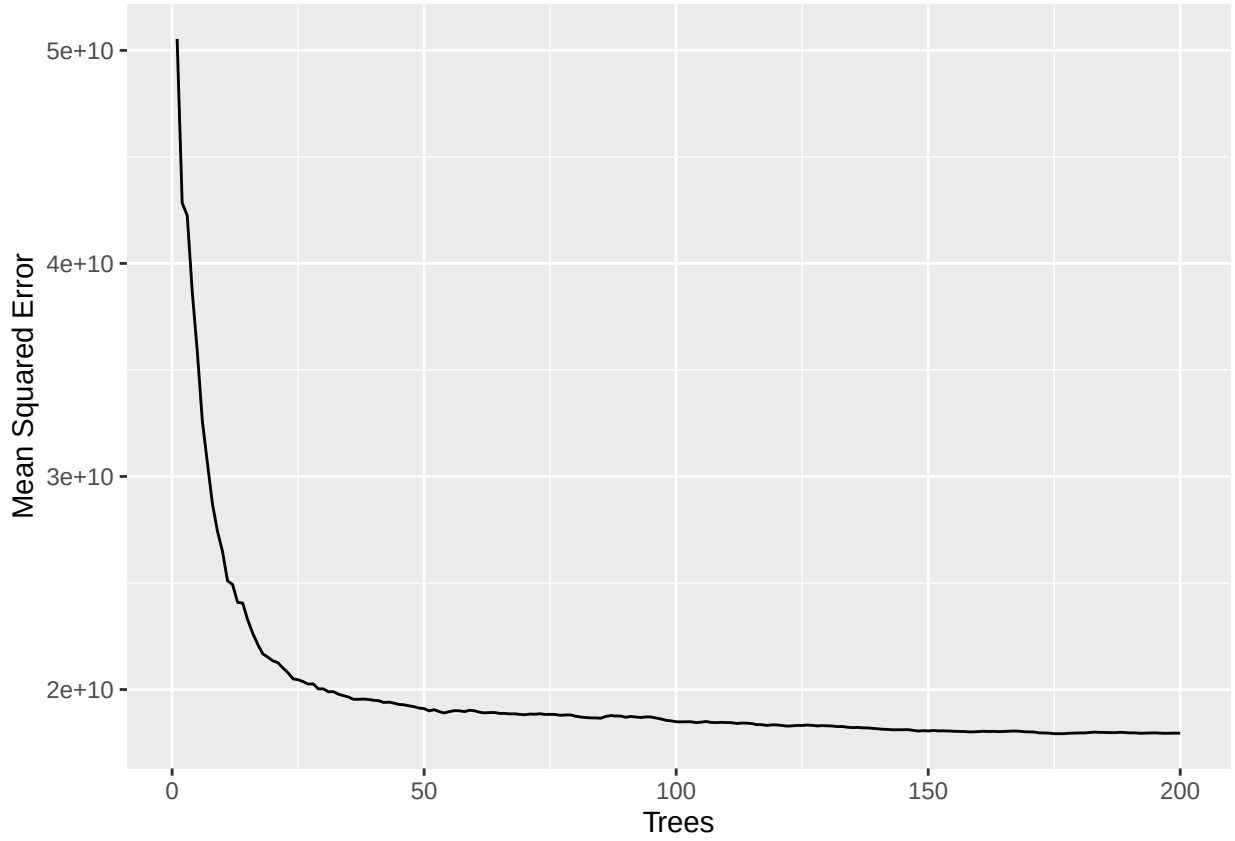
## Random Forest Model

The Random Forest model is a powerful ensemble learning method used for both classification and regression tasks. It operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees. Random Forests correct for decision trees' habit of overfitting to their training set by introducing randomness in the tree-building process. This randomness can come from building trees on different samples of the data (bootstrap aggregating or bagging) or considering a random subset of features for splitting at each node. The model is robust against overfitting, can handle large datasets with higher dimensionality, and can estimate

the importance of variables used in the classification or regression.

```
# Cross validate number of features!!...work in progress

# Fitting the Random Forest model
rf = randomForest(price ~ .,
                  data = train.dat,
                  ntree = 200,
                  importance=TRUE)

summary(rf)
```

```
##
## Call:
##  randomForest(formula = price ~ ., data = train.dat, ntree = 200,      importance = TRUE)
##                Type of random forest: regression
##                      Number of trees: 200
## No. of variables tried at each split: 5
##
##           Mean of squared residuals: 17948059705
##                     % Var explained: 86.28
```



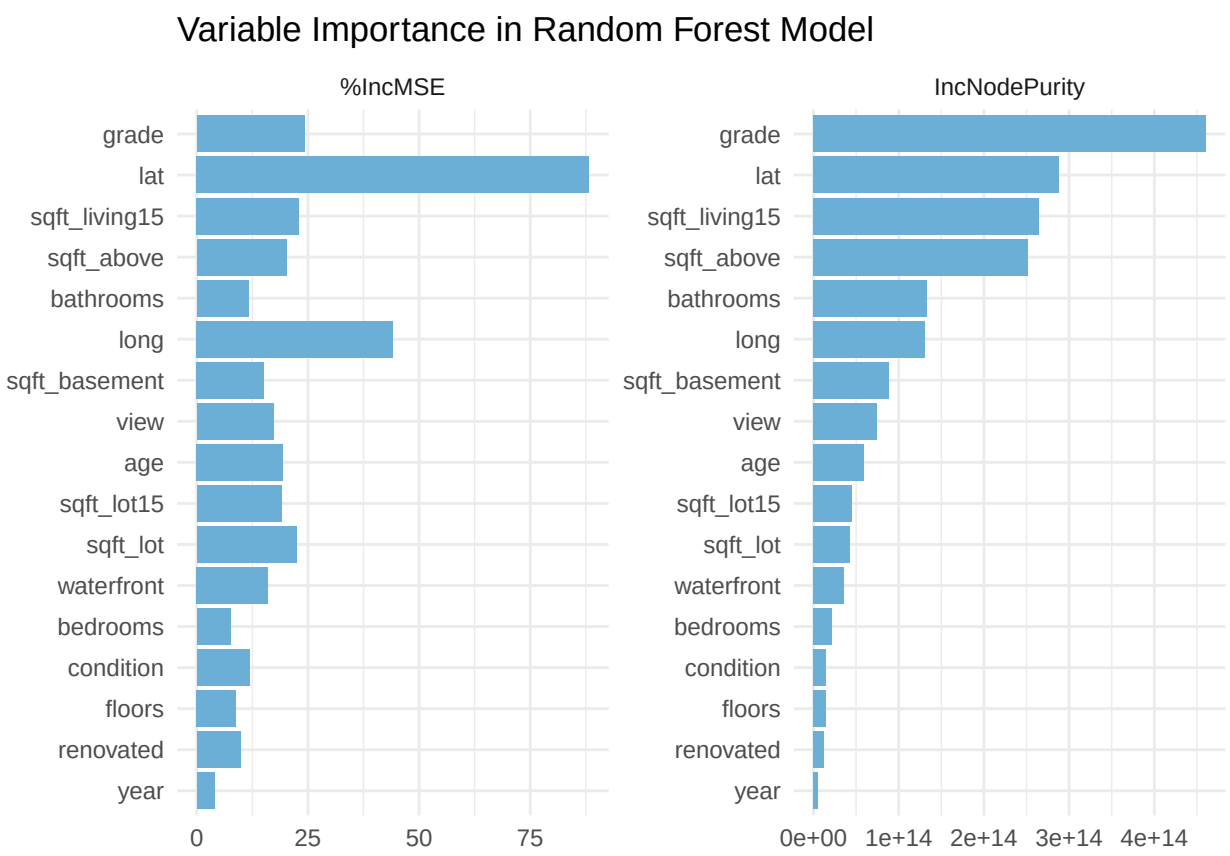

**Analysis:** This plot depicts the mean squared error (MSE) across the number of trees in the model. The MSE sharply decreases as more trees are added, especially evident in the initial phase with fewer trees. As the number of trees reaches around 50, the decrease in MSE begins to plateau, indicating that adding more trees has diminishing returns on model performance. The model, consisting of 200 trees, explains approximately 86.09% of the variance, showcasing a high level of model accuracy. This suggests that the

Random Forest model has a strong predictive capability for the housing price data, with a substantial portion of the variability in the response variable accounted for by the predictors used in the model.

### Variable Significance in Random Forest Modeling

This subsection delves into the variable importance generated by the Random Forest model, providing insight into which predictors most significantly impact the target variable, house price. The analysis illustrates the relative influence of each variable through two metrics: the mean decrease in accuracy and the mean decrease in node purity.

```r
# Create a Dataframe with Random Forest variable importance
rf_importance <- as.data.frame(importance(rf))

# Create a tidy data frame for ggplot
rf_importance$Variable <- rownames(rf_importance)
rf_importance <- rf_importance %>%
  tidyr::gather(Measure, Value, -Variable)

# Plot RF variable importance
ggplot(rf_importance, aes(x = reorder(Variable, Value), y = Value)) +
  geom_col(fill="#6baed6") +
  facet_wrap(~Measure, scales = "free") +
  coord_flip() +
  theme_minimal() +
  labs(x = NULL, y = NULL, title = "Variable Importance in Random Forest Model") +
  theme(legend.position = "none")
```



**Analysis:** This plot provides a clear visualization of the features that have the most substantial impact on predicting house prices. The length of the bars represents the importance of each variable, with 'grade' and 'lat' being the most significant predictors according to both measures used: the percentage increase in Mean Squared Error (%IncMSE) and Increase in Node Purity (IncNodePurity). This visualization is essential to understand which variables contribute most to the model's predictive power and potentially guide feature selection.

```
# Random Forest Test Results
rf_train_pred = predict(rf, newdata = train.dat)
rf_test_pred = predict(rf, newdata = test.dat)

rf_train_results = postResample(pred = rf_train_pred, obs = train.dat$price)
rf_test_results = postResample(pred = rf_test_pred, obs = test.dat$price)
rf_test_sse = sum((rf_test_pred - test.dat$price)^2)

# Append to the Results Data Frame
results.df = rbind(results.df,data.frame(model = "Random Forest Model",
                            R.Squared.Train = unname(rf_train_results[2]),
                            R.Squared.Test = unname(rf_test_results[2]),
                            RMSE.test = unname(rf_test_results[1]),
                            SSE.test = rf_test_sse))
```

## Support Vector Machine (SVM) Model

### SVM Model Construction

This subsection discusses the creation of the Support Vector Machine model. It entails the training phase on the dataset, where the SVM algorithm learns to find the best hyperplane that categorizes the data points.

```
# Build the SVM model
svm_model <- svm(price ~ ., data = train.dat)
print(summary(svm_model))
```

```
##
## Call:
## svm(formula = price ~ ., data = train.dat)
##
##
## Parameters:
##    SVM-Type:  eps-regression
##  SVM-Kernel:  radial
##        cost:  1
##       gamma:  0.05882353
##     epsilon:  0.1
##
##
## Number of Support Vectors:  9020
```

**Analysis:** The SVM model summary indicates it's an epsilon-type regression with a radial basis function kernel. The cost parameter is set to 1, which controls the trade-off between allowing training errors and forcing rigid margins. Gamma, set at approximately 0.0588, defines the influence of a single training example, with lower values meaning 'far' and higher values meaning 'close'. The epsilon of 0.1 specifies the epsilon-tube within which no penalty is associated in the training loss function with points predicted within a distance epsilon from the actual value. The model has a large number of support vectors, amounting to 9020, which could imply a complex model that may be at risk of overfitting.

### SVM Model Evaluation

In this part, we assess the performance of the SVM model using the test dataset. The Root Mean Square Error (RMSE) metric provides insight into the average deviation of the predicted house prices from the actual values.

```
# Prediction and Performance
svm_predictions <- predict(svm_model, test.dat)
svm_rmse <- sqrt(mean((svm_predictions - test.dat$price)^2))
print(paste("SVM RMSE:", svm_rmse))
```

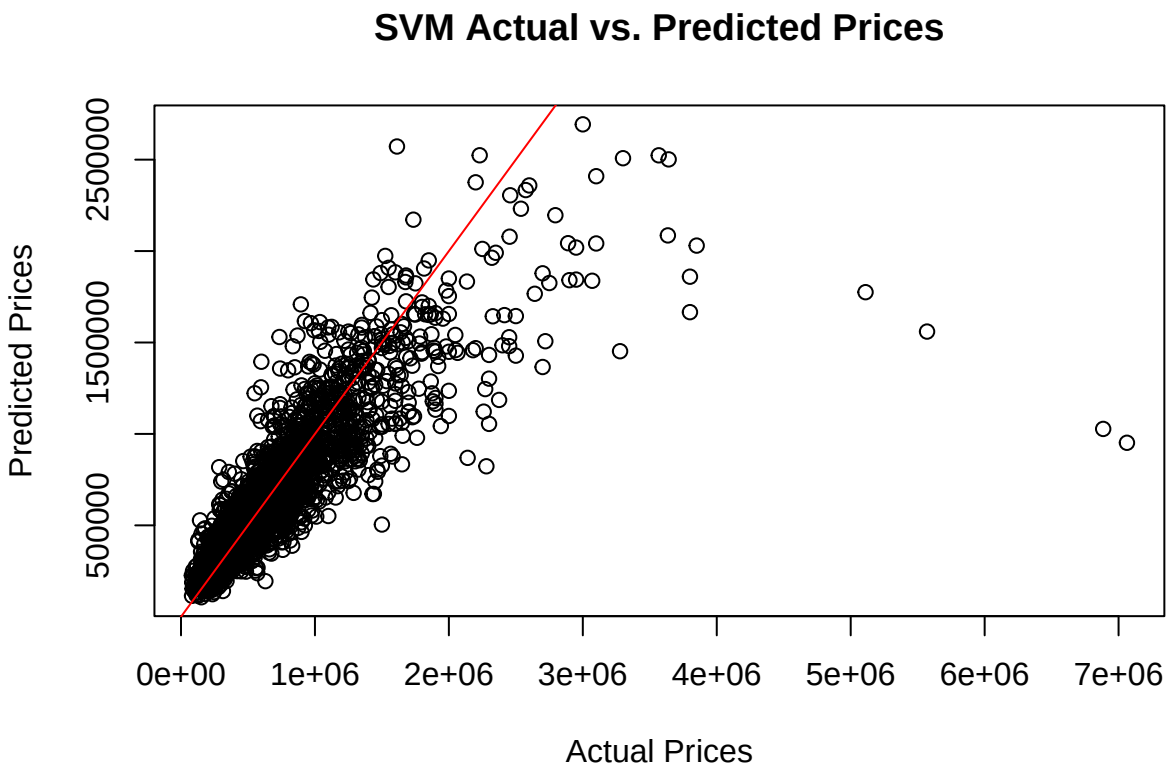
```
## [1] "SVM RMSE: 195393.382261799"
```

**Analysis:** The reported RMSE value for the SVM model is $195,393.38, which suggests that on average, the model's price predictions deviate from the actual sale prices by this amount. Given the high value, this may indicate that the model is not predicting the prices with a high degree of accuracy. In the context of house prices, such a large RMSE could be considered substantial, and it suggests that model parameters may need tuning or the model itself may require a more in-depth evaluation to identify areas of improvement.

### SVM Model Visualization

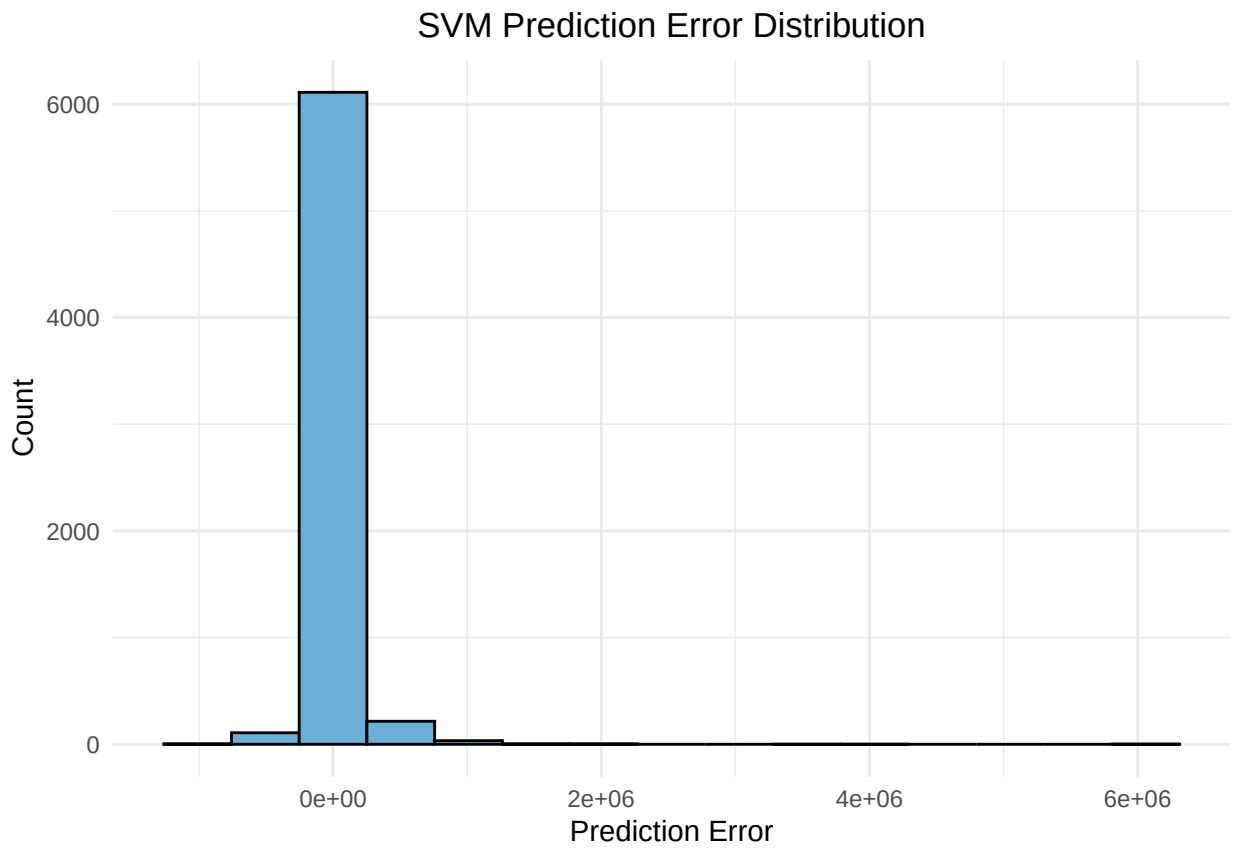
This subsection is dedicated to the visual exploration of the Support Vector Machine model's predictive performance. Through graphical representations such as scatter plots of predicted versus actual values and histograms of prediction errors, we can intuitively assess the accuracy and distribution of the model's predictions, and identify patterns or anomalies in the data. These visual analyses are critical for conveying complex statistical results in a clear and actionable format.

```
plot(test.dat$price, svm_predictions,
     main="SVM Actual vs. Predicted Prices",
     xlab="Actual Prices", ylab="Predicted Prices")
abline(0, 1, col="red")
```



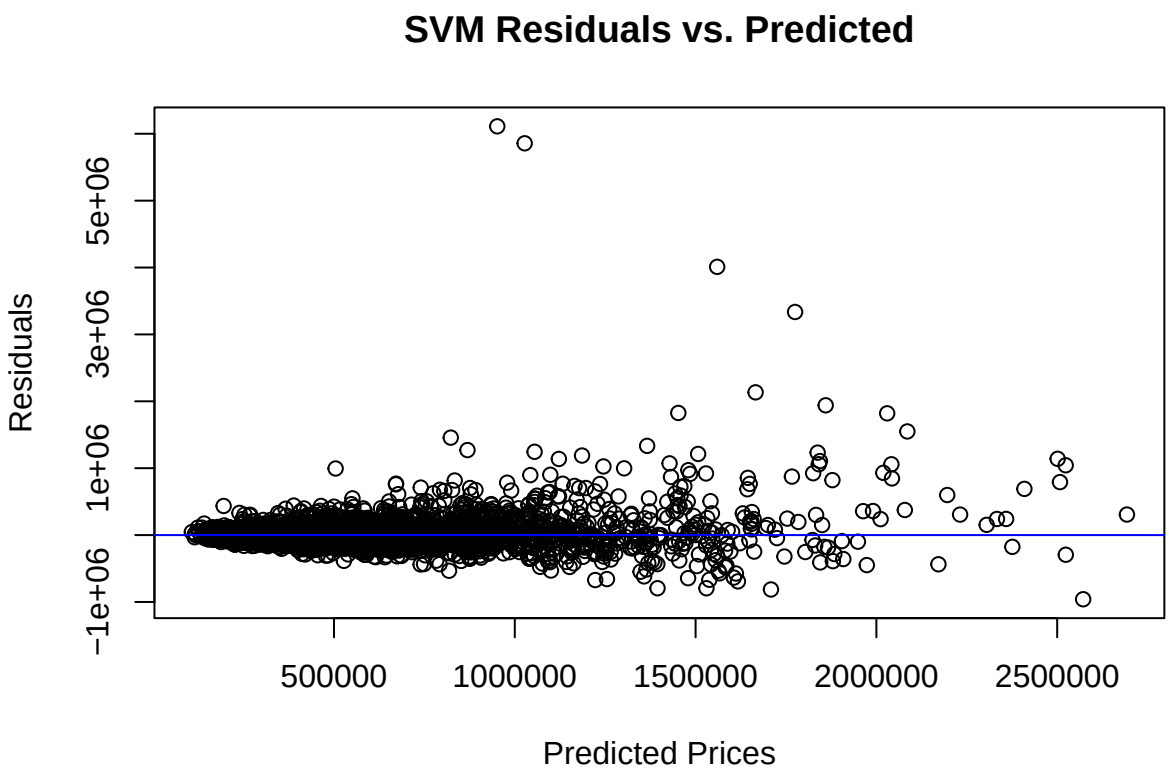

**Analysis:** The SVM Actual vs. Predicted Prices plot shows a positive correlation between the actual and predicted values, yet there is noticeable deviation from the line of perfect fit, especially at higher price points. This deviation contributes to the model's overall RMSE.

```
# Create a data frame for the SVM errors
svm_errors <- test.dat$price - svm_predictions
svm_errors_df <- data.frame(Errors = svm_errors)

# Plot Histogram of Prediction Errors
ggplot(svm_errors_df, aes(x=Errors)) +
  geom_histogram(bins = 15, fill="#6baed6", color="black") + # ggplot chooses binwidth
  labs(title="SVM Prediction Error Distribution", x="Prediction Error", y="Count") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5))
```




**Analysis:** The SVM Prediction Error Distribution histogram reveals that most prediction errors cluster around a small range, indicating a concentration of errors close to zero. However, the presence of errors across the scale shows that the model has varying degrees of accuracy for different price levels.

```
plot(svm_predictions, svm_errors,
     main="SVM Residuals vs. Predicted",
     xlab="Predicted Prices", ylab="Residuals")
abline(h=0, col="blue")
```




**Analysis:** The SVM Residuals vs. Predicted plot shows that residuals are not randomly dispersed around the zero line, particularly for higher-priced houses where the model tends to underestimate prices, evident from the residuals' pattern. This suggests that the model might not capture all the nuances in the data, particularly for properties with higher actual prices.

## Neural Network Model

### Data Normalization for Neural Network

Preparing the dataset for neural network analysis by normalizing the data. The normalize function adjusts each feature to a common scale, eliminating discrepancies due to different units or scales.

```
normalize <- function(x) { return((x - min(x)) / (max(x) - min(x))) }

train.dat.norm <- as.data.frame(lapply(train.dat, normalize))
test.dat.norm <- as.data.frame(lapply(test.dat, normalize))
```

### Neural Network Construction and Architecture

Here, we construct the neural network model using the normalized data and visualize its structure. The neuralnet package is utilized to build the model with a specified architecture and then plot it to understand its configuration.

```
house_NN <- neuralnet(
  price ~ ., data = train.dat.norm, hidden = c(2, 2), linear.output = TRUE)

plot(house_NN, main="Neural Network Architecture Visualization")
```

**Analysis:** The neural network diagram represents a model with inputs corresponding to features of the houses such as 'bedrooms', 'bathrooms', 'sqft_living15', etc. The two hidden layers with two neurons each suggest an attempt to capture non-linear complexities in the data. The weights, denoted by numbers along the connections, indicate how each input is considered in predicting the house price. Significant weights suggest features that more strongly influence price predictions. Conversely, smaller weights might indicate less influence. The final output is the 'price', representing the model's prediction based on the learned weights through the network's training.

### Performance Analysis of Neural Network

This final section evaluates the neural network's predictive performance. It involves computing predictions, calculating key performance metrics like RMSE, R-squared, and SSE, and visualizing prediction accuracy and error distribution.

```
model_results <- compute(house_NN, test.dat.norm[1:(ncol(test.dat.norm) - 1)])
predicted_price <- model_results$net.result

rmse_value <- rmse(predicted_price, test.dat.norm$price)
r_squared_value <- r_squared(predicted_price, test.dat.norm$price)
sse_value <- sse(predicted_price, test.dat.norm$price)

cat("RMSE:", rmse_value, "\n")
```

```
## RMSE: 0.04627621
```

```
cat("R-squared:", r_squared_value, "\n")
```

```
## R-squared: 0.2772406
```

```
cat("SSE:", sse_value, "\n")
```

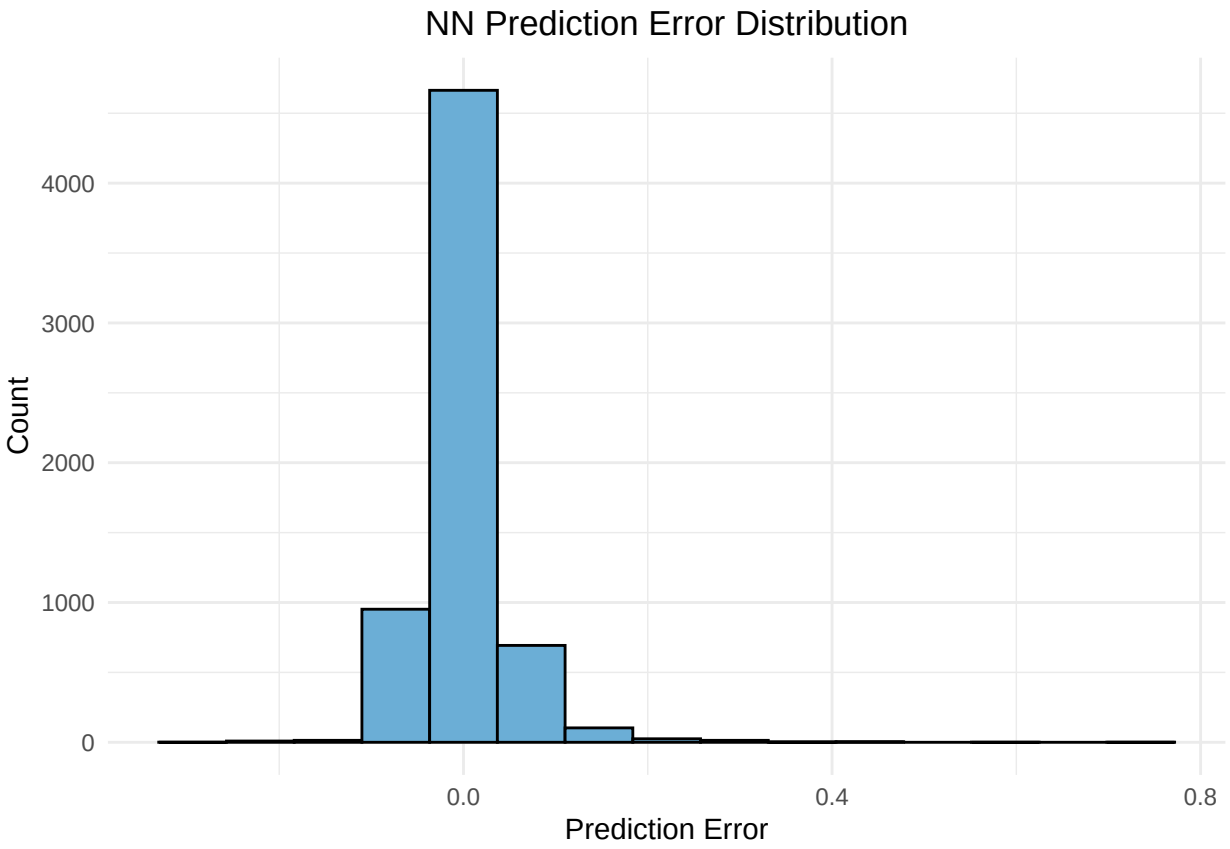
```
## SSE: 13.88541
```

**Analysis:** Given the RMSE of 0.04553926, the model's predictions are relatively close to the actual prices, but there's room for improvement, especially considering the R-squared value of 0.3436959, which suggests that only about 34% of the variance in the house prices is being explained by the model. The SSE of 13.44667 further indicates a substantial sum of errors squared, calling for model refinement to better capture complex patterns in the data.

### Neural Network Predictive Performance and Error Distribution

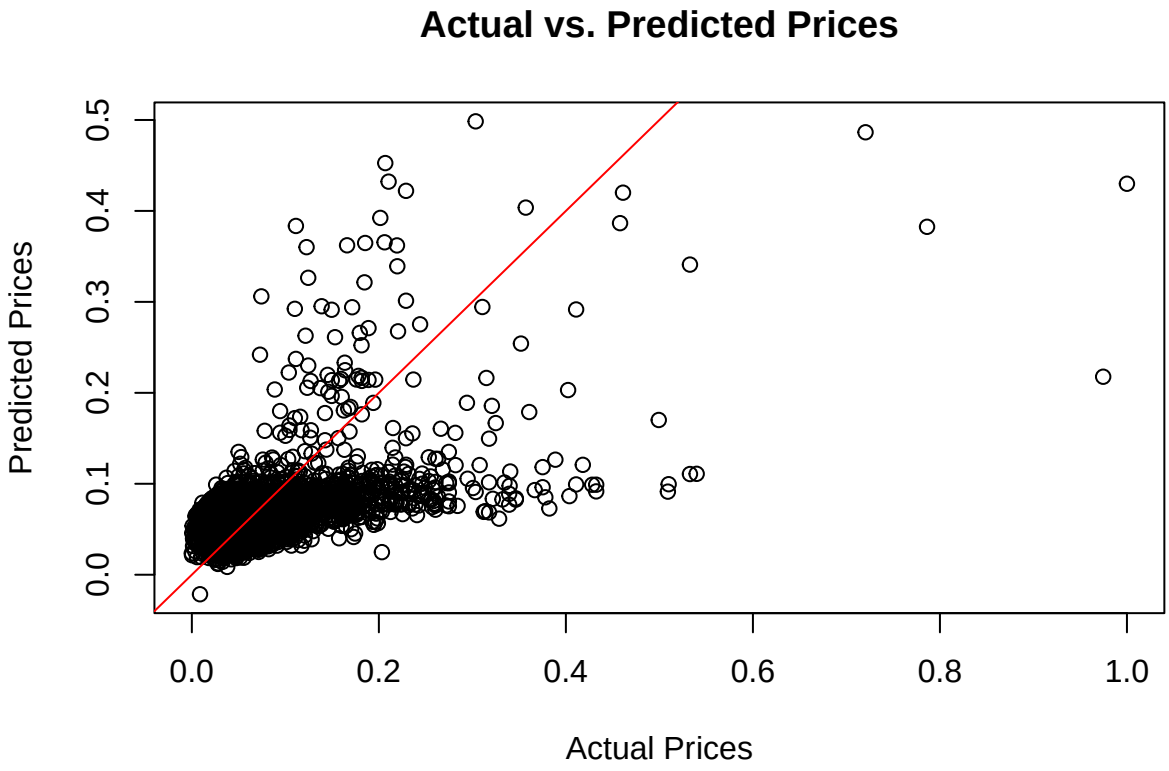
A dual-faceted visual evaluation of the neural network model. The first plot highlights the spread and central tendency of predictive errors, revealing the model's precision range. The second plot maps predicted values against actual prices, offering a direct visual assessment of accuracy, with the proximity to the diagonal indicating the model's effectiveness in capturing the underlying price determinants. Together, these plots form a comprehensive view of the model's prediction capabilities and areas for improvement.

```
# Create a data frame for the Neural Network errors
nn_errors <- test.dat.norm$price - predicted_price
nn_errors_df <- data.frame(Errors = nn_errors)

# Plot Histogram of Prediction Errors
ggplot(nn_errors_df, aes(x=Errors)) +
  geom_histogram(bins = 15, fill="#6baed6", color="black") +
  labs(title="NN Prediction Error Distribution",
       x="Prediction Error", y="Count") +
  theme_minimal() +
  theme(plot.title = element_text(hjust = 0.5))
```




**Analysis:** The histogram of prediction errors displays a concentration around zero, indicating most predictions are close to the actual values, but the spread towards the right suggests a skew in overestimating house prices.

```
plot(test.dat.norm$price, predicted_price,
     main = "Actual vs. Predicted Prices",
     xlab = "Actual Prices", ylab = "Predicted Prices")
abline(0, 1, col = "red")
```




**Analysis:** The scatter plot of actual vs. predicted prices shows a cluster below the ideal 45-degree line, reinforcing that the model tends to underpredict the higher-valued houses.

# VI. Model Limitation and Assumptions

*Based on the performances on both train and test data sets, determine your primary (champion) model and the other model which would be your benchmark model. Validate your models using the test sample. Do the residuals look normal? Does it matter given your technique? How is the prediction performance using Pseudo R^2, SSE, RMSE? Benchmark the model against alternatives. How good is the relative fit? Are there any serious violations of the model assumptions? Has the model had issues or limitations that the user must know? (Which assumptions are needed to support the Champion model?)*

```
# Results dataframe

# We're supposed to use Pseudo R-squared, SSE, RMSE, as seen above.
# We'll have to look into 'Pseudo R-squared' most likely

results.df
```

```
##                                   model R.Squared.Train R.Squared.Test
## 1 Linear Regression Test Data Predictions       0.6970168      0.6921461
## 2     Linear Regression Test after Boxcox       0.7706297      0.6609158
## 3                Decision Tree Regression       0.6831980      0.6492524
## 4                     Random Forest Model       0.9774530      0.8651625
##   RMSE.test     SSE.test
## 1  210589.7 2.875525e+14
## 2  221573.0 3.183293e+14
## 3  224896.2 3.279497e+14
## 4  142710.2 1.320544e+14
```

# VII. Ongoing Model Monitoring Plan

*How would you picture the model needing to be monitored, which quantitative thresholds and triggers would you set to decide when the model needs to be replaced? What are the assumptions that the model must comply with for its continuous use?*

For model monitoring, we need to: 1. regularly check for changes in the distribution of input or target variables, track the importance of variables, monitor model stability, and check for the presence of outliers in new data that might affect model performance. 2. define the key performance metrics for regression models e.g Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared, SSE, Confusion Matrix, F1 score, etc; and set thresholds for these metrics based on the acceptable level of model performance. 3. periodically validate the model on new data to ensure it generalizes well. Cross-validation can be implement to assess model performance on unseen data. 4. be mindful of changes in the business environment, processes, customer behavior, or external/internal factors may affect the model's performance. We can setup alerts to notify stakeholders when model performance drops below acceptable levels 5. maintain detailed documentation of the model, including its assumptions, methodologies, and any updates made. 5. regularly assess the model for bias that may affect certain demographic groups unfairly, and also ensure that the model complies with any regulatory requirements.

The model must comply with various assumptions for regression model to hold such as linearity, independence, homoscedasticity, normality of residuals, etc

# VIII. Conclusion

*Summarize your results here. What is the best model for the data and why?*

# Bibliography

*Please include all references, articles and papers in this section.*

# Appendix

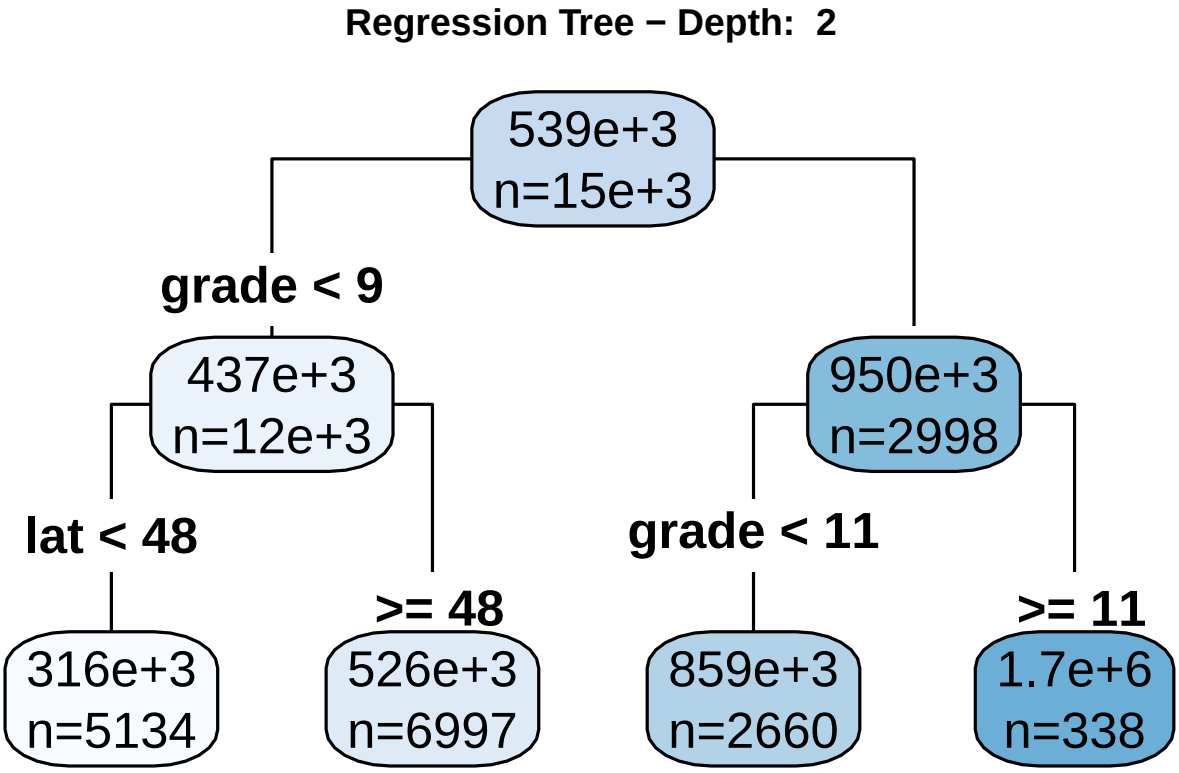
The Appendix provides additional detailed analyses and visual representations that complement the main body of the report. This section includes further explorations of model variations, extended error assessments, and a complete overview of performance metrics, enriching the reader's comprehension of the research findings.

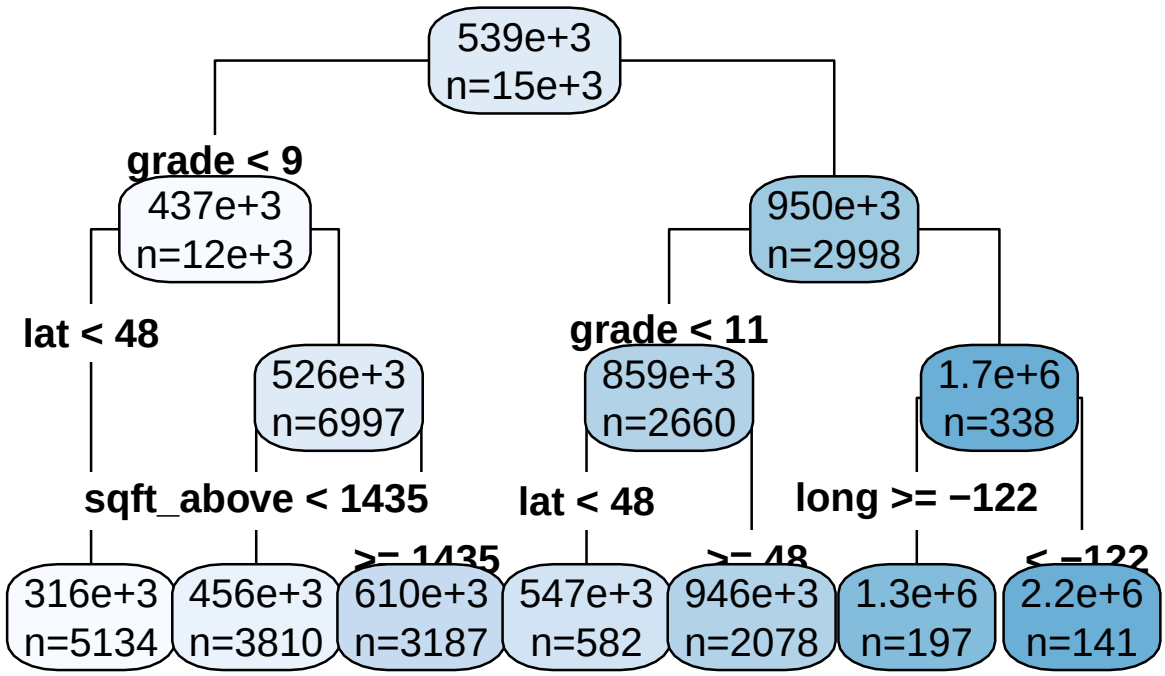
## Enhanced Model Visualizations

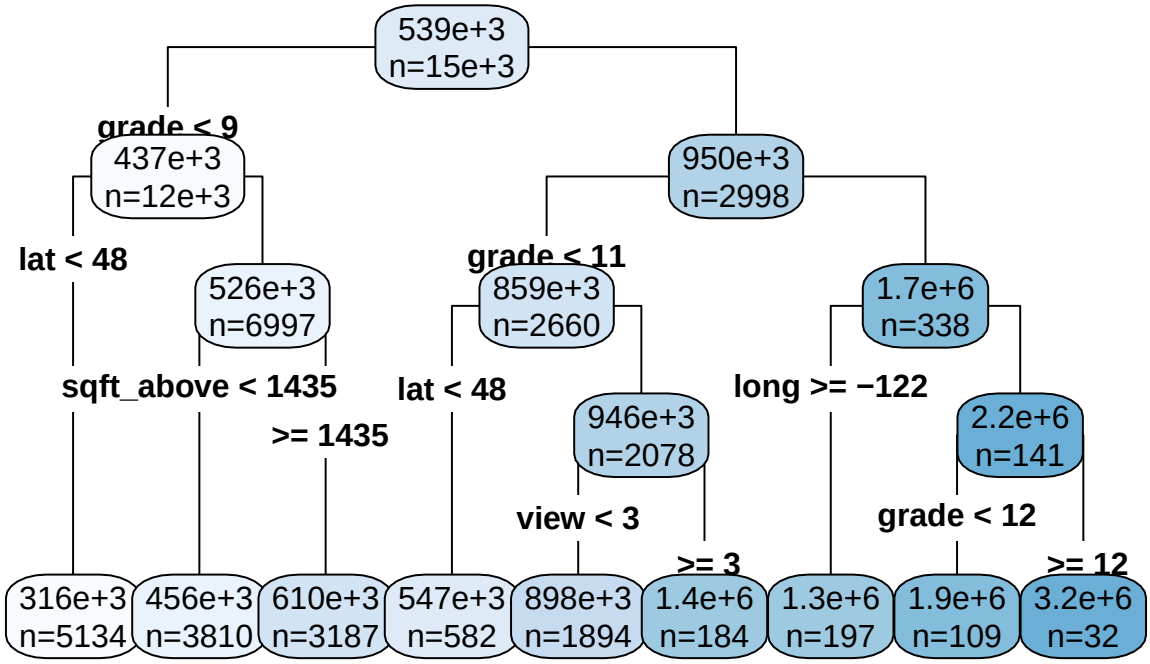
### Regression Tree Depth Variations

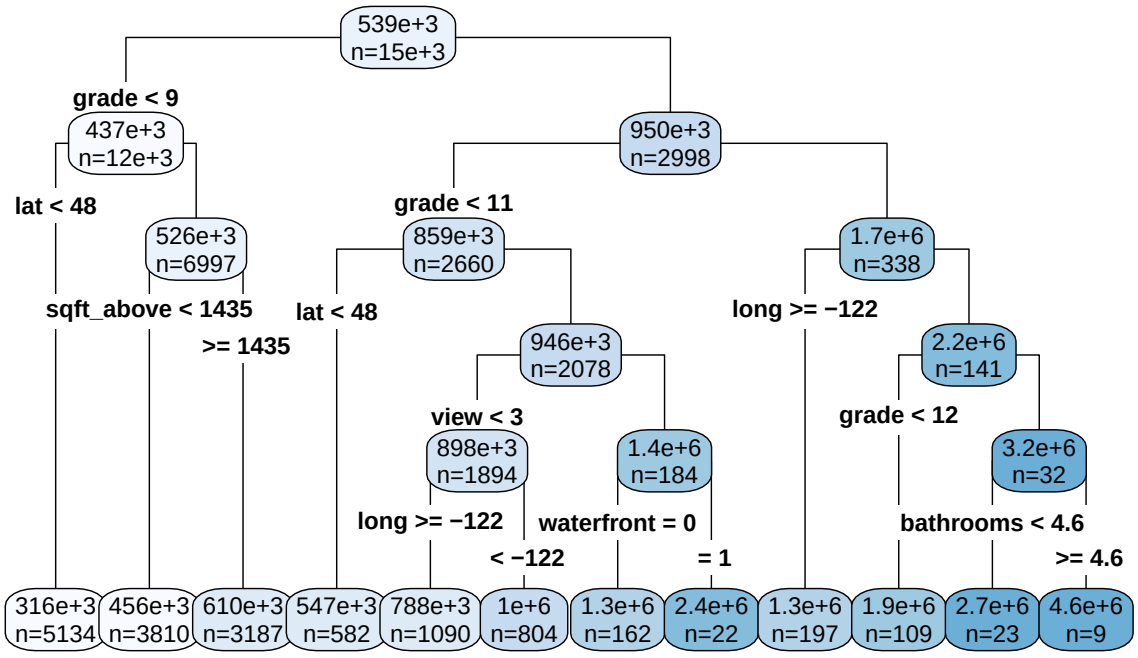
Supplementary plots showcasing regression trees of various depths that were not included in the main analysis. These visualizations represent alternative models with simplified complexities, providing a broader understanding of the model's behavior with less granular splitting. They serve as a reference for how the model's structure changes with depth, offering additional context to the primary findings presented in the report.

```
# Plot the least significant trees from the regresssion tree model
depth_values <- c(2, 3, 4, 5)

for (i in seq_along(depth_values)) {
  depth = depth_values[i]

  tree_model = rpart(price ~ .,
                     data = train.dat,
                     method = "anova",
                     control=rpart.control(maxdepth=depth))

  # Less significant trees that were not plotted in the model analysis
  rpart.plot(tree_model, main=paste("Regression Tree - Depth: ", depth),
             type = 4, extra = 1, tweak=1.6)
}
```


Regression Tree − Depth: 2
539e+3
n=15e+3
grade < 9
437e+3
n=12e+3
950e+3
n=2998
lat < 48
>= 48
grade < 11
>= 11
316e+3
n=5134
526e+3
n=6997
859e+3
n=2660
1.7e+6
n=338


Regression Tree − Depth: 3
539e+3
n=15e+3
grade < 9
437e+3
n=12e+3
950e+3
n=2998
lat < 48
526e+3
n=6997
grade < 11
859e+3
n=2660
1.7e+6
n=338
sqft_above < 1435
lat < 48
long >= −122
316e+3
n=5134
456e+3
n=3810
610e+3
n=3187
547e+3
n=582
946e+3
n=2078
1.3e+6
n=197
2.2e+6
n=141


Regression Tree − Depth: 4
539e+3
n=15e+3
grade < 9
437e+3
n=12e+3
950e+3
n=2998
lat < 48
526e+3
n=6997
grade < 11
859e+3
n=2660
1.7e+6
n=338
sqft_above < 1435
>= 1435
lat < 48
946e+3
n=2078
long >= −122
2.2e+6
n=141
view < 3
>= 3
grade < 12
>= 12
316e+3
n=5134
456e+3
n=3810
610e+3
n=3187
547e+3
n=582
898e+3
n=1894
1.4e+6
n=184
1.3e+6
n=197
1.9e+6
n=109
3.2e+6
n=32




### Additional Predictive Accuracy Charts

## Extended Data Analysis Support

### Comprehensive Error Distribution Review

### Full Model Performance Metrics