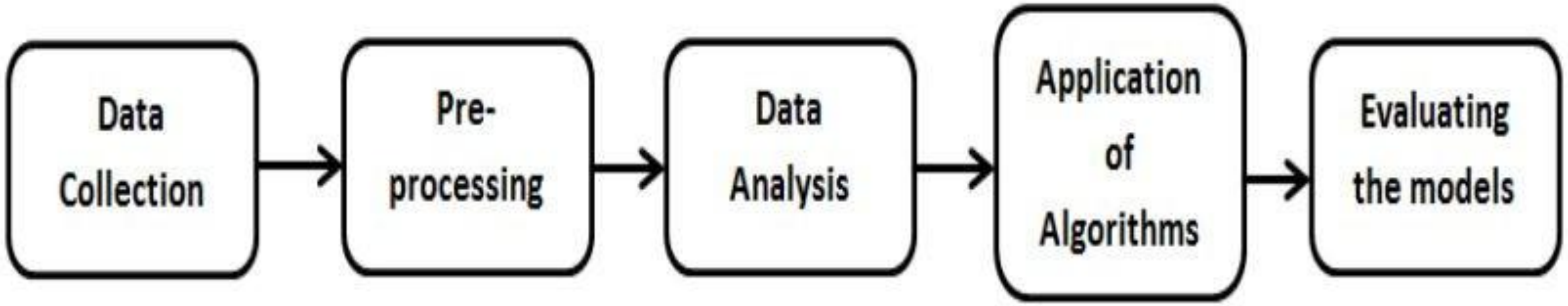
# Smart Predictive Modeling for Rental Property Prices Using Different Algorithms

**Mayank Raj Kolwal**

# Methodology



# Data Set Overview

| Feature Name | Description | Type |
|---|---|---|
| Date | Date on which the dwelling was sold | String |
| Price | Price of the dwelling which we have to predict so this is our target variable | Integer |
| bedrooms | Number of bedrooms per dwelling | Integer |
| bathrooms | Number of bathrooms per dwelling | Float |
| sqft_living | Square Footage of the dwelling | Integer |
| sqft_lot | Square footage of the lot | Integer |
| floors | Total floors (levels) in dwelling | Float |
| waterfront | dwelling which has a view to a waterfront | Integer |
| view | How many times the dwelling has been viewed | Integer |
| condition | How good is the condition (Overall) | Integer |
| grade | Grade of the dwelling | Integer |
| sqft_above | Square footage of the dwelling apart from basement | Integer |
| sqft_basement | Square footage of the basement | Integer |
| yr_built | Built year | Integer |
| yr_rennovated | Year when dwelling was renovated | Integer |
| zipcode | Zip | Integer |
| lat | Latitude coordinate | Float |
| long | Longitude coordinate | Float |
| sqft_living15 | Living room area in 2015 (implies some renovation) | Integer |
| sqft_lot15 | Lot size area in 2015 (implies some renovations) | Integer |

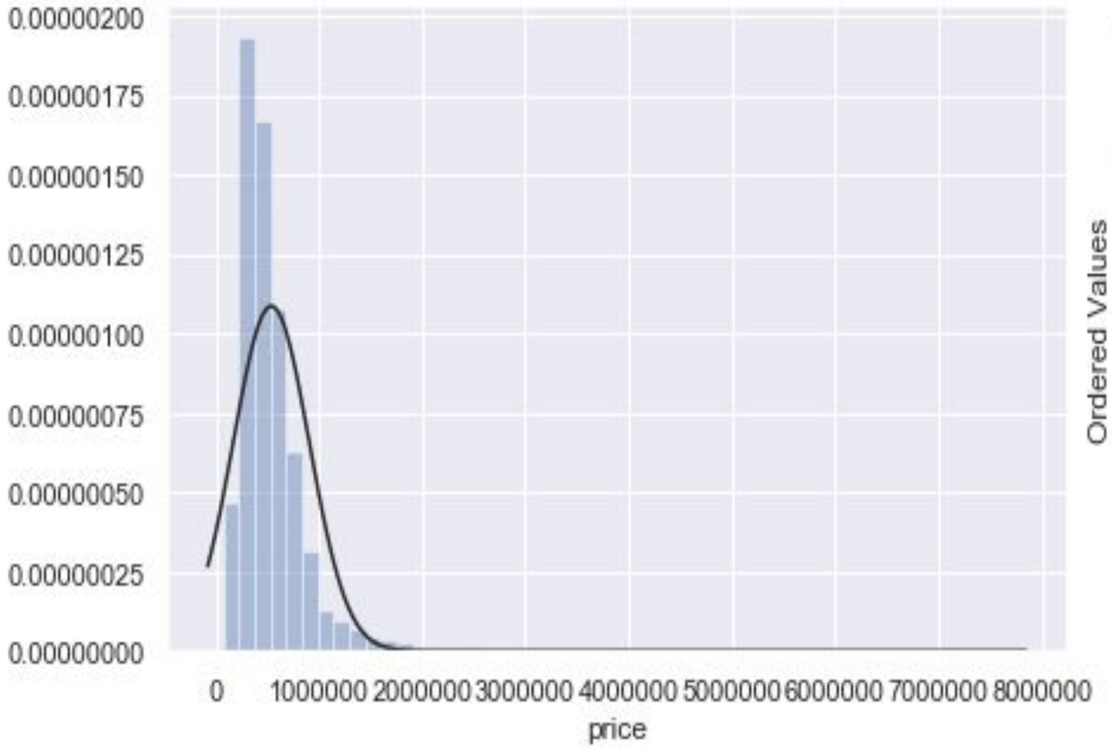
# Data Pre-Processing

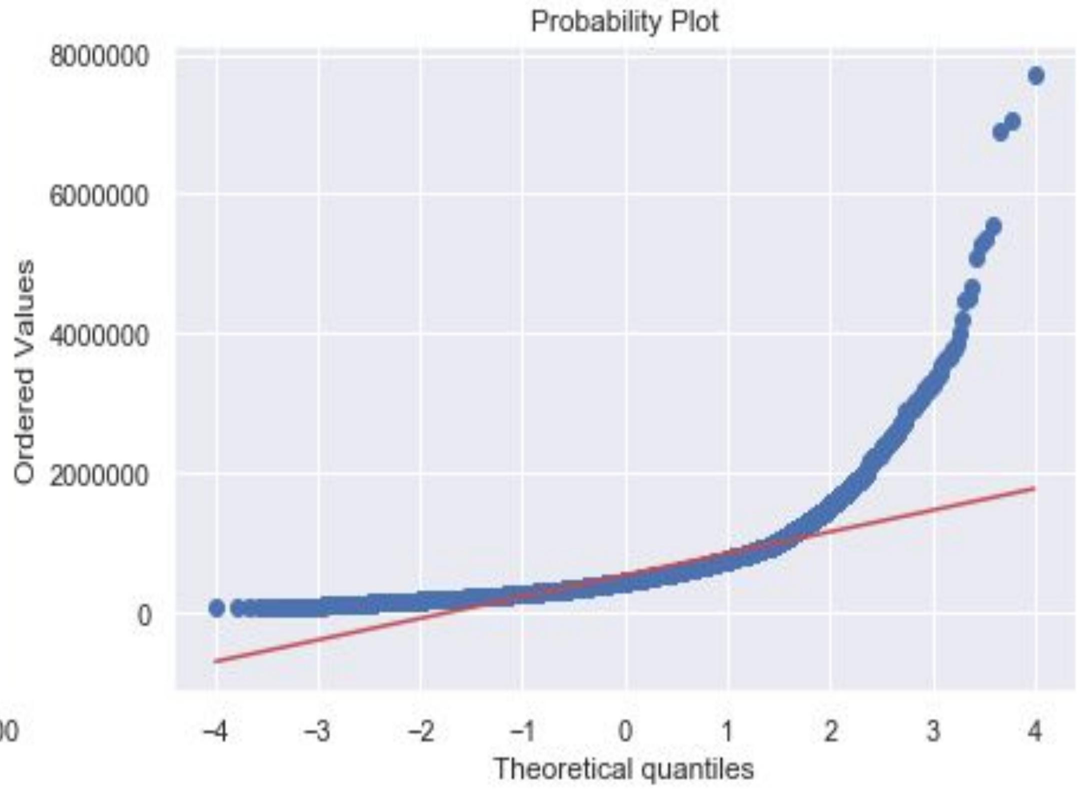
- Data Cleaning
- Statistical Analysis
- Feature Construction
- Identifying Outliers
- Data Conversion
- Collinearity Problem
- Data Visualization

# Data Cleaning

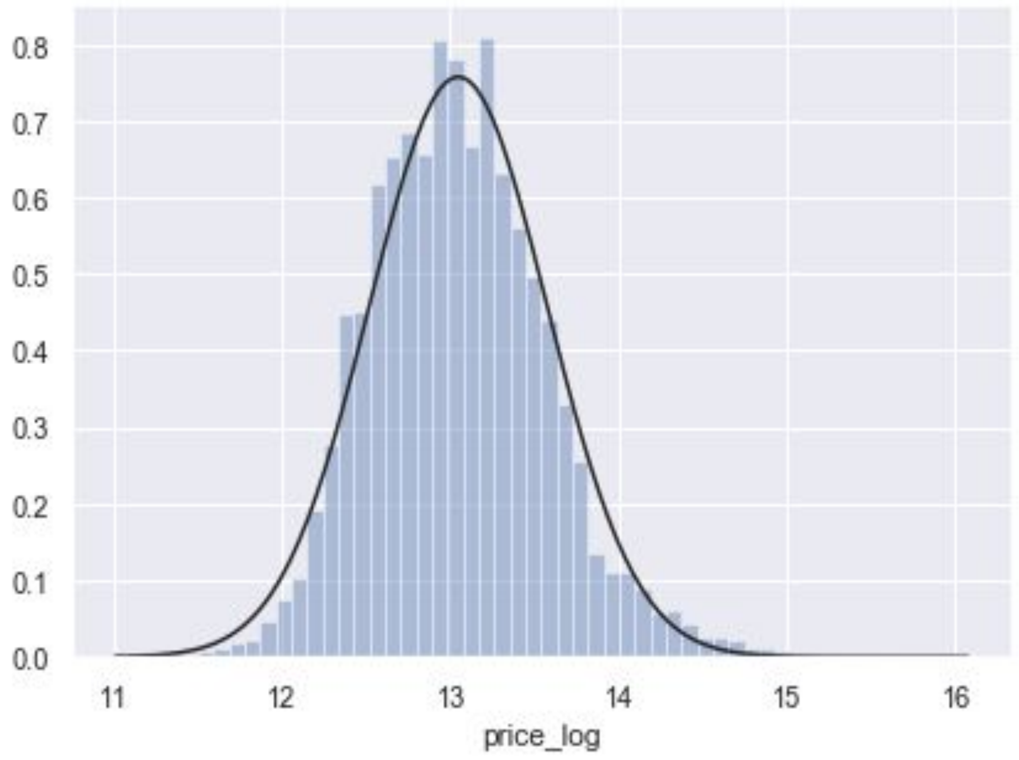
```
Data columns (total 21 columns):
id               21613 non-null int64
date             21613 non-null object
price            21613 non-null int64
bedrooms         21613 non-null int64
bathrooms        21613 non-null float64
sqft_living      21613 non-null int64
sqft_lot         21613 non-null int64
floors           21613 non-null float64
waterfront       21613 non-null int64
view             21613 non-null int64
condition        21613 non-null int64
grade            21613 non-null int64
sqft_above       21613 non-null int64
sqft_basement    21613 non-null int64
yr_built         21613 non-null int64
yr_renovated     21613 non-null int64
zipcode          21613 non-null int64
lat              21613 non-null float64
long             21613 non-null float64
sqft_living15    21613 non-null int64
sqft_lot15       21613 non-null int64
dtypes: float64(4), int64(16), object(1)
```

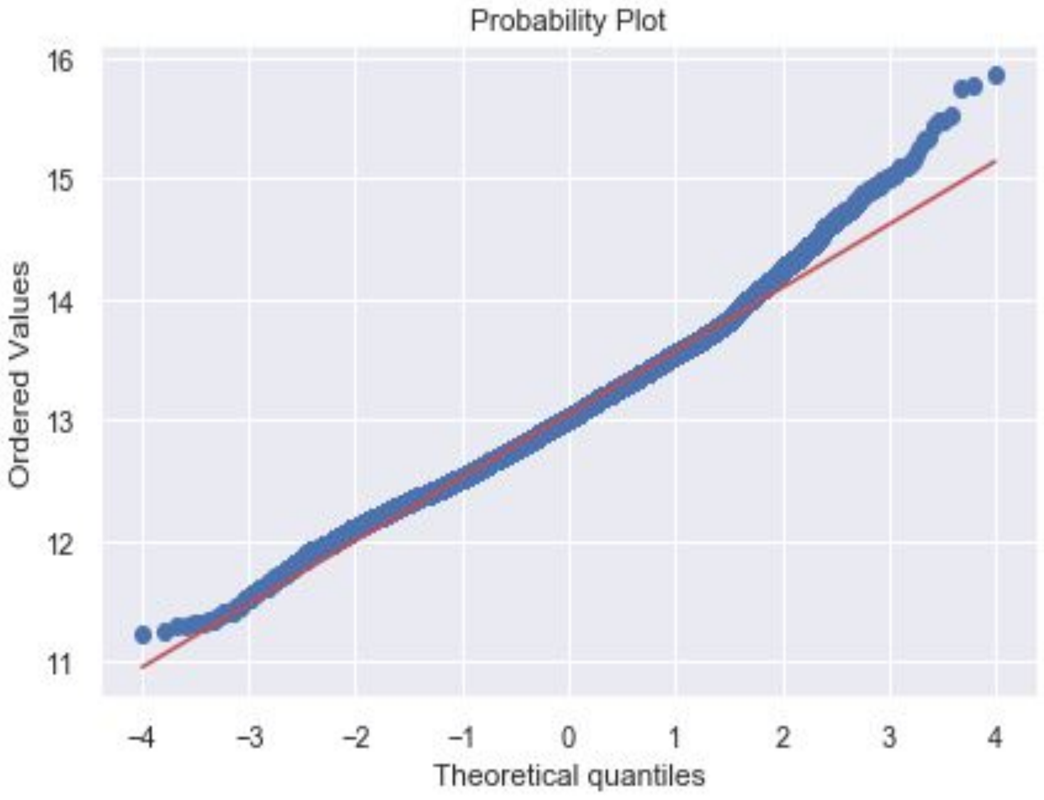
# Statistical Analysis of Price Feature



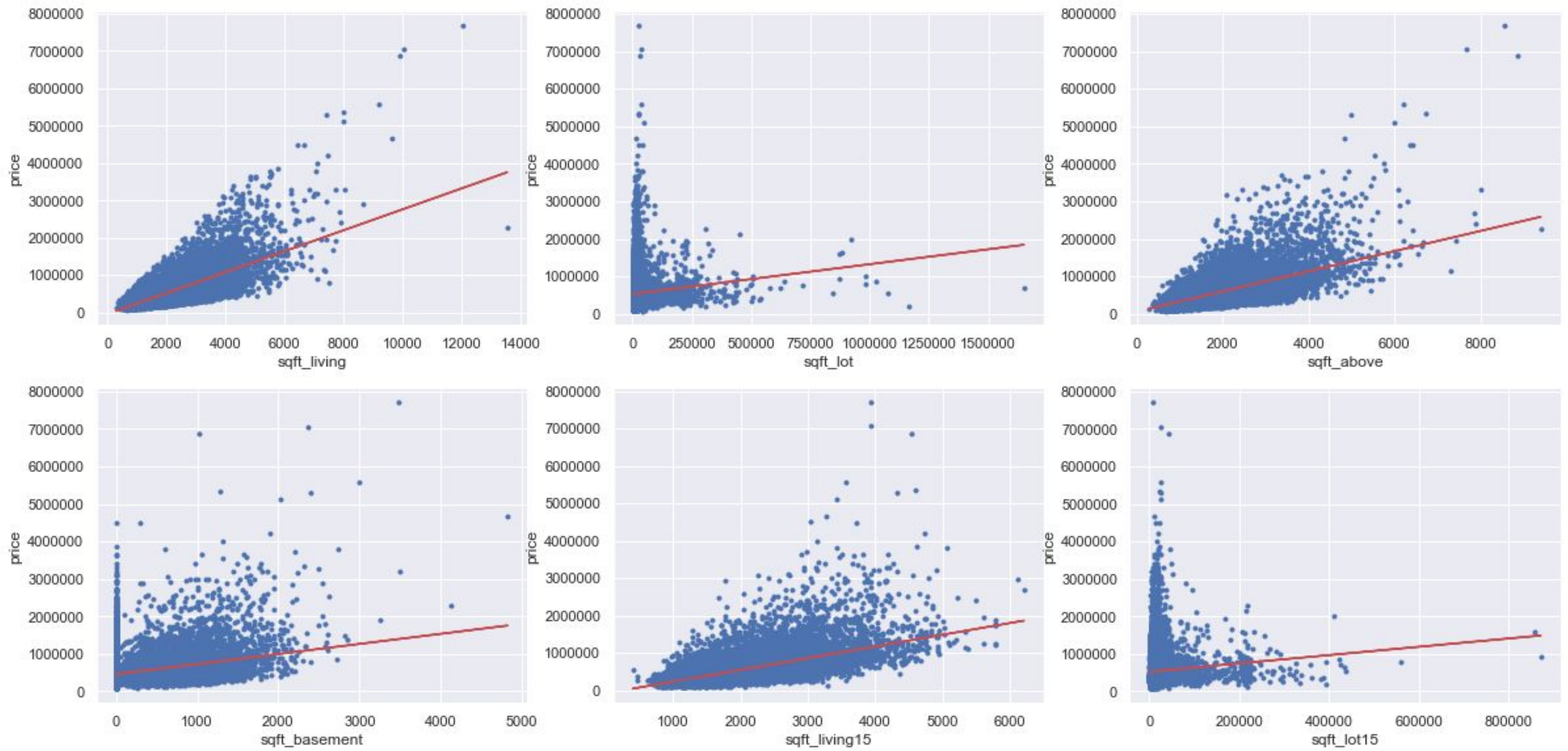



# Logarithmic Transformation of Price

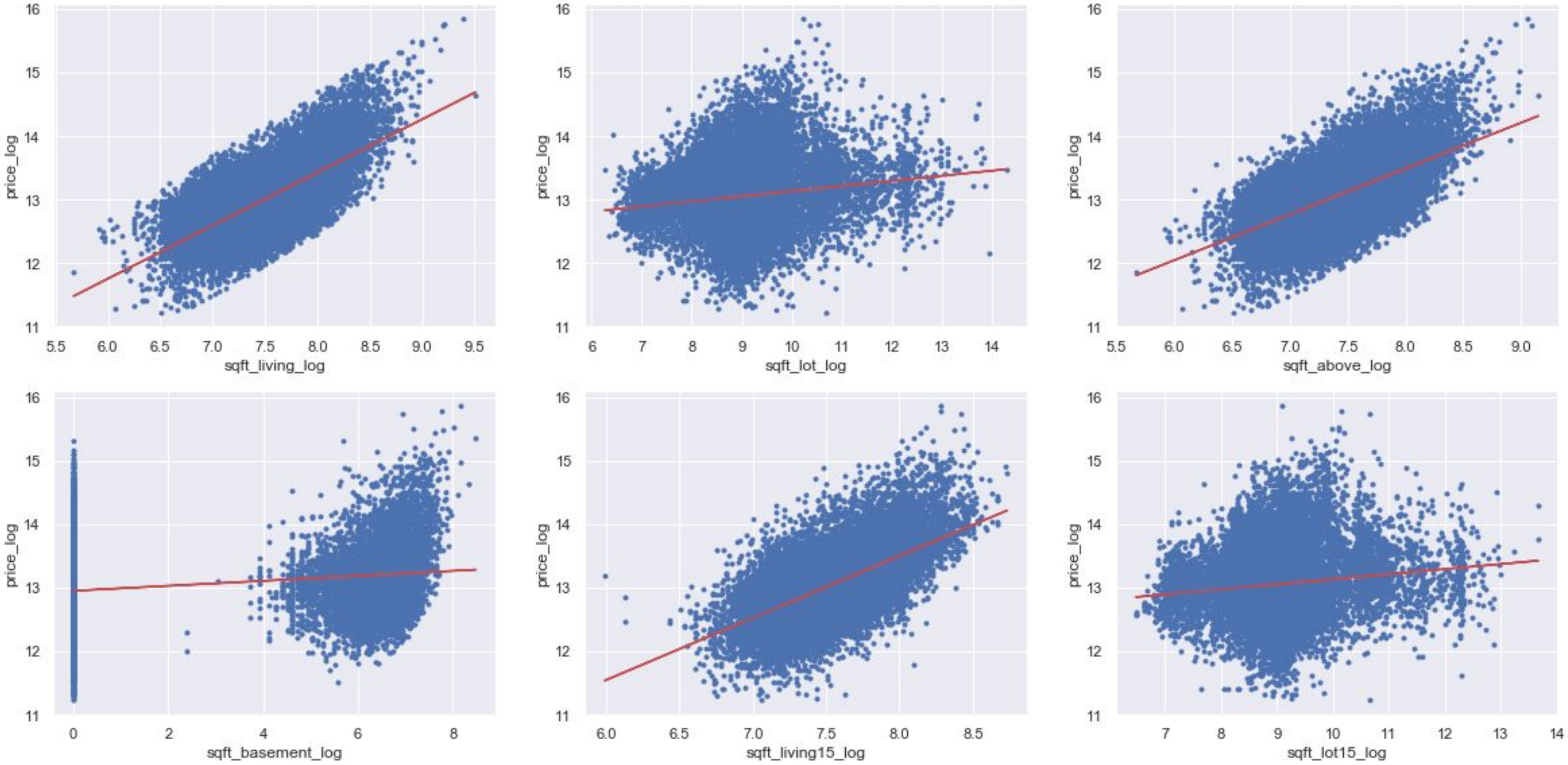


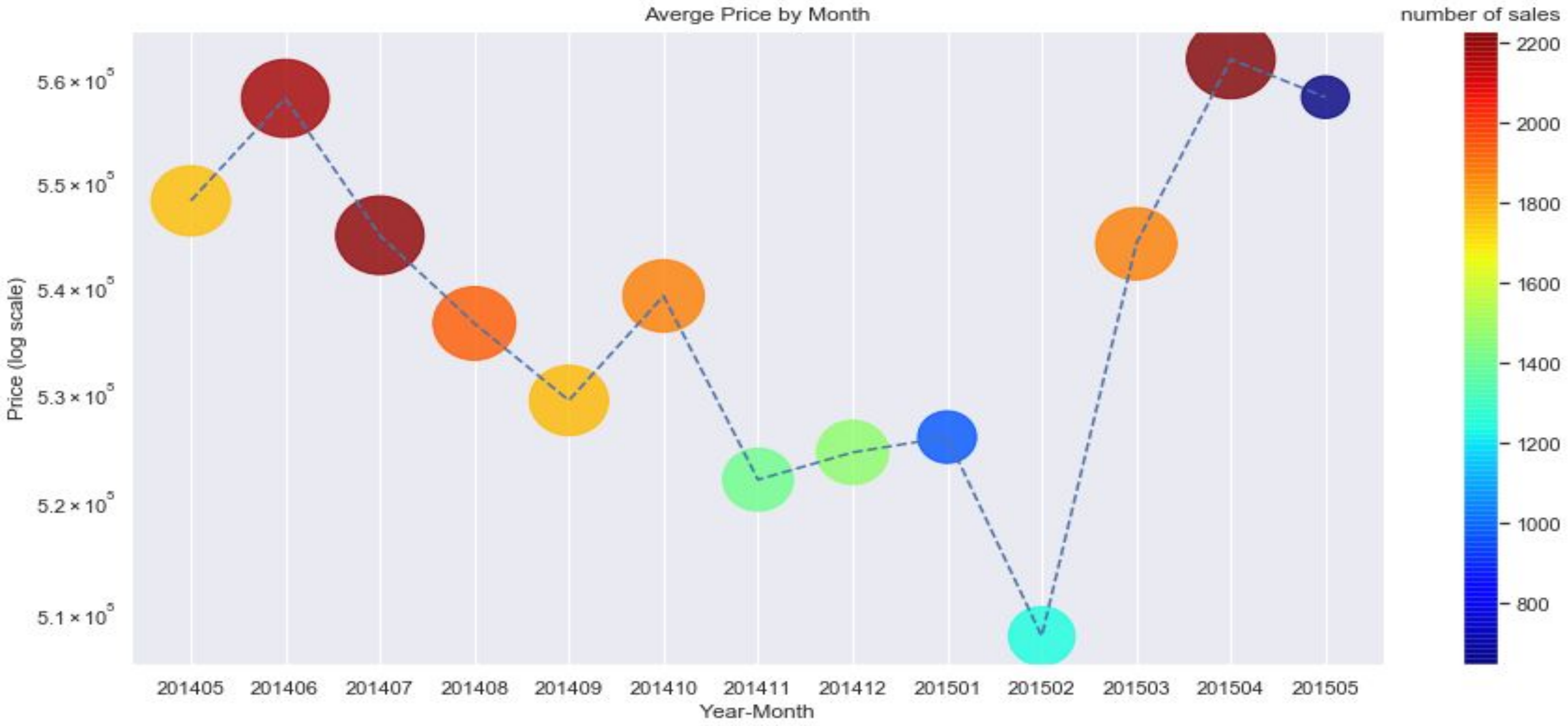
# Too Much skewness in numerical Features



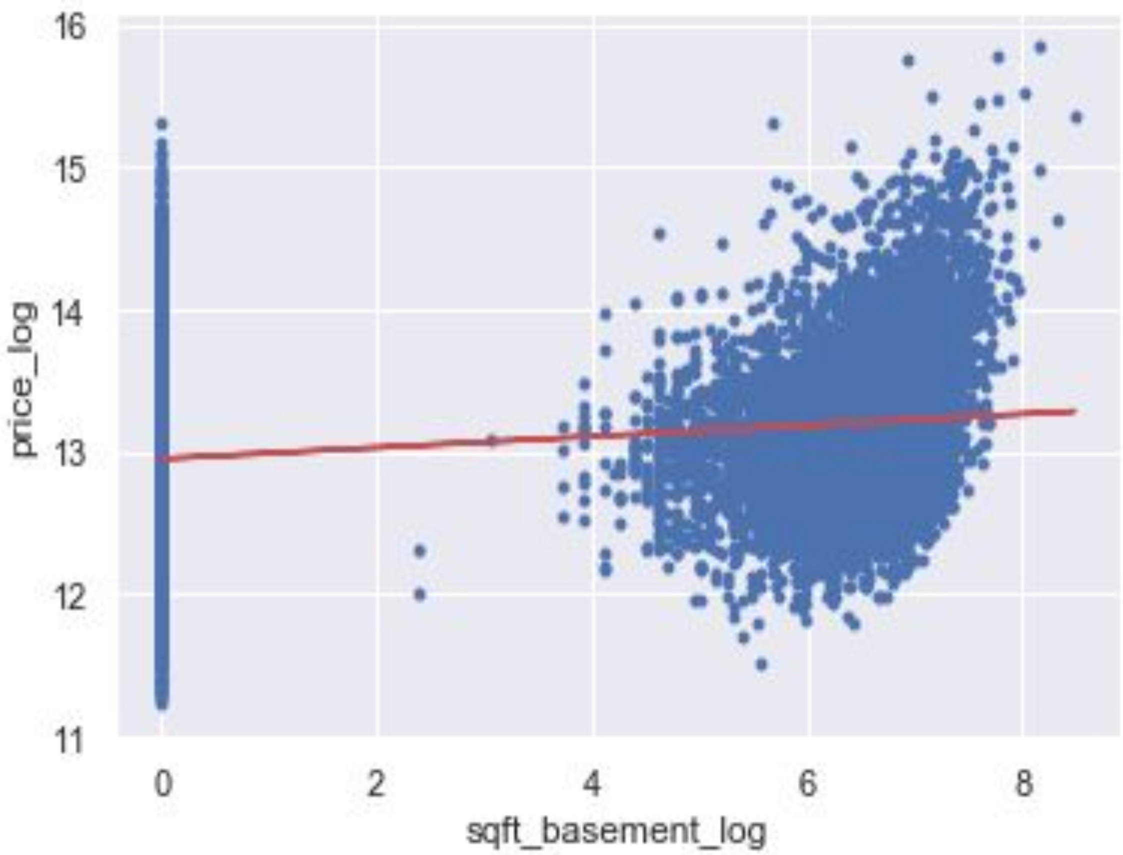
# After Log Transformation of numerical features

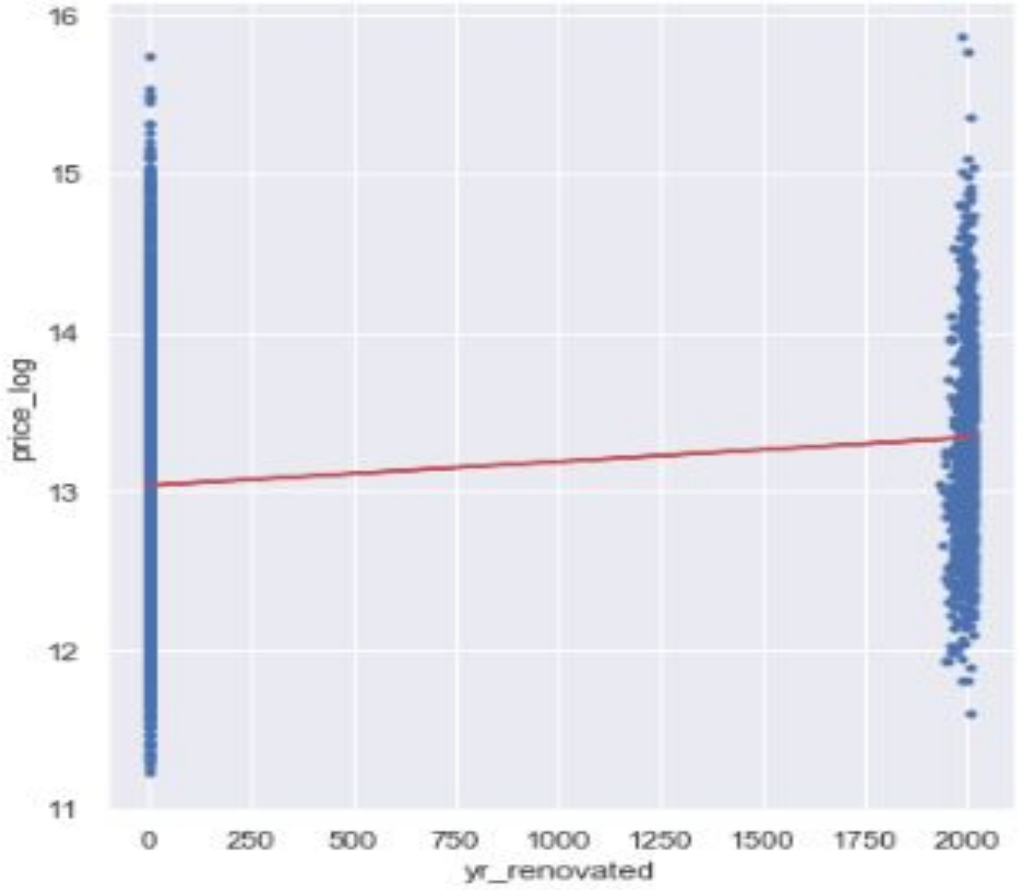


# Feature Construction- Seasonality of house Price

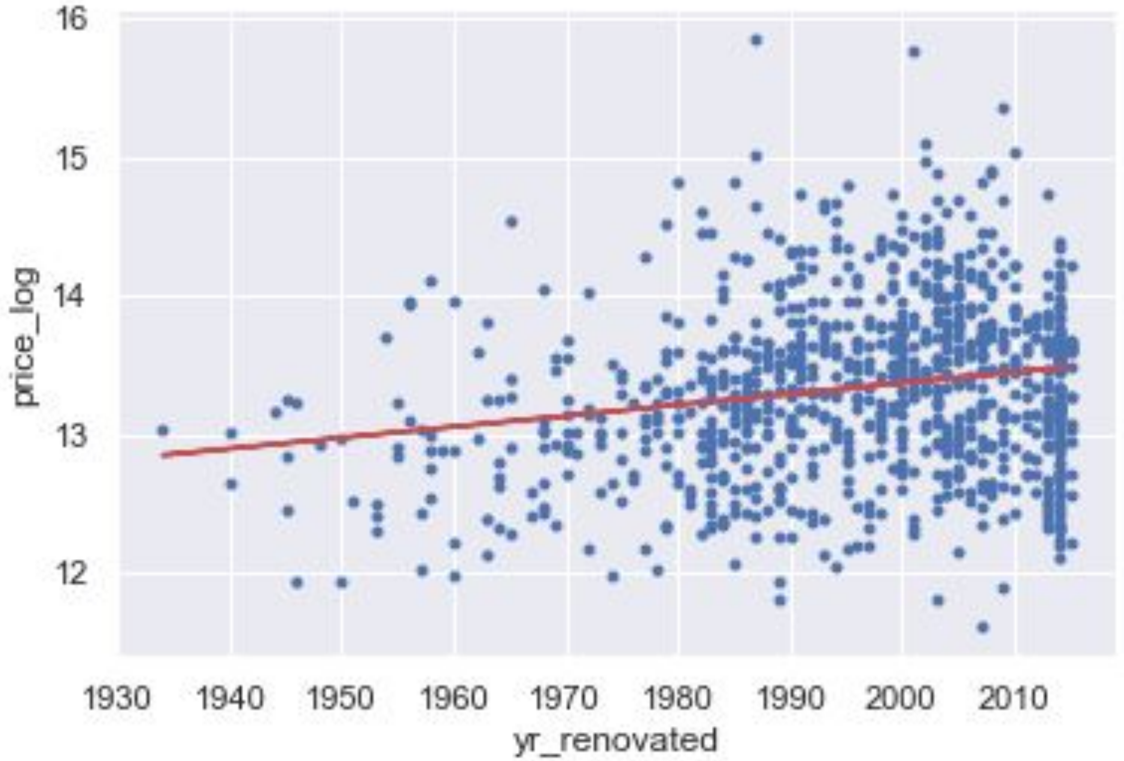


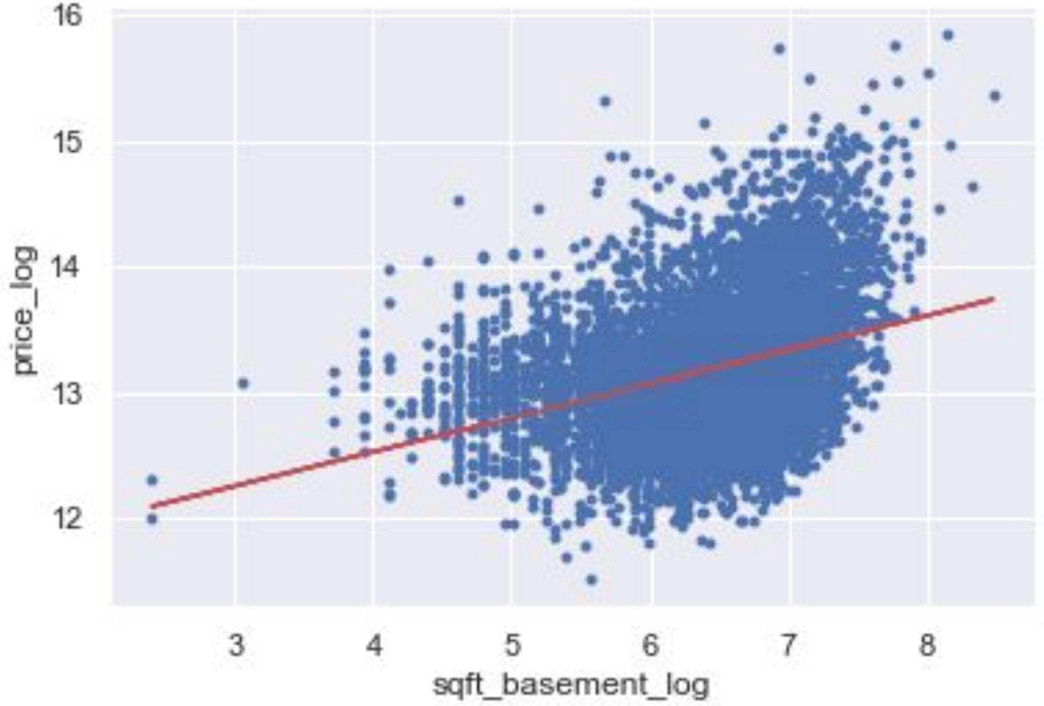
# Feature extraction from basement area and year renovation attribute



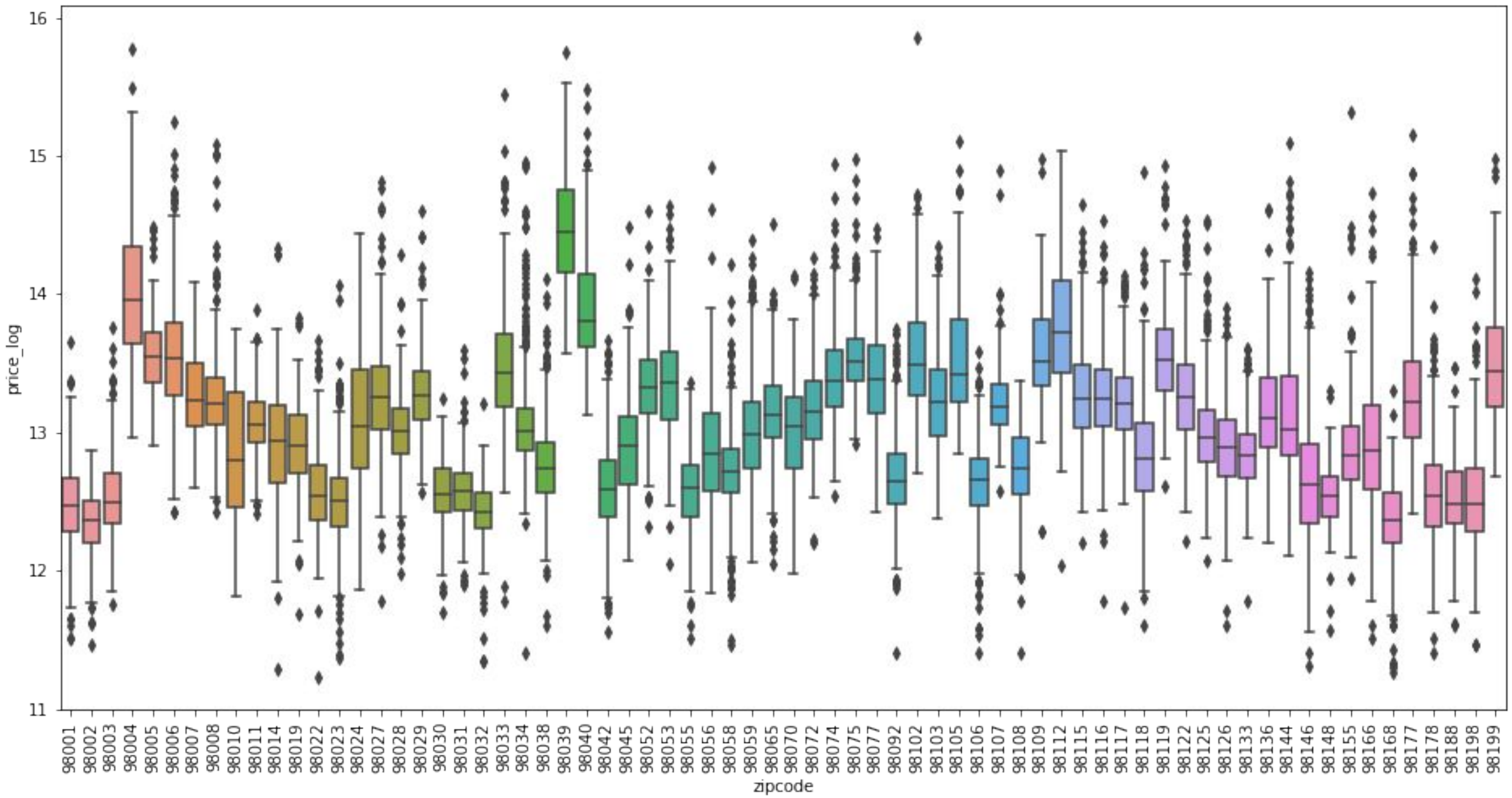
# After Feature Extraction of basement area and year of renovation



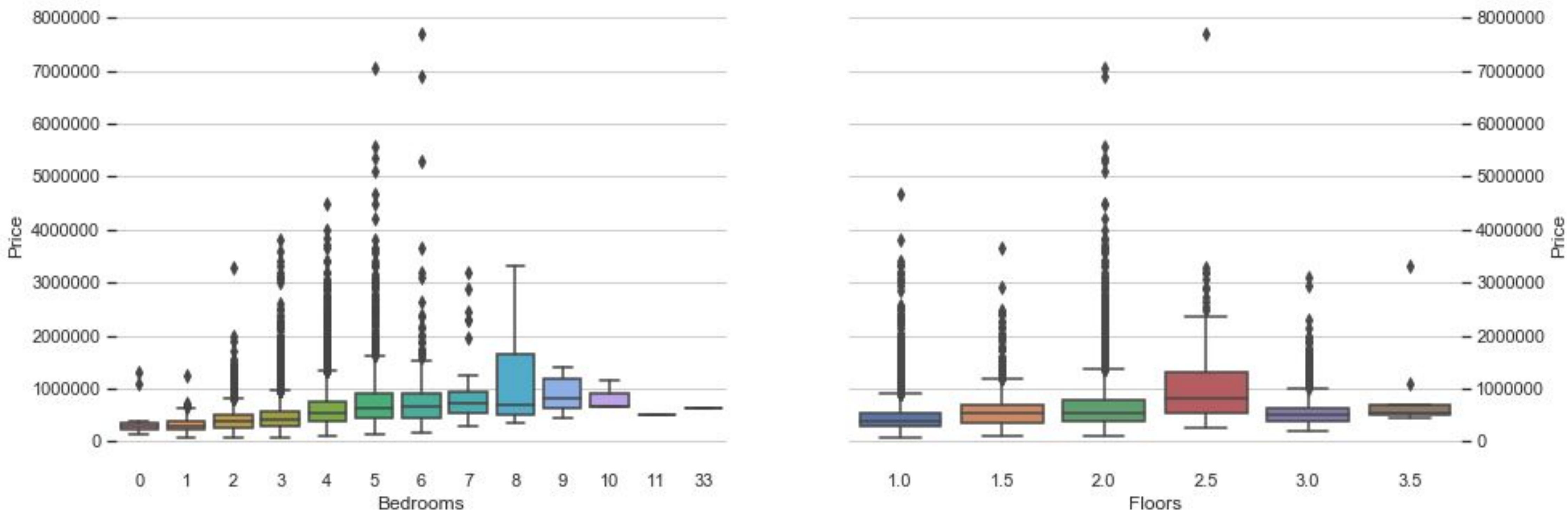



# Identifying Outliers

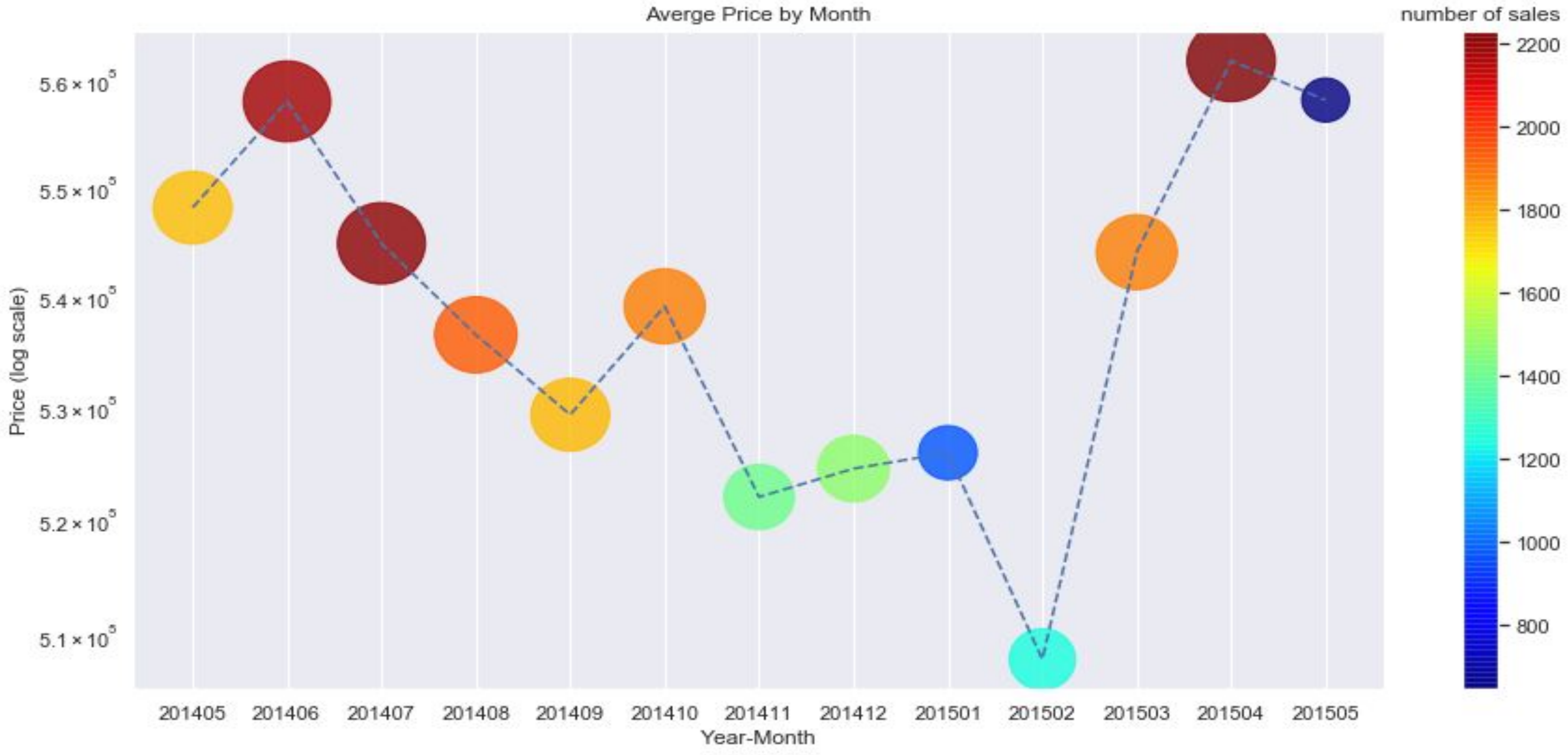
# Data Conversion of zip code



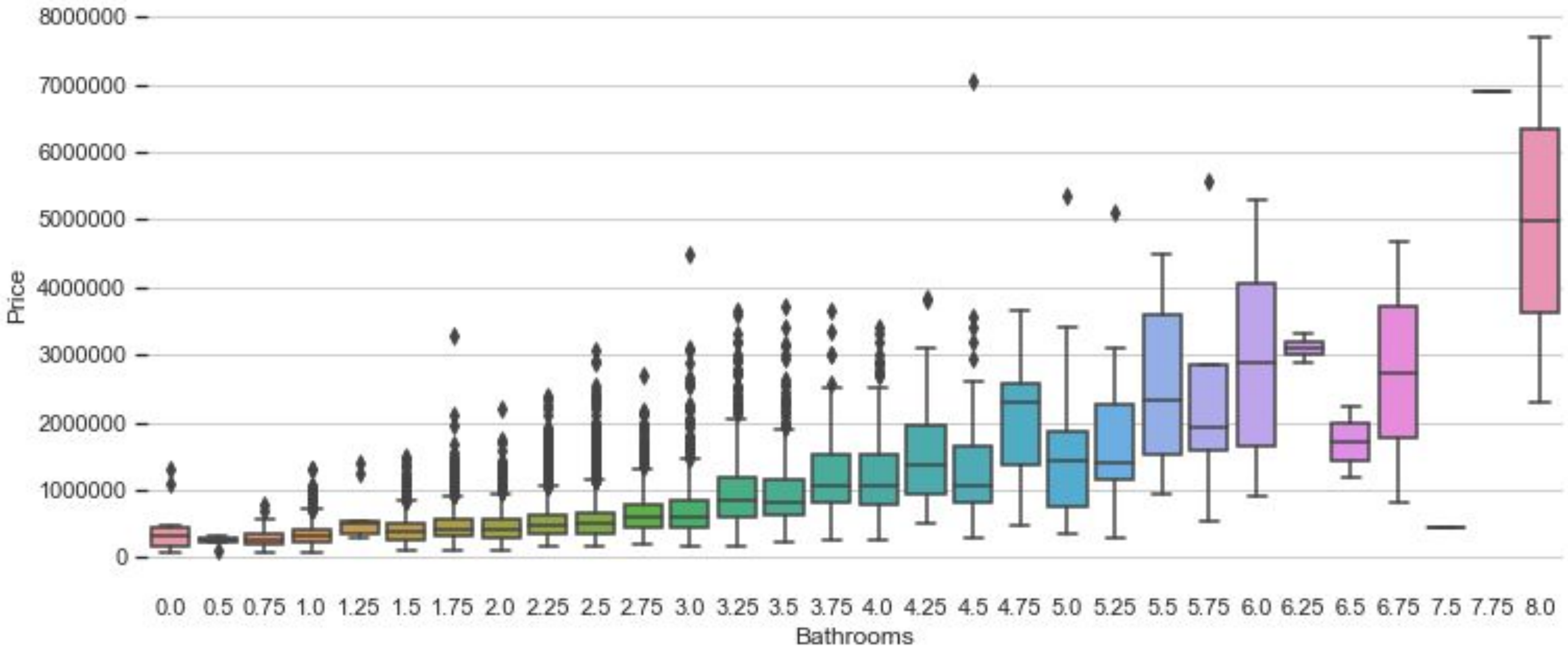
# Data conversion of bedrooms and Floors



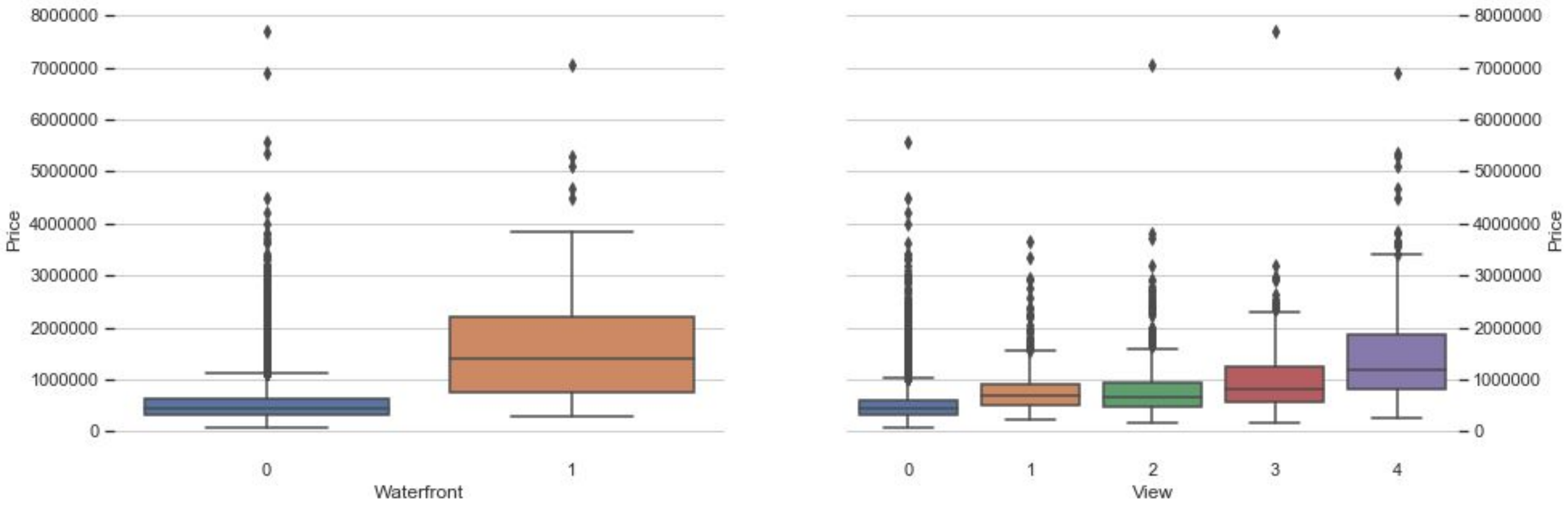
# Data conversion of seasonality attribute



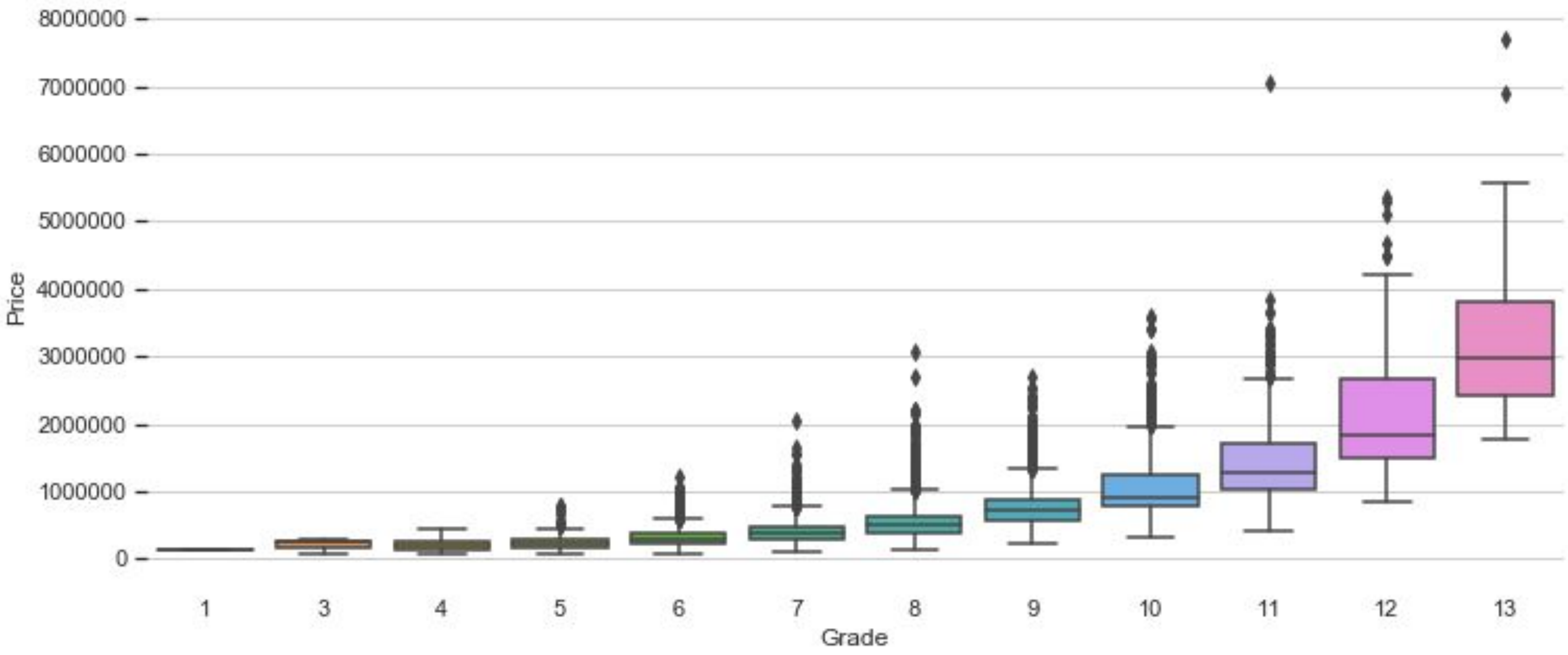
# Bathrooms Feature



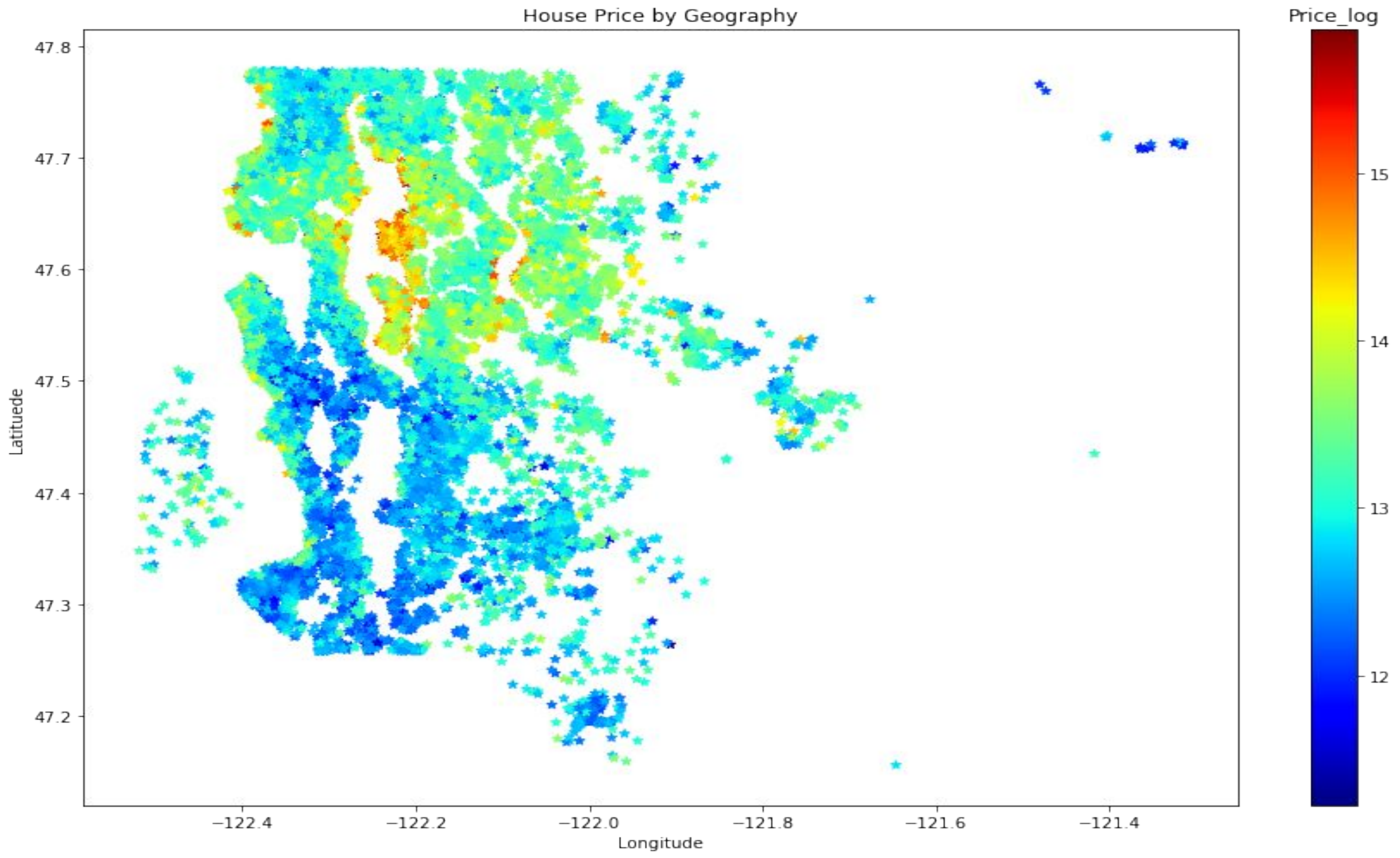
# Water front and view feature



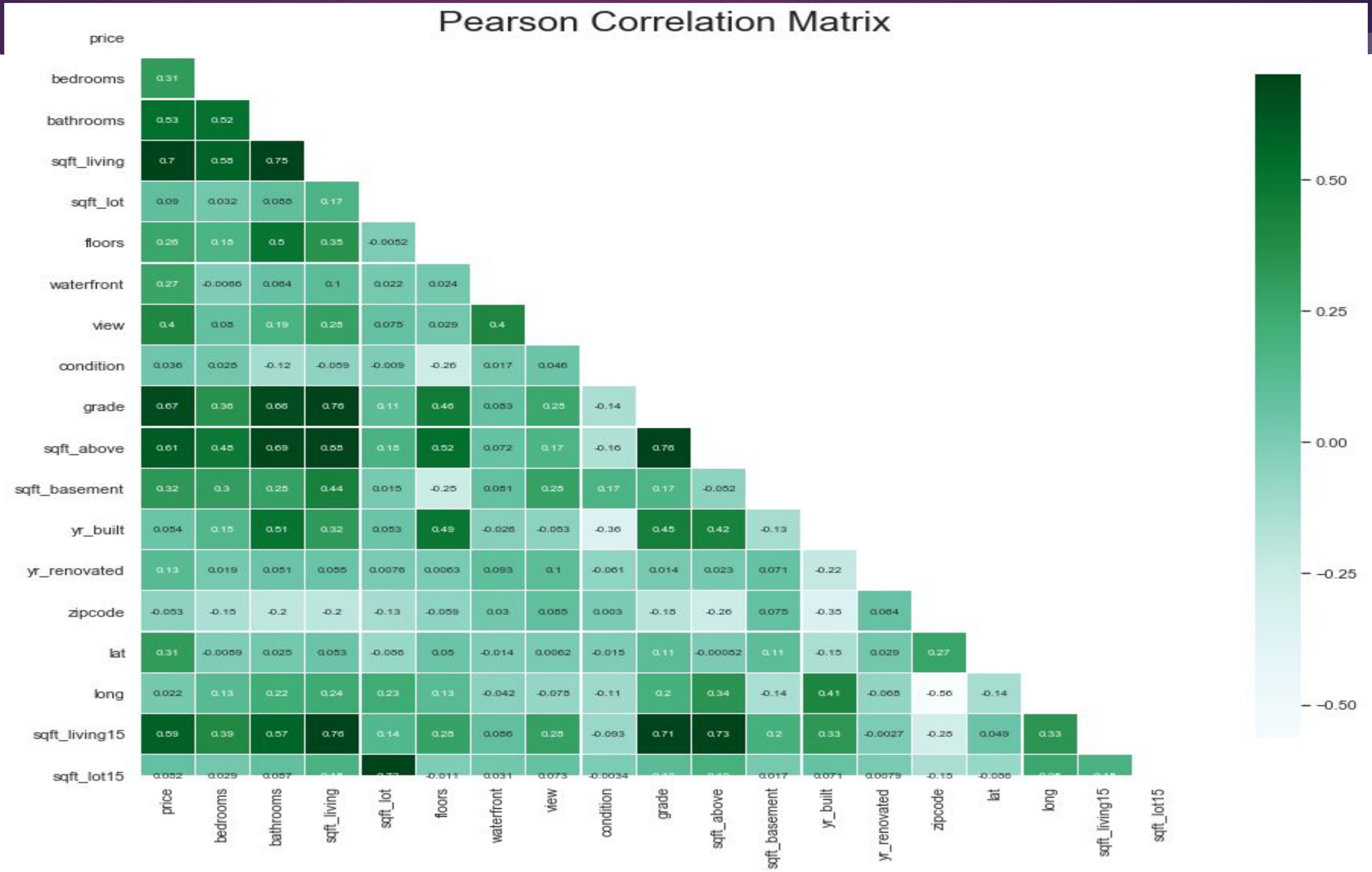
# Grade Feature



# Data Visualization of geography feature



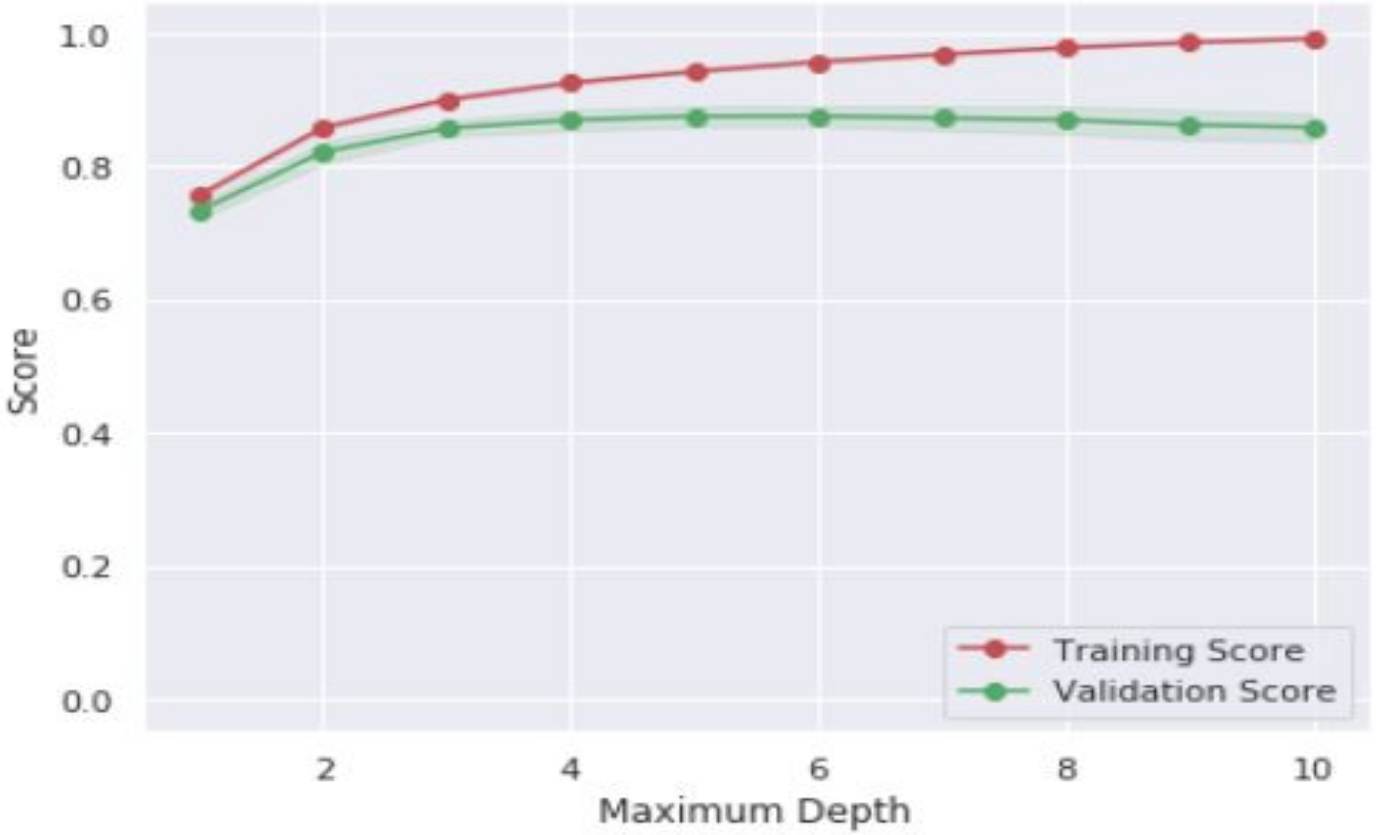
# Correlation Among Features



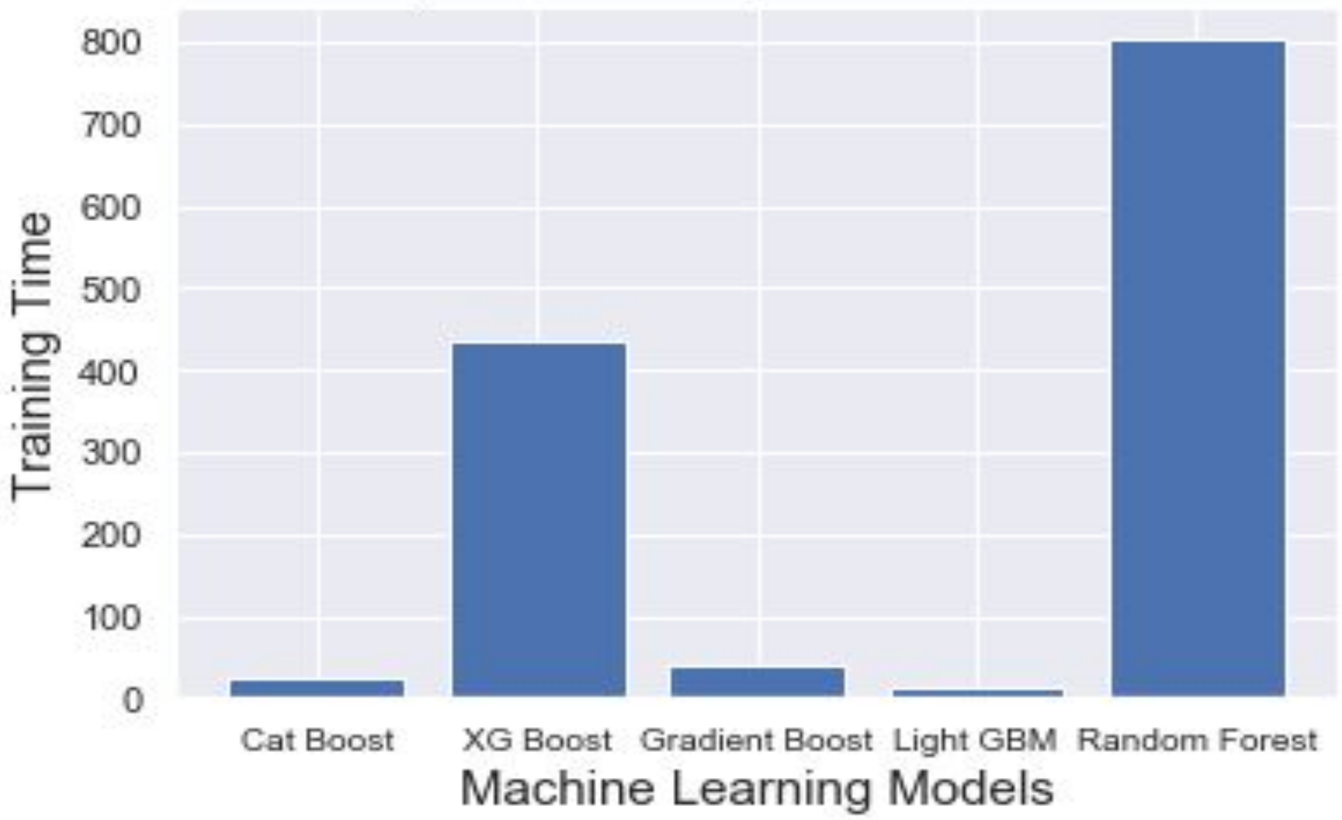
# Models Evaluation based on manual tuning of hyper parameters

| Model | Root Mean Squared Error (RMSE) | Mean Absolute Error (MAE) | R-squared (train) | R-squared (test) | Adjusted R-squared (train) | Adjusted R-squared (test) | Explained Variance (train) | Explained Variance (test) | 5-Fold Cross Validation |
|---|---|---|---|---|---|---|---|---|---|
| Cat Boost | 0.1515 | 0.1073 | 0.9551 | 0.9150 | 0.9551 | 0.9146 | 0.9551 | 0.9150 | 0.9145 |
| XGBoost | 0.1545 | 0.1089 | 0.9858 | 0.9115 | 0.9858 | 0.9111 | 0.9858 | 0.9115 | 0.9107 |
| Gradient Boost | 0.1537 | 0.1101 | 0.9296 | 0.9125 | 0.9295 | 0.9121 | 0.9296 | 0.9125 | 0.9090 |
| Light GBM | 0.1577 | 0.1125 | 0.9883 | 0.9078 | 0.9883 | 0.9074 | 0.9883 | 0.9078 | 0.9067 |
| Random Forest Regression | 0.1703 | 0.1221 | 0.9849 | 0.8925 | 0.9849 | 0.8921 | 0.9849 | 0.8925 | 0.8898 |

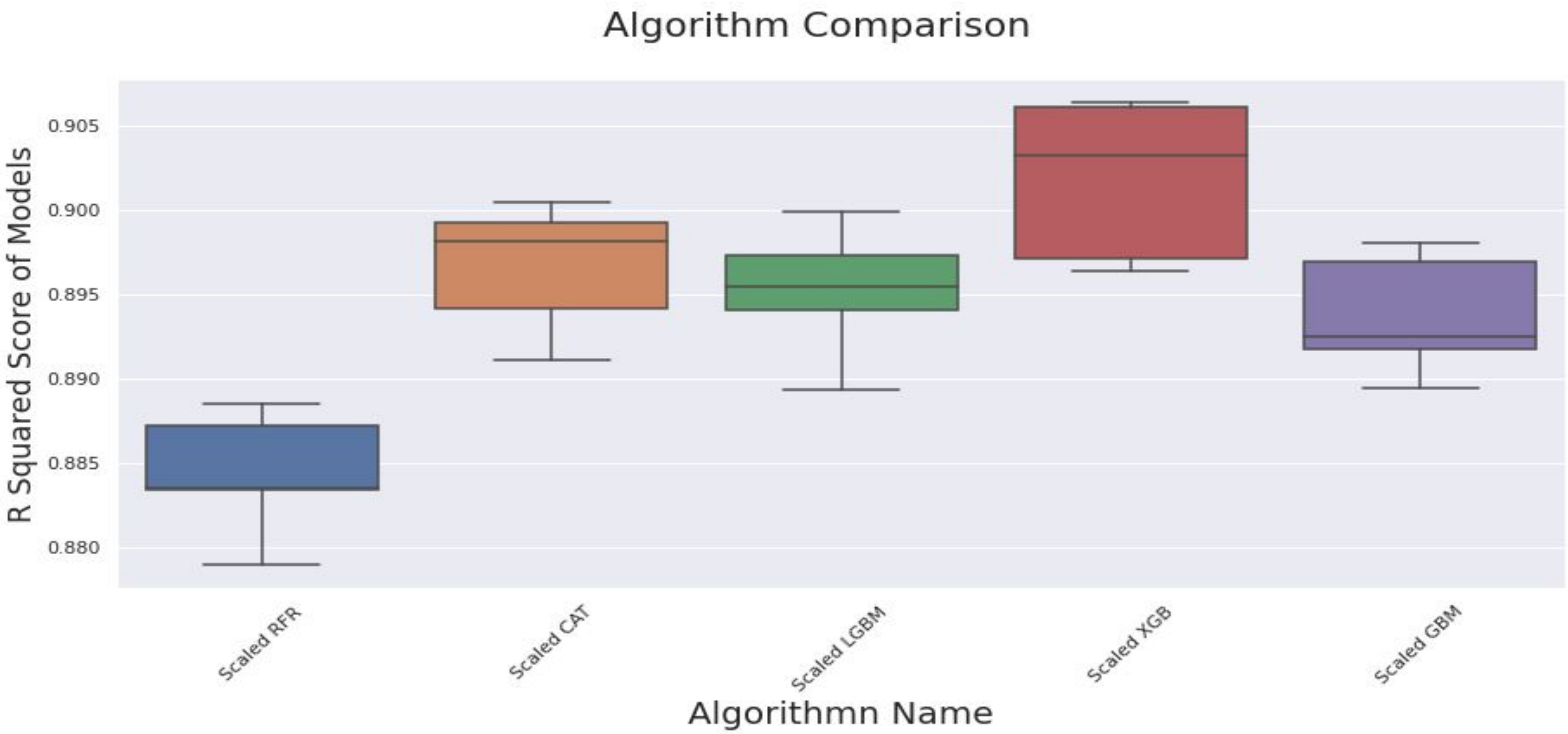
# Why number of folds are set as 5 in cross validation score



# Comparison of training time of all models



# Models Evaluation based on automatic hyper parameter tuning



# Future Enhancement of House Price Forecasting

- Considering more factors influencing the dwelling prices
- Adding Safety feature
- Using Deep Learning
- Using Principal component analysis
- Zip code feature engineering
- Using stacked model

# Why does Organization’s need this predictive model?

- possibly many real-estate firm’s are interested in intelligent decision making regarding house price forecasting.
- The Organization’s will use this data to help clients purchase properties at affordable price.
- Current process is good but manual and time consuming
- Organization’s wants an edge over competition