hw_house_price_india

DataSloth

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version: nb

This project will predict the price of Indian house using linear regression by R Programming

Source : data.world
type of source: xlsx

Start with load library

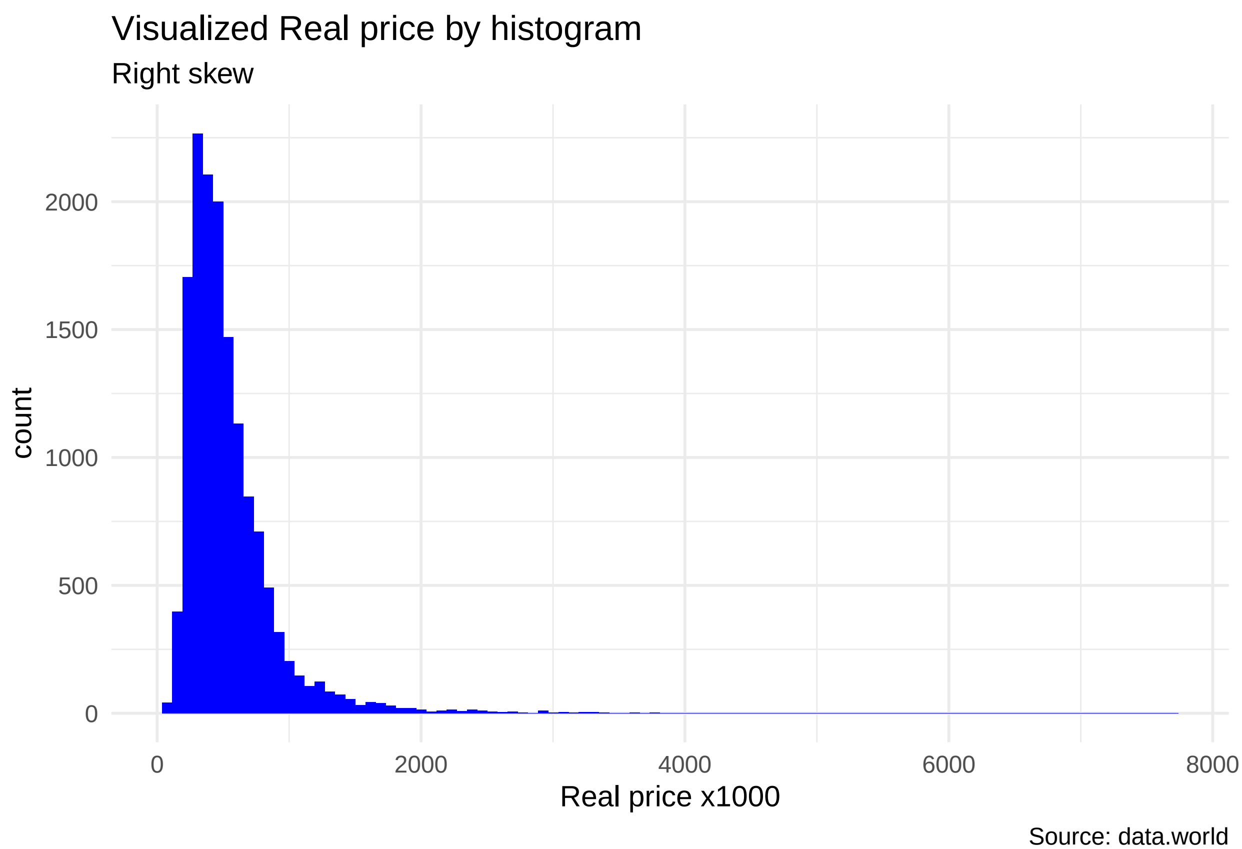
```
#load library
library(tidyverse)
library(caret)
library(mlbench)
library(readxl)
library(ggplot2)
```

Load data file to dataframe("df1 = sheet1, df2 = sheet2")

```
# Load data
df1<-read_excel("hpi.xlsx", sheet = 1)
df2<-read_excel("hpi.xlsx", sheet = 2)
```

Visualized data(df1) ~ Price

```
ggplot(df1, aes(Price/1000)) +
  geom_histogram(bins = 100, fill="blue") +
  theme_minimal() +
  labs(
    title = "Visualized Real price by histogram",
    subtitle = "Right skew",
    x = "Real price x1000",
    caption = "Source: data.world"
  )
```



Note: Right skew distribution, not proper for build model but try it.

Create function split_data

```
split_data <- function(df) {
  set.seed(42)
  n <- nrow(df)
  id <- sample(1:n, size = 0.8*n)
  train_df <- df[id, ]
  test_df <- df[-id, ]
  list(train_df, test_df)
}
```

1.Use full data and real price to build model

1.1 Split full df1 and real price

```
prep_data <- split_data(df1)
train_data <- prep_data[[1]]
test_data <- prep_data[[2]]
```

1.2 Train model full df1 and real price

1.2.1 Train

```
model <- train(Price ~ .,
               data = train_data[ ,-c(1,2)], #remove id and date
               method = "lm")
```

1.2.2 Show model and summary model

```
model ; summary(model)
```

```
## Linear Regression
##
## 11696 samples
##    20 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 11696, 11696, 11696, 11696, 11696, 11696, ...
## Resampling results:
##
##   RMSE      Rsquared  MAE
##   192549.8  0.711037  123219.8
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

```
##
## Call:
## lm(formula = .outcome ~ ., data = dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1111112   -96339    -8097    75756  3896879
##
## Coefficients: (1 not defined because of singularities)
##                                                   Estimate Std. Error t value
## (Intercept)                                     -6.807e+07  1.241e+07  -5.485
## `\\`number of bedrooms\\``                      -3.545e+04  2.577e+03 -13.759
## `\\`number of bathrooms\\``                      4.235e+04  4.250e+03   9.966
## `\\`living area\\``                              1.409e+02  5.716e+00  24.652
## `\\`lot area\\``                                -5.479e-03  6.445e-02  -0.085
## `\\`number of floors\\``                         6.220e+03  4.677e+03   1.330
## `\\`waterfront present\\``                       6.331e+05  2.217e+04  28.558
## `\\`number of views\\``                          4.595e+04  2.800e+03  16.408
## `\\`condition of the house\\``                   3.138e+04  2.994e+03  10.479
## `\\`grade of the house\\``                       1.003e+05  2.814e+03  35.648
## `\\`Area of the house(excluding basement)\\``    3.560e+01  5.671e+00   6.278
## `\\`Area of the basement\\``                            NA         NA      NA
## `\\`Built Year\\``                              -2.509e+03  9.334e+01 -26.879
```

```
## `\\`Renovation Year\\``                             2.295e+01  4.574e+00   5.016
## `\\`Postal Code\\``                                 2.610e+02  1.006e+02   2.596
## Lattitude                                           5.509e+05  1.429e+04  38.557
## Longitude                                          -9.900e+04  1.566e+04  -6.323
## living_area_renov                                   2.529e+01  4.512e+00   5.606
## lot_area_renov                                     -3.178e-01  9.726e-02  -3.268
## `\\`Number of schools nearby\\``                    3.513e+03  2.178e+03   1.613
## `\\`Distance from the airport\\``                   1.344e+01  1.993e+02   0.067
##                                                    Pr(>|t|)
## (Intercept)                                        4.22e-08 ***
## `\\`number of bedrooms\\``                          < 2e-16 ***
## `\\`number of bathrooms\\``                         < 2e-16 ***
## `\\`living area\\``                                 < 2e-16 ***
## `\\`lot area\\``                                    0.93226
## `\\`number of floors\\``                            0.18359
## `\\`waterfront present\\``                          < 2e-16 ***
## `\\`number of views\\``                             < 2e-16 ***
## `\\`condition of the house\\``                      < 2e-16 ***
## `\\`grade of the house\\``                          < 2e-16 ***
## `\\`Area of the house(excluding basement)\\`` 3.56e-10 ***
## `\\`Area of the basement\\``                             NA
## `\\`Built Year\\``                                  < 2e-16 ***
## `\\`Renovation Year\\``                            5.34e-07 ***
## `\\`Postal Code\\``                                 0.00946 **
## Lattitude                                           < 2e-16 ***
## Longitude                                          2.67e-10 ***
## living_area_renov                                  2.12e-08 ***
## lot_area_renov                                      0.00109 **
## `\\`Number of schools nearby\\``                    0.10684
## `\\`Distance from the airport\\``                   0.94624
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 192300 on 11676 degrees of freedom
## Multiple R-squared:  0.7136, Adjusted R-squared:  0.7131
## F-statistic:  1531 on 19 and 11676 DF,  p-value: < 2.2e-16
```

1.3 score~predict model

```r
p <- predict(model, newdata = test_data)
```

1.4 Evaluate model

Create function to calculate MAE, MSE, RMSE

```r
cal_mae <- function(actual, predict) {
  error <- actual - predict
  mean(abs(error))
```

```r
}

cal_mse <- function(actual, predict) {
  error <- actual - predict
  mean(error**2)
}

cal_rmse <- function(actual, predict) {
  error <- actual - predict
  sqrt(mean(error**2))
}

r_train <- function(A,P,M = model) {
  mae_log <- cal_mae(A$log_price, P)
  mse_log <- cal_mse(A$log_price, P)
  rmse_log <- cal_rmse(A$log_price, P)
  mae_expo <- cal_mae(exp(A$log_price), exp(P))
  mse_expo <- cal_mse(exp(A$log_price), exp(P))
  rmse_expo <- cal_rmse(exp(A$log_price), exp(P))
  print("--Evaulation of TRAIN--");
  print(paste("MAE_log_train : ",mae_log)) ;
  print(paste("MSE_log_train : ",mse_log)) ;
  print(paste("RMSE_log_train : ",rmse_log)) ;
  print(paste("MAE_expo_train : ",mae_expo)) ;
  print(paste("MSE_expo_train : ",mse_expo)) ;
  print(paste("RMSE_expo_train : ",rmse_expo)) ;
  print(paste("MAE_model : "  ,      M[[4]][[4]])) ;
  print(paste("Rsquared_model : "  , M[[4]][[3]])) ;
  print(paste("RMSE_model : " ,      M[[4]][[2]])) ;
  list(mae_log, mse_log, rmse_log, mae_expo, mse_expo, rmse_expo)
}

r_test <- function(A,P,M = model) {
  mae_log <- cal_mae(A$log_price, P)
  mse_log <- cal_mse(A$log_price, P)
  rmse_log <- cal_rmse(A$log_price, P)
  mae_expo <- cal_mae(exp(A$log_price), exp(P))
  mse_expo <- cal_mse(exp(A$log_price), exp(P))
  rmse_expo <- cal_rmse(exp(A$log_price), exp(P))
  print("--Evaulation of TEST--");
  print(paste("MAE_log_test : ",mae_log)) ;
  print(paste("MSE_log_test : ",mse_log)) ;
  print(paste("RMSE_log_test : ",rmse_log)) ;
  print(paste("MAE_expo_test : ",mae_expo)) ;
  print(paste("MSE_expo_test : ",mse_expo)) ;
  print(paste("RMSE_expo_test : ",rmse_expo)) ;
  print(paste("MAE_model : "  ,      M[[4]][[4]])) ;
  print(paste("Rsquared_model : "  , M[[4]][[3]])) ;
  print(paste("RMSE_model : " ,      M[[4]][[2]])) ;
  list(mae_log, mse_log, rmse_log, mae_expo, mse_expo, rmse_expo)
}
```

Create function to show error of model and save result to list, note: error in real price and logarithm price

1.5 Show error of model full df1 and real price

```
print(paste("MAE_test : "  , cal_mae(test_data$Price, p)))
```

```
## [1] "MAE_test :  128122.818842742"
```

```
print(paste("MSE_test : "  , cal_mse(test_data$Price, p)))
```

```
## [1] "MSE_test :  53518979494.8183"
```

```
print(paste("RMSE_test : " , cal_rmse(test_data$Price, p)))
```

```
## [1] "RMSE_test :  231341.694242128"
```

```
print(paste("MAE_model : "  ,      model[[4]][[4]]))
```

```
## [1] "MAE_model :  123219.80420048"
```

```
print(paste("Rsquared_model : "  , model[[4]][[3]]))
```

```
## [1] "Rsquared_model :  0.711036950308182"
```

```
print(paste("RMSE_model : " ,      model[[4]][[2]]))
```

```
## [1] "RMSE_model :  192549.824849158"
```

The model(full data, real price) : high error compare train and test, Rsquared_model : 0.711036950308182

So correct the Right skew distribution by take logarithm price(log_price)

2. Use full data and logarithm price to build model

2.1 Create log_price and Split full df1 with log_price to df1_log

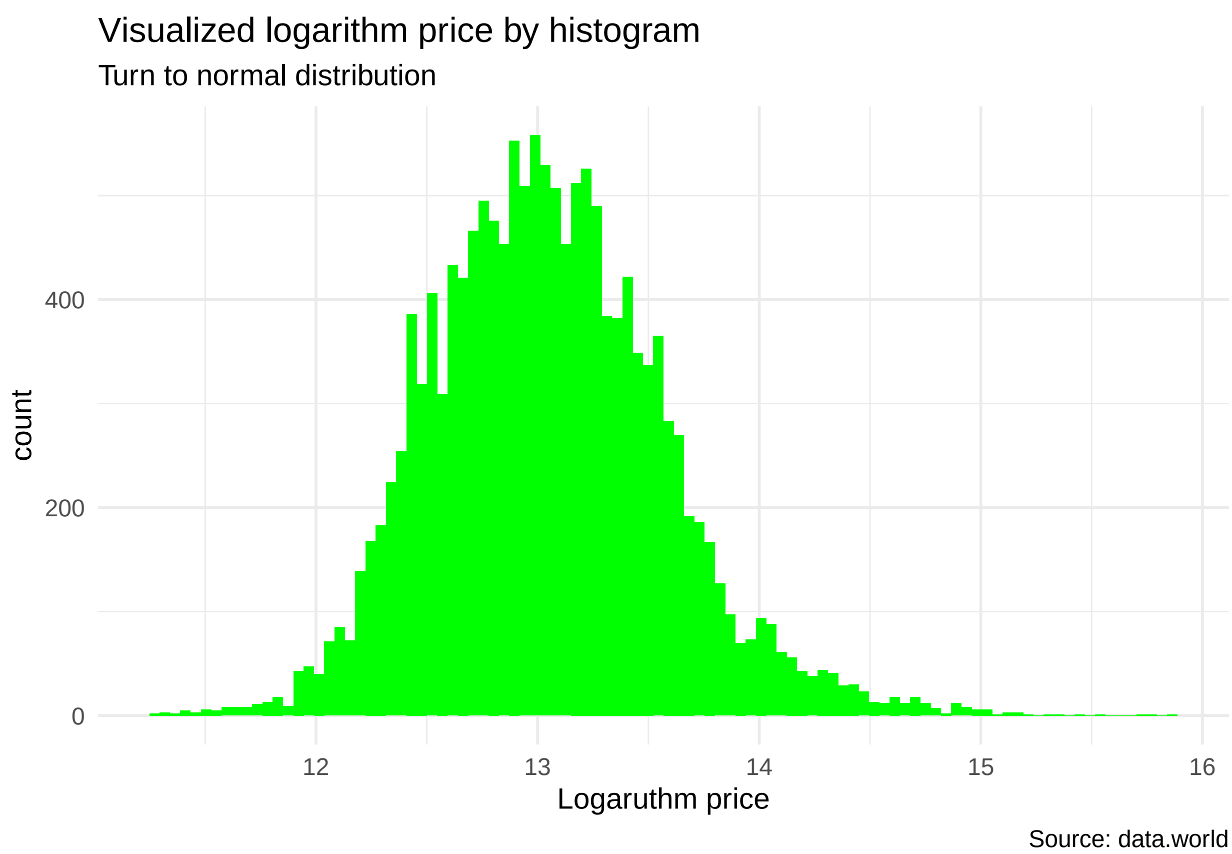
```
df1_log <- df1 %>%
  mutate(log_price = log(Price))

# Split full df1_log

prep_data_log <- split_data(df1_log)
train_data_log <- prep_data_log[[1]]
test_data_log <- prep_data_log[[2]]
```

Visualized data(df1_log) ~ log_price

```
ggplot(df1_log, aes(log_price)) +
  geom_histogram(bins = 100, fill="green") +
  theme_minimal() +
  labs(
    title = "Visualized logarithm price by histogram",
    subtitle = "Turn to normal distribution",
    x = "Logaruthm price",
    caption = "Source: data.world"
  )
```



2.2 Train model df1_log and log_price

2.2.1 Train

```
set.seed(42)
model_log <- train(log_price ~ .,
               data = train_data_log[ , -c(1,2,23)], #remove price,id,date
               method = "lm")
```

2.2.2 calculate train error

2.2.2.1 predict train model_log

```r
p_log_train <- predict(model_log, newdata = train_data_log)
```

2.2.2.2 calculate train error from model_log with logarithm price and real price_exp(log)

```r
model_log_r_train <- r_train(train_data_log, p_log_train, model_log)
```

```
## [1] "--Evaulation of TRAIN--"
## [1] "MAE_log_train :  0.186876611630186"
## [1] "MSE_log_train :  0.0592234337771878"
## [1] "RMSE_log_train :  0.243358652562813"
## [1] "MAE_expo_train :  106108.300922603"
## [1] "MSE_expo_train :  32179140733.112"
## [1] "RMSE_expo_train :  179385.45295846"
## [1] "MAE_model :  0.188182348161632"
## [1] "Rsquared_model :  0.783296783181617"
## [1] "RMSE_model :  0.245141773832881"
```

2.3 score~predict model(model_log)

```r
p_log_test <- predict(model_log, newdata = test_data_log)
```

2.4 Evaluate model(model_log)

```r
model_log_r_test <- r_test(test_data_log, p_log_test, model_log)
```

```
## [1] "--Evaulation of TEST--"
## [1] "MAE_log_test :  0.193446178197938"
## [1] "MSE_log_test :  0.0648345743548279"
## [1] "RMSE_log_test :  0.254626342617624"
## [1] "MAE_expo_test :  119667.914904593"
## [1] "MSE_expo_test :  125501870360.535"
## [1] "RMSE_expo_test :  354262.431483406"
## [1] "MAE_model :  0.188182348161632"
## [1] "Rsquared_model :  0.783296783181617"
## [1] "RMSE_model :  0.245141773832881"
```

After train model use real price vs logarithm price

find out the important variable for tuning the new model(model_log_s) for lower error or high accuracy

```
## [1] "variable importance of --> model"
```

```
## lm variable importance
##
##                                                    Overall
## Lattitude                                       100.00000
## `\\`grade of the house\\``                        92.44341
## `\\`waterfront present\\``                        74.02204
## `\\`Built Year\\``                                69.66113
## `\\`living area\\``                               63.87331
## `\\`number of views\\``                           42.45423
## `\\`number of bedrooms\\``                        35.57289
## `\\`condition of the house\\``                    27.05106
## `\\`number of bathrooms\\``                       25.71746
## Longitude                                        16.25183
## `\\`Area of the house(excluding basement)\\``     16.13526
## living_area_renov                                14.38876
## `\\`Renovation Year\\``                           12.85816
## lot_area_renov                                    8.31543
## `\\`Postal Code\\``                                6.56831
## `\\`Number of schools nearby\\``                   4.01476
## `\\`number of floors\\``                           3.27998
## `\\`lot area\\``                                   0.04566
## `\\`Distance from the airport\\``                  0.00000
```

```
## [1] "variable importance of --> model_log"
```

```
## lm variable importance
##
##                                                    Overall
## Lattitude                                       100.00000
## `\\`grade of the house\\``                        63.49513
## `\\`Built Year\\``                                39.30658
## `\\`living area\\``                               30.85679
## `\\`condition of the house\\``                    25.85637
## living_area_renov                                24.40844
## `\\`number of views\\``                           23.01281
## `\\`waterfront present\\``                        19.73784
## `\\`number of bathrooms\\``                       18.30983
## `\\`Postal Code\\``                               18.06680
## `\\`number of floors\\``                          16.05220
## `\\`Renovation Year\\``                           12.04673
## `\\`lot area\\``                                   7.21650
## `\\`number of bedrooms\\``                         6.90855
## Longitude                                         4.33343
## `\\`Area of the house(excluding basement)\\``      1.72684
## lot_area_renov                                    1.61028
## `\\`Distance from the airport\\``                  0.05296
## `\\`Number of schools nearby\\``                   0.00000
```

3. Select 5 same important variable from varImp model and model_log

3.1 Subset data from df1 to df1_s and split data

```
# select varImp from above model for create new model
# subset data to df1_s

df1_s <- df1_log %>%
  select(lat = Lattitude,
         grade = `grade of the house`,
         bld_yr = `Built Year`,
         lv_area = `living area`,
         no_view = `number of views`,
         log_price,Price)

prep_data_s <- split_data(df1_s)
train_data_s <- prep_data_s[[1]]
test_data_s <- prep_data_s[[2]]
```

3.2 Train model df1_s and log_price

3.2.1 Train

```
set.seed(42)
model_log_s <- train(log_price ~ lat + grade + bld_yr + lv_area + no_view,
                    data = train_data_s,
                    method = "lm")
```

3.2.2 calculate train error

3.2.2.1 predict train model_log_s

```
p_log_s_train <- predict(model_log_s, newdata = train_data_s)
```

3.2.2.2 calculate train error from model_log with logarithm price and real price_exp(log)

```
## evaluate train model_log_s
model_log_s_r_train <- r_train(train_data_s, p_log_s_train, model_log_s)
```

```
## [1] "--Evaulation of TRAIN--"
## [1] "MAE_log_train :  0.200017418153185"
## [1] "MSE_log_train :  0.0665572466155991"
## [1] "RMSE_log_train :  0.257986911713752"
## [1] "MAE_expo_train :  113400.360686776"
## [1] "MSE_expo_train :  35852543842.0516"
## [1] "RMSE_expo_train :  189347.679790515"
```

```
## [1] "MAE_model :  0.2006551916661"
## [1] "Rsquared_model :  0.758228581081455"
## [1] "RMSE_model :  0.258947268432132"
```

3.3 score~predict model(model_log_s)

```r
p_log_s_test <- predict(model_log_s, newdata = test_data_s)
```

3.4 Evaluate model(model_log)

```r
model_log_s_r_test <- r_test(test_data_s, p_log_s_test, model_log_s)
```

```
## [1] "--Evaulation of TEST--"
## [1] "MAE_log_test :  0.205768259455702"
## [1] "MSE_log_test :  0.0725033088154798"
## [1] "RMSE_log_test :  0.269264384602717"
## [1] "MAE_expo_test :  128244.175354101"
## [1] "MSE_expo_test :  196314300729.85"
## [1] "RMSE_expo_test :  443073.696725331"
## [1] "MAE_model :  0.2006551916661"
## [1] "Rsquared_model :  0.758228581081455"
## [1] "RMSE_model :  0.258947268432132"
```

Now we build model from important variable, calculate error for evaluate model, Next tuning the parameter, train control and resample technic

4. The final model

4.1 TrainControl repeatCV

```r
set.seed(42)
ctrl <- trainControl(
  method = "repeatedcv",
  number = 5,
  repeats = 5,
  verboseIter = TRUE
)
```

4.2 Train final model df1_s and log_price

4.2.1 Train

```r
set.seed(42)
model_lm_final <- train(log_price ~ lat + grade + bld_yr + lv_area + no_view,
                        data = train_data_s,
```

```r
                      method = "lm",
                      preProcess = c("center", "scale"),
                      trControl = ctrl)
```

```
## + Fold1.Rep1: intercept=TRUE
## - Fold1.Rep1: intercept=TRUE
## + Fold2.Rep1: intercept=TRUE
## - Fold2.Rep1: intercept=TRUE
## + Fold3.Rep1: intercept=TRUE
## - Fold3.Rep1: intercept=TRUE
## + Fold4.Rep1: intercept=TRUE
## - Fold4.Rep1: intercept=TRUE
## + Fold5.Rep1: intercept=TRUE
## - Fold5.Rep1: intercept=TRUE
## + Fold1.Rep2: intercept=TRUE
## - Fold1.Rep2: intercept=TRUE
## + Fold2.Rep2: intercept=TRUE
## - Fold2.Rep2: intercept=TRUE
## + Fold3.Rep2: intercept=TRUE
## - Fold3.Rep2: intercept=TRUE
## + Fold4.Rep2: intercept=TRUE
## - Fold4.Rep2: intercept=TRUE
## + Fold5.Rep2: intercept=TRUE
## - Fold5.Rep2: intercept=TRUE
## + Fold1.Rep3: intercept=TRUE
## - Fold1.Rep3: intercept=TRUE
## + Fold2.Rep3: intercept=TRUE
## - Fold2.Rep3: intercept=TRUE
## + Fold3.Rep3: intercept=TRUE
## - Fold3.Rep3: intercept=TRUE
## + Fold4.Rep3: intercept=TRUE
## - Fold4.Rep3: intercept=TRUE
## + Fold5.Rep3: intercept=TRUE
## - Fold5.Rep3: intercept=TRUE
## + Fold1.Rep4: intercept=TRUE
## - Fold1.Rep4: intercept=TRUE
## + Fold2.Rep4: intercept=TRUE
## - Fold2.Rep4: intercept=TRUE
## + Fold3.Rep4: intercept=TRUE
## - Fold3.Rep4: intercept=TRUE
## + Fold4.Rep4: intercept=TRUE
## - Fold4.Rep4: intercept=TRUE
## + Fold5.Rep4: intercept=TRUE
## - Fold5.Rep4: intercept=TRUE
## + Fold1.Rep5: intercept=TRUE
## - Fold1.Rep5: intercept=TRUE
## + Fold2.Rep5: intercept=TRUE
## - Fold2.Rep5: intercept=TRUE
## + Fold3.Rep5: intercept=TRUE
## - Fold3.Rep5: intercept=TRUE
## + Fold4.Rep5: intercept=TRUE
## - Fold4.Rep5: intercept=TRUE
## + Fold5.Rep5: intercept=TRUE
```

```
## - Fold5.Rep5: intercept=TRUE
## Aggregating results
## Fitting final model on full training set
```

4.2.2 calculate train error

4.2.2.1 predict train model_lm_final

```r
p_lm_final_train <- predict(model_lm_final, newdata = train_data_s)
```

4.2.2.2 calculate train error from model_lm_final with logarithm price and real price_exp(log)

```r
model_lm_final_r_train <- r_train(train_data_s, p_lm_final_train, model_lm_final)
```

```
## [1] "--Evaulation of TRAIN--"
## [1] "MAE_log_train :  0.200017418153186"
## [1] "MSE_log_train :  0.0665572466155991"
## [1] "RMSE_log_train :  0.257986911713752"
## [1] "MAE_expo_train :  113400.360686775"
## [1] "MSE_expo_train :  35852543842.0519"
## [1] "RMSE_expo_train :  189347.679790516"
## [1] "MAE_model :  0.200122500185454"
## [1] "Rsquared_model :  0.7591336843618"
## [1] "RMSE_model :  0.258095431757117"
```

4.3 score~predict model(model_lm_final)

```r
# test model_lm_final
p_lm_final_test <- predict(model_lm_final, newdata = test_data_s)
```

4.4 Evaluate model(model_lm_final)

```r
model_lm_final_r_test <- r_test(test_data_s, p_lm_final_test, model_lm_final)
```

```
## [1] "--Evaulation of TEST--"
## [1] "MAE_log_test :  0.205768259455706"
## [1] "MSE_log_test :  0.0725033088154796"
## [1] "RMSE_log_test :  0.269264384602717"
## [1] "MAE_expo_test :  128244.175354096"
## [1] "MSE_expo_test :  196314300729.781"
## [1] "RMSE_expo_test :  443073.696725252"
## [1] "MAE_model :  0.200122500185454"
## [1] "Rsquared_model :  0.7591336843618"
## [1] "RMSE_model :  0.258095431757117"
```

Summary Evaluationn