Linear Regression Coding Assignment-1

```
# Load essential libraries
library(ggplot2)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
# Set ggplot theme for plotting
My_Theme = theme(axis.text.x = element_text(size = 9),
   axis.text.y = element_text(size = 9),
   axis.title.x = element_text(size = 11),
   axis.title.y = element_text(size = 11),
   plot.title = element_text(size = 12, hjust = 0.5, face = "bold"))
```

```
# Load the house price dataset
hData = read.csv("Data/houseprices.csv")
str(hData)
```

```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : chr  "BTM Layout" "BTM Layout" "BTM Layout" "BTM Layout" ...
##  $ area          : int  565 1837 1280 2220 1113 1332 1815 1400 3006 1600 ...
##  $ rent          : int  20060 97434 54448 117000 34388 36394 112000 41266 129000 92849 ...
##  $ price_per_sqft: int  6195 9254 7422 9234 5391 4767 10744 5143 7485 10125 ...
##  $ facing        : chr  "North-West" "East" "East" "North" ...
##  $ BHK           : int  1 3 2 3 2 2 3 2 4 3 ...
##  $ bathrooms     : int  1 3 2 3 2 2 2 2 5 2 ...
##  $ parking       : chr  "Bike" "Bike and Car" "Car" "Bike and Car" ...
```

```
hData = read.csv('Data/houseprices.csv', header = TRUE, stringsAsFactors = FALSE, na.strings = c("", "NA
str(hData)
```

```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : chr  "BTM Layout" "BTM Layout" "BTM Layout" "BTM Layout" ...
##  $ area          : int  565 1837 1280 2220 1113 1332 1815 1400 3006 1600 ...
##  $ rent          : int  20060 97434 54448 117000 34388 36394 112000 41266 129000 92849 ...
```

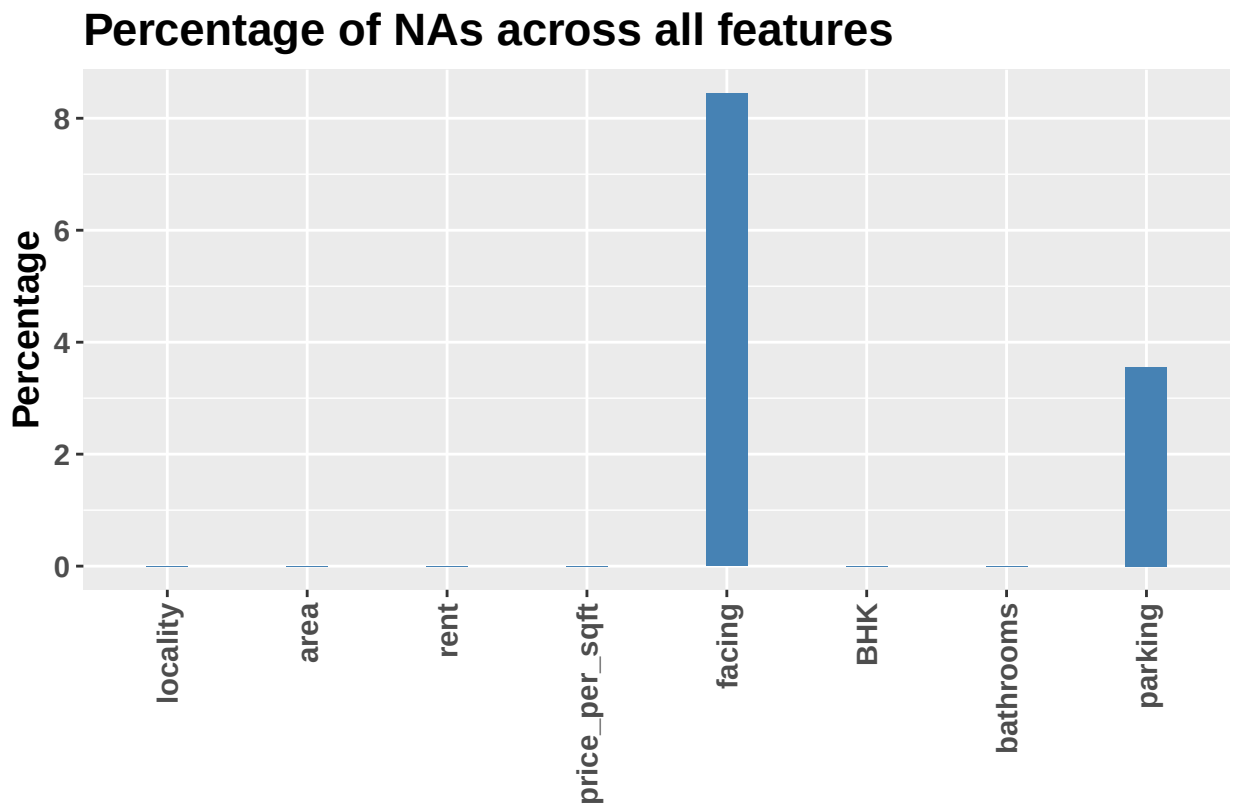
```
##  $ price_per_sqft: int  6195 9254 7422 9234 5391 4767 10744 5143 7485 10125 ...
##  $ facing        : chr  "North-West" "East" "East" "North" ...
##  $ BHK           : int  1 3 2 3 2 2 3 2 4 3 ...
##  $ bathrooms     : int  1 3 2 3 2 2 2 2 5 2 ...
##  $ parking       : chr  "Bike" "Bike and Car" "Car" "Bike and Car" ...
```

```
# Convert 'locality', 'facing' and 'parking' columns to factors
categorical_cols = c("locality", "facing", "parking")
hData[categorical_cols] = lapply(hData[categorical_cols], as.factor)
str(hData)
```

```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : Factor w/ 9 levels "Attibele","BTM Layout",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ area          : int  565 1837 1280 2220 1113 1332 1815 1400 3006 1600 ...
##  $ rent          : int  20060 97434 54448 117000 34388 36394 112000 41266 129000 92849 ...
##  $ price_per_sqft: int  6195 9254 7422 9234 5391 4767 10744 5143 7485 10125 ...
##  $ facing        : Factor w/ 7 levels "East","North",..: 4 1 1 2 1 7 3 6 1 5 ...
##  $ BHK           : int  1 3 2 3 2 2 3 2 4 3 ...
##  $ bathrooms     : int  1 3 2 3 2 2 2 2 5 2 ...
##  $ parking       : Factor w/ 3 levels "Bike","Bike and Car",..: 1 2 3 2 2 2 3 2 2 2 ...
```

```
# Continuous columns
continuous_cols = setdiff(colnames(hData), categorical_cols)
```

```
# Plot percentage of NAs in each column of the data frame
hData_NA = setNames(stack(sapply(hData, function(x){(sum(is.na(x))/length(x))*100}))[2:1], c('Feature',
p = ggplot(data = hData_NA, aes(x = Feature, y = Value)) +
  geom_bar(stat = 'identity', fill = 'steelblue', width = 0.3) +
  theme(text = element_text(size = 14, face = 'bold'),
  axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5)) +
  xlab('') + ylab('Percentage') +
  ggtitle('Percentage of NAs across all features')
p
```




```
categorical_cols1 = c('facing', 'parking')
# Add NA as a factor level for categorical columns facing and parking only
hData[categorical_cols1] = lapply(hData[categorical_cols1], addNA)
str(hData)
```

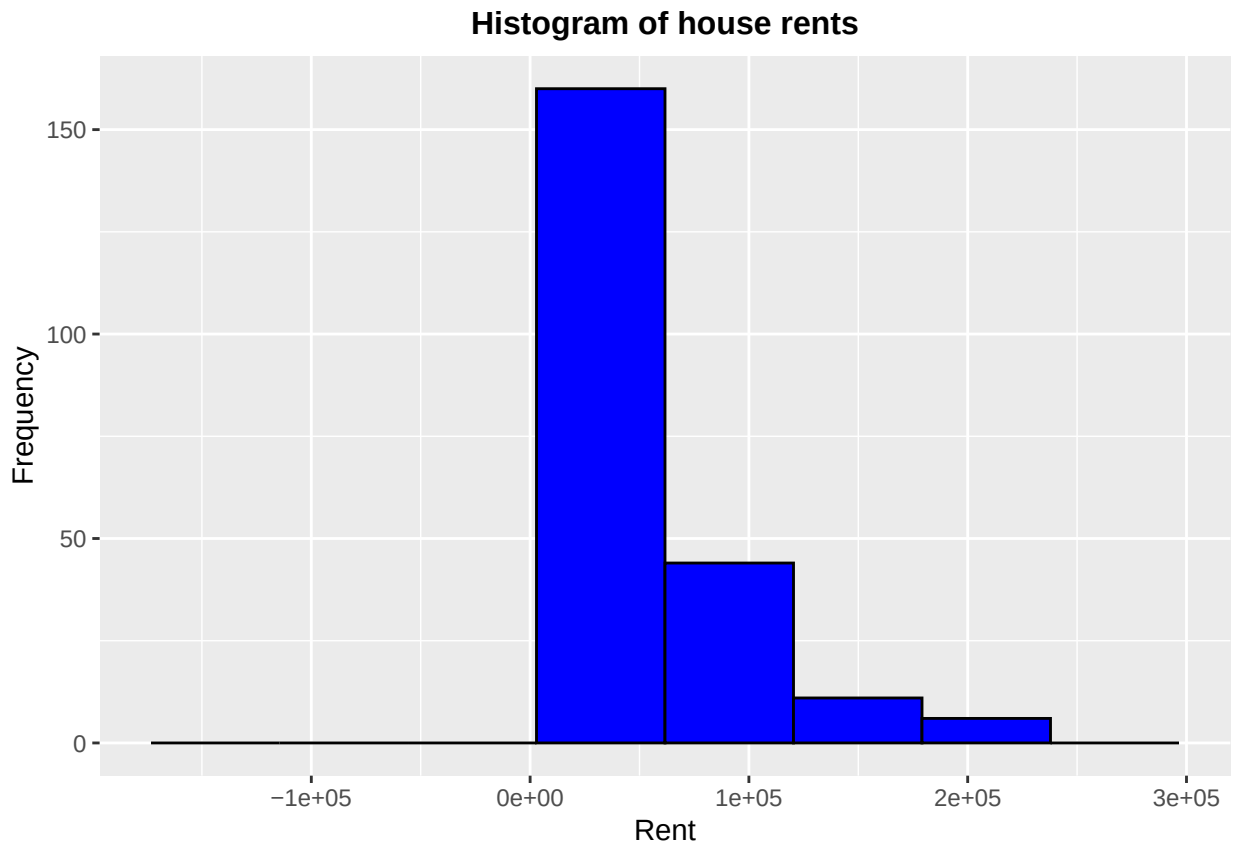
```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : Factor w/ 9 levels "Attibele","BTM Layout",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ area          : int  565 1837 1280 2220 1113 1332 1815 1400 3006 1600 ...
##  $ rent          : int  20060 97434 54448 117000 34388 36394 112000 41266 129000 92849 ...
##  $ price_per_sqft: int  6195 9254 7422 9234 5391 4767 10744 5143 7485 10125 ...
##  $ facing        : Factor w/ 8 levels "East","North",..: 4 1 1 2 1 7 3 6 1 5 ...
##  $ BHK           : int  1 3 2 3 2 2 3 2 4 3 ...
##  $ bathrooms     : int  1 3 2 3 2 2 2 2 5 2 ...
##  $ parking       : Factor w/ 4 levels "Bike","Bike and Car",..: 1 2 3 2 2 2 3 2 2 2 ...
```

```
# Calculate the mean and standard deviation of rent
mean_rent <- mean(hData$rent, na.rm = TRUE)
sd_rent <- sd(hData$rent, na.rm = TRUE)

# Create histogram
p = ggplot(data = hData) +
  geom_histogram(aes(x = rent, y = after_stat(count)),
                 breaks = seq(mean_rent - 4 * sd_rent, mean_rent + 4 * sd_rent, by = sd_rent),
                 color = 'black', fill = 'blue') +
  labs(x = 'Rent', y = 'Frequency') +
```

```
  ggtitle('Histogram of house rents') +
  My_Theme

# Display the plot
p
```




```
# Build a linear model to predict price per square feet as a function of rent. How accurate is the mode
model = lm(data=hData, price_per_sqft ~ rent)
summary(model)
```

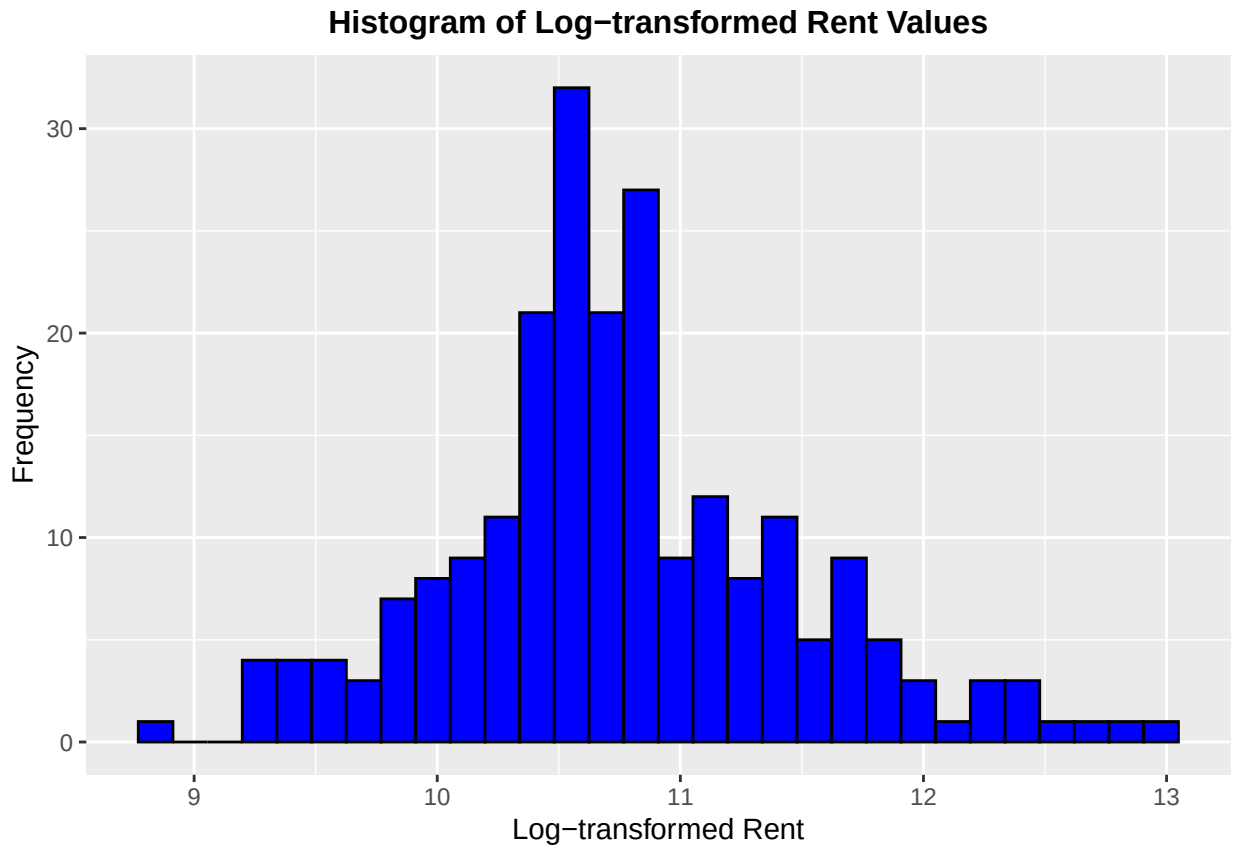
```
##
## Call:
## lm(formula = price_per_sqft ~ rent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6415.5 -1116.9  -340.6  1193.6  5270.1
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.591e+03  1.960e+02   23.42   <2e-16 ***
## rent        3.844e-02  2.305e-03   16.68   <2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
```

```
## Residual standard error: 2026 on 223 degrees of freedom
## Multiple R-squared:  0.5551, Adjusted R-squared:  0.5531
## F-statistic: 278.2 on 1 and 223 DF,  p-value: < 2.2e-16
```

The model is explaining 0.5531 of varinace for this given dataset the model is about 55% accurate

```
# Make a histogram of log-transformed rent values
hData['logrent'] = log(hData$rent)
p = ggplot(data = hData) +
  geom_histogram(aes(x = logrent), bins = 30, color = 'black', fill = 'blue') +
  labs(x = 'Log-transformed Rent', y = 'Frequency') +
  ggtitle('Histogram of Log-transformed Rent Values') +
  My_Theme  # You can replace this with your custom theme (e.g., My_Theme)

# Display the plot
p
```




```
# Build a linear model to predict price per square feet as a function of logrent. Did log-transforming
model = lm(data=hData, price_per_sqft ~ logrent)
summary(model)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ logrent, data = hData)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7406.1  -966.0  -325.3   968.0  5970.3
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -31058.9     1752.8  -17.72   <2e-16 ***
## logrent       3535.5      162.6   21.74   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1720 on 223 degrees of freedom
## Multiple R-squared:  0.6794, Adjusted R-squared:  0.6779
## F-statistic: 472.5 on 1 and 223 DF,  p-value: < 2.2e-16
```

The model accuracy has imporved by 12 % the accuracy of the model obtained after using logrent as predictor is about 67%

```
# Build a linear model to predict log of price per square feet as a function of logrent. Did log-transf
hData['logprice_per_sqft'] = log(hData$price_per_sqft)
model = lm(logprice_per_sqft ~ logrent, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = logprice_per_sqft ~ logrent, data = hData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.21981 -0.12244 -0.00241  0.17319  0.56131
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.49328    0.24805   14.08   <2e-16 ***
## logrent      0.48973    0.02302   21.28   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2434 on 223 degrees of freedom
## Multiple R-squared:   0.67,  Adjusted R-squared:  0.6685
## F-statistic: 452.7 on 1 and 223 DF,  p-value: < 2.2e-16
```

The model accuracy has decreased by 1 % the accuracy of the model obtained after using log-transforming the response variable price per square feet as response is about 66%, SO the models accuracy is decreased.

```
# Build a linear model to predict sqrt of price per square feet as a function of logrent. Did sqrt-tran
hData['sqrtprice_per_sqft'] = sqrt(hData$price_per_sqft)
model = lm(sqrtprice_per_sqft ~ logrent, data = hData)
summary(model)
```

```
##
## Call:
```

```
## lm(formula = sqrtprice_per_sqft ~ logrent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -46.536  -5.489  -1.030   6.830  24.025
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -137.769      9.882  -13.94   <2e-16 ***
## logrent       20.401      0.917   22.25   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.696 on 223 degrees of freedom
## Multiple R-squared:  0.6894, Adjusted R-squared:  0.688
## F-statistic: 494.9 on 1 and 223 DF,  p-value: < 2.2e-16
```

The model accuracy has imporved by 1 % the accuracy of the model obtained after using sqrt-transforming the response variable price per square feet as response is about 68%, SO the models accuracy is Increased.

```
# Build a linear model to predict price per sqft as a function of area and rent. Did adding area as an
model = lm(price_per_sqft ~ area + rent, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ area + rent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7500.7  -751.5  -221.9   849.9  6367.8
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.455e+03  2.164e+02   29.82   <2e-16 ***
## area        -2.521e+00  2.079e-01  -12.13   <2e-16 ***
## rent         6.653e-02  2.928e-03   22.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1575 on 222 degrees of freedom
## Multiple R-squared:  0.7324, Adjusted R-squared:   0.73
## F-statistic: 303.8 on 2 and 222 DF,  p-value: < 2.2e-16
```

Only rent as the predictor the models accuracy was 55% after using the area as a new predictor the models accuracy is increased to 73%.

the coefficent estimates for area beta1 is that the change in the price_per_sqft of a house when the area of the house is increased by 1 unit (1 sqr feet) and by keeping the rent predictor fixed.

the coefficent estimates for area beta2 is that the change in the price per sqft of a house when the rent of the house is increased by 1 unit ($ increase) and by keep the area predictor fixed.

```r
# Build a linear model to predict sqrt of price per sqft as a function of area and logrent. Did adding
model = lm(sqrtprice_per_sqft ~ area + logrent, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ area + logrent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -10.297  -4.238  -1.777   3.361  17.935
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.382e+02  8.414e+00  -28.31   <2e-16 ***
## area        -1.307e-02  7.243e-04  -18.04   <2e-16 ***
## logrent      3.147e+01  8.482e-01   37.11   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.189 on 222 degrees of freedom
## Multiple R-squared:  0.874,  Adjusted R-squared:  0.8729
## F-statistic: 770.2 on 2 and 222 DF,  p-value: < 2.2e-16
```

the model accuracy is increased when compared to only logrent as the predictor.

the coefficent estimates for area beta1 is that the change in the sqrt_price_per_sqft of a house when the area of the house is increased by 1 unit (1 sqr feet) and by keeping the logrent predictor fixed.

the coefficent estimates for area beta2 is that the change in the sqrt_price per_sqft of a house when the logrent of the house is increased by 1 unit ($ increase) and by keep the area predictor fixed.

```r
# Build a linear model to predict sqrt of price per sqft as a function of logarea and logrent. Did log-
hData['logarea'] = log(hData$area)
model = lm(sqrt(price_per_sqft) ~ logarea + logrent, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = sqrt(price_per_sqft) ~ logarea + logrent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.8882 -1.4545 -0.9082  0.7440 19.6434
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -73.5869     2.8088  -26.20   <2e-16 ***
## logarea     -38.4642     0.6911  -55.66   <2e-16 ***
## logrent      40.0275     0.4252   94.13   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 2.513 on 222 degrees of freedom
## Multiple R-squared:  0.9792, Adjusted R-squared:  0.979
## F-statistic:  5233 on 2 and 222 DF,  p-value: < 2.2e-16
```

The model accuracy is improved to 97%.

```
# Build a linear model to predict price per sqft as a function of area, rent, and parking (compared to
model = lm(price_per_sqft ~ area + rent, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ area + rent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7500.7  -751.5  -221.9   849.9  6367.8
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.455e+03  2.164e+02   29.82   <2e-16 ***
## area        -2.521e+00  2.079e-01  -12.13   <2e-16 ***
## rent         6.653e-02  2.928e-03   22.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1575 on 222 degrees of freedom
## Multiple R-squared:  0.7324, Adjusted R-squared:   0.73
## F-statistic: 303.8 on 2 and 222 DF,  p-value: < 2.2e-16
```

```
model1 = lm(price_per_sqft ~ area + rent + parking, data = hData)
summary(model1)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ area + rent + parking, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7465.5  -752.6  -208.9   842.4  6565.3
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          5.860e+03  5.393e+02  10.866   <2e-16 ***
## area                -2.453e+00  2.170e-01 -11.301   <2e-16 ***
## rent                 6.578e-02  3.008e-03  21.867   <2e-16 ***
## parkingBike and Car  5.319e+02  4.865e+02   1.093    0.275
## parkingCar           8.863e+02  5.468e+02   1.621    0.106
## parkingNA            2.724e+02  7.223e+02   0.377    0.706
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 1575 on 219 degrees of freedom
## Multiple R-squared:  0.736,  Adjusted R-squared:   0.73
## F-statistic: 122.1 on 5 and 219 DF,  p-value: < 2.2e-16
```

The model accuracy is the same even after add the parking as a new predictor.

```
# Build a linear model to predict sqrt of price per sqft as a function of logarea, logrent, and locality
model = lm(sqrt(price_per_sqft) ~ logarea + logrent + locality, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = sqrt(price_per_sqft) ~ logarea + logrent + locality,
##     data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5577 -1.1073 -0.2527  0.4398 16.6760
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -70.01549    2.95936 -23.659  < 2e-16 ***
## logarea                 -37.69954    0.74724 -50.451  < 2e-16 ***
## logrent                  39.35270    0.56700  69.405  < 2e-16 ***
## localityBTM Layout       -2.92678    0.71814  -4.076 6.47e-05 ***
## localityElectronic City  -2.77473    0.67493  -4.111 5.61e-05 ***
## localityIndiranagar      -1.17372    0.80139  -1.465  0.14449
## localityJayanagar         0.02791    0.87628   0.032  0.97462
## localityK R Puram        -3.32188    0.67817  -4.898 1.90e-06 ***
## localityMalleshwaram     -0.96970    0.83368  -1.163  0.24606
## localityMarathahalli     -3.09626    0.67094  -4.615 6.78e-06 ***
## localityYalahanka        -1.84366    0.66641  -2.767  0.00616 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.238 on 214 degrees of freedom
## Multiple R-squared:  0.9841, Adjusted R-squared:  0.9834
## F-statistic:  1326 on 10 and 214 DF,  p-value: < 2.2e-16
```

The model accuracy is improved to 98%.

```
# Build a linear model to predict price per sqft as a function of area, rent, and parking. How many lev
levels_parking = levels(as.factor(hData$parking))
num_levels = length(levels_parking)
model = lm(price_per_sqft ~ area + rent + parking, data = hData)
summary(model)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ area + rent + parking, data = hData)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -7465.5  -752.6  -208.9   842.4  6565.3
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          5.860e+03  5.393e+02  10.866   <2e-16 ***
## area                -2.453e+00  2.170e-01 -11.301   <2e-16 ***
## rent                 6.578e-02  3.008e-03  21.867   <2e-16 ***
## parkingBike and Car  5.319e+02  4.865e+02   1.093    0.275
## parkingCar           8.863e+02  5.468e+02   1.621    0.106
## parkingNA            2.724e+02  7.223e+02   0.377    0.706
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1575 on 219 degrees of freedom
## Multiple R-squared:  0.736,  Adjusted R-squared:   0.73
## F-statistic: 122.1 on 5 and 219 DF,  p-value: < 2.2e-16
```

parking have 4 levels parkingBike is the reference. parking 3 new variables are introduced.

the coefficent estimates for area beta1 is that the change in the price_per_sqft of a house when the area of the house is increased by 1 unit (1 sqr feet) and by keeping the all other predictor fixed.

the coefficent estimates for area beta2 is that the change in the price_per_sqft of a house when the rent of the house is increased by 1 unit ($ increased) and by keeping the all other predictor fixed.

the coefficent estimates for area beta3 is that the change in the price_per_sqft of a house when the house parking as Bike and Car parking availabity and by keeping the all other predictor fixed.

the coefficent estimates for area beta4 is that the change in the price_per_sqft of a house when the house parking as only Car parking availabity and by keeping the all other predictor fixed.

the coefficent estimates for area beta4 is that the change in the price_per_sqft of a house when the house as no parking availabity and by keeping the all other predictor fixed.

Yes parking perdictor as less significant to the model.

```r
# Create new columns corresponding to scaled versions of the continuous columns
continuous_cols = c("area", "rent", "price_per_sqft")
hData[paste0('scaled_', continuous_cols)] = lapply(hData[continuous_cols], scale)
str(hData)
```

```
## 'data.frame':    225 obs. of  15 variables:
##  $ locality             : Factor w/ 9 levels "Attibele","BTM Layout",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ area                 : int  565 1837 1280 2220 1113 1332 1815 1400 3006 1600 ...
##  $ rent                 : int  20060 97434 54448 117000 34388 36394 112000 41266 129000 92849 ...
##  $ price_per_sqft       : int  6195 9254 7422 9234 5391 4767 10744 5143 7485 10125 ...
##  $ facing               : Factor w/ 8 levels "East","North",..: 4 1 1 2 1 7 3 6 1 5 ...
##  $ BHK                  : int  1 3 2 3 2 2 3 2 4 3 ...
##  $ bathrooms            : int  1 3 2 3 2 2 2 2 5 2 ...
##  $ parking              : Factor w/ 4 levels "Bike","Bike and Car",..: 1 2 3 2 2 2 3 2 2 2 ...
##  $ logrent              : num  9.91 11.49 10.91 11.67 10.45 ...
##  $ logprice_per_sqft    : num  8.73 9.13 8.91 9.13 8.59 ...
##  $ sqrtprice_per_sqft   : num  78.7 96.2 86.2 96.1 73.4 ...
##  $ logarea              : num  6.34 7.52 7.15 7.71 7.01 ...
##  $ scaled_area          : num [1:225, 1] -1.041 0.496 -0.177 0.959 -0.379 ...
```

```
##   ..- attr(*, "scaled:center")= num 1426
##   ..- attr(*, "scaled:scale")= num 827
##  $ scaled_rent          : num [1:225, 1] -0.708 0.609 -0.123 0.942 -0.464 ...
##   ..- attr(*, "scaled:center")= num 61652
##   ..- attr(*, "scaled:scale")= num 58729
##  $ scaled_price_per_sqft: num [1:225, 1] -0.253 0.757 0.152 0.75 -0.518 ...
##   ..- attr(*, "scaled:center")= num 6961
##   ..- attr(*, "scaled:scale")= num 3030
```

```
# Build a linear model to predict scaled price per sqft as a function of scaled area and scaled rent. C
model = lm(price_per_sqft ~ area + rent, data= hData)
summary(model)
```

```
##
## Call:
## lm(formula = price_per_sqft ~ area + rent, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7500.7  -751.5  -221.9   849.9  6367.8
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.455e+03  2.164e+02   29.82   <2e-16 ***
## area        -2.521e+00  2.079e-01  -12.13   <2e-16 ***
## rent         6.653e-02  2.928e-03   22.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1575 on 222 degrees of freedom
## Multiple R-squared:  0.7324, Adjusted R-squared:   0.73
## F-statistic: 303.8 on 2 and 222 DF,  p-value: < 2.2e-16
```

```
model_scaled = lm(scaled_price_per_sqft ~ scaled_area + scaled_rent, data = hData)
summary(model_scaled)
```

```
##
## Call:
## lm(formula = scaled_price_per_sqft ~ scaled_area + scaled_rent,
##     data = hData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.47520 -0.24798 -0.07323  0.28045  2.10132
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.534e-17  3.464e-02    0.00        1
## scaled_area -6.882e-01  5.674e-02  -12.13   <2e-16 ***
## scaled_rent  1.289e+00  5.674e-02   22.72   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.5196 on 222 degrees of freedom
## Multiple R-squared:  0.7324, Adjusted R-squared:   0.73
## F-statistic: 303.8 on 2 and 222 DF,  p-value: < 2.2e-16
```

the scaling of the predictors haven't imporved the model's accuracy.

```
# Rebuild a linear model to predict sqrt of price per sqft as a function of logarea, logrent, and local
model = lm(data = hData, sqrtprice_per_sqft ~ logarea + logrent + locality)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ logarea + logrent + locality,
##     data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5577 -1.1073 -0.2527  0.4398 16.6760
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
## (Intercept)             -70.01549    2.95936 -23.659  < 2e-16 ***
## logarea                 -37.69954    0.74724 -50.451  < 2e-16 ***
## logrent                  39.35270    0.56700  69.405  < 2e-16 ***
## localityBTM Layout       -2.92678    0.71814  -4.076 6.47e-05 ***
## localityElectronic City  -2.77473    0.67493  -4.111 5.61e-05 ***
## localityIndiranagar      -1.17372    0.80139  -1.465  0.14449
## localityJayanagar         0.02791    0.87628   0.032  0.97462
## localityK R Puram        -3.32188    0.67817  -4.898 1.90e-06 ***
## localityMalleshwaram     -0.96970    0.83368  -1.163  0.24606
## localityMarathahalli     -3.09626    0.67094  -4.615 6.78e-06 ***
## localityYalahanka        -1.84366    0.66641  -2.767  0.00616 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.238 on 214 degrees of freedom
## Multiple R-squared:  0.9841, Adjusted R-squared:  0.9834
## F-statistic:  1326 on 10 and 214 DF,  p-value: < 2.2e-16
```

```
# Split data into train (80%) and test (20%) sets and evaluate model performance on train and test sets
ind = sample(nrow(hData), size = floor(0.8 * nrow(hData)), replace = FALSE)
hData_train = hData[ind, ]
hData_test = hData[-ind, ]

# Build the model using the training data
model = lm(sqrtprice_per_sqft ~ logarea + logrent + locality, data = hData_train)

# Calculate RMSE (Root Mean Squared Error) on train data
train_error = sqrt(mean((hData_train$price_per_sqft - predict(model, hData_train))^2))

# Calculate RMSE (Root Mean Squared Error) on test data
test_error = sqrt(mean((hData_test$price_per_sqft - predict(model, hData_test))^2))
```

```r
# Print RMSE for train and test sets
print(paste("Train RMSE: ", train_error))
```

```
## [1] "Train RMSE:  7551.05019595404"
```

```r
print(paste("Test RMSE: ", test_error))
```

```
## [1] "Test RMSE:  7331.94168234861"
```

there is no much variability in the model performance across different test sets setting the test error +/- 10 % to the train error.

```r
# Set a seed for reproducibility (optional, you can remove or change the seed each time for different s
#set.seed(123)

# Initialize vectors to store RMSE values
train_errors <- numeric(10)
test_errors <- numeric(10)

# Repeat the model training and error calculation 10 times
for (i in 1:10) {

  # Generate a new random sample for training data each time
  ind <- sample(nrow(hData), size = floor(0.8 * nrow(hData)), replace = FALSE)

  # Split the data into training and test sets
  hData_train <- hData[ind, ]
  hData_test <- hData[-ind, ]

  # Build the model using the training data
  model <- lm(sqrtprice_per_sqft ~ logarea + logrent + locality, data = hData_train)

  # Calculate RMSE (Root Mean Squared Error) on train data
  train_error <- sqrt(mean((hData_train$price_per_sqft - predict(model, hData_train))^2))

  # Calculate RMSE (Root Mean Squared Error) on test data
  test_error <- sqrt(mean((hData_test$price_per_sqft - predict(model, hData_test))^2))

  # Store the RMSE results in the vectors
  train_errors[i] <- train_error
  test_errors[i] <- test_error
}

# Print the RMSE results for each iteration
for (i in 1:10) {
  print(paste("Iteration ", i, " - Train RMSE: ", train_errors[i], " Test RMSE: ", test_errors[i]))
}
```

```
## [1] "Iteration  1  - Train RMSE:  7380.51373609001  Test RMSE:  7996.65677553628"
## [1] "Iteration  2  - Train RMSE:  7391.08328387459  Test RMSE:  7957.16219899049"
## [1] "Iteration  3  - Train RMSE:  7588.57634052008  Test RMSE:  7174.77868659564"
## [1] "Iteration  4  - Train RMSE:  7478.12627879856  Test RMSE:  7624.69817395202"
```

```
## [1] "Iteration  5  - Train RMSE:  7542.23730060706  Test RMSE:  7367.90604080351"
## [1] "Iteration  6  - Train RMSE:  7492.14268436449  Test RMSE:  7570.01225399189"
## [1] "Iteration  7  - Train RMSE:  7476.10522563353  Test RMSE:  7632.65212525028"
## [1] "Iteration  8  - Train RMSE:  7426.59871378916  Test RMSE:  7824.2258488574"
## [1] "Iteration  9  - Train RMSE:  7328.08305072506  Test RMSE:  8187.37209306717"
## [1] "Iteration  10  - Train RMSE:  7473.00527737882  Test RMSE:  7645.69035308306"
```

```r
# Optionally, you can calculate the average RMSE across all iterations
avg_train_error <- mean(train_errors)
avg_test_error <- mean(test_errors)

print(paste("Average Train RMSE: ", avg_train_error))
```

```
## [1] "Average Train RMSE:  7457.64718917814"
```

```r
print(paste("Average Test RMSE: ", avg_test_error))
```

```
## [1] "Average Test RMSE:  7698.11545501277"
```