Linear Regression Coding Assignment-1

```r
# 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
```

```r
# Load the house price dataset
hData = read.csv('houseprices_cleaned.csv')
str(hData)
```

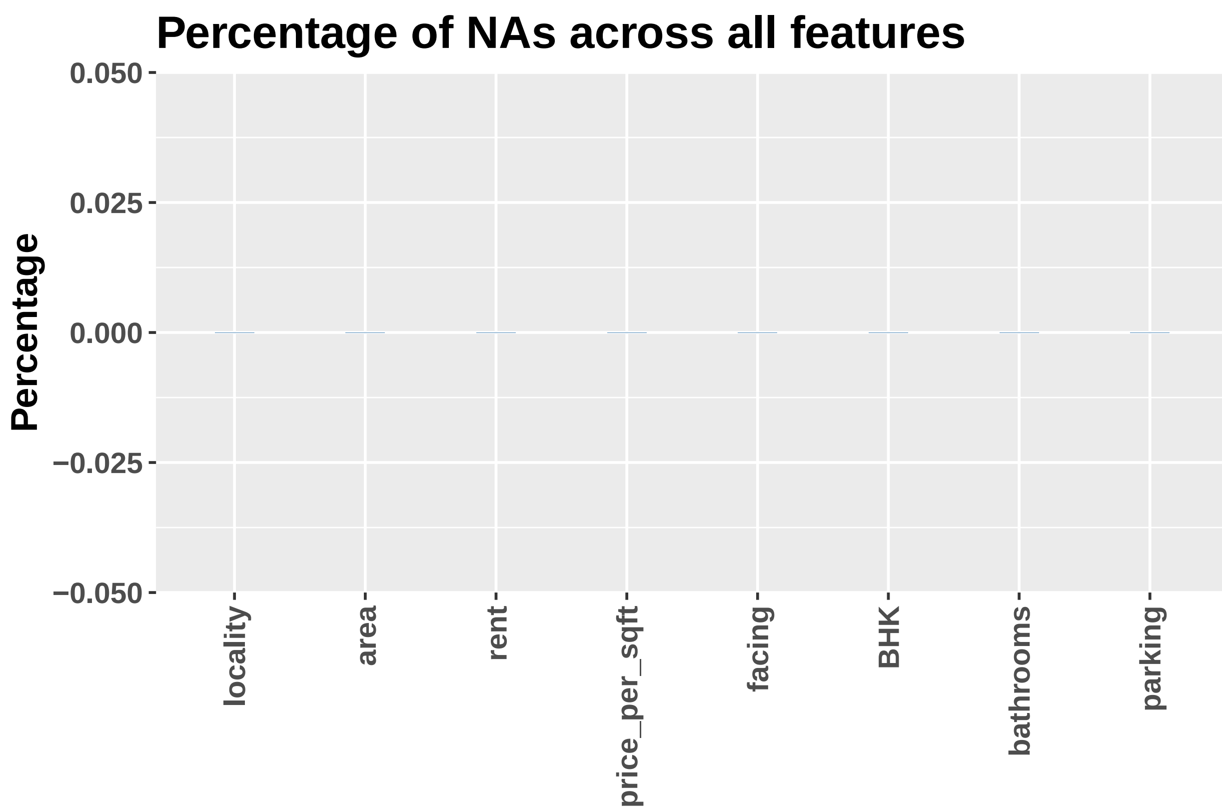
```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : chr  "BTM Layout" "BTM Layout" "BTM Layout" "BTM Layout" ...
##  $ area          : num  565 1837 1280 2220 1113 ...
##  $ rent          : num  20060 97434 54448 117000 34388 ...
##  $ price_per_sqft: num  6195 9254 7422 9234 5391 ...
##  $ 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" ...
```

```r
# 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          : num  565 1837 1280 2220 1113 ...
##  $ rent          : num  20060 97434 54448 117000 34388 ...
##  $ price_per_sqft: num  6195 9254 7422 9234 5391 ...
##  $ facing        : Factor w/ 8 levels "","East","North",..: 5 2 2 3 2 8 4 7 2 6 ...
##  $ 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",..: 2 3 4 3 3 3 4 3 3 3 ...
```

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

```r
# 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
```



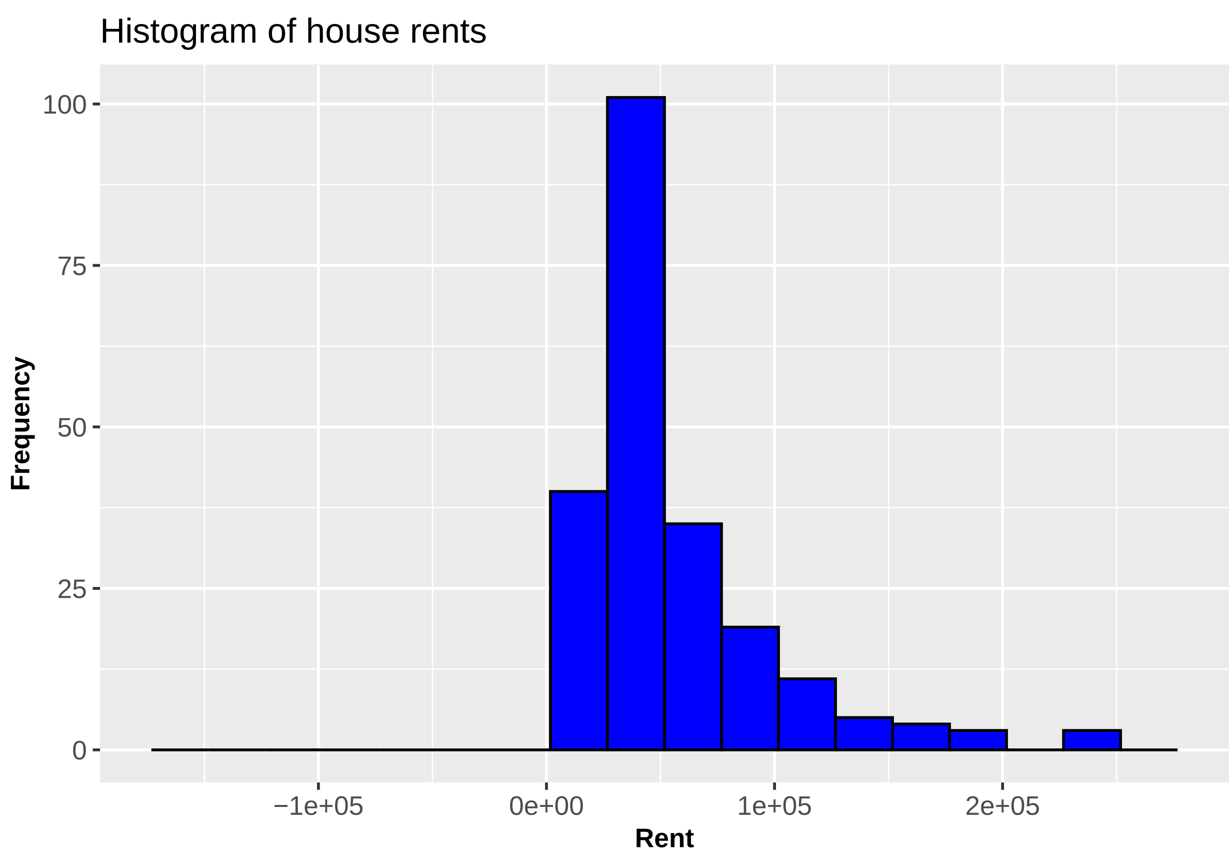

```r
# Add NA as a factor level for categorical columns

hData[categorical_cols] = lapply(hData[categorical_cols],addNA)
str(hData)
```

```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : Factor w/ 10 levels "Attibele","BTM Layout",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ area          : num  565 1837 1280 2220 1113 ...
##  $ rent          : num  20060 97434 54448 117000 34388 ...
##  $ price_per_sqft: num  6195 9254 7422 9234 5391 ...
##  $ facing        : Factor w/ 9 levels "","East","North",..: 5 2 2 3 2 8 4 7 2 6 ...
##  $ 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/ 5 levels "","Bike","Bike and Car",..: 2 3 4 3 3 3 4 3 3 3 ...
```

```r
# Make a histogram of rent values
p = ggplot(data = hData) +
  geom_histogram(aes(x = rent, y = after_stat(count)), breaks = seq(mean(hData$rent)-4*sd(hData$rent), m
  labs(x = 'Rent', y = 'Frequency')  +
   theme(axis.text = element_text(size = 8),
   axis.text.x = element_text(size = 10),
   axis.text.y = element_text(size = 10),
   axis.title = element_text(size = 10, face = "bold"))  +
  ggtitle('Histogram of house rents')
p
```

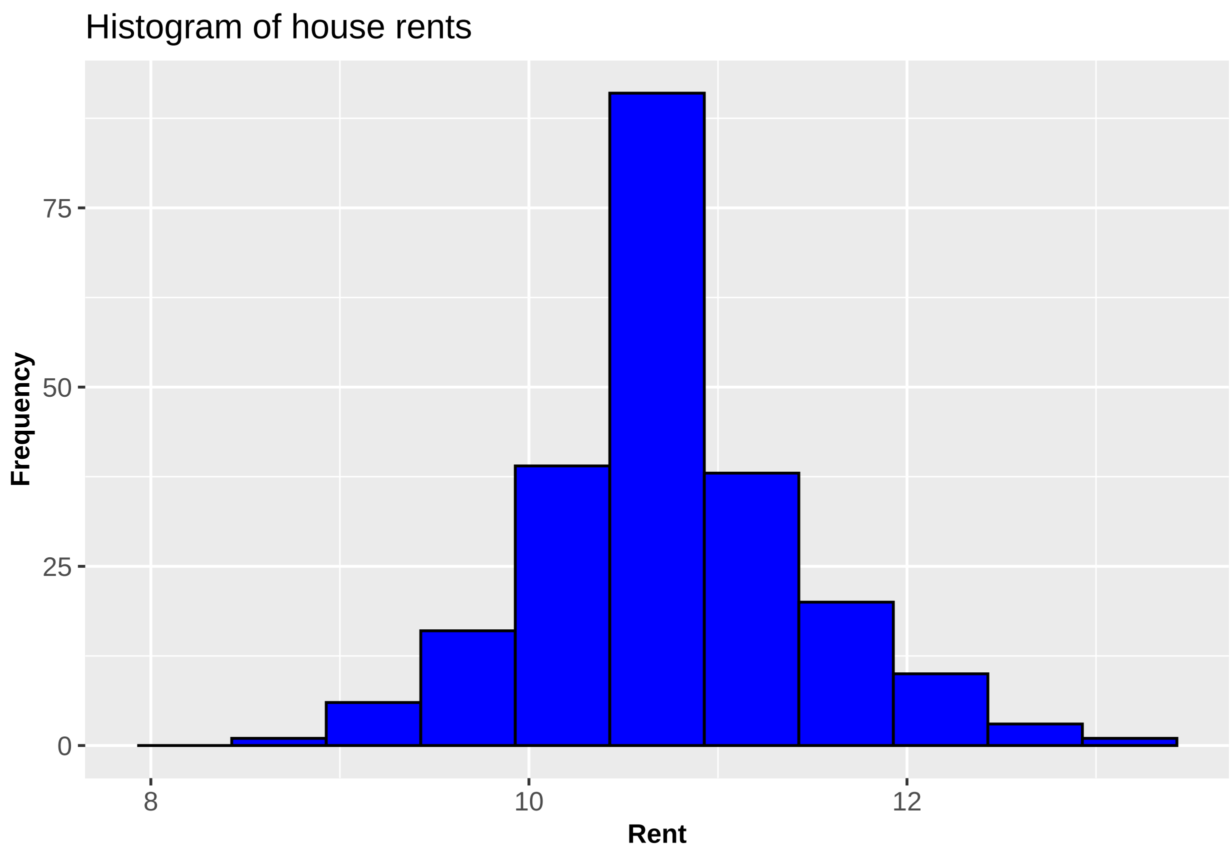



```r
# Build a linear model to predict price per square feet as a function of rent. How accurate is the mode
model = lm(data = hData,price_per_sqft ~ rent)
summary(model)
```

```
##
## 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
```

```r
# Make a histogram of log-transform
hData['logrent'] = log(hData['rent'])
p = ggplot(data = hData) +
  geom_histogram(aes(x = logrent, y = after_stat(count)), breaks = seq(mean(hData$logrent)-4*sd(hData$lo
  labs(x = 'Rent', y = 'Frequency')  +
   theme(axis.text = element_text(size = 8),
   axis.text.x = element_text(size = 10),
   axis.text.y = element_text(size = 10),
   axis.title = element_text(size = 10, face = "bold"))  +
  ggtitle('Histogram of house rents')
p
```



```r
# 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
```

```r
print('accuracy increases')
```

```
## [1] "accuracy increases"
```

```r
# 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(data = hData,logprice_per_sqft ~ logrent)
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
```

```r
#accuracy decreases but barely
```

```r
# 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(data = hData,sqrtprice_per_sqft ~ logrent)
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
```

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

```r
#the coefficents for rent and area mean that for unint increase in rent or area keeping everying else c
#the model is more accurate comapred to only rent as a predictor
```

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

```r
#the model is more accurate
```

```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(data = hData,sqrtprice_per_sqft ~ logarea + logrent )
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_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
```

```r
#the model is the most accurate among the rest
```

```r
# Build a linear model to predict price per sqft as a function of area, rent, and parking (compared to
model = lm(data = hData,price_per_sqft ~ area + rent + parking )
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)          6.133e+03  6.251e+02   9.810   <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         -2.724e+02  7.223e+02  -0.377    0.706
## parkingBike and Car  2.595e+02  5.780e+02   0.449    0.654
## parkingCar           6.139e+02  6.305e+02   0.974    0.331
## ---
## 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
```

```r
#the model is just as accurate even after adding parking
```

```r
# Build a linear model to predict sqrt of price per sqft as a function of logarea, logrent, and localit
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
```

```r
#the model is slightly more accuarate than just using logrent and logarea
```

```r
# Build a linear model to predict price per sqft as a function of area, rent, and parking. How many lev
model = lm(data = hData,price_per_sqft ~ area + rent + parking )
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)          6.133e+03  6.251e+02   9.810   <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         -2.724e+02  7.223e+02  -0.377    0.706
## parkingBike and Car  2.595e+02  5.780e+02   0.449    0.654
## parkingCar           6.139e+02  6.305e+02   0.974    0.331
## ---
## 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
```

```r
#there are 3 levels
#since the ep values are not close to 0 it might indicate non linear relationship
```

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

```
## 'data.frame':    225 obs. of  17 variables:
##  $ locality             : Factor w/ 10 levels "Attibele","BTM Layout",..: 2 2 2 2 2 2 2 2 2 2 ...
##  $ area                 : num  565 1837 1280 2220 1113 ...
##  $ rent                 : num  20060 97434 54448 117000 34388 ...
```

```
##  $ price_per_sqft       : num  6195 9254 7422 9234 5391 ...
##  $ facing               : Factor w/ 9 levels "","East","North",..: 5 2 2 3 2 8 4 7 2 6 ...
##  $ 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/ 5 levels "","Bike","Bike and Car",..: 2 3 4 3 3 3 4 3 3 3 ...
##  $ 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
##  $ scaled_BHK           : num [1:225, 1] -1.993 0.741 -0.626 0.741 -0.626 ...
##   ..- attr(*, "scaled:center")= num 2.46
##   ..- attr(*, "scaled:scale")= num 0.731
##  $ scaled_bathrooms     : num [1:225, 1] -0.686 0.209 -0.239 0.209 -0.239 ...
##   ..- attr(*, "scaled:center")= num 2.53
##   ..- attr(*, "scaled:scale")= num 2.23
```

```r
# Build a linear model to predict scaled price per sqft as a function of scaled area and scaled rent. C
model_scaled = lm(data = hData, scaled_price_per_sqft ~ scaled_area + scaled_rent)
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)  1.421e-16  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
```

```r
#scaling doesnt help in this case
```

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

```r
# Split data into train (80%) and test (20%) sets and evaluate model performance on train and test sets
set.seed(123)
ind = sample(nrow(hData), size = floor(0.8*nrow(hData)), replace = FALSE)
hData_train = hData[ind, ]
hData_test = hData[-ind, ]
# 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))

print(train_error)
```

```
## [1] 7531.232
```

```r
print(test_error)
```

```
## [1] 7412.905
```

```
#there isnt overfitting both the train and test modelperfom close to the same
```