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
```

```
# Load the house price dataset
hData = read.csv('houseprices_cleaned 1.csv', header = TRUE, stringsAsFactors = FALSE, na.strings = c("", "NA", "not availab
le", "Not Available"))
str(hData)
```

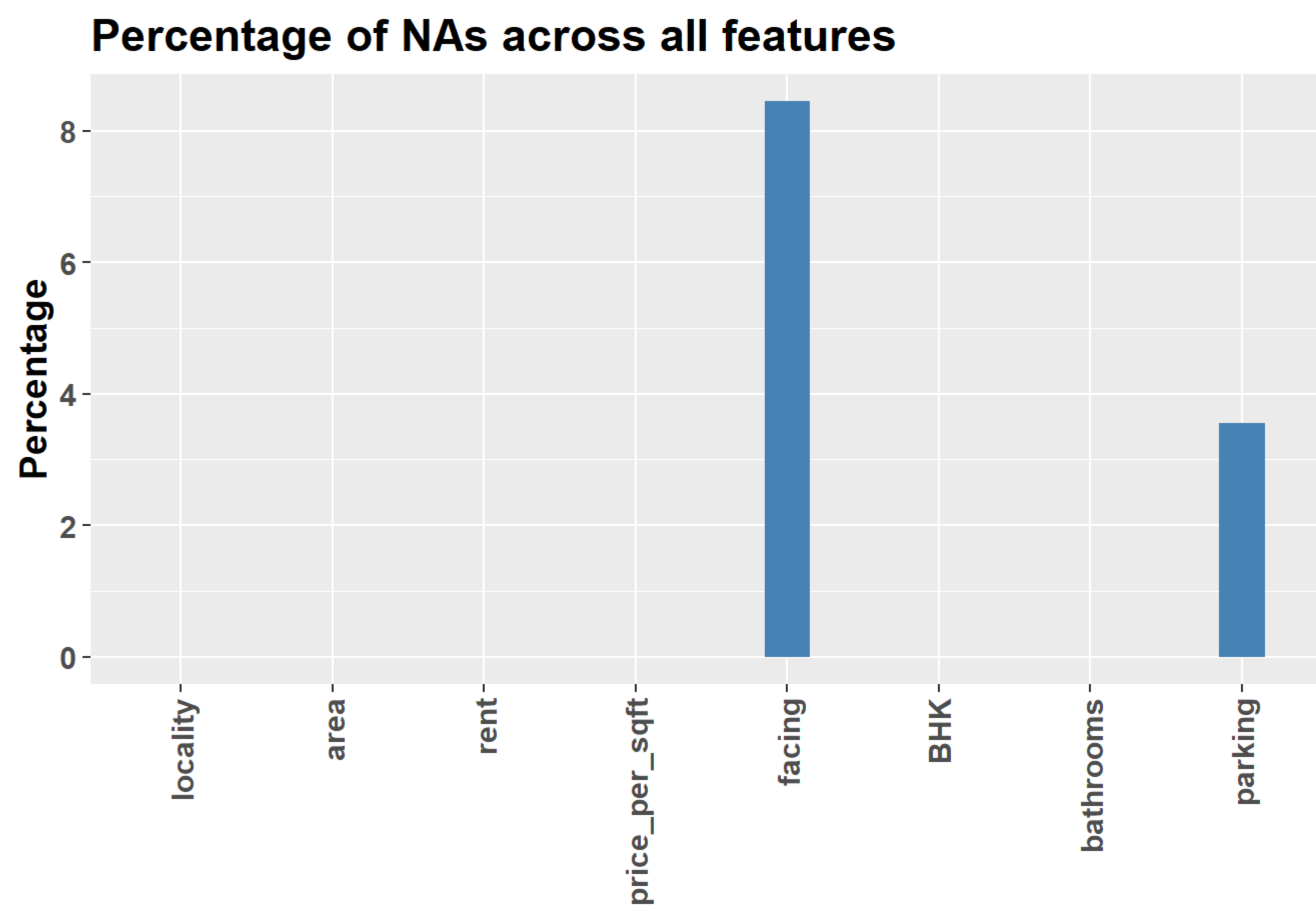
```
## 'data.frame':    225 obs. of  8 variables:
##  $ locality      : chr  "BTM Layout" "BTM Layout" "BTM Layout" "BTM Layout" ...
##  $ area          : num  565 1837 1280 2220 1113 ...
##  $ rent          : num  20060 97434 54448 117000 34388 ...
##  $ price_per_sqft: num  6195 9254 7422 9234 5391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

```
# 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/ 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 ...
```

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

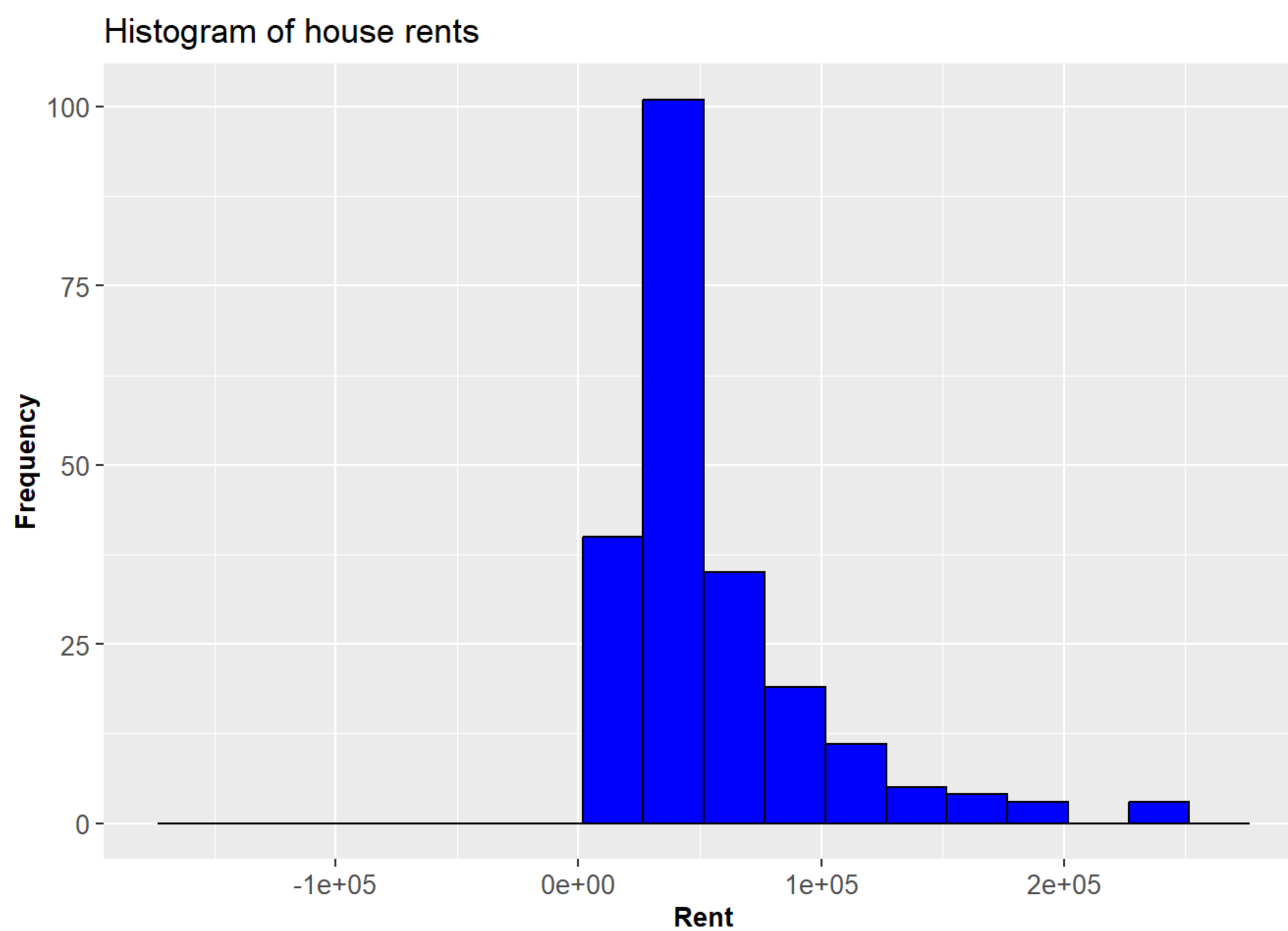
```r
# Plot percentage of NAs in each column of the data frame
hData_NA = setNames(stack(sapply(hData, function(x){(sum(is.na(x))/length(x))*100}))[2:1], c('Feature','Value'))
p = ggplot(data = hData_NA, aes(x = Feature, y = Value)) +
  geom_bar(stat = 'identity', fill = 'steelblue', width = 0.3) +
  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/ 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 ...
```

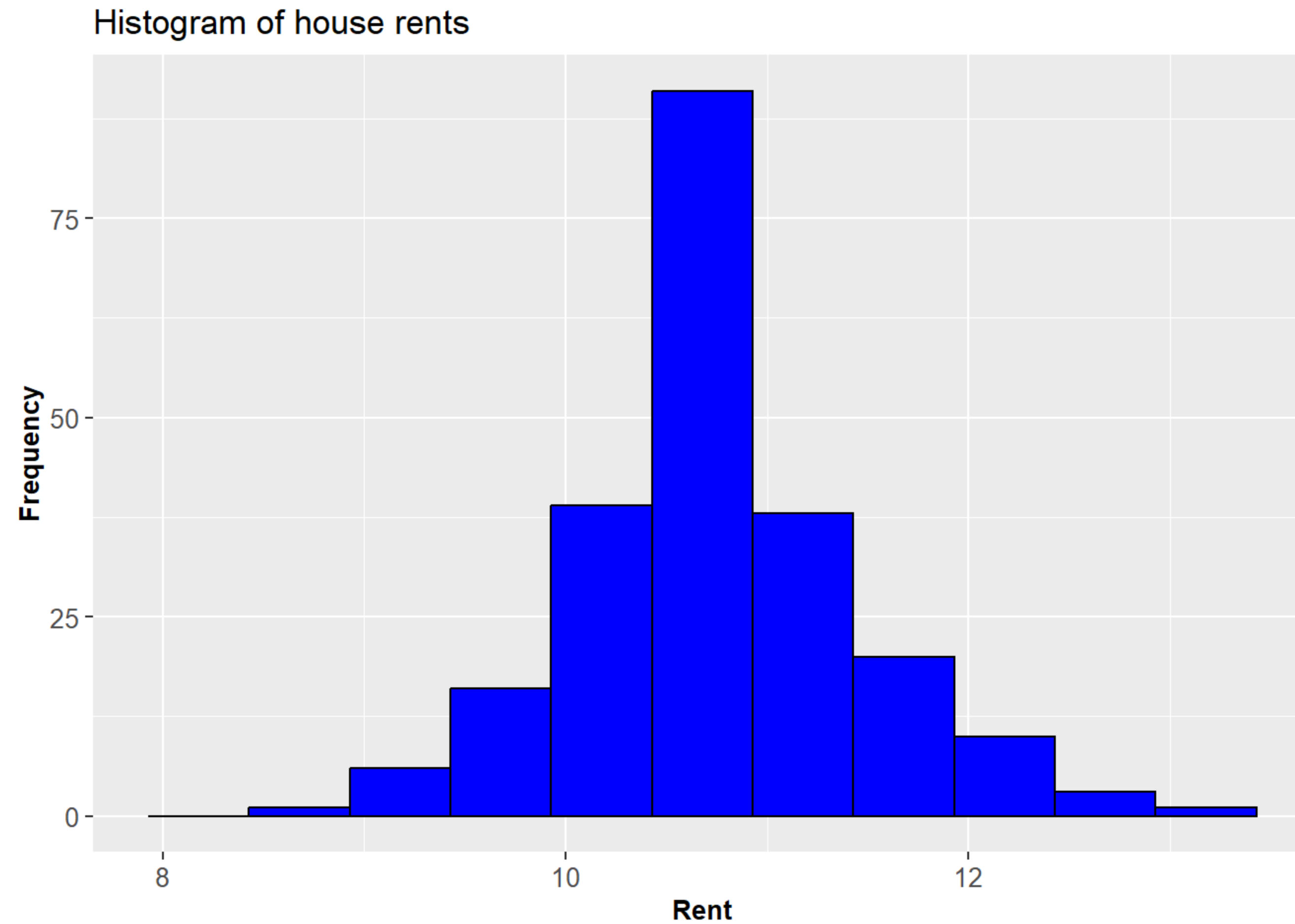
```
# Make a histogram of rent values
p = ggplot(data = hData) +
  geom_histogram(aes(x = rent , y = after_stat(count)), breaks = seq(mean(hData$rent)-4*sd(hData$rent), mean(hData$rent)+4*s
d(hData$rent), by = 25000), color = 'black', fill = 'blue') +
  labs(x = 'Rent', y = 'Frequency')  +
   theme(axis.text = 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
```




```
# Build a linear model to predict price per square feet as a function of rent. How accurate is the model?
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
```

```
# Make a histogram of log-transformed rent values
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$logrent), mean(hData$l
ogrent)+4*sd(hData$logrent), by = 0.5), color = 'black', fill = 'blue') +
  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
```




```
# Build a linear model to predict price per square feet as a function of logrent. Did log-transforming rent help improve the model accuracy?
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
```

```
# Build a linear model to predict log of price per square feet as a function of logrent. Did log-transforming the response v
ariable price per square feet improve the model accuracy?
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
```

```
# Build a linear model to predict sqrt of price per square feet as a function of logrent. Did sqrt-transforming the response
variable price per square feet improve the model accuracy?
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 additional predictor improve model accuracy (compared to only rent as the predictor)? Also, interpret the coefficient estimates for area and rent practically.
model = lm(data=hData, sqrtprice_per_sqft ~ rent + area)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ rent + area, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -44.429  -4.352  -0.189   6.523  33.966
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.940e+01  1.330e+00   59.70   <2e-16 ***
## rent         3.740e-04  1.799e-05   20.79   <2e-16 ***
## area        -1.461e-02  1.277e-03  -11.44   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.675 on 222 degrees of freedom
## Multiple R-squared:  0.6921, Adjusted R-squared:  0.6893
## F-statistic: 249.5 on 2 and 222 DF,  p-value: < 2.2e-16
```

```r
# Build a linear model to predict sqrt of price per sqft as a function of area and logrent. Did adding area as an additional predictor improve model accuracy (compared to only logrent as the predictor)? Also, interpret the coefficient estimates for area and logrent practically.
model = lm(data=hData, sqrtprice_per_sqft ~ logrent + area)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ logrent + area, 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 ***
## logrent      3.147e+01  8.482e-01   37.11   <2e-16 ***
## area        -1.307e-02  7.243e-04  -18.04   <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
# Build a linear model to predict sqrt of price per sqft as a function of logarea and logrent. Did log-transforming area imp
rove model accuracy?
hData['logarea'] = log(hData['area'])
model = lm(data=hData, sqrtprice_per_sqft ~ logrent + logarea)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ logrent + logarea, 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 ***
## logrent      40.0275     0.4252   94.13   <2e-16 ***
## logarea     -38.4642     0.6911  -55.66   <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
# Build a linear model to predict price per sqft as a function of area, rent, and parking (compared to just using area and r
ent as predictors). Did adding parking as an additional predictor improve model accuracy?
model = lm(data=hData, sqrtprice_per_sqft ~ rent + area + parking)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ rent + area + parking, data = hData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -44.158  -4.964  -0.126   6.481  35.519
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          7.510e+01  3.310e+00  22.687   <2e-16 ***
## rent                 3.686e-04  1.847e-05  19.963   <2e-16 ***
## area                -1.414e-02  1.332e-03 -10.613   <2e-16 ***
## parkingBike and Car  3.912e+00  2.986e+00   1.310   0.1915
## parkingCar           6.040e+00  3.356e+00   1.800   0.0733 .
## parkingNA            2.610e+00  4.434e+00   0.589   0.5567
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.665 on 219 degrees of freedom
## Multiple R-squared:  0.6969, Adjusted R-squared:   0.69
## F-statistic: 100.7 on 5 and 219 DF,  p-value: < 2.2e-16
```

```
# Build a linear model to predict sqrt of price per sqft as a function of logarea, logrent, and locality. Did adding localit
y as an additional predictor improve model accuracy (compared to just using logarea and logrent as predictors)?
model = lm(data=hData, sqrtprice_per_sqft ~ logrent + logarea + locality)
summary(model)
```

```
##
## Call:
## lm(formula = sqrtprice_per_sqft ~ logrent + logarea + 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 ***
## logrent                  39.35270    0.56700  69.405  < 2e-16 ***
## logarea                 -37.69954    0.74724 -50.451  < 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
```

```
# Build a linear model to predict price per sqft as a function of area, rent, and parking. How many levels does the categori
cal feature parking have? How many new variables are introduced for the categorical variable parking? Interpret all regressi
on coefficient estimates except the intercept coefficient estimate beta0 practically. Do the p-values suggest any insignific
ant features (that is, features which probably don't have a linear relationship with the response variable?
model = lm(data=hData, sqrtprice_per_sqft ~ rent + area + parking)
```

```
# 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/ 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
##  $ 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
```

```
# Build a linear model to predict scaled price per sqft as a function of scaled area and scaled rent. Compare this with the model built using unscaled data: that is, predict price per sqft as a function of area and rent. Does scaling help?
model_unscaled = lm(price_per_sqft~rent+area,data= hData)
```

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

```
##
## Call:
## lm(formula = scaled_price_per_sqft ~ scaled_rent + scaled_area,
##     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_rent  1.289e+00  5.674e-02   22.72   <2e-16 ***
## scaled_area -6.882e-01  5.674e-02  -12.13   <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
```

```
# Rebuild a linear model to predict sqrt of price per sqft as a function of logarea, logrent, and locality which we will eva
luate using a train-test split of the dataset
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. Run this cell multi
ple times for a random splitting of the data into train and test sets and report the model performance on the resulting trai
n and test sets. Is there much variability in the model performance across different test sets? If that is the case, then th
e model is not generalizing well and is overfitting the train set. Is it the case here?
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$sqrtprice_per_sqft - predict(model, newdata=hData_train))^2))

# Calculate RMSE (root-mean-squared-error) on test data
test_error = sqrt(mean((hData_train$sqrtprice_per_sqft - predict(model, newdata=hData_test))^2))

print(train_error)
```

```
## [1] 2.249116
```

```
print(test_error)
```

```
## [1] 23.61829
```