271 Final

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Question 1

Analyze each of these variables (as well as a combination of them) very carefully and use them (or a subset of them) to build a model and test hypotheses to address the questions. Also address potential (statistical) issues that may be casued by omitted variables. The philanthropist group hires a think tank to examine the relationship between the house values and neighborhood characteristics. For instance, they are interested in the extent to which houses in neighbhorhood with desirable features command higher values. They are specifically interested in environmental features, such as proximity to water body (i.e. lake, river, or ocean) or air quality.

Preparation for data analysis

```r
#Set Directory

#Ted
setwd("~/Documents/271 Final")

#Marlea
#setwd("C://Users/gwina003/Downloads/Final")

#Julian
#data <- read.csv("//vivica/Documents/MIDS/W271/271-Final/houseValueData.csv")

#Load Relevant Libraries
library(ggplot2)
library(car)
library(reshape2)
library(grid)
library(astsa)
library(forecast)
```

```
## Loading required package: zoo
##
## Attaching package: 'zoo'
##
## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric
##
## Loading required package: timeDate
## This is forecast 6.2
##
##
## Attaching package: 'forecast'
##
## The following object is masked from 'package:astsa':
```

```
##
##     gas
```

```r
library(quantmod)
```

```
## Loading required package: xts
## Loading required package: TTR
## Version 0.4-0 included new data defaults. See ?getSymbols.
```

```r
library(fGarch)
```

```
## Loading required package: timeSeries
##
## Attaching package: 'timeSeries'
##
## The following object is masked from 'package:zoo':
##
##     time<-
##
## Loading required package: fBasics
##
##
## Rmetrics Package fBasics
## Analysing Markets and calculating Basic Statistics
## Copyright (C) 2005-2014 Rmetrics Association Zurich
## Educational Software for Financial Engineering and Computational Science
## Rmetrics is free software and comes with ABSOLUTELY NO WARRANTY.
## https://www.rmetrics.org --- Mail to: info@rmetrics.org
##
## Attaching package: 'fBasics'
##
## The following object is masked from 'package:TTR':
##
##     volatility
##
## The following object is masked from 'package:astsa':
##
##     nyse
##
## The following object is masked from 'package:car':
##
##     densityPlot
```

```r
library(tseries)
library(gridExtra)
library(scales)
library(plyr)
library(GGally)
library(sandwich)
library(lmtest)
```

Read data and conduct initial variable examination

```
#Read dataset
data <- read.csv("houseValueData.csv")

#Changed with water to factor based on documentation; this is a categorical variable rather than an int
data$withWater <- as.factor(data$withWater)

#Initial variable examination
str(data)
```

```
## 'data.frame':    400 obs. of  11 variables:
##  $ crimeRate_pc     : num  37.6619 0.5783 0.0429 22.5971 0.0664 ...
##  $ nonRetailBusiness: num  0.181 0.0397 0.1504 0.181 0.0405 ...
##  $ withWater        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ ageHouse         : num  78.7 67 77.3 89.5 74.4 71.3 68.2 97.3 92.2 96.2 ...
##  $ distanceToCity   : num  2.71 4.12 7.82 1.95 5.54 ...
##  $ distanceToHighway: int  24 5 4 24 5 5 5 5 3 5 ...
##  $ pupilTeacherRatio: num  23.2 16 21.2 23.2 19.6 23.9 22.2 17.7 20.8 17.7 ...
##  $ pctLowIncome     : int  18 9 13 41 8 9 12 18 5 4 ...
##  $ homeValue        : int  245250 1125000 463500 166500 672750 596250 425250 483750 852750 1125000 .
##  $ pollutionIndex   : num  52.9 42.5 31.4 55 36 37 34.9 72.1 33.8 45.5 ...
##  $ nBedRooms        : num  4.2 6.3 4.25 3 4.86 ...
```

```
sum(is.na(data))
```

```
## [1] 0
```

```
summary(data)
```

```
##   crimeRate_pc      nonRetailBusiness withWater    ageHouse
##  Min.   : 0.00632   Min.   :0.0074    0:373     Min.   :  2.90
##  1st Qu.: 0.08260   1st Qu.:0.0513    1: 27     1st Qu.: 45.67
##  Median : 0.26600   Median :0.0969              Median : 77.95
##  Mean   : 3.76256   Mean   :0.1115              Mean   : 68.93
##  3rd Qu.: 3.67481   3rd Qu.:0.1810              3rd Qu.: 94.15
##  Max.   :88.97620   Max.   :0.2774              Max.   :100.00
##  distanceToCity   distanceToHighway pupilTeacherRatio  pctLowIncome
##  Min.   : 1.228   Min.   : 1.000    Min.   :15.60     Min.   : 2.00
##  1st Qu.: 3.240   1st Qu.: 4.000    1st Qu.:19.90     1st Qu.: 8.00
##  Median : 6.115   Median : 5.000    Median :21.90     Median :14.00
##  Mean   : 9.638   Mean   : 9.582    Mean   :21.39     Mean   :15.79
##  3rd Qu.:13.628   3rd Qu.:24.000    3rd Qu.:23.20     3rd Qu.:21.00
##  Max.   :54.197   Max.   :24.000    Max.   :25.00     Max.   :49.00
##    homeValue        pollutionIndex    nBedRooms
##  Min.   : 112500   Min.   :23.50   Min.   :1.561
##  1st Qu.: 384188   1st Qu.:29.88   1st Qu.:3.883
##  Median : 477000   Median :38.80   Median :4.193
##  Mean   : 499584   Mean   :40.61   Mean   :4.266
##  3rd Qu.: 558000   3rd Qu.:47.58   3rd Qu.:4.582
##  Max.   :1125000   Max.   :72.10   Max.   :6.780
```

The provided dataset contains 400 observations of 11 variables, with no missing values. Below is a view of the histograms of all numeric variables in the dataset.

```
#Histogram of variables
ggplot(melt(data[,-3]), aes(value)) + geom_histogram(color = "black", fill = "white") + facet_wrap(~vari
```

```
## No id variables; using all as measure variables
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
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## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```
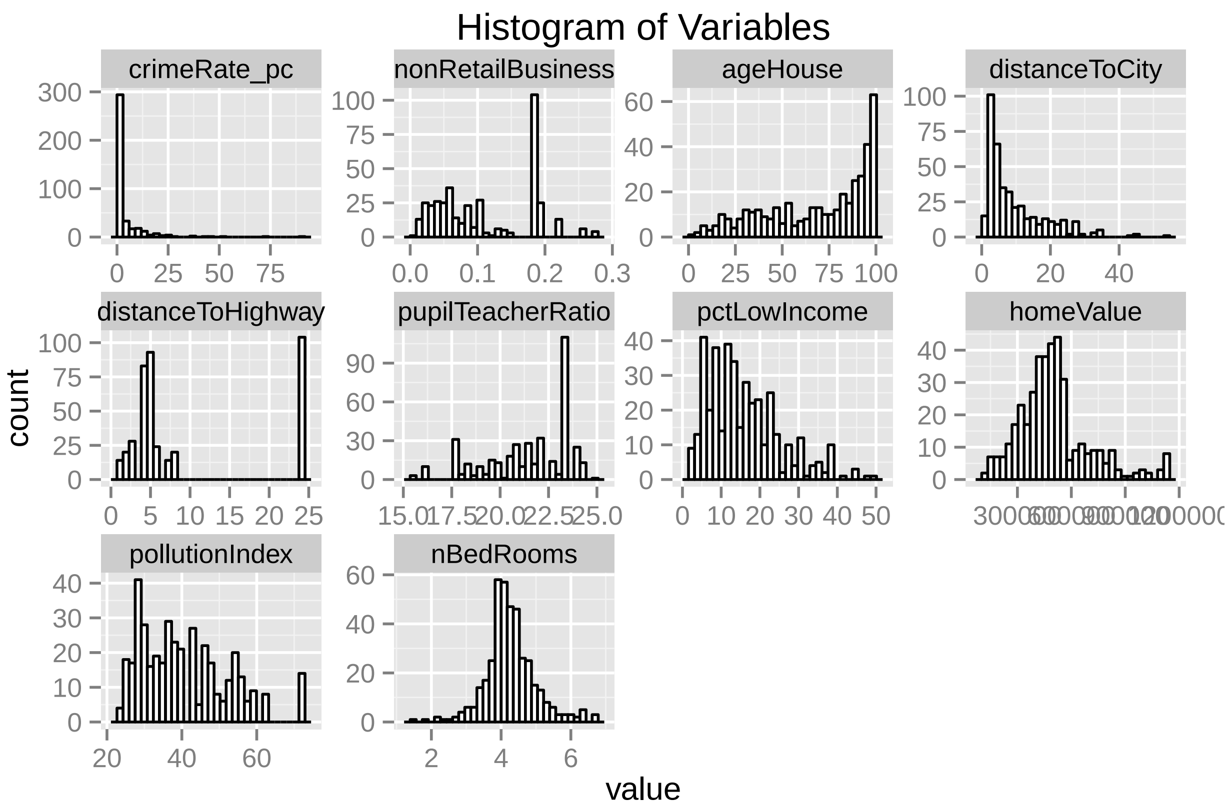



In order to get detailed summary statistics, we use the following function:

```
#Detailed summary statistics function
ContStat = function(x,y) {
#x must be a vector, not a dataframe
#y is the number of decimal points to round data to
StatLen  = length(x)
StatNA = sum(is.na(x))
StatMean = summary(x)["Mean"]
StatMin  = summary(x)["Min."]
```

```
StatMax= summary(x)["Max."]
StatSd  = sd(x)

StatQuan = quantile(x,c(0.01,0.05,0.1,0.25,0.5,0.75,0.9,0.95,0.99))

rownms =c("N", "#NA's","Mean","Min","Max","Std", "1%","5%","10%","25%","50%","75%","90%","95%","99%")

Stats = c(StatLen,StatNA,StatMean,StatMin,StatMax,StatSd, StatQuan)

ContStatDF = as.data.frame(Stats, row.names=rownms)
ContStatDF = round(ContStatDF,y)
return(ContStatDF)
}
```

In order to output histograms and scatterplots of each variable, we use the following function:

```
#Histogram and Scatterplot of variables
Graphs = function(x, y) {
#vect must be a vector, not a dataframe
#y is a string, the name of the variable of interest.  Used for labeling the graphs

subdata = data[,c(x,'homeValue')]
names(subdata)[1] = 'variable'

hist =  ggplot(data=subdata, aes(variable)) + geom_histogram() + ggtitle("Histogram")+ scale_x_continuo

sp = ggplot(data=subdata, aes(x=variable, y=homeValue)) +  geom_point(shape=16) +  ggtitle("Scatterplot

output = grid.arrange(hist, sp, ncol=2,nrow=1, top = textGrob(paste("Histogram and Scatterplot of" , y

return(output)
}
```

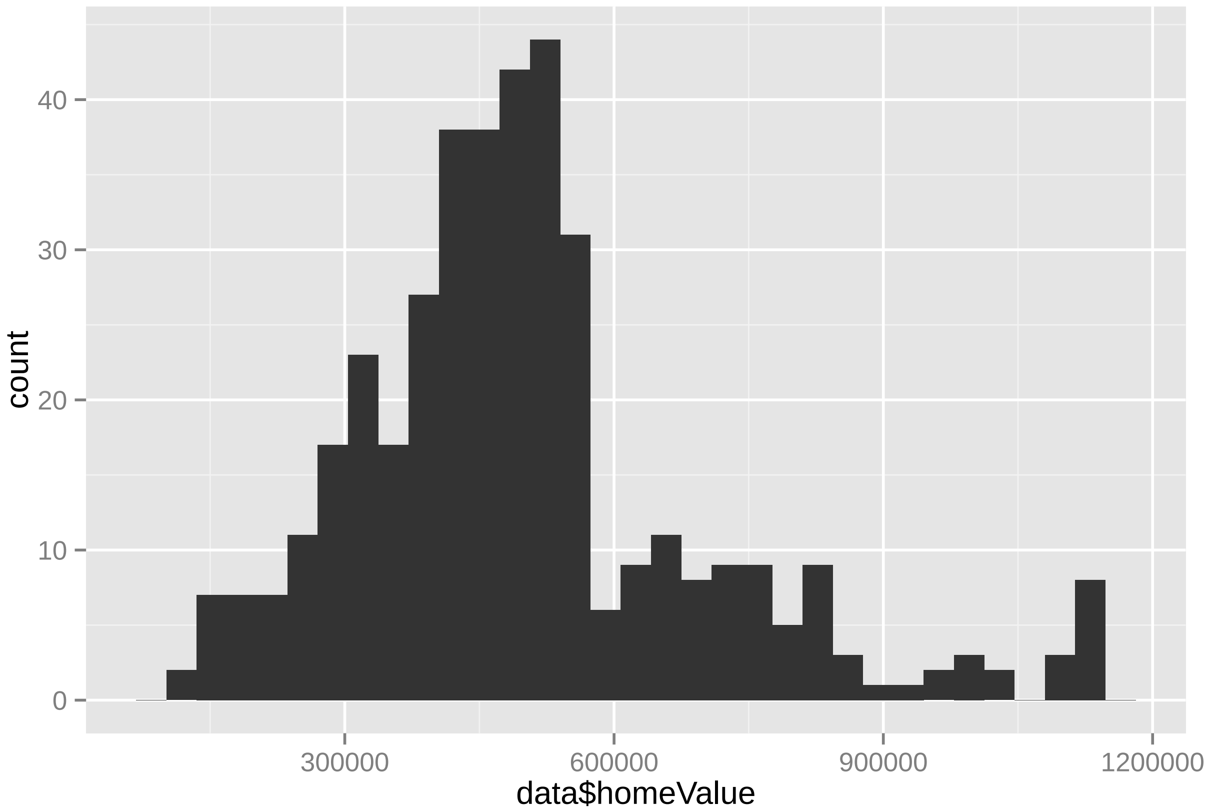
Detailed Variable Examination

We will now take a more detailed examination of each of the variables and their relationship with our variable of interest: homeValue.

HomeValue
First, homeValue itself. From the attached text file, homeValue is defined as *median price of single-family house in the neig*

```
#Examine HomeValue
ggplot(data=data, aes(data$homeValue)) + geom_histogram()
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
ContStat(data$homeValue,0)
```

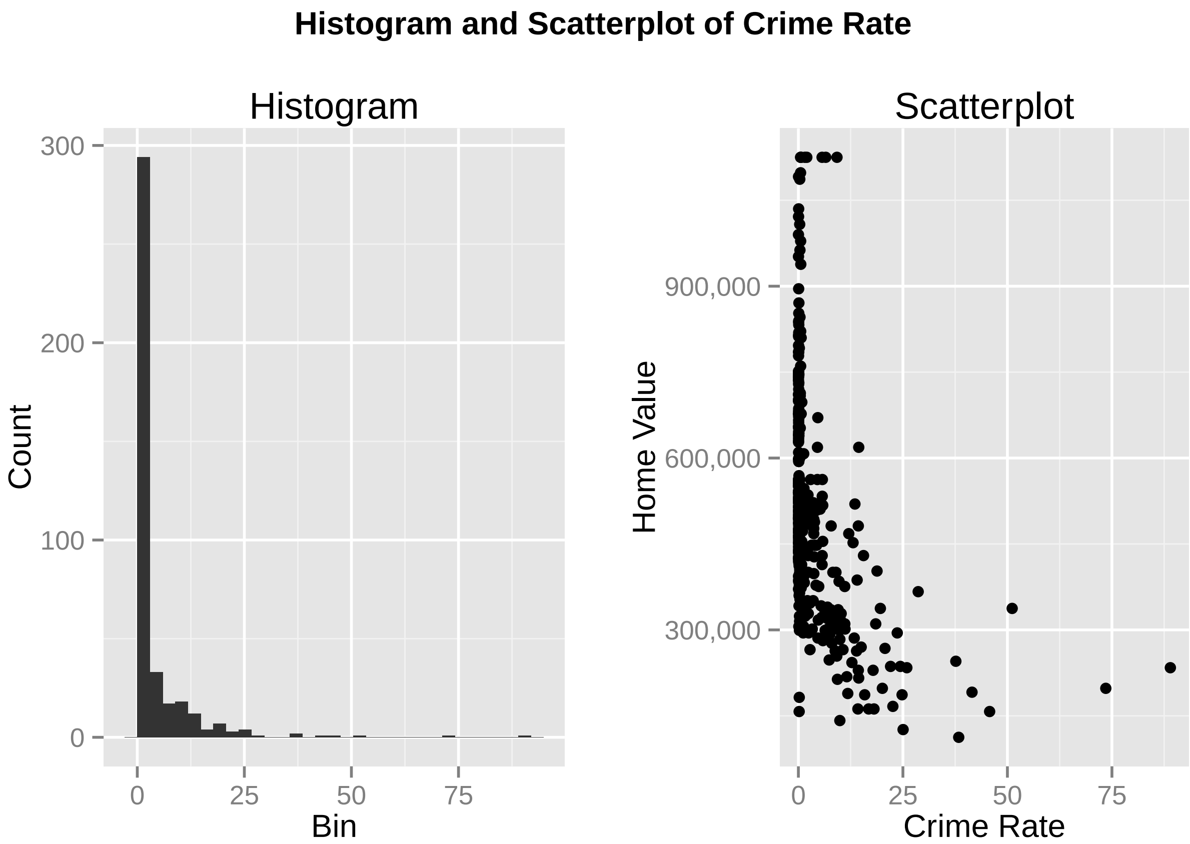
```
##          Stats
## N          400
## #NA's        0
## Mean    499600
## Min     112500
## Max    1125000
## Std     196116
## 1%      157500
## 5%      229500
## 10%     291825
## 25%     384188
## 50%     477000
## 75%     558000
## 90%     749475
## 95%     871987
## 99%    1125000
```

The range of the variable is 112,500 through 1,125,000 There dont appear to be any values that are unreasonable for the homeValue variable. The histogram shows a strong right skew of the variable with many of the values clustered together between the first and third quartile. While this is the target variable of interest, I will also create a log (homeValue) price and use both of them to find the model with the best fit.

CrimeRate_pc
Next lets take a look at the crimeRatepc variable which is defined as *crime rate per capita, measured by number of crimes per 1000 residents in neighborhood.*

```r
#Examine CrimeRate_pc
Graphs('crimeRate_pc', 'Crime Rate')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                grob
## 1 1 (2-2,1-1) arrange      gtable[layout]
## 2 2 (2-2,2-2) arrange      gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.543]
```

```r
ContStat(data$crimeRate_pc,2)
```

```
##         Stats
## N      400.00
## #NA's    0.00
## Mean     3.76
## Min      0.01
## Max     88.98
## Std      8.87
## 1%       0.01
## 5%       0.03
## 10%      0.04
## 25%      0.08
```

```
## 50%     0.27
## 75%     3.67
## 90%    11.20
## 95%    18.11
## 99%    41.57
```

Crime rate per capita shows a slight negative correlation against Home Value. However, there is an extremely large number of neighborhoods that have a crime rate of zero or close to zero. The scatterplot shows that crime rate is more dispersed around areas of lower home value. That being said, there appears to be a small ceiling in the scatterplot- six points that all seem to have the same home value but with varying crime rates. Lets take a closer look at those points.

```r
#Examine ceiling effect
subset(data, homeValue>1100000)
```

```
##     crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
## 2        0.57834            0.0397         0     67.0       4.116839
## 10       2.01019            0.1958         0     96.2       3.143511
## 18       6.53876            0.1810         1     97.5       1.343007
## 69       5.66998            0.1810         1     96.8       1.629199
## 164      1.51902            0.1958         1     93.9       3.433753
## 172      0.52693            0.0620         0     83.0       5.476381
## 216      0.61154            0.0397         0     86.9       2.563433
## 370      9.23230            0.1810         0    100.0       1.283993
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 2                   5              16.0            9   1125000
## 10                  5              17.7            4   1125000
## 18                 24              23.2            3   1125000
## 69                 24              23.2            4   1125000
## 164                 5              17.7            4   1125000
## 172                 8              20.4            5   1125000
## 216                 5              16.0            6   1125000
## 370                24              23.2           12   1125000
##     pollutionIndex nBedRooms
## 2             42.5     6.297
## 10            45.5     5.929
## 18            48.1     5.016
## 69            48.1     4.683
## 164           45.5     6.375
## 172           35.4     6.725
## 216           49.7     6.704
## 370           48.1     4.216
```

These points seem to indicate that there is a maximum limit on the homeValue. These values likely represent areas in which the median price is greater than 1125000. This means these data points are not likely to be continuous, and thus will be difficult to accurately predict these points as these observations could have a true median homeValue of 1125000 or even ten or fifty times that value. Having identified this ceiling, we should check to see if there is a floor for the minimum home value.

```r
#Examine potential floor effect
subset(data, homeValue<126000)
```

```
##     crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
```

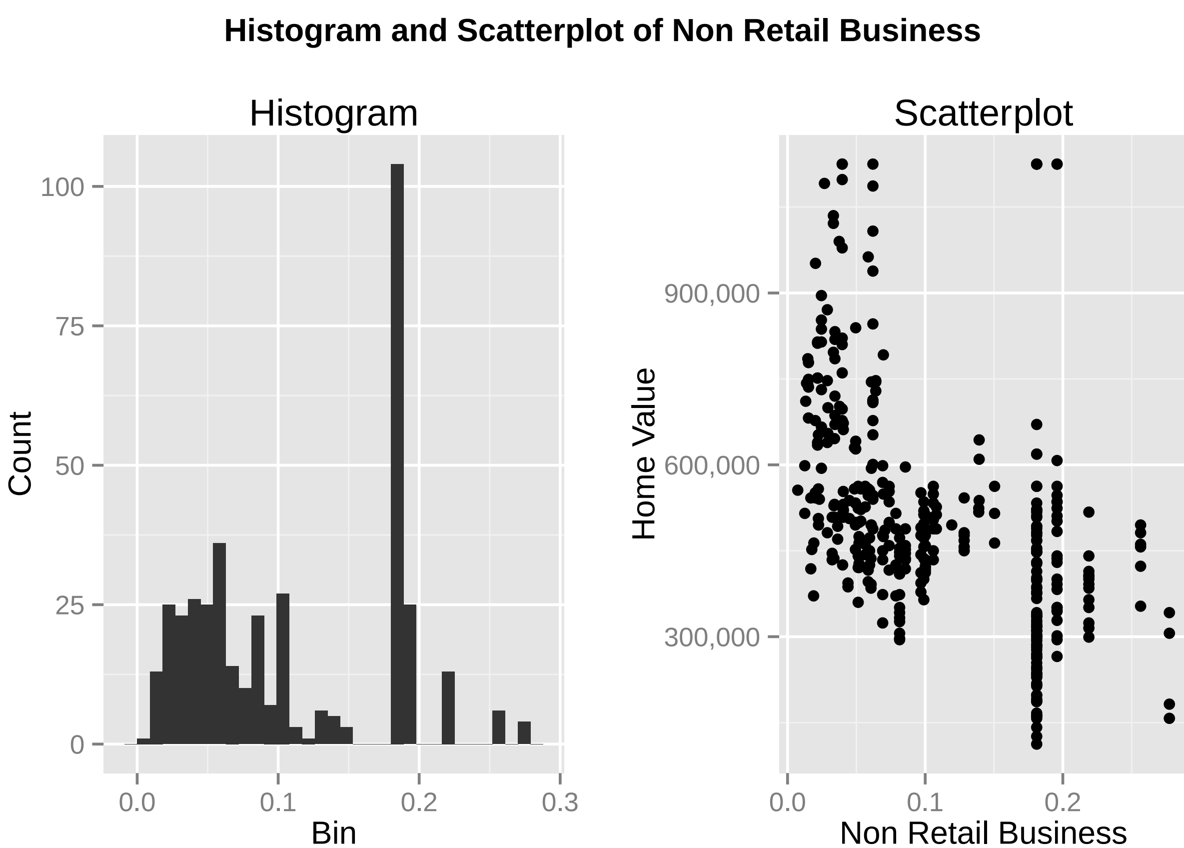
```
## 342      38.3518             0.181         0       100        1.891958
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 342                24              23.2           39    112500
##     pollutionIndex nBedRooms
## 342           54.3     3.453
```

With only one value at the minimum, it seems unlikely that there is a minimum limit to the home value.

NonRetailBusiness
Next let's take a look at the nonRetailBusiness variable which is defined as *the proportion of non-retail business acres per neighborhood.*

```
#Examine nonRetailBusiness
Graphs('nonRetailBusiness', 'Non Retail Business')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name               grob
## 1 1 (2-2,1-1) arrange      gtable[layout]
## 2 2 (2-2,2-2) arrange      gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.629]
```

```r
ContStat(data$nonRetailBusiness,2)
```

```
##         Stats
## N      400.00
## #NA's    0.00
## Mean     0.11
## Min      0.01
## Max      0.28
## Std      0.07
## 1%       0.01
## 5%       0.02
## 10%      0.03
## 25%      0.05
## 50%      0.10
## 75%      0.18
## 90%      0.20
## 95%      0.22
## 99%      0.26
```

The range for non retail business is 0.01 through 0.28. There is a negative correlation between the percentage of non retail business and the home value. While the data on the left side of the scatterplot seems to be random according to Non Retail Business, on the right side of the scatterplot, the values create a series of lines. We will now take a deeper look and find the most common values for this variable.

```r
#Frequencies of nonRetailBusiness
freqs = count(data$nonRetailBusiness)
freqs[with(freqs,order(-freq)),]
```

```
##          x freq
## 66 0.1810  104
## 67 0.1958   25
## 54 0.0814   15
## 47 0.0620   14
## 68 0.2189   13
## 30 0.0397   10
## 57 0.0990   10
## 58 0.1001    9
## 55 0.0856    8
## 59 0.1059    8
## 18 0.0246    7
## 32 0.0405    7
## 42 0.0586    7
## 49 0.0691    7
## 56 0.0969    7
## 14 0.0218    6
## 26 0.0344    6
## 38 0.0513    6
## 39 0.0519    6
## 52 0.0738    6
## 62 0.1283    6
## 69 0.2565    6
## 36 0.0493    5
```

```
## 6  0.0152    4
## 20 0.0289    4
## 41 0.0564    4
## 43 0.0596    4
## 53 0.0787    4
## 70 0.2774    4
## 15 0.0224    3
## 22 0.0324    3
## 23 0.0333    3
## 25 0.0341    3
## 37 0.0495    3
## 40 0.0532    3
## 46 0.0609    3
## 48 0.0641    3
## 50 0.0696    3
## 60 0.1081    3
## 64 0.1392    3
## 65 0.1504    3
## 2  0.0125    2
## 5  0.0147    2
## 7  0.0169    2
## 13 0.0203    2
## 21 0.0293    2
## 24 0.0337    2
## 27 0.0364    2
## 33 0.0439    2
## 34 0.0449    2
## 35 0.0486    2
## 44 0.0606    2
## 45 0.0607    2
## 63 0.1389    2
## 1  0.0074    1
## 3  0.0132    1
## 4  0.0138    1
## 8  0.0176    1
## 9  0.0189    1
## 10 0.0191    1
## 11 0.0201    1
## 12 0.0202    1
## 16 0.0225    1
## 17 0.0231    1
## 19 0.0268    1
## 28 0.0375    1
## 29 0.0378    1
## 31 0.0400    1
## 51 0.0707    1
## 61 0.1193    1
```

There are 104 records here (over 25%!) with the same value of 0.1810 for the percentage of non retail business. This is a curious result. Lets examine these records in detail.

```r
#Subset data
subset(data, nonRetailBusiness==.181)
```

```
##     crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
## 1       37.66190             0.181         0     78.7       2.705847
## 4       22.59710             0.181         0     89.5       1.950823
## 18       6.53876             0.181         1     97.5       1.343007
## 22      11.81230             0.181         0     76.5       2.547510
## 26      19.60910             0.181         0     97.9       1.552272
## 32       9.33889             0.181         0     95.6       2.954682
## 33       8.05579             0.181         0     95.4       4.139166
## 40       8.64476             0.181         0     92.6       2.541151
## 42       4.64689             0.181         0     67.6       4.423733
## 54       5.44114             0.181         0     98.2       3.937717
## 68      11.16040             0.181         0     94.6       3.339460
## 69       5.66998             0.181         1     96.8       1.629199
## 71       5.66637             0.181         0    100.0       3.043082
## 72      13.52220             0.181         0    100.0       1.934814
## 73       5.87205             0.181         0     96.0       2.286494
## 78      88.97620             0.181         0     91.9       1.745607
## 81      13.07510             0.181         0     56.7       5.263925
## 89      18.49820             0.181         0    100.0       1.228052
## 91       5.73116             0.181         0     77.0       7.120808
## 96       8.20058             0.181         0     80.3       5.131823
## 99      14.23620             0.181         0    100.0       2.066578
## 102     12.04820             0.181         0     87.6       2.913955
## 121     10.67180             0.181         0     94.8       3.002142
## 131      3.77498             0.181         0     84.7       5.407221
## 139      4.26131             0.181         0     81.3       4.357413
## 141      3.16360             0.181         0     48.2       6.006601
## 144      9.51363             0.181         0     94.1       4.321347
## 150      5.20177             0.181         1     83.4       4.965919
## 157     14.33370             0.181         0     88.0       2.913955
## 158      3.67822             0.181         0     96.2       3.286556
## 159     15.57570             0.181         0     71.0       5.518825
## 165      3.56868             0.181         0     75.0       5.482740
## 166      7.02259             0.181         0     95.3       2.733089
## 170     15.02340             0.181         0     97.3       3.279310
## 171      4.22239             0.181         1     89.0       2.803642
## 173     10.23300             0.181         0     96.7       3.455379
## 175     12.80230             0.181         0     96.6       2.782241
## 180     45.74610             0.181         0    100.0       2.246048
## 181      4.54192             0.181         0     88.0       4.382726
## 183      7.83932             0.181         0     65.4       5.686754
## 186     14.43830             0.181         0    100.0       1.843221
## 188     16.81180             0.181         0     98.1       1.764574
## 189      6.28807             0.181         0     96.4       3.207921
## 192      5.29305             0.181         0     82.5       3.448504
## 196      4.66883             0.181         0     87.9       4.557777
## 197      8.98296             0.181         1     97.4       3.333175
## 201     14.33370             0.181         0    100.0       2.099021
## 204      3.84970             0.181         1     91.0       4.346582
## 206      9.32909             0.181         0     98.7       3.690331
## 210      7.99248             0.181         0    100.0       1.981129
## 213     25.04610             0.181         0    100.0       2.097543
## 214     11.10810             0.181         0    100.0       1.292967
## 218     28.65580             0.181         0    100.0       2.098810
```

```
## 220      5.82401           0.181        0     64.7       7.166294
## 226      7.05042           0.181        0     85.1       3.084474
## 233     23.64820           0.181        0     96.2       1.686053
## 234      4.75237           0.181        0     86.5       4.155532
## 235     18.08460           0.181        0    100.0       2.640609
## 237      9.91655           0.181        0     77.8       1.913953
## 242     11.08740           0.181        0    100.0       2.696557
## 245      9.18702           0.181        0    100.0       2.079827
## 248      9.82349           0.181        0     98.8       1.631697
## 249     18.81100           0.181        0    100.0       2.024309
## 252      5.58107           0.181        0     87.9       3.832849
## 254      3.69311           0.181        0     88.4       4.519688
## 255     17.86670           0.181        0    100.0       1.686053
## 257      8.49213           0.181        0     86.1       3.160245
## 275      8.24809           0.181        0     99.3       4.201759
## 276     25.94060           0.181        0     89.1       2.222904
## 278      3.47428           0.181        1     82.9       2.803642
## 290      3.69695           0.181        0     91.4       2.453429
## 294     51.13580           0.181        0    100.0       1.738711
## 296     41.52920           0.181        0     85.4       2.136970
## 302     14.42080           0.181        0     93.3       3.037741
## 305      9.92485           0.181        0     96.6       3.525691
## 312      3.83684           0.181        0     91.1       3.779233
## 320     13.35980           0.181        0     94.7       2.520527
## 321      6.39312           0.181        0     97.4       3.546246
## 325      8.79212           0.181        0     70.6       3.186891
## 327     15.86030           0.181        0     95.4       2.815191
## 332     24.39380           0.181        0    100.0       1.846643
## 336     22.05110           0.181        0     92.4       2.713520
## 337      6.96215           0.181        0     97.0       2.855160
## 340     73.53410           0.181        0    100.0       2.567078
## 341     10.06230           0.181        0     94.3       3.248145
## 342     38.35180           0.181        0    100.0       1.891958
## 344      5.69175           0.181        0     79.8       7.578136
## 347      7.52601           0.181        0     98.3       3.492387
## 352      5.70818           0.181        0     74.9       6.859073
## 356      4.87141           0.181        0     93.6       3.805081
## 357     13.91340           0.181        0     95.0       3.588005
## 359      7.36711           0.181        0     78.1       2.876769
## 364     11.57790           0.181        0     97.0       2.493201
## 365     14.05070           0.181        0    100.0       1.969563
## 366     20.08490           0.181        0     91.2       1.791178
## 368      3.67367           0.181        0     51.9       9.159096
## 370      9.23230           0.181        0    100.0       1.283993
## 376      9.72418           0.181        0     97.2       3.190845
## 378      4.55587           0.181        0     87.9       2.149320
## 382     24.80170           0.181        0     96.0       2.343483
## 383      7.75223           0.181        0     83.7       5.143350
## 387      5.82115           0.181        0     89.9       5.198162
## 389     20.71620           0.181        0    100.0       1.299845
## 393      4.34879           0.181        0     84.0       5.903200
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 1                  24              23.2           18    245250
## 4                  24              23.2           41    166500
```

```
## 18                   24              23.2             3  1125000
## 22                   24              23.2            29   189000
## 26                   24              23.2            17   337500
## 32                   24              23.2            31   213750
## 33                   24              23.2            23   310500
## 40                   24              23.2            19   310500
## 42                   24              23.2            14   670500
## 54                   24              23.2            22   342000
## 68                   24              23.2            29   301500
## 69                   24              23.2             4  1125000
## 71                   24              23.2            21   414000
## 72                   24              23.2            17   519750
## 73                   24              23.2            24   281250
## 78                   24              23.2            22   234000
## 81                   24              23.2            18   452250
## 89                   24              23.2            49   310500
## 91                   24              23.2             8   562500
## 96                   24              23.2            21   303750
## 99                   24              23.2            26   162000
## 102                  24              23.2            18   468000
## 121                  24              23.2            30   265500
## 131                  24              23.2            21   427500
## 139                  24              23.2            16   508500
## 141                  24              23.2            18   447750
## 144                  24              23.2            24   335250
## 150                  24              23.2            14   510750
## 157                  24              23.2            16   481500
## 158                  24              23.2            12   468000
## 159                  24              23.2            23   429750
## 165                  24              23.2            18   522000
## 166                  24              23.2            20   319500
## 170                  24              23.2            32   270000
## 171                  24              23.2            18   378000
## 173                  24              23.2            23   328500
## 175                  24              23.2            30   243000
## 180                  24              23.2            47   157500
## 181                  24              23.2             9   562500
## 183                  24              23.2            16   481500
## 186                  24              23.2            25   618750
## 188                  24              23.2            39   162000
## 189                  24              23.2            22   335250
## 192                  24              23.2            24   522000
## 196                  24              23.2            24   285750
## 197                  24              23.2            22   400500
## 201                  24              23.2            39   229500
## 204                  24              23.2            16   488250
## 206                  24              23.2            23   317250
## 210                  24              23.2            31   276750
## 213                  24              23.2            34   126000
## 214                  24              23.2            44   310500
## 218                  24              23.2            25   366750
## 220                  24              23.2            13   517500
## 226                  24              23.2            29   301500
## 233                  24              23.2            30   294750
```

```
## 234                24              23.2          23    317250
## 235                24              23.2          37    162000
## 237                24              23.2          38    141750
## 242                24              23.2          19    375750
## 245                24              23.2          30    254250
## 248                24              23.2          27    299250
## 249                24              23.2          44    402750
## 252                24              23.2          20    321750
## 254                24              23.2          18    398250
## 255                24              23.2          28    229500
## 257                24              23.2          22    326250
## 275                24              23.2          21    400500
## 276                24              23.2          34    234000
## 278                24              23.2           6    492750
## 290                24              23.2          17    492750
## 294                24              23.2          12    337500
## 296                24              23.2          35    191250
## 302                24              23.2          23    216000
## 305                24              23.2          21    283500
## 312                24              23.2          18    447750
## 320                24              23.2          20    285750
## 321                24              23.2          31    299250
## 325                24              23.2          22    263250
## 327                24              23.2          31    186750
## 332                24              23.2          36    236250
## 336                24              23.2          28    236250
## 337                24              23.2          21    339750
## 340                24              23.2          26    198000
## 341                24              23.2          25    317250
## 342                24              23.2          39    112500
## 344                24              23.2          19    429750
## 347                24              23.2          24    292500
## 352                24              23.2           9    533250
## 356                24              23.2          23    375750
## 357                24              23.2          19    263250
## 359                24              23.2          27    247500
## 364                24              23.2          33    218250
## 365                24              23.2          27    387000
## 366                24              23.2          39    198000
## 368                24              23.2          13    477000
## 370                24              23.2          12   1125000
## 376                24              23.2          25    384750
## 378                24              23.2           8    618750
## 382                24              23.2          25    186750
## 383                24              23.2          20    335250
## 387                24              23.2          13    454500
## 389                24              23.2          30    267750
## 393                24              23.2          20    447750
##     pollutionIndex nBedRooms
## 1             52.9     4.202
## 4             55.0     3.000
## 18            48.1     5.016
## 22            56.8     4.824
## 26            52.1     5.313
```

```
## 32              52.9     4.380
## 33              43.4     3.427
## 40              54.3     4.193
## 42              46.4     4.980
## 54              56.3     4.655
## 68              59.0     4.629
## 69              48.1     4.683
## 71              59.0     4.219
## 72              48.1     1.863
## 73              54.3     4.405
## 78              52.1     4.968
## 81              43.0     3.713
## 89              51.8     2.138
## 91              38.2     5.061
## 96              56.3     3.936
## 99              54.3     4.343
## 102             46.4     3.648
## 121             59.0     4.459
## 131             50.5     3.952
## 139             62.0     4.112
## 141             50.5     3.759
## 144             56.3     4.728
## 150             62.0     4.127
## 157             46.4     4.229
## 158             62.0     3.362
## 159             43.0     3.926
## 165             43.0     4.437
## 166             56.8     4.006
## 170             46.4     3.304
## 171             62.0     3.803
## 173             46.4     4.185
## 175             59.0     3.854
## 180             54.3     2.519
## 181             62.0     4.398
## 183             50.5     4.209
## 186             44.7     4.852
## 188             55.0     3.277
## 189             59.0     4.341
## 192             55.0     4.051
## 196             56.3     3.976
## 197             62.0     4.212
## 201             55.0     2.880
## 204             62.0     4.395
## 206             56.3     4.185
## 210             55.0     3.520
## 213             54.3     3.987
## 214             51.8     2.906
## 218             44.7     3.155
## 220             38.2     4.242
## 226             46.4     4.103
## 233             52.1     4.380
## 234             56.3     4.525
## 235             52.9     4.434
## 237             54.3     3.852
```

```
## 242          56.8     4.411
## 245          55.0     3.536
## 248          52.1     4.794
## 249          44.7     2.628
## 252          56.3     4.436
## 254          56.3     4.376
## 255          52.1     4.223
## 257          43.4     4.348
## 275          56.3     5.393
## 276          52.9     3.304
## 278          56.8     6.780
## 290          56.8     2.963
## 294          44.7     3.757
## 296          54.3     3.531
## 302          59.0     4.461
## 305          59.0     4.251
## 312          62.0     4.251
## 320          54.3     3.887
## 321          43.4     4.162
## 325          43.4     3.565
## 327          52.9     3.896
## 332          55.0     2.652
## 336          59.0     3.818
## 337          55.0     3.713
## 340          52.9     3.957
## 341          43.4     4.833
## 342          54.3     3.453
## 344          43.3     4.114
## 347          56.3     4.417
## 352          38.2     4.750
## 356          46.4     4.484
## 357          56.3     4.208
## 359          52.9     4.193
## 364          55.0     3.036
## 365          44.7     4.657
## 366          55.0     2.368
## 368          43.3     4.312
## 370          48.1     4.216
## 376          59.0     4.406
## 378          56.8     1.561
## 382          54.3     3.349
## 383          56.3     4.301
## 387          56.3     4.513
## 389          50.9     2.138
## 393          43.0     4.167
```

Not only do these records have the same value for Non Retail Business, but also for distance to highway and pupil teacher ratio. This could indicate a problem because 25% of our records have the same value for 3 of 10 variables. It is very likely that these three can be used together for any model due to multicolinearity.

There was also a high number of records that had a value of 0.1958 for the non retail business variable. Let's take a look at those as well.

```r
#Subset data
subset(data, nonRetailBusiness==.1958)
```

```
##     crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
## 8        1.65660            0.1958         0     97.3       2.159562
## 10       2.01019            0.1958         0     96.2       3.143511
## 34       2.30040            0.1958         0     96.1       3.277562
## 43       2.24236            0.1958         0     91.8       4.117927
## 87       1.12658            0.1958         1     88.0       2.142929
## 90       1.34284            0.1958         0    100.0       2.464640
## 97       1.80028            0.1958         0     79.2       4.128541
## 142      3.53501            0.1958         1     82.6       2.438214
## 149      1.49632            0.1958         0    100.0       2.103460
## 161      2.36862            0.1958         0     95.7       1.833771
## 164      1.51902            0.1958         1     93.9       3.433753
## 191      2.44953            0.1958         0     95.2       3.692681
## 198      1.42502            0.1958         0    100.0       2.483967
## 199      2.14918            0.1958         0     98.5       2.170677
## 205      2.92400            0.1958         0     93.0       3.747410
## 262      1.20742            0.1958         0     94.6       4.128541
## 272      1.41385            0.1958         1     96.0       2.446936
## 309      2.44668            0.1958         0     94.0       2.417907
## 323      2.15505            0.1958         0    100.0       1.947124
## 324      3.32105            0.1958         1    100.0       1.562284
## 329      1.27346            0.1958         1     92.6       2.557514
## 334      2.73397            0.1958         0     94.9       1.965851
## 369      2.77974            0.1958         0     97.8       1.608498
## 377      2.31390            0.1958         0     97.3       4.027714
## 390      2.33099            0.1958         0     93.8       1.973898
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 8                   5              17.7           18    483750
## 10                  5              17.7            4   1125000
## 34                  5              17.7           14    535500
## 43                  5              17.7           14    510750
## 87                  5              17.7           15    344250
## 90                  5              17.7            8    546750
## 97                  5              17.7           15    535500
## 142                 5              17.7           19    351000
## 149                 5              17.7           16    441000
## 161                 5              17.7           38    328500
## 164                 5              17.7            4   1125000
## 191                 5              17.7           14    501750
## 198                 5              17.7            9    524250
## 199                 5              17.7           20    436500
## 205                 5              17.7           12    562500
## 262                 5              17.7           18    391500
## 272                 5              17.7           19    382500
## 309                 5              17.7           20    294750
## 323                 5              17.7           21    351000
## 324                 5              17.7           34    301500
## 329                 5              17.7            6    607500
## 334                 5              17.7           27    346500
## 369                 5              17.7           37    265500
```

```
## 377                  5             17.7           15    429750
## 390                  5             17.7           36    400500
##     pollutionIndex nBedRooms
## 8             72.1     4.122
## 10            45.5     5.929
## 34            45.5     4.319
## 43            45.5     3.854
## 87            72.1     3.012
## 90            45.5     4.066
## 97            45.5     3.877
## 142           72.1     4.152
## 149           72.1     3.404
## 161           72.1     2.926
## 164           45.5     6.375
## 191           45.5     4.402
## 198           72.1     4.510
## 199           72.1     3.709
## 205           45.5     4.101
## 262           45.5     3.875
## 272           72.1     4.129
## 309           72.1     3.272
## 323           72.1     3.628
## 324           72.1     3.403
## 329           45.5     4.250
## 334           72.1     3.597
## 369           72.1     2.903
## 377           45.5     3.880
## 390           72.1     3.186
```

The same issue as above with another 25 sharing the same values.

```r
#Subset data
subset(data, nonRetailBusiness==.0814)
```

```
##     crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
## 48       1.00245            0.0814         0     87.3      10.083736
## 52       1.38799            0.0814         0     82.0       9.152856
## 64       0.98843            0.0814         0    100.0       9.542017
## 103      0.72580            0.0814         0     69.5       8.453050
## 105      0.75026            0.0814         0     94.1      10.701905
## 113      0.62739            0.0814         0     56.5      11.089802
## 120      0.63796            0.0814         0     84.5      10.945402
## 167      0.85204            0.0814         0     89.2       9.234841
## 240      0.95577            0.0814         0     88.8      10.912060
## 258      0.77299            0.0814         0     94.4      10.917157
## 274      1.25179            0.0814         0     98.1       8.458038
## 314      0.67191            0.0814         0     90.3      11.821981
## 358      1.15172            0.0814         0     95.0       8.419944
## 367      1.23247            0.0814         0     91.7       9.104822
## 398      0.80271            0.0814         0     36.6       8.453050
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 48                  4                24           15    472500
## 52                  4                24           35    297000
```

```
## 64                     4                24           25    326250
## 103                    4                24           14    409500
## 105                    4                24           20    351000
## 113                    4                24           10    447750
## 120                    4                24           13    409500
## 167                    4                24           17    441000
## 240                    4                24           22    333000
## 258                    4                24           16    414000
## 274                    4                24           27    306000
## 314                    4                24           18    373500
## 358                    4                24           23    294750
## 367                    4                24           24    342000
## 398                    4                24           14    454500
##     pollutionIndex nBedRooms
## 48            38.8     4.674
## 52            38.8     3.950
## 64            38.8     3.813
## 103           38.8     3.727
## 105           38.8     3.924
## 113           38.8     3.834
## 120           38.8     4.096
## 167           38.8     3.965
## 240           38.8     4.047
## 258           38.8     4.495
## 274           38.8     3.570
## 314           38.8     3.813
## 358           38.8     3.701
## 367           38.8     4.142
## 398           38.8     3.456
```

The same issue with another 15 sharing the same values. These 15 also have the same value for pollutionIndex. In fact, when nonRetailBusiness values of 0.0620, 0.2189, 0.0397, 0.0990, 0.1001 and 0.0856 are further examined, we notice that they all have the same values for pollutionindex, distance to highway and pupil teacher ratio. These variables will likely not contribute much together, as they tend to vary together as a group.

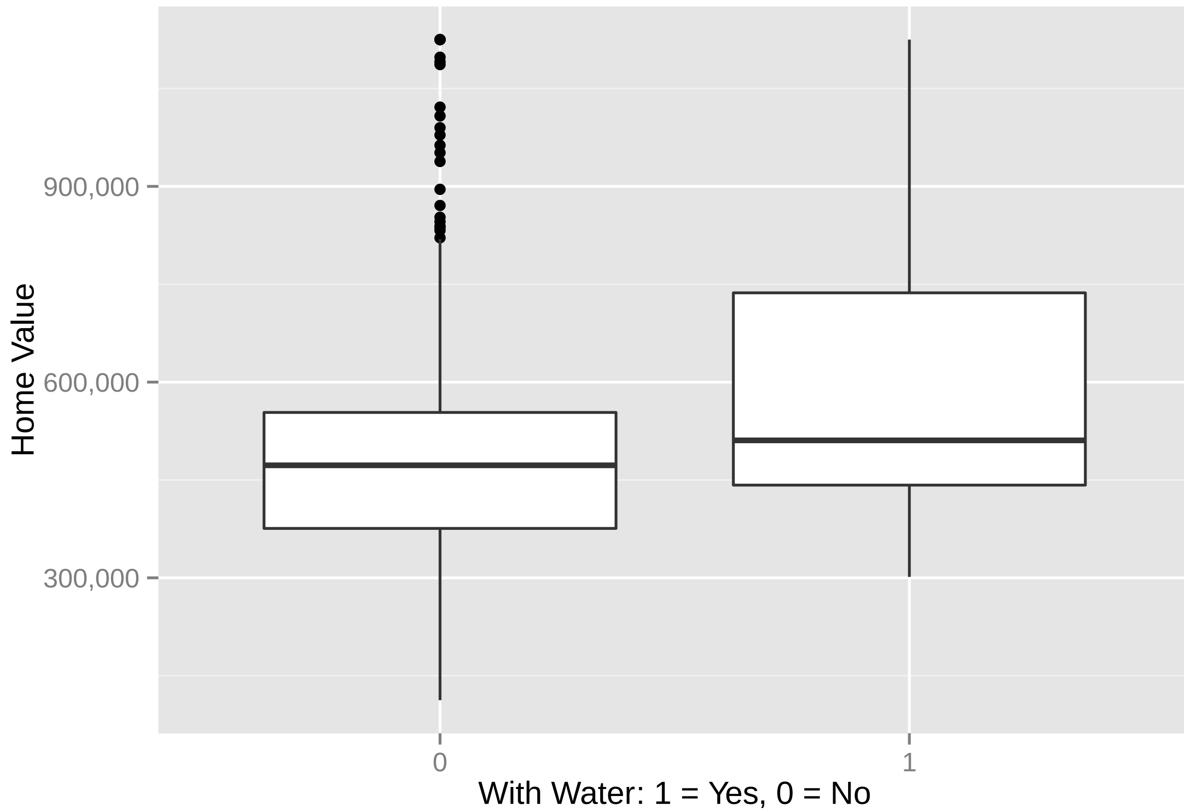
WithWater
The next variable is withwater which is defined as *whether the neighborhood is within 5 miles of a water body (lake, river, e*

As this is a binary variable, the functions created above are not appropriate.

```
#Examine withWater
table(data$withWater)
```

```
##
##   0   1
## 373  27
```

```
ggplot(data, aes(withWater, homeValue)) + geom_boxplot() +  scale_y_continuous(name = "Home Value", labe
```



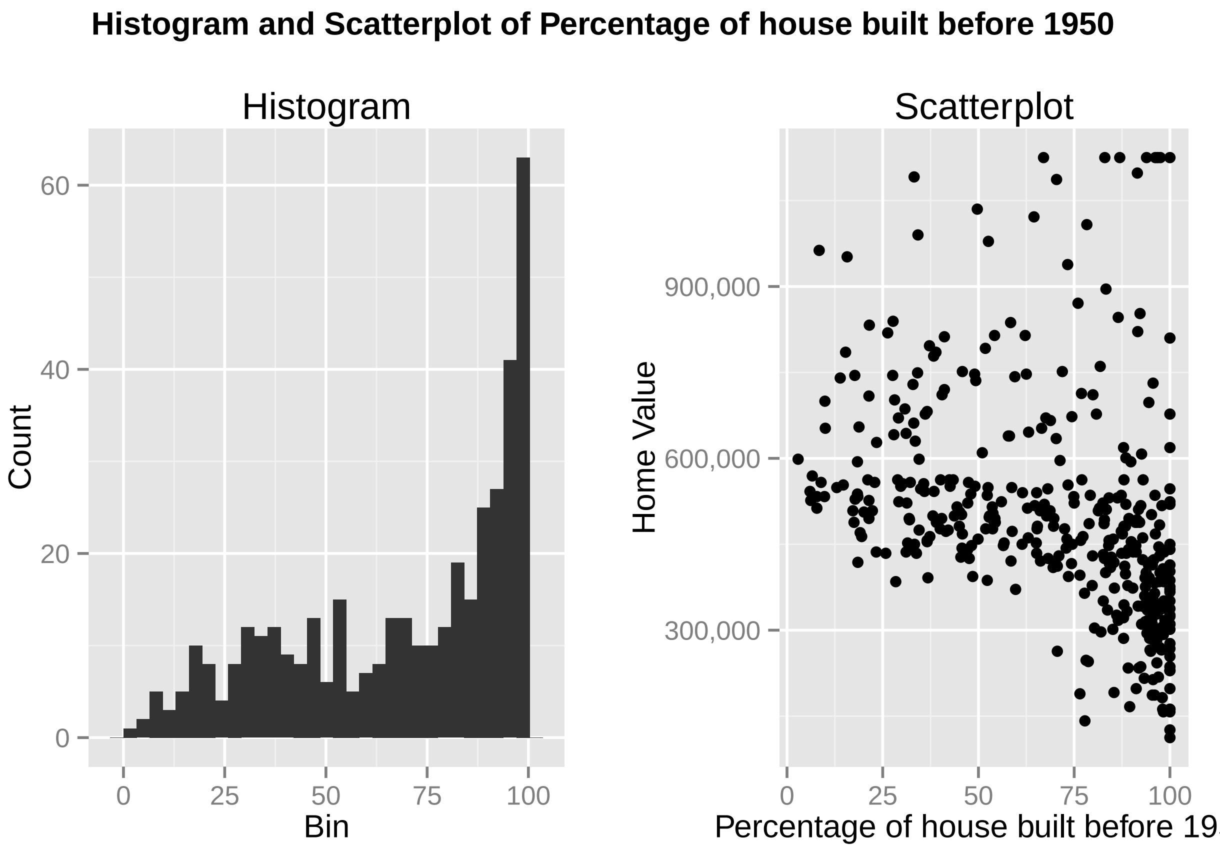
With water tends to have a slightly higher median home value than without water. Neighborhoods without water do tend to see some higher home values, but these are considered outliers that fall outside of the upper whisker.

---

ageHouse
Now we will examine ageHouse, which is defined as *proportion of houses built before 1950*

```
#Examine ageHouse
Graphs('ageHouse', 'Percentage of house built before 1950')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                grob
## 1 1 (2-2,1-1) arrange      gtable[layout]
## 2 2 (2-2,2-2) arrange      gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.774]
```

```
ContStat(data$ageHouse,1)
```

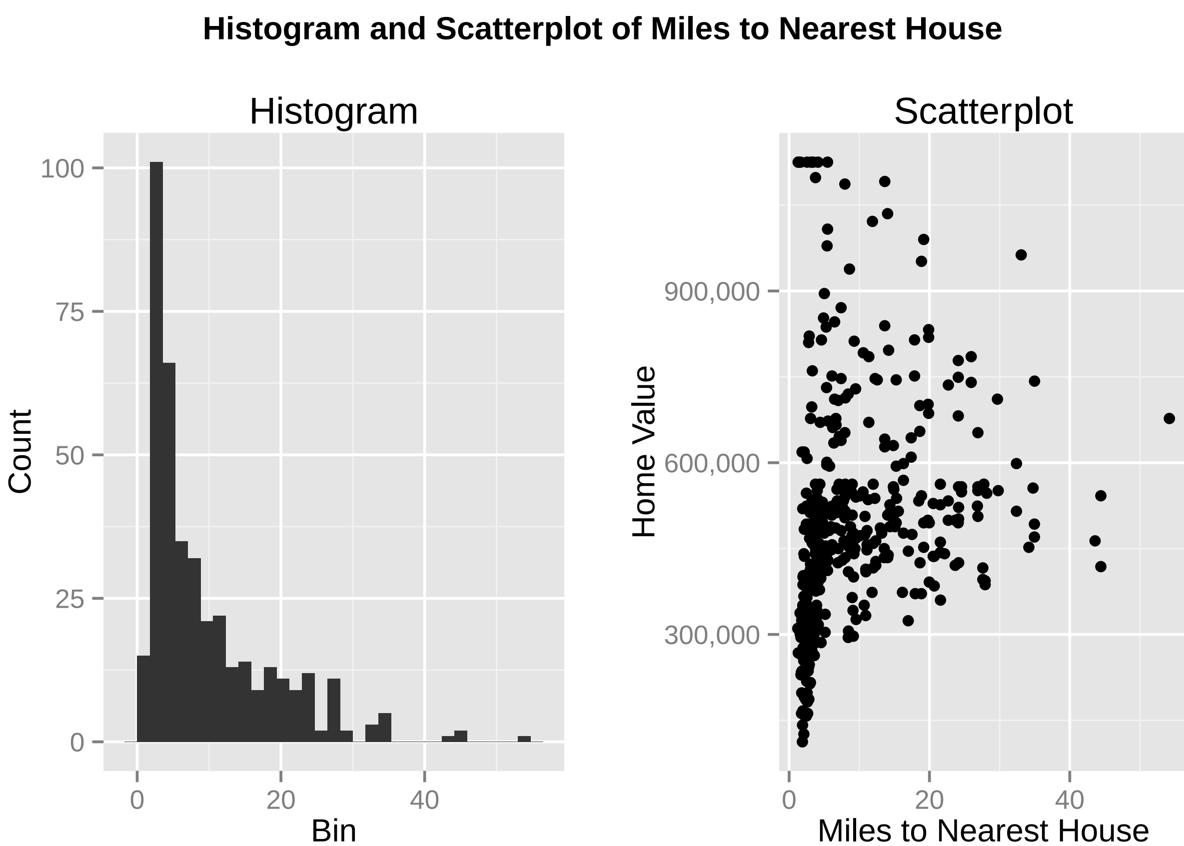
```
##       Stats
## N     400.0
## #NA's   0.0
## Mean   68.9
## Min     2.9
## Max   100.0
## Std    28.0
## 1%      7.8
## 5%     18.4
## 10%    27.7
## 25%    45.7
## 50%    77.9
## 75%    94.1
## 90%    98.4
## 95%   100.0
## 99%   100.0
```

The range here is from 2.9 through 100.0 with a left skew indicating many of these neighborhoods have older homes (built before 1950). With such age buckets, there is ambiguity between neighborhoods built in 1950 and those in 1850. This might account for the larger variation in older neighborhoods home value. Even so, the newer neighborhoods seem to have higher home values, especially given that there is less of a spread than for older homes. Average age of the home would be a better variable in this case.

distanceToCity
distanceToCity is next which is *distance to the nearest city (measured in miles)*

```
#Examine distanceToCity
Graphs('distanceToCity', 'Miles to Nearest House')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                grob
## 1 1 (2-2,1-1) arrange      gtable[layout]
## 2 2 (2-2,2-2) arrange      gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.860]
```

```
ContStat(data$distanceToCity ,1)
```

```
##        Stats
## N      400.0
## #NA's    0.0
## Mean     9.6
```

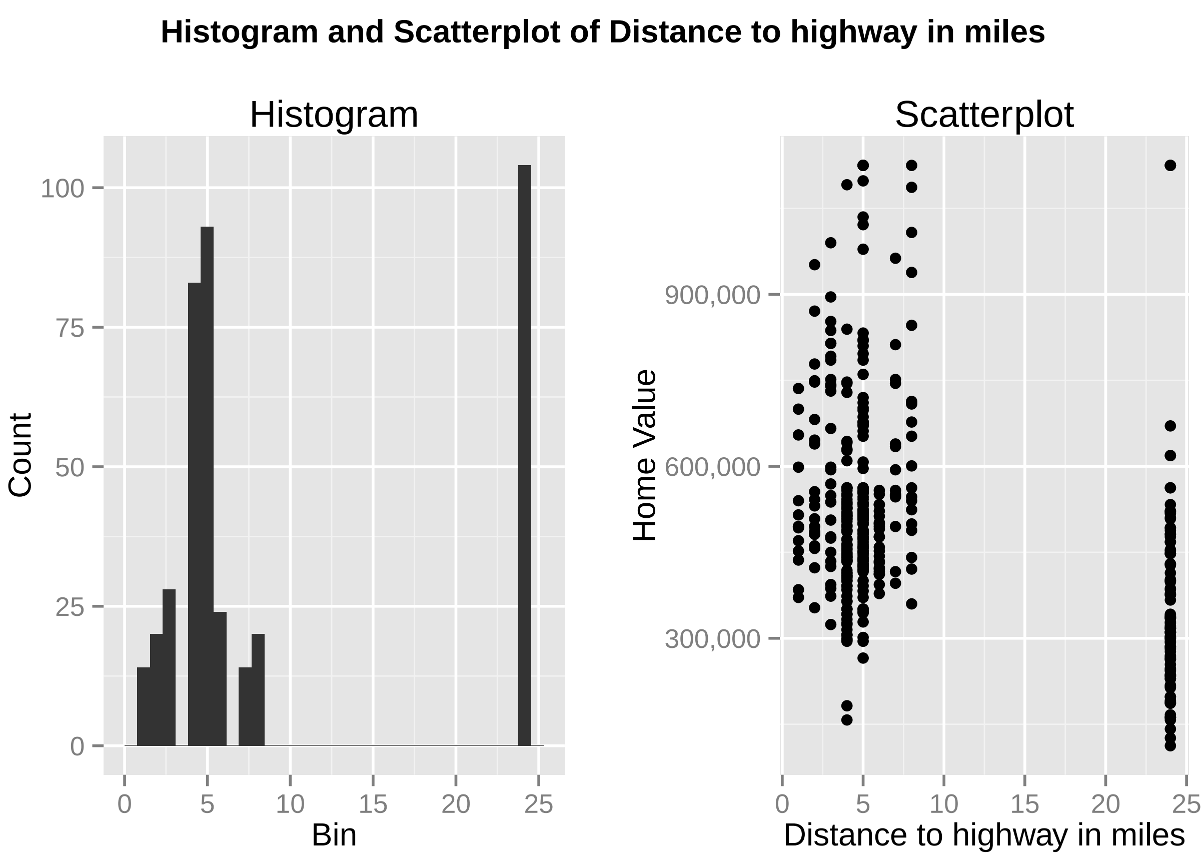
```
## Min      1.2
## Max     54.2
## Std      8.8
## 1%       1.3
## 5%       1.9
## 10%      2.2
## 25%      3.2
## 50%      6.1
## 75%     13.6
## 90%     22.7
## 95%     26.9
## 99%     35.1
```

Interestingly, the minimum value here is not 0 which indicates that none of these neighborhoods are actually in the city. The histogram tends to be right skewed, indicating that many neighborhoods are close to the city, while a few are over 40 miles from the city.

distanceToHighway
distanceToHighway is next which is *distances to the nearest highway (measured in miles)*

```
#Examine distance to highway
Graphs('distanceToHighway', 'Distance to highway in miles')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```



```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                grob
## 1 1 (2-2,1-1) arrange      gtable[layout]
## 2 2 (2-2,2-2) arrange      gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.946]
```

```
ContStat(data$distanceToHighway ,1)
```

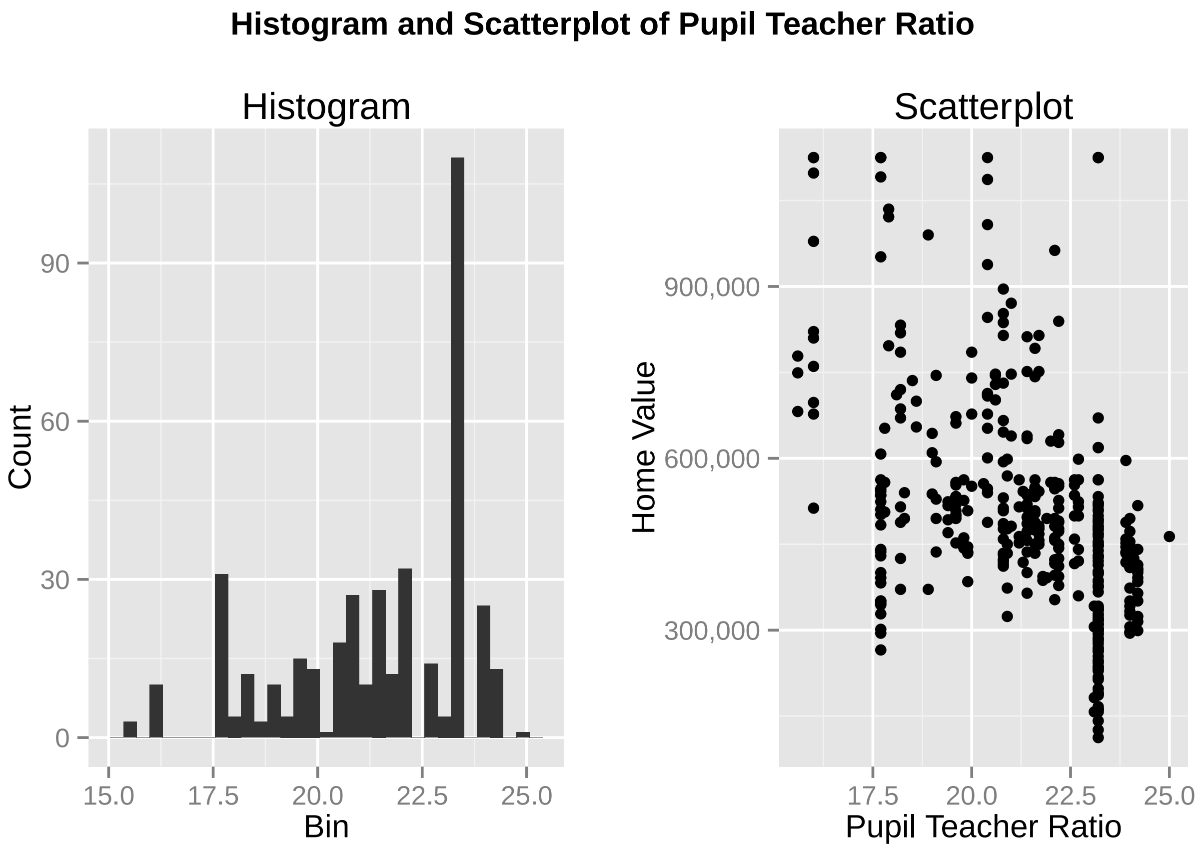
```
##       Stats
## N     400.0
## #NA's   0.0
## Mean    9.6
## Min     1.0
## Max    24.0
## Std     8.7
## 1%      1.0
## 5%      2.0
## 10%     3.0
## 25%     4.0
## 50%     5.0
## 75%    24.0
## 90%    24.0
## 95%    24.0
## 99%    24.0
```

Distance to highway has a mean of 9.6, yet the most frequent value is 24, which occurs over 100 times in the dataset. There doesn't seem to be a clear relationship between home value and distance to highway, especially given the gap in values between 9 and 24. As stated previously, this variable probably will not contribute much to predicting home value.

pupilTeacherRatio
pupilTeacherRatio is next which is *average pupil-teacher ratio in all the schools in the neighborhood*

```
#Examine pupil teacher ratio
Graphs('pupilTeacherRatio', 'Pupil Teacher Ratio')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                 grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1032]
```

```
ContStat(data$pupilTeacherRatio ,1)
```

```
##        Stats
## N      400.0
## #NA's    0.0
## Mean    21.4
## Min     15.6
## Max     25.0
## Std      2.2
## 1%      16.0
## 5%      17.7
## 10%     17.7
## 25%     19.9
## 50%     21.9
## 75%     23.2
## 90%     23.2
## 95%     24.0
## 99%     24.2
```

```r
#Get mode of pupil teacher ratio
Mode <- function(x) {
  ux <- unique(x)
  ux[which.max(tabulate(match(x, ux)))]
}

Mode(data$pupilTeacherRatio)
```

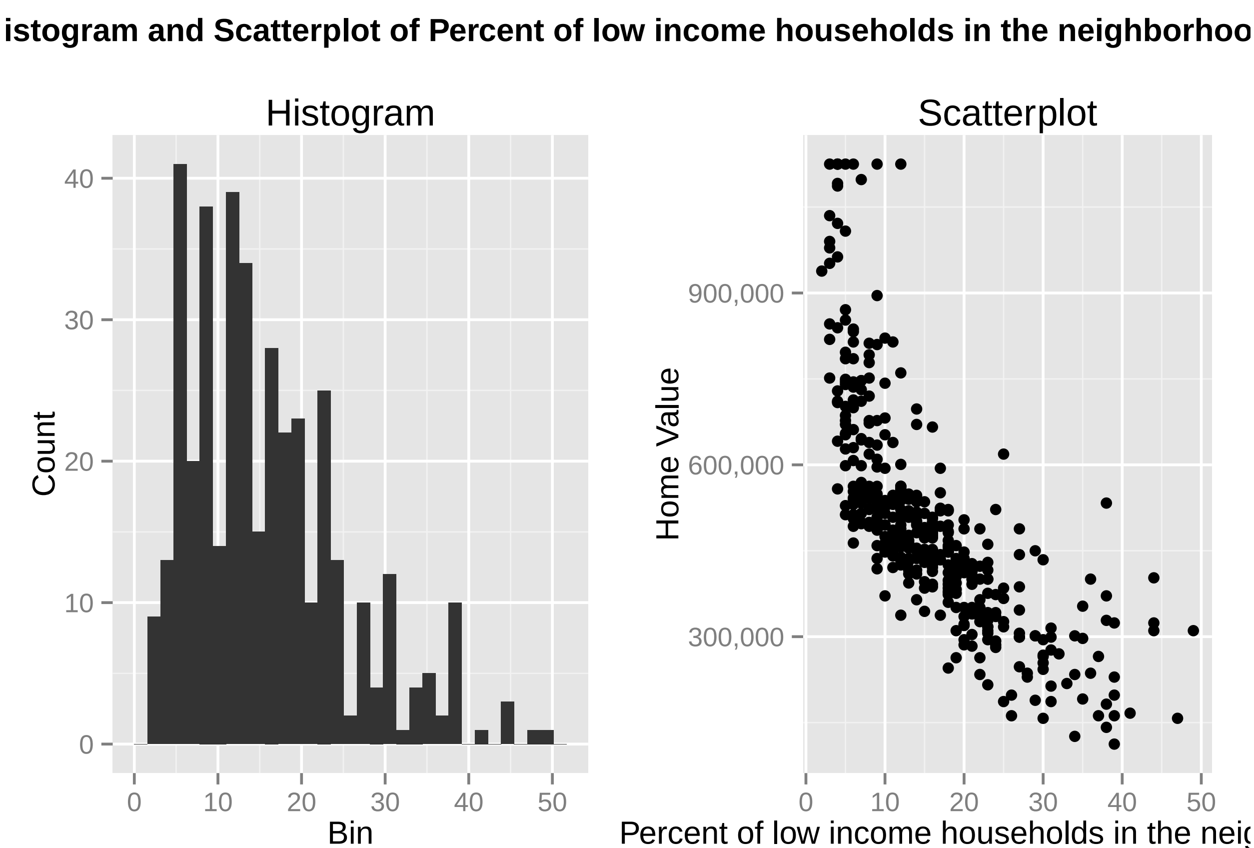
```
## [1] 23.2
```

Pupil teacher ratio has a mean of 21.4, but has a strikingly frequent amount at 23.2. As discussed previously, this tends to covary with two of the other variables in the dataset. There does seem to be a negative relationship between pupil teacher ratio and home value.

pctLowIncome
The next variable is pctLowIncome which is *percentage of low income household in the neighborhood*

```r
#Examine pctLowIncome
Graphs('pctLowIncome', 'Percent of low income households in the neighborhood')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
```

```
##   z     cells    name                  grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1118]
```

```r
ContStat(data$pctLowIncome ,1)
```

```
##       Stats
## N     400.0
## #NA's   0.0
## Mean   15.8
## Min     2.0
## Max    49.0
## Std     9.3
## 1%      3.0
## 5%      4.0
## 10%     5.0
## 25%     8.0
## 50%    14.0
## 75%    21.0
## 90%    29.1
## 95%    35.0
## 99%    44.0
```

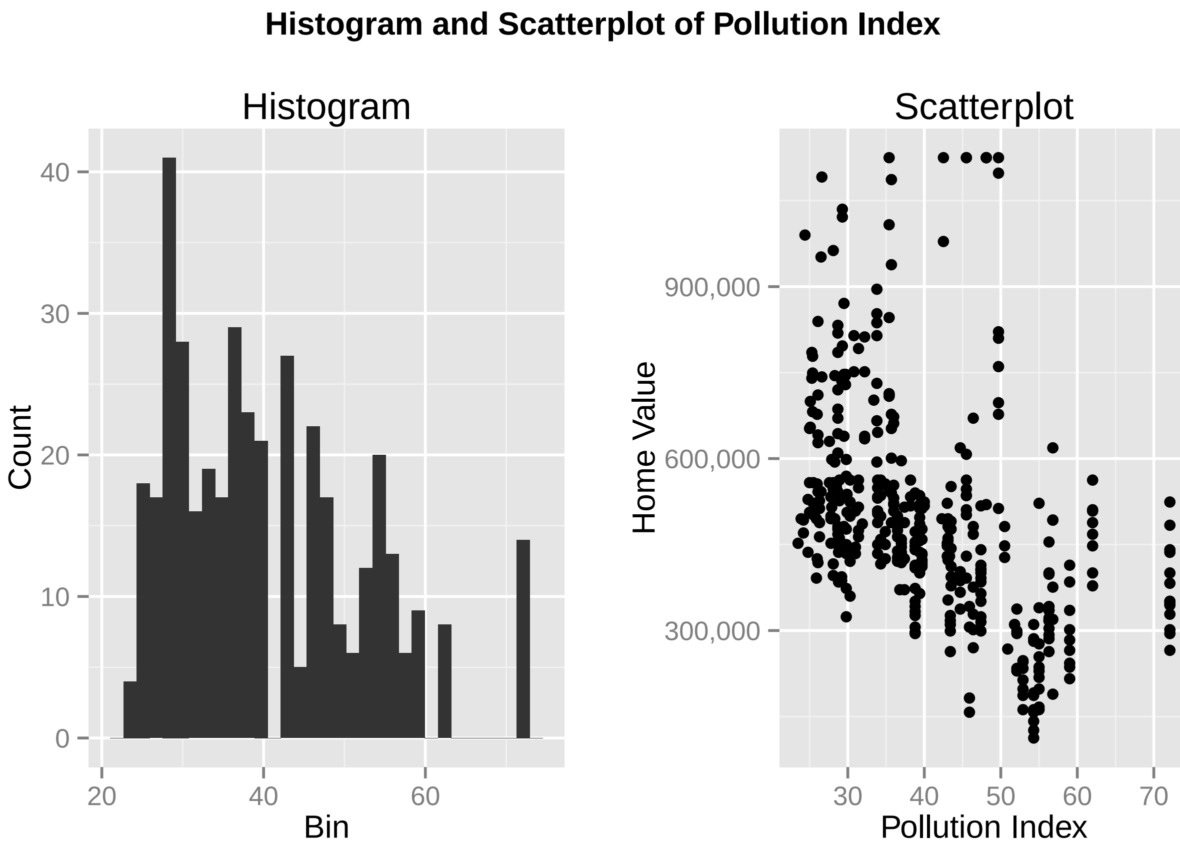
There is a very strong negative correlation on this scatterplot, unsurprisingly. If you have a low income its unlikely that you can afford a house with a high value. This variable is also right skewed, as demonstrated by the histogram.

---

pollutionIndex
The next variable is pollutionIndex which is defined as *scaled between 0 and 100, with 0 being the best and 100 being the worst (i.e. uninhabitable).* Even though it is highly correlated with non retail business, distance to highway and pupil teacher ratio, we will investigate it because the philanthropist group is interested.

```r
#Examine pollutionIndex
Graphs('pollutionIndex', 'Pollution Index')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1204]
```

```
ContStat(data$pollutionIndex ,1)
```

```
##        Stats
## N      400.0
## #NA's    0.0
## Mean    40.6
## Min     23.5
## Max     72.1
## Std     11.8
## 1%      24.4
## 5%      25.9
## 10%     27.6
## 25%     29.9
## 50%     38.8
## 75%     47.6
## 90%     56.3
## 95%     62.0
## 99%     72.1
```

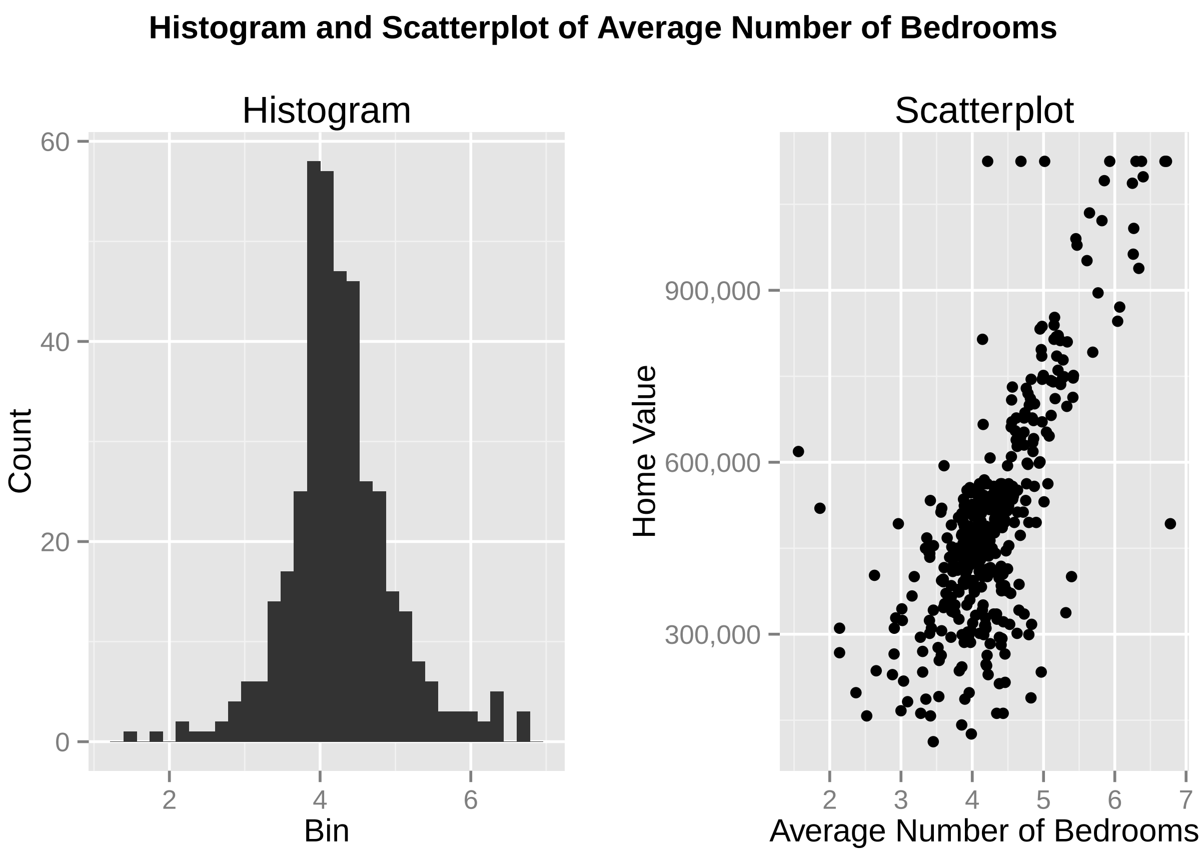
The scatterplot displays multiple segments: high home values and relativey low polution, medium home value and medium pollution, and low home value and high polution. There does seem to be a negative correlation between pollution index and home value, although the scatterplot shows a lot of variation. The histrogram shows a right skew.

---

nBedRooms
The final variable is nBedRooms which is *the average number of bed rooms in the single family houses in the neighborhood*

```
Graphs('nBedRooms', 'Average Number of Bedrooms')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                 grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1290]
```

```
ContStat(data$nBedRooms ,1)
```

```
##       Stats
## N     400.0
## #NA's   0.0
## Mean    4.3
## Min     1.6
```

```
## Max      6.8
## Std      0.7
## 1%       2.4
## 5%       3.3
## 10%      3.5
## 25%      3.9
## 50%      4.2
## 75%      4.6
## 90%      5.1
## 95%      5.5
## 99%      6.4
```

Finally! A normally distributed variable. This one is also positively correlated with home value. This will likely be one of the most useful of the prediction variables. It ranges from 1.6 to 6.4, which are reasonable average bedrooms for houses.

Decisions based off data exploration:

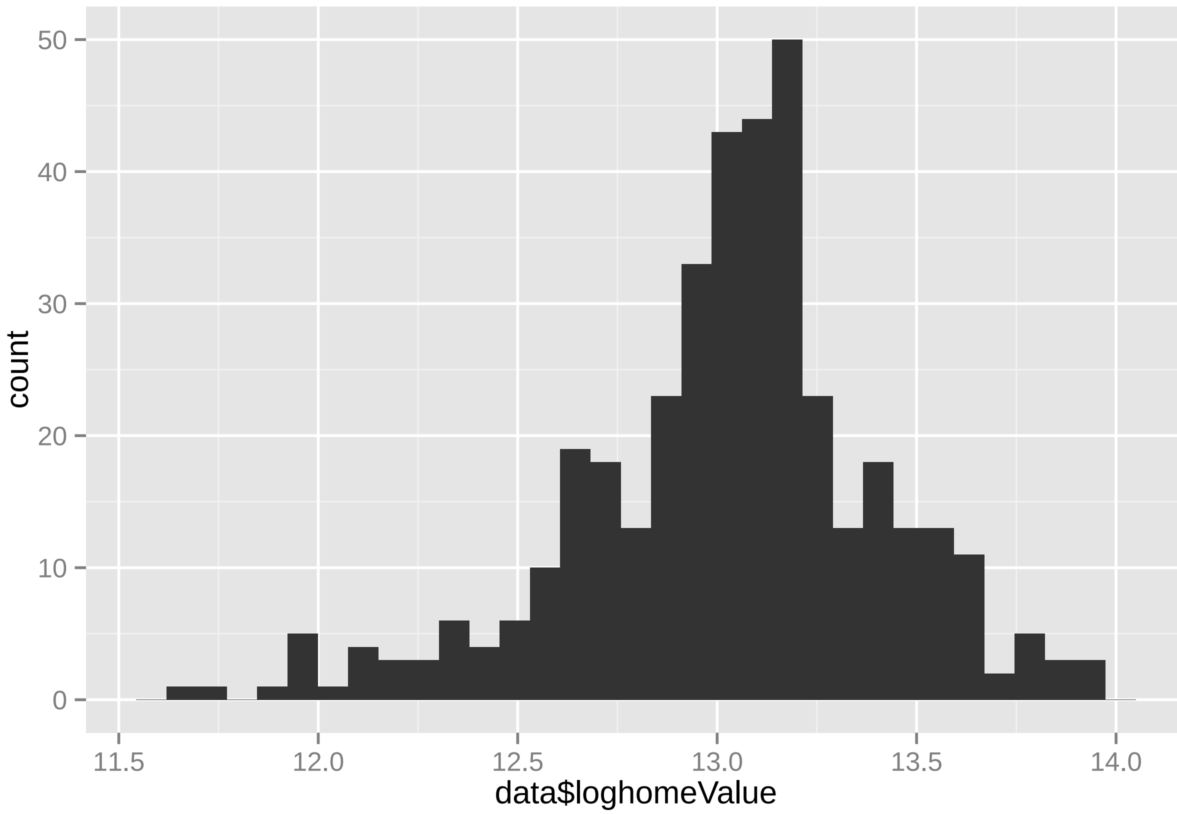
From the original dataset, the following decisions were then made.

1. Eliminate the variables non retail business, distance to highway and student pupil ratio as they have too much colinearity with each other. We suspect there may be some sampling error or additional information that we would have to ask the client for.
2. While pollutionindex is correlated with the three above, as the group specifically asked about it, it will be kept in the model for now.
3. Create a transformation of home value, log home value, that will be used for fitting the model. Whichever outcome variable performs the best will be used.
4. No other transformations will be used at this time. If the model fit is poor, then transformations will be considered.
5. For home value, there are 8 records that are categorical rather than continuous. These are the values that likely mean 1125000 or greater. Because we do not know the true value, we will not include them in our model.

First, we will subset the data and transform some of the variables:

```r
#Subset data to remove categorical home values (ceiling)
data = subset(data, homeValue!=1125000)

#Create log home value
data$loghomeValue = log(data$homeValue)

#Examine Transformation
ggplot(data=data, aes(data$loghomeValue)) + geom_histogram()
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```r
ContStat(data$loghomeValue ,1)
```

```
##        Stats
## N      392.0
## #NA's    0.0
## Mean    13.0
## Min     11.6
## Max     13.9
## Std      0.4
## 1%      12.0
## 5%      12.3
## 10%     12.6
## 25%     12.8
## 50%     13.1
## 75%     13.2
## 90%     13.5
## 95%     13.6
## 99%     13.8
```

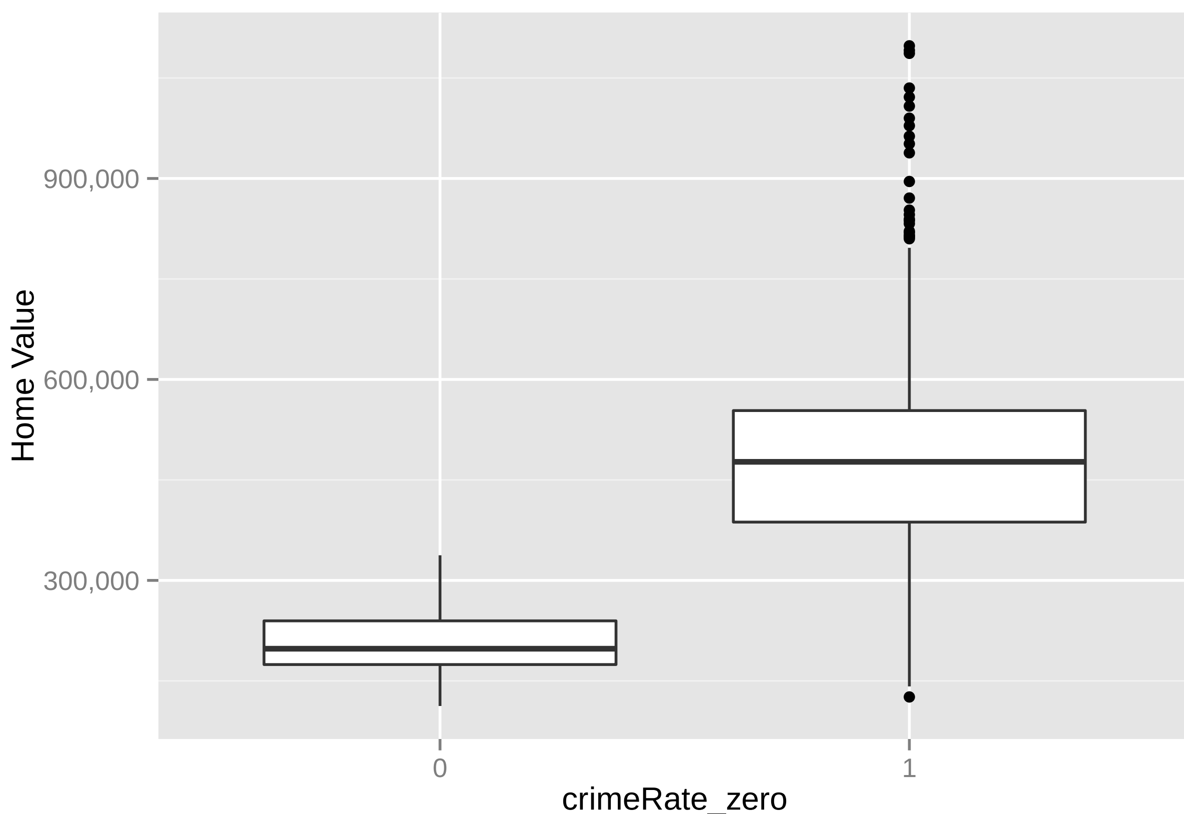
As expected, the log home value transformation has made the histogram more normal, although there is a tail to the left.

We also will create two new binary variables, crimeRate_zero which indicates a very low crime rate and older neighborhood which indicates if 100% of the houses was built before 1950. Finally we have newerneighborhood which indicates if 25% or less of the houses were built before 1950.

```r
#Create Indicator Variables

data$crimeRate_zero[data$crimeRate_pc < 30.0] <- 1
data$crimeRate_zero[data$crimeRate_pc >= 30.0] <- 0
data$crimeRate_zero <-as.factor(data$crimeRate_zero)

data$olderneighborhood [data$ageHouse >= 100.00] <- 1
data$olderneighborhood [data$ageHouse < 100.00] <- 0
data$olderneighborhood <- as.factor(data$olderneighborhood )

#crimeRate_zero
table(data$crimeRate_zero)
```

```
##
##   0   1
##   7 385
```

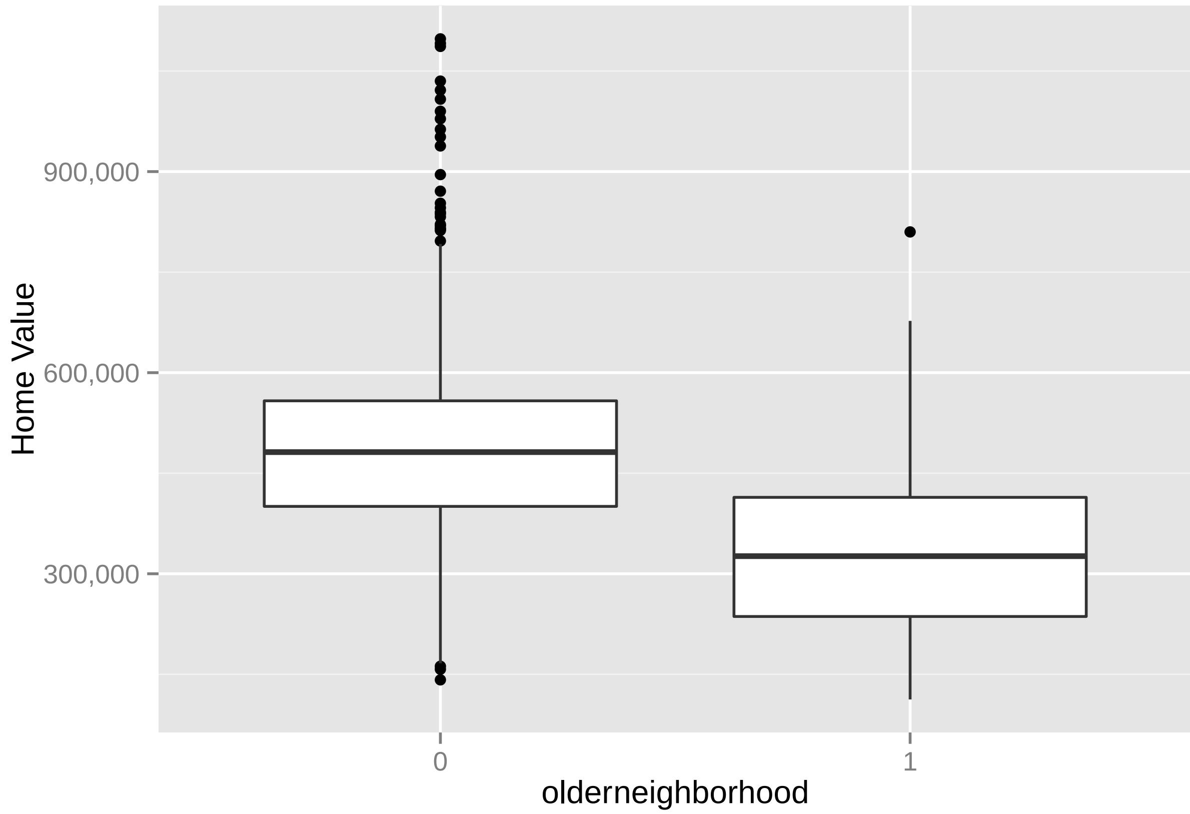
```r
ggplot(data, aes(crimeRate_zero, homeValue)) + geom_boxplot() +  scale_y_continuous(name = "Home Value"
```




```r
#olderneighborhood
table(data$olderneighborhood)
```

```
##
##   0   1
## 359  33
```

```
ggplot(data, aes(olderneighborhood, homeValue)) + geom_boxplot() +  scale_y_continuous(name = "Home Valu
```



All of the transformations box plots look reasonable.

Now we will create two models using the variables identifed above. One will have homevalue as the dependent variable while the other will have the log of home value.

```
#Create Models

lm = lm(homeValue ~ crimeRate_pc+crimeRate_zero+olderneighborhood  +withWater+ageHouse+distanceToCity+pc

lmlog = lm(loghomeValue ~ crimeRate_pc+crimeRate_zero+olderneighborhood  +withWater+ageHouse+distanceToC

#Summarize Models
summary(lm)
```

```
##
## Call:
## lm(formula = homeValue ~ crimeRate_pc + crimeRate_zero + olderneighborhood +
##     withWater + ageHouse + distanceToCity + pctLowIncome + pollutionIndex +
##     nBedRooms, data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -330218  -60134  -16285   43761  380624
##
## Coefficients:
```

```
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        417154.0    75963.4   5.492 7.28e-08 ***
## crimeRate_pc        -3986.5     1016.9  -3.920 0.000105 ***
## crimeRate_zero1    -41282.7    58995.0  -0.700 0.484499
## olderneighborhood1  98808.5    19671.4   5.023 7.83e-07 ***
## withWater1          39616.0    20395.2   1.942 0.052821 .
## ageHouse             -768.0      299.1  -2.568 0.010617 *
## distanceToCity      -3653.5      843.1  -4.334 1.88e-05 ***
## pctLowIncome        -7689.8      894.1  -8.601  < 2e-16 ***
## pollutionIndex      -2455.2      682.6  -3.597 0.000364 ***
## nBedRooms          100418.7     9345.3  10.745  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 94670 on 382 degrees of freedom
## Multiple R-squared:  0.7183, Adjusted R-squared:  0.7117
## F-statistic: 108.2 on 9 and 382 DF,  p-value: < 2.2e-16
```

```r
summary(lmlog)
```

```
##
## Call:
## lm(formula = loghomeValue ~ crimeRate_pc + crimeRate_zero + olderneighborhood +
##     withWater + ageHouse + distanceToCity + pctLowIncome + pollutionIndex +
##     nBedRooms, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.80163 -0.11237 -0.01670  0.09919  0.70865
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)        13.2878102  0.1516800  87.604  < 2e-16 ***
## crimeRate_pc       -0.0114508  0.0020304  -5.640 3.32e-08 ***
## crimeRate_zero1    -0.0418476  0.1177983  -0.355   0.7226
## olderneighborhood1  0.1669108  0.0392789   4.249 2.70e-05 ***
## withWater1          0.1014851  0.0407241   2.492   0.0131 *
## ageHouse           -0.0008501  0.0005973  -1.423   0.1554
## distanceToCity     -0.0068534  0.0016834  -4.071 5.69e-05 ***
## pctLowIncome       -0.0220012  0.0017852 -12.324  < 2e-16 ***
## pollutionIndex     -0.0055078  0.0013629  -4.041 6.43e-05 ***
## nBedRooms           0.1191352  0.0186602   6.384 4.99e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.189 on 382 degrees of freedom
## Multiple R-squared:  0.7582, Adjusted R-squared:  0.7525
## F-statistic: 133.1 on 9 and 382 DF,  p-value: < 2.2e-16
```

Let’s remove the nonsignificant variables and take another look:

```r
#Create Models

lm = lm(homeValue ~ crimeRate_pc+withWater+olderneighborhood+distanceToCity+pctLowIncome+pollutionIndex+

lmlog = lm(loghomeValue ~ crimeRate_pc+withWater+olderneighborhood+distanceToCity+pctLowIncome+pollutio

#Summarize Models
summary(lm)
```

```
##
## Call:
## lm(formula = homeValue ~ crimeRate_pc + withWater + olderneighborhood +
##     distanceToCity + pctLowIncome + pollutionIndex + nBedRooms,
##     data = data)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -323388  -60694  -18064   45957  360869
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)        376236.5    56293.3   6.684 8.23e-11 ***
## crimeRate_pc        -3309.1      647.5  -5.111 5.07e-07 ***
## withWater1          41144.9    20483.7   2.009 0.045272 *
## olderneighborhood1  91740.4    19615.6   4.677 4.04e-06 ***
## distanceToCity      -2812.7      781.5  -3.599 0.000361 ***
## pctLowIncome        -8584.9      829.5 -10.349  < 2e-16 ***
## pollutionIndex      -3126.2      636.6  -4.911 1.35e-06 ***
## nBedRooms           95459.6     9210.4  10.364  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 95280 on 384 degrees of freedom
## Multiple R-squared:  0.7132, Adjusted R-squared:  0.7079
## F-statistic: 136.4 on 7 and 384 DF,  p-value: < 2.2e-16
```

```r
summary(lmlog)
```

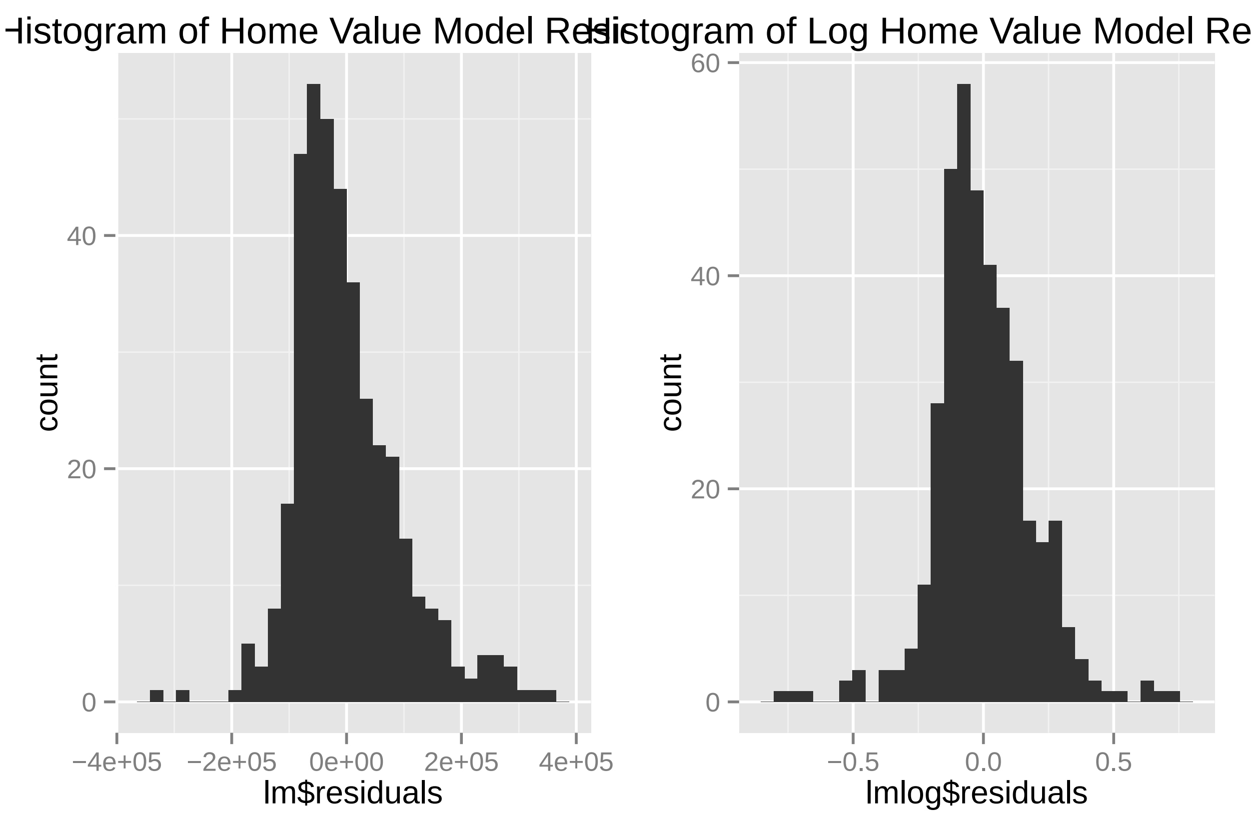
```
##
## Call:
## lm(formula = loghomeValue ~ crimeRate_pc + withWater + olderneighborhood +
##     distanceToCity + pctLowIncome + pollutionIndex + nBedRooms,
##     data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.80152 -0.11084 -0.01713  0.10312  0.70685
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        13.245866   0.111698 118.587  < 2e-16 ***
## crimeRate_pc       -0.010752   0.001285  -8.369 1.09e-15 ***
```

```
## withWater1           0.103092   0.040644   2.536 0.011593 *
## olderneighborhood1  0.159125   0.038921   4.088 5.29e-05 ***
## distanceToCity     -0.005922   0.001551  -3.819 0.000156 ***
## pctLowIncome       -0.022982   0.001646 -13.962  < 2e-16 ***
## pollutionIndex     -0.006244   0.001263  -4.943 1.15e-06 ***
## nBedRooms           0.113694   0.018275   6.221 1.29e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1891 on 384 degrees of freedom
## Multiple R-squared:  0.7569, Adjusted R-squared:  0.7524
## F-statistic: 170.8 on 7 and 384 DF,  p-value: < 2.2e-16
```

Now everything in the model is significantly accounting for variance. Lets take a look at histograms of the residuals.

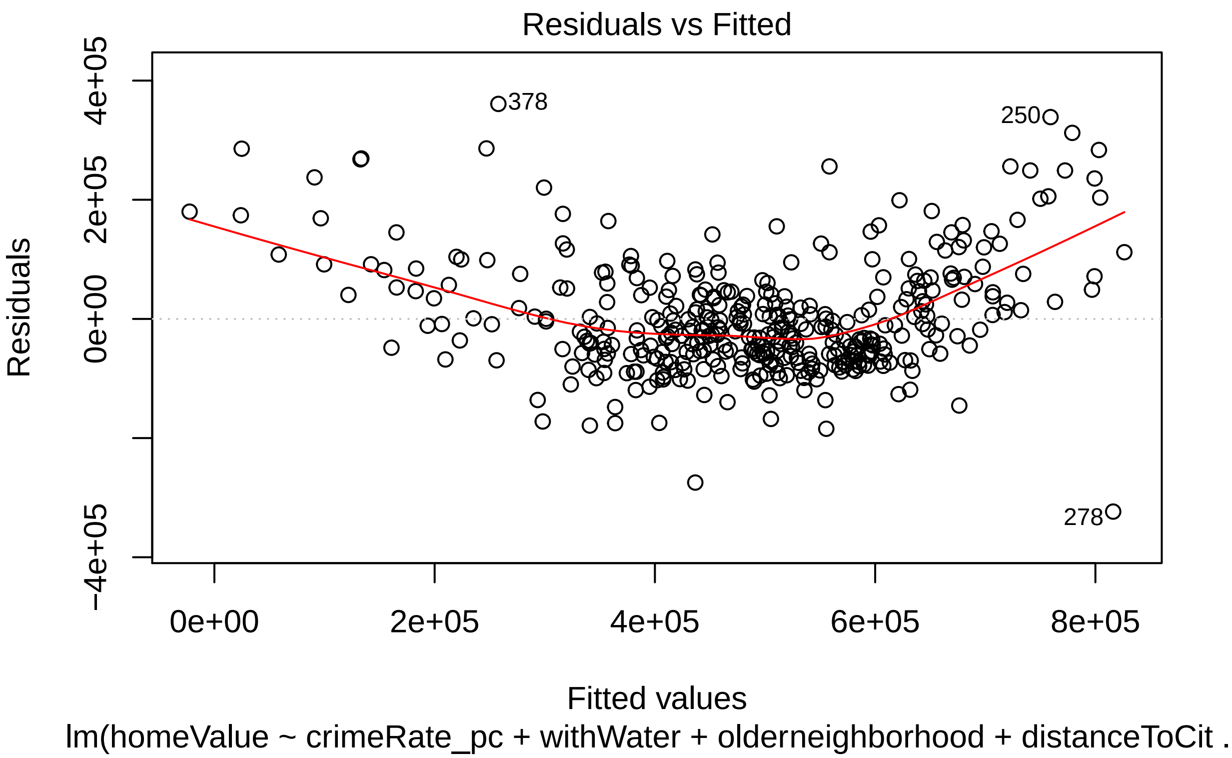
```
lmresid = ggplot(data=lm, aes(lm$residuals)) + geom_histogram() +  ggtitle("Histogram of Home Value Mode
lmlogresid =ggplot(data=lmlog, aes(lmlog$residuals)) + geom_histogram() +  ggtitle("Histogram of Log Hom

grid.arrange(lmresid, lmlogresid, ncol=2,nrow=1)
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```

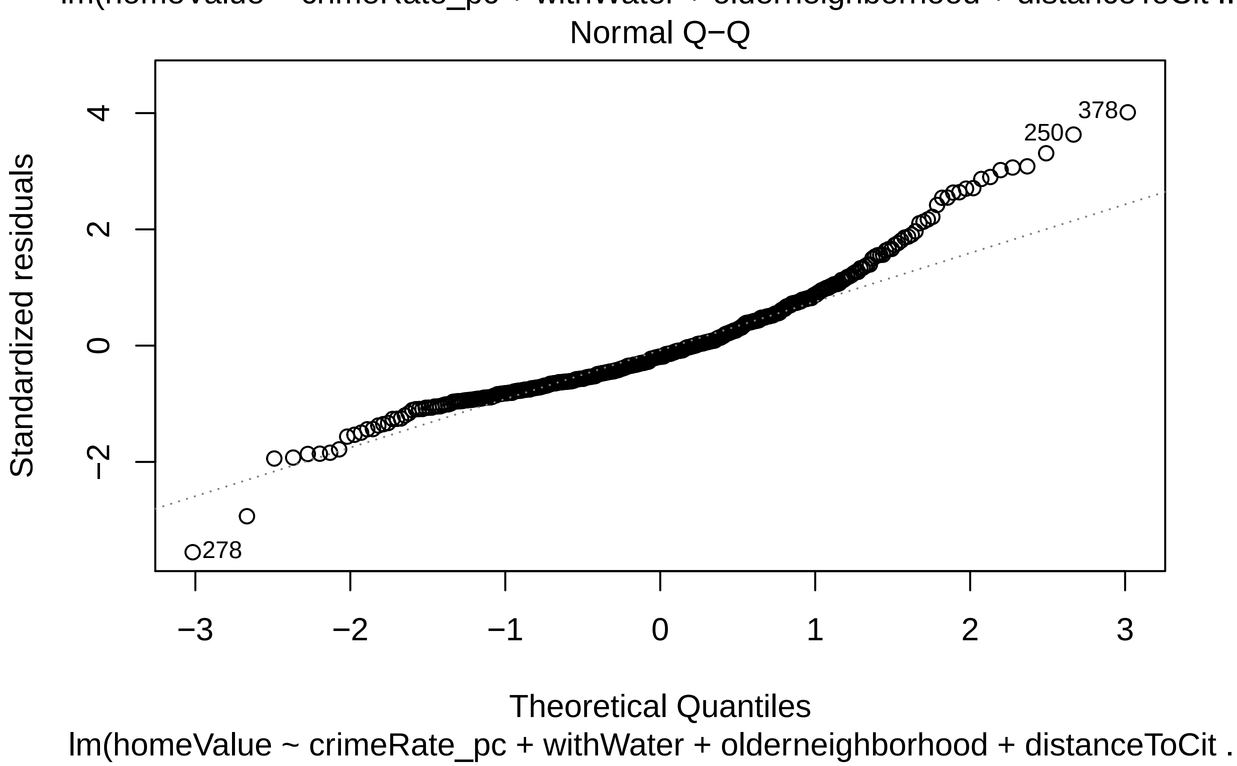


Both sets of residuals are fairly normal, although the log home value residuals are more normal. That in addition to its higher r squared score makes it the favorite thus far. However, lets take a look at the residual disagnostic plots for them before any final decision or addition or transformation of variables is undertaken.

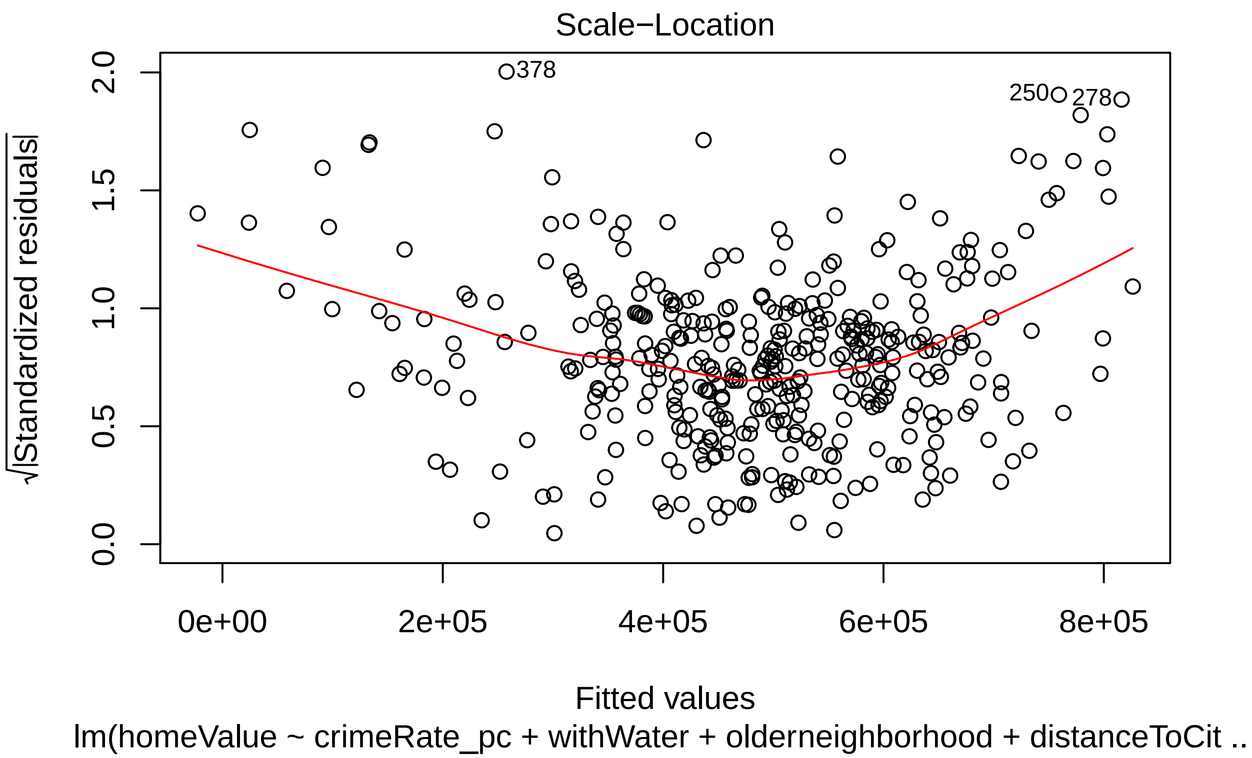
```r
plot(lm)
```

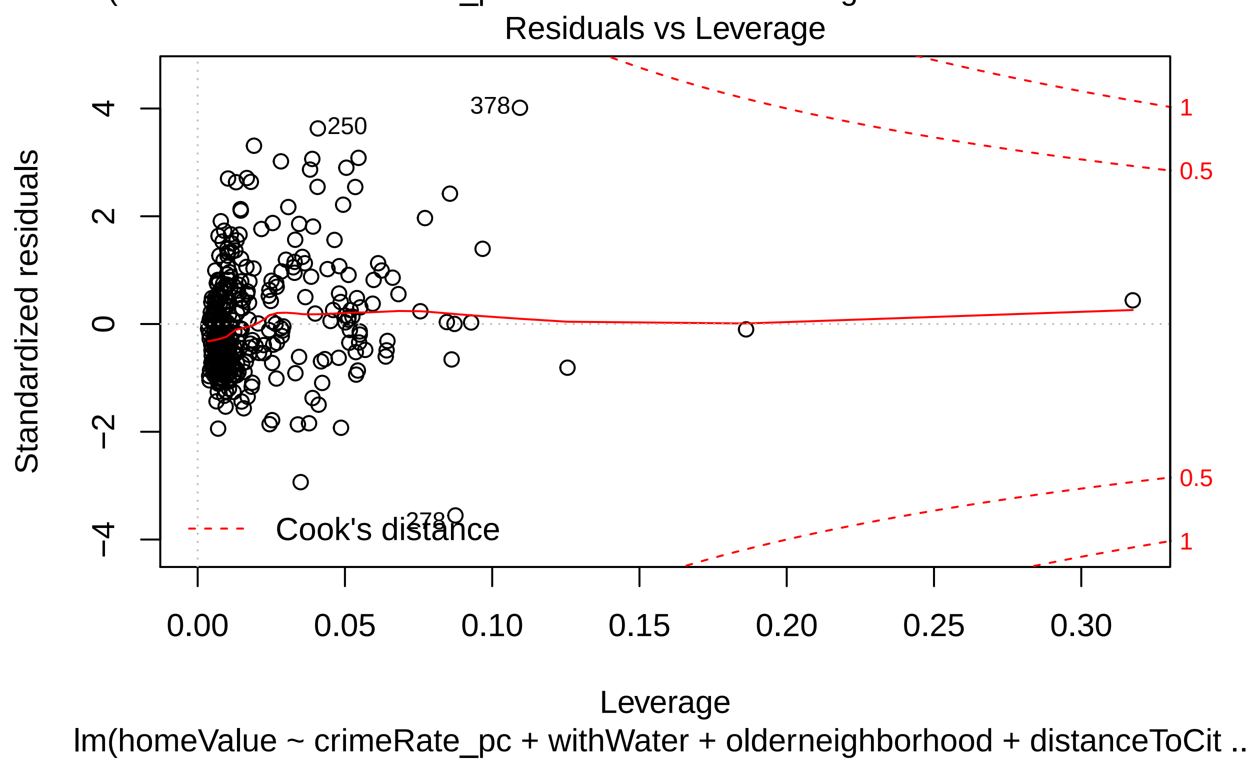


Residuals vs Fitted
Residuals
4e+05
2e+05
0e+00
−4e+05
378
250
278
0e+00
2e+05
4e+05
6e+05
8e+05
Fitted values
lm(homeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceToCit ..

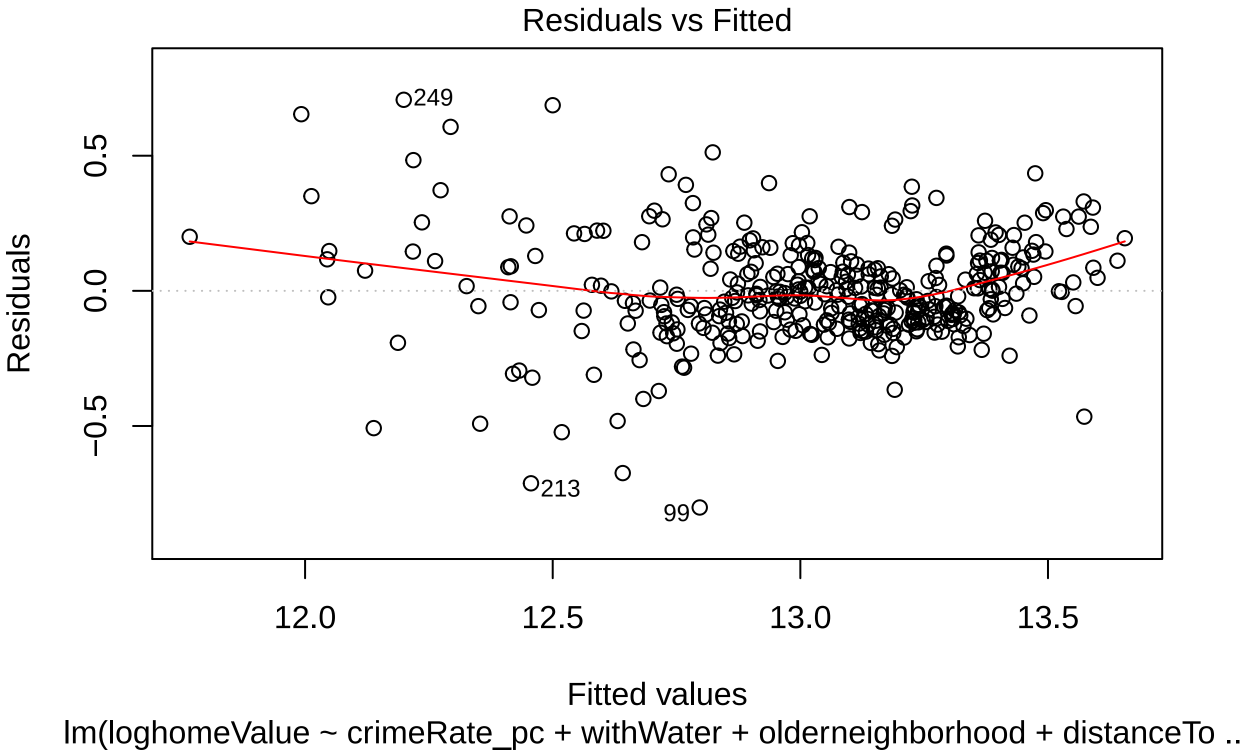


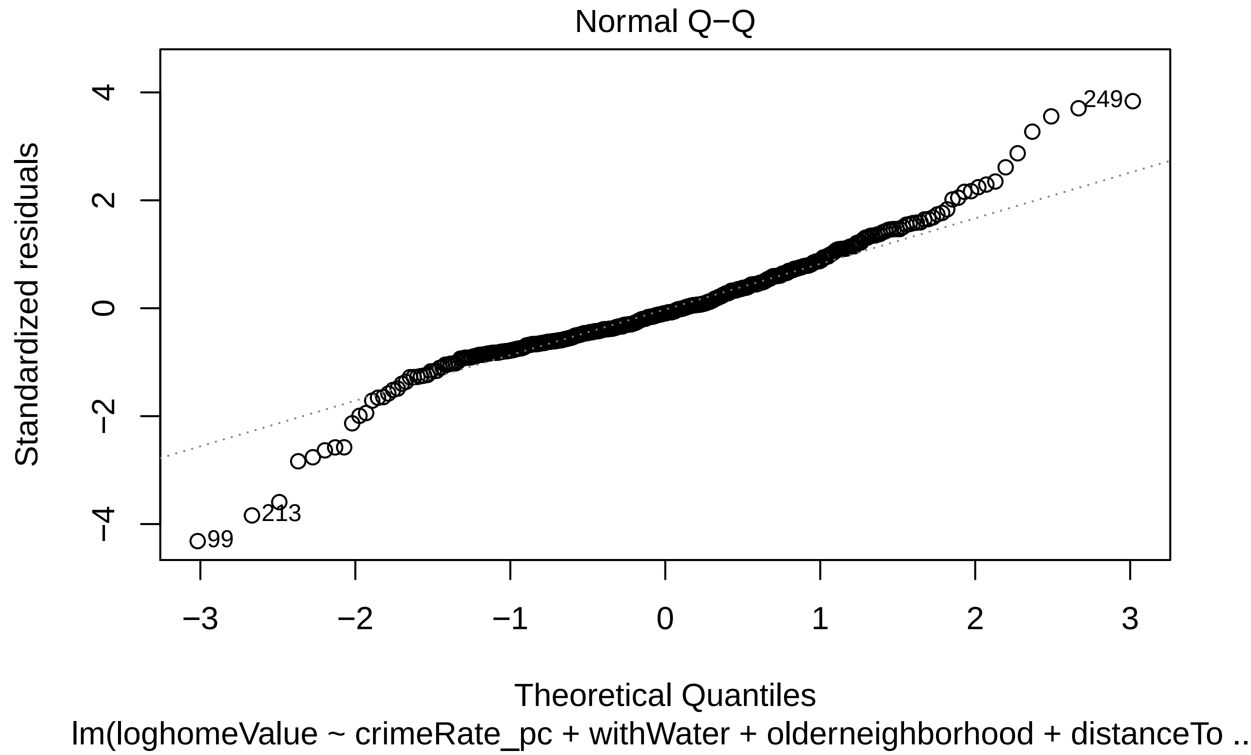
Normal Q−Q
Standardized residuals
4
2
0
−2
378
250
278
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(homeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceToCit ..

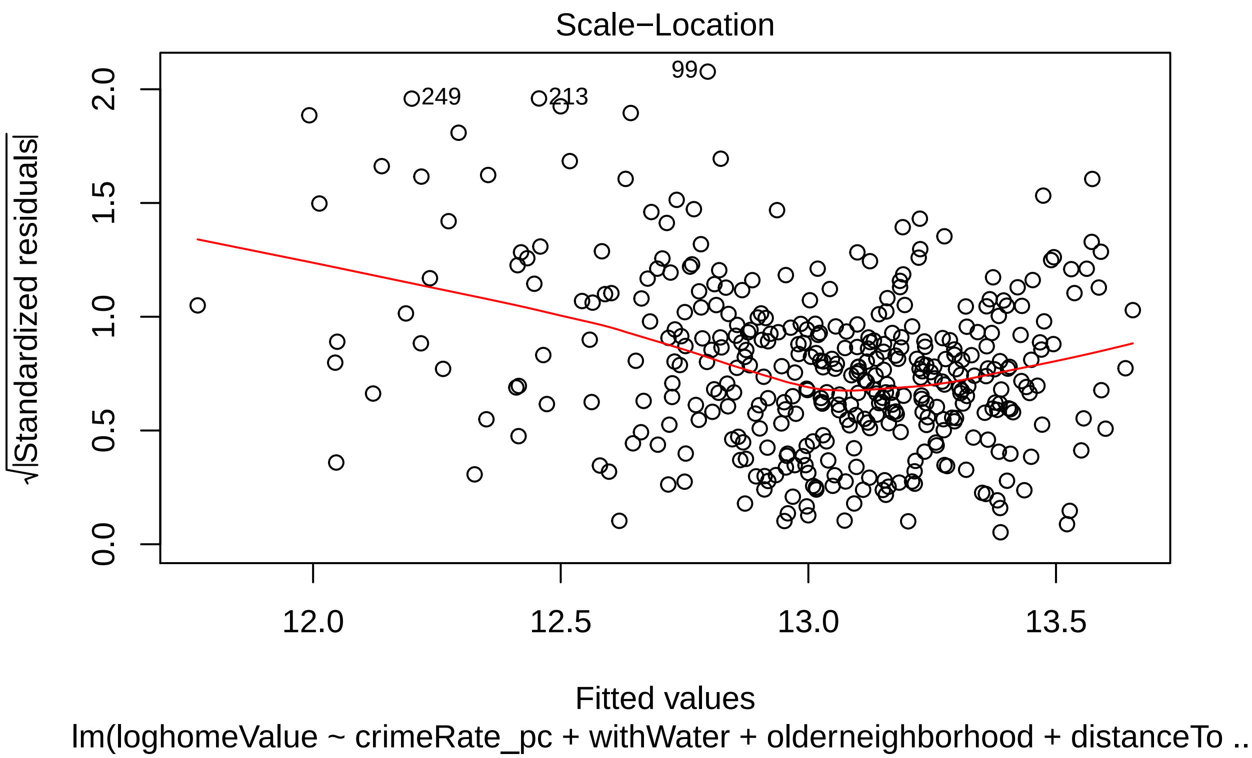

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
378
250
278
0e+00
2e+05
4e+05
6e+05
8e+05
Fitted values
lm(homeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceToCit ..

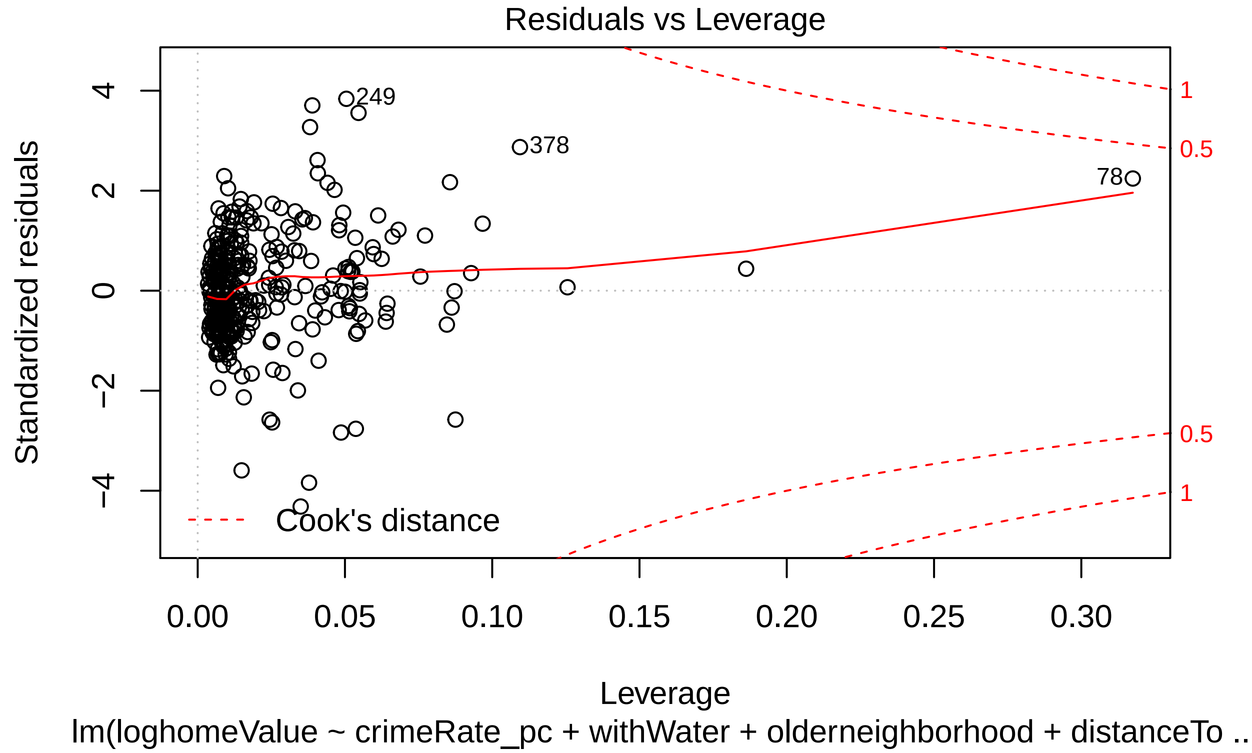

Residuals vs Leverage
Standardized residuals
−4
−2
0
2
4
378
250
278
1
0.5
0.5
1
Cook's distance
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Leverage
lm(homeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceToCit ..

```r
plot(lmlog)
```


Residuals vs Fitted
249
213
99
Residuals
0.5
0.0
−0.5
12.0
12.5
13.0
13.5
Fitted values
lm(loghomeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceTo ..


Normal Q−Q
249
213
99
Standardized residuals
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(loghomeValue ~ crimeRate_pc + withWater + olderneighborhood + distanceTo ..





Both models show evidence of heteroscedasticity in their residuals vs fitted plots. We would want the residuals to be an even band with no obvious clustering or curvature. Clearly this is not the case. The log home value model is worse in this sense than the normal one. Both Q-Q plots show that the residuals are pretty normally distributed. We know this because they closely follow the straight line which would indicate a normal distribution.

Both scale-location plots also indicate some heteroscedasticity. Again, if the errors were homoskedastic we would expect an even distribution of errors. There is both clustering and curvature indicated by the smoothing function. Finally, the leverage plot indicates that while there are points with a large amount of leverage, they are within our bounds.

There are several issues with these plots that suggest we do not perfectly meet the definition of the Classical Linear Model. However, we can say that we have met the asymptotic assumptions of linear regression. Generally asymptotic assumptions can be used on a sample that is greater than 30, which we clearly have met. We have already met the first three conditions, by having linear parameters, assuming the data came from a random sample, and showing no multicolinearity. Therefore, we will test for exogeneity. Exogeneity is defined as no correlation between a particular x variable and the error terms in our model.

```
#Test regular model
cov(data$crimeRate_pc, lm$residuals)
```

```
## [1] -3.869249e-11
```

```
cov(data$distanceToCity, lm$residuals)
```

```
## [1] -5.075092e-12
```

```
cov(data$pctLowIncome, lm$residuals)
```

```
## [1] 2.841953e-12
```

```
cov(data$pollutionIndex, lm$residuals)
```

```
## [1] -1.82579e-10
```

```
cov(data$nBedRooms, lm$residuals)
```

```
## [1] -1.076656e-11
```

```
#Test log model
cov(data$crimeRate_pc, lmlog$residuals)
```

```
## [1] -1.428265e-17
```

```
cov(data$distanceToCity, lmlog$residuals)
```

```
## [1] -5.448972e-17
```

```
cov(data$pctLowIncome, lmlog$residuals)
```

```
## [1] 1.906822e-17
```

```
cov(data$pollutionIndex, lmlog$residuals)
```

```
## [1] -3.48146e-16
```

```r
cov(data$nBedRooms, lmlog$residuals)
```

```
## [1] -2.221271e-17
```

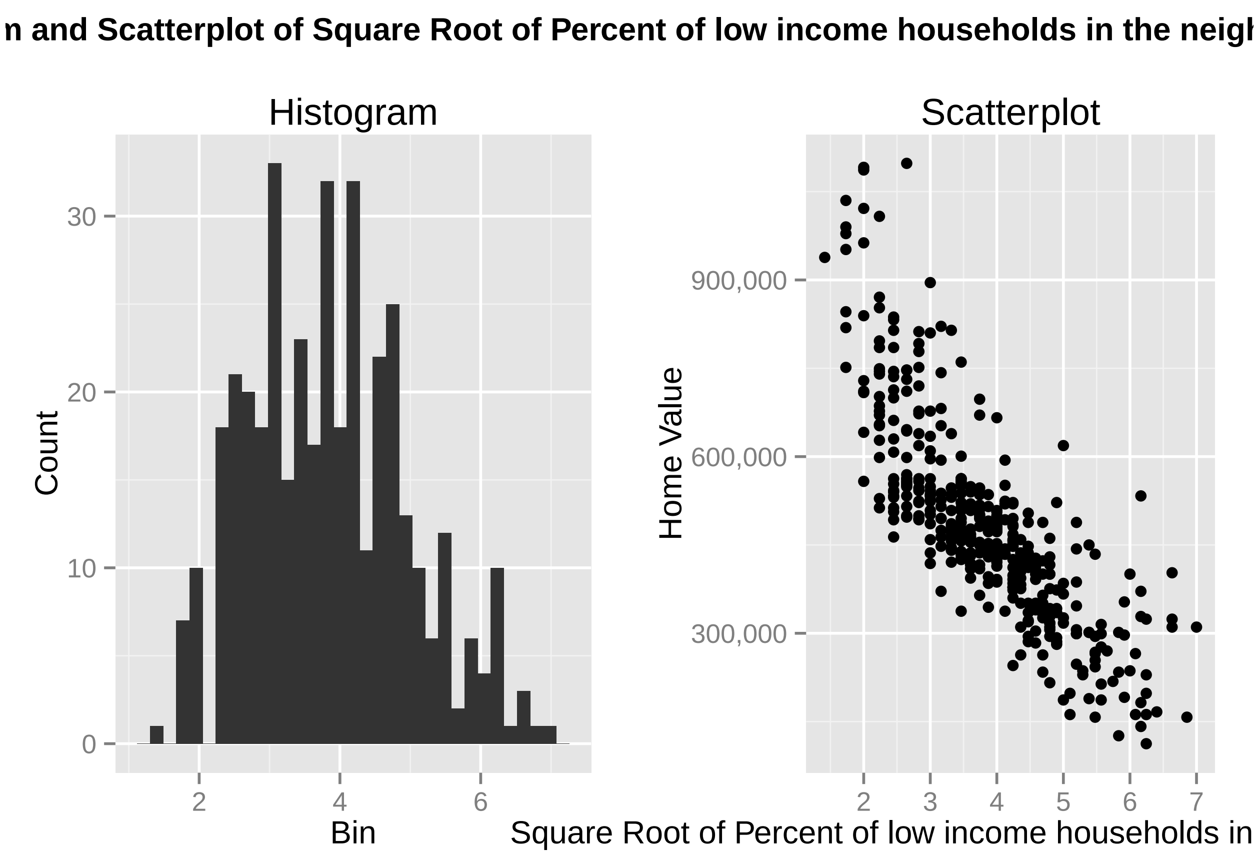
As all of these values are quite small, we believe it is reasonable to assume we have met exogeneity. This means that we can claim our model parameters are consistent, which means that the bias decreases as the number of observations increases. This means we are reasonably confident we can use these statistics to estimate our population parameters.

Moving forward to improve our model, we can either transform variables or add interaction terms.

From the original variable analysis, we know that crimerate_pc and pctLowIncome are skewed to the left. Let's take a look at their distributions when square rooted.

```r
data$sqrtpctIncome = sqrt(data$pctLowIncome)
Graphs('sqrtpctIncome', 'Square Root of Percent of low income households in the neighborhood')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```

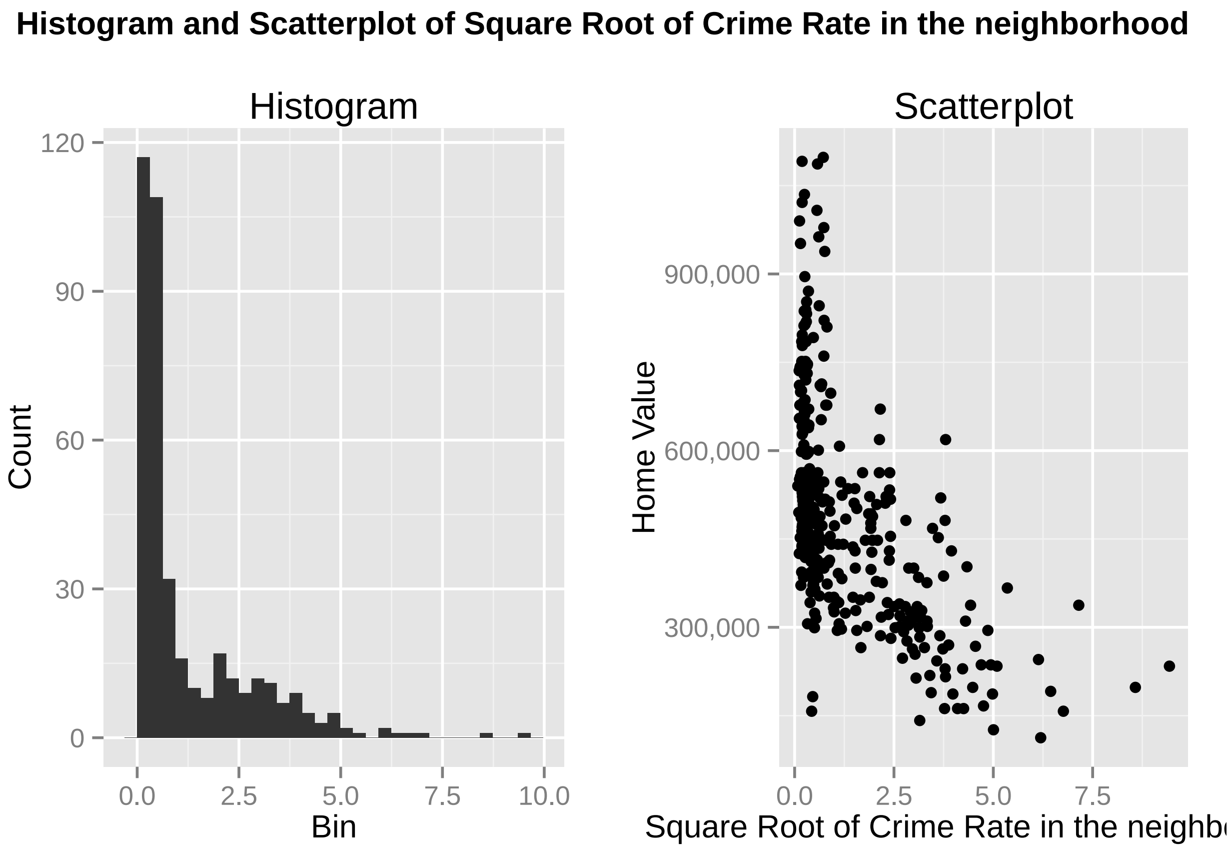



```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                 grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1622]
```

The histogram looks far more normal and the scatterplot was not affected negatively which is a great sign.

```
data$sqrtcrimeRate_pc = sqrt(data$crimeRate_pc)
Graphs('sqrtcrimeRate_pc', 'Square Root of Crime Rate in the neighborhood')
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust this.
```




```
## TableGrob (2 x 2) "arrange": 3 grobs
##   z     cells    name                 grob
## 1 1 (2-2,1-1) arrange       gtable[layout]
## 2 2 (2-2,2-2) arrange       gtable[layout]
## 3 3 (1-1,1-2) arrange text[GRID.text.1708]
```

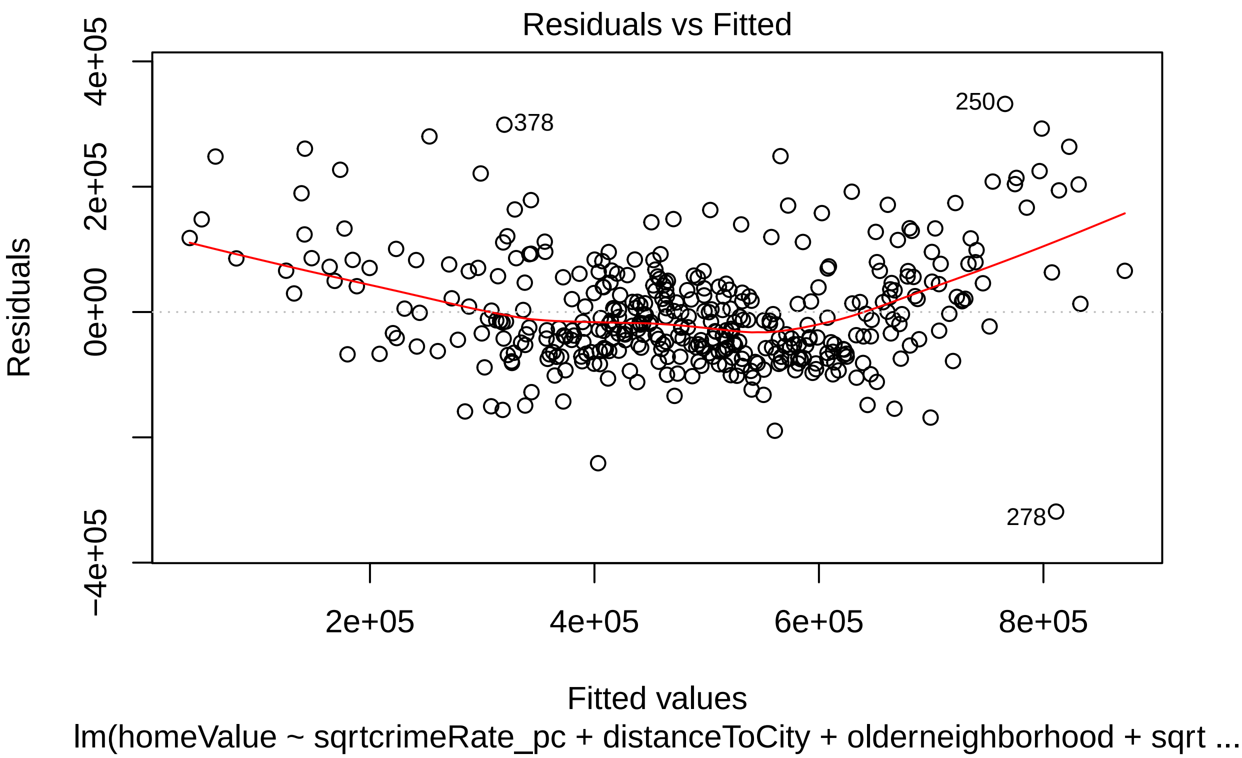
With such a strong left skew, even the square root here does not make the data any more normal in the histogram. However, model performance may have improved.

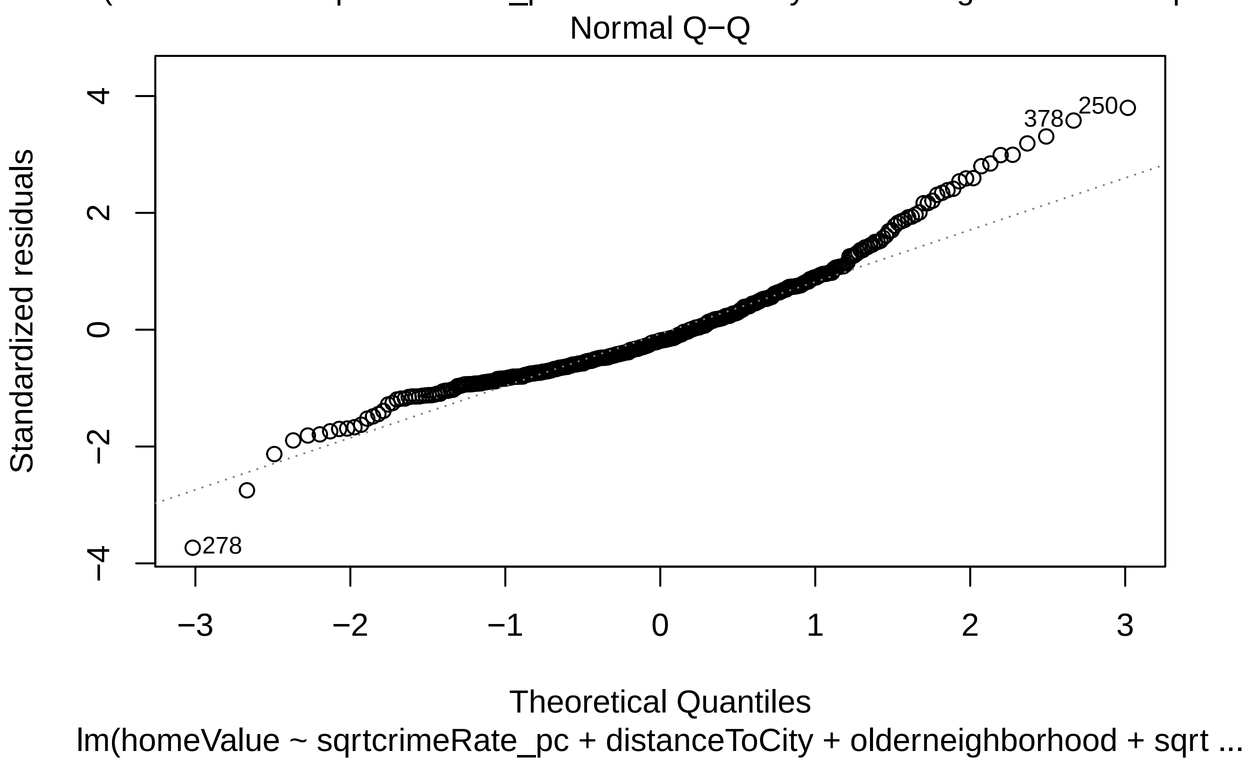
```
#Adding square root of crime and square root of percent income
lm = lm(homeValue ~ sqrtcrimeRate_pc+distanceToCity+olderneighborhood+sqrtpctIncome +pollutionIndex+nBe
lmlog = lm(loghomeValue ~ (crimeRate_pc+distanceToCity+olderneighborhood+sqrtpctIncome +pollutionIndex+
```

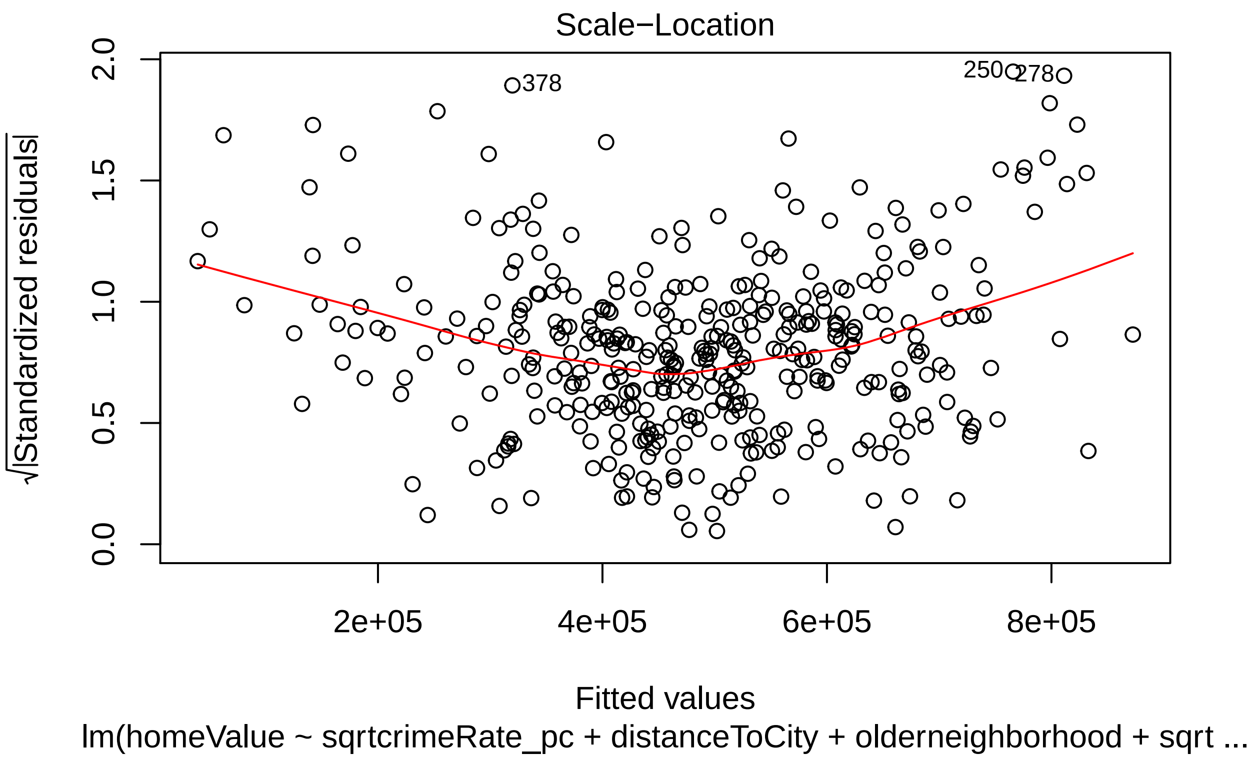
The fit indicated by the r squared value is slightly better, adding the square root of crime and percent low income increased R^2 by a little more than 1%. Given that this is a small increase and it limits interpretability, we will not include this in our final model. The purpose of this model was to aid in explaining, rather than predicting. If we were predicting, we might choose to include these variables.

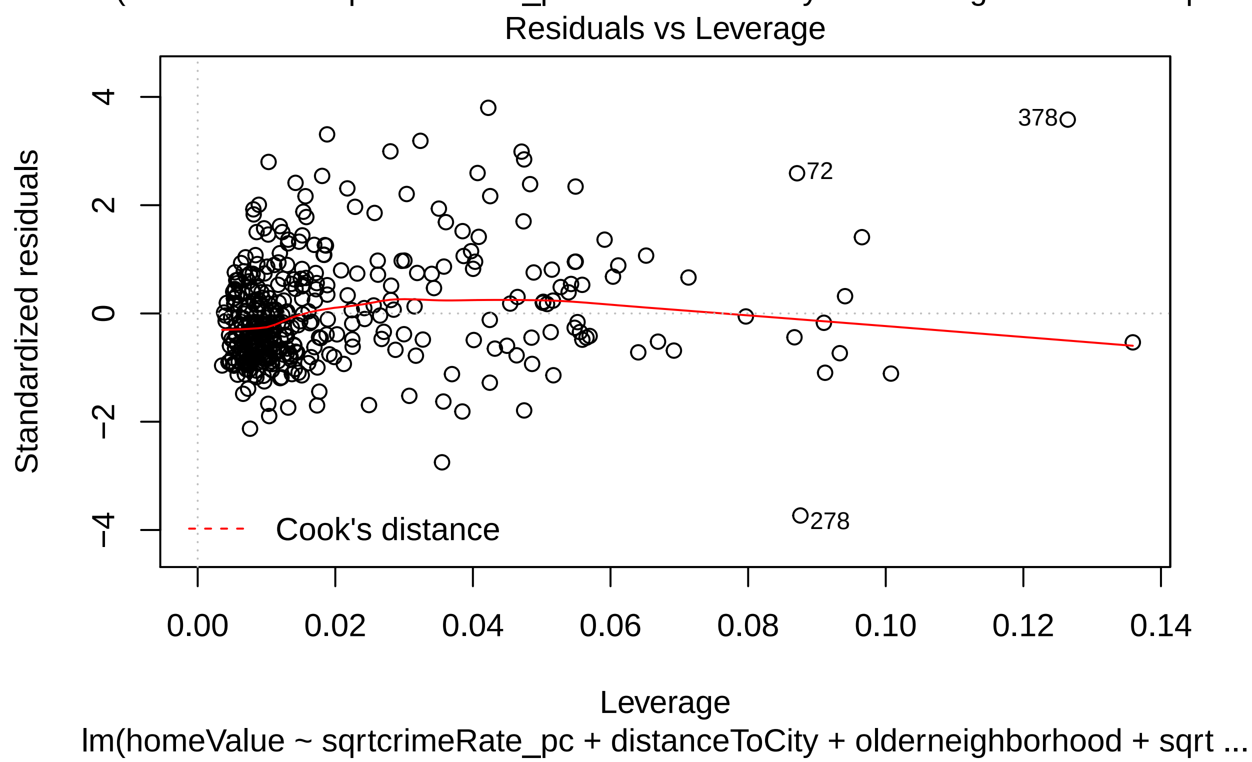
Let's examine a few of the outliers:

```r
plot(lm)
```

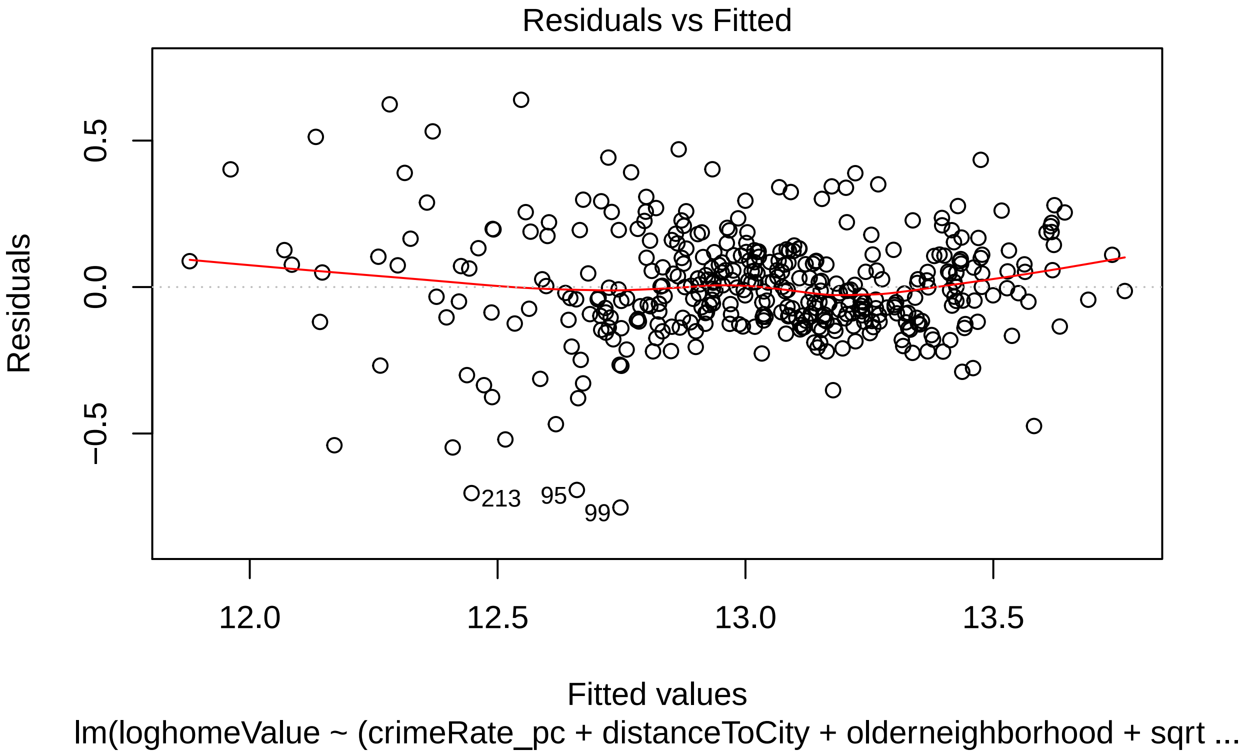

Residuals vs Fitted
Residuals
4e+05
2e+05
0e+00
−4e+05
2e+05
4e+05
6e+05
8e+05
378
250
278
Fitted values
lm(homeValue ~ sqrtcrimeRate_pc + distanceToCity + olderneighborhood + sqrt ...

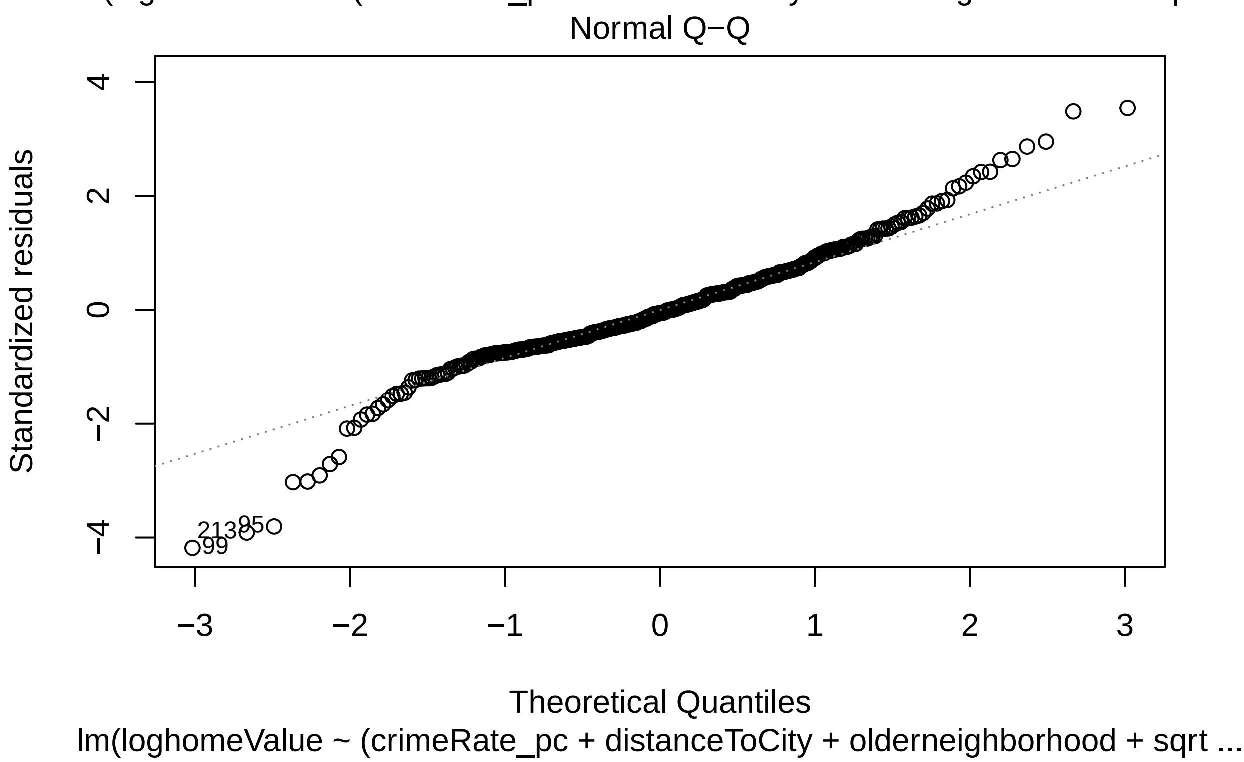

Normal Q−Q
Standardized residuals
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
378
250
278
Theoretical Quantiles
lm(homeValue ~ sqrtcrimeRate_pc + distanceToCity + olderneighborhood + sqrt ...

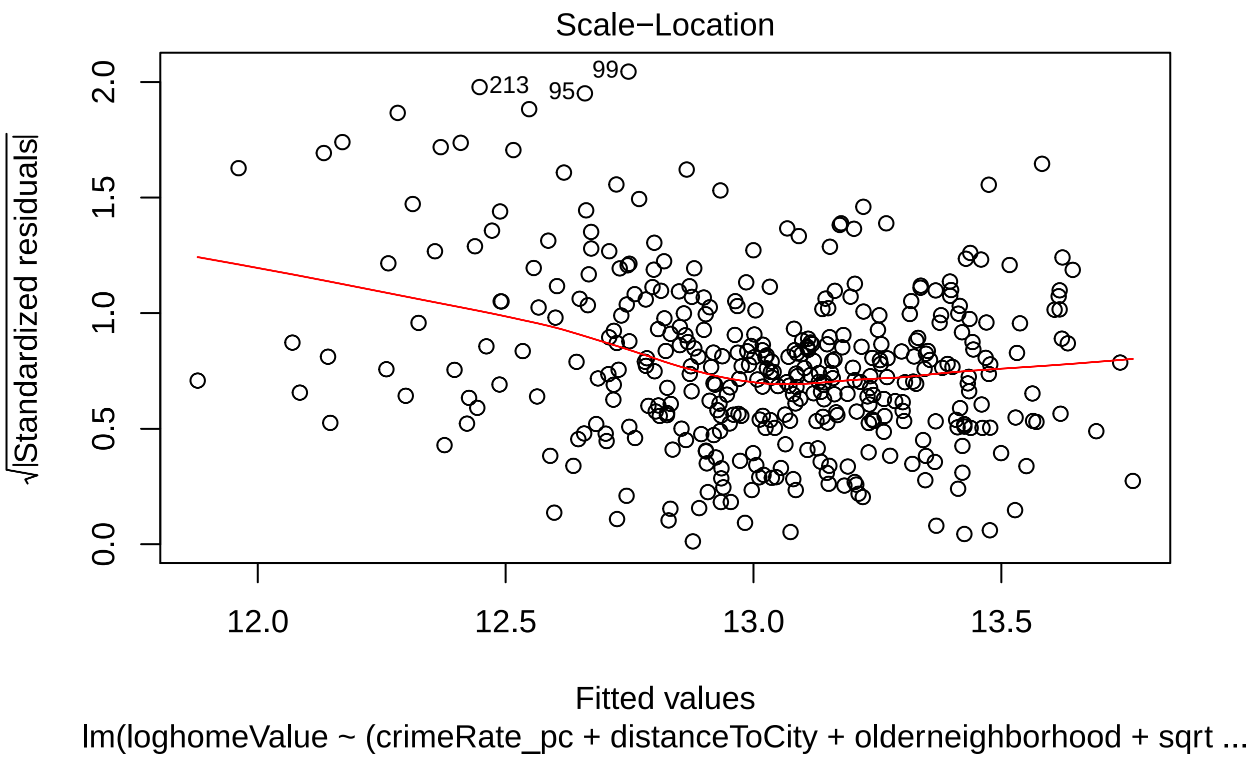

Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2e+05
4e+05
6e+05
8e+05
378
250
278
Fitted values
lm(homeValue ~ sqrtcrimeRate_pc + distanceToCity + olderneighborhood + sqrt ...

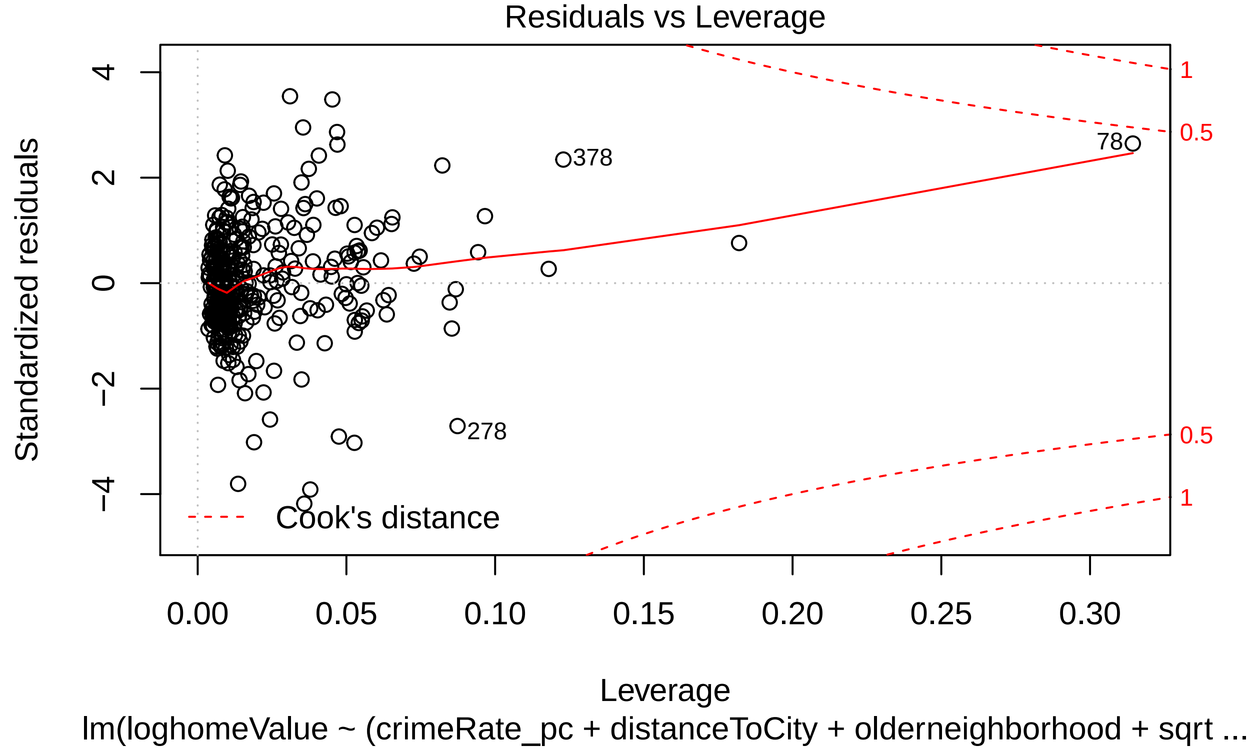

Residuals vs Leverage
Standardized residuals
−4
−2
0
2
4
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
378
72
278
Cook's distance
Leverage
lm(homeValue ~ sqrtcrimeRate_pc + distanceToCity + olderneighborhood + sqrt ...

```r
plot(lmlog)
```


Residuals vs Fitted
Residuals
0.5
0.0
−0.5
213
95
99
12.0
12.5
13.0
13.5
Fitted values
lm(loghomeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + sqrt ...


Normal Q−Q
Standardized residuals
4
2
0
−2
−4
213
95
99
−3
−2
−1
0
1
2
3
Theoretical Quantiles
lm(loghomeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + sqrt ...






```
data[c(250,378,278,72,99,95,213),]
```

```
##      crimeRate_pc nonRetailBusiness withWater ageHouse distanceToCity
## 257       8.49213            0.1810         0     86.1       3.160245
## 386       0.24980            0.2189         0     98.2       2.268630
## 285       0.06162            0.0439         0     52.3      27.933429
```

```
## 76       0.15876           0.1081         0     17.5      14.360658
## 103      0.72580           0.0814         0     69.5       8.453050
## 99      14.23620           0.1810         0    100.0       2.066578
## 220      5.82401           0.1810         0     64.7       7.166294
##     distanceToHighway pupilTeacherRatio pctLowIncome homeValue
## 257                24              23.2           22    326250
## 386                 4              24.2           27    299250
## 285                 3              21.8           16    387000
## 76                  4              22.2           12    488250
## 103                 4              24.0           14    409500
## 99                 24              23.2           26    162000
## 220                24              23.2           13    517500
##     pollutionIndex nBedRooms loghomeValue crimeRate_zero olderneighborhood
## 257           43.4     4.348     12.69542              1                 0
## 386           47.4     3.857     12.60903              1                 0
## 285           29.2     3.898     12.86618              1                 0
## 76            26.3     3.961     13.09858              1                 0
## 103           38.8     3.727     12.92269              1                 0
## 99            54.3     4.343     11.99535              1                 1
## 220           38.2     4.242     13.15676              1                 0
##     sqrtpctIncome sqrtcrimeRate_pc
## 257      4.690416        2.9141259
## 386      5.196152        0.4998000
## 285      4.000000        0.2482338
## 76       3.464102        0.3984470
## 103      3.741657        0.8519390
## 99       5.099020        3.7730889
## 220      3.605551        2.4132986
```

Quite a few of these outliers are areas of low income but have a relatively large number of bed rooms. Let's test for a potential interaction.

```
#Add interaction term
lm = lm(homeValue ~ (crimeRate_pc+distanceToCity+olderneighborhood+pctLowIncome +pollutionIndex+nBedRoor

lmlog = lm(loghomeValue ~ (crimeRate_pc+distanceToCity+olderneighborhood+pctLowIncome +pollutionIndex+nI
summary(lmlog)
```

```
##
## Call:
## lm(formula = loghomeValue ~ (crimeRate_pc + distanceToCity +
##     olderneighborhood + pctLowIncome + pollutionIndex + nBedRooms +
##     pctLowIncome * nBedRooms + withWater), data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.72420 -0.09643 -0.00864  0.09582  0.63097
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            12.702517   0.119465 106.328  < 2e-16 ***
## crimeRate_pc           -0.010757   0.001174  -9.161  < 2e-16 ***
## distanceToCity         -0.006161   0.001417  -4.347 1.77e-05 ***
```

```
## olderneighborhood1      0.082214   0.036641   2.244  0.02542 *
## pctLowIncome            0.014223   0.004507   3.156  0.00173 **
## pollutionIndex         -0.004704   0.001168  -4.028 6.79e-05 ***
## nBedRooms               0.239389   0.022023  10.870  < 2e-16 ***
## withWater1              0.082158   0.037224   2.207  0.02790 *
## pctLowIncome:nBedRooms -0.009979   0.001140  -8.757  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1728 on 383 degrees of freedom
## Multiple R-squared:  0.7974, Adjusted R-squared:  0.7932
## F-statistic: 188.4 on 8 and 383 DF,  p-value: < 2.2e-16
```

```
#Summarize Models
summary(lmlog)
```

```
##
## Call:
## lm(formula = loghomeValue ~ (crimeRate_pc + distanceToCity +
##     olderneighborhood + pctLowIncome + pollutionIndex + nBedRooms +
##     pctLowIncome * nBedRooms + withWater), data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.72420 -0.09643 -0.00864  0.09582  0.63097
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            12.702517   0.119465 106.328  < 2e-16 ***
## crimeRate_pc           -0.010757   0.001174  -9.161  < 2e-16 ***
## distanceToCity         -0.006161   0.001417  -4.347 1.77e-05 ***
## olderneighborhood1      0.082214   0.036641   2.244  0.02542 *
## pctLowIncome            0.014223   0.004507   3.156  0.00173 **
## pollutionIndex         -0.004704   0.001168  -4.028 6.79e-05 ***
## nBedRooms               0.239389   0.022023  10.870  < 2e-16 ***
## withWater1              0.082158   0.037224   2.207  0.02790 *
## pctLowIncome:nBedRooms -0.009979   0.001140  -8.757  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1728 on 383 degrees of freedom
## Multiple R-squared:  0.7974, Adjusted R-squared:  0.7932
## F-statistic: 188.4 on 8 and 383 DF,  p-value: < 2.2e-16
```

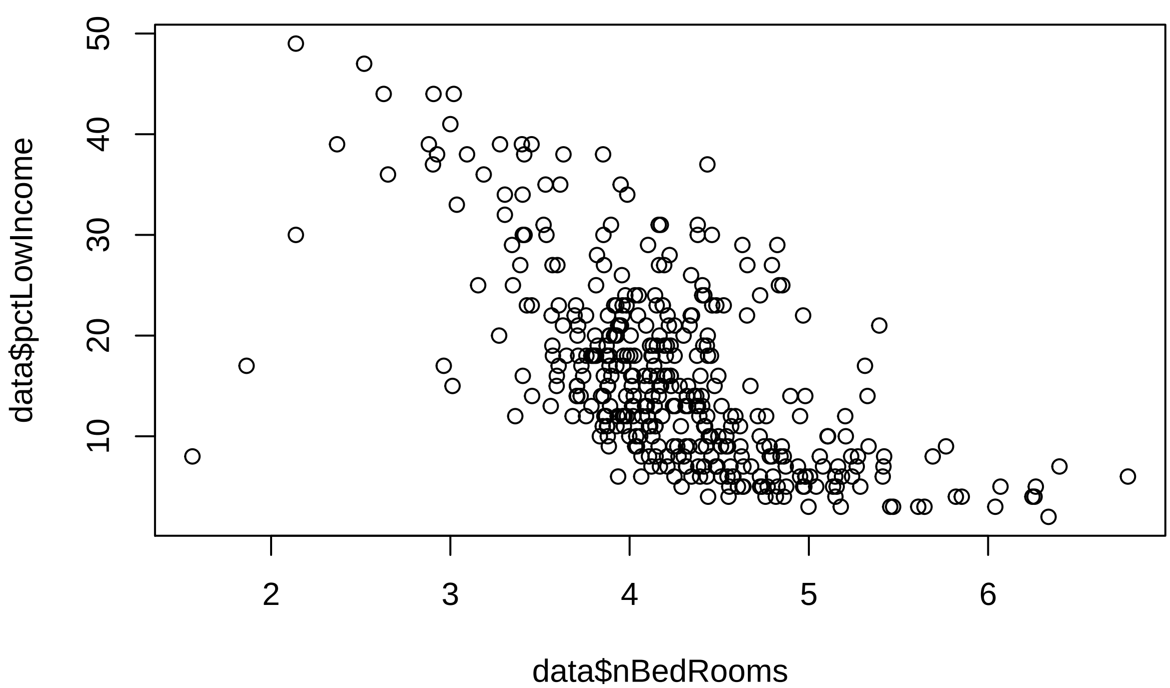
```
summary(lm)
```

```
##
## Call:
## lm(formula = homeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood +
##     pctLowIncome + pollutionIndex + nBedRooms + pctLowIncome *
##     nBedRooms + withWater), data = data)
##
## Residuals:
```

```
##     Min      1Q  Median      3Q     Max
## -459631  -50600   -9029   42418  422714
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)               -9294.6    53964.3  -0.172 0.863343
## crimeRate_pc              -3312.8      530.4  -6.246 1.12e-09 ***
## distanceToCity            -2982.3      640.3  -4.658 4.42e-06 ***
## olderneighborhood1        37168.5    16551.5   2.246 0.025297 *
## pctLowIncome              17813.8     2035.9   8.750  < 2e-16 ***
## pollutionIndex            -2033.2      527.5  -3.854 0.000136 ***
## nBedRooms                184646.7     9948.2  18.561  < 2e-16 ***
## withWater1                26291.2    16814.8   1.564 0.118744
## pctLowIncome:nBedRooms    -7080.8      514.8 -13.755  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 78050 on 383 degrees of freedom
## Multiple R-squared:  0.808,  Adjusted R-squared:  0.804
## F-statistic: 201.5 on 8 and 383 DF,  p-value: < 2.2e-16
```

Wow! Adding this interaction term increased our R^2 by four percent, indicating that we are now explaining four percentage points more variance than we were previously. Let's briefly examine this interaction:

```r
#Examine Relationship
plot(data$nBedRooms,data$pctLowIncome)
```



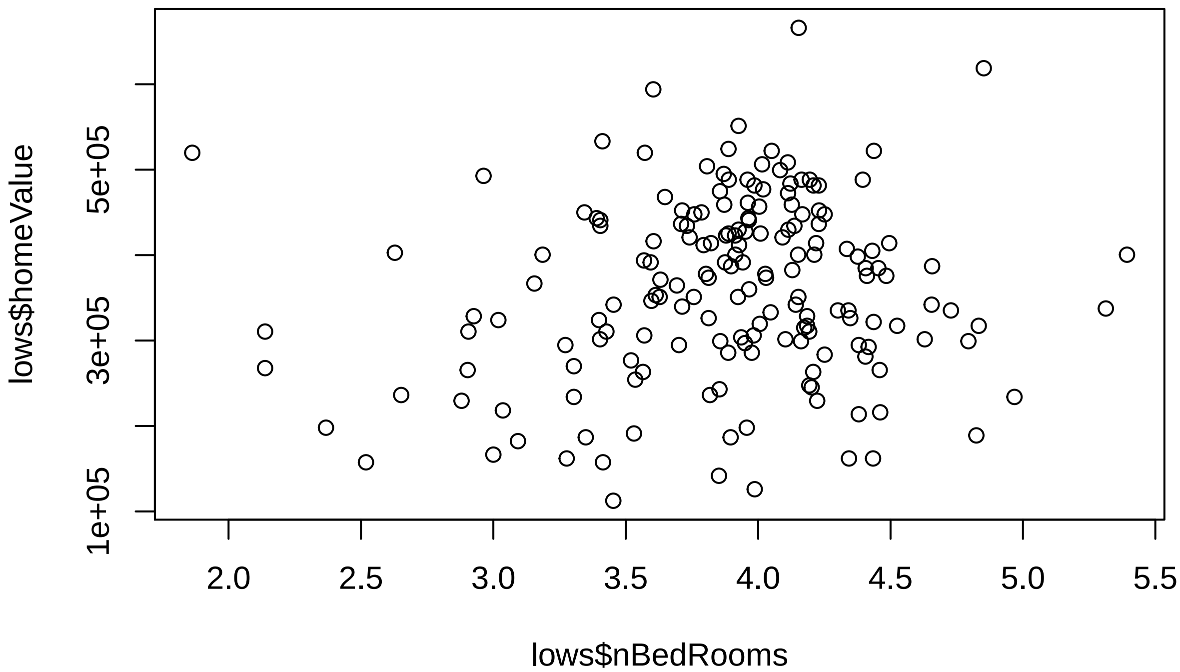

```r
#Create high/low indicators based on the mean
mean(data$pctLowIncome)
```

```
## [1] 15.99745
```

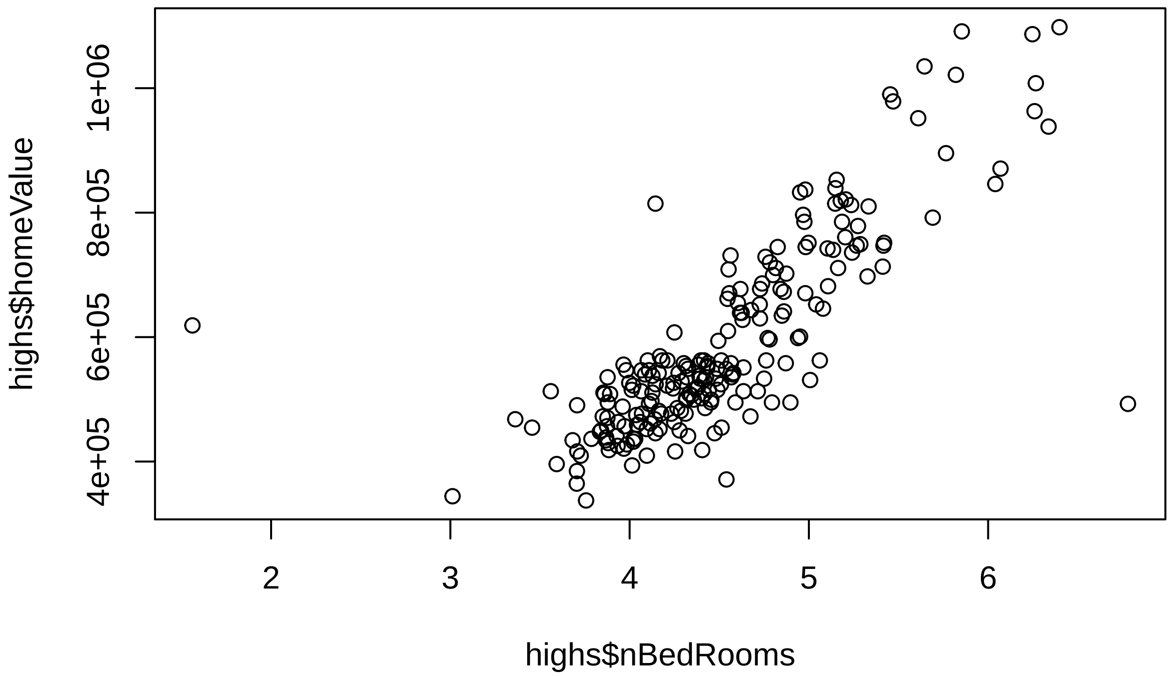
```
data$lowincome[data$pctLowIncome >= 16] <- 1
data$lowincome[data$pctLowIncome < 16] <- 0
mean(data$nBedRooms)
```

```
## [1] 4.235551
```

```
data$fewrooms[data$nBedRooms >= 4.2] <- 1
data$fewrooms[data$nBedRooms < 4.2] <- 0
data$fewrooms <-as.factor(data$fewrooms)

#plot relationships
lows <- subset(data, lowincome==1)
plot(lows$nBedRooms,lows$homeValue)
```




```
highs <- subset(data, lowincome==0)
plot(highs$nBedRooms,highs$homeValue)
```




```r
#Plot mean of income and number of bedrooms
mean(highs$nBedRooms)
```

```
## [1] 4.52466
```

```r
mean(lows$nBedRooms)
```

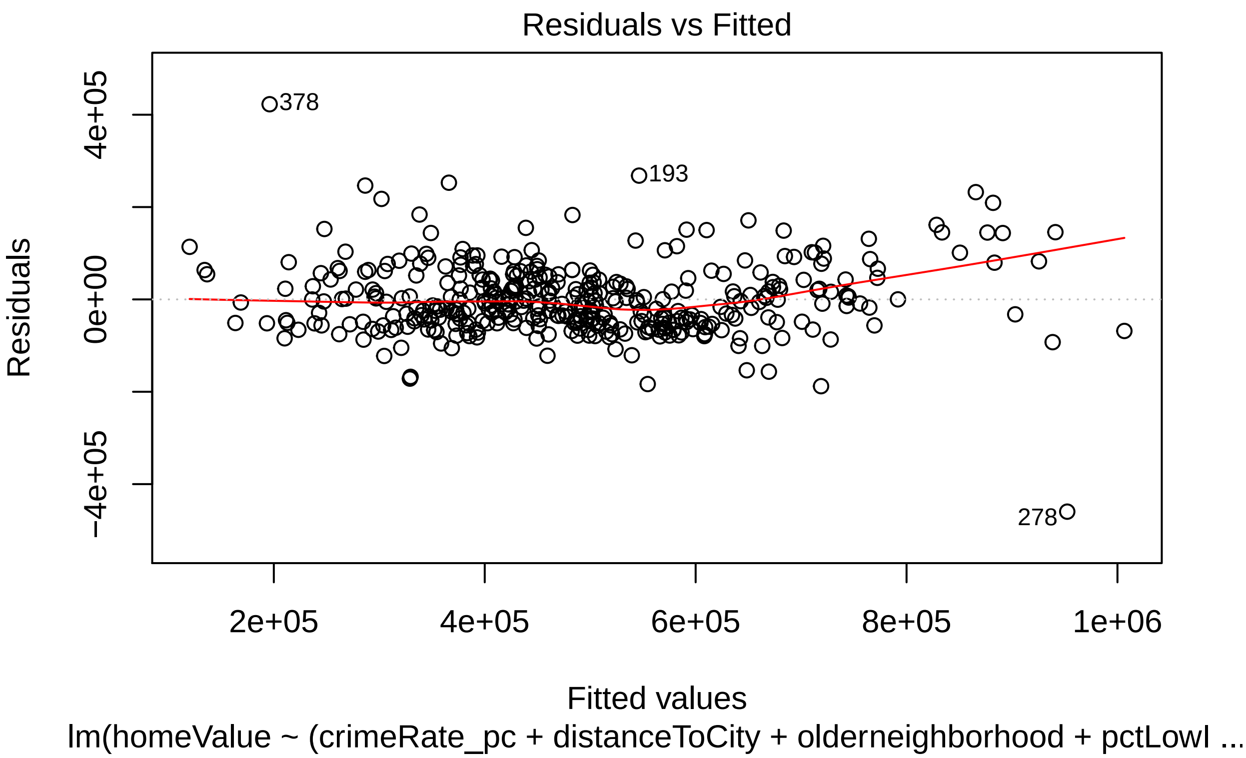
```
## [1] 3.884373
```

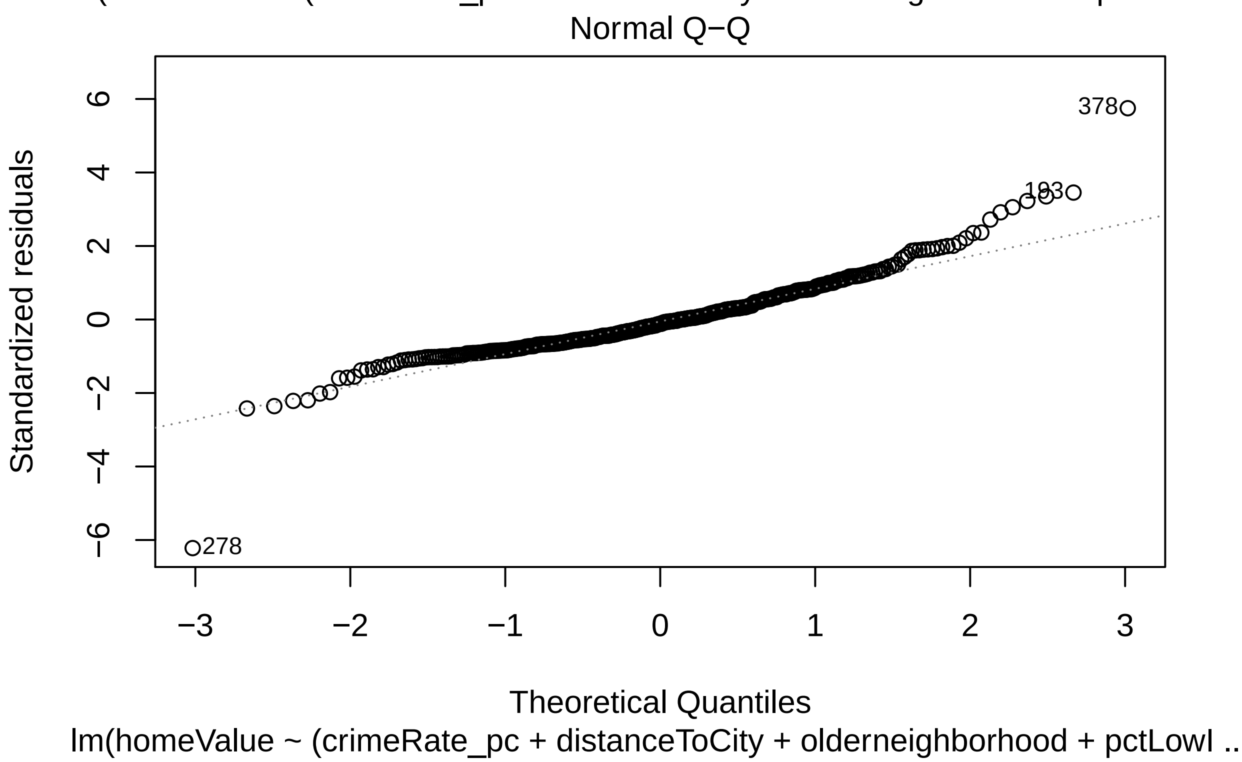
```r
#Show means between group 1 (low income) by group 2 (few rooms)
mytable <- table(data$homeValue, data$fewrooms, data$lowincome)
aggregate(data$homeValue, by=list(data$fewrooms, data$lowincome), mean)
```

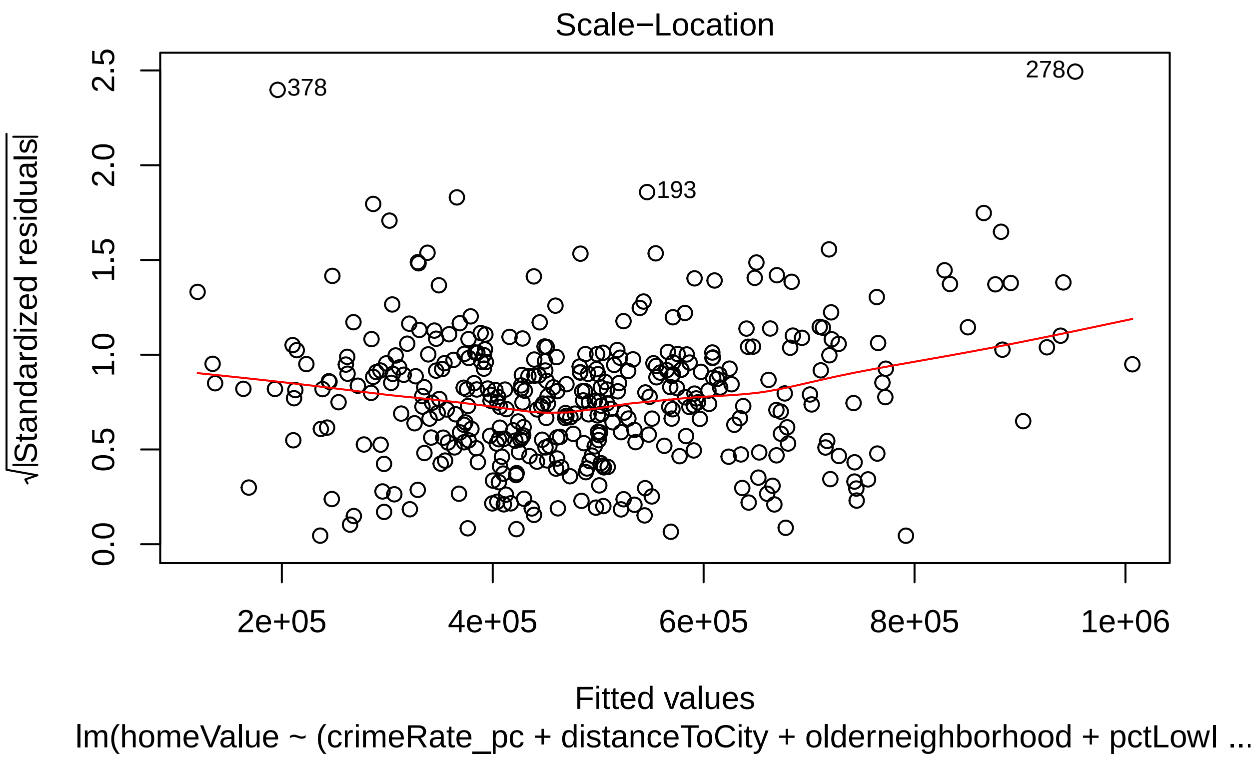
```
##   Group.1 Group.2        x
## 1       0       0 477353.6
## 2       1       0 643779.3
## 3       0       1 367380.7
## 4       1       1 346150.0
```

This is very interesting. There is a clear positive relationship between number of bedrooms and home value among high income groups. However, among low income groups, there is not nearly as clear of a relationship between number of bedrooms and home value. This is also evident in the means across groups. For low income areas, the difference in home value between houses with few rooms and many rooms is 21,230.70, while the difference in home value for high income areas between few rooms and many rooms is 166,425.70. That's quite a difference and is an interesting finding. Let's plot the residuals one last time:

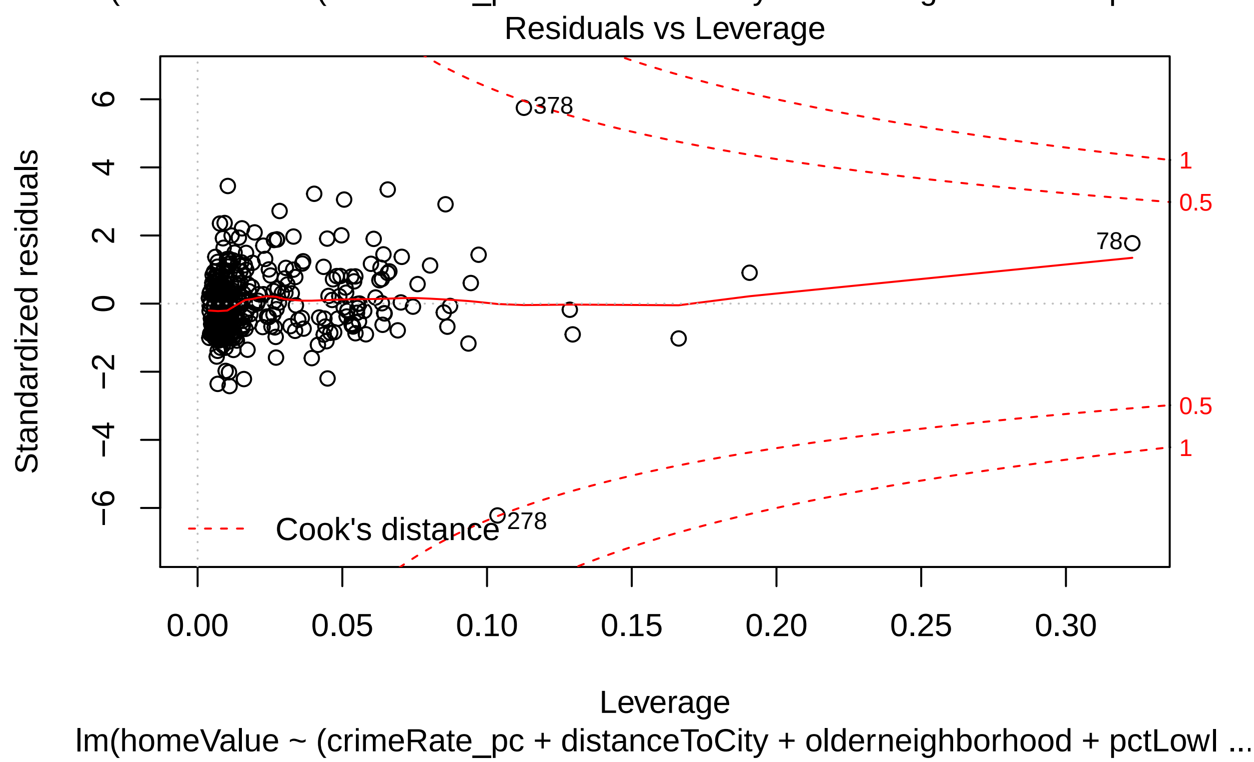
```r
plot(lm)
```


Residuals vs Fitted
Residuals
4e+05
0e+00
−4e+05
2e+05
4e+05
6e+05
8e+05
1e+06
378
193
278
Fitted values
lm(homeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctLowI ...


Normal Q−Q
Standardized residuals
6
4
2
0
−2
−4
−6
−3
−2
−1
0
1
2
3
378
193
278
Theoretical Quantiles
lm(homeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctLowI ...

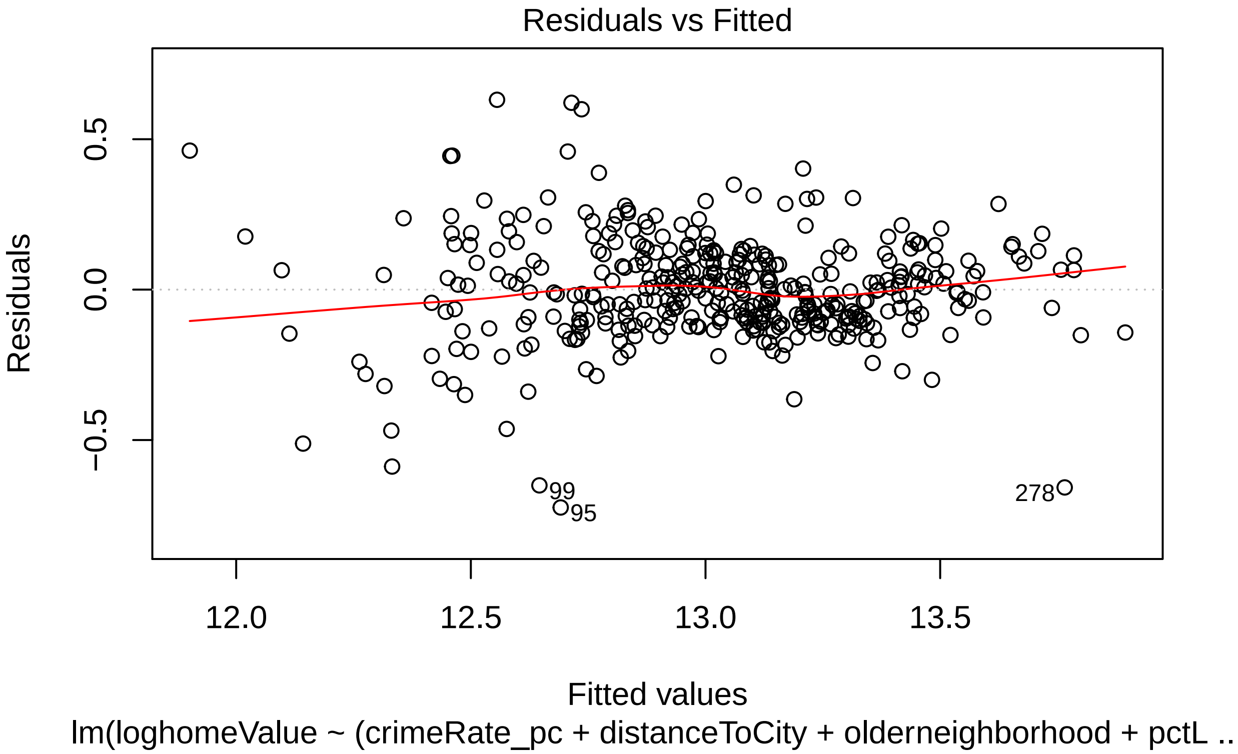


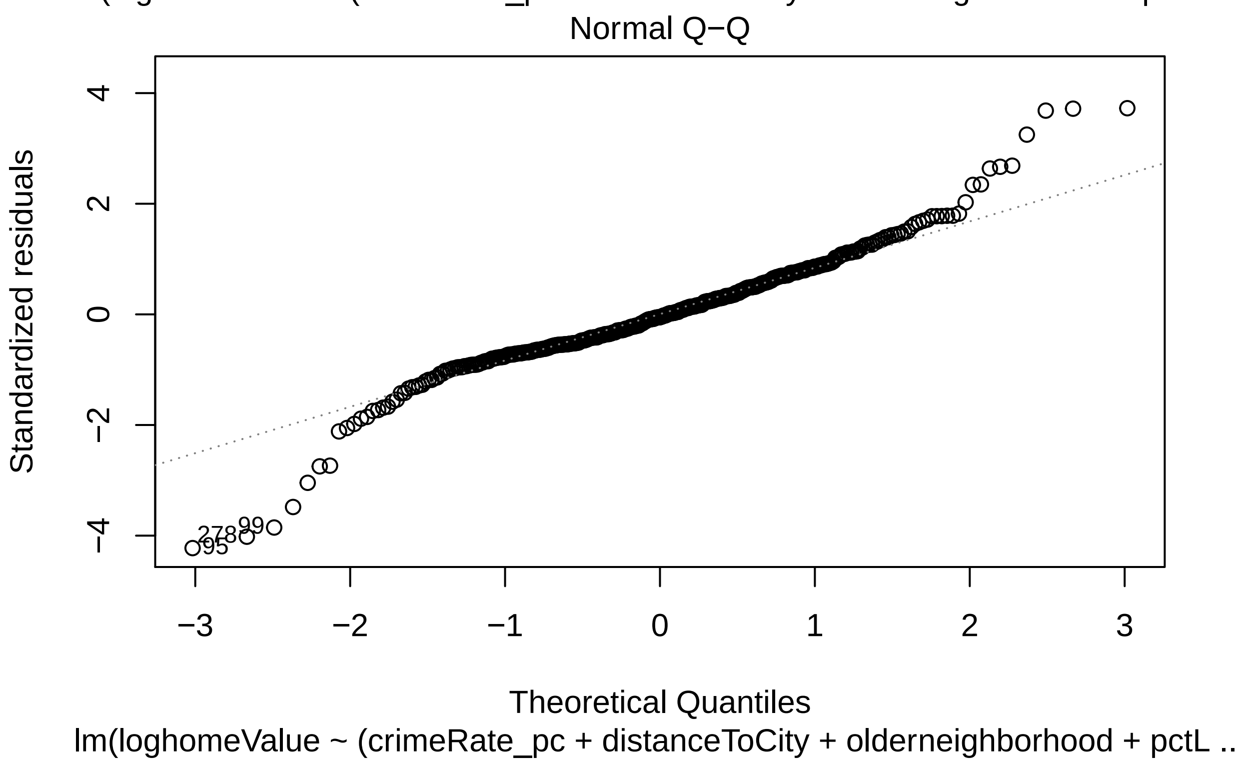
Scale−Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
2.5
378
278
193
2e+05
4e+05
6e+05
8e+05
1e+06
Fitted values
lm(homeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctLowI ...

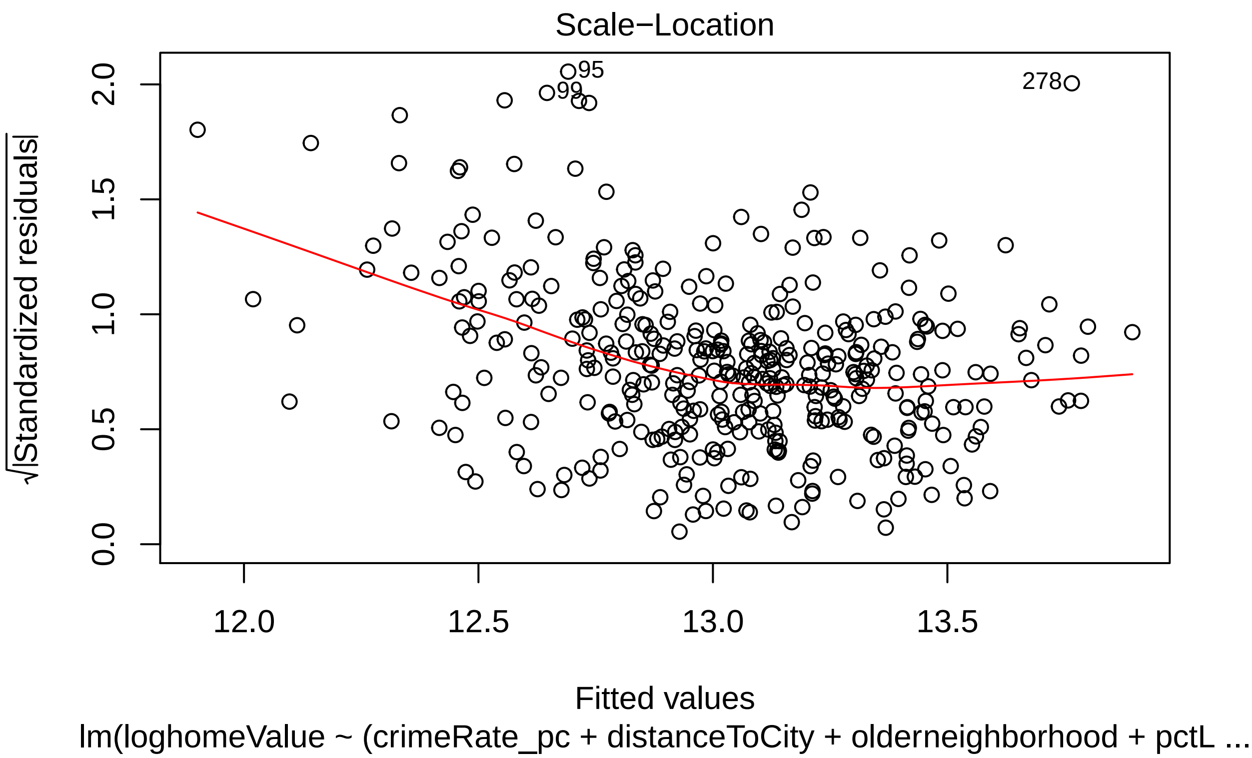


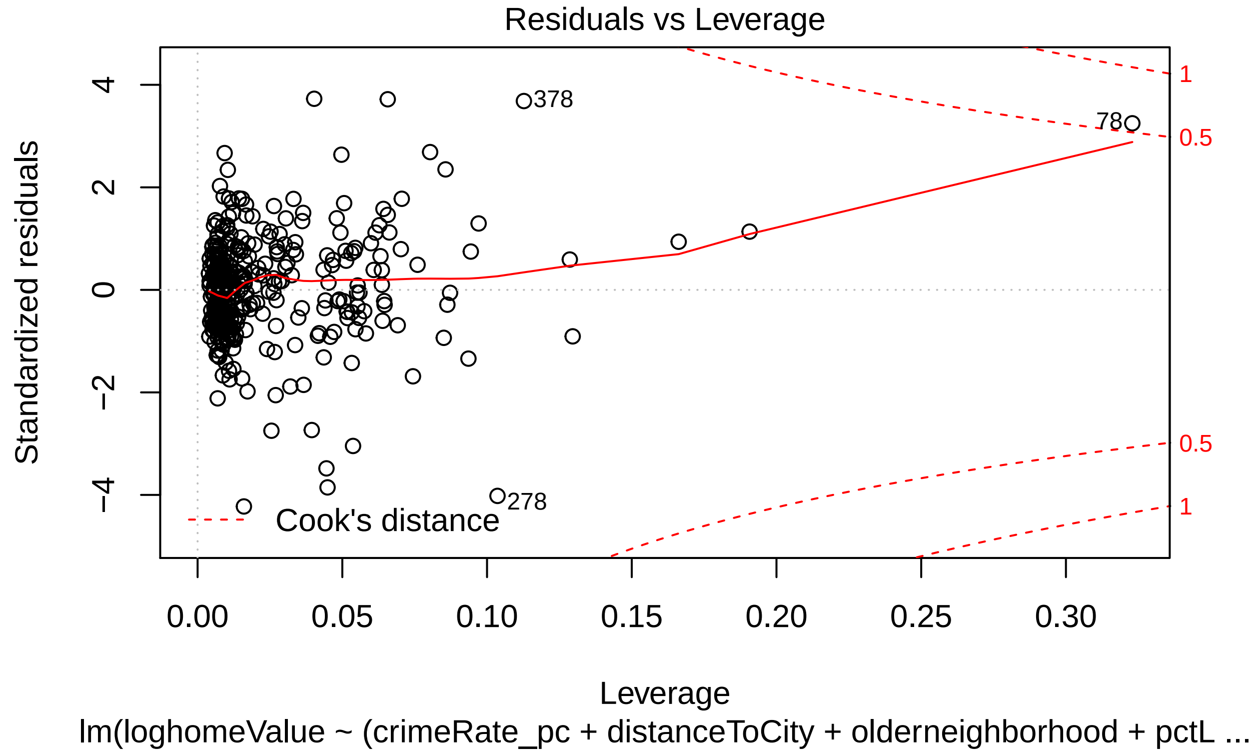
Residuals vs Leverage
Standardized residuals
−6
−4
−2
0
2
4
6
378
78
278
1
0.5
0.5
1
Cook's distance
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Leverage
lm(homeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctLowI ...


```
plot(lmlog)
```


Residuals vs Fitted
Residuals
0.5
0.0
−0.5
12.0
12.5
13.0
13.5
99
95
278
Fitted values
lm(loghomeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctL ...


Normal Q−Q
Standardized residuals
4
2
0
−2
−4
−3
−2
−1
0
1
2
3
278
99
95
Theoretical Quantiles
lm(loghomeValue ~ (crimeRate_pc + distanceToCity + olderneighborhood + pctL ...





There still seems to be slight heteroscedasticity, but the plots look much better. To account for the slight heteroskedasticity, We will use robust standard errors to answer the questions of the group.

```
lm$newse<-vcovHC(lmlog)
coeftest(lmlog,lm$newse)
```

```
##
## t test of coefficients:
##
##                          Estimate Std. Error t value  Pr(>|t|)
## (Intercept)            12.7025175  0.1980926 64.1241 < 2.2e-16 ***
## crimeRate_pc           -0.0107574  0.0028246 -3.8084 0.0001628 ***
## distanceToCity         -0.0061615  0.0012493 -4.9318 1.217e-06 ***
## olderneighborhood1      0.0822142  0.0622091  1.3216 0.1870977
## pctLowIncome            0.0142231  0.0074476  1.9098 0.0569116 .
## pollutionIndex         -0.0047037  0.0014274 -3.2953 0.0010747 **
## nBedRooms               0.2393895  0.0380374  6.2935 8.496e-10 ***
## withWater1              0.0821581  0.0373887  2.1974 0.0285896 *
## pctLowIncome:nBedRooms -0.0099793  0.0017491 -5.7054 2.326e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Specifically, the group wanted to know how environmental features affect the value of a home. There are two variables in our model that address this, the binary withWater variable and the pollution index.

Because we are using a log scale for home Value, we have to interpret this as follows:

The neighborhood being within 5 miles of water had increases the value of the home 8.3% versus not being in that proximity.

For every one unit increase in the pollutionIndex as it is calculated, the value of the home descreases by 0.5%.

We did find a significant interaction between number of rooms and percent low income. For higher income areas, the more rooms typically means the higher value of house. For lower income areas, the relationship between number of rooms and house value is not as clear.

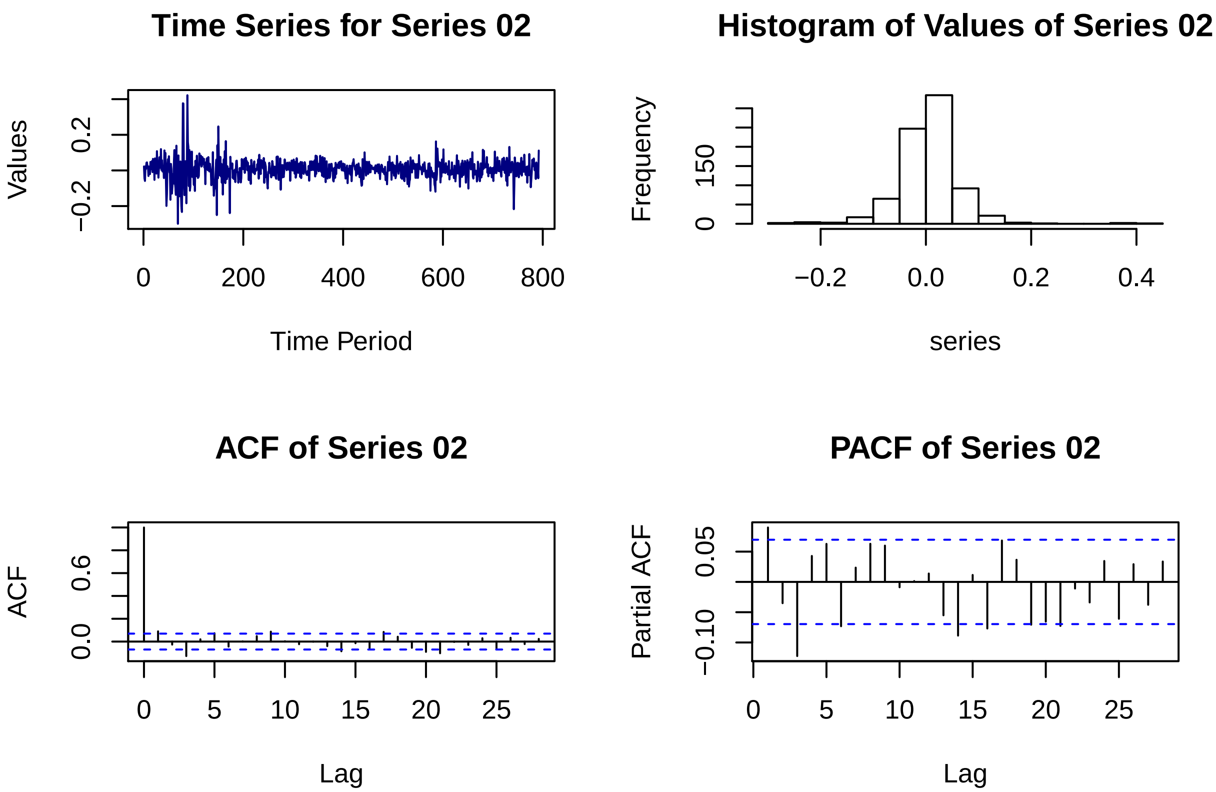
Additionally, we found that crime rate tended to show a 1.1% decrease in value, and distance to city showed a .6% decrease in home value. Being in a neighborhood wit 100% of homes built before 1950 tended to increase the value by 8.2%.

This evidence does suggest that environmental features affect the value of a home. They may not be as impactful as other features, but there is still a link between the environment and the value of a house.

Question 2

Build a time-series model for the series in series02.txt and use it to perform a 24-step ahead forecast.

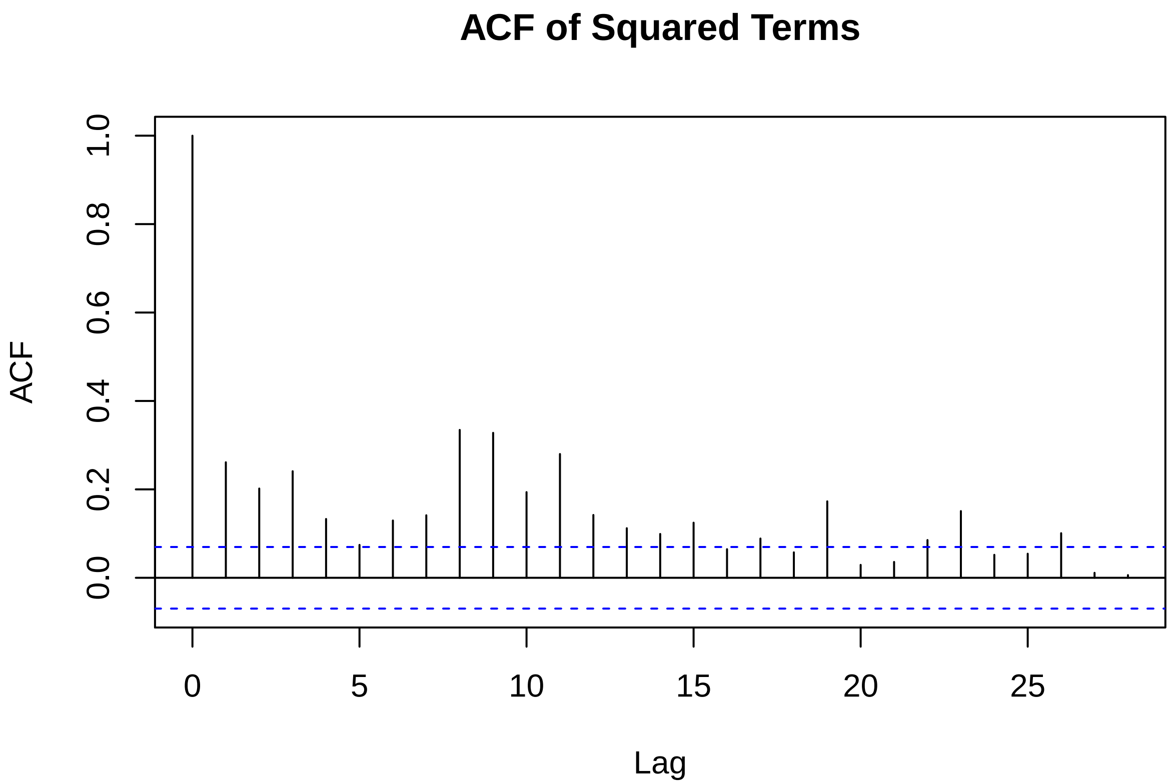
```r
#Import data
series <- read.table("series02.txt")
series <- ts(series$V1)

#Plot data
par(mfrow = c(2,2))
plot.ts(series, col = "navy", xlab = "Time Period", ylab = "Values", main = "Time Series for Series 02")
hist(series, main = "Histogram of Values of Series 02")
acf(series, main = "ACF of Series 02")
pacf(series, main = "PACF of Series 02")
```



Notice the general structure of the series. There seems to be a long run average, where the values are fluctuating around a central axis but with with a major series of spikes in the beginning signaling serious volatility. There does not seem to be seasonality or a trend. The ACF interestingly shows a sharp drop after the 0 lag, but slightly statistically significant lags throughout the series. The PACF also shows slight significance at several lags after the most significant at what looks like the 3rd lag.

We suspect there is non-constant variance present in this series, so we will plot a correlogram of the squared values of a mean adjusted version of this series (adjusted so the mean is zero).

```
#Autocorrelation Function
par(mfrow = c(1,1))
acf((series - mean(series))^2, main = "ACF of Squared Terms")
```



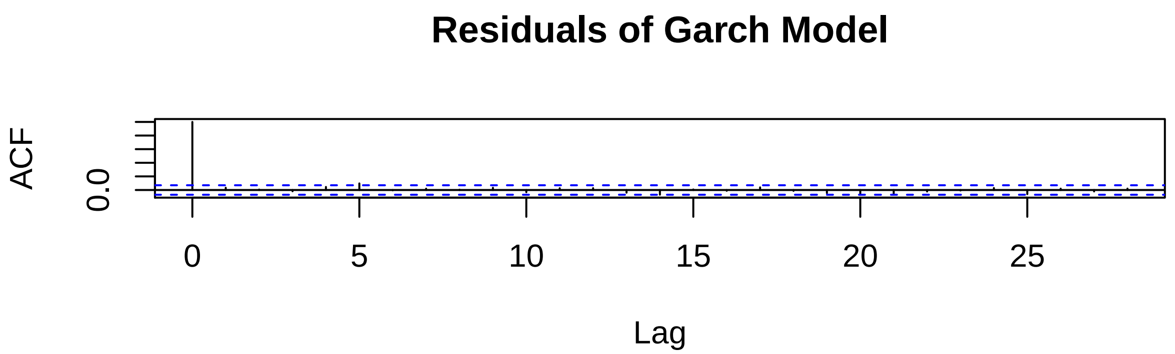
The square values that are plotted are equivalent to the variance. What the statistically significant values indicate is that there is serial correlation, meaning conditional heteroskedasticity. In plain English, this means that the variance is not constant throughout the series, rather the variance depends on what window of time we are looking at. This violates a core assumption of stationarity, meaning we will have to use a non-stationary model to fit this data.

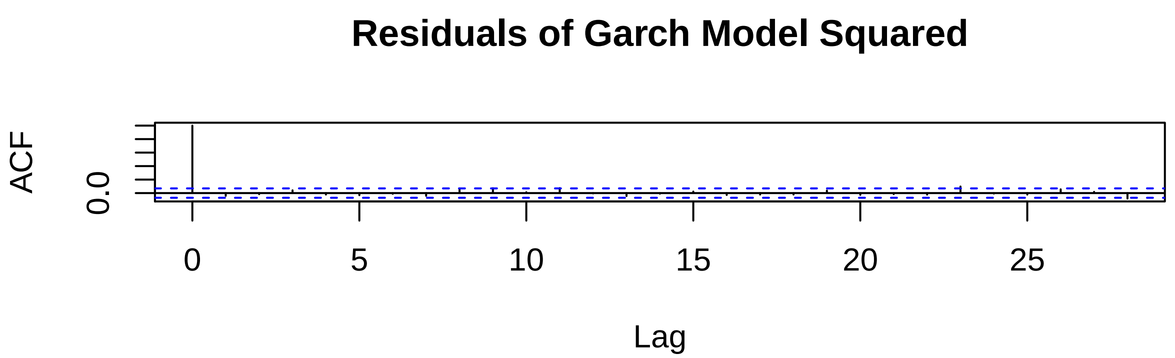
```
garch.fit <- garchFit(~garch(1,1), data = series, trace = FALSE, include.mean = FALSE)
garch.fit
```

```
##
## Title:
##  GARCH Modelling
##
## Call:
##  garchFit(formula = ~garch(1, 1), data = series, include.mean = FALSE,
##     trace = FALSE)
##
## Mean and Variance Equation:
##  data ~ garch(1, 1)
## <environment: 0x7f9ae4466778>
##  [data = series]
##
## Conditional Distribution:
##  norm
##
## Coefficient(s):
##      omega      alpha1       beta1
## 7.8467e-05  1.1530e-01  8.6147e-01
##
```

```
## Std. Errors:
##  based on Hessian
##
## Error Analysis:
##         Estimate  Std. Error  t value Pr(>|t|)
## omega  7.847e-05   2.915e-05    2.692  0.00711 **
## alpha1 1.153e-01   2.124e-02    5.428  5.7e-08 ***
## beta1  8.615e-01   2.183e-02   39.462  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
##  1257.974    normalized:  1.588351
##
## Description:
##  Fri Dec 18 07:31:38 2015 by user:
```

```
par(mfrow = c(2,1))
#Note standardized residuals because garchFit calculates residuals differently
acf(residuals(garch.fit, standardize = TRUE), main = "Residuals of Garch Model")
acf(residuals(garch.fit, standardize = TRUE)^2, main = "Residuals of Garch Model Squared")
```






```
Box.test(residuals(garch.fit, standardize = TRUE), type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(garch.fit, standardize = TRUE)
```

```
## X-squared = 0.87562, df = 1, p-value = 0.3494
```

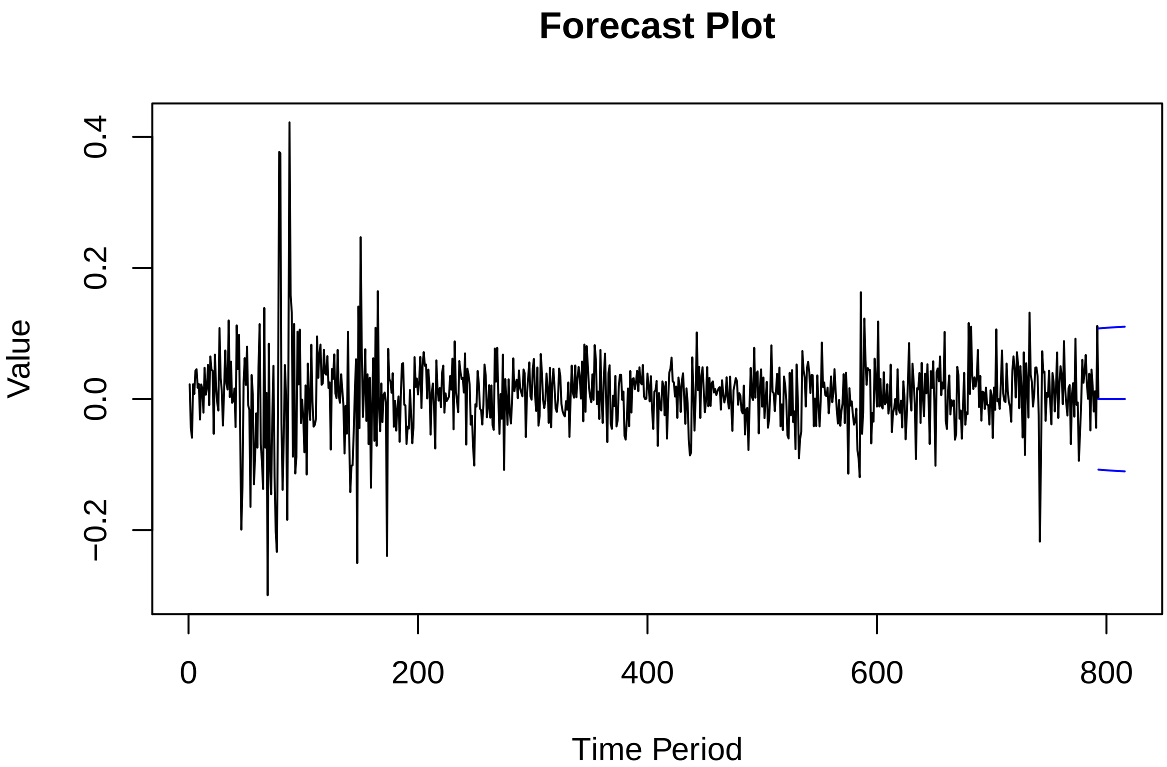
Notice that with the ACF of both the series residuals and squared residuals there is no autocorrelation. This suggests the residuals are behaving like white noise and thus the model is a good fit. The residuals also fail to reject the null hypothesis that the residuals are independent. The coefficients are all statistically significant, meaning we reject the null hypothesis that the coefficients are 0. Therefore, we believe this model is a good fit for forecasting.

```
preds <- predict(garch.fit, n.ahead = 24)
lower <- preds$meanForecast - 1.96 * preds$meanError
upper <- preds$meanForecast + 1.96 * preds$meanError
cbind(lower, preds$meanForecast, upper)
```

```
##            lower      upper
##  [1,] -0.1077285 0 0.1077285
##  [2,] -0.1078761 0 0.1078761
##  [3,] -0.1080200 0 0.1080200
##  [4,] -0.1081604 0 0.1081604
##  [5,] -0.1082973 0 0.1082973
##  [6,] -0.1084309 0 0.1084309
##  [7,] -0.1085613 0 0.1085613
##  [8,] -0.1086884 0 0.1086884
##  [9,] -0.1088125 0 0.1088125
## [10,] -0.1089335 0 0.1089335
## [11,] -0.1090517 0 0.1090517
## [12,] -0.1091669 0 0.1091669
## [13,] -0.1092793 0 0.1092793
## [14,] -0.1093890 0 0.1093890
## [15,] -0.1094961 0 0.1094961
## [16,] -0.1096006 0 0.1096006
## [17,] -0.1097025 0 0.1097025
## [18,] -0.1098020 0 0.1098020
## [19,] -0.1098991 0 0.1098991
## [20,] -0.1099939 0 0.1099939
## [21,] -0.1100864 0 0.1100864
## [22,] -0.1101766 0 0.1101766
## [23,] -0.1102647 0 0.1102647
## [24,] -0.1103507 0 0.1103507
```

We have printed the forecast above. The 0 predicted value should make sense, this is a model of volatility. We will plot the results below

```
par(mfrow = c(1,1))
plot.ts(c(series, preds$meanForecast), xlab = "Time Period", ylab = "Value", main = "Forecast Plot")
lines(c(rep(NA, 792), preds$meanForecast), col = "blue")
lines(c(rep(NA, 792), lower), col = "blue")
lines(c(rep(NA, 792), upper), col = "blue")
```

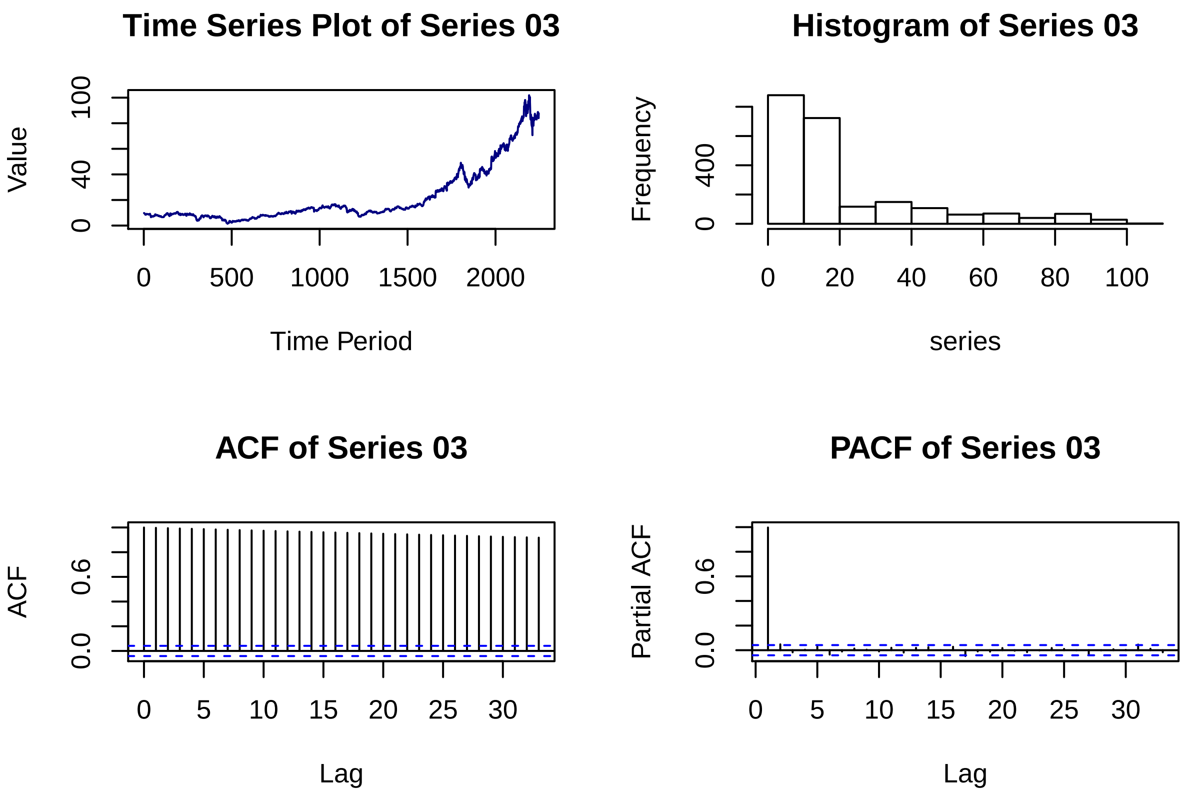


The two blue lines represent the 95% confidence interval of the predicted volatility. These seem to be in line with the long run average of the series.

Question 3

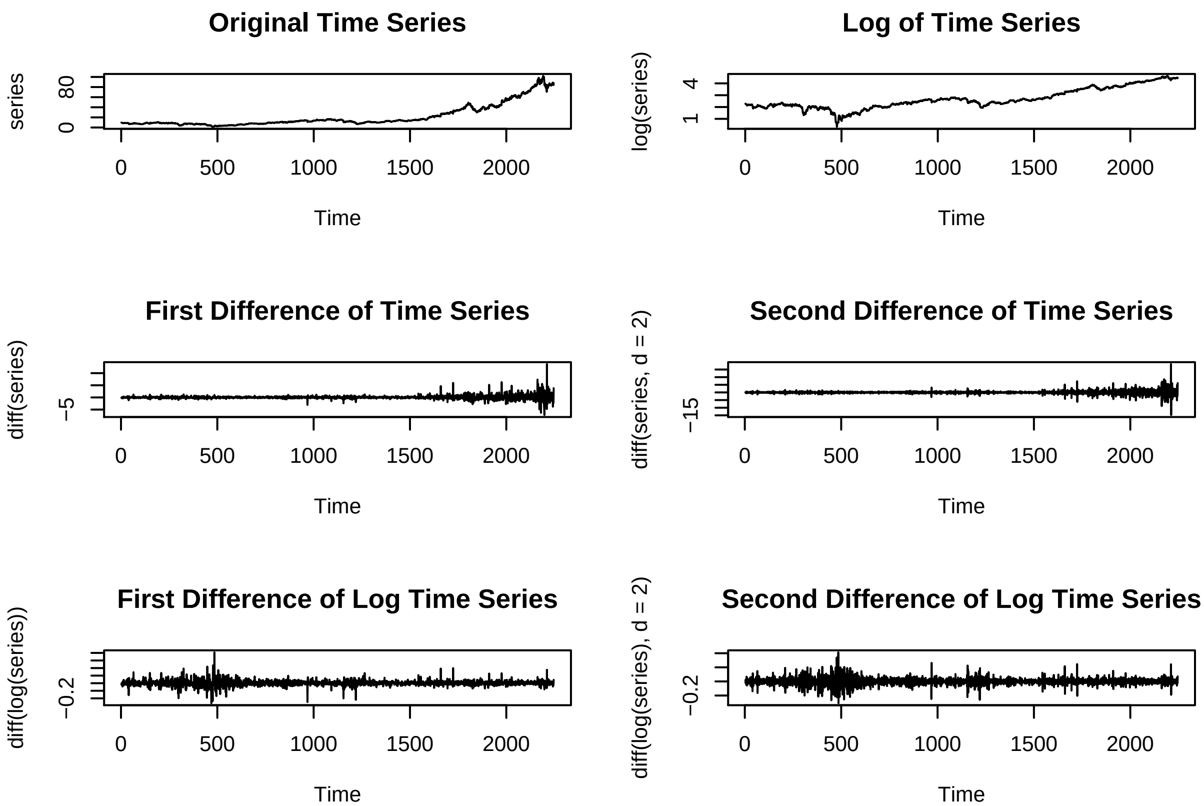
Build a time-series model for the series in series03.csv and use it to perform a 24-step ahead forecast

```
#Load data
series <- read.csv("series03.csv")
series <- ts(series$X9.88)

#Plot data
par(mfrow = c(2,2))
plot.ts(series, xlab = "Time Period", ylab = "Value", main = "Time Series Plot of Series 03", col = "na
hist(series, main = "Histogram of Series 03")
acf(series, main = "ACF of Series 03")
pacf(series, main = "PACF of Series 03")
```



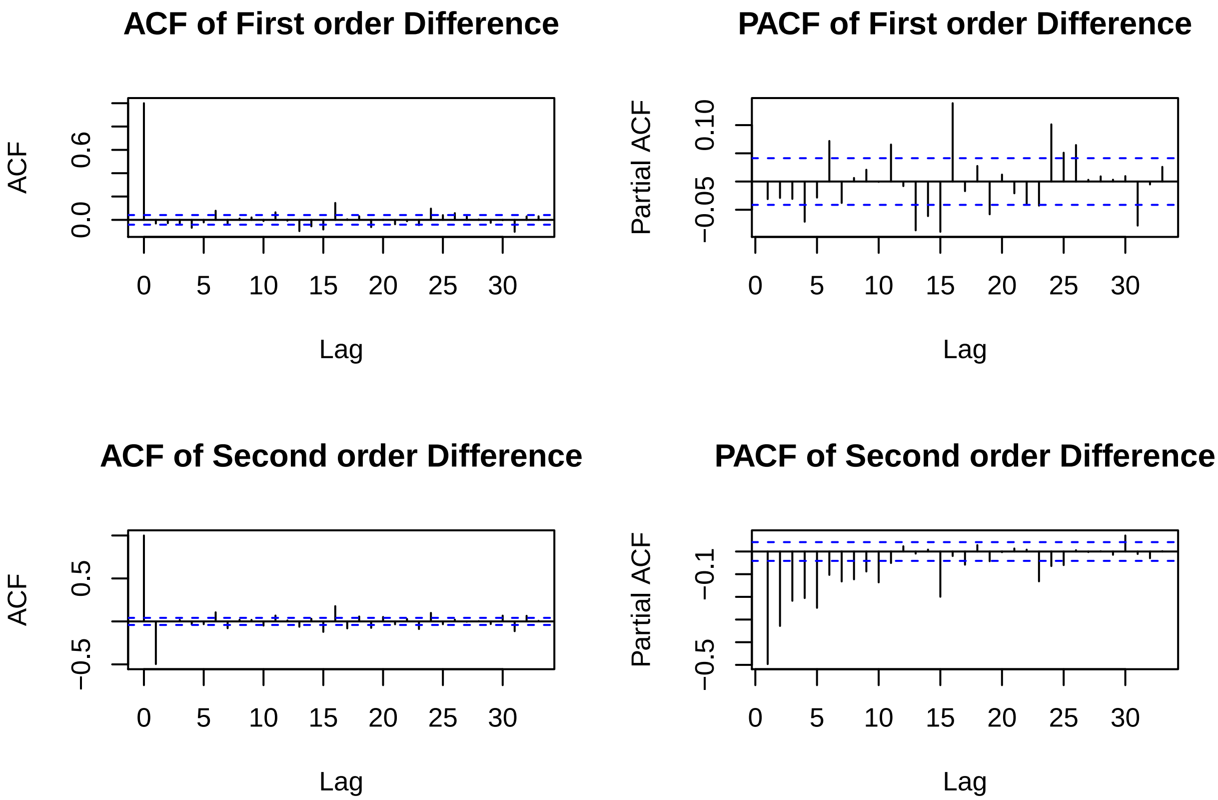
Notice from the time series plot that there is significant trend going on, specifically, a long term upward trend. The ACF shows significance through all past lags while the PACF is only siginficant for the first lag. There does not seem to be any seasonality. This looks like the realization of a random walk with drift process.

```
#Plot different time series to suggest differencing
par(mfrow = c(3, 2))
plot.ts(series, main = "Original Time Series")
plot.ts(log(series), main = "Log of Time Series")
plot.ts(diff(series), main = "First Difference of Time Series")
plot.ts(diff(series, d = 2), main = "Second Difference of Time Series")
plot.ts(diff(log(series)), main = "First Difference of Log Time Series")
plot.ts(diff(log(series), d = 2), main = "Second Difference of Log Time Series")
```

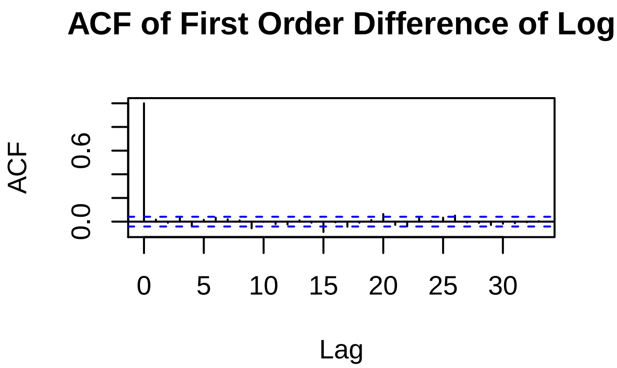


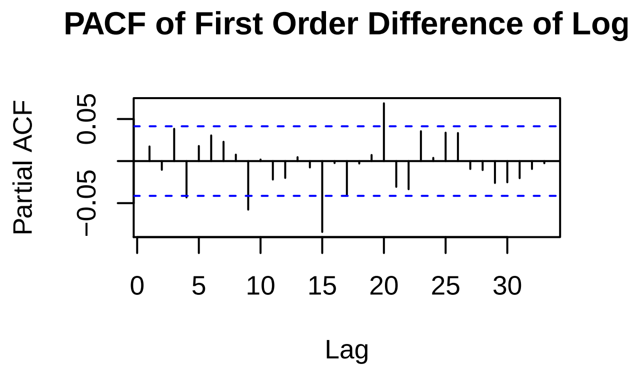
It is clear from the original time series plot that the series is not stationary. Before proceeding to build a model we must render the series as stationary.

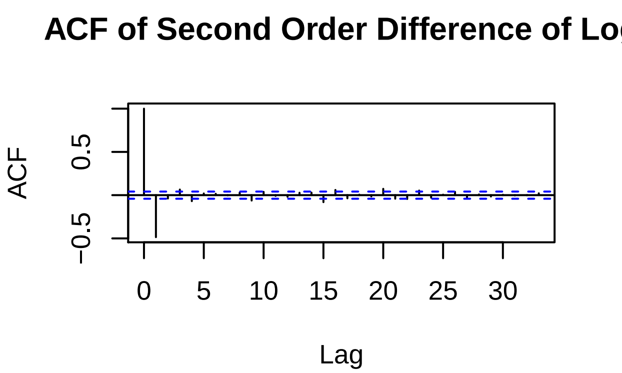
```
#Transform the series for stationarity
par(mfrow = c(2,2))
acf(diff(series), main = "ACF of First order Difference")
pacf(diff(series), main = "PACF of First order Difference")
acf(diff(series, d= 2), main = "ACF of Second order Difference")
pacf(diff(series, d = 2), main = "PACF of Second order Difference")
```

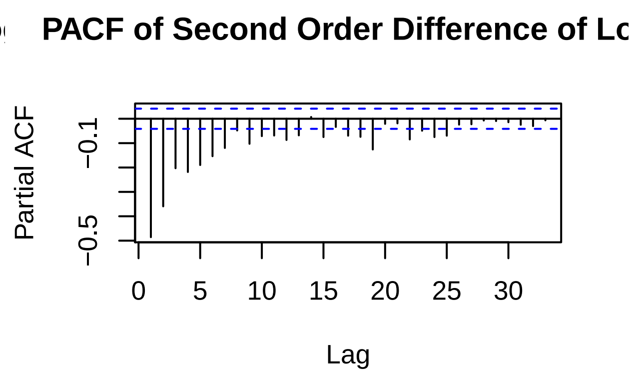



```r
acf(diff(log(series)), main = "ACF of First Order Difference of Log")
pacf(diff(log(series)), main = "PACF of First Order Difference of Log")
acf(diff(log(series), d = 2), main = "ACF of Second Order Difference of Log")
pacf(diff(log(series), d = 2), main = "PACF of Second Order Difference of Log")
```









From examining these plots, it seems as though the second order difference provides the best transformation into white noise. In both cases the ACF shows a sharp cut off (suggesting an MA term) while the PACF gradually declines. The first order difference shows a lot of volatility in the PACF, suggesting correlations that are not easily captured.

Between the second order difference and the second order difference of the log, the second order difference of the log seems to look more like white noise. There are fewer significant autocorrelations (which might be due to sampling) in the second order difference of the log and it decays more smoothly. Therefore, we will use the second order difference of the log to estimate the model.

```
#Function to select the best ARIMA based on AIC
get.best.arima <- function(x.ts, maxord = c(1,1,1))
{
  best.aic <- 1e8
  n <- length(x.ts)
  for (p in 0:maxord[1]) for (d in 0:maxord[2]) for (q in 0:maxord[3])
  {
    fit <- arima(x.ts, order = c(p, d, q), method = "ML")
    fit.aic <- -2 * fit$loglik + (log(n) + 1) * length(fit$coef)
    if (fit.aic < best.aic)
    {
      best.aic <- fit.aic
      best.fit <- fit
      best.model <- c(p, d, q)
    }
  }
  list(best.aic, best.fit, best.model)
}
```

```r
auto.arima(log(series), allowdrift = FALSE)
```

```
## Series: log(series)
## ARIMA(0,1,0)
##
## sigma^2 estimated as 0.001456:  log likelihood=4146.46
## AIC=-8290.91   AICc=-8290.91   BIC=-8285.2
```

```r
mod <- auto.arima(log(series), d = 2)
```

```
## Warning in auto.arima(log(series), d = 2): Unable to fit final model using
## maximum likelihood. AIC value approximated
```

```r
mod
```

```
## Series: log(series)
## ARIMA(2,2,1)
##
## Coefficients:
##          ar1      ar2      ma1
##       0.0139  -0.0120  -0.9886
## s.e.  0.0212   0.0213   0.0030
##
## sigma^2 estimated as 0.001476:  log likelihood=4129.66
## AIC=-8238.81   AICc=-8238.79   BIC=-8215.94
```

```r
t(confint(mod))
```

```
##                 ar1         ar2        ma1
## 2.5 %  -0.02770088 -0.05363241 -0.9944319
## 97.5 %  0.05550080  0.02970417 -0.9828398
```

Here we try using the auto.arima() function to find the best model. When using the auto.arima() function it suggests the first order difference of the log series. However, we saw above that this was not the best model examining the ACF and PACF so we instead specificed the order of differencing to be 2. When doing this, the suggested model is an ARIMA(2, 2, 1) model. However, examining the confidence intervals, we find that the 2 AR terms contain 0 in their confidence interval. That means we will fail to reject the null hypothesis these coefficients are 0. The MA term however does not contain 0 in its confidence interval and therefore we can reject the null hypothesis. Therefore, we will construct an ARIMA(0, 2, 1) model.

```r
#Fit ARIMA (0,2,1)
model <- arima(log(series), order = c(0, 2, 1))
model
```

```
##
## Call:
## arima(x = log(series), order = c(0, 2, 1))
##
## Coefficients:
##           ma1
```

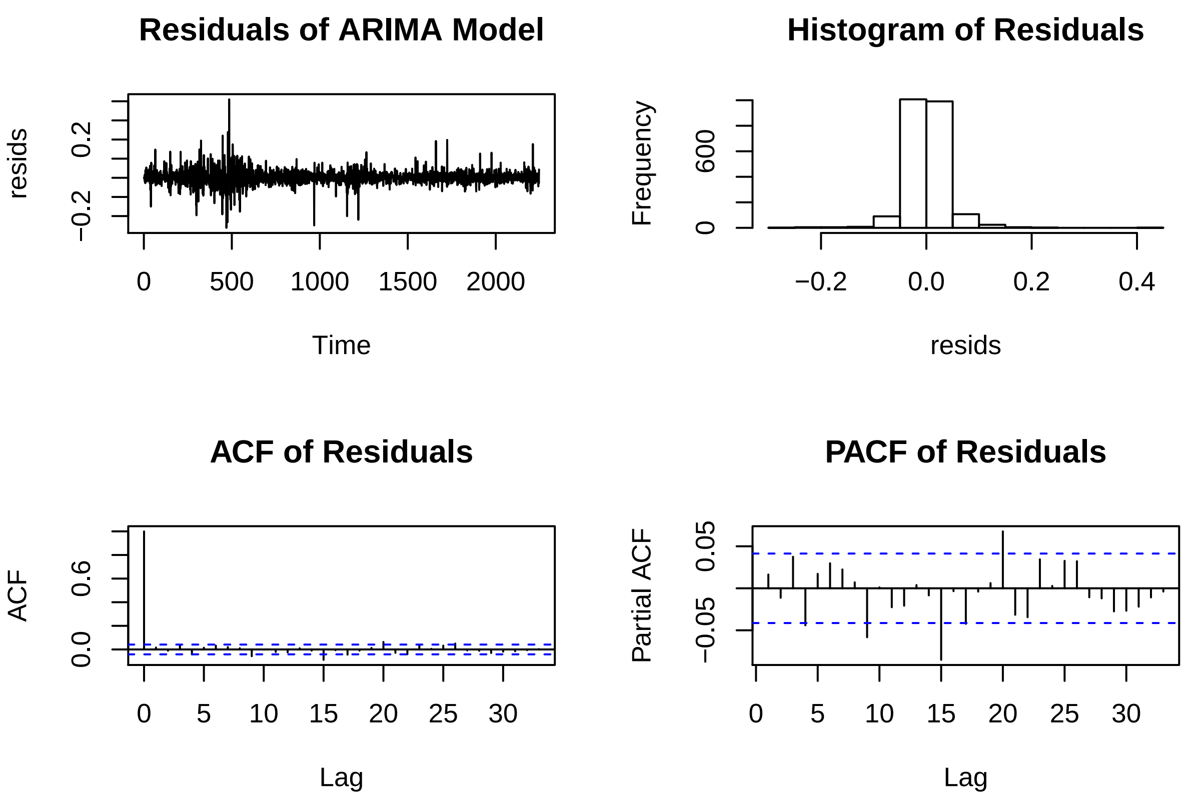
```
##       -0.9997
## s.e.   0.0026
##
## sigma^2 estimated as 0.001456:  log likelihood = 4141,  aic = -8278
```

```
t(confint(model))
```

```
##                 ma1
## 2.5 %  -1.0048193
## 97.5 % -0.9944951
```

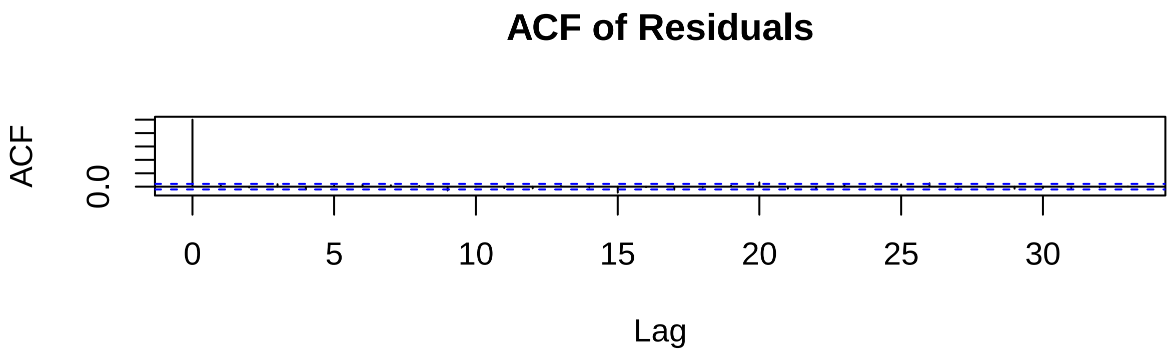
0 is not contained in the confidence interval so this coefficient is statistically significant.

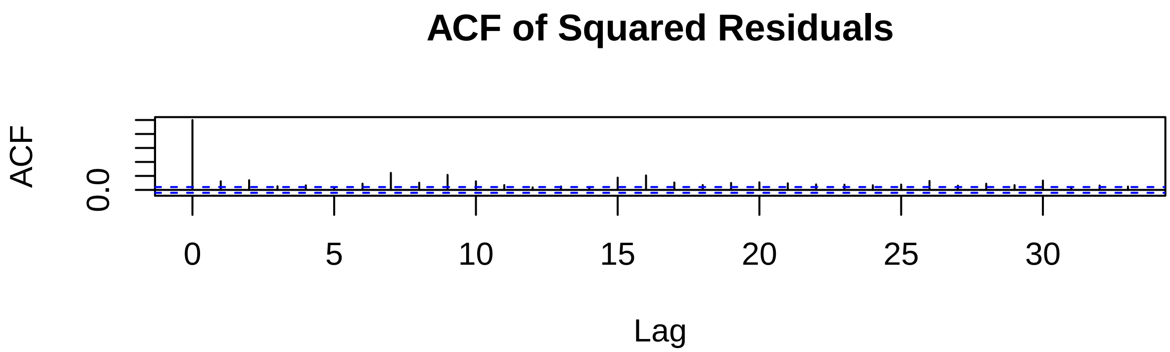
```
#Diagnostic plots of residuals
resids <- model$residuals
par(mfrow = c(2,2))
plot.ts(resids, main = "Residuals of ARIMA Model")
hist(resids, main = "Histogram of Residuals")
acf(resids, main = "ACF of Residuals")
pacf(resids, main = "PACF of Residuals")
```



These residual diagnostics suggest a reasonably good approximation of white noise. The ACF and PACF however do show quite a bit of volatility, so we will examine the squared residuals because we suspect there is non-constant variance.

```
#Plot residuals and squared residuals
par(mfrow = c(2,1))
acf(resids, main = "ACF of Residuals")
acf(resids^2, main = "ACF of Squared Residuals")
```





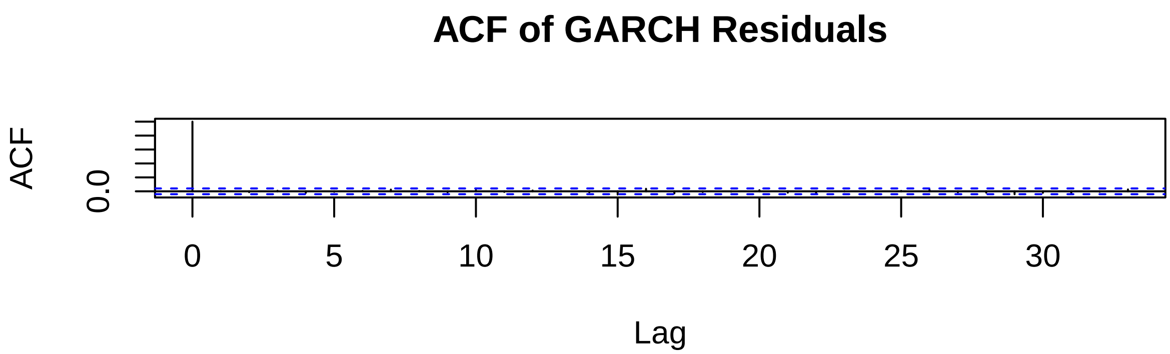
As we had suspected, the squared residuals show statistically significant terms at different intervals. Clearly, this suggests there is non-constant variance. Therefore, we will fit a GARCH model to the residuals.

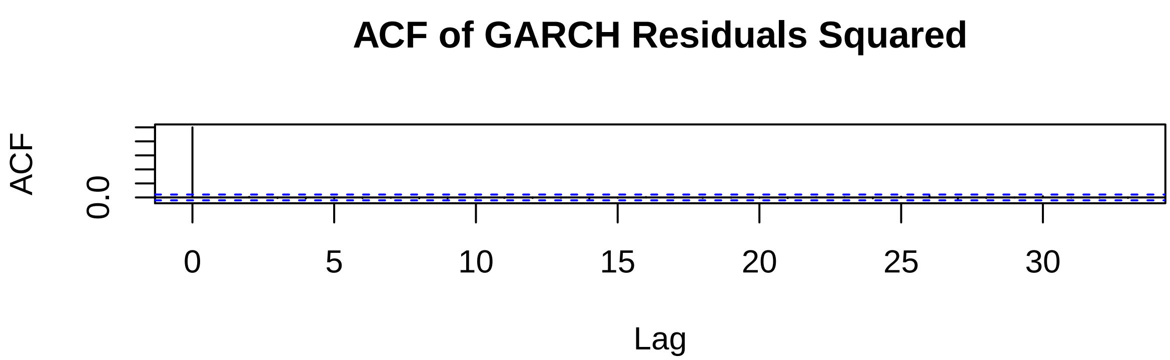
```
#Fit GARCH model
garch.fit <- garchFit(~garch(1,1), data = resids, include.mean = FALSE, trace = FALSE)
garch.fit
```

```
##
## Title:
##  GARCH Modelling
##
## Call:
##  garchFit(formula = ~garch(1, 1), data = resids, include.mean = FALSE,
##     trace = FALSE)
##
## Mean and Variance Equation:
##  data ~ garch(1, 1)
## <environment: 0x7f9ae4315e98>
##  [data = resids]
##
## Conditional Distribution:
##  norm
##
## Coefficient(s):
##      omega      alpha1       beta1
## 5.5007e-05  8.2207e-02  8.7660e-01
##
## Std. Errors:
##  based on Hessian
```

```
##
## Error Analysis:
##         Estimate  Std. Error  t value Pr(>|t|)
## omega  5.501e-05   1.540e-05    3.572 0.000354 ***
## alpha1 8.221e-02   2.102e-02    3.911 9.18e-05 ***
## beta1  8.766e-01   2.986e-02   29.355  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log Likelihood:
##  4453.374    normalized:  1.982802
##
## Description:
##  Fri Dec 18 07:31:41 2015 by user:
```

```r
par(mfrow = c(2,1))
acf(residuals(garch.fit, standardize = TRUE),  main = "ACF of GARCH Residuals")
acf(residuals(garch.fit, standardize = TRUE)^2, main = "ACF of GARCH Residuals Squared")
```






```r
Box.test(residuals(garch.fit, standardize = TRUE), type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  residuals(garch.fit, standardize = TRUE)
## X-squared = 0.0083375, df = 1, p-value = 0.9272
```

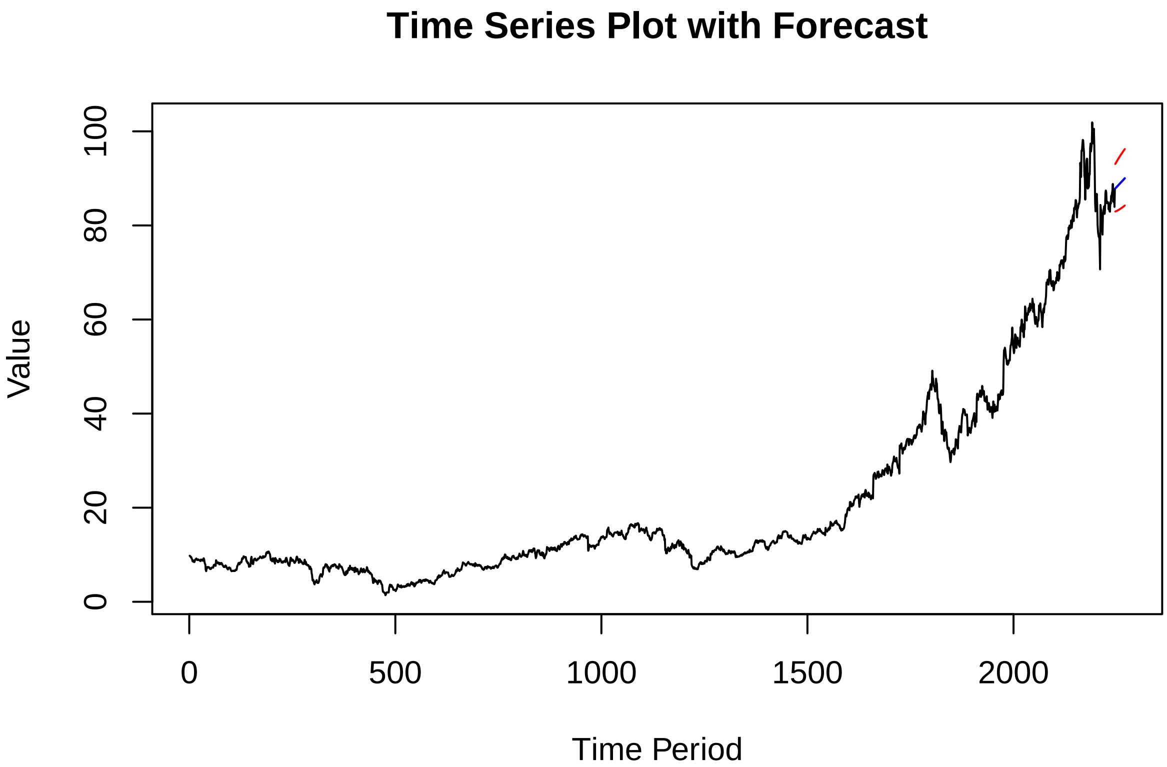
The GARCH model shows statistically significant coefficients, meaning we will reject our null hypothesis that the coefficients are 0. Further, notice that the residuals now are not significant, meaning this series approximates white noise. The residuals also fail to reject the null hypothesis of the Ljung-Box test, meaning we cannot say the residuals are not independent. Therefore, we will use this model for forecasting.

According to Cowpertwait, the fitted GARCH model on the residuals will not affect the average prediction, because the mean of residual errors is 0. However, it does affect the variance of predicted values. Therefore, we will use the ARIMA component of our model to provide point estimates for our forecast and the GARCH model to supply the standard error for the confidence interval.

```
preds <- forecast(model, h = 24)
std <- predict(garch.fit, n.ahead = 24)

#set confidence intervals
lower <- c(preds$mean - 1.96 * std$meanError)
upper <- c(preds$mean + 1.96 * std$meanError)
#display
cbind(exp(lower), exp(preds$mean), exp(upper))
```

```
## Time Series:
## Start = 2247
## End = 2270
## Frequency = 1
##      exp(lower) exp(preds$mean) exp(upper)
## 2247   82.95421        87.86284   93.06193
## 2248   82.98800        87.95579   93.22096
## 2249   83.02458        88.04883   93.37712
## 2250   83.06379        88.14197   93.53061
## 2251   83.10546        88.23521   93.68159
## 2252   83.14946        88.32854   93.83021
## 2253   83.19565        88.42198   93.97662
## 2254   83.24391        88.51551   94.12095
## 2255   83.29412        88.60914   94.26333
## 2256   83.34618        88.70288   94.40385
## 2257   83.39999        88.79671   94.54264
## 2258   83.45546        88.89064   94.67979
## 2259   83.51251        88.98467   94.81539
## 2260   83.57106        89.07880   94.94952
## 2261   83.63103        89.17303   95.08227
## 2262   83.69236        89.26736   95.21371
## 2263   83.75498        89.36178   95.34392
## 2264   83.81883        89.45631   95.47296
## 2265   83.88386        89.55094   95.60088
## 2266   83.95000        89.64567   95.72776
## 2267   84.01722        89.74050   95.85365
## 2268   84.08545        89.83543   95.97860
## 2269   84.15467        89.93046   96.10265
## 2270   84.22482        90.02559   96.22586
```

```
par(mfrow = c(1,1))
plot.ts(c(series, exp(preds$mean)), xlab = "Time Period", ylab = "Value", main = "Time Series Plot with
lines(c(rep(NA, 2246), exp(preds$mean)), col = "blue")
lines(c(rep(NA, 2246), exp(upper)), col = "red")
lines(c(rep(NA, 2246), exp(lower)), col = "red")
```

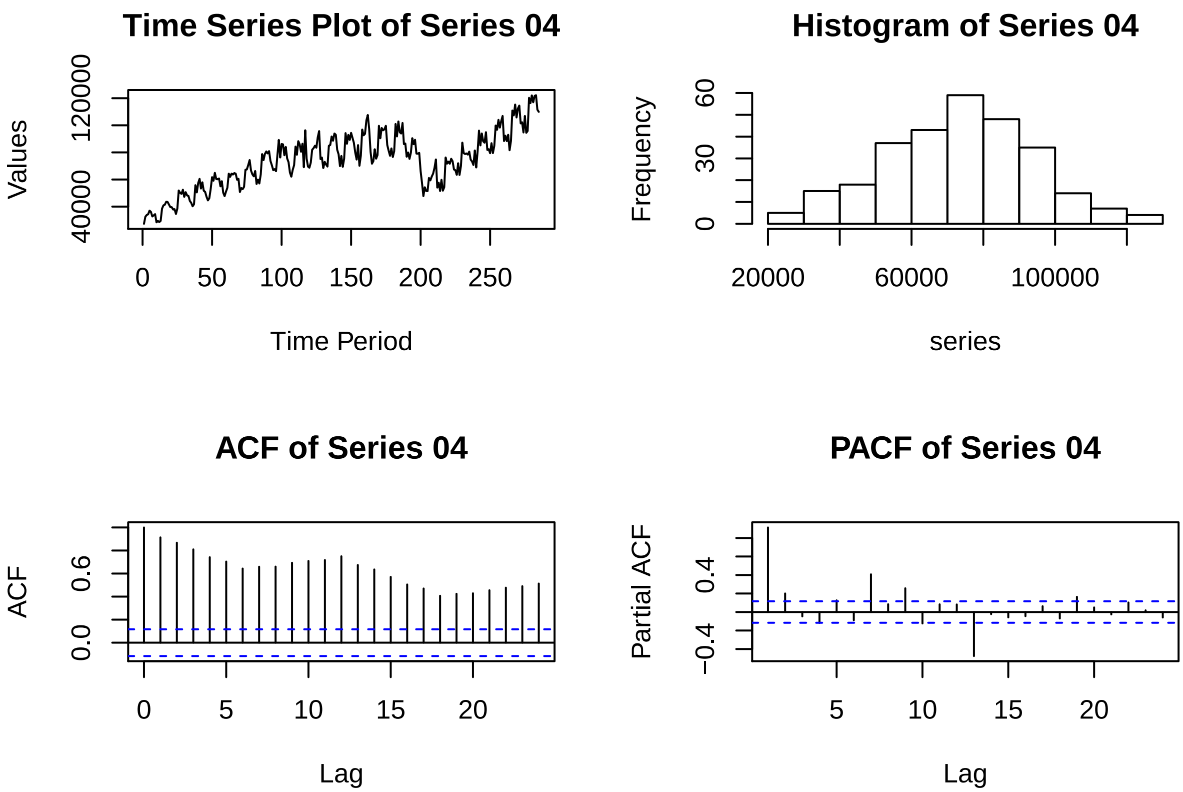


Above we have displayed and plotted a 24 step forecast. The bounds in red represent the a 95% confidence interval, while the blue line is the mean forecast. The general trend upwards seems to continue, which logically makes sense.

Question 4

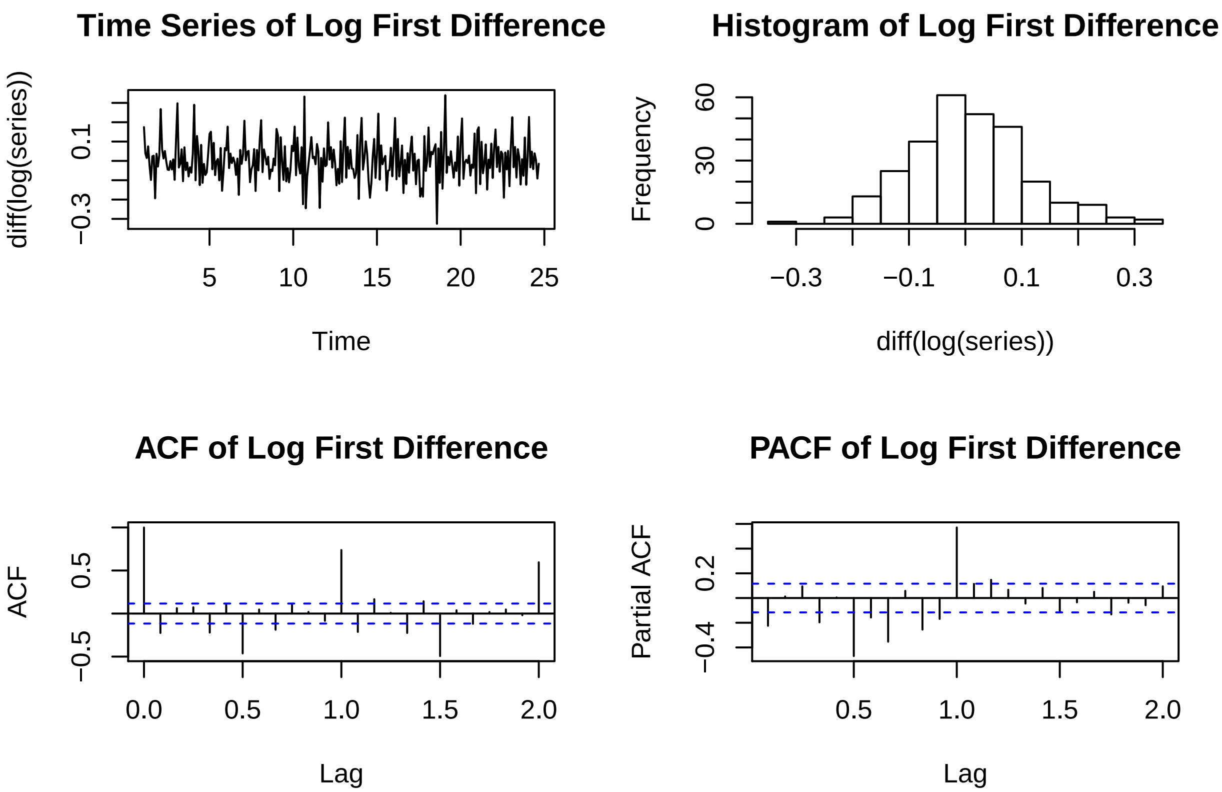
Build a time-series model for the series in series04.csv and use it to perform a 24-step ahead forecast. Possible models include AR, MA, ARMA, ARIMA, Seasonal ARIMA, GARCH, ARIMA-GARCH, or Seasonal ARIMA-GARCH models. Note that the original series may need to be transformed before it be modelled.

```
#Import data
series <- read.csv("series04.csv")
series <- ts(series$X25182)

#Plot data
par(mfrow = c(2,2))
plot.ts(series, xlab = "Time Period", ylab = "Values", main = "Time Series Plot of Series 04")
hist(series, main = "Histogram of Series 04")
acf(series, main = "ACF of Series 04")
pacf(series, main = "PACF of Series 04")
```



From the time series plot it should be obvious that there is seasonality in this series, suggesting seasonal lag terms will be needed. The series shows a general upwards trend, and we would argue this series is definitely not stationary. The ACF show statistically significant lags persisting but at different heights, further suggesting non-stationarity and seasonality.

```r
#Transform series for stationary
series <- read.csv("series04.csv")
series <- ts(series$X25182, frequency = 12)

par(mfrow = c(2,2))
plot.ts(diff(log(series)), main = "Time Series of Log First Difference")
hist(diff(log(series)), main = "Histogram of Log First Difference")
acf(diff(log(series)), main = "ACF of Log First Difference")
pacf(diff(log(series)), main = "PACF of Log First Difference")
```



We are reimporting the series and setting the frequency to 12. We suspect the seasonality occurs on a monthly basis and counted 24 trough to peak cycles, indicating a seasonal period of 12. As is generally good practice we will take the log of the series and take the first difference to render the series more stationary.

The time series plot of the differenced series resembles white noise. However, the ACF shows regular significance suggesting seasonal terms will be needed there. The PACF also shows seasonality although somewhat less as it decreases eventually. Both plots also show significance at the first lag suggesting non-seasonal terms will also be needed.

```r
#Function to find the best ARIMA model. Credit to Cowpertwait and Metcalfe.
get.best.arima.seas <- function(x.ts, maxord = c(1,1,1,1,1,1)) {
  best.aic <- 1e8
  n <- length(x.ts)
  for (p in 0:maxord[1]) for(d in 0:maxord[2]) for(q in 0:maxord[3])
    for (P in 0:maxord[4]) for(D in 0:maxord[5]) for(Q in maxord[6])
    {
      fit <- arima(x.ts, order = c(p, d, q), seas = list(order = c(P,D,Q), 12), method = "CSS")
      fit.aic <- -2 * fit$loglik + (log(n) + 1) * length(fit$coef)
      if (fit.aic < best.aic)
      {
        best.aic <- fit.aic
        best.fit <- fit
        best.model <- c(p, d, q, P, D, Q)
      }
    }
  list(best.aic, best.fit, best.model)
}

get.best.arima.seas(log(series), maxord = rep(3, 6))
```

```
## [[1]]
## [1] -811.9272
##
## [[2]]
##
## Call:
## arima(x = x.ts, order = c(p, d, q), seasonal = list(order = c(P, D, Q), 12),
##     method = "CSS")
##
## Coefficients:
##           ar1     ar2     ar3     ma1     ma2      ma3    sar1    sar2
##       -0.1864  0.1633  0.9602  0.8195  0.4838  -0.4573  0.6859  0.2926
## s.e.   0.0059  0.0021  0.0098  0.0081     NaN      NaN  0.0671  0.0702
##          sma1     sma2    sma3  intercept
##       -0.3415  -0.3488  0.0524    11.1926
## s.e.   0.0862   0.0749  0.0606     2.0218
##
## sigma^2 estimated as 0.002562:  part log likelihood = 445.88
##
## [[3]]
## [1] 3 0 3 2 0 3
```

```
auto.arima(log(series), d = 1, D = 1) #note specified the use of seasonality
```

```
## Series: log(series)
## ARIMA(2,1,0)(2,1,2)[12]
##
## Coefficients:
##           ar1      ar2    sar1     sar2     sma1    sma2
##       -0.3788  -0.2638  0.5919  -0.2884  -1.2183  0.4125
## s.e.   0.0620   0.0601  0.2195   0.0892   0.2195  0.1862
##
## sigma^2 estimated as 0.003037:  log likelihood=396.79
## AIC=-779.57   AICc=-779.15   BIC=-754.33
```

```
#get.best -> (3, 0, 3) (2, 0, 3) [12]
#auto -> (2, 1, 0) (2, 1, 2) [12]

mod <- auto.arima(log(series), d = 1, D = 1)
mod2 <- arima(log(series), order = c(3, 0, 3), seasonal = list(order = c(2, 0, 3), 12))
mod
```

```
## Series: log(series)
## ARIMA(2,1,0)(2,1,2)[12]
##
## Coefficients:
##           ar1      ar2    sar1     sar2     sma1    sma2
##       -0.3788  -0.2638  0.5919  -0.2884  -1.2183  0.4125
## s.e.   0.0620   0.0601  0.2195   0.0892   0.2195  0.1862
##
## sigma^2 estimated as 0.003037:  log likelihood=396.79
## AIC=-779.57   AICc=-779.15   BIC=-754.33
```

```r
mod2
```

```
##
## Call:
## arima(x = log(series), order = c(3, 0, 3), seasonal = list(order = c(2, 0, 3),
##     12))
##
## Coefficients:
##           ar1     ar2     ar3     ma1     ma2      ma3    sar1    sar2
##       -0.1859  0.1848  0.9720  0.8376  0.4928  -0.4074  0.8325  0.1519
## s.e.   0.0131  0.0126  0.0124  0.0598  0.0755   0.0587  0.6131  0.6077
##          sma1     sma2    sma3  intercept
##       -0.5152  -0.2522  0.0995    11.1842
## s.e.   0.6123   0.3912  0.1020     1.5779
##
## sigma^2 estimated as 0.002691:  log likelihood = 421.43,  aic = -816.86
```

We utilized both the auto.arima() function and the get.best.arima.seas() function (from the time series textbook) to acquire suggested model fits. However, we know the model should include a first difference and a seasonal difference from our previous investigation. Otherwise the model will not be stationary, and we will be unable to fit a model to it. The auto.arima() model's AIC is slightly higher -779.5714051 versus -816.8591981, but we believe that the model suggested by auto arima will better satisfy our assumptions. Therefore, we will investigate this model going forward.

```r
#Model comparisons
t(confint(mod))
```

```
##                ar1        ar2      sar1       sar2       sma1       sma2
## 2.5 %  -0.5003736 -0.3816227 0.1616603 -0.4632530 -1.6484367 0.04750577
## 97.5 % -0.2572684 -0.1459414 1.0222092 -0.1134823 -0.7882052 0.77746222
```

```r
#Base comparison model is (2, 1, 0)(2, 1, 2)[12] with AIC -779.5714
mod3 <- arima(log(series), order = c(3, 1, 0), seasonal = list(order = c(2, 1, 2), 12))
mod4 <- arima(log(series), order = c(2, 1, 1), seasonal = list(order = c(2, 1, 2), 12))
mod5 <- arima(log(series), order = c(2, 1, 0), seasonal = list(order = c(3, 1, 2), 12))
mod6 <- arima(log(series), order = c(2, 1, 0), seasonal = list(order = c(2, 1, 3), 12))
AIC(mod3)
```

```
## [1] -778.6494
```

```r
AIC(mod4)
```

```
## [1] -779.2913
```

```r
AIC(mod5)
```

```
## [1] -775.8237
```

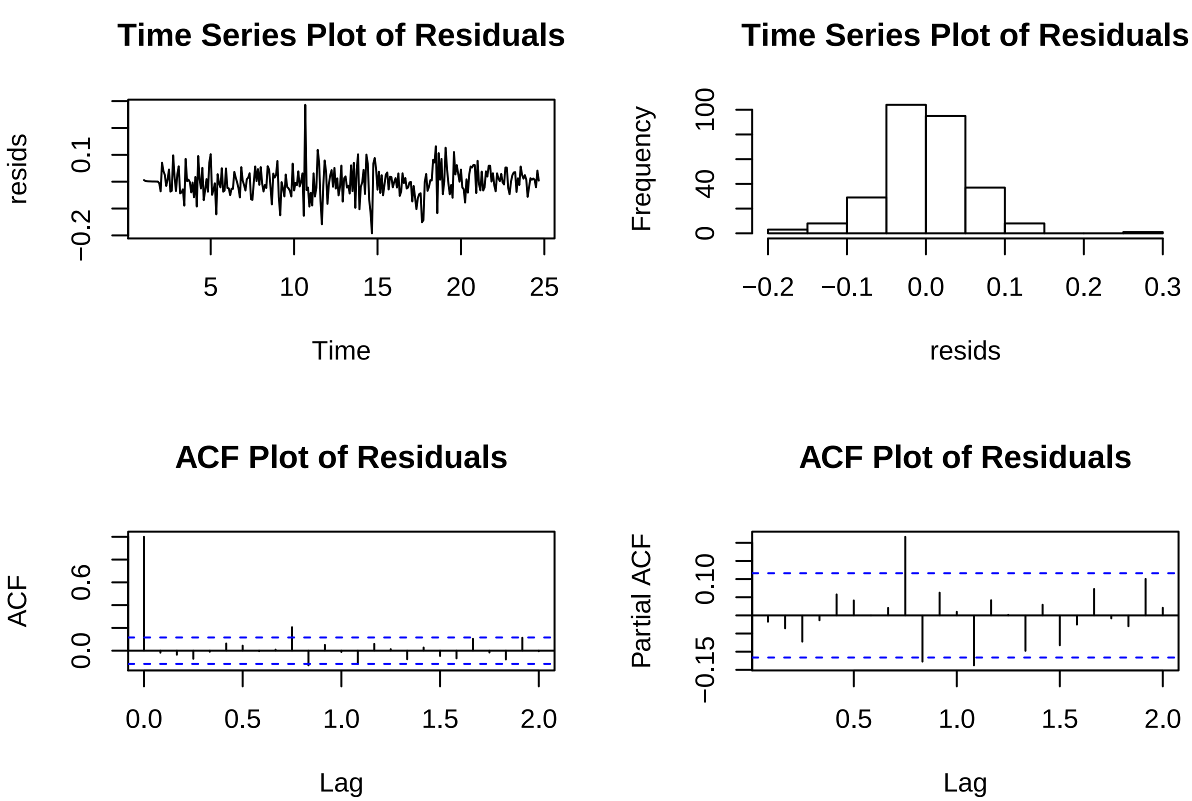
```r
AIC(mod6)
```

```
## [1] -774.8587
```

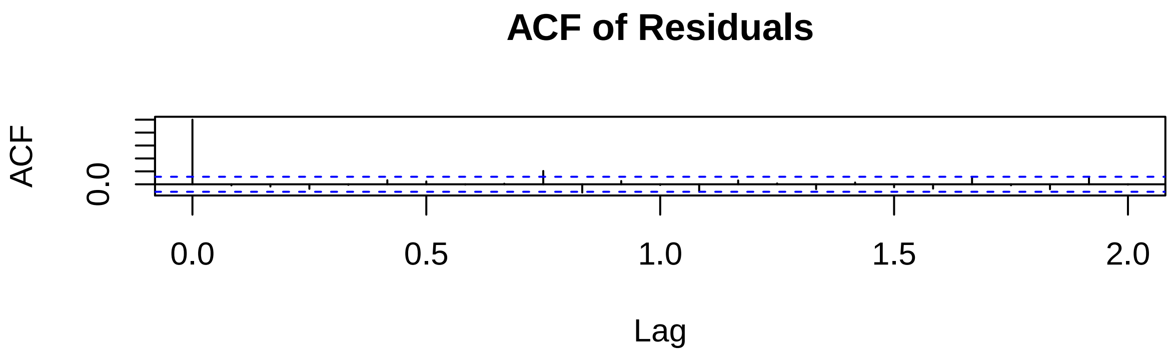
Note that 0 is not contained in the confidence intervals of any of the terms for our model, which is currently ARIMA(2, 1, 0)(2, 1, 2)[12]. This means that we reject the null hypothesis and conclude that the evidence supports the alternative hypothesis that our model coefficients are different from 0. Further, above we have deliberately attempted to overfit our data by providing additional parameters. In all cases the AIC increases, suggesting that these models do not do a better job of explaining our data simply. In general, one wants a model that minimizes the AIC.

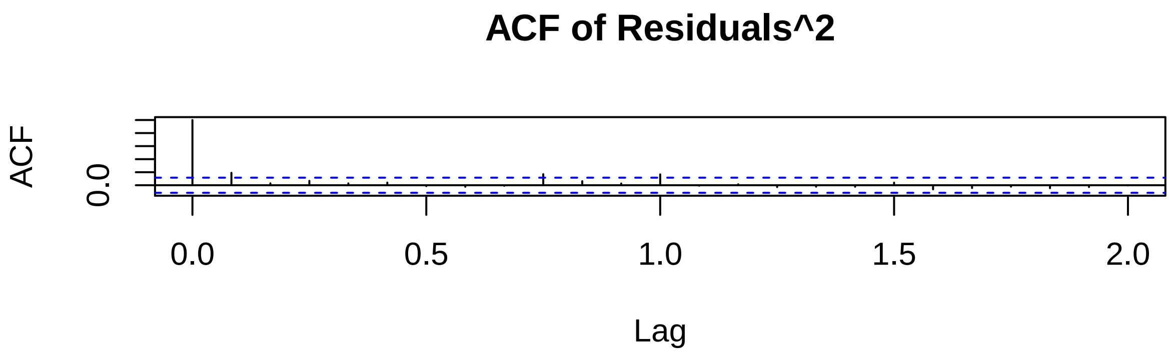
Therefore, we will continue with residual diagnostics for our chosen model:

```r
#Examine model residuals
par(mfrow = c(2,2))
resids <- mod$residuals
plot.ts(resids, main = "Time Series Plot of Residuals")
hist(resids, main = "Time Series Plot of Residuals")
acf(resids, main = "ACF Plot of Residuals")
pacf(resids, main = "ACF Plot of Residuals")
```




```r
par(mfrow = c(2, 1))
acf(resids, main = "ACF of Residuals")
acf(resids^2, main = "ACF of Residuals^2")
```






```r
Box.test(resids, type = "Ljung-Box")
```

```
##
##  Box-Ljung test
##
## data:  resids
## X-squared = 0.087567, df = 1, p-value = 0.7673
```

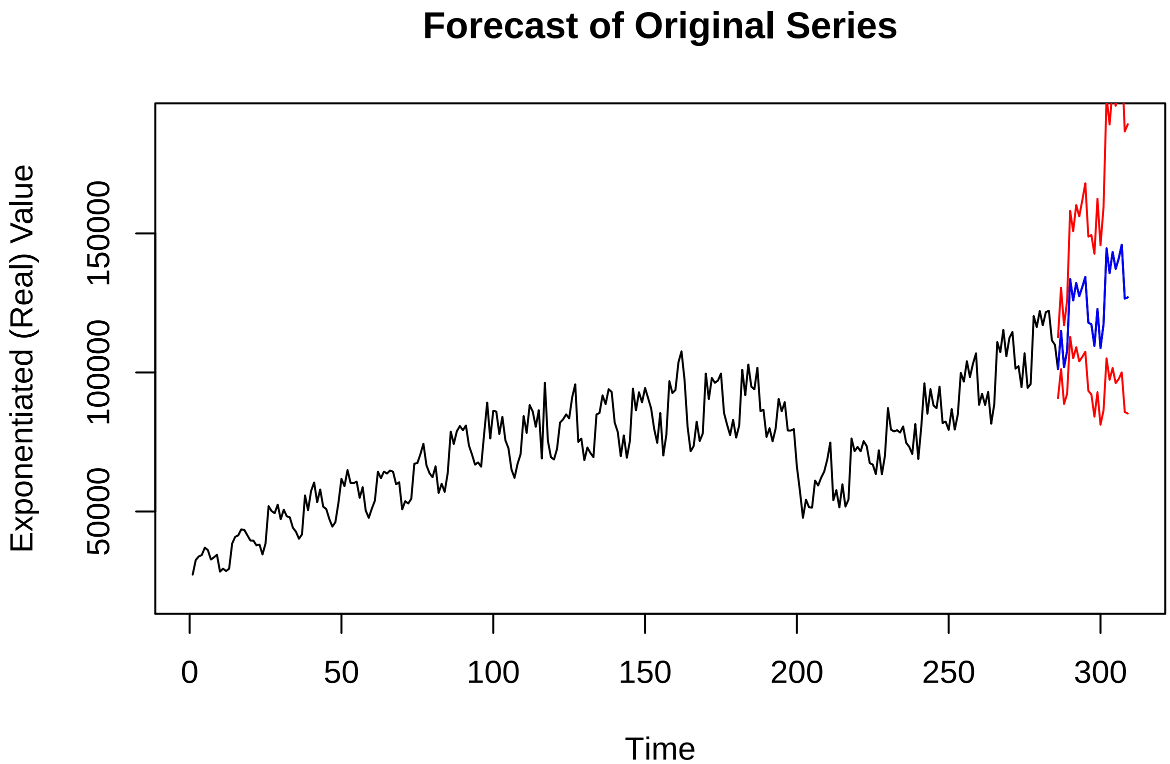
Overall, the residuals appear to largely resemble white noise. The time series plot looks fairly like white noise, with no obvious patterns suggesting seasonality or a trend. There is one large spike, which we would need to know more about this data to properly try to account for. This was noted in the time series plot of the original data. The ACF shows one significant term at around 3/4 and the PACF shows two significant terms around the same area. However, there are no highly significant terms in the early part of the model (beyond the expected term of the ACF) and there is no repeating pattern of terms that are significant. Further, the residuals fail to reject the null hypothesis of the Ljung-Box test, meaning that the evidence suggests the observations are independent. There are some terms that are significant in the residual squared ACF, but none are highly significant and as there are only three, this does not represent a large enough number to suggest our residuals are behaving other than white noise.

We will note here that the residuals do not perfectly resemble white noise. There are still several lags showing statistical significant, which is not what we would want to see. However, we believe that we have fit the best possible model with the available information that we have. We would like to know more about the data and sampling methods to be able to fit the most appropriate possible model. We do however believe that we have satistified the conditions of stationarity and residuals behaving as white noise sufficiently to be able to forecast.

```r
preds <- forecast(mod, h = 24)

cbind(exp(preds$lower[,2]), exp(preds$mean), exp(preds$upper[,2]))
```

```
##        exp(preds$lower[, 2]) exp(preds$mean) exp(preds$upper[, 2])
## Oct 24              90775.86        101129.7              112664.4
## Nov 24             101196.08        114917.2              130498.9
## Dec 24              88706.19        101851.3              116944.2
## Jan 25              92278.71        107730.5              125769.7
## Feb 25             112843.37        133594.9              158162.5
## Mar 25             105095.66        125894.4              150809.2
## Apr 25             109064.58        132183.1              160202.0
## May 25             103982.17        127423.5              156149.2
## Jun 25             105605.76        130754.3              161891.6
## Jul 25             107464.20        134377.2              168030.2
## Aug 25              93413.05        117920.8              148858.3
## Sep 25              92079.99        117300.2              149428.1
## Oct 25              84114.30        109561.5              142707.2
## Nov 25              92911.16        122869.7              162488.2
## Dec 25              81203.66        108784.0              145731.8
## Jan 26              86415.40        117407.7              159515.3
## Feb 26             105062.60        144638.6              199122.5
## Mar 26              97389.68        135741.1              189195.2
## Apr 26             101601.04        143333.0              202206.2
## May 26              96168.30        137264.1              195921.4
## Jun 26              97658.32        140970.3              203491.4
## Jul 26             100016.30        145963.3              213018.0
## Aug 26              85810.67        126572.0              186695.5
## Sep 26              85226.66        127019.1              189305.3
```

```
plot.ts(c(series, exp(preds$mean)), ylim = c(20000, 190000), xlab = "Time", ylab = "Exponentiated (Real
lines(c(rep(NA, 285), exp(preds$mean)), col = "blue")
lines(c(rep(NA, 285), exp(preds$lower[,2])), col = "red")
lines(c(rep(NA, 285), exp(preds$upper[,2])), col = "red")
```



Again the blue value is the mean prediction while the red represent 95% confidence intervals. Notice the upper limit really takes off, which is probably in part due to the general rising trend. The mean predictions actually look very logically like what might be expected from this series.

NOTES SECTION AND APPENDIX:

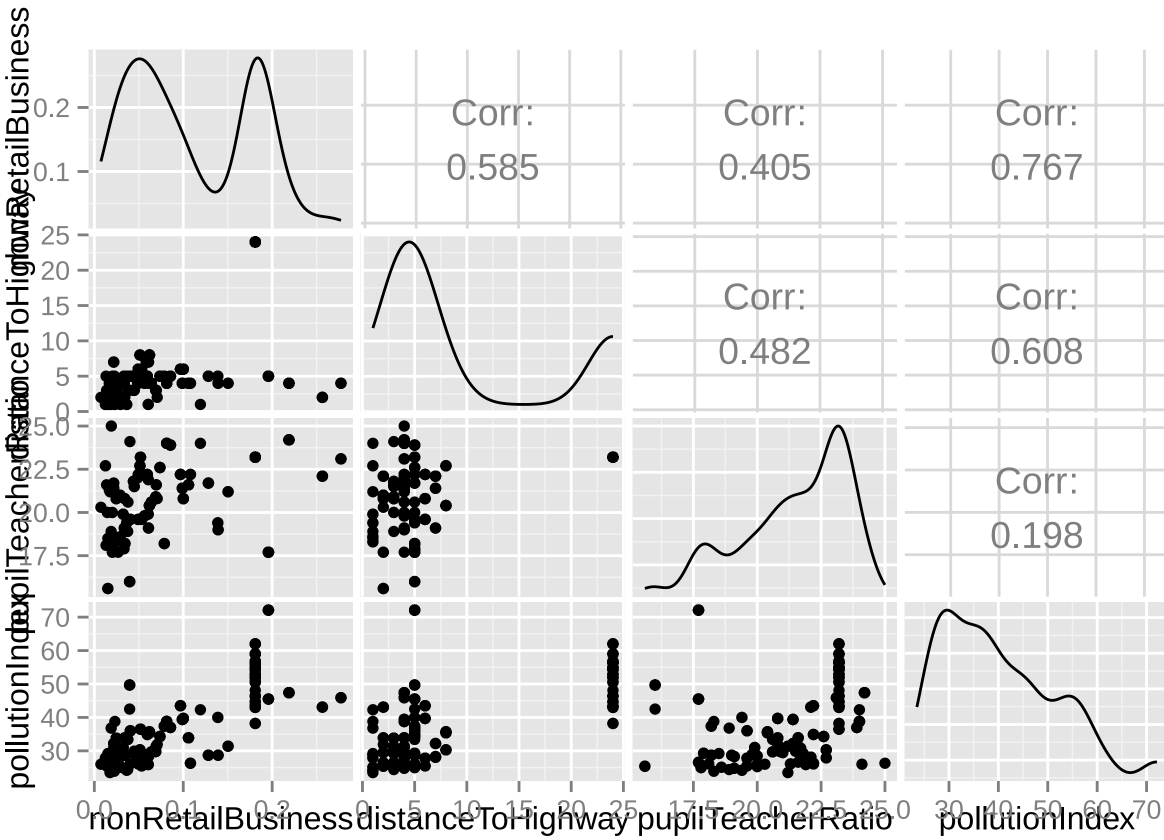
probably can be ultimately deleted.

I did the following to see if the issue was the variables or the records before I found the scope of the problem. Tossing all the records is too much, but I didnt want to delete this yet.

With the identification of variables that seem to strongly correlate, I want to do a couple of scatterplot matrices.

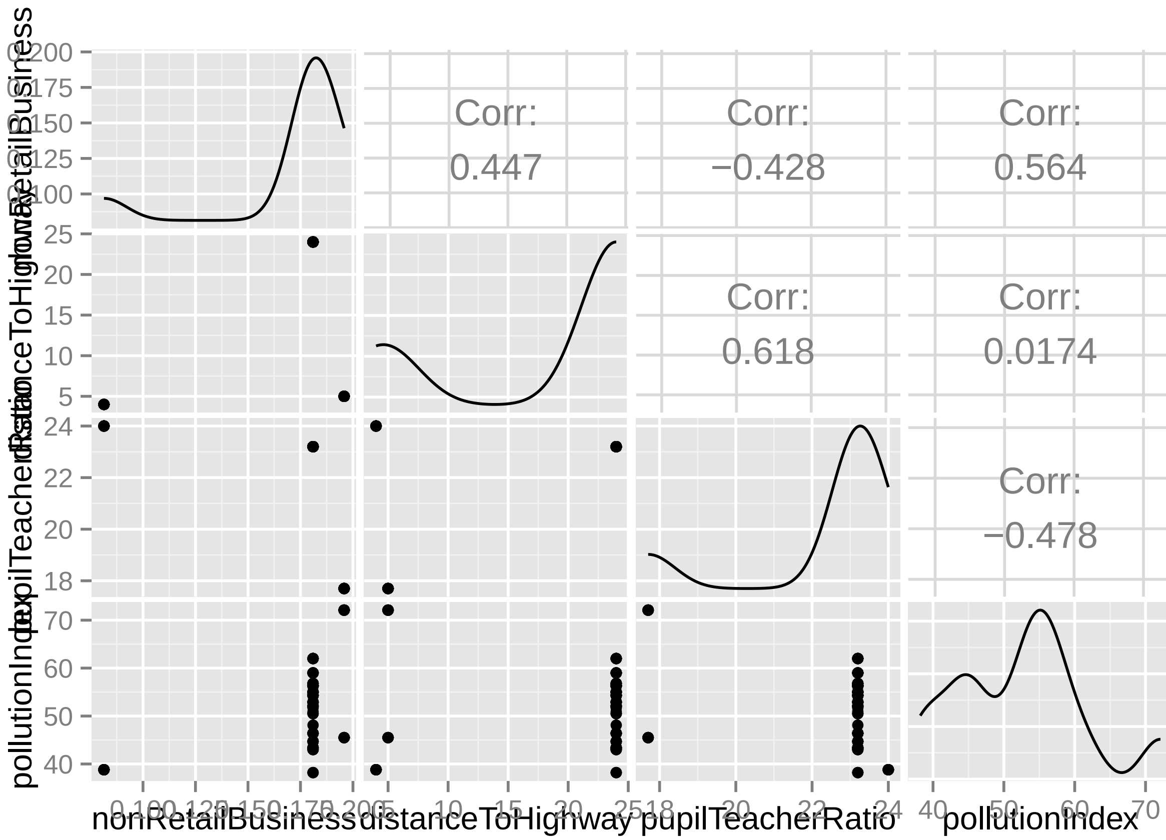
I will start with the first four identified.

```
data3 = data[,c("nonRetailBusiness","distanceToHighway","pupilTeacherRatio","pollutionIndex")]
ggpairs(data3)
```



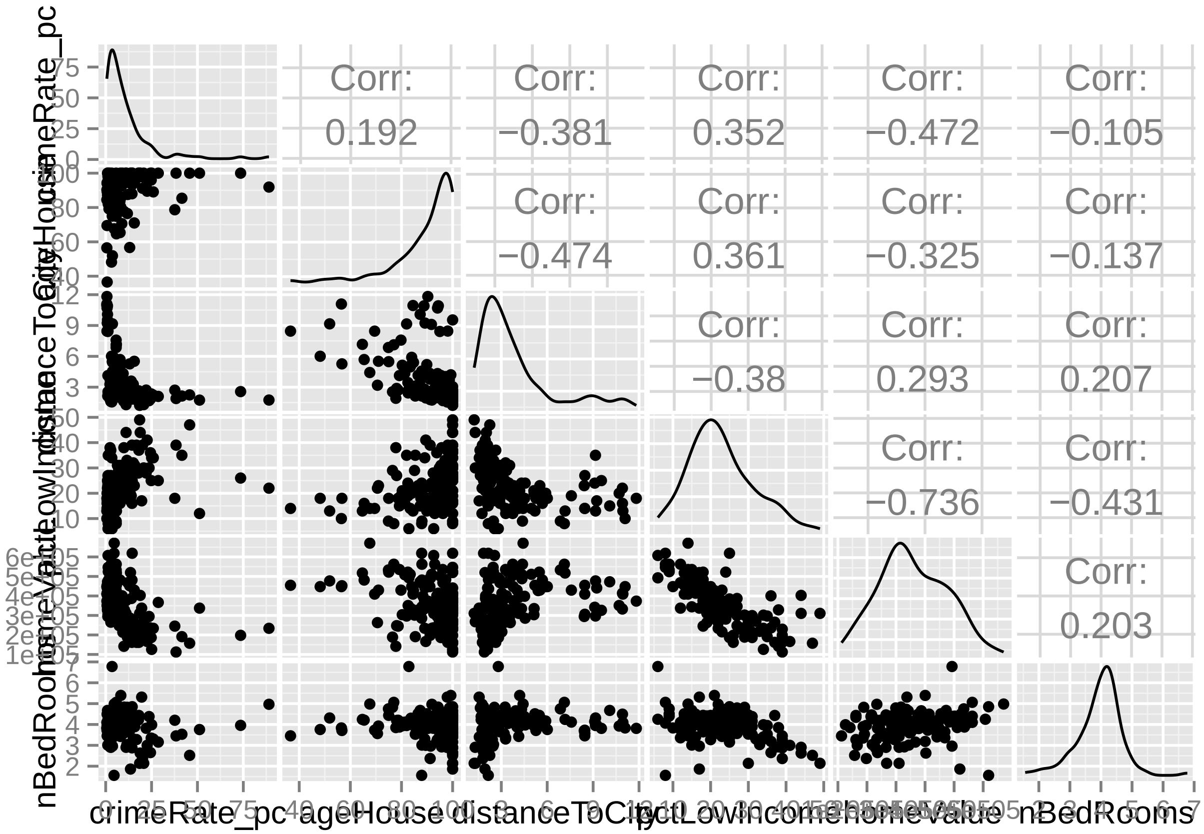
Surprisingly, there is not a super strong correlation between the variables (except between Non Retail Business and pollutionindex). Perhaps the problem is with those records then and not the variables themselves. Another subset will be created will just those 144 records first identified and anoother scatterplot matrix created.

```
data2 = data[,c("nonRetailBusiness","distanceToHighway","pupilTeacherRatio","pollutionIndex")]
data3 = subset(data2, nonRetailBusiness==.181|nonRetailBusiness==.1958|nonRetailBusiness==.0814 )
ggpairs(data3)
```



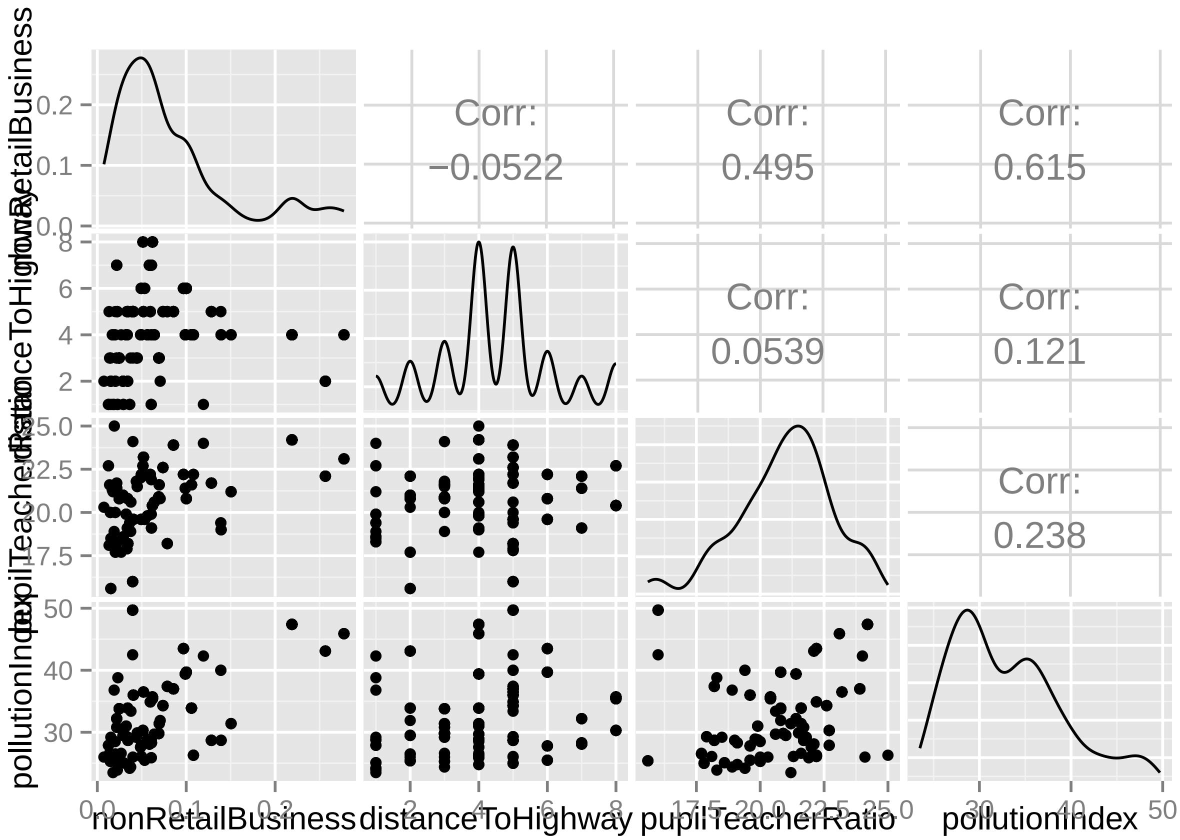
There is far too much colinearity with these records for comfort. I want to examine these 144 records in a scatterplot matrix with the other variables selected.

```
data2 = subset(data, nonRetailBusiness==.181|nonRetailBusiness==.1958|nonRetailBusiness==.0814 )
data3 = data2[,c("crimeRate_pc","ageHouse","distanceToCity","pctLowIncome","homeValue","nBedRooms")]
ggpairs(data3)
```

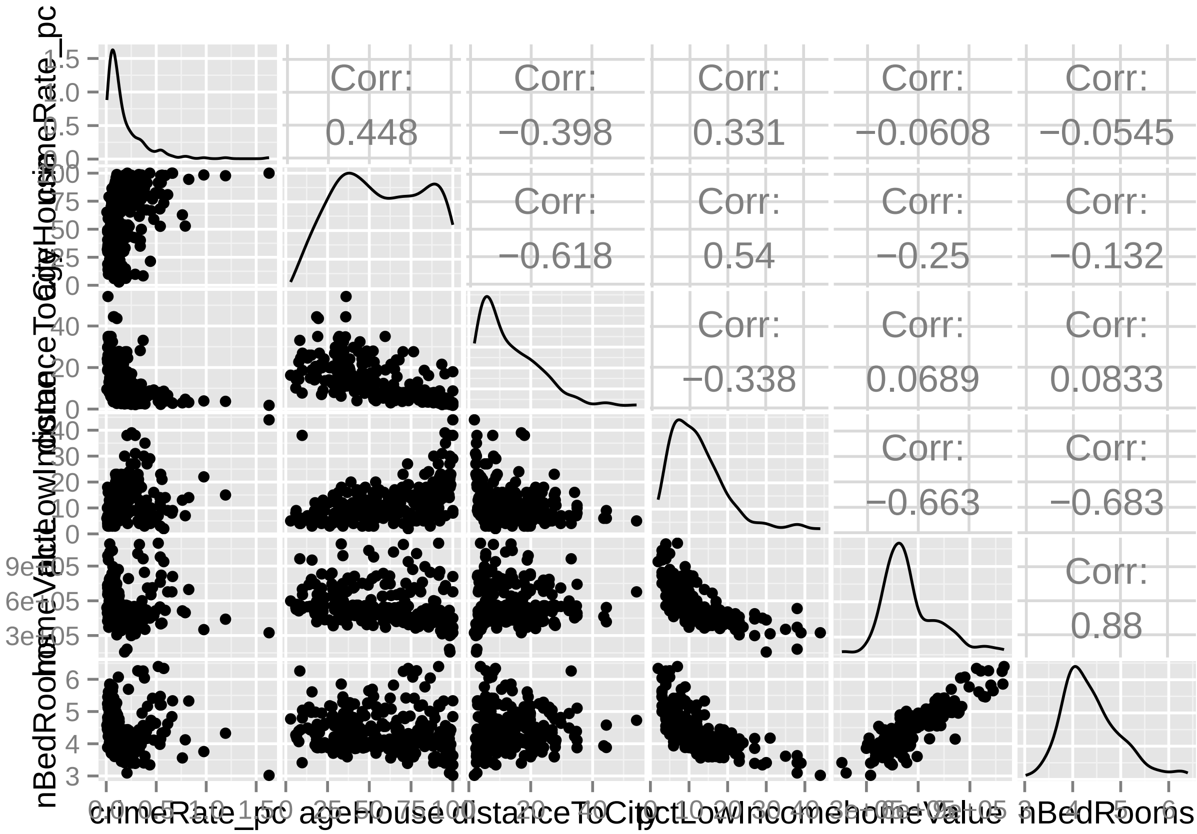


The matrix here causes me no concern. I am still unsure of whether or records or the variables are the problem here, so I will use the other 256 records and do the same two matrices.

```
data2 = data[,c("nonRetailBusiness","distanceToHighway","pupilTeacherRatio","pollutionIndex")]
data3 = subset(data2, nonRetailBusiness!=.181&nonRetailBusiness!=.1958&nonRetailBusiness!=.0814 )
ggpairs(data3)
```




```r
data2 = subset(data, nonRetailBusiness!=.181&nonRetailBusiness!=.1958&nonRetailBusiness!=.0814 )
data3 = data2[,c("crimeRate_pc","ageHouse","distanceToCity","pctLowIncome","homeValue","nBedRooms")]
ggpairs(data3)
```



After all the examination of the variables and records, I have decided that the problem is with those 144 records. I will create a new subset of the remaining 256 and continue to use all variables.

```
data = subset(data, nonRetailBusiness!=.181&nonRetailBusiness!=.1958&nonRetailBusiness!=.0814 )
```
