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Introduction

The purpose of this analysis is to review a set crime data in support of understanding determinants of crime and generating policy recommendations for local governments for this political campaign. This analysis is based on a set of county-level data from North Carolina from 1987. However, this data set is not inclusive of all North Carolina counties.

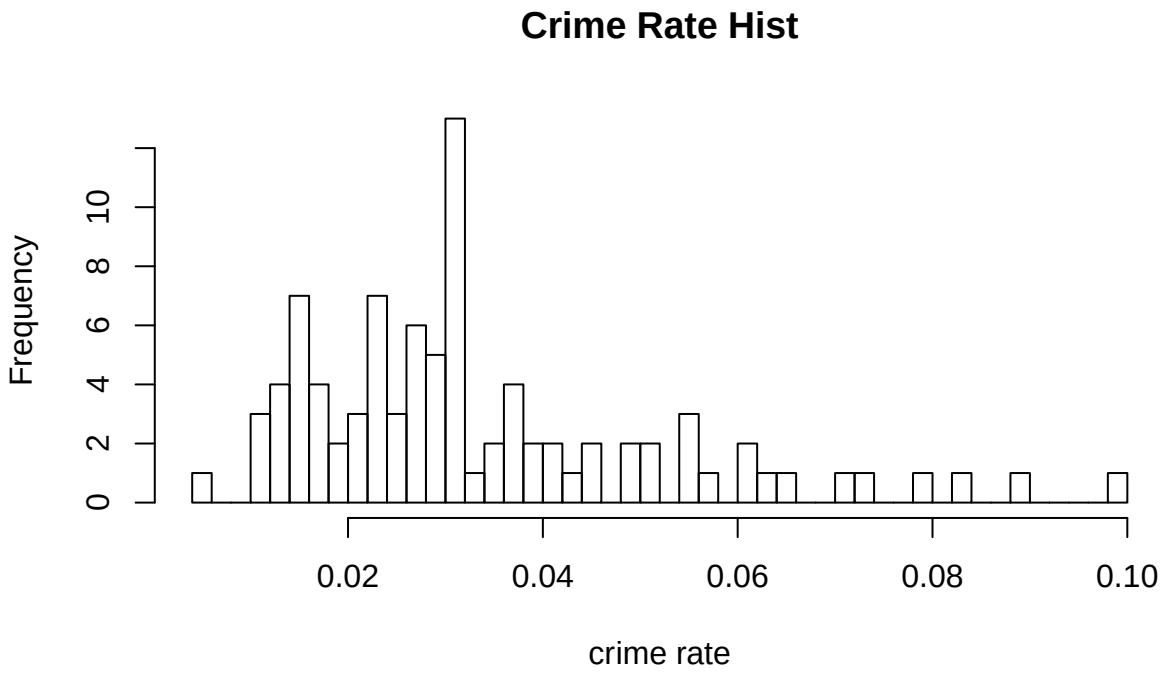
In our first stage, an exploratory data analysis was undertaken in order to better understand the data set, the variables, anomolies, and any variable transformations that may need to be done to provide a robust set of models. We also examined the relationships between variables from a variety of perspectives to support model building. Our second stage consisted of building and analyzing a set of linear models to determine the right mix of signficant explanatory variables, to identify best fit models, and to test all CLM assumptions. We use a backwards approach to model construction, meaning we first build a model that includes all the data we are given then remove the data with the least explanatory power.

Following that, we then explain why the information for the variables removed is already incorporated into the model and thus why it is excluded from the final model. We address bias, omitted variables, parsimony, and discussion of causality here. We conclude this paper with high-level set of recommendations and related notes.

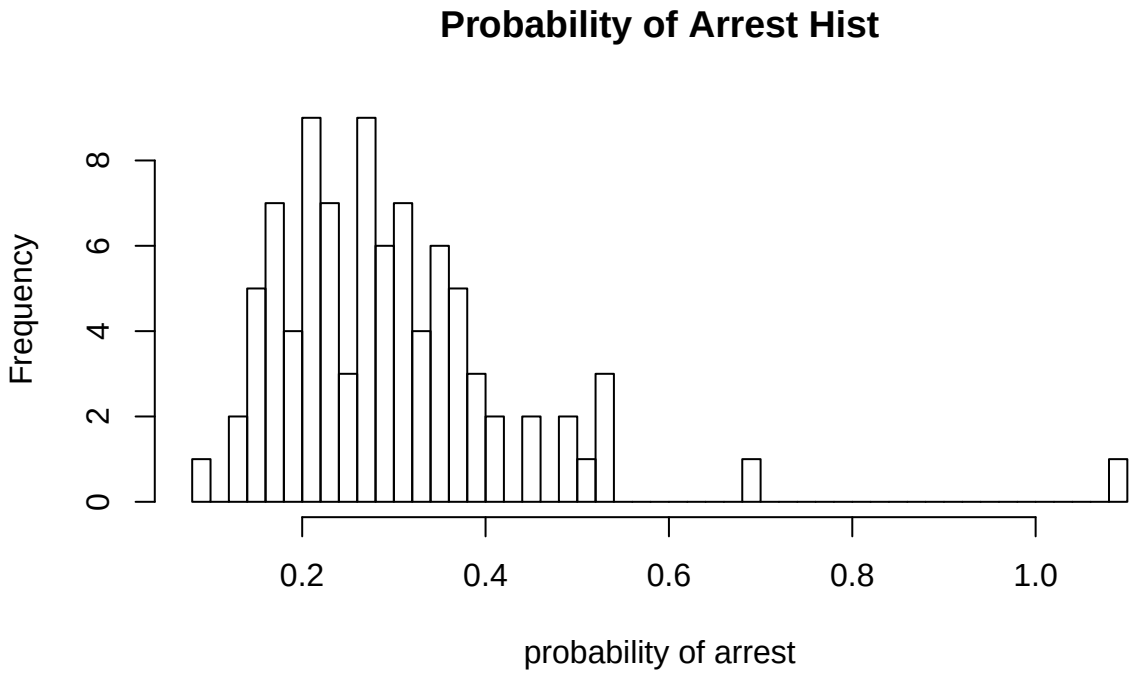
Exploratory Analysis

A thorough exploratory analysis of the crimes data set was to better understand the data set, the variables, anomolies, and any variable transformations that may need to be done to provide a robust set of models. Outlier data was reviewed for significance and possible patterns. We also examined the relationships between variables from a variety of perspectives to support model building. Histograms were run on all variables to understand their distributions. A select set for our key variables (crmrte, prbarr, prbconv, polpc, pctmin80) is provided here.

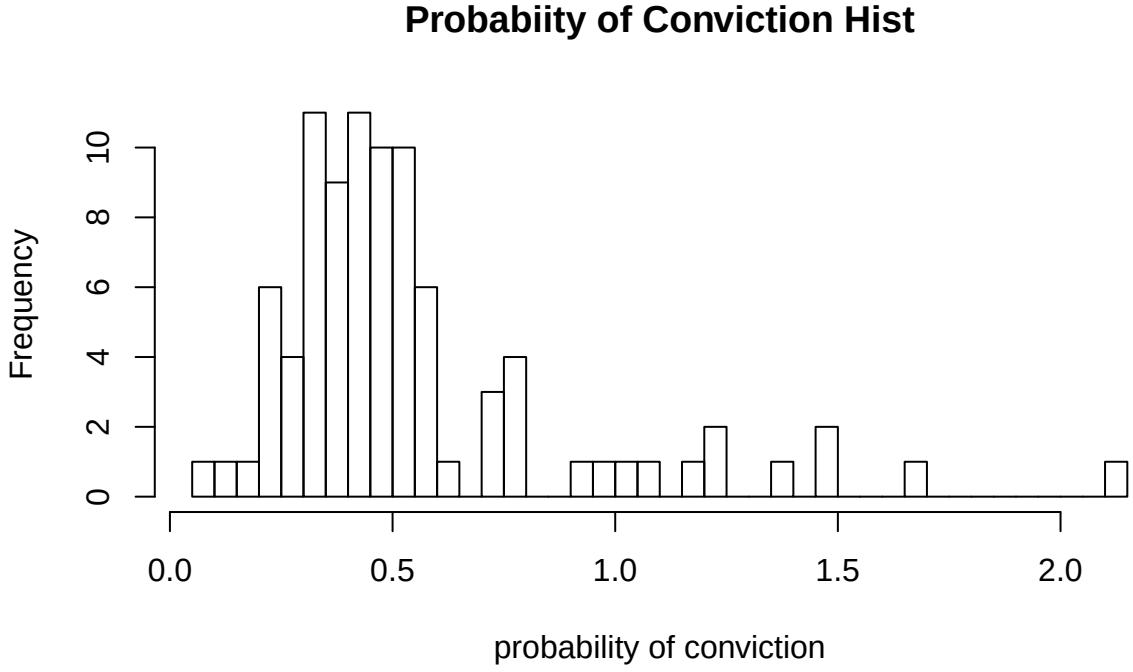
```
hist(crime$crmrte, breaks = 50, xlab = "crime rate", ylab = "Frequency", main = "Crime Rate Hist")
```



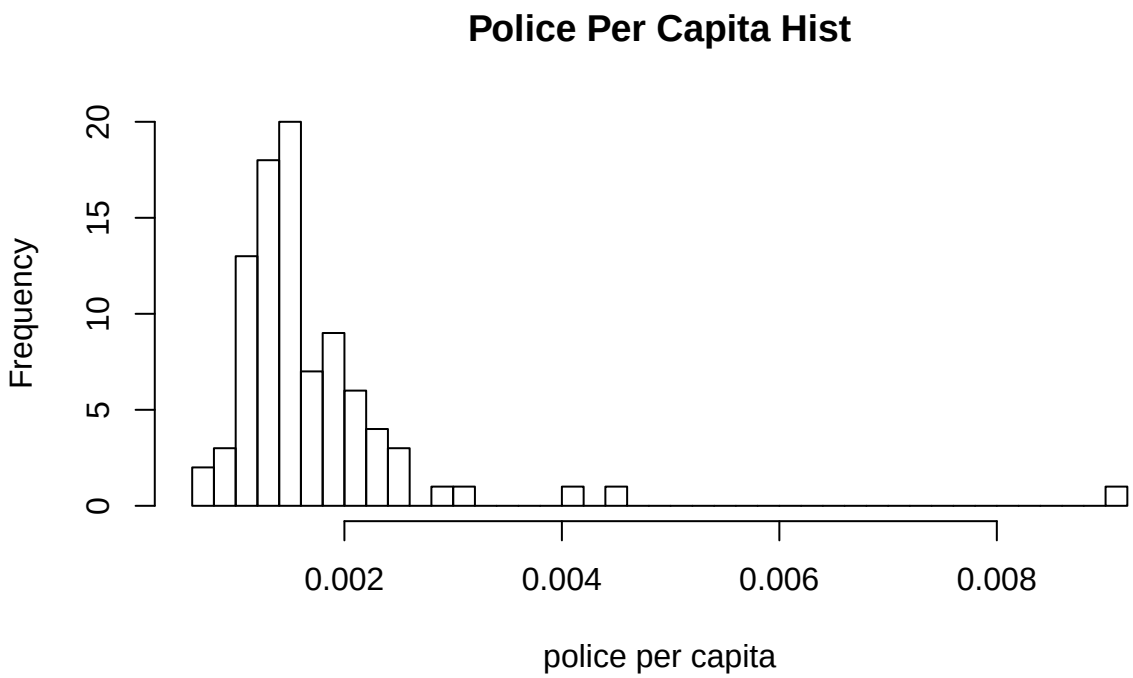

```
hist(crime$prbarr, breaks = 50, xlab = "probability of arrest", ylab = "Frequency", main = "Probability
```



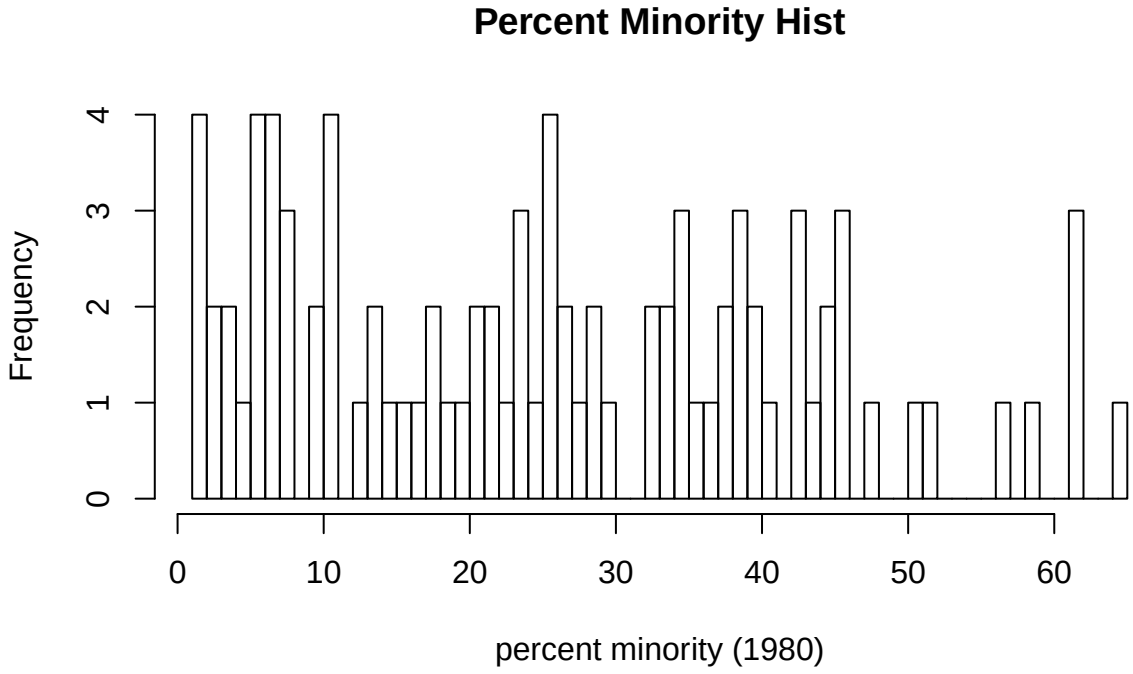

```
hist(crime$prbconv, breaks = 50, xlab = "probability of conviction", ylab = "Frequency", main = "Probabi
```




```
hist(crime$polpc, breaks = 50, xlab = "police per capita", ylab = "Frequency", main = "Police Per Capita
```

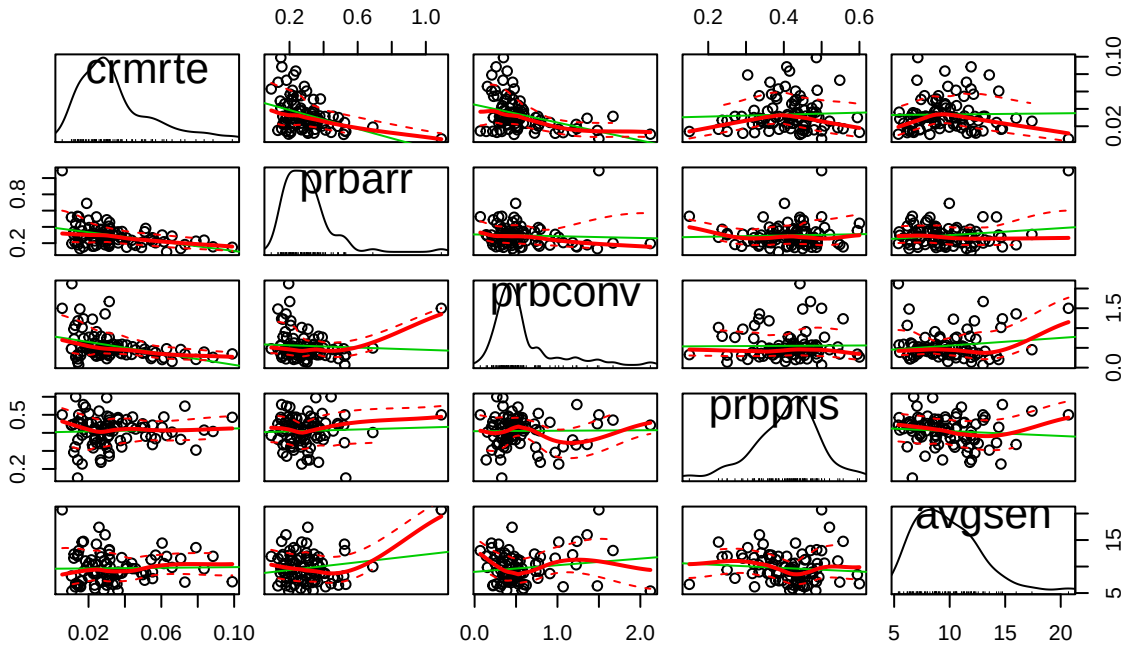



```
hist(crime$pctmin80, breaks = 50, xlab = "percent minority (1980)", ylab = "Frequency", main = "Percent
```

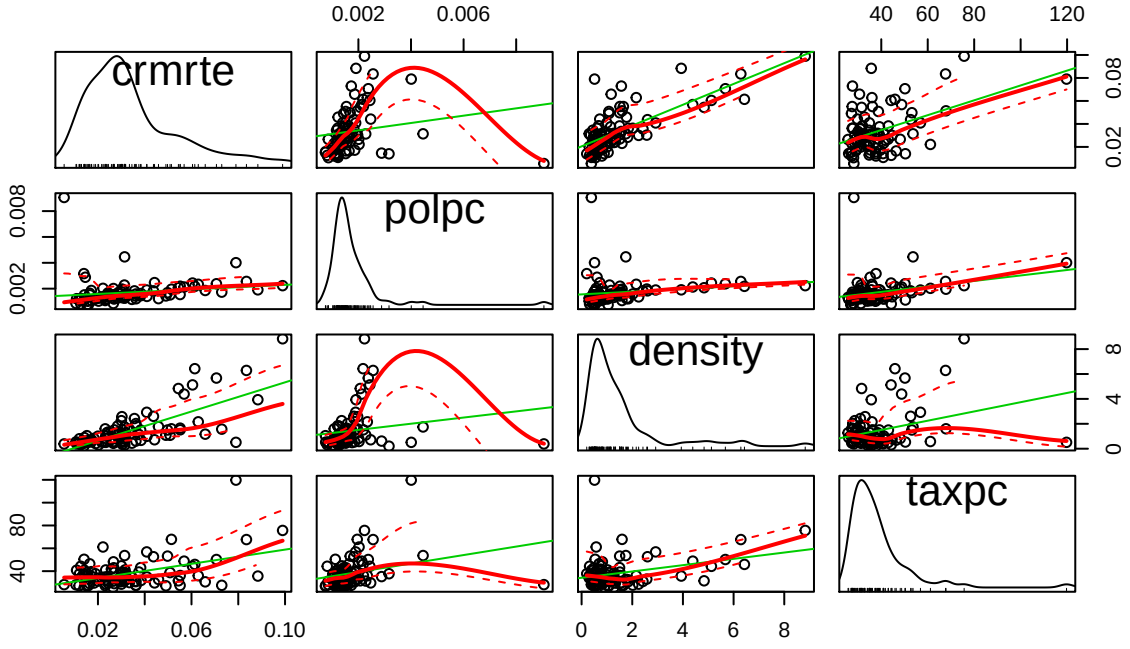


Scatterplot matrices were developed for several variables to get an initial understanding of variable relationships.

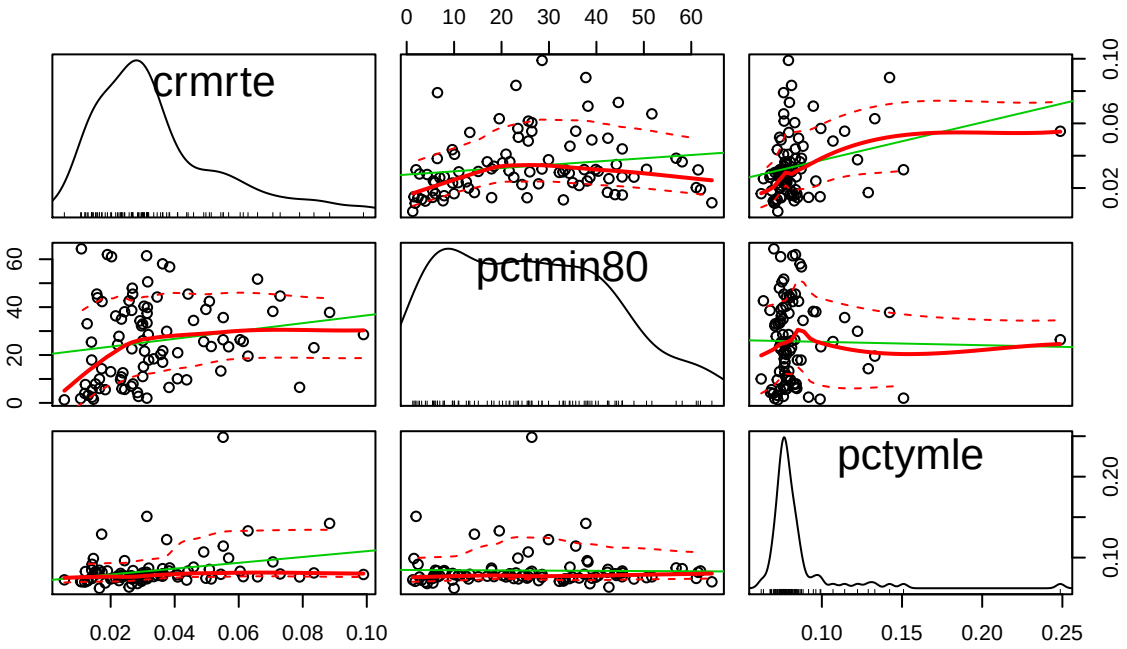
```
scatterplotMatrix(~crmrte + prbarr + prbconv + prbpris + avgsen, data=crime)
```



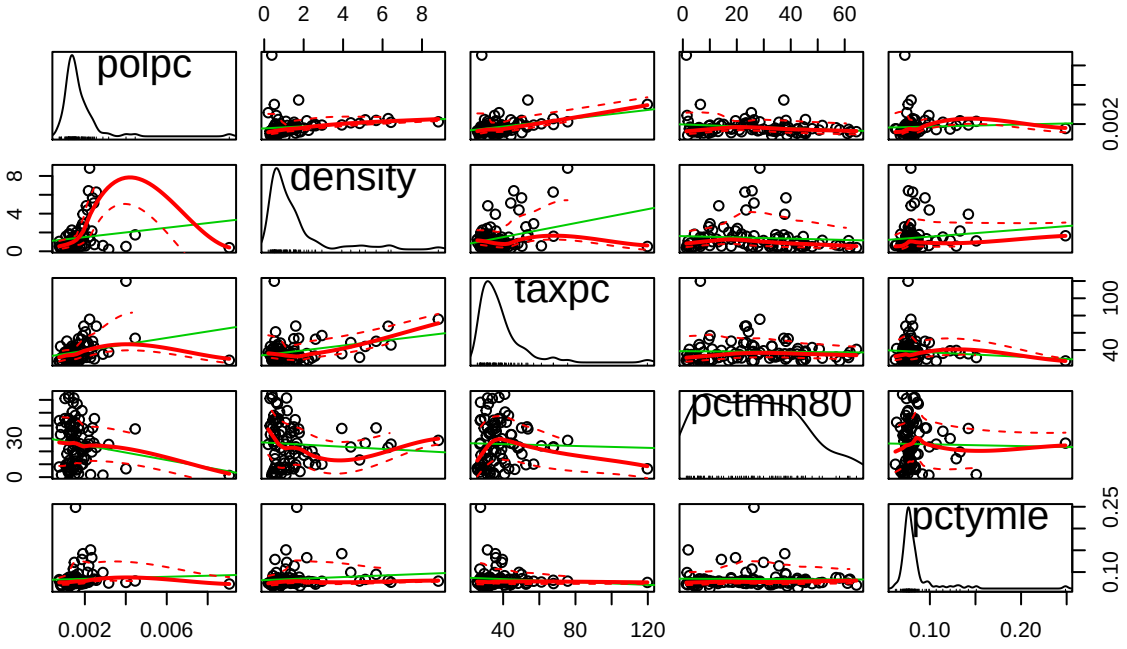

```
scatterplotMatrix(~crmrte + polpc + density + taxpc, data=crime)
```




```
scatterplotMatrix(~crmrte + pctmin80 + pctymle, data=crime)
```




```
scatterplotMatrix(~polpc + density + taxpc + pctmin80 + pctymle, data=crime)
```



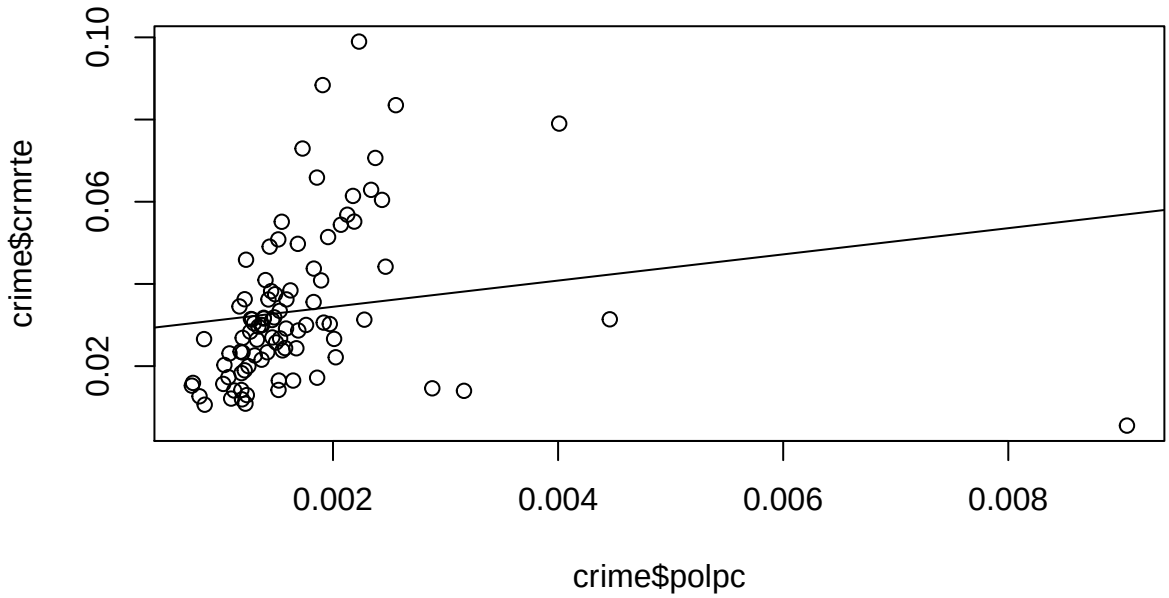
Finally, we added to this by analyzing bivariate and multivariate relationships between a number of variables and combinations of variables. We looked at the R squared values, adjusted R squared values, p values, and correlation values for significance. Several of these are included below.

```
plot(crime$polpc, crime$crmrte)
model3 <- lm(crmrte~polpc, data = crime)
model3
```

```
Call:
lm(formula = crmrte ~ polpc, data = crime)
```

```
Coefficients:
(Intercept)        polpc
    0.02806      3.18839
```

```
abline(model3)
```




```
summary(model3)
```

```

Call:
lm(formula = crmrte ~ polpc, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.051400 -0.011799 -0.003837  0.006455  0.063787

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.02806    0.00395   7.105 2.99e-10 ***
polpc        3.18839    2.00318   1.592    0.115
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01873 on 88 degrees of freedom
Multiple R-squared:  0.02798,   Adjusted R-squared:  0.01694
F-statistic: 2.533 on 1 and 88 DF,  p-value: 0.115
```

```
cor(crime$crmrte, crime$polpc, use="pairwise.complete.obs")
```

```
[1] 0.1672816
```

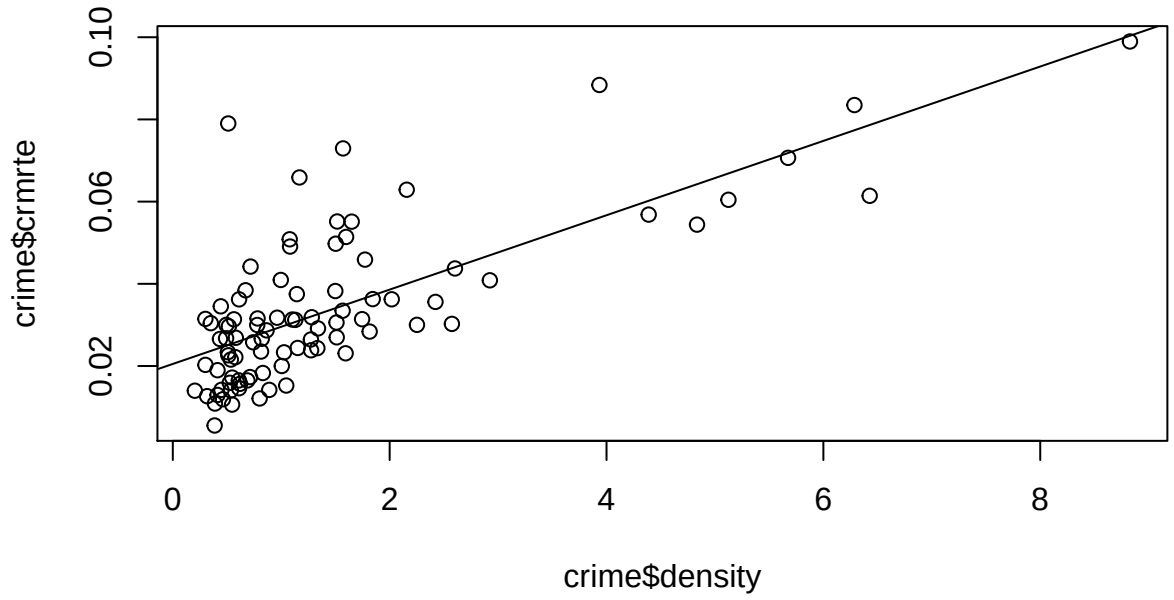
```
plot(crime$density, crime$crmrte)
model4 <- lm(crmrte~density, data = crime)
model4
```

```

Call:
lm(formula = crmrte ~ density, data = crime)
```

```
Coefficients:
(Intercept)      density
   0.020503     0.009046
```

```
abline(model4)
```




```
summary(model4)
```

```
Call:
lm(formula = crmrte ~ density, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.018459 -0.009471 -0.002741  0.004902  0.053887

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0205027  0.0018954  10.817  < 2e-16 ***
density     0.0090458  0.0009087   9.955 4.45e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01303 on 88 degrees of freedom
Multiple R-squared:  0.5297,    Adjusted R-squared:  0.5243
F-statistic:  99.1 on 1 and 88 DF,  p-value: 4.45e-16
```

```
cor(crime$crmrte, crime$density, use="pairwise.complete.obs")
```

```
[1] 0.7277783
```

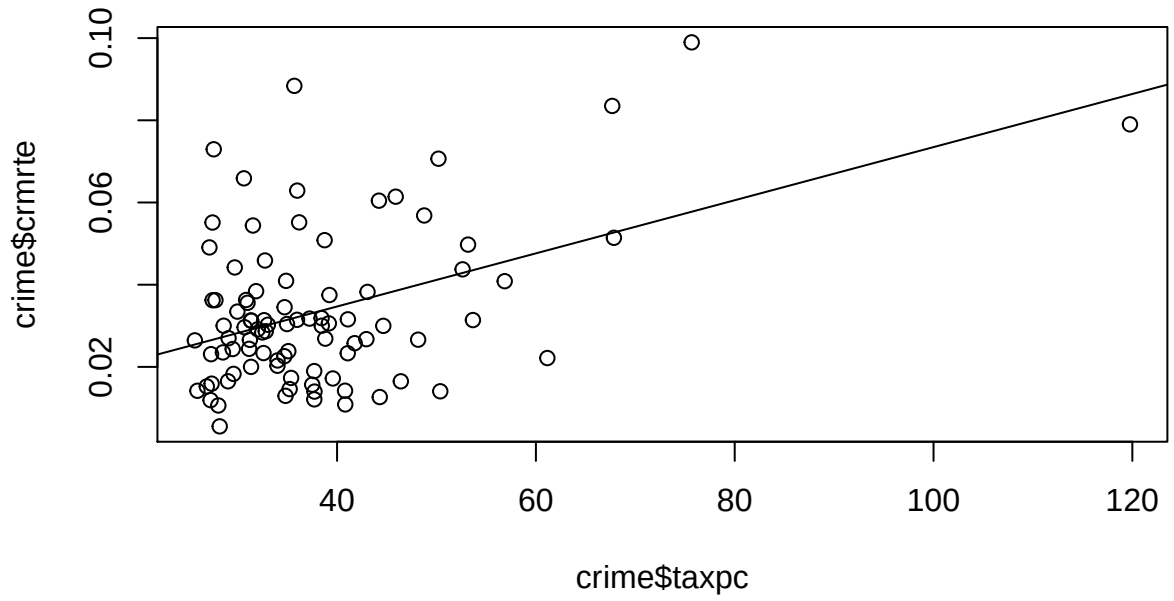
```
plot(crime$taxpc, crime$crmrte)
model5 <- lm(crmrte~taxpc, data = crime)
model5
```

```
Call:
```

```
lm(formula = crmrte ~ taxpc, data = crime)

Coefficients:
(Intercept)        taxpc
  0.0088444    0.0006464
```

```
abline(model5)
```




```
summary(model5)
```

```
Call:
lm(formula = crmrte ~ taxpc, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.027343 -0.010886 -0.002133  0.006679  0.056466

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0088444  0.0055339   1.598    0.114
taxpc       0.0006464  0.0001372   4.710 9.18e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01697 on 88 degrees of freedom
Multiple R-squared:  0.2013,    Adjusted R-squared:  0.1923
F-statistic: 22.19 on 1 and 88 DF,  p-value: 9.181e-06
```

```
cor(crime$crmrte, crime$taxpc, use="pairwise.complete.obs")
```

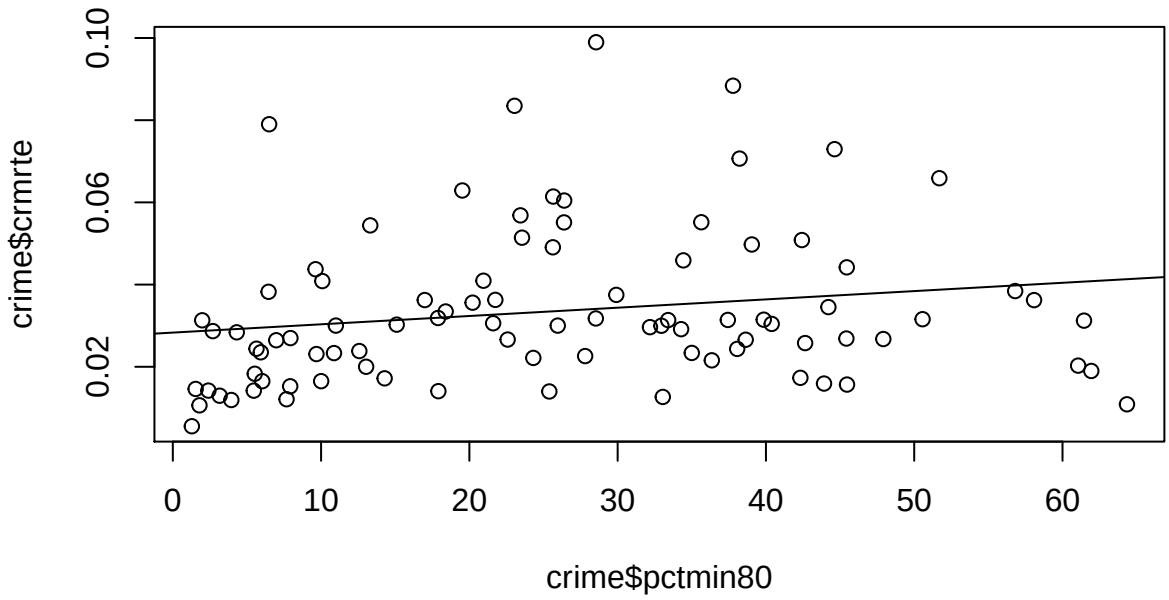
```
[1] 0.4487151
```

```
plot(crime$pctmin80, crime$crmrte)
model6 <- lm(crmrte~pctmin80, data = crime)
model6
```

```
Call:
lm(formula = crmrte ~ pctmin80, data = crime)

Coefficients:
(Intercept)     pctmin80
   0.028316     0.000202
```

```
abline(model6)
```




```
summary(model6)
```

```
Call:
lm(formula = crmrte ~ pctmin80, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.030444 -0.011928 -0.004692  0.007969  0.064884

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0283161  0.0035861   7.896 7.55e-12 ***
pctmin80    0.0002020  0.0001166   1.733   0.0866 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01868 on 88 degrees of freedom
Multiple R-squared:  0.033, Adjusted R-squared:  0.02201
F-statistic: 3.003 on 1 and 88 DF,  p-value: 0.08662
```

```
cor(crime$crmrte, crime$pctmin80, use="pairwise.complete.obs")
```

```
[1] 0.1816506
```

```
model21 <- lm(crmrte~polpc + density + taxpc, data = crime)
summary(model21)
```

```
Call:
lm(formula = crmrte ~ polpc + density + taxpc, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.016453 -0.007955 -0.002938  0.003917  0.042047

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0087751  0.0042403   2.069  0.04150 *
polpc       -0.1086169  1.3896572  -0.078  0.93788
density      0.0080949  0.0009183   8.816 1.17e-13 ***
taxpc        0.0003480  0.0001094   3.181  0.00204 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01243 on 86 degrees of freedom
Multiple R-squared:  0.5814,    Adjusted R-squared:  0.5668
F-statistic: 39.82 on 3 and 86 DF,  p-value: 3.122e-16
```

```
model22 <- lm(crmrte~polpc + density, data = crime)
summary(model22)
```

```
Call:
lm(formula = crmrte ~ polpc + density, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.025716 -0.009161 -0.002382  0.004857  0.051552

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.0189880  0.0029109   6.523 4.38e-09 ***
polpc       0.9731434  1.4162336   0.687    0.494
density     0.0089433  0.0009235   9.684 1.79e-15 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01307 on 87 degrees of freedom
Multiple R-squared:  0.5322,    Adjusted R-squared:  0.5214
F-statistic: 49.49 on 2 and 87 DF,  p-value: 4.442e-15
```

```
model29 <- lm(crmrte~pctmin80 + pctymle + density, data = crime)
summary(model29)
```

```
Call:
lm(formula = crmrte ~ pctmin80 + pctymle + density, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.021145 -0.006220 -0.001704  0.003676  0.060281
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -5.920e-04  5.072e-03  -0.117  0.90735
pctmin80     2.665e-04  7.314e-05   3.643  0.00046 ***
pctymle      1.709e-01  5.318e-02   3.213  0.00185 **
density      8.966e-03  8.228e-04  10.897  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01169 on 86 degrees of freedom
Multiple R-squared:  0.6301,    Adjusted R-squared:  0.6172
F-statistic: 48.83 on 3 and 86 DF,  p-value: < 2.2e-16
```

```r
model31 <- lm(crmrte~pctmin80 + density, data = crime)
summary(model31)
```

```
Call:
lm(formula = crmrte ~ pctmin80 + density, data = crime)

Residuals:
      Min        1Q    Median        3Q       Max
-0.023115 -0.007062 -0.002932  0.003894  0.059163

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 1.340e-02  2.737e-03   4.896 4.47e-06 ***
pctmin80    2.639e-04  7.695e-05   3.430 0.000926 ***
density     9.266e-03  8.601e-04  10.773  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.0123 on 87 degrees of freedom
Multiple R-squared:  0.5857,    Adjusted R-squared:  0.5762
F-statistic: 61.49 on 2 and 87 DF,  p-value: < 2.2e-16
```

Building a Model

To build the model, we use a backwards approach. We first build a model that includes all the data we are given then remove the data with the least explanatory power. Following that, we then explain why the information for the variables removed is already incorporated into the model and thus why it is excluded from the final model.

```
model_1<-lm(crime$crmrte~crime$prbarr+crime$prbconv+crime$prbpris
                    +crime$avgsen+crime$polpc+crime$density+crime$taxpc
                    +crime$west+crime$central+crime$urban+crime$pctmin80
                    +crime$wcon+crime$wtuc+crime$wtrd+crime$wfir+crime$wser
                    +crime$wmfg+crime$wfed+crime$wsta+crime$wloc+crime$mix
                    +crime$pctymle)

summary(model_1)
```

```
Call:
lm(formula = crime$crmrte ~ crime$prbarr + crime$prbconv + crime$prbpris +
    crime$avgsen + crime$polpc + crime$density + crime$taxpc +
    crime$west + crime$central + crime$urban + crime$pctmin80 +
    crime$wcon + crime$wtuc + crime$wtrd + crime$wfir + crime$wser +
    crime$wmfg + crime$wfed + crime$wsta + crime$wloc + crime$mix +
    crime$pctymle)

Residuals:
       Min         1Q     Median         3Q        Max
-0.0168836 -0.0039309 -0.0004161  0.0046227  0.0228050

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.333e-02  1.972e-02   0.676 0.501164
crime$prbarr   -5.135e-02  9.919e-03  -5.177 2.24e-06 ***
crime$prbconv  -1.854e-02  3.770e-03  -4.917 5.97e-06 ***
crime$prbpris   4.159e-03  1.209e-02   0.344 0.731917
crime$avgsen   -3.958e-04  4.241e-04  -0.933 0.354003
crime$polpc     6.918e+00  1.546e+00   4.476 3.03e-05 ***
crime$density   5.156e-03  1.400e-03   3.682 0.000464 ***
crime$taxpc     1.676e-04  9.530e-05   1.759 0.083168 .
crime$west     -2.416e-03  4.190e-03  -0.577 0.566193
crime$central  -4.163e-03  2.869e-03  -1.451 0.151468
crime$urban     5.814e-04  6.382e-03   0.091 0.927681
crime$pctmin80  3.277e-04  9.886e-05   3.315 0.001484 **
crime$wcon      2.406e-05  2.794e-05   0.861 0.392189
crime$wtuc      5.257e-06  1.511e-05   0.348 0.729007
crime$wtrd      2.896e-05  4.641e-05   0.624 0.534745
crime$wfir     -3.482e-05  2.749e-05  -1.267 0.209657
crime$wser     -1.887e-06  5.678e-06  -0.332 0.740741
crime$wmfg     -8.792e-06  1.435e-05  -0.613 0.542111
crime$wfed      2.981e-05  2.562e-05   1.164 0.248655
crime$wsta     -2.326e-05  2.597e-05  -0.895 0.373764
crime$wloc      1.337e-05  4.897e-05   0.273 0.785627
crime$mix      -1.936e-02  1.472e-02  -1.315 0.192895
crime$pctymle   1.035e-01  4.522e-02   2.288 0.025298 *
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.008317 on 67 degrees of freedom
Multiple R-squared:  0.854, Adjusted R-squared:  0.8061
F-statistic: 17.81 on 22 and 67 DF,  p-value: < 2.2e-16
```

From here we trim the variables with the least explanatory power, but also it should be noted that some variables simply have very little correlation with our dependant variable crime rate, such as average sentence and probability of prison.

```
model_2<-lm(crime$crmrte~crime$density+crime$prbarr+crime$prbconv+
             crime$polpc+crime$pctmin80)
summary(model_2)$adj.r.square
```

```
[1] 0.7929876
```

```
dat_1<-data.frame(crime$crmrte,crime$avgsen,crime$prbpris)
cor(dat_1)
```

```
              crime.crmrte crime.avgsen crime.prbpris
crime.crmrte    1.00000000   0.01979653    0.04799540
crime.avgsen    0.01979653   1.00000000   -0.09468083
crime.prbpris   0.04799540  -0.09468083    1.00000000
```

[NOTE: this doesn't quite make sense. There are only 3 variables directly above. Do you mean the model_2 data?] From here, we see that these 5 variables contain almost all of the information of the other variables. Now that we have a model, we need to understand why these 5 variables cover all of the information we need for the model.

Density seems to be the strongest predictor of crime rate in the data. We include it first but it should be noted that if the urban flag is used in lew of density the model loses very little explanatory power because the two are highly correlated so little information is added by including it, and since density is more highly correlated with our dependant variable we choose to use it over the urban flag.

```
summary(lm(crime$crmrte~crime$urban+crime$prbarr+crime$prbconv+
             crime$polpc+crime$pctmin80))$adj.r.squared
```

```
[1] 0.7302545
```

```
dat1<-data.frame(crime$crmrte,crime$density,crime$urban)
cor(dat1)
```

```
              crime.crmrte crime.density crime.urban
crime.crmrte     1.0000000     0.7277783   0.6150631
crime.density    0.7277783     1.0000000   0.8206825
crime.urban      0.6150631     0.8206825   1.0000000
```

Next we turn to wages. Even alone they seem to have little predictive power. It may be that case that what we really want to measure is not wages but unemployment as it may be that case that even if one doesn't have much money, they are at least employed and therefore will commit less crimes.

```
summary(lm(crime$crmrte~crime$wcon+crime$wtuc+crime$wtrd+crime$wfir
           +crime$wser+crime$wmfg+crime$wfed+crime$wsta+crime$wloc))
```

```
Call:
lm(formula = crime$crmrte ~ crime$wcon + crime$wtuc + crime$wtrd +
    crime$wfir + crime$wser + crime$wmfg + crime$wfed + crime$wsta +
    crime$wloc)
```

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.035348 -0.009720 -0.003703  0.006302  0.052214

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.898e-02  2.390e-02  -2.887  0.00501 **
crime$wcon   6.737e-05  4.800e-05   1.404  0.16431
crime$wtuc  -8.665e-07  2.747e-05  -0.032  0.97492
crime$wtrd   1.245e-04  8.289e-05   1.501  0.13718
crime$wfir  -6.460e-05  5.016e-05  -1.288  0.20150
crime$wser  -5.261e-06  8.428e-06  -0.624  0.53424
crime$wmfg   3.333e-05  2.573e-05   1.295  0.19889
crime$wfed   7.975e-05  4.379e-05   1.821  0.07230 .
crime$wsta   8.239e-05  4.497e-05   1.832  0.07062 .
crime$wloc   1.162e-05  8.493e-05   0.137  0.89156
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01636 on 80 degrees of freedom
Multiple R-squared:  0.3253,    Adjusted R-squared:  0.2494
F-statistic: 4.285 on 9 and 80 DF,  p-value: 0.0001451
```

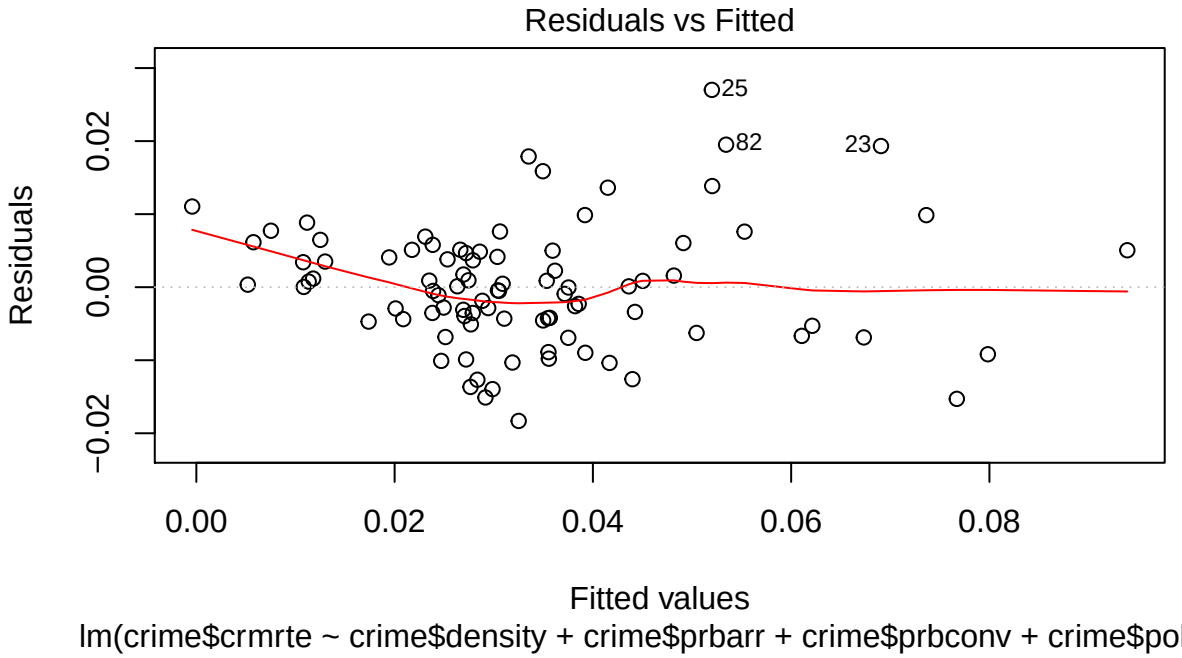
Verify Assumptions

Here we verify the the six assumptions of our model:

1) Linearity of the Parameters
2) Random Sampling
3) No Perfect Multicollinearity
4) Zero Conditional Mean
5) Homoskedasticity
6) Normality of Residuals

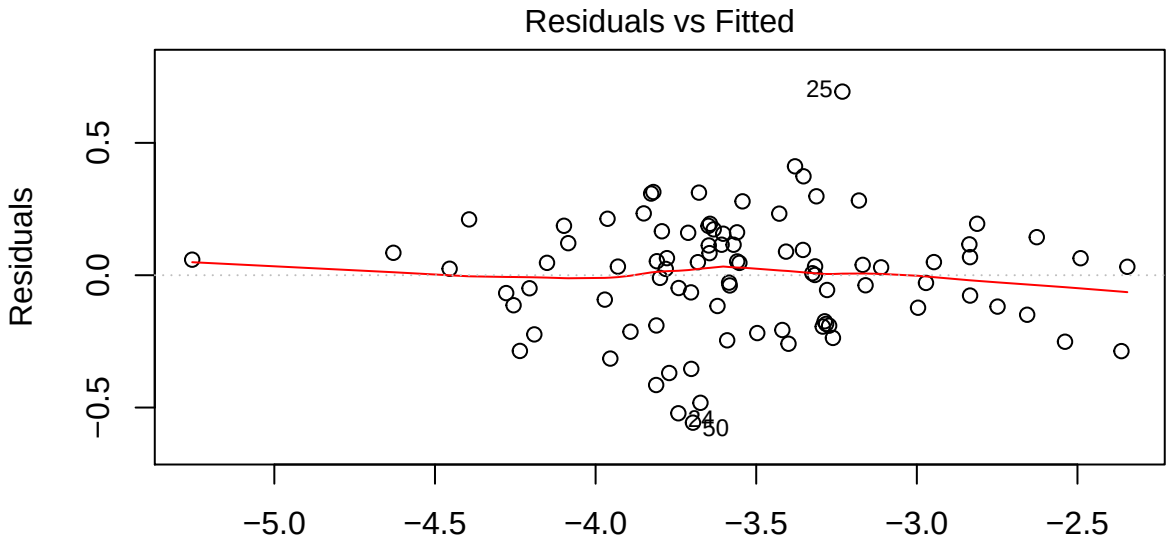
First we check for linearity by looking at the Residuals vs Fitted plot.

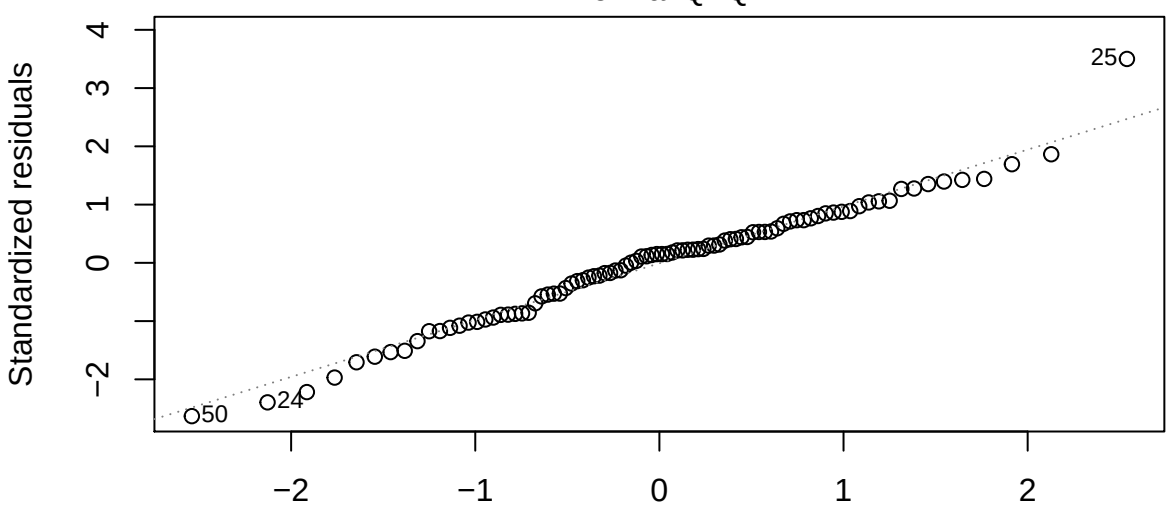
```
plot(model_2, which=1)
```

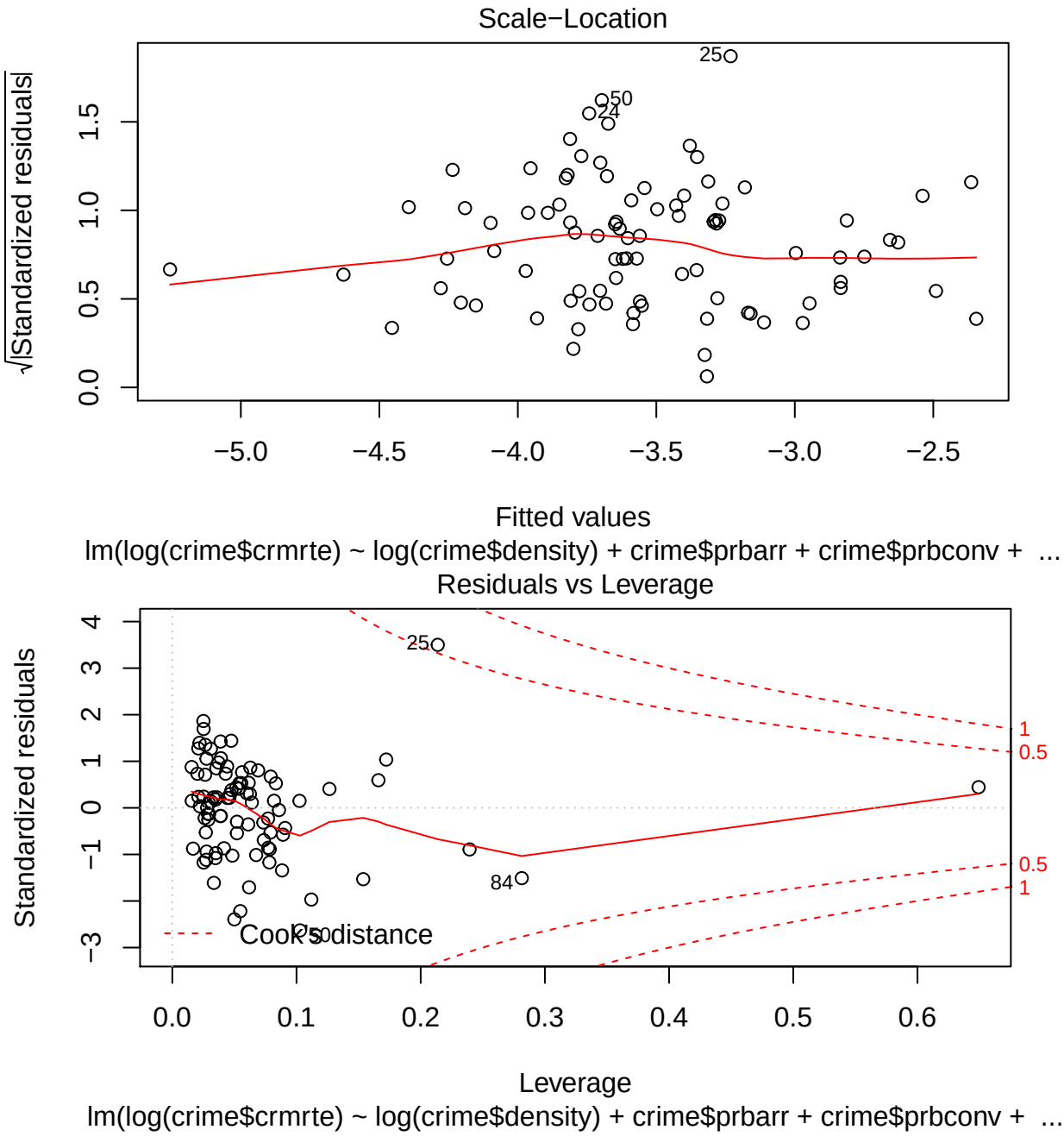


Here we see evidence of nonlinear relationship at the lower end of the range of our dependant variable. We address this by looking at the log-log relationship with respect to crimerte, density, and polpc, our variables that show the strongest evidence of skew.

```
model_3<-lm(log(crime$crmrte)~log(crime$density)+crime$prbarr+crime$prbconv+
              log(crime$polpc)+crime$pctmin80)
plot(model_3)
```


Residuals vs Fitted
Residuals
0.5
0.0
−0.5
25
24
50
−5.0
−4.5
−4.0
−3.5
−3.0
−2.5
Fitted values
lm(log(crime$crmrte) ~ log(crime$density) + crime$prbarr + crime$prbconv + ...


Normal Q−Q
Standardized residuals
4
3
2
1
0
−2
25
24
50
−2
−1
0
1
2
Theoretical Quantiles
lm(log(crime$crmrte) ~ log(crime$density) + crime$prbarr + crime$prbconv + ...



This plot is very strong evidence that the log-log transform takes care of the linearity assumption and the zero conditional mean assumption. Additionally, the normal QQ plot fits extremely well so we can safely assume we have normality of our residuals.

```
dat_2<-data.frame(log(crime$density),log(crime$polpc),crime$prbarr,
                  crime$prbconv,crime$pctmin80)
vif(dat_2)
```

```
           Variables      VIF
1 log.crime.density. 1.578154
2   log.crime.polpc. 1.303623
3       crime.prbarr 1.420060
4      crime.prbconv 1.109106
```

```
5     crime.pctmin80 1.043042
```

To check for multicollinearity we use the measured variance inflation factors shown above. These values are sufficiently low for each of our independant variables so there is very little evidence of multicollinearity.

For the assumption of a random sample, we have to assume that the person gathering the data for the model took proper precautions to gather a truly random sample. We could gather a second sample and compare the distributions of the two samples and see how similar they are, but this would likely be costly and time consuming. For the purposes of this study, we assume that the person gathering the information used due diligence to gather a sample would truly is representative of the larger population of counties that the candidate intends to represent.

Referring back to the Residuals vs Fitted plot, we see strong evidence of f heteroskedasticity and will use robust standard errors when assessing our model from here.

```
coeftest(model_3, vcov=vcovHC)
```

```
t test of coefficients:

                     Estimate Std. Error t value  Pr(>|t|)
(Intercept)        -0.1056145  0.9616514 -0.1098 0.9128092
log(crime$density)  0.2917154  0.0639652  4.5605 1.722e-05 ***
crime$prbarr       -1.6789191  0.2852187 -5.8864 7.848e-08 ***
crime$prbconv      -0.6122263  0.1029381 -5.9475 6.040e-08 ***
log(crime$polpc)    0.4546253  0.1297689  3.5033 0.0007391 ***
crime$pctmin80      0.0127636  0.0015183  8.4066 9.274e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
se.model = coeftest(model_3, vcov = vcovHC)[ , "Std. Error"]
```

Conclusions

```
stargazer(model_3, type="text", se=list(se.model))
```

```
================================================
                        Dependent variable:
                    ----------------------------
                               crmrte)
------------------------------------------------
density)                      0.292***
                               (0.064)

prbarr                        -1.679***
                               (0.285)

prbconv                       -0.612***
                               (0.103)

polpc)                        0.455***
                               (0.130)

pctmin80                      0.013***
                               (0.002)

Constant                       -0.106
                               (0.962)

------------------------------------------------
Observations                     90
R2                              0.843
Adjusted R2                     0.834
Residual Std. Error       0.223 (df = 84)
F Statistic           90.516*** (df = 5; 84)
================================================
Note:               *p<0.1; **p<0.05; ***p<0.01
```