

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.

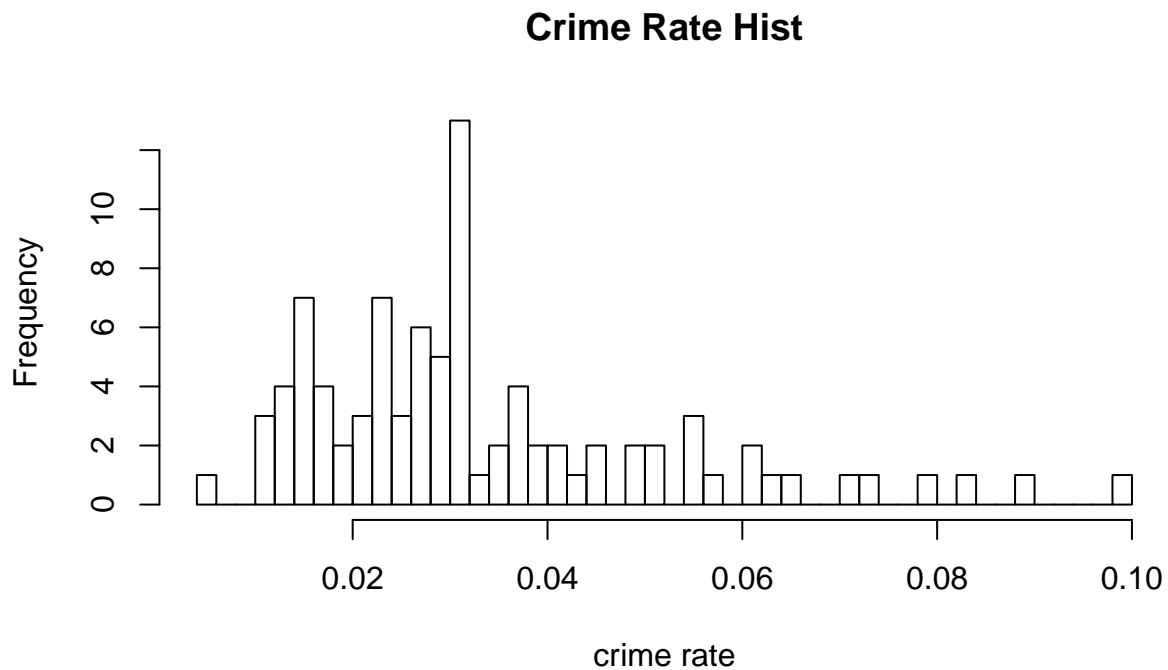
In our first stage, an exploratory data analysis was undertaken in order to better understand the data set, the variables, anomalies, and any variable transformations that may need to be done to provide a robust set of models. We also examined the relationships between variables from a variety of perspectives to support model building. Our second stage consisted of building and analyzing a set of linear models to determine the right mix of significant 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

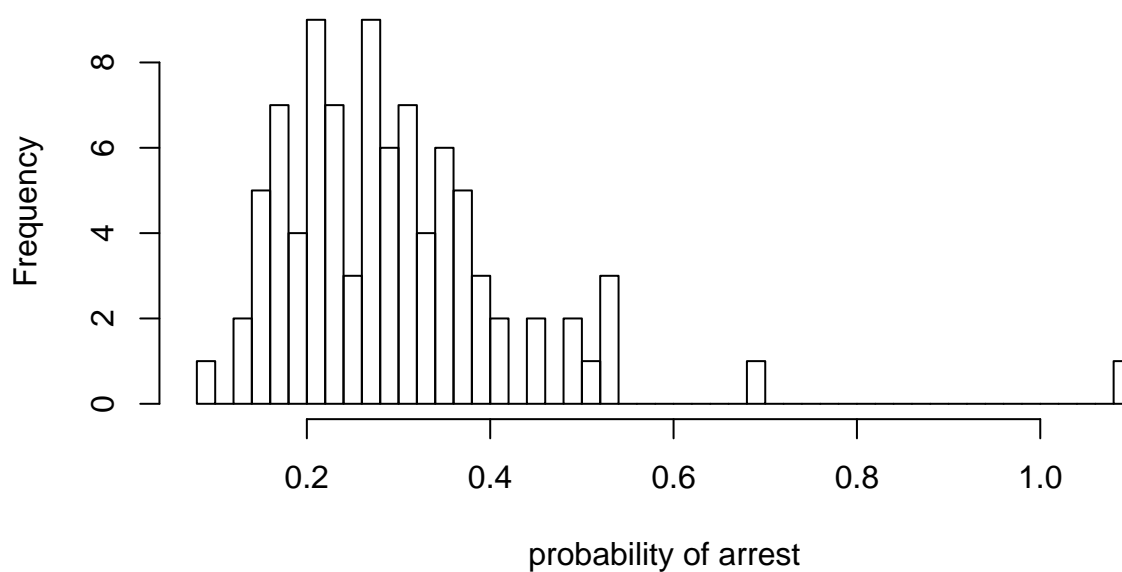
A thorough exploratory analysis of the crimes data set was to better understand the data set, the variables, anomalies, and any variable transformations that may need to be done to provide a robust set of models. Outlier data was reviewed for significance and possible patterns. We also examined the relationships 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")
```



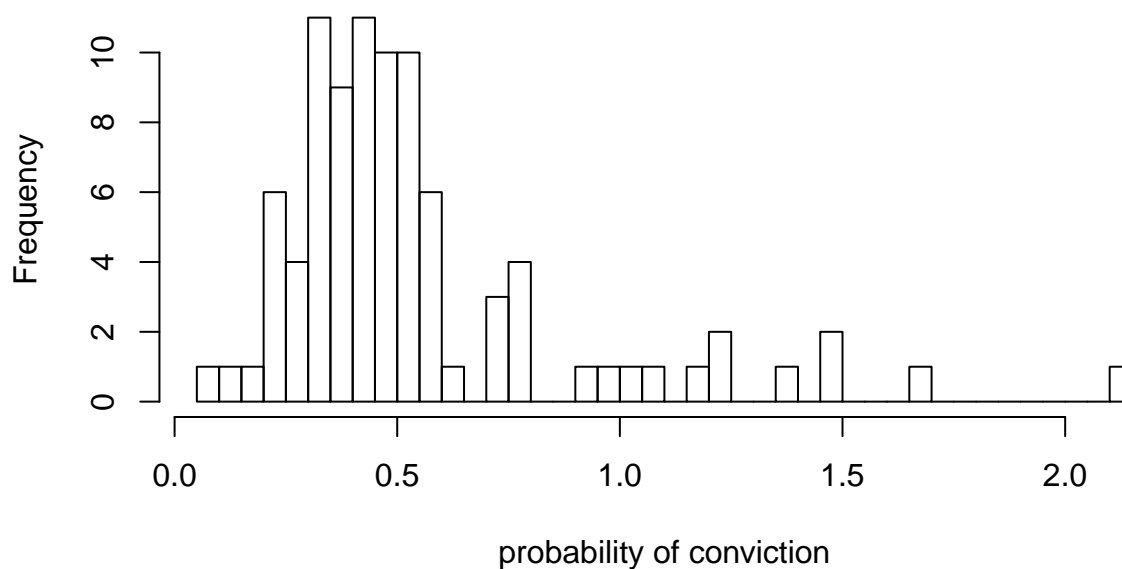
```
hist(crime$prbarr, breaks = 50, xlab = "probability of arrest", ylab = "Frequency", main = "Probability
```

Probability of Arrest Hist

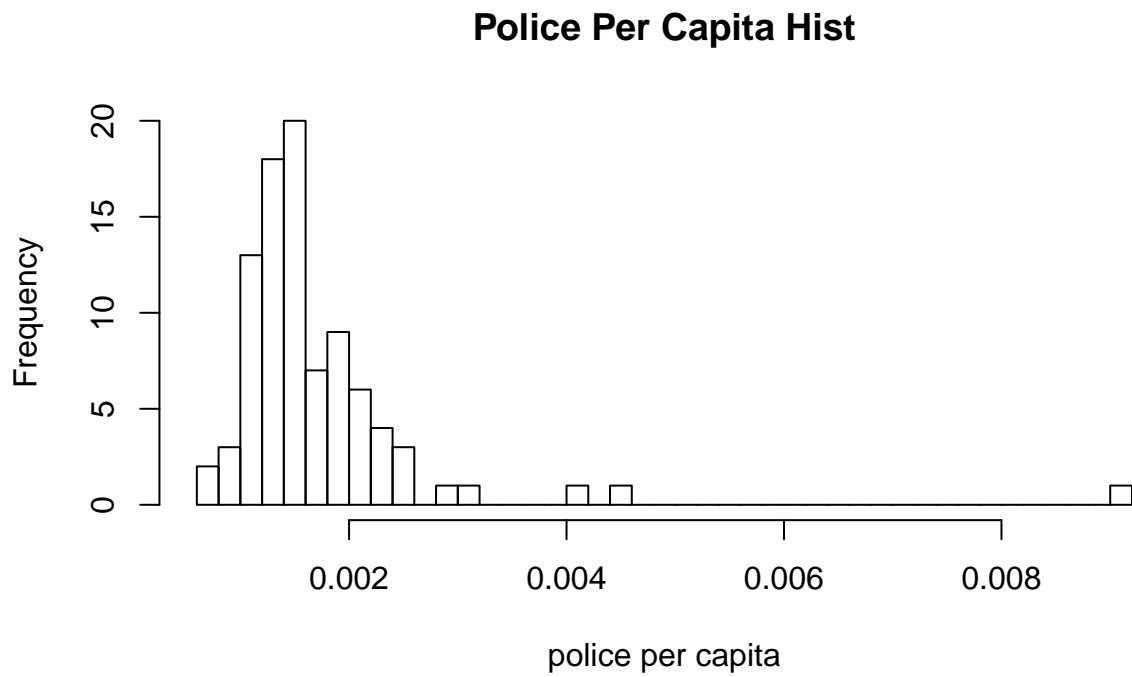


```
hist(crime$prbconv, breaks = 50, xlab = "probability of conviction", ylab = "Frequency", main = "Probab
```

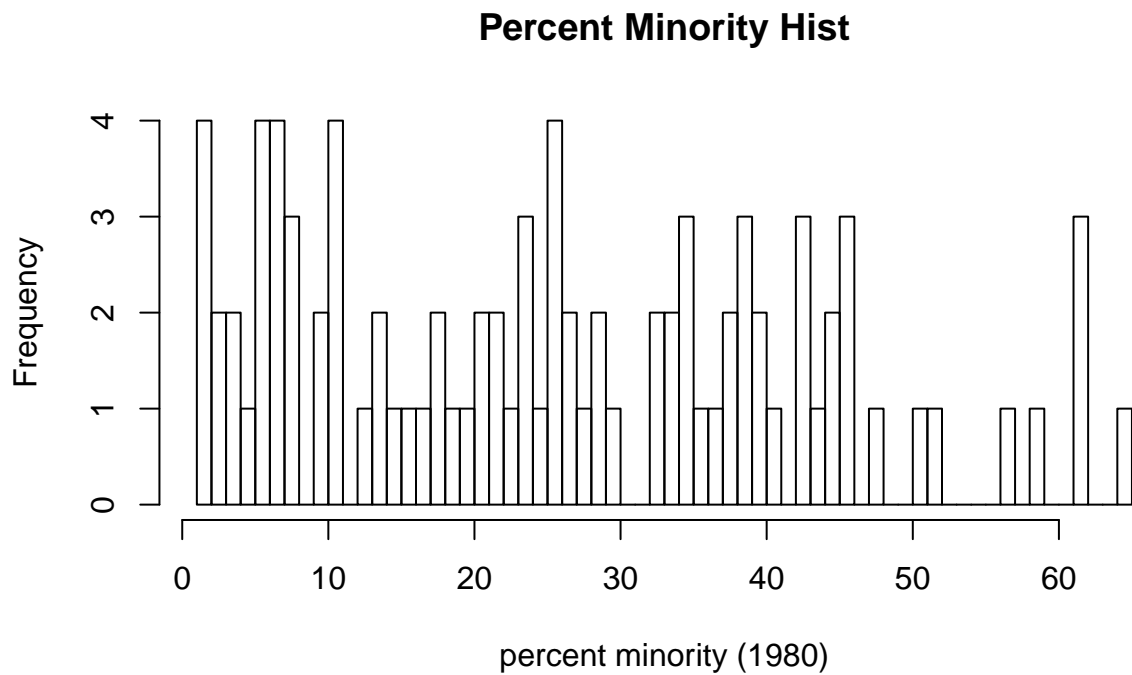
Probability of Conviction Hist



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

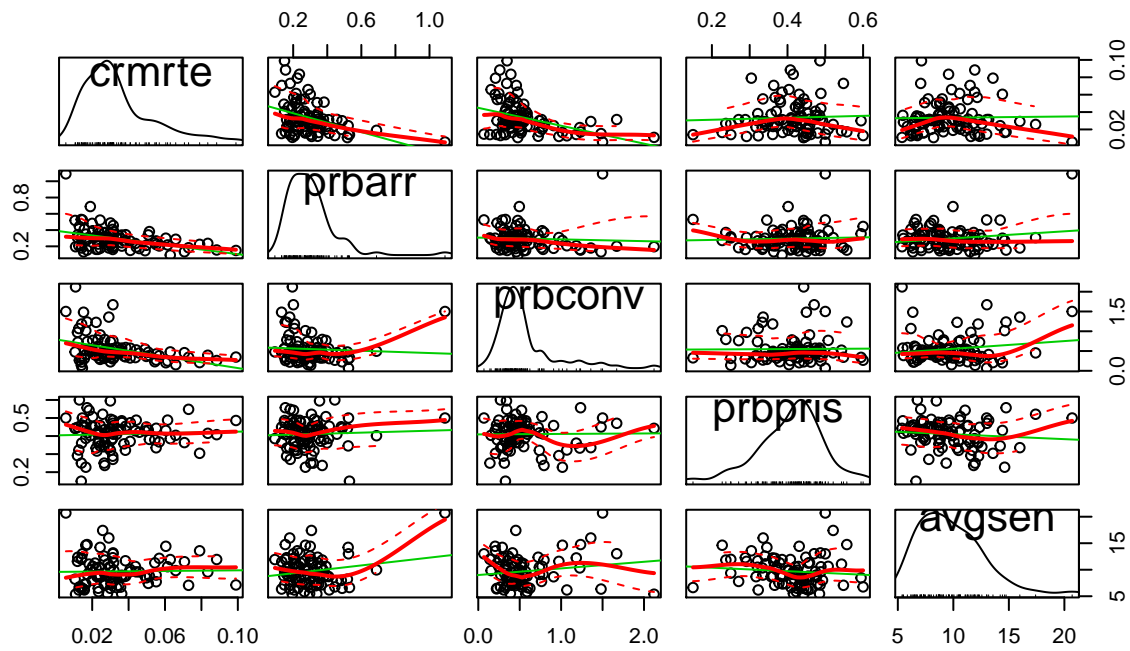


```
hist(crime$pctmin80, breaks = 50, xlab = "percent minority (1980)", ylab = "Frequency", main = "Percent
```

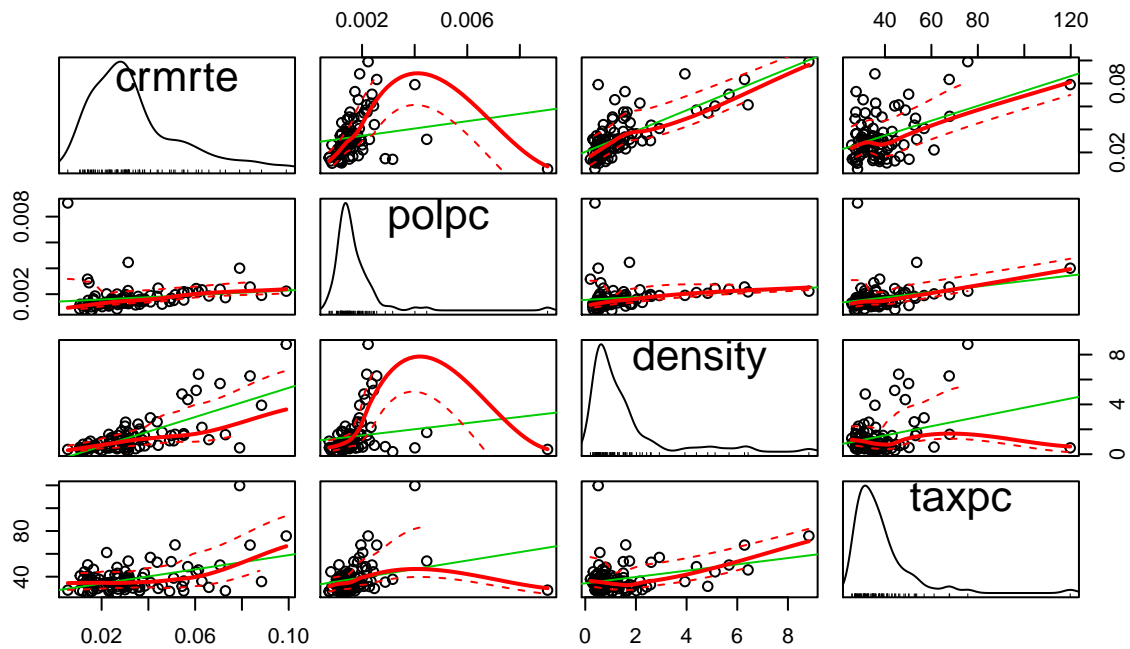


Scatterplot matrices were developed for several variables to get an initial understanding of variable relationships.

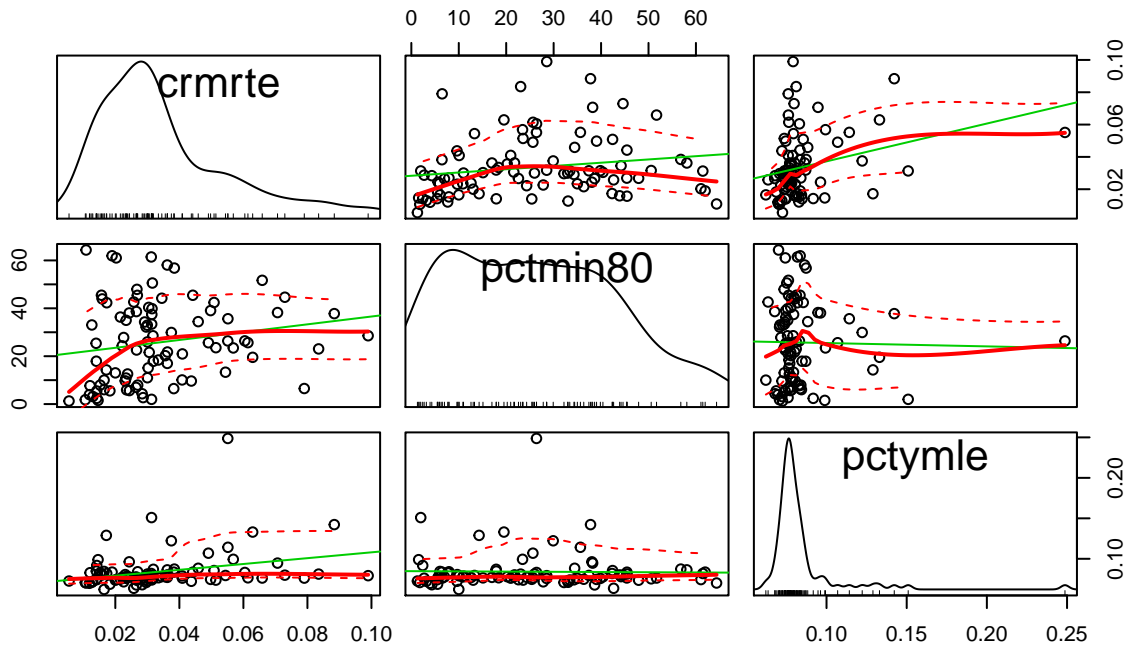
```
scatterplotMatrix(~crrmrte + prbarr + prbconv + prbpris + avgsen, data=crime)
```



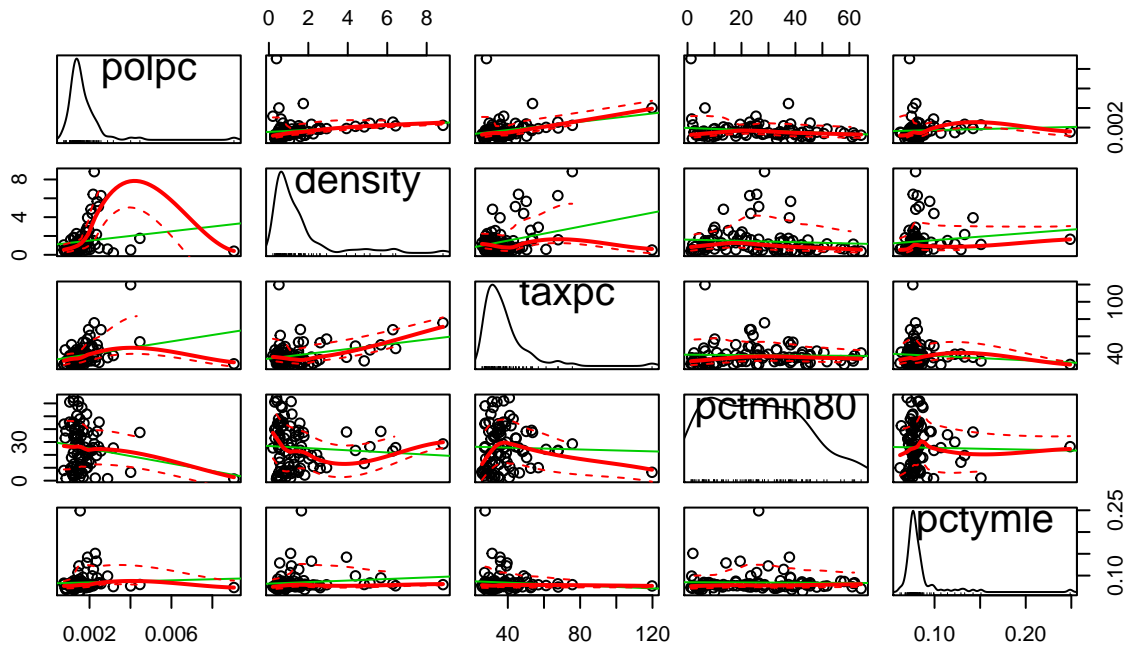
```
scatterplotMatrix(~crrmrte + polpc + density + taxpc, data=crime)
```



```
scatterplotMatrix(~crm rte + 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$polpc, crime$crrmrte)
model3 <- lm(crrmrte~polpc, data = crime)
model3
```

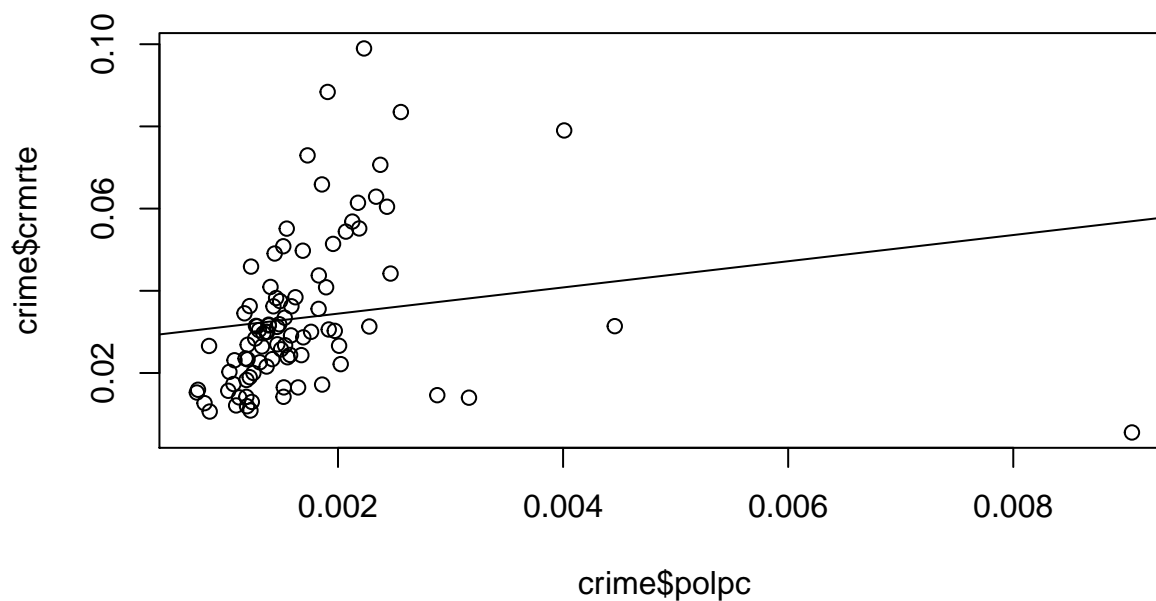
Call:

```
lm(formula = crrmrte ~ polpc, data = crime)
```

Coefficients:

```
(Intercept)      polpc
    0.02806      3.18839
```

```
abline(model3)
```



```
summary(model3)
```

Call:

```
lm(formula = crrmrte ~ 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$crmte, crime$polpc, use="pairwise.complete.obs")
```

```
[1] 0.1672816
```

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

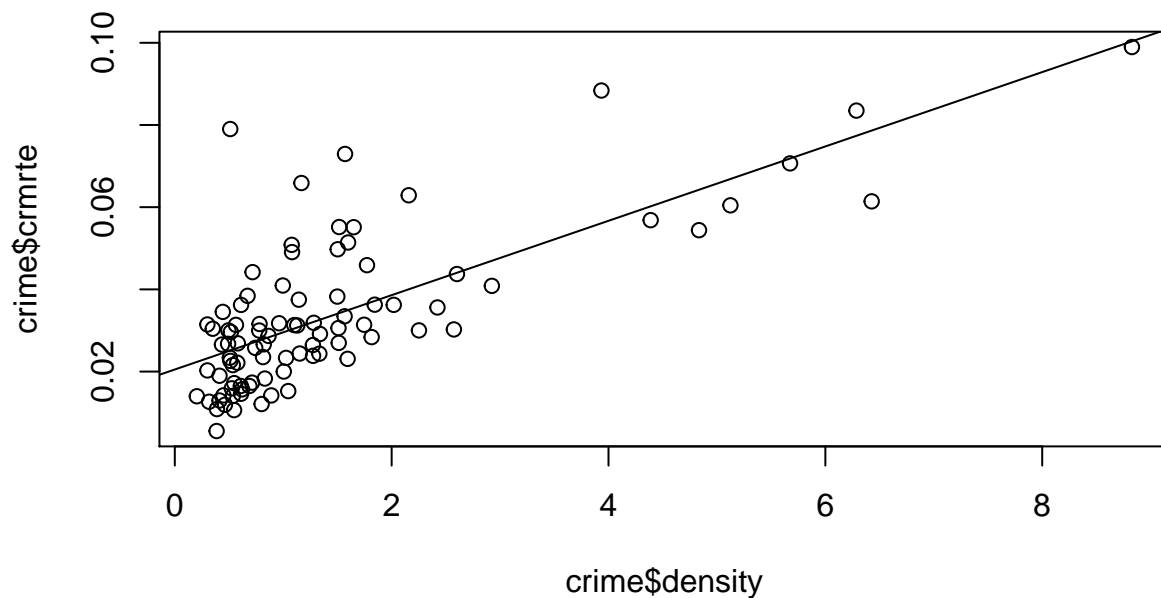
Call:

```
lm(formula = crmte ~ density, data = crime)
```

Coefficients:

```
(Intercept)      density
  0.020503      0.009046
```

```
abline(model4)
```



```
summary(model4)
```

Call:

```
lm(formula = crmte ~ 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)

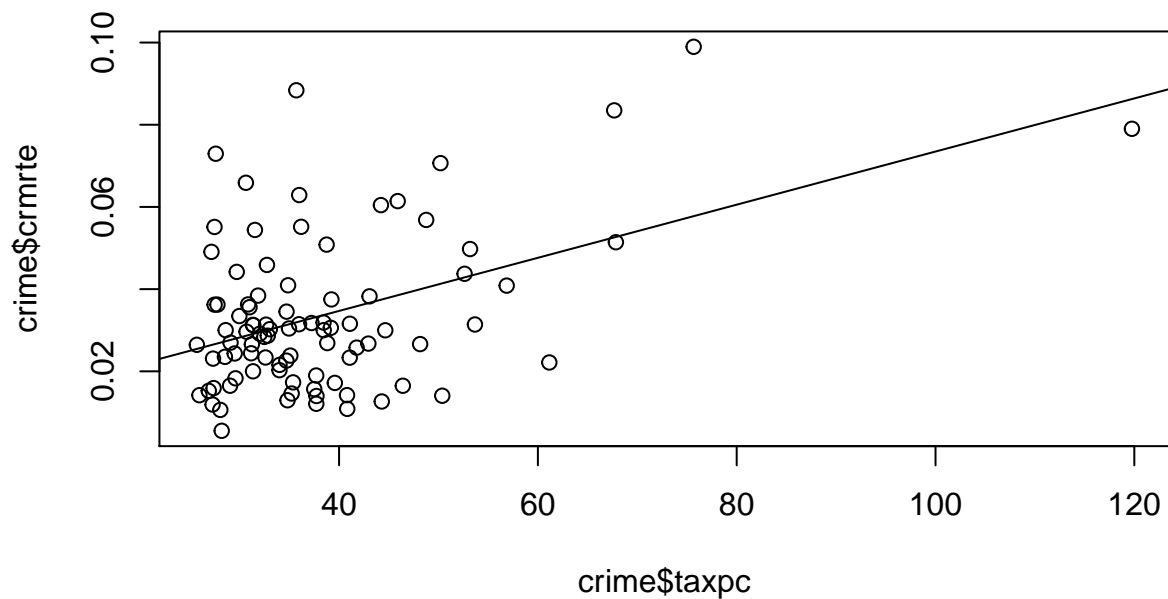
```

```

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
```

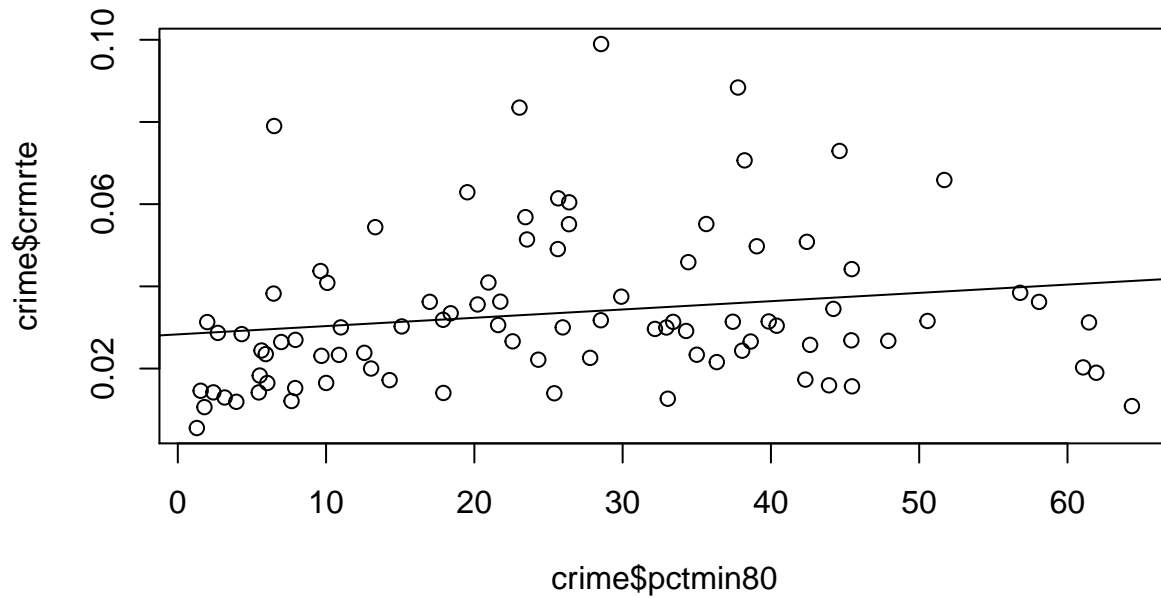
Call:

```
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

```

```

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 build 3 separate models and with each iteration we remove variables. We first build a model that includes all the data we are given then remove the data with the least explanatory power. Throughout, we 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$crmte~crime$prbarr+crime$prbconv+crime$prbpris
            +crime$avgsgen+crime$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$crmte ~ crime$prbarr + crime$prbconv + crime$prbpris +
    crime$avgsgen + crime$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\$avgsgen	-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 to produce model 2 or the trimmed model. We note that while the r squared drops slightly, the adjusted r squared actually goes up.

```
model_2<-lm(crime$crmrt~crime$density+crime$prbarr+crime$prbconv+
            crime$polpc+crime$pctmin80+crime$taxpc+crime$pctymle)
summary(model_2)
```

Call:

```
lm(formula = crime$crmrt ~ crime$density + crime$prbarr + crime$prbconv +
    crime$polpc + crime$pctmin80 + crime$taxpc + crime$pctymle)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-0.0181805	-0.0052377	-0.0000983	0.0047007	0.0240021

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1.761e-02	6.561e-03	2.683	0.00882	**
crime\$density	5.462e-03	6.955e-04	7.854	1.36e-11	***
crime\$prbarr	-5.579e-02	8.955e-03	-6.230	1.90e-08	***
crime\$prbconv	-1.882e-02	2.919e-03	-6.448	7.37e-09	***
crime\$polpc	6.524e+00	1.269e+00	5.140	1.83e-06	***
crime\$pctmin80	3.560e-04	5.379e-05	6.618	3.50e-09	***
crime\$taxpc	1.874e-04	7.876e-05	2.380	0.01964	*
crime\$pctymle	8.855e-02	4.089e-02	2.165	0.03326	*

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

```
Residual standard error: 0.00829 on 82 degrees of freedom
```

```
Multiple R-squared:  0.8225,    Adjusted R-squared:  0.8074
```

```
F-statistic: 54.28 on 7 and 82 DF,  p-value: < 2.2e-16
```

Some of these variables can be discarded simply on the grounds that they have very little correlation with the dependant variable.

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

	crime.crmrt	crime.avgsen	crime.prbpris
crime.crmrt	1.00000000	0.01979653	0.04799540
crime.avgsen	0.01979653	1.00000000	-0.09468083
crime.prbpris	0.04799540	-0.09468083	1.00000000

For wages it seems even alone they 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$crmrt~crime$wcon+crime$wtuc+crime$wtrd+crime$wfir
            +crime$wser+crime$wmfg+crime$wfed+crime$wsta+crime$wloc))
```

Call:

```
lm(formula = crime$crmte ~ crime$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

To address why none of the flag variables, urban, west, and central, were not included in the trimmed model, we see that all three variables are highly correlated with values that are also in the model, but have higher correlations with the dependant variable. Or in the case of west, it is does have a higher correlation than pctmin80, but after removing the effects of including density into the model, it loses most of it's value.

```
dat_2<-data.frame(crime$crmte,crime$density,crime$pctmin80,  
                  crime$prbconv,crime$urban, crime$west, crime$central)  
cor(dat_2)
```

	crime.crmte	crime.density	crime.pctmin80	crime.prbconv
crime.crmte	1.0000000	0.72777835	0.18165059	-0.38596559
crime.density	0.7277783	1.00000000	-0.07470698	-0.22791204
crime.pctmin80	0.1816506	-0.07470698	1.00000000	0.06249824
crime.prbconv	-0.3859656	-0.22791204	0.06249824	1.00000000
crime.urban	0.6150631	0.82068254	0.01619569	-0.19709186
crime.west	-0.3803387	-0.19458889	-0.62451443	0.07198455
crime.central	0.1658803	0.35682850	-0.05487554	-0.04640007

	crime.urban	crime.west	crime.central
crime.crmte	0.61506307	-0.38033874	0.16588032
crime.density	0.82068254	-0.19458889	0.35682850
crime.pctmin80	0.01619569	-0.62451443	-0.05487554
crime.prbconv	-0.19709186	0.07198455	-0.04640007
crime.urban	1.00000000	-0.08000341	0.15927023
crime.west	-0.08000341	1.00000000	-0.42986348
crime.central	0.15927023	-0.42986348	1.00000000

Finally we trim off the two variables with the lowest significance to produce our final model. Taxpc and pctymle do add value to model but at the cost of brevity and understanding.


```
model_3<-lm(crime$crmte~crime$density+crime$prbarr+crime$prbconv+
            crime$polpc+crime$pctmin80)
summary(model_3)
```

Call:

```
lm(formula = crime$crmte ~ crime$density + crime$prbarr + crime$prbconv +
    crime$polpc + crime$pctmin80)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-0.0183081	-0.0046706	-0.0000045	0.0049657	0.0270131

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.345e-02	3.541e-03	9.447	7.47e-15 ***
crime\$density	5.551e-03	7.157e-04	7.756	1.86e-11 ***
crime\$prbarr	-6.614e-02	8.497e-03	-7.783	1.65e-11 ***
crime\$prbconv	-2.162e-02	2.849e-03	-7.588	4.02e-11 ***
crime\$polpc	8.139e+00	1.176e+00	6.923	8.21e-10 ***
crime\$pctmin80	3.739e-04	5.538e-05	6.752	1.77e-09 ***

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

Residual standard error: 0.008593 on 84 degrees of freedom

Multiple R-squared: 0.8046, Adjusted R-squared: 0.793

F-statistic: 69.19 on 5 and 84 DF, p-value: < 2.2e-16

```
AIC(model_2)
```

```
[1] -597.6594
```

```
AIC(model_3)
```

```
[1] -593.0191
```

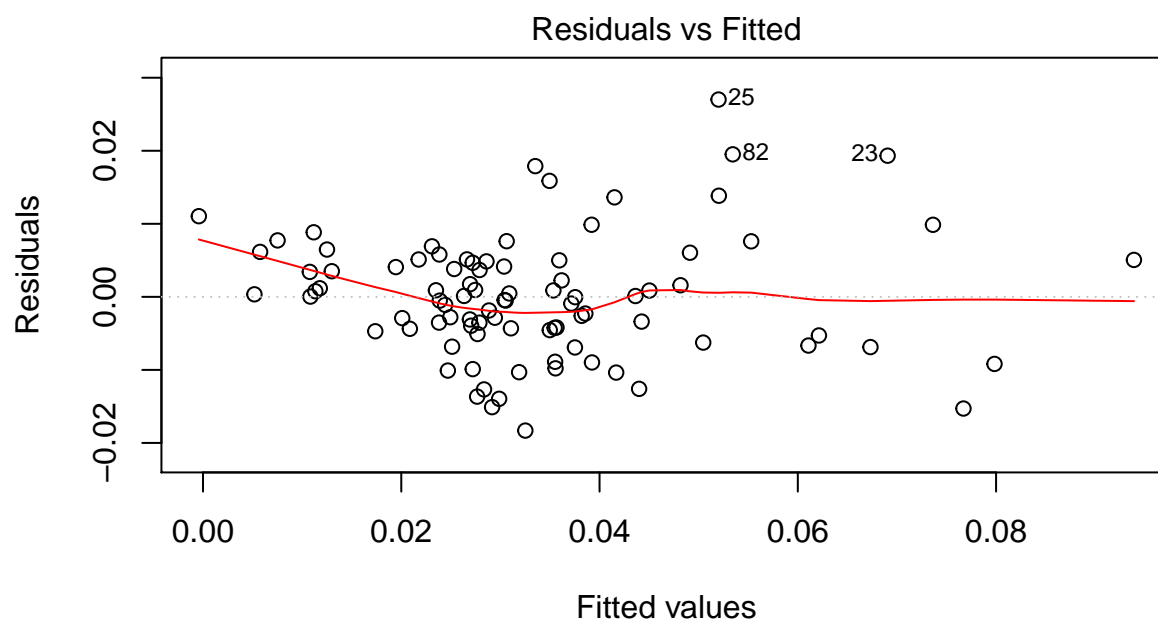
Verify Assumptions

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.

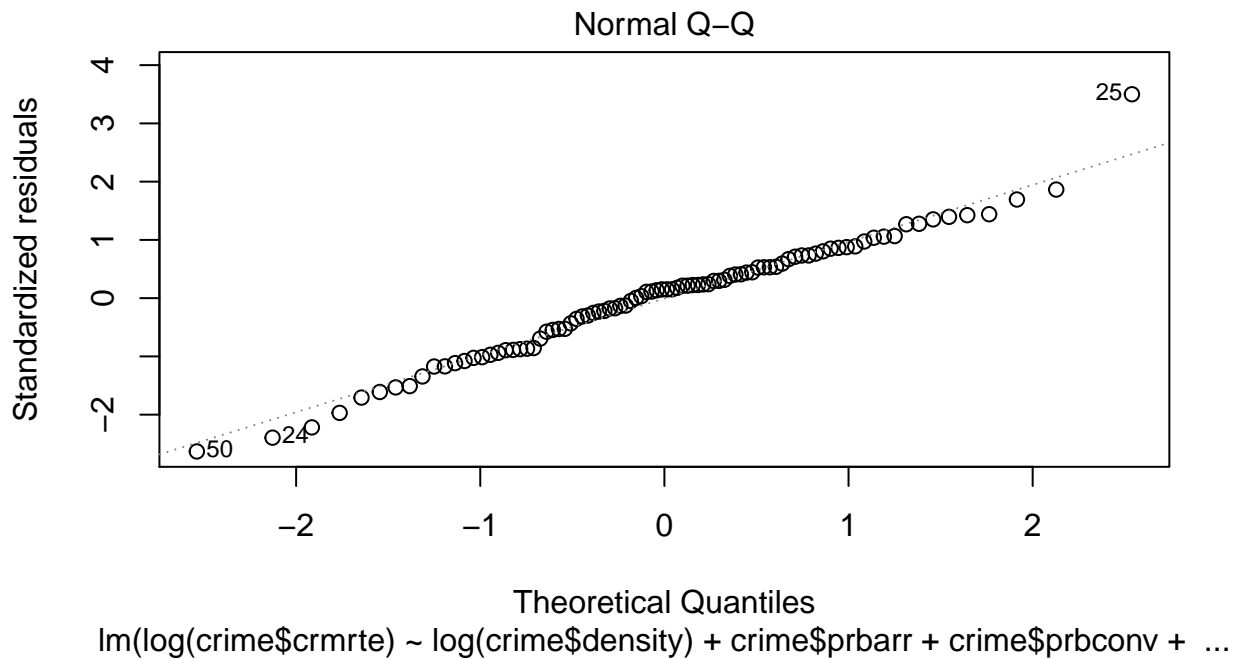
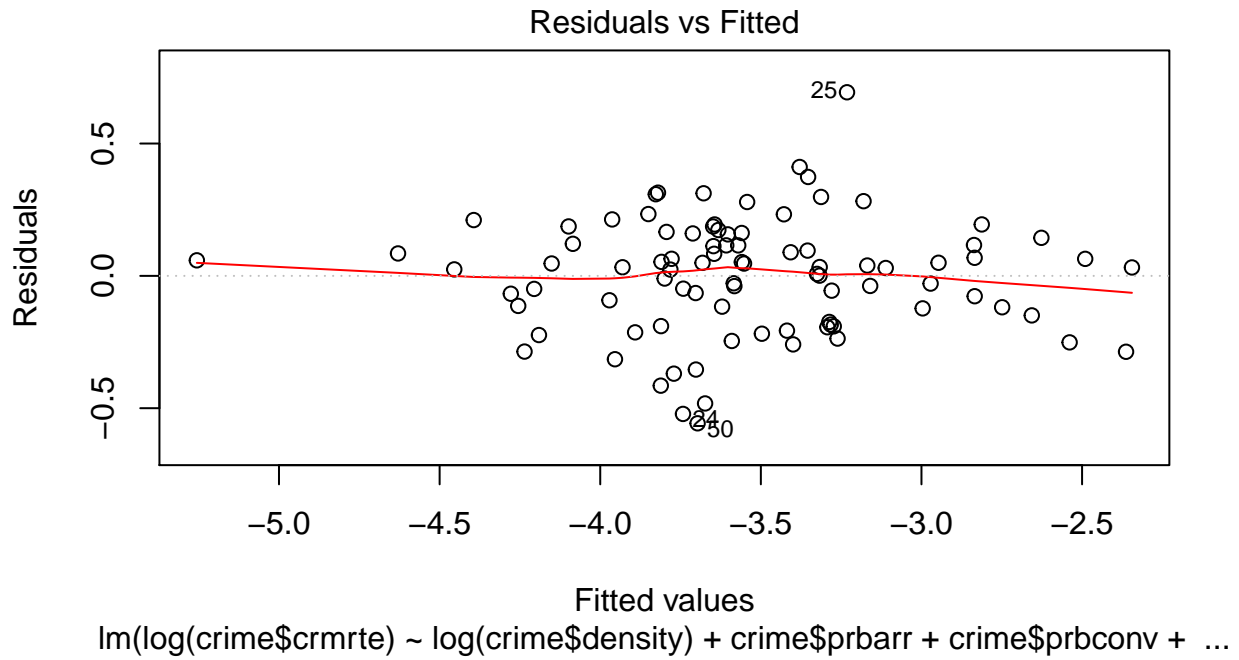
```
plot(model_3, which=1)
```

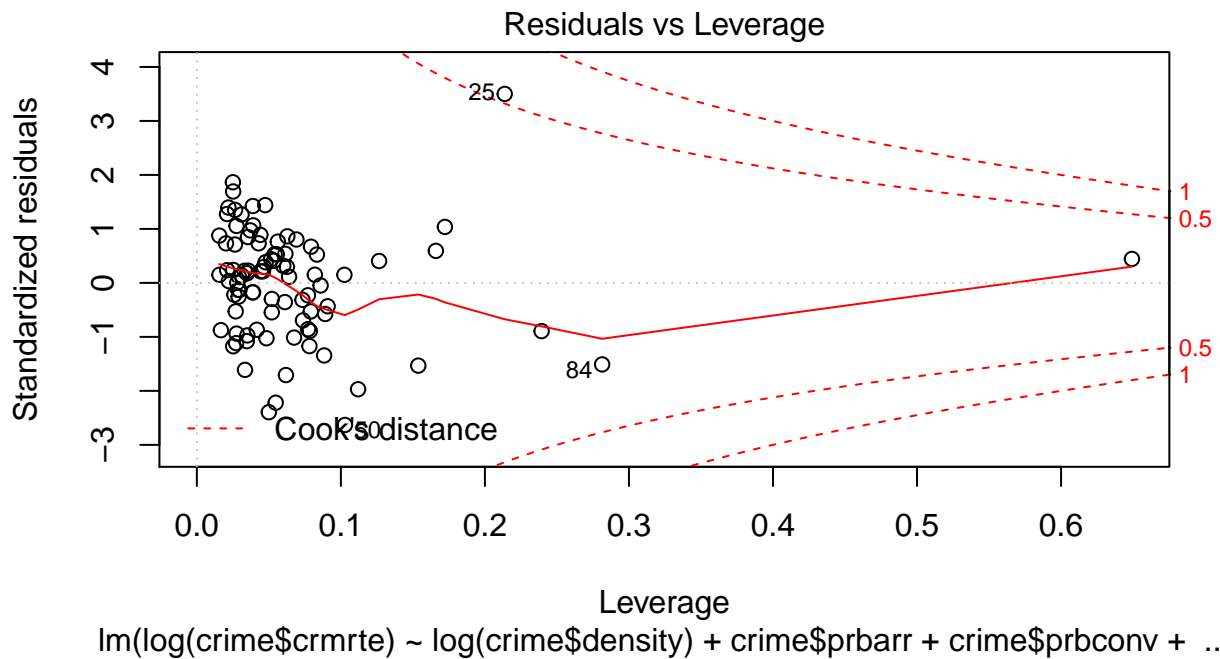
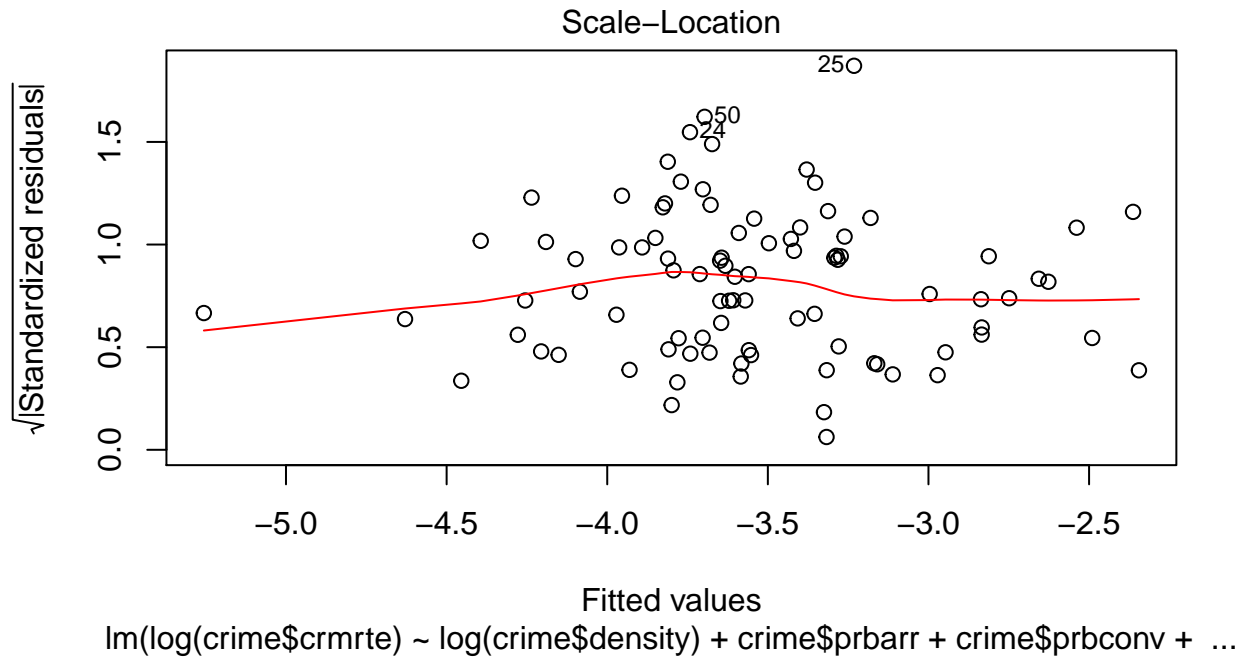


`lm(crime$crmte ~ crime$density + crime$prbarr + crime$prbconv + crime$polp ...`

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_4<-lm(log(crime$crmte)~log(crime$density)+crime$prbarr+crime$prbconv+
            log(crime$polpc)+crime$pctmin80)
plot(model_4)
```





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_3<-data.frame(log(crime$density),log(crime$polpc),crime$prbarr,
                  crime$prbconv,crime$pctmin80)
vif(dat_3)
```

```

      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 independent 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 be 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 heteroskedasticity and will use robust standard errors when assessing our model from here.

```
coeftest(model_4, 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_4, vcov = vcovHC)[ , "Std. Error"]
```

Conclusions

The strongest variables showing correlation with crimrate are : population density, probability of arrest, probability of conviction, police per capita and percent minority. There are a few observations wrt these variables that are key to consider before we make policy decisions.

- a. In order to make policy changes based on these decisions, we would need an idea of causality, not just correlations. However, it is hard to interpret causality here since several key variables that could affect crime rate are missing here e.g unemployment rate, poverty rate. So it would be very helpful to get data on these variables for doing analysis on causality
- b. With current data, we can make an attempt to apply judgement to the relationships that show up as significant to then make policy choices. In this context :
 1. • while population density and percent minority are significant variables, there is very little we can do from a policy point of view to change these. However, it is important to include these variables in the model to be able to see the effect of the other variables net of these.
 2. Both probability of arrest and probability of conviction show significant negative correlation with crime rate. It suggests that the higher the likelihood of being arrested and convicted for a crime, the lesser the likelihood of a crime. ie arrest and conviction are significant deterrants to crime. Hence policy changes that lead to an increase in catching the criminals would be good to reduce crime.
 3. Interestingly, average sentence, and probability of prison sentence did not show up as significant, even though they are not very correlated with the other two variables that show the adverse consequence of crime for the criminal ie probability of arrest, and probability of conviction. This suggests that whether the criminal is caught and convicted is more important than the magnitude or nature of the sentence if convicted. So policy should focus on law enforcement initiatives that lead to greater success in arrest and conviction.
 4. Police per capita has a positive correlation with crime rate. Clearly, increasing police cannot lead to increase in crime rate. This may be a case where increase in crime rate leads to increasing the size of the police force ie the causality is the other way. Since we want to increase the probability of arrest and conviction, one way to do that is to increase the police force, not reduce it. In fact, we can see a significant positive correlation of police per cap with probability of arrest. Note that it is possible that the desired outcomes can also be achieved by focusing the existing police force on arresting criminals vs other activities like traffic etc.

```
stargazer(model_4, 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