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Introduction

Exploratory Analysis

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.

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

```
[1] 0.7929876
```

```r
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
```

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.

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

```
[1] 0.7302545
```

```r
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.

```r
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
```

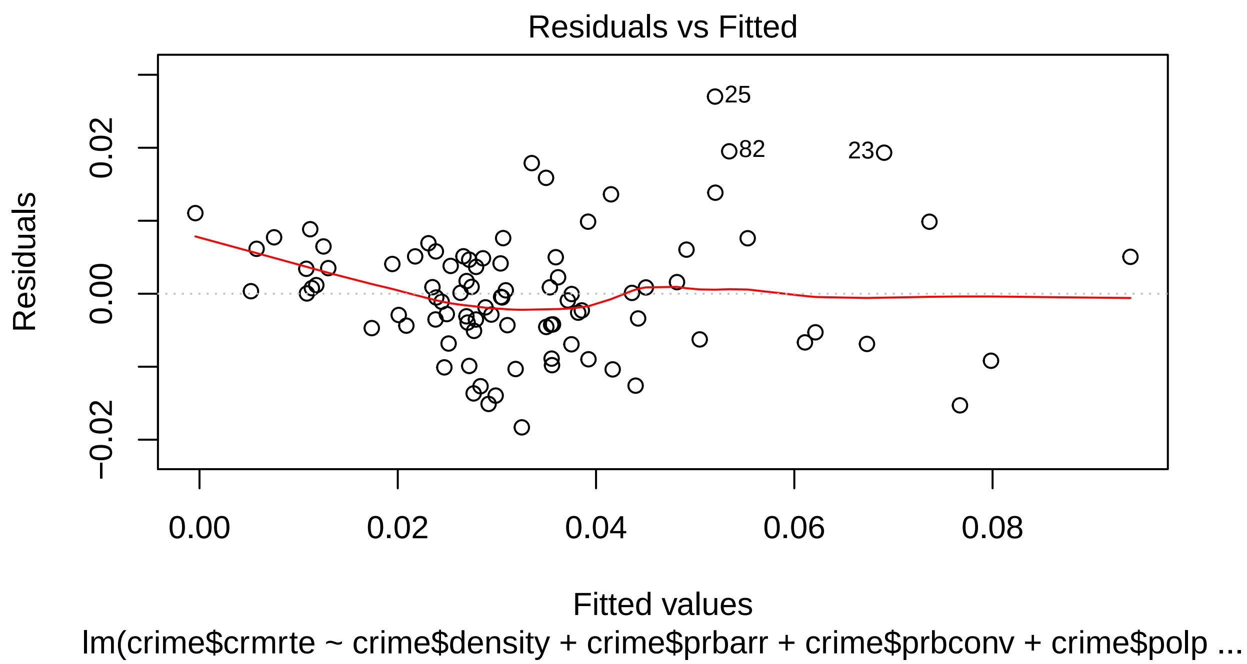
Verify Assumptions

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

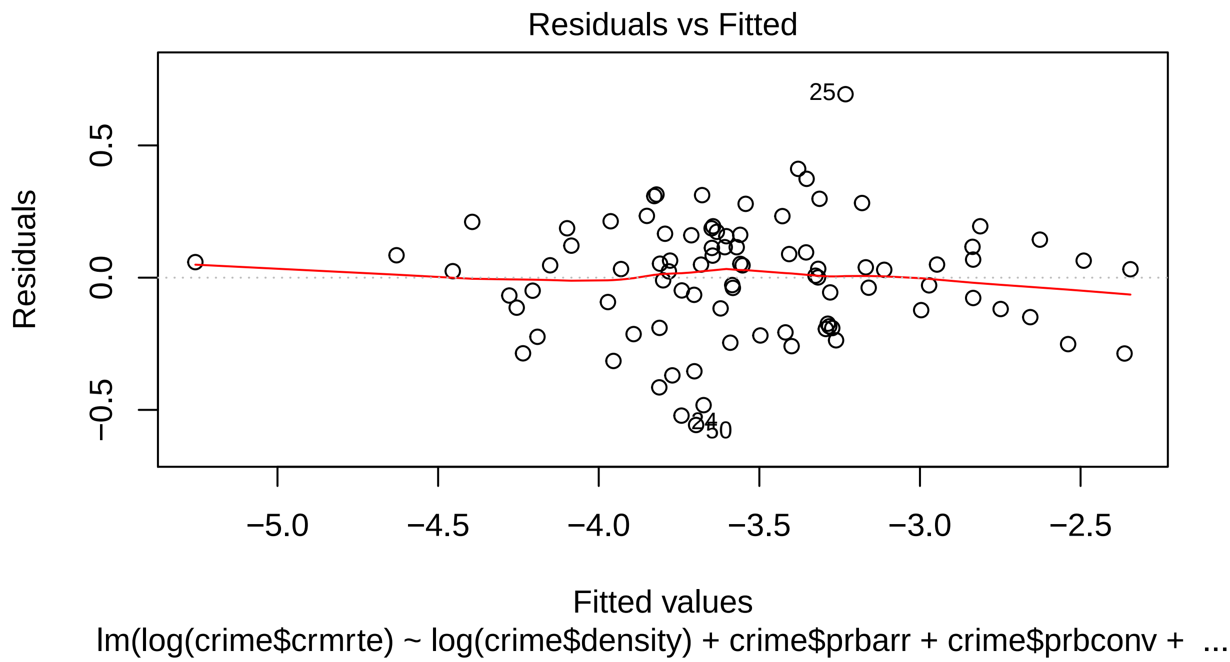
First we check for linearity by looking at the Residuals vs Fitted plot.

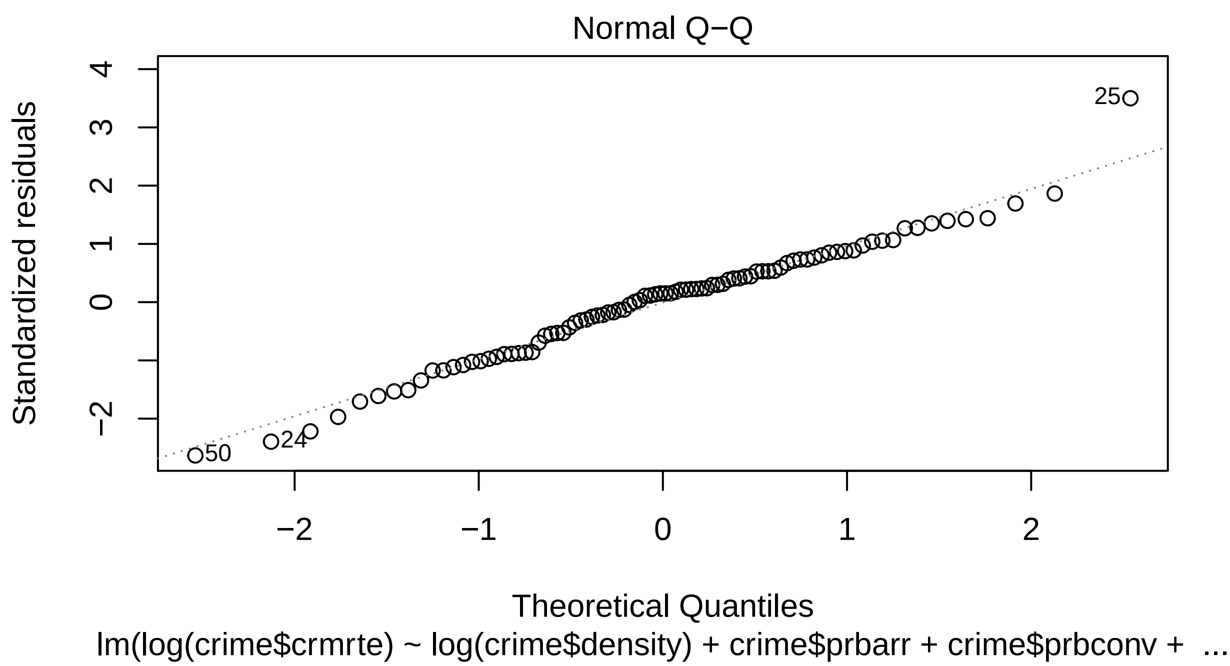
```r
plot(model_2, which=1)
```

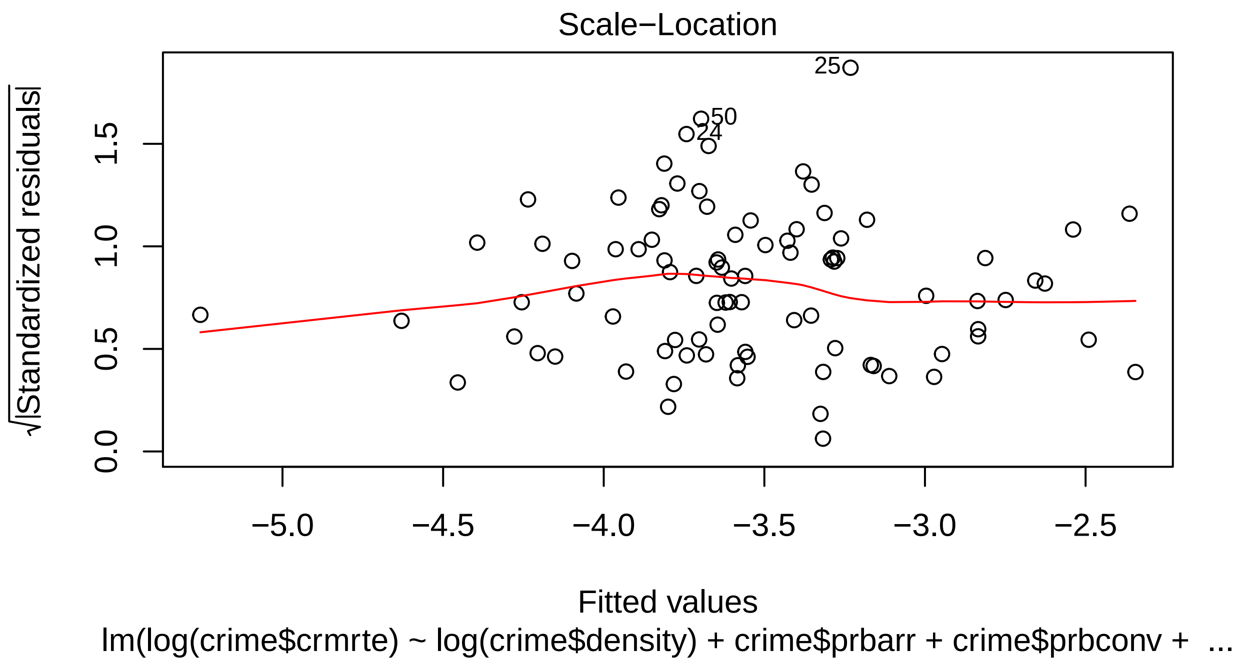


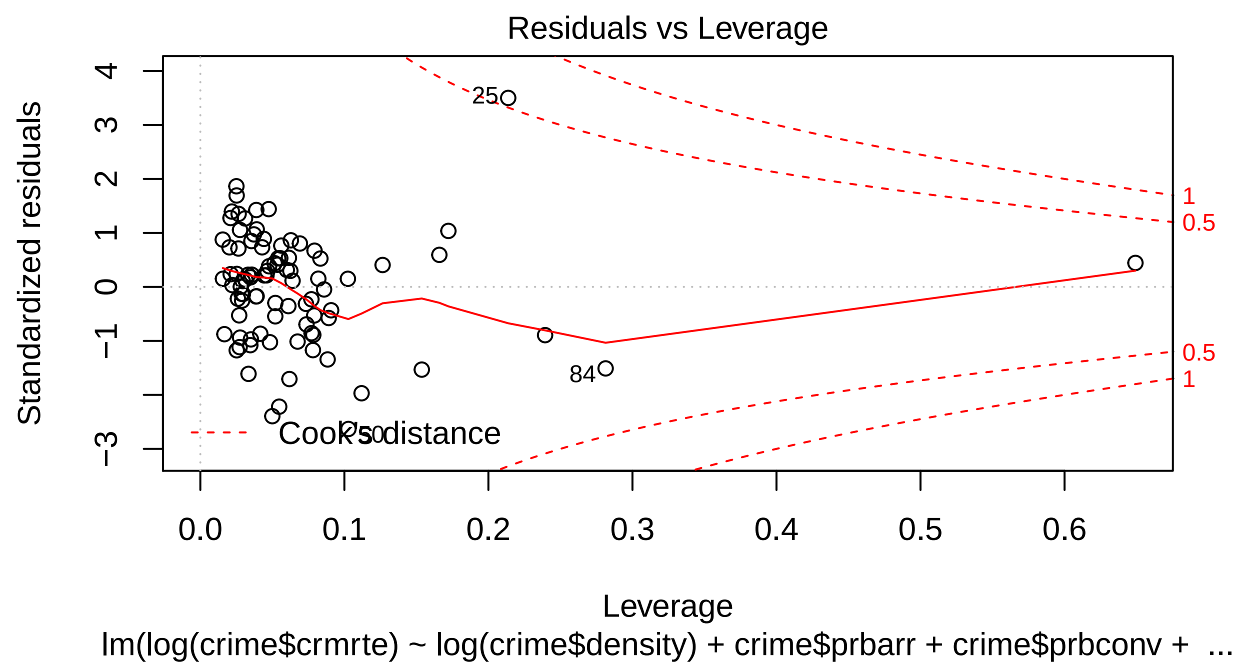
Here we see evidence of nonlinear relationship at the lower end of the range of our dependant variable. We address this by looking at the log-log relationship with respect to crimerte, density, and polpc, our variables that show the strongest evidence of skew.

```r
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
−2
0
1
2
3
4
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.

To check for multicollinearity to check the variance inflation factors for our dependant variables:

```r
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
```

Here we have rather low variance inflation factors for each of our independant variables so there is little evidence of multicollinearity.

Conclusions