Regression Competition

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```r
d <- read.csv("http://andrewpbray.github.io/data/crime-train.csv")
#summary(d)
library(ggplot2)
library(glmnet)
```

```
## Loading required package: Matrix

## Loading required package: foreach

## Loaded glmnet 2.0-16
```

```r
library(leaps)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

Fitting the model

```r
group_D_fit <- function(training_data) {
  group_D_process(training_data)

lm(data = training_data, ViolentCrimesPerPop ~
            factor(state)
          + racePctWhite
          + pctUrban
          + PctEmploy
          + MalePctDivorce
          + MalePctDivorce2
          + PctKids2Par
          + PctKids2Par2
          + PctWorkMom
          + PctPersDenseHous
          + NumStreet
          + PctVacantBoarded
          + PctImmigRec8
          + PctImmigRec82
          + PctIlleg
          + PctHousOccup
          + PctWorkMom*MalePctDivorce
          + pctUrban*racePctWhite
```

```
          + PctEmploy*racePctWhite
          + pctUrban*PctHousOccup
          + PctEmploy*pctUrban
          + PctIlleg*PctEmploy
          + PctImmigRec8*PctVacantBoarded
          + PctNotHSGrad
          + PctLess9thGrade
          + NumInShelters
          + PctEmploy*pctUrban
          + PctIlleg*PctEmploy
          + PctImmigRec8*PctVacantBoarded
          + PctNotHSGrad
          + PctLess9thGrade
          + NumInShelters)


}
```

Computing MSE

```
group_D_MSE <- function(model, data){
  n <- nrow(data)
  ys <- data$ViolentCrimesPerPop
  y_hats <- predict(model, data)
  residuals <- y_hats - ys
  MSE <- sum(residuals^2)/n
  MSE
}
```

Process

```
group_D_process<- function(d){
  d$MalePctDivorce2 <- d$MalePctDivorce^2
  d$PctKids2Par2 <- d$PctKids2Par^2
  d$PctImmigRec82 <- d$PctImmigRec8^2
  d
}
```

Automated Fit Forward

Here, we chose to minimize the BIC.

```
group_D_automated_fit <- function(data){
  install.packages("leaps")
  library(leaps)

  data <- data %>%
    select(population:MedRent, ViolentCrimesPerPop)

  forward <- regsubsets(ViolentCrimesPerPop ~ ., data = data,
```

```
                nvmax = 25, method = "forward")
  sum.fwd <- summary(forward)
  i <- which.min(sum.fwd$bic)
  coefs <- coef(forward, i)
  predictors <- names(coefs)[-1]
  f <- as.formula(
    paste("ViolentCrimesPerPop",
          paste(predictors, collapse = " + "),
          sep = " ~ "))

  lm(f, data = data)


}
```

Below, we examine the MSE.

```
m1 <- group_D_automated_fit(d)
```

```
## Installing package into '/home/clajelli/R/x86_64-pc-linux-gnu-library/3.5'
## (as 'lib' is unspecified)
```

```
group_D_MSE(m1, d)
```

```
## [1] 0.01887956
```

Automated Fit Backward

Again, we chose the model with the lowest BIC.

```
group_D_automated_fit_back <- function(data){
  install.packages("leaps")
  library(leaps)

  data <- data %>%
    select(population:MedRent, ViolentCrimesPerPop)

  backward <- regsubsets(ViolentCrimesPerPop ~ ., data = data,
                nvmax = 25, method = "backward")

  sum.bwd <- summary(backward)

  i <- which.min(sum.bwd$bic)
  coefs <- coef(backward, i)
  predictors <- names(coefs)[-1]
  fb <- as.formula(
    paste("ViolentCrimesPerPop",
          paste(predictors, collapse = " + "),
          sep = " ~ "))

  lm(fb, data = data)
  #summary(b)

}
```

Checking the MSE for the backwards one, we see that it is slightly lower that the forward one and therefore it will be our preferred model.

```
m2 <- group_D_automated_fit_back(d)
```

```
## Installing package into '/home/clajelli/R/x86_64-pc-linux-gnu-library/3.5'
## (as 'lib' is unspecified)
```

```
summary(m2)
```

```
##
## Call:
## lm(formula = fb, data = data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.52036 -0.07609 -0.01511  0.05387  0.73858
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.19047    0.04378   4.350 1.54e-05 ***
## population      -1.33892    0.35781  -3.742 0.000196 ***
## racePctWhite    -0.28172    0.03513  -8.019 3.85e-15 ***
## numbUrban        1.48973    0.35634   4.181 3.23e-05 ***
## MalePctDivorce   0.33315    0.03758   8.865  < 2e-16 ***
## PctWorkMom      -0.11890    0.02897  -4.104 4.48e-05 ***
## PctIlleg         0.31122    0.04209   7.393 3.65e-13 ***
## PctHousLess3BR   0.12293    0.03816   3.222 0.001326 **
## RentLowQ        -0.43094    0.08492  -5.075 4.84e-07 ***
## MedRent          0.41784    0.08921   4.684 3.32e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1371 on 790 degrees of freedom
## Multiple R-squared:  0.6633, Adjusted R-squared:  0.6595
## F-statistic: 172.9 on 9 and 790 DF,  p-value: < 2.2e-16
```

```
group_D_MSE(m2, d)
```

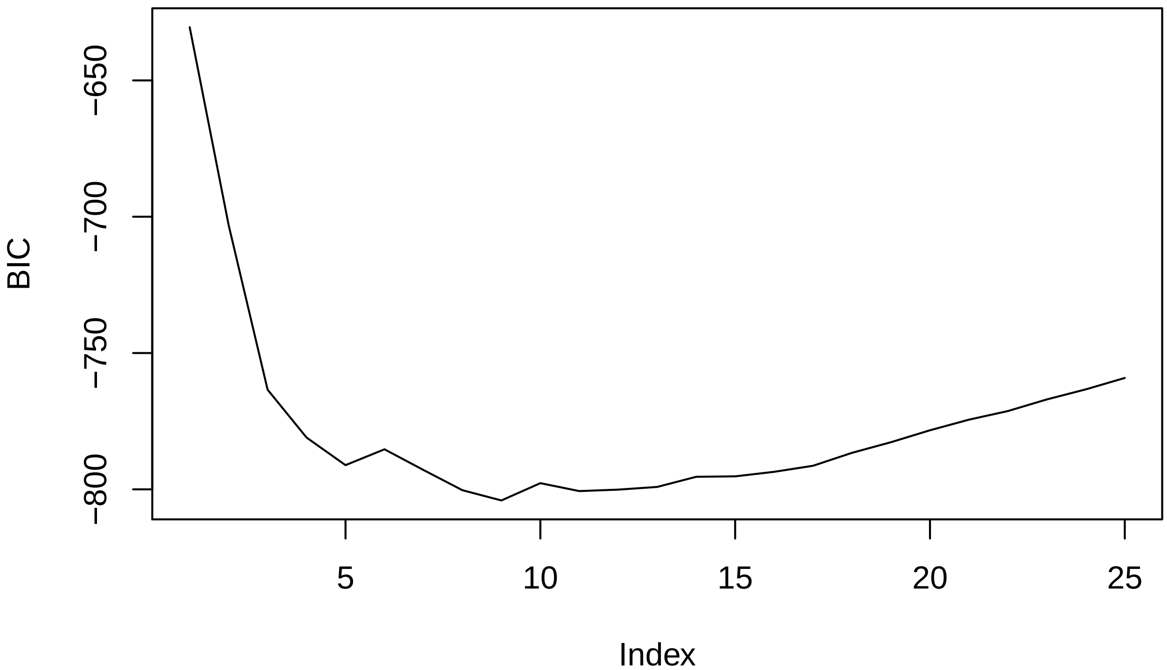
```
## [1] 0.01855925
```

Looking at how the adjusted

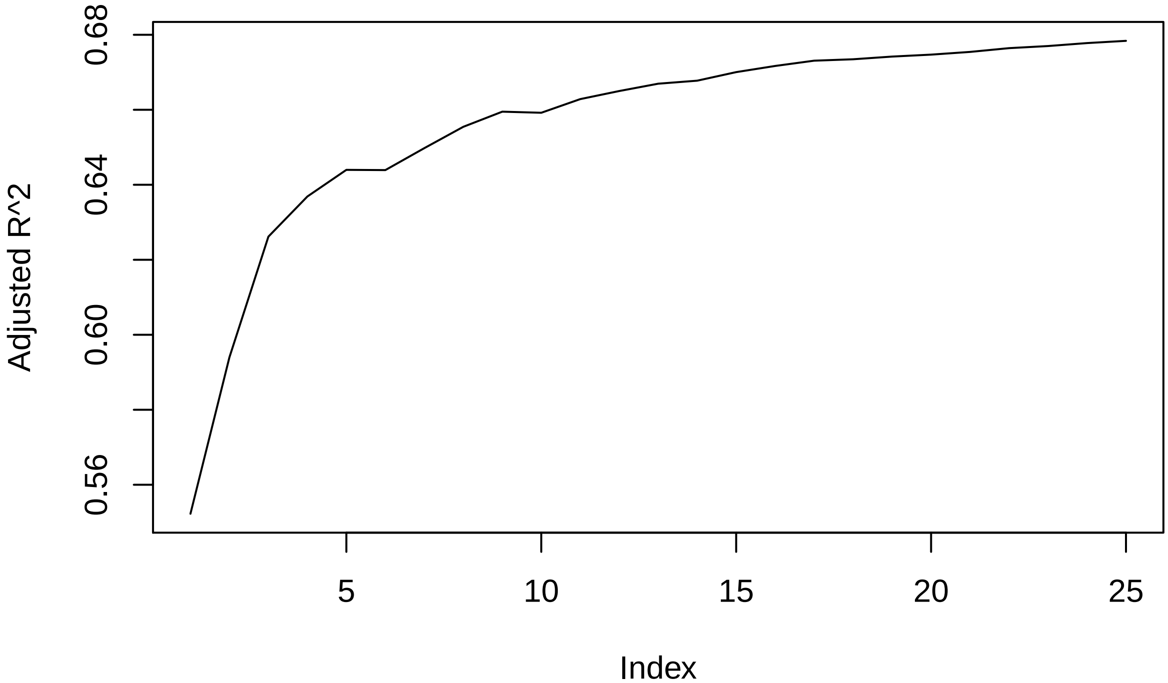
$$R^2$$

and BIC changes with the number of predictors. We see that while the adjusted R^2 keeps creeping upwards with more predictors the BIC is minimized around 7 or 8 predictors.

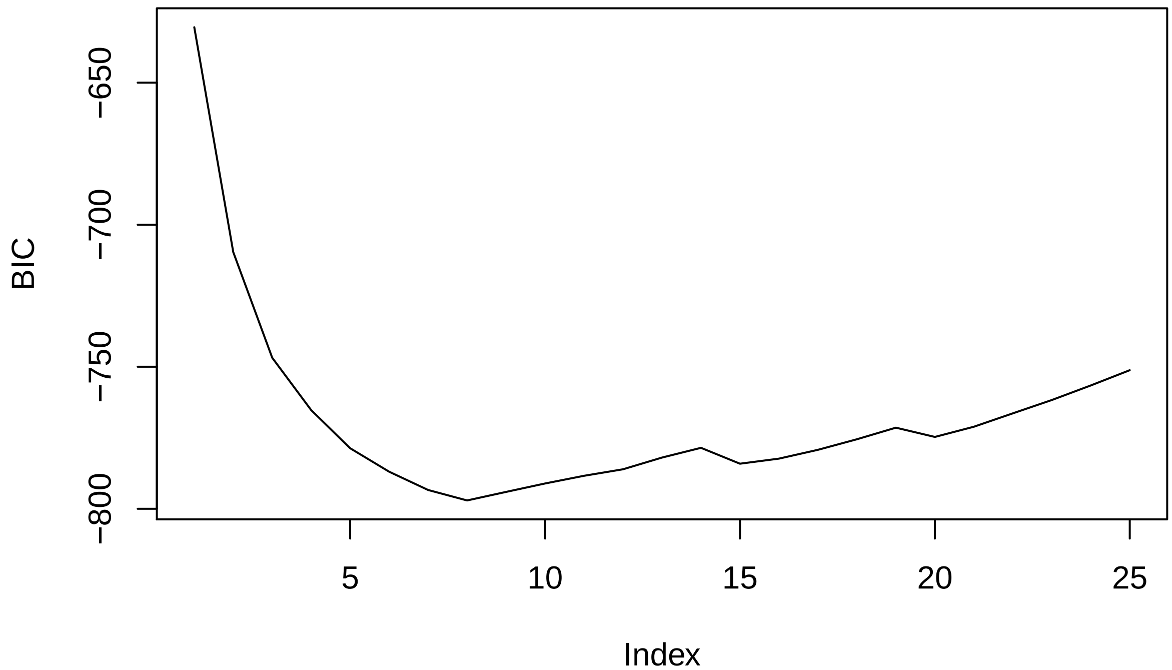
```
dsmall <- d %>%
    select(population:MedRent, ViolentCrimesPerPop)

backward <- regsubsets(ViolentCrimesPerPop ~ ., data = dsmall, nvmax = 25, method = "backward")
forward <- regsubsets(ViolentCrimesPerPop ~ ., data = dsmall, nvmax = 25, method = "forward")
b <- summary(backward)
plot(b$bic, type = "l", ylab = "BIC")
```



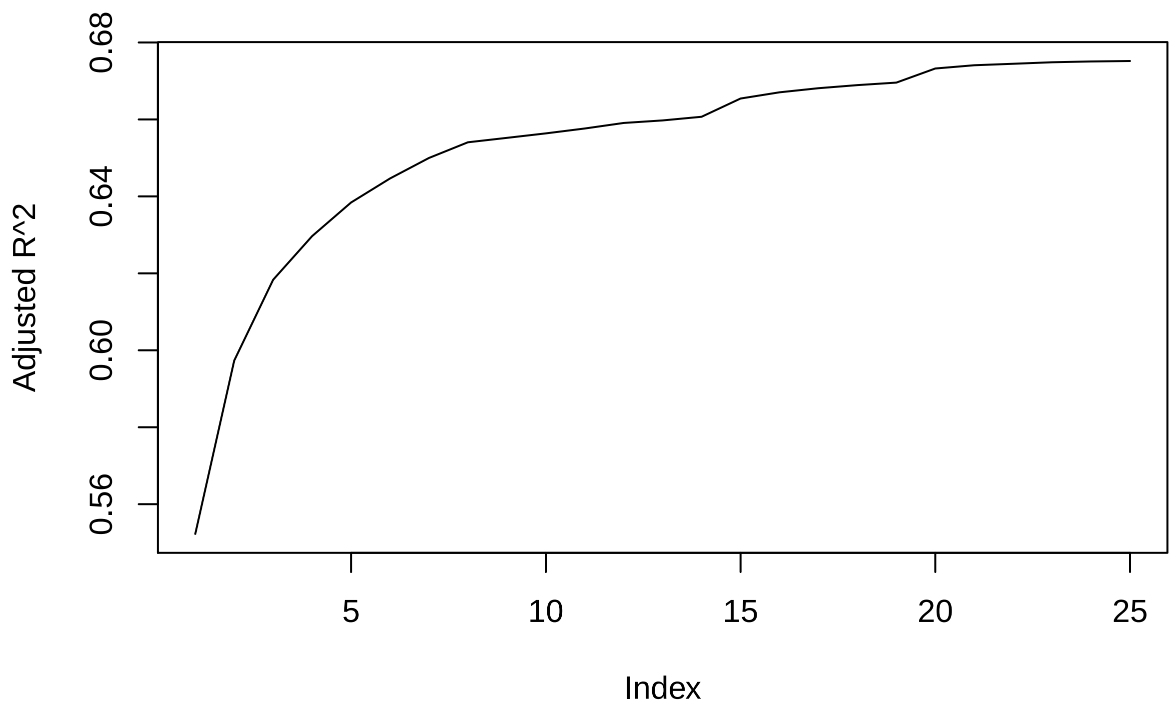

```r
plot(b$adjr2, type = "l", ylab = "Adjusted R^2")
```




```r
f <- summary(forward)
plot(f$bic, type = "l", ylab = "BIC")
```




```
plot(f$adjr2, type = "l", ylab = "Adjusted R^2")
```




```
forward <- regsubsets(ViolentCrimesPerPop ~ ., data = dsmall,
                nvmax = 25, method = "forward")
attributes(forward)
```

```
## $names
##  [1] "np"       "nrbar"    "d"        "rbar"     "thetab"
##  [6] "first"    "last"     "vorder"   "tol"      "rss"
## [11] "bound"    "nvmax"    "ress"     "ir"       "nbest"
## [16] "lopt"     "il"       "ier"      "xnames"   "method"
```

```
## [21] "force.in"  "force.out" "sserr"     "intercept" "lindep"
## [26] "nullrss"   "nn"        "call"
##
## $class
## [1] "regsubsets"
```

Started by examining the correlation between the predictor variables and ViolentCrimesPerPop, to get an idea of which ones could be good predictors.

```
#install.packages("Hmisc")
#library("Hmisc")
bool <- sapply(d, is.numeric)
num_only <- d[,bool]

matrix <- cor(num_only)
matrix <- matrix[,"ViolentCrimesPerPop"]
matrix
```

```
##                state            population         householdsize
##          -0.19867891            0.37066532           -0.03861389
##          racepctblack          racePctWhite          racePctAsian
##           0.61396953           -0.68885560            0.07698748
##          racePctHisp            agePct12t21           agePct12t29
##           0.37526637            0.03858255            0.14025298
##          agePct16t24            agePct65up             numbUrban
##           0.08207684            0.06033189            0.37483077
##             pctUrban             medIncome              pctWWage
##           0.15474311           -0.41384940           -0.29962918
##          pctWFarmSelf            pctWInvInc            pctWSocSec
##          -0.19174832           -0.57620572            0.12082657
##          pctWPubAsst            pctWRetire             medFamInc
##           0.59227263           -0.08997653           -0.42398363
##            perCapInc           whitePerCap           blackPerCap
##          -0.34862287           -0.22204504           -0.26352732
##          indianPerCap           AsianPerCap           OtherPerCap
##          -0.09625260           -0.16996957           -0.10880239
##           HispPerCap           NumUnderPov         PctPopUnderPov
##          -0.25883292            0.45390778            0.53779772
##      PctLess9thGrade          PctNotHSGrad           PctBSorMore
##           0.45567237            0.51567720           -0.33150986
##        PctUnemployed             PctEmploy           PctEmplManu
##           0.53731986           -0.32740291            0.01761068
##       PctEmplProfServ         PctOccupManu       PctOccupMgmtProf
##          -0.10331277            0.33476343           -0.36141065
##       MalePctDivorce         MalePctNevMarr          FemalePctDiv
##           0.54018366            0.31010841            0.56419032
##          TotalPctDiv            PersPerFam            PctFam2Par
##           0.56515609            0.17194429           -0.70528060
##          PctKids2Par       PctYoungKids2Par           PctTeen2Par
##          -0.73929315           -0.66897706           -0.65329249
##   PctWorkMomYoungKids            PctWorkMom              NumIlleg
##          -0.06341328           -0.19196402            0.49542797
##             PctIlleg              NumImmig        PctImmigRecent
##           0.74352441            0.32492255            0.17054361
##          PctImmigRec5          PctImmigRec8         PctImmigRec10
```

```
##           0.20884691           0.26657334           0.31277465
##       PctRecentImmig          PctRecImmig5          PctRecImmig8
##           0.28087817           0.29501202           0.30279580
##        PctRecImmig10      PctSpeakEnglOnly   PctNotSpeakEnglWell
##           0.31827795          -0.32244668           0.38597995
##      PctLargHouseFam      PctLargHouseOccup      PersPerOccupHous
##           0.43062883           0.33953706          -0.01870530
##    PersPerOwnOccHous     PersPerRentOccHous        PctPersOwnOccup
##          -0.08508545           0.25020053          -0.53377983
##      PctPersDenseHous       PctHousLess3BR              MedNumBR
##           0.50540251           0.49694082          -0.39714251
##           HousVacant          PctHousOccup          PctHousOwnOcc
##           0.40353909          -0.26979027          -0.48147523
##     PctVacantBoarded        PctVacMore6Mos        MedYrHousBuilt
##           0.50895955           0.02399628          -0.17513688
##       PctHousNoPhone        PctWOFullPlumb        OwnOccLowQuart
##           0.48488275           0.38798494          -0.19113369
##          OwnOccMedVal          OwnOccHiQuart              RentLowQ
##          -0.17423559          -0.16223122          -0.23616004
##           RentMedian             RentHighQ               MedRent
##          -0.22219135          -0.21184794          -0.22753962
##    MedRentPctHousInc      MedOwnCostPctInc MedOwnCostPctIncNoMtg
##           0.32846021           0.06093440           0.04860191
##        NumInShelters             NumStreet         PctForeignBorn
##           0.39694511           0.35737606           0.25346691
##      PctBornSameState        PctSameHouse85         PctSameCity85
##          -0.06845675          -0.11254574           0.13192565
##       PctSameState85              LandArea               PopDens
##           0.03032880           0.18847682           0.34196833
##        PctUsePubTrans   LemasPctOfficDrugUn    ViolentCrimesPerPop
##           0.21336825           0.36681475           1.00000000
```

Used a lasso regression approach to decide on the best predictors to include in the model.

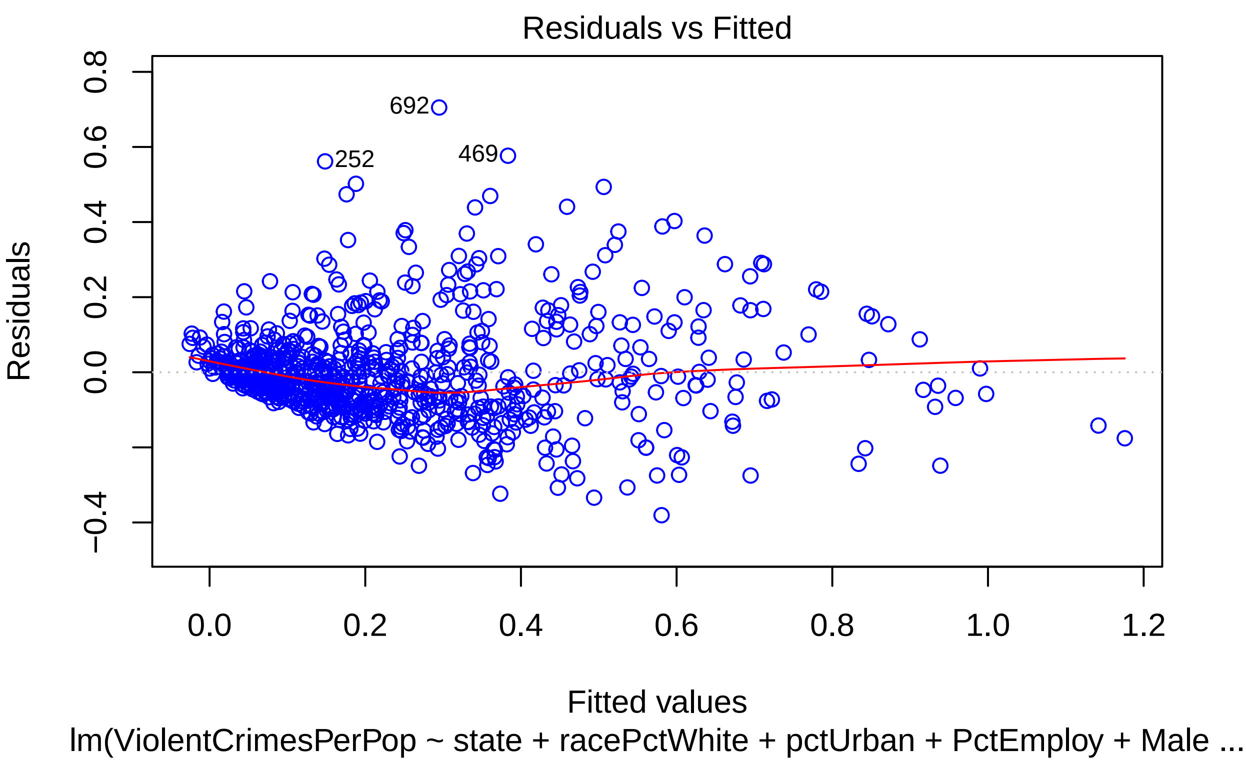
```
#set.seed(489)
#x_vars <- model.matrix(ViolentCrimesPerPop~. , num_only)[,-1]
#y_var <- num_only$ViolentCrimesPerPop
#lambda_seq <- 10^seq(2, -2, by = -.1)
#train = sample(1:nrow(x_vars), nrow(x_vars)/2)
#test = (-train)
#ytest = y[test]
#cv_output <- cv.glmnet(x_vars[train,], y_var[train],
                       #alpha = 1, lambda = lambda_seq)
#best_lam <- cv_output$lambda.min
#lasso.mod <- glmnet(x_vars[train,], y_var[train], alpha = 1, lambda = lambda)
#lasso.pred <- predict(lasso.mod, s = bestlam, newx = x_vars[test,])
#x <- cor(num_only)
#lasso_best <- glmnet(x_vars[train,], y_var[train], alpha = 1, lambda = best_lam)
#pred <- predict(lasso_best, s = best_lam, newx = x_vars[test,])
#final <- cbind(y_var[test], pred)
#head(final)
```

Checked for non linear relationships using residual and normal plots with the chosen variables and added a couple squared terms where it appeared appropriate.

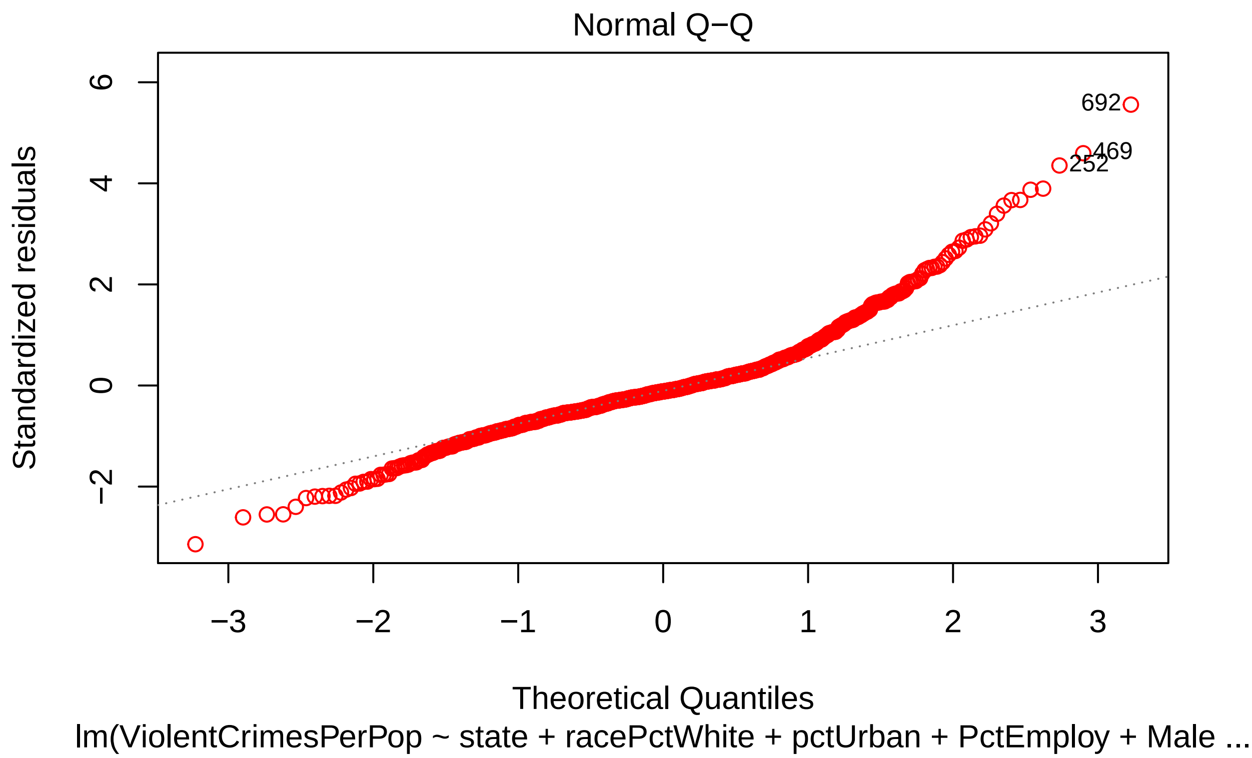
```r
MalePctDivorce2 <- (d$MalePctDivorce)^2
PctKids2Par2 <-(d$PctKids2Par)^2
PctImmigRec82 <- (d$PctImmigRec8)^2
#pctdensehouse2 <- (d$PctPersDenseHous)^2
#m2 <- lm(data = d, ViolentCrimesPerPop ~ state + racePctWhite + pctUrban + PctUnemployed + PctEmploy +
#m3 <- lm(data = d, ViolentCrimesPerPop ~  state + racePctWhite + pctUrban + PctUnemployed + MalePctDiv
#m4 <- lm(data = d, ViolentCrimesPerPop ~  state + racePctWhite + pctUrban + PctUnemployed + MalePctDiv
#ggplot(d, (aes(x = LemasPctOfficDrugUn , y = ViolentCrimesPerPop))) + geom_point(position = "jitter")
```

Added some interaction terms that impoved the R^2, adjusted R^2 and MSE. Looked at plots of residuals. Residuals vs fitted values appeared pretty good despite a slight dip.

```r
m7 <- lm(data = d, ViolentCrimesPerPop ~  state + racePctWhite + pctUrban  + PctEmploy + MalePctDivorce

plot(m7, which=1, col=c("blue"))
```




```r
plot(m7, which=2, col=c("red"))
```




```r
#summary(m7)
#group_D_MSE(m7, d)
```

Added back some variables that were not included in the lasso, but improved the model. Noticed some poor residuals at the more extreme values.

```r
m11 <- lm(data = d, ViolentCrimesPerPop ~  factor(state) + racePctWhite + pctUrban  + PctEmploy + MalePc
summary(m11)
```

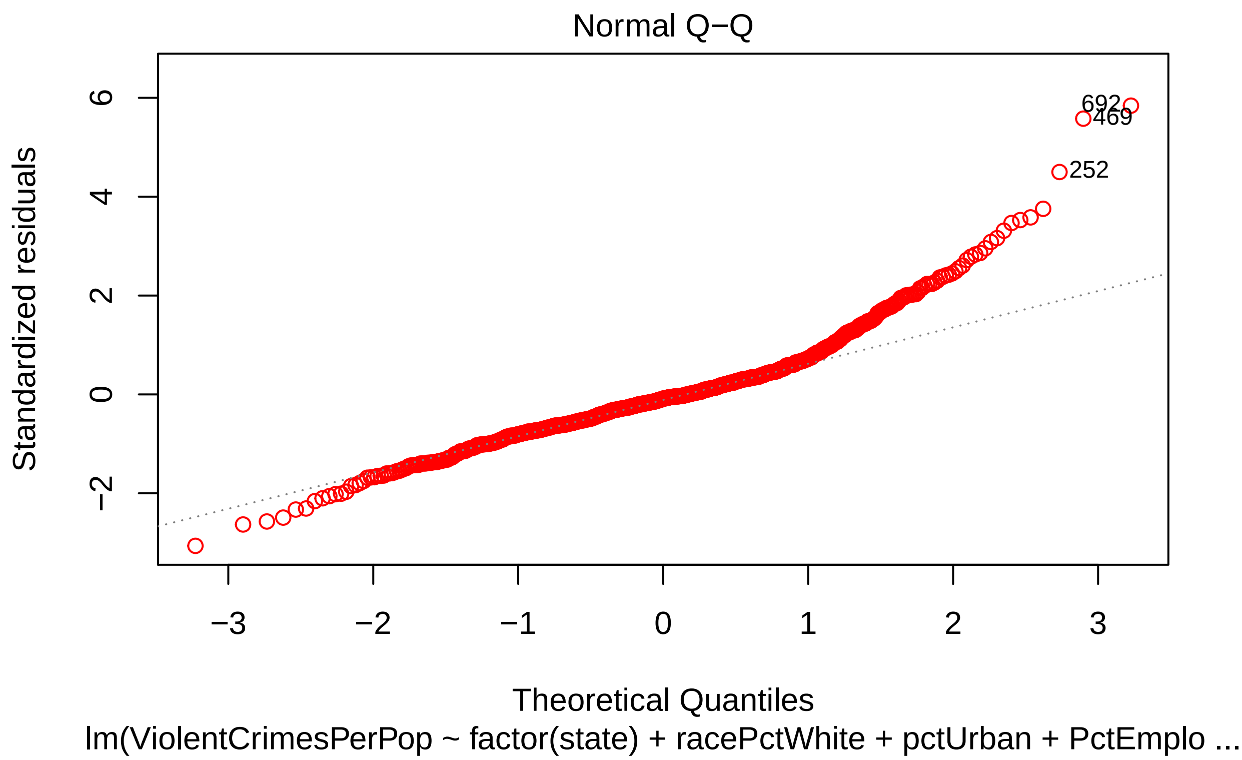
```
##
## Call:
## lm(formula = ViolentCrimesPerPop ~ factor(state) + racePctWhite +
##     pctUrban + PctEmploy + MalePctDivorce + MalePctDivorce^2 +
##     PctKids2Par + PctKids2Par^2 + PctWorkMom + PctPersDenseHous +
##     NumStreet + PctVacantBoarded + PctImmigRec8 + PctImmigRec8^2 +
##     PctIlleg + PctHousOccup + PctWorkMom * MalePctDivorce + pctUrban *
##     racePctWhite + PctEmploy * racePctWhite + pctUrban * PctHousOccup +
##     PctEmploy * pctUrban + PctIlleg * PctEmploy + PctImmigRec8 *
##     PctVacantBoarded + PctNotHSGrad + PctLess9thGrade + NumInShelters +
##     PctEmploy * pctUrban + PctIlleg * PctEmploy + PctImmigRec8 *
##     PctVacantBoarded + PctNotHSGrad + PctLess9thGrade + NumInShelters,
##     data = d)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.35269 -0.07361 -0.01086  0.04494  0.71466
##
## Coefficients:
##                                Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   0.4112001  0.1387024   2.965 0.003128 **
## factor(state)2               -0.1421297  0.1353742  -1.050 0.294108
```

```
## factor(state)4            -0.1029670  0.0637838  -1.614 0.106888
## factor(state)5            -0.1578449  0.0498027  -3.169 0.001591 **
## factor(state)6            -0.1027411  0.0386599  -2.658 0.008042 **
## factor(state)8            -0.1336471  0.0511594  -2.612 0.009175 **
## factor(state)9            -0.1822639  0.0415871  -4.383 1.34e-05 ***
## factor(state)12           -0.0189972  0.0415190  -0.458 0.647407
## factor(state)13           -0.1866278  0.0479136  -3.895 0.000107 ***
## factor(state)16           -0.1531316  0.0969082  -1.580 0.114497
## factor(state)18           -0.1345293  0.0431615  -3.117 0.001899 **
## factor(state)19           -0.0410532  0.0622479  -0.660 0.509774
## factor(state)21           -0.1454542  0.0531040  -2.739 0.006311 **
## factor(state)22           -0.2280464  0.0546191  -4.175 3.33e-05 ***
## factor(state)23           -0.2238731  0.0566277  -3.953 8.45e-05 ***
## factor(state)24           -0.1314355  0.0828686  -1.586 0.113153
## factor(state)25           -0.0808962  0.0380796  -2.124 0.033970 *
## factor(state)27           -0.1858728  0.0971838  -1.913 0.056188 .
## factor(state)28           -0.2550116  0.0527116  -4.838 1.60e-06 ***
## factor(state)29           -0.1091633  0.0468878  -2.328 0.020173 *
## factor(state)32           -0.1573377  0.0982231  -1.602 0.109620
## factor(state)33           -0.1858497  0.0551858  -3.368 0.000797 ***
## factor(state)34           -0.1871036  0.0353853  -5.288 1.64e-07 ***
## factor(state)36           -0.2154638  0.0436754  -4.933 1.00e-06 ***
## factor(state)37           -0.1385367  0.0435482  -3.181 0.001528 **
## factor(state)38           -0.2023313  0.0679039  -2.980 0.002981 **
## factor(state)39           -0.1931397  0.0380657  -5.074 4.94e-07 ***
## factor(state)40           -0.1926520  0.0457180  -4.214 2.82e-05 ***
## factor(state)41           -0.2018225  0.0563507  -3.582 0.000364 ***
## factor(state)42           -0.1627450  0.0398160  -4.087 4.84e-05 ***
## factor(state)44           -0.1548377  0.0505245  -3.065 0.002259 **
## factor(state)45           -0.0474661  0.0519182  -0.914 0.360886
## factor(state)46           -0.1363641  0.0981100  -1.390 0.164976
## factor(state)47           -0.0881303  0.0444084  -1.985 0.047566 *
## factor(state)48           -0.1218307  0.0382073  -3.189 0.001490 **
## factor(state)49           -0.1575874  0.0549081  -2.870 0.004222 **
## factor(state)50           -0.2356500  0.0962349  -2.449 0.014570 *
## factor(state)51           -0.2398559  0.0459355  -5.222 2.31e-07 ***
## factor(state)53           -0.1737736  0.0477565  -3.639 0.000293 ***
## factor(state)54           -0.1928352  0.0619917  -3.111 0.001939 **
## factor(state)55           -0.1666619  0.0426808  -3.905 0.000103 ***
## factor(state)56           -0.1785575  0.0827548  -2.158 0.031277 *
## racePctWhite              -0.2385404  0.1107573  -2.154 0.031586 *
## pctUrban                   0.1952759  0.0580465   3.364 0.000808 ***
## PctEmploy                 -0.3151692  0.2056409  -1.533 0.125799
## MalePctDivorce             0.2683803  0.0966151   2.778 0.005612 **
## PctKids2Par               -0.0824103  0.0968535  -0.851 0.395115
## PctWorkMom                -0.0172031  0.0766088  -0.225 0.822386
## PctPersDenseHous          -0.0284675  0.0552688  -0.515 0.606657
## NumStreet                  0.1009727  0.0536773   1.881 0.060352 .
## PctVacantBoarded           0.0192847  0.0532844   0.362 0.717515
## PctImmigRec8               0.0009149  0.0372881   0.025 0.980432
## PctIlleg                   0.2518983  0.1244616   2.024 0.043341 *
## PctHousOccup              -0.1160975  0.0540048  -2.150 0.031899 *
## PctNotHSGrad               0.2016649  0.1011110   1.994 0.046467 *
## PctLess9thGrade           -0.0852119  0.0861635  -0.989 0.323010
```

```
## NumInShelters                   0.0843425  0.0623508   1.353 0.176563
## MalePctDivorce:PctWorkMom      -0.1260923  0.1554167  -0.811 0.417446
## racePctWhite:pctUrban          -0.2597827  0.0564834  -4.599 4.99e-06 ***
## racePctWhite:PctEmploy          0.4644071  0.1996022   2.327 0.020254 *
## pctUrban:PctHousOccup           0.1379663  0.0635187   2.172 0.030170 *
## pctUrban:PctEmploy             -0.0930252  0.0677950  -1.372 0.170433
## PctEmploy:PctIlleg              0.0394544  0.2279420   0.173 0.862628
## PctVacantBoarded:PctImmigRec8   0.1746203  0.1163871   1.500 0.133955
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1257 on 736 degrees of freedom
## Multiple R-squared:  0.7361, Adjusted R-squared:  0.7136
## F-statistic: 32.59 on 63 and 736 DF,  p-value: < 2.2e-16
```

```r
plot(m11, which=2, col=c("red"))
```

```
## Warning: not plotting observations with leverage one:
##   27
```



Assessed the final models looking by two different criterion statistics.

```r
AIC(m7)
```

```
## [1] -953.1708
```

```r
BIC(m7)
```

```
## [1] -798.5786
```

```r
AIC(m11)
```

```
## [1] -984.1071
```

```r
BIC(m11)
```

```
## [1] -679.6074
```