

Homework 8 by Haritha Pulletikurti

Question 11.1

Using the crime data set `uscrime.txt` from Questions 8.2, 9.1, and 10.1, build a regression model using:

1. Stepwise regression
2. Lasso
3. Elastic net

For Parts 2 and 3, remember to scale the data first – otherwise, the regression coefficients will be on different scales and the constraint won't have the desired effect.

For Parts 2 and 3, use the `glmnet` function in R.

Notes on R:

- For the elastic net model, what we called λ in the videos, `glmnet` calls "alpha"; you can get a range of results by varying alpha from 1 (lasso) to 0 (ridge regression) [and, of course, other values of alpha in between].
- In a function call like `glmnet(x,y,family="mgaussian",alpha=1)` the predictors `x` need to be in R's matrix format, rather than data frame format. You can convert a data frame to a matrix using `as.matrix` – for example, `x <- as.matrix(data[,1:n-1])`
- Rather than specifying a value of `T`, `glmnet` returns models for a variety of values of `T`.

Answer:

Stepwise Regression Techniques: As we all know,

Bias: is the difference between average prediction of our model and the correct value we are trying to predict.

Variance: is the variability of the model prediction based on different data sets i.e. Training / validation/Test data sets.

Best Model: We all know the best model is considered to have low bias and low variance.

If n = Number of data points and p = number of predictors

Case 1: if n is very large than p i.e. $n \gg p$, then the least squared regression model tends to have low bias and low variance.

Case 2: if n is not much larger than p i.e. $n > p$, then there can be lot of variability in least squares fit resulting in overfitting.

Case 3: If n is smaller than p , i.e. $n < p$, then the variance is infinite as there is no longer a unique least squared estimate.

There are many approaches for variable selection i.e. excluding the irrelevant variables from a multiple regression model like the ones mentioned below

Forward Step wise Regression:

Step 1: Let M_0 denote the null model which contains no predictors.

Step 2: For $k = 0, \dots, p-1$

- a) Consider all $p-k$ models that augment the predictors in the set M_k with one additional predictor.

- b) Choose best among the $p-k$ models, call it M_{k+1} . Here best is defined as having the smallest RSS or highest R^2 .

Step3: Select the single best model from among the M_0, \dots, M_p using cross validated predictor error AIC, BIC or adjusted R^2 .

Backward Stepwise Elimination:

Step 1: Let M_0 denote the full model which contains all the predictors.

Step 2: For $k = p, p-1, \dots, 1$

- a) Consider all k models that contain all but one of the predictors in the set M_k , for a total of $k-1$ predictors.
- b) Choose best among these k models, call it M_{k-1} . Here best is defined as having the smallest RSS or highest R^2 .

Step3: Select the single best model from among the M_0, \dots, M_p using cross validated predictor error AIC, BIC or adjusted R^2 .

Backward selection requires that the number of samples n is larger than number of variables in p so that full model can be fit. In contrast Forward selection model can be used even when $n < p$ and so is the only viable subset method when p is large.

Stepwise Regression: is a combination of both forward selection and backward elimination.

1. Start with no predictors.

2.1 Find the best new predictor if it is good enough

- a) add that factor, fit model with current set of factors.
- b) Remove factors with high p value.
- c) Check if we have enough factors. If not repeat from steps 2.1.

2.2 If the chosen new predictor is not good enough

- a) remove factors with high p -value
- b) fit the model with final set of factors.

Optimal Model: The model that contains all the predictors will always have the smallest RSS and the largest R^2 , since these quantities are related to training error. We should choose the model that has the low-test error. Since these measurements are not suitable to choose between models with different number of predictors, the best way to choose the model is by checking AIC, BIC and Adjusted R^2 .

[References: An Introduction to Statistical Learning Text book].

Forward Regression

```
rm(list = ls())
set.seed(82)
uscrime<- read.table("uscrime.txt", stringsAsFactors = FALSE, header = TRUE)

uscrime[1:3,]

##      M So   Ed  Po1 Po2    LF   M.F Pop   NW   U1  U2 Wealth Ineq    Prob
## 1 15.1   1  9.1  5.8 5.6 0.510  95.0  33 30.1 0.108 4.1   3940 26.1 0.084602
## 2 14.3   0 11.3 10.3 9.5 0.583 101.2  13 10.2 0.096 3.6   5570 19.4 0.029599
```

```

## 3 14.2 1 8.9 4.5 4.4 0.533 96.9 18 21.9 0.094 3.3 3180 25.0 0.083401
##      Time Crime
## 1 26.2011 791
## 2 25.2999 1635
## 3 24.3006 578

# Scale the data
Scaleduscrime <- as.data.frame(scale(uscrime[,c(1,3:15)]))
Scaleduscrime <- cbind(uscrime[,2],Scaleduscrime,uscrime[,16])
colnames(Scaleduscrime)[1] <- "So"
colnames(Scaleduscrime)[16] <- "Crime"

Scaleduscrime[1:3,]

##      So      M      Ed      Po1      Po2      LF      M.F
## 1 1 0.9886930 -1.3085099 -0.9085105 -0.8666988 -1.2667456 -1.1206050
## 2 0 0.3521372 0.6580587 0.6056737 0.5280852 0.5396568 0.9834175
## 3 1 0.2725678 -1.4872888 -1.3459415 -1.2958632 -0.6976051 -0.4758239
##      Pop      NW      U1      U2      Wealth      Ineq      Prob
## 1 -0.09500679 1.943738564 0.69510600 0.8313680 -1.3616094 1.679364 1.6497631
## 2 -0.62033844 0.008483424 0.02950365 0.2393332 0.3276683 0.000000 -0.7693365
## 3 -0.48900552 1.146296747 -0.08143007 -0.1158877 -2.1492481 1.403647 1.5969416
##      Time Crime
## 1 -0.05599367 791
## 2 -0.18315796 1635
## 3 -0.32416470 578

# Split the data into Training and Test Datasets.
library(caret)

## Loading required package: lattice

## Loading required package: ggplot2

randomrows <- createDataPartition(y=1:nrow(Scaleduscrime),p=0.7, list = FALSE)
TrainingData = Scaleduscrime[randomrows,]
TestData = Scaleduscrime[-randomrows,]
dim(TrainingData)

## [1] 35 16

dim(TestData)

## [1] 12 16

library(olsrr)

##
## Attaching package: 'olsrr'

## The following object is masked from 'package:datasets':
##
##      rivers

## -----

# Perform Forward Regression using aic
model<-lm(Crime~.,data = TrainingData)
Forwardfit.aic <-ols_step_forward_aic(model, details = TRUE)

## Forward Selection Method
## -----

```

```
##
## Candidate Terms:
##
## 1 . So
## 2 . M
## 3 . Ed
## 4 . Po1
## 5 . Po2
## 6 . LF
## 7 . M.F
## 8 . Pop
## 9 . NW
## 10 . U1
## 11 . U2
## 12 . Wealth
## 13 . Ineq
## 14 . Prob
## 15 . Time
##
## Step 0: AIC = 507.0876
## Crime ~ 1
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po1           1    495.841    1128626.869    2453269.016    0.315      0.294
## Po2           1    496.326    1094409.821    2487486.064    0.306      0.284
## Prob          1    497.633     999751.467    2582144.419    0.279      0.257
## Pop           1    499.351     869842.365    2712053.520    0.243      0.220
## Time          1    502.489     615451.183    2966444.703    0.172      0.147
## Wealth        1    502.537     611427.125    2970468.761    0.171      0.146
## U2            1    507.541     154871.969    3427023.917    0.043      0.014
## Ed            1    507.567     152323.822    3429572.063    0.043      0.014
## Ineq          1    508.547      54884.610    3527011.276    0.015     -0.015
## M.F           1    508.844      24841.604    3557054.282    0.007     -0.023
## So            1    508.940      15112.715    3566783.170    0.004     -0.026
## NW            1    508.988      10216.386    3571679.500    0.003     -0.027
## M             1    509.016       7344.408    3574551.478    0.002     -0.028
## U1            1    509.038      5105.396    3576790.489    0.001     -0.029
## LF            1    509.085       314.577    3581581.309    0.000     -0.030
## -----
##
##
## - Po1
##
##
## Step 1 : AIC = 495.8411
## Crime ~ Po1
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ineq          1    491.397     412570.973    2040698.043    0.430      0.395
## M             1    491.519     405405.508    2047863.508    0.428      0.393
## Time          1    494.656     213421.255    2239847.762    0.375      0.336
## So            1    494.849     201012.706    2252256.311    0.371      0.332
## NW            1    495.057     187592.705    2265676.311    0.367      0.328
## Prob          1    496.070     121066.144    2332202.872    0.349      0.308
## Pop           1    496.667      80947.348    2372321.668    0.338      0.296
## Wealth        1    497.570     18934.023    2434334.994    0.320      0.278
## M.F           1    497.651     13278.426    2439990.591    0.319      0.276
```

```

## U2          1    497.681    11227.973    2442041.043    0.318    0.276
## U1          1    497.733     7586.205    2445682.812    0.317    0.275
## Po2         1    497.746     6676.168    2446592.848    0.317    0.274
## Ed          1    497.764     5367.968    2447901.049    0.317    0.274
## LF          1    497.780     4263.764    2449005.252    0.316    0.274
## -----
##
## - Ineq
##
##
## Step 2 : AIC = 491.3966
## Crime ~ Po1 + Ineq
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Wealth        1    484.774    445589.256    1595108.787    0.555    0.512
## Prob          1    486.606    359892.126    1680805.917    0.531    0.485
## Ed            1    487.472    317758.831    1722939.212    0.519    0.472
## M.F           1    490.587    157410.744    1883287.299    0.474    0.423
## M             1    490.768    147630.923    1893067.120    0.471    0.420
## Time          1    491.324    117321.510    1923376.533    0.463    0.411
## LF            1    491.955     82341.568    1958356.475    0.453    0.400
## U1            1    493.363     1980.571    2038717.472    0.431    0.376
## U2            1    493.379     1023.689    2039674.354    0.431    0.375
## Pop           1    493.380      951.595    2039746.449    0.431    0.375
## NW            1    493.390      357.619    2040340.424    0.430    0.375
## So            1    493.396      41.327    2040656.716    0.430    0.375
## Po2           1    493.397       2.564    2040695.479    0.430    0.375
## -----
##
## - Wealth
##
##
## Step 3 : AIC = 484.7744
## Crime ~ Po1 + Ineq + Wealth
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## M             1    478.186    347075.378    1248033.409    0.652    0.605
## Prob          1    482.112    198933.020    1396175.767    0.610    0.558
## Time          1    483.484    143109.094    1451999.694    0.595    0.541
## Ed            1    484.913     82605.957    1512502.830    0.578    0.521
## M.F           1    485.267     67258.096    1527850.691    0.573    0.517
## U1            1    486.536    10834.128    1584274.660    0.558    0.499
## NW            1    486.625     6785.588    1588323.200    0.557    0.497
## So            1    486.685     4046.061    1591062.727    0.556    0.497
## LF            1    486.694     3659.550    1591449.238    0.556    0.496
## U2            1    486.707     3086.595    1592022.192    0.556    0.496
## Pop           1    486.719     2526.835    1592581.952    0.555    0.496
## Po2           1    486.745     1337.351    1593771.436    0.555    0.496
## -----
##
## - M
##
##
## Step 4 : AIC = 478.1863
## Crime ~ Po1 + Ineq + Wealth + M
##
## -----

```

```
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Prob          1      477.124    104553.541    1143479.868    0.681      0.626
## U1            1      477.869     79970.953    1168062.456    0.674      0.618
## Ed           1      478.051     73880.461    1174152.948    0.672      0.616
## U2           1      478.557     56776.806    1191256.603    0.667      0.610
## M.F          1      478.723     51097.530    1196935.879    0.666      0.608
## Time         1      478.757     49954.024    1198079.385    0.666      0.608
## NW           1      479.845     12104.006    1235929.403    0.655      0.595
## So           1      479.968      7776.684    1240256.725    0.654      0.594
## LF           1      480.134      1847.025    1246186.383    0.652      0.592
## Po2          1      480.142     1595.606    1246437.803    0.652      0.592
## Pop          1      480.144     1494.654    1246538.755    0.652      0.592
## -----
```

```
##
## - Prob
##
```

```
## Step 5 : AIC = 477.124
## Crime ~ Po1 + Ineq + Wealth + M + Prob
##
```

```
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ed            1      476.040     96447.490    1047032.378    0.708      0.645
## U1            1      476.409     85335.284    1058144.584    0.705      0.641
## U2            1      477.242     59865.135    1083614.733    0.697      0.633
## M.F          1      477.574     49526.924    1093952.944    0.695      0.629
## LF           1      478.890     7619.524    1135860.344    0.683      0.615
## Time         1      478.950     5669.305    1137810.563    0.682      0.614
## Po2          1      479.035     2913.147    1140566.721    0.682      0.613
## Pop          1      479.098      841.502    1142638.366    0.681      0.613
## NW           1      479.105      626.205    1142853.662    0.681      0.613
## So           1      479.124       7.427    1143472.441    0.681      0.612
## -----
```

```
## - Ed
##
```

```
## Step 6 : AIC = 476.04
## Crime ~ Po1 + Ineq + Wealth + M + Prob + Ed
##
```

```
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## U2            1      473.509    127134.753     919897.625    0.743      0.677
## U1            1      475.456     74522.160     972510.218    0.728      0.658
## LF           1      476.002     59212.052     987820.326    0.724      0.653
## Time         1      477.007     30442.920    1016589.459    0.716      0.643
## NW           1      477.574     13847.376    1033185.003    0.712      0.637
## So           1      477.702     10061.297    1036971.081    0.710      0.635
## M.F          1      477.730      9223.807    1037808.571    0.710      0.635
## Pop          1      477.942      2924.112    1044108.266    0.709      0.633
## Po2          1      478.020      596.911    1046435.467    0.708      0.632
## -----
```

```
## - U2
##
```

```
## Step 7 : AIC = 473.5091
## Crime ~ Po1 + Ineq + Wealth + M + Prob + Ed + U2
```

```

##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Time          1    474.294    31378.195    888519.430    0.752    0.676
## LF            1    474.787    18781.605    901116.020    0.748    0.671
## So            1    475.244    6935.270    912962.355    0.745    0.667
## NW            1    475.325    4822.279    915075.346    0.745    0.666
## U1            1    475.449    1579.265    918318.360    0.744    0.665
## Pop           1    475.492     462.964    919434.661    0.743    0.664
## M.F           1    475.505      99.901    919797.724    0.743    0.664
## Po2           1    475.507      50.328    919847.297    0.743    0.664
## -----
##
##
## No more variables to be added.
##
## Variables Entered:
##
## - Po1
## - Ineq
## - Wealth
## - M
## - Prob
## - Ed
## - U2
##
##
## Final Model Output
## -----
##
##                               Model Summary
## -----
## R                               0.862      RMSE                184.581
## R-Squared                       0.743      Coef. Var              20.622
## Adj. R-Squared                   0.677      MSE                   34070.282
## Pred R-Squared                   0.504      MAE                    127.287
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                               Sum of
##                               Squares      DF      Mean Square      F      Sig.
## -----
## Regression    2661998.261          7      380285.466    11.162    0.0000
## Residual      919897.625         27      34070.282
## Total        3581895.886         34
## -----
##
##                               Parameter Estimates
## -----
##
## model      Beta      Std. Error      Std. Beta      t      Sig.      lower
upper
## -----
## (Intercept) 882.916      32.809              26.911    0.000      815.598
950.234

```

```
##          Po1      164.745      67.323      0.481      2.447      0.021      26.610
302.880
##          Ineq      378.075      75.204      1.183      5.027      0.000      223.769
532.381
##          Wealth    266.440     114.685      0.827      2.323      0.028      31.125
501.755
##           M       140.702      45.849      0.457      3.069      0.005      46.628
234.776
##          Prob     -122.299      60.001     -0.321     -2.038      0.051     -245.410
0.813
##           Ed       129.626      59.133      0.408      2.192      0.037       8.294
250.958
##          U2        72.373      37.465      0.217      1.932      0.064      -4.500
149.245
```

```
## -----
--
```

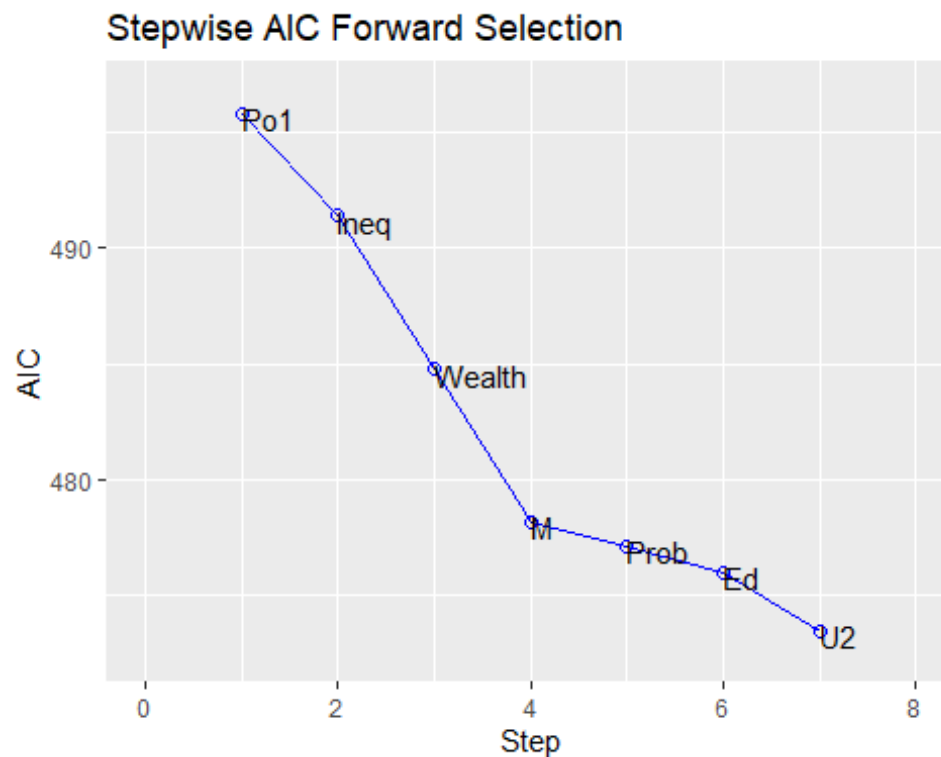
Forwardfit.aic

```
##
```

```
##                               Selection Summary
```

```
## -----
## Variable      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po1           495.841    1128626.869    2453269.016    0.31509    0.29434
## Ineq          491.397    1541197.843    2040698.043    0.43027    0.39467
## Wealth        484.774    1986787.099    1595108.787    0.55467    0.51158
## M             478.186    2333862.477    1248033.409    0.65157    0.60511
## Prob          477.124    2438416.018    1143479.868    0.68076    0.62572
## Ed            476.040    2534863.508    1047032.378    0.70769    0.64505
## U2            473.509    2661998.261     919897.625    0.74318    0.67660
## -----
```

```
plot(Forwardfit.aic)
```

Analysis : The Forward Selection Model started with no predictors and at each step added one predictor (selection was based on the least AIC) until the model can no longer be improved.

Here the best Model that the Forward Selection Model gave us is Crime ~ M + Ed + Po1 + U2 + Wealth + Ineq + Prob with AIC = 473.509.

Backward Elimination model using aic

```
BackwardFit.aic <- ols_step_backward_aic(model, details = TRUE)
```

```
## Backward Elimination Method
```

```
## -----
```

```
##
```

```
## Candidate Terms:
```

```
##
```

```
## 1 . So
```

```
## 2 . M
```

```
## 3 . Ed
```

```
## 4 . Po1
```

```
## 5 . Po2
```

```
## 6 . LF
```

```
## 7 . M.F
```

```
## 8 . Pop
```

```
## 9 . NW
```

```
## 10 . U1
```

```
## 11 . U2
```

```
## 12 . Wealth
```

```
## 13 . Ineq
```

```
## 14 . Prob
```

```
## 15 . Time
```

```
##
```

```
## Step 0: AIC = 484.7026
## Crime ~ So + M + Ed + Po1 + Po2 + LF + M.F + Pop + NW + U1 + U2 + Wealth + Ineq + Prob + Time
```

```
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Pop          1    482.714      250.498    802109.470    0.776      0.619
## Po2          1    482.759      1293.475    803152.447    0.776      0.619
## So           1    482.772      1583.973    803442.946    0.776      0.619
## Po1          1    483.175     10902.572    812761.545    0.773      0.614
## NW           1    483.487     18171.034    820030.007    0.771      0.611
## U1           1    483.552     19705.007    821563.980    0.771      0.610
## Time         1    484.499     42220.203    844079.176    0.764      0.599
## U2           1    484.625     45268.764    847127.737    0.763      0.598
## LF           1    484.721     47608.402    849467.375    0.763      0.597
## Prob         1    484.765     48676.878    850535.851    0.763      0.596
## M.F          1    485.236     60195.359    862054.332    0.759      0.591
## M            1    486.290     86547.099    888406.072    0.752      0.578
## Wealth       1    486.643     95547.301    897406.274    0.749      0.574
## Ed           1    489.051    159477.034    961336.007    0.732      0.544
## Ineq         1    498.583    460403.892   1262262.865    0.648      0.401
## -----
```

```
##
##
## Variables Removed:
```

```
##
## - Pop
##
```

```
## Step 1 : AIC = 482.7135
## Crime ~ So + M + Ed + Po1 + Po2 + LF + M.F + NW + U1 + U2 + Wealth + Ineq + Prob + Time
```

```
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po2          1    480.761      1092.172    803201.643    0.776      0.637
## So           1    480.795      1857.929    803967.400    0.776      0.637
## Po1          1    481.208     11404.397    813513.867    0.773      0.632
## NW           1    481.517     18630.550    820740.020    0.771      0.629
## U1           1    481.632     21336.603    823446.074    0.770      0.628
## U2           1    482.671     46130.102    848239.573    0.763      0.617
## Time         1    482.682     46415.770    848525.240    0.763      0.616
## LF           1    482.918     52137.655    854247.125    0.762      0.614
## Prob         1    483.000     54156.417    856265.887    0.761      0.613
## M.F          1    483.382     63543.681    865653.151    0.758      0.609
## M            1    484.493     91466.915    893576.385    0.751      0.596
## Wealth       1    484.643     95304.099    897413.570    0.749      0.594
## Ed           1    487.051    159226.701    961336.172    0.732      0.565
## Ineq         1    497.712    501540.763   1303650.234    0.636      0.411
## -----
```

```
##
## - Po2
##
```

```
## Step 2 : AIC = 480.7612
## Crime ~ So + M + Ed + Po1 + LF + M.F + NW + U1 + U2 + Wealth + Ineq + Prob + Time
```

```
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
```

```
## So          1      478.826      1489.580      804691.223      0.775      0.653
## NW          1      479.526      17745.888      820947.531      0.771      0.646
## U1          1      479.641      20448.211      823649.854      0.770      0.645
## U2          1      480.675      45147.670      848349.313      0.763      0.634
## LF          1      480.962      52120.699      855322.342      0.761      0.631
## Prob        1      481.015      53419.316      856620.959      0.761      0.630
## Time        1      481.166      57138.700      860340.343      0.760      0.629
## M.F         1      481.409      63130.298      866331.940      0.758      0.626
## M           1      482.616      93524.644      896726.287      0.750      0.613
## Wealth      1      482.900      100836.714      904038.357      0.748      0.610
## Po1         1      484.060      131278.377      934480.019      0.739      0.597
## Ed          1      485.551      171951.057      975152.700      0.728      0.579
## Ineq        1      496.058      513397.425      1316599.068      0.632      0.432
## -----
```

```
##
## - So
##
##
```

```
## Step 3 : AIC = 478.826
```

```
## Crime ~ M + Ed + Po1 + LF + M.F + NW + U1 + U2 + Wealth + Ineq + Prob + Time
```

```
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## NW          1      477.619      18436.438      823127.661      0.770      0.660
## U1          1      477.683      19940.065      824631.288      0.770      0.660
## U2          1      478.721      44775.544      849466.766      0.763      0.649
## Prob        1      479.053      52859.310      857550.533      0.761      0.646
## LF          1      479.394      61251.778      865943.000      0.758      0.643
## Time        1      479.412      61702.685      866393.907      0.758      0.642
## M.F         1      479.425      62022.316      866713.538      0.758      0.642
## M           1      480.623      92197.866      896889.088      0.750      0.630
## Wealth      1      480.985      101529.518      906220.741      0.747      0.626
## Po1         1      482.791      149525.604      954216.827      0.734      0.606
## Ed          1      483.714      175023.558      979714.780      0.726      0.596
## Ineq        1      494.433      526093.088      1330784.311      0.628      0.451
## -----
```

```
##
## - NW
##
##
```

```
## Step 4 : AIC = 477.6188
```

```
## Crime ~ M + Ed + Po1 + LF + M.F + U1 + U2 + Wealth + Ineq + Prob + Time
```

```
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## U1          1      476.087      11090.766      834218.426      0.767      0.670
## Prob        1      477.222      38573.581      861701.242      0.759      0.659
## U2          1      477.261      39549.547      862677.208      0.759      0.659
## M.F         1      477.473      44785.628      867913.289      0.758      0.657
## LF          1      477.653      49263.265      872390.925      0.756      0.655
## Time        1      478.203      63076.242      886203.902      0.753      0.649
## Wealth      1      481.272      144278.457      967406.117      0.730      0.617
## Ed          1      481.717      156678.104      979805.765      0.726      0.612
## Po1         1      482.173      169529.771      992657.432      0.723      0.607
## M           1      482.893      190144.934      1013272.594      0.717      0.599
## Ineq        1      498.234      747540.956      1570668.617      0.561      0.379
## -----
```

```
##
## - U1
```

```

##
##
## Step 5 : AIC = 476.0873
## Crime ~ M + Ed + Po1 + LF + M.F + U2 + Wealth + Ineq + Prob + Time
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## M.F           1      475.513    34675.622    868894.049    0.757      0.670
## Prob          1      475.603    36928.143    871146.569    0.757      0.669
## U2            1      475.700    39342.180    873560.606    0.756      0.668
## LF            1      475.733    40167.458    874385.885    0.756      0.668
## Time          1      476.664    63728.189    897946.616    0.749      0.659
## Ed            1      479.718    145606.358    979824.784    0.726      0.628
## Po1           1      480.497    167650.813    1001869.239    0.720      0.620
## Wealth        1      481.909    208893.018    1043111.445    0.709      0.604
## M             1      482.058    213358.113    1047576.540    0.708      0.602
## Ineq          1      499.484    889266.996    1723485.423    0.519      0.346
## -----
##
## - M.F
##
##
## Step 6 : AIC = 475.5127
## Crime ~ M + Ed + Po1 + LF + U2 + Wealth + Ineq + Prob + Time
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## LF            1      474.294    19625.381    888519.430    0.752      0.676
## Time          1      474.787    32221.971    901116.020    0.748      0.671
## Prob          1      476.232    70188.887    939082.935    0.738      0.657
## U2            1      476.848    86876.467    955770.516    0.733      0.651
## Po1           1      478.776    141000.520    1009894.568    0.718      0.631
## Wealth        1      480.625    195800.679    1064694.728    0.703      0.611
## Ed            1      481.134    211377.795    1080271.844    0.698      0.606
## M             1      483.066    272702.069    1141596.117    0.681      0.583
## Ineq          1      497.983    879375.429    1748269.477    0.512      0.362
## -----
##
## - LF
##
##
## Step 7 : AIC = 474.2944
## Crime ~ M + Ed + Po1 + U2 + Wealth + Ineq + Prob + Time
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Time          1      473.509    31378.195    919897.625    0.743      0.677
## Prob          1      474.594    60326.174    948845.604    0.735      0.666
## U2            1      477.007    128070.028    1016589.459    0.716      0.643
## Wealth        1      478.818    182046.544    1070565.974    0.701      0.624
## Po1           1      478.957    186295.061    1074814.491    0.700      0.622
## Ed            1      479.144    192054.947    1080574.377    0.698      0.620
## M             1      481.507    267525.139    1156044.570    0.677      0.594
## Ineq          1      496.044    862794.994    1751314.425    0.511      0.384
## -----
##
## - Time
##

```

```

##
## Step 8 : AIC = 473.5091
## Crime ~ M + Ed + Po1 + U2 + Wealth + Ineq + Prob
##
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## U2             1      476.040    127134.753    1047032.378    0.708      0.645
## Prob           1      476.519    141548.376    1061446.001    0.704      0.640
## Ed             1      477.242    163717.108    1083614.733    0.697      0.633
## Wealth         1      477.888    183890.591    1103788.216    0.692      0.626
## Po1            1      478.520    204022.573    1123920.198    0.686      0.619
## M              1      481.982    320862.878    1240760.503    0.654      0.579
## Ineq           1      494.632    861088.259    1780985.884    0.503      0.396
## -----
##
##
## No more variables to be removed.
##
## Variables Removed:
##
## - Pop
## - Po2
## - So
## - NW
## - U1
## - M.F
## - LF
## - Time
##
##
## Final Model Output
## -----
##
##                               Model Summary
## -----
## R                               0.862      RMSE                               184.581
## R-Squared                       0.743      Coef. Var                          20.622
## Adj. R-Squared                  0.677      MSE                               34070.282
## Pred R-Squared                  0.504      MAE                               127.287
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                               Sum of
##                               Squares      DF      Mean Square      F      Sig.
## -----
## Regression      2661998.261           7      380285.466    11.162    0.0000
## Residual         919897.625          27      34070.282
## Total          3581895.886          34
## -----
##
##                               Parameter Estimates
## -----
##
## model      Beta      Std. Error      Std. Beta      t      Sig.      lower
upper
## -----

```

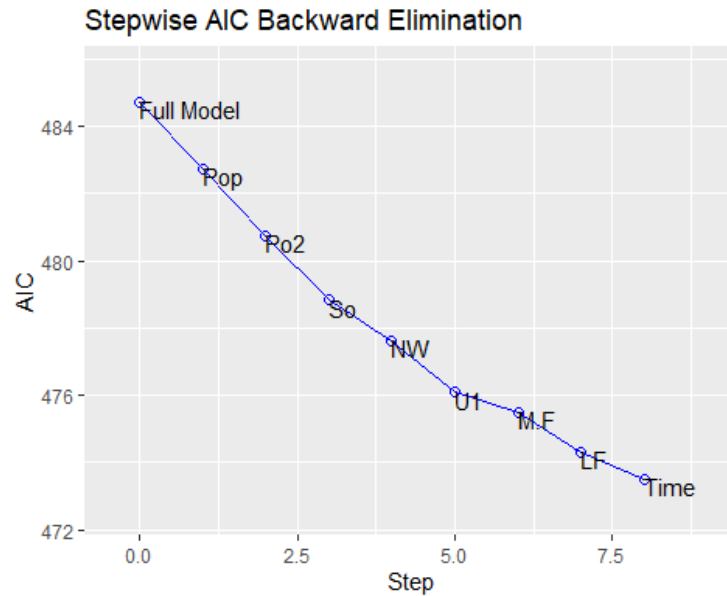
```
--
## (Intercept)      882.916      32.809              26.911      0.000      815.598
950.234
##              M      140.702      45.849      0.457      3.069      0.005      46.628
234.776
##              Ed      129.626      59.133      0.408      2.192      0.037      8.294
250.958
##              Po1      164.745      67.323      0.481      2.447      0.021      26.610
302.880
##              U2       72.373      37.465      0.217      1.932      0.064      -4.500
149.245
##      Wealth      266.440      114.685      0.827      2.323      0.028      31.125
501.755
##              Ineq      378.075      75.204      1.183      5.027      0.000      223.769
532.381
##              Prob     -122.299      60.001      -0.321      -2.038      0.051      -245.410
0.813
## -----
--
```

BackwardFit.aic

```
##
##
##              Backward Elimination Summary
## -----
## Variable      AIC      RSS      Sum Sq      R-Sq      Adj. R-Sq
## -----
## Full Model    484.703    801858.973    2780036.913    0.77614    0.59940
## Pop           482.714    802109.470    2779786.415    0.77607    0.61931
## Po2           480.761    803201.643    2778694.243    0.77576    0.63695
## So            478.826    804691.223    2777204.663    0.77534    0.65281
## NW            477.619    823127.661    2758768.225    0.77020    0.66029
## U1            476.087    834218.426    2747677.459    0.76710    0.67006
## M.F           475.513    868894.049    2713001.837    0.75742    0.67009
## LF            474.294    888519.430    2693376.455    0.75194    0.67562
## Time          473.509    919897.625    2661998.261    0.74318    0.67660
## -----
```

Analysis: The Backward Elimination Summary method removed 8 predictors which are listed above. It started from model with full predictors, at each step it removed the predictor which resulted the highest AIC. It continued until it removed Pop, Po2, So, NW, U1, MF, LF, Time. This is shown below in the Elimination Plot.

`plot(BackwardFit.aic)`



Analysis: The Backward Elimination Model, suggests that the Best Model is Crime ~ M + Ed + Po1 + U2 + Wealth + Ineq + Prob with AIC = 473.5091.

Stepwise Regression using both directions and aic

```
model = model<-lm(Crime~.,data = TrainingData)

StepwiseBothFit.aic<- ols_step_both_aic(model, details = TRUE)

## Stepwise Selection Method
## -----
##
## Candidate Terms:
##
## 1 . So
## 2 . M
## 3 . Ed
## 4 . Po1
## 5 . Po2
## 6 . LF
## 7 . M.F
## 8 . Pop
## 9 . NW
## 10 . U1
## 11 . U2
## 12 . Wealth
## 13 . Ineq
## 14 . Prob
## 15 . Time
##
## Step 0: AIC = 507.0876
## Crime ~ 1
##
```

```

##
## Variables Entered/Removed:
##
## Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po1           1      495.841    1128626.869    2453269.016    0.315      0.294
## Po2           1      496.326    1094409.821    2487486.064    0.306      0.284
## Prob          1      497.633     999751.467    2582144.419    0.279      0.257
## Pop           1      499.351     869842.365    2712053.520    0.243      0.220
## Time          1      502.489     615451.183    2966444.703    0.172      0.147
## Wealth        1      502.537     611427.125    2970468.761    0.171      0.146
## U2            1      507.541     154871.969    3427023.917    0.043      0.014
## Ed            1      507.567     152323.822    3429572.063    0.043      0.014
## Ineq          1      508.547      54884.610    3527011.276    0.015     -0.015
## M.F           1      508.844      24841.604    3557054.282    0.007     -0.023
## So            1      508.940      15112.715    3566783.170    0.004     -0.026
## NW            1      508.988      10216.386    3571679.500    0.003     -0.027
## M             1      509.016       7344.408    3574551.478    0.002     -0.028
## U1            1      509.038      5105.396    3576790.489    0.001     -0.029
## LF            1      509.085       314.577    3581581.309    0.000     -0.030
## -----
##
## - Po1 added
##
## Step 1 : AIC = 495.8411
## Crime ~ Po1
##
## Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ineq          1      491.397    1541197.843    2040698.043    0.430      0.395
## M             1      491.519    1534032.377    2047863.508    0.428      0.393
## Time          1      494.656    1342048.124    2239847.762    0.375      0.336
## So            1      494.849    1329639.575    2252256.311    0.371      0.332
## NW            1      495.057    1316219.575    2265676.311    0.367      0.328
## Prob          1      496.070    1249693.014    2332202.872    0.349      0.308
## Pop           1      496.667    1209574.218    2372321.668    0.338      0.296
## Wealth        1      497.570    1147560.892    2434334.994    0.320      0.278
## M.F           1      497.651    1141905.295    2439990.591    0.319      0.276
## U2            1      497.681    1139854.842    2442041.043    0.318      0.276
## U1            1      497.733    1136213.074    2445682.812    0.317      0.275
## Po2           1      497.746    1135303.037    2446592.848    0.317      0.274
## Ed            1      497.764    1133994.837    2447901.049    0.317      0.274
## LF            1      497.780    1132890.633    2449005.252    0.316      0.274
## -----
##
## - Ineq added
##
## Step 2 : AIC = 491.3966
## Crime ~ Po1 + Ineq
##
## Remove Existing Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ineq          1      495.841    1128626.869    2453269.016    0.315      0.294

```



```

## Po1          1    508.547    54884.610    3527011.276    0.015    -0.015
## -----
##
##                                     Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Wealth        1    484.774    1986787.099    1595108.787    0.555    0.512
## Prob          1    486.606    1901089.969    1680805.917    0.531    0.485
## Ed            1    487.472    1858956.673    1722939.212    0.519    0.472
## M.F           1    490.587    1698608.587    1883287.299    0.474    0.423
## M             1    490.768    1688828.766    1893067.120    0.471    0.420
## Time          1    491.324    1658519.352    1923376.533    0.463    0.411
## LF            1    491.955    1623539.410    1958356.475    0.453    0.400
## U1            1    493.363    1543178.414    2038717.472    0.431    0.376
## U2            1    493.379    1542221.531    2039674.354    0.431    0.375
## Pop           1    493.380    1542149.437    2039746.449    0.431    0.375
## NW            1    493.390    1541555.461    2040340.424    0.430    0.375
## So            1    493.396    1541239.170    2040656.716    0.430    0.375
## Po2           1    493.397    1541200.407    2040695.479    0.430    0.375
## -----
##
## - Wealth added
##
##
## Step 3 : AIC = 484.7744
## Crime ~ Po1 + Ineq + Wealth
##
##                                     Remove Existing Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po1           1    487.950    1732586.652    1849309.234    0.484    0.451
## Wealth        1    491.397    1541197.843    2040698.043    0.430    0.395
## Ineq          1    497.570    1147560.892    2434334.994    0.320    0.278
## -----
##
##                                     Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## M             1    478.186    2333862.477    1248033.409    0.652    0.605
## Prob          1    482.112    2185720.119    1396175.767    0.610    0.558
## Time          1    483.484    2129896.192    1451999.694    0.595    0.541
## Ed            1    484.913    2069393.056    1512502.830    0.578    0.521
## M.F           1    485.267    2054045.195    1527850.691    0.573    0.517
## U1            1    486.536    1997621.226    1584274.660    0.558    0.499
## NW            1    486.625    1993572.686    1588323.200    0.557    0.497
## So            1    486.685    1990833.159    1591062.727    0.556    0.497
## LF            1    486.694    1990446.648    1591449.238    0.556    0.496
## U2            1    486.707    1989873.693    1592022.192    0.556    0.496
## Pop           1    486.719    1989313.933    1592581.952    0.555    0.496
## Po2           1    486.745    1988124.450    1593771.436    0.555    0.496
## -----
##
## - M added
##
##
## Step 4 : AIC = 478.1863
## Crime ~ Po1 + Ineq + Wealth + M
##

```

```
## Remove Existing Variables
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Po1         1    482.752    2076346.586    1505549.300    0.580    0.539
## M           1    484.774    1986787.099    1595108.787    0.555    0.512
## Wealth      1    490.768    1688828.766    1893067.120    0.471    0.420
## Ineq        1    492.661    1583622.645    1998273.240    0.442    0.388
## -----
##
## Enter New Variables
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Prob         1    477.124    2438416.018    1143479.868    0.681    0.626
## U1           1    477.869    2413833.430    1168062.456    0.674    0.618
## Ed           1    478.051    2407742.938    1174152.948    0.672    0.616
## U2           1    478.557    2390639.283    1191256.603    0.667    0.610
## M.F          1    478.723    2384960.007    1196935.879    0.666    0.608
## Time         1    478.757    2383816.501    1198079.385    0.666    0.608
## NW           1    479.845    2345966.483    1235929.403    0.655    0.595
## So           1    479.968    2341639.161    1240256.725    0.654    0.594
## LF           1    480.134    2335709.502    1246186.383    0.652    0.592
## Po2          1    480.142    2335458.083    1246437.803    0.652    0.592
## Pop          1    480.144    2335357.131    1246538.755    0.652    0.592
## -----
##
## - Prob added
##
## Step 5 : AIC = 477.124
## Crime ~ Po1 + Ineq + Wealth + M + Prob
##
## Remove Existing Variables
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Prob         1    478.186    2333862.477    1248033.409    0.652    0.605
## Po1          1    479.725    2277777.427    1304118.458    0.636    0.587
## M            1    482.112    2185720.119    1396175.767    0.610    0.558
## Wealth       1    486.619    1993842.141    1588053.745    0.557    0.498
## Ineq         1    492.983    1677190.103    1904705.783    0.468    0.397
## -----
##
## Enter New Variables
## -----
## Variable    DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ed           1    476.040    2534863.508    1047032.378    0.708    0.645
## U1           1    476.409    2523751.302    1058144.584    0.705    0.641
## U2           1    477.242    2498281.153    1083614.733    0.697    0.633
## M.F          1    477.574    2487942.942    1093952.944    0.695    0.629
## LF           1    478.890    2446035.542    1135860.344    0.683    0.615
## Time         1    478.950    2444085.323    1137810.563    0.682    0.614
## Po2          1    479.035    2441329.165    1140566.721    0.682    0.613
## Pop          1    479.098    2439257.520    1142638.366    0.681    0.613
## NW           1    479.105    2439042.223    1142853.662    0.681    0.613
## So           1    479.124    2438423.445    1143472.441    0.681    0.612
## -----
##
## - Ed added
```

```
##
##
## Step 6 : AIC = 476.04
## Crime ~ Po1 + Ineq + Wealth + M + Prob + Ed
##
## Remove Existing Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Ed            1      477.124    2438416.018    1143479.868    0.681      0.626
## Prob          1      478.051    2407742.938    1174152.948    0.672      0.616
## Wealth        1      480.146    2335313.915    1246581.971    0.652      0.592
## M             1      481.161    2298631.492    1283264.394    0.642      0.580
## Po1           1      481.348    2291757.391    1290138.495    0.640      0.578
## Ineq          1      494.862    1683760.669    1898135.217    0.470      0.379
## -----
##
## Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## U2            1      473.509    2661998.261    919897.625    0.743      0.677
## U1            1      475.456    2609385.668    972510.218    0.728      0.658
## LF            1      476.002    2594075.559    987820.326    0.724      0.653
## Time          1      477.007    2565306.427    1016589.459    0.716      0.643
## NW            1      477.574    2548710.883    1033185.003    0.712      0.637
## So            1      477.702    2544924.805    1036971.081    0.710      0.635
## M.F           1      477.730    2544087.315    1037808.571    0.710      0.635
## Pop           1      477.942    2537787.620    1044108.266    0.709      0.633
## Po2           1      478.020    2535460.419    1046435.467    0.708      0.632
## -----
##
## - U2 added
##
##
## Step 7 : AIC = 473.5091
## Crime ~ Po1 + Ineq + Wealth + M + Prob + Ed + U2
##
## Remove Existing Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## U2            1      476.040    2534863.508    1047032.378    0.708      0.645
## Prob          1      476.519    2520449.884    1061446.001    0.704      0.640
## Ed            1      477.242    2498281.153    1083614.733    0.697      0.633
## Wealth        1      477.888    2478107.670    1103788.216    0.692      0.626
## Po1           1      478.520    2457975.688    1123920.198    0.686      0.619
## M             1      481.982    2341135.382    1240760.503    0.654      0.579
## Ineq          1      494.632    1800910.001    1780985.884    0.503      0.396
## -----
##
## Enter New Variables
## -----
## Variable      DF      AIC      Sum Sq      RSS      R-Sq      Adj. R-Sq
## -----
## Time          1      474.294    2693376.455    888519.430    0.752      0.676
## LF            1      474.787    2680779.866    901116.020    0.748      0.671
## So            1      475.244    2668933.530    912962.355    0.745      0.667
## NW            1      475.325    2666820.540    915075.346    0.745      0.666
## U1            1      475.449    2663577.526    918318.360    0.744      0.665
## Pop           1      475.492    2662461.225    919434.661    0.743      0.664
```

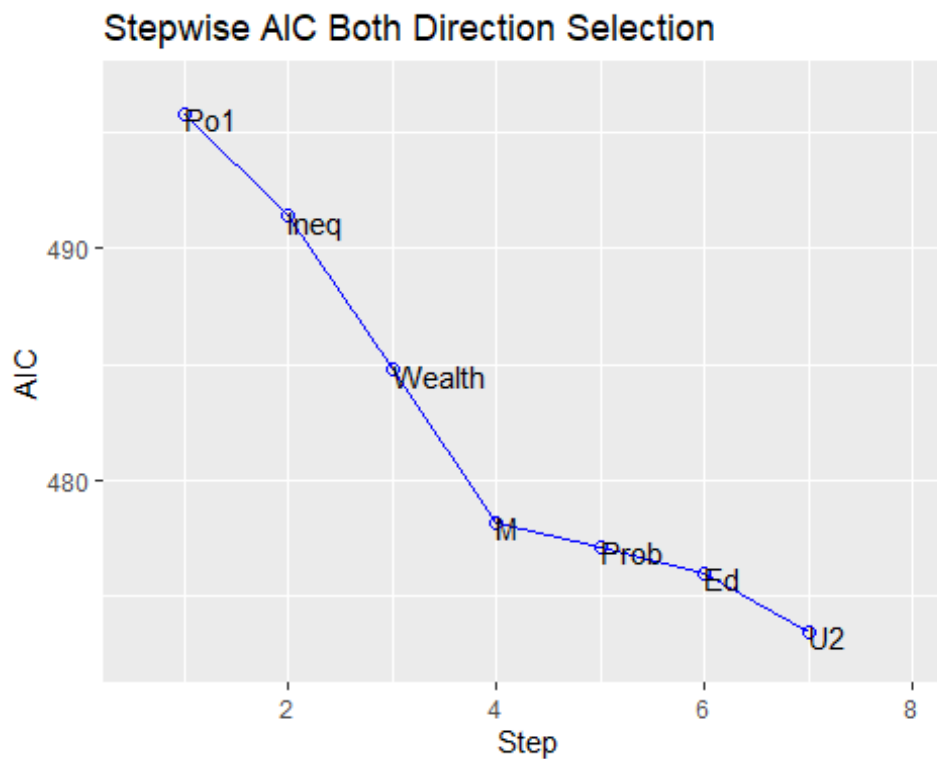
```

## M.F          1    475.505    2662098.161    919797.724    0.743    0.664
## Po2          1    475.507    2662048.589    919847.297    0.743    0.664
## -----
##
##
## No more variables to be added or removed.
##
## Final Model Output
## -----
##
##                               Model Summary
## -----
## R                               0.862          RMSE                184.581
## R-Squared                       0.743          Coef. Var           20.622
## Adj. R-Squared                  0.677          MSE                34070.282
## Pred R-Squared                  0.504          MAE                 127.287
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##                               ANOVA
## -----
##                               Sum of
##                               Squares      DF      Mean Square      F      Sig.
## -----
## Regression    2661998.261          7      380285.466    11.162    0.0000
## Residual      919897.625          27      34070.282
## Total        3581895.886          34
## -----
##
##                               Parameter Estimates
## -----
##
## model      Beta      Std. Error      Std. Beta      t      Sig      lower
upper
## -----
## (Intercept) 882.916      32.809              26.911    0.000      815.598
950.234
## Po1         164.745      67.323              0.481     2.447    0.021      26.610
302.880
## Ineq        378.075      75.204              1.183     5.027    0.000      223.769
532.381
## Wealth      266.440     114.685              0.827     2.323    0.028      31.125
501.755
## M           140.702      45.849              0.457     3.069    0.005      46.628
234.776
## Prob       -122.299      60.001             -0.321    -2.038    0.051     -245.410
0.813
## Ed          129.626      59.133              0.408     2.192    0.037       8.294
250.958
## U2          72.373      37.465              0.217     1.932    0.064      -4.500
149.245
## -----
##
##
StepwiseBothFit.aic
##
##

```

```
##                                     Stepwise Summary
## -----
## Variable      Method      AIC      RSS      Sum Sq      R-Sq      Adj. R-Sq
## -----
## Po1           addition    495.841  2453269.016  1128626.869  0.31509  0.29434
## Ineq          addition    491.397  2040698.043  1541197.843  0.43027  0.39467
## Wealth        addition    484.774  1595108.787  1986787.099  0.55467  0.51158
## M             addition    478.186  1248033.409  2333862.477  0.65157  0.60511
## Prob          addition    477.124  1143479.868  2438416.018  0.68076  0.62572
## Ed            addition    476.040  1047032.378  2534863.508  0.70769  0.64505
## U2            addition    473.509  919897.625  2661998.261  0.74318  0.67660
## -----
```

```
plot(StepwiseBothFit.aic)
```



#Analysis:

Stepwise Regression is a combination of both Forward and Backward Regression.

All the three methods, Forward Regression, Backward Elimination and

Stepwise Regression in both Directions returned the model

with `lm(Crime~Po1 + Ineq + Wealth + Prob + M + Ed + U2)` using the Scaled Training Data.

```
BestModelWithTrainingData<- lm(Crime~Po1 + Ineq + Wealth + M + Ed + U2 +Prob, data =
Training Data)
summary(BestModelWithTrainingData)
```

```
##
## Call:
## lm(formula = Crime ~ Po1 + Ineq + Wealth + M + Ed + U2 + Prob,
##     data = Training Data)
```

```
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -267.58 -125.25   -6.28    96.12   451.18
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    882.92     32.81   26.911 < 2e-16 ***
## Po1            164.74     67.32    2.447  0.02119 *
## Ineq           378.08     75.20    5.027  2.83e-05 ***
## Wealth         266.44    114.69    2.323  0.02794 *
## M              140.70     45.85    3.069  0.00485 **
## Ed             129.63     59.13    2.192  0.03717 *
## U2             72.37     37.47    1.932  0.06395 .
## Prob          -122.30     60.00   -2.038  0.05143 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 184.6 on 27 degrees of freedom
## Multiple R-squared:  0.7432, Adjusted R-squared:  0.6766
## F-statistic: 11.16 on 7 and 27 DF, p-value: 1.476e-06

BestModelwithTestData<- lm(Crime~Po1 + Ineq + Wealth + M + Ed + U2 + Prob, data = TestData)
summary(BestModelwithTestData)

##
## Call:
## lm(formula = Crime ~ Po1 + Ineq + Wealth + M + Ed + U2 + Prob,
##     data = TestData)
##
## Residuals:
##      2          5          8         18         21         22         25
## 163.97555 -73.52705  81.19548  57.51035   0.72107 -64.95555  -0.07717
##     26     27     42     43     45
## -128.98342 -28.64515  20.95836  15.66399 -43.83645
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    919.86     43.57   21.111 2.98e-05 ***
## Po1            399.55     60.51    6.604  0.00273 **
## Ineq           108.45    102.27    1.060  0.34872
## Wealth        -113.01    100.27   -1.127  0.32277
## M              131.94     62.07    2.126  0.10070
## Ed             294.87     94.78    3.111  0.03583 *
## U2             163.74     50.80    3.223  0.03218 *
## Prob          -86.44     35.89   -2.409  0.07366 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 128.9 on 4 degrees of freedom
## Multiple R-squared:  0.9798, Adjusted R-squared:  0.9444
## F-statistic: 27.67 on 7 and 4 DF, p-value: 0.003117
```

Analysis:

The Initial Model had 15 predictors. The Stepwise Selection model, forward regression and backward elimination models, all these three methods removed the same predictors and suggested best model as Crime~Po1 + Ineq + Wealth + Prob + M + Ed + U2 using the Scaled Training Data.

- b. Lasso Regression
- c. Elastic.Net Regression

[illegible]

```

alpha = 0.5 ,
n folds = 8,
n lambda = 20,
type.measure = "mse",
family = "gaussian",
standardize = TRUE)

model_elasticnet_alpha0.5.predicted<-
predict(model_elasticnet_alpha0.5,s=model_elasticnet_alpha0.5$lambda.1se,newx=as.matrix(TestDa
ta[, -16]))
#Lambda.1se is the value of lambda,that resulted in the simplest model(model with few non zero
parameters)
#and was within 1 standard error of the lambda that had the smallest sum.
model_elasticnet_alpha0.5.predicted

##           1
## 2  1111.1050
## 5   971.0996
## 8  1087.6278
## 18  691.4622
## 21  928.0997
## 22  743.8468
## 25  568.1519
## 26 1292.4630
## 27  631.7364
## 42  357.4658
## 43 1015.9012
## 45  772.1347

# Find the accuracy
sse = sum((model_elasticnet_alpha0.5.predicted - TestData[,16])^2)
totalSumofSquares = sum((TestData[,16]-mean(TestData[,16]))^2)
RSquared = 1- (sse/totalSumofSquares)
AdjustedRSquared = RSquared - (1-RSquared)*15/(nrow(TestData)-15-1)
AdjustedRSquared

## [1] 2.25108

RSquared

## [1] 0.5450617

#Lets try more values of alpha
# We create the Elastic.NET fit using the cv.glmnet() function,
#which takes alpha values from 0.0,0.1,..1.0.
list_of_fits <- list()
for(i in 0:10)
{
  fit.name <- paste0("alpha",i/10)
  list_of_fits[[fit.name]] <- cv.glmnet(x=as.matrix(TrainingData[, -16]),
    y = as.matrix(TrainingData[,16]),
    alpha = i/10 ,
    n folds = 8,
    n lambda = 20,
    type.measure = "mse",
    family = "gaussian",
    standardize = FALSE)
}

results <- data.frame()
# This for loop will give us the error values for each model from above.
for(i in 0:10)

```



```
{
  fit.name <- paste0("alpha",i/10)
  predicted <- predict(list_of_fits[[fit.name]],
                      s=list_of_fits[[fit.name]]$lambda.1se,newx=as.matrix(TestData[, -16]))

  # Find the accuracy
  sse = sum((predicted - TestData[,16])^2)
  totalSumofSquares = sum((TestData[,16]-mean(TestData[,16]))^2)
  RSquared = 1- (sse/totalSumofSquares)
  temp <- data.frame(alpha=i/10, Rsquared=RSquared, fit.name)
  results <- rbind(results, temp)
}
```

results

```
##      alpha      Rsquared fit.name
## 1      0.0  0.192802377  alpha0
## 2      0.1  0.151978925  alpha0.1
## 3      0.2 -0.005634715  alpha0.2
## 4      0.3 -0.005634715  alpha0.3
## 5      0.4 -0.005634715  alpha0.4
## 6      0.5  0.281999903  alpha0.5
## 7      0.6  0.151110822  alpha0.6
## 8      0.7 -0.005634715  alpha0.7
## 9      0.8 -0.005634715  alpha0.8
## 10     0.9  0.218213133  alpha0.9
## 11     1.0 -0.005634715  alpha1
```

model_elasticnet_alpha0.5\$glmnet.fit

```
##
## Call: glmnet(x = as.matrix(TrainingData[, -16]), y = as.matrix(TrainingData[,      16]),
##             alpha = 0.5, nlambda = 20, family = "gaussian", standardize = TRUE)
##
##      Df  %Dev Lambda
## 1      0  0.00 359.10
## 2      4 19.67 221.20
## 3      5 31.22 136.20
## 4      7 38.91  83.89
## 5     13 51.28  51.66
## 6     13 63.84  31.82
## 7     13 70.37  19.59
## 8     14 73.82  12.07
## 9     15 75.76   7.43
## 10    15 76.79   4.58
## 11    14 77.25   2.82
## 12    13 77.42   1.74
## 13    13 77.51   1.07
## 14    14 77.55   0.66
## 15    14 77.57   0.41
## 16    15 77.58   0.25
## 17    15 77.60   0.15
## 18    15 77.61   0.09
## 19    15 77.61   0.06
## 20    15 77.61   0.04
```

Analysis:

For Using Lasso and Elastic.Net Regression in R, we used glmnet library.

Lasso Regression Penalty = Sum of Squared Residuals + $\text{Lambda1}(|\text{var1}| + \dots + |\text{varx}|) + \text{Lambda2}(\text{var1}^2 + \dots + \text{varx}^2)$.

Glmnet interprets these Lambda's differently.

Glmnet has a single Lambda as shown:

Regression Penalty = Sum of Squared Residuals + $\text{Lambda} * [\alpha * (|\text{var1}| + \dots + |\text{varx}|) + (1 - \alpha) (\text{var1}^2 + \dots + \text{varx}^2)]$.

When $\alpha = 0$, Lasso penalty goes to zero and the model reduces to ridge regression.

When $\alpha = 1$, Ridge regression penalty goes to zero and the model reduces to Lasso regression.

When $0 < \alpha < 1$, then the model reduces to Elastic.Net.

Lambda controls how much penalty to apply to the regression.

When $\text{Lambda} = 0$, the model reduces to Linear Regression as penalty = 0.

When $\text{Lambda} > 0$, then Elastic.Net penalty kicks in.

Run glmnet for finding Lasso and ElasticNet Best Models and these results are obtained

##	alpha	Rsquared	fit.name	
## 1	0.0	0.192802377	alpha0	-> This fit is Ridge Regression
## 2	0.1	0.151978925	alpha0.1	-> This fit is Elastic.Net Regression
## 3	0.2	-0.005634715	alpha0.2	-> This fit is Elastic.Net Regression
## 4	0.3	-0.005634715	alpha0.3	-> This fit is Elastic.Net Regression
## 5	0.4	-0.005634715	alpha0.4	-> This fit is Elastic.Net Regression
## 6	0.5	0.281999903	alpha0.5	-> This fit is Elastic.Net Regression
## 7	0.6	0.151110822	alpha0.6	-> This fit is Elastic.Net Regression
## 8	0.7	-0.005634715	alpha0.7	-> This fit is Elastic.Net Regression
## 9	0.8	-0.005634715	alpha0.8	-> This fit is Elastic.Net Regression
## 10	0.9	0.218213133	alpha0.9	-> This fit is Elastic.Net Regression
## 11	1.0	-0.005634715	alpha1	-> This fit is Lasso Regression

The Highest RSquared error is for model fit with $\alpha = 0.5$ which is an Elastic.Net Regression. This model seems to be better than the rest.

Next best model is model fit with $\alpha = 0.9$ which is also from Elastic.net Regression.

The $\alpha = 0$ is the Ridge Regression Model and $\alpha = 1$ is the Lasso Model.

Based on the RSquared, Elastic.Net wins, then Ridge Regression is the next best and the next will be Lasso.

For the Best Elastic.Net Model, the lambda values ranged between 0.04 to 359.10 in the cv model.