

HW8 - KELLY “SCOTT” SIMS

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 `lambda` 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`.

```
library(olsrr)

##
## Attaching package: 'olsrr'

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

data <- read.table('uscrime.txt', header = TRUE, stringsAsFactors = FALSE)
head(data)

##      M So   Ed  Po1  Po2    LF   M.F Pop   NW    U1  U2 Wealth Ineq
## 1 15.1  1  9.1  5.8  5.6 0.510  95.0  33 30.1 0.108 4.1   3940 26.1
## 2 14.3  0 11.3 10.3  9.5 0.583 101.2  13 10.2 0.096 3.6   5570 19.4
## 3 14.2  1  8.9  4.5  4.4 0.533  96.9  18 21.9 0.094 3.3   3180 25.0
## 4 13.6  0 12.1 14.9 14.1 0.577  99.4 157  8.0 0.102 3.9   6730 16.7
## 5 14.1  0 12.1 10.9 10.1 0.591  98.5  18  3.0 0.091 2.0   5780 17.4
## 6 12.1  0 11.0 11.8 11.5 0.547  96.4  25  4.4 0.084 2.9   6890 12.6
##      Prob    Time Crime
## 1 0.084602 26.2011    791
## 2 0.029599 25.2999   1635
## 3 0.083401 24.3006    578
## 4 0.015801 29.9012   1969
## 5 0.041399 21.2998   1234
## 6 0.034201 20.9995    682
```

STEPWISE REGRESSION

For stepwise regression, thankfully R already has a module that will handle the very iterative process of adding and subtracting features while training the model and analyzing it. Let’s put that function to use and build regression models using **Stepwise Regression**. The `ols_step_both_p` function selects features based on p-value. Because of this, we can set the upper and lower bounds of the p-value for the function to take into consideration when it is selecting its features. We will set the “pent” equal to 0.1, meaning variables with p value less than 0.1 will enter into the model. Will will set “prem” equal to 0.3 meaning variables with p value more than 0.3 will not enter into the model

```
stepwise.model <- lm(Crime ~., data = data)
step <- ols_step_both_p(stepwise.model, pent = 0.1, prem = 0.3, details = TRUE)
```

Stepwise Selection Method

##

Candidate Terms:

##

1. M

2. So

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

##

We are selecting variables based on p value...

##

##

Stepwise Selection: Step 1

##

- Po1 added

##

Model Summary

## R	0.688	RMSE	283.926
------	-------	------	---------

## R-Squared	0.473	Coef. Var	31.370
--------------	-------	-----------	--------

## Adj. R-Squared	0.461	MSE	80613.907
-------------------	-------	-----	-----------

## Pred R-Squared	0.393	MAE	218.298
-------------------	-------	-----	---------

RMSE: Root Mean Square Error

MSE: Mean Square Error

MAE: Mean Absolute Error

##

ANOVA

##		Sum of				
##		Squares	DF	Mean Square	F	Sig.

## Regression	3253301.823	1	3253301.823	40.357	0.0000
---------------	-------------	---	-------------	--------	--------

## Residual	3627625.836	45	80613.907		
-------------	-------------	----	-----------	--	--

## Total	6880927.660	46			
----------	-------------	----	--	--	--

##

Parameter Estimates

##	model	Beta	Std. Error	Std. Beta	t	Sig.	lower	upper
----	-------	------	------------	-----------	---	------	-------	-------

## (Intercept)		144.464	126.693		1.140	0.260	-110.708	399.636
----------------	--	---------	---------	--	-------	-------	----------	---------

```
##          Po1      89.485      14.086      0.688      6.353      0.000      61.114      117.856
```

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

```
##
```

```
##
```

```
##
```

```
## Stepwise Selection: Step 2
```

```
##
```

```
## - Ineq added
```

```
##
```

```
##          Model Summary
```

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

```
## R          0.762      RMSE          256.187
```

```
## R-Squared    0.580      Coef. Var      28.305
```

```
## Adj. R-Squared 0.561      MSE          65631.982
```

```
## Pred R-Squared 0.486      MAE          189.666
```

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

```
## RMSE: Root Mean Square Error
```

```
## MSE: Mean Square Error
```

```
## MAE: Mean Absolute Error
```

```
##
```

```
##          ANOVA
```

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

```
##          Sum of      DF      Mean Square      F      Sig.
```

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

```
## Regression    3993120.467      2      1996560.233      30.421      0.0000
```

```
## Residual      2887807.193      44      65631.982
```

```
## Total         6880927.660      46
```

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

```
##
```

```
##          Parameter Estimates
```

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

```
##          model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
```

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

```
## (Intercept)   -944.662      343.947           -2.747      0.009      -1637.841      -251.482
```

```
##          Po1      124.148      16.375           0.954      7.582           91.147      157.149
```

```
##          Ineq      40.953      12.198           0.422      3.357           16.370      65.536
```

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

```
##
```

```
##
```

```
##
```

```
##          Model Summary
```

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

```
## R          0.762      RMSE          256.187
```

```
## R-Squared    0.580      Coef. Var      28.305
```

```
## Adj. R-Squared 0.561      MSE          65631.982
```

```
## Pred R-Squared 0.486      MAE          189.666
```

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

```
## RMSE: Root Mean Square Error
```

```
## MSE: Mean Square Error
```

```
## MAE: Mean Absolute Error
```

```
##
```

```
##          ANOVA
```

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

	Sum of				
	Squares	DF	Mean Square	F	Sig.
Regression	3993120.467	2	1996560.233	30.421	0.0000
Residual	2887807.193	44	65631.982		
Total	6880927.660	46			

Parameter Estimates							
model	Beta	Std. Error	Std. Beta	t	Sig.	lower	upper
(Intercept)	-944.662	343.947		-2.747	0.009	-1637.841	-251.482
Po1	124.148	16.375	0.954	7.582	0.000	91.147	157.149
Ineq	40.953	12.198	0.422	3.357	0.002	16.370	65.536

Stepwise Selection: Step 3

- Ed added

Model Summary			
R	0.816	RMSE	231.314
R-Squared	0.666	Coef. Var	25.557
Adj. R-Squared	0.642	MSE	53505.987
Pred R-Squared	0.575	MAE	165.776

RMSE: Root Mean Square Error

MSE: Mean Square Error

MAE: Mean Absolute Error

ANOVA					
	Sum of				
	Squares	DF	Mean Square	F	Sig.
Regression	4580170.224	3	1526723.408	28.534	0.0000
Residual	2300757.435	43	53505.987		
Total	6880927.660	46			

Parameter Estimates							
model	Beta	Std. Error	Std. Beta	t	Sig.	lower	upper
(Intercept)	-3275.409	769.137		-4.259	0.000	-4826.521	-1724.297
Po1	124.314	14.785	0.955	8.408	0.000	94.497	154.131
Ineq	75.058	15.077	0.774	4.978	0.000	44.652	105.463
Ed	157.869	47.661	0.457	3.312	0.002	61.752	253.987

```

##
##
##           Model Summary
## -----
## R                0.816      RMSE                231.314
## R-Squared        0.666      Coef. Var            25.557
## Adj. R-Squared   0.642      MSE                53505.987
## Pred R-Squared   0.575      MAE                165.776
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##           ANOVA
## -----
##           Sum of
##           Squares      DF      Mean Square      F      Sig.
## -----
## Regression      4580170.224      3      1526723.408      28.534      0.0000
## Residual        2300757.435      43       53505.987
## Total          6880927.660      46
## -----
##
##           Parameter Estimates
## -----
##           model      Beta      Std. Error      Std. Beta      t      Sig.      lower      upper
## -----
## (Intercept)    -3275.409      769.137              -4.259      0.000      -4826.521      -1724.297
## Po1             124.314      14.785       0.955      8.408      0.000       94.497      154.131
## Ineq            75.058      15.077       0.774      4.978      0.000       44.652      105.463
## Ed             157.869      47.661       0.457      3.312      0.002       61.752      253.987
## -----
##
##
## Stepwise Selection: Step 4
##
## - M added
##
##           Model Summary
## -----
## R                0.837      RMSE                221.540
## R-Squared        0.700      Coef. Var            24.477
## Adj. R-Squared   0.672      MSE                49079.828
## Pred R-Squared   0.609      MAE                155.220
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##           ANOVA
## -----
##           Sum of
##           Squares      DF      Mean Square      F      Sig.

```

```
## -----
## Regression      4819574.863      4    1204893.716    24.55    0.0000
## Residual        2061352.797     42     49079.828
## Total           6880927.660     46
## -----
```

```
##
##                                     Parameter Estimates
## -----
##      model      Beta    Std. Error    Std. Beta      t      Sig      lower      upper
## -----
## (Intercept)   -4249.222    858.514              -4.950    0.000   -5981.774   -2516.671
##      Po1       129.804     14.377      0.997     9.029    0.000    100.790    158.818
##      Ineq       64.091     15.270      0.661     4.197    0.000     33.276     94.906
##      Ed        166.050     45.797      0.480     3.626    0.001     73.628    258.472
##      M         76.022     34.421      0.247     2.209    0.033      6.557    145.487
## -----
```

```
##
##                                     Model Summary
## -----
## R              0.837      RMSE              221.540
## R-Squared      0.700      Coef. Var        24.477
## Adj. R-Squared 0.672      MSE              49079.828
## Pred R-Squared 0.609      MAE              155.220
## -----
```

```
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
```

```
##                                     ANOVA
## -----
##      Sum of
##      Squares      DF      Mean Square      F      Sig.
## -----
## Regression      4819574.863      4    1204893.716    24.55    0.0000
## Residual        2061352.797     42     49079.828
## Total           6880927.660     46
## -----
```

```
##
##                                     Parameter Estimates
## -----
##      model      Beta    Std. Error    Std. Beta      t      Sig      lower      upper
## -----
## (Intercept)   -4249.222    858.514              -4.950    0.000   -5981.774   -2516.671
##      Po1       129.804     14.377      0.997     9.029    0.000    100.790    158.818
##      Ineq       64.091     15.270      0.661     4.197    0.000     33.276     94.906
##      Ed        166.050     45.797      0.480     3.626    0.001     73.628    258.472
##      M         76.022     34.421      0.247     2.209    0.033      6.557    145.487
## -----
```

```
## Stepwise Selection: Step 5
```


- Prob added

Model Summary			
## R	0.859	RMSE	209.721
## R-Squared	0.738	Coef. Var	23.171
## Adj. R-Squared	0.706	MSE	43982.690
## Pred R-Squared	0.641	MAE	147.842
RMSE: Root Mean Square Error			
MSE: Mean Square Error			
MAE: Mean Absolute Error			

ANOVA					
	Sum of Squares	DF	Mean Square	F	Sig.
## Regression	5077637.365	5	1015527.473	23.089	0.0000
## Residual	1803290.295	41	43982.690		
## Total	6880927.660	46			

Parameter Estimates							
## model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
## (Intercept)	-4064.574	816.279		-4.979	0.000	-5713.084	-2416.064
## Po1	121.229	14.063	0.932	8.621	0.000	92.829	149.629
## Ineq	68.310	14.559	0.705	4.692	0.000	38.907	97.714
## Ed	160.153	43.422	0.463	3.688	0.001	72.460	247.845
## M	79.689	32.620	0.259	2.443	0.019	13.811	145.566
## Prob	-3867.271	1596.552	-0.227	-2.422	0.020	-7091.573	-642.969

Model Summary			
## R	0.859	RMSE	209.721
## R-Squared	0.738	Coef. Var	23.171
## Adj. R-Squared	0.706	MSE	43982.690
## Pred R-Squared	0.641	MAE	147.842
RMSE: Root Mean Square Error			
MSE: Mean Square Error			
MAE: Mean Absolute Error			

ANOVA					
	Sum of Squares	DF	Mean Square	F	Sig.

```
## Regression      5077637.365      5      1015527.473      23.089      0.0000
## Residual        1803290.295     41      43982.690
## Total           6880927.660     46
```

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

Parameter Estimates

```
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
## (Intercept)   -4064.574      816.279              -4.979      0.000      -5713.084      -2416.064
##      Po1       121.229      14.063              0.932      8.621      0.000      92.829      149.629
##      Ineq       68.310      14.559              0.705      4.692      0.000      38.907      97.714
##      Ed        160.153      43.422              0.463      3.688      0.001      72.460      247.845
##      M         79.689      32.620              0.259      2.443      0.019      13.811      145.566
##      Prob      -3867.271     1596.552             -0.227     -2.422      0.020     -7091.573     -642.969
## -----
```

```
##
```

```
##
```

```
##
```

```
## Stepwise Selection: Step 6
```

```
##
```

```
## - U2 added
```

```
##
```

Model Summary

```
## -----
## R              0.875      RMSE              200.690
## R-Squared      0.766      Coef. Var          22.174
## Adj. R-Squared 0.731      MSE              40276.421
## Pred R-Squared 0.666      MAE              138.674
## -----
```

```
## RMSE: Root Mean Square Error
```

```
## MSE: Mean Square Error
```

```
## MAE: Mean Absolute Error
```

```
##
```

ANOVA

```
## -----
##      Sum of
##      Squares      DF      Mean Square      F      Sig.
## -----
## Regression     5269870.803      6      878311.801     21.807     0.0000
## Residual       1611056.856     40      40276.421
## Total          6880927.660     46
## -----
```

```
##
```

```
##
```

Parameter Estimates

```
## -----
##      model      Beta      Std. Error      Std. Beta      t      Sig      lower      upper
## -----
## (Intercept)   -5040.505      899.843              -5.602      0.000     -6859.156     -3221.854
##      Po1       115.024      13.754              0.884      8.363      0.000      87.227      142.821
##      Ineq       67.653      13.936              0.698      4.855      0.000      39.488      95.818
##      Ed        196.471      44.754              0.568      4.390      0.000     106.019     286.923
##      M         105.020      33.299              0.341      3.154      0.003      37.719     172.320
##      Prob      -3801.836     1528.097             -0.224     -2.488      0.017     -6890.236     -713.436
```



```

##          U2          89.366          40.906          0.195          2.185          0.035          6.693          172.039
## -----
##
##
##
##
##              Model Summary
## -----
## R              0.875          RMSE              200.690
## R-Squared      0.766          Coef. Var          22.174
## Adj. R-Squared 0.731          MSE              40276.421
## Pred R-Squared 0.666          MAE              138.674
## -----
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
##
##              ANOVA
## -----
##              Sum of
##              Squares          DF          Mean Square          F          Sig.
## -----
## Regression      5269870.803          6          878311.801          21.807          0.0000
## Residual        1611056.856          40          40276.421
## Total           6880927.660          46
## -----
##
##              Parameter Estimates
## -----
##              model          Beta          Std. Error          Std. Beta          t          Sig          lower          upper
## -----
## (Intercept)    -5040.505          899.843              -5.602          0.000          -6859.156          -3221.854
## Po1            115.024          13.754              0.884          8.363          0.000          87.227          142.821
## Ineq           67.653          13.936              0.698          4.855          0.000          39.488          95.818
## Ed             196.471          44.754              0.568          4.390          0.000          106.019          286.923
## M              105.020          33.299              0.341          3.154          0.003          37.719          172.320
## Prob          -3801.836          1528.097             -0.224          -2.488          0.017          -6890.236          -713.436
## U2             89.366          40.906              0.195          2.185          0.035          6.693          172.039
## -----
##
##
##
## No more variables to be added/removed.
##
##
## Final Model Output
## -----
##
##              Model Summary
## -----
## R              0.875          RMSE              200.690
## R-Squared      0.766          Coef. Var          22.174
## Adj. R-Squared 0.731          MSE              40276.421
## Pred R-Squared 0.666          MAE              138.674
## -----

```

```
## RMSE: Root Mean Square Error
## MSE: Mean Square Error
## MAE: Mean Absolute Error
```

```
##
```

```
## ANOVA
```

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

	Sum of Squares	DF	Mean Square	F	Sig.
## Regression	5269870.803	6	878311.801	21.807	0.0000
## Residual	1611056.856	40	40276.421		
## Total	6880927.660	46			

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

```
##
```

```
##
```

```
## Parameter Estimates
```

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

## model	Beta	Std. Error	Std. Beta	t	Sig	lower	upper
## (Intercept)	-5040.505	899.843		-5.602	0.000	-6859.156	-3221.854
## Po1	115.024	13.754	0.884	8.363	0.000	87.227	142.821
## Ineq	67.653	13.936	0.698	4.855	0.000	39.488	95.818
## Ed	196.471	44.754	0.568	4.390	0.000	106.019	286.923
## M	105.020	33.299	0.341	3.154	0.003	37.719	172.320
## Prob	-3801.836	1528.097	-0.224	-2.488	0.017	-6890.236	-713.436
## U2	89.366	40.906	0.195	2.185	0.035	6.693	172.039

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

```
step
```

```
##
```

```
##
```

```
## Stepwise Selection Summary
```

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

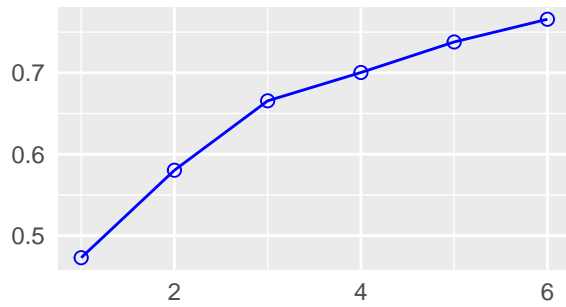
## Step	Variable	Added/ Removed	R-Square	Adj. R-Square	C(p)	AIC	RMSE
## 1	Po1	addition	0.473	0.461	39.9970	668.3155	283.9259
## 2	Ineq	addition	0.580	0.561	25.0710	659.5957	256.1874
## 3	Ed	addition	0.666	0.642	13.6390	650.9145	231.3136
## 4	M	addition	0.700	0.672	10.1620	647.7503	221.5397
## 5	Prob	addition	0.738	0.706	6.2580	643.4641	209.7205
## 6	U2	addition	0.766	0.731	3.8600	640.1661	200.6899

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

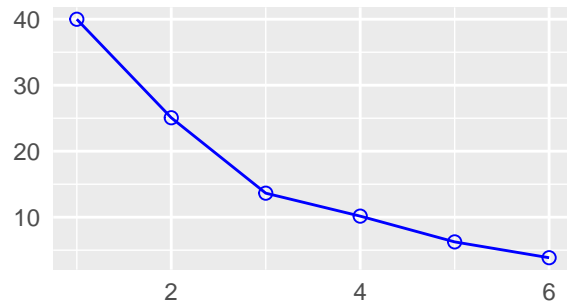
Analysis We can see above that each step is a concatenation of the previous model, starting at Po1*, and the next feature. We can see at the bottom of the iterations, we ended up with a model that had 15 candidates for features but now is constructed by only 6 of them. The stepwise selection summary shows that with each feature addition, RMSE, AIC, and C(p) were dropping, while R-squared and Adjusted R-squared are increasing. This is the effect we like to see. We can plot the model to illustrate how much these metrics changed with each addition of a new feature.

```
plot(step)
```

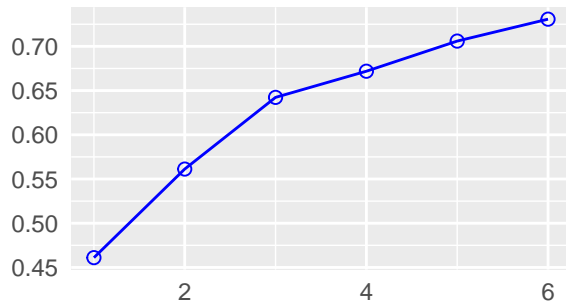
R-Square



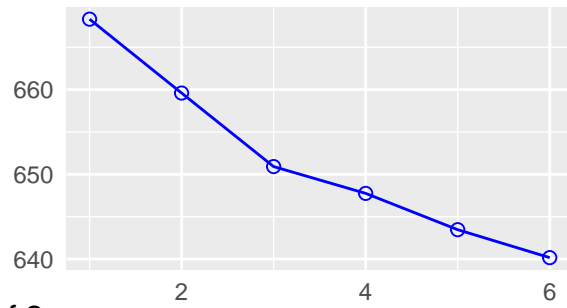
C(p)



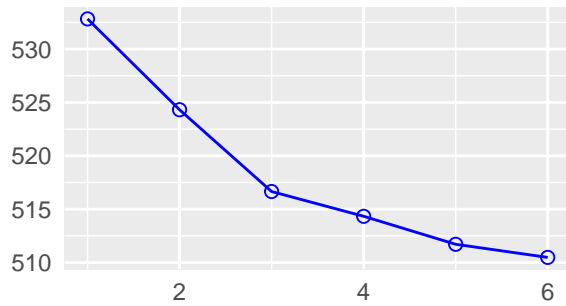
Adj. R-Square



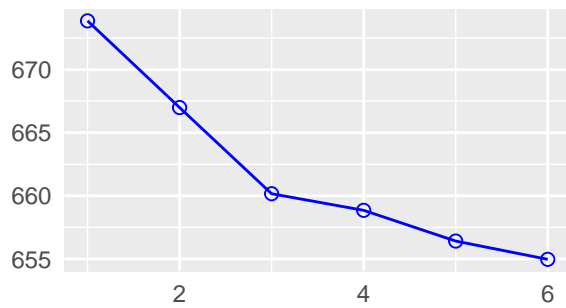
AIC



SBIC



SBC



```
#Unseen data given a previous HW assignment
new.data <- data.frame("M"= 14,
  "So" = 0,
```

```
"Ed" = 10,
"Po1" = 12,
"Po2" = 15.5,
"LF" = .640,
"M.F" = 94,
"Pop" = 150,
"NW" = 1.1,
"U1" = .120,
"U2" = 3.6,
"Wealth" = 3200,
"Ineq" = 20.1,
"Prob" = .04,
"Time" = 39)
```

Let's use the best model from Stepwise Regression to predict on the unseen data that was presented in Week 5 for the Crime data. Predictions on previous models were in the range of 1100 to 1350. So we should expect to see a prediction from this model within that range.

```
best_step.model <- step$model
unseen_step <- new.data[,c('Po1', 'Ineq', 'Ed', 'M', 'Prob', 'U2')]
predict(best_step.model, unseen_step)
```

```
##          1
## 1304.245
```

The prediction is well within the expected range of Crime predictions.

LASSO REGRESSION

Next, we will implement LASSO Regression, which can consequently drive feature coefficients to zero with a high enough hyperparameter of alpha (lambda). Let's see what features LASSO selects vs Stepwise

```
require(glmnet)
```

```
## Loading required package: glmnet
## Loading required package: Matrix
## Loading required package: foreach
## Loaded glmnet 2.0-16
```

```
require(caret)
```

```
## Loading required package: caret
## Loading required package: lattice
## Loading required package: ggplot2
```

```
set.seed(42)
```

```
#Scale the train data
x <- as.data.frame(data[,1:15])
pp = preProcess(x)
scaled_x <- as.matrix(predict(pp, x))
#Scale the test data
scaled_test <- as.matrix(predict(pp, new.data))
```

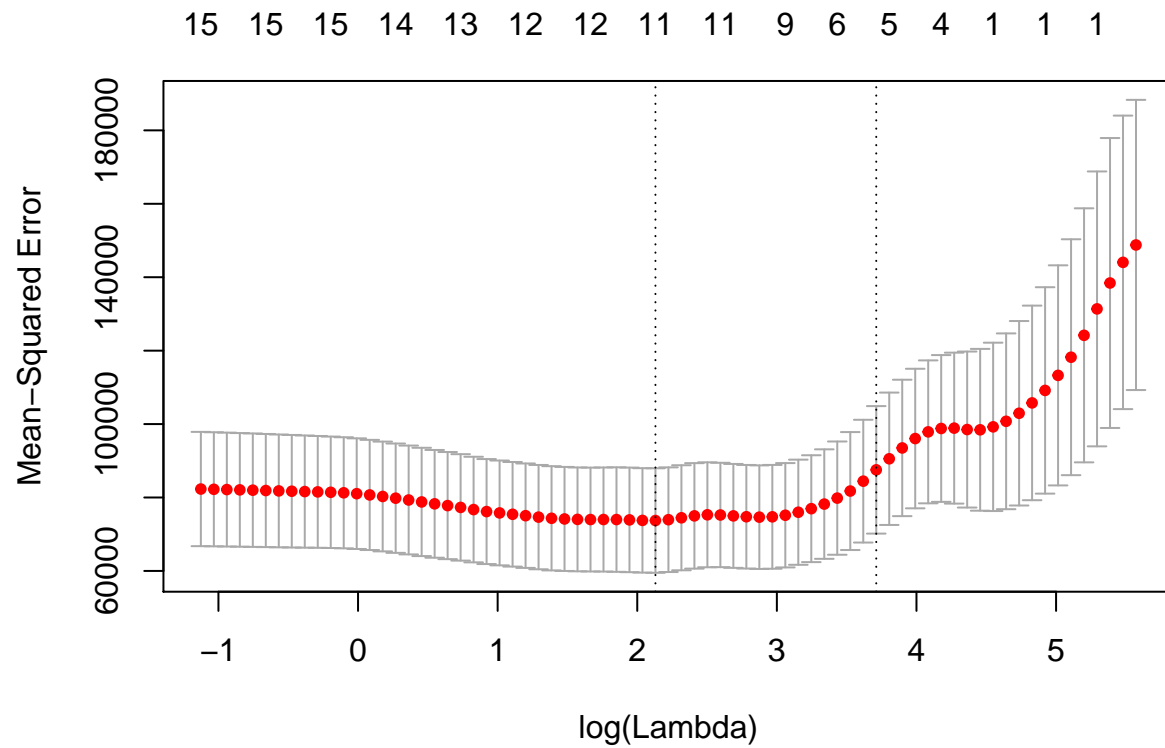
```
#target variable
```

```
y <- data[,16]
```

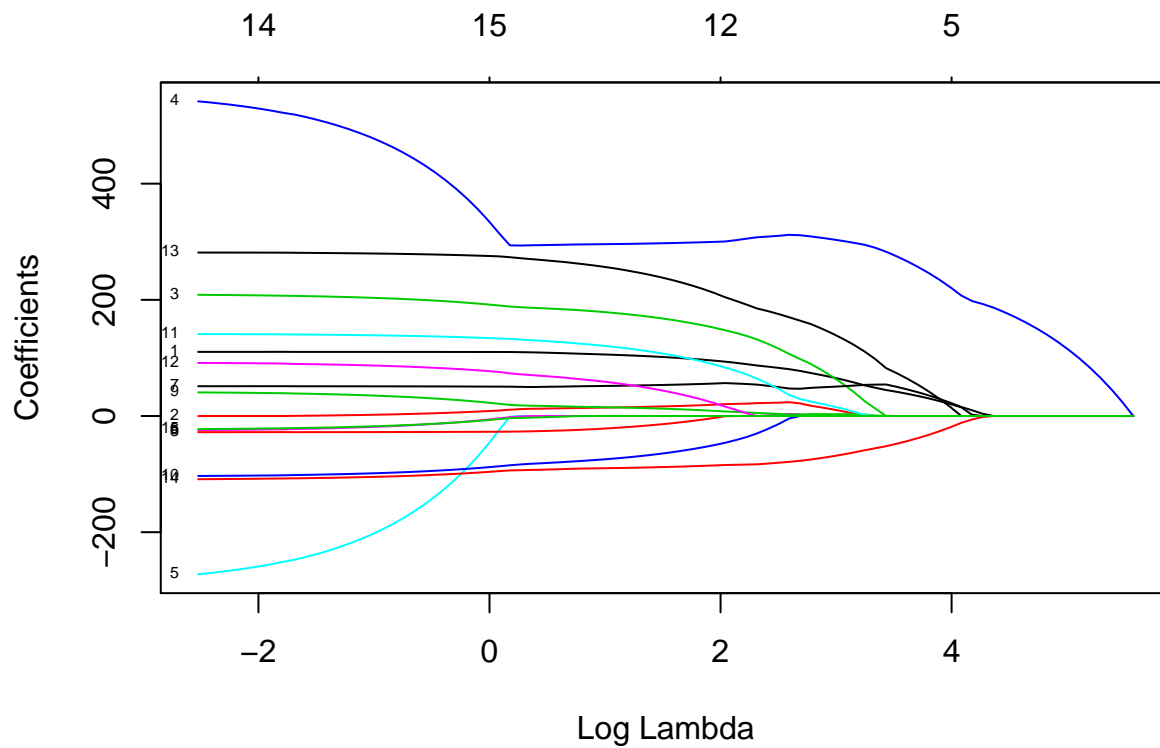
```
lasso <- cv.glmnet(scaled_x,y, family = 'gaussian', alpha = 1, parallel = TRUE)
```

```
## Warning: executing %dopar% sequentially: no parallel backend registered
```

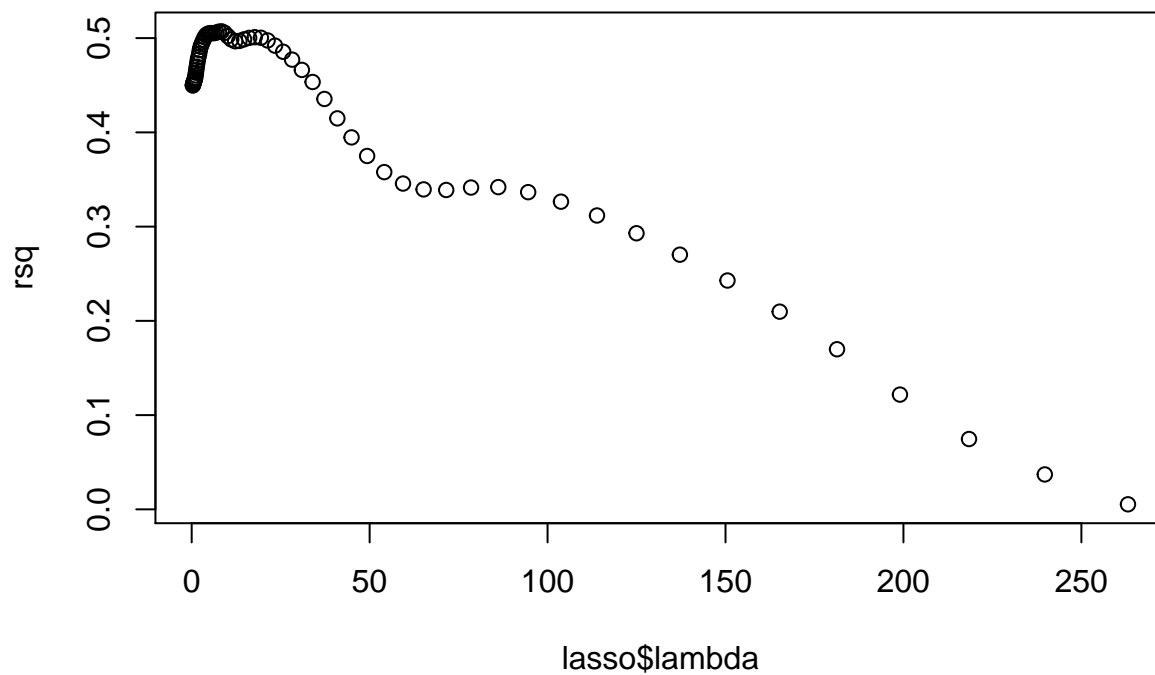
```
plot(lasso)
```



```
plot(lasso$glmnet.fit, xvar='lambda', label = TRUE)
```



```
rsq = 1 - lasso$cvm/var(y)
plot(lasso$lambda,rsq)
```



```
coefficients <- coef(lasso, s=lasso$lambda.min)
coefficients
```

```
## 16 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 905.085106
```

```
## M          91.605916
## So         20.875623
## Ed        143.159609
## Po1       302.645106
## Po2        .
## LF         .
## M.F       55.995942
## Pop        .
## NW         7.047715
## U1        -41.517302
## U2         78.040254
## Wealth    10.762412
## Ineq      198.440786
## Prob      -83.952696
## Time       .
```

```
paste('Minimum MSE: ', min(lasso$cvm))
```

```
## [1] "Minimum MSE: 73725.9799218528"
```

```
paste('Maximum R^2: ', max(rsq))
```

```
## [1] "Maximum R^2: 0.507131124727598"
```

Above in the first graph, we are basically witnessing the relationship between the regularization tuning parameter lambda, and Mean Squared Error. The two dotted lines is lambda min and lambda 1se (standard error) which is the best lambda that minimizes mean squared error and the lambda that is 1 standard error from lambda min. At the very top of the graph, the numbers represent how many non zero coefficients there are. Therefore, the cross validated model appears to have selected 11 non zero features and a lambda min of approx. $2.1(\log)$. The second graph shows how the coefficients for all 15 features are adjusted as lambda is adjusted. We can see that as lambda increases, more and more features trend towards zero. Also, we can see that the most optimal model selected 11 of the initial 15 features where Po2, LF, Pop and Time are all zero. The minimum cross validated MSE (minimum square error) was 73725 for this model selection in comparison to stepwise's 40,276. Stepwise's R^2 was also better at 0.766, and the lasso model is a mere 0.51. Next Let's next predict Crime using this model and the new data. Again we are looking for values between 1000 and 1350

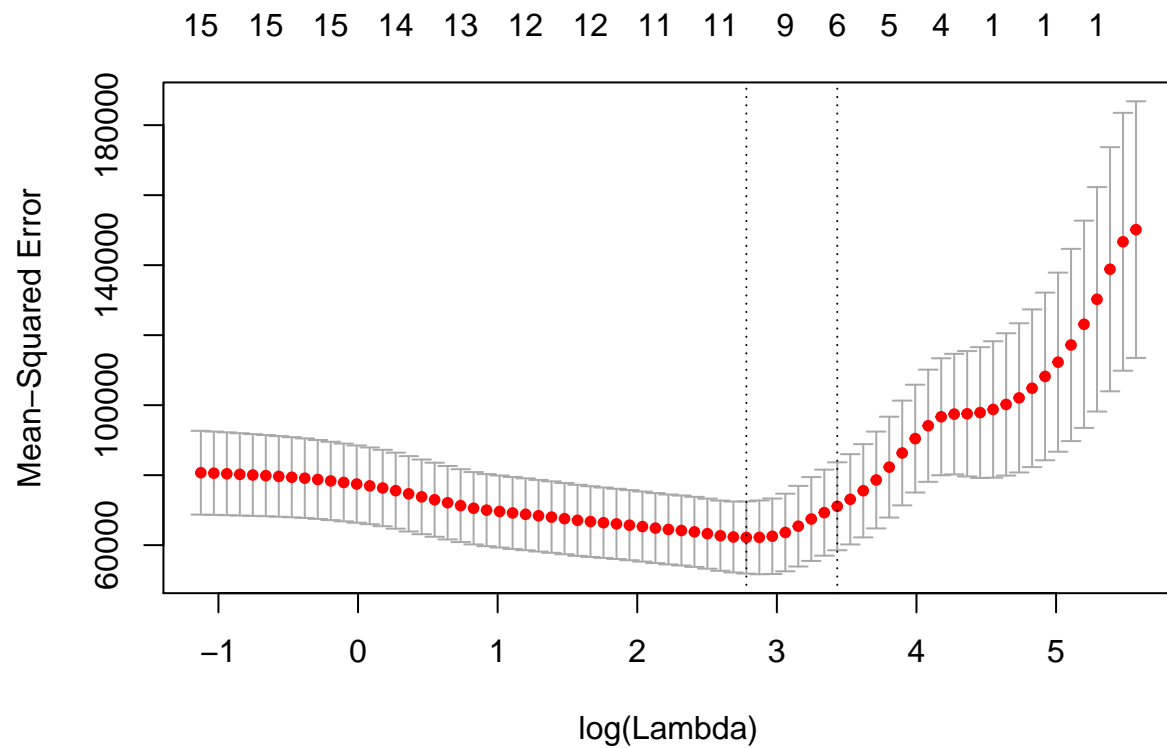
```
coefficients[1] + coefficients[2]*scaled_test[1] + coefficients[3]*scaled_test[2] + coefficients[4]*scaled_test[3]
```

```
## [1] 1097.259
```

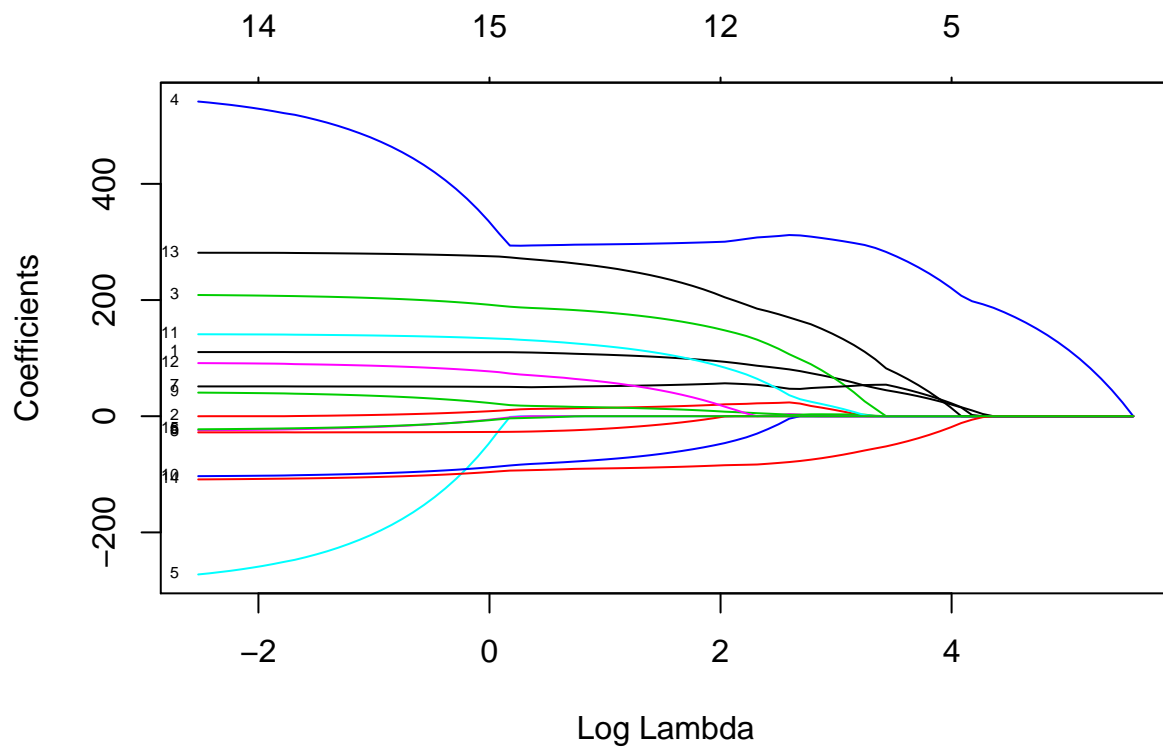
This model predict 1097, in comparison to the 1304 the Stepwise Model predicted. Next we will use an elastic net model which uses a combination of LASSO and RIDGE regression

Elastic Net

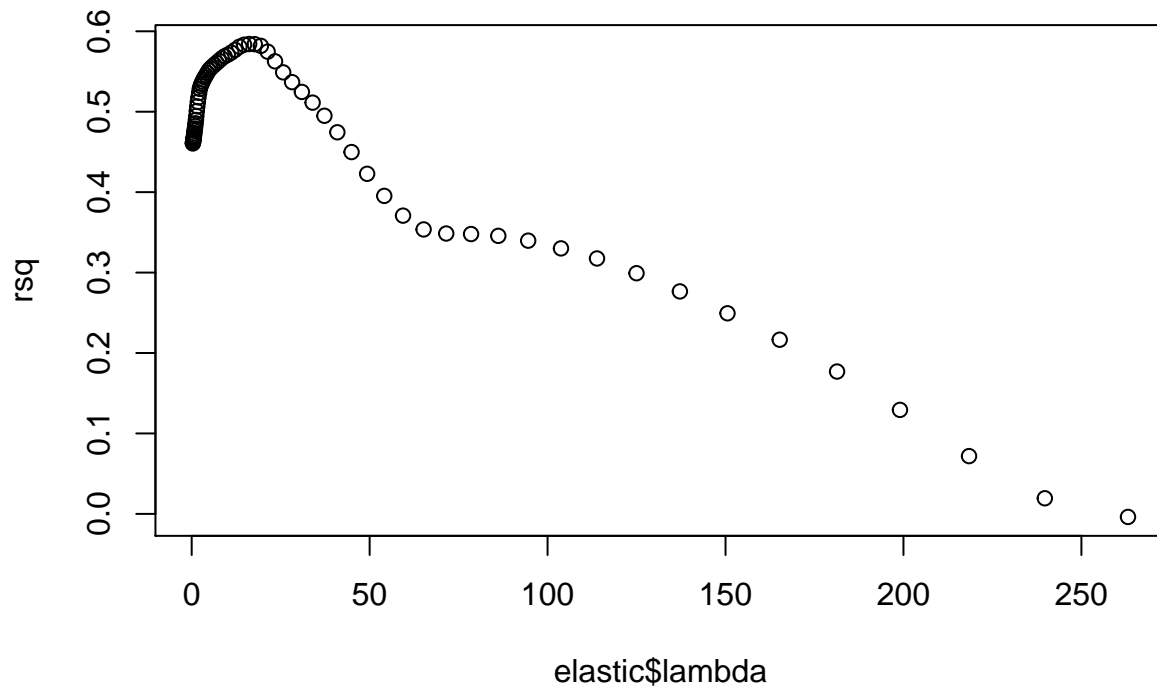
```
set.seed(24)
elastic <- cv.glmnet(x = scaled_x, y = y, family = 'gaussian')
plot(elastic)
```



```
plot(elastic$glmnet.fit, xvar='lambda', label = TRUE)
```



```
coefficients <- coef(elastic, s = 'lambda.min')
rsq = 1 - elastic$cvm/var(y)
plot(elastic$lambda,rsq)
```

```
coefficients
```

```
## 16 x 1 sparse Matrix of class "dgCMatrix"
##              1
## (Intercept) 905.0851064
## M           74.0174295
## So          17.7133651
## Ed          89.5805899
## Po1         309.1881837
## Po2         .
## LF          0.4790569
## M.F         48.4916943
## Pop         .
## NW          3.2640901
## U1          .
## U2         24.9595863
## Wealth     .
## Ineq       158.3327124
## Prob      -74.8230648
## Time       .
```

```
paste('Minimum MSE: ', min(elastic$cvm))
```

```
## [1] "Minimum MSE: 62201.8759075783"
```

```
paste('Maximum R^2: ', max(rsq))
```

```
## [1] "Maximum R^2: 0.584171432500491"
```

The elastic net model improved upon the LASSO model slightly with a MSE score of 62,201 and R^2 score of 0.58. This however is still not as good as the stepwise method. This can mean one of two things, either stepwise was a better method of model selection or it is overfitting the data. Finally, let's predict on the unseen data with the coefficients from elastic net

```
coefficients[1] + coefficients[2]*scaled_test[1] + coefficients[3]*scaled_test[2] + coefficients[4]*scaled_test[3]
## [1] 1204.24
```