Project 1

MSIT 423, Spring 2019
Due: April 27, 2:00pm

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```
library(car)
```

```
## Loading required package: carData
```

```
library(corrplot)
```

```
## corrplot 0.84 loaded
```

0.1 Loading the data from the csv file

```
setwd("~/Desktop/2019/NU/2019-spring/MSIT423/project1")
bike<-read.csv("bike.csv")
bike$avgbf= (bike$Limited_Business_License+bike$Retail_Food_Establishment)/2
```

```
dmg <- bike[,c(3:5,8,10:13,45,47)]
cor(dmg)
```

```
##                    CTA_BUS_STATIONS CTA_TRAIN_STATIONS BIKE_ROUTES
## CTA_BUS_STATIONS          1.0000000         0.76391087  0.57678715
## CTA_TRAIN_STATIONS        0.7639109         1.00000000  0.68212020
## BIKE_ROUTES               0.5767872         0.68212020  1.00000000
## CAPACITY                  0.4670364         0.60617220  0.46837336
## POPULATION_SQ_MILE        0.3038109         0.08970660  0.09750206
## CBD                       0.7233554         0.85270533  0.63539809
## MINORITY                 -0.1816221        -0.23396665 -0.25718405
## EDU                       0.1119116         0.09380398  0.12139609
## trips                     0.4300325         0.52622037  0.51112087
## avgbf                     0.7953145         0.94037689  0.72820843
##                        CAPACITY POPULATION_SQ_MILE        CBD   MINORITY
## CTA_BUS_STATIONS     0.4670364         0.30381094  0.7233554 -0.1816221
## CTA_TRAIN_STATIONS   0.6061722         0.08970660  0.8527053 -0.2339666
## BIKE_ROUTES          0.4683734         0.09750206  0.6353981 -0.2571841
## CAPACITY             1.0000000         0.11211830  0.6093845 -0.2152348
## POPULATION_SQ_MILE   0.1121183         1.00000000  0.1817645 -0.2667885
## CBD                  0.6093845         0.18176454  1.0000000 -0.1686462
## MINORITY            -0.2152348        -0.26678850 -0.1686462  1.0000000
## EDU                  0.1899403         0.26077076  0.1216539 -0.3768247
## trips                0.5944283         0.21655885  0.5269037 -0.6369958
## avgbf                0.6075820         0.08185719  0.8826539 -0.2018209
##                             EDU      trips       avgbf
```

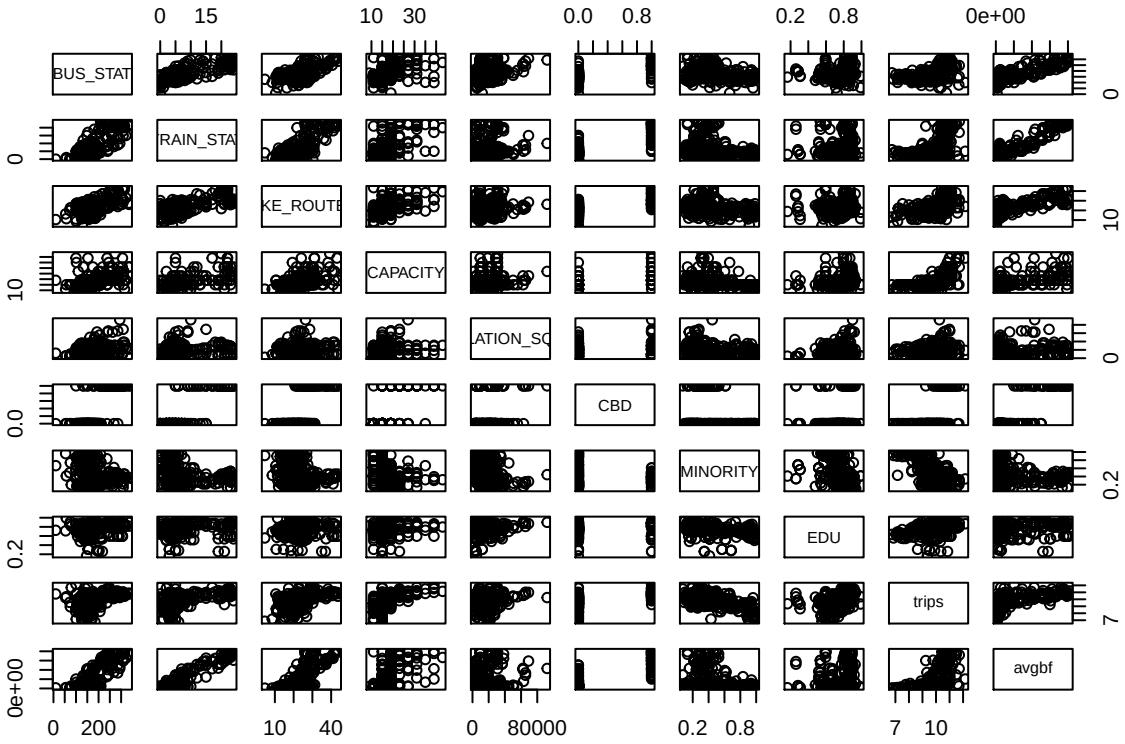
```
## CTA_BUS_STATIONS    0.11191158  0.4300325  0.79531447
## CTA_TRAIN_STATIONS  0.09380398  0.5262204  0.94037689
## BIKE_ROUTES         0.12139609  0.5111209  0.72820843
## CAPACITY            0.18994029  0.5944283  0.60758200
## POPULATION_SQ_MILE  0.26077076  0.2165588  0.08185719
## CBD                 0.12165392  0.5269037  0.88265393
## MINORITY           -0.37682469 -0.6369958 -0.20182091
## EDU                 1.00000000  0.3584473  0.14569653
## trips               0.35844727  1.0000000  0.56766421
## avgbf               0.14569653  0.5676642  1.00000000
```

```
plot(dmg)
library(MASS)
#tran1=cbind(log(com1.2[,c(1:6,9)]),com1.2[,7:8],com1.2[,10:11])
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loading required package: foreach
```

```
## Loaded glmnet 2.0-16
```



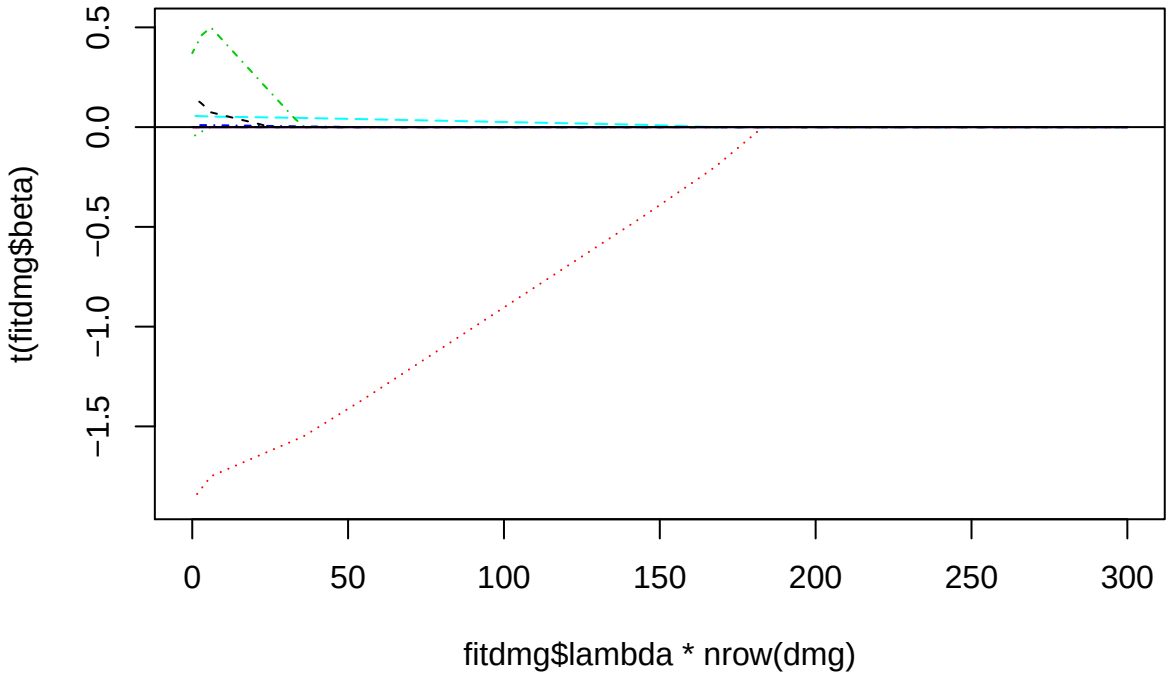

```
lam = seq(0,300,length=101)/nrow(dmg)
x = model.matrix(trips~., dmg)
fitdmg=glmnet(x,dmg$trips, alpha=1, lambda = lam)
cv.lasso=cv.glmnet(x, dmg$trips, alpha=1, lambda = lam)
cv.lasso$lambda.min
```

```
## [1] 0
```

```
coef(cv.lasso,s="lambda.min")
```

```
## 11 x 1 sparse Matrix of class "dgCMatrix"
##                                  1
## (Intercept)          9.251243e+00
## (Intercept)          .
## CTA_BUS_STATIONS    -1.391762e-03
## CTA_TRAIN_STATIONS -4.999291e-02
## BIKE_ROUTES          9.881654e-03
## CAPACITY             5.672128e-02
## POPULATION_SQ_MILE   1.988521e-06
## CBD                  1.555312e-01
## MINORITY            -1.870577e+00
## EDU                  3.708170e-01
## avgbf                4.329040e-06
```

```
matplot(fitdmg$lambda*nrow(dmg), t(fitdmg$beta), type="l"); abline(h=0)
```




```
#fit the model
fit2.1= lm(trips~ CTA_BUS_STATIONS+ CTA_TRAIN_STATIONS + BIKE_ROUTES + CAPACITY +I(MINORITY^
summary(fit2.1)
```

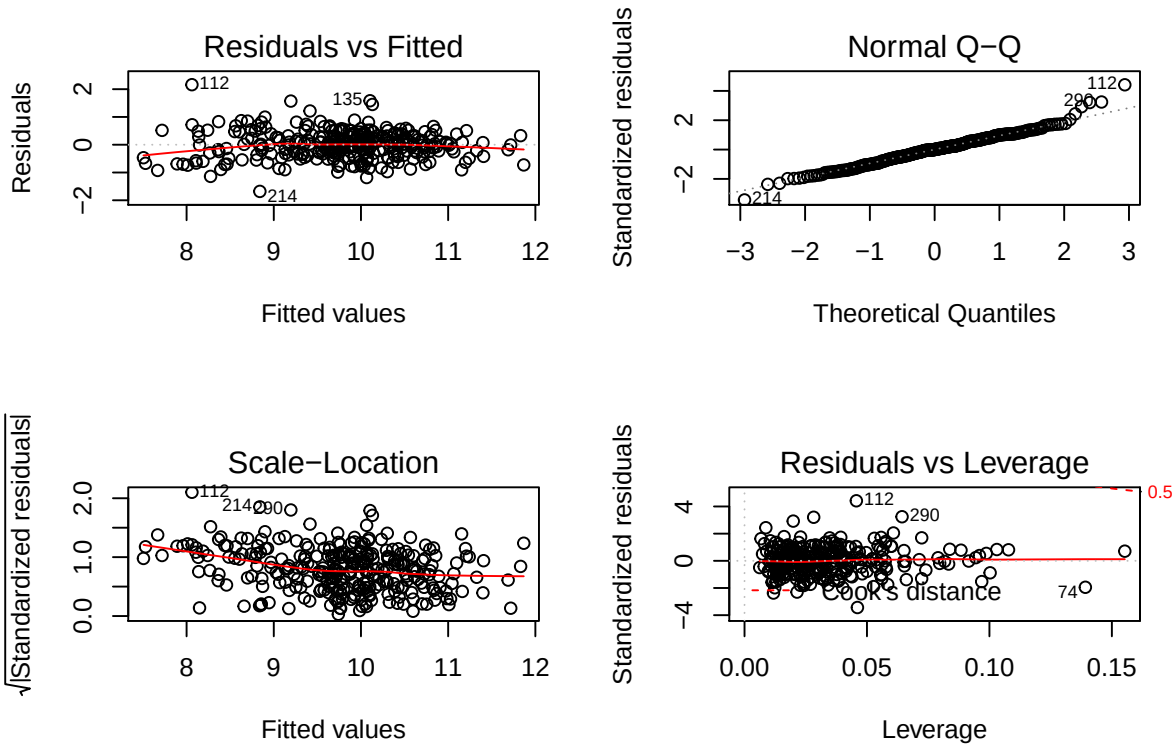
```
##
## Call:
## lm(formula = trips ~ CTA_BUS_STATIONS + CTA_TRAIN_STATIONS +
##     BIKE_ROUTES + CAPACITY + I(MINORITY^2) + EDU + CBD + POPULATION_SQ_MILE +
##     log(avgbf), data = dmg)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -1.68025 -0.30942  0.00193  0.31565  2.16113
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          5.271e+00  5.185e-01  10.165  < 2e-16 ***
## CTA_BUS_STATIONS    -1.380e-03  9.308e-04  -1.482  0.13932
## CTA_TRAIN_STATIONS -2.980e-02  1.092e-02  -2.730  0.00672 **
## BIKE_ROUTES          3.492e-03  6.559e-03   0.532  0.59483
## CAPACITY             5.235e-02  7.089e-03   7.385 1.63e-12 ***
## I(MINORITY^2)       -1.512e+00  1.227e-01 -12.322  < 2e-16 ***
## EDU                  4.379e-01  2.533e-01   1.729  0.08494 .
## CBD                  2.210e-01  1.495e-01   1.479  0.14034
## POPULATION_SQ_MILE   2.638e-06  2.609e-06   1.011  0.31280
## log(avgbf)           3.684e-01  5.388e-02   6.837 4.78e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5009 on 290 degrees of freedom
## Multiple R-squared:  0.7357, Adjusted R-squared:  0.7275
## F-statistic: 89.71 on 9 and 290 DF,  p-value: < 2.2e-16
```

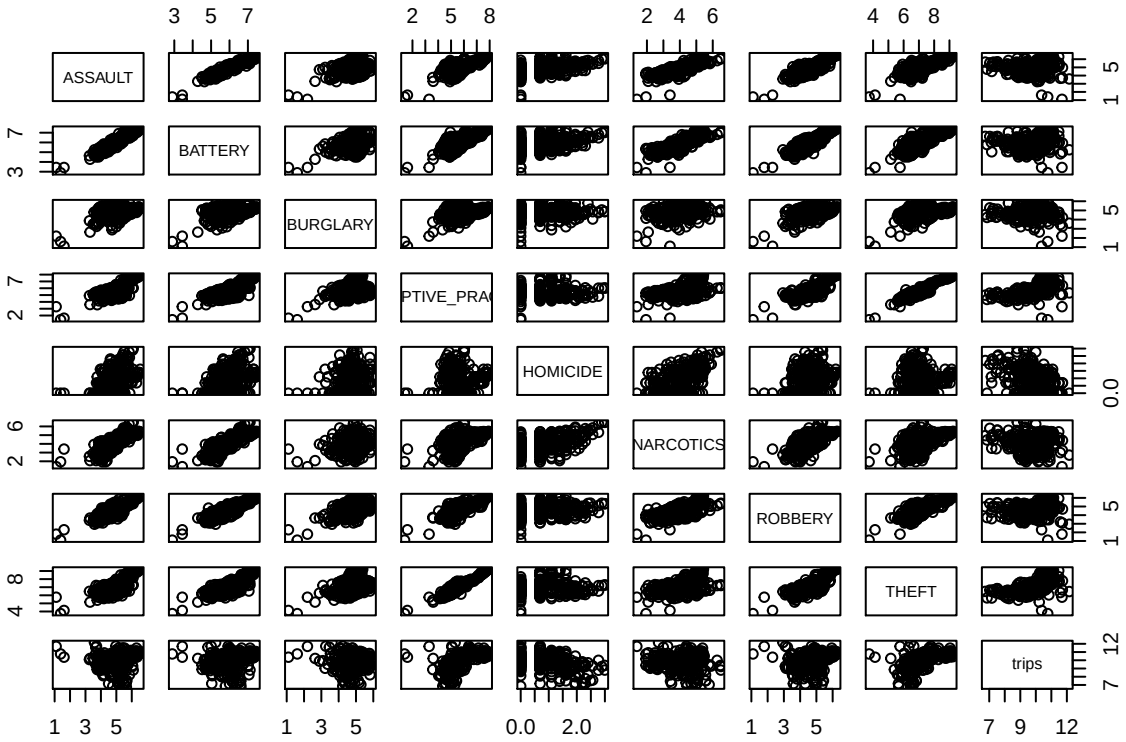
```
vif(fit2.1)
```

```
##   CTA_BUS_STATIONS CTA_TRAIN_STATIONS        BIKE_ROUTES
##           3.035598           5.908774           2.265607
##           CAPACITY      I(MINORITY^2)                EDU
##           1.732919           1.407974           1.232317
##                CBD POPULATION_SQ_MILE         log(avgbf)
##           4.380889           1.334459           4.860235
```

```
#diagnostic
library(car)
par(mfrow=c(2,2))
plot(fit2.1)
```




```
#crime
crime <- bike[,c(15,16,17,22,24,31,40,43,45)]
plot(crime)
```




```
dmgcrime<- cbind(dmg[,c(1:10)], bike[,c(15,16,17,22,24,31,40,43)])
cor(dmgcrime)
```

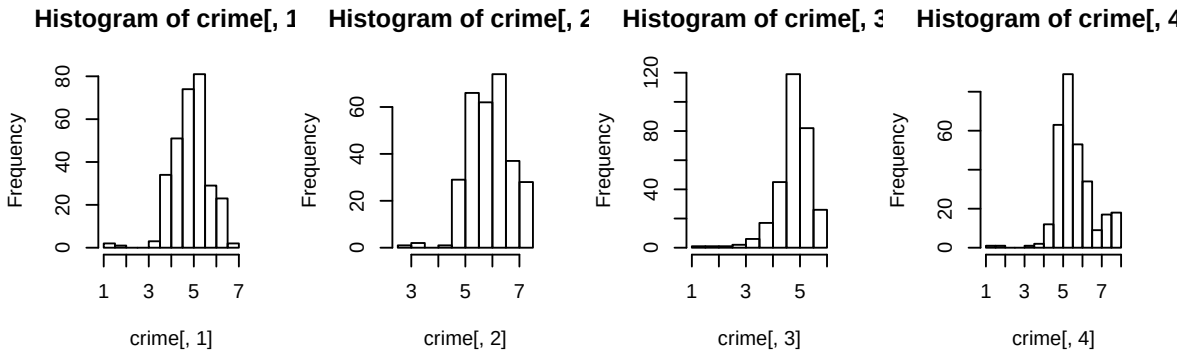
```
##                     CTA_BUS_STATIONS CTA_TRAIN_STATIONS BIKE_ROUTES
## CTA_BUS_STATIONS          1.0000000        0.763910868  0.57678715
## CTA_TRAIN_STATIONS        0.7639109        1.000000000  0.68212020
## BIKE_ROUTES               0.5767872        0.682120205  1.00000000
## CAPACITY                  0.4670364        0.606172200  0.46837336
## POPULATION_SQ_MILE        0.3038109        0.089706600  0.09750206
## CBD                       0.7233554        0.852705331  0.63539809
## MINORITY                 -0.1816221       -0.233966650 -0.25718405
## EDU                       0.1119116        0.093803985  0.12139609
## trips                     0.4300325        0.526220374  0.51112087
## avgbf                     0.7953145        0.940376886  0.72820843
## ASSAULT                   0.7422541        0.521785160  0.39011575
## BATTERY                   0.7480613        0.477795269  0.40225401
## BURGLARY                  0.2820593        0.005800537  0.04504342
## DECEPTIVE_PRACTICE        0.8421596        0.747351310  0.68669188
## HOMICIDE                  0.1548896       -0.076293964 -0.04640741
## NARCOTICS                 0.5716115        0.368524372  0.21314223
## ROBBERY                   0.7034665        0.493954187  0.43069032
## THEFT                     0.8285750        0.712237374  0.67737098
##                        CAPACITY POPULATION_SQ_MILE         CBD     MINORITY
## CTA_BUS_STATIONS     0.46703643         0.30381094  0.72335537 -0.181622091
## CTA_TRAIN_STATIONS   0.60617220         0.08970660  0.85270533 -0.233966650
## BIKE_ROUTES          0.46837336         0.09750206  0.63539809 -0.257184052
## CAPACITY             1.00000000         0.11211830  0.60938449 -0.215234763
## POPULATION_SQ_MILE   0.11211830         1.00000000  0.18176454 -0.266788498
## CBD                  0.60938449         0.18176454  1.00000000 -0.168646219
## MINORITY            -0.21523476        -0.26678850 -0.16864622  1.000000000
## EDU                  0.18994029         0.26077076  0.12165392 -0.376824694
## trips                0.59442833         0.21655885  0.52690369 -0.636995823
## avgbf                0.60758200         0.08185719  0.88265393 -0.201820906
## ASSAULT              0.27377761         0.21899064  0.50168689  0.211183759
## BATTERY              0.30094054         0.29395427  0.48945661  0.119227137
## BURGLARY            -0.06941903         0.37339738 -0.07374079 -0.271585779
## DECEPTIVE_PRACTICE   0.51195387         0.30829189  0.72777513 -0.317739027
## HOMICIDE            -0.09992196        -0.04727424 -0.05253500  0.540184937
## NARCOTICS            0.17894224         0.28818816  0.35433147  0.254880261
## ROBBERY              0.27292261         0.27898949  0.45414679 -0.001395701
## THEFT                0.48344579         0.30971845  0.69537643 -0.323389957
##                             EDU       trips       avgbf     ASSAULT
## CTA_BUS_STATIONS     0.11191158  0.43003247  0.79531447  0.74225410
## CTA_TRAIN_STATIONS   0.09380398  0.52622037  0.94037689  0.52178516
## BIKE_ROUTES          0.12139609  0.51112087  0.72820843  0.39011575
## CAPACITY             0.18994029  0.59442833  0.60758200  0.27377761
## POPULATION_SQ_MILE   0.26077076  0.21655885  0.08185719  0.21899064
## CBD                  0.12165392  0.52690369  0.88265393  0.50168689
## MINORITY            -0.37682469 -0.63699582 -0.20182091  0.21118376
## EDU                  1.00000000  0.35844727  0.14569653 -0.03318352
## trips                0.35844727  1.00000000  0.56766421  0.03970275
```

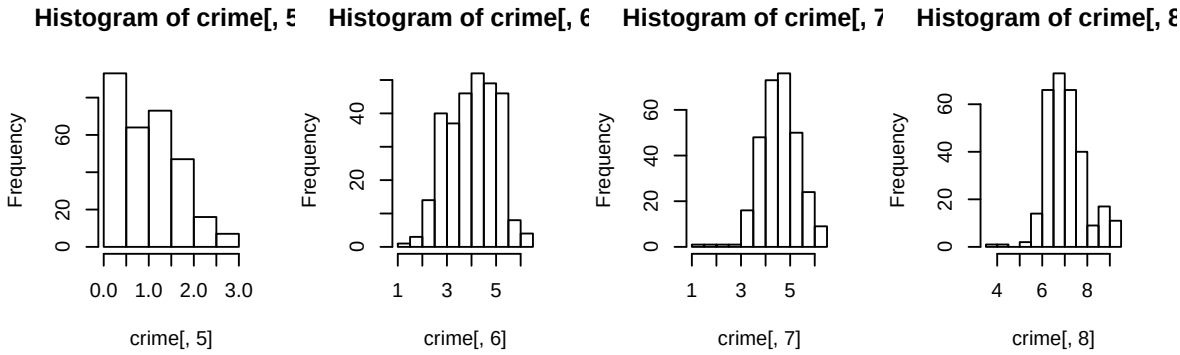
```
## avgbf               0.14569653  0.56766421  1.00000000  0.52695955
## ASSAULT            -0.03318352  0.03970275  0.52695955  1.00000000
## BATTERY             0.05513185  0.13209566  0.48812407  0.95044632
## BURGLARY            0.13222405 -0.01963150 -0.02669805  0.40054925
## DECEPTIVE_PRACTICE  0.19035762  0.52870467  0.76061970  0.74865873
## HOMICIDE           -0.16807883 -0.38873064 -0.01966505  0.49335299
## NARCOTICS          -0.03492525 -0.05937600  0.31785731  0.82507026
## ROBBERY             0.06050953  0.17675697  0.48578539  0.85239606
## THEFT               0.21617174  0.55132574  0.74548015  0.72866970
##                       BATTERY     BURGLARY DECEPTIVE_PRACTICE    HOMICIDE
## CTA_BUS_STATIONS   0.74806126  0.282059270         0.84215964  0.15488955
## CTA_TRAIN_STATIONS 0.47779527  0.005800537         0.74735131 -0.07629396
## BIKE_ROUTES        0.40225401  0.045043419         0.68669188 -0.04640741
## CAPACITY           0.30094054 -0.069419026         0.51195387 -0.09992196
## POPULATION_SQ_MILE 0.29395427  0.373397382         0.30829189 -0.04727424
## CBD                0.48945661 -0.073740794         0.72777513 -0.05253500
## MINORITY           0.11922714 -0.271585779        -0.31773903  0.54018494
## EDU                0.05513185  0.132224050         0.19035762 -0.16807883
## trips              0.13209566 -0.019631495         0.52870467 -0.38873064
## avgbf              0.48812407 -0.026698048         0.76061970 -0.01966505
## ASSAULT            0.95044632  0.400549254         0.74865873  0.49335299
## BATTERY            1.00000000  0.440713898         0.77256304  0.45614052
## BURGLARY           0.44071390  1.000000000         0.36014661  0.11070927
## DECEPTIVE_PRACTICE 0.77256304  0.360146614         1.00000000  0.03784259
## HOMICIDE           0.45614052  0.110709265         0.03784259  1.00000000
## NARCOTICS          0.83870461  0.241867382         0.50869141  0.52605669
## ROBBERY            0.88774347  0.551816547         0.77885944  0.28496565
## THEFT              0.77242350  0.422622699         0.94960488  0.04357397
##                      NARCOTICS      ROBBERY       THEFT
## CTA_BUS_STATIONS    0.57161154  0.703466477  0.82857496
## CTA_TRAIN_STATIONS  0.36852437  0.493954187  0.71223737
## BIKE_ROUTES         0.21314223  0.430690316  0.67737098
## CAPACITY            0.17894224  0.272922615  0.48344579
## POPULATION_SQ_MILE  0.28818816  0.278989495  0.30971845
## CBD                 0.35433147  0.454146791  0.69537643
## MINORITY            0.25488026 -0.001395701 -0.32338996
## EDU                -0.03492525  0.060509535  0.21617174
## trips              -0.05937600  0.176756974  0.55132574
## avgbf               0.31785731  0.485785392  0.74548015
## ASSAULT             0.82507026  0.852396057  0.72866970
## BATTERY             0.83870461  0.887743468  0.77242350
## BURGLARY            0.24186738  0.551816547  0.42262270
## DECEPTIVE_PRACTICE  0.50869141  0.778859440  0.94960488
## HOMICIDE            0.52605669  0.284965650  0.04357397
## NARCOTICS           1.00000000  0.696017454  0.48488441
## ROBBERY             0.69601745  1.000000000  0.80600736
## THEFT               0.48488441  0.806007365  1.00000000
```

```
x2 = model.matrix(trips~., dmgcrime)
withcrime.lasso=cv.glmnet(x2, dmgcrime$trips, alpha=1, lambda = lam)
coef(withcrime.lasso, s="lambda.min")
```

```
## 19 x 1 sparse Matrix of class "dgCMatrix"
##                                 1
## (Intercept)         8.373237e+00
## (Intercept)         .
## CTA_BUS_STATIONS    .
## CTA_TRAIN_STATIONS -3.655162e-03
## BIKE_ROUTES         .
## CAPACITY            4.677113e-02
## POPULATION_SQ_MILE  3.415981e-06
## CBD                 .
## MINORITY           -1.327583e+00
## EDU                 3.631000e-01
## avgbf               7.700012e-07
## ASSAULT            -3.193913e-01
## BATTERY             .
## BURGLARY           -3.217129e-01
## DECEPTIVE_PRACTICE  .
## HOMICIDE           -1.835976e-02
## NARCOTICS          -7.280841e-03
## ROBBERY             .
## THEFT               5.597133e-01
```

```
#tran1=cbind(log(com1.2[,c(1:6,9)]),com1.2[,7:8],com1.2[,10:11])
par(mfrow=c(2,4))
hist(crime[,1])
hist(crime[,2])
hist(crime[,3])
hist(crime[,4])
hist(crime[,5])
hist(crime[,6])
hist(crime[,7])
hist(crime[,8])
```






```
#find the best performance
set.seed(12345)
train = runif(nrow(dmgcrime))<.5
fitall= lm(trips~ ASSAULT + BATTERY
+ log(DECEPTIVE_PRACTICE) + log(ROBBERY) + log(THEFT) + log((HOMICIDE+2)*5) + sqrt(NARCOTICS
         + CTA_BUS_STATIONS+ CTA_TRAIN_STATIONS +
             BIKE_ROUTES + CAPACITY +I(MINORITY^2) + EDU +CBD + POPULATION_SQ_MILE
, data=dmgcrime, subset = train)
fitstepwise= step(fitall)
```

```
## Start:  AIC=-197.38
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CTA_BUS_STATIONS + CTA_TRAIN_STATIONS +
##     BIKE_ROUTES + CAPACITY + I(MINORITY^2) + EDU + CBD + POPULATION_SQ_MILE
##
##                           Df Sum of Sq    RSS     AIC
## - BIKE_ROUTES              1    0.0115 23.013 -199.32
## - EDU                      1    0.0404 23.042 -199.15
## - CTA_BUS_STATIONS         1    0.0483 23.050 -199.10
## - CTA_TRAIN_STATIONS       1    0.0487 23.051 -199.10
## - POPULATION_SQ_MILE       1    0.1530 23.155 -198.50
## - CBD                      1    0.2688 23.271 -197.84
## - log(THEFT)               1    0.2754 23.277 -197.80
## <none>                                23.002 -197.38
## - log(DECEPTIVE_PRACTICE)  1    0.3522 23.354 -197.36
```

```
## - log((HOMICIDE + 2) * 5)  1    0.4668 23.469 -196.71
## - log(ROBBERY)             1    0.6687 23.671 -195.57
## - sqrt(NARCOTICS)          1    0.9605 23.962 -193.94
## - ASSAULT                  1    1.3746 24.377 -191.66
## - BATTERY                  1    1.9149 24.917 -188.75
## - BURGLARY                 1    2.2661 25.268 -186.89
## - log(avgbf)               1    2.5418 25.544 -185.44
## - CAPACITY                 1    4.4908 27.493 -175.66
## - I(MINORITY^2)            1    8.0944 31.096 -159.28
##
## Step:  AIC=-199.32
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CTA_BUS_STATIONS + CTA_TRAIN_STATIONS +
##     CAPACITY + I(MINORITY^2) + EDU + CBD + POPULATION_SQ_MILE
##
##                           Df Sum of Sq    RSS     AIC
## - CTA_TRAIN_STATIONS       1    0.0433 23.057 -201.07
## - EDU                      1    0.0454 23.059 -201.06
## - CTA_BUS_STATIONS         1    0.0584 23.072 -200.98
## - POPULATION_SQ_MILE       1    0.1505 23.164 -200.45
## - CBD                      1    0.2667 23.280 -199.79
## - log(THEFT)               1    0.2761 23.290 -199.73
## - log(DECEPTIVE_PRACTICE)  1    0.3464 23.360 -199.33
## <none>                                23.013 -199.32
## - log((HOMICIDE + 2) * 5)  1    0.4575 23.471 -198.70
## - log(ROBBERY)             1    0.6701 23.683 -197.50
## - sqrt(NARCOTICS)          1    0.9828 23.996 -195.76
## - ASSAULT                  1    1.5251 24.538 -192.78
## - BATTERY                  1    1.9632 24.977 -190.43
## - BURGLARY                 1    2.2648 25.278 -188.83
## - log(avgbf)               1    2.7475 25.761 -186.32
## - CAPACITY                 1    4.4793 27.493 -177.66
## - I(MINORITY^2)            1    8.2626 31.276 -160.52
##
## Step:  AIC=-201.07
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CTA_BUS_STATIONS + CAPACITY + I(MINORITY^2) +
##     EDU + CBD + POPULATION_SQ_MILE
##
##                           Df Sum of Sq    RSS     AIC
## - EDU                      1    0.0396 23.096 -202.84
## - CTA_BUS_STATIONS         1    0.1072 23.164 -202.45
## - POPULATION_SQ_MILE       1    0.2066 23.263 -201.88
## - log(THEFT)               1    0.2852 23.342 -201.43
## <none>                                23.057 -201.07
## - log(DECEPTIVE_PRACTICE)  1    0.3690 23.426 -200.96
```

```
## - log((HOMICIDE + 2) * 5)  1    0.4235 23.480 -200.65
## - CBD                      1    0.5623 23.619 -199.86
## - log(ROBBERY)             1    0.6426 23.699 -199.41
## - sqrt(NARCOTICS)          1    1.2706 24.327 -195.93
## - ASSAULT                  1    1.5859 24.643 -194.22
## - BURGLARY                 1    2.2743 25.331 -190.56
## - BATTERY                  1    2.2872 25.344 -190.49
## - log(avgbf)               1    2.7569 25.814 -188.05
## - CAPACITY                 1    4.5909 27.648 -178.92
## - I(MINORITY^2)            1    8.2668 31.323 -162.32
##
## Step:  AIC=-202.84
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CTA_BUS_STATIONS + CAPACITY + I(MINORITY^2) +
##     CBD + POPULATION_SQ_MILE
##
##                            Df Sum of Sq    RSS     AIC
## - CTA_BUS_STATIONS          1    0.0986 23.195 -204.27
## - POPULATION_SQ_MILE        1    0.1736 23.270 -203.84
## - log(THEFT)                1    0.2892 23.386 -203.19
## <none>                                  23.096 -202.84
## - log(DECEPTIVE_PRACTICE)   1    0.3647 23.461 -202.76
## - log((HOMICIDE + 2) * 5)   1    0.4513 23.548 -202.27
## - CBD                       1    0.5900 23.686 -201.49
## - log(ROBBERY)              1    0.6730 23.769 -201.02
## - sqrt(NARCOTICS)           1    1.2478 24.344 -197.84
## - ASSAULT                   1    1.5687 24.665 -196.10
## - BATTERY                   1    2.3071 25.403 -192.18
## - BURGLARY                  1    2.3076 25.404 -192.18
## - log(avgbf)                1    2.7399 25.836 -189.93
## - CAPACITY                  1    4.5629 27.659 -180.86
## - I(MINORITY^2)             1    8.2712 31.367 -164.13
##
## Step:  AIC=-204.27
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CAPACITY + I(MINORITY^2) + CBD +
##     POPULATION_SQ_MILE
##
##                            Df Sum of Sq    RSS     AIC
## - POPULATION_SQ_MILE        1    0.1482 23.343 -205.43
## - log(THEFT)                1    0.3501 23.545 -204.28
## <none>                                  23.195 -204.27
## - log(DECEPTIVE_PRACTICE)   1    0.4615 23.656 -203.65
## - log((HOMICIDE + 2) * 5)   1    0.4628 23.658 -203.65
## - CBD                       1    0.6548 23.850 -202.57
## - log(ROBBERY)              1    0.6707 23.866 -202.48
```

```
## - sqrt(NARCOTICS)          1    1.2172 24.412 -199.47
## - ASSAULT                  1    1.7282 24.923 -196.72
## - BATTERY                  1    2.2579 25.453 -193.92
## - BURGLARY                 1    2.6700 25.865 -191.78
## - log(avgbf)               1    2.8206 26.015 -191.01
## - CAPACITY                 1    4.5428 27.738 -182.49
## - I(MINORITY^2)            1    8.2897 31.485 -165.63
##
## Step:  AIC=-205.43
## trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) + log(ROBBERY) +
##     log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CAPACITY + I(MINORITY^2) + CBD
##
##                            Df Sum of Sq    RSS     AIC
## <none>                                  23.343 -205.43
## - log(THEFT)                1    0.3751 23.718 -205.31
## - log(DECEPTIVE_PRACTICE)   1    0.4158 23.759 -205.08
## - log((HOMICIDE + 2) * 5)   1    0.5086 23.852 -204.56
## - log(ROBBERY)              1    0.6273 23.970 -203.90
## - CBD                       1    0.6371 23.980 -203.84
## - sqrt(NARCOTICS)           1    1.1017 24.445 -201.29
## - ASSAULT                   1    1.8920 25.235 -197.06
## - BATTERY                   1    2.2505 25.594 -195.19
## - BURGLARY                  1    2.5222 25.865 -193.78
## - log(avgbf)                1    2.7231 26.066 -192.75
## - CAPACITY                  1    4.5626 27.906 -183.68
## - I(MINORITY^2)             1    8.3664 31.709 -166.69
```

```
yhatsw = predict(fitstepwise, dmgcrime[!train,])
mean((dmgcrime$trips[!train] - yhatsw)^2)       # MSE=0.2378
```

```
## [1] 0.2362196
```

```
summary(fitstepwise)
```

```
##
## Call:
## lm(formula = trips ~ ASSAULT + BATTERY + log(DECEPTIVE_PRACTICE) +
##     log(ROBBERY) + log(THEFT) + log((HOMICIDE + 2) * 5) + sqrt(NARCOTICS) +
##     BURGLARY + log(avgbf) + CAPACITY + I(MINORITY^2) + CBD, data = dmgcrime,
##     subset = train)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.20405 -0.25034  0.04595  0.27144  1.36659
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              6.134946   1.466084   4.185 5.47e-05 ***
```

```
## ASSAULT                  -0.643555   0.206354  -3.119 0.002275 **
## BATTERY                   0.839063   0.246683   3.401 0.000911 ***
## log(DECEPTIVE_PRACTICE) -1.534933   1.049856  -1.462 0.146344
## log(ROBBERY)              1.065775   0.593497   1.796 0.075050 .
## log(THEFT)                2.078658   1.496852   1.389 0.167500
## log((HOMICIDE + 2) * 5) -0.378426   0.234029  -1.617 0.108503
## sqrt(NARCOTICS)          -0.795019   0.334066  -2.380 0.018897 *
## BURGLARY                 -0.399642   0.110985  -3.601 0.000462 ***
## log(avgbf)                0.277958   0.074291   3.741 0.000282 ***
## CAPACITY                  0.045608   0.009417   4.843 3.85e-06 ***
## I(MINORITY^2)            -1.613821   0.246078  -6.558 1.44e-09 ***
## CBD                      -0.334516   0.184839  -1.810 0.072835 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4411 on 120 degrees of freedom
## Multiple R-squared:  0.8113, Adjusted R-squared:  0.7924
## F-statistic: 42.99 on 12 and 120 DF,  p-value: < 2.2e-16
```

```
vif(fitstepwise)
```

```
##                  ASSAULT                  BATTERY log(DECEPTIVE_PRACTICE)
##                15.247552                22.402693                17.763554
##             log(ROBBERY)                log(THEFT) log((HOMICIDE + 2) * 5)
##                 5.765965                20.683153                 2.666346
##          sqrt(NARCOTICS)                 BURGLARY              log(avgbf)
##                 4.634383                 2.809277                 5.901447
##                 CAPACITY           I(MINORITY^2)                      CBD
##                 1.860583                 3.295204                 4.175639
```

```
fitred= lm(trips~
 #    ASSAULT
       + BATTERY
#+ log(DECEPTIVE_PRACTICE)
+ ROBBERY
#  +log(THEFT)
+ log((HOMICIDE+2)*5)
+ sqrt(NARCOTICS)
+BURGLARY
+log(avgbf)
#+ CAPACITY +I(MINORITY^2) + EDU +CBD
, data=dmgcrime, subset = train)
fitred
```

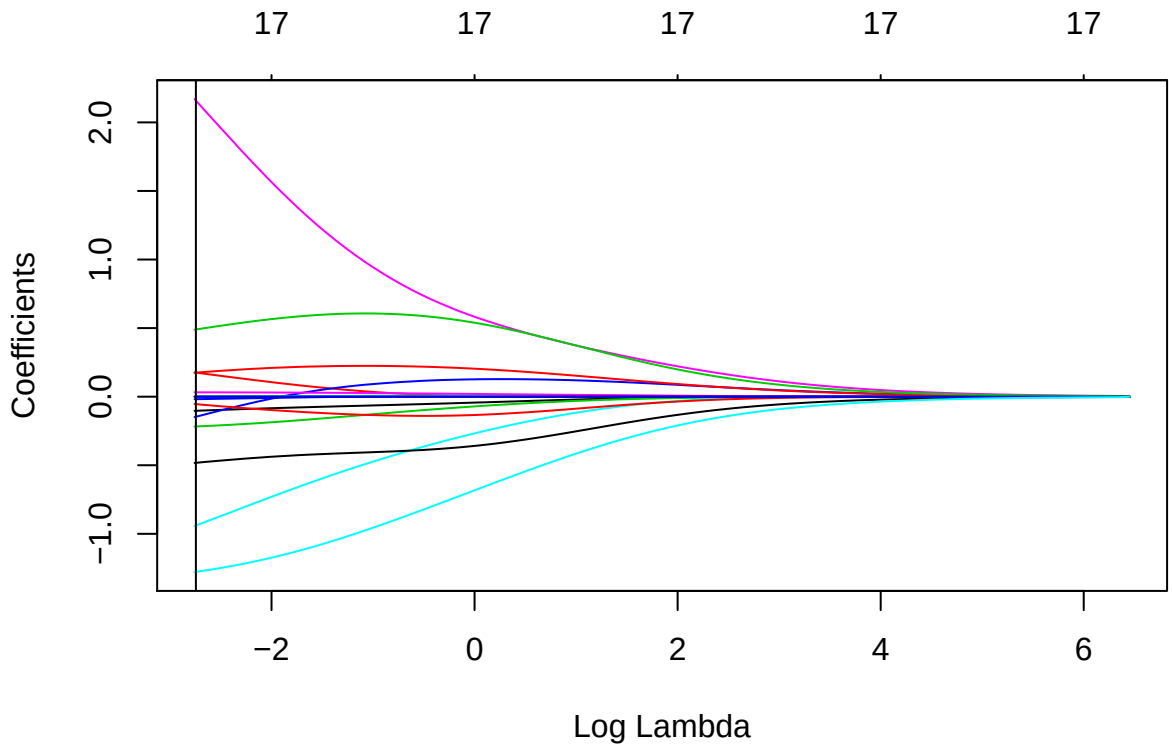
```
##
## Call:
## lm(formula = trips ~ +BATTERY + ROBBERY + log((HOMICIDE + 2) *
##     5) + sqrt(NARCOTICS) + BURGLARY + log(avgbf), data = dmgcrime,
##     subset = train)
```

```
##
## Coefficients:
##              (Intercept)                   BATTERY                   ROBBERY
##                  6.58935                   0.23567                  -0.01873
## log((HOMICIDE + 2) * 5)          sqrt(NARCOTICS)                  BURGLARY
##                 -0.93399                  -0.95357                   0.13329
##               log(avgbf)
##                  0.52297
```

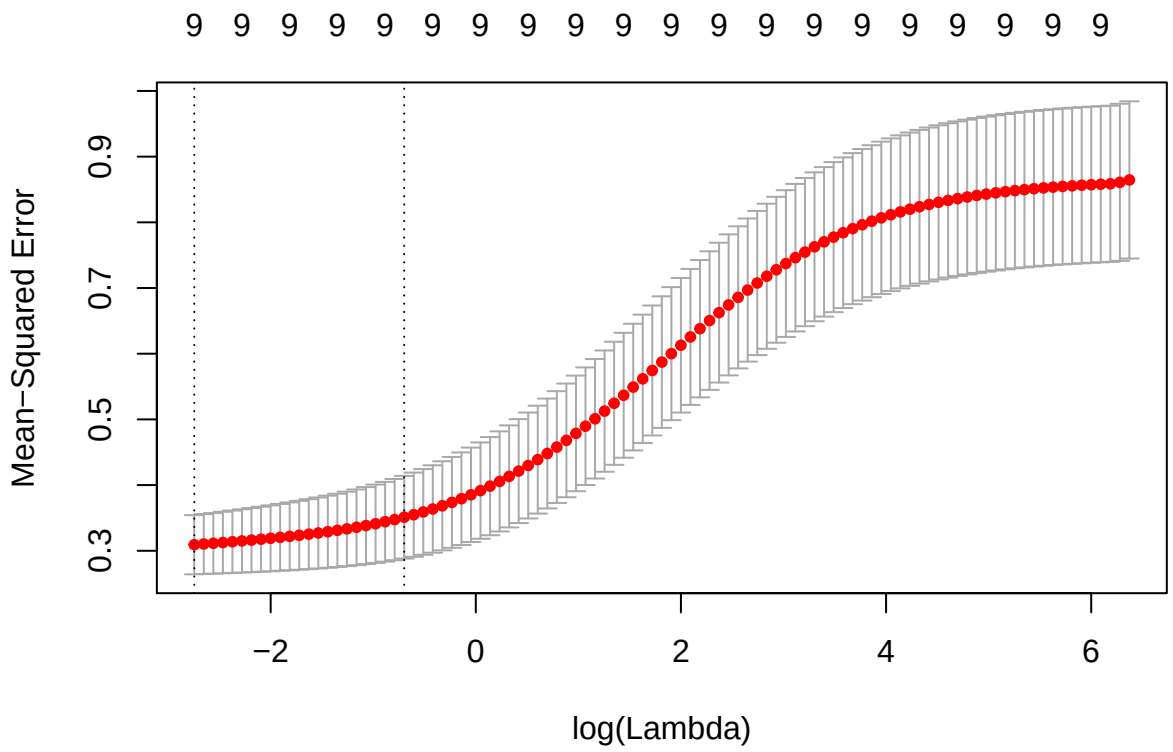
```
#Ridge
dmgtrans=cbind(dmg[,c(1:6,8:10)],dmg[,7]^2)
dmgcrime2= cbind(crime[,1:3],log(crime[,c(4,7:8)]),log((crime[,5]+2)*5),sqrt(crime[,6]),dmgt
train2 = runif(nrow(dmgcrime2))<.5
xr = model.matrix(trips ~ ., dmgcrime2)
fit.ridge = glmnet(xr[train2,], dmgcrime2$trips[train2], alpha=0)
plot(fit.ridge, xvar="lambda")
fit.cv.rd = cv.glmnet(x[train2,], dmgcrime2$trips[train2], alpha=0) # find optimal lambda
fit.cv.rd$lambda.min        # optimal value of lambda
```

```
## [1] 0.06425702
```

```
abline(v=log(fit.cv.rd$lambda.min))
```



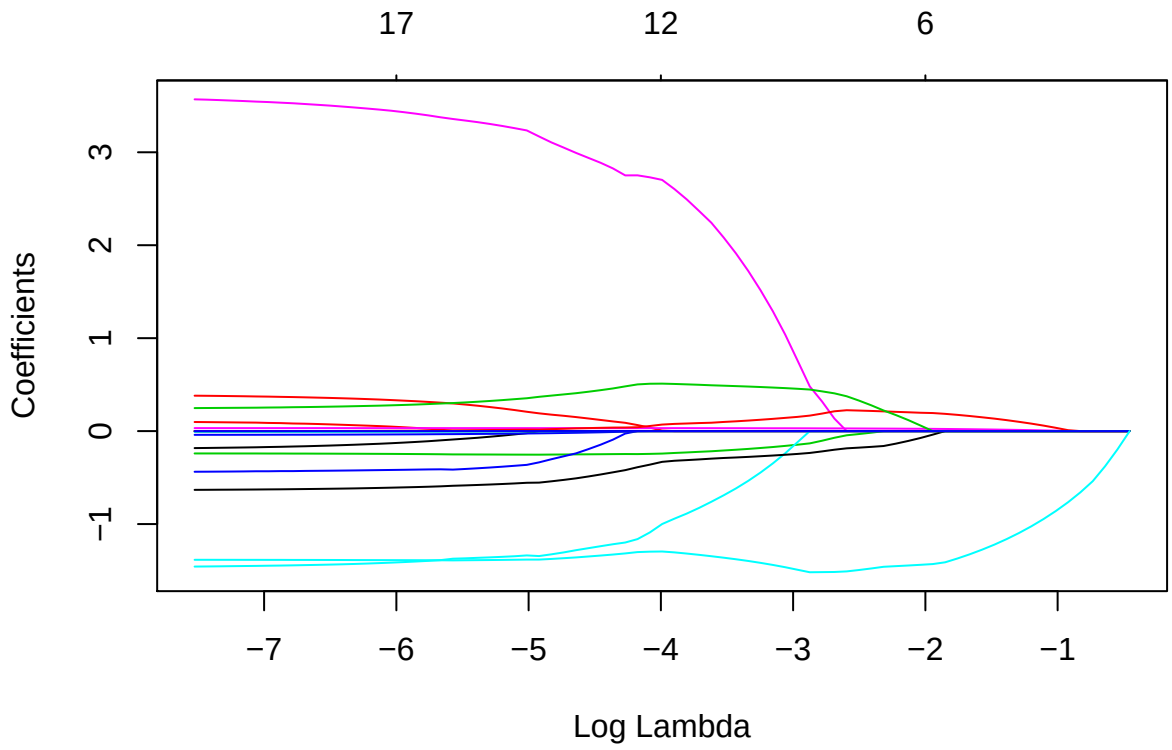

```
plot(fit.cv.rd)          # plot MSE vs. log(lambda)
```




```
yhat = predict(fit.ridge, s=fit.cv.rd$lambda.min, newx=xr[!train2,])  # find yhat for best m
mean((dmgcrime2$trips[!train2] - yhat)^2)      # MSE=0.27
```

```
## [1] 0.2722699
```

```
#Lasso
fit.lasso = glmnet(xr[train2,], dmgcrime2$trips[train2], alpha=1)
plot(fit.lasso, xvar="lambda")
```




```
fit.cv.la = cv.glmnet(xr[train2,], dmgcrime2$trips[train2], alpha=1)
yhatla = predict(fit.lasso, s=fit.cv.la$lambda.min, newx=xr[!train2,])
mean((dmgcrime2$trips[!train2] - yhatla)^2)      # MSE=0.27177
```

```
## [1] 0.271772
```

```
summary(fit.lasso)
```

```
##           Length Class     Mode
## a0          77   -none-    numeric
## beta      1386   dgCMatrix S4
## df          77   -none-    numeric
## dim          2   -none-    numeric
## lambda      77   -none-    numeric
## dev.ratio   77   -none-    numeric
## nulldev      1   -none-    numeric
## npasses      1   -none-    numeric
## jerr         1   -none-    numeric
## offset       1   -none-    logical
## call         4   -none-    call
## nobs         1   -none-    numeric
```

```
coef(fit.cv.la,s="lambda.min")
```

```
## 19 x 1 sparse Matrix of class "dgCMatrix"
##                                       1
## (Intercept)                6.909980e+00
## (Intercept)                .
```

```
## ASSAULT                      -1.362651e-01
## BATTERY                       3.396608e-01
## BURGLARY                     -2.446829e-01
## DECEPTIVE_PRACTICE           -4.197462e-01
## ROBBERY                      -1.420033e+00
## THEFT                         3.459512e+00
## `log((crime[, 5] + 2) * 5)` -6.112912e-01
## `sqrt(crime[, 6])`           5.394357e-02
## CTA_BUS_STATIONS              .
## CTA_TRAIN_STATIONS           -3.634209e-02
## BIKE_ROUTES                  -7.454278e-03
## CAPACITY                      3.229239e-02
## POPULATION_SQ_MILE            6.465691e-06
## CBD                           2.681339e-03
## EDU                           2.738475e-01
## avgbf                         2.798785e-06
## `dmg[, 7]^2`                 -1.387952e+00
```

```
#random forest
library(gam)
```

```
## Loading required package: splines
```

```
## Loaded gam 1.16
```

```
library(randomForest)
```

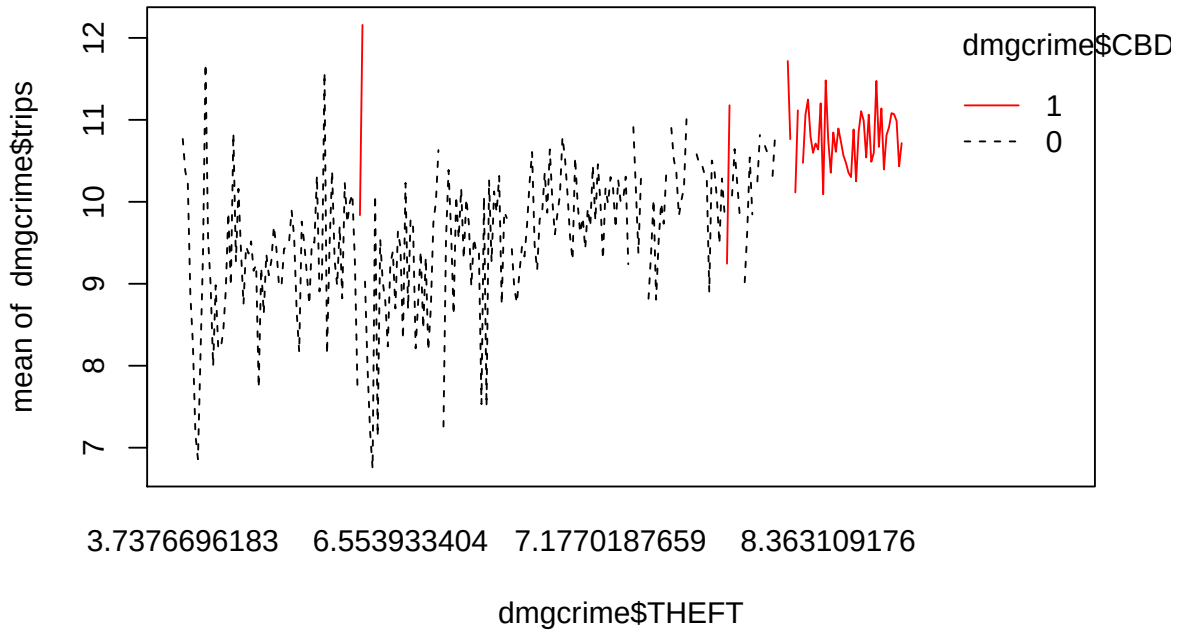
```
## randomForest 4.6-14
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

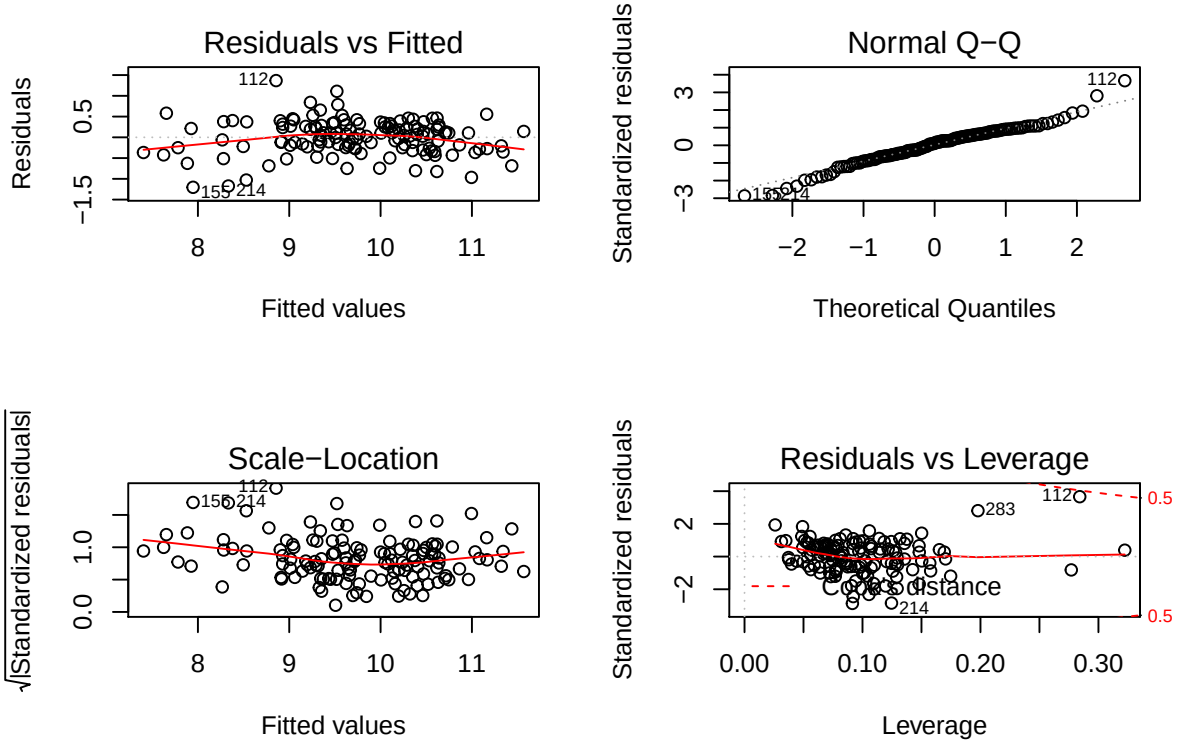
```
colnames(dmgcrime2)[7] <- "homocidetrans"
colnames(dmgcrime2)[8] <- "narcoticstrans"
colnames(dmgcrime2)[18] <- "combineddmgtrans"
fitrf=randomForest(trips ~ ., data=dmgcrime2, importance=T)
fitrf
```

```
##
## Call:
##  randomForest(formula = trips ~ ., data = dmgcrime2, importance = T)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 5
##
##           Mean of squared residuals: 0.2266479
##                     % Var explained: 75.3
```

```
interaction.plot(dmgcrime$THEFT, dmgcrime$CBD, dmgcrime$trips, col=1:2)
```




```
par(mfrow=c(2,2))
plot(fitstepwise)
```




```
vif(fitstepwise)
```

```
##                    ASSAULT                    BATTERY log(DECEPTIVE_PRACTICE)
##                  15.247552                  22.402693                  17.763554
```

```
##            log(ROBBERY)              log(THEFT) log((HOMICIDE + 2) * 5)
##                5.765965               20.683153                2.666346
##         sqrt(NARCOTICS)                BURGLARY              log(avgbf)
##                4.634383                2.809277                5.901447
##                CAPACITY           I(MINORITY^2)                     CBD
##                1.860583                3.295204                4.175639
```