CUNY Data 621 HW3 Logiistical Regression

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Introduction

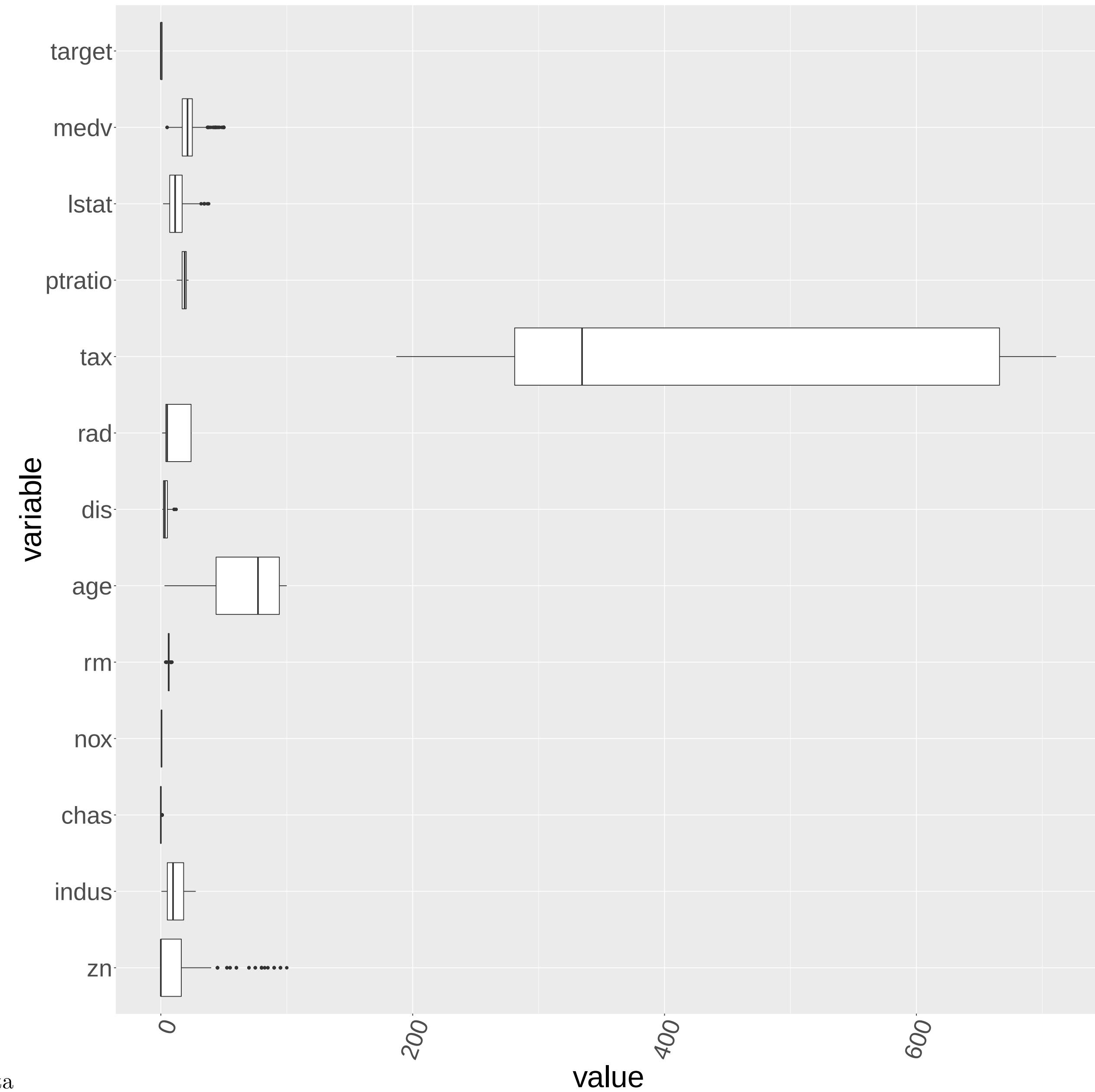
This assignement we will do a logistical regression to predict crime giving an input dataset. A training and evaluation dataset have been provided.

To accomplish this I am going to use the following libraries: 1. ggplot2 2. reshape2 3. coreplot 4. forecast 5. dplyr 6. Deducer

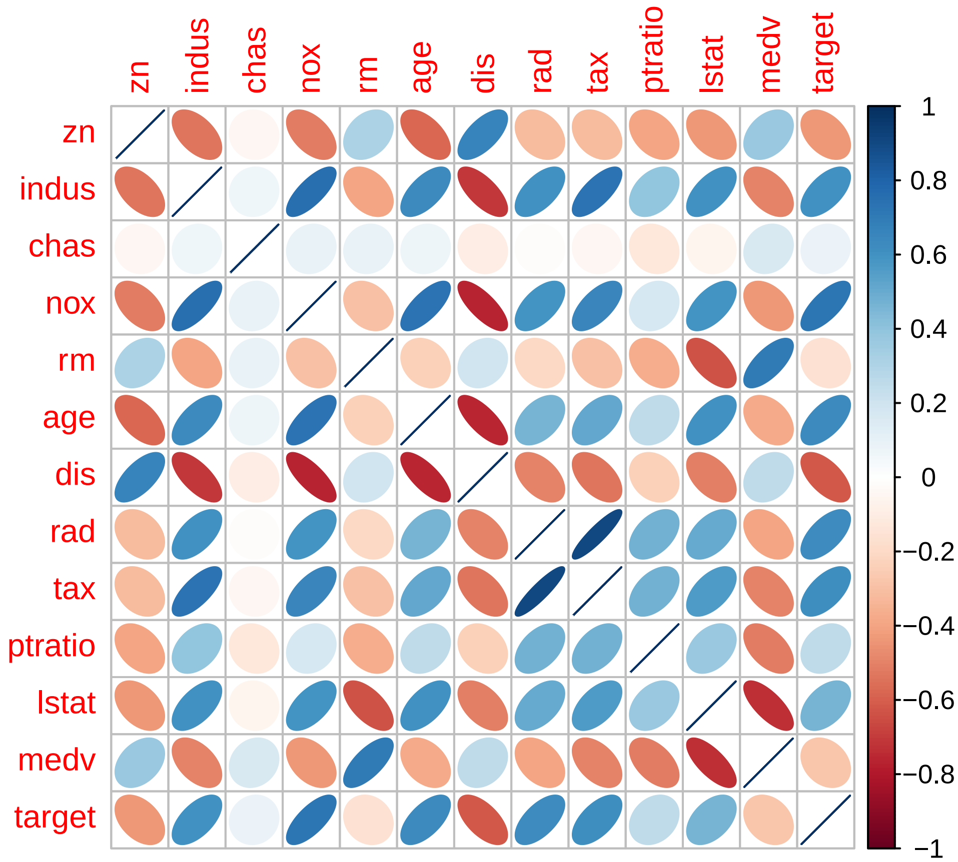
Data Exploration

Summary Statistics:

```
##        zn             indus             chas              nox
##  Min.   :  0.00   Min.   : 0.460   Min.   :0.00000   Min.   :0.3890
##  1st Qu.:  0.00   1st Qu.: 5.145   1st Qu.:0.00000   1st Qu.:0.4480
##  Median :  0.00   Median : 9.690   Median :0.00000   Median :0.5380
##  Mean   : 11.58   Mean   :11.105   Mean   :0.07082   Mean   :0.5543
##  3rd Qu.: 16.25   3rd Qu.:18.100   3rd Qu.:0.00000   3rd Qu.:0.6240
##  Max.   :100.00   Max.   :27.740   Max.   :1.00000   Max.   :0.8710
##        rm             age              dis              rad
##  Min.   :3.863   Min.   :  2.90   Min.   : 1.130   Min.   : 1.00
##  1st Qu.:5.887   1st Qu.: 43.88   1st Qu.: 2.101   1st Qu.: 4.00
##  Median :6.210   Median : 77.15   Median : 3.191   Median : 5.00
##  Mean   :6.291   Mean   : 68.37   Mean   : 3.796   Mean   : 9.53
##  3rd Qu.:6.630   3rd Qu.: 94.10   3rd Qu.: 5.215   3rd Qu.:24.00
##  Max.   :8.780   Max.   :100.00   Max.   :12.127   Max.   :24.00
##       tax           ptratio         lstat             medv
##  Min.   :187.0   Min.   :12.6   Min.   : 1.730   Min.   : 5.00
##  1st Qu.:281.0   1st Qu.:16.9   1st Qu.: 7.043   1st Qu.:17.02
##  Median :334.5   Median :18.9   Median :11.350   Median :21.20
##  Mean   :409.5   Mean   :18.4   Mean   :12.631   Mean   :22.59
##  3rd Qu.:666.0   3rd Qu.:20.2   3rd Qu.:16.930   3rd Qu.:25.00
##  Max.   :711.0   Max.   :22.0   Max.   :37.970   Max.   :50.00
##      target
##  Min.   :0.0000
##  1st Qu.:0.0000
##  Median :0.0000
##  Mean   :0.4914
##  3rd Qu.:1.0000
##  Max.   :1.0000
```



Box Plot of data

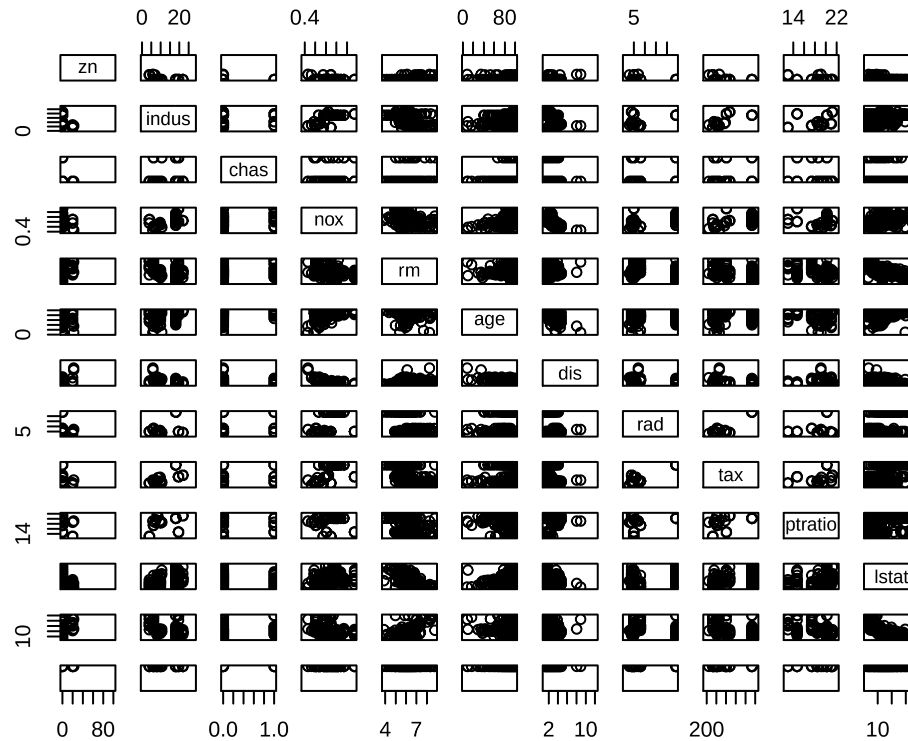


Correlation Plot of Data:

Correlation Matrix:

```
##                  zn       indus        chas         nox          rm
## zn       1.00000000 -0.53826643 -0.04016203 -0.51704518  0.31981410
## indus   -0.53826643  1.00000000  0.06118317  0.75963008 -0.39271181
## chas    -0.04016203  0.06118317  1.00000000  0.09745577  0.09050979
## nox     -0.51704518  0.75963008  0.09745577  1.00000000 -0.29548972
## rm       0.31981410 -0.39271181  0.09050979 -0.29548972  1.00000000
## age     -0.57258054  0.63958182  0.07888366  0.73512782 -0.23281251
## dis      0.66012434 -0.70361886 -0.09657711 -0.76888404  0.19901584
## rad     -0.31548119  0.60062839 -0.01590037  0.59582984 -0.20844570
## tax     -0.31928408  0.73222922 -0.04676476  0.65387804 -0.29693430
## ptratio -0.39103573  0.39468980 -0.12866058  0.17626871 -0.36034706
## lstat   -0.43299252  0.60711023 -0.05142322  0.59624264 -0.63202445
## medv     0.37671713 -0.49617432  0.16156528 -0.43012267  0.70533679
## target  -0.43168176  0.60485074  0.08004187  0.72610622 -0.15255334
##                 age         dis         rad         tax    ptratio
## zn      -0.57258054  0.66012434 -0.31548119 -0.31928408 -0.3910357
## indus    0.63958182 -0.70361886  0.60062839  0.73222922  0.3946898
## chas     0.07888366 -0.09657711 -0.01590037 -0.04676476 -0.1286606
## nox      0.73512782 -0.76888404  0.59582984  0.65387804  0.1762687
## rm      -0.23281251  0.19901584 -0.20844570 -0.29693430 -0.3603471
## age      1.00000000 -0.75089759  0.46031430  0.51212452  0.2554479
## dis     -0.75089759  1.00000000 -0.49499193 -0.53425464 -0.2333394
## rad      0.46031430 -0.49499193  1.00000000  0.90646323  0.4714516
## tax      0.51212452 -0.53425464  0.90646323  1.00000000  0.4744223
## ptratio  0.25544785 -0.23333940  0.47145160  0.47442229  1.0000000
```

```
## lstat    0.60562001 -0.50752800  0.50310125  0.56418864  0.3773560
## medv    -0.37815605  0.25669476 -0.39766826 -0.49003287 -0.5159153
## target   0.63010625 -0.61867312  0.62810492  0.61111331  0.2508489
##              lstat       medv      target
## zn      -0.43299252  0.3767171 -0.43168176
## indus    0.60711023 -0.4961743  0.60485074
## chas    -0.05142322  0.1615653  0.08004187
## nox      0.59624264 -0.4301227  0.72610622
## rm      -0.63202445  0.7053368 -0.15255334
## age      0.60562001 -0.3781560  0.63010625
## dis     -0.50752800  0.2566948 -0.61867312
## rad      0.50310125 -0.3976683  0.62810492
## tax      0.56418864 -0.4900329  0.61111331
## ptratio  0.37735605 -0.5159153  0.25084892
## lstat    1.00000000 -0.7358008  0.46912702
## medv    -0.73580078  1.0000000 -0.27055071
## target   0.46912702 -0.2705507  1.00000000
```



Scatterplats for each variable against the target:

Transformations

Since the data does not look normally distributed, I am going to perform a Box-Cox transfomration on each of the input variables. The labdas for each variable are as follows:

```
##          lambda variable
## 1   0.07538486       zn
## 2  -0.08779326    indus
## 3   0.47220206     chas
## 4  -0.99992425      nox
## 5   0.28832202       rm
```

```
## 6   1.99992425      age
## 7  -0.61031032      dis
## 8  -0.33539473      rad
## 9  -0.99992425      tax
## 10  1.99992425  ptratio
## 11 -0.17920211    lstat
## 12 -0.09049268     medv
```

Build Models

I will bild a model starting with all the variables are removing the least signifigant variables until the AIC starts increaseing

Summary of model will all varirables (model1):

```
##
## Call:
## glm(formula = target ~ ., family = binomial, data = crime_transformed_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0857  -0.1090  -0.0005   0.1040   3.5539
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.045e+02  1.629e+01   6.413 1.43e-10 ***
## zn          -5.404e-01  5.688e-01  -0.950 0.342083
## indus       -6.930e+00  8.486e+00  -0.817 0.414123
## chas         6.668e-01  7.567e-01   0.881 0.378228
## nox         -7.454e+01  1.166e+01  -6.391 1.65e-10 ***
## rm          -9.119e-01  7.382e-01  -1.235 0.216730
## age          3.586e-04  1.097e-04   3.268 0.001083 **
## dis         -1.443e+01  3.136e+00  -4.601 4.20e-06 ***
## rad         -1.800e+01  4.312e+00  -4.174 2.99e-05 ***
## tax          3.080e+02  4.097e+02   0.752 0.452159
## ptratio      1.327e-02  3.867e-03   3.430 0.000603 ***
## lstat        2.156e-02  5.465e-02   0.395 0.693184
## medv         2.588e-01  7.437e-02   3.480 0.000502 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 645.88  on 465  degrees of freedom
## Residual deviance: 187.92  on 453  degrees of freedom
## AIC: 213.92
##
## Number of Fisher Scoring iterations: 8
```

If I drop all non signifigant variables I am left with the following variables:nox, age, dis, pratio, mdev. Therefore I am going to build a model with thoses variables.
Here is the summary for that model (model2)

```r
model2 <- glm(target~nox+ age+dis+ rad+ptratio+medv  , data =crime_transformed_df, family=binomial )
summary(model2)
```

```
##
## Call:
## glm(formula = target ~ nox + age + dis + rad + ptratio + medv,
##     family = binomial, data = crime_transformed_df)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9517  -0.1563  -0.0018   0.1220   3.3766
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  9.114e+01  1.339e+01   6.806 1.00e-11 ***
## nox         -7.209e+01  1.062e+01  -6.786 1.15e-11 ***
## age          3.151e-04  8.489e-05   3.711 0.000206 ***
## dis         -1.242e+01  2.720e+00  -4.566 4.98e-06 ***
## rad         -1.438e+01  2.840e+00  -5.064 4.11e-07 ***
## ptratio      1.189e-02  2.991e-03   3.977 6.99e-05 ***
## medv         1.609e-01  3.647e-02   4.411 1.03e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 645.88  on 465  degrees of freedom
## Residual deviance: 196.11  on 459  degrees of freedom
## AIC: 210.11
##
## Number of Fisher Scoring iterations: 7
```

The least signifigant variable of all the variables left is age, so I will drop that variable and create a model with the remaining variables.
Here is the summary of that model:

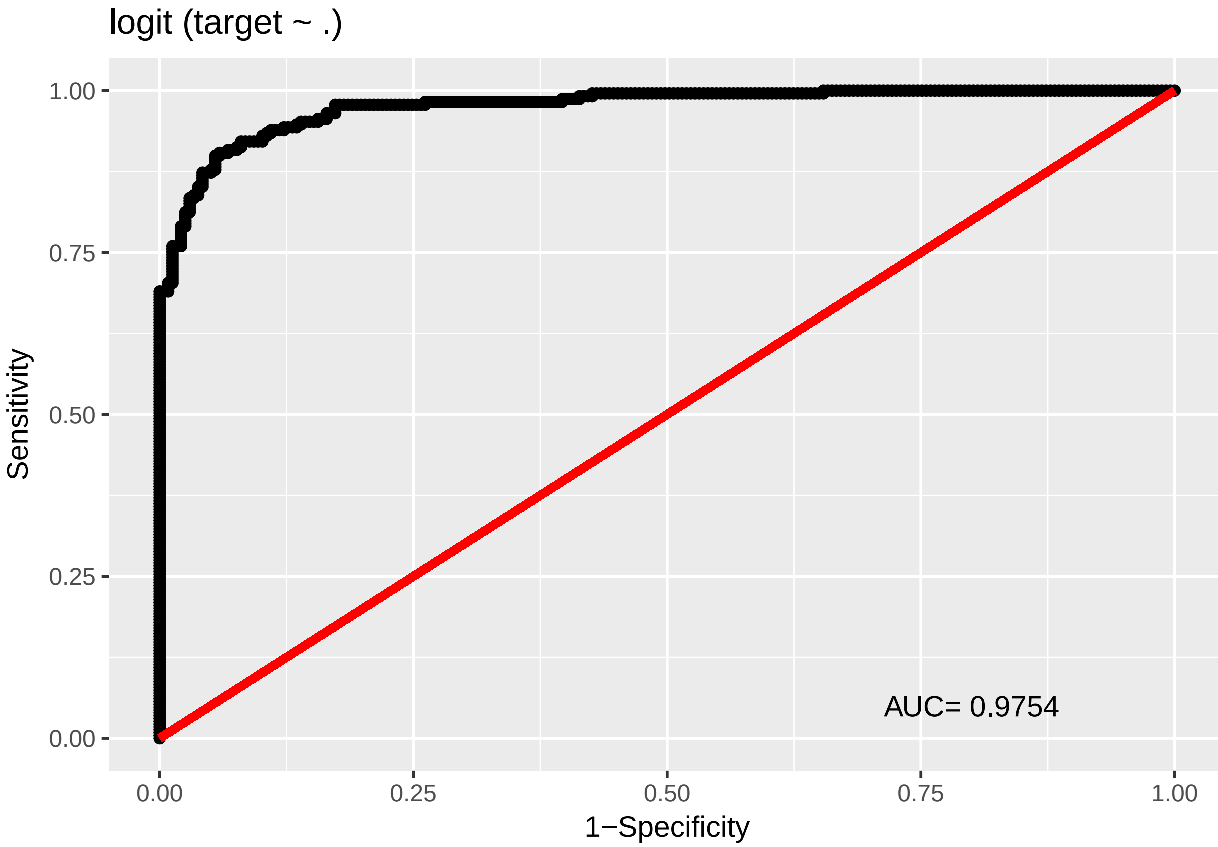
```
##
## Call:
## glm(formula = target ~ nox + dis + rad + ptratio + medv, family = binomial,
##     data = crime_transformed_df)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.28102  -0.20082  -0.00392   0.11758   3.01871
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  93.454841  12.836413   7.280 3.33e-13 ***
## nox         -73.167876  10.047631  -7.282 3.29e-13 ***
## dis          -8.839983   2.407010  -3.673 0.000240 ***
## rad         -13.009411   2.664509  -4.882 1.05e-06 ***
## ptratio       0.009869   0.002781   3.548 0.000388 ***
## medv          0.116046   0.030818   3.765 0.000166 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 645.88  on 465  degrees of freedom
## Residual deviance: 211.10  on 460  degrees of freedom
## AIC: 223.1
##
## Number of Fisher Scoring iterations: 7
```

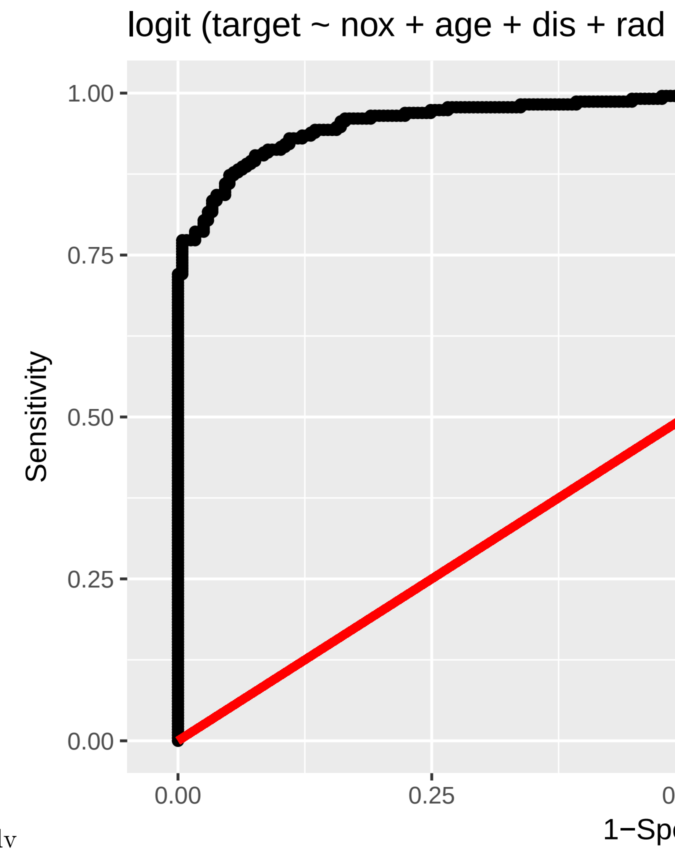
Since AIC started to go up, I am going to stop removing variables.

Select Models:

I am going to select the model based on area under the ROC curve (A/K/A AUC) and AIC.

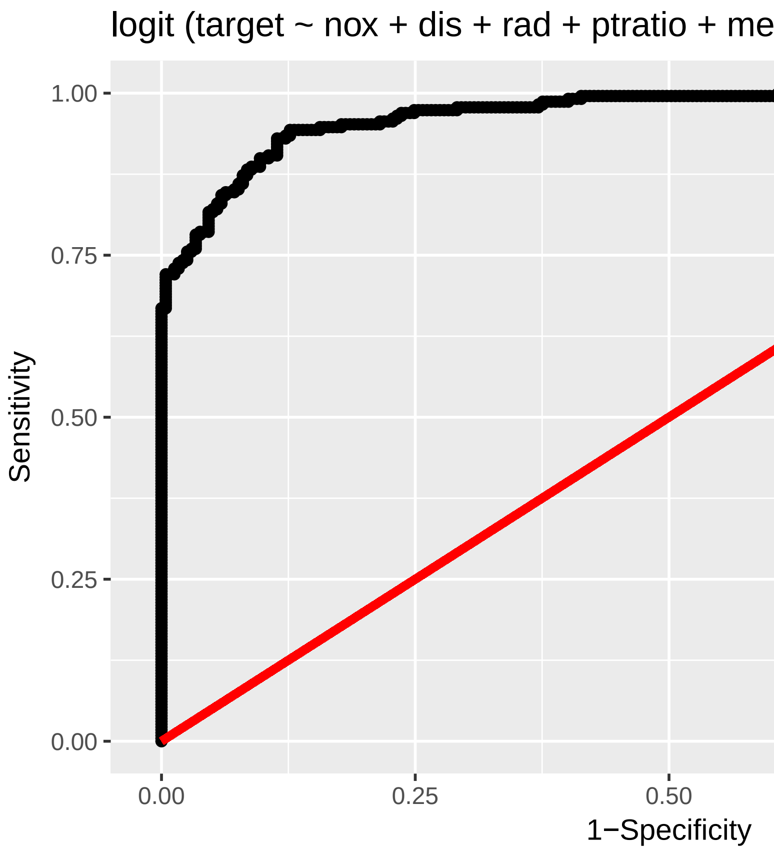


The AIC for model1 is 213.9225599



Model2 Variables in Model 2: nox + age + dis + rad + ptratio + medv

The AIC for model1 is 210.1054573



Model3 Variables: nox + age + dis + rad + ptratio + medv,
The AIC for model3 is 223.1014769

Based the fact that the area under the curve for model 1 and model 2 are virtually identical and the AIC for model 2 is about 1/2 the AIC for model 1 I am going to select model2.

Make Predications

```
##    prediction zn indus chas   nox    rm  age    dis rad tax ptratio lstat
## 1           0  0  7.07    0 0.469 7.185 61.1 4.9671   2 242    17.8  4.03
## 2           0  0  8.14    0 0.538 6.096 84.5 4.4619   4 307    21.0 10.26
## 3           0  0  8.14    0 0.538 6.495 94.4 4.4547   4 307    21.0 12.80
## 4           0  0  8.14    0 0.538 5.950 82.0 3.9900   4 307    21.0 27.71
## 5           0  0  5.96    0 0.499 5.850 41.5 3.9342   5 279    19.2  8.77
## 6           0 25  5.13    0 0.453 5.741 66.2 7.2254   8 284    19.7 13.15
## 7           0 25  5.13    0 0.453 5.966 93.4 6.8185   8 284    19.7 14.44
## 8           0  0  4.49    0 0.449 6.630 56.1 4.4377   3 247    18.5  6.53
## 9           0  0  4.49    0 0.449 6.121 56.8 3.7476   3 247    18.5  8.44
## 10          0  0  2.89    0 0.445 6.163 69.6 3.4952   2 276    18.0 11.34
## 11          0  0 25.65    0 0.581 5.856 97.0 1.9444   2 188    19.1 25.41
## 12          1  0 25.65    0 0.581 5.613 95.6 1.7572   2 188    19.1 27.26
## 13          0  0 21.89    0 0.624 5.637 94.7 1.9799   4 437    21.2 18.34
## 14          0  0 19.58    0 0.605 6.101 93.0 2.2834   5 403    14.7  9.81
## 15          0  0 19.58    0 0.605 5.880 97.3 2.3887   5 403    14.7 12.03
## 16          0  0 10.59    1 0.489 5.960 92.1 3.8771   4 277    18.6 17.27
## 17          0  0  6.20    0 0.504 6.552 21.4 3.3751   8 307    17.4  3.76
## 18          0  0  6.20    0 0.507 8.247 70.4 3.6519   8 307    17.4  3.95
```

```
## 19          0 22  5.86    0 0.431 6.957   6.8 8.9067   7 330    19.1  3.53
## 20          0 90  2.97    0 0.400 7.088  20.8 7.3073   1 285    15.3  7.85
## 21          0 80  1.76    0 0.385 6.230  31.5 9.0892   1 241    18.2 12.93
## 22          0 33  2.18    0 0.472 6.616  58.1 3.3700   7 222    18.4  8.93
## 23          0  0  9.90    0 0.544 6.122  52.8 2.6403   4 304    18.4  5.98
## 24          0  0  7.38    0 0.493 6.415  40.1 4.7211   5 287    19.6  6.12
## 25          0  0  7.38    0 0.493 6.312  28.9 5.4159   5 287    19.6  6.15
## 26          0  0  5.19    0 0.515 5.895  59.6 5.6150   5 224    20.2 10.56
## 27          0 80  2.01    0 0.435 6.635  29.7 8.3440   4 280    17.0  5.99
## 28          0  0 18.10    0 0.718 3.561  87.9 1.6132  24 666    20.2  7.12
## 29          0  0 18.10    1 0.631 7.016  97.5 1.2024  24 666    20.2  2.96
## 30          0  0 18.10    0 0.584 6.348  86.1 2.0527  24 666    20.2 17.64
## 31          0  0 18.10    0 0.740 5.935  87.9 1.8206  24 666    20.2 34.02
## 32          0  0 18.10    0 0.740 5.627  93.9 1.8172  24 666    20.2 22.88
## 33          0  0 18.10    0 0.740 5.818  92.4 1.8662  24 666    20.2 22.11
## 34          0  0 18.10    0 0.740 6.219 100.0 2.0048  24 666    20.2 16.59
## 35          0  0 18.10    0 0.740 5.854  96.6 1.8956  24 666    20.2 23.79
## 36          0  0 18.10    0 0.713 6.525  86.5 2.4358  24 666    20.2 18.13
## 37          0  0 18.10    0 0.713 6.376  88.4 2.5671  24 666    20.2 14.65
## 38          0  0 18.10    0 0.655 6.209  65.4 2.9634  24 666    20.2 13.22
## 39          0  0  9.69    0 0.585 5.794  70.6 2.8927   6 391    19.2 14.10
## 40          1  0 11.93    0 0.573 6.976  91.0 2.1675   1 273    21.0  5.64
##    medv
## 1  34.7
## 2  18.2
## 3  18.4
## 4  13.2
## 5  21.0
## 6  18.7
## 7  16.0
## 8  26.6
## 9  22.2
## 10 21.4
## 11 17.3
## 12 15.7
## 13 14.3
## 14 25.0
## 15 19.1
## 16 21.7
## 17 31.5
## 18 48.3
## 19 29.6
## 20 32.2
## 21 20.1
## 22 28.4
## 23 22.1
## 24 25.0
## 25 23.0
## 26 18.5
## 27 24.5
## 28 27.5
## 29 50.0
## 30 14.5
## 31  8.4
```

```
## 32 12.8
## 33 10.5
## 34 18.4
## 35 10.8
## 36 14.1
## 37 17.7
## 38 21.4
## 39 18.3
## 40 23.9
```

Appendix (R Code)

Setup

library(ggplot2) library(reshape2) library(corrplot) library(forecast) library(dplyr) library(Deducer)

crime_df <- read.csv("crime-training-data.csv")

Data Exploration

summary(crime_df) ggplot(data = melt(crime_df), aes(x=variable, y=value)) + geom_boxplot() + coord_flip() + theme(text = element_text(size=40), axis.text.x = element_text(angle=70, hjust=1))

M <- cor((crime_df)) corrplot(M, method = "ellipse")

pairs(crime_df, col=crime_df$target)

Transformations

calculate_labbdas <- function(df){ df <- df[,1:ncol(df)] l1 <- numeric(ncol(df)) for (i in 1:ncol(df)){ l1[i] <- BoxCox.lambda(df[,i]) } return(data.frame(l1, colnames(df))) }

box_cox_lambdas <- calculate_labbdas(dplyr::select(crime_df, -target)) colnames(box_cox_lambdas) <- c("lambda", "variable")

box_cox_lambdas

crime_transformed_df <- crime_df crime_transformed_df$zn < -crime_transformed_df$zn ^ (filter(box_cox_lambdas, variable=="zn")$lambda)crime_transformed_df$indus <- crime_transformed_df$indus^(filter(box_cox_lam$ "$indus$")lambda) crime_transformed_df$chas < -crime_transformed_df$chas ^ (filter(box_cox_lambdas, variable=="chas")$lambda)crime_transformed_df$nox <- crime_transformed_df$nox^(filter(box_cox_lambdas, variable ==$ "nox")lambda) crime_transformed_df$nox < -crime_transformed_df$nox ^ (filter(box_cox_lambdas, variable=="rm")$lambda)crime_transformed_df$age <- crime_transformed_df$age^(filter(box_cox_lambdas, variable ==$ "age")lambda) crime_transformed_df$dis < -crime_transformed_df$dis ^ (filter(box_cox_lambdas, variable=="dis")$lambda)crime_transformed_df$rad <- crime_transformed_df$rad^(filter(box_cox_lambdas, variable ==$ "rad")lambda) crime_transformed_df$tax < -crime_transformed_df$tax ^ (filter(box_cox_lambdas, variable=="tax")$lambda)crime_transformed_df$ptratio <- crime_transformed_df$ptratio^(filter(box_cox_lambdas, variable ==$ "$ptratio$")lambda)

Build Models

model1 <- glm(target~., data =crime_transformed_df, family=binomial) summary(model1) model2 <- glm(target~nox+ age+dis+ rad+ptratio+medv , data =crime_transformed_df, family=binomial) summary(model2)

model3 <- glm(target~nox+dis+ rad+ptratio+medv , , data =crime_transformed_df, family=binomial) summary(model3)

Select Models:

rocplot(model1)

rocplot(model2)

rocplot(model3)

Make Predications

crime_eval_df <- read.csv("crime-evaluation-data.csv") crime_eval_transformed_df <- crime_eval_df crime_eval_transformed_df$zn < -crime_eval_transformed_df$zn ^ (filter(box_cox_lambdas, variable=="zn")$lambda)crime_ev$ <- crime_eval_transformed_df$indus^(filter(box_cox_lambdas, variable == "indus")$lambda) crime_eval_transformed_df$chas <$ $-crime_eval_transformed_df$chas ^ (filter(box_cox_lambdas, variable=="chas")$lambda)crime_eval_transformed_df$nox <- crime_eval_transformed_df$nox^(filter(box_cox_lambdas, variable == "nox")$lambda) crime_eval_transformed_df$nox <$ $-crime_eval_transformed_df$nox ^ (filter(box_cox_lambdas, variable=="rm")$lambda)crime_eval_transformed_df$age <- crime_eval_transformed_df$age^(filter(box_cox_lambdas, variable == "age")$lambda) crime_eval_transformed_df$dis <$ $-crime_eval_transformed_df$dis ^ (filter(box_cox_lambdas, variable=="dis")$lambda)crime_eval_transformed_df$rad <- crime_eval_transformed_df$rad^(filter(box_cox_lambdas, variable == "rad")$lambda) crime_eval_transformed_df$tax <$ $-crime_eval_transformed_df$tax ^ (filter(box_cox_lambdas, variable=="tax")$lambda)crime_eval_transformed_df$ptratio <- crime_eval_transformed_df$ptratio^(filter(box_cox_lambdas, variable == "ptratio")$lambda)

probs <- predict(model2,crime_eval_df) prediction <- ifelse (probs > .5 ,1,0)

cbind(prediction, crime_eval_df)