# Assignment 3

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**Abstract**

This papers using logistic regression to analyze the Boston Crime Dataset to predict if an area has crime above or bellow the median. This work is completed for the CUNY course DATA 621

## Contents



# 1 Data Exploration

## 1.1 The Data Frames

Table 1: Sample of Values for the Training Set

| zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | lstat | medv | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | 4.93 | 0 | 0.428 | 6.481 | 18.5 | 6.1899 | 6 | 300 | 16.6 | 6.36 | 23.7 | 0 |
| 0 | 18.10 | 0 | 0.655 | 5.759 | 48.2 | 3.0665 | 24 | 666 | 20.2 | 14.13 | 19.9 | 1 |
| 25 | 4.86 | 0 | 0.426 | 6.727 | 33.5 | 5.4007 | 4 | 281 | 19.0 | 5.29 | 28.0 | 0 |
| 0 | 18.10 | 0 | 0.718 | 4.963 | 91.4 | 1.7523 | 24 | 666 | 20.2 | 14.00 | 21.9 | 1 |
| 0 | 18.10 | 0 | 0.770 | 6.251 | 91.1 | 2.2955 | 24 | 666 | 20.2 | 14.19 | 19.9 | 1 |
| 45 | 3.44 | 0 | 0.437 | 7.178 | 26.3 | 6.4798 | 5 | 398 | 15.2 | 2.87 | 36.4 | 0 |

The training or labled dataset is comprised of 12 categorical and continuous variables and one `target` variable that indicates if an area is higher crime.

Table 2: Sample of Values for the Test Set

| zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | lstat | medv |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 19.58 | 0 | 0.605 | 5.880 | 97.3 | 2.3887 | 5 | 403 | 14.7 | 12.03 | 19.1 |
| 0 | 18.10 | 0 | 0.713 | 6.376 | 88.4 | 2.5671 | 24 | 666 | 20.2 | 14.65 | 17.7 |

| zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | lstat | medv |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 80 | 2.01 | 0 | 0.435 | 6.635 | 29.7 | 8.3440 | 4 | 280 | 17.0 | 5.99 | 24.5 |
| 0 | 11.93 | 0 | 0.573 | 6.976 | 91.0 | 2.1675 | 1 | 273 | 21.0 | 5.64 | 23.9 |
| 0 | 8.14 | 0 | 0.538 | 6.495 | 94.4 | 4.4547 | 4 | 307 | 21.0 | 12.80 | 18.4 |
| 80 | 1.76 | 0 | 0.385 | 6.230 | 31.5 | 9.0892 | 1 | 241 | 18.2 | 12.93 | 20.1 |

The evaluation set is a similar data frame but excludes the target variable. As such it cannot be used for cross validation.

- `zn`: proportion of residential land zoned for large lots (over 25000 square feet) (predictor variable)
- `indus`: proportion of non-retail business acres per suburb (predictor variable)
- `chas`: a dummy var. for whether the suburb borders the Charles River (1) or not (0) (predictor variable)
- `nox`: nitrogen oxides concentration (parts per 10 million) (predictor variable)
- `rm`: average number of rooms per dwelling (predictor variable)
- `age`: proportion of owner-occupied units built prior to 1940 (predictor variable)
- `dis`: weighted mean of distances to five Boston employment centers (predictor variable)
- `rad`: index of accessibility to radial highways (predictor variable)
- `tax`: full-value property-tax rate per $10,000 (predictor variable)
- `ptratio`: pupil-teacher ratio by town (predictor variable)
- `lstat`: lower status of the population (percent) (predictor variable)
- `medv`: median value of owner-occupied homes in $1000s (predictor variable)
- `target`: whether the crime rate is above the median crime rate (1) or not (0) (response variable)

## 1.2 Descriptive Statistics

Table 3: Summary Statistics

| zn | indus | chas | nox | rm | age |
|---|---|---|---|---|---|
| Min. : 0.00 | Min. : 0.460 | Min. :0.00000 | Min. :0.3890 | Min. :3.863 | Min. : 2.90 |
| 1st Qu.: 0.00 | 1st Qu.: 5.145 | 1st Qu.:0.00000 | 1st Qu.:0.4480 | 1st Qu.:5.887 | 1st Qu.: 43.88 |
| Median : 0.00 | Median : 9.690 | Median :0.00000 | Median :0.5380 | Median :6.210 | Median : 77.15 |
| Mean : 11.58 | Mean :11.105 | Mean :0.07082 | Mean :0.5543 | Mean :6.291 | Mean : 68.37 |
| 3rd Qu.: 16.25 | 3rd Qu.:18.100 | 3rd Qu.:0.00000 | 3rd Qu.:0.6240 | 3rd Qu.:6.630 | 3rd Qu.: 94.10 |
| Max. :100.00 | Max. :27.740 | Max. :1.00000 | Max. :0.8710 | Max. :8.780 | Max. :100.00 |

Table 4: Summary Statistics

| dis | rad | tax | ptratio | lstat | medv | target |
|---|---|---|---|---|---|---|
| Min. : 1.130 | Min. : 1.00 | Min. :187.0 | Min. :12.6 | Min. : 1.730 | Min. : 5.00 | Min. :0.0000 |
| 1st Qu.: 2.101 | 1st Qu.: 4.00 | 1st Qu.:281.0 | 1st Qu.:16.9 | 1st Qu.: 7.043 | 1st Qu.:17.02 | 1st Qu.:0.0000 |
| Median : 3.191 | Median : 5.00 | Median :334.5 | Median :18.9 | Median :11.350 | Median :21.20 | Median :0.0000 |
| Mean : 3.796 | Mean : 9.53 | Mean :409.5 | Mean :18.4 | Mean :12.631 | Mean :22.59 | Mean :0.4914 |
| 3rd Qu.: 5.215 | 3rd Qu.:24.00 | 3rd Qu.:666.0 | 3rd Qu.:20.2 | 3rd Qu.:16.930 | 3rd Qu.:25.00 | 3rd Qu.:1.0000 |
| Max. :12.127 | Max. :24.00 | Max. :711.0 | Max. :22.0 | Max. :37.970 | Max. :50.00 | Max. :1.0000 |

Table 5: Descriptive Statistics

| | vars | n | mean | sd | median |
|---|---|---|---|---|---|
| zn | 1 | 466 | 11.5772532 | 23.3646511 | 0.00000 |
| indus | 2 | 466 | 11.1050215 | 6.8458549 | 9.69000 |
| chas | 3 | 466 | 0.0708155 | 0.2567920 | 0.00000 |
| nox | 4 | 466 | 0.5543105 | 0.1166667 | 0.53800 |
| rm | 5 | 466 | 6.2906738 | 0.7048513 | 6.21000 |
| age | 6 | 466 | 68.3675966 | 28.3213784 | 77.15000 |
| dis | 7 | 466 | 3.7956929 | 2.1069496 | 3.19095 |
| rad | 8 | 466 | 9.5300429 | 8.6859272 | 5.00000 |
| tax | 9 | 466 | 409.5021459 | 167.9000887 | 334.50000 |
| ptratio | 10 | 466 | 18.3984979 | 2.1968447 | 18.90000 |
| lstat | 11 | 466 | 12.6314592 | 7.1018907 | 11.35000 |
| medv | 12 | 466 | 22.5892704 | 9.2396814 | 21.20000 |
| target | 13 | 466 | 0.4914163 | 0.5004636 | 0.00000 |

Table 6: Descriptive Statistics

| | trimmed | mad | min | max |
|---|---|---|---|---|
| zn | 5.3542781 | 0.0000000 | 0.0000 | 100.0000 |
| indus | 10.9082353 | 9.3403800 | 0.4600 | 27.7400 |
| chas | 0.0000000 | 0.0000000 | 0.0000 | 1.0000 |
| nox | 0.5442684 | 0.1334340 | 0.3890 | 0.8710 |
| rm | 6.2570615 | 0.5166861 | 3.8630 | 8.7800 |
| age | 70.9553476 | 30.0226500 | 2.9000 | 100.0000 |
| dis | 3.5443647 | 1.9144814 | 1.1296 | 12.1265 |
| rad | 8.6978610 | 1.4826000 | 1.0000 | 24.0000 |
| tax | 401.5080214 | 104.5233000 | 187.0000 | 711.0000 |
| ptratio | 18.5970588 | 1.9273800 | 12.6000 | 22.0000 |
| lstat | 11.8809626 | 7.0720020 | 1.7300 | 37.9700 |
| medv | 21.6304813 | 6.0045300 | 5.0000 | 50.0000 |
| target | 0.4893048 | 0.0000000 | 0.0000 | 1.0000 |

Table 7: Descriptive Statistics

| | range | skew | kurtosis | se |
|---|---|---|---|---|
| zn | 100.0000 | 2.1768152 | 3.8135765 | 1.0823466 |
| indus | 27.2800 | 0.2885450 | -1.2432132 | 0.3171281 |
| chas | 1.0000 | 3.3354899 | 9.1451313 | 0.0118957 |
| nox | 0.4820 | 0.7463281 | -0.0357736 | 0.0054045 |
| rm | 4.9170 | 0.4793202 | 1.5424378 | 0.0326516 |
| age | 97.1000 | -0.5777075 | -1.0098814 | 1.3119625 |
| dis | 10.9969 | 0.9988926 | 0.4719679 | 0.0976026 |
| rad | 23.0000 | 1.0102788 | -0.8619110 | 0.4023678 |
| tax | 524.0000 | 0.6593136 | -1.1480456 | 7.7778214 |
| ptratio | 9.4000 | -0.7542681 | -0.4003627 | 0.1017669 |
| lstat | 36.2400 | 0.9055864 | 0.5033688 | 0.3289887 |
| medv | 45.0000 | 1.0766920 | 1.3737825 | 0.4280200 |
| target | 1.0000 | 0.0342293 | -2.0031131 | 0.0231835 |

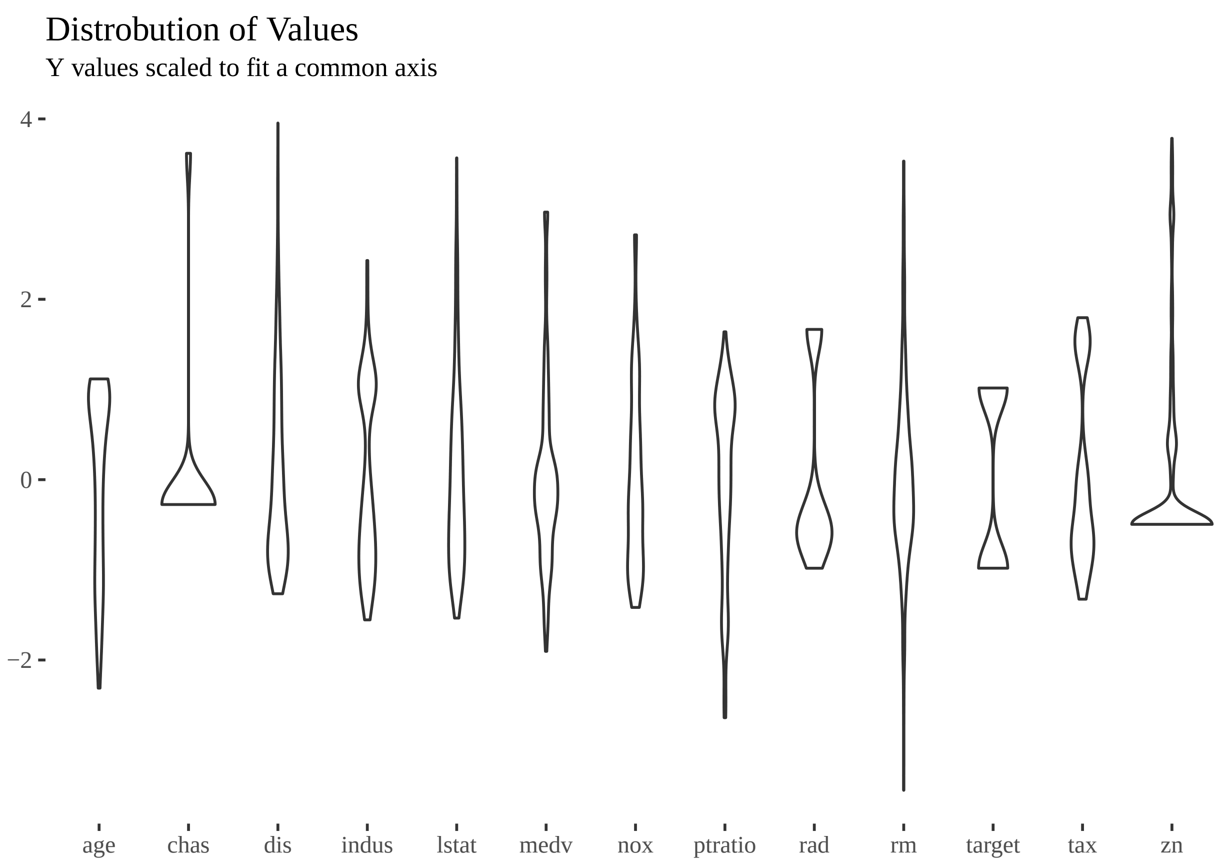
The count of NA values for each variable is given below.

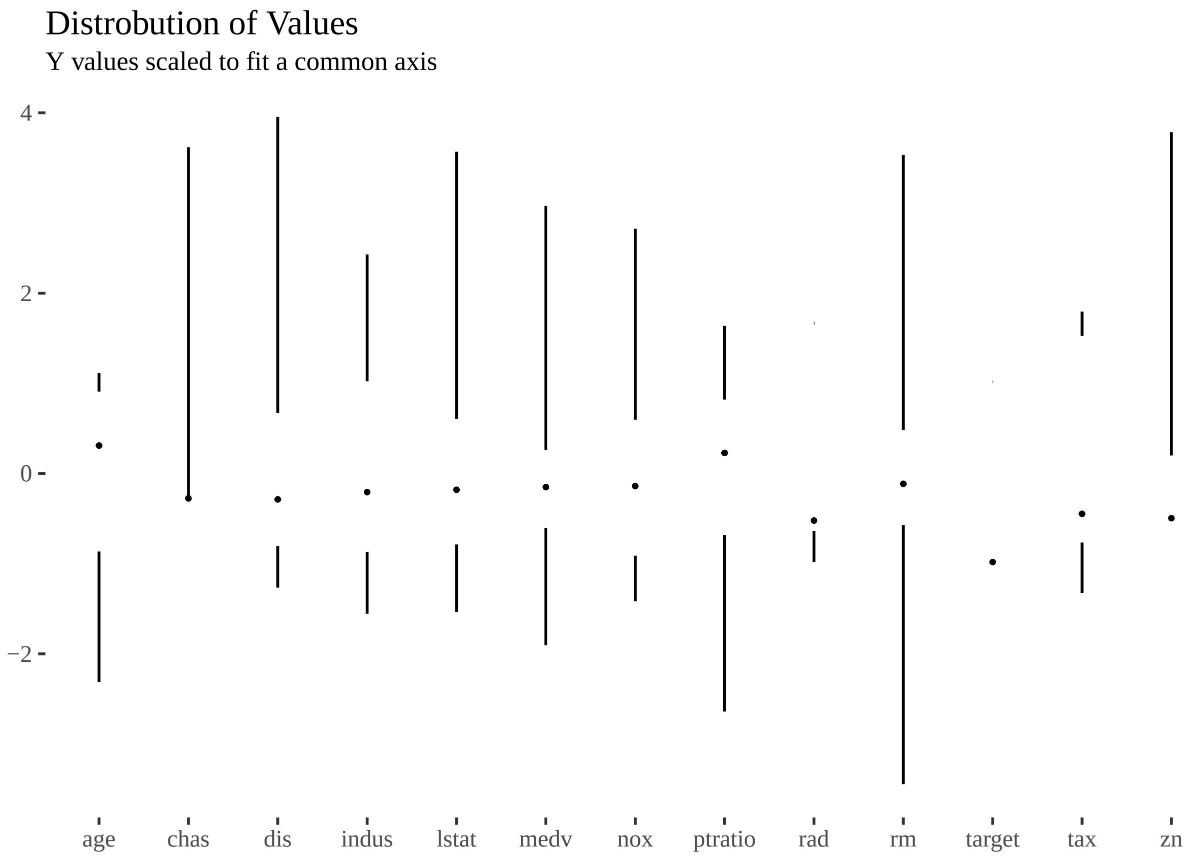
Table 8: Count of NA Values

| zn | indus | chas | nox | rm | age | dis | rad | tax | ptratio | lstat | medv | target |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

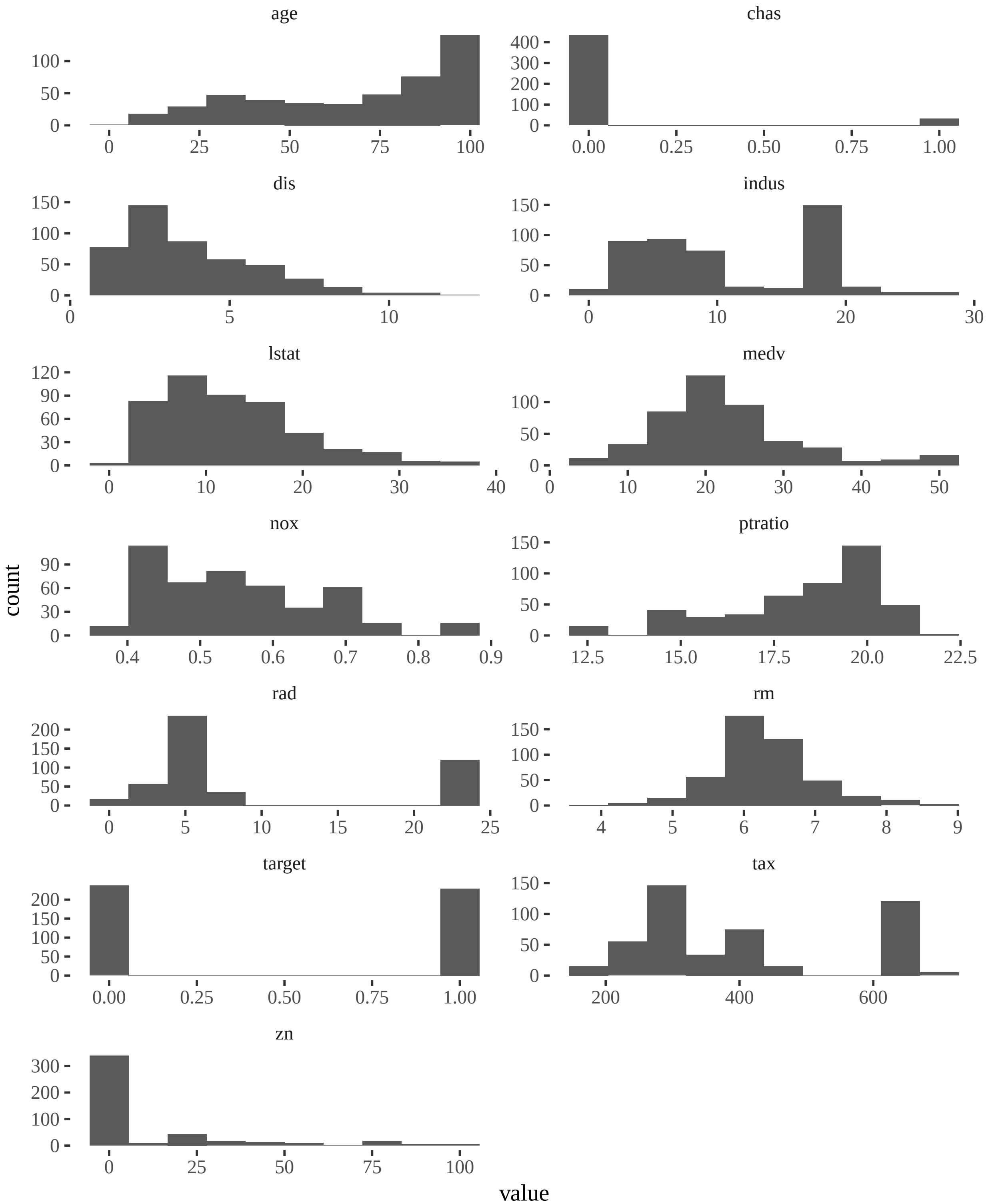
There are no missing values.

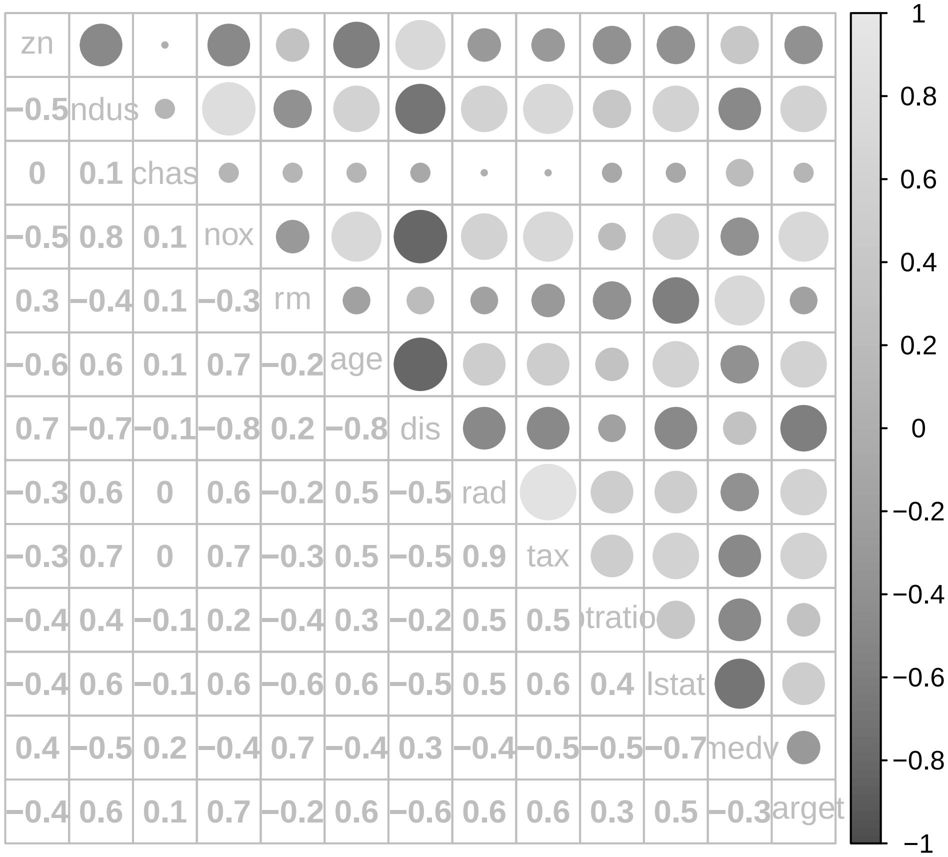
## 1.3 Graphical EDA



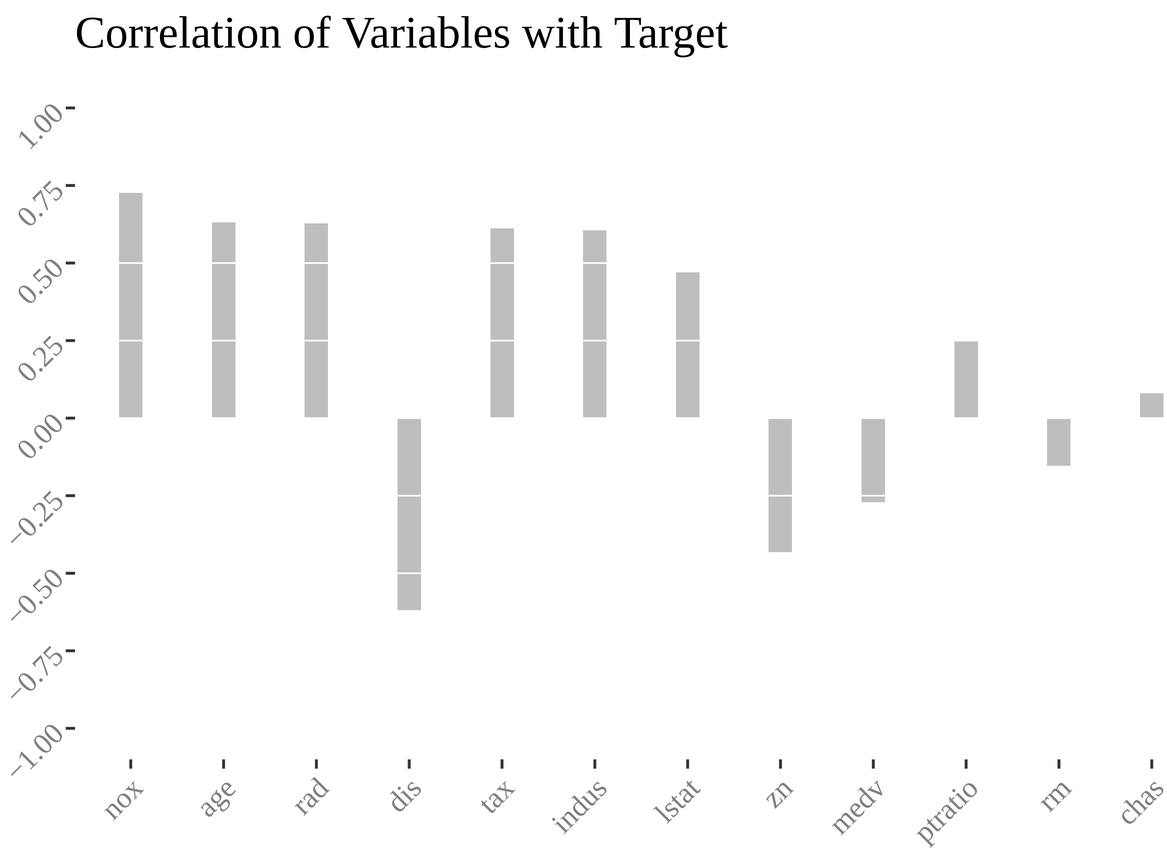



From these two graphs we can see that many of distrobutions are skewed in one direction or another. It is also interesting to see that the target variable is below zero. This means that the median and mean values are different.


age
chas
dis
indus
lstat
medv
nox
ptratio
rad
rm
target
tax
zn
count
value




This correlation plot shows that while there are some higly corrlated variables, the most correlated variable is only 0.9, which doesn't raise alarm bells.




There are some interesting correlations here. Namely indus, nox, age, rad, tax all have a correlation over 0.5. The lowest correlation with the target variable is chas.

We will see which variables play more of a role during our logistic classification, but this gives a good preview.

## 2 Data Preperation

Transformation of variables is less needed for logistic regresion because normallacy is not a requriment. As such, we need to ask ourselves wethere or not transforming variables will lead to a better model. This will focus on the interaction between variables. Logistic regression is 'linear' and an exhaustive search of all possible combinations/pollynomials would be difficult even if we limited them to three degrees each. Instead, I suggest a test where we fit an extreamly non-linear model `KNN` on the data and compare the ROC to the ROC from a simple logistic regression. If there is little difference, it can be safe to assume that the underlying relationship is linear.

I used this example to create a KNN model.

```
## Warning: package 'ISLR' was built under R version 3.4.2

## Warning: package 'caret' was built under R version 3.4.3

## Loading required package: lattice

## Warning in as.POSIXlt.POSIXct(Sys.time()): unknown timezone 'zone/tz/2018c.
## 1.0/zoneinfo/America/Edmonton'

##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift

## Loading required package: gplots

##
## Attaching package: 'gplots'

## The following object is masked from 'package:stats':
##
##     lowess

## Warning: package 'pROC' was built under R version 3.4.4

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following object is masked from 'package:plotROC':
##
##     ggroc

## The following object is masked from 'package:glmnet':
##
##     auc

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var

##
## AboveMed BelowMed
## 49.14286 50.85714

## Created from 350 samples and 12 variables
##
## Pre-processing:
##   - centered (12)
##   - ignored (0)
##   - scaled (12)

## Warning in train.default(x, y, weights = w, ...): The metric "Accuracy" was
## not in the result set. ROC will be used instead.
```

# 3 Build Models

This project will focus on automated variable selection. New techniques will be compared to the basic logistic regression.

The baisic logistic regreission gives a summary of:

% latex table generated in R 3.4.0 by xtable 1.8-2 package %

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | -1.6014 | 0.3595 | -4.45 | 0.0000 |
| zn | -0.0010 | 0.0009 | -1.02 | 0.3064 |
| indus | 0.0031 | 0.0043 | 0.73 | 0.4664 |
| chas | 0.0060 | 0.0588 | 0.10 | 0.9190 |
| nox | 1.9722 | 0.2633 | 7.49 | 0.0000 |
| rm | 0.0250 | 0.0315 | 0.79 | 0.4282 |
| age | 0.0032 | 0.0009 | 3.51 | 0.0005 |
| dis | 0.0125 | 0.0141 | 0.89 | 0.3758 |
| rad | 0.0207 | 0.0043 | 4.77 | 0.0000 |
| tax | -0.0003 | 0.0003 | -1.07 | 0.2874 |
| ptratio | 0.0115 | 0.0093 | 1.23 | 0.2180 |
| lstat | 0.0045 | 0.0039 | 1.16 | 0.2469 |
| medv | 0.0089 | 0.0030 | 2.98 | 0.0031 |

Here we have the output of all provided variables without any transformation.

If we do a stepwise selection to find the variables that limit the scope but still provide excelent performance we get:

% latex table generated in R 3.4.0 by xtable 1.8-2 package %

| | Step | Df | Deviance | Resid. Df | Resid. Dev | AIC |
|---|---|---|---|---|---|---|
| 1 | | | | 453.00 | 44.11 | 251.85 |
| 2 | - chas | 1.00 | 0.00 | 454.00 | 44.11 | 249.86 |
| 3 | - indus | 1.00 | 0.05 | 455.00 | 44.16 | 248.43 |
| 4 | - rm | 1.00 | 0.05 | 456.00 | 44.22 | 246.97 |
| 5 | - dis | 1.00 | 0.06 | 457.00 | 44.27 | 245.57 |
| 6 | - zn | 1.00 | 0.06 | 458.00 | 44.34 | 244.23 |
| 7 | - lstat | 1.00 | 0.08 | 459.00 | 44.42 | 243.07 |
| 8 | - tax | 1.00 | 0.13 | 460.00 | 44.54 | 242.39 |

(Intercept) nox age rad ptratio -1.412836094 1.956694224 0.003531713 0.017106647 0.012716341 medv 0.008021190 target ~ nox + age + rad + ptratio + medv % latex table generated in R 3.4.0 by xtable 1.8-2 package %

| | Estimate | Std. Error | z value | Pr(>\|z\|) |
|---|---|---|---|---|
| (Intercept) | -24.9365 | 3.6834 | -6.77 | 0.0000 |
| nox | 25.3348 | 4.0841 | 6.20 | 0.0000 |
| age | 0.0194 | 0.0093 | 2.08 | 0.0371 |
| rad | 0.5126 | 0.1148 | 4.46 | 0.0000 |
| ptratio | 0.2742 | 0.0987 | 2.78 | 0.0055 |
| medv | 0.0854 | 0.0280 | 3.05 | 0.0023 |

This presentation offers an interesting critique of stepwise selection and some of the issue that make it less ideal.

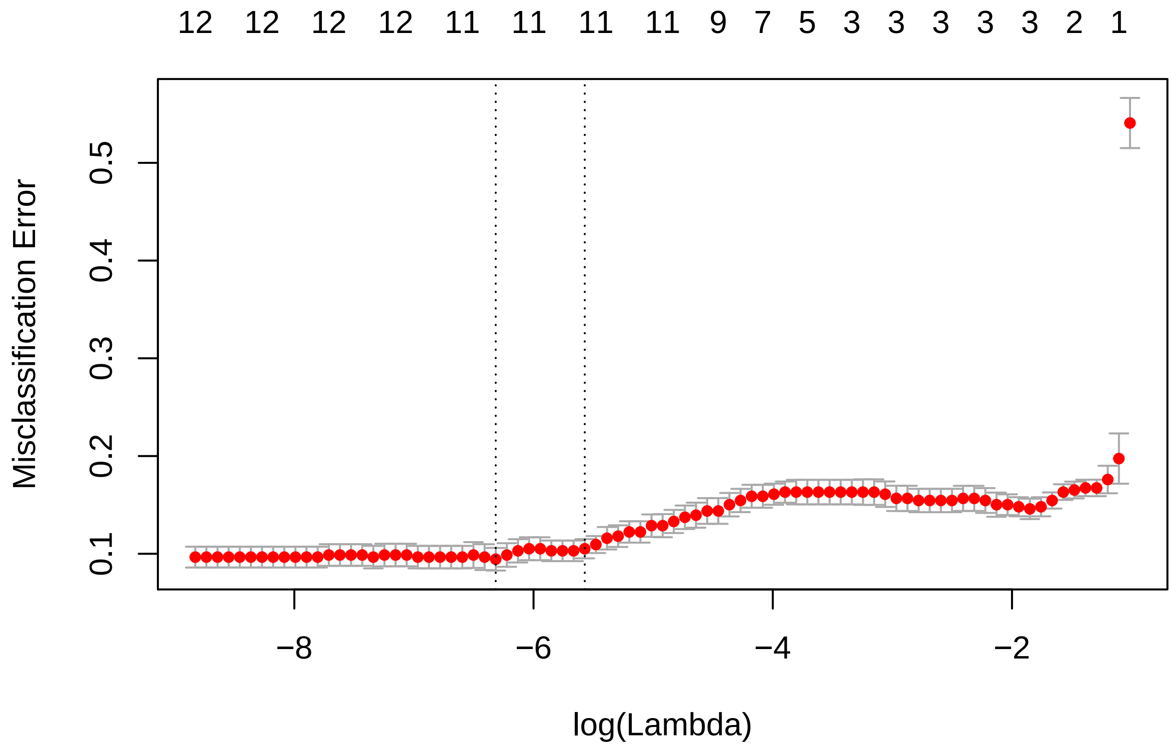
This model selection using the steps algorithm selects significantly fewer variables.

```
## Morgan-Tatar search since family is non-gaussian.
```

```
## BIC
## BICq equivalent for q in (0.0115719591613259, 0.54658790604255)
## Best Model:
##                 Estimate  Std. Error   z value     Pr(>|z|)
## (Intercept) -19.867421883 2.368324820 -8.388808 4.910965e-17
## nox          35.633515210 4.523677298  7.877113 3.350331e-15
## rad           0.637642983 0.119444473  5.338405 9.376777e-08
## tax          -0.008145957 0.002332059 -3.493032 4.775700e-04
```

Looking at lasso logistic regression might give us a better model selection and coefficent values. Below is the results.

```
## Warning in aucDF$lasso.prob <- predict(lasso.model, type = "response", newx
## = X, : Coercing LHS to a list
```




```
## 13 x 1 sparse Matrix of class "dgCMatrix"
##                         1
## (Intercept) -25.016113852
## zn           -0.025749251
## indus        -0.041630599
## chas          0.755989557
## nox          30.620136853
## rm            .
## age           0.019060550
## dis           0.278520115
## rad           0.330360865
## tax          -0.002594363
## ptratio       0.198760128
## lstat         0.013804668
## medv          0.073090589
```

This models coefficents deviate significantly from a normal `glm` model that excludes the one variable dropped. This is because LASSO penializes large coefficents. For example, `glm` model excluding `rm` is:

```
## % latex table generated in R 3.4.0 by xtable 1.8-2 package
## %
## \begin{tabular}{rrrrr}
##   \hline
##  & Estimate & Std. Error & z value & Pr($>$$|$z$|$) \\
##   \hline
## (Intercept) & -41.6494 & 6.5038 & -6.40 & 0.0000 \\
```

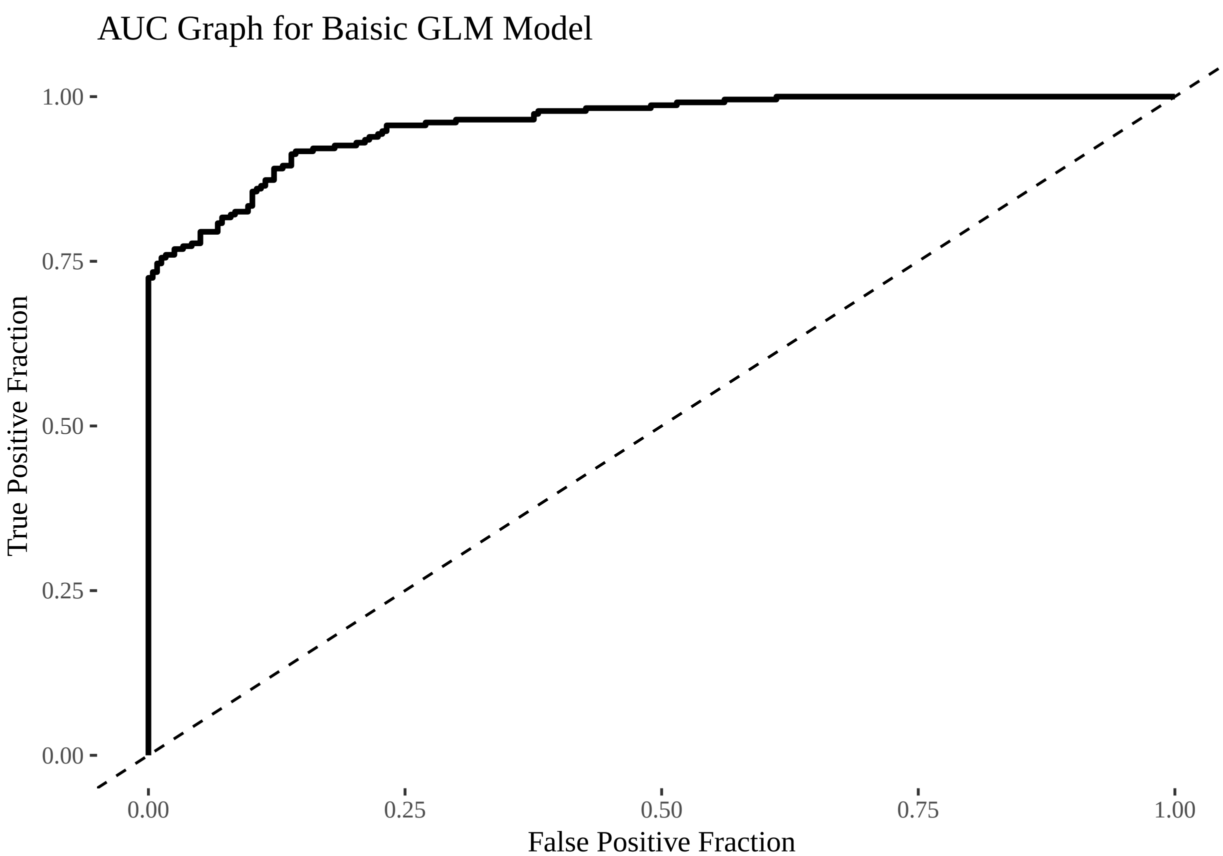
```
##   zn & -0.0684 & 0.0344 & -1.99 & 0.0467 \\
##   indus & -0.0634 & 0.0475 & -1.34 & 0.1819 \\
##   chas & 0.9311 & 0.7575 & 1.23 & 0.2190 \\
##   nox & 48.0922 & 7.7282 & 6.22 & 0.0000 \\
##   age & 0.0284 & 0.0116 & 2.44 & 0.0146 \\
##   dis & 0.6915 & 0.2183 & 3.17 & 0.0015 \\
##   rad & 0.6439 & 0.1592 & 4.04 & 0.0001 \\
##   tax & -0.0063 & 0.0029 & -2.15 & 0.0314 \\
##   ptratio & 0.3618 & 0.1139 & 3.18 & 0.0015 \\
##   lstat & 0.0625 & 0.0496 & 1.26 & 0.2074 \\
##   medv & 0.1379 & 0.0414 & 3.33 & 0.0009 \\
##    \hline
## \end{tabular}
```

# 4 Chose a Model

Model selection in the previous section used a variety of different methods ranging from none to BIC to AIC. As such it is unfair to select a criteria that we have used already.

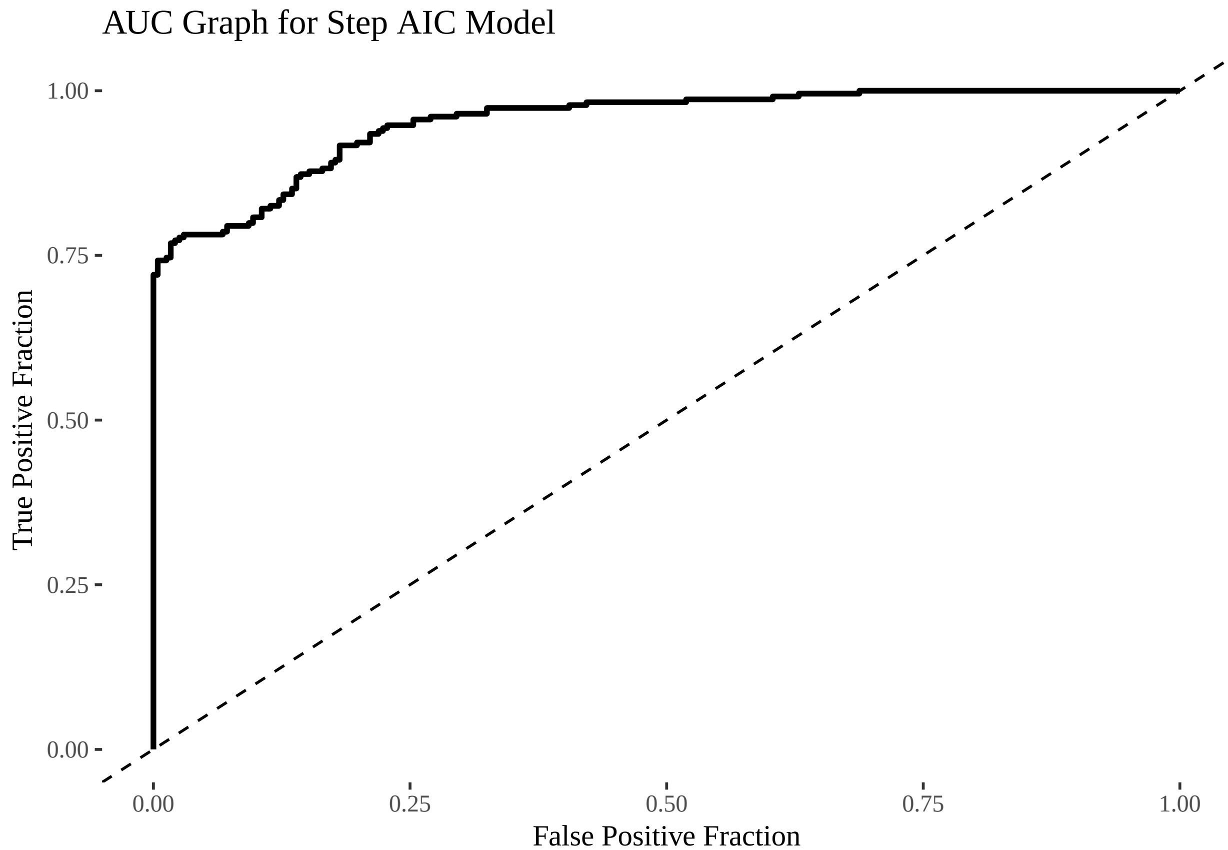
I've chosen to use AUC because it is easily understood and provides a nice visual way to differentiate model performance.

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



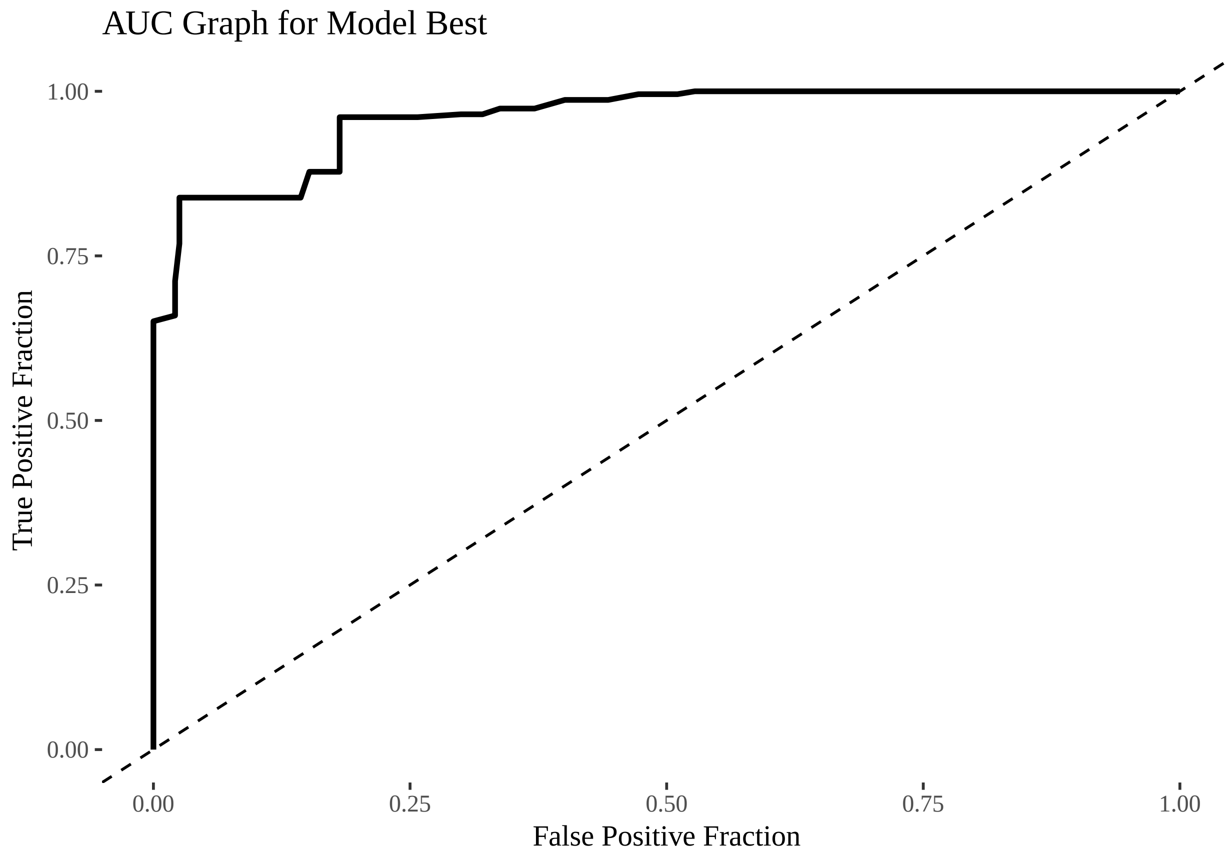

```
##
## [[2]]
## Area under the curve: 0.9582
```

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

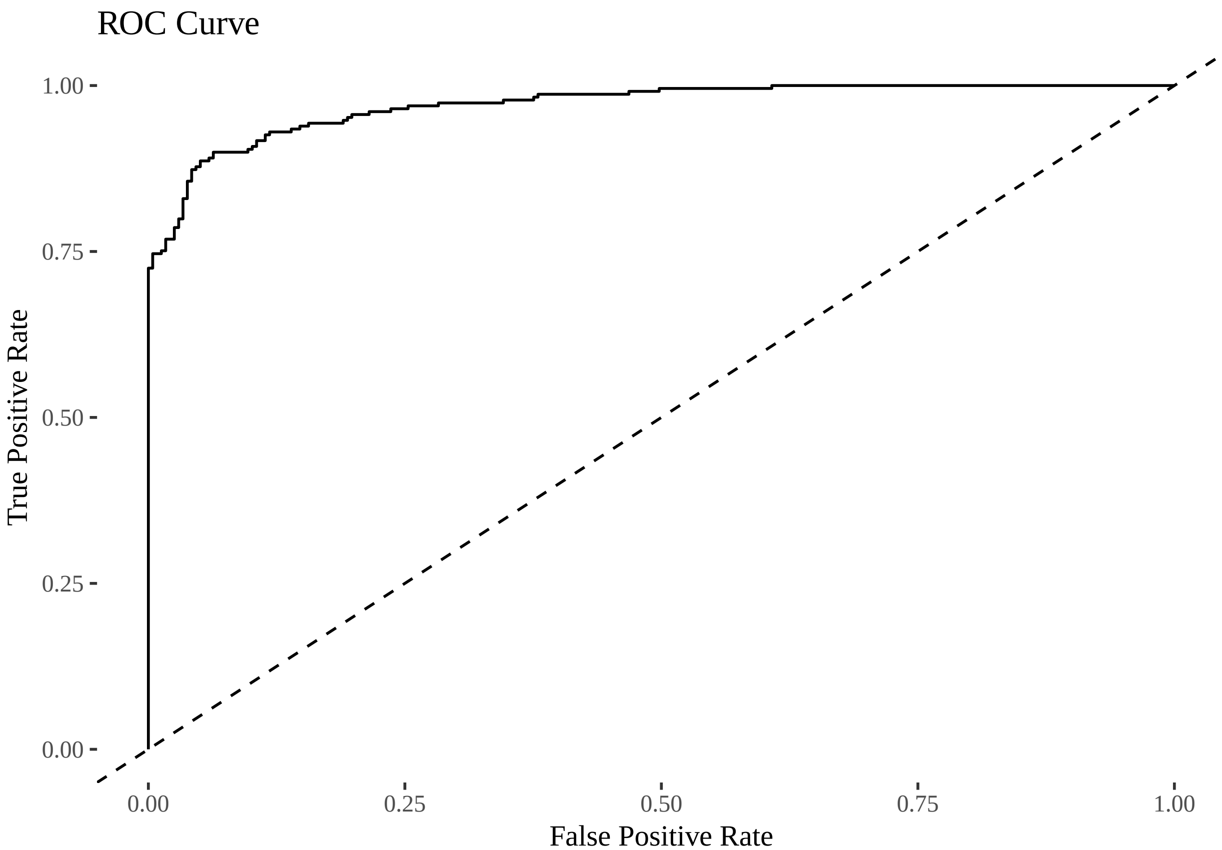



```
##
## [[2]]
## Area under the curve: 0.9527
```

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




```
##
## [[2]]
## Area under the curve: 0.9594
```




```
## [[1]]
## [1] 0.9707405
```

### 4.1 Which model?

All models performed well with no model below 0.95. The best model was the LASSO model. This has advantages over the stepwise selection as the pdf linked above goes over. This means we can confidently select this mode.

### 4.2 Prediction

The predictions for the test set are given below. The first column corresponds to the probabilities and the second column correpsonds to the actual prediction (the rounded probabilities).

| Predicted_Probabilities | Predicted_Outcome |
|---:|---:|
| 0.0963140 | 0 |
| 0.5356428 | 1 |
| 0.5936776 | 1 |
| 0.4598782 | 0 |
| 0.1547428 | 0 |
| 0.2045212 | 0 |
| 0.2436646 | 0 |
| 0.0436209 | 0 |
| 0.0276064 | 0 |
| 0.0185725 | 0 |

| Predicted_Probabilities | Predicted_Outcome |
|---:|---:|
| 0.4210005 | 0 |
| 0.3801533 | 0 |
| 0.7748370 | 1 |
| 0.6441183 | 1 |
| 0.5754163 | 1 |
| 0.3168680 | 0 |
| 0.3026643 | 0 |
| 0.8173990 | 1 |
| 0.0721549 | 0 |
| 0.0004601 | 0 |
| 0.0007037 | 0 |
| 0.1341159 | 0 |
| 0.2420760 | 0 |
| 0.1925227 | 0 |
| 0.1680612 | 0 |
| 0.4552867 | 0 |
| 0.0060445 | 0 |
| 0.9999766 | 1 |
| 0.9999699 | 1 |
| 0.9971125 | 1 |
| 0.9999687 | 1 |
| 0.9999764 | 1 |
| 0.9999713 | 1 |
| 0.9999855 | 1 |
| 0.9999749 | 1 |
| 0.9999491 | 1 |
| 0.9999619 | 1 |
| 0.9997567 | 1 |
| 0.7232785 | 1 |
| 0.4978899 | 0 |

# 5 Apendix

```
knitr::opts_chunk$set(echo = FALSE)
# Libraries
##################
library(MASS)
library(car)
library(leaps)
library(tidyverse)
library(knitr)
library(kableExtra)
library(psych)
library(ggthemes)
library(corrplot)
library(glmnet)
library(bestglm)
library(xtable)
options(xtable.floating = FALSE)
options(xtable.timestamp = "")
```

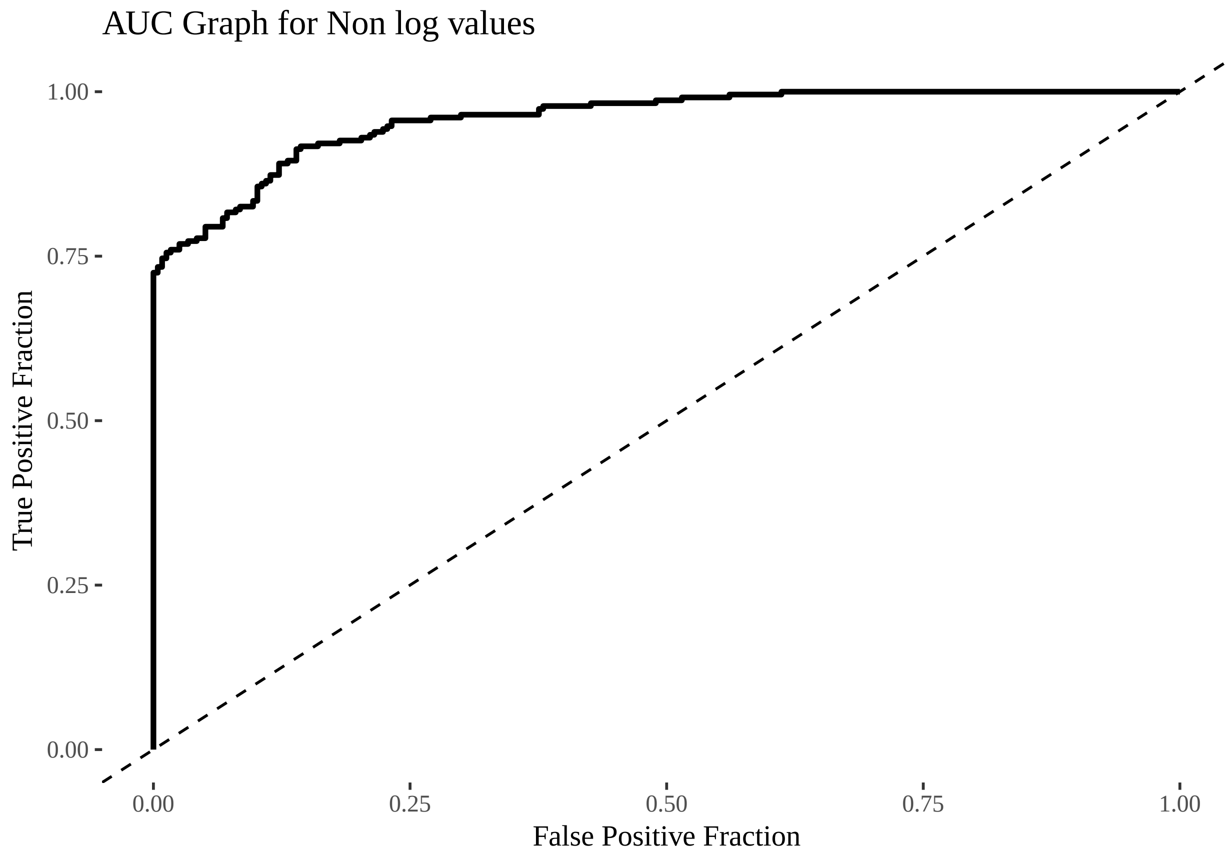
```
####################
# Loading the data
df <- read_csv('/Users/kailukowiak/DATA621/Assignments/Assignment3/crime-training-data_modified.csv')
df %>% sample_n(6) %>% kable(caption = 'Sample of Values for the Training Set')
testDF <- read_csv('/Users/kailukowiak/DATA621/Assignments/Assignment3/crime-evaluation-data_modified.c
testDF %>% sample_n(6) %>% kable(caption = 'Sample of Values for the Test Set')
###############################
# Summary Tables
SumTab <- summary(df)
SumTab1 <- SumTab[, 1:6]
SumTab2 <- SumTab[, 7:13]
kable(SumTab1, caption = 'Summary Statistics')
kable(SumTab2, caption = 'Summary Statistics')
#####################
dis <- describe(df)
dis[, 1:5] %>% kable(caption = 'Descriptive Statistics')
dis[, 6:9] %>% kable(caption = 'Descriptive Statistics')
dis[, 10:13] %>% kable(caption = 'Descriptive Statistics')
map(df, ~sum(is.na(.))) %>% t() %>% kable(caption = 'Count of NA Values')
df %>%
  scale() %>%
  as_tibble() %>%
  gather() %>%
  ggplot(aes(x = key, y = value)) +
  theme_tufte() +
  geom_violin()+
  #geom_tufteboxplot(outlier.colour="black")+
  theme(axis.title=element_blank()) +
  ylab('Scaled Values')+
  xlab('Variable')+
  ggtitle('Distrobution of Values', subtitle = 'Y values scaled to fit a common axis')
df %>%
  scale() %>%
  as_tibble() %>%
  gather() %>%
  ggplot(aes(x = key, y = value)) +
  theme_tufte() +
  # geom_violin()+
  geom_tufteboxplot(outlier.colour="black")+
  theme(axis.title=element_blank()) +
  ylab('Scaled Values')+
  xlab('Variable')+
  ggtitle('Distrobution of Values', subtitle = 'Y values scaled to fit a common axis')
ggplot(data = gather(df), mapping = aes(x = value)) +
  geom_histogram(bins = 10) + facet_wrap(~key, ncol = 2, scales = 'free') +
  theme_tufte()
corr <- round(cor(df), 1)
corrplot.mixed(corr, lower.col = 'grey', upper.col = gray.colors(100), tl.col='grey')
corr2 <- corr
diag(corr2) <- 0
ind <- which(corr2 == max(corr2), arr.ind = TRUE)

maxCorr <- corr[ind][1]
```

```
corrDF <- cor(x = df[, 1:12], y = df$target) %>%
  as_tibble() %>%
  rename(Correlation = V1) %>%
  mutate(VarNames = names(df[, 1:12]))

ggplot(corrDF, aes(x= reorder(VarNames, -abs(Correlation)), y=Correlation)) +
  ggtitle('Correlation of Variables with Target') +
  theme_tufte(base_size=14, ticks=T) +
  geom_bar(width=0.25, fill="gray", stat = "identity") +
  theme(axis.title=element_blank()) +
  scale_y_continuous(breaks=seq(-1, 1, 0.25)) +
  geom_hline(yintercept=seq(-1, 1, 0.25), col="white", lwd=.3) +
  theme(axis.text = element_text(angle = 45, hjust = 1, colour = 'grey50'))

interestingCorr <- corrDF %>% filter(Correlation >= 0.5)
library(ISLR)
library(caret)
library(ROCR)
library(plotROC)
library(pROC)
set.seed(300)
#Spliting data as training and test set. Using createDataPartition() function from caret
df1 = df
df1$target <- ifelse(df1$target == 1, 'AboveMed', 'BelowMed')
indxTrain <- createDataPartition(y = df1$target,p = 0.75,list = FALSE)
training <- df1[indxTrain,]
testing <- df1[-indxTrain,]

#Checking distibution in origanl data and partitioned data
prop.table(table(training$target)) * 100



trainX <- training[,names(training) != "target"] # Make this target
preProcValues <- preProcess(x = trainX,method = c("center", "scale"))
preProcValues

training$target <- as.factor(training$target)
set.seed(400)
ctrl <- trainControl(method="repeatedcv",repeats = 3,classProbs=TRUE,summaryFunction = twoClassSummary)
#ctrl <- trainControl(method="repeatedcv",repeats = 3) #,classProbs=TRUE,summaryFunction = twoClassSumm
knnFit <- train(target ~ ., data = training, method = "knn", trControl = ctrl, preProcess = c("center",

#Output of kNN fit
knnAUC <- knnFit$results[1,2]

mod1 <- glm(target~., data = df, family = 'binomial')
prob = predict(mod1,type = c("response"))
g <- roc(target ~ prob, data = df)
logAUC <- g$auc
# plot(knnFit)
#
# plot(knnFit, print.thres = 0.5, type="S")
```

```r
#
# #AUC(training, knnFit, 'Test')
mod1 <- glm(target ~ ., data = df)
#summary(mod1)
library(xtable)
xtable(mod1)
step <- stepAIC(mod1, direction="both", trace = FALSE)
xtable(step$anova)
step$coefficients
formulaLength <- length(step$coefficients)
formulaNames <- names(step$coefficients)[2:formulaLength]
stepFormula <- as.formula(paste("target~", paste(formulaNames, collapse="+")))
stepFormula
stepModel <- glm(formula = stepFormula, family = binomial, data = df)
xtable(stepModel)
df1 <- df
df1 <- dplyr::rename(df1, y = target)
df1$y <- as.factor(df1$y)
df1 <- data.frame(df1)
BestGLMModel <- bestglm(df1, family = binomial)
#xtable(BestGLMModel)
BestGLMModel
X <-df %>% dplyr::select(-target)
X <- data.matrix(X)
#X <- as.matrix(X, ncol=12)
y <- as.factor(df$target)
fit = glmnet(X, y, family = "binomial")
library(ROCR)
aucDF <- X
lasso.model = cv.glmnet(X, y, family = "binomial", type.measure = 'class')

aucDF$lasso.prob <- predict(lasso.model, type="response", newx = X, s = 'lambda.1se')
pred <- prediction(aucDF$lasso.prob, y)


cvfit = cv.glmnet(X, y, family = "binomial", type.measure = "class")
plot(cvfit)
coef(cvfit, s = "lambda.1se")


#plot(perf,colorize=FALSE, col="black") # plot ROC curve
#lines(c(0,1),c(0,1),col = "gray", lty = 4 )
mod3 <- glm(target ~ . -rm, family = 'binomial', data = df)
xtable(mod3)
AUC <- function(df, mod, modelName){
  library(plotROC)
  library(pROC)
  prob = predict(mod,type = c("response"))
  df$prob=prob
  p = ggplot(df, aes(d = target, m = prob)) +
    geom_roc(n.cuts = 0) +
    ggtitle(paste('AUC Graph for', modelName)) +
    xlab("False Positive Fraction") +
```

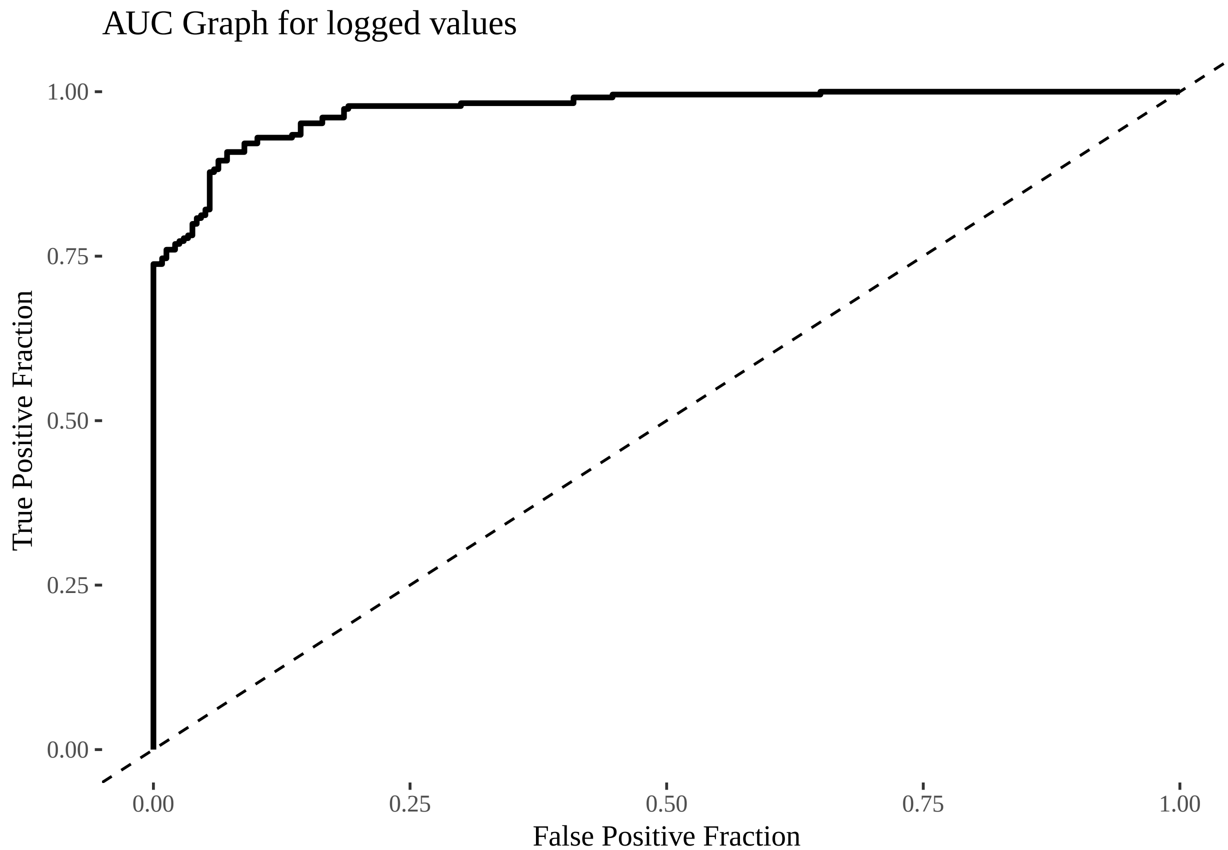
```
    ylab('True Positive Fraction') +
    geom_abline(linetype = 'dashed') +
    theme_tufte()

  g <- roc(target ~ prob, data = df)
  return(list(p, g$auc))
}
AUC(df, mod1, 'Baisic GLM Model')
AUC(df, step, 'Step AIC Model')

AUC(df, BestGLMModel$BestModel, 'Model Best')
fittedGLMcv <- predict(cvfit, X, s = "lambda.1se", type = "class")

perf <- performance(pred,"tpr","fpr")
auc <-  performance(pred,"auc") # shows calculated AUC for model
auc <- auc@y.values

roc.data <- data.frame(fpr=unlist(perf@x.values),
                       tpr=unlist(perf@y.values))

ggplot(roc.data, aes(x=fpr, ymin=0, ymax=tpr)) +
    #geom_ribbon(alpha=0.2) +
    geom_line(aes(y=tpr)) +
    geom_abline(slope=1, intercept=0, linetype='dashed') +
    ggtitle("ROC Curve") +
    ylab('True Positive Rate') +
    xlab('False Positive Rate') + theme_tufte()
auc
testMat <- data.matrix(testDF)
PredictedProbabilities <- predict(cvfit,type = "response", newx =  testMat)
PredictedValues <- round(PredictedProbabilities)
predDF <- data.frame(PredictedProbabilities, PredictedValues)
colnames(predDF) <- c('Predicted_Probabilities', 'Predicted_Outcome')
predDF %>% kable()

# Test to see if logged values are better

nonLog <- mod1

logDF <- df
#logDF$zn <- log(logDF$zn)
#logDF$chas <- log(logDF$chas)
logDF$rad <- log(logDF$rad)
logDF$tax <- log(logDF$tax)
logData <- glm(target~., family = binomial(), data = logDF)

AUC(df, nonLog, 'Non log values')
AUC(logDF, logData, 'logged values')
```

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




```
##
## [[2]]
## Area under the curve: 0.9582
```

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




```
##
## [[2]]
## Area under the curve: 0.9729
```