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
0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	9.08	20.6	0
0	10.59	1	0.489	6.064	59.1	4.2392	4	277	18.6	14.66	24.4	0

zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	lstat	medv	target
80	0.46	0	0.422	7.875	32.0	5.6484	4	255	14.4	2.97	50.0	0
0	19.58	0	0.605	5.875	94.6	2.4259	5	403	14.7	14.43	17.4	1
0	8.56	0	0.520	6.405	85.4	2.7147	5	384	20.9	10.63	18.6	0
0	8.14	0	0.538	5.834	56.5	4.4986	4	307	21.0	8.47	19.9	1

The training or labeled data-set 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
80	2.01	0	0.435	6.635	29.7	8.3440	4	280	17.0	5.99	24.5
0	9.90	0	0.544	6.122	52.8	2.6403	4	304	18.4	5.98	22.1
0	25.65	0	0.581	5.613	95.6	1.7572	2	188	19.1	27.26	15.7
80	1.76	0	0.385	6.230	31.5	9.0892	1	241	18.2	12.93	20.1
0	18.10	0	0.740	5.935	87.9	1.8206	24	666	20.2	34.02	8.4
90	2.97	0	0.400	7.088	20.8	7.3073	1	285	15.3	7.85	32.2

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. : 0.46	Min. :0.00000	Min. :0.3890	Min. :3.863	Min. : 2.90
1st Qu.: 0.00	1st Qu.: 4.95	1st Qu.:0.00000	1st Qu.:0.4480	1st Qu.:5.914	1st Qu.: 42.60
Median : 0.00	Median : 8.56	Median :0.00000	Median :0.5380	Median :6.212	Median : 78.70
Mean : 11.63	Mean :10.82	Mean :0.06877	Mean :0.5537	Mean :6.290	Mean : 68.47
3rd Qu.: 12.50	3rd Qu.:18.10	3rd Qu.:0.00000	3rd Qu.:0.6310	3rd Qu.:6.635	3rd Qu.: 94.30
Max. :100.00	Max. :27.74	Max. :1.00000	Max. :0.8710	Max. :8.780	Max. :100.00

Table 4: Summary Statistics

dis	rad	tax	ptratio	lstat	medv	target
Min. : 1.137	Min. : 1.000	Min. :187.0	Min. :12.60	Min. : 1.73	Min. : 5.00	Min. :0.0000
1st Qu.: 2.122	1st Qu.: 4.000	1st Qu.:279.0	1st Qu.:16.90	1st Qu.: 6.93	1st Qu.:17.10	1st Qu.:0.0000
Median : 3.272	Median : 5.000	Median :334.0	Median :18.70	Median :11.22	Median :21.40	Median :0.0000
Mean : 3.859	Mean : 9.691	Mean :410.3	Mean :18.39	Mean :12.69	Mean :22.55	Mean :0.4928
3rd Qu.: 5.245	3rd Qu.:24.000	3rd Qu.:666.0	3rd Qu.:20.20	3rd Qu.:17.15	3rd Qu.:25.00	3rd Qu.:1.0000
Max. :12.127	Max. :24.000	Max. :711.0	Max. :22.00	Max. :37.97	Max. :50.00	Max. :1.0000

Table 5: Descriptive Statistics

	vars	n	mean	sd	median
zn	1	349	11.6260745	23.6489200	0.0000
indus	2	349	10.8193696	6.6782429	8.5600
chas	3	349	0.0687679	0.2534224	0.0000
nox	4	349	0.5536673	0.1156325	0.5380
rm	5	349	6.2898166	0.6996892	6.2120
age	6	349	68.4659026	28.5326363	78.7000
dis	7	349	3.8594074	2.1545755	3.2721
rad	8	349	9.6905444	8.7383056	5.0000
tax	9	349	410.3323782	168.2920068	334.0000
ptratio	10	349	18.3925501	2.1983148	18.7000
lstat	11	349	12.6881375	7.2526767	11.2200
medv	12	349	22.5544413	9.1875799	21.4000
target	13	349	0.4928367	0.5006665	0.0000

Table 6: Descriptive Statistics

	trimmed	mad	min	max
zn	5.3113879	0.0000000	0.000	100.0000
indus	10.6644840	7.8874320	0.460	27.7400
chas	0.0000000	0.0000000	0.000	1.0000
nox	0.5440306	0.1334340	0.389	0.8710
rm	6.2626619	0.5100144	3.863	8.7800
age	71.0153025	28.7624400	2.900	100.0000
dis	3.6059804	1.9180396	1.137	12.1265
rad	8.8932384	1.4826000	1.000	24.0000
tax	402.3629893	103.7820000	187.000	711.0000
ptratio	18.5900356	2.2239000	12.600	22.0000
lstat	11.9572954	7.2054360	1.730	37.9700
medv	21.6516014	5.9304000	5.000	50.0000
target	0.4911032	0.0000000	0.000	1.0000

Table 7: Descriptive Statistics

	range	skew	kurtosis	se
zn	100.0000	2.1917947	3.8342510	1.2658977
indus	27.2800	0.2899568	-1.2653685	0.3574781

	range	skew	kurtosis	se
chas	1.0000	3.3935161	9.5433212	0.0135654
nox	0.4820	0.7206164	-0.1524685	0.0061897
rm	4.9170	0.3707688	1.6988180	0.0374535
age	97.1000	-0.5814285	-1.0376731	1.5273170
dis	10.9895	1.0132483	0.5501147	0.1153318
rad	23.0000	0.9753459	-0.9421318	0.4677508
tax	524.0000	0.6610306	-1.1789015	9.0084646
ptratio	9.4000	-0.7501466	-0.3992644	0.1176731
lstat	36.2400	0.8762742	0.3760690	0.3882269
medv	45.0000	1.0528443	1.3980740	0.4917999
target	1.0000	0.0285332	-2.0049060	0.0268001

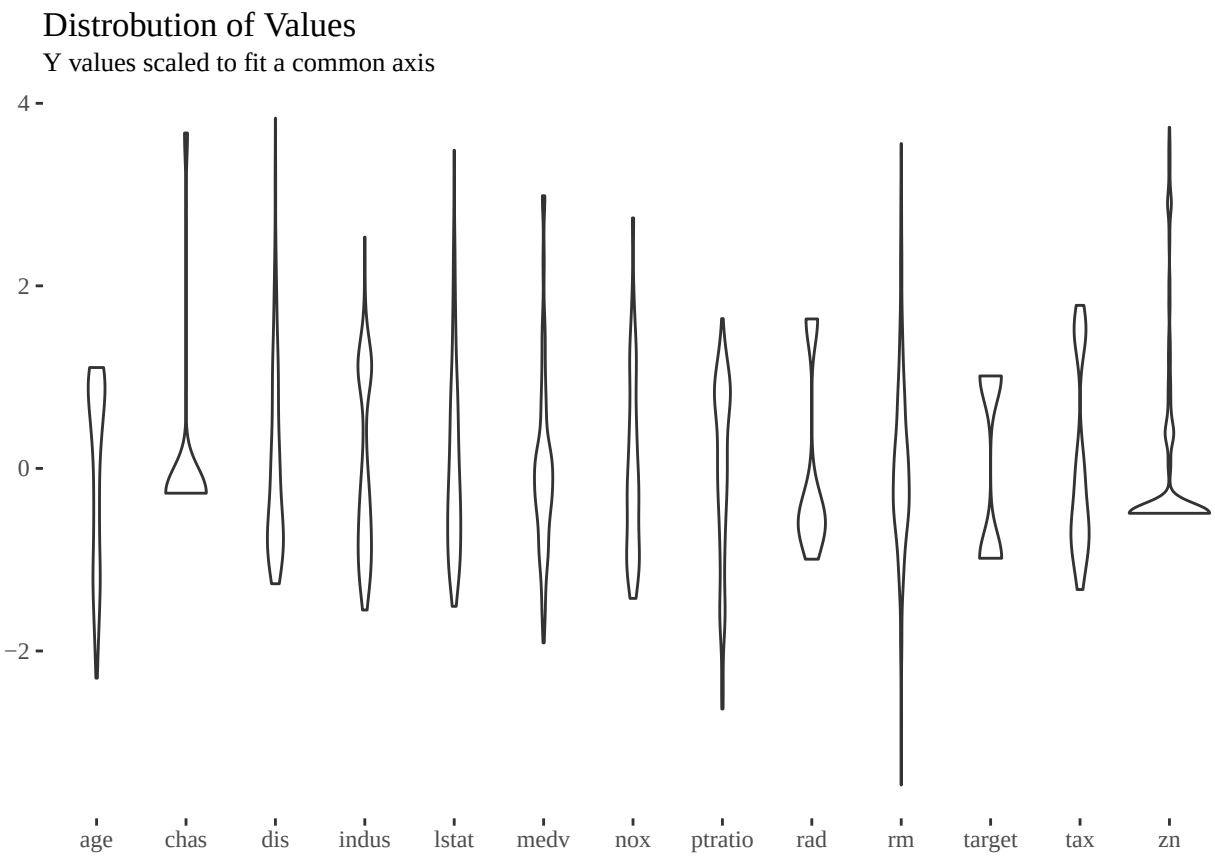
The count of NA values for each variable is given below.

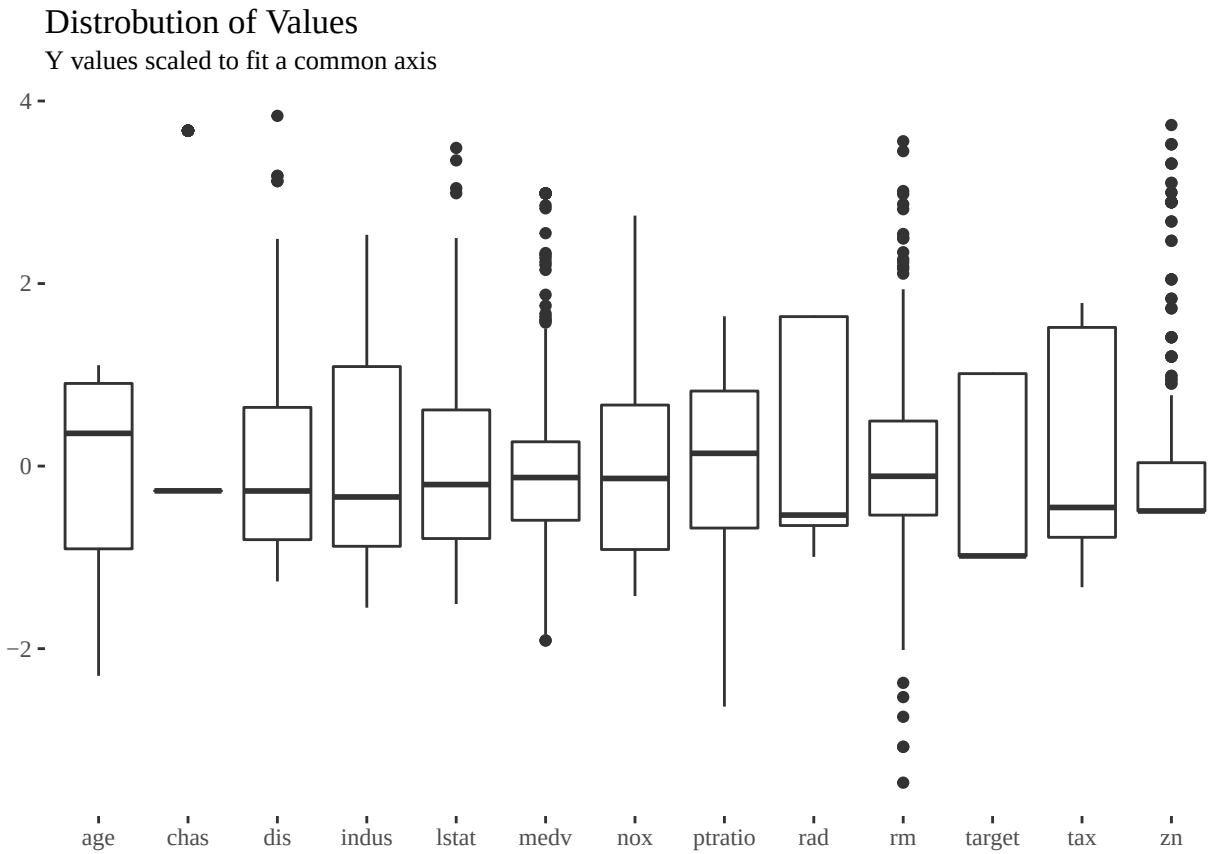
Table 8: Count of NA Values

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

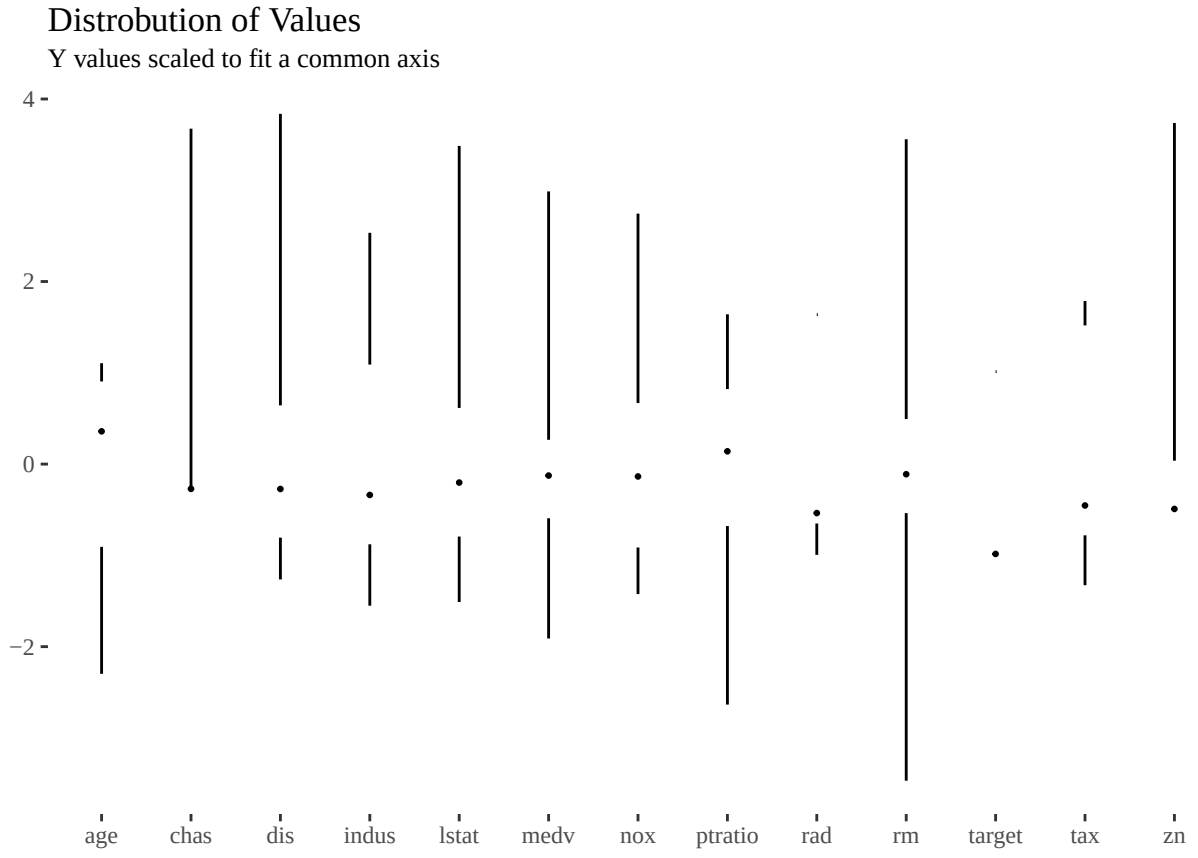
There are no missing values.

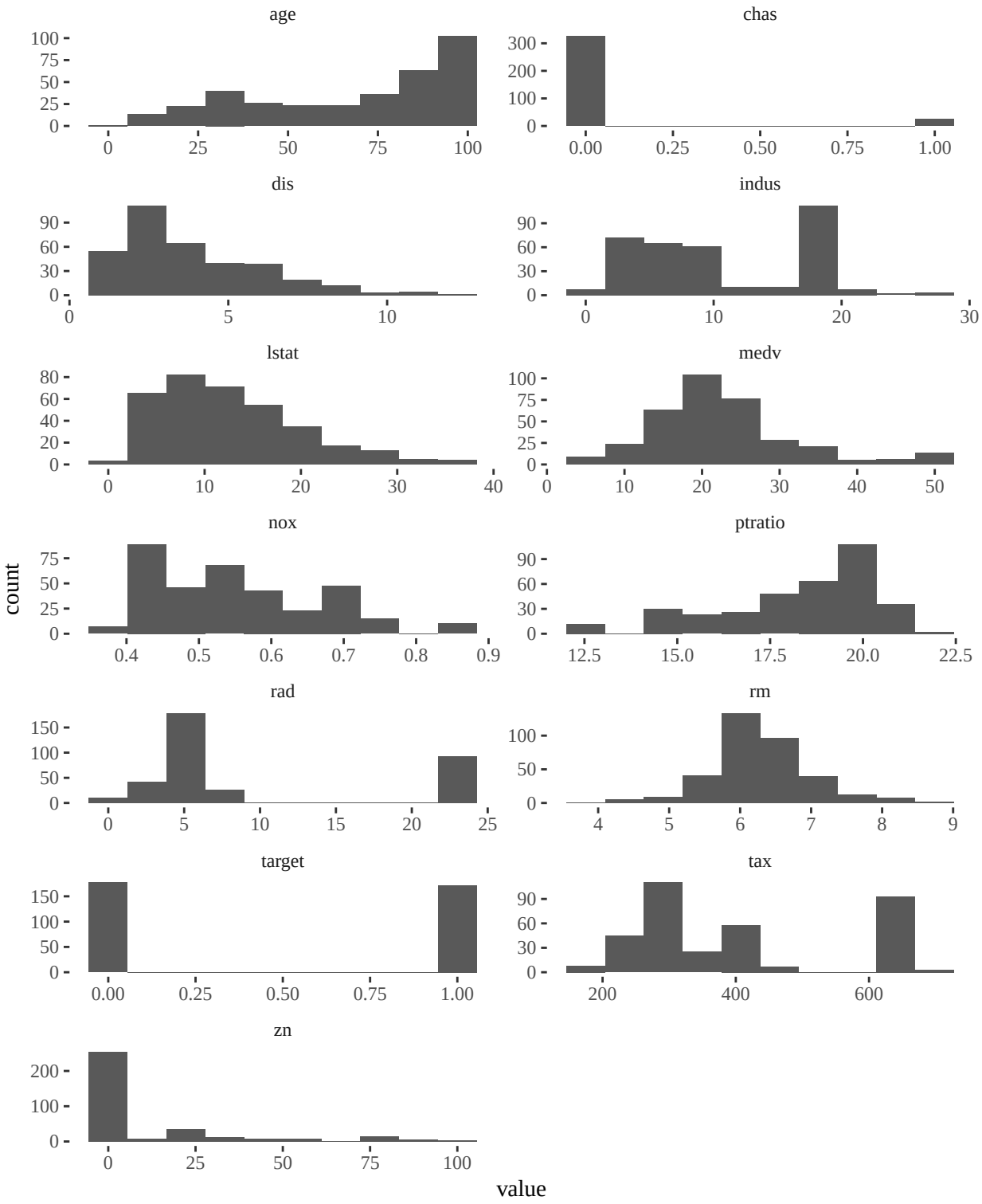
1.3 Graphical EDA

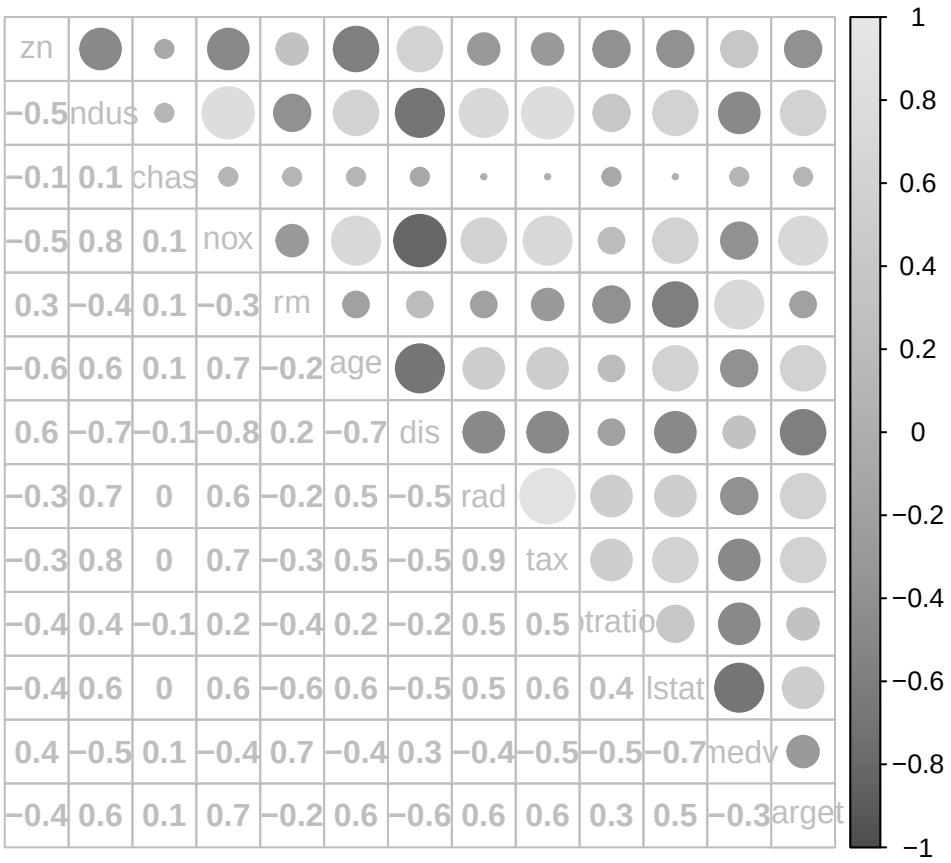




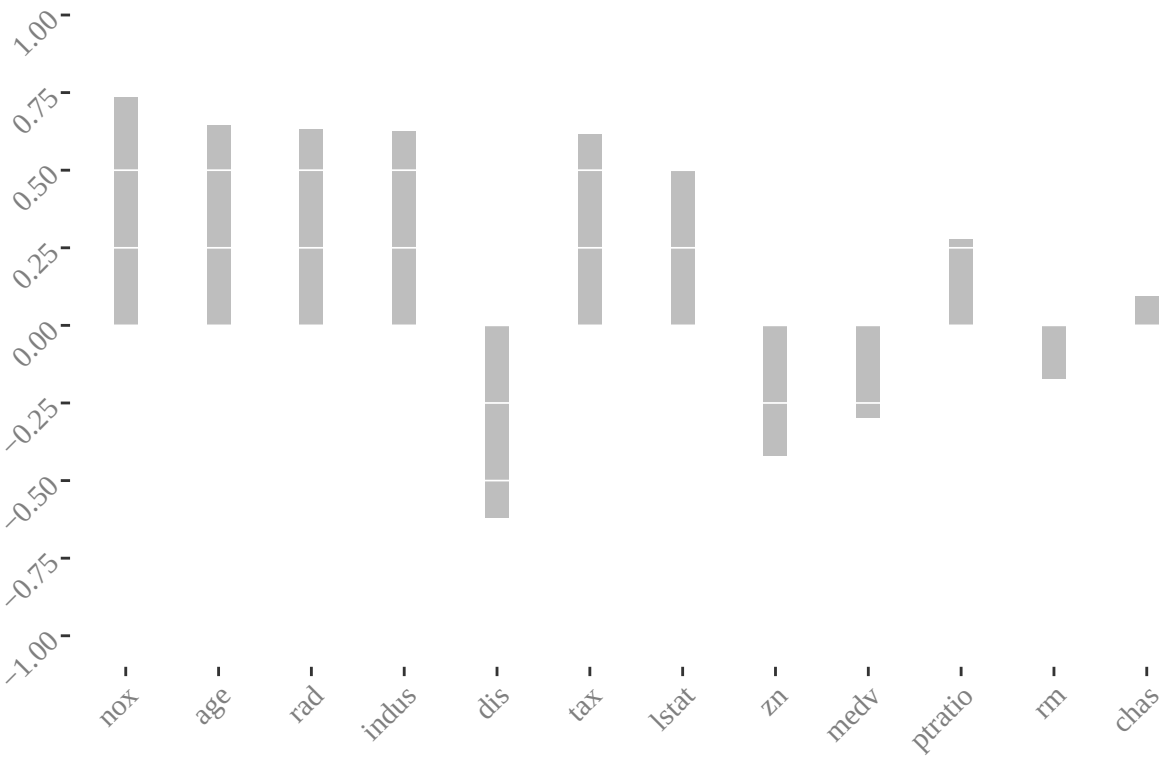
From these two graphs we can see that many of distributions are skewed in one direction or another. It is also interesting to see that the target variable is below zero. This means that the median and mean values are different.


Distrobution of Values
Y values scaled to fit a common axis
4
2
0
−2
age
chas
dis
indus
lstat
medv
nox
ptratio
rad
rm
target
tax
zn


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



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



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. However we will transform some variables, which have a large skewness, to see if they aid in prediction.

The other reason to transform variables is to account for interactions between variables. Logistic regression is 'linear' and an exhaustive search of all possible combinations/polynomials would be difficult even if we limited them to three degrees each. Instead, I suggest a test where we fit an extremely 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.

```
##
## AboveMed BelowMed
## 49.23664 50.76336
```

```
## Created from 262 samples and 12 variables
##
## Pre-processing:
##   - centered (12)
##   - ignored (0)
##   - scaled (12)
```

The AUC for the KNN Model is 0.9469005 and for the logistic regression model it was 0.9745763. This leads me to believe that there is little need to transformation.

2.1 Transformed Skewed Variables

zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	lstat	medv	target
0	19.58	0	0.605	7.929	96.2	2.0459	1.609438	5.998937	14.7	3.70	50.0	1
0	19.58	1	0.871	5.403	100.0	1.3216	1.609438	5.998937	14.7	26.82	13.4	1
0	18.10	0	0.740	6.485	100.0	1.9784	3.178054	6.501290	20.2	18.85	15.4	1
30	4.93	0	0.428	6.393	7.8	7.0355	1.791759	5.703782	16.6	5.19	23.7	0
0	2.46	0	0.488	7.155	92.2	2.7006	1.098612	5.262690	17.8	4.82	37.9	0
0	8.56	0	0.520	6.781	71.3	2.8561	1.609438	5.950643	20.9	7.67	26.5	0

3 Build Models

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

3.1 Baisic Logistic Regression

The basic logistic regression 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)	-1.5691	0.4135	-3.79	0.0002
zn	-0.0001	0.0011	-0.13	0.8949
indus	0.0044	0.0052	0.83	0.4053
chas	0.0377	0.0688	0.55	0.5840
nox	1.9124	0.3071	6.23	0.0000
rm	0.0210	0.0356	0.59	0.5563
age	0.0036	0.0010	3.41	0.0007
dis	0.0039	0.0154	0.25	0.8006
rad	0.0207	0.0053	3.94	0.0001
tax	-0.0005	0.0003	-1.47	0.1418
ptratio	0.0187	0.0108	1.74	0.0824
lstat	0.0038	0.0047	0.80	0.4220
medv	0.0072	0.0035	2.05	0.0410

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

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

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-35.2120	10.2397	-3.44	0.0006
zn	-0.0318	0.0339	-0.94	0.3478
indus	-0.0659	0.0611	-1.08	0.2803
chas	1.1977	0.8344	1.44	0.1512
nox	49.5514	9.5362	5.20	0.0000
rm	-0.5580	0.8055	-0.69	0.4885
age	0.0427	0.0168	2.54	0.0110
dis	0.6297	0.2494	2.53	0.0116
rad	3.1670	0.8487	3.73	0.0002
tax	-2.0727	1.3951	-1.49	0.1374
ptratio	0.5311	0.1505	3.53	0.0004
lstat	0.0156	0.0671	0.23	0.8167
medv	0.1780	0.0815	2.18	0.0289

3.2 Stepwise Selection on Baisic Model

If we do a step wise selection to find the variables that limit the scope but still provide excellent 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				336.00	32.77	192.88
2	- zn	1.00	0.00	337.00	32.78	190.90
3	- dis	1.00	0.00	338.00	32.78	188.95
4	- chas	1.00	0.03	339.00	32.81	187.27
5	- rm	1.00	0.03	340.00	32.85	185.64
6	- lstat	1.00	0.04	341.00	32.88	184.04
7	- indus	1.00	0.08	342.00	32.96	182.89
8	- tax	1.00	0.19	343.00	33.15	182.87

(Intercept) nox age rad ptratio -1.465415204 1.907574669 0.004001734 0.015012689 0.017546279 medv 0.007089771 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)	-26.0356	4.4780	-5.81	0.0000
nox	25.5766	4.7958	5.33	0.0000
age	0.0253	0.0106	2.38	0.0172
rad	0.4785	0.1343	3.56	0.0004
ptratio	0.3198	0.1146	2.79	0.0053
medv	0.0829	0.0352	2.36	0.0184

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

3.3 BestGLM Model Selection

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

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

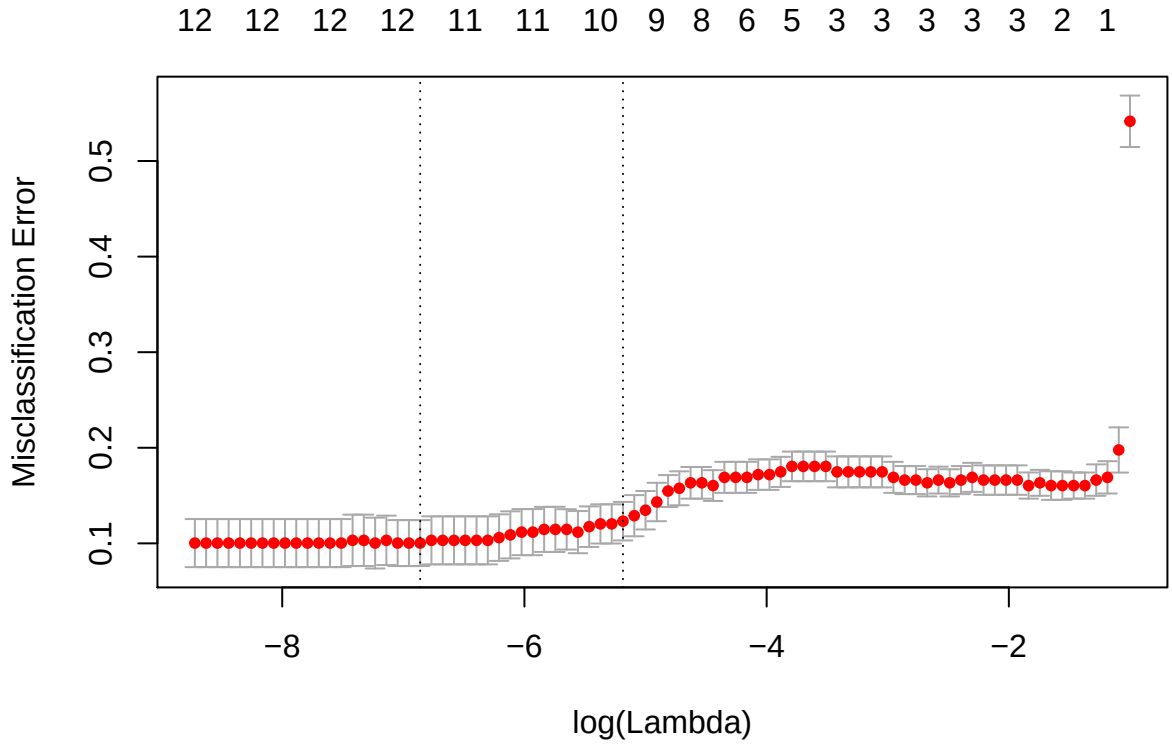
```
## BIC
## BICq equivalent for q in (0.495732559154941, 0.727289587248084)
## Best Model:
```

```
##                 Estimate  Std. Error   z value     Pr(>|z|)
## (Intercept) -26.70502487 4.575177070 -5.836938 5.316887e-09
## nox          36.69943157 6.533152682  5.617415 1.938352e-08
## age           0.02602591 0.011040026  2.357414 1.840272e-02
## rad           0.71071771 0.165357912  4.298057 1.723020e-05
## tax          -0.01191998 0.003369439 -3.537676 4.036653e-04
## ptratio       0.28308970 0.101901509  2.778072 5.468254e-03
```

3.4 LASSO Regression

Looking at lasso logistic regression might give us a better model selection and coefficient 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) -2.137026e+01
## zn          -5.705184e-04
## indus       -2.579330e-02
## chas         8.674276e-01
## nox          2.660746e+01
## rm           .
## age          2.085135e-02
## dis          7.687419e-02
## rad          2.582184e-01
## tax         -3.004888e-03
## ptratio      2.153470e-01
## lstat        .
```

```
## medv          3.928790e-02
```

3.5 Regular logostic without LASSO Dropped Variable

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

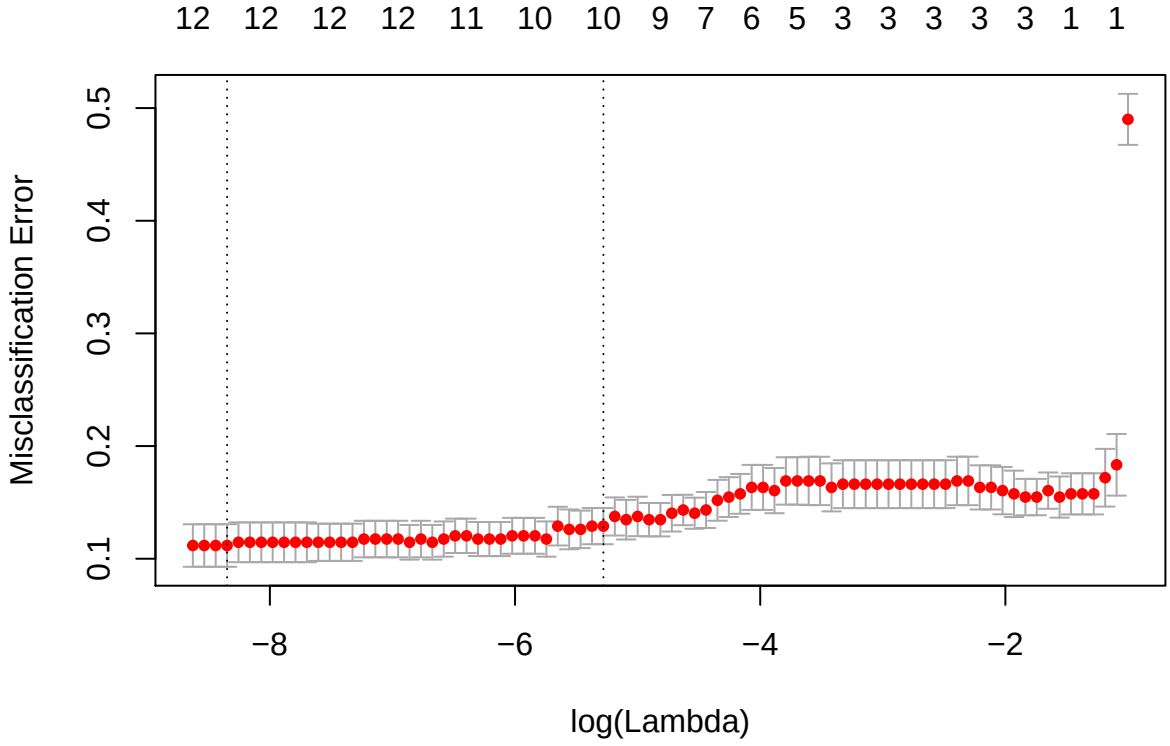
% latex table generated in R 3.4.0 by xtable 1.8-2 package %

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-43.9971	8.2367	-5.34	0.0000
zn	-0.0341	0.0354	-0.96	0.3354
indus	-0.0508	0.0615	-0.83	0.4088
chas	1.0168	0.8580	1.19	0.2360
nox	49.4185	9.3588	5.28	0.0000
age	0.0344	0.0139	2.48	0.0133
dis	0.5737	0.2388	2.40	0.0163
rad	0.6378	0.1840	3.47	0.0005
tax	-0.0080	0.0037	-2.17	0.0299
ptratio	0.4768	0.1385	3.44	0.0006
lstat	0.0529	0.0617	0.86	0.3911
medv	0.1365	0.0542	2.52	0.0118

This is interesting because we can see how different the coefficents are even though it has the same variables.

3.6 Lasso with scaled variable

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



```
## 13 x 1 sparse Matrix of class "dgCMatrix"
##                           1
## (Intercept) -21.224861771
## zn           -0.002140195
## indus        -0.024757093
## chas          0.826579803
## nox          27.624321487
## rm            .
## age           0.022062974
## dis           0.104288383
## rad           1.998322536
## tax          -0.847081644
## ptratio       0.269609591
## lstat         .
## medv          0.049454065
```

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.

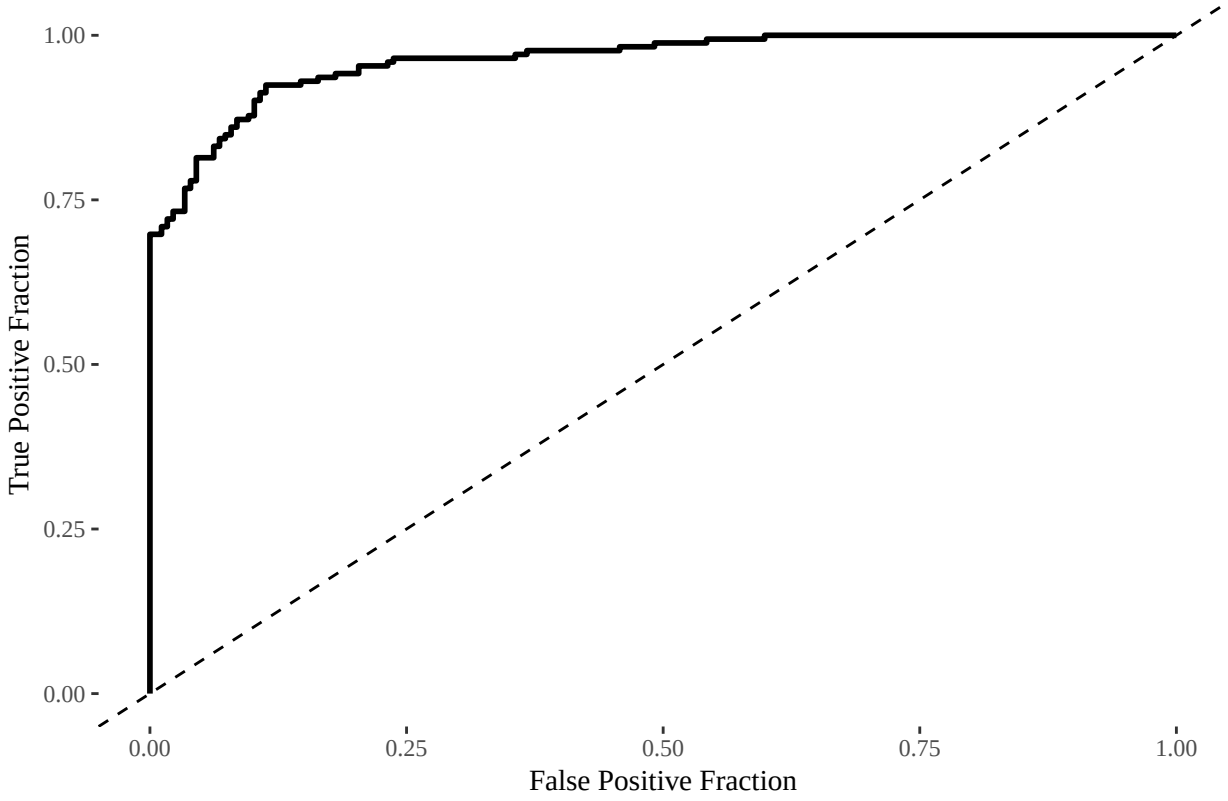
I've chosen to use AUC because it is easily understood and provides a nice visual way to differentiate model performance.

4.1 Baisic GLM Model

We see this model has good performance, especially for a dataset that has roughly equal numbers of positive and negative examples.

4.2 GLM Model Evaluation

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

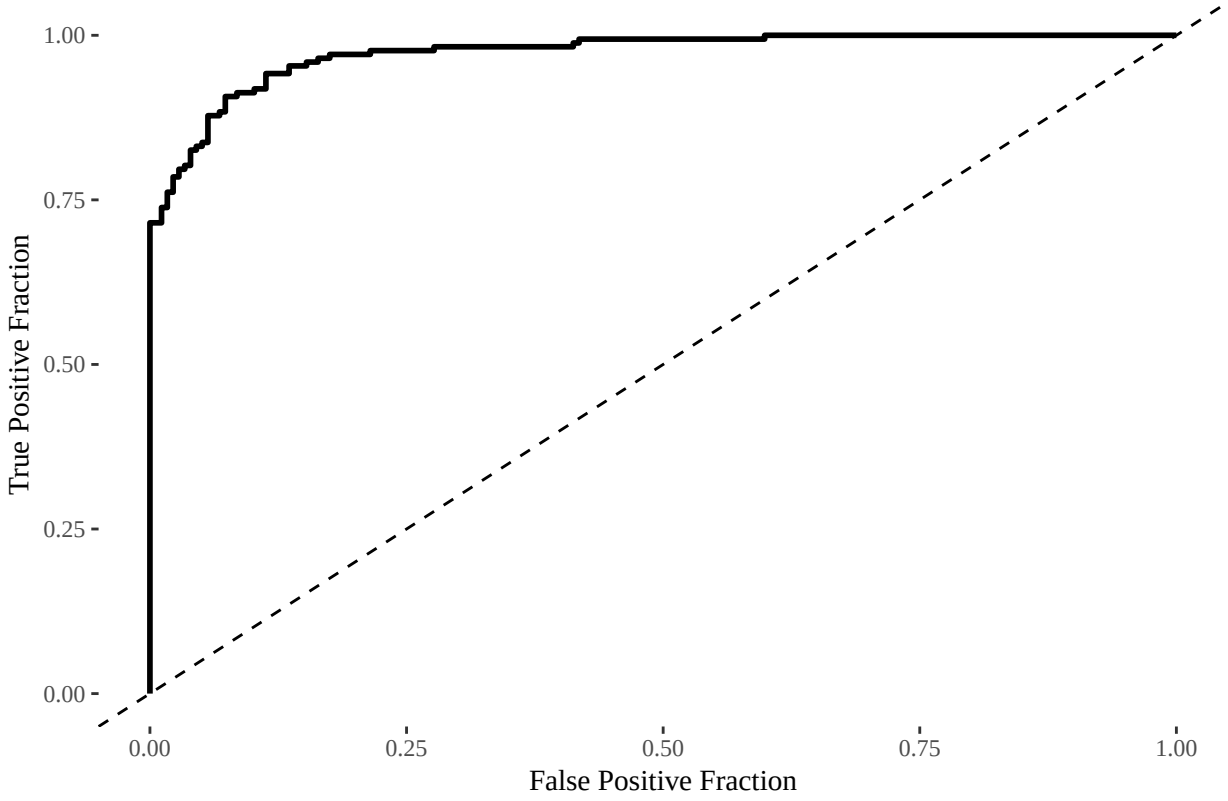



```
##
## [[2]]
## Area under the curve: 0.9622
```

4.3 Scaled GLM Model

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

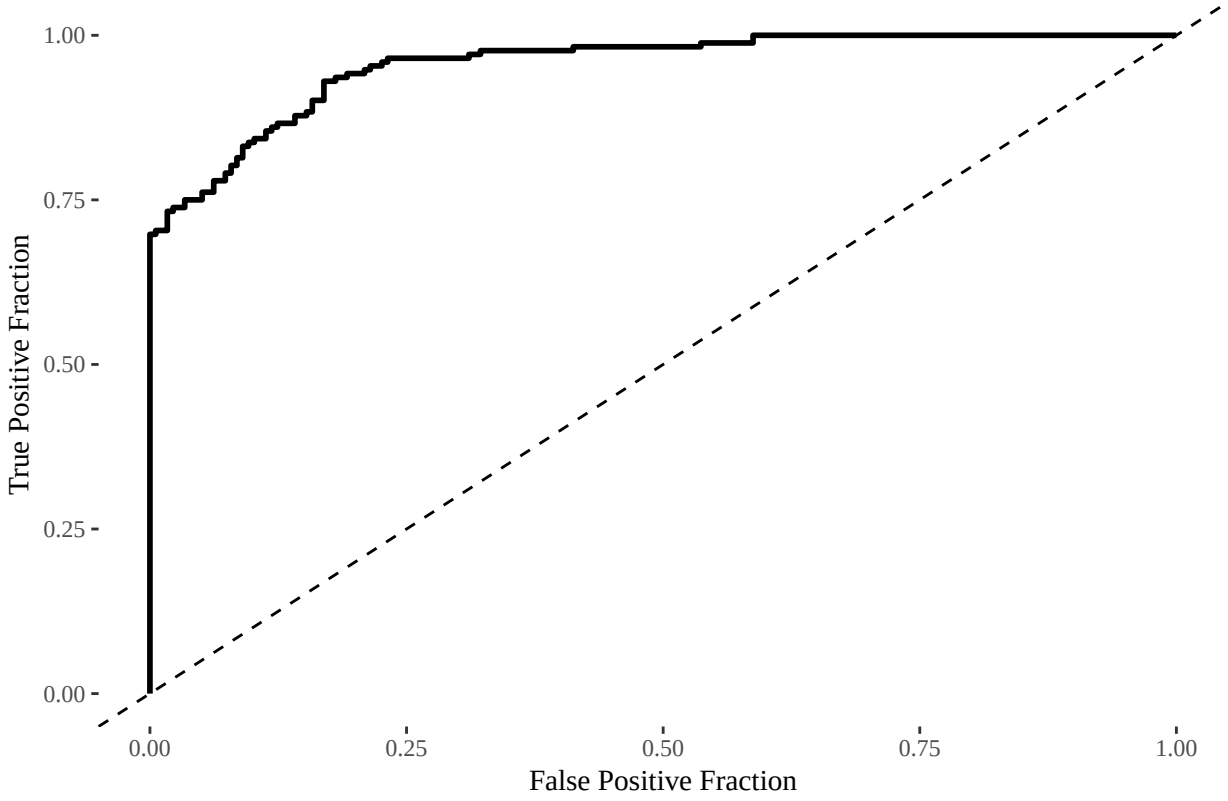
AUC Graph for Sclaed GLM




```
##
## [[2]]
## Area under the curve: 0.9731
```

4.4 STEPWISE AIC MODEL

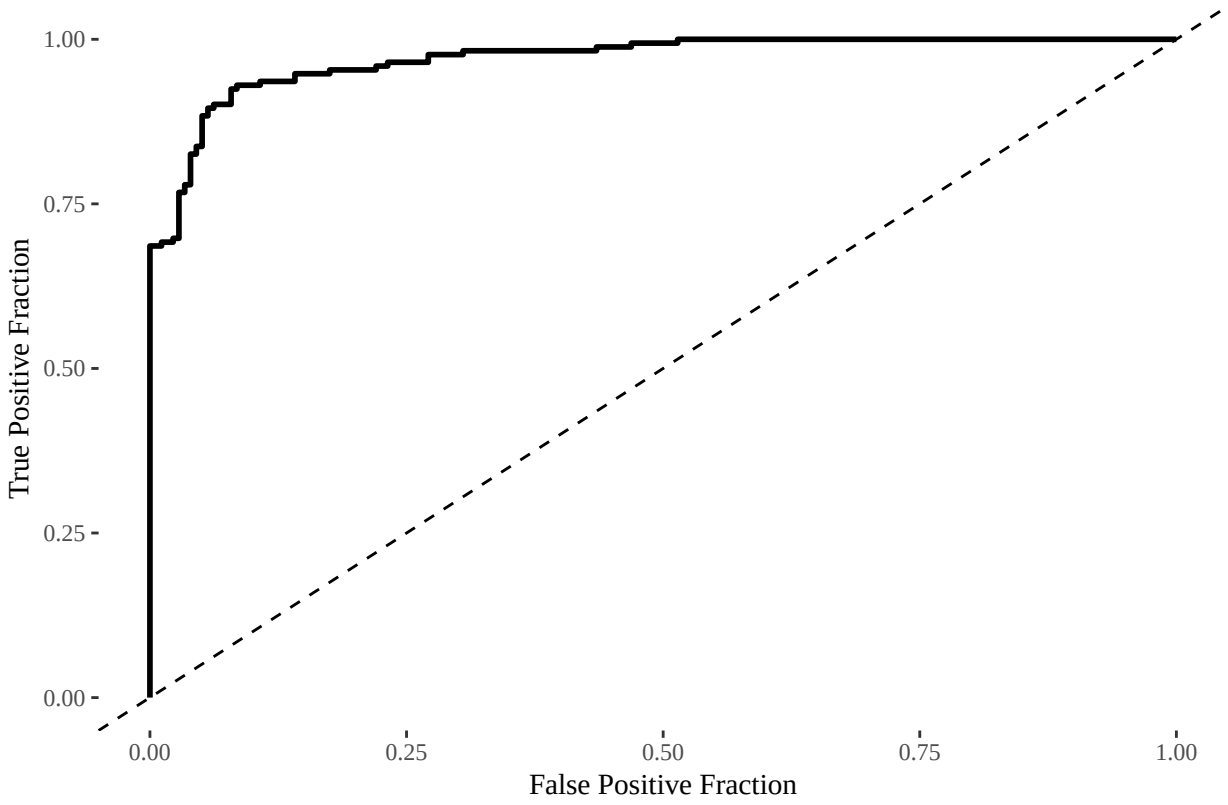
```
## [[1]]
```




```
##
## [[2]]
## Area under the curve: 0.9555
```

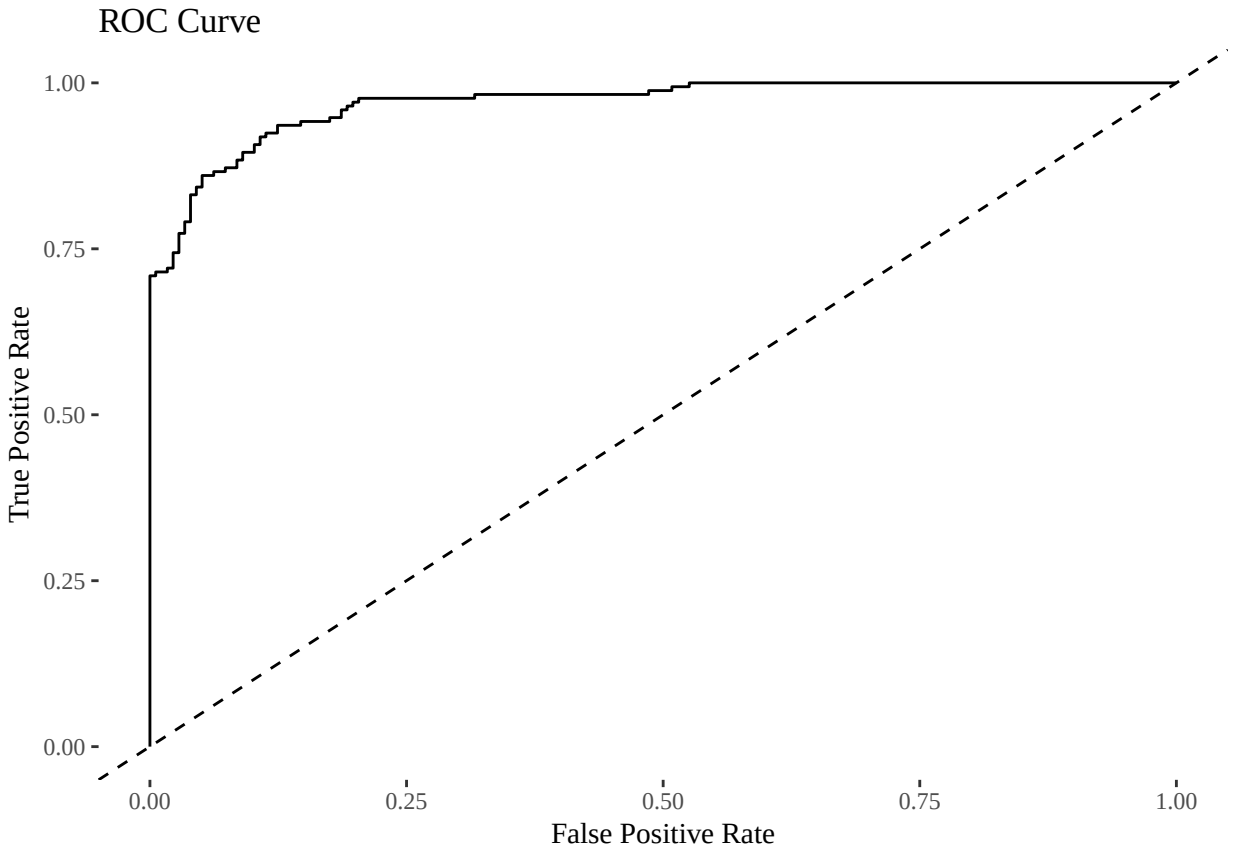
4.5 BestGLM Model

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



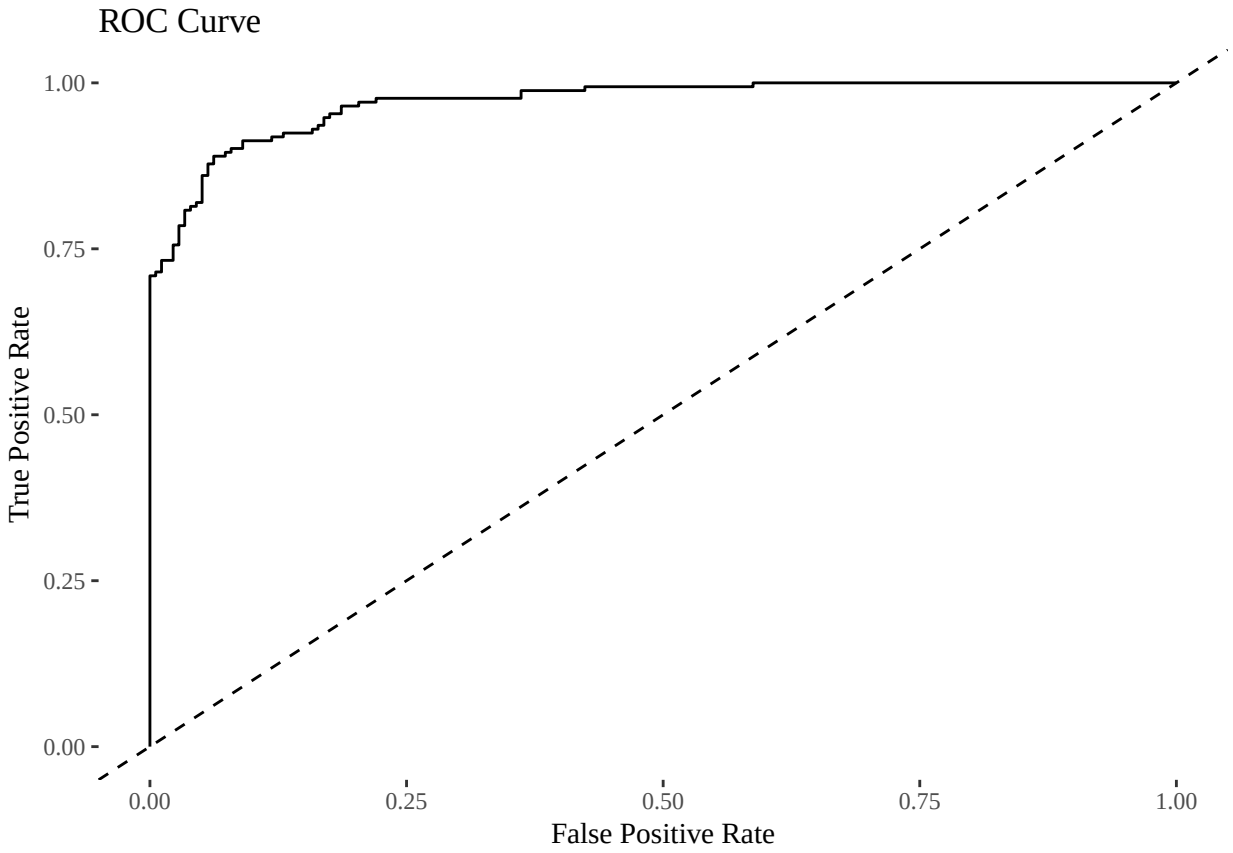

```
##
## [[2]]
## Area under the curve: 0.9703
```

4.6 Lasso Model




```
## [[1]]
## [1] 0.9693864
```

4.7 Scaled LASSO




```
## [[1]]
## [1] 0.9704047
```

4.8 Which model?

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

4.9 Prediction

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

Predicted_Probabilities	Predicted_Outcome
0.0807547	0
0.5466745	1
0.5989220	1
0.4756189	0
0.1588705	0
0.2077610	0
0.2872710	0
0.0489397	0

Predicted_Probabilities	Predicted_Outcome
0.0399902	0
0.0298739	0
0.5850308	1
0.5589784	1
0.8377960	1
0.6375749	1
0.6060673	1
0.3803760	0
0.2164483	0
0.6216056	1
0.0411823	0
0.0027372	0
0.0036157	0
0.2319278	0
0.2896272	0
0.1662590	0
0.1334174	0
0.3936344	0
0.0215032	0
0.9998567	1
0.9997873	1
0.9915944	1
0.9998336	1
0.9998765	1
0.9998610	1
0.9999140	1
0.9998744	1
0.9997322	1
0.9997788	1
0.9985988	1
0.7042626	1
0.6297986	1

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)
```

```
library(caTools)
options(xtable.floating = FALSE)
options(xtable.timestamp = "")
####################
# Loading the data
LabledDF <- read_csv('/Users/kailukowiak/DATA621/Assignments/Assignment3/crime-training-data_modified.cs

set.seed(101)
sample = sample.split(LabledDF$zn, SplitRatio = .75)
df <- subset(LabledDF, sample == TRUE)
testDF <- subset(LabledDF, sample == FALSE)
df %>% sample_n(6) %>% kable(caption = 'Sample of Values for the Training Set')
evalDF <- read_csv('/Users/kailukowiak/DATA621/Assignments/Assignment3/crime-evaluation-data_modified.cs
evalDF %>% 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)) +
  # geom_violin()+
  # geom_tufteboxplot(outlier.colour="black", outlier.shape = 22)+
  geom_boxplot()+
  theme_tufte() +
  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
```

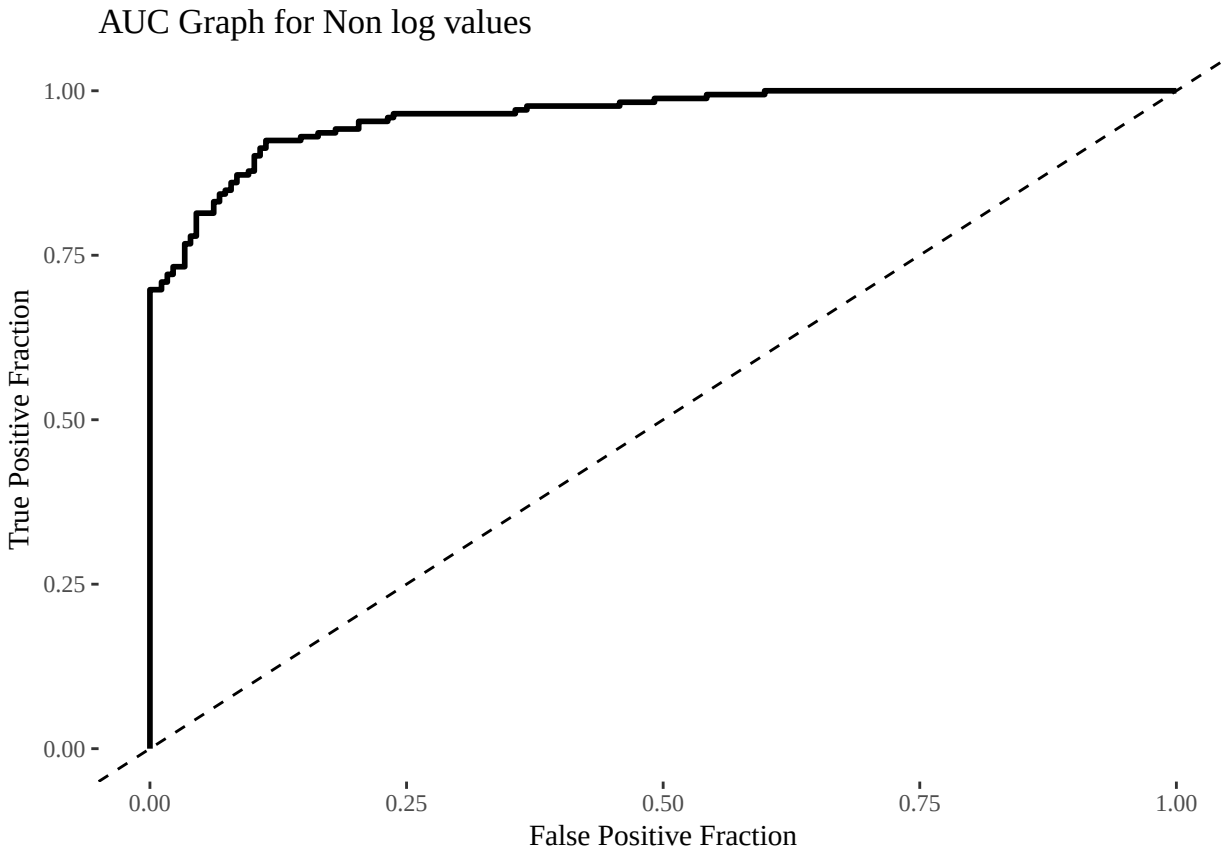
```r
trainX <- training[,names(training) != "target"] # Make this target
preProcValues <- preProcess(x = trainX,method = c("center", "scale"))
preProcValues

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$auc
logDF <- df
logDF$rad <- log(logDF$rad)
logDF$tax <- log(logDF$tax)

# Test Set
logTestDF <- testDF
logTestDF$rad <- log(logTestDF$rad)
logTestDF$tax <- log(logTestDF$tax)

logDF %>% head() %>% kable()
mod1 <- glm(target ~ ., data = df)
#summary(mod1)
library(xtable)
xtable(mod1)
logData <- glm(target~., family = binomial(), data = logDF)
xtable(logData)
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)
```

```r
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")
mod3 <- glm(target ~ . -rm, family = 'binomial', data = df)
xtable(mod3)
logX <- logDF %>% dplyr::select(-target)
logX <- data.matrix(logX)
y <- as.factor(logDF$target)

# Testing Data
logXTest <- logTestDF %>% dplyr::select(-target)
logXTest <- as.matrix(logXTest)
yTest <- as.factor(logTestDF$target)

# Fitting
fit = glmnet(logX, y, family = "binomial")
library(ROCR)
aucDF <- logX
lasso.model = cv.glmnet(logX, y, family = "binomial", type.measure = 'class')

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


cvfitLOG = cv.glmnet(logX, y, family = "binomial", type.measure = "class")
plot(cvfitLOG)
coef(cvfitLOG, s = "lambda.1se")
AUC <- function(testDF, 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(testDF, mod1, 'Baisic GLM Model')
```

```
AUC(logTestDF, logData, 'Sclaed GLM')
AUC(testDF, step, 'Step AIC Model')

AUC(testDF, BestGLMModel$BestModel, 'Model Best')
#testX <- a
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
fittedGLMcvLog <- predict(cvfitLOG, logXTest, s = "lambda.1se", type = "class")

perf <- performance(predScaled,"tpr","fpr")
auc <-  performance(predScaled,"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(evalDF)
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)
```

```r
logDF$tax <- log(logDF$tax)
logData <- glm(target~., family = binomial(), data = logDF)

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

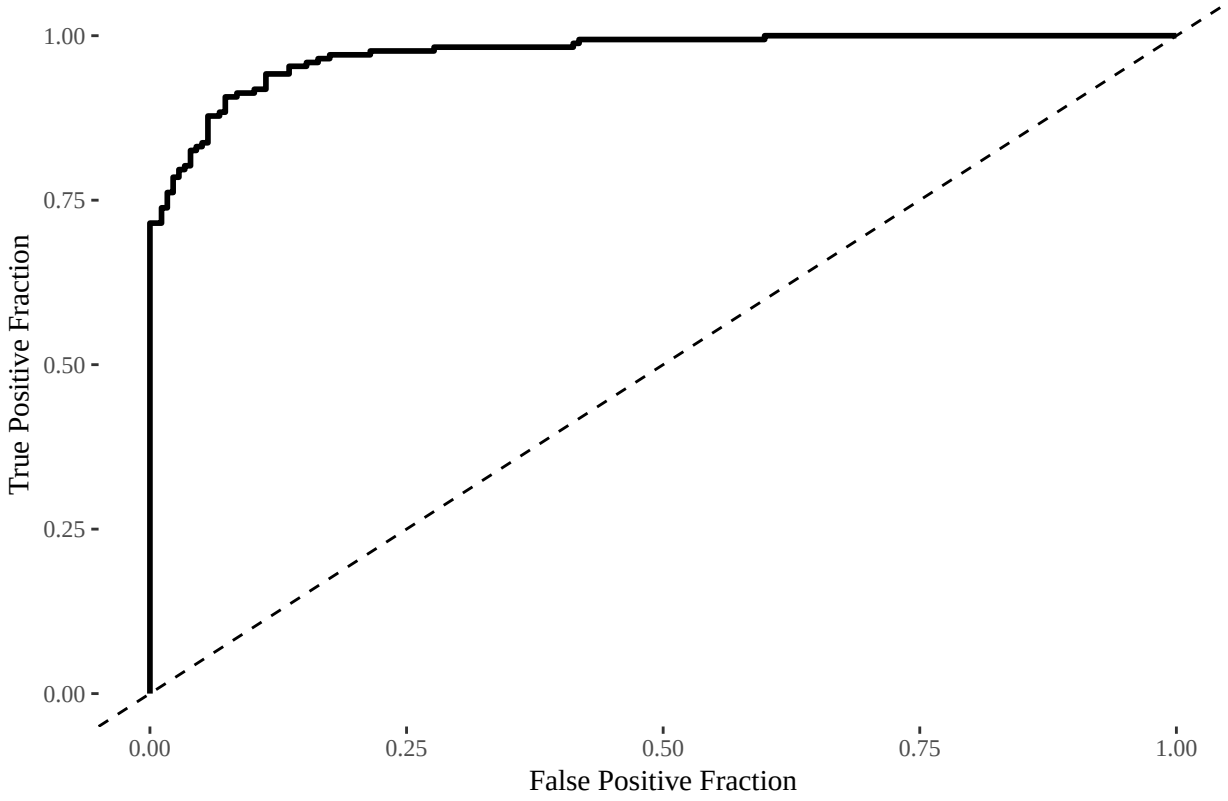
```
## [[1]]
```




```
##
## [[2]]
## Area under the curve: 0.9622
```

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

AUC Graph for logged values




```
##
## [[2]]
## Area under the curve: 0.9731
```