# Home Work Assignment - 03

*Critical Thinking Group 5*

## Contents

# Overview

The data set contains approximately 466 records and 14 variables. Each record has information on crime for various neighborhoods of a major city. Each record has a response variable indicating whether or not the crime rate is above the median crime rate (1) or not (0).

The objective is to build a binary logistic regression model on the training data set to predict whether the neighborhood will be at risk for high crime levels. In addition, we will provide classifications and probabilities for the evaluation data set using the binary logistic regression model.

# 1 Data Exploration Analysis

In section we will explore and gain some insights into the dataset by pursuing the below high level steps and inquiries:
-Variable identification
-Variable Relationships
-Data summary analysis
-Outliers and Missing Values Identification

## 1.1 Variable identification

First let's display and examine the data dictionary or the data columns as shown in table 1

Table 1: Variable Description

| Variable | Description |
|---|---|
| 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) |
| black | 1000(Bk - 0.63)2 where Bk is the proportion of blacks 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) |

We notice that all variables are numeric except for two variables: the response variable "target" which is binary and the predictor variable "chas" which is a dummy binary variable indicating whether the suburb borders the Charles River (1) or not (0).
Based on the original dataset, our predictor input is made of 13 variables. And our response variable is one variable called target.
Following is the summary of the train data set variable 1-5

Table: Summary of Variables 1 to 5

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

Following is the summary of the train data set variable 7-12

Table: Summary of Variables 6-11

| age | dis | rad | tax | ptratio | black |
|---|---|---|---|---|---|
| Min. : 2.90 | Min. : 1.130 | Min. : 1.00 | Min. :187.0 | Min. :12.6 | Min. : 0.32 |
| 1st Qu.: 43.88 | 1st Qu.: 2.101 | 1st Qu.: 4.00 | 1st Qu.:281.0 | 1st Qu.:16.9 | 1st Qu.:375.61 |
| Median : 77.15 | Median : 3.191 | Median : 5.00 | Median :334.5 | Median :18.9 | Median :391.34 |
| Mean : 68.37 | Mean : 3.796 | Mean : 9.53 | Mean :409.5 | Mean :18.4 | Mean :357.12 |
| 3rd Qu.: 94.10 | 3rd Qu.: 5.215 | 3rd Qu.:24.00 | 3rd Qu.:666.0 | 3rd Qu.:20.2 | 3rd Qu.:396.24 |
| Max. :100.00 | Max. :12.127 | Max. :24.00 | Max. :711.0 | Max. :22.0 | Max. :396.90 |

Following is the summary of the train data set variable 12-14

Table: Summary of Variables 12-14

| lstat | medv | target |
|---|---|---|
| Min. : 1.730 | Min. : 5.00 | Min. :0.0000 |
| 1st Qu.: 7.043 | 1st Qu.:17.02 | 1st Qu.:0.0000 |
| Median :11.350 | Median :21.20 | Median :0.0000 |
| Mean :12.631 | Mean :22.59 | Mean :0.4914 |
| 3rd Qu.:16.930 | 3rd Qu.:25.00 | 3rd Qu.:1.0000 |
| Max. :37.970 | Max. :50.00 | Max. :1.0000 |

Following is the analysis on missing values in data set

Table 5: Missing Values

| | |
|---|---|
| zn | 0 |
| indus | 0 |
| chas | 0 |

| | |
|---|---|
| nox | 0 |
| rm | 0 |
| age | 0 |
| dis | 0 |
| rad | 0 |
| tax | 0 |
| ptratio | 0 |
| black | 0 |
| lstat | 0 |
| medv | 0 |
| target | 0 |

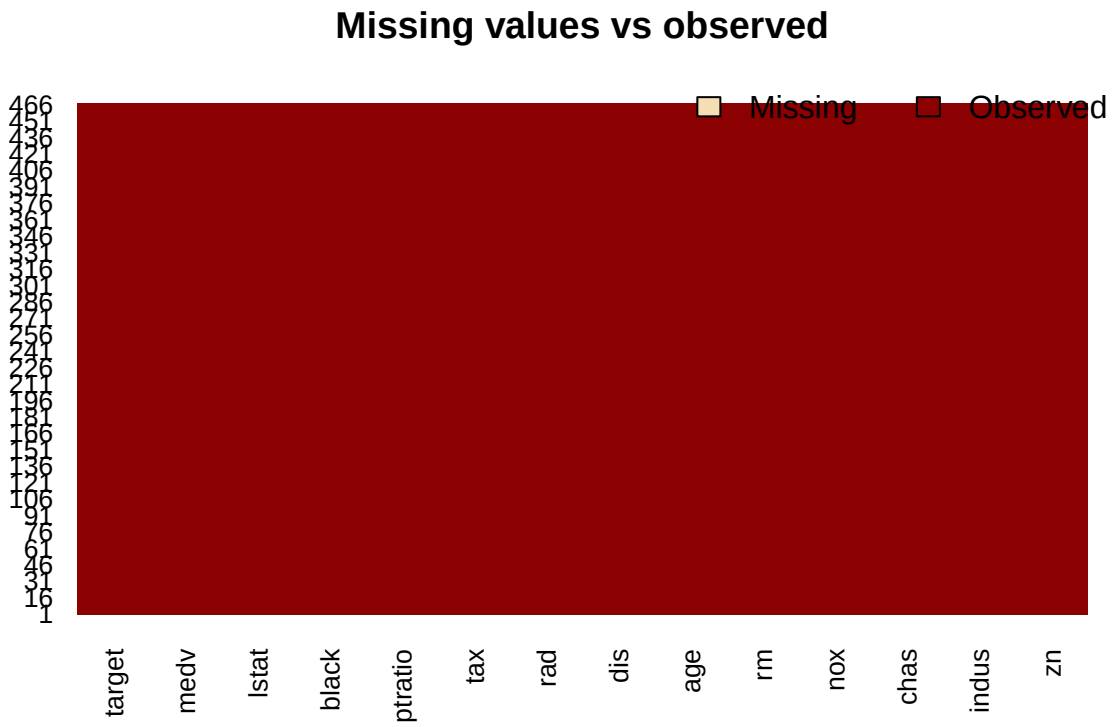



Table 6: Unique Values

| | |
|---|---|
| zn | 26 |
| indus | 73 |
| chas | 2 |
| nox | 79 |
| rm | 419 |
| age | 333 |
| dis | 380 |
| rad | 9 |
| tax | 63 |
| ptratio | 46 |
| black | 331 |

| | |
|---|---|
| lstat | 424 |
| medv | 218 |
| target | 2 |

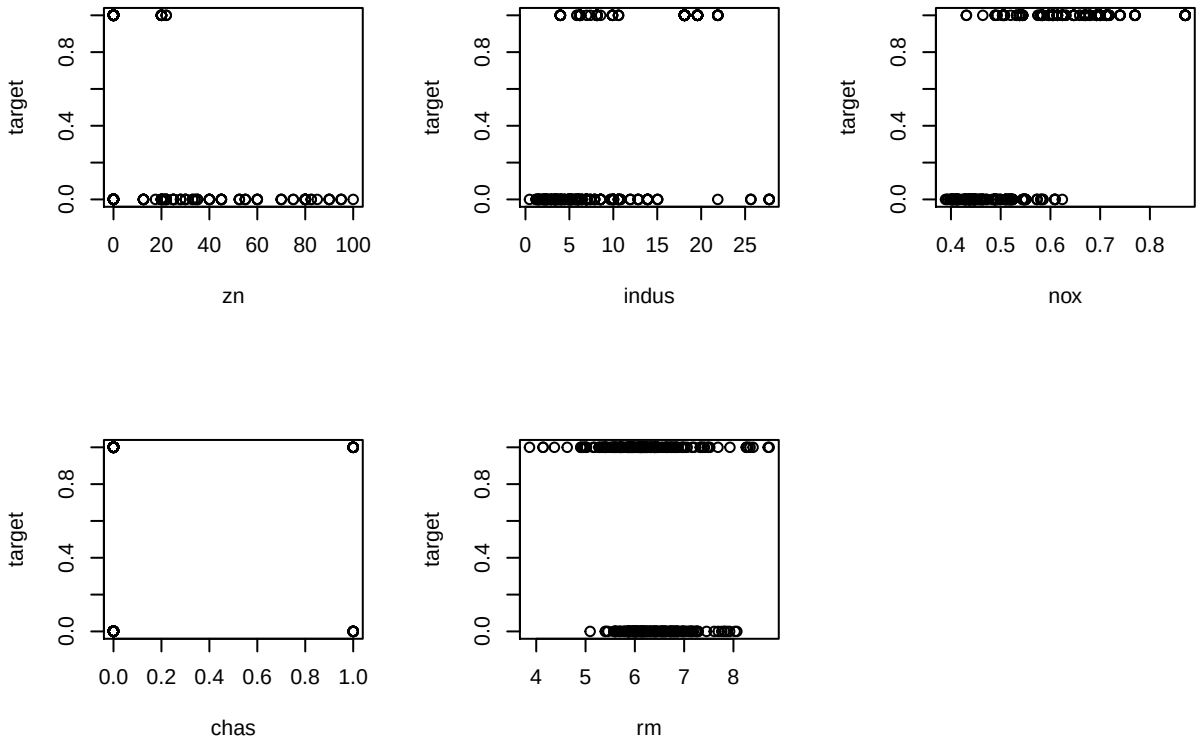
Based on the analysis above it can be seen that there is no missing value in the data set. Also count of unqiue values for each variable is shown above

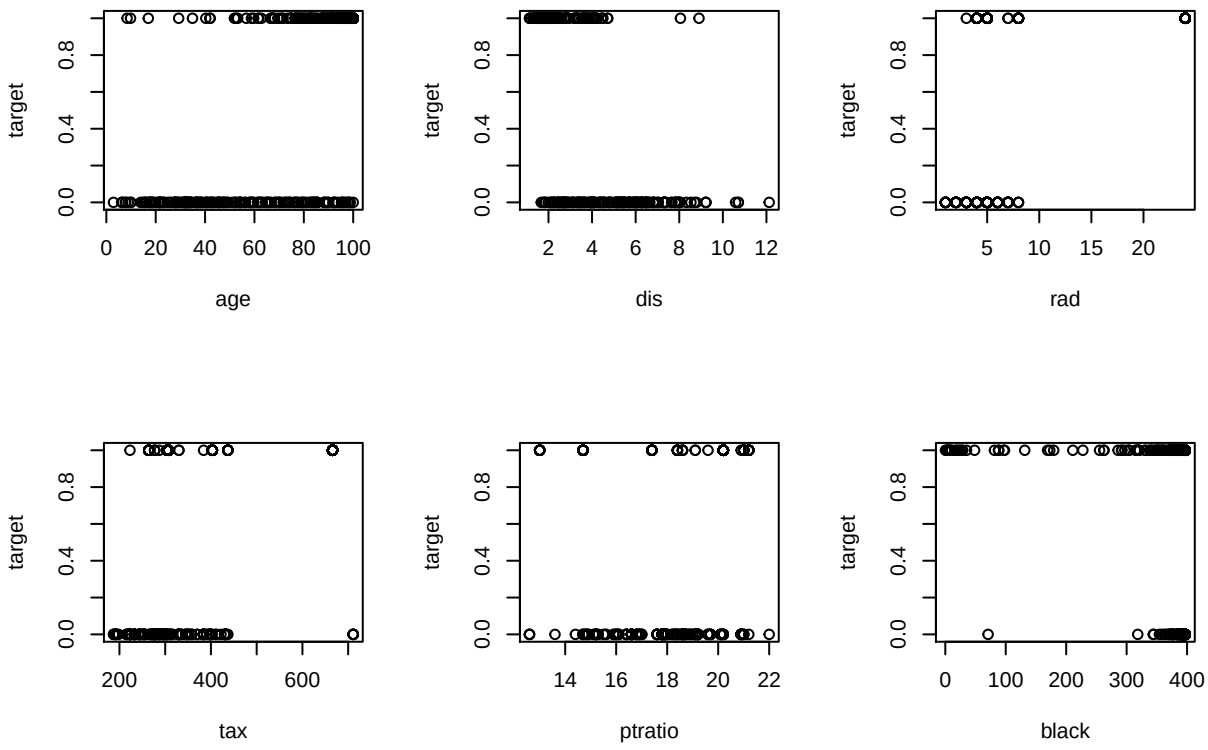
Break up of target variable count in train data set

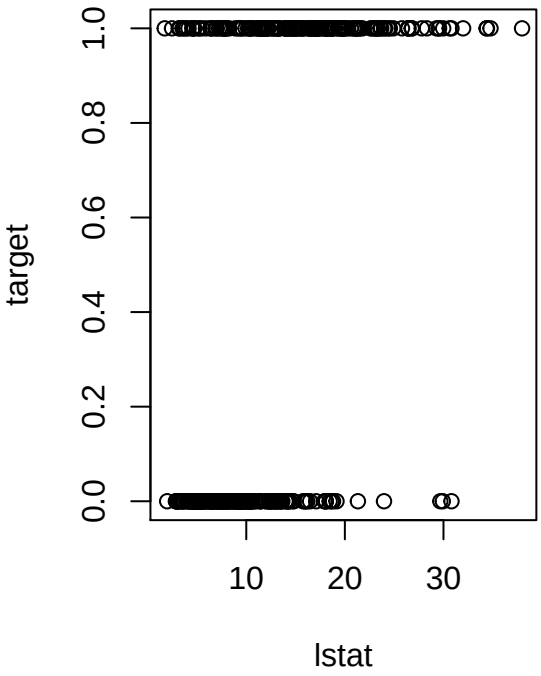
```
##   Var1 Freq
## 1    0  237
## 2    1  229
```

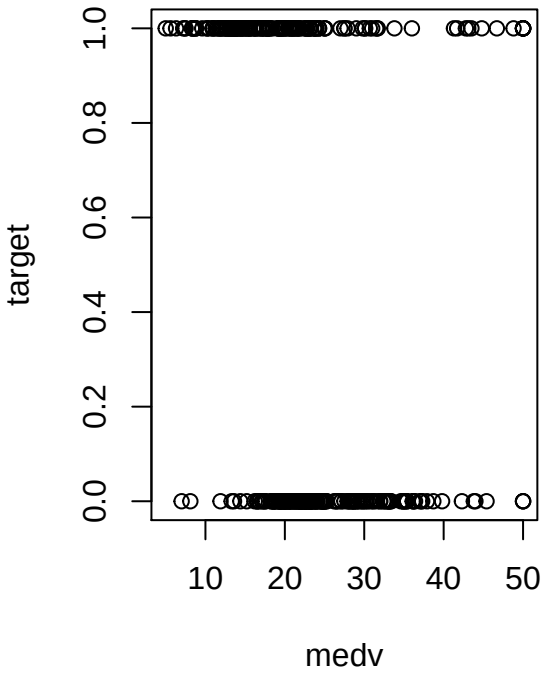
% split of target variable is given above table which shows data is almost evanly split between binary outcome 0 and 1
Train data set will be Split into train data(80% of train set) and validation set (20% of train set)to evalute the perforamnce of the models on the validation set. Train subset will be used to build the models.

Two data set has been created city_crime_train (80% of train data), and train_test (20% of train data).
In next step below relationship between the target variable and dependent variables is shown in three charts.




target
0.0
0.4
0.8
0
20
40
60
80
100
age
target
0.0
0.4
0.8
2
4
6
8
10
12
dis
target
0.0
0.4
0.8
5
10
15
20
rad
target
0.0
0.4
0.8
200
400
600
tax
target
0.0
0.4
0.8
14
16
18
20
22
ptratio
target
0.0
0.4
0.8
0
100
200
300
400
black


target
0.0
0.2
0.4
0.6
0.8
1.0
10
20
30
lstat


target
0.0
0.2
0.4
0.6
0.8
1.0
10
20
30
40
50
medv

## 1.2 Data Analysis

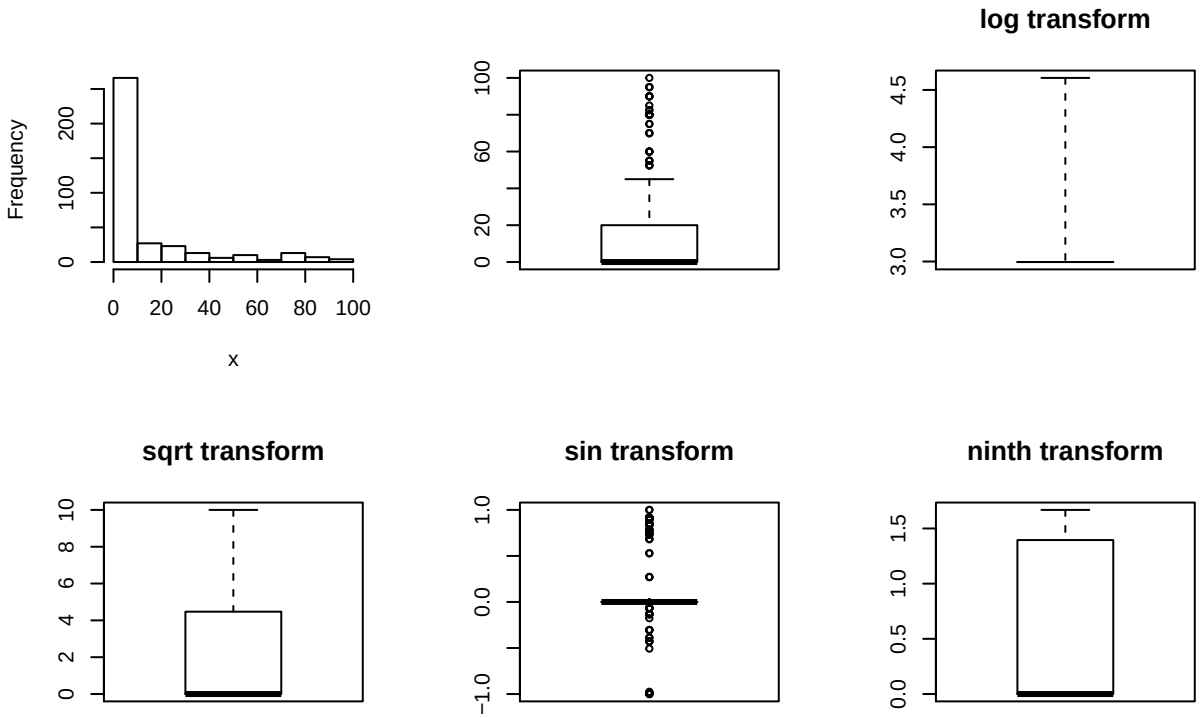
In this section, relationship between target variable with our dependent variables has been explored using correlation, central tendency, and dispersion As shown in table 2.

It is clear from the table that most of the variables are having storng correlation with the target variable.

## 1.3 Outliers and Missing Values Identification

In this section univariate analysis is being caarried out and boxplots diagrams are being used to determine the outliers in variables and decide on whether to act on the outliers. Along with boxplot, Histrogram, Sin, Log,Sqrt,nth transformation diagrams are used to evaluate best transformation to handle outliers.

Analysis of variable zn:proportion of residential land zoned for large lots




For zn, we can see that there are large number of values with 0. ninth transformation seem better for this variable..(1)

*

**Please note that we have created similar figures to figure 1 above for each remaining variable. However, we hid the remaining figures for ease of streamlining the report as they have similar shapes. However, we have drawn the below observations from each remaining figure.

For indus, we can see that there is a spike toward right side of he distribution. Looking at the sqrt transformation it appears that distribution is close to normal and having two peaks after transformation.

For nox, there is a long right tail.

For rm, there are some outliers as we can see from box plot. This variable will need some transformation to handle the outliers.

age of the building variable is skewed heavily towards right side. We will need some transformation for this variable and looks sin transformation is best option for this case

For this variable dis, there are some outliers which needs transformation to handle those outliers. log transformation looks best suited for this scenario.

For rad variable distribution is not uniform as seen from the chart and will need transformation.

For tax variable is not uniformly distributed but there is no outlier for this variable.

For pratio has right aligned peak but no outliers are there in data set.

The variable lstat has long right tail and lef skewed

# 2. Data Preparation

Now that we have completed the preliminary analysis, we will be cleaning and consolidating data into one dataset for use in analysis and modeling. We will be puring the belwo steps as guidlines:
- Outliers treatment
- Missing values treatment
- Data transformation

## 2.1 Outliers treatment and transformation

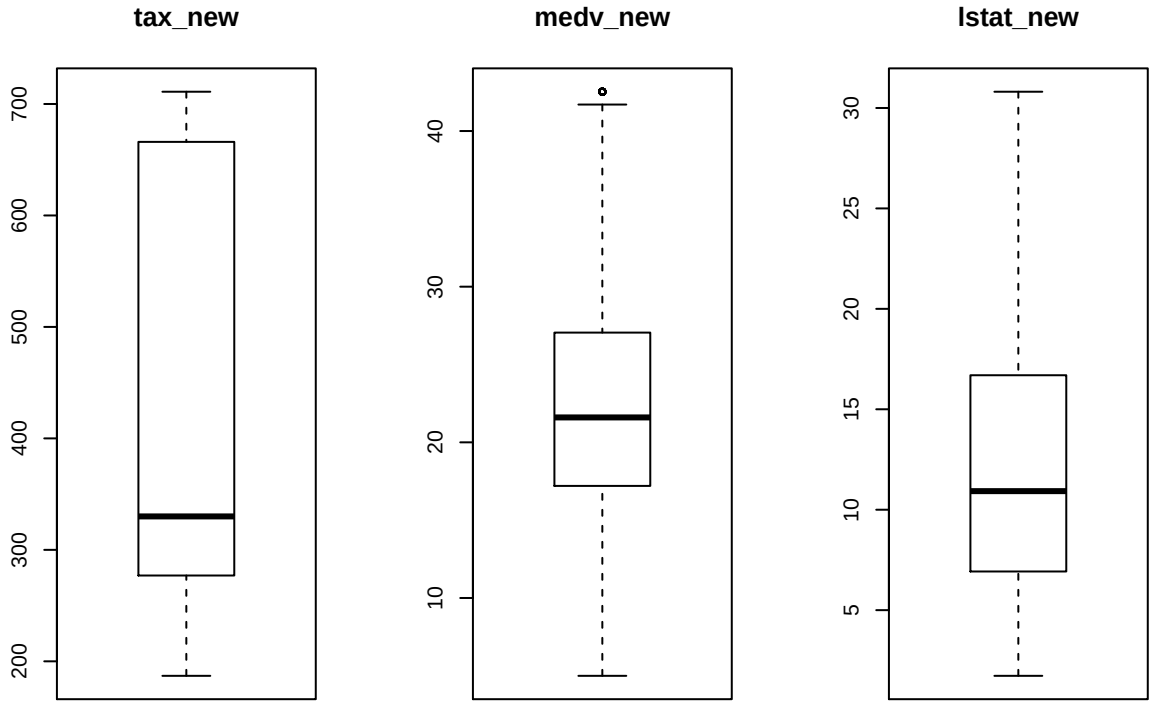
For outliers, we will create 2 sets of variables.

The first set uses the capping method. In this method, we will replace all outliers that lie outside the 1.5 times of IQR limits. We will cap it by replacing those observations less than the lower limit with the value of 5th %ile and those that lie above the upper limit with the value of 95th %ile.

Accordingly we create the following new variables while retaining the original variables.

city_crime_train$tax$ $city_crime_train$medv
city_crime_train$lstat

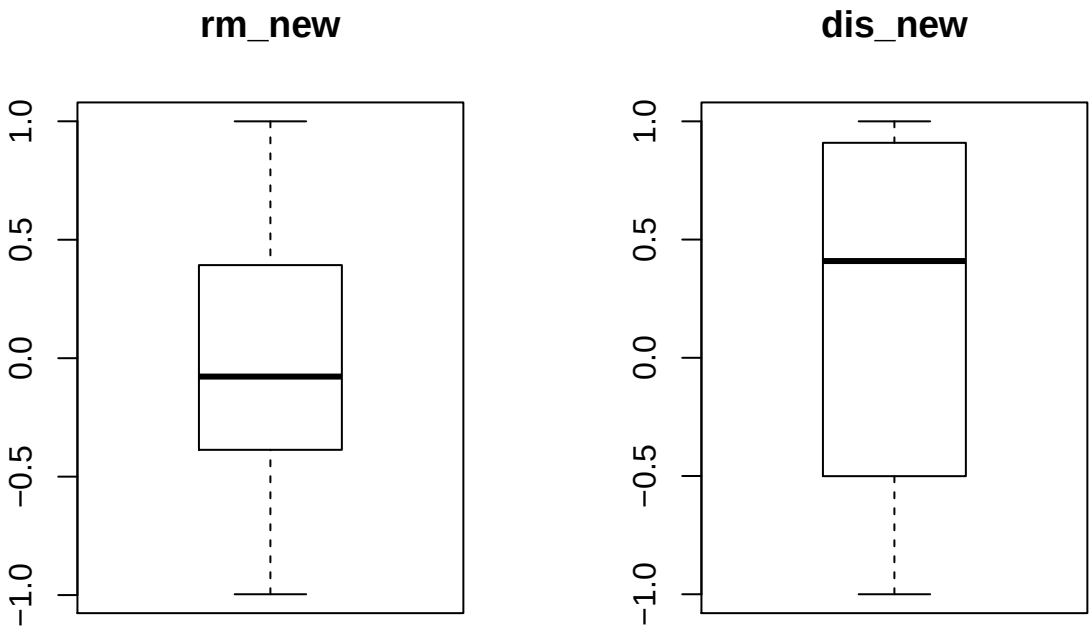
Below boxplots shows distribution of variables after outliers treatment.




In the second set, we will use the sin transformation and create the following variables:

city_crime_train_mod$rm_new$ $city_crime_train_mod$dis_new

Below is the boxplot after sin transformation of above variable.




Additional transformation was performed on following variables
1. using bucket for zn, with set of values 0 and 1 2. Converting chas to a factor variale of 0 and 1 3. Converting target to a factor variale of 0 and 1

Below we evaluate correlation of target with new variables

All new variables seem to have a positive correlation with target. However, some of them do not seem to have a strong correlation. Lets see how they perform while modeling.

# 3 Build Models

Following strategy has been adoped to build models for this scenario:

(i) Building model 1 using given variables by using logit function.

(ii) Using step function to enhance model 1 and create model 2.

(iii) Building model 3 using tranformed variables also by using logit function.

(iv) Using step function to enhance model 3 and create model 4.

(v) Using Linear discrement analysis model create model 5 with given variables.

(vi) Using Linear discrement analysis model create model 6 with transformed variables.

Below is a summary table showing models and their respective variables.

### 3.1.1 Model One by using all given variables

In this model, we will be using all the given variables in train data set. We will create model using logic function and we will highlight the summary of the model.

```
##
## Call:
## glm(formula = target ~ ., family = "binomial", data = city_crime_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8791  -0.1299  -0.0025   0.0011   3.4785
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -41.462153   8.250799  -5.025 5.03e-07 ***
## zn           -0.060580   0.039153  -1.547 0.121799
## indus        -0.063885   0.059335  -1.077 0.281618
## chas1         0.789391   0.865818   0.912 0.361912
## nox          53.413503  10.013666   5.334 9.60e-08 ***
## rm           -0.647942   0.904430  -0.716 0.473739
## age           0.028835   0.015680   1.839 0.065915 .
## dis           0.800917   0.268877   2.979 0.002894 **
## rad           0.721751   0.195662   3.689 0.000225 ***
## tax          -0.007065   0.003490  -2.024 0.042948 *
## ptratio       0.440768   0.159366   2.766 0.005679 **
## black        -0.009591   0.006025  -1.592 0.111412
## lstat         0.096941   0.062429   1.553 0.120469
## medv          0.236940   0.091276   2.596 0.009436 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 514.63  on 371  degrees of freedom
## Residual deviance: 140.71  on 358  degrees of freedom
## AIC: 168.71
##
## Number of Fisher Scoring iterations: 9
```

**Interpretation for model 1**

(i) Based on the outcome it can be seen that indus,chas,rm,age,black and lstat are not statistically significant.

(ii)As for the statistically significant variables, nox has the lowest p-value suggesting a strong association of the nox of the target varible. other important varibles are dis,rad,tax,ptratio,medv. AIC value for the model1 =168.71.

(iii) The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variables.

a. For every one unit change in nox, the log odds of crime rate above median value incremases by 53.41.

b. For a one unit increase in dis, the log odds of crime rate above median value incremases by 0.80.

c. For a one unit increase in rad, the log odds of crime rate above median value incremases by 0.72.

d. For a one unit increase in tax, the log odds of crime rate above median value incremases by -0.007.

e. For a one unit increase in ptratio, the log odds of crime rate above median value incremases by 0.44.

f. For a one unit increase in medv , the log odds of crime rate above median value incremases by 0.23.

### 3.1.2 Model two with step function (backward process) with all given variables

```
##
## Call:
## glm(formula = target ~ zn + nox + age + dis + rad + tax + ptratio +
##     black + lstat + medv, family = "binomial", data = city_crime_train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9258  -0.1459  -0.0024   0.0013   3.3934
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -39.282116   7.705519  -5.098 3.43e-07 ***
## zn           -0.064656   0.037414  -1.728 0.083964 .
## nox          46.617168   8.074920   5.773 7.78e-09 ***
## age           0.025273   0.013545   1.866 0.062065 .
## dis           0.710480   0.249767   2.845 0.004447 **
```

```
## rad           0.775881   0.182072   4.261 2.03e-05 ***
## tax          -0.009144   0.003082  -2.967 0.003011 **
## ptratio       0.359297   0.135081   2.660 0.007817 **
## black        -0.008384   0.005737  -1.462 0.143871
## lstat         0.110624   0.055650   1.988 0.046829 *
## medv          0.181460   0.053572   3.387 0.000706 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 514.63  on 371  degrees of freedom
## Residual deviance: 142.85  on 361  degrees of freedom
## AIC: 164.85
##
## Number of Fisher Scoring iterations: 9
```

**Interpretation for model 2**

(i)It can be seen that zn,age,black are not statistically significant.

(ii)As for the statistically significant variables, nox has the lowest p-value suggesting a strong association of the nox of the target varible. other important varibles are dis,rad,tax,ptratio,medv,lstat. AIC value for the model1 =164.85

(iii) The logistic regression coefficients give the change in the log odds of the outcome for a one unit increase in the predictor variables.

a. For every one unit change in nox, the log odds of crime rate above median value incremases by 46.61.

b. For a one unit increase in dis, the log odds of crime rate above median value incremases by 0.71.

c. For a one unit increase in rad, the log odds of crime rate above median value incremases by 0.77.

d. For a one unit increase in tax, the log odds of crime rate above median value incremases by -0.009.

e. For a one unit increase in ptratio, the log odds of crime rate above median value incremases by 0.35.

f. For a one unit increase in medv , the log odds of crime rate above median value incremases by 0.18

(iv) there were 9 ierations in backward steps before final model was selected

### 3.1.3 Model three with transformed variables

In this model, transformed variables are being used with the logic function.

```
##
## Call:
## glm(formula = target ~ . - zn - tax - lstat - medv, family = "binomial",
##     data = city_crime_train_mod)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.7883  -0.1410  -0.0026   0.0005   3.3645
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -68.319369  16.418997  -4.161 3.17e-05 ***
## indus        -0.001867   0.067017  -0.028 0.977778
## chas1         0.366993   0.849076   0.432 0.665577
## nox          56.080643  10.147964   5.526 3.27e-08 ***
## rm            2.995884   2.385419   1.256 0.209147
## age           0.043435   0.018166   2.391 0.016805 *
## dis           0.472036   0.331312   1.425 0.154231
## rad           0.838409   0.237364   3.532 0.000412 ***
## ptratio       0.468316   0.176293   2.656 0.007896 **
## black        -0.010739   0.005922  -1.813 0.069782 .
## tax_new      -0.005285   0.003663  -1.443 0.149151
## medv_new      0.283102   0.106228   2.665 0.007698 **
## lstat_new     0.050027   0.074958   0.667 0.504515
## rm_new       -5.052053   2.830695  -1.785 0.074304 .
## dis_new      -1.886385   0.552223  -3.416 0.000636 ***
## zn_new1      -0.363834   1.036508  -0.351 0.725574
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 514.63  on 371  degrees of freedom
## Residual deviance: 124.11  on 356  degrees of freedom
## AIC: 156.11
##
## Number of Fisher Scoring iterations: 9
```

**Interpretation for model 3**

(i)From this model it can be seen following variables are relevant for this model-nox, dis, rad, ptratio , tax_new, medv_new,lstat_new
(ii) number of integration is 9 and AIC value =169.71.

**Notes: Similar explanation of model coefficient will be applicable here as described for model 1 & 2 and is not repreated here.**

### 3.1.4 Model with transformed variable and with with backward step function

In this model, transformed variables are being used with the step function and backward process.

```
##
## Call:
## glm(formula = target ~ nox + age + dis + rad + ptratio + black +
##     tax_new + medv_new + rm_new + dis_new, family = "binomial",
##     data = city_crime_train_mod)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0158  -0.1472  -0.0031   0.0005   3.1030
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -52.779764   9.739144  -5.419 5.98e-08 ***
## nox          56.509319   9.188179   6.150 7.74e-10 ***
## age           0.051467   0.016215   3.174 0.001503 **
## dis           0.564992   0.255943   2.207 0.027280 *
## rad           0.849127   0.212643   3.993 6.52e-05 ***
## ptratio       0.533319   0.159365   3.347 0.000818 ***
## black        -0.010960   0.005943  -1.844 0.065147 .
## tax_new      -0.004534   0.003144  -1.442 0.149355
## medv_new      0.342778   0.095427   3.592 0.000328 ***
## rm_new       -2.358513   1.028472  -2.293 0.021835 *
## dis_new      -1.865533   0.488896  -3.816 0.000136 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 514.63  on 371  degrees of freedom
## Residual deviance: 126.80  on 361  degrees of freedom
## AIC: 148.8
##
## Number of Fisher Scoring iterations: 9
```

**Interpretation for model 4**

(i)From this model it can be seen following variables are relevant for this model-nox, dis, rad, ptratio , tax_new, medv_new,lstat_new
(ii) number of integration is 9 and AIC value =165.8.

### 3.1,5 Model three with Linear discrement analysis

In this model Linear discrement analysis function has been used with given set of variables in traning data.

```
## Call:
## lda(target ~ ., data = city_crime_train)
##
## Prior probabilities of groups:
##         0         1
## 0.5268817 0.4731183
##
## Group means:
##          zn     indus      chas1       nox       rm      age      dis
## 0 22.012755  6.956327 0.05102041 0.4689730 6.401296 50.37398 5.086538
## 1  1.613636 15.291193 0.07954545 0.6428523 6.176631 86.38864 2.459868
##         rad      tax  ptratio    black     lstat     medv
## 0  4.107143 308.4949 17.76990 388.6647  9.199235 25.18724
## 1 14.880682 509.6932 18.74773 327.2894 15.959148 20.24148
##
```

```
## Coefficients of linear discriminants:
##                   LD1
## zn      -0.0047914631
## indus    0.0281044279
## chas1   -0.0556293189
## nox      7.9109306913
## rm       0.1658180998
## age      0.0131973114
## dis      0.0840623852
## rad      0.1027832012
## tax     -0.0019152605
## ptratio  0.0090391049
## black   -0.0009160458
## lstat    0.0248449648
## medv     0.0425514709
```

**Interpretation for model 5**

### 3.1.6 Model with Linear discrement analysis with transformed data

In this model Linear discrement analysis function has been used with transformed set of variables in traning data.

```
## Call:
## lda(target ~ . - zn - rm - dis - tax - lstat - medv, data = city_crime_train_mod)
##
## Prior probabilities of groups:
##         0         1
## 0.5268817 0.4731183
##
## Group means:
##       indus      chas1       nox      age       rad  ptratio    black
## 0  6.956327 0.05102041 0.4689730 50.37398  4.107143 17.76990 388.6647
## 1 15.291193 0.07954545 0.6428523 86.38864 14.880682 18.74773 327.2894
##    tax_new medv_new lstat_new      rm_new    dis_new    zn_new1
## 0 308.4949 25.04528  9.199235  0.08333182 -0.0504096 0.46938776
## 1 509.6932 19.86151 15.724247 -0.11166891  0.5106930 0.07954545
##
## Coefficients of linear discriminants:
##                    LD1
## indus      0.022452946
## chas1     -0.186416323
## nox        7.970446650
## age        0.015169354
## rad        0.100159450
## ptratio   -0.014404341
## black     -0.001159202
## tax_new   -0.001196341
## medv_new   0.047596449
## lstat_new  0.016840318
## rm_new    -0.008946209
## dis_new   -0.340985994
```

```
## zn_new1   -0.001832533
```

**Interpretation for model 6**

# 4 Model Selection

In section we will further examine all six models. We will apply a model selection strategy defined below to compare the models.

## 4.1 Model selection strategy:

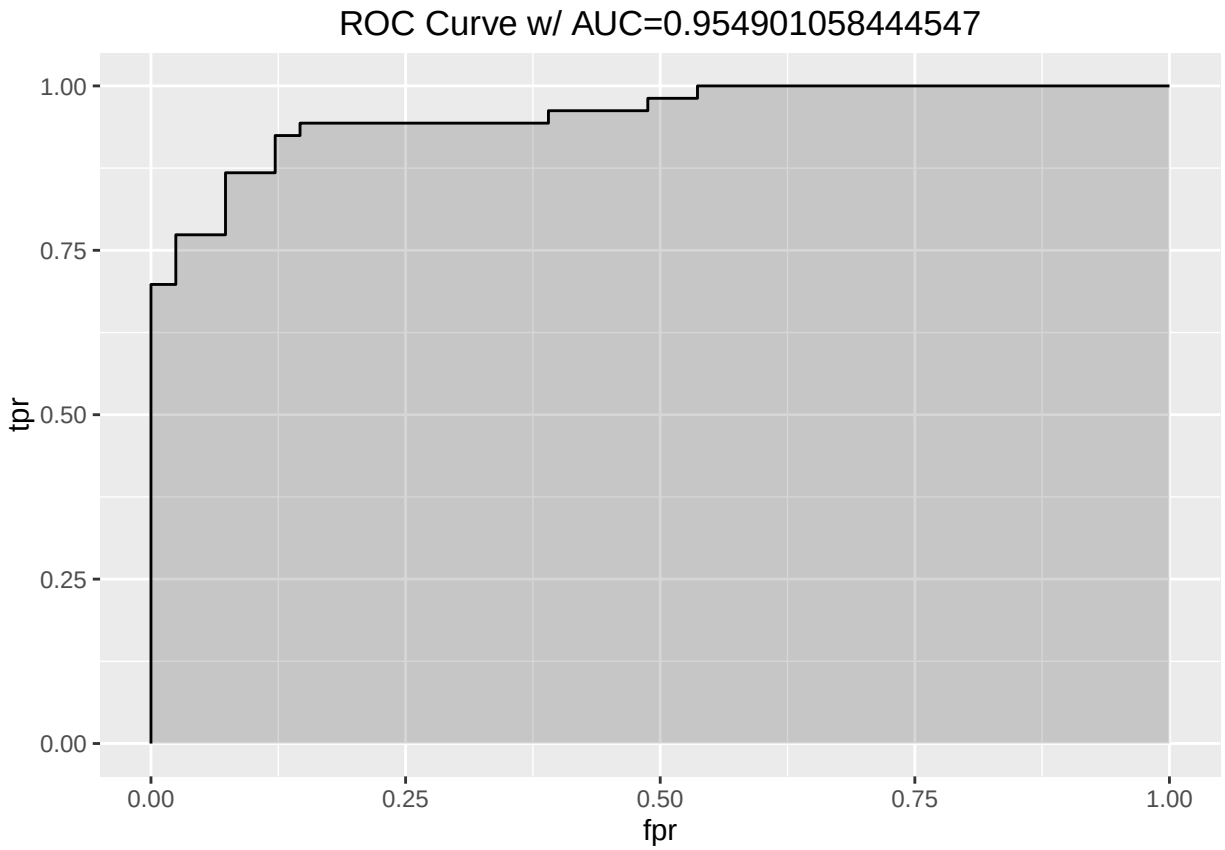
Following model selection strategy has been used for this assignment:

(i) Compare accuracy of the models & confusion matrix
(ii) Compare Precision,Sensitivity,Specificity,F1 score
(iii) Compare AUC curve for the models

Following function Eval() will be used to calculate various metrics related to the model like Accuracy, Sensitivity, Precision , Specificity and F1 score

### 4.1.1 Model1 Evaluation

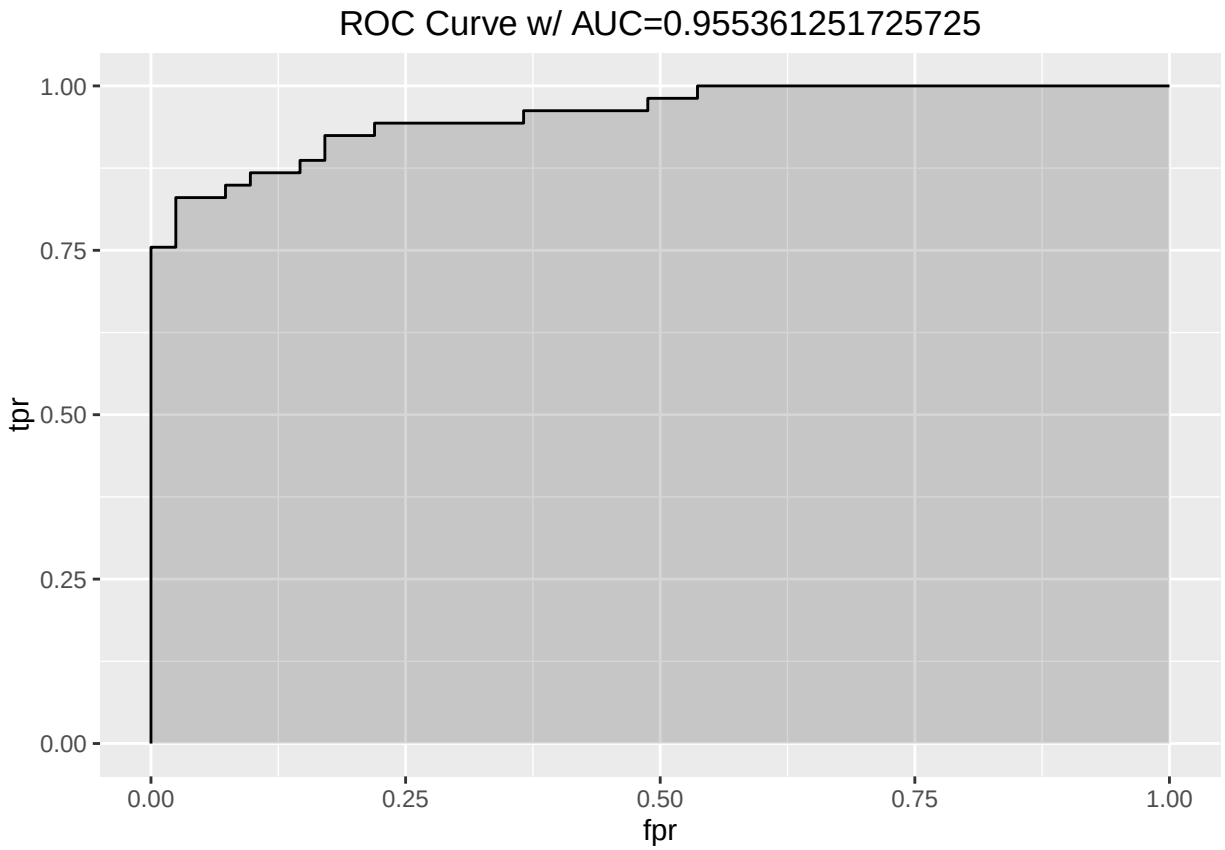
```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.9042553 0.09574468 0.9245283   0.9074074         0.9 0.9283174
```




Looking at the key metrics this can be concluded this model has high accuracy 0.9042553 and low error rate 0.09574468. AUC for this model is 0.9549 which is very good. the optimal value for AUC is (0,1) closer) it goes to 1 values better the model outcome is.

### 4.1.2 Model2 Evaluation

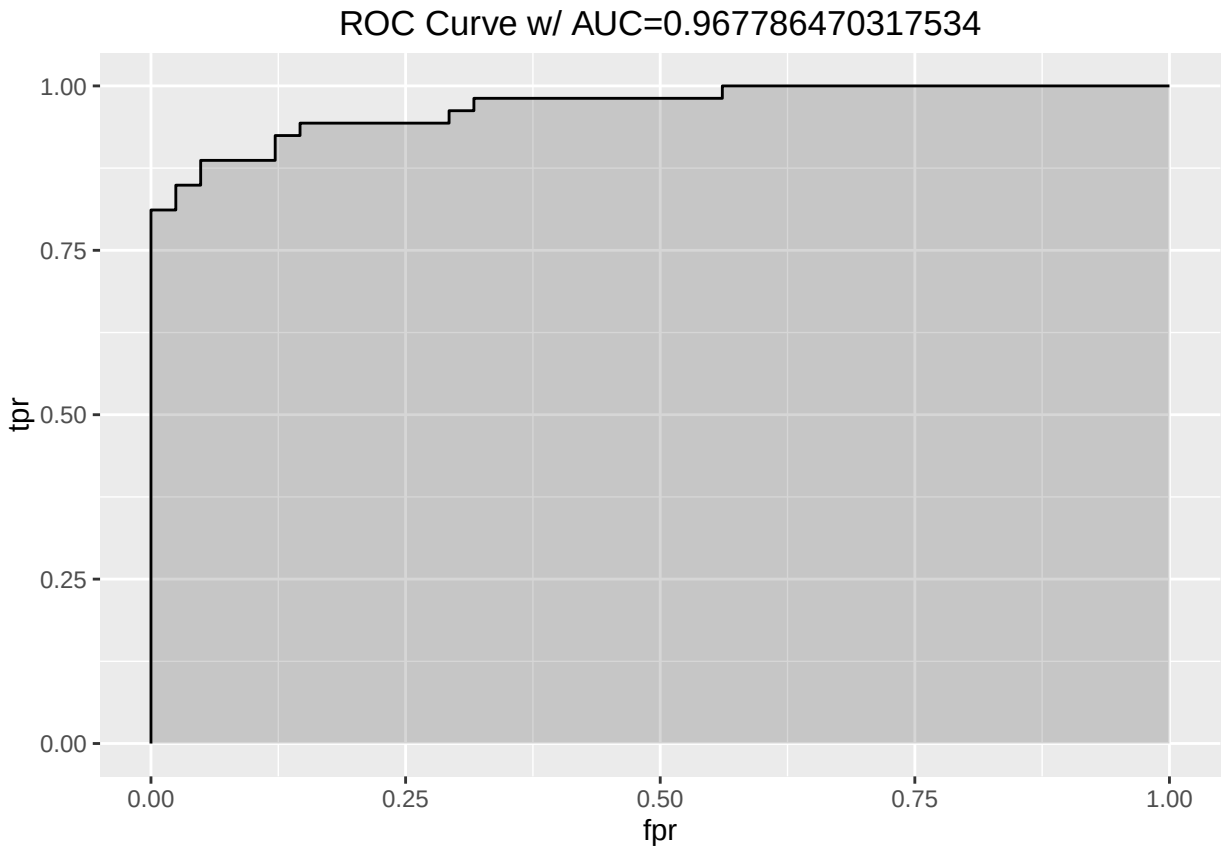
```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.8723404  0.1276596 0.9056604   0.8727273   0.8717949 0.9061444
```




Looking at the key metrics this can be concluded this model has high accuracy 0.8723404 and low error rate 0.12765957.AUC curve for this model is 0.9553 which is very good.

### 4.1.3 Model3 Evaluation

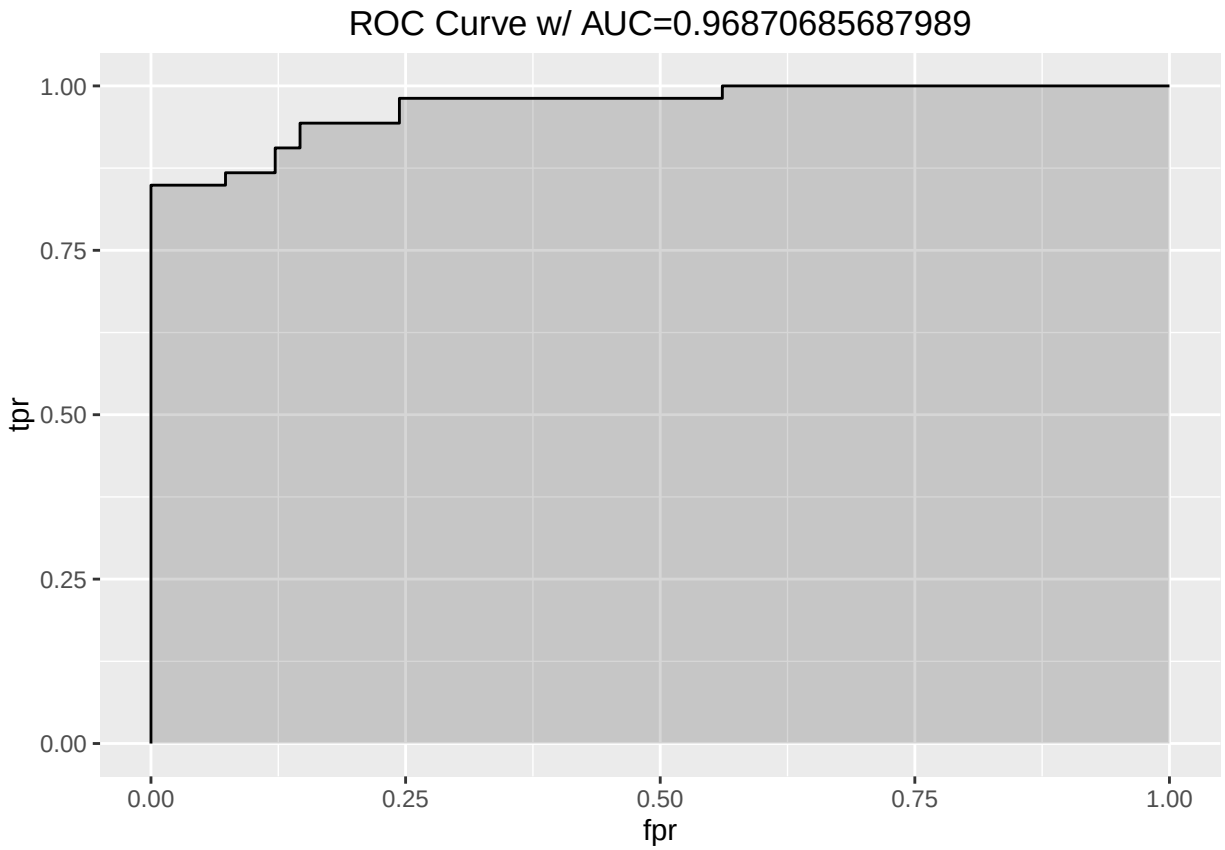
```
##   Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.893617   0.106383 0.9245283   0.8909091   0.8974359 0.9211541
```




Looking at the key metrics this can be concluded this model has high accuracy 0.8936170and low error rate 0.10638298.AUC curve for this model is 0.9558 which is very good.

### 4.1.4 Model4 Evaluation

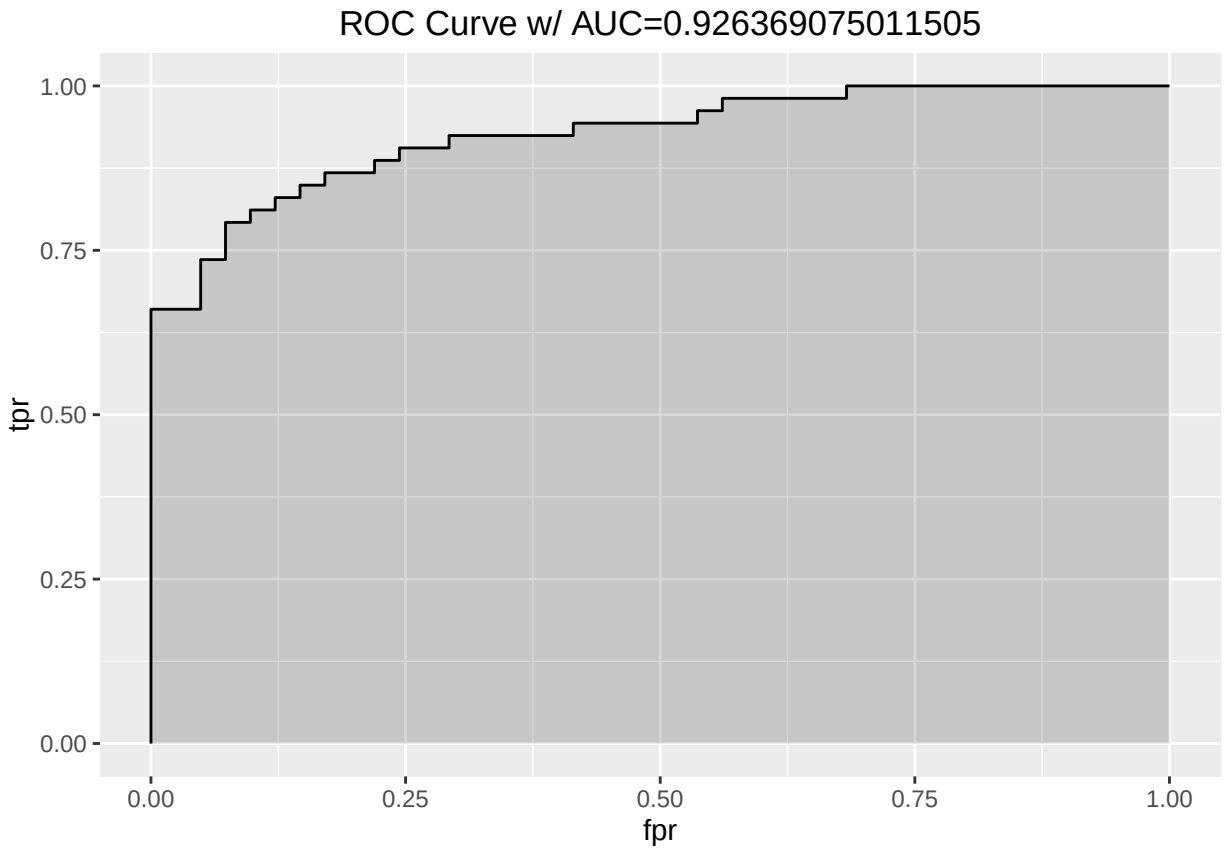
```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.8829787  0.1170213 0.9056604   0.8888889       0.875 0.9127916
```




Looking at the key metrics this can be concluded this model has high accuracy 0.8829787 and low error rate 0.11702128.AUC curve for this model is 0.9549 which is very good.

### 4.1.5 Model5 Evaluation

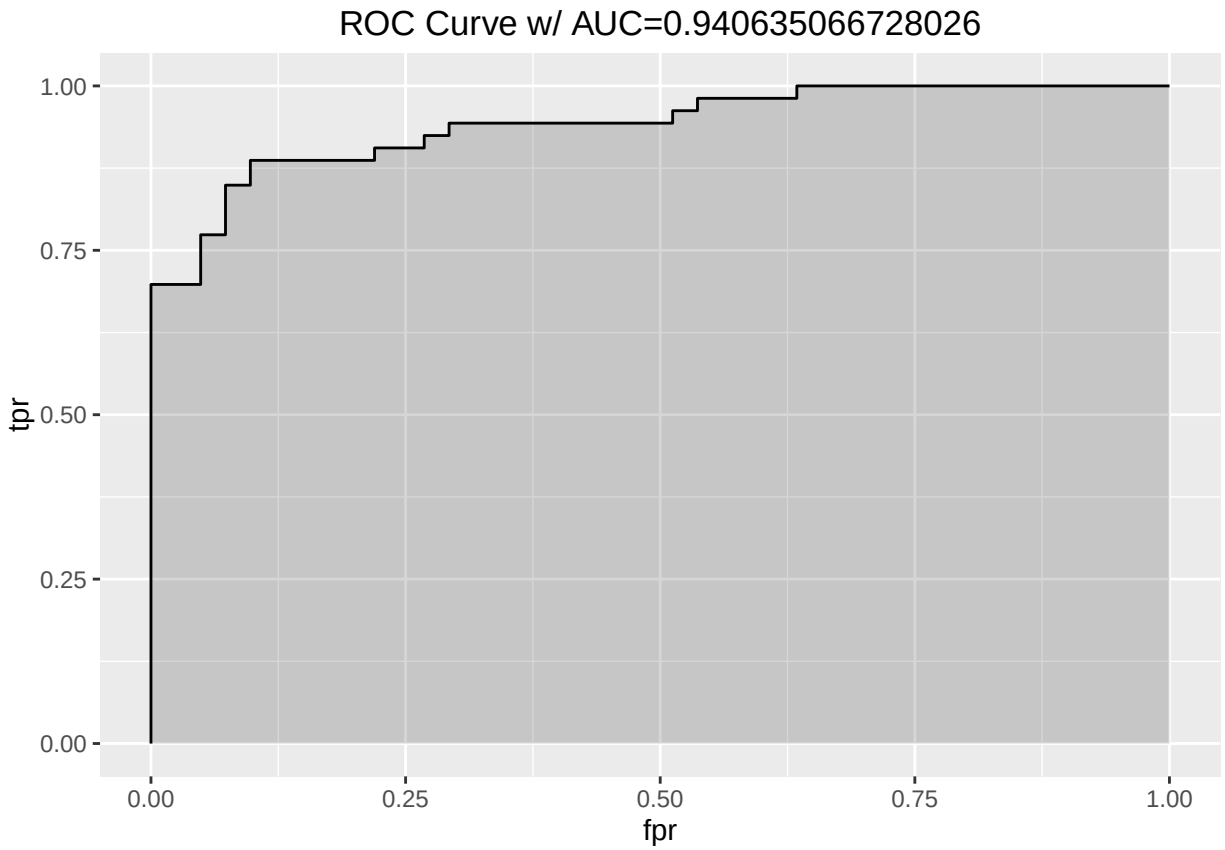
```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.8297872  0.1702128 0.7358491   0.9512195   0.7358491 0.8297872
```




Looking at the key metrics this can be concluded this model has relatively low accuracy0.8297872 and higher error rate 0.1702127 compared to other models.AUC curve for this model is 0.9263.

### 4.1.6 Model6 Evaluation

```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.8297872  0.1702128 0.7358491   0.9512195   0.7358491 0.8297872
```




Looking at the key metrics this can be concluded this model has relatively low accuracy 0.8297872 and higher error rate 0.17021277 compared to other models.AUC curve for this model is 0.930.

## 4.2 Final Model Seletion

Following is the comparison of various metrics for above 6 models

```
##    Accuracy Error_Rate Precision sensitivity specificity  F1_Score
## 1 0.9042553 0.09574468 0.9245283   0.9074074   0.9000000 0.9283174
## 2 0.8723404 0.12765957 0.9056604   0.8727273   0.8717949 0.9061444
## 3 0.8936170 0.10638298 0.9245283   0.8909091   0.8974359 0.9211541
## 4 0.8829787 0.11702128 0.9056604   0.8888889   0.8750000 0.9127916
## 5 0.8297872 0.17021277 0.7358491   0.9512195   0.7358491 0.8297872
## 6 0.8297872 0.17021277 0.7358491   0.9512195   0.7358491 0.8297872
```

From the comparison table it can be concluded model 1 is the best model with very high accuracy rate of 90.42%. Further analysis has been carried out on this model below-
(i) Estimate confidence interval for coefficient (ii) wald test to understand effect of variable in the model (iii) odds ratios and 95% CI

```
##                      2.5 %        97.5 %
## (Intercept) -57.633422451 -2.529088e+01
## zn           -0.137318897  1.615847e-02
## indus        -0.180179675  5.240896e-02
```

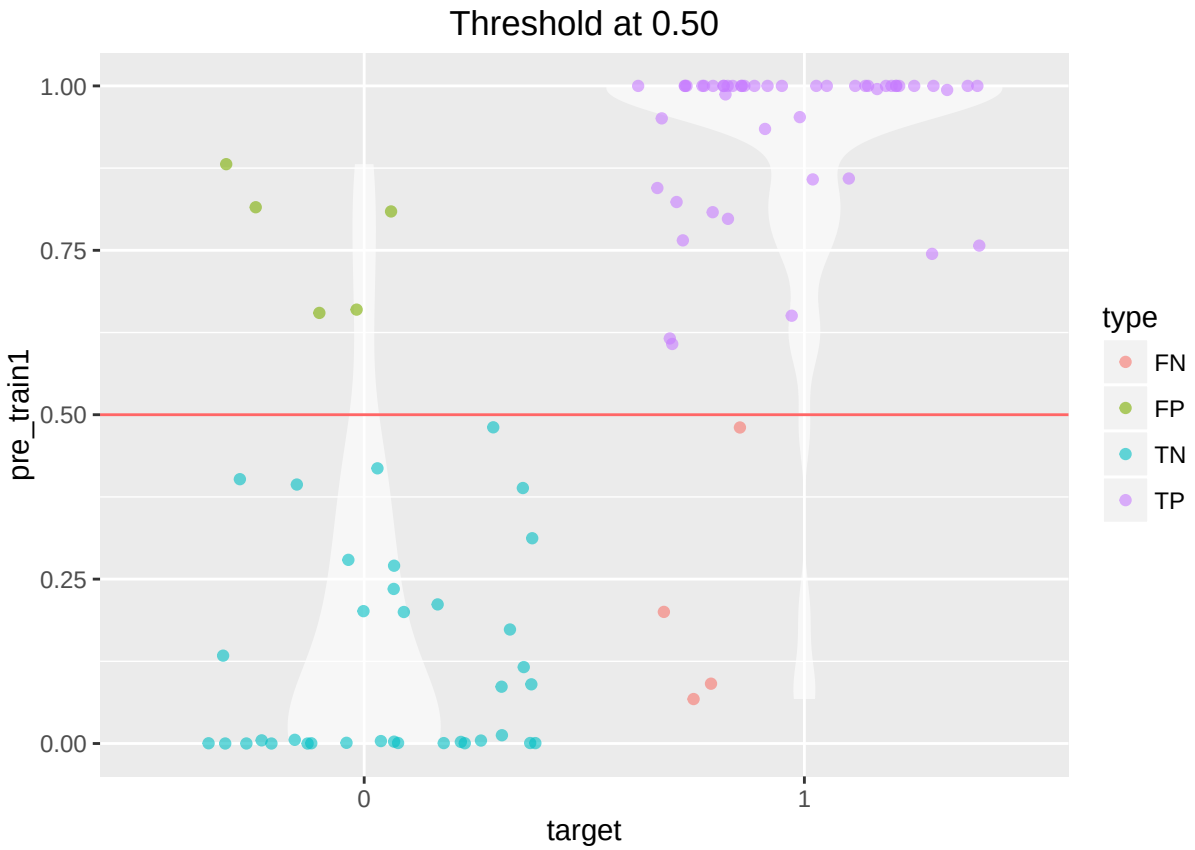
```
## chas1        -0.907581097  2.486362e+00
## nox          33.787078022  7.303993e+01
## rm           -2.420592622  1.124709e+00
## age          -0.001896677  5.956762e-02
## dis           0.273928524  1.327906e+00
## rad           0.338261333  1.105240e+00
## tax          -0.013905482 -2.242516e-04
## ptratio       0.128416628  7.531198e-01
## black        -0.021400089  2.217745e-03
## lstat        -0.025418331  2.193000e-01
## medv          0.058041222  4.158385e-01
```

```
## Wald test:
## ----------
##
## Chi-squared test:
## X2 = 13.6, df = 1, P(> X2) = 0.00023
```

```
##                       OR        2.5 %       97.5 %
## (Intercept) 9.844998e-19 9.335179e-26 1.038266e-11
## zn          9.412183e-01 8.716922e-01 1.016290e+00
## indus       9.381125e-01 8.351201e-01 1.053807e+00
## chas1       2.202054e+00 4.034991e-01 1.201748e+01
## nox         1.574670e+23 4.715650e+14 5.258208e+31
## rm          5.231212e-01 8.886894e-02 3.079319e+00
## age         1.029255e+00 9.981051e-01 1.061378e+00
## dis         2.227583e+00 1.315121e+00 3.773133e+00
## rad         2.058033e+00 1.402507e+00 3.019950e+00
## tax         9.929600e-01 9.861908e-01 9.997758e-01
## ptratio     1.553900e+00 1.137027e+00 2.123615e+00
## black       9.904547e-01 9.788273e-01 1.002220e+00
## lstat       1.101795e+00 9.749020e-01 1.245205e+00
## medv        1.267365e+00 1.059759e+00 1.515641e+00
```

The chi-squared test statistic of 13.6 , with one degrees of freedom is associated with a p-value of 0.00023 indicating that the overall effect of tax is statistically significant.

odds ratios and 95% CI
# Distribution of the Predictions




Cconsidering the target has value 1 (crime above median) and 0 when crime is below median, then the above plot illustrates the tradeoff that to be made upon choosing a reasonable threshold. If treshold is increased the the number of false positive (FP) results is lowered, while the number of false negative (FN) results increases.