

Home Work Assignment - 03

Critical Thinking Group 5

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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)

##	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      black      lstat
## Min.    :187.0   Min.    :12.6    Min.    : 0.32    Min.    : 1.730
## 1st Qu.:281.0   1st Qu.:16.9    1st Qu.:375.61   1st Qu.: 7.043
## Median :334.5   Median :18.9    Median :391.34   Median :11.350
## Mean    :409.5   Mean    :18.4    Mean    :357.12   Mean    :12.631
## 3rd Qu.:666.0   3rd Qu.:20.2    3rd Qu.:396.24   3rd Qu.:16.930
## Max.    :711.0   Max.    :22.0    Max.    :396.90   Max.    :37.970
##      medv      target
## Min.    : 5.00   Min.    :0.0000
## 1st Qu.:17.02   1st Qu.:0.0000
## Median :21.20   Median :0.0000
## Mean    :22.59   Mean    :0.4914
## 3rd Qu.:25.00   3rd Qu.:1.0000
## Max.    :50.00   Max.    :1.0000

## 'data.frame': 40 obs. of 13 variables:
## $ zn      : int 0 0 0 0 0 25 25 0 0 0 ...
## $ indus   : num 7.07 8.14 8.14 8.14 5.96 5.13 5.13 4.49 4.49 2.89 ...
## $ chas    : int 0 0 0 0 0 0 0 0 0 0 ...
## $ nox     : num 0.469 0.538 0.538 0.538 0.499 0.453 0.453 0.449 0.449 0.445 ...
## $ rm      : num 7.18 6.1 6.5 5.95 5.85 ...
## $ age     : num 61.1 84.5 94.4 82 41.5 66.2 93.4 56.1 56.8 69.6 ...
## $ dis     : num 4.97 4.46 4.45 3.99 3.93 ...
## $ rad     : int 2 4 4 4 5 8 8 3 3 2 ...
## $ tax     : int 242 307 307 307 279 284 284 247 247 276 ...
## $ ptratio: num 17.8 21 21 21 19.2 19.7 19.7 18.5 18.5 18 ...
## $ black   : num 393 380 388 233 397 ...
## $ lstat   : num 4.03 10.26 12.8 27.71 8.77 ...
## $ medv    : num 34.7 18.2 18.4 13.2 21 18.7 16 26.6 22.2 21.4 ...

```

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.

Table 2: 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

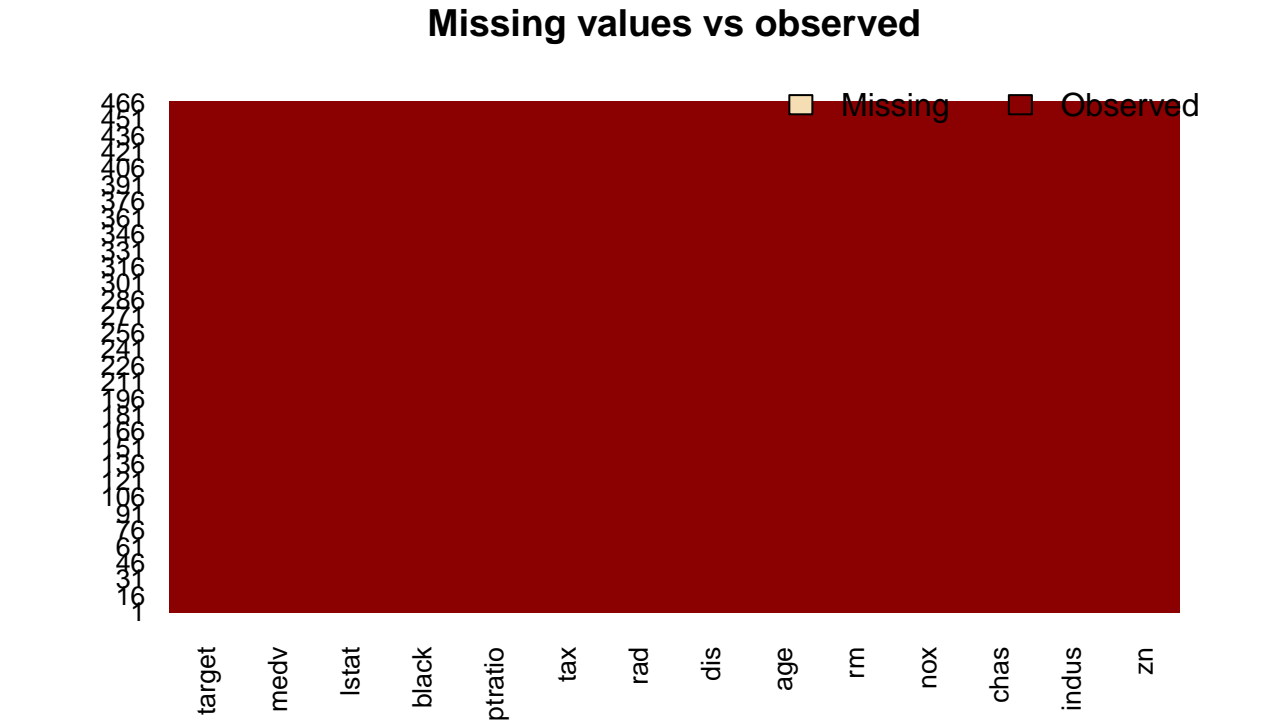


Table 3: Unique Values

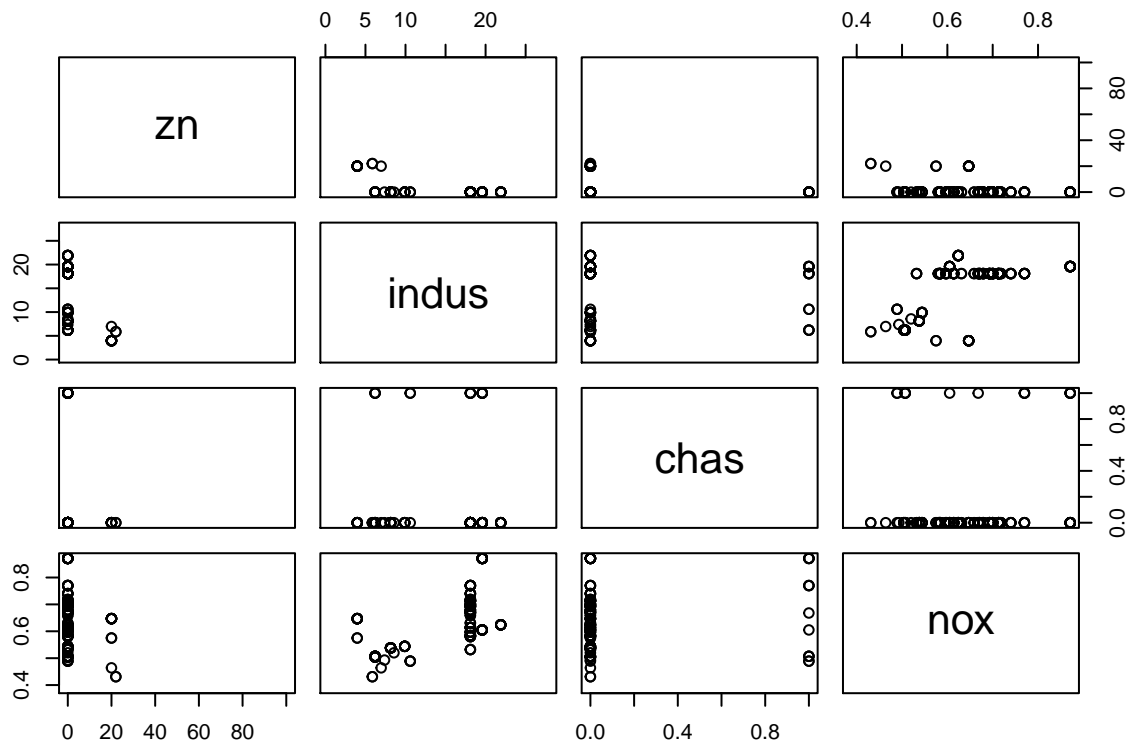
zn	26
indus	73
chas	2
nox	79
rm	419
age	333
dis	380
rad	9
tax	63
ptratio	46
black	331
lstat	424
medv	218
target	2

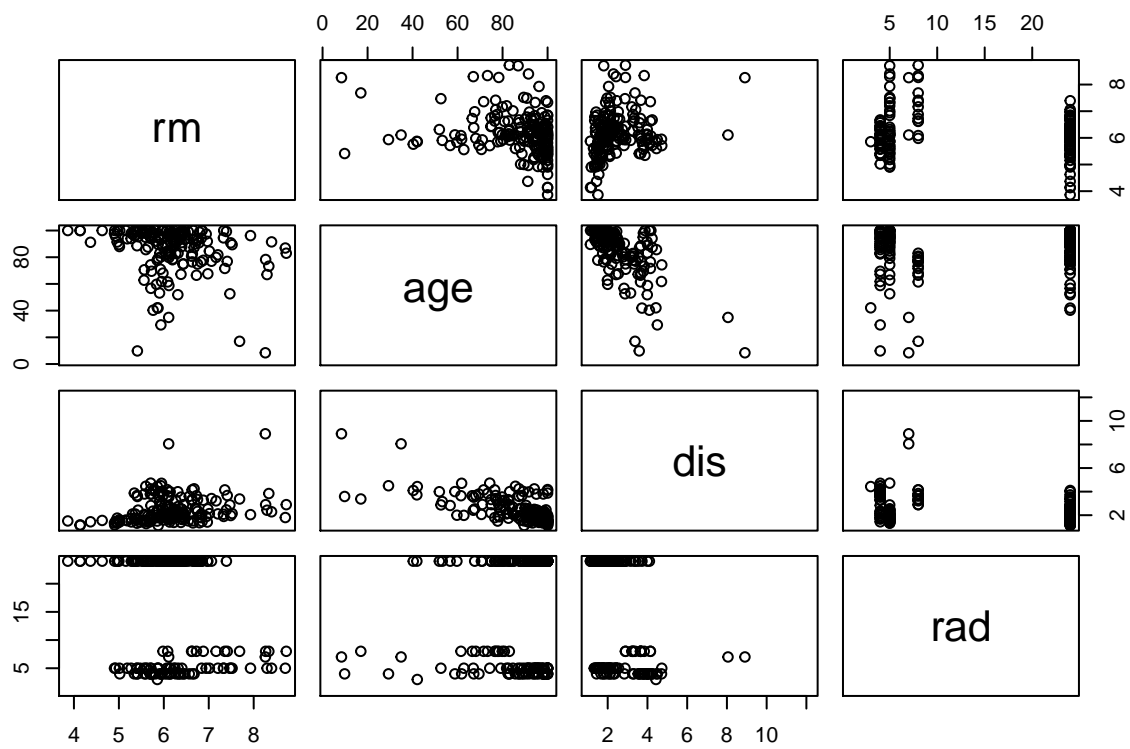
```
##
##      0      1
## 0.5085837 0.4914163
```

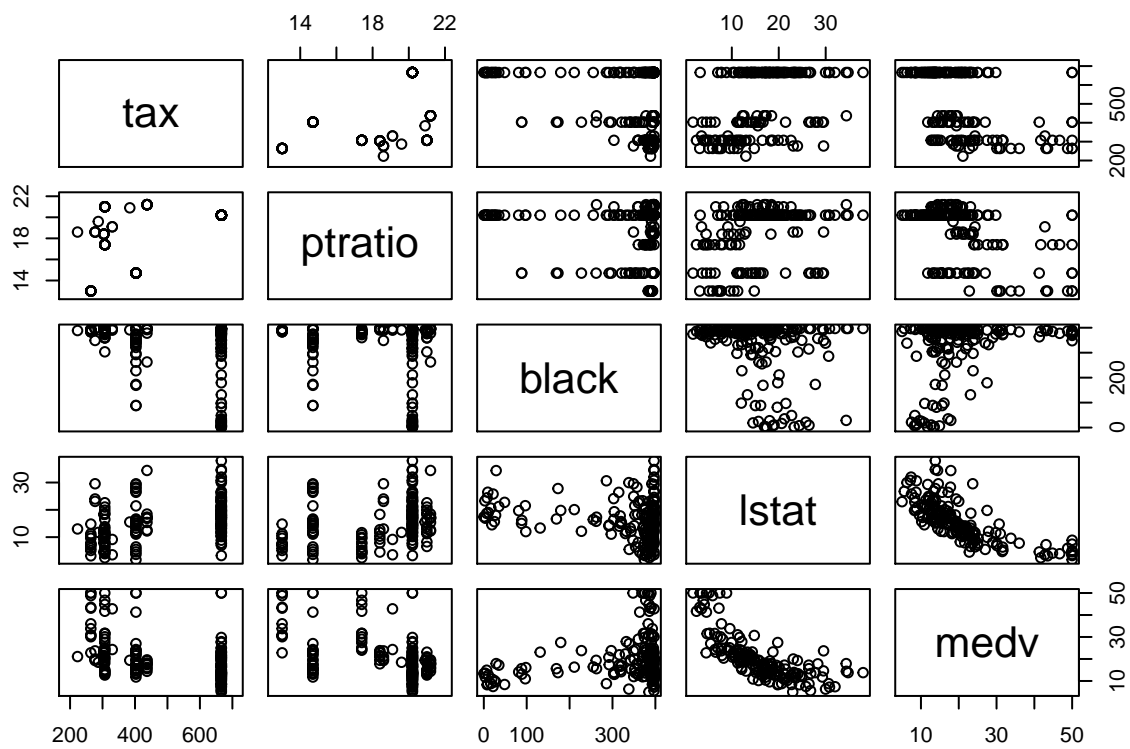
Based on the analysis above it can be seen that there is no missing value in the data set. Also count of unqiue values for each variable is shown above. Also % split of target variable is given above table which shows data is almost evanly split between binary outcome 0 and 1.

Train data set will be Split into train data(80% of train set) and validation set (20% of train set)to evalute the performnce 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.







1.2 Data Summary Analysis

In this section, we will create summary data to better understand the initial relationship variables have with our dependent variable using correlation, central tendency, and dispersion As shown in table 2.

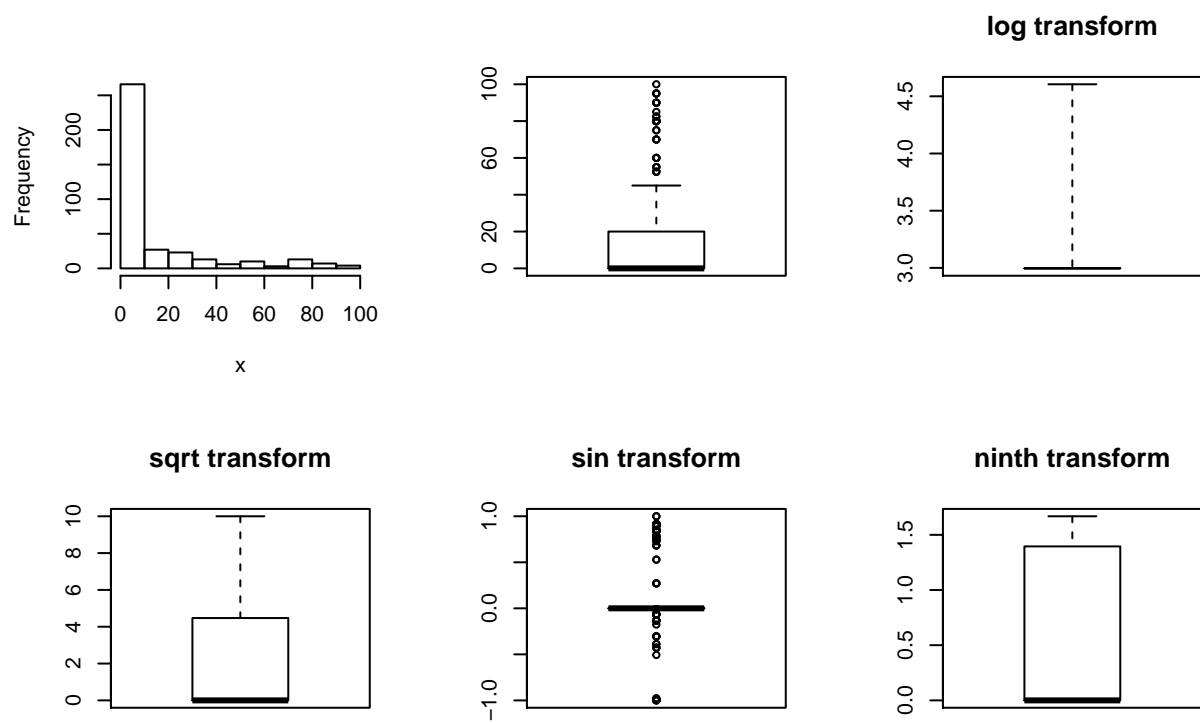
##	vars	n	mean	sd	median	trimmed	mad	min	max	range
## zn	1	372	12.36	24.06	0.00	6.04	0.00	0.00	100.00	100.00
## indus	2	372	10.90	6.90	8.56	10.66	7.90	0.46	27.74	27.28
## chas	3	372	0.06	0.25	0.00	0.00	0.00	0.00	1.00	1.00
## nox	4	372	0.55	0.12	0.52	0.54	0.12	0.39	0.87	0.48
## rm	5	372	6.30	0.70	6.21	6.27	0.53	3.86	8.72	4.86
## age	6	372	67.41	28.69	76.50	69.83	30.91	2.90	100.00	97.10
## dis	7	372	3.84	2.13	3.32	3.60	2.05	1.13	12.13	11.00
## rad	8	372	9.20	8.54	5.00	8.28	1.48	1.00	24.00	23.00
## tax	9	372	403.69	167.05	330.00	394.00	108.23	187.00	711.00	524.00
## ptratio	10	372	18.23	2.22	18.60	18.41	2.37	12.60	22.00	9.40
## black	11	372	359.63	88.60	391.96	384.77	7.33	0.32	396.90	396.58
## lstat	12	372	12.40	7.03	10.93	11.62	6.77	1.73	37.97	36.24
## medv	13	372	22.85	9.07	21.60	21.98	6.97	5.00	50.00	45.00
## target	14	372	0.47	0.50	0.00	0.47	0.00	0.00	1.00	1.00
##	skew	kurtosis	se							
## zn	2.05	3.20	1.25							
## indus	0.34	-1.21	0.36							
## chas	3.53	10.50	0.01							
## nox	0.84	0.09	0.01							
## rm	0.39	1.48	0.04							
## age	-0.53	-1.09	1.49							
## dis	0.96	0.38	0.11							
## rad	1.10	-0.67	0.44							
## tax	0.72	-1.05	8.66							
## ptratio	-0.67	-0.52	0.12							
## black	-3.10	8.55	4.59							
## lstat	0.95	0.60	0.36							
## medv	0.97	1.11	0.47							
## target	0.11	-1.99	0.03							

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

1.3 Outliers and Missing Values Identification

In this section univariate analysis is being carried 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, Histogram, 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 the 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 like 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 left 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 purging the below steps as guidelines:

- Outliers treatment
- Missing values treatment
- Data transformation

2.1 Outliers treatment and transformation

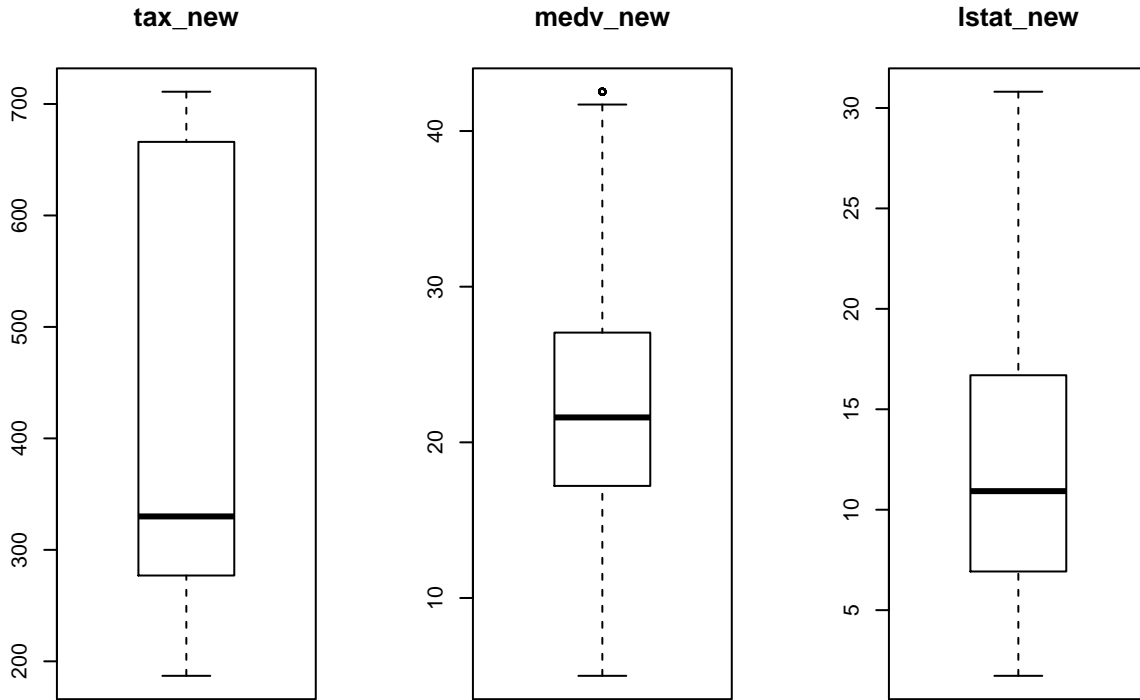
For outliers, we will create 2 sets of variables.

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$tax_new city_crime_train$medv_new
city_crime_train$lstat_new
```

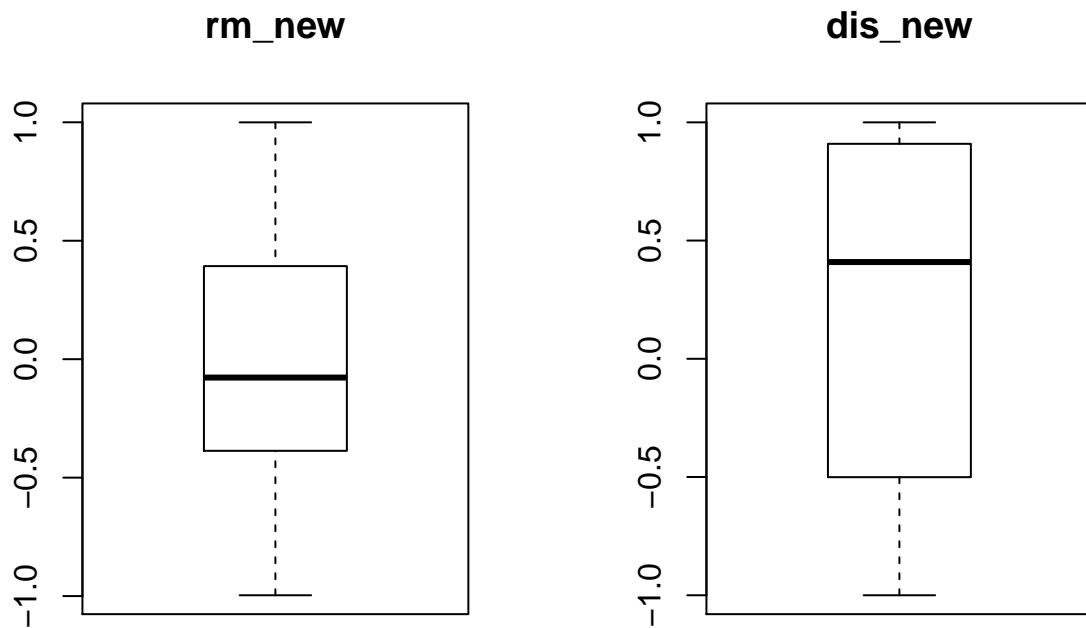
Below boxplots shows distribution of variables after outliers treatment.



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

```
city_crime_train_mod$rm_new city_crime_train_mod$oddis_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 variable of 0 and 1
3. Converting target to a factor variable 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

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

3.1.1 Model One by using all given variable

In this model, we will be using the original variables. We will create model and we will highlight the variables that being recommended using the AIC value.

First we will produce the summary model as per below:

```
##
## 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
## chas        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

## (Intercept)          zn          indus          chas          nox
## 9.844998e-19 9.412183e-01 9.381125e-01 2.202054e+00 1.574670e+23
##          rm          age          dis          rad          tax
## 5.231212e-01 1.029255e+00 2.227583e+00 2.058033e+00 9.929600e-01
##          ptratio        black          lstat          medv
## 1.553900e+00 9.904547e-01 1.101795e+00 1.267365e+00
```

model interpretation for model 1

Below we analyze and the fitting and interpret what the model is telling us.

- i. First of all, we can see 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 variable. other important variables 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 backward step function with all given variables

```
stepmodel1 <- step(model1, direction="backward")

## Start:  AIC=168.71
## target ~ zn + indus + chas + nox + rm + age + dis + rad + tax +
##          ptratio + black + lstat + medv
##
##           Df Deviance    AIC
## - rm       1   141.22 167.22
## - chas     1   141.55 167.55
## - indus    1   141.93 167.93
## <none>      140.71 168.71
## - lstat    1   143.06 169.06
## - black    1   143.68 169.68
## - zn       1   143.99 169.99
## - age      1   144.45 170.45
## - tax      1   144.93 170.93
## - medv     1   148.67 174.67
## - ptratio  1   149.29 175.29
## - dis      1   150.97 176.97
## - rad      1   171.94 197.94
## - nox      1   195.65 221.65
##
## Step:  AIC=167.22
## target ~ zn + indus + chas + nox + age + dis + rad + tax + ptratio +
##          black + lstat + medv
```

```
##
##           Df Deviance    AIC
## - chas      1   142.10 166.10
## - indus      1   142.37 166.37
## <none>       141.22 167.22
## - black      1   144.02 168.02
## - age        1   144.48 168.48
## - zn         1   144.74 168.74
## - lstat      1   145.13 169.13
## - tax        1   145.97 169.97
## - ptratio    1   149.78 173.78
## - dis        1   150.97 174.97
## - medv       1   156.73 180.73
## - rad        1   172.26 196.26
## - nox        1   196.29 220.29
##
## Step: AIC=166.1
## target ~ zn + indus + nox + age + dis + rad + tax + ptratio +
##         black + lstat + medv
##
##           Df Deviance    AIC
## - indus      1   142.85 164.85
## <none>       142.10 166.10
## - black      1   144.69 166.69
## - age        1   145.65 167.65
## - zn         1   146.09 168.09
## - lstat      1   146.43 168.43
## - tax        1   148.34 170.34
## - ptratio    1   149.90 171.90
## - dis        1   151.42 173.42
## - medv       1   157.16 179.16
## - rad        1   177.68 199.68
## - nox        1   196.44 218.44
##
## Step: AIC=164.85
## target ~ zn + nox + age + dis + rad + tax + ptratio + black +
##         lstat + medv
##
##           Df Deviance    AIC
## <none>       142.85 164.85
## - black      1   145.21 165.21
## - age        1   146.69 166.69
## - lstat      1   146.75 166.75
## - zn         1   146.89 166.89
## - ptratio    1   150.46 170.46
## - dis        1   151.87 171.87
## - tax        1   154.08 174.08
## - medv       1   157.59 177.59
## - rad        1   184.71 204.71
## - nox        1   203.12 223.12
```

```
summary(stepmodel1)
```

```
##
```

```
## 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
```

model interpretation for model 2

Below we analyze and the fitting and interpret what the model is telling us.

i. First of all, we can see 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 variable. Other important variables 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 increases by 46.61.
- b. For a one unit increase in dis, the log odds of crime rate above median value increases by 0.71.
- c. For a one unit increase in rad, the log odds of crime rate above median value increases by 0.77.
- d. For a one unit increase in tax, the log odds of crime rate above median value increases by -0.009.
- e. For a one unit increase in ptratio, the log odds of crime rate above median value increases 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 iterations in backward steps before final model was selected

3.1.3 Model three- model with transformed variables

In this model, we will be using the some transformed variables.

First we will produce the summary model as per below:

```
##
## 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_new       -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
```

3.1.4 Model with transformed variable and with with backward step function

```
stepmodel2<- step(model2, direction="backward")
```

```
## Start: AIC=156.11
## target ~ (zn + indus + chas + nox + rm + age + dis + rad + tax +
##          ptratio + black + lstat + medv + tax_new + medv_new + lstat_new +
##          rm_new + dis_new + zn_new) - zn - tax - lstat - medv
##
##              Df Deviance    AIC
## - indus      1   124.11 154.11
## - zn_new     1   124.24 154.24
## - chas       1   124.30 154.30
## - lstat_new  1   124.54 154.54
## - rm        1   125.88 155.88
## - dis       1   126.02 156.01
## <none>      1   124.11 156.11
## - tax_new   1   126.11 156.11
## - black     1   127.44 157.44
## - rm_new    1   127.97 157.97
## - age       1   130.93 160.93
## - ptratio   1   131.81 161.81
## - medv_new  1   132.41 162.41
## - dis_new   1   138.64 168.64
## - rad       1   149.17 179.17
## - nox       1   186.38 216.38
##
## Step: AIC=154.11
## target ~ chas + nox + rm + age + dis + rad + ptratio + black +
##          tax_new + medv_new + lstat_new + rm_new + dis_new + zn_new
##
##              Df Deviance    AIC
## - zn_new     1   124.24 152.24
## - chas       1   124.31 152.31
## - lstat_new  1   124.55 152.55
## - rm        1   125.88 153.88
## - dis       1   126.04 154.04
## <none>      1   124.11 154.11
## - tax_new   1   127.03 155.03
## - black     1   127.45 155.45
## - rm_new    1   127.97 155.97
## - age       1   130.96 158.96
## - ptratio   1   131.82 159.82
## - medv_new  1   132.55 160.55
## - dis_new   1   140.43 168.43
## - rad       1   155.61 183.61
## - nox       1   196.97 224.97
##
## Step: AIC=152.24
## target ~ chas + nox + rm + age + dis + rad + ptratio + black +
##          tax_new + medv_new + lstat_new + rm_new + dis_new
##
##              Df Deviance    AIC
## - chas       1   124.50 150.50
## - lstat_new  1   124.56 150.56
```

```

## - rm          1    125.97 151.97
## - dis          1    126.08 152.08
## <none>         1    124.24 152.24
## - tax_new      1    127.18 153.18
## - black        1    127.72 153.72
## - rm_new       1    128.22 154.22
## - age          1    131.29 157.29
## - medv_new     1    132.64 158.64
## - ptratio      1    134.36 160.36
## - dis_new      1    143.38 169.38
## - rad          1    157.08 183.08
## - nox          1    196.97 222.97
##
## Step:  AIC=150.5
## target ~ nox + rm + age + dis + rad + ptratio + black + tax_new +
##          medv_new + lstat_new + rm_new + dis_new
##
##           Df Deviance    AIC
## - lstat_new  1    124.91 148.91
## - rm         1    126.15 150.15
## - dis        1    126.19 150.19
## <none>        1    124.50 150.50
## - tax_new    1    127.58 151.58
## - black      1    127.91 151.91
## - rm_new     1    128.38 152.38
## - age        1    131.80 155.80
## - medv_new   1    133.04 157.04
## - ptratio    1    134.38 158.38
## - dis_new    1    144.36 168.36
## - rad        1    158.12 182.12
## - nox        1    196.98 220.98
##
## Step:  AIC=148.91
## target ~ nox + rm + age + dis + rad + ptratio + black + tax_new +
##          medv_new + rm_new + dis_new
##
##           Df Deviance    AIC
## - rm         1    126.80 148.80
## - dis        1    126.88 148.88
## <none>        1    124.91 148.91
## - tax_new    1    127.77 149.77
## - black      1    128.14 150.14
## - rm_new     1    130.21 152.21
## - medv_new   1    133.39 155.39
## - ptratio    1    135.25 157.25
## - age        1    135.57 157.57
## - dis_new    1    145.13 167.13
## - rad        1    159.22 181.22
## - nox        1    198.49 220.49
##
## Step:  AIC=148.8
## target ~ nox + age + dis + rad + ptratio + black + tax_new +
##          medv_new + rm_new + dis_new
##

```

##		Df	Deviance	AIC
##	<none>		126.80	148.80
##	- tax_new	1	129.00	149.00
##	- black	1	130.37	150.37
##	- dis	1	130.87	150.87
##	- rm_new	1	132.36	152.36
##	- age	1	138.72	158.72
##	- ptratio	1	139.68	159.68
##	- medv_new	1	142.98	162.98
##	- dis_new	1	146.97	166.97
##	- rad	1	160.12	180.12
##	- nox	1	203.79	223.79

3.1,5 Model three with Linear discrement analysis

3.1.6 Model with Linear discrement analysis with transformed data

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.

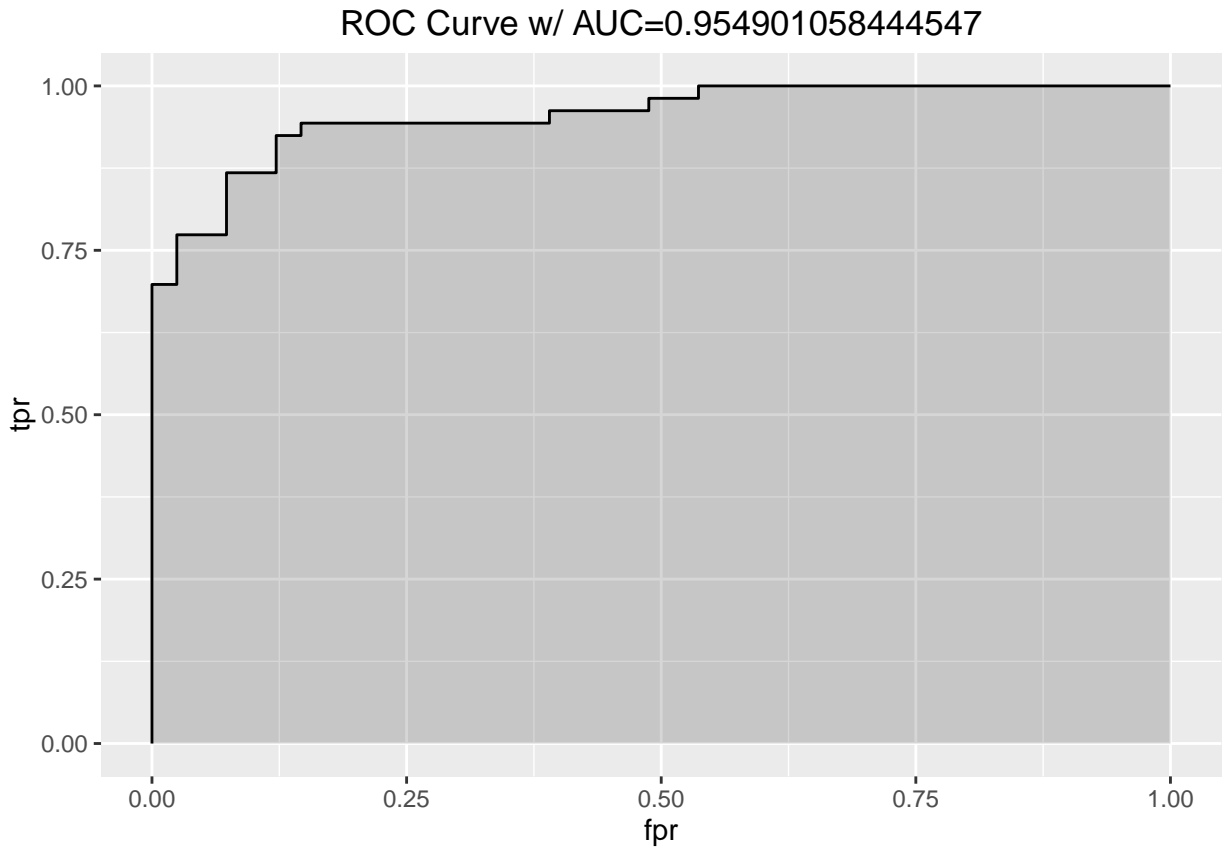
4.1 Model selection strategy:

Following model selection strategy has been used for this assignment:

- (1) Compare accuracy of the models & confusion matrix
- (2) Compare Precision,Sensitivity,Specificity,F1 score
- (3) Compare AUC curve for the models

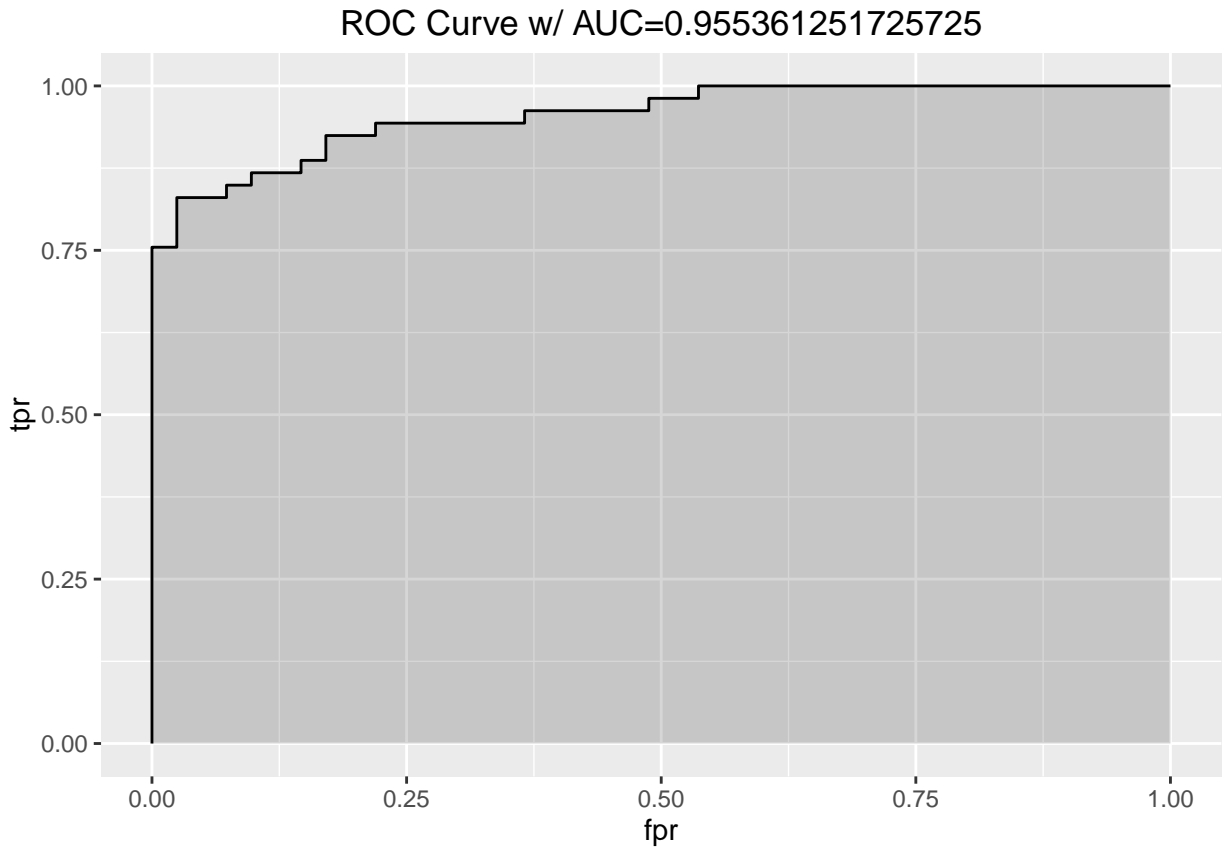
4.1.1 Model1 Evaluation

##	Accuracy	Error_Rate	Precision	sensitivity	specificity	F1_Score
## 1	0.5744681	0.4255319	0.9245283	0.5764706	0.5555556	0.9416097



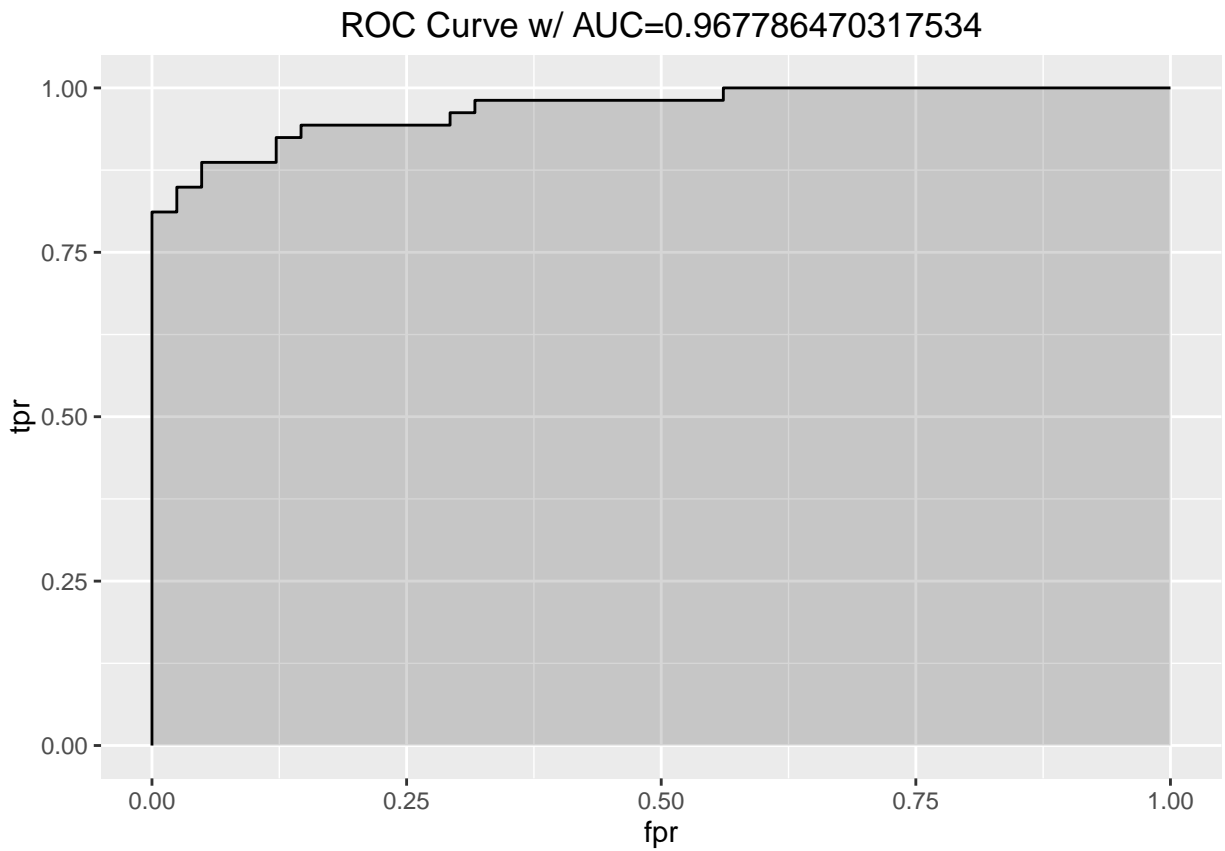
4.1.2 Model2 Evaluation

```
##      Accuracy Error_Rate Precision sensitivity specificity F1_Score
## 1 0.5851064  0.4148936 0.9056604   0.5853659   0.5833333 0.9072354
```



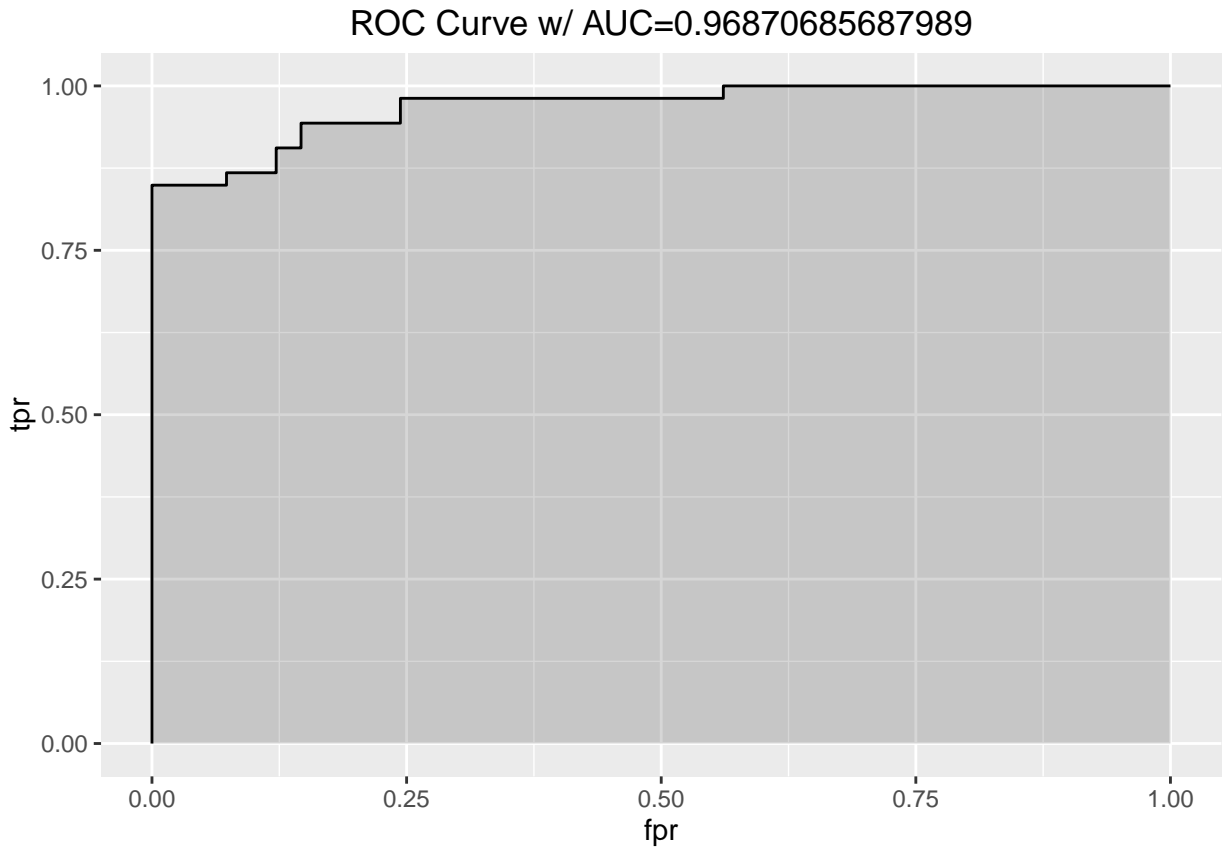
4.1.3 Model3 Evaluation

##	Accuracy	Error_Rate	Precision	sensitivity	specificity	F1_Score
## 1	0.5851064	0.4148936	0.9245283	0.5833333	0.6	0.9115068



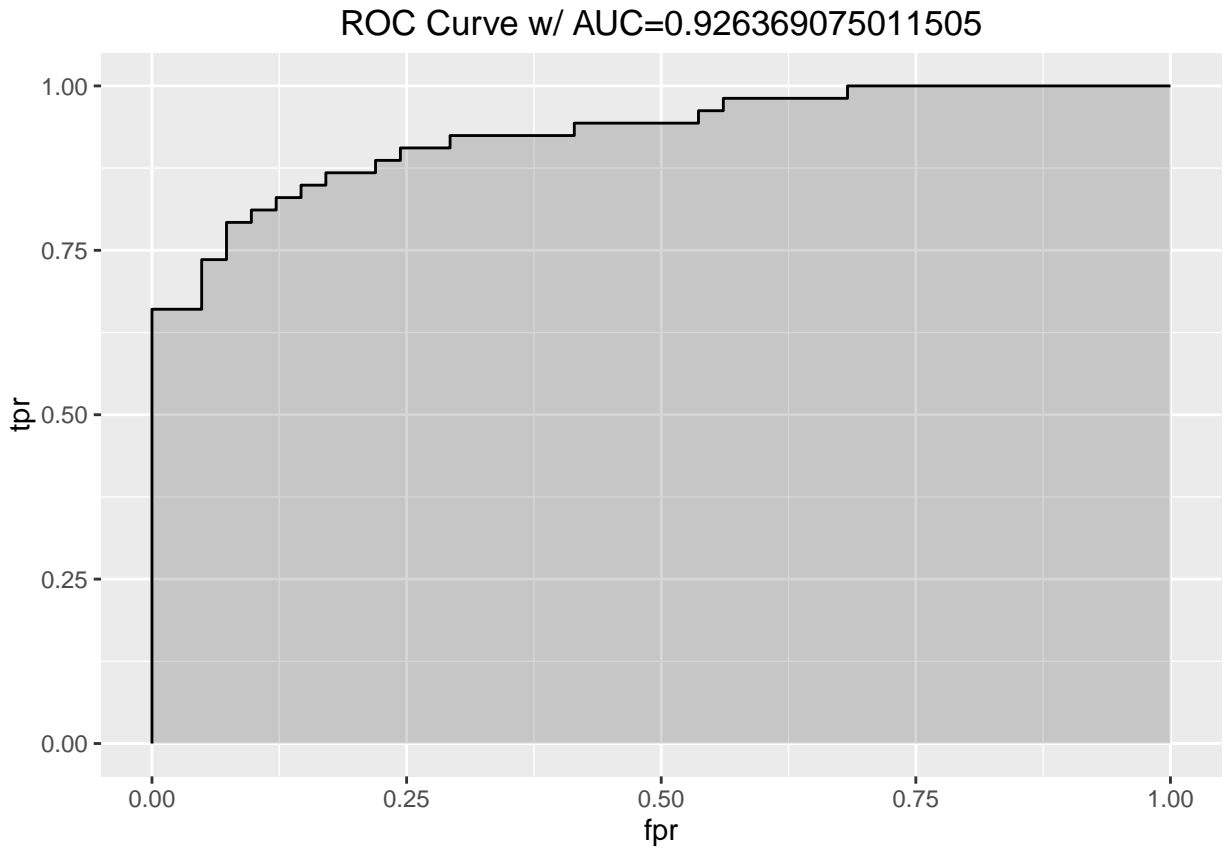
4.1.4 Model4 Evaluation

##	Accuracy	Error_Rate	Precision	sensitivity	specificity	F1_Score
## 1	0.5744681	0.4255319	0.9056604	0.5783133	0.5454545	0.9321417



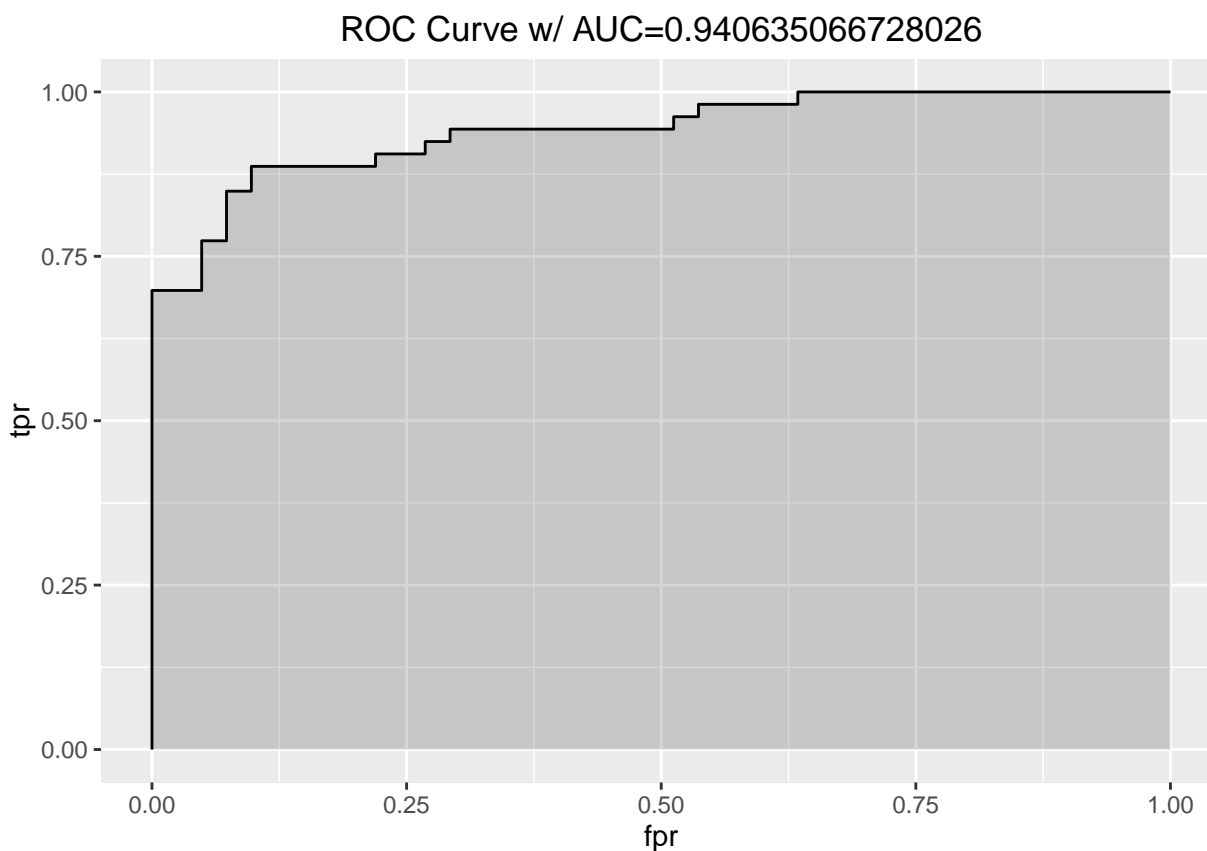
4.1.5 Model5 Evaluation

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

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
```



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	0.5744681	0.4255319	0.9245283	0.5764706	0.5555556	0.9416097
## 2	0.5851064	0.4148936	0.9056604	0.5853659	0.5833333	0.9072354
## 3	0.5851064	0.4148936	0.9245283	0.5833333	0.6000000	0.9115068
## 4	0.5744681	0.4255319	0.9056604	0.5783133	0.5454545	0.9321417
## 5	0.8297872	0.1702128	0.7358491	0.9512195	0.7358491	0.8297872
## 6	0.8297872	0.1702128	0.7358491	0.9512195	0.7358491	0.8297872