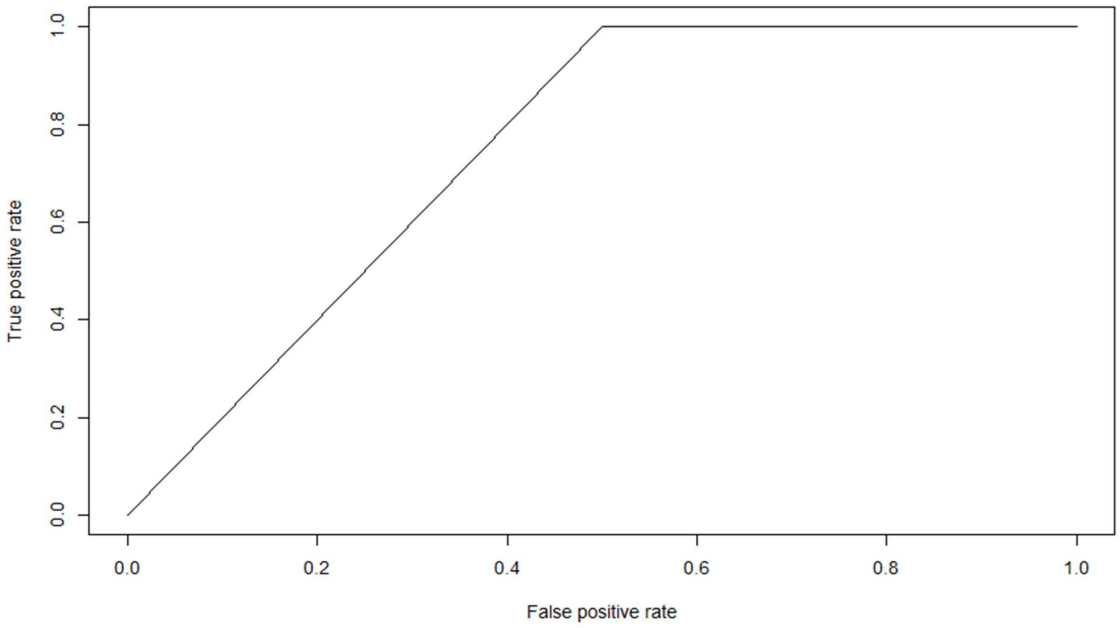
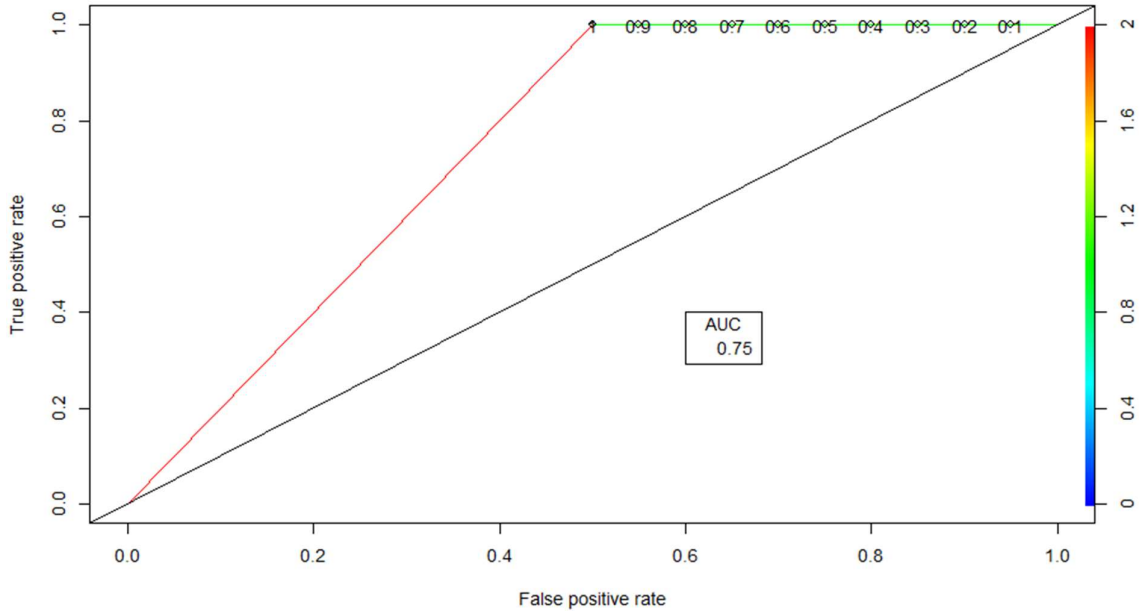
```
> # Summary of dataset in package
> summary(mtcars)
      mpg             cyl             disp             hp             drat             wt             qsec      
 Min.   :10.40   Min.   :4.000   Min.   : 71.1   Min.   : 52.0   Min.   :2.760   Min.   :1.513   Min.   :14.50  
 1st Qu.:15.43   1st Qu.:4.000   1st Qu.:120.8   1st Qu.: 96.5   1st Qu.:3.080   1st Qu.:2.581   1st Qu.:16.89  
 Median :19.20   Median :6.000   Median :196.3   Median :123.0   Median :3.695   Median :3.325   Median :17.71  
 Mean   :20.09   Mean   :6.188   Mean   :230.7   Mean   :146.7   Mean   :3.597   Mean   :3.217   Mean   :17.85  
 3rd Qu.:22.80   3rd Qu.:8.000   3rd Qu.:326.0   3rd Qu.:180.0   3rd Qu.:3.920   3rd Qu.:3.610   3rd Qu.:18.90  
 Max.   :33.90   Max.   :8.000   Max.   :472.0   Max.   :335.0   Max.   :4.930   Max.   :5.424   Max.   :22.90  
       vs               am              gear            carb      
 Min.   :0.0000   Min.   :0.0000   Min.   :3.000   Min.   :1.000  
 1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:3.000   1st Qu.:2.000  
 Median :0.0000   Median :0.0000   Median :4.000   Median :2.000  
 Mean   :0.4375   Mean   :0.4062   Mean   :3.688   Mean   :2.812  
 3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:4.000   3rd Qu.:4.000  
 Max.   :1.0000   Max.   :1.0000   Max.   :5.000   Max.   :8.000  
> # Loading package
> library(caTools)
> library(ROCR)
> # Splitting dataset
> split <- sample.split(mtcars, SplitRatio = 0.8)
> split
 [1]  TRUE  TRUE  TRUE  TRUE FALSE  TRUE  TRUE FALSE  TRUE FALSE  TRUE
> train_reg <- subset(mtcars, split == "TRUE")
> test_reg <- subset(mtcars, split == "FALSE")
> # Training model
> logistic_model <- glm(vs ~ wt + disp,
+                       data = train_reg,
+                       family = "binomial")
> logistic_model

Call:  glm(formula = vs ~ wt + disp, family = "binomial", data = train_reg)

Coefficients:
(Intercept)          wt        disp  
    3.87861      0.61985     -0.02875  

Degrees of Freedom: 22 Total (i.e. Null);  20 Residual
Null Deviance:      30.79
Residual Deviance: 13.7         AIC: 19.7
> # Summary
> summary(logistic_model)

Call:
glm(formula = vs ~ wt + disp, family = "binomial", data = train_reg)

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  3.87861    3.69659   1.049   0.2941
wt           0.61985    1.91238   0.324   0.7458
disp        -0.02875    0.01683  -1.708   0.0877 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 30.789  on 22  degrees of freedom
Residual deviance: 13.698  on 20  degrees of freedom
AIC: 19.698

Number of Fisher Scoring iterations: 6
```

```
> predict_reg <- predict(logistic_model,
+                        test_reg, type = "response")
> predict_reg
  Hornet Sportabout           Merc 240D           Merc 280 Lincoln Continental         Honda Civic 
        0.012892171         0.837357726         0.767248735         0.002514631         0.937232611 
      Toyota Corona       Porsche 914-2        Ferrari Dino          Volvo 142E 
        0.875880620         0.851546762         0.806469464         0.893153655 
> # Changing probabilities
> predict_reg <- ifelse(predict_reg >0.5, 1, 0)
> # Evaluating model accuracy
> # using confusion matrix
> table(test_reg$vs, predict_reg)
   predict_reg
    0 1
  0 2 2
  1 0 5
> missing_classerr <- mean(predict_reg != test_reg$vs)
> print(paste('Accuracy =', 1 - missing_classerr))
[1] "Accuracy = 0.777777777777778"
> # ROC-AUC Curve
> ROCPred <- prediction(predict_reg, test_reg$vs)
> ROCPer <- performance(ROCPred, measure = "tpr",
+                       x.measure = "fpr")
> auc <- performance(ROCPred, measure = "auc")
> auc <- auc@y.values[[1]]
> auc
[1] 0.75
> # Plotting curve
> plot(ROCPer)
> plot(ROCPer, colorize = TRUE,
+      print.cutoffs.at = seq(0.1, by = 0.1),
+      main = "ROC CURVE")
> abline(a = 0, b = 1)
> auc <- round(auc, 4)
> legend(.6, .4, auc, title = "AUC", cex = 1)
>
```


True positive rate
0.0
0.2
0.4
0.6
0.8
1.0
False positive rate

ROC CURVE


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
AUC
0.75
True positive rate
False positive rate
0.0
0.2
0.4
0.6
0.8
1.0
0
0.4
0.8
1.2
1.6
2