```r
library(readxl)

data <- read_excel("Book1.xlsx")

library(mice)

#Multivariate Imputation using pmm method


data = data.frame(data)
```

```r
#all information are true for the following variables
summary(data3)
```

```
##      Long_1          Long_2          Long_3          Long_4
##  Min.   :  100   Min.   : 0.000   Min.   :    0   Min.   :   0.0
##  1st Qu.: 1100   1st Qu.: 1.000   1st Qu.:    0   1st Qu.: 161.0
##  Median : 2300   Median : 2.000   Median :    0   Median : 231.0
##  Mean   : 2745   Mean   : 2.823   Mean   : 1788   Mean   : 257.4
##  3rd Qu.: 4100   3rd Qu.: 4.000   3rd Qu.:  833   3rd Qu.: 323.0
##  Max.   :10000   Max.   :34.000   Max.   :15352   Max.   :1174.0
##      Long_5          Long_6          Long_7          Long_8
##  Min.   :  0.00   Min.   : 0.00   Min.   : 0.00   Min.   :     0
##  1st Qu.: 11.00   1st Qu.: 2.00   1st Qu.:11.00   1st Qu.:  3440
##  Median : 39.00   Median : 4.00   Median :18.00   Median : 12015
##  Mean   : 66.04   Mean   : 6.28   Mean   :24.76   Mean   : 28475
##  3rd Qu.:104.00   3rd Qu.: 8.00   3rd Qu.:35.00   3rd Qu.: 30468
##  Max.   :686.00   Max.   :87.00   Max.   :97.00   Max.   :996223
##      Long_9          Long_10          Short_1         Short_2
##  Min.   :  0.000   Min.   :-10000.0   Mode :logical   Mode :logical
##  1st Qu.:  2.000   1st Qu.:  -346.0   FALSE:2657      FALSE:2527
##  Median :  3.000   Median :     0.0   TRUE :1942      TRUE :2072
##  Mean   :  5.746   Mean   :    78.1
##  3rd Qu.:  5.000   3rd Qu.:   403.0
##  Max.   :223.000   Max.   : 20000.0
##  Short_3         Short_4         Short_5         Short_6         Short_7
##  Mode:logical   Mode:logical   Mode :logical   Mode:logical   Mode :logical
##  TRUE:1814      TRUE:1836      FALSE:2         TRUE:1836      FALSE:144
##  NA's:2785      NA's:2763      TRUE :4597      NA's:2763      TRUE :4455
##
##
##
##   Short_8         Short_9         Short_10
##  Mode :logical   Mode :logical   Mode :logical
##  FALSE:50        FALSE:3138      FALSE:2815
##  TRUE :4549      TRUE :1461      TRUE :1784
##
##
##
```

```r
data3$Short_3 <- TRUE
data3$Short_4 <- TRUE
data3$Short_6 <- TRUE
```

```r
#they are all true, so no useful for modeling

data_filled <- data.frame(data[,1:4], data3)

write.csv(data_filled, file = "data_filled.csv")
train_data <- data_filled[data_filled$TrainVal == "Train_60", ]
val_data <- data_filled[data_filled$TrainVal == "Val_40", ]



head(train_data)
```

```
##   UniqueID submission_year target TrainVal Long_1 Long_2 Long_3 Long_4 Long_5
## 1   984TAH            2015      0 Train_60   1800      6      0    221      0
## 3   394ETK            2015      1 Train_60    700      1      0    147     17
## 4   036KQK            2015      0 Train_60   1700      2      0    461    187
## 5   996RNP            2015      0 Train_60    600      3      0     96     30
## 8   283LEL            2015      0 Train_60    200      3      0    218    190
## 9   695XKD            2015      0 Train_60   5000      7   8963     68     39
##   Long_6 Long_7 Long_8 Long_9 Long_10 Short_1 Short_2 Short_3 Short_4 Short_5
## 1     15      6   1575      7      15   FALSE    TRUE    TRUE    TRUE    TRUE
## 3     10     12   9587      4    3279   FALSE    TRUE    TRUE    TRUE    TRUE
## 4      6      4    210      2   -2139    TRUE   FALSE    TRUE    TRUE    TRUE
## 5     11      5  43650      4     316    TRUE    TRUE    TRUE    TRUE    TRUE
## 8      6     17  34298      1       0   FALSE    TRUE    TRUE    TRUE    TRUE
## 9     26     34   6312      4     229    TRUE    TRUE    TRUE    TRUE    TRUE
##   Short_6 Short_7 Short_8 Short_9 Short_10
## 1    TRUE    TRUE    TRUE   FALSE    FALSE
## 3    TRUE    TRUE    TRUE   FALSE     TRUE
## 4    TRUE    TRUE    TRUE    TRUE     TRUE
## 5    TRUE    TRUE    TRUE   FALSE    FALSE
## 8    TRUE    TRUE    TRUE   FALSE     TRUE
## 9    TRUE   FALSE    TRUE   FALSE     TRUE
```

```r
model1 <- glm(target~., data = train_data[,-c(1,4)], family = binomial(link="logit"))

summary(model1)
```

```
##
## Call:
## glm(formula = target ~ ., family = binomial(link = "logit"),
##     data = train_data[, -c(1, 4)])
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8183  -0.7291  -0.6409  -0.4807   2.2067
##
## Coefficients: (3 not defined because of singularities)
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -5.284e+01  3.519e+02  -0.150  0.88062
## submission_year  2.012e-02  6.718e-02   0.300  0.76454
## Long_1          -4.626e-05  2.689e-05  -1.720  0.08542 .
```

```
## Long_2           5.497e-02  1.692e-02   3.248  0.00116 **
## Long_3           1.008e-05  1.425e-05   0.707  0.47948
## Long_4          -1.005e-03  3.739e-04  -2.687  0.00722 **
## Long_5          -1.507e-03  7.274e-04  -2.072  0.03826 *
## Long_6           4.174e-02  7.674e-03   5.440 5.34e-08 ***
## Long_7          -2.046e-03  2.941e-03  -0.696  0.48658
## Long_8           4.194e-08  8.611e-07   0.049  0.96115
## Long_9          -1.638e-03  3.456e-03  -0.474  0.63545
## Long_10         -1.937e-06  1.343e-05  -0.144  0.88532
## Short_1TRUE     -1.859e-02  9.500e-02  -0.196  0.84488
## Short_2TRUE     -2.056e-02  9.503e-02  -0.216  0.82871
## Short_3TRUE             NA         NA      NA       NA
## Short_4TRUE             NA         NA      NA       NA
## Short_5TRUE      1.120e+01  3.247e+02   0.034  0.97248
## Short_6TRUE             NA         NA      NA       NA
## Short_7TRUE      5.366e-01  3.104e-01   1.729  0.08387 .
## Short_8TRUE     -5.451e-01  4.117e-01  -1.324  0.18546
## Short_9TRUE     -1.039e-01  1.064e-01  -0.977  0.32881
## Short_10TRUE    -1.368e-02  1.006e-01  -0.136  0.89188
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2986.3  on 2767  degrees of freedom
## Residual deviance: 2854.2  on 2749  degrees of freedom
## AIC: 2892.2
##
## Number of Fisher Scoring iterations: 11
```

```r
predict_train <- predict(model1, type = "response")

predict_class <- round(predict_train )


confusion_mat_train <- table(predict_class, train_data$target)
confusion_mat_train
```

```
##
## predict_class    0    1
##             0 2116  593
##             1   15   44
```

```r
library(caret)

#show some measures
confusionMatrix(factor(predict_class), factor(train_data$target), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2116  593
```

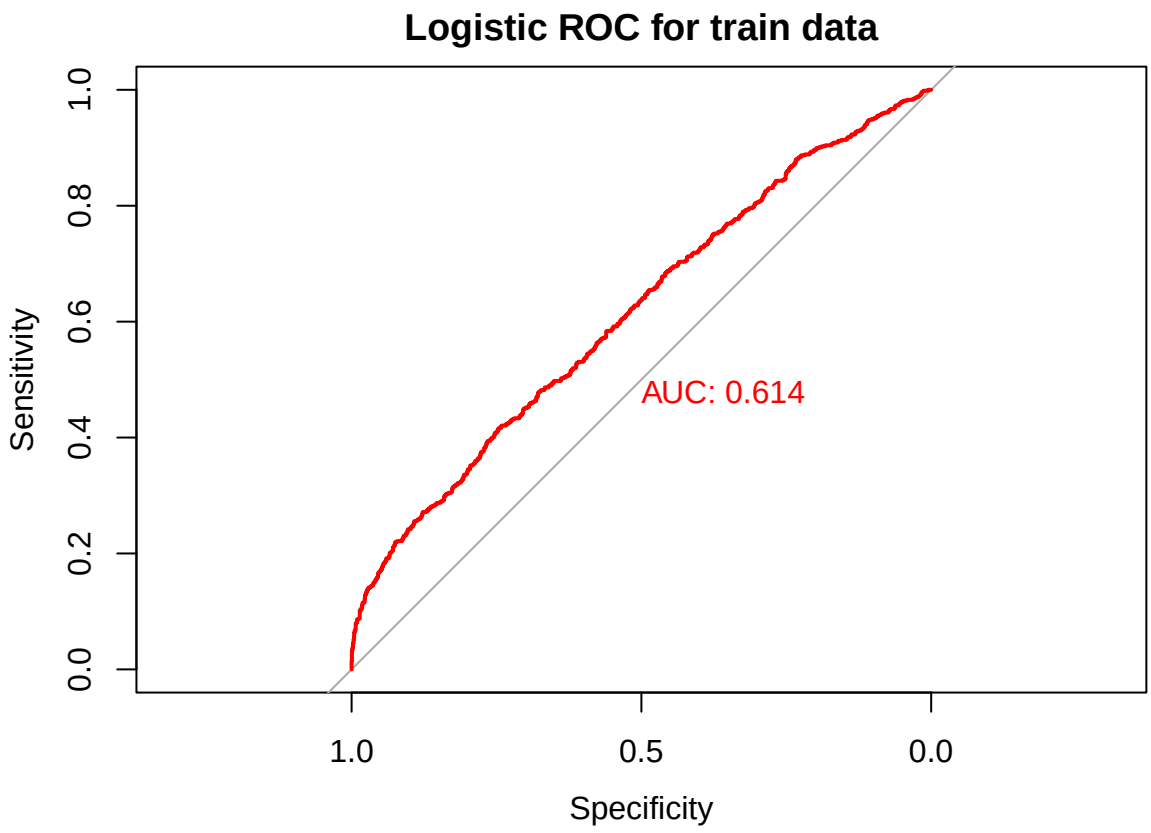
```
##          1   15   44
##
##                Accuracy : 0.7803
##                  95% CI : (0.7645, 0.7956)
##     No Information Rate : 0.7699
##     P-Value [Acc > NIR] : 0.09857
##
##                   Kappa : 0.091
##
##  Mcnemar's Test P-Value : < 2e-16
##
##             Sensitivity : 0.06907
##             Specificity : 0.99296
##          Pos Pred Value : 0.74576
##          Neg Pred Value : 0.78110
##              Prevalence : 0.23013
##          Detection Rate : 0.01590
##    Detection Prevalence : 0.02132
##       Balanced Accuracy : 0.53102
##
##        'Positive' Class : 1
##
```

```r
#ROC curve with auc

library(pROC)

r = roc(train_data$target, predict_train)

plot(r, col = "red", print.auc = TRUE, main = "Logistic ROC for train data")
```




```
predict_val <- predict(model1, val_data, type = "response")

predict_class <- round(predict_val )


confusion_mat_val <- table(predict_class, val_data$target)
confusion_mat_val
```

```
##
## predict_class    0    1
##             0 1403  401
##             1   11   16
```

```
#show some measures
confusionMatrix(factor(predict_class), factor(val_data$target), positive = "1")
```

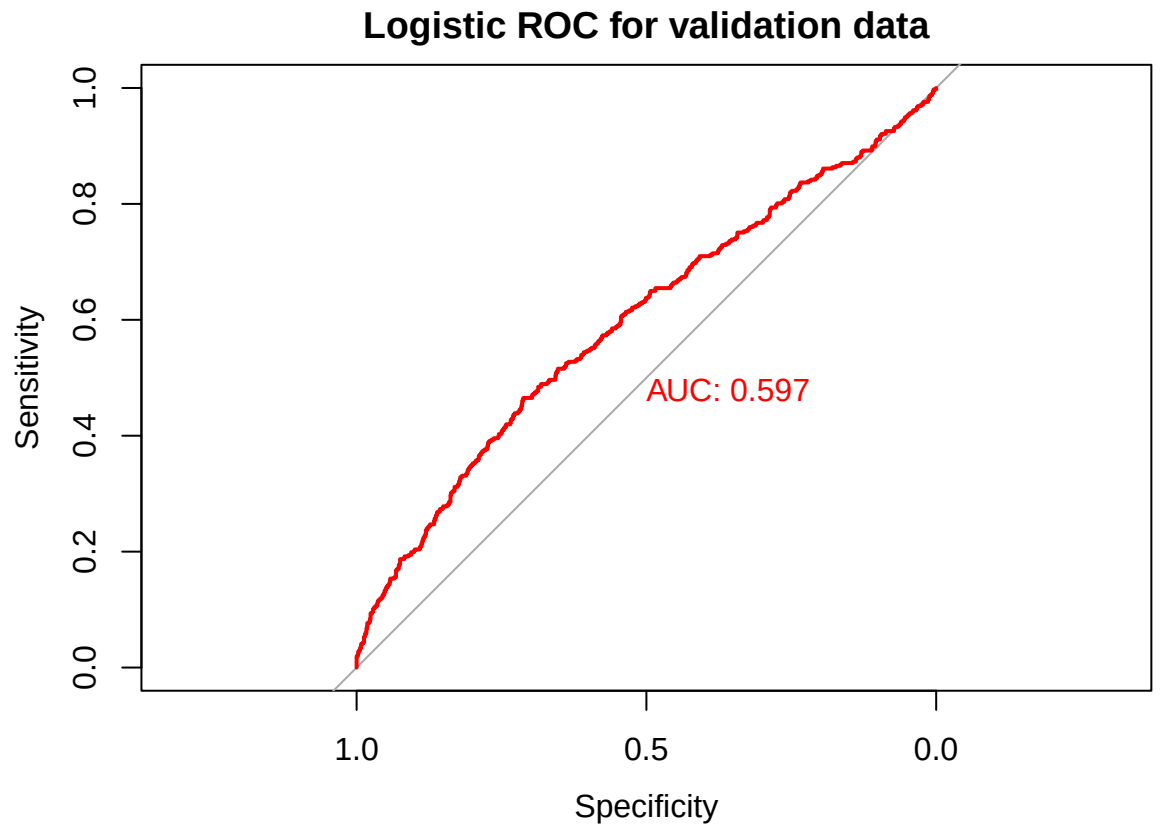
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1403  401
##          1   11   16
##
##                Accuracy : 0.775
##                  95% CI : (0.7552, 0.7939)
```

```
##     No Information Rate : 0.7723
##     P-Value [Acc > NIR] : 0.4028
##
##                   Kappa : 0.0456
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.038369
##             Specificity : 0.992221
##          Pos Pred Value : 0.592593
##          Neg Pred Value : 0.777716
##              Prevalence : 0.227744
##          Detection Rate : 0.008738
##    Detection Prevalence : 0.014746
##       Balanced Accuracy : 0.515295
##
##        'Positive' Class : 1
##
```

```r
#ROC curve with auc

r2 = roc(val_data$target, predict_val)

plot(r2, col = "red", print.auc = TRUE, main = "Logistic ROC for validation data")
```



```
library(xgboost)
traindata <- list(data = data.matrix(train_data[,-c(1,3,4)]),
                  label = train_data$target)
dtrain <- xgb.DMatrix(data = traindata$data, label = traindata$label)
valdata <- list(data = data.matrix(val_data[,-c(1,3,4)]),
                  label = val_data$target)
dval <- xgb.DMatrix(data =  valdata$data, label = valdata$label)

param <- list(max_depth = 2, eta = 1,  nthread = 2,
              objective = "binary:logistic", eval_metric = "auc")
model1 <- xgb.train(param, data = dtrain,nrounds = 2 )


predict_train <- predict(model1, newdata = dtrain, type = "response")

predict_class <- round(predict_train )


confusion_mat_train <- table(predict_class, train_data$target)
confusion_mat_train
```

```
##
## predict_class    0    1
##             0 2109  577
##             1   22   60
```

```
library(caret)

#show some measures
confusionMatrix(factor(predict_class), factor(train_data$target), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 2109  577
##          1   22   60
##
##                Accuracy : 0.7836
##                  95% CI : (0.7678, 0.7988)
##     No Information Rate : 0.7699
##     P-Value [Acc > NIR] : 0.04445
##
##                   Kappa : 0.1207
##
##  Mcnemar's Test P-Value : < 2e-16
##
##             Sensitivity : 0.09419
##             Specificity : 0.98968
##          Pos Pred Value : 0.73171
##          Neg Pred Value : 0.78518
##              Prevalence : 0.23013
```

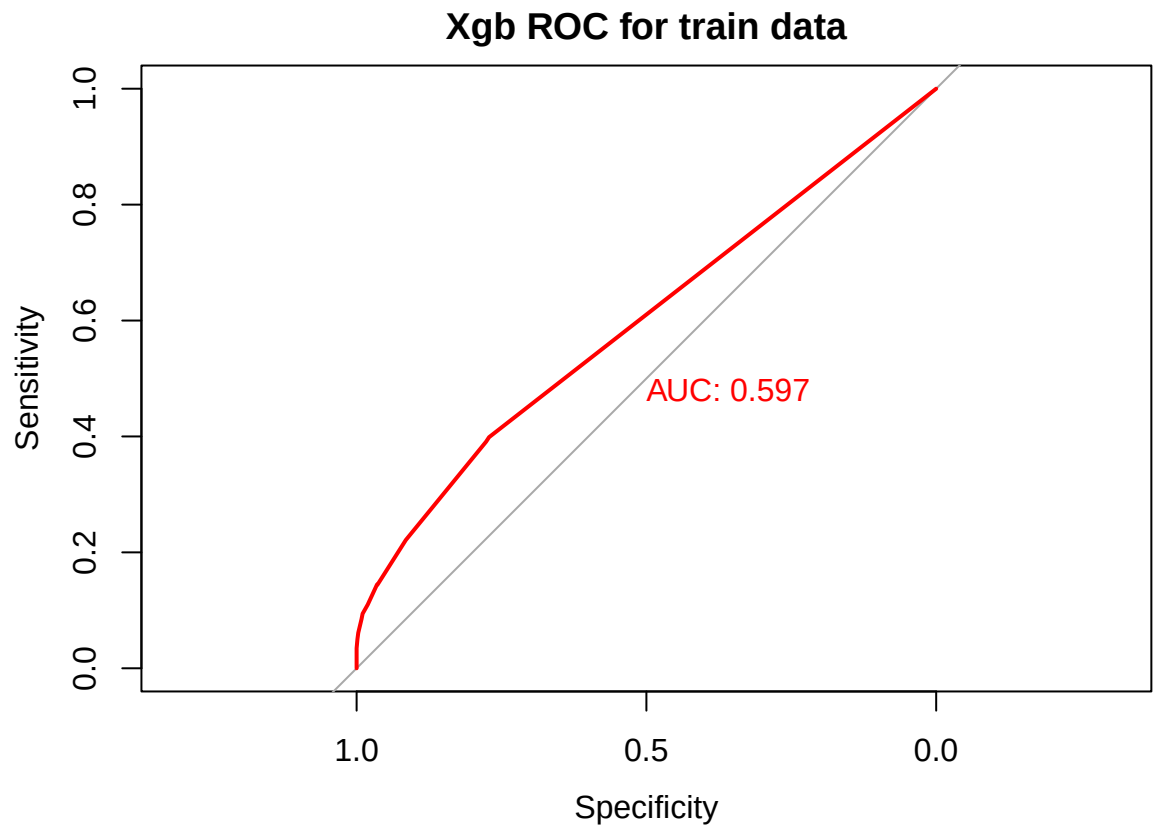
```
##          Detection Rate : 0.02168
##    Detection Prevalence : 0.02962
##       Balanced Accuracy : 0.54193
##
##        'Positive' Class : 1
##
```

```r
#ROC curve with auc

library(pROC)

r = roc(train_data$target, predict_train)

plot(r, col = "red", print.auc = TRUE, main = "Xgb ROC for train data")
```




```r
predict_val <- predict(model1, dval, type = "response")

predict_class <- round(predict_val )


confusion_mat_val <- table(predict_class, val_data$target)
confusion_mat_val
```

```
##
## predict_class    0    1
```

```
##             0 1393  386
##             1   21   31
```

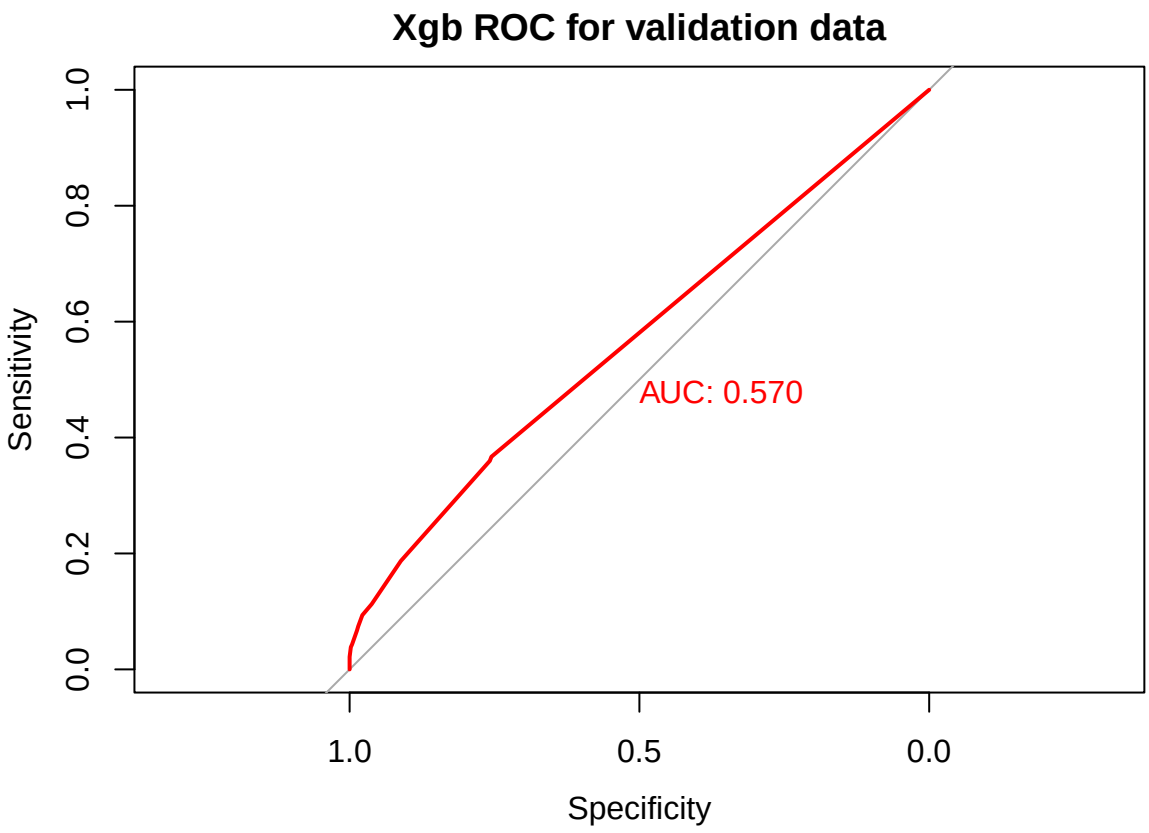
```r
#show some measures
confusionMatrix(factor(predict_class), factor(val_data$target), positive = "1")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    0    1
##          0 1393  386
##          1   21   31
##
##                Accuracy : 0.7777
##                  95% CI : (0.758, 0.7966)
##     No Information Rate : 0.7723
##     P-Value [Acc > NIR] : 0.2995
##
##                   Kappa : 0.086
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.07434
##             Specificity : 0.98515
##          Pos Pred Value : 0.59615
##          Neg Pred Value : 0.78302
##              Prevalence : 0.22774
##          Detection Rate : 0.01693
##    Detection Prevalence : 0.02840
##       Balanced Accuracy : 0.52974
##
##        'Positive' Class : 1
##
```

```r
#ROC curve with auc

r2 = roc(val_data$target, predict_val)

plot(r2, col = "red", print.auc = TRUE, main = "Xgb ROC for validation data")
```


Xgb ROC for validation data
Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
AUC: 0.570
1.0
0.5
0.0
Specificity