Churn Prediction Model for Telecom Companies

Group_8

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```
setwd("~/Desktop/R/64036-002/Group_proj")  #set working directory
Customer <- read.csv("Churn_Train.csv")  #load the data
load("Customers_To_Predict.RData")
summary(Customer)
```

```
##     state           account_length     area_code         international_plan
##  Length:3333        Min.   :-209.00   Length:3333        Length:3333
##  Class :character   1st Qu.:  72.00   Class :character   Class :character
##  Mode  :character   Median : 100.00   Mode  :character   Mode  :character
##                     Mean   :  97.32
##                     3rd Qu.: 127.00
##                     Max.   : 243.00
##                     NA's   :501
##  voice_mail_plan    number_vmail_messages total_day_minutes total_day_calls
##  Length:3333        Min.   :-10.000       Min.   :   0.0    Min.   :  0.0
##  Class :character   1st Qu.:  0.000       1st Qu.: 149.3    1st Qu.: 87.0
##  Mode  :character   Median :  0.000       Median : 190.5    Median :101.0
##                     Mean   :  7.333       Mean   : 418.9    Mean   :100.3
##                     3rd Qu.: 16.000       3rd Qu.: 237.8    3rd Qu.:114.0
##                     Max.   : 51.000       Max.   :2185.1    Max.   :165.0
##                     NA's   :200           NA's   :200       NA's   :200
##  total_day_charge total_eve_minutes total_eve_calls total_eve_charge
##  Min.   : 0.00    Min.   :   0.0    Min.   :  0.0   Min.   : 0.00
##  1st Qu.:24.45    1st Qu.: 170.5    1st Qu.: 87.0   1st Qu.:14.14
##  Median :30.65    Median : 209.9    Median :100.0   Median :17.09
##  Mean   :30.63    Mean   : 324.3    Mean   :100.1   Mean   :17.08
##  3rd Qu.:36.84    3rd Qu.: 257.6    3rd Qu.:114.0   3rd Qu.:20.00
##  Max.   :59.64    Max.   :1244.2    Max.   :170.0   Max.   :30.91
##  NA's   :200      NA's   :301       NA's   :200     NA's   :200
##  total_night_minutes total_night_calls total_night_charge total_intl_minutes
##  Min.   : 23.2       Min.   : 33.0     Min.   : 1.040     Min.   : 0.00
##  1st Qu.:167.3       1st Qu.: 87.0     1st Qu.: 7.530     1st Qu.: 8.50
##  Median :201.4       Median :100.0     Median : 9.060     Median :10.30
##  Mean   :201.2       Mean   :100.1     Mean   : 9.054     Mean   :10.23
##  3rd Qu.:235.3       3rd Qu.:113.0     3rd Qu.:10.590     3rd Qu.:12.10
##  Max.   :395.0       Max.   :175.0     Max.   :17.770     Max.   :20.00
##  NA's   :200                           NA's   :200        NA's   :200
##  total_intl_calls total_intl_charge number_customer_service_calls
##  Min.   : 0.00    Min.   :0.000     Min.   :0.000
##  1st Qu.: 3.00    1st Qu.:2.300     1st Qu.:1.000
##  Median : 4.00    Median :2.780     Median :1.000
##  Mean   : 4.47    Mean   :2.762     Mean   :1.561
##  3rd Qu.: 6.00    3rd Qu.:3.270     3rd Qu.:2.000
```

```
##  Max.   :20.00    Max.   :5.400     Max.   :9.000
##  NA's   :301      NA's   :200       NA's   :200
##     churn
##  Length:3333
##  Class :character
##  Mode  :character
##
##
##
##
```

Data Exploration

```r
xtabs(~churn+state, data = Customer) #churn distribution by state
```

```
##      state
## churn AK AL AR AZ CA CO CT DC DE FL GA HI IA ID IL IN KS KY LA MA MD ME MI MN
##   no  49 72 44 60 25 57 62 49 52 55 46 50 41 64 53 62 57 51 47 54 53 49 57 69
##   yes  3  8 11  4  9  9 12  5  9  8  8  3  3  9  5  9 13  8  4 11 17 13 16 15
##      state
## churn MO MS MT NC ND NE NH NJ NM NV NY OH OK OR PA RI SC SD TN TX UT VA VT WA
##   no  56 51 54 57 56 56 47 50 56 52 68 68 52 67 37 59 46 52 48 54 62 72 65 52
##   yes  7 14 14 11  6  5  9 18  6 14 15 10  9 11  8  6 14  8  5 18 10  5  8 14
##      state
## churn WI WV WY
##   no  71 96 68
##   yes  7 10  9
```

Comment

Early observations for churn customers:
1) There is 19% of churn rate in the training data
2) AR, KS, MA, MD, ME, MI, MN, MS, MT, NC, NJ, NV, NY, OH, OR, SC, TX, WA have higher churn rate.

Data Preparation

```r
#Clean and transform the data
Customer <- Customer[, -c(1:3)] #delete state, account length and area code

#Change negative data in account_length and number_vmail_message to positive
Customer <- Customer%>%
  #mutate(account_length = ifelse(account_length <0, abs(account_length), account_length))%>%
  mutate(number_vmail_messages = ifelse(number_vmail_messages <0, abs(number_vmail_messages), number_vma

#Change binary columns to 0 and 1
Customer$international_plan <- ifelse(Customer$international_plan=="yes", 1, 0)
Customer$voice_mail_plan <- ifelse(Customer$voice_mail_plan=="yes", 1, 0)

#Change data attribute from character to factor, the data is coded as 1 as no and 2 as yes
Customer$churn <- as.factor(Customer$churn)

#impute missing values with mean
Customer[, c(3:10, 11:16)] <- Customer[, c(3:10, 11:16)]%>%
    mutate_if(is.numeric, function(x) ifelse(is.na(x), median(x, na.rm = T), x))
```

Data partition

```
#Partition the given training data into 70% training data and 30% testing data
set.seed(111)
index_train <- createDataPartition(Customer$churn, p=0.7, list= F)
Cust_train <- Customer[index_train, ]
Cust_test <- Customer[-index_train, ]
```

Run logistic regression model

```
set.seed(1)
log_model <- glm(churn~., data = Cust_train, family = 'binomial')
```

Run knn model

```
set.seed(2)
knn_model <- train(data = Cust_train, churn~., method = "knn", metric = "Accuracy",
      trControl= trainControl(), tuneGrid = NULL, tuneLength = 3)
```

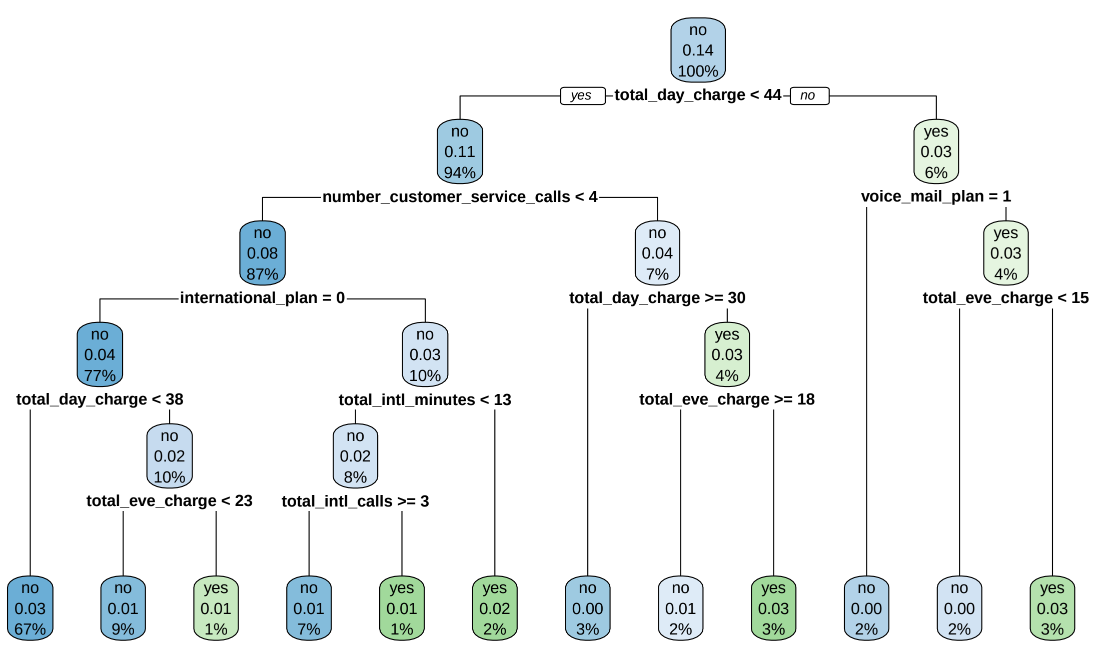
Run NB model

```
library(e1071)
set.seed(3)
nb_model <- naiveBayes(churn~., data = Cust_train)
Predict_test_labels_nb <- predict(nb_model, Cust_test, type = "raw")
```

Run Decision Tree

```
set.seed(4)
library(rpart)
library(rpart.plot)
#agnes or hclust object does not work with later prediction
dt_model <- rpart(churn~., data = Cust_test,method = "class") #class for binary
rpart.plot(dt_model, extra = 110, main = "Dendrogram of rpart")
```

Dendrogram of rpart

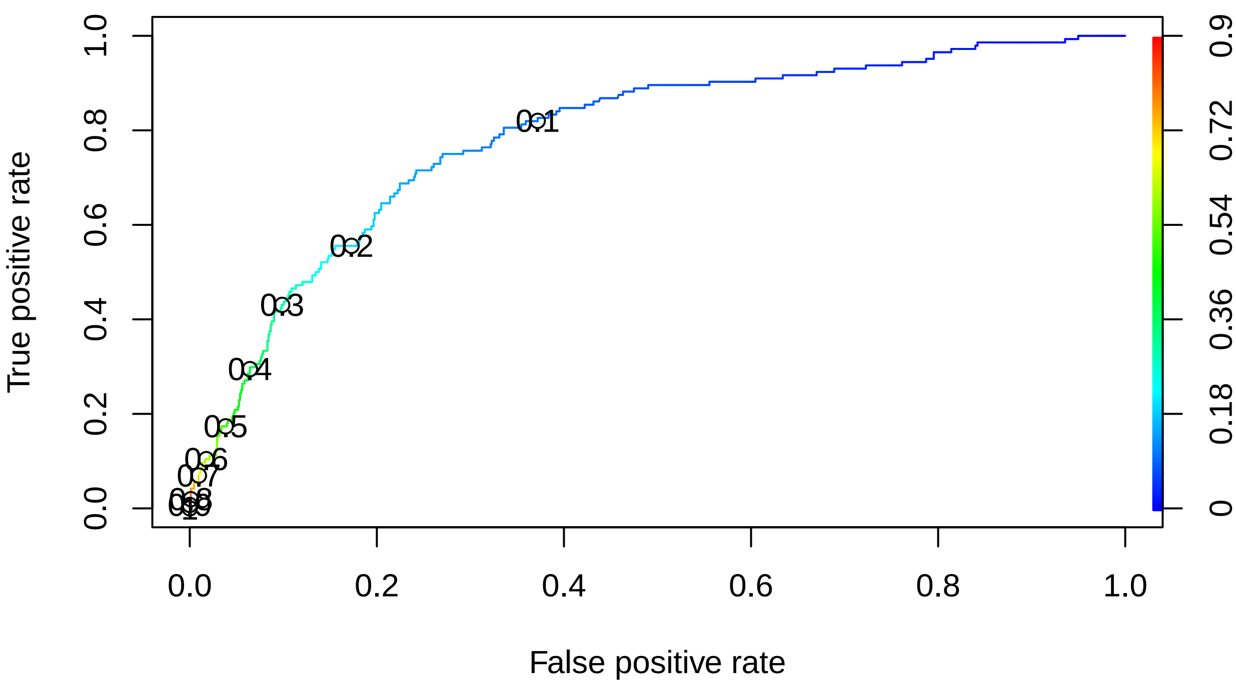


Model Testing

```
#Test the logistic regression model and return in probability
log_test_prob <- predict(log_model, Cust_test, type = "response")
#log_test <- cbind(Cust_test, log_test_prob)

#Test the knn model
knn_test_prob <- predict(knn_model, Cust_test, type = "prob")

#Test the nb model
nb_test_prob <- predict(nb_model, Cust_test, type = "raw")

#Test the dt model- (predict does not apply to "hclust" or "agnes" object)
dt_test_prob <- predict(dt_model, Cust_test, type = "prob")
```

Model Comparison: Thresholding, best cutoff point, confusion table and ROC

```
#logistic regression
pred_log_test <- prediction(log_test_prob, Cust_test$churn)#create prediction obj

#TPR FPR plot
roc_perf_log_test <- performance(pred_log_test, measure = "tpr", x.measure = "fpr")
plot(roc_perf_log_test,colorize=TRUE,print.cutoffs.at=seq(0.1,by=0.1))
```




```
#TPR/FPR cutoff graph<br>

#cut-off trade-off between FPR and TPR, we want to reduce False Negative
cost_perf = performance(pred_log_test, "cost")
pred_log_test@cutoffs[[1]][which.min(cost_perf@y.values[[1]])]#best cutoff 0.539
```

```
##       47
## 0.774522
```

```r
#Logistic regression AUC value
auc.perf = performance(pred_log_test, measure = "auc")
auc.perf@y.values
```

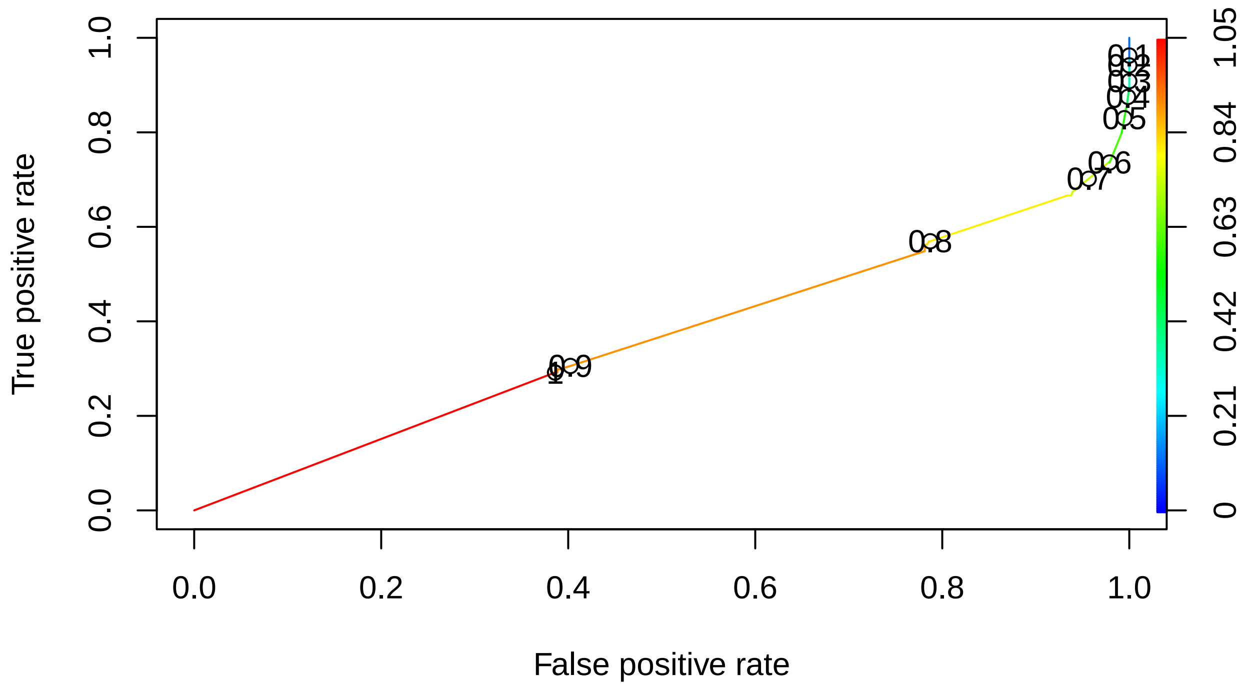
```
## [[1]]
## [1] 0.7860624
```

```r
#Confusion table
confusionMatrix(as.factor(ifelse(log_test_prob>0.5064, "yes", "no")), Cust_test$churn, positive = "yes")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no yes
##        no  825 119
##        yes  30  25
##
##                Accuracy : 0.8509
##                  95% CI : (0.8272, 0.8724)
##     No Information Rate : 0.8559
##     P-Value [Acc > NIR] : 0.6927
##
##                   Kappa : 0.1864
##
##  Mcnemar's Test P-Value : 5.626e-13
##
##             Sensitivity : 0.17361
##             Specificity : 0.96491
##          Pos Pred Value : 0.45455
##          Neg Pred Value : 0.87394
##              Prevalence : 0.14414
##          Detection Rate : 0.02503
##    Detection Prevalence : 0.05506
##       Balanced Accuracy : 0.56926
##
##        'Positive' Class : yes
##
```

Logistic Regression Metric
True Positive (TP) = 26
True Negative (TN) = 835
False Positive (FP) = 20
False Negative (FN) = 118
Miscalculations = 138
Accuracy = 86.19%
Sensitivity = 18.06%
Specificity = 97.66%

```r
#KNN
pred_knn_test <- prediction(knn_test_prob[,1], Cust_test$churn)
#plot TPR - FPR
roc_perf_knn_test <- performance(pred_knn_test, measure = "tpr", x.measure = "fpr")
plot(roc_perf_knn_test,colorize=TRUE,print.cutoffs.at=seq(0.1,by=0.1))
```




```r
#Calculate ROC value for binary classifier
roc.curve(Cust_test$churn, knn_test_prob[,1], plotit= F)
```

```
## Area under the curve (AUC): 0.635
```

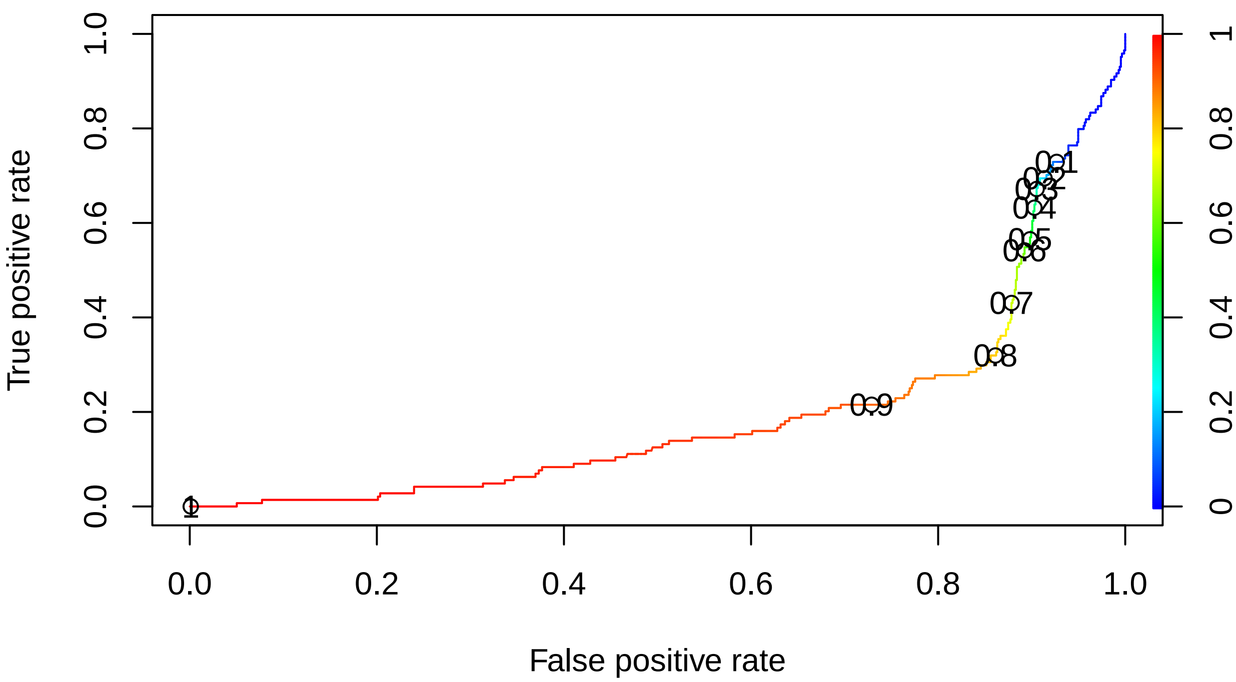
```r
confusionMatrix(as.factor(ifelse(knn_test_prob[,1]>0.94, "yes", "no")), Cust_test$churn, positive = "ye
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no yes
##        no  525 102
##        yes 330  42
##
##                Accuracy : 0.5676
##                  95% CI : (0.5362, 0.5986)
##     No Information Rate : 0.8559
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : -0.0569
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.29167
##             Specificity : 0.61404
##          Pos Pred Value : 0.11290
##          Neg Pred Value : 0.83732
##              Prevalence : 0.14414
##          Detection Rate : 0.04204
##    Detection Prevalence : 0.37237
##       Balanced Accuracy : 0.45285
##
##        'Positive' Class : yes
```

```
##
```

KNN Metric
True Positive (TP) = 32
True Negative (TN) = 585
False Positive (FP) = 270
False Negative (FN) = 112
Miscalculations = 382
Accuracy = 61.76%
Specificity = 68.42%
Sensitivity = 22.22%

```r
#Naive Bayes
pred_nb_test <- prediction(nb_test_prob[,1], Cust_test$churn)
roc_perf_nb_test <- performance(pred_nb_test, measure = "tpr", x.measure = "fpr")
plot(roc_perf_nb_test,colorize=TRUE,print.cutoffs.at=seq(0.1,by=0.1))
```




```r
#Calculate ROC value for binary classifier
roc.curve(Cust_test$churn, nb_test_prob[,1], plotit= F)
```

```
## Area under the curve (AUC): 0.808
```

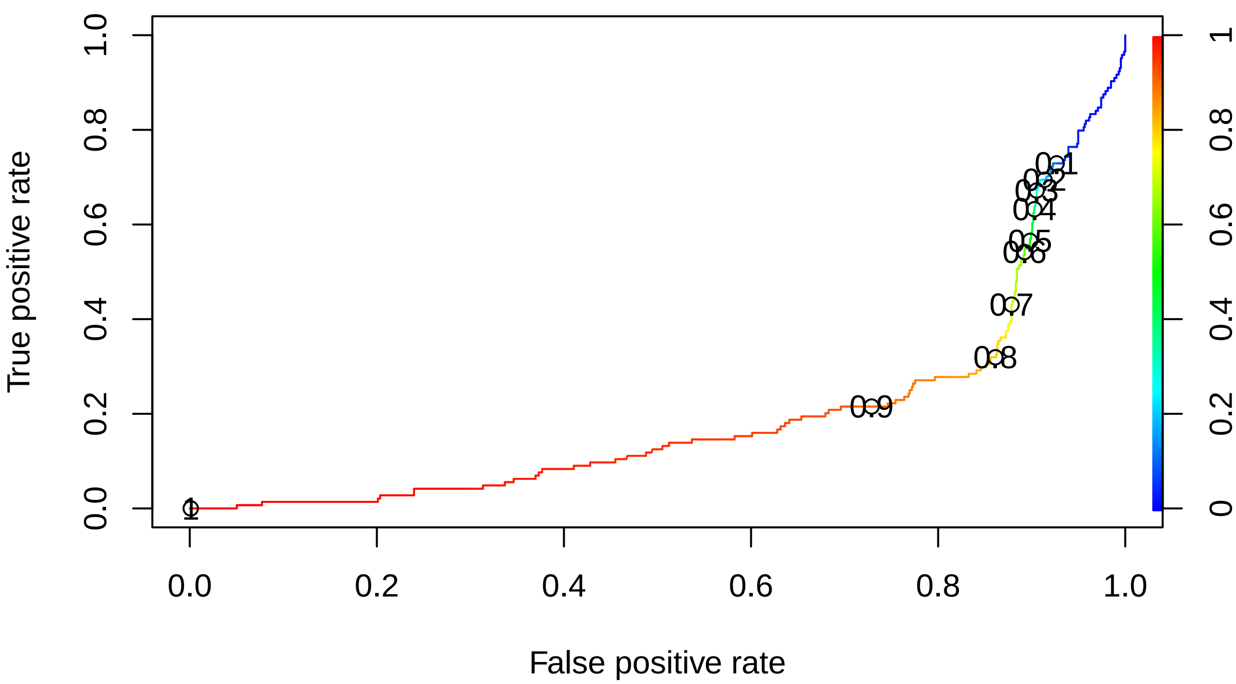
```r
confusionMatrix(as.factor(ifelse(nb_test_prob[,1]>0.95, "yes", "no")), Cust_test$churn, positive = "yes
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no yes
##        no  412 124
##        yes 443  20
##
##                Accuracy : 0.4324
##                  95% CI : (0.4014, 0.4638)
##     No Information Rate : 0.8559
```

```
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : -0.1974
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.13889
##             Specificity : 0.48187
##          Pos Pred Value : 0.04320
##          Neg Pred Value : 0.76866
##              Prevalence : 0.14414
##          Detection Rate : 0.02002
##    Detection Prevalence : 0.46346
##       Balanced Accuracy : 0.31038
##
##        'Positive' Class : yes
##
```

Naive Bayes Metric
True Positive (TP) = 14
True Negative (TN) = 471
False Positive (FP) = 384
False Negative (FN) = 130
Miscalculations = 514
Accuracy = 48.55%
Specificity = 55.09%
Sensitivity = 9.72%

```
#decision tree (dt): create prediction object for ROCR evaluation
pred_dt_test <- prediction(dt_test_prob[,1], Cust_test$churn)
roc_perf_dt_test <- performance(pred_dt_test, measure = "tpr", x.measure = "fpr")
plot(roc_perf_nb_test,colorize=TRUE,print.cutoffs.at=seq(0.1,by=0.1))
```



```
#Calculate ROC value for binary classifier
roc.curve(Cust_test$churn, dt_test_prob[,1], plotit= F)
```

```
## Area under the curve (AUC): 0.866
```

```
confusionMatrix(as.factor(ifelse(dt_test_prob[,1]>0.967, "yes", "no")), Cust_test$churn, positive = "yes
```

```
## Warning in confusionMatrix.default(as.factor(ifelse(dt_test_prob[, 1] > : Levels
## are not in the same order for reference and data. Refactoring data to match.
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  no yes
##        no  855 144
##        yes   0   0
##
##                Accuracy : 0.8559
##                  95% CI : (0.8325, 0.8771)
##     No Information Rate : 0.8559
##     P-Value [Acc > NIR] : 0.5222
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.0000
##             Specificity : 1.0000
##          Pos Pred Value :    NaN
##          Neg Pred Value : 0.8559
##              Prevalence : 0.1441
##          Detection Rate : 0.0000
##    Detection Prevalence : 0.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : yes
##
```

Decision Tree Metric
True Positive (TP) = 0
True Negative (TN) = 836
False Positive (FP) = 19
False Negative (FN) = 144
Miscalculations = 163
Accuracy = 83.68%
Specificity = 97.78%
Sensitivity = 0.0%

Conclusion
Decision Tree and Logistic Regression model have good performance in accuracy, ROC value and specificity. LR model has a better sensitivity but DT has better ROC value which means the model is better. We will choose to apply DT on the test data.

Test Data Prediction

```r
#updating the binary variables
Customers_To_Predict$international_plan <- ifelse(Customers_To_Predict$international_plan =="yes", 1, 0
Customers_To_Predict$voice_mail_plan <- ifelse(Customers_To_Predict$voice_mail_plan =="yes", 1, 0)

#apply DT model on the test data
customer_test <- predict(dt_model, Customers_To_Predict, type = "prob")
x <- cbind(Customers_To_Predict, customer_test)

#set cutoff value
x$prob <- ifelse(x$'no'>0.967, "no", "yes")
Customers_To_Predict$churn_prob <- x$prob
```

```r
write_xlsx(Customers_To_Predict, "Customer_to_Predict")
```

Conclusion

The test data has been updated with additional variable "churn_prob" which provide the probability of churn for each customer. The model aims to reduce false negatives and tolerates more on false positives. It will cost more on the company to miss a churning customer than to mis-classify un-churning customers. If provided with the promotion cost, cost for false positive and false negative, we can further calculate the total saving cost for the company.