Customer Churn

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Customer Churn Prediction

In this project, we will be analyzing a telecom churn dataset. The objective of the analysis is to develop a model to predict whether a customer will churn or not. The dataset consists of 7043 observations and 23 variables. The dataset contains a mix of categorical and continuous variables. I have copied the dataset from kaggle:https://www.kaggle.com/datasets/datazng/telecom-company-churn-rate-call-center-data/discussion/392565

Load data

```
library(readxl)
telecom_data <- read_excel("data/telecom-churn-rate-dataset.xlsx")
#View(telecom_churn_rate_dataset)
```

```
dim(telecom_data)
```

```
## [1] 7043   23
```

```
names(telecom_data)
```

```
##  [1] "customerID"       "gender"           "SeniorCitizen"    "Partner"
##  [5] "Dependents"       "tenure"           "PhoneService"     "MultipleLines"
##  [9] "InternetService"  "OnlineSecurity"   "OnlineBackup"     "DeviceProtection"
## [13] "TechSupport"      "StreamingTV"      "StreamingMovies"  "Contract"
## [17] "PaperlessBilling" "PaymentMethod"    "MonthlyCharges"   "TotalCharges"
## [21] "numAdminTickets"  "numTechTickets"   "Churn"
```

```
str(telecom_data)
```

```
## tibble [7,043 x 23] (S3: tbl_df/tbl/data.frame)
##  $ customerID      : chr [1:7043] "7590-VHVEG" "5575-GNVDE" "3668-QPYBK" "7795-CFOCW" ...
##  $ gender          : chr [1:7043] "Female" "Male" "Male" "Male" ...
##  $ SeniorCitizen   : num [1:7043] 0 0 0 0 0 0 0 0 0 0 ...
##  $ Partner         : chr [1:7043] "Yes" "No" "No" "No" ...
##  $ Dependents      : chr [1:7043] "No" "No" "No" "No" ...
##  $ tenure          : num [1:7043] 1 34 2 45 2 8 22 10 28 62 ...
##  $ PhoneService    : chr [1:7043] "No" "Yes" "Yes" "No" ...
##  $ MultipleLines   : chr [1:7043] "No phone service" "No" "No" "No phone service" ...
##  $ InternetService : chr [1:7043] "DSL" "DSL" "DSL" "DSL" ...
```

```
##  $ OnlineSecurity  : chr [1:7043] "No" "Yes" "Yes" "Yes" ...
##  $ OnlineBackup    : chr [1:7043] "Yes" "No" "Yes" "No" ...
##  $ DeviceProtection: chr [1:7043] "No" "Yes" "No" "Yes" ...
##  $ TechSupport     : chr [1:7043] "No" "No" "No" "Yes" ...
##  $ StreamingTV     : chr [1:7043] "No" "No" "No" "No" ...
##  $ StreamingMovies : chr [1:7043] "No" "No" "No" "No" ...
##  $ Contract        : chr [1:7043] "Month-to-month" "One year" "Month-to-month" "One year" ...
##  $ PaperlessBilling: chr [1:7043] "Yes" "No" "Yes" "No" ...
##  $ PaymentMethod   : chr [1:7043] "Electronic check" "Mailed check" "Mailed check" "Bank transfer (au
##  $ MonthlyCharges  : num [1:7043] 29.9 57 53.9 42.3 70.7 ...
##  $ TotalCharges    : num [1:7043] 29.9 1889.5 108.2 1840.8 151.7 ...
##  $ numAdminTickets : num [1:7043] 0 0 0 0 0 0 0 0 0 0 ...
##  $ numTechTickets  : num [1:7043] 0 0 0 3 0 0 0 0 2 0 ...
##  $ Churn           : chr [1:7043] "No" "No" "Yes" "No" ...
```

Find the number of unique values in each variable.

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
sapply(telecom_data, n_distinct)
```

```
##       customerID           gender    SeniorCitizen          Partner
##             7043                2                2                2
##       Dependents           tenure     PhoneService    MultipleLines
##                2               73                2                3
##  InternetService   OnlineSecurity     OnlineBackup DeviceProtection
##                3                3                3                3
##      TechSupport      StreamingTV  StreamingMovies         Contract
##                3                3                3                3
## PaperlessBilling    PaymentMethod   MonthlyCharges     TotalCharges
##                2                4             1585             6531
##  numAdminTickets   numTechTickets            Churn
##                6               10                2
```

There are not any missing values in the dataset.

```
colSums(is.na(telecom_data))
```

```
##       customerID           gender    SeniorCitizen          Partner
##                0                0                0                0
```

```
##       Dependents           tenure     PhoneService    MultipleLines 
##                0                0                0                0 
##  InternetService   OnlineSecurity     OnlineBackup DeviceProtection 
##                0                0                0                0 
##      TechSupport      StreamingTV  StreamingMovies         Contract 
##                0                0                0                0 
## PaperlessBilling    PaymentMethod   MonthlyCharges     TotalCharges 
##                0                0                0               11 
##  numAdminTickets   numTechTickets            Churn 
##                0                0                0
```

Remove the observations having missing values.

```
telecom_data <- na.omit(telecom_data)
```

```
dim(telecom_data)
```

```
## [1] 7032   23
```

Now the rows having missing values have been removed. Checking if there are any mising values again.

```
colSums(is.na(telecom_data))
```

```
##       customerID           gender    SeniorCitizen          Partner 
##                0                0                0                0 
##       Dependents           tenure     PhoneService    MultipleLines 
##                0                0                0                0 
##  InternetService   OnlineSecurity     OnlineBackup DeviceProtection 
##                0                0                0                0 
##      TechSupport      StreamingTV  StreamingMovies         Contract 
##                0                0                0                0 
## PaperlessBilling    PaymentMethod   MonthlyCharges     TotalCharges 
##                0                0                0                0 
##  numAdminTickets   numTechTickets            Churn 
##                0                0                0
```

Converting the categorical variables to factor.

```
telecom_data[, sapply(telecom_data, is.character)] <- lapply(telecom_data[, sapply(telecom_data, is.cha
```

Check whether the categorical are now factor or not.

```
str(telecom_data)
```

```
## tibble [7,032 x 23] (S3: tbl_df/tbl/data.frame)
##  $ customerID      : Factor w/ 7032 levels "0002-ORFBO","0003-MKNFE",..: 5366 3954 2559 5525 6501 65
##  $ gender          : Factor w/ 2 levels "Female","Male": 1 2 2 2 1 1 2 1 1 2 ...
##  $ SeniorCitizen   : num [1:7032] 0 0 0 0 0 0 0 0 0 0 ...
##  $ Partner         : Factor w/ 2 levels "No","Yes": 2 1 1 1 1 1 1 1 2 1 ...
##  $ Dependents      : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 2 1 1 2 ...
##  $ tenure          : num [1:7032] 1 34 2 45 2 8 22 10 28 62 ...
```

```
##  $ PhoneService    : Factor w/ 2 levels "No","Yes": 1 2 2 1 2 2 2 1 2 2 ...
##  $ MultipleLines   : Factor w/ 3 levels "No","No phone service",..: 2 1 1 2 1 3 3 2 3 1 ...
##  $ InternetService : Factor w/ 3 levels "DSL","Fiber optic",..: 1 1 1 1 2 2 2 1 2 1 ...
##  $ OnlineSecurity  : Factor w/ 3 levels "No","No internet service",..: 1 3 3 3 1 1 1 3 1 3 ...
##  $ OnlineBackup    : Factor w/ 3 levels "No","No internet service",..: 3 1 3 1 1 1 3 1 1 3 ...
##  $ DeviceProtection: Factor w/ 3 levels "No","No internet service",..: 1 3 1 3 1 3 1 1 3 1 ...
##  $ TechSupport     : Factor w/ 3 levels "No","No internet service",..: 1 1 1 3 1 1 1 1 3 1 ...
##  $ StreamingTV     : Factor w/ 3 levels "No","No internet service",..: 1 1 1 1 1 3 3 1 3 1 ...
##  $ StreamingMovies : Factor w/ 3 levels "No","No internet service",..: 1 1 1 1 1 3 1 1 3 1 ...
##  $ Contract        : Factor w/ 3 levels "Month-to-month",..: 1 2 1 2 1 1 1 1 1 2 ...
##  $ PaperlessBilling: Factor w/ 2 levels "No","Yes": 2 1 2 1 2 2 2 1 2 1 ...
##  $ PaymentMethod   : Factor w/ 4 levels "Bank transfer (automatic)",..: 3 4 4 1 3 3 2 4 3 1 ...
##  $ MonthlyCharges  : num [1:7032] 29.9 57 53.9 42.3 70.7 ...
##  $ TotalCharges    : num [1:7032] 29.9 1889.5 108.2 1840.8 151.7 ...
##  $ numAdminTickets : num [1:7032] 0 0 0 0 0 0 0 0 0 0 ...
##  $ numTechTickets  : num [1:7032] 0 0 0 3 0 0 0 0 2 0 ...
##  $ Churn           : Factor w/ 2 levels "No","Yes": 1 1 2 1 2 2 1 1 2 1 ...
##  - attr(*, "na.action")= 'omit' Named int [1:11] 489 754 937 1083 1341 3332 3827 4381 5219 6671 ...
##   ..- attr(*, "names")= chr [1:11] "489" "754" "937" "1083" ...
```

```r
library(magrittr)
library(dplyr)
customer_status <- telecom_data %>% group_by(gender) %>% summarise(num_customers = n())
customer_status
```

```
## # A tibble: 2 x 2
##   gender num_customers
##   <fct>          <int>
## 1 Female          3483
## 2 Male            3549
```

As Customer ID is not related to the regression, using variables except customerID variable. Removing this from the dataframe

```r
telecom_data <- select(telecom_data, -customerID)
```

Logistic regression with all other variables considered.

```r
logistic_reg1 <- glm(Churn ~ ., family = binomial, data = telecom_data)
summary(logistic_reg1)
```

```
##
## Call:
## glm(formula = Churn ~ ., family = binomial, data = telecom_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.7730  -0.4598  -0.0797   0.2386   3.8509
##
## Coefficients: (7 not defined because of singularities)
##                                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)                           1.4285935  1.0245216   1.394 0.163197
```

```
## genderMale                            -0.0957337  0.0764895  -1.252 0.210718
## SeniorCitizen                          0.2698725  0.1045992   2.580 0.009878 **
## PartnerYes                            -0.0549046  0.0943263  -0.582 0.560519
## DependentsYes                         -0.0930284  0.1081090  -0.861 0.389511
## tenure                                -0.0683092  0.0072093  -9.475  < 2e-16 ***
## PhoneServiceYes                        0.2408302  0.8188660   0.294 0.768680
## MultipleLinesNo phone service                 NA         NA      NA       NA
## MultipleLinesYes                       0.5188060  0.2209888   2.348 0.018892 *
## InternetServiceFiber optic             1.8314326  1.0126636   1.809 0.070524 .
## InternetServiceNo                     -1.9160048  1.0191497  -1.880 0.060108 .
## OnlineSecurityNo internet service             NA         NA      NA       NA
## OnlineSecurityYes                     -0.3581201  0.2254677  -1.588 0.112209
## OnlineBackupNo internet service               NA         NA      NA       NA
## OnlineBackupYes                       -0.2108974  0.2221889  -0.949 0.342529
## DeviceProtectionNo internet service           NA         NA      NA       NA
## DeviceProtectionYes                    0.0071828  0.2227764   0.032 0.974279
## TechSupportNo internet service                NA         NA      NA       NA
## TechSupportYes                        -0.0492909  0.2281475  -0.216 0.828950
## StreamingTVNo internet service                NA         NA      NA       NA
## StreamingTVYes                         0.3565925  0.4135539   0.862 0.388543
## StreamingMoviesNo internet service            NA         NA      NA       NA
## StreamingMoviesYes                     0.3587087  0.4142150   0.866 0.386492
## ContractOne year                      -0.8510954  0.1558515  -5.461 4.74e-08 ***
## ContractTwo year                      -2.4370384  0.3004879  -8.110 5.05e-16 ***
## PaperlessBillingYes                    0.3191673  0.0854006   3.737 0.000186 ***
## PaymentMethodCredit card (automatic) -0.2092096  0.1431671  -1.461 0.143934
## PaymentMethodElectronic check          0.1326731  0.1182345   1.122 0.261812
## PaymentMethodMailed check             -0.2372223  0.1337243  -1.774 0.076069 .
## MonthlyCharges                        -0.0355461  0.0402637  -0.883 0.377327
## TotalCharges                          -0.0002083  0.0000880  -2.367 0.017947 *
## numAdminTickets                       -0.0514773  0.0300145  -1.715 0.086330 .
## numTechTickets                         1.4598345  0.0532417  27.419  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8143.4  on 7031  degrees of freedom
## Residual deviance: 4257.2  on 7006  degrees of freedom
## AIC: 4309.2
##
## Number of Fisher Scoring iterations: 7
```

Considering only the variables having significant

modeling_data = telecom_data %>% dplyr::select(-customerID)

```
logistic_reg <- glm(Churn ~ SeniorCitizen + tenure + MultipleLines + Contract + PaperlessBilling + Tota
summary(logistic_reg)
```

```
##
## Call:
## glm(formula = Churn ~ SeniorCitizen + tenure + MultipleLines +
##     Contract + PaperlessBilling + TotalCharges + numTechTickets,
```

```
##     family = binomial, data = telecom_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.9517  -0.5189  -0.0862   0.2388   4.0840
##
## Coefficients:
##                                 Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -2.756e-01  7.308e-02  -3.771 0.000162 ***
## SeniorCitizen                  5.774e-01  9.761e-02   5.916 3.30e-09 ***
## tenure                        -9.959e-02  6.643e-03 -14.993  < 2e-16 ***
## MultipleLinesNo phone service  3.416e-01  1.300e-01   2.628 0.008578 **
## MultipleLinesYes               6.188e-01  8.869e-02   6.977 3.01e-12 ***
## ContractOne year              -1.308e+00  1.484e-01  -8.811  < 2e-16 ***
## ContractTwo year              -2.992e+00  2.877e-01 -10.399  < 2e-16 ***
## PaperlessBillingYes            6.563e-01  7.910e-02   8.298  < 2e-16 ***
## TotalCharges                   1.961e-04  7.336e-05   2.674 0.007505 **
## numTechTickets                 1.412e+00  5.122e-02  27.576  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8143.4  on 7031  degrees of freedom
## Residual deviance: 4579.8  on 7022  degrees of freedom
## AIC: 4599.8
##
## Number of Fisher Scoring iterations: 7
```

Data Partition and Modelling

```r
library(caret)
```

```
## Loading required package: ggplot2

## Loading required package: lattice
```

```r
data_partition <- telecom_data
#telecom_data$Churn = as.factor(telecom_data$Churn)
data_partition$leave = ifelse(data_partition$Churn == "Yes","Churn","Not")
data_partition$leave = as.factor(data_partition$leave)
data_partition = data_partition %>% dplyr::select(-Churn) #removing the column with numbers, otherwise

set.seed(1)
test.indices = createDataPartition(data_partition$leave, p = 0.2, list = FALSE) #classic 80/20 train-te
test_partition = data_partition[test.indices,]
train_partition = data_partition[-test.indices,]
```

```r
model_train = train(leave ~ SeniorCitizen + tenure + MultipleLines + Contract + PaperlessBilling + Tota

predTrain = predict(model_train, train_partition)
predTest = predict(model_train, test_partition)
```

For Training data, the Confusion Matrix:

```
confusionMatrix(predTrain, train_partition$leave, positive = "Churn")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn  Not
##      Churn   997  367
##      Not     498 3763
##
##                Accuracy : 0.8462
##                  95% CI : (0.8365, 0.8556)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5946
##
##  Mcnemar's Test P-Value : 9.864e-06
##
##             Sensitivity : 0.6669
##             Specificity : 0.9111
##          Pos Pred Value : 0.7309
##          Neg Pred Value : 0.8831
##              Prevalence : 0.2658
##          Detection Rate : 0.1772
##    Detection Prevalence : 0.2425
##       Balanced Accuracy : 0.7890
##
##        'Positive' Class : Churn
##
```

For Testing data, the Confusion Matrix:

```
confusionMatrix(predTest, test_partition$leave, positive = "Churn")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn Not
##      Churn   253  92
##      Not     121 941
##
##                Accuracy : 0.8486
##                  95% CI : (0.8288, 0.867)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.6023
##
##  Mcnemar's Test P-Value : 0.05504
##
##             Sensitivity : 0.6765
```

```
##             Specificity : 0.9109
##          Pos Pred Value : 0.7333
##          Neg Pred Value : 0.8861
##              Prevalence : 0.2658
##          Detection Rate : 0.1798
##    Detection Prevalence : 0.2452
##       Balanced Accuracy : 0.7937
##
##        'Positive' Class : Churn
##
```

Cross-validation

```
train_control <- trainControl(method="cv", number=15) #10-fold cross validation
model_cv <- caret::train(leave ~ SeniorCitizen + tenure + MultipleLines + Contract + PaperlessBilling +
print(model_cv)
```

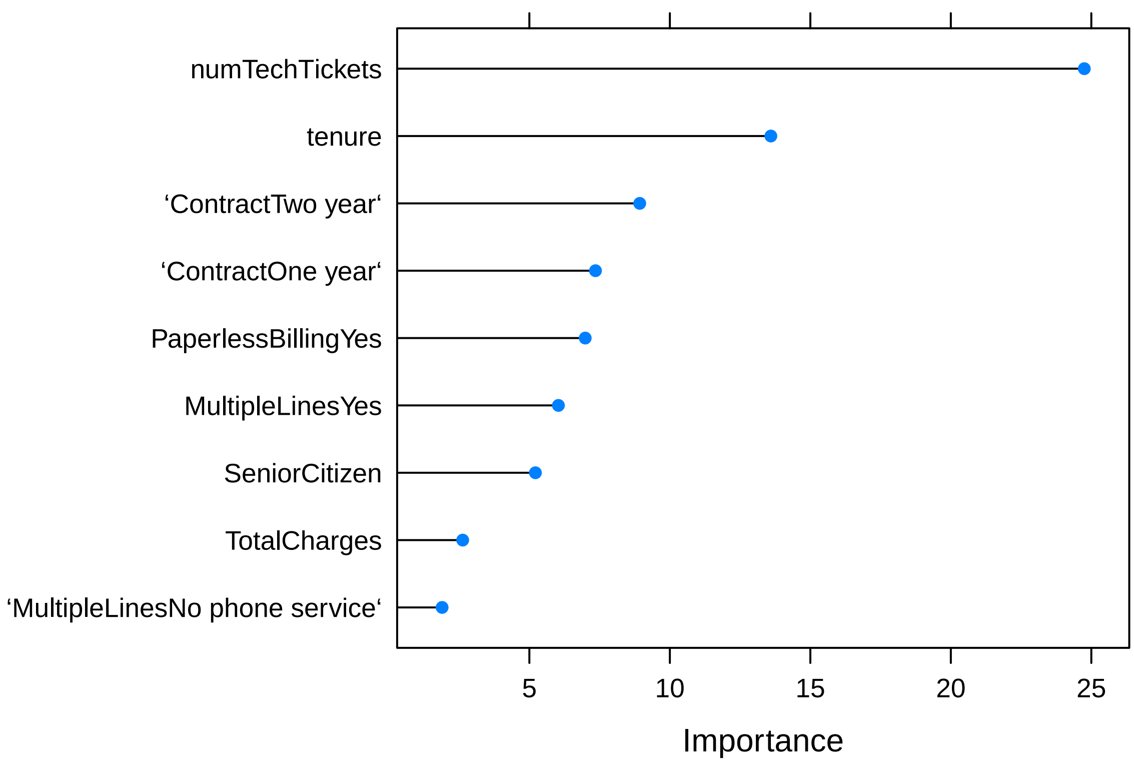
```
## Generalized Linear Model
##
## 5625 samples
##    7 predictor
##    2 classes: 'Churn', 'Not'
##
## No pre-processing
## Resampling: Cross-Validated (15 fold)
## Summary of sample sizes: 5251, 5250, 5250, 5250, 5250, 5250, ...
## Resampling results:
##
##   Accuracy   Kappa
##   0.8444451  0.5910879
```

```
predTest.cv <- predict(model_cv, test_partition)
cmTest.cv = confusionMatrix(predTest.cv, test_partition$leave)
cmTest.cv
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn Not
##      Churn   253  92
##      Not     121 941
##
##                Accuracy : 0.8486
##                  95% CI : (0.8288, 0.867)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.6023
##
##  Mcnemar's Test P-Value : 0.05504
##
```

```
##             Sensitivity : 0.6765
##             Specificity : 0.9109
##          Pos Pred Value : 0.7333
##          Neg Pred Value : 0.8861
##              Prevalence : 0.2658
##          Detection Rate : 0.1798
##    Detection Prevalence : 0.2452
##       Balanced Accuracy : 0.7937
##
##        'Positive' Class : Churn
##
```

```
importance <- varImp(model_train, scale=FALSE)
plot(importance)
```



Decision Tree

```
library(party)
```

```
## Loading required package: grid
```

```
## Loading required package: mvtnorm
```

```
## Loading required package: modeltools

## Loading required package: stats4

## Loading required package: strucchange

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

## Loading required package: sandwich

##
## Attaching package: 'party'

## The following object is masked from 'package:dplyr':
##
##     where
```

```
tree <- ctree(leave~., data = train_partition)
```

```
treePredTrain <- predict(tree, train_partition, type = "response")

confusionMatrix(treePredTrain,train_partition$leave)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn  Not
##      Churn  1078  337
##      Not     417 3793
##
##                Accuracy : 0.866
##                  95% CI : (0.8568, 0.8748)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.6506
##
##  Mcnemar's Test P-Value : 0.004015
##
##             Sensitivity : 0.7211
##             Specificity : 0.9184
##          Pos Pred Value : 0.7618
##          Neg Pred Value : 0.9010
##              Prevalence : 0.2658
```

```
##          Detection Rate : 0.1916
##    Detection Prevalence : 0.2516
##       Balanced Accuracy : 0.8197
##
##        'Positive' Class : Churn
##
```

```r
treePredTest <- predict(tree, test_partition, type = "response")

confusionMatrix(treePredTest,test_partition$leave)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn Not
##      Churn   259 100
##      Not     115 933
##
##                Accuracy : 0.8472
##                  95% CI : (0.8273, 0.8656)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.6034
##
##  Mcnemar's Test P-Value : 0.3397
##
##             Sensitivity : 0.6925
##             Specificity : 0.9032
##          Pos Pred Value : 0.7214
##          Neg Pred Value : 0.8903
##              Prevalence : 0.2658
##          Detection Rate : 0.1841
##    Detection Prevalence : 0.2552
##       Balanced Accuracy : 0.7979
##
##        'Positive' Class : Churn
##
```

Cross Validation: Decision Tree

```r
train_control_tree <- trainControl(method="cv", number=10)
model_tree <- caret::train(leave~., data=train_partition, trControl=train_control_tree, method="ctree")

print(model_tree)
```

```
## Conditional Inference Tree
##
## 5625 samples
##   21 predictor
##    2 classes: 'Churn', 'Not'
##
```

```
## No pre-processing
## Resampling: Cross-Validated (10 fold)
## Summary of sample sizes: 5063, 5063, 5062, 5062, 5062, 5063, ...
## Resampling results across tuning parameters:
##
##   mincriterion  Accuracy   Kappa
##   0.01          0.8400005  0.5862875
##   0.50          0.8485370  0.6015289
##   0.99          0.8488913  0.6135117
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mincriterion = 0.99.
```

```
predTest_tree <- predict(model_tree, test_partition)
tree_cv = confusionMatrix(predTest_tree, test_partition$leave)
tree_cv
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Churn Not
##      Churn   260 109
##      Not     114 924
##
##                Accuracy : 0.8415
##                  95% CI : (0.8214, 0.8602)
##     No Information Rate : 0.7342
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.5922
##
##  Mcnemar's Test P-Value : 0.7888
##
##             Sensitivity : 0.6952
##             Specificity : 0.8945
##          Pos Pred Value : 0.7046
##          Neg Pred Value : 0.8902
##              Prevalence : 0.2658
##          Detection Rate : 0.1848
##    Detection Prevalence : 0.2623
##       Balanced Accuracy : 0.7948
##
##        'Positive' Class : Churn
##
```