Assignment 2 - Logistic Regression

Eoin Flynn

5 March 2018

Bond University
Data Science

Contents

Introduction

In this report we will develop a logistic regression model that will build upon our decision tree from our previous report. Once created, the model will allow us to predict whether customers outside of our dataset will Churn and with what liklihood.

Functions

This section will hold all of the functions that will be used throughout this markdown.

```
# Create a decision tree
createDecisionTreeModel <- function(formula, dataset, maxdepth) {
    suppressMessages(library(party))
    decisionTreeModel <- ctree(formula, data = dataset, controls = ctree_control(maxdepth = maxdepth))

    return(decisionTreeModel)
}

# Change rows to factors
setRowAsFactor <- function(dataset, columns) {
    for (column in columns) {
        dataset[, column] <- as.factor(dataset[, column])
    }
    return(dataset)
}

# Create a logistic regression model
createLogisticRegressionModel <- function(formula, family = binomial,
    dataset) {
    logisticRegressionModel = glm(formula, family = family, data = dataset)

    return(logisticRegressionModel)
}

# Create a prediction dataframe
createPrediction_df <- function(model, dataset, predictionType = "response",
    oneClass, zeroClass) {
    # Run the prediction
    prediction <- suppressWarnings(predict(model, dataset, type = predictionType))
    # Convert to a dataframe
    prediction_df <- data.frame(prediction)
    # Rename the column to reference easier
    colnames(prediction_df) <- "probabilities"
    # Add a row for the classification
    prediction_df$classification <- rep(zeroClass, nrow(prediction_df))
    # Convert all probabilites above 0.5 to be the affirmative
    # class
    prediction_df$classification[prediction_df$probabilities >
        0.5] <- oneClass
    prediction_df$classification <- as.factor(prediction_df$classification)


    return(prediction_df)
```

```
}

# Get model performance for plotting ROC curve
getModelPerformance <- function(model, dataset, outcomeColumn,
    type = "response", xAxis = "tpr", yAxis = "fpr") {
    suppressMessages(library(ROCR))
    # Create a predict variable
    predict <- predict(model, dataset, type = type)
    # Create a predicition variable
    predicition <- prediction(predict, outcomeColumn)
    # Create the performance variable
    performance <- performance(predicition, xAxis, yAxis)

    return(performance)
}

# Plot ROC curves
plotROCCurves <- function(model1, model2, main, model1Colour = "#009900",
    model2Colour = "#FF8000", model1Name, model2Name, legendLocation = "bottomright") {
    plot(model1, main = main, col = model1Colour, print.auc = TRUE)
    plot(model2, add = T, col = model2Colour)
    legend(legendLocation, legend = paste(rep(c(model1Name, model2Name))),
        col = c(model1Colour, model2Colour), cex = 0.8, fill = c(model1Colour,
            model2Colour))
}

# Calculate AUC. Returns as a decimal
getAUC <- function(outcomeColumn, dataset, model, oneClass, zeroClass) {
    suppressMessages(library(ModelMetrics))
    prediction_df <- createPrediction_df(model, dataset, oneClass = oneClass,
        zeroClass = zeroClass)
    auc <- auc(outcomeColumn, prediction_df$classification)

    return(auc)
}

# Create a confusion matrix. Returns a confusion matrix
createConfusionMatrix <- function(model, dataset, outcomeColumn,
    oneClass, zeroClass) {
    suppressMessages(library(caret))
    prediction_df <- createPrediction_df(model, dataset, oneClass = oneClass,
        zeroClass = zeroClass)
    userConfusionMatrix <- table(outcomeColumn, prediction_df$classification)

    return(userConfusionMatrix)
}

# Create a new customer for predicition. Returns a dataframe
createCustomer <- function(originalDataset, gender, SeniorCitizen,
    Partner, Dependents, tenure, PhoneService, MultipleLines,
    InternetService, OnlineSecurity, OnlineBackup, DeviceProtection,
    TechSupport, StreamingTV, StreamingMovies, Contract, PaperlessBilling,
    PaymentMethod, MontlyCharges, TotalCharges, Churn) {
```

```
    # Create a copy of the original dataset and keep one row that
    # will be overridden with the new data.
    newCustomer <- customerDataset[1, ]

    newCustomer$gender <- gender
    newCustomer$SeniorCitizen <- SeniorCitizen
    newCustomer$Partner <- Partner
    newCustomer$Dependents <- Dependents
    newCustomer$tenure <- tenure
    newCustomer$PhoneService <- PhoneService
    newCustomer$MultipleLines <- MultipleLines
    newCustomer$InternetService <- InternetService
    newCustomer$OnlineSecurity <- OnlineSecurity
    newCustomer$OnlineBackup <- OnlineBackup
    newCustomer$DeviceProtection <- DeviceProtection
    newCustomer$TechSupport <- TechSupport
    newCustomer$StreamingTV <- StreamingTV
    newCustomer$StreamingMovies <- StreamingMovies
    newCustomer$Contract <- Contract
    newCustomer$PaperlessBilling <- PaperlessBilling
    newCustomer$PaymentMethod <- PaymentMethod
    newCustomer$MonthlyCharges <- MontlyCharges
    newCustomer$TotalCharges <- TotalCharges
    newCustomer$Churn <- Churn

    # Convert fields that are factors
    newCustomer <- setRowAsFactor(newCustomer, c("gender", "SeniorCitizen",
        "Partner", "Dependents", "PhoneService", "MultipleLines",
        "InternetService", "OnlineSecurity", "OnlineBackup",
        "DeviceProtection", "TechSupport", "StreamingTV", "StreamingMovies",
        "Contract", "PaperlessBilling", "PaymentMethod", "Churn"))

    return(newCustomer)
}
```

Data

In this section we will load in our data and do some basic data exploration.

```
suppressMessages(library(RMySQL))

USER <- "root"
PASSWORD <- "A13337995"
HOST <- "localhost"
DBNAME <- "world"

statement <- "Select * from world.customerChurn"
db <- dbConnect(MySQL(), user = USER, password = PASSWORD, host = HOST,
    dbname = DBNAME, port = 3306)
customerDataset <- dbGetQuery(db, statement = statement)
dbDisconnect(db)
```

```
## [1] TRUE
```

```r
# Loops through and changes all relevant rows to factors and
# returns the dataset post modification


customerDataset <- setRowAsFactor(customerDataset, c("gender",
    "SeniorCitizen", "Partner", "Dependents", "PhoneService",
    "MultipleLines", "InternetService", "OnlineSecurity", "OnlineBackup",
    "DeviceProtection", "TechSupport", "StreamingTV", "StreamingMovies",
    "Contract", "PaperlessBilling", "PaymentMethod", "Churn"))

# Drop the columns that will not be needed
customerDataset <- customerDataset[, -which(names(customerDataset) %in%
    c("customerID"))]
```

Split Data

We will now split our data into test and training sets. The purpose of this is to create a sample of data that the model has never seen before in order to gauge its accuracy. The training set will consist of 80% of the data while the remaining 20% will constitute the test set.

```r
suppressMessages(library(caTools))

# Set the seed to reproducability
set.seed(12216)

# Create our two datasets
sample <- sample.split(customerDataset, SplitRatio = 0.8)
train_df <- subset(customerDataset, sample == TRUE)
test_df <- subset(customerDataset, sample == FALSE)

# We can now see that the data is split approximately 80:20
print(sprintf("The full dataset has %s observations", NROW(customerDataset)))
```

```
## [1] "The full dataset has 7032 observations"
```

```r
print(sprintf("The training dataset has %s observations", NROW(train_df)))
```

```
## [1] "The training dataset has 5628 observations"
```

```r
print(sprintf("The testing dataset has %s observations", NROW(test_df)))
```

```
## [1] "The testing dataset has 1404 observations"
```

```r
# Check to see how many customers churned in each dataset
table(train_df$Churn)
```

```
##
##   No  Yes
## 4120 1508
```

```r
table(test_df$Churn)
```

```
##
##   No  Yes
## 1043  361
```

```r
# We can see that each dataset holds approximately the same
# proportion of customers who churned
print(sprintf("%.2f%% of the training set churned", ((NROW(subset(train_df,
    Churn == "Yes")))/NROW(train_df) * 100)))
```

```
## [1] "26.79% of the training set churned"
```

```r
print(sprintf("%.2f%% of the testing set churned", ((NROW(subset(test_df,
    Churn == "Yes")))/NROW(test_df) * 100)))
```

```
## [1] "25.71% of the testing set churned"
```

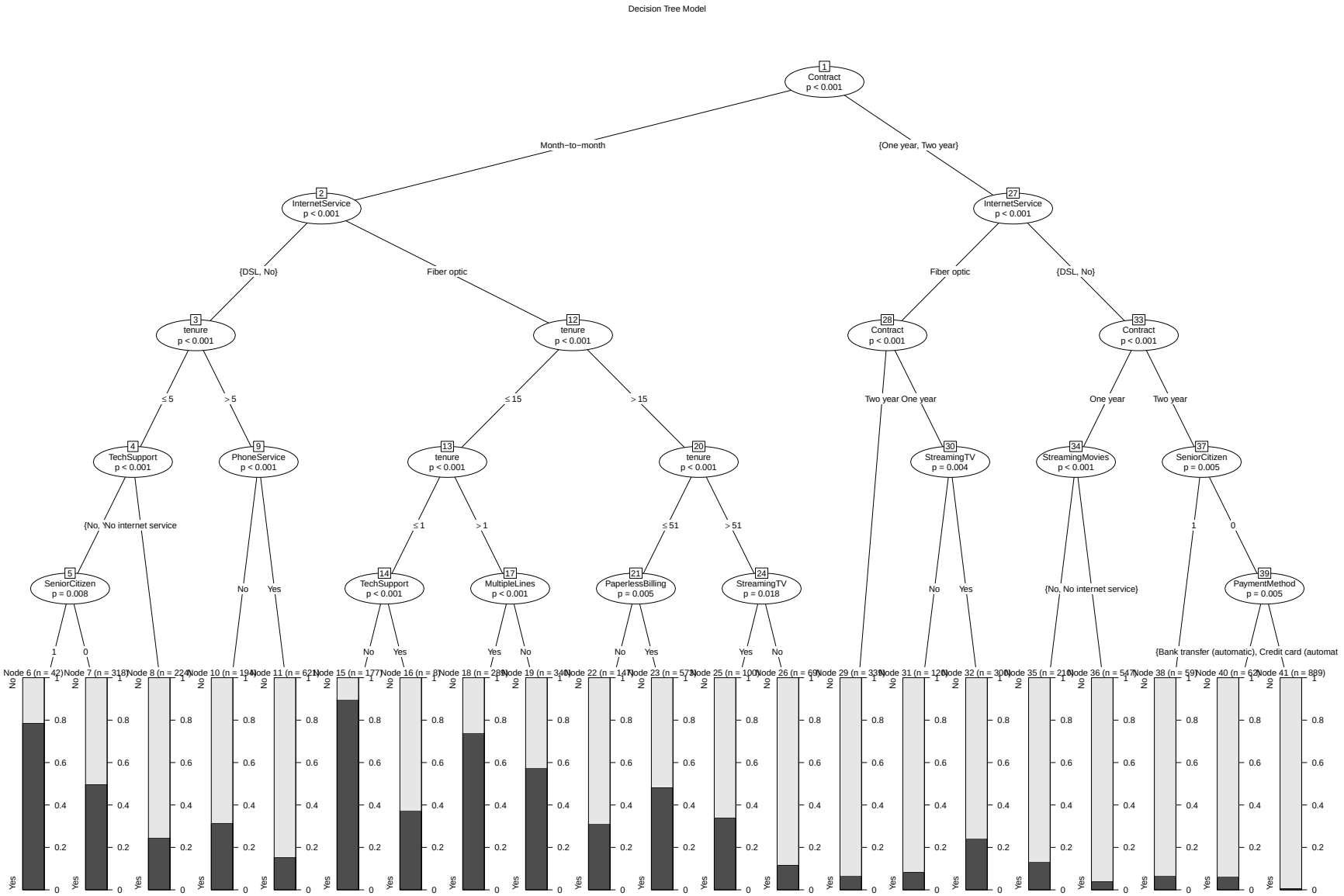
Decision Tree

We want to first make a decision tree to determine which variables are best able to predict whether a customer will churn. We already know from our previous report that the optimal model is however this time the tree will only be run on the training dataset.

```r
# Create and plot the decision tree
decisionTreeModel = createDecisionTreeModel(formula = Churn ~
    ., dataset = train_df, maxdepth = 5)
```

```r
plot(decisionTreeModel, main = "Decision Tree Model", type = "extended",
    newpage = TRUE)
```

∞


Decision Tree Model
1 Contract p < 0.001
Month−to−month
{One year, Two year}
2 InternetService p < 0.001
27 InternetService p < 0.001
{DSL, No}
Fiber optic
Fiber optic
{DSL, No}
3 tenure p < 0.001
12 tenure p < 0.001
28 Contract p < 0.001
33 Contract p < 0.001
≤ 5
> 5
≤ 15
> 15
Two year
One year
One year
Two year
4 TechSupport p < 0.001
9 PhoneService p < 0.001
13 tenure p < 0.001
20 tenure p < 0.001
30 StreamingTV p = 0.004
34 StreamingMovies p < 0.001
37 SeniorCitizen p = 0.005
{No, No internet service}
≤ 1
> 1
≤ 51
> 51
No
Yes
1
0
5 SeniorCitizen p = 0.008
14 TechSupport p < 0.001
17 MultipleLines p < 0.001
21 PaperlessBilling p = 0.005
24 StreamingTV p = 0.018
{No, No internet service}
39 PaymentMethod p = 0.005
{Bank transfer (automatic), Credit card (automat
Node 6 (n = 42)
Node 7 (n = 318)
Node 8 (n = 224)
Node 10 (n = 194)
Node 11 (n = 621)
Node 15 (n = 177)
Node 16 (n = 8)
Node 18 (n = 288)
Node 19 (n = 340)
Node 22 (n = 147)
Node 23 (n = 573)
Node 25 (n = 100)
Node 26 (n = 69)
Node 29 (n = 338)
Node 31 (n = 120)
Node 32 (n = 300)
Node 35 (n = 210)
Node 36 (n = 547)
Node 38 (n = 59)
Node 40 (n = 62)
Node 41 (n = 889)
No
Yes
0
0.2
0.4
0.6
0.8
1

###Decision Tree Results From looking at the decision tree it is clear that the top three variables are Contract, InternetService, and Tenure. Below those three levels, other variables such as StreamingTV, and TechSupport become relevant. To develop the best performing model with this dataset we will create a regression using only those three top level variables, and then a second using all variables. The results from each model will then be compared before the best model is presented to management.

Logistic Regression

We will now create multiple logistic regressions using GLM package. We will compare and then optimize before providing a final model to management for business use.

All Variables Logistic Regression

In this section we will create a logistic regression using all variables in the training dataset and look at statistical significance of each. Later in the report we will assess the accuracy of this model against others.

```
# We will start by first making a regression using all
# variables
allVariablesLogisticRegressionModel <- createLogisticRegressionModel(formula = Churn ~
    ., dataset = train_df)

# Print a summary of the regression
print("Model Summary")
```

```
## [1] "Model Summary"
```

```
summary(allVariablesLogisticRegressionModel)
```

```
##
## Call:
## glm(formula = formula, family = family, data = dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9271  -0.6763  -0.2846   0.7434   3.4193
##
## Coefficients: (7 not defined because of singularities)
##                                       Estimate Std. Error z value
## (Intercept)                           1.168e+00  9.050e-01   1.290
## genderMale                            5.431e-02  7.237e-02   0.750
## SeniorCitizen1                        2.279e-01  9.429e-02   2.417
## PartnerYes                            3.171e-02  8.752e-02   0.362
## DependentsYes                        -1.351e-01  1.002e-01  -1.348
## tenure                               -5.790e-02  6.865e-03  -8.434
## PhoneServiceYes                       1.985e-01  7.223e-01   0.275
## MultipleLinesNo phone service                NA         NA      NA
## MultipleLinesYes                      4.521e-01  1.974e-01   2.290
## InternetServiceFiber optic            1.765e+00  8.883e-01   1.987
## InternetServiceNo                    -1.900e+00  8.981e-01  -2.116
## OnlineSecurityNo internet service            NA         NA      NA
## OnlineSecurityYes                    -2.001e-01  1.994e-01  -1.003
## OnlineBackupNo internet service              NA         NA      NA
## OnlineBackupYes                       6.721e-02  1.948e-01   0.345
```

```
## DeviceProtectionNo internet service          NA         NA      NA
## DeviceProtectionYes                    1.476e-01  1.965e-01   0.751
## TechSupportNo internet service               NA         NA      NA
## TechSupportYes                        -1.518e-01  2.011e-01  -0.755
## StreamingTVNo internet service               NA         NA      NA
## StreamingTVYes                         6.178e-01  3.625e-01   1.704
## StreamingMoviesNo internet service           NA         NA      NA
## StreamingMoviesYes                     5.822e-01  3.650e-01   1.595
## ContractOne year                      -6.773e-01  1.197e-01  -5.657
## ContractTwo year                      -1.424e+00  2.001e-01  -7.114
## PaperlessBillingYes                    3.382e-01  8.284e-02   4.083
## PaymentMethodCredit card (automatic) -5.187e-02  1.273e-01  -0.407
## PaymentMethodElectronic check          3.014e-01  1.056e-01   2.855
## PaymentMethodMailed check             -4.768e-02  1.280e-01  -0.372
## MonthlyCharges                        -4.160e-02  3.531e-02  -1.178
## TotalCharges                           2.991e-04  7.846e-05   3.813
##                                      Pr(>|z|)
## (Intercept)                          0.197001
## genderMale                           0.452970
## SeniorCitizen1                       0.015645 *
## PartnerYes                           0.717142
## DependentsYes                        0.177760
## tenure                                < 2e-16 ***
## PhoneServiceYes                      0.783462
## MultipleLinesNo phone service              NA
## MultipleLinesYes                     0.022016 *
## InternetServiceFiber optic           0.046872 *
## InternetServiceNo                    0.034383 *
## OnlineSecurityNo internet service          NA
## OnlineSecurityYes                    0.315685
## OnlineBackupNo internet service            NA
## OnlineBackupYes                      0.730109
## DeviceProtectionNo internet service        NA
## DeviceProtectionYes                  0.452539
## TechSupportNo internet service             NA
## TechSupportYes                       0.450396
## StreamingTVNo internet service             NA
## StreamingTVYes                       0.088343 .
## StreamingMoviesNo internet service         NA
## StreamingMoviesYes                   0.110691
## ContractOne year                     1.54e-08 ***
## ContractTwo year                     1.13e-12 ***
## PaperlessBillingYes                  4.45e-05 ***
## PaymentMethodCredit card (automatic) 0.683705
## PaymentMethodElectronic check        0.004305 **
## PaymentMethodMailed check            0.709541
## MonthlyCharges                       0.238771
## TotalCharges                         0.000138 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 6542.0  on 5627  degrees of freedom
```

```
## Residual deviance: 4674.1  on 5604  degrees of freedom
## AIC: 4722.1
##
## Number of Fisher Scoring iterations: 6
```

All Variables Logistic Regression Results

From the model's summary we can see that our top three variables identified earlier are all have a high statistical significance. TotalCharges is also statistically different from zero however since the decision tree deemed that it had no predictive information we will not be including it in our model building

Top Three Logistic Regression

We will now create our logistic regression using only the top three variables from our decision tree (Contract, InternetService, and Tenure)

```
# We will start by first making a regression using all
# variables
topThreeLogisticRegressionModel <- createLogisticRegressionModel(formula = Churn ~
    Contract + InternetService + tenure, dataset = train_df)

# Print a summary of the regression
print("Model Summary")
```

```
## [1] "Model Summary"
```

```
summary(topThreeLogisticRegressionModel)
```

```
##
## Call:
## glm(formula = formula, family = family, data = dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5640  -0.6746  -0.3077   0.8350   3.1500
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -0.257388   0.070388  -3.657 0.000255 ***
## ContractOne year            -0.870290   0.113829  -7.646 2.08e-14 ***
## ContractTwo year            -1.740473   0.191348  -9.096  < 2e-16 ***
## InternetServiceFiber optic   1.163022   0.080631  14.424  < 2e-16 ***
## InternetServiceNo           -1.121017   0.131645  -8.515  < 2e-16 ***
## tenure                      -0.031107   0.002167 -14.353  < 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: 6542.0  on 5627  degrees of freedom
## Residual deviance: 4852.3  on 5622  degrees of freedom
## AIC: 4864.3
##
## Number of Fisher Scoring iterations: 6
```

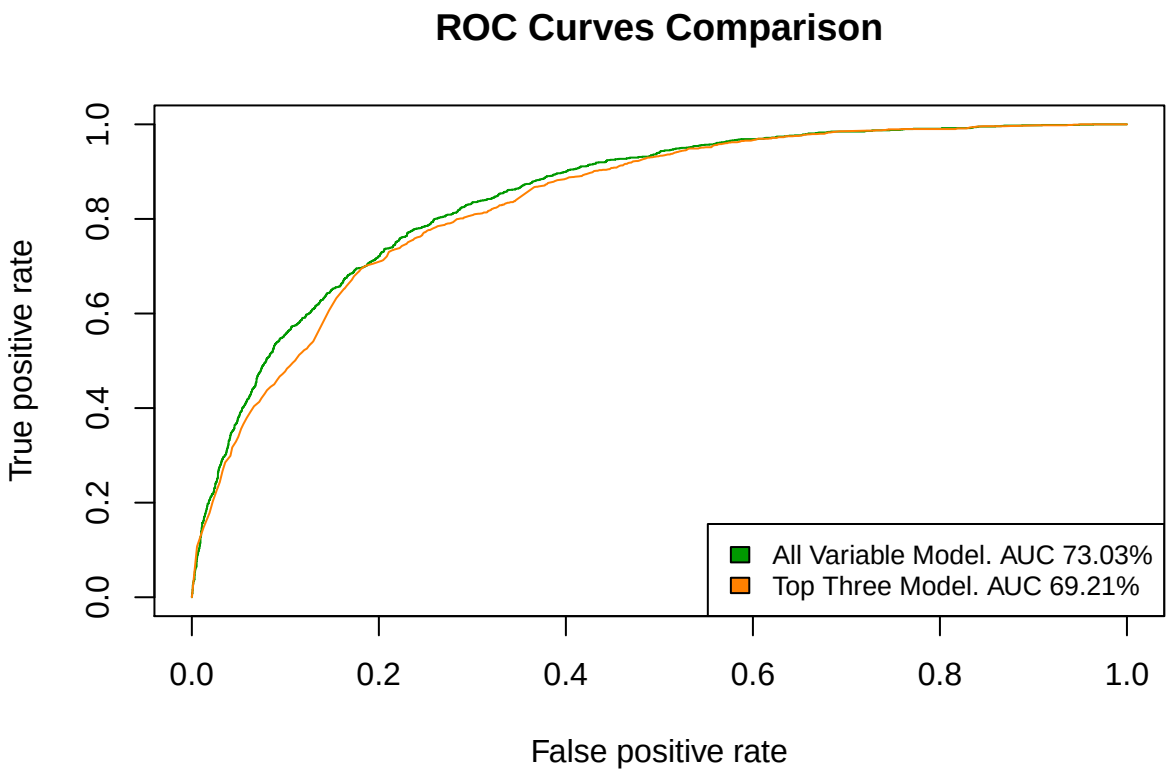
Model Comparison

Now that we have created our two models we will test their accuracy against the training dataset and also the test dataset. One of the easiest ways to see which model is more accurate is to use an ROC curve and measure the area under each curve, the larger the area under the curve the more accurate the model is. We will first test each model using the training dataset before testing each one individually with the test dataset to gauge how robust they are. Once we have established whether the models are robust we will create a pair of confusion matricies using the test dataset to see which model had the highest percentage of churns predicted correctly.

```
suppressMessages(library(caret))
suppressMessages(library(ROCR))

# Get the performance of each model
allVariableModelPerformance <- getModelPerformance(allVariablesLogisticRegressionModel,
    dataset = train_df, outcomeColumn = train_df$Churn)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

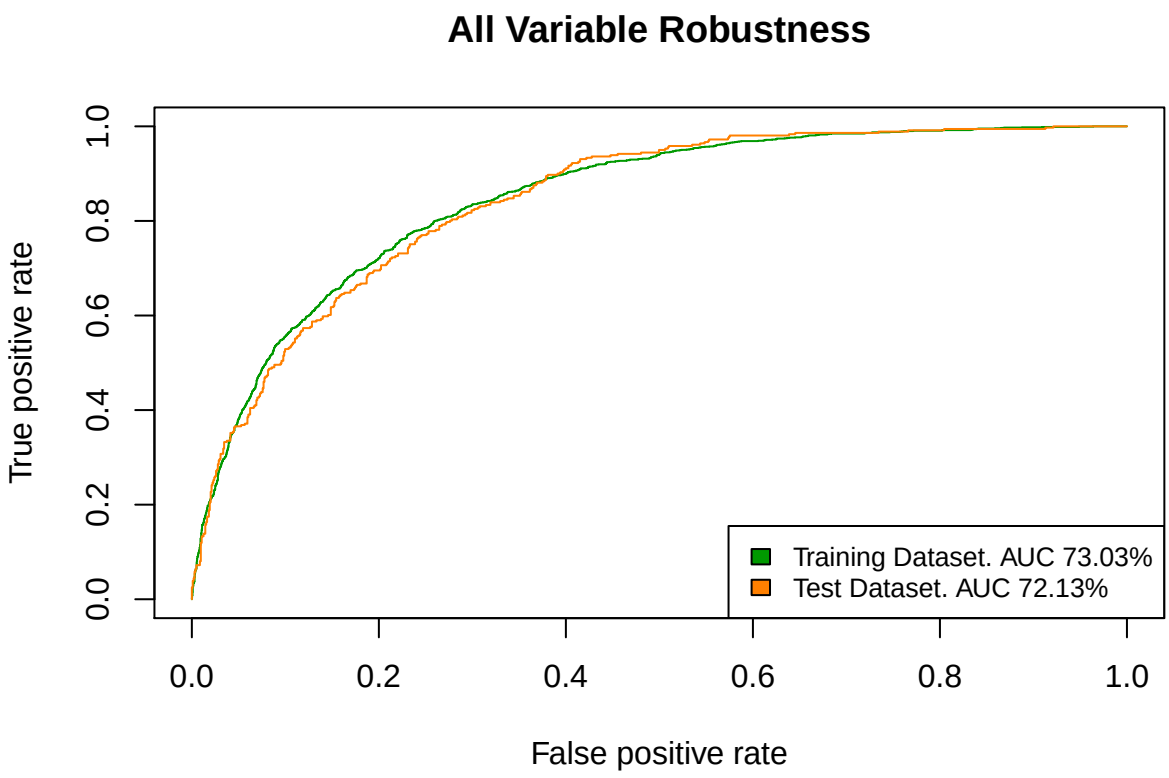
```
topThreeModelPerformance <- getModelPerformance(topThreeLogisticRegressionModel,
    dataset = train_df, outcomeColumn = train_df$Churn)

# Get the AUC
allVariableModelAUC <- getAUC(train_df$Churn, train_df, allVariablesLogisticRegressionModel,
    oneClass = "Yes", zeroClass = "No")
topThreeModelAUC <- getAUC(train_df$Churn, train_df, topThreeLogisticRegressionModel,
    oneClass = "Yes", zeroClass = "No")

# Plot the ROC curves
plotROCCurves(allVariableModelPerformance, topThreeModelPerformance,
    main = "ROC Curves Comparison", model1Name = sprintf("All Variable Model. AUC %.2f%%",
        allVariableModelAUC * 100), model2Name = sprintf("Top Three Model. AUC %.2f%%",
        topThreeModelAUC * 100))
```



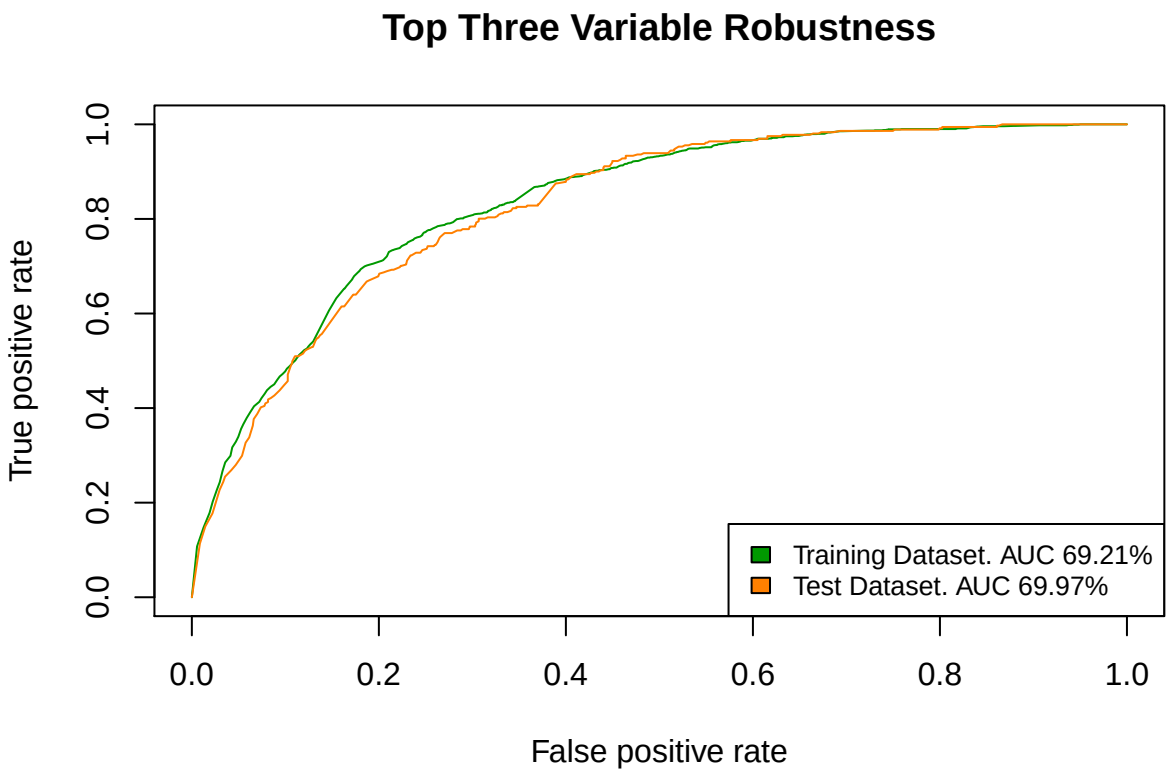

```
# Check the allVariableModel for overfitting
allVariableModelPerformanceTest <- getModelPerformance(allVariablesLogisticRegressionModel,
    dataset = test_df, outcomeColumn = test_df$Churn)
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type =
## ifelse(type == : prediction from a rank-deficient fit may be misleading
```

```
allVariableModelAUCTest <- getAUC(test_df$Churn, test_df, allVariablesLogisticRegressionModel,
    oneClass = "Yes", zeroClass = "No")
plotROCCurves(allVariableModelPerformance, allVariableModelPerformanceTest,
    main = "All Variable Robustness", model1Name = sprintf("Training Dataset. AUC %.2f%%",
        allVariableModelAUC * 100), model2Name = sprintf("Test Dataset. AUC %.2f%%",
        allVariableModelAUCTest * 100))
```




```
# Check the topThreeModel for overfitting
topThreeModelPerformanceTest <- getModelPerformance(topThreeLogisticRegressionModel,
    dataset = test_df, outcomeColumn = test_df$Churn)
topThreeModelAUCTest <- getAUC(test_df$Churn, test_df, topThreeLogisticRegressionModel,
    oneClass = "Yes", zeroClass = "No")
plotROCCurves(topThreeModelPerformance, topThreeModelPerformanceTest,
    main = "Top Three Variable Robustness", model1Name = sprintf("Training Dataset. AUC %.2f%%",
        topThreeModelAUC * 100), model2Name = sprintf("Test Dataset. AUC %.2f%%",
        topThreeModelAUCTest * 100))
```




```
# Create confusion matricies to compare predicitons
print("All Variable Model Confusion Matrix")
```

```
## [1] "All Variable Model Confusion Matrix"
```

```
allVariableConfusionMatrix <- createConfusionMatrix(allVariablesLogisticRegressionModel,
    test_df, test_df$Churn, oneClass = "Yes", zeroClass = "No")
allVariableConfusionMatrix
```

```
##
## outcomeColumn  No Yes
##           No  924 119
##           Yes 160 201
```

```
allVariableYesCorrectPercentage <- allVariableConfusionMatrix[2,
    2]/sum(allVariableConfusionMatrix)
sprintf("The All Variable Model predicted yes correctly %.2f%% of the time",
    allVariableYesCorrectPercentage * 100)
```

```
## [1] "The All Variable Model predicted yes correctly 14.32% of the time"
```

```
print("Top Three Variable Confusion Matrix")
```

```
## [1] "Top Three Variable Confusion Matrix"
```

```
topThreeConfusionMatrix <- createConfusionMatrix(topThreeLogisticRegressionModel,
    test_df, test_df$Churn, oneClass = "Yes", zeroClass = "No")
topThreeConfusionMatrix
```

```
##
```

```
## outcomeColumn  No Yes
##           No  928 115
##           Yes 177 184
```

```
topThreeYesCorrectPercentage <- topThreeConfusionMatrix[2, 2]/sum(topThreeConfusionMatrix)
sprintf("The Top Three Model predicted yes correctly %.2f%% of the time",
    topThreeYesCorrectPercentage * 100)
```

```
## [1] "The Top Three Model predicted yes correctly 13.11% of the time"
```

Model Comparison Discussion

Looking at the ROC Curves Comparison graph we can see that the two models have a similar AUC with the All Variable Model only slightly outperforming the Top Three Model. The following two ROC curves show us that both models are robust and have not been overfit since they are approximately as accurate of the test dataset as they are on the training dataset. In line with the results from the ROC curve, the All Variable model also out performs the topThreeModel in terms of the highest percentage of Churns predicited correctly. For these reasons we will be presenting the All Variable Model to management.

Model

After testing different combinations of predictive factors we were able to produce this model which accurately predicts the whether a customer will churn 14.32% of the time. For example, if we take a customer who is on a month-to-month plan, has fiber optic internet, and has been with the company for one year, we can feed that information into the model a predict how likely they are to Churn.

```
# Create a new customer
newCustomer <- createCustomer(customerDataset, gender = "Female",
    SeniorCitizen = 0, Partner = "Yes", Dependents = "No", tenure = 1,
    PhoneService = "Yes", MultipleLines = "No", InternetService = "Fiber optic",
    OnlineSecurity = "No", OnlineBackup = "No", DeviceProtection = "No",
    TechSupport = "No", StreamingTV = "Yes", StreamingMovies = "Yes",
    Contract = "Month-to-month", PaperlessBilling = "Yes", PaymentMethod = "Bank transfer (automatic)",
    MontlyCharges = 34.5, TotalCharges = 49, Churn = "Yes")
newCustomerPrediciton <- createPrediction_df(allVariablesLogisticRegressionModel,
    dataset = newCustomer, oneClass = "Yes", zeroClass = "No")
newCustomerPrediciton
```

```
##   probabilities classification
## 1     0.9616977            Yes
```

The model has predicited that a customer with these parameters has a 96.17% liklihood of churning. To understand this result a better we should turn our attention to the odds ratios produced by the model.

```
print("Odds Ratios")
```

```
## [1] "Odds Ratios"
```

```
exp(coef(allVariablesLogisticRegressionModel))
```

```
##                          (Intercept)                           genderMale
##                            3.2142616                            1.0558152
##                        SeniorCitizen1                          PartnerYes
##                            1.2559792                            1.0322134
##                         DependentsYes                               tenure
```

```
##                           0.8736378                           0.9437414
##                    PhoneServiceYes       MultipleLinesNo phone service
##                           1.2195730                                  NA
##                   MultipleLinesYes          InternetServiceFiber optic
##                           1.5716412                           5.8440322
##                  InternetServiceNo    OnlineSecurityNo internet service
##                           0.1495586                                  NA
##                  OnlineSecurityYes     OnlineBackupNo internet service
##                           0.8186677                                  NA
##                    OnlineBackupYes  DeviceProtectionNo internet service
##                           1.0695253                                  NA
##                DeviceProtectionYes      TechSupportNo internet service
##                           1.1590444                                  NA
##                     TechSupportYes      StreamingTVNo internet service
##                           0.8591911                                  NA
##                     StreamingTVYes   StreamingMoviesNo internet service
##                           1.8547853                                  NA
##                 StreamingMoviesYes                     ContractOne year
##                           1.7900570                           0.5079813
##                   ContractTwo year                 PaperlessBillingYes
##                           0.2408675                           1.4024619
## PaymentMethodCredit card (automatic)       PaymentMethodElectronic check
##                           0.9494527                           1.3517921
##           PaymentMethodMailed check                      MonthlyCharges
##                           0.9534397                           0.9592580
##                       TotalCharges
##                           1.0002992
```

We can see from these statistics that being on the Fiber optic network makes a customer 5.844 times more likely to churn as opposed to not being on it. A main driver behind this statistic could be sub-optimal network speeds. The type of customer who uses a fiber optic network is someone who needs the fastest possible internet speeds, whether it be for business or personal use. It could be worth the company's time and resources to further invest into this network to reduce the liklihood of a customer churning. Not offering the network is illadvised since customers will opt for other providers who do offer the network, even if its speeds are also below expectations.