K Nearest

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Contents

Introduction

In this report we will build upon the information gathered from our decision tree and logistic regression models to build a K-Nearest Neighbour model that can be used to predict whether a customer will churn. We will complete a series of tests to produce the best possible model using the customer dataset provided to us.

Functions

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

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



# Get the models predictions
getPredictions <- function(model, dataset, outcomeColumn, type = "prob") {
    suppressMessages(library(ROCR))

    probability <- as.numeric(predict(model, newdata = customerDataset,
        type = "prob")[, 2])
    predictions <- prediction(probability, outcomeColumn)

    return(predictions)
}

# Get the model AUC and return it
getModelAUC <- function(model, dataset, outcomeColumn, type = "prob") {
    suppressMessages(library(ROCR))



    prediction <- getPredictions(model = model, dataset = dataset,
        outcomeColumn = outcomeColumn)
    auc <- performance(prediction, "auc")@y.values


    return(auc)
}


# Plot ROC curves
plotROCCurves <- function(model1Prediction, model2Prediction,
    main, model1Colour = "#009900", model2Colour = "#FF8000",
    model1Name, model2Name, legendLocation = "bottomright") {
    suppressMessages(library(ROCR))

    model1Performance <- performance(model1Prediction, "tpr",
```

```
        "fpr")
    model2Performance <- performance(model2Prediction, "tpr",
        "fpr")

    plot(model1Performance, main = main, col = model1Colour,
        print.auc = TRUE)
    plot(model2Performance, add = T, col = model2Colour)
    legend(legendLocation, legend = paste(rep(c(model1Name, model2Name))),
        col = c(model1Colour, model2Colour), cex = 0.8, fill = c(model1Colour,
            model2Colour))
}

# 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(prediction_df$classification,
        outcomeColumn)

    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)
}

# Gets a dataframe from a locally hosted MySQL server.
# Returns a dataframe
loadDataframeFromMySQL <- function(user, password, host = "localhost",
    dbname, statement, port = 3306) {
    suppressMessages(library(RMySQL))

    # Connect to the server
    dataBase <- dbConnect(MySQL(), user = user, password = password,
        host = host, dbname = dbname, port = port)
    # Retrieve the info the from the specified server
    dataframe <- dbGetQuery(dataBase, statement = statement)
    # Close the connection to the server
    dbDisconnect(dataBase)

    return(dataframe)

}

# Returns a predictive model
predictiveModel <- function(formula, dataset, method, neighbours = 1:10,
    metric = "Accuracy", trControl) {
    suppressMessages(library(caret))
    model <- train(formula, data = dataset, method = method,
        tuneGrid = expand.grid(.k = neighbours), metric = metric,
        trControl = trControl)

    return(model)
}

# Returns a train control object to be fed into a predictive
# model
trainControlObject <- function(method = "repeatedcv", number = 10,
    repeats) {
    suppressMessages(library(caret))
    object <- trainControl(method = method, number = number,
        repeats = repeats)

    return(object)
}

# Create and return a dataframe of the classifications and
```

```
# their probabilities
createPrediction_df <- function(model, dataset, predictionType = "prob",
    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) <- c("NegativeProb", "PositiveProb")
    # 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$PositiveProb >
        0.5] <- oneClass
    prediction_df$classification <- as.factor(prediction_df$classification)


    return(prediction_df)
}

# Calculate the accuracy of accurately predicting yes
getYesAccuracy <- function(confusionMatrix, asDecimal = F) {
    accuracy <- confusionMatrix[2, 2]/(confusionMatrix[2, 1] +
        confusionMatrix[2, 2])
    if (asDecimal) {
        return(accuracy)
    } else {
        return(accuracy * 100)
    }
}
```

Data

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

```
customerDataset <- loadDataframeFromMySQL(user = "root", password = "A13337995",
    dbname = "world", statement = "Select * from world.customerChurn")

# Loop through and change 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"))]
```

Model

We will create two models, one using all variables from the customer dataset, the other using the top three variables outlined in our decision tree paper. The top three variables are the type of contract, the type of internet service, and the customer's tenure. We will test our models between 3 and 45 neighbours as 1 and 2 neighbours typically have little value and more than 45 may make the model prone to overfitting. After the models have been created we will examine their overall accuracy and how accurate they are when they predict that a customer will churn. Once we have established which model has the greatest accuracy for the business's intended use we will examine if any other number of neighbours close to the one chosen by R would provide a better model for the intended use case.

Model Creation

We will now create our two models and explore their results.

```
suppressMessages(library(caret))
set.seed(12216)


allVariableModel <- predictiveModel(formula = Churn ~ ., dataset = customerDataset,
    method = "knn", neighbours = 3:45, trControl = trainControlObject(repeats = 5))

topThreeModel <- predictiveModel(formula = Churn ~ Contract +
    InternetService + tenure, dataset = customerDataset, method = "knn",
    neighbours = 3:45, trControl = trainControlObject(repeats = 5))
allVariableModel
```

```
## k-Nearest Neighbors
##
## 7032 samples
##   19 predictor
##    2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 5 times)
## Summary of sample sizes: 6329, 6329, 6329, 6329, 6329, 6329, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    3  0.7512522  0.3332301
##    4  0.7495158  0.3265884
##    5  0.7636237  0.3495568
##    6  0.7629710  0.3468718
##    7  0.7714460  0.3628864
##    8  0.7711625  0.3617007
##    9  0.7791257  0.3774556
##   10  0.7770776  0.3691445
##   11  0.7814279  0.3769666
##   12  0.7803761  0.3714237
##   13  0.7825934  0.3727722
##   14  0.7821668  0.3697731
##   15  0.7828208  0.3706669
##   16  0.7827635  0.3693149
##   17  0.7826787  0.3668893
```

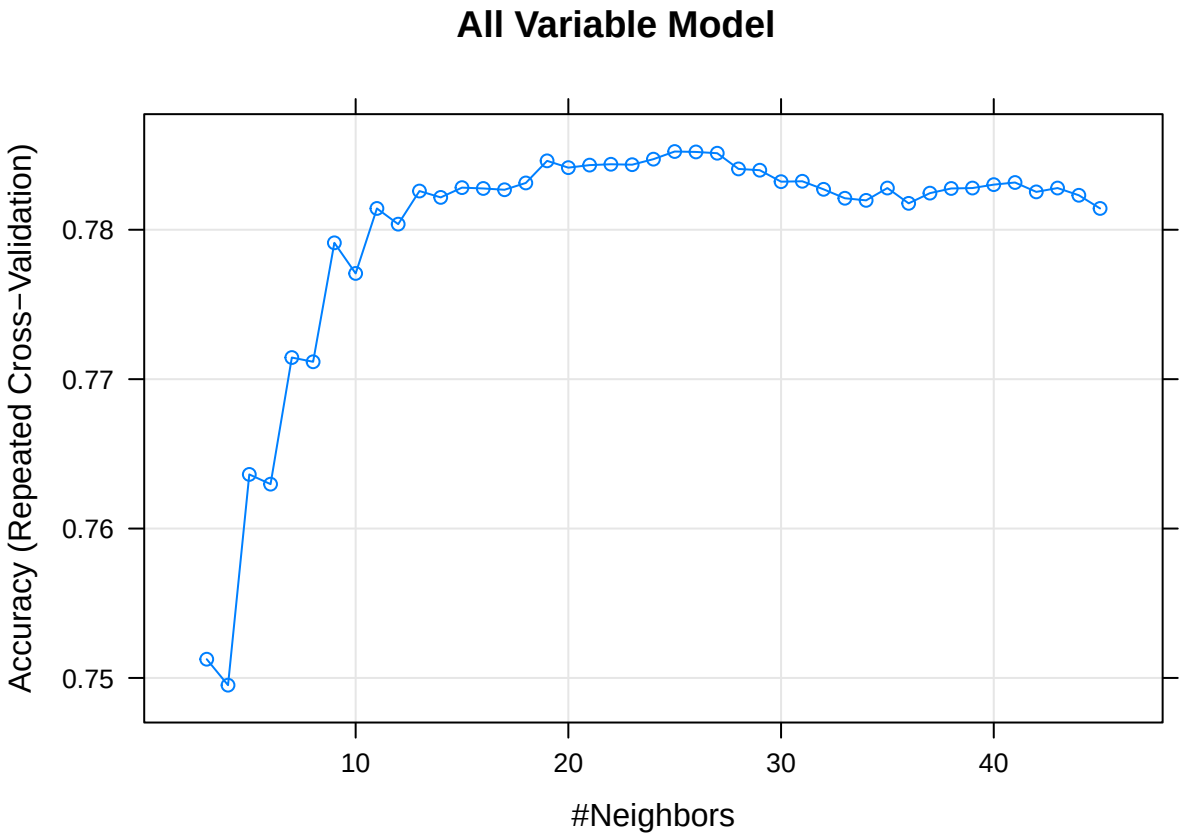
```
##   18  0.7831342  0.3660530
##   19  0.7846132  0.3698433
##   20  0.7841578  0.3680674
##   21  0.7843281  0.3677020
##   22  0.7843851  0.3662550
##   23  0.7843569  0.3646770
##   24  0.7847263  0.3653045
##   25  0.7852386  0.3651236
##   26  0.7852093  0.3639776
##   27  0.7851246  0.3633728
##   28  0.7840721  0.3593145
##   29  0.7839874  0.3580086
##   30  0.7832193  0.3549772
##   31  0.7832469  0.3545445
##   32  0.7827063  0.3518629
##   33  0.7821095  0.3502417
##   34  0.7819674  0.3483380
##   35  0.7827932  0.3499306
##   36  0.7817686  0.3458876
##   37  0.7824518  0.3473010
##   38  0.7827645  0.3474467
##   39  0.7827927  0.3466259
##   40  0.7830206  0.3464548
##   41  0.7831633  0.3465271
##   42  0.7825365  0.3427540
##   43  0.7827927  0.3438432
##   44  0.7823087  0.3414474
##   45  0.7814273  0.3376478
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was k = 25.
```

```
topThreeModel
```

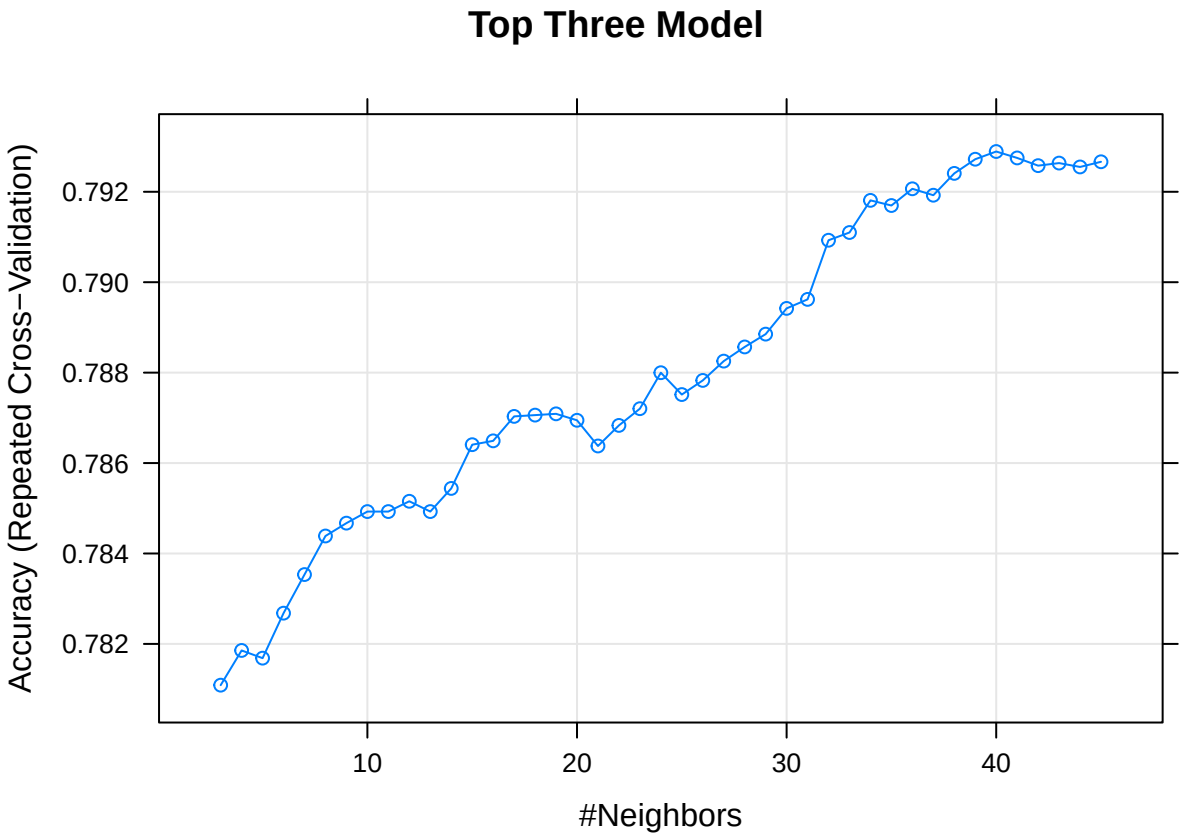
```
## k-Nearest Neighbors
##
## 7032 samples
##    3 predictor
##    2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 5 times)
## Summary of sample sizes: 6330, 6329, 6329, 6329, 6328, 6328, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    3  0.7810877  0.4101355
##    4  0.7818552  0.4122577
##    5  0.7816849  0.4112815
##    6  0.7826802  0.4132486
##    7  0.7835338  0.4140237
##    8  0.7843868  0.4151292
##    9  0.7846713  0.4154510
##   10  0.7849275  0.4161003
##   11  0.7849271  0.4159485
```

```
##   12  0.7851549  0.4166810
##   13  0.7849273  0.4160800
##   14  0.7854392  0.4169988
##   15  0.7864066  0.4188277
##   16  0.7864915  0.4182480
##   17  0.7870320  0.4185549
##   18  0.7870605  0.4168363
##   19  0.7870886  0.4149821
##   20  0.7869462  0.4131081
##   21  0.7863777  0.4105335
##   22  0.7868327  0.4101205
##   23  0.7872025  0.4092336
##   24  0.7879987  0.4100534
##   25  0.7875155  0.4075588
##   26  0.7878281  0.4080975
##   27  0.7882550  0.4088138
##   28  0.7885680  0.4094095
##   29  0.7888520  0.4095492
##   30  0.7894213  0.4106512
##   31  0.7896203  0.4099117
##   32  0.7909286  0.4115054
##   33  0.7910994  0.4107424
##   34  0.7918103  0.4119777
##   35  0.7916964  0.4108626
##   36  0.7920662  0.4118698
##   37  0.7919239  0.4119186
##   38  0.7924073  0.4137182
##   39  0.7927202  0.4150493
##   40  0.7928910  0.4155434
##   41  0.7927487  0.4150273
##   42  0.7925782  0.4144677
##   43  0.7926349  0.4145292
##   44  0.7925496  0.4141824
##   45  0.7926635  0.4145938
##
## Accuracy was used to select the optimal model using  the largest value.
## The final value used for the model was k = 40.
```

```r
plot(allVariableModel, main = "All Variable Model")
```




```
plot(topThreeModel, main = "Top Three Model")
```



###Model Outputs
We can see that each model uses a largely different value of K. Where the All Variable Model uses only 25 neighbours to achieve it's peak accuracy, the Top Three Variable model uses 40. The plots show the increases and decreases in accuracy with the change in the number of neighbours for each model.

Model Comparison

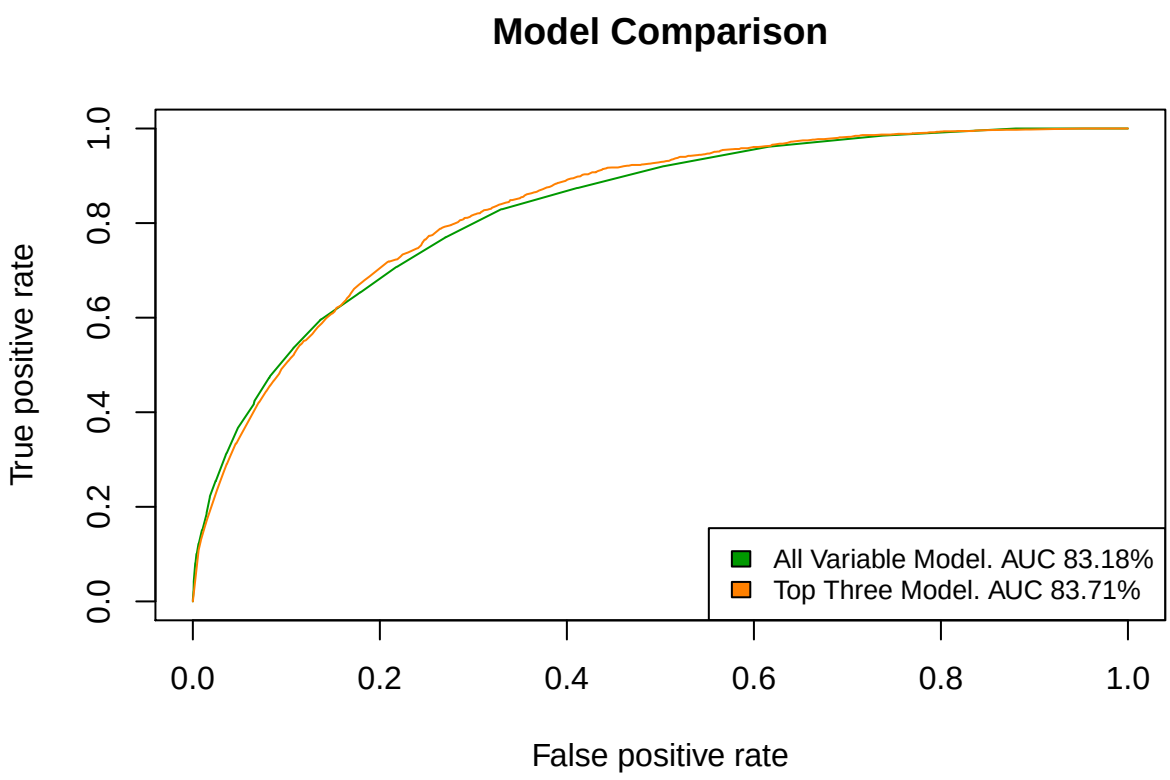
The two models produce similar guideline accuracy results being withing 2% of one another however the best strategy for testing their true accuracy is to create an AUC curve and compare the results.

```
# Create the prediction statistics that are used to plot the
# AUC
model1Predicitions <- getPredictions(allVariableModel, customerDataset,
    customerDataset$Churn)
model2Predicitions <- getPredictions(topThreeModel, customerDataset,
    customerDataset$Churn)

# Calculate the AUC for each model
allVariableModelAUC <- as.numeric(getModelAUC(model = allVariableModel,
    dataset = customerDataset, outcomeColumn = customerDataset$Churn,
    type = "prob"))
topThreeModelAUC <- as.numeric(getModelAUC(model = topThreeModel,
    dataset = customerDataset, outcomeColumn = customerDataset$Churn,
    type = "prob"))

# Plot the ROC curves on the same graph for comparison
```

```
plotROCCurves(model1Prediction = model1Predicitions, model2Prediction = model2Predicitions,
    main = "Model Comparison", model1Name = sprintf("All Variable Model. AUC %.2f%%",
        allVariableModelAUC * 100), model2Name = sprintf("Top Three Model. AUC %.2f%%",
        topThreeModelAUC * 100))
```




```
# Create a confusion matrix for each model
model1ConfusionMatrix <- createConfusionMatrix(allVariableModel,
    customerDataset, customerDataset$Churn, oneClass = "Yes",
    zeroClass = "No")

model2ConfusionMatrix <- createConfusionMatrix(topThreeModel,
    customerDataset, customerDataset$Churn, oneClass = "Yes",
    zeroClass = "No")
model1ConfusionMatrix
```

```
##      outcomeColumn
##         No  Yes
##   No  4826 1086
##   Yes  337  783
```

```
model2ConfusionMatrix
```

```
##      outcomeColumn
##         No  Yes
##   No  4736 1016
##   Yes  427  853
```

```r
# Calculate the difference in the AUC
aucDifference <- (topThreeModelAUC - allVariableModelAUC) * 100

# Accuracy of the yes predictions
model1YesAccuracy <- getYesAccuracy(model1ConfusionMatrix)
model2YesAccuracy <- getYesAccuracy(model2ConfusionMatrix)
```

Model Comparison Results

Looking at the model's AUC we can see that the top three model is still the most accurate overall, beating the all variable model by 0.53%. Where the top three model begins to faulter is how accurately it predicts yes as it is only accurate 66.64% where the All Variable Model is correct when it predicts that a customer will churn 69.91% of the time. Given that the main use case for this model will be to accurately predict that someone will churn, the All Variable Model will be the one we will attempt to further optimise and then present to management.

Model Optimisation

The model KNN model produced by R gives the optimal number of neighours for the best overall accuracy, however we are only interested in the accuracy of the yes predicitions. We will now see if changing the number of neighbours within a range of three on either side of the optimal number produced by R will improve our accuracy.

```r
# Loop through a range of values and print their yes accuracy
for (neighbours in 22:28) {
    model <- predictiveModel(formula = Churn ~ ., dataset = customerDataset,
        method = "knn", neighbours = neighbours, trControl = trainControlObject(repeats = 5))
    confusionMatrix <- createConfusionMatrix(model, customerDataset,
        customerDataset$Churn, oneClass = "Yes", zeroClass = "No")
    yesAccuracy <- getYesAccuracy(confusionMatrix)
    print(sprintf("The accuracy of %s neighbours is %.2f%%.",
        neighbours, yesAccuracy))
}
```

```
## [1] "The accuracy of 22 neighbours is 71.13%."
## [1] "The accuracy of 23 neighbours is 69.75%."
## [1] "The accuracy of 24 neighbours is 71.41%."
## [1] "The accuracy of 25 neighbours is 69.91%."
## [1] "The accuracy of 26 neighbours is 71.88%."
## [1] "The accuracy of 27 neighbours is 70.58%."
## [1] "The accuracy of 28 neighbours is 71.62%."
```

Model Optimisation Results

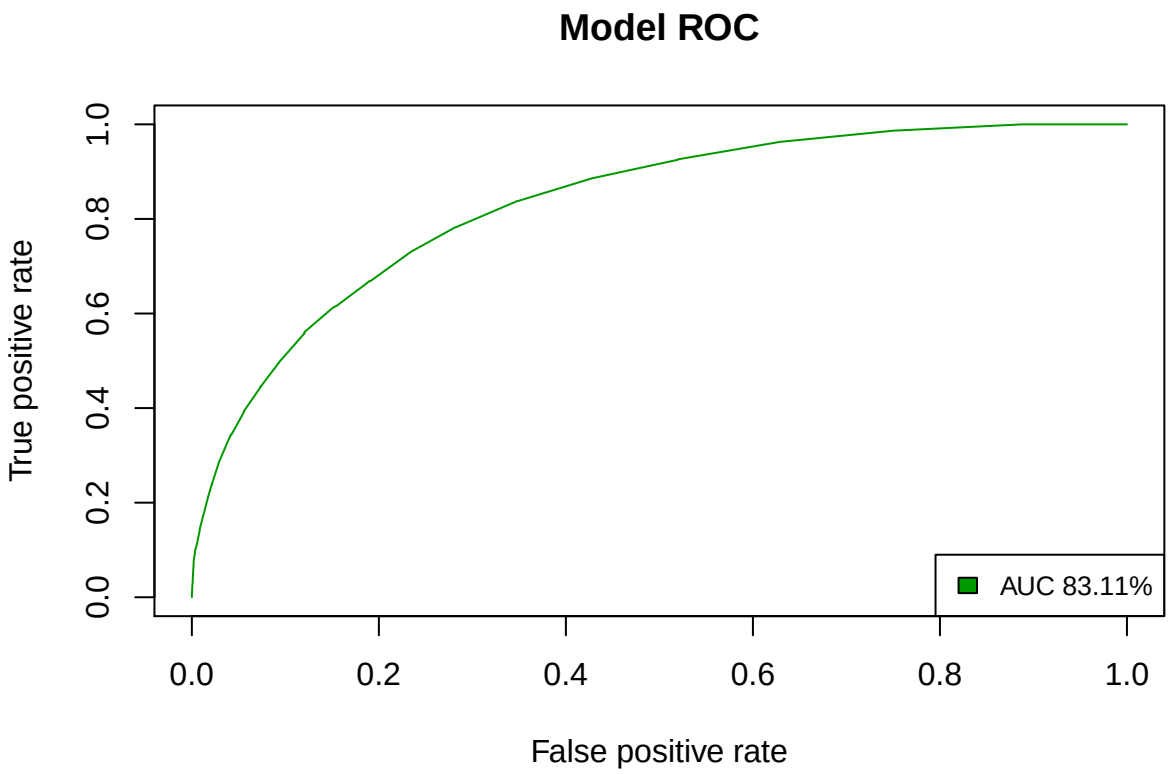
The results so us that increasing the number of neighbours to 26 marginally increases the accuracy of the yes predictions therefore that is the model that we will be presenting to management.

Model

```r
# A collection of all results related to the final model that
# can be referenced in the dicussion below This code chunk
# does not print any values
finalModel <- predictiveModel(formula = Churn ~ ., dataset = customerDataset,
    method = "knn", neighbours = 26, trControl = trainControlObject(repeats = 5))
finalModelPredicitions <- getPredictions(finalModel, customerDataset,
    customerDataset$Churn)
finalModelPerformance <- performance(finalModelPredicitions,
    "tpr", "fpr")
finalModelAUC <- as.numeric(getModelAUC(model = finalModel, dataset = customerDataset,
    outcomeColumn = customerDataset$Churn, type = "prob"))
# Not printed but used in the yes accuracy
finalModelConfusionMatrix <- createConfusionMatrix(finalModel,
    customerDataset, customerDataset$Churn, oneClass = "Yes",
    zeroClass = "No")
finalModelYesAccuracy <- getYesAccuracy(finalModelConfusionMatrix)
```

After developing a series of K-nearest neighbour models we were able to create a baseline model and optimise it to best fit its intended use case. As you can see from the ROC plot below, the model has an overall accuracy of 83.11%, but more importantly the accuracy of the model's yes predictions are 71.88%. The model did produce 288 false positives but a misclassification that small should be of no real convern considering how accurate the model is at predicting yes all other times.

```r
plot(finalModelPerformance, main = "Model ROC", col = "#009900",
    print.auc = TRUE)
legend("bottomright", legend = paste(rep(sprintf("AUC %.2f%%",
    finalModelAUC * 100))), col = "#009900", cex = 0.8, fill = "#009900")
```



If we create a dummy customer we can test to see whether they will churn.

```
# Create a new customer
newCustomer <- createCustomer(customerDataset, gender = "Male",
    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 = 34.5, Churn = "Yes")
finalModelPredicition <- createPrediction_df(finalModel, newCustomer,
    oneClass = "Yes", zeroClass = "No")
finalModelPredicition
```

```
##   NegativeProb PositiveProb classification
## 1    0.3461538    0.6538462            Yes
```

The model predicts that a male who has a one year tenure, streams TV and has a fibre optic internet service will churn, and based on the results from our testing we can say that with a 71.88% chance of being correct. From an output such as this we would make recommendations to upgrade your fiber network or invest further into your tv streaming service.

Conclusion

Given the model's accuracy when it predicts that a customer will churn, we can advise that this model should be used in everyday business operations. There may be parameters outside of those provided in the

dataset which would improve the accuracy of the model but that can be visited at a later time. For now this model will work for its intended business use.