Assignment 2 - Logistic Regression

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Contents

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)
}

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

    return(logisticRegressionModel)
}
```

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
```

```
# 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.

```
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"
```

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

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

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

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

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

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

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

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

```
# 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"
```

```
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"
```

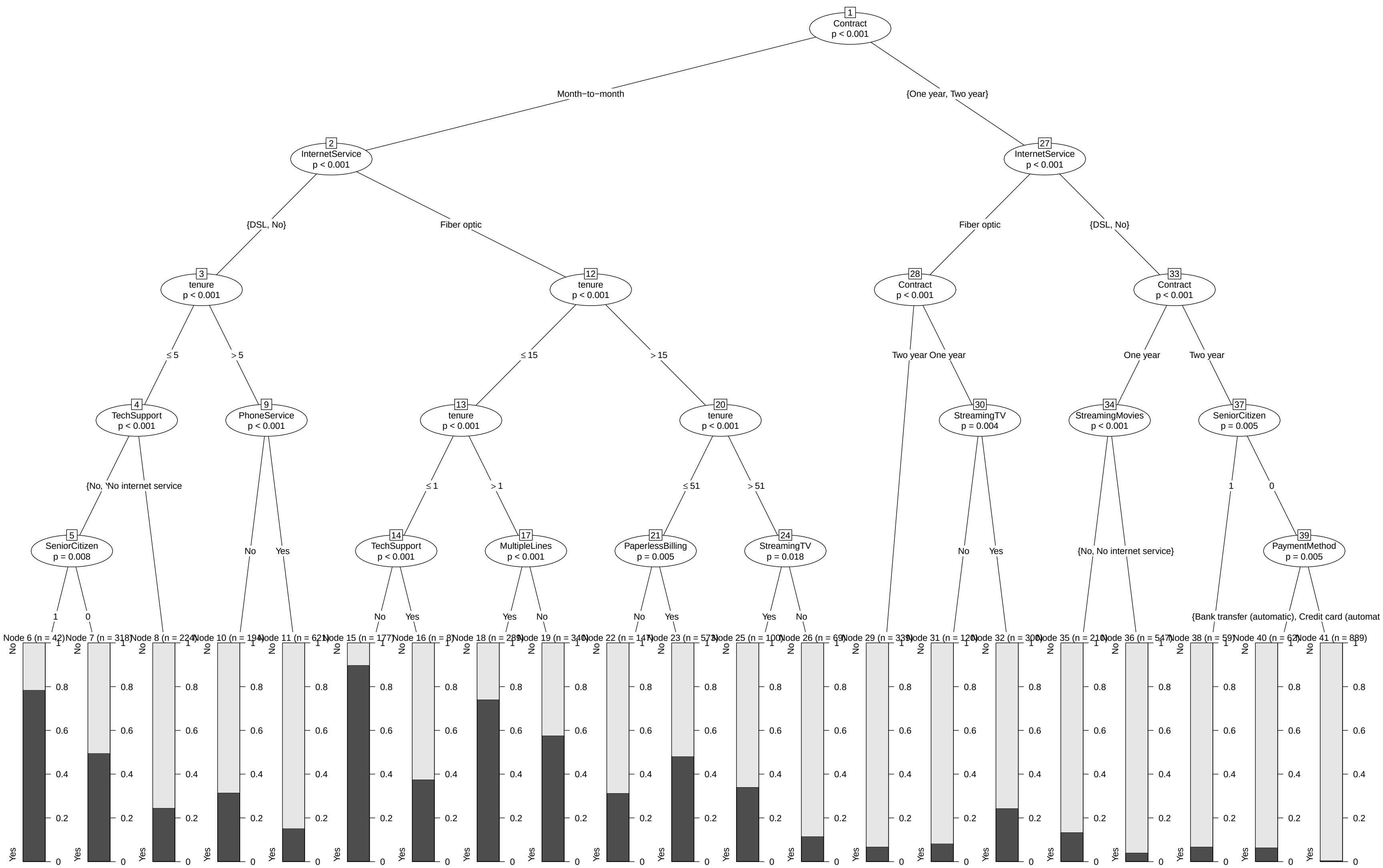
Decision Tree

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.

```
# 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



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.

```r
# 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"
```

```r
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
```

```r
# Convert Betas into odds ratio
print("Odds Ratios")
```

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

```r
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
```

From the model's summary we can see that our top three variables identified earlier are all have a high statistical significance. The surprising variable here is TotalCharges which also has a high statistical significance but was not featured on the decision tree. To evaluate what information can be gained from TotalCharges a third model will be created in which it will feature.

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)

```r
# 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"
```

```r
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
```

```r
# Convert Betas into odds ratio
print("Odds Ratios")
```

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

```r
exp(coef(topThreeLogisticRegressionModel))
```

```
##                (Intercept)           ContractOne year
##                  0.7730685                  0.4188300
##           ContractTwo year InternetServiceFiber optic
##                  0.1754374                  3.1995868
##          InternetServiceNo                     tenure
##                  0.3259482                  0.9693719
```

Top Four Logistic Regression

Using the top three variables from before, we will now add TotalCharges to the model to see whether it being statistically significant will later contribute to its accuracy

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

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

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

```r
summary(topFourLogisticRegressionModel)
```

```
##
## Call:
## glm(formula = formula, family = family, data = dataset)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.5418  -0.7107  -0.3114   0.8545   3.4266
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                -1.285e-01  7.843e-02  -1.638 0.101394
## ContractOne year           -8.937e-01  1.148e-01  -7.787 6.86e-15 ***
## ContractTwo year           -1.819e+00  1.943e-01  -9.362  < 2e-16 ***
## InternetServiceFiber optic  9.823e-01  9.375e-02  10.478  < 2e-16 ***
## InternetServiceNo          -1.071e+00  1.336e-01  -8.014 1.11e-15 ***
## tenure                     -5.306e-02  6.347e-03  -8.359  < 2e-16 ***
## TotalCharges                2.552e-04  6.809e-05   3.748 0.000178 ***
## ---
## 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: 4837.6  on 5621  degrees of freedom
## AIC: 4851.6
##
## Number of Fisher Scoring iterations: 6
```

```r
# Convert Betas into odds ratio
print("Odds Ratios")
```

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

```r
exp(coef(topFourLogisticRegressionModel))
```

```
##                (Intercept)           ContractOne year
##                  0.8794384                  0.4091301
##           ContractTwo year InternetServiceFiber optic
##                  0.1621591                  2.6706938
##          InternetServiceNo                     tenure
```

```
##                   0.3427437                          0.9483276
##                TotalCharges
##                   1.0002553
```

Model Comparison

Now that we have create all three models we will test their accuracy against the training dataset and also the test dataset