Data Mining and Data Analytics for Analysing Customer Churn Rate

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Abstract — This research paper describes how to determine the various factors impacting the customers churn rate in telecom industry. And what factors impact customer to move from one telecom source to another. Using data analytics and data mining will analyze the factors for churn rate.

Index Terms — Data analytics; Data mining; R; Churn rate.

I. INTRODUCTION

One of the most critical factors in customer relationship management that directly impacts a company's long-term profitability is customer attrition. When a company can better predict if a customer is likely to cut ties, it can take a more targeted approach to mitigate customer turnover.

Telecommunications Company is concerned about the number of customers leaving their landline business for cable competitors. The company needs to know which customers are leaving and attempt to mitigate continued customer loss. This paper describes the methods to analyze customer data to identify why customers are leaving and potential indicators to explain why those customers are leaving so the company can make an informed plan to mitigate further loss.

II. ANALYSIS APPROACH

A. Tool Selection

Firstly, we need to choose the best appropriate tools to perform the analysis on the data set. For this paper we are choose R programming to analyze the churn rate of the customer due to the fact that R provides various inbuilt packages and also features making statistical analysis of large data sets simple. R has the integrated development environment available in R studio and is accessible from number of scripting language and hence makes it easier to view and analyze the code. With R almost every tool a data scientist might need to manipulate and evaluate structured data is included. What isn't in the base package has often been built and shared by other programmers and is freely available to download. Hence, based on the advantages of R programming it's been chosen for the analysis of the customer data.

B. Descriptive Method

Multiple correspondence analysis will be used to analyze the variables which contribute most to the customer churn rate. To check if there is any collinearity and eliminate such

data from analysis. This data analysis technique for nominal categorical data, used to detect and represent underlying structures in a data set. Binning to create categorical variables if there any continuous.

C. Prediction Method

Logistic regression will be used as the target and dependent variables are categorical values and logistic regression holds good for the analysis.

III. DATA EXPLORATION AND PREPARATION

Before beginning the analysis, the target variable has to be determined in the data and indicate if the specific type of data the target variable is using. The target variable in this research is the "Churn" variable. The data which is used by the target variable will be either "Yes" or "No" and it is categorical.

"Fig.1" shows the rest of the variables used in the analysis process.

```
> str(churn)
Classes 'tbl_df', 'tbl' and 'data.frame':   7043 obs. of  21 variables:
 $ customerID    : chr  "7590-VHVEG" "5575-GNVEDE" "3668-QPYBK" "7795-CFOCW" ...
 $ gender        : chr  "Female" "Male" "Male" "Male" ...
 $ SeniorCitizen : num  0 0 0 0 0 0 0 0 0 0 ...
 $ Partner       : chr  "Yes" "No" "No" "No" ...
 $ Dependents    : chr  "No" "No" "No" "No" ...
 $ tenure        : num  1 34 2 45 2 8 22 10 28 62 ...
 $ PhoneService  : chr  "No" "Yes" "Yes" "No" ...
 $ MultipleLines : chr  "No phone service" "No" "No" "No phone service" ...
 $ InternetService : chr  "DSL" "DSL" "DSL" "DSL" ...
 $ OnlineSecurity : chr  "No" "Yes" "Yes" "Yes" ...
 $ OnlineBackup  : chr  "Yes" "No" "Yes" "No" ...
 $ DeviceProtection : chr  "No" "Yes" "No" "Yes" ...
 $ TechSupport   : chr  "No" "No" "No" "Yes" ...
 $ StreamingTV   : chr  "No" "No" "No" "No" ...
 $ StreamingMovies : chr  "No" "No" "No" "No" ...
 $ Contract      : chr  "Month-to-month" "one year" "Month-to-month" "one year" ...
 $ PaperlessBilling : chr  "Yes" "No" "Yes" "No" ...
 $ PaymentMethod : chr  "Electronic check" "Mailed check" "Mailed check" "Bank transfer (automatic)" ...
 $ MonthlyCharges : num  29.9 57 53.9 42.3 70.7 ...
 $ TotalCharges  : num  29.9 1889.5 108.2 1840.8 151.7 ...
 $ churn        : chr  "No" "No" "Yes" "No" ...
```

Fig. 1. Data set for analyzing customer churn factors.

"Fig.2" provides the details of independent.

Independent Variables	
gender	Male, Female
SeniorCitizen	0 or 1
Partner	Yes or No
Dependents	Yes or No
tenure	Numeric
PhoneService	Yes or No
MultipleLines	Yes, No, No Phone service
InternetService	DSL, Fiber Optic, No
OnlineSecurity	Yes, No, No Internet Service
OnlineBackup	Yes, No, No Internet Service
DeviceProtection	Yes, No, No Internet Service
TechSupport	Yes, No, No Internet Service
StreamingTV	Yes, No, No Internet Service
StreamingMovies	Yes, No, No Internet Service
Contract	Month-to-Month, One year, Two year
PaperlessBilling	Yes or No
PaymentMethod	Electronic Check, Mailed Check, Bank Transfer (automatic), Credit Card (automatic)
MonthlyCharges	Numeric
TotalCharges	Numeric

Fig. 2. Independent variable for analyzing customer churn factors.

A. Data preparation

- Data preparation is very important step in any data analysis. As whole data set might not contribute entirely due to various factors such as outliers etc.
- In this analysis the data preparation is done by reducing the number of independent variables which are continuous and might not contribute much.
- Reduce number of categorical variable values. Make them into factors which will help in analysis.
- MonthlyCharges and TotalCharges are of similar values and both of them might not be required and one of the column can be dropped.

- Reduce the binary value to “No” instead of “No Internet Service” wherever possible.
- Bin the “Tenure” column for the analysis instead of continuous qualitative values.

B. Statistical Identity

“Fig.3” provides the details of the variables used pre and post cleaning of data preparation and divided into dependent and independent variables.

Name	Type (pre-cleaning)	Type (post-cleaning)	Dependent/ Independent	Notes
customer ID	Random(Categorical)	Dropped	Dropped	Dropped due to lack of predictive characteristics.
Gender	Binary	Dropped	Dropped	Dropped from analysis due to lack of variance.
SeniorCitizen	Binary	Binary	Independent	
Partner	Binary	Binary	Independent	
Dependents	Binary	Binary	Independent	
PhoneService	Binary	Binary	Independent	
MultipleLines	Categorical	Binary	Independent	Reduced to a binary value by the recoding of the “No phone service” to “No”.
InternetService	Categorical	Categorical	Independent	Three levels
OnlineSecurity	Categorical	Binary	Independent	Reduced to a binary value by the recoding of the “No internet service” to “No”.
OnlineBackup	Categorical	Binary	Independent	
DeviceProtection	Categorical	Binary	Independent	
TechSupport	Categorical	Binary	Independent	
StreamingTV	Categorical	Binary	Independent	
StreamingMovies	Categorical	Binary	Independent	
Contract	Categorical	Categorical	Independent	Three levels: Month-to-Month One-year Two-year
PaperlessBilling	Binary	Binary	Independent	
PaymentMethod	Categorical	Categorical	Independent	Four levels
Churn	Binary	Binary	Dependent	
Tenure	Continuous	Categorical	Independent	Converted to Categorical variable by binning the values by year. Six levels.
MonthlyCharges	Continuous	Categorical	Independent	Converted to Categorical variable by binning the values by \$20 increments
TotalCharges	Continuous	Dropped	Dropped	Dropped to high correlation to tenure.

Fig. 3. Statistical identity and variable preparation

C. Raw data

The Raw data has been cleaned and the same is mentioned in “Fig.4”. Various possible values for each variable

identified is described to give better understanding of the data we are looking at.

Column Name	Description	Possible Values
customerID	Sequence of the customer	Character
gender	Gender of the customer	Male, Female
SeniorCitizen	Whether customer is senior citizen or not	0 or 1
Partner	Whether customer has partner or not	Yes or No
Dependents	Whether customer has dependent or not	Yes or No
tenure	Number of months customer has stayed	Numeric
PhoneService	Whether customer has phone service or not	Yes or No
MultipleLines	If customer has multiple services	Yes, No, No Phone service
InternetService	Customer's internet service provider	DSL, Fiber Optic, No
OnlineSecurity	If customer has online security or not	Yes, No, No Internet Service
OnlineBackup	If customer has online backup or not	Yes, No, No Internet Service
DeviceProtection	If customer has device protection or not	Yes, No, No Internet Service
TechSupport	If customer has tech support or not	Yes, No, No Internet Service
StreamingTV	If customer has streaming or not	Yes, No, No Internet Service
StreamingMovies	If customer has streaming movies or not	Yes, No, No Internet Service
Contract	Contract term of the customer	Month-to-Month, One year, Two year
PaperlessBilling	If customer has paperless billing or not	Yes or No
PaymentMethod	Customer payment method	Electronic Check, Mailed Check, Bank Transfer (automatic), Credit Card (automatic)
MonthlyCharges	Amount charged to the customer on month	Numeric
TotalCharges	Total amount charged to the customer	Numeric
Churn	Whether customer churned or not	Yes or No

Fig. 4. Raw data variable preparation

Import the raw data into the R and verify that variables are as expected with the values which was mapped to. Let's run commands to verify if there are any missing data. "Fig.5" provides there is 11 missing data for the "Total Charges".

```
> sapply(churn, function(x) sum(is.na(x)))
customerID      gender SeniorCitizen      Partner      Dependents      tenure      PhoneService
0              0          0            0            0            0              0
MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV
0              0          0            0            0            0              0
StreamingMovies      Contract PaperlessBilling PaymentMethod MonthlyCharges TotalCharges      Churn
0              0          0            0            0            11          0
```

Fig. 5. Missing TotalCharges values.

"Fig.6" shows after removing the missing data.

```
sapply(churn, function(x) sum(is.na(x)))
customerID      gender SeniorCitizen      Partner      Dependents      tenure      PhoneService
0              0          0            0            0            0              0
MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection TechSupport StreamingTV
0              0          0            0            0            0              0
streamingMovies      Contract PaperlessBilling PaymentMethod MonthlyCharges TotalCharges      Churn
0              0          0            0            0            0              0
```

Fig. 6. Removing missing TotalCharges values.

The raw data set chosen has 21 columns and 7032 rows of data. Other cleanup activities performed on this data set includes

- "No Internet service" is converted to "No".
- "No Phone Service" is converted to "No"
- Group the "Tenure" into bins based on the months. Minimum value is 1 and maximum value is 72. So, group into 5 tenure groups.
- Change the values in the column "SeniorCitizen" 0 – "No" and 1 – "Yes".
- Removed the column "CustomerID", "Gender" and "TotalCharges" as we don't need for analysis. These columns don't predict the churn rate and it's of least importance in analysis. The churn rate is not dependent on the gender to predict if the customer is staying or leaving the telecom company.
- "Fig.7" shows that "Monthly Charges" and "Total Charges" are correlated. So, one of them will be removed from the model. "Total Charges" will be removed.

Fig. 7. Correlation plot for numerical variables.

"Fig.8" shows bar plots for categorical variables.

Fig. 8. Bar plots for categorical variables.

“Fig.9” provides the multiple correspondence analysis plot for different variables used in the analysis.

Fig. 9. MCA plot.

“Fig.10” provides the information based on MCA analysis, the customer with month-month contract is near to the target variable “Churn” and it shows that customers more likely to churn when they are on month-to-month contract. Overall customer turn rate is 26.6%

```
> round(prop.table(table(training$Churn))*100,1)

  No  Yes
 73.4 26.6
```

Fig. 10. Customer churn rate analysis

D. Logistic Regression analysis

Logistic regression is used for binary classification. Since, “Churn” variable is categorical and contains “Yes” or “No” values. Logistic regression will be appropriate.

“Fig.11 provides the logistic regression model values.

```
> LogModel <- glm(as.factor(Churn) ~ ., family=binomial(link="logit"), data = training)
> print(summary(LogModel))

Call:
glm(formula = as.factor(Churn) ~ ., family = binomial(link = "logit"),
    data = training)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0455  -0.6608  -0.2828   0.6629   3.1169

Coefficients: (7 not defined because of singularities)

Coefficients: (7 not defined because of singularities)
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -2.819374    0.525843  -5.362 8.25e-08 ***
genderMale      0.003598    0.078014   0.046  0.96321
SeniorCitizenYes 0.271726    0.100483   2.704  0.00685 **
PartnerYes     -0.026625    0.094137  -0.283  0.77731
DependentsYes  -0.127052    0.108834  -1.167  0.24305
PhoneServiceYes -1.211216    0.399897  -3.029  0.00246 **
MultipleLinesYes -0.052431    0.197759  -0.265  0.79091
InternetServiceFiber optic -0.003940    0.453192  -0.009  0.99306
InternetServiceNo 0.145242    0.465510   0.312  0.75504
OnlineSecurityNo internet service NA          NA          NA          NA
OnlineSecurityYes -0.531662    0.132924  -4.000 6.34e-05 ***
OnlineBackupNo internet service NA          NA          NA          NA
OnlineBackupYes -0.375409    0.125959  -2.980  0.00288 **
DeviceProtectionNo internet service NA          NA          NA          NA
DeviceProtectionYes -0.296927    0.127998  -2.320  0.02035 *
TechSupportNo internet service NA          NA          NA          NA
TechSupportYes -0.529940    0.132779  -3.991 6.58e-05 ***
StreamingTVNo internet service NA          NA          NA          NA
StreamingTVYes -0.052479    0.198720  -0.264  0.79171
StreamingMoviesNo internet service NA          NA          NA          NA
StreamingMoviesYes -0.890261    0.132207  -6.734 1.65e-11 ***
ContractOne year -1.625720    0.212864  -7.637 2.22e-14 ***
ContractTwo year 0.279033    0.089462   3.119  0.00181 **
PaperlessBillingYes -0.224648    0.136214  -1.649  0.09910 .
PaymentMethodCredit card (automatic) 0.176107    0.112245   1.569  0.11666
PaymentMethodElectronic check -0.111615    0.136404  -0.818  0.41321
PaymentMethodMailed check 0.038045    0.017030   2.234  0.02548 *
MonthlyCharges 1.760788    0.203981   8.632 < 2e-16 ***
tenure_group0-12 Month 0.871131    0.200502   4.345 1.39e-05 ***
tenure_group12-24 Month 0.420460    0.184558   2.278  0.02271 *
tenure_group24-48 Month 0.204193    0.198000   1.031  0.30241
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5702.8  on 4923  degrees of freedom
Residual deviance: 4056.6  on 4899  degrees of freedom
AIC: 4106.6

Number of Fisher Scoring iterations: 6
```

Fig. 11. Logistic regression model

The top three most relevant features include:

- Contact
- Tenure_group
- PaperlessBilling

“Fig.12” provides the assessment of the logistic regression model with the accuracy value.

```
> testing$Churn <- as.character(testing$Churn)
> testing$Churn[testing$Churn=="No"] <- "0"
> testing$Churn[testing$Churn=="Yes"] <- "1"
> fitted.results <- predict(LogModel,newdata=testing,type='response')
Warning message:
In predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type ==
"prediction from a rank-deficient fit may be misleading
> fitted.results <- ifelse(fitted.results > 0.5,1,0)
> misclassificationError <- mean(fitted.results != testing$Churn)
> print(paste('Logistic Regression Accuracy',1-misclassificationError))
[1] "Logistic Regression Accuracy 0.790796963946869"
```

Fig. 12. Logistic regression model accuracy

“Fig.13” provides the fit for the linear regression.

```
> glm.fit <- glm(as.factor(Churn) ~ ., family = binomial(link = "logit"), data = training)
> print(summary(glm.fit))

Call:
glm(formula = as.factor(Churn) ~ ., family = binomial(link = "logit"),
    data = training)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.0455  -0.6608  -0.2828   0.6629   3.1169

Coefficients: (7 not defined because of singularities)
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -2.819374    0.525843  -5.362 8.25e-08 ***
genderMale      0.003598    0.078014   0.046  0.96321
SeniorCitizenYes 0.271726    0.100483   2.704  0.00685 **
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DependentsYes  -0.127052    0.108834  -1.167  0.24305
PhoneServiceYes -1.211216    0.399897  -3.029  0.00246 **
MultipleLinesYes -0.052431    0.197759  -0.265  0.79091
InternetServiceFiber optic -0.003940    0.453192  -0.009  0.99306
InternetServiceNo 0.145242    0.465510   0.312  0.75504
OnlineSecurityNo internet service NA          NA          NA          NA
OnlineSecurityYes -0.531662    0.132924  -4.000 6.34e-05 ***
OnlineBackupNo internet service NA          NA          NA          NA
OnlineBackupYes -0.375409    0.125959  -2.980  0.00288 **
DeviceProtectionNo internet service NA          NA          NA          NA
DeviceProtectionYes -0.296927    0.127998  -2.320  0.02035 *
TechSupportNo internet service NA          NA          NA          NA
TechSupportYes -0.529940    0.132779  -3.991 6.58e-05 ***
StreamingTVNo internet service NA          NA          NA          NA
StreamingTVYes -0.052479    0.198720  -0.264  0.79171
StreamingMoviesNo internet service NA          NA          NA          NA
StreamingMoviesYes -0.890261    0.132207  -6.734 1.65e-11 ***
ContractOne year -1.625720    0.212864  -7.637 2.22e-14 ***
ContractTwo year 0.279033    0.089462   3.119  0.00181 **
PaperlessBillingYes -0.224648    0.136214  -1.649  0.09910 .
PaymentMethodCredit card (automatic) 0.176107    0.112245   1.569  0.11666
PaymentMethodElectronic check -0.111615    0.136404  -0.818  0.41321
PaymentMethodMailed check 0.038045    0.017030   2.234  0.02548 *
MonthlyCharges 1.760788    0.203981   8.632 < 2e-16 ***
tenure_group0-12 Month 0.871131    0.200502   4.345 1.39e-05 ***
tenure_group12-24 Month 0.420460    0.184558   2.278  0.02271 *
tenure_group24-48 Month 0.204193    0.198000   1.031  0.30241
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5702.8  on 4923  degrees of freedom
Residual deviance: 4056.6  on 4899  degrees of freedom
AIC: 4106.6

Number of Fisher Scoring iterations: 6
```

Fig. 13. Fit for Logistic regression model.

“Fig.14” provides the details of confusion matrix for logistic regression.

```
> print("Confusion Matrix for Logistic Regression"); table(testing$Churn, fitted.results > 0.5)
[1] "Confusion Matrix for Logistic Regression"

      FALSE TRUE
0  1398  150
1   291  269
```

Fig. 14. Confusion matrix for Logistic regression model.

“Fig.15” provides the details of odds ratio for logistic regression.


```
> library(MASS)
> exp(cbind(OR=coef(LogModel), confint(LogModel)))
waiting for profiling to be done...
```

	OR	2.5 %	97.5 %
(Intercept)	0.05964325	0.02119996	0.1666320
genderMale	1.00360461	0.86129385	1.1694707
SeniorCitizenYes	1.31222686	1.07750092	1.5978119
PartnerYes	0.97372680	0.80973399	1.1712329
DependentsYes	0.88068762	0.71098219	1.0894511
PhoneServiceYes	0.29783478	0.13573883	0.6511131
MultipleLinesYes	0.94892016	0.64390183	1.3982374
InternetServiceFiber optic	0.99606811	0.40981210	2.4227947
InternetServiceNo	1.15631979	0.46465478	2.8827173
OnlineSecurityNo internet service	NA	NA	NA
OnlineSecurityYes	0.58762749	0.45246881	0.7619945
OnlineBackupNo internet service	NA	NA	NA
OnlineBackupYes	0.68700846	0.53649243	0.8791407
DeviceProtectionNo internet service	NA	NA	NA
DeviceProtectionYes	0.74309841	0.57801253	0.9547844
TechSupportNo internet service	NA	NA	NA
TechSupportYes	0.58864010	0.45336068	0.7630630
StreamingTVNo internet service	NA	NA	NA
StreamingTVYes	0.94887406	0.64270463	1.4009128
StreamingMoviesNo internet service	NA	NA	NA
StreamingMoviesYes	NA	NA	NA
ContractOne year	0.41054860	0.31573427	0.5303448
ContractTwo year	0.19676989	0.12801575	0.2953526
PaperlessBillingYes	1.32185115	1.10953794	1.5757407
PaymentMethodCredit card (automatic)	0.79879699	0.61120449	1.0427932
PaymentMethodElectronic check	1.19256526	0.95751459	1.4869963
PaymentMethodMailed check	0.89438858	0.68467736	1.1689223
MonthlyCharges	1.03877827	1.00471286	1.0740905
tenure_group0-12 Month	5.81701832	3.91517656	8.7146409
tenure_group12-24 Month	2.38961248	1.61788594	3.5526587
tenure_group24-48 Month	1.52266230	1.06374360	2.1945860
tenure_group48-60 Month	1.22653488	0.83228754	1.8103268

Fig. 15. Odds ratio for Logistic regression

“Fig.16” provides details of the variables in tree plot.

Fig. 16. Tree plot for Logistic regression

IV. LOGISTIC REGRESSION CONCLUSION

Logistic regression works better when there is single decision is to be made. Decision tree can be used when there is more than one decision to be made. Decision tree can be scaled up to more complex and more liable to over fit.

Logistic regression is useful when there is categorical variable to analyze. Logistic regression is simple and has low variance and less prone to over fitting the values.

Based on the “Fig.16”, “Contract” is the most important variable to predict customer churn or not. Customer contract even if its one year or two year contract and even without paperless billing, customer is less likely to churn. If the customer is on month-to-month contract and tenure group of 0-12 months and paperless billing is more likely to churn.

REFERENCES

- [1] Selva Prabhakaran, 2016-2017, Logistic Regression. Available [Online] <http://r-statistics.co/Logistic-Regression-With-R.html>.

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