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Statistical and Machine Learning Techniques for Prediction of Customer Churn in Telecom

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ABSTRACT: Telecommunication is one of the fastest growing industries covering 90% of the world population.The rapid growth of telecom users worldwide is also accompanied with increase in number of telecom providers, leading to more fierce competition in this market. Hence it makes more sense for the telecom providers to retain their customers and gain profit equivalent to the investment necessary for acquisition of new customers. Section 1 gives a brief introduction about customer churn and also presents the objectives of the study. Section 2 discusses the predictive modeling techniques that have been used to predict customer churn. Section 3 presents the results of the predictive analysis of the customer churn data using techniques like logistic regression, decision tree, random forest and gradient boosting. A conclusion based on the results is given in section 4.

KEYWORDS: Churn management, Customer churn, Gradient Boosting, Predictive modelling, Telecom industry.

I. INTRODUCTION

Customer churn or subscriber churn is also similar to attrition, which is the process of customers switching from one service provider to another anonymously. Telecom Churns can be classified in two main categories: Involuntary and Voluntary. Managing customer churn is of great concern to global telecommunications service companies and it is becoming a more serious problem as the market matures.

The journals pertinent to telecom churn prediction that were referred for the study are: Manpreet Kaur, Dr. Prerna Mahajan;2015. “Churn Prediction in Telecom Industry Using R.”, Dr. M.Balasubramanian , M.Selvarani ;2014. “Churn Prediction In Mobile Telecom System Using Data Mining Techniques.”, Rahul J. Jadhav, Usharani T. Pawar, “Churn Prediction in Telecommunication Using Data Mining Technology.” For the application of data mining techniques we have referred to the journals: M. Berry and G. Linoff. “Mastering Data Mining.” John Wiley and Sons, New York, USA, 2000., Yu-Teng Chang, “Applying Data Mining To Telecom Churn Management”, IJRIC , 2009 67 – 77 and for the application of decision tree method we have referred to the journal, Hangxia Ma, Min Qin, Jianxia Wang. (2009), “Analysis of the Business Customer Churn Based on Decision Tree Method”, The Ninth International Conference on Control and Automation, Guangzhou, China.

The objectives of the study are to predict if a customer is likely to discontinue using the services of a provider using learning methods and to understand the factors that drives them to their decisions.This study is based on the secondary data from an open source data analytics, reporting and integration platform called KNIME , the Konstanz Information Miner. The link for the customer churn data is https://www.knime.org/knime-applications/churn-prediction.

II. PREDICTIVE MODELING TECHNIQUES AND METHODOLOGY

II.1 FACTOR ANALYSIS

Factor analysis is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. The factor analysis model is given by

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$$\mathbf{x} - \mu = \mathbf{LF} + \boldsymbol{\varepsilon}.$$

Also we will impose the following assumptions on **F**.

- **F** and $\boldsymbol{\varepsilon}$ are independent.
- $\mathbf{E(F) = 0}$.
- $\mathbf{Cov(F) = I}$ (to make sure that the factors are uncorrelated).

II.2 LOGISTIC REGRESSION

Logistic Regression is a classification algorithm. It is used to predict a binary outcome (1 / 0, Yes / No, True / False) given a set of independent variables. To represent binary / categorical outcome, we use dummy variables. In simple words, it predicts the probability of occurrence of an event by fitting data to a logit function.

Odds = p/(1-p) = probability of event occurrence/probability of non-event occurrence

ln(odds) = ln(p/(1-p))

logit(p) = ln(p/(1-p)) = b0+b1x1+b2x2+b3x3+...+bkxk ,

where p is the probability of presence of the characteristic of interest. It chooses parameters that maximize the likelihood of observing the sample values rather than that minimize the sum of squared errors (like in ordinary regression).

Confusion Matrix: It is nothing but a tabular representation of Actual vs Predicted values. This helps us to find the accuracy of the model and avoid overfitting.

Area Under The Roc Curve (Auc – Roc): The ROC curve is the plot between sensitivity and (1- specificity). (1- specificity) is also known as false positive rate and sensitivity is also known as True Positive rate.

II.3 DECISION TREES

Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables.

Gini Index: Gini index says, if we select two items from a population at random then they must be of same class and probability for this is 1 if population is pure. It performs only Binary splits. Higher the value of Gini higher the homogeneity. CART uses Gini method to create binary splits. Calculate Gini for sub-nodes, using formula sum of square of probability for success and failure (p^2+q^2). Calculate Gini for split using weighted Gini score of each node of that split.

II.4 RANDOM FOREST

Random Forest is a trademark term for an ensemble of decision trees. In Random Forest, we have a collection of decision trees (so known as "Forest"). To classify a new object based on attributes, each tree gives a classification and we say the tree "votes" for that class. The forest chooses the classification having the most votes (over all the trees in the forest).

Variable Importance: In every tree grown in the forest, put down the oob cases and count the number of votes cast for the correct class. Now randomly permute the values of variable m in the oob cases and put these cases down the tree. Subtract the number of votes for the correct class in the variable-m-permuted oob data from the number of votes for the correct class in the untouched oob data. The average of this number over all trees in the forest is the raw importance score for variable m.

II.5 GRADIENT BOOSTING

Gradient boosting machines are a family of powerful machine-learning techniques that have shown considerable success in a wide range of practical applications. They are highly customizable to the particular needs of the application, like being learned with respect to different loss functions.

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III. APPLICATION OF MODELING TECHNIQUES IN THE PREDICTIVE ANALYSIS OF CUSTOMER CHURN

III.1 LOGISTIC REGRESSION

In order for our analysis to be valid, our model has to satisfy the assumptions of logistic regression. Therefore, before we use our model to make any statistical inference, we check for outliers in our data that may have an impact on the estimates of the coefficients. In our case 28 observations out of the total of 3333 turned out to be outliers. They were then removed from the data.Another important assumption is that the data should be free of multicollinearity. The multicollinearity diagnosis for the Churn data is provided in the following Section III.1.1

III.1.1 Multicollinearity Diagnosis

Table III.1 : Collinearity Diagnostics

Dimension	Eigenvalue	Condition Index	Variance Proportions													
			(Constant)	Account_Length	Vmail_Message	Day_Mins	Eve_Mins	CustServ_Calls	Intl_Plan	Vmail_Plan	Day_Calls	Eve_Calls	Night_Calls	Night_Charge	Intl_Calls	Intl_Charge
1	10.64	1.000	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
2	1.356	2.802	.00	.00	.02	.00	.00	.00	.00	.02	.00	.00	.00	.00	.00	.00
3	.894	3.451	.00	.00	.00	.00	.00	.00	.99	.00	.00	.00	.00	.00	.00	.00
4	.396	5.186	.00	.00	.00	.00	.00	.96	.01	.00	.00	.00	.00	.00	.02	.00
5	.214	7.047	.00	.02	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00	.96	.00
6	.125	9.222	.00	.93	.00	.03	.01	.00	.00	.00	.00	.00	.00	.01	.00	.01
7	.080	11.551	.00	.01	.00	.81	.02	.00	.00	.00	.00	.00	.00	.02	.00	.13
8	.067	12.640	.00	.00	.00	.05	.13	.00	.00	.00	.00	.00	.01	.14	.00	.66
9	.061	13.264	.00	.00	.00	.00	.55	.00	.00	.00	.00	.00	.00	.43	.00	.00
10	.048	14.925	.00	.01	.00	.04	.18	.00	.00	.00	.13	.18	.11	.29	.00	.10
11	.038	16.648	.00	.00	.01	.00	.00	.00	.00	.01	.65	.08	.24	.00	.00	.00
12	.037	16.944	.00	.00	.01	.00	.00	.00	.00	.01	.02	.55	.42	.00	.00	.00
13	.031	18.447	.00	.00	.96	.00	.00	.00	.00	.96	.00	.00	.02	.00	.00	.00
14	.006	41.716	1.00	.03	.00	.06	.12	.01	.00	.00	.18	.18	.20	.10	.01	.09

From the above Table III.1, collinearity is spotted by finding 2 or more variables that have large proportions of variance that correspond to large conditional indices i.e., those conditional indices in the range of 30 or larger. In our case for a conditional index of 41.975 we have three variables : Day_Calls, Eve_Calls and Night_Calls which have relatively large proportion of variances. Therefore factor Analysis is performed only for the three variables: Day_Calls, Eve_Calls and Night_Calls using SPSS and the corresponding factor scores are obtained.

III.1.2 FITTING THE LOGISTIC REGRESSION MODEL USING FACTOR SCORES

Using the factor scores obtained from factor analysis as the new variable, we will now fit a logistic regression model including the factor scores but excluding the variables Day_Calls, Eve_Calls and Night_Calls on the development data. The resulting model provided the following output.

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Some of the important independent variables which turned up as significant on the basis of p-value are listed in Table III.2

Table III.2 : List of significant independent variables from Logistic model.

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)	Significance
(Intercept)	-7.792639	0.631843	-12.333	< 2e-16	***
Vmail_Message	0.044105	0.020771	2.123	0.033722	*
Eve_Mins	0.00585	0.001405	4.163	3.14E-05	***
CustServ_Calls	0.56987	0.047853	11.909	< 2e-16	***
Intl_Plan	2.227873	0.179635	12.402	< 2e-16	***
Vmail_Plan	-2.275755	0.670033	-3.396	0.000683	***
Day_Charge	0.071303	0.007677	9.288	< 2e-16	***
Night_Charge	0.082183	0.029803	2.758	0.005824	**
Intl_Calls	-0.080596	0.030279	-2.662	0.007772	**
Intl_Charge	0.326496	0.090331	3.614	0.000301	***

It can be noted that another way of evaluating the fit of the logistic regression model is through a Classification Table.

Accuracy Measures: The classification table for the logistic regression model on the test data is given below:

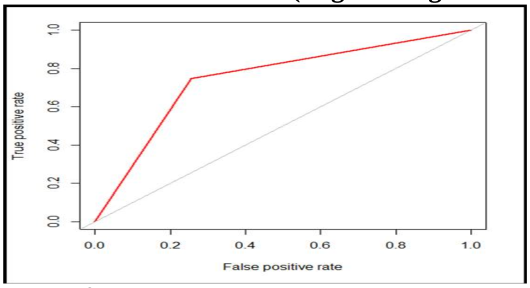
Table III.3: Classification table(Logistic regression)

	Predicted	
Observed	No Churn	Churn
No Churn	642	198
Churn	37	114

From the above classification Table 3.3 the accuracy of the Logistic Regression model fitted on the test data is 0.762, that is, 76.2% of the total number of predictions are correct. We make use of classification Table 3.3 to visualize the performance of the logistic regression model by the ROC curve and summarize its performance in a single number by computing the AUC.

Area Under The Curve: The AUC obtained for the development data for the logistic regression model is 0.761. The AUC obtained for the test data is 0.736.

Figure .III.1 ROC for test data (Logistic Regression model)



Since the AUC value obtained for the logistic regression model is 0.736 we try to improve the model performance by applying Decision Tree which is discussed in Section III.2

III.2 DECISION TREE

CART model in R is a decision tree model which makes development data as input with 18 variables. It performs a univariate split with respect to independent variables which gives maximum information gain from root node to child node. The class method deals with the case when response variable is a categorical variable.

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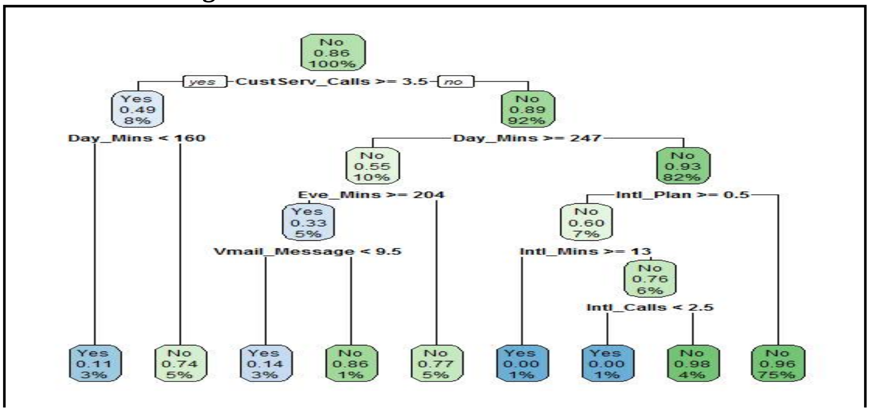
Figure III.2 Decision tree from CART model



From the above Figure III.2 it can be seen that the first split happened on the basis of " CustServ_Calls". Further splits happened on the basis of "Day_Mins", "Eve_Mins", "Intl_Plan", "Int_Calls" and ""Vmail_Message". Having found the significant independent variables we will now evaluate the fit of the CART model through a Classification Table.

Accuracy Measures: The classification table for the CART model on the test data is given below:

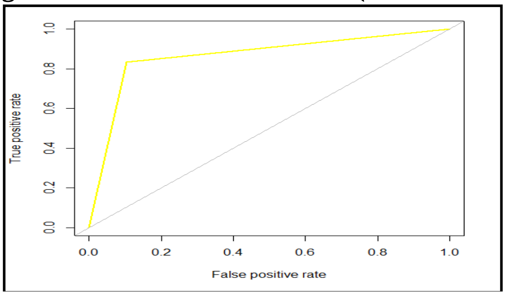
Table III.4:Classification table(CART)

	Predicted	
Observed	No Churn	Churn
No Churn	759	89
Churn	25	126

From the above classification Table III.4 the accuracy of the CART model fitted on the test data is 0.885, that is, 88.5% of the total number of predictions are correct. We make use of classification Table 3.4 to visualize the performance of the CART model by the ROC curve and summarize its performance in a single number by computing the AUC.

Area Under The Curve: The AUC obtained for the development data for the CART model is 0.863. The AUC obtained for the test data is 0.865.

Figure .III.3 ROC for test data (CART model)



Since the AUC value obtained for the CART model is 0.865, we try to improve the prediction accuracy by applying Random Forest which is discussed in Section III.3

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III.3 RANDOM FOREST

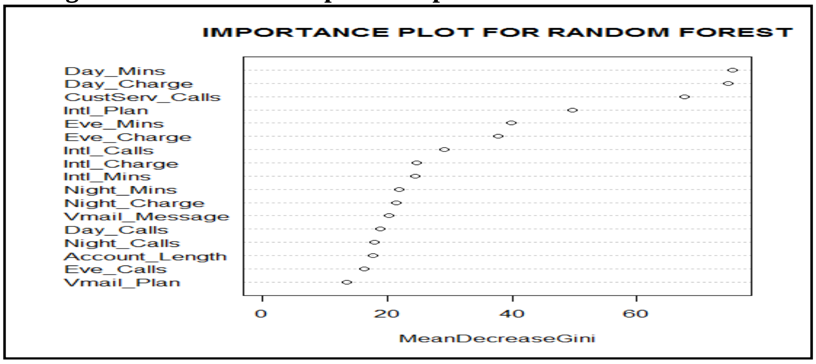
The relative importance of the independent variables based on the Mean Decrease Gini Index have been obtained by applying the random forest model to the customer churn data. We have listed the independent variables based on Mean Decrease Gini below.

Table III.5: Variable importance measures from random forest model.

Variable	Mean Decrease Gini
Day_Mins	75.36329
Day_Charge	74.51449
CustServ_Calls	67.49087
Intl_Plan	49.71943
Eve_Mins	39.72101
Eve_Charge	37.7947
Intl_Calls	28.9858
Intl_Charge	24.72174
Intl_Mins	24.44756
Night_Mins	21.89088
Night_Charge	21.30365
Vmail_Message	20.32958
Day_Calls	18.90698
Night_Calls	17.845
Account_Length	17.7104
Eve_Calls	16.22263
Vmail_Plan	13.53145

In a similar fashion, an importance plot also has been obtained. The variable importance plot from the Random Forest Model is shown below:

Figure .III.4 Variable importance plot of variables in the model.



Clearly the most important factor causing churn is total daytime minutes. The number of calls to customer care, total international minutes, international plan and Eve_Mins have all featured as prominent predictors of churn. The duration of account with the company has little effect on churn. We will now evaluate the fit of the Random Forest model through a Classification Table.

Accuracy Measures: The Classification table for Random forest on test data is given below

Table III.6:Classification table(Random Forest)

	Predicted	
Observed	No Churn	Churn
No Churn	725	123
Churn	20	131

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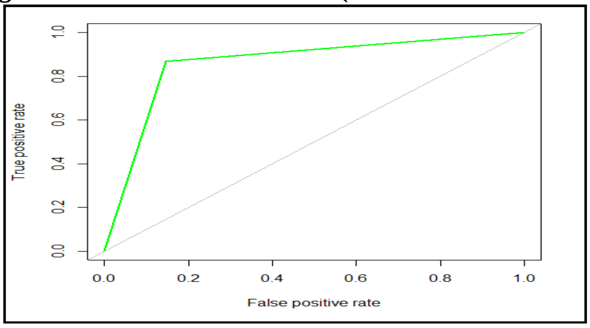
From the above classification Table 3.6 the accuracy of the Random Forest model fitted on the test data is 0.856, that is, 85.6% of the total number of predictions are correct. We make use of classification Table 3.6 to visualize the performance of the Random Forest model by the ROC curve and summarize its performance in a single number by computing the AUC.

Area Under The Curve: The AUC obtained for the development data for the random forest model is 0.866. The AUC obtained for the test data is 0.861.

Figure .III.5 ROC for test data(Random Forest Model)



Since the AUC value obtained for the Random Forest model is 0.861 we try to improve the prediction accuracy by applying Gradient Boosting which is discussed in Section III.4

III.4 GRADIENT BOOSTING

An ensemble model, Gradient Boosted trees also have been applied on the train data. While modeling, the relative influence for each of the variables has been calculated and are reported in the Table 3.7

Table III.7: Relative influence for each variable from Gradient Boost

Variable	Relative influence
Day_Mins	30.7825398
CustServ_Calls	15.479735
Eve_Mins	12.128158
Intl_Plan	11.7703732
Intl_Mins	8.3666423
Vmail_Message	8.3211073
Intl_Calls	8.170761
Night_Mins	2.1259985
Day_Calls	0.9681254
Night_Calls	0.6860177
Eve_Calls	0.3914047
Account_Length	0.3525193
Night_Charge	0.2903753
Eve_Charge	0.1662425
Vmail_Plan	0
Day_Charge	0
Intl_Charge	0

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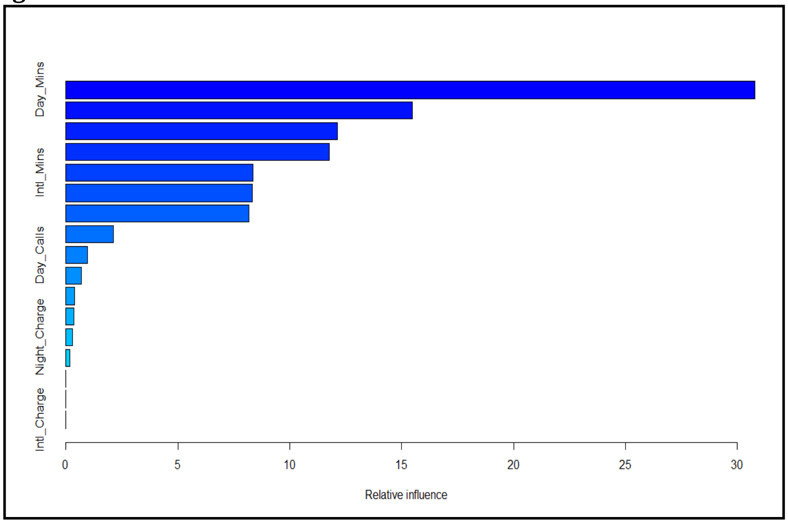
It can be seen from Table III.7 that among the 17 predictors, 14 had non-zero influence. The most important among those predictors with high relative influence are Day_Mins, CustServ_Calls, Eve_Mins, Intl_Plan and Intl_Mins.

An importance plot has also been obtained. The variable importance plot from the Gradient Boosting Model is shown below:

Figure .III.6: Relative Influence of variables from the Gradient Boosting model.



From Figure .6 it can be observed that the most important factors causing churn are Day_Mins, CustServ_Calls, Eve_Mins, Intl_Plan and Intl_Mins. We will now evaluate the fit of the Gradient Boosting model through a Classification Table.

Accuracy Measures: The Classification table for Gradient Boosting model on test data is given below

Table III.8: Classification table(Gradient Boosting)

	Predicted	
Observed	No Churn	Churn
No Churn	742	106
Churn	20	131

From the above classification Table 3.8 the accuracy of the Gradient Boosting model fitted on the test data is 0.873, that is, 87.3% of the total number of predictions are correct. We make use of classification Table 3.8 to visualize the performance of the Gradient Boosting model by the ROC curve and summarize its performance in a single number by computing the AUC.

Area Under The Curve: The AUC obtained for the development data for the Gradient Boosting model is 0.913 .The AUC obtained for the test data is 0.884.It can be seen that the AUC obtained from the gradient boosting model is much higher than the previous models.

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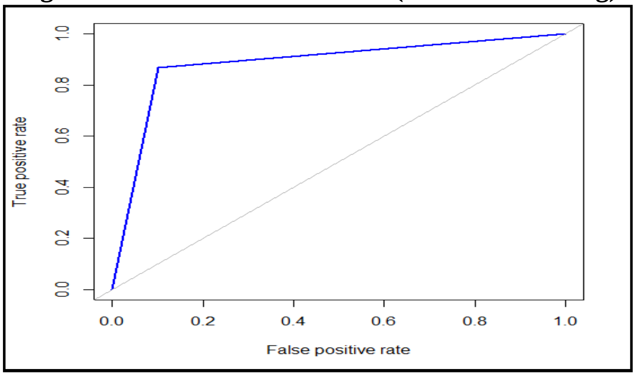
Figure .III.7 ROC for test data(Gradient boosting)



III.5 COMPARISON OF PREDICTIVE MODELS

On the comparison of the AUC values of the test data, gradient boosting and decision trees seem to have good predictive power. From all the variable importance plots, it can be seen that tree based models i.e., CART, Random Forest and Gradient Boosting tend to give similar set of important independent variables. The most important independent variables can be observed to be :Day_Mins, CustServ_Calls,Intl_Plan and Eve_Mins.

IV. CONCLUSION

Based on all the results, the following recommendations are made. There is a strong correlation between higher total day minutes and churn. Almost half the customers with international plan end up switching to other providers. This could be due to a variety of factors. The voice mail plan seems to be popular with the customers. But not ‘enough’ customers seem to have opted for it. Customer’s account duration doesn’t seem to affect churn.

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