Customer Retention by Reducing Customer Churning

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Customer Churn Analysis

Introduction

Customer churn arises when there is a termination in association between a customer and some company/business for whatsoever reason and thus costs the company a great amount. Customers are the base that empowers any business. Even if a single customer leaves the system, company suffers with losses. Further, as understood from previous researchers to acquire new customer in comparison to keeping the existing one is 5-6 times more expensive. As a result, businesses have started taking steps to reduce customer churn. One industry that focusses on churn rates with great importance is the telecommunications sector, in which will be discussed in this report. In regards with some previous studies in this field, it can be interpreted that Machine Learning can help and proves to be a boon in such situations. We use Deep Learning with Keras for this analysis in place of the traditional machine learning algorithms.

Dataset

The dataset that we will consider is the large telecommunications carrier company which wants to improve the profitability by reducing the churning of the existing customers because acquiring new ones in regards with existing costs them more and reduces the profit. Predicting churn is important issue but due to what factors it occurs is the most critical aspect for business that provides services that are contract based.

Technical Perspective

Some Prerequisites

- We use some R libraries for carrying out this study which are installed using the install.packages() function. The use of each is explained further in the report. These libraries can then be loaded by using the library() function.
- As we are going to use Keras package, we will need to first install (if not already installed) this package by using the install_keras() function.
- Once this is done we import the dataset using the read.csv() function.

Pre-processing

Real world data is messy and hence needs sufficient pre-processing to reach a stage where modelling algorithms can be applied. Preprocessing is carried out in following steps:

1) Data Pruning

Pruning is basically the process of deleting unnecessary rows or columns which are not required as part of our analysis. “CustomerID” is deleted as we do not require to model the unique identifier. 11 missing values in “Total charges” are dealt with by using the drop.na() function from tidyr as we would still be left with 99.8% of the records. A Prune_Function() is created in R for solving this purpose.

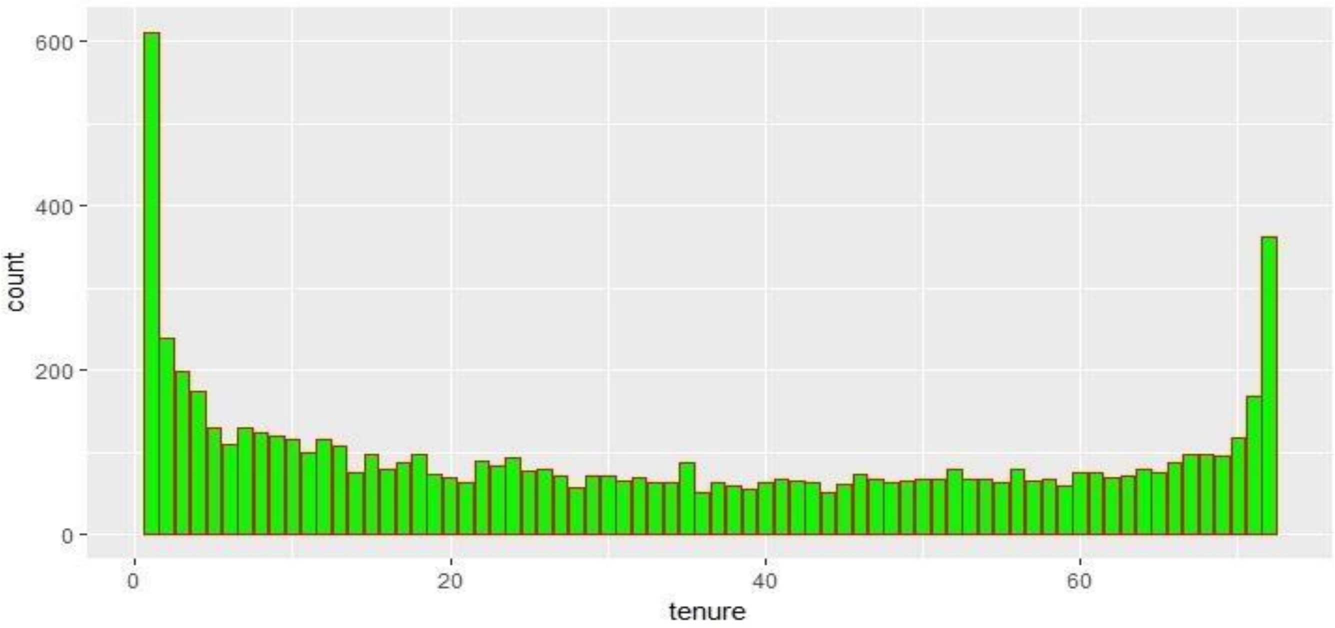
2) Data Splitting

Splitting the data into train and test is done using the initial_split() function from rsample library. This package provides useful sampling of data and returns a rsplit object. Ratio of 70:30 is used as it provides better accuracy in comparison others.

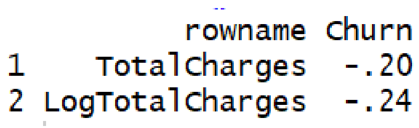
3) Data Transformation/ Exploratory Factor Analysis

Artificial Neural Networks (ANN) work best when they are scaled, encoded using one hot and centered. Additionally, some other transformations can also be used to find associations between the fields which would help in modelling.

- "Tenure" is divided into 6 groups of 1 year each by creating a TenureGroup() function as it is a numeric feature and works well when discretised into groups.



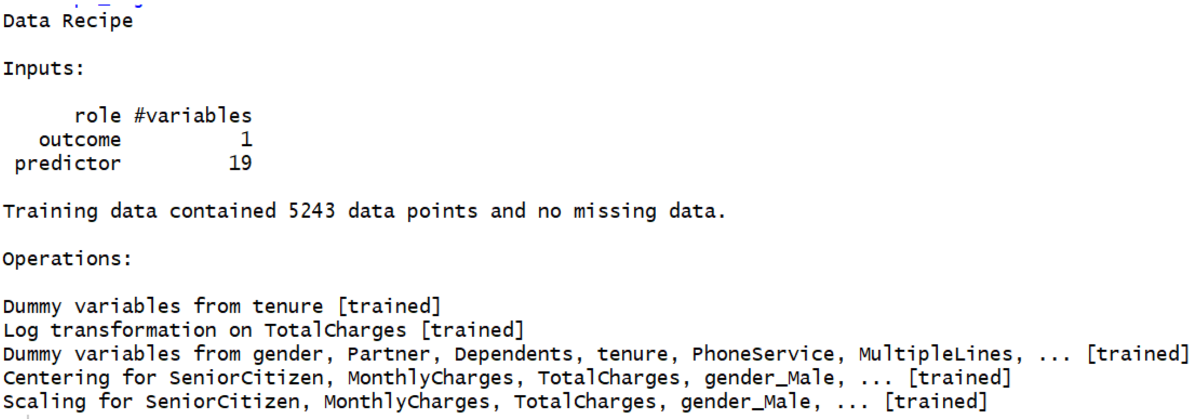
- The "Total charges" field data is not normal and hence to deal with it we need to discretise the data for normal distribution. There are different ways but we use Log transformation here which is done using the log() function. The Log and Total Charges are tested for correlation for surety. This is done using the correlate(), focus() and fashion() functions from tidyr basically used for formatting. Transformation will increase the accuracy of ANN considering the magnitude between churn and log value.



```
          rowname Churn
1    TotalCharges  -.20
2 LogTotalCharges  -.24
```

- One Hot Encoding technique is used to convert the categorical fields to sparse data which is necessary while modelling ANNs. These train with speed and accuracy when one hot encoded, scaled, normalised and centered. We have 3 multiple category field which needs to be encoded

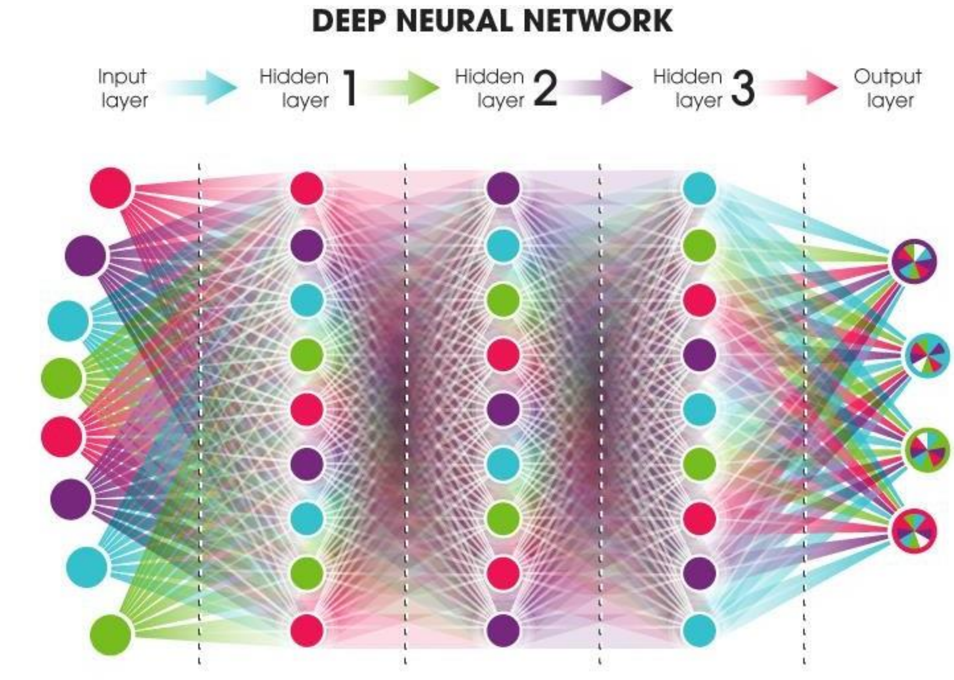
- Finally, we include all of these into a recipe() function developed by Max Kuhn. It takes an “recipe_object” argument like all models take and the transformations are added using step() functions like step_discretize(), step_log(), step_dummy(), step_center(), step_scale(). The last step is to use prep() function for passing the dataset. After this we apply the recipe to the bake() function for transforming the data which can be understood for modelling. Finally, the target vectors are created.



```
Data Recipe

Inputs:

      role #variables
   outcome          1
 predictor         19

Training data contained 5243 data points and no missing data.

Operations:

Dummy variables from tenure [trained]
Log transformation on TotalCharges [trained]
Dummy variables from gender, Partner, Dependents, tenure, PhoneService, MultipleLines, ... [trained]
Centering for SeniorCitizen, MonthlyCharges, TotalCharges, gender_Male, ... [trained]
Scaling for SeniorCitizen, MonthlyCharges, TotalCharges, gender_Male, ... [trained]
```

Deep Learning Model using Keras

The basis is to train a multi-layer neural network, a deep neural network known as multi-layer perceptron. The logic behind this is that it gives more accurate and precise predictions. There are several packages available but keras package is used because it has straightforward implementation, it is fast and easy to implement.



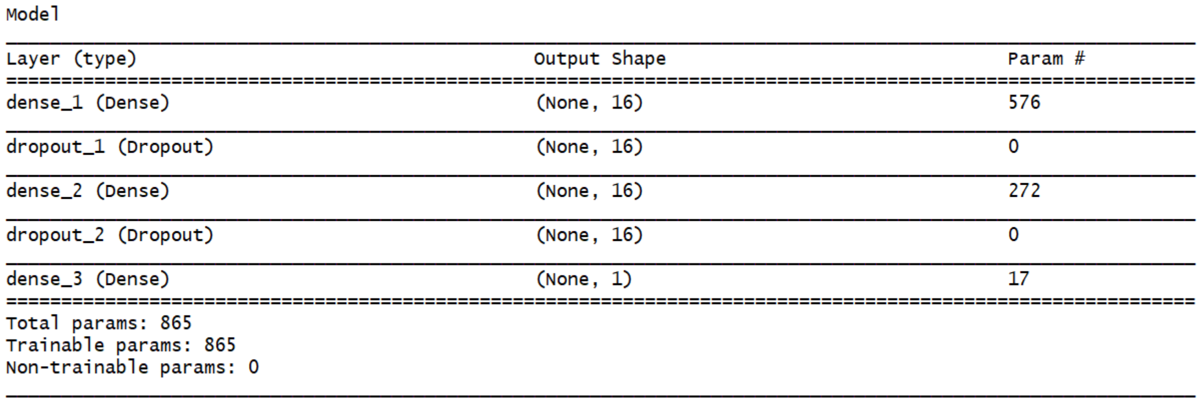
neuralnetworksanddeeplearning.com - Michael Nielsen, Yoshua Bengio, Ian Goodfellow, and Aaron Courville, 2016.

Steps for modelling neural networks:

1) By using keras_model_sequential() function, we initialise the keras model that we are going to build. It contains a layer stack.
2) We then apply layers to this model starting with the input layer where we supply our data. Next, we create 2 hidden layers using layer_dense() function. These provide weights to non-linear activation. Parameters are selected as kernel_initializer="uniform" and activation = "relu". These are basic optimisation parameters. Dropout layers are created next using layer_dropout() function to overcome over-fitting by 10% using the rate parameter. Lastly, we parameterise the output layer with basic binary parameters as kernel_initializer = "uniform" and the activation = "sigmoid".

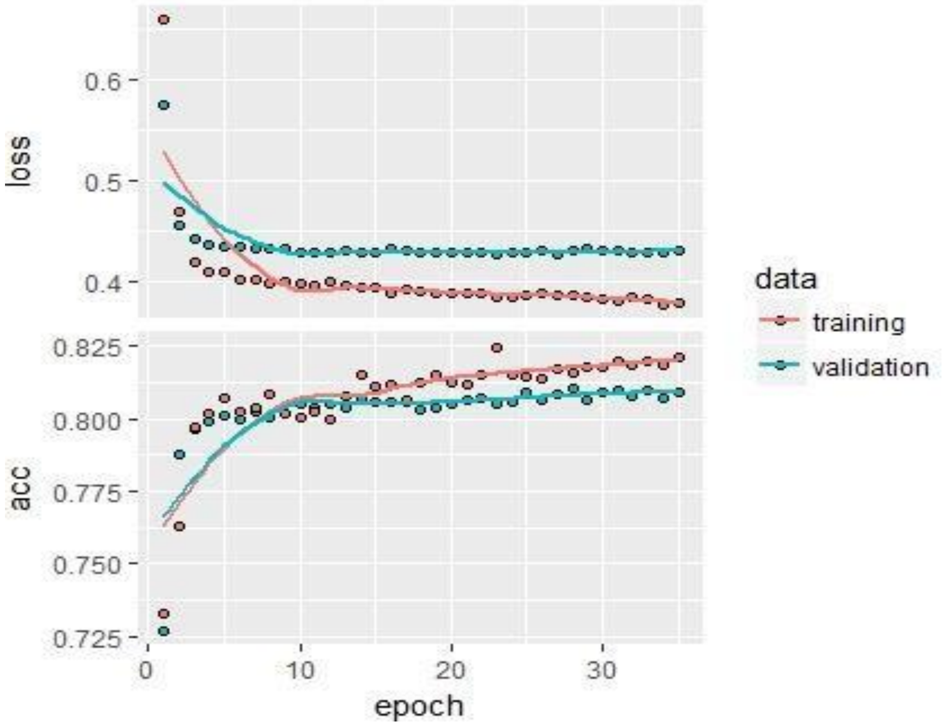
3) Last step involves compiling the model using compile() function and again using basic and popular binary parameters as optimizer = “adam”, loss = “binary_crossentropy” and metrics = c(“accuracy”) of checking the accuracy.

The final model looks like this:

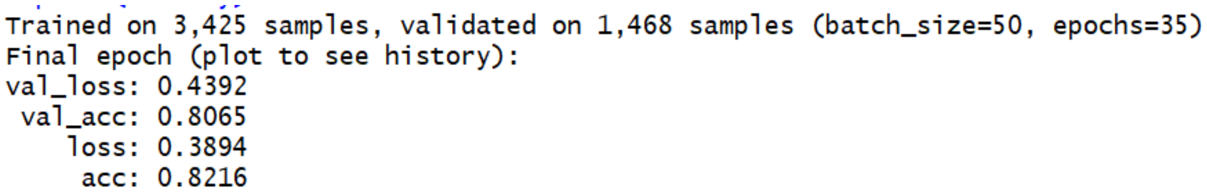


```
Model
________________________________________________________________________________________________________
Layer (type)                                  Output Shape                              Param #
========================================================================================================
dense_1 (Dense)                               (None, 16)                                576
________________________________________________________________________________________________________
dropout_1 (Dropout)                           (None, 16)                                0
________________________________________________________________________________________________________
dense_2 (Dense)                               (None, 16)                                272
________________________________________________________________________________________________________
dropout_2 (Dropout)                           (None, 16)                                0
________________________________________________________________________________________________________
dense_3 (Dense)                               (None, 1)                                 17
========================================================================================================
Total params: 865
Trainable params: 865
Non-trainable params: 0
________________________________________________________________________________________________________
```

fit() function is used to run neural network to check the accuracy between training and validation which should be minimal. Parameters like batch_size =50 which usually should be high which shows number of samples per gradient, epoch = 35 which should also be high as training cycles are controlled by this and validation_split = 0.30 to overcome overfitting by using 30% validation data. We can plot history using the plot() function:



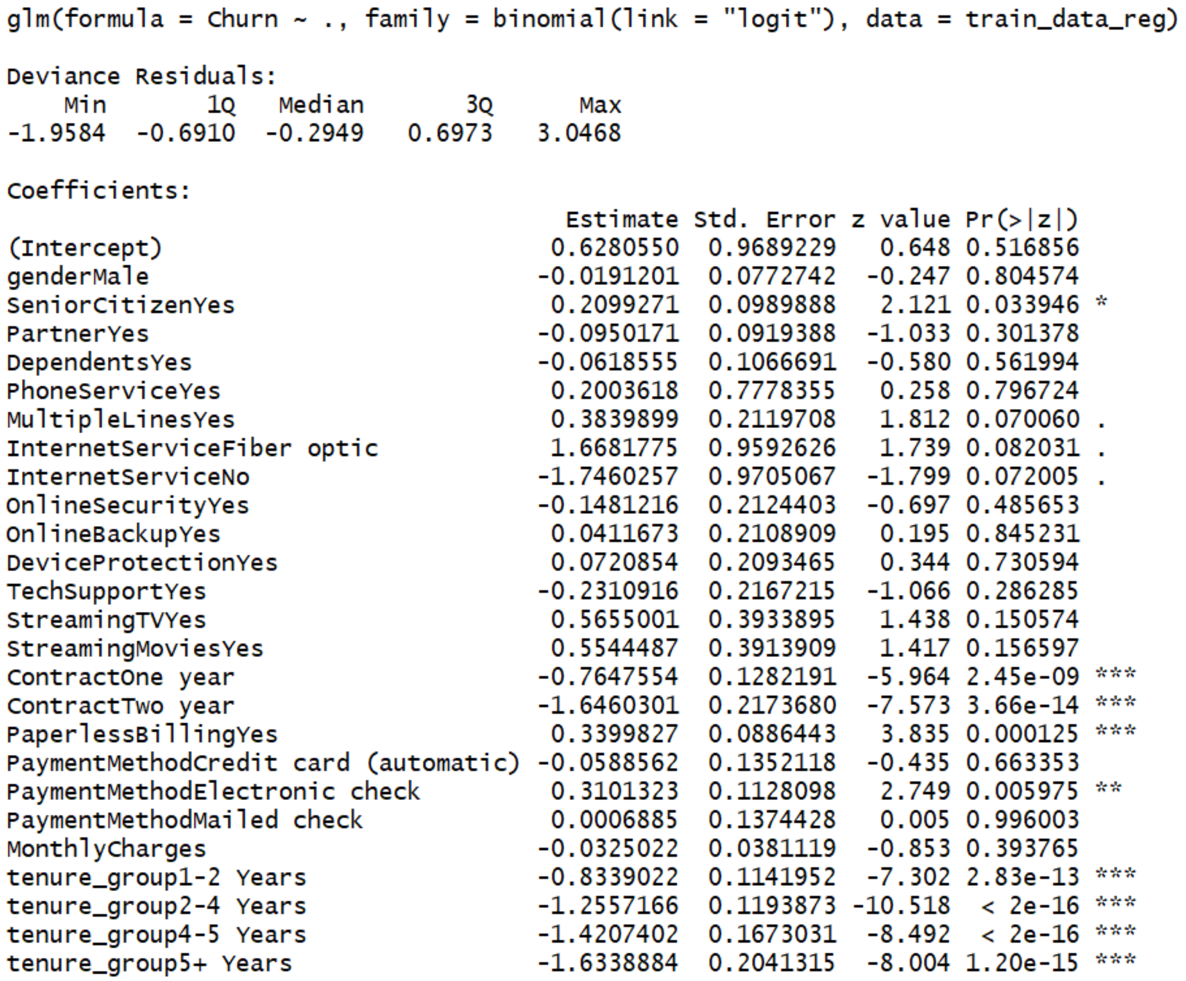
We visualise the accuracy of validation and loss levelling off. The curve has started to flatten which is an indication that we should stop training with the following results:



```
Trained on 3,425 samples, validated on 1,468 samples (batch_size=50, epochs=35)
Final epoch (plot to see history):
val_loss: 0.4392
 val_acc: 0.8065
    loss: 0.3894
     acc: 0.8216
```

Logistic Regression Modelling

The LR model was developed which provided a similar accuracy to ANN. As the target variable is categorical, logistic regression is suitable.



```
glm(formula = Churn ~ ., family = binomial(link = "logit"), data = train_data_reg)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.9584  -0.6910  -0.2949   0.6973   3.0468

Coefficients:
                                       Estimate Std. Error z value Pr(>|z|)
(Intercept)                           0.6280550  0.9689229   0.648 0.516856
genderMale                           -0.0191201  0.0772742  -0.247 0.804574
SeniorCitizenYes                      0.2099271  0.0989888   2.121 0.033946 *
PartnerYes                           -0.0950171  0.0919388  -1.033 0.301378
DependentsYes                        -0.0618555  0.1066691  -0.580 0.561994
PhoneServiceYes                       0.2003618  0.7778355   0.258 0.796724
MultipleLinesYes                      0.3839899  0.2119708   1.812 0.070060 .
InternetServiceFiber optic            1.6681775  0.9592626   1.739 0.082031 .
InternetServiceNo                    -1.7460257  0.9705067  -1.799 0.072005 .
OnlineSecurityYes                    -0.1481216  0.2124403  -0.697 0.485653
OnlineBackupYes                       0.0411673  0.2108909   0.195 0.845231
DeviceProtectionYes                   0.0720854  0.2093465   0.344 0.730594
TechSupportYes                       -0.2310916  0.2167215  -1.066 0.286285
StreamingTVYes                        0.5655001  0.3933895   1.438 0.150574
StreamingMoviesYes                    0.5544487  0.3913909   1.417 0.156597
ContractOne year                     -0.7647554  0.1282191  -5.964 2.45e-09 ***
ContractTwo year                     -1.6460301  0.2173680  -7.573 3.66e-14 ***
PaperlessBillingYes                   0.3399827  0.0886443   3.835 0.000125 ***
PaymentMethodCredit card (automatic) -0.0588562  0.1352118  -0.435 0.663353
PaymentMethodElectronic check         0.3101323  0.1128098   2.749 0.005975 **
PaymentMethodMailed check             0.0006885  0.1374428   0.005 0.996003
MonthlyCharges                       -0.0325022  0.0381119  -0.853 0.393765
tenure_group1-2 Years                -0.8339022  0.1141952  -7.302 2.83e-13 ***
tenure_group2-4 Years                -1.2557166  0.1193873 -10.518  < 2e-16 ***
tenure_group4-5 Years                -1.4207402  0.1673031  -8.492  < 2e-16 ***
tenure_group5+ Years                 -1.6338884  0.2041315  -8.004 1.20e-15 ***
```

Tenure groups, Paperless Billing, Contract, were the variables that were found to be statistically significant. These can be used as selected features for other models as well.

(Appendix A for more info)

For calculating the estimates Estimations_Function() is the own function created in R.

Business Perspective

Business and Churn

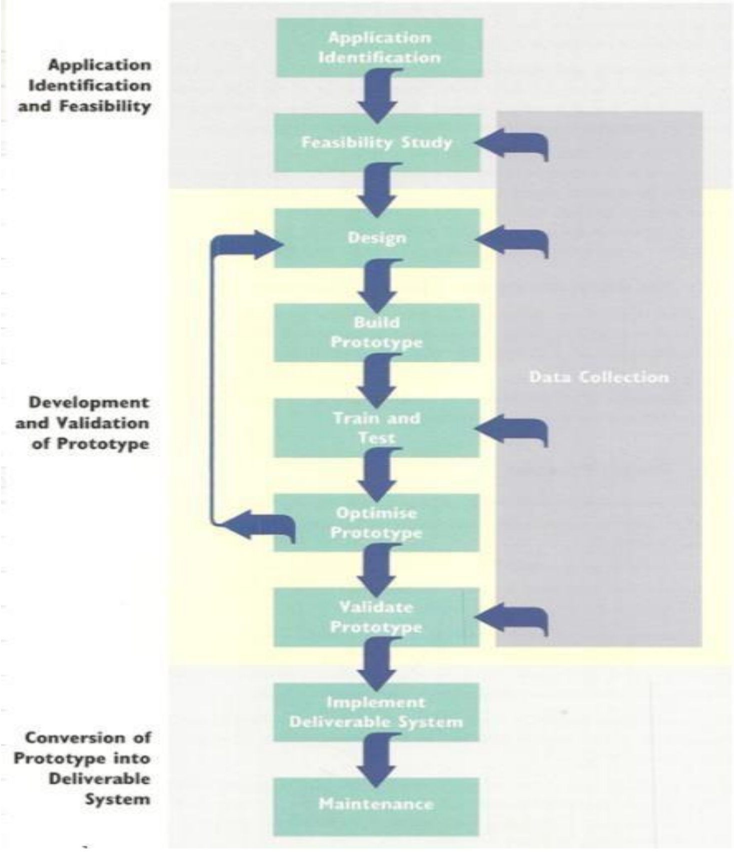
A business that handles the churn rate in an organised way is a sign of a balanced and mature business. Telecommunication industry is the best example of this where customers change network providers quite frequently due to the competitiveness of the industry. Most of the cases of churn happen here because significant knowledge about churn drivers have been generated.

There are not as such strategies which are in use that can help these companies to reduce churn. Machine learning has great importance in this field and past research has proved that by using modelling on the large datasets of these industries, analysis and trends can be determined on predicting and reducing churn.

Another aspect of this is vast number of customers means huge turnover and if customers start to churn this would impact the profit of the company and in turn the performance. Hence, it is of utmost importance to reduce customer churning in this sector, because gathering new customers rather than retention of existing results a more expensive cost approach.

Project Life Cycle

As this study has a greater organisational impact, we have used the project life cycle to implement the entire process and analysis.


Application Identification and Feasibility
Development and Validation of Prototype
Conversion of Prototype into Deliverable System
Application Identification
Feasibility Study
Design
Build Prototype
Train and Test
Optimise Prototype
Validate Prototype
Implement Deliverable System
Maintenance
Data Collection

This covers the entire process of the project starting from gathering ideas and implementing it to validating it and bringing it to reality to make it work in real-time.

A basic methodology that can be implemented to solve the problem of churn which can be depicted and explained as below.

Stage 1: Modelling risk to account for factors affecting risk and profit

Stage 2: A Decision Model that helps to take into account the affects on customer lifetime value (CLV) and the probablity of customers leaving the system.

Stage 3: A futher qualitative analysis that allows for actions that helps deliver best performance with regards to customers and company.

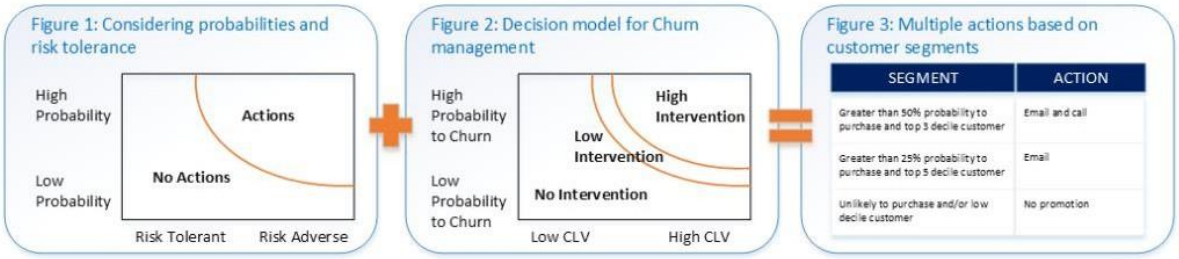


Figure 1: Considering probabilities and risk tolerance
High Probability
Low Probability
Actions
No Actions
Risk Tolerant
Risk Adverse
Figure 2: Decision model for Churn management
High Probability to Churn
Low Probability to Churn
High Intervention
Low Intervention
No Intervention
Low CLV
High CLV
Figure 3: Multiple actions based on customer segments

SEGMENT	ACTION
Greater than 50% probability to purchase and top 3 decile customer	Email and call
Greater than 25% probability to purchase and top 5 decile customer	Email
Unlikely to purchase and/or low decile customer	No promotion

Business assesses the tolerance of risk with regard to churn

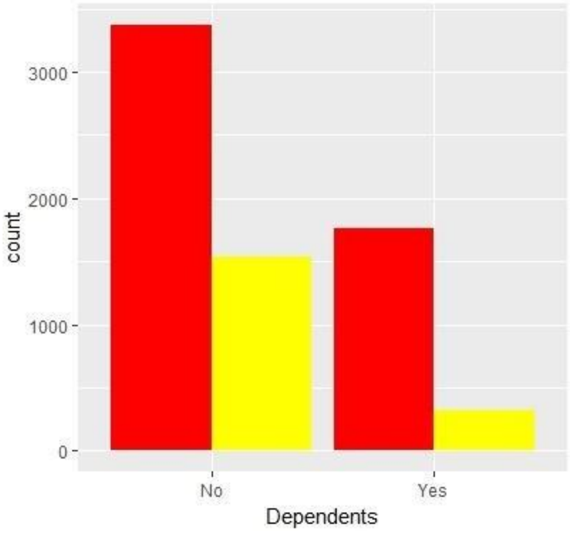
Decision model is based on customer lifetime value

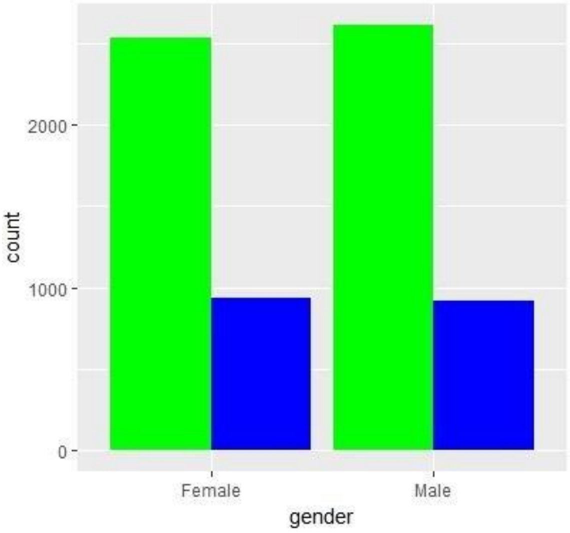
Customer Segmentation (example of a policy)

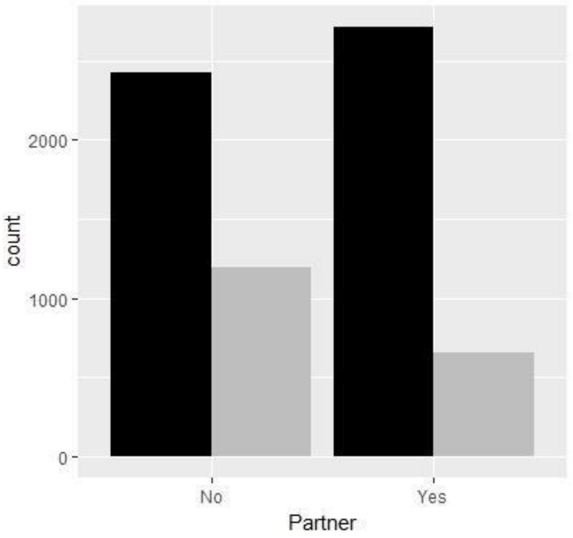
A systematic interaction between the models is important if we were to deliver a comprehensive approach of reduction in churn. The complete cycle that the model follows is a generalised structure, applicable to many business problems. Machine Learning and Artificial Intelligence implementation is ideal for these problems, as they collect exhaustive noisy data about the customers and considering the growth of technologies like Deep Learning, Story Telling and many more, businesses will flourish employing multiple layers of smart solutions that enhance customer satisfaction and performance of the industry.

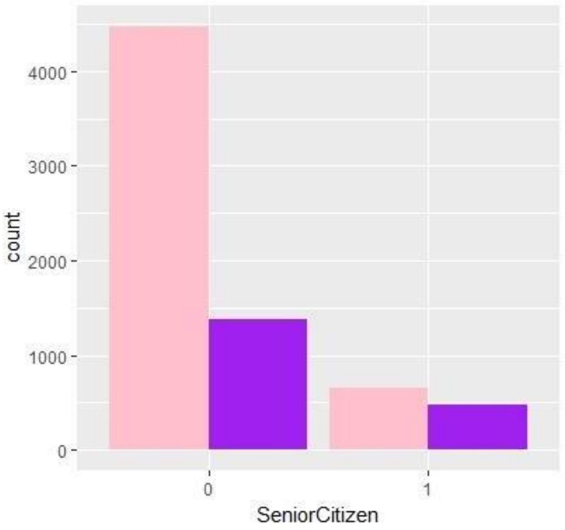
Visualisations

We will first start with some visualisations which can be used as a part of management decisions. Some basic visualisations at the initial stage always help in deciding strategies while modelling ahead.









Conclusions from these visualisations indicate that

1) Customers with no dependents are likely to churn more than the ones that have more dependents.

It can also be found out that the cost of no dependents churning is affecting the company the highest and this needs to be critically figured out that why are the customers with no dependents churning more and what can be done to retain them. Cost and number of customers that churn can be shown below.

CHURNING WITH REGARDS TO NO DEPENDENTS	
TOTAL NUMBER OF CUSTOMERS	1532
TOTAL COST	2227347

2) There is not as such discrimination in gender of the people that churn.

3) Customers with no partners churn more than with partners.

It is depicted that customers with no partners churn more and this affects the business as well but comparatively its less than no dependents and some strategy needs to be implemented while modelling so that we can reduce churning and enhance retention. The table shows the statistics

CHURNING WITH REGARDS TO NO DEPENDENTS	
TOTAL NUMBER OF CUSTOMERS	1196
TOTAL COST	1295126

It would be interesting to check that how many customers are there with no dependents and no partners that churn, considering their correlation with literature it should be high.

4) The percentage of Senior Citizens churning is quite high, 471 of them churned.

Algorithms used in this prototype are:

1) Deep Learning with Keras
2) Logistic Regression

Scoring Methods and Interpretations

	PRECISION	RECALL	ACCURACY	PREDICTION CONFUSION MATRIX
DEEP LEARNING	0.658	0.528	80%	Truth Prediction no yes no 1354 275 yes 160 308
LOGISTIC REGRESSION	-	-	80%	FALSE 0 94 82 4 1 173

These models are evaluated based on the Confusion Matrix, Recall, Precision and Accuracy. These are the performance indicators which in general test the performance of the models and the levels of accuracy the models predict. When implementing machine learning, the aim is not to develop a perfect model but to evaluate the probability of correct prediction generation.

Precision

It indicates that how often the model has predicted as “yes” and it is yes.

$$precision = \frac{true\ positives}{true\ positives + false\ positives}$$

Recall

It indicates that how often the predicted “yes” is correct.

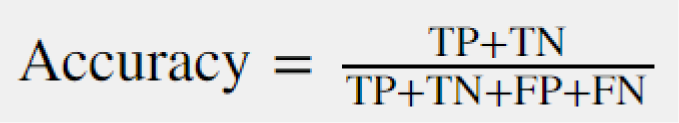
$$recall = \frac{true\ positives}{true\ positives\ + false\ negatives}$$

Precision and Recall parameters are critical for business cases. The main aim of the business is to balance the costs of customers that want to leave and targeting them for retention, instead of targeting the whole set which will include loyal customers.

In our case, precision and recall are quite good which should be above 0.5 ideally and are actually above.

Accuracy

Finally, the accuracy gives the proportion of correct cases determined by the model.



$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

The accuracy of all 3 models is approximately around 80% which means that the models are correctly predicted without any biases and no perfect model is found amongst all 3.

Confusion matrix

A confusion matrix determines results in a tabular form by combining the actual vs predicted outputs of a machine learning model. It basically consists of 4 quadrants which can be evaluated as following in our case:

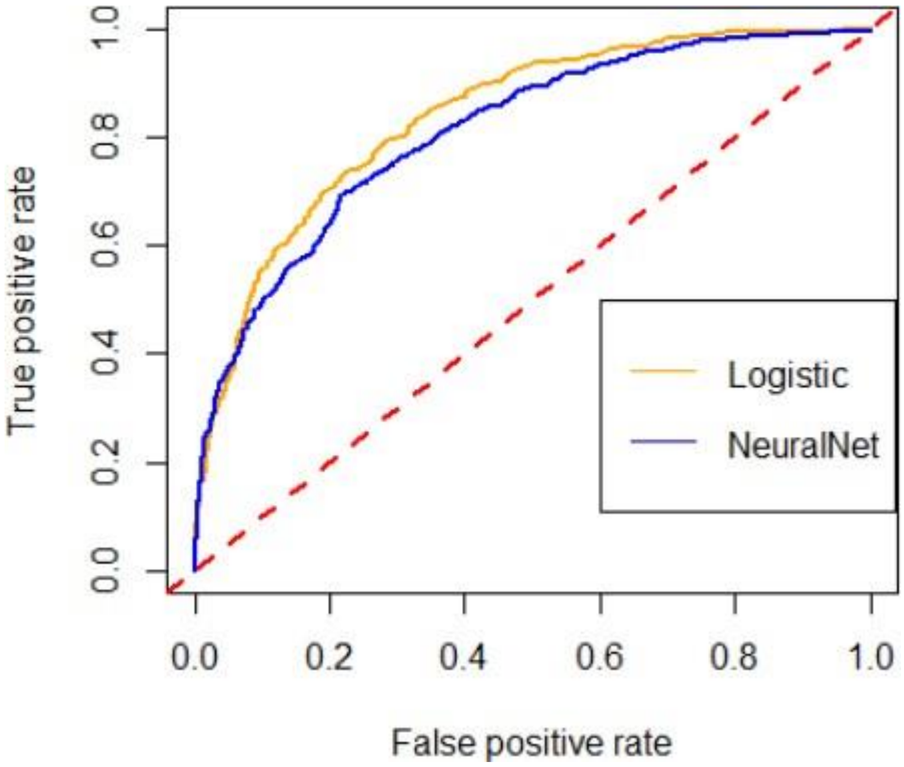
TN – we entice all these subscribers by spending 10% of their 12-month revenue and assume we then retain all of them. So, we gain 90% of their 12-month revenue.

FP – we miss enticing these subscribers and so they leave. Cost of this customer loss is equal to their 12-month revenue to the business, plus we need to replace them, which is $750 each expenditure.

FN - we wrongly entice these subscribers by spending 10% of their 12-month revenue which is a loss to the business.

TP – describes the number that model correctly predicts the churn customers.

Another way of identifying the models estimate is by using the ROC curve. The area under the curve provides the estimation of the model and values being more than 0.5 shows that the models performed well.



Customer Lifetime Value (CLV)

It is the future profits that can be generated by a customer by considering the discounted values. The most important values for the business are the cost and revenue estimates. Forecasting revenues is difficult and hence companies tend to be more critical of this. It is also the current value of the future cash flows attributed by the company to the customer during the entire association of the customer with the business. Machine Learning Models are required to predict these features which would help the business know where they stand.

The formula that can be implemented for calculating the CLV is:

$$CLV = \sum_{t=1}^{n} (r)^t \frac{P_t}{(1+d)^t}$$

where,

- *t*t is a time period, e.g. the first year(*t*t=1), the second year(*t*t=2)
- *n*n is the total number of periods the customer will stay before he/she finally churns
- *r*r is the retention rate/possibility
- *pi*pi is the profit the customer will contribute in the Period t
- *d*d is the discount rate

The CLV is a problem until we optimise it using threshold values and then select the data according to the best selected threshold based on performance. The thresholds used are:

THRESHOLD	TP	TN	FP	FN	ACCURACY
0.1	350	514	512	21	62%
0.2	324	671	355	47	71%
0.3	273	806	229	98	78%
0.4	231	868	158	140	79%
0.5	187	928	98	184	80%
0.6	139	971	55	232	79%
0.7	86	1001	25	285	78%
0.8	29	1002	4	342	75%
0.9	0	1026	0	371	73%
1.0	0	1026	0	371	73%

We select the threshold with 0.3 as it provides the best predictions in terms of the Uplit, Profit and ROI.

These parameters are calculated as follows:

It is the TotalCharges per subscriber record that we will need to use to make the calculation depending upon where the classification falls in the quadrants TP, FP, TN or FN. The threshold is set from the model which gives FPR 35% and TPR is 85% and we use 20% of the dataset as test data to generate.

The mean of TotalCharges field is selected so that it's a more genuine approach in working through the calculations considering the field does not follow normal distribution and to avoid any biases.

UPLIFT		**FPR=27%** **TPR=79%**
NET REVENUE FROM SUBSCRIBERS WE RETAIN BY SPENDING THE 10%.	(TP*90%*TotalCharges)	$560,933
WRONGLY ENTICED SUBSCRIBERS	(-FP*10%*TotalCharges)	-$50226
LOST REVENUE DUE TO MISSED SUBSCRIBERS THAT WE DID NOT ENTICE AND SO LOST	(-FN*TotalCharges)	-$223734
COST TO REPLACE THE LOST SUBSCRIBERS	(-FN*$750)	-$73500
	Sum for Total uplift from using the model on the test dataset	$213473

We can consider presenting this as a comparison to "if no model existed". The cost to the business would have been all those who churned in the dataset, P=TP+FN. If we assume that the same subscriber revenue lost due to churn is exactly replaced when these are substituted with new subscribers by spending $750 to acquire them, then we simply get:

$$P=TP+FN$$

$$P = 371$$

nomodel= (P*$750), where P is the number of subscribers that churned

= 371 * 750 = $278250

In this case *nomodel* is $278250.

The additional ‘profit’ to the business when the model is in place is: *nomodel*-uplift, so $64777

Return on Investment (ROI)

Alternatively, the business might examine being the gain from investment divided by the investment. Using the above, the investment is:

		FPR=27%, **TPR=79%**
SUBSCRIBERS WE RETAIN BY SPENDING THE 10%.	(TP*10%*TotalCharges)	$62326
WRONGLY ENTICED SUBSCRIBERS	(-FP*10%*TotalCharges)	-$50226
COST TO REPLACE THE LOST SUBSCRIBERS	(-FN*$750)	-$73500
	Invested based on the model churn predictors	$186052

The model gained the revenue from (subscribers we retain- subscribers we lost)

= ($560,933 - $223734) = $337199.

The amount invested by the business=$186052.

$$\text{ROI}=\frac{investment}{gain\ from\ investment}$$

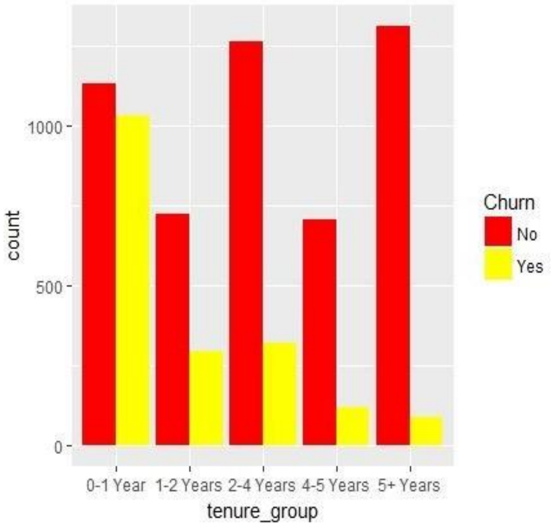
= 181 %

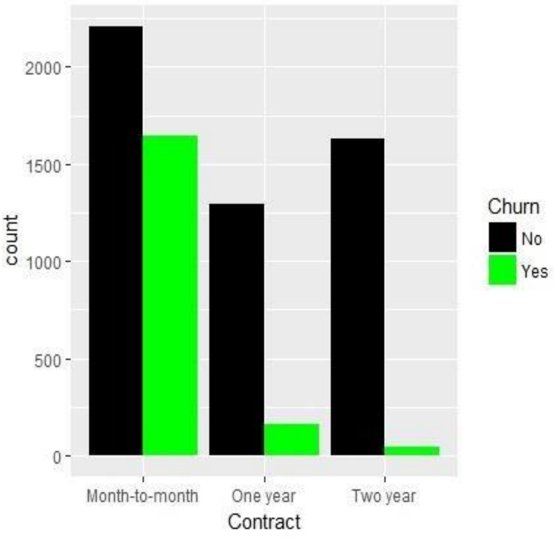
All these figures state that out model fits well.

Conclusions and Recommendations

Feature Investigation based on highly significant variables suggested the following conclusions based on which recommendations can be provided:

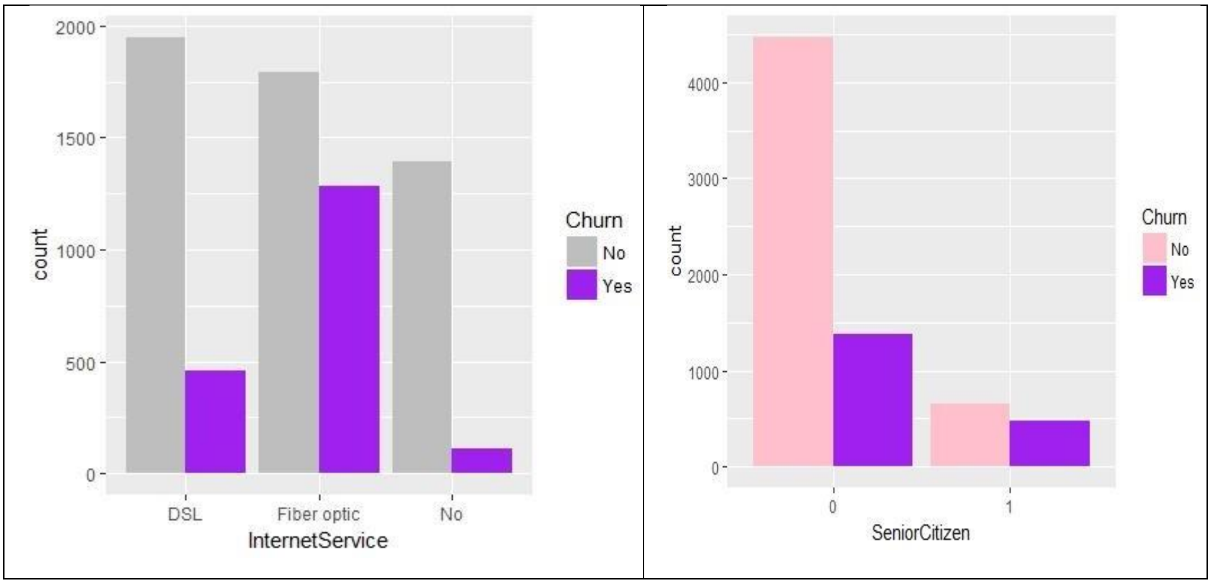
1) Customers with Tenure group 0-1 year are more likely to churn. The trend shows that higher the tenure group lower the churn rate and hence it is recommended to attract customers for higher tenure.





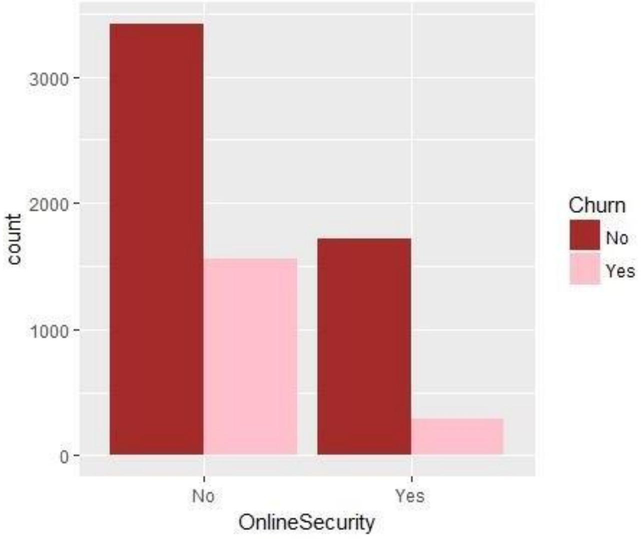
2) Customers with one and two-year contracts are less likely to leave and hence its recommended to attract customers for a larger contract period.

3) Customers that use fibre optic cable service are more likely to leave and hence it is recommended to attract customers with other types.

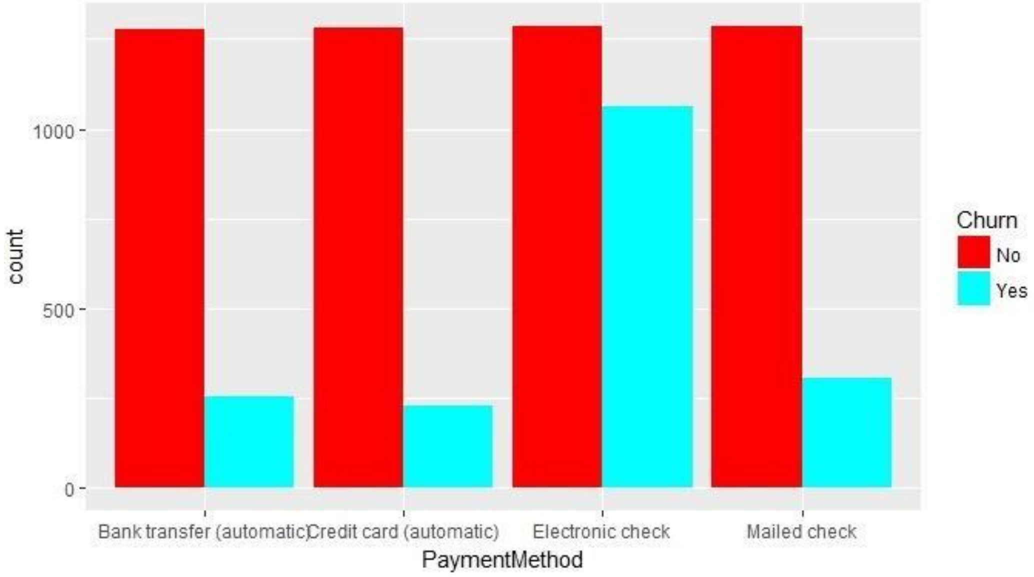


4) It is suggested to attract non-senior citizens because these are more likely to churn.

5) Customers without online security are more likely to churn and hence it should be taken care of providing online security to avoid churning.



6) Customers who have opted for Electronic Check as their payment method are more likely to churn and hence this method should be avoided in future.



Customer churning is a very expensive issue. The good news is that the models which we built are sufficiently accurate and can be applied to this business area to reduce customer churning. Moreover, the revenue generated is genuine and the analysis suggest that the above features needs to be investigated and taken care of.

Appendix 1

Preprocessing in Logistic Regression (LR)

LR only accepts binary values and hence SeniorCitizen field is converted to binary values. Missing Values are deleted using complete.cases() function. Tenure is converted to 6 groups for better analysing that which groups churns more because the data is widely distributed. Tenure_group() function is created for the same. customerID, tenure and MonthlyCharges fields are converted to null that is they are removed as they are unique identifiers.

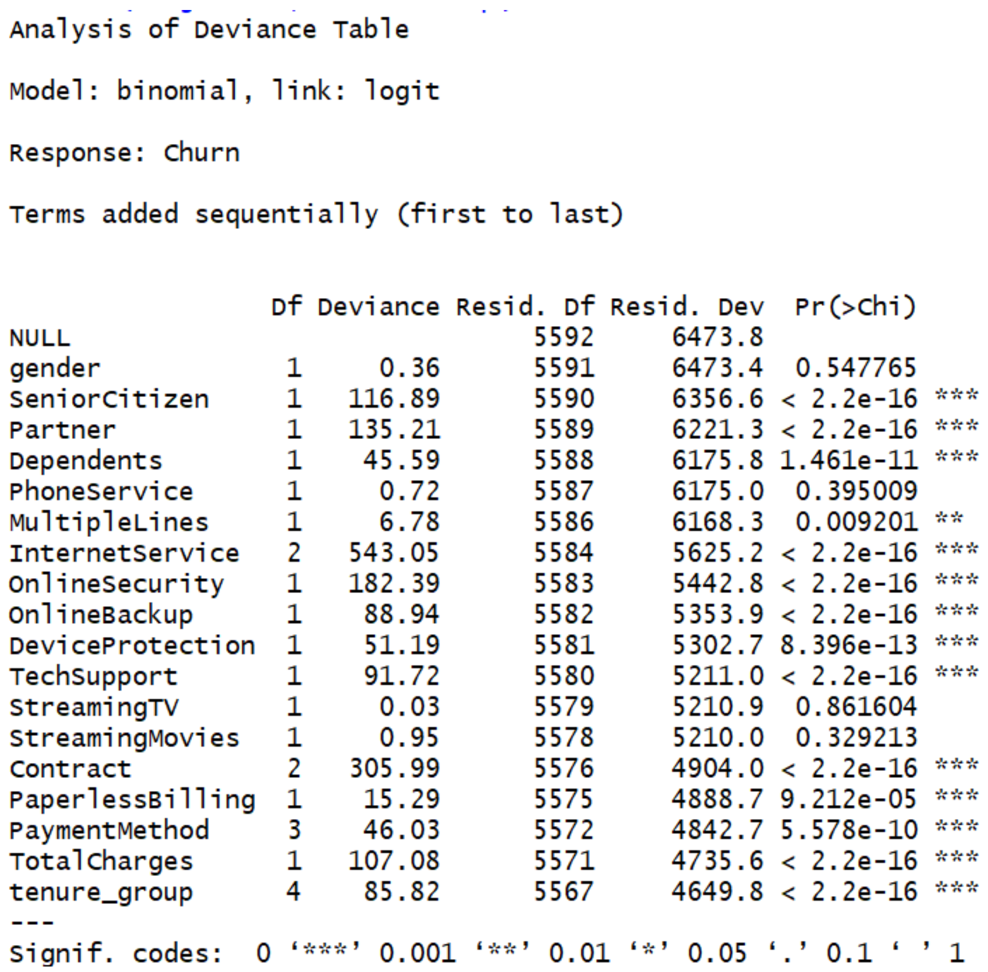
Data Partition is done in the ratio 80:20 using the data_partition() function.

Modelling in LR

Glm() function is used to model LR. We provide family = binomial as we are predicting a categorical target variable. Summary() is used to plot model summary.

Anova() function is used to analyse the deviance when adding variables one by one.

The results of Anova are:

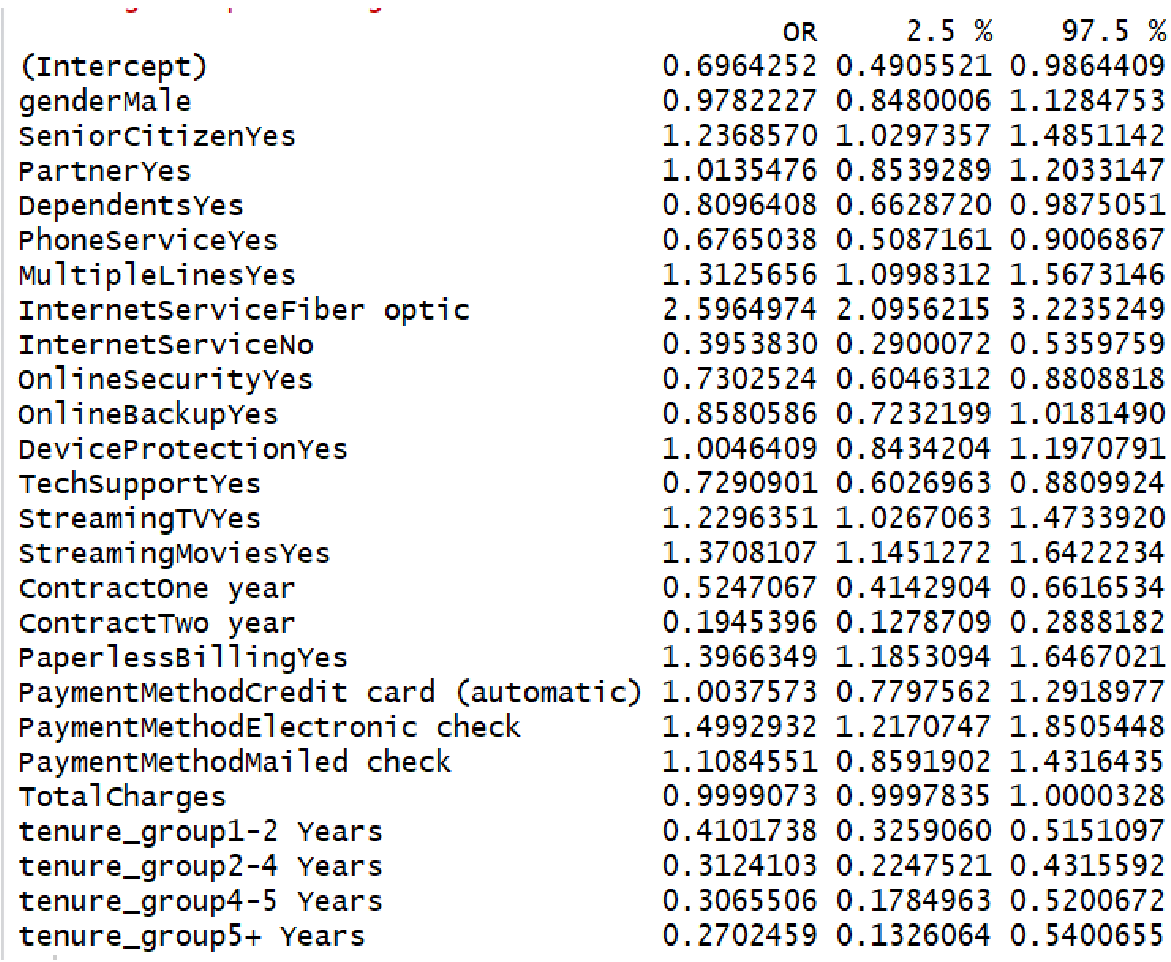


```
Analysis of Deviance Table

Model: binomial, link: logit

Response: Churn

Terms added sequentially (first to last)


                 Df Deviance Resid. Df Resid. Dev  Pr(>Chi)    
NULL                              5592     6473.8              
gender            1     0.36      5591     6473.4  0.547765    
SeniorCitizen     1   116.89      5590     6356.6 < 2.2e-16 ***
Partner           1   135.21      5589     6221.3 < 2.2e-16 ***
Dependents        1    45.59      5588     6175.8 1.461e-11 ***
PhoneService      1     0.72      5587     6175.0  0.395009    
MultipleLines     1     6.78      5586     6168.3  0.009201 ** 
InternetService   2   543.05      5584     5625.2 < 2.2e-16 ***
OnlineSecurity    1   182.39      5583     5442.8 < 2.2e-16 ***
OnlineBackup      1    88.94      5582     5353.9 < 2.2e-16 ***
DeviceProtection  1    51.19      5581     5302.7 8.396e-13 ***
TechSupport       1    91.72      5580     5211.0 < 2.2e-16 ***
StreamingTV       1     0.03      5579     5210.9  0.861604    
StreamingMovies   1     0.95      5578     5210.0  0.329213    
Contract          2   305.99      5576     4904.0 < 2.2e-16 ***
PaperlessBilling  1    15.29      5575     4888.7 9.212e-05 ***
PaymentMethod     3    46.03      5572     4842.7 5.578e-10 ***
TotalCharges      1   107.08      5571     4735.6 < 2.2e-16 ***
tenure_group      4    85.82      5567     4649.8 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Odds ratio provides the odds of an event happening and is very important with regards to LR. We use

exp(cbind(OR=coef(LReg_Model), confint(LReg_Model)))

to plot the odds ratio using MASS library.



```
                                         OR     2.5 %    97.5 %
(Intercept)                       0.6964252 0.4905521 0.9864409
genderMale                        0.9782227 0.8480006 1.1284753
SeniorCitizenYes                  1.2368570 1.0297357 1.4851142
PartnerYes                        1.0135476 0.8539289 1.2033147
DependentsYes                     0.8096408 0.6628720 0.9875051
PhoneServiceYes                   0.6765038 0.5087161 0.9006867
MultipleLinesYes                  1.3125656 1.0998312 1.5673146
InternetServiceFiber optic        2.5964974 2.0956215 3.2235249
InternetServiceNo                 0.3953830 0.2900072 0.5359759
OnlineSecurityYes                 0.7302524 0.6046312 0.8808818
OnlineBackupYes                   0.8580586 0.7232199 1.0181490
DeviceProtectionYes               1.0046409 0.8434204 1.1970791
TechSupportYes                    0.7290901 0.6026963 0.8809924
StreamingTVYes                    1.2296351 1.0267063 1.4733920
StreamingMoviesYes                1.3708107 1.1451272 1.6422234
ContractOne year                  0.5247067 0.4142904 0.6616534
ContractTwo year                  0.1945396 0.1278709 0.2888182
PaperlessBillingYes               1.3966349 1.1853094 1.6467021
PaymentMethodCredit card (automatic) 1.0037573 0.7797562 1.2918977
PaymentMethodElectronic check     1.4992932 1.2170747 1.8505448
PaymentMethodMailed check         1.1084551 0.8591902 1.4316435
TotalCharges                      0.9999073 0.9997835 1.0000328
tenure_group1-2 Years             0.4101738 0.3259060 0.5151097
tenure_group2-4 Years             0.3124103 0.2247521 0.4315592
tenure_group4-5 Years             0.3065506 0.1784963 0.5200672
tenure_group5+ Years              0.2702459 0.1326064 0.5400655
```

We then use predict function to predicted the actual vs predicted outputs using predict() function and plotting the confusion matrix. LR proves to be a good prediction with an accuracy of 80% approximately.