

TELCO CUSTOMER CHURN PREDICTION

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1.EXECUTIVE SUMMARY

Telecom industry is one of the industries which is cursed by cut throat competition and customers usually navigate through companies in search of better services, value for money, products and overall experience. Given the constant investment in equipment, modern technology and Research and development, telecom companies often try to poach customers subscribed to rival companies. Hence, it is important for companies to protect their customers by getting feedback and understanding the needs and problems of the customers. This feedback can be used along with other customer behaviors to predict whether a customer is likely to leave (churn) the company or not. This project serves the problem by comparing machine learning models trained on consumer data. The dataset leveraged for the scope of this project is from IBM. The features include data on consumer subscriptions, charges, tenure with the company, demographic information and products used. The target variable is the label for each customer as churned or not churned. The dataset is randomly divided into training, validation and testing datasets in the ratio- 70:15:15 respectively. Different machine learning models are trained and evaluated to compare key statistics using a confusion matrix. The scope of the project can be expanded to include more features and data points for use in industrial applications.

1.1 PROJECT MOTIVATION

To effectively retain consumers, telecommunications businesses must be able to predict customer attrition. Getting new clients is more expensive than keeping your current ones. Large telecoms companies are attempting to create models to identify which consumers are more likely to change and take appropriate action as a result.

In this article, we develop a model to forecast a customer's likelihood of leaving by examining its characteristics: (1) demographic data, (2) account data, and (3) services data. Our goal is to find a data-driven solution that would enable us to lower churn rates, which will boost customer happiness and business income.

2. DATA SOURCE

The data is an open-sourced dataset first published in 2020 on the IBM platform. The dataset consists of 7043 data points/rows and 33 features/columns. Dimension reduction techniques are implemented which is explained in detail in this report.

[LINK TO THE DATASET](#)

3. DATA DESCRIPTION

Demographics

CustomerID: A unique ID that identifies each customer.

Count: A value used in reporting/dashboarding to sum up the number of customers in a filtered set.

Gender: The customer's gender: Male, Female

Age: The customer's current age, in years, at the time the fiscal quarter ended.

Senior Citizen: Indicates if the customer is 65 or older: Yes, No

Married: Indicates if the customer is married: Yes, No

Dependents: Indicates if the customer lives with any dependents: Yes, No. Dependents could be children, parents, grandparents, etc.

Number of Dependents: Indicates the number of dependents that live with the customer.

Location

CustomerID: A unique ID that identifies each customer.

Count: A value used in reporting/dashboarding to sum up the number of customers in a filtered set.

Country: The country of the customer's primary residence.

State: The state of the customer's primary residence.

City: The city of the customer's primary residence.

Zip Code: The zip code of the customer's primary residence.

Lat Long: The combined latitude and longitude of the customer's primary residence.

Latitude: The latitude of the customer's primary residence.

Longitude: The longitude of the customer's primary residence.

Population

ID: A unique ID that identifies each row.

Zip Code: The zip code of the customer's primary residence.

Population: A current population estimate for the entire Zip Code area.

Services

CustomerID: A unique ID that identifies each customer.

Count: A value used in reporting/dashboarding to sum up the number of customers in a filtered set.

Quarter: The fiscal quarter that the data has been derived from .

Referred a Friend: Indicates if the customer has ever referred a friend or family member to this company: Yes, No

Number of Referrals: Indicates the number of referrals to date that the customer has made.

Tenure in Months: Indicates the total amount of months that the customer has been with the company by the end of the quarter specified above.

Offer: Identifies the last marketing offer that the customer accepted, if applicable. Values include None, Offer A, Offer B, Offer C, Offer D, and Offer E.

Phone Service: Indicates if the customer subscribes to home phone service with the company: Yes, No

Avg Monthly Long Distance Charges: Indicates the customer's average long distance charges, calculated to the end of the quarter specified above.

Multiple Lines: Indicates if the customer subscribes to multiple telephone lines with the company: Yes, No

Internet Service: Indicates if the customer subscribes to Internet service with the company: No, DSL, Fiber Optic, Cable.

Avg Monthly GB Download: Indicates the customer's average download volume in gigabytes, calculated to the end of the quarter specified above.

Online Security: Indicates if the customer subscribes to an additional online security service provided by the company: Yes, No

Online Backup: Indicates if the customer subscribes to an additional online backup service provided by the company: Yes, No

Device Protection Plan: Indicates if the customer subscribes to an additional device protection plan for their Internet equipment provided by the company: Yes, No

Premium Tech Support: Indicates if the customer subscribes to an additional technical support plan from the company with reduced wait times: Yes, No

Streaming TV: Indicates if the customer uses their Internet service to stream television programming from a third party provider: Yes, No. The company does not charge an additional fee for this service.

Streaming Movies: Indicates if the customer uses their Internet service to stream movies from a third party provider: Yes, No. The company does not charge an additional fee for this service.

Streaming Music: Indicates if the customer uses their Internet service to stream music from a third party provider: Yes, No. The company does not charge an additional fee for this service.

Unlimited Data: Indicates if the customer has paid an additional monthly fee to have unlimited data downloads/uploads: Yes, No

Contract: Indicates the customer's current contract type: Month-to-Month, One Year, Two Year.

Paperless Billing: Indicates if the customer has chosen paperless billing: Yes, No

Payment Method: Indicates how the customer pays their bill: Bank Withdrawal, Credit Card, Mailed Check

Monthly Charge: Indicates the customer's current total monthly charge for all their services from the company.

Total Charges: Indicates the customer's total charges, calculated to the end of the quarter specified above.

Total Refunds: Indicates the customer's total refunds, calculated to the end of the quarter specified above.

Total Extra Data Charges: Indicates the customer's total charges for extra data downloads above those specified in their plan, by the end of the quarter specified above.

Total Long Distance Charges: Indicates the customer's total charges for long distance above those specified in their plan, by the end of the quarter specified above.

Status

CustomerID: A unique ID that identifies each customer.

Count: A value used in reporting/dashboarding to sum up the number of customers in a filtered set.

Quarter: The fiscal quarter that the data has been derived from .

Satisfaction Score: A customer's overall satisfaction rating of the company from 1 (Very Unsatisfied) to 5 (Very Satisfied).

Satisfaction Score Label: Indicates the text version of the score (1-5) as a text string.

Customer Status: Indicates the status of the customer at the end of the quarter: Churned, Stayed, or Joined

Churn Label: Yes = the customer left the company this quarter. No = the customer remained with the company. Directly related to Churn Value.

Churn Value: 1 = the customer left the company this quarter. 0 = the customer remained with the company. Directly related to Churn Label.

Churn Score: A value from 0-100 that is calculated using the predictive tool IBM SPSS Modeler. The model incorporates multiple factors known to cause churn. The higher the score, the more likely the customer will churn.

Churn Score Category: A calculation that assigns a Churn Score to one of the following categories: 0-10, 11-20, 21-30, 31-40, 41-50, 51-60, 61-70, 71-80, 81-90, and 91-100

CLTV: Customer Lifetime Value. A predicted CLTV is calculated using corporate formulas and existing data. The higher the value, the more valuable the customer. High value customers should be monitored for churn.

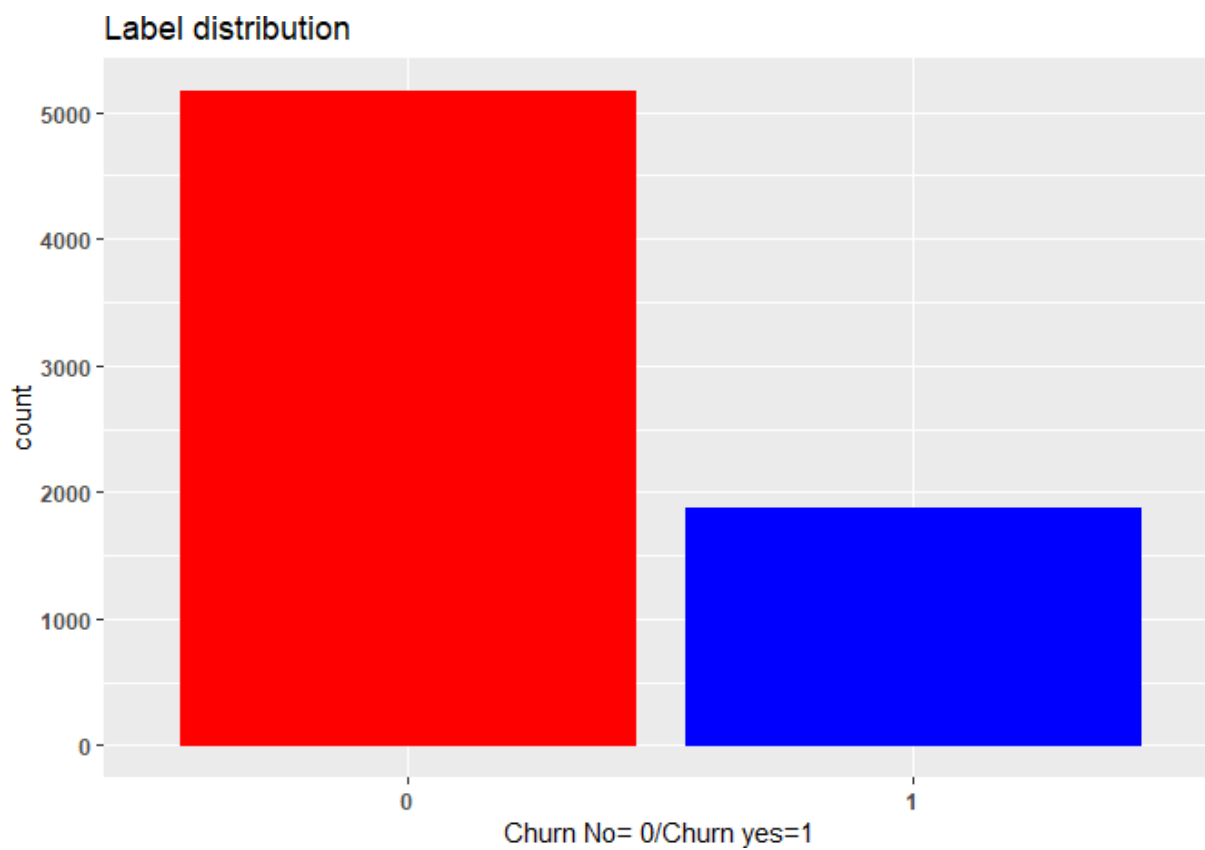
CLTV Category: A calculation that assigns a CLTV value to one of the following categories: 2000-2500, 2501-3000, 3001-3500, 3501-4000, 4001-4500, 4501-5000, 5001-5500, 5501-6000, 6001-6500, and 6501-7000.

Churn Category: A high-level category for the customer's reason for churning: Attitude, Competitor, Dissatisfaction, Other, Price. When they leave the company, all customers are asked about their reasons for leaving. Directly related to Churn Reason.

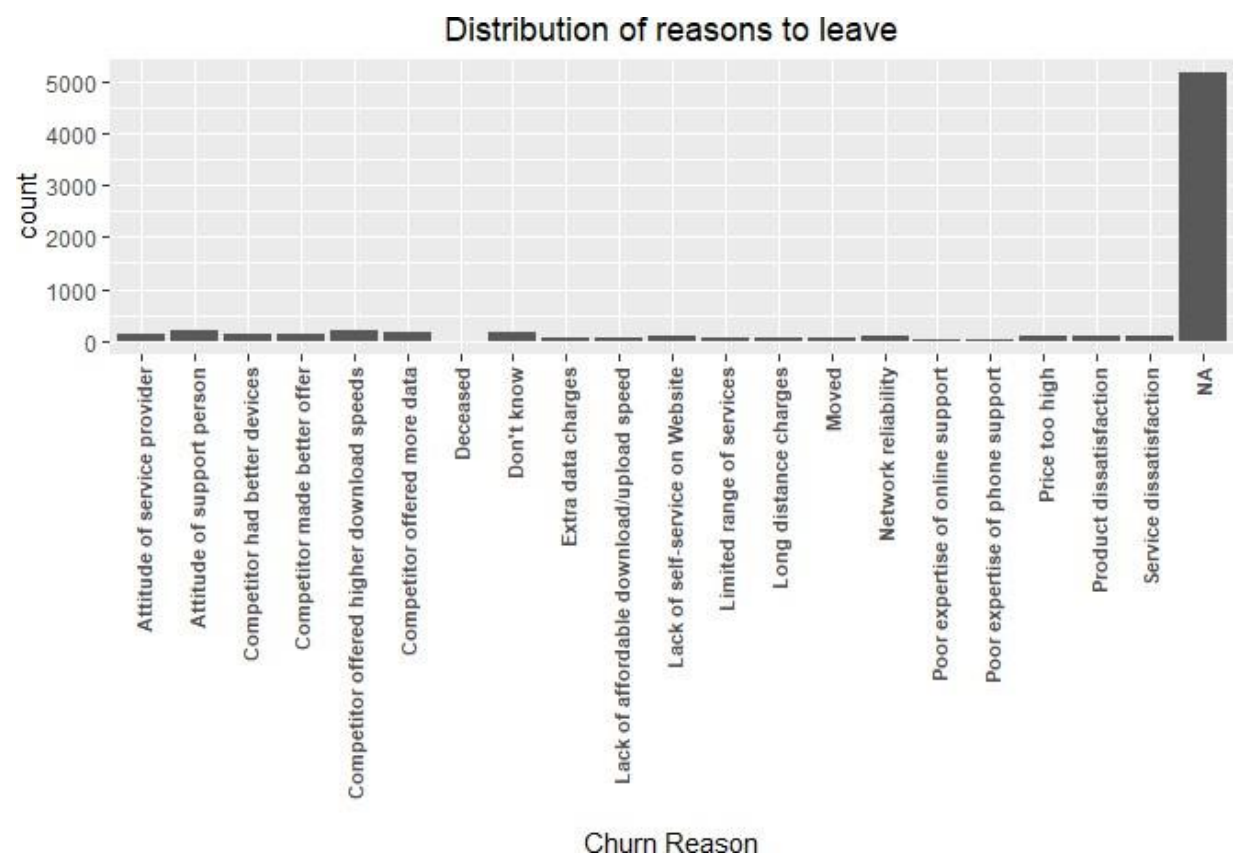
Churn Reason: A customer's specific reason for leaving the company. Directly related to Churn Category.

EXPLORATORY DATA ANALYSIS

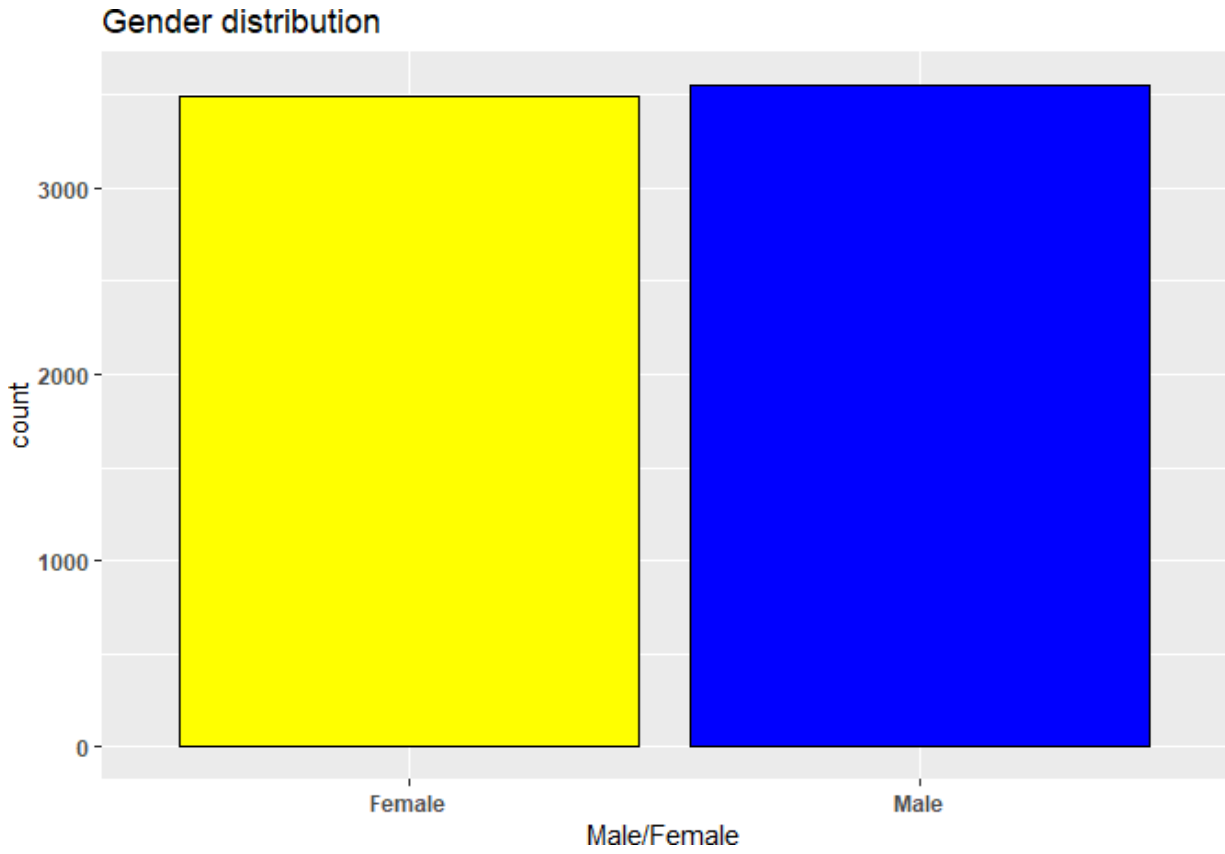
Label Distribution:



Distribution Of Reason To Leave:

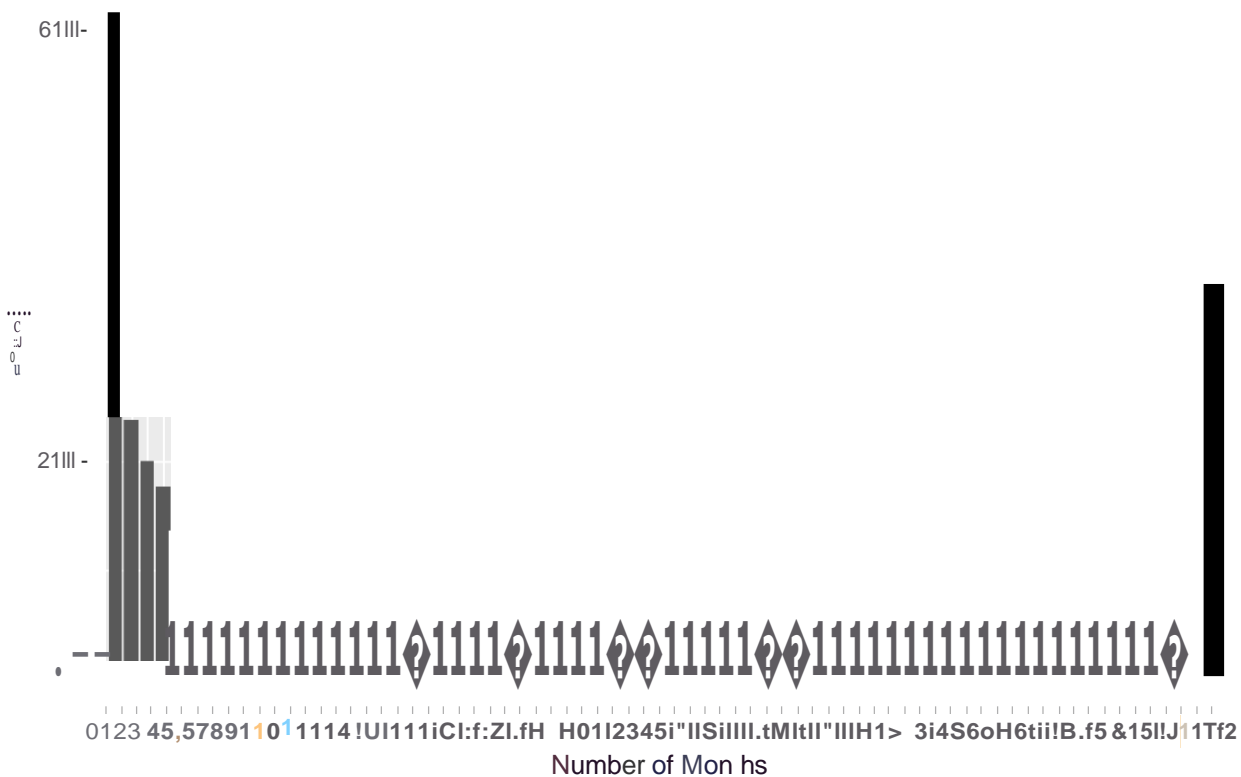


Gender Distribution:

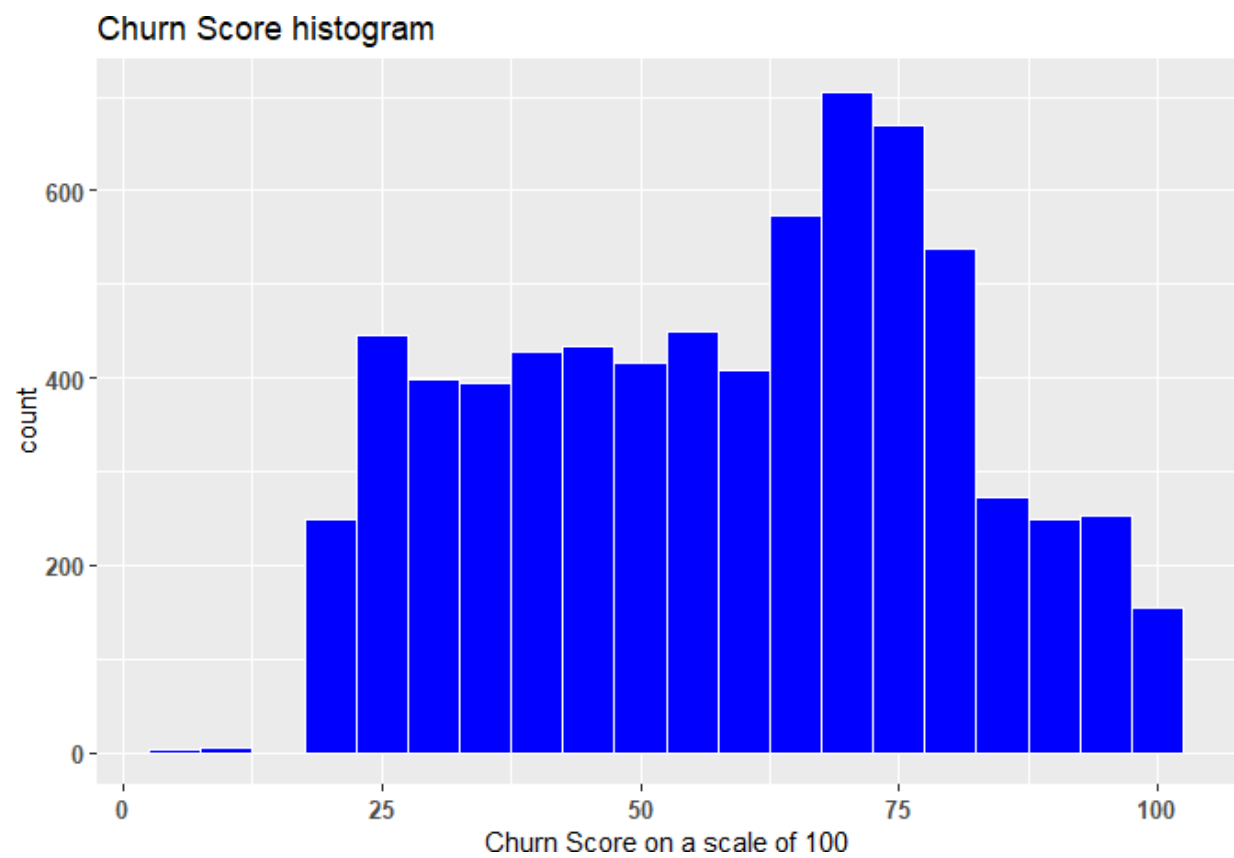


Tenure Months:

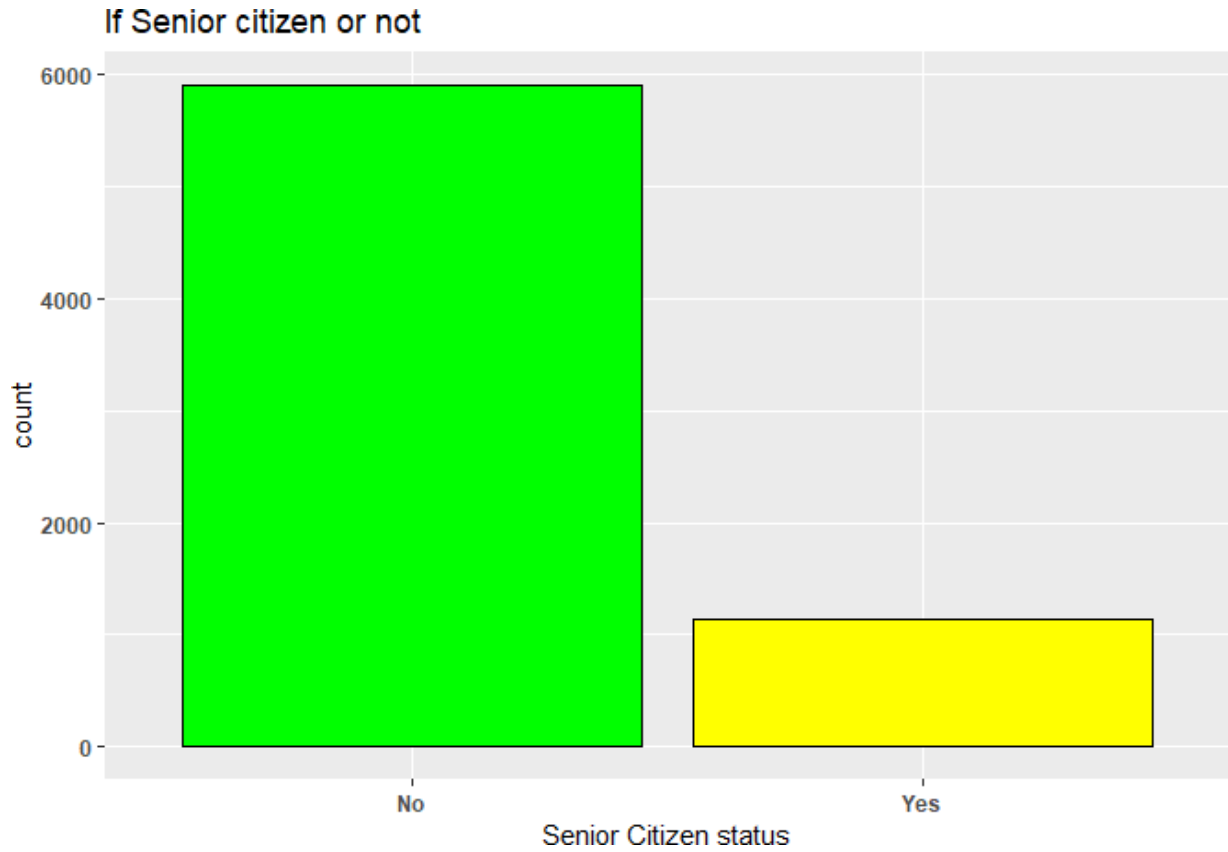
Tenure Months



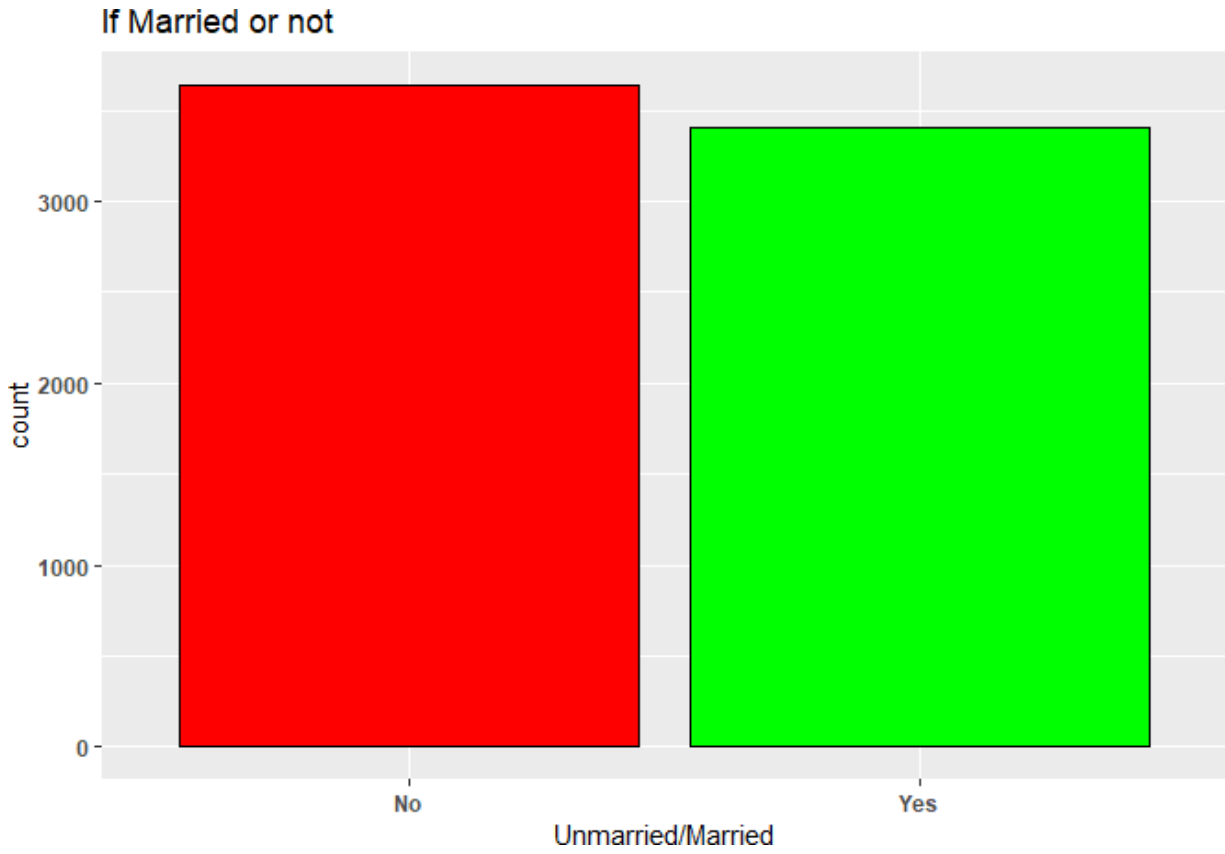
Churn Score Histogram:



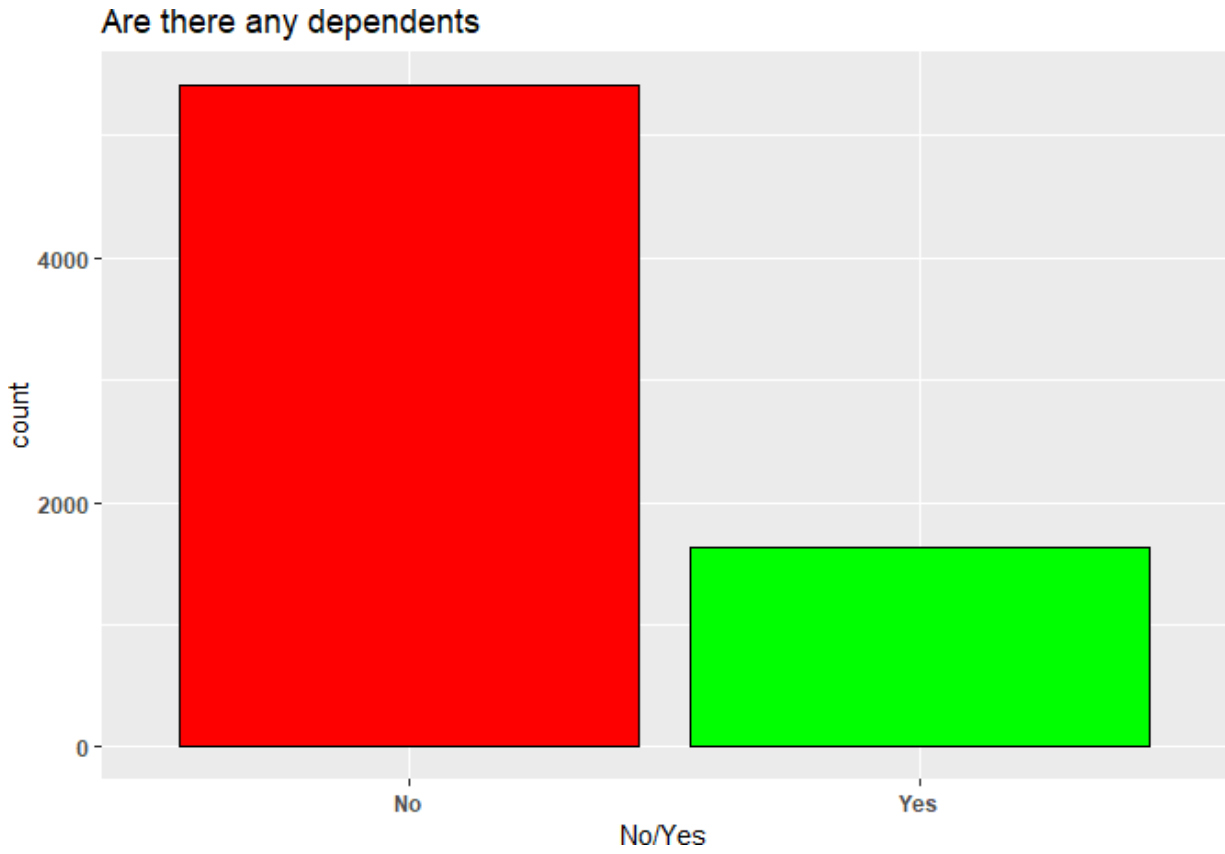
If Senior Citizen or Not:



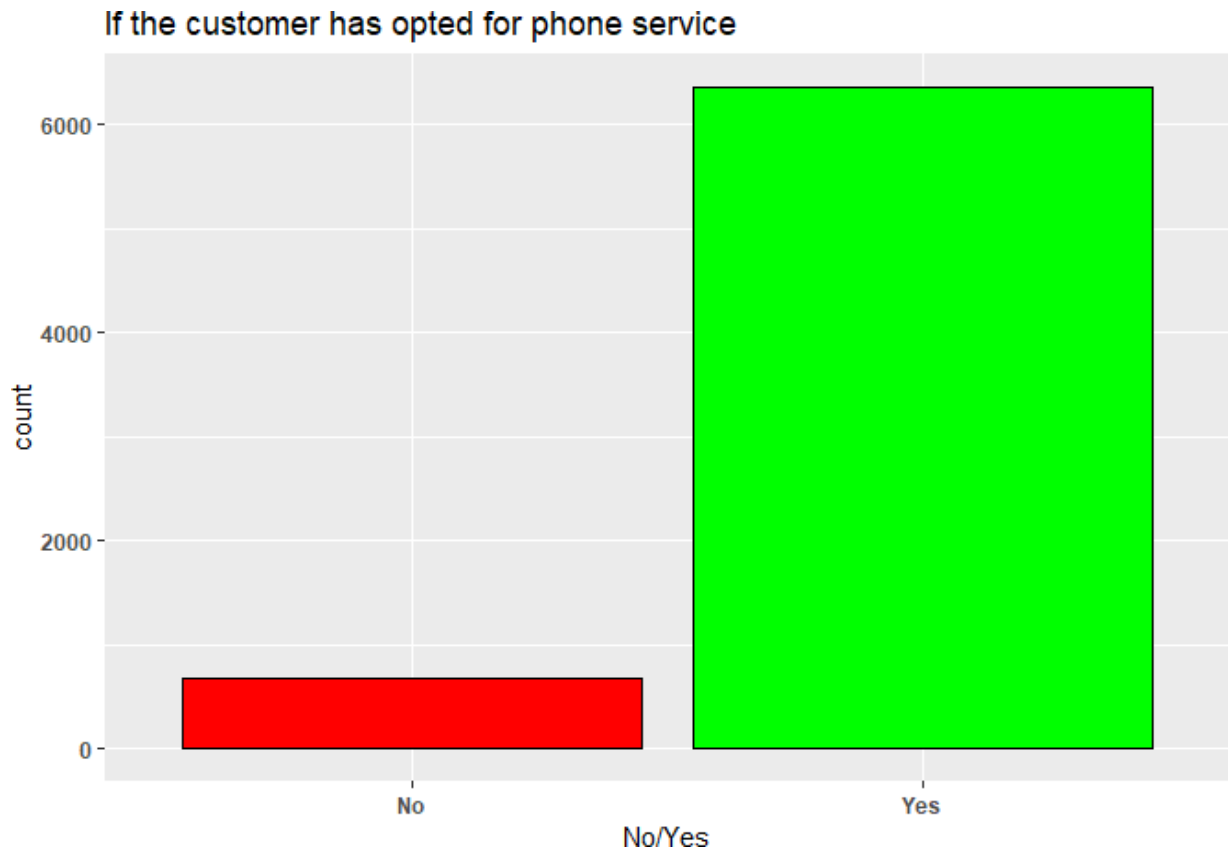
If Married Or Not:



Are There Any Dependents:



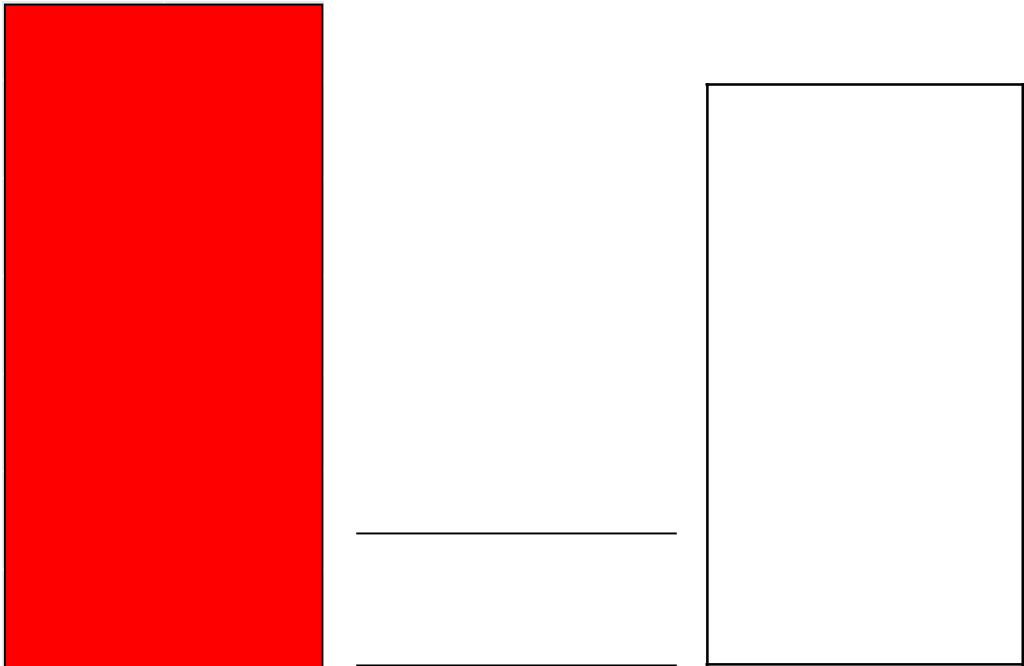
If the customer has opted for phone service:



If the customer has opted for multiple-lines:

Im the customer has opted for multiple-lines

2@H,-
.....
C
F
0
u

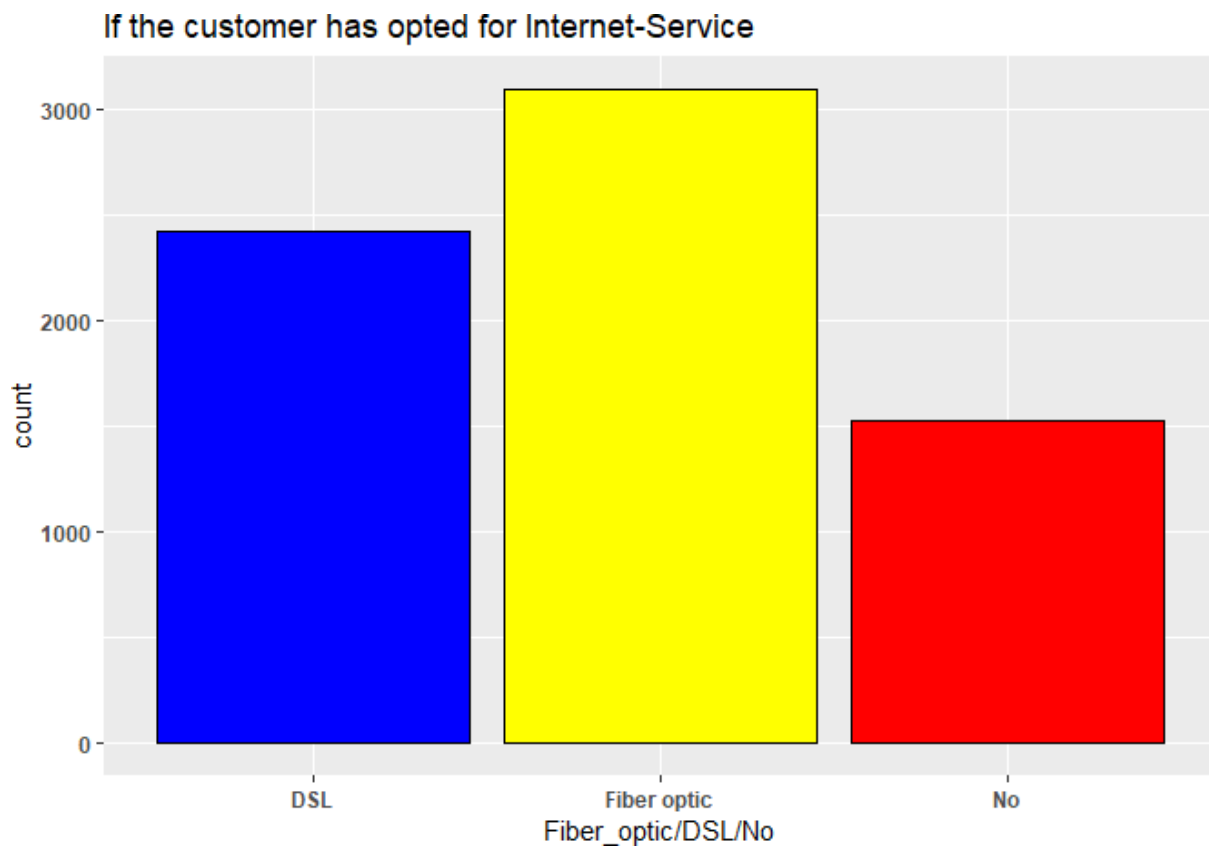


No

No phone service
No/No lines/Yes

Yes

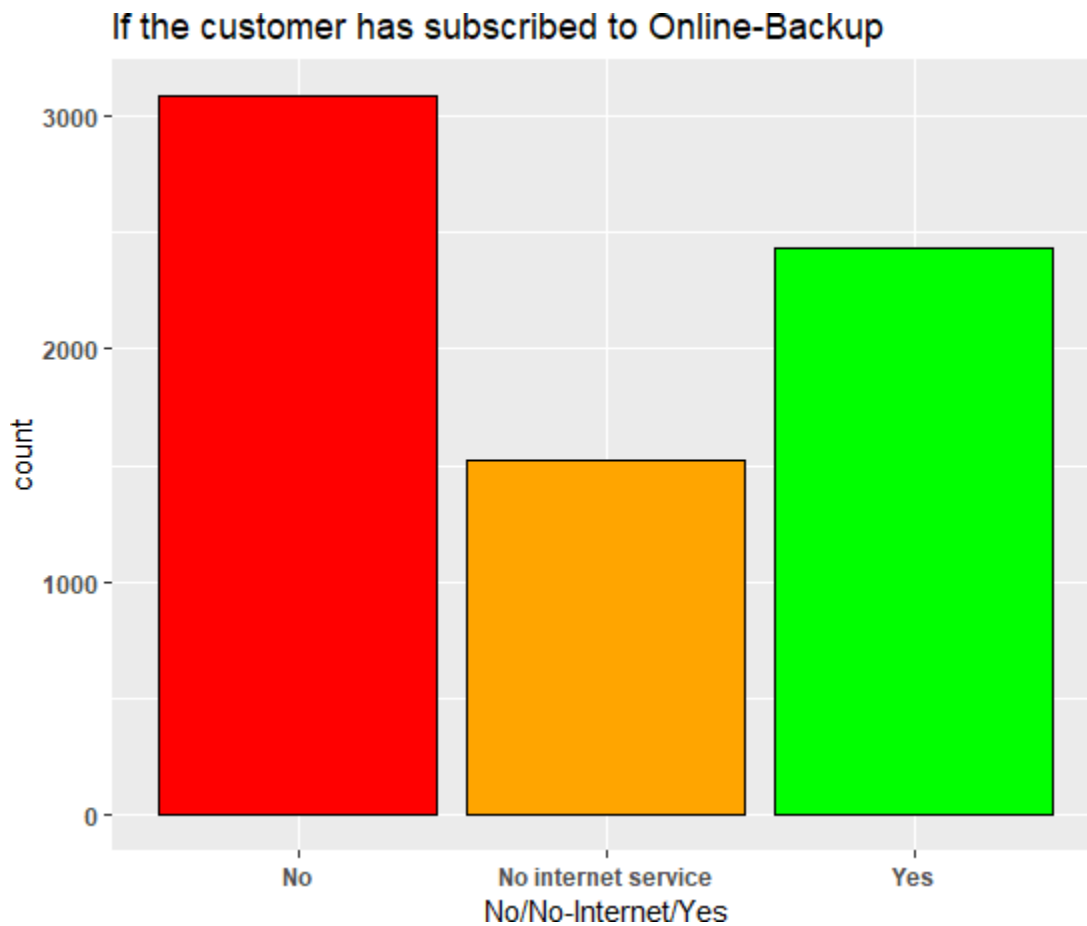
If the customer has opted for Internet-Service:



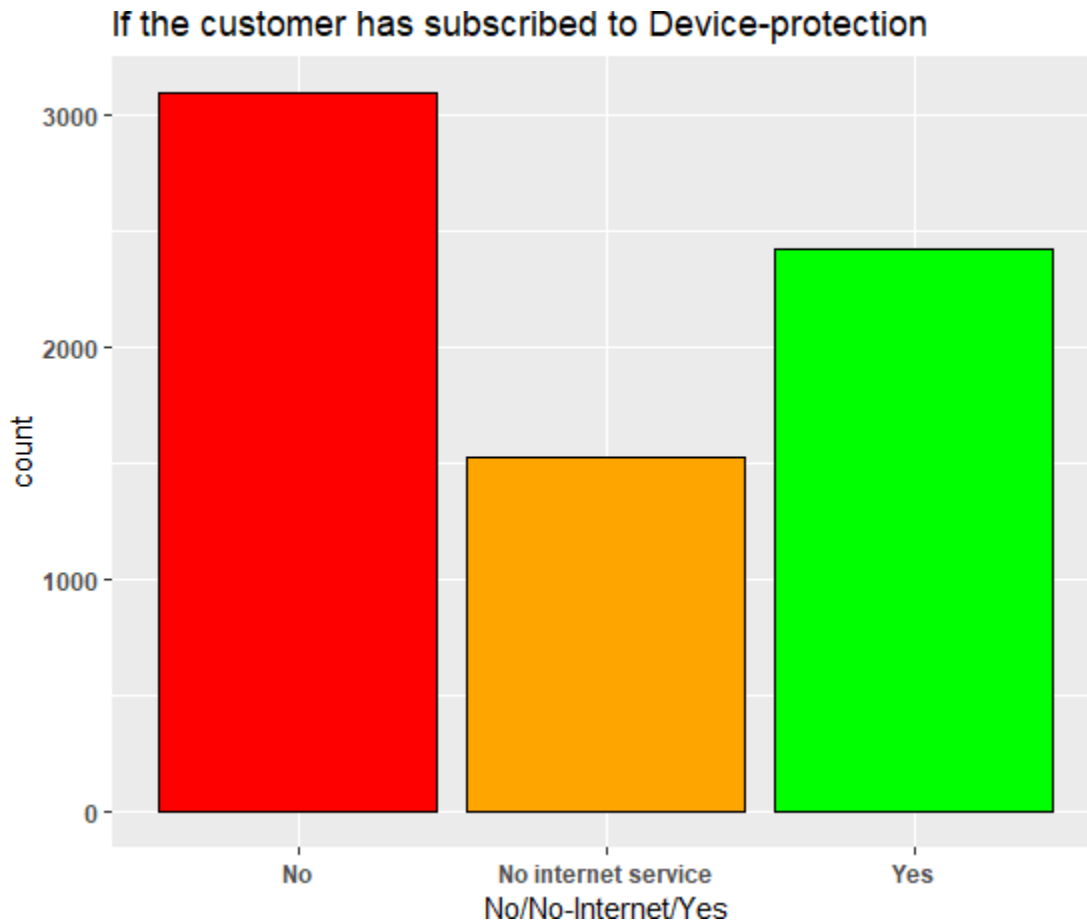
If the customer has subscribed to Online Security:



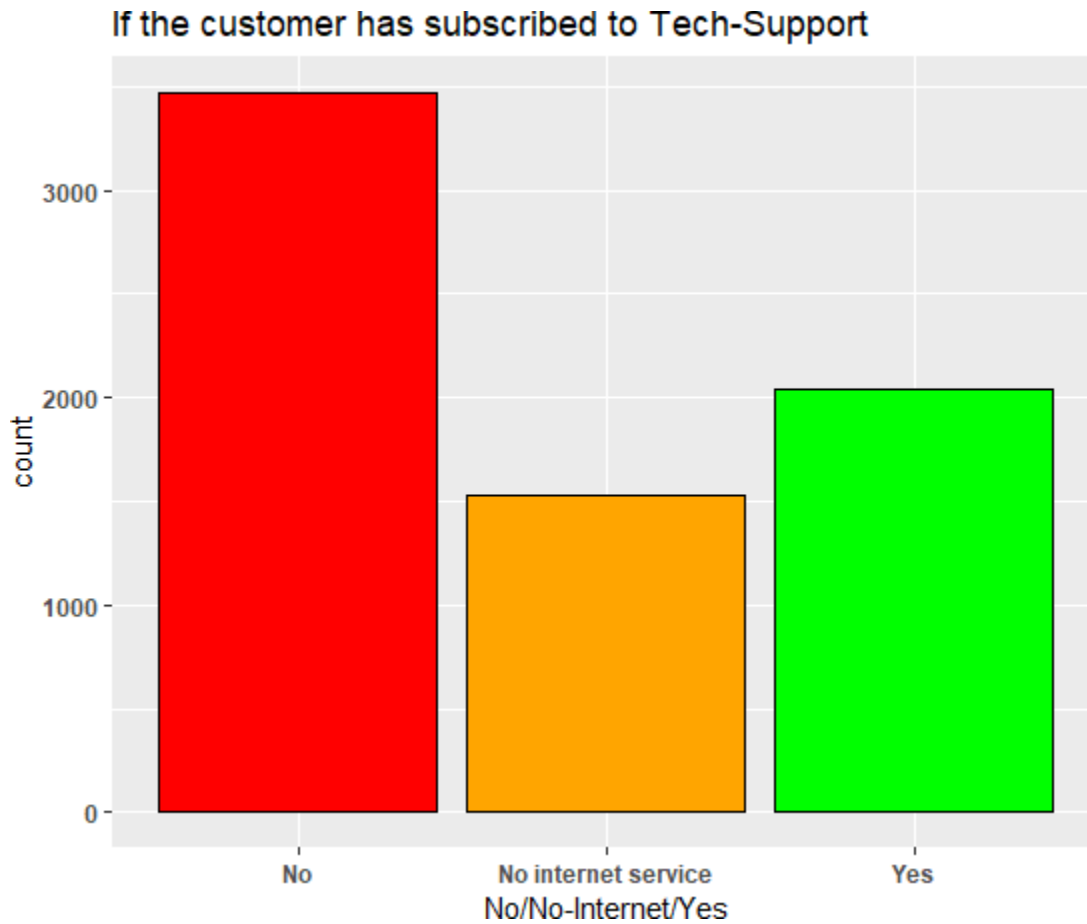
If the customer has subscribed to Online-Backup:



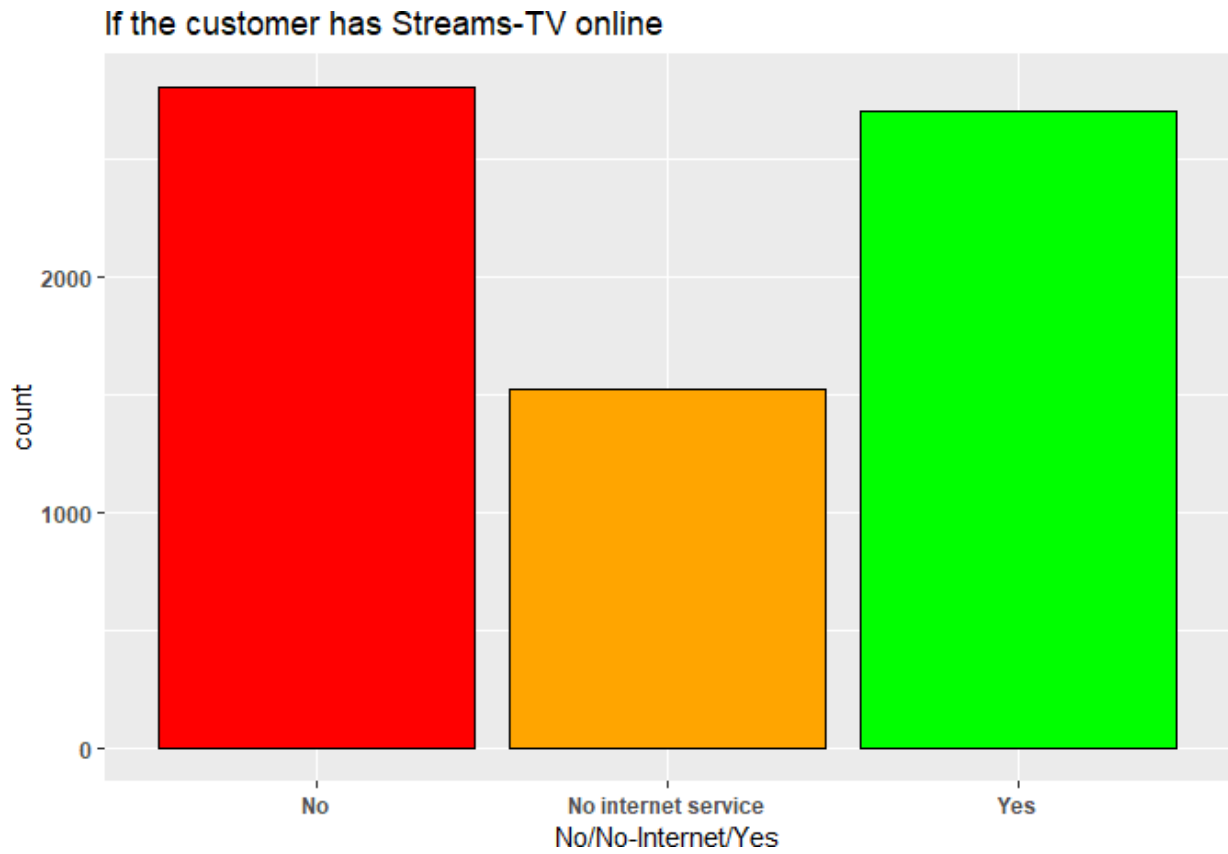
If the customer has subscribed to Device-protection:



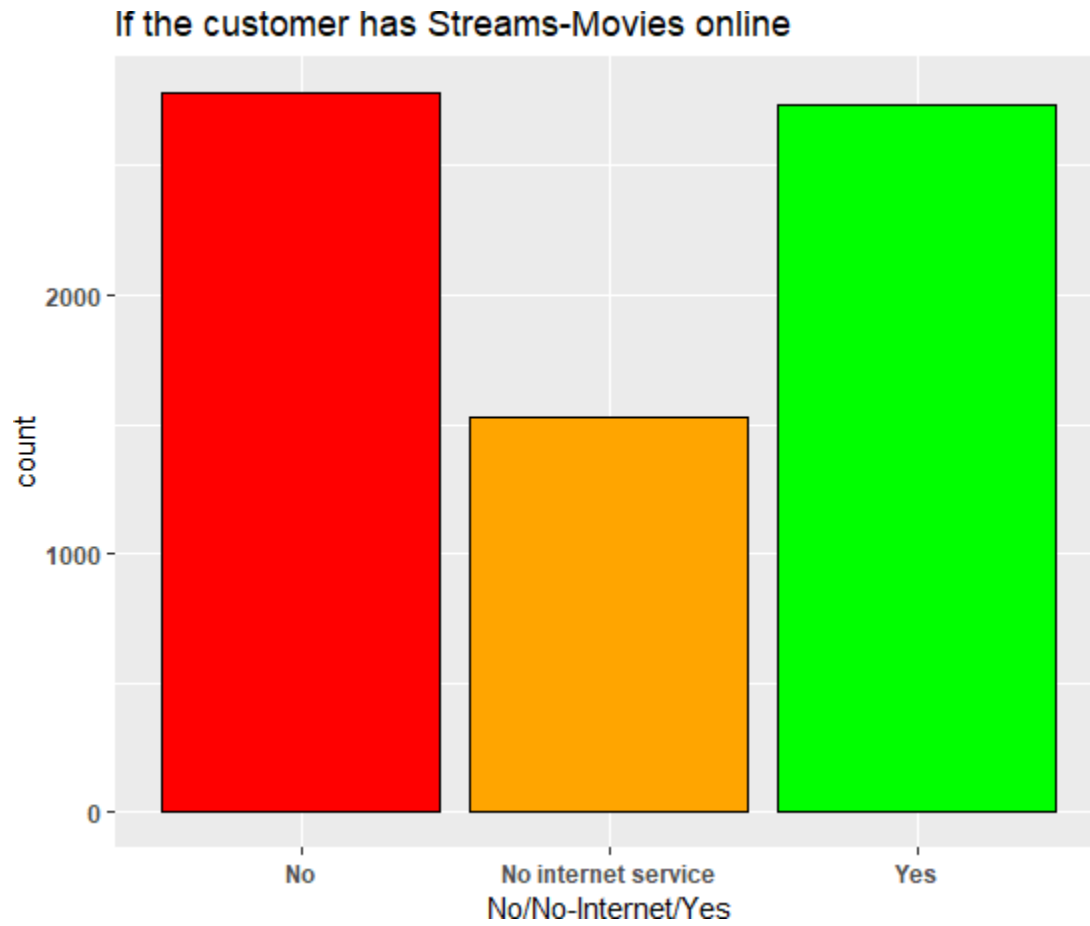
If the customer has subscribed to Tech-Support:



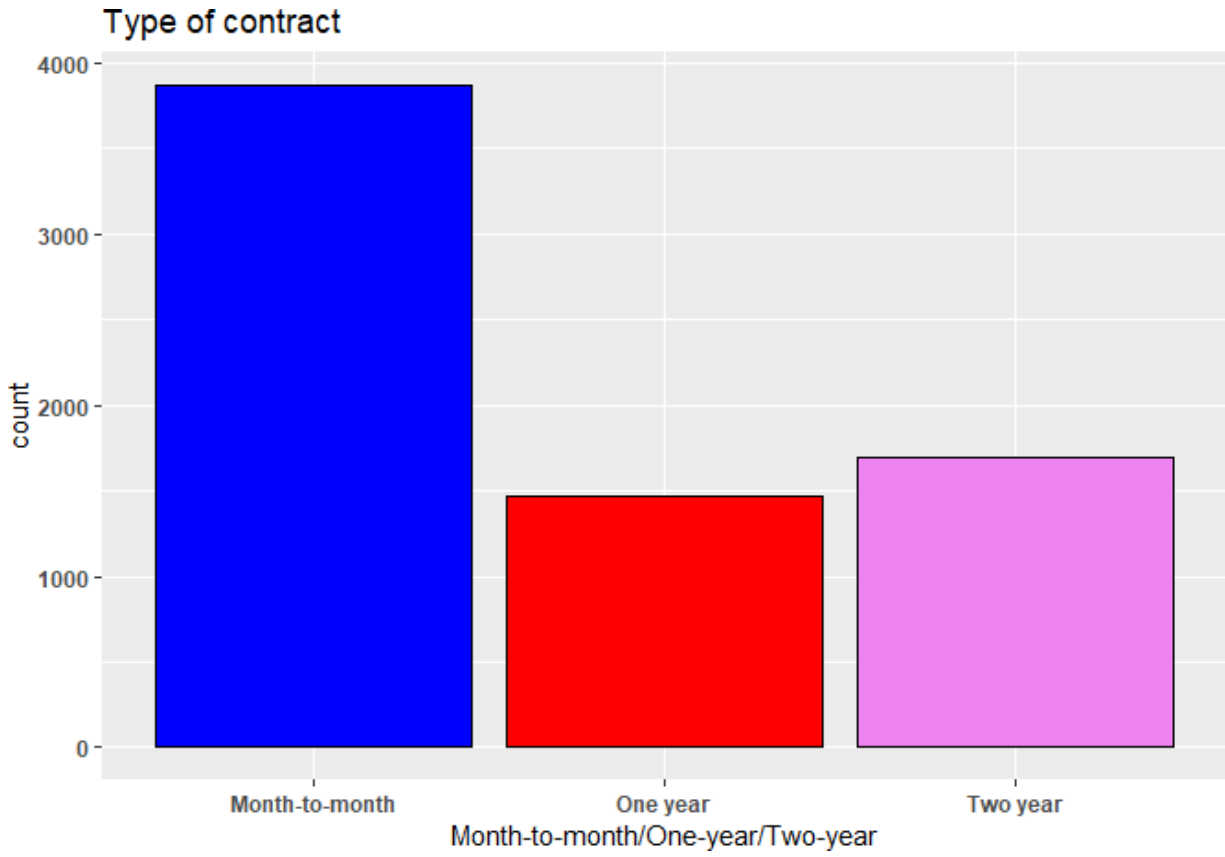
If the customer has Streams-TV online:



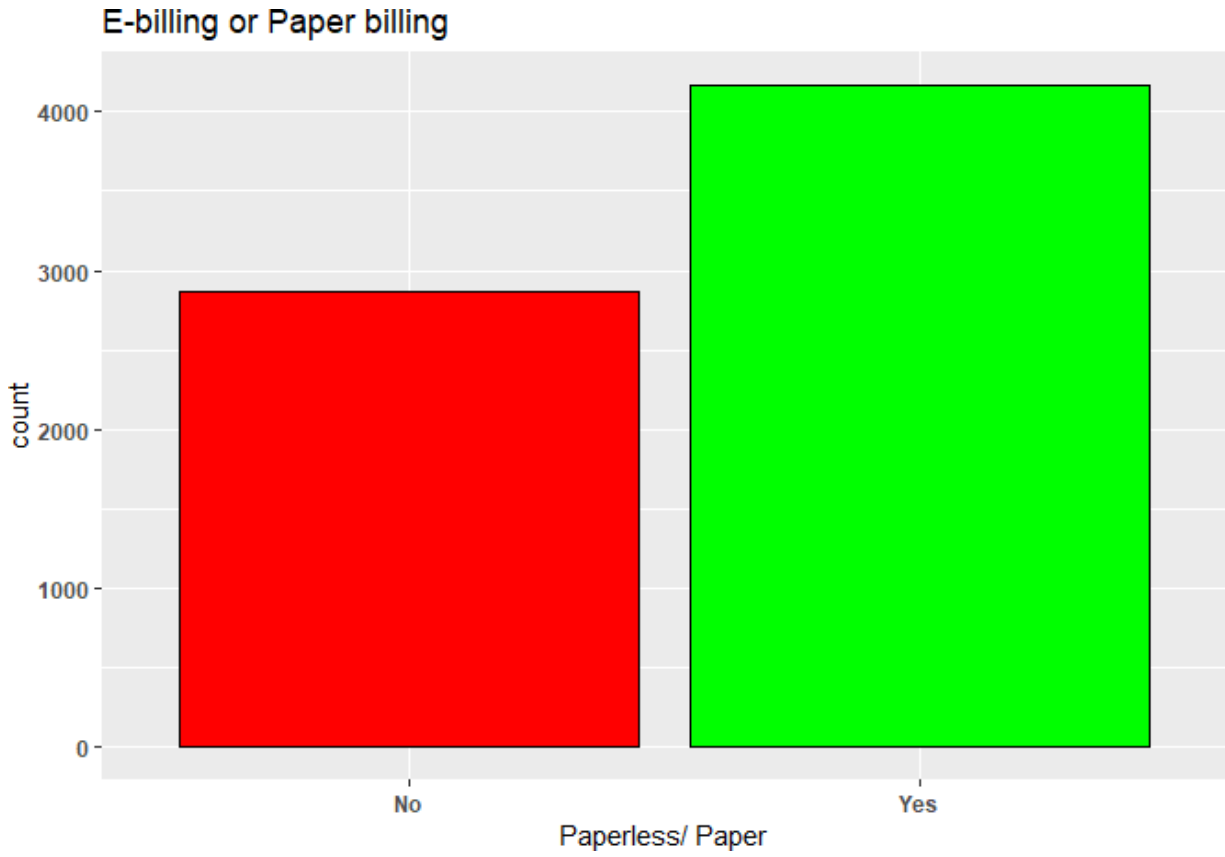
If the customer has Streams-Movies online:



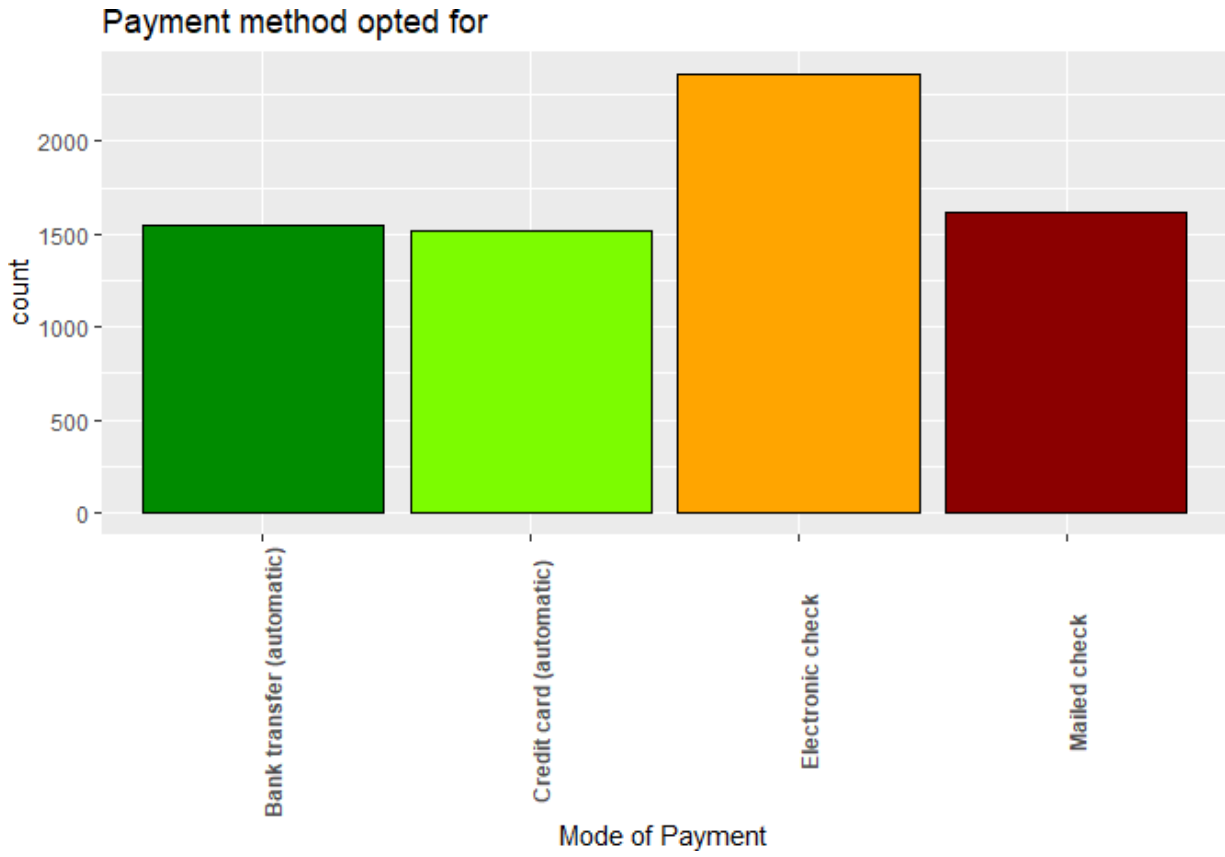
Type of contract:



E-billing or Paper billing:

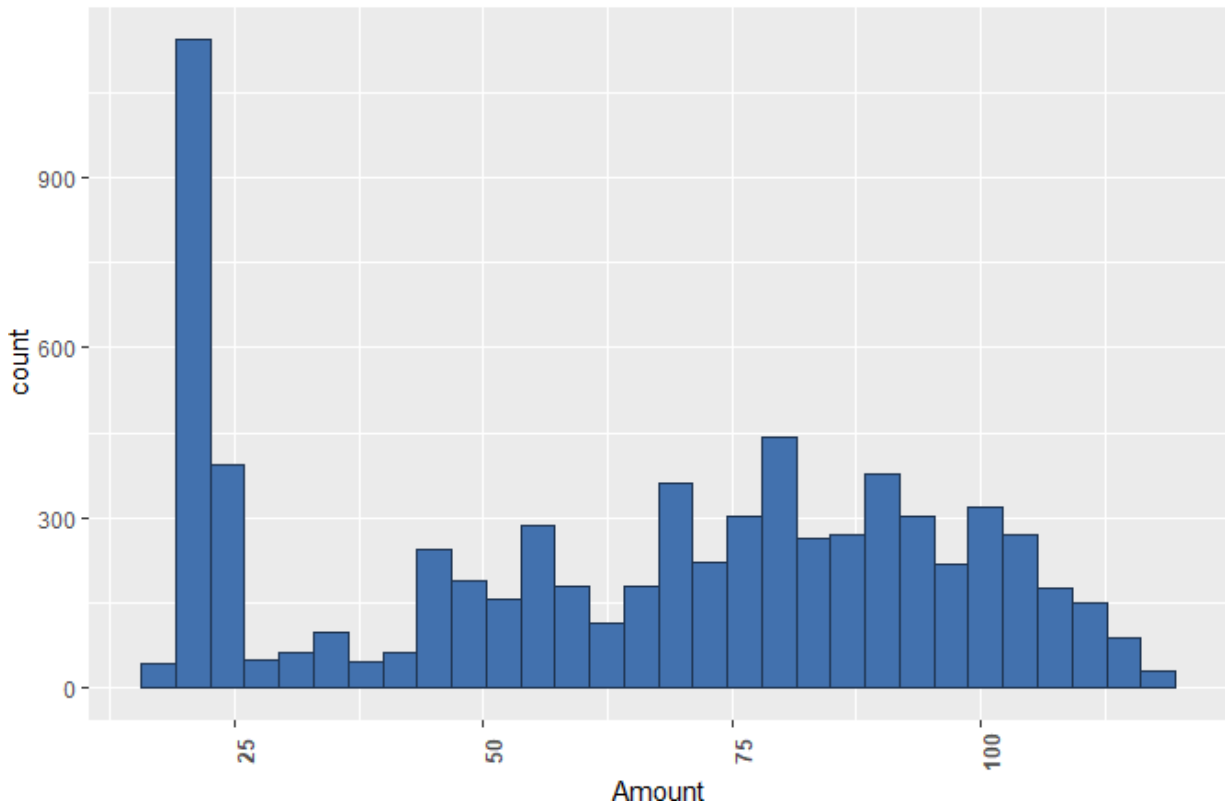


Payment method opted for:



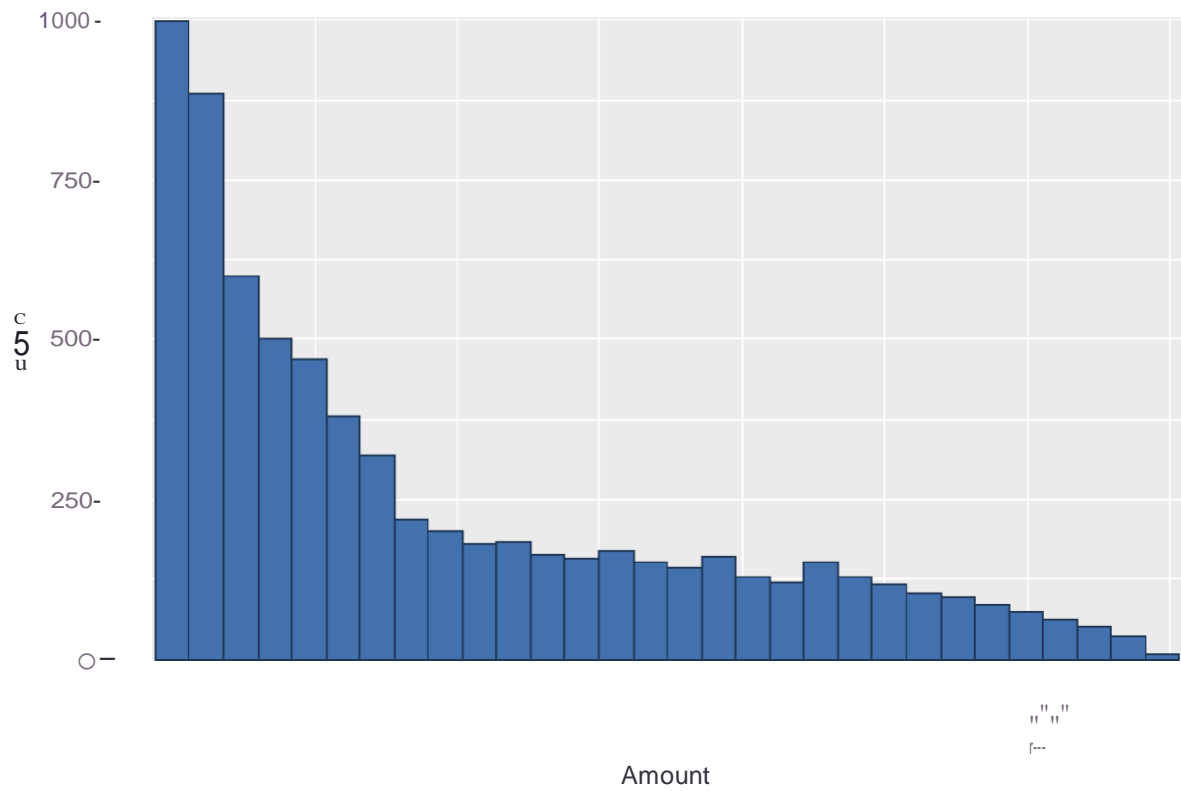
Charges paid on a Monthly basis:

Charges paid on a Monthly basis



Total Charges paid:

Total Charges paid



5. DIMENSION REDUCTION/FEATURE ENGINEERING

Dimension reduction or feature engineering is a set of techniques practiced to reduce the number of features without losing important information. Furthermore, categorical features are encoded using one-hot encoding technique while reducing the number of categories.

5.1 ONE-HOT ENCODING

1. Churn Reason feature is concatenated to less number of categories- 5 categories. The categories chosen are:

| Reason | Category |
|---|------------------|
| Attitude of support person | Customer service |
| Attitude of service provider | Customer service |
| Service dissatisfaction | Customer service |
| Lack of self-service on Website | Customer service |
| Poor expertise of phone support | Customer service |
| Poor expertise of online support | Customer service |
| Competitor offered higher download speeds | Competitor |
| Competitor offered more data | Competitor |
| Competitor had better devices | Competitor |
| Competitor made better offer | Competitor |
| Network reliability | Product |
| Product dissatisfaction | Product |
| Limited range of services | Product |
| Price too high | Price |

| | |
|--|-------|
| Extra data charges | Price |
| Long distance charges | Price |
| Lack of affordable download/upload speed | Price |
| Moved | Other |
| Deceased | Other |

2. Gender variable is converted to numerical using one-hot encoding where Male is assigned 0 and Female is assigned 1.
3. Senior.Citizen variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
4. Partner variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
5. Dependent variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
6. Phone.Service variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
7. Multiple.Lines variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
8. Online.Security variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
9. Online.Backup variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
10. Device.Protection variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
11. Tech.Support variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
12. Streaming.TV variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
13. Streaming.Movies variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
14. Paperless.Billing variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.

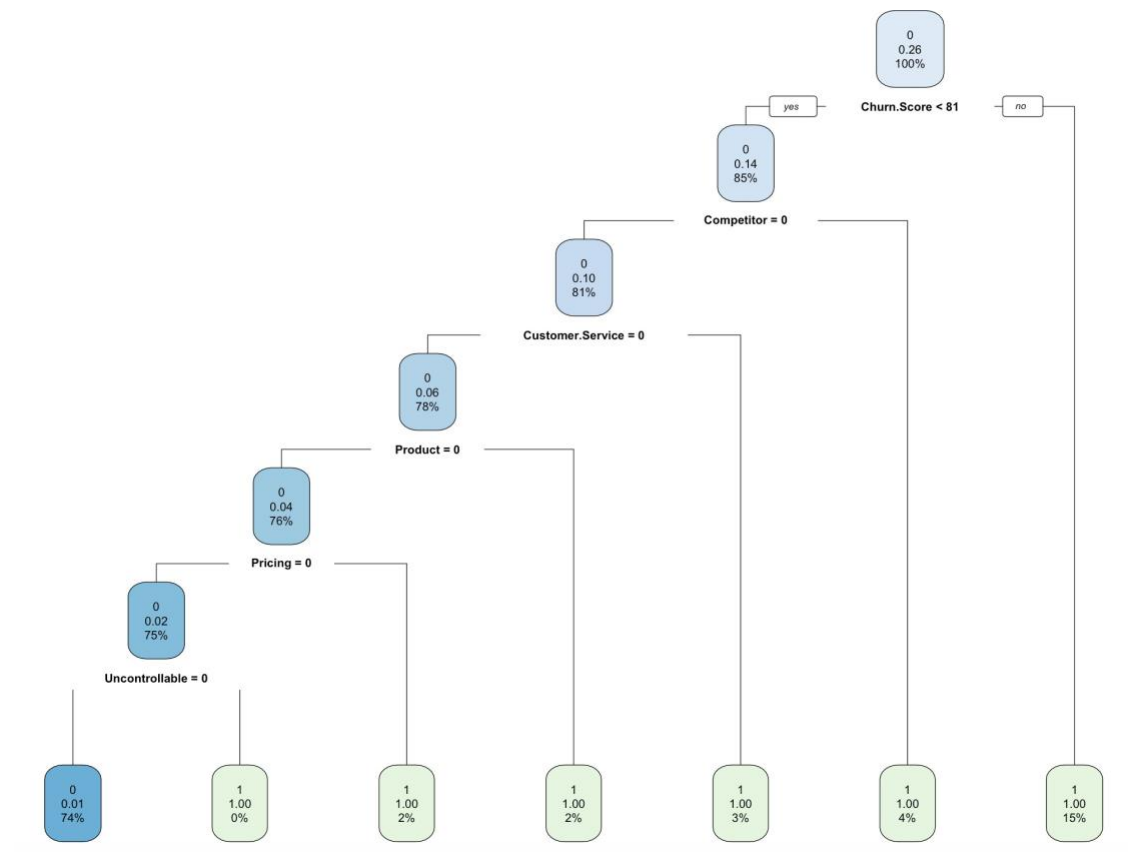
15. Churn.Label variable is converted to numerical using one-hot encoding where No is assigned 0 and Yes is assigned 1.
16. Internet.Service variable is converted to numerical using one-hot encoding where No is assigned 0, DSL assigned is assigned 1 and No DSL is assigned 2.
17. Contract variable is converted to numerical using one-hot encoding where 'One Year' is assigned 0 and 'Two Year' is assigned 1 and 'Three Year' is assigned 2.
18. Payment.method variable is converted to numerical using one-hot encoding where 'Credit card (automatic) ' is assigned 0 and 'Bank Transfer (automatic)' is assigned 1, 'Electronic check' is assigned 2 and 'Cash' is assigned 3.
19. The zipcode has been replaced by

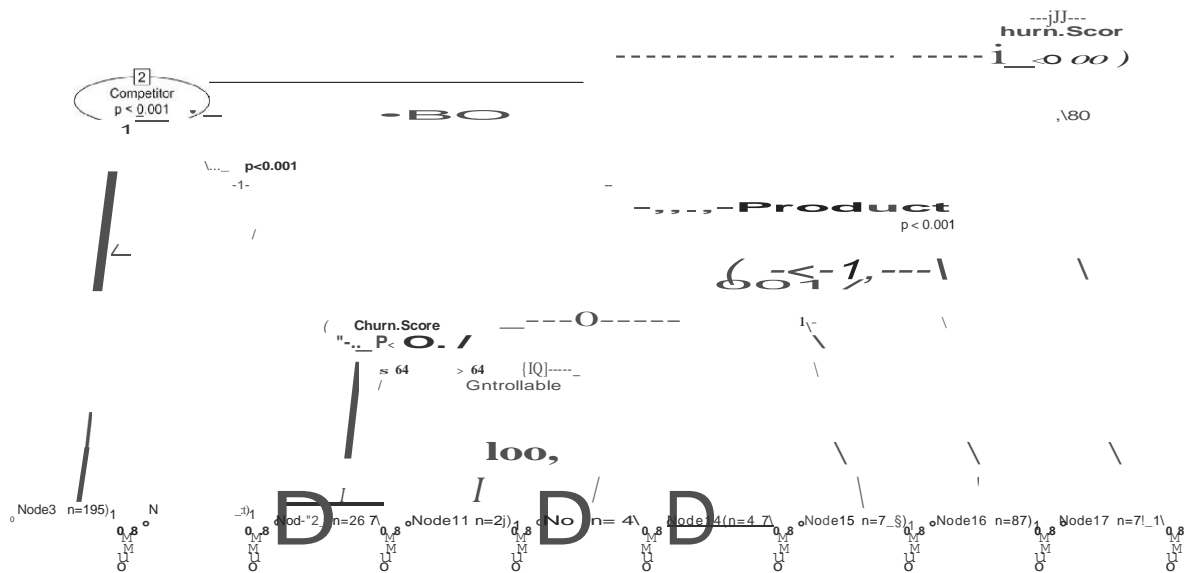
1. DATA MODELLING:

1.1. Model 1 – Decision Tree:

The Decision Tree is a powerful and widely used tool for classification and prediction. A flowchart is similar to a tree structure, with each internal node representing a test on an attribute, each branch representing a test outcome, and each leaf node (terminal node) holding a class label.

DEFAULT TREE:





```
> tree <- rpart(Churn.Labelenco ~ ., data = train, cp = 0.01, maxdepth = 22)
> rpart.plot(tree)
> tree <- rpart(Churn.Labelenco ~ ., data = train, cp = 0.01, maxdepth = 22)
> rpart.plot(tree)
> rpart.rules(tree)
Churn.Labelenco
0.01 when Churn.Score < 81 & Competitor is 0 & Customer.Service is 0 & Product is 0 & Pricing is 0 & Uncontrollable is 0
1.00 when Churn.Score < 81 & Competitor is 0 & Customer.Service is 0 & Product is 0 & Pricing is 0 & Uncontrollable is 1
1.00 when Churn.Score < 81 & Competitor is 0 & Customer.Service is 0 & Product is 0 & Pricing is 1
1.00 when Churn.Score < 81 & Competitor is 0 & Customer.Service is 0 & Product is 1
1.00 when Churn.Score < 81 & Competitor is 0 & Customer.Service is 1
1.00 when Churn.Score < 81 & Competitor is 1
1.00 when Churn.Score >= 81
> ctree <- ctree(Churn.Labelenco ~ ., train)
> plot(ctree_)
> printcp(tree)
```

Classification tree:

```
rpart(formula = Churn.Labelenco ~ ., data = train, cp = 0.01,
      maxdepth = 22)
```

Variables actually used in tree construction:

```
[1] Churn.Score Competitor Customer.Service Pricing Product Uncontrollable
```

Root node error: 1296/4891 = 0.26498

n= 4891

| CP | nsplit | rel error | xerror | xstd | |
|----|----------|-----------|----------|----------|-----------|
| 1 | 0.548611 | 0 | 1.000000 | 1.000000 | 0.0238149 |
| 2 | 0.150463 | 1 | 0.451389 | 0.451389 | 0.0175110 |
| 3 | 0.124228 | 2 | 0.300926 | 0.300926 | 0.0146178 |
| 4 | 0.067130 | 3 | 0.176698 | 0.176698 | 0.0113999 |
| 5 | 0.057870 | 4 | 0.109568 | 0.109568 | 0.0090603 |
| 6 | 0.018519 | 5 | 0.051698 | 0.051698 | 0.0062725 |
| 7 | 0.010000 | 6 | 0.033179 | 0.033179 | 0.0050375 |

```
> prp(tree, type= 1, extra= 1, under= FALSE, split.font= 1, varlen = -10)
> # Checking the models on validation set
> pred_trees <- predict(tree, validation, type = "class")
> summary(pred_trees)
 0 1
785 273
```

Model Accuracy of Validation Data of the Deepest Tree- 0.9924:

```
> confusionMatrix(pred_trees, validation$Churn.Labelenco )  
Confusion Matrix and Statistics
```

```
      Reference  
Prediction 0  1  
0      777  8  
1       0 273
```

```
      Accuracy : 0.9924  
      95% CI : (0.9852, 0.9967)  
No Information Rate : 0.7344  
P-Value [Acc > NIR] : < 2e-16
```

```
      Kappa : 0.9804
```

```
McNemar's Test P-Value : 0.01333
```

```
      Sensitivity : 1.0000  
      Specificity : 0.9715  
      Pos Pred Value : 0.9898  
      Neg Pred Value : 1.0000  
      Prevalence : 0.7344  
      Detection Rate : 0.7344  
      Detection Prevalence : 0.7420  
      Balanced Accuracy : 0.9858
```

```
      'Positive' Class : 0
```

```
> # Testing the model on testing set  
> pred_trees <- predict(tree, test, type = "class")  
> summary(pred_trees)  
 0  1  
822 272
```

Model Accuracy of Validation Data of the Deepest Tree- 0.9817:

```
> confusionMatrix(pred_trees, test$Churn.Labelenco)
Confusion Matrix and Statistics
```

```

      Reference
Prediction 0  1
      0 802 20
      1   0 272
```

```

      Accuracy      0.9817
      95% CI      (0.9719, 0.9888)
No Information Rate 0.7331
P-Value [Ace> NIR] < 2.2e-16
```

```
      Kappa      0.9522
```

```
McNemar's Test P-Value 2.152e-05
```

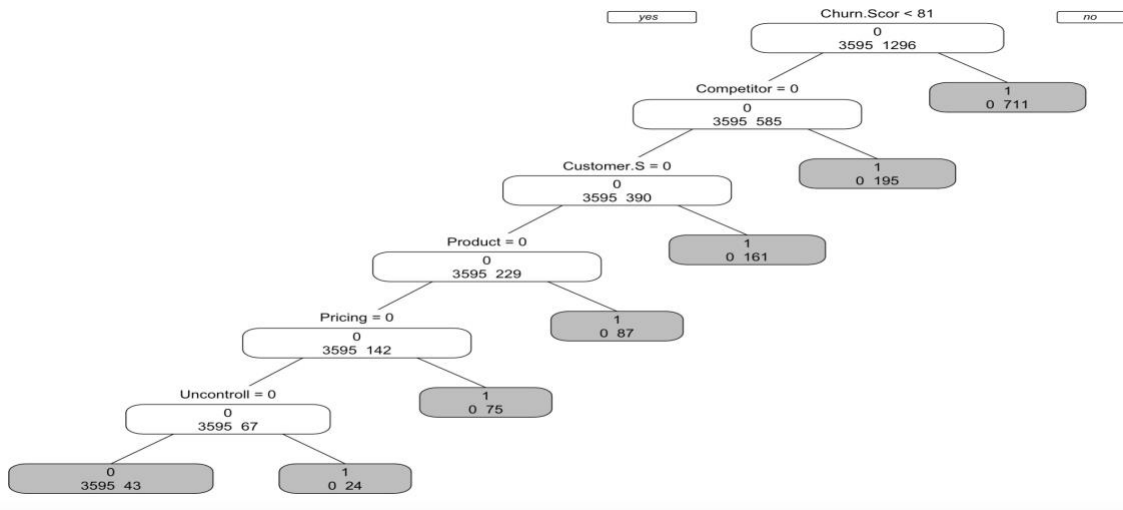
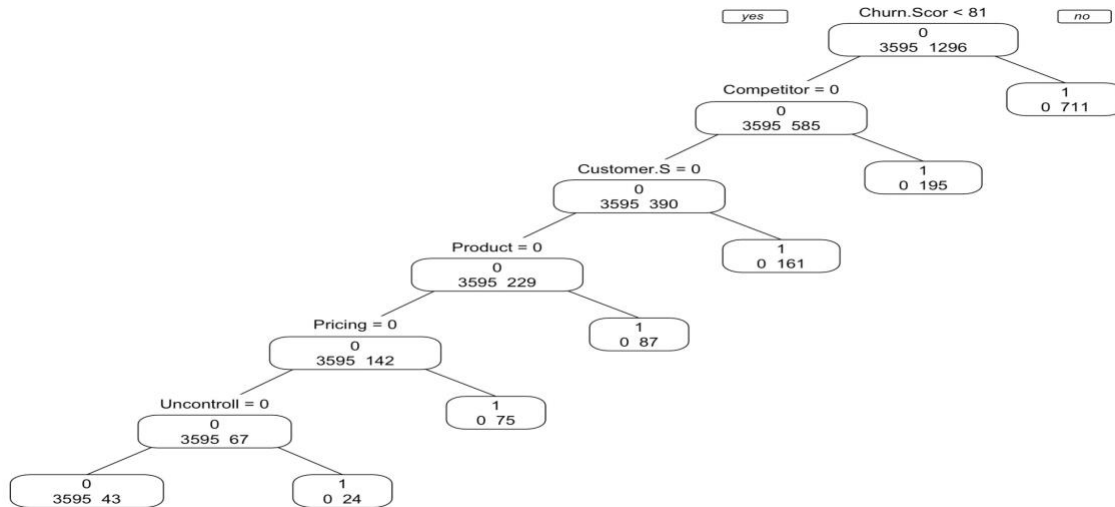
```

      Sensitivity 1.0000
      Specificity 0.9315
      Pos Pred Value 0.9757
      Neg Pred Value 1.0000
      Prevalence 0.7331
      Detection Rate 0.7331
      Detection Prevalence 0.7514
      Balanced Accuracy 0.9658
```

```
'Positive' Class 0
```

```
> tree<- rpart(Churn.Labelenco ~ data= train, cp = 0.01, maxdepth = 22)
> rpart.plot(tree)
```

1.2. PRUNED TREE



Model Accuracy of Validation Data of the Deepest Tree- 0.9924:

Confusion Matrix and Statistics

| | Reference | |
|------------|-----------|-----|
| Prediction | 0 | 1 |
| 0 | 777 | 8 |
| 1 | 0 | 273 |

Accuracy : 0.9924
95% CI : (0.9852, 0.9967)
No Information Rate : 0.7344
P-Value [Acc > NIR] : < 2e-16

Kappa : 0.9804

McNemar's Test P-Value : 0.01333

Sensitivity : 1.0000
Specificity : 0.9715
Pos Pred Value : 0.9898
Neg Pred Value : 1.0000
Prevalence : 0.7344
Detection Rate : 0.7344
Detection Prevalence : 0.7420
Balanced Accuracy : 0.9858

'Positive' Class : 0

Model Accuracy of Validation Data of the Deepest Tree- 0.9817:

Confusion Matrix and Statistics

| | Reference | |
|------------|-----------|-----|
| Prediction | 0 | 1 |
| 0 | 802 | 20 |
| 1 | 0 | 272 |

Accuracy : 0.9817
95% CI : (0.9719, 0.9888)
No Information Rate : 0.7331
P-Value [Acc > NIR] : < 2.2e-16

Kappa : 0.9522

McNemar's Test P-Value : 2.152e-05

Sensitivity : 1.0000
Specificity : 0.9315
Pos Pred Value : 0.9757
Neg Pred Value : 1.0000
Prevalence : 0.7331
Detection Rate : 0.7331
Detection Prevalence : 0.7514
Balanced Accuracy : 0.9658

'Positive' Class : 0

1.3. Logistic Regression

```
> options(scipen = 11)
> summary(logit_model)
```

Call:
glm(formula = Churn.Labelenco ~ ., family = "binomial", data = train)

Deviance Residuals:

| Min | 1Q | Median | 3Q | Max |
|--------------|--------------|--------------|--------------|--------------|
| -0.000002409 | -0.000002409 | -0.000002409 | -0.000002409 | -0.000002409 |

Coefficients:

| | Estimate | Std. Error | z value | Pr(> z) |
|------------------------|------------|------------|---------|----------|
| (Intercept) | -2.657e+01 | 5.916e+05 | 0 | 1 |
| Longitude | 4.658e-15 | 4.757e+03 | 0 | 1 |
| Tenure.Months | -7.166e-16 | 1.993e+03 | 0 | 1 |
| Monthly.Charges | -1.077e-14 | 1.027e+04 | 0 | 1 |
| Total.Charges | -9.645e-18 | 2.220e+01 | 0 | 1 |
| Churn.Score | 3.738e-16 | 1.003e+03 | 0 | 1 |
| CLTV | 7.424e-20 | 8.689e+00 | 0 | 1 |
| Customer.Service1 | 6.586e-14 | 4.009e+04 | 0 | 1 |
| Competitor1 | -7.461e-16 | 3.944e+04 | 0 | 1 |
| Product1 | 3.917e-15 | 4.489e+04 | 0 | 1 |
| Pricing1 | -2.268e-16 | 4.517e+04 | 0 | 1 |
| Uncontrollable1 | 1.128e-14 | 6.979e+04 | 0 | 1 |
| Genderenco1 | 2.312e-14 | 2.014e+04 | 0 | 1 |
| Senior.Citizenenco1 | 8.518e-14 | 2.394e+04 | 0 | 1 |
| Partnerenco1 | -2.448e-14 | 2.225e+04 | 0 | 1 |
| Dependentsenco1 | 3.926e-15 | 4.383e+04 | 0 | 1 |
| Phone.Serviceenco1 | 2.454e-13 | 2.077e+05 | 0 | 1 |
| Multiple.Linesenco1 | -7.719e-15 | 5.702e+04 | 0 | 1 |
| Online.Securityenco1 | 2.815e-14 | 5.814e+04 | 0 | 1 |
| Online.Backupenco1 | 2.317e-14 | 5.656e+04 | 0 | 1 |
| Device.Protectionenco1 | 1.281e-13 | 5.559e+04 | 0 | 1 |
| Tech.Supportenco1 | 2.308e-14 | 5.839e+04 | 0 | 1 |
| Streaming.TVenco1 | 1.552e-13 | 1.058e+05 | 0 | 1 |
| Streaming.Moviesenco1 | 1.396e-13 | 1.044e+05 | 0 | 1 |
| Paperless.Billingenco1 | 1.181e-14 | 2.430e+04 | 0 | 1 |
| Internet.Serviceenco1 | 2.486e-13 | 2.616e+05 | 0 | 1 |
| Internet.Serviceenco2 | 5.463e-13 | 5.159e+05 | 0 | 1 |
| Contractenco1 | 2.595e-14 | 6.918e+04 | 0 | 1 |
| Contractenco2 | 4.880e-16 | 4.205e+04 | 0 | 1 |
| Payment.Methodenco1 | -1.548e-13 | 3.955e+04 | 0 | 1 |
| Payment.Methodenco2 | -1.714e-13 | 3.221e+04 | 0 | 1 |
| Payment.Methodenco3 | -1.524e-13 | 3.972e+04 | 0 | 1 |
| Avg_Score | -7.042e-16 | 1.074e+03 | 0 | 1 |

(Dispersion parameter for binomial family taken to be 1)

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 0.000000000000 on 1295 degrees of freedom
Residual deviance: 0.000000075188 on 1263 degrees of freedom
(3635 observations deleted due to missingness)
AIC: 66

Number of Fisher Scoring iterations: 25

Confusion Matrix and Statistics

| | Reference | |
|------------|-----------|-----|
| Prediction | 0 | 1 |
| 0 | 802 | 20 |
| 1 | 0 | 272 |

| | |
|---------------------|------------------|
| Accuracy | 0.9817 |
| 95% CI | (0.9719, 0.9888) |
| No Information Rate | 0.7331 |
| P-Value [Ace> NIR] | < 2.2e-16 |

| | |
|-------|--------|
| Kappa | 0.9522 |
|-------|--------|

| | |
|------------------------|-----------|
| Mcnemar's Test P-Value | 2.152e-05 |
|------------------------|-----------|

| | |
|----------------------|--------|
| Sensitivity | 1.0000 |
| Specificity | 0.9315 |
| Pas Pred Value | 0.9757 |
| Neg Pred Value | 1.0000 |
| Prevalence | 0.7331 |
| Detection Rate | 0.7331 |
| Detection Prevalence | 0.7514 |
| Balanced Accuracy | 0.9658 |

| | |
|------------------|---|
| 'Positive' Class | 0 |
|------------------|---|

6. Conclusions

As per the scope of work performed in this project and comparing the results from various models like Decision trees, pruned trees, random forests, and Logistic Regression, we recommend the use of Random forests as the model was correctly able to predict the customers' churn the best. Moreover, the main disadvantage of Random forest trees i.e extreme sensitivity to change in data is automatically avoided here as the data collected for such a measure is mostly automated for every telecom company and hence no chance of error. A set system of rules are ensured in an industry setting to collect the data.

Presentation Recording:

https://cometmail-my.sharepoint.com/:v:/g/personal/mxp210085_utdallas_edu/Eb-wmsE5G6FKiM9xgazmjJEbBo9EK_XNXJFjV8VE28Wmww