# Telco customer churn

*by Ketao Li, Kush Halani, Josue Romain, Juan Peña, Priyanka Patil*

**Abstract** Customer churn is a big challenge for large companies,especially in the highly competitive telecom industry. Due to the effect on the revenues of the companies, they are seeking to find ways to predict potential customer to churn. Therefore, identifying the factors that lead to customer churn is very important to take necessary actions to avoid this churn.Our work is to develop a churn prediction model which helps telecom operators to predict customers who are most likely subject to churn.

### Background

In an industry as competitive as Telecom, leading companies know that the key to success is not just about acquiring new customers, but rather, retaining existing ones. But how do you know which customers are at risk and why, and which negative experiences and interactions have the biggest impact on churn across touchpoints and channels over time.

### Objective

The objective of this research is to find a supervised, binary classification model that would provide accurate forecast of telco customer churn.

## Data Analysis

The data set we are going to use for our research contains customer's attributes. There are over 7044 records. It has been sourced from Kaggle.

### Data Dictionary

| Column Name | Column Description |
|---|---|
| customerID | Customer ID |
| gender | Whether the customer is a male or a female |
| SeniorCitizen | Whether the customer is a senior citizen or not (1, 0) |
| Partner | Whether the customer has a partner or not (Yes, No) |
| Dependents | Whether the customer has dependents or not (Yes, No) |
| tenure | Number of months the customer has stayed with the company |
| PhoneService | Whether the customer has a phone service or not (Yes, No) |
| MultipleLines | Whether the customer has multiple lines or not (Yes, No, No phone service) |
| InternetService | Customer's internet service provider (DSL, Fiber optic, No) |
| OnlineSecurity | Whether the customer has online security or not (Yes, No, No internet service) |
| OnlineBackup | Whether the customer has online backup or not (Yes, No, No internet service) |
| DeviceProtection | Whether the customer has device protection or not (Yes, No, No internet service) |
| TechSupport | Whether the customer has tech support or not (Yes, No, No internet service) |
| StreamingTV | Whether the customer has streaming TV or not (Yes, No, No internet service) |
| StreamingMovies | Whether the customer has streaming movies or not (Yes, No, No internet service) |

| Column Name | Column Description |
|---|---|
| Contract | The contract term of the customer (Month-to-month, One year, Two year) |
| PaperlessBilling | Whether the customer has paperless billing or not (Yes, No) |
| PaymentMethod | The customer's payment method (Electronic check, Mailed check, Bank transfer (automatic), Credit card (automatic)) |
| MonthlyCharges | The amount charged to the customer monthly |
| TotalCharges | The total amount charged to the customer |
| Churn | Whether the customer churned or not (Yes or No) |

### Data Exploration

Let's take a close look at the data set.

```
customerData = read.csv("../data/WA_Fn-UseC_-Telco-Customer-Churn.csv",
                        header = TRUE, na.strings = c("NA","","#NA"),sep=",")
```

To have the full picture of the data let's print the data summary and sample.

| customerID | gender | SeniorCitizen | Partner | Dependents | tenure | PhoneService | MultipleLines |
|---|---|---|---|---|---|---|---|
| 0002-ORFBO: 1 | Female:3488 | Min. :0.0000 | No :3641 | No :4933 | Min. : 0.00 | No : 682 | No :3390 |
| 0003-MKNFE: 1 | Male :3555 | 1st Qu.:0.0000 | Yes:3402 | Yes:2110 | 1st Qu.: 9.00 | Yes:6361 | No phone service: 682 |
| 0004-TLHLJ: 1 | | Median :0.0000 | | | Median :29.00 | | Yes :2971 |
| 0011-IGKFF: 1 | | Mean :0.1621 | | | Mean :32.37 | | |
| 0013-EXCHZ: 1 | | 3rd Qu.:0.0000 | | | 3rd Qu.:55.00 | | |
| 0013-MHZWF: 1 | | Max. :1.0000 | | | Max. :72.00 | | |
| (Other) :7037 | | | | | | | |

| InternetService | OnlineSecurity | OnlineBackup | DeviceProtection | TechSupport | StreamingTV | Stream |
|---|---|---|---|---|---|---|
| DSL :2421 | No :3498 | No :3088 | No :3095 | No :3473 | No :2810 | No :27 |
| Fiber optic:3096 | No internet service:1526 | No internet service:1526 | No internet service:1526 | No internet service:1526 | No internet service:1526 | No int |
| No :1526 | Yes :2019 | Yes :2429 | Yes :2422 | Yes :2044 | Yes :2707 | Yes :27 |

| PaperlessBilling | PaymentMethod | MonthlyCharges | TotalCharges | Churn |
|---|---|---|---|---|
| No :2872 | Bank transfer (automatic):1544 | Min. : 18.25 | Min. : 18.8 | No :5174 |
| Yes:4171 | Credit card (automatic) :1522 | 1st Qu.: 35.50 | 1st Qu.: 401.4 | Yes:1869 |
| | Electronic check :2365 | Median : 70.35 | Median :1397.5 | |
| | Mailed check :1612 | Mean : 64.76 | Mean :2283.3 | |
| | | 3rd Qu.: 89.85 | 3rd Qu.:3794.7 | |
| | | Max. :118.75 | Max. :8684.8 | |
| | | | NA's :11 | |

**Table 2:** `telco customer churn data Summary`

| | customerID | gender | SeniorCitizen | Partner | Dependents | tenure | PhoneService | MultipleLines | InternetService | OnlineSecurity | OnlineBackup | DeviceProtecti |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 7590-VHVEG | Female | 0 | Yes | No | 1 | No | No phone service | DSL | No | Yes | No |
| 2 | 5575-GNVDE | Male | 0 | No | No | 34 | Yes | No | DSL | Yes | No | Yes |
| 3 | 3668-QPYBK | Male | 0 | No | No | 2 | Yes | No | DSL | Yes | Yes | No |
| 4 | 7795-CFOCW | Male | 0 | No | No | 45 | No | No phone service | DSL | Yes | No | Yes |
| 5 | 9237-HQITU | Female | 0 | No | No | 2 | Yes | No | Fiber optic | No | No | No |
| 6 | 9305-CDSKC | Female | 0 | No | No | 8 | Yes | Yes | Fiber optic | No | No | Yes |
| 7 | 1452-KIOVK | Male | 0 | No | Yes | 22 | Yes | Yes | Fiber optic | No | Yes | No |
| 8 | 6713-OKOMC | Female | 0 | No | No | 10 | No | No phone service | DSL | Yes | No | No |
| 9 | 7892-POOKP | Female | 0 | Yes | No | 28 | Yes | Yes | Fiber optic | No | No | Yes |
| 10 | 6388-TABGU | Male | 0 | No | Yes | 62 | Yes | No | DSL | Yes | Yes | No |

| TechSupport | StreamingTV | StreamingMovies | Contract | PaperlessBilling | PaymentMethod | MonthlyCharges | TotalCharges | Churn |
|---|---|---|---|---|---|---|---|---|
| No | No | No | Month-to-month | Yes | Electronic check | 29.85 | 29.85 | No |
| No | No | No | One year | No | Mailed check | 56.95 | 1889.50 | No |
| No | No | No | Month-to-month | Yes | Mailed check | 53.85 | 108.15 | Yes |
| Yes | No | No | One year | No | Bank transfer (automatic) | 42.30 | 1840.75 | No |
| No | No | No | Month-to-month | Yes | Electronic check | 70.70 | 151.65 | Yes |
| No | Yes | Yes | Month-to-month | Yes | Electronic check | 99.65 | 820.50 | Yes |
| No | Yes | No | Month-to-month | Yes | Credit card (automatic) | 89.10 | 1949.40 | No |
| No | No | No | Month-to-month | No | Mailed check | 29.75 | 301.90 | No |
| Yes | Yes | Yes | Month-to-month | Yes | Electronic check | 104.80 | 3046.05 | Yes |
| No | No | No | One year | No | Bank transfer (automatic) | 56.15 | 3487.95 | No |

**Table 3:** `telco customer churn data`

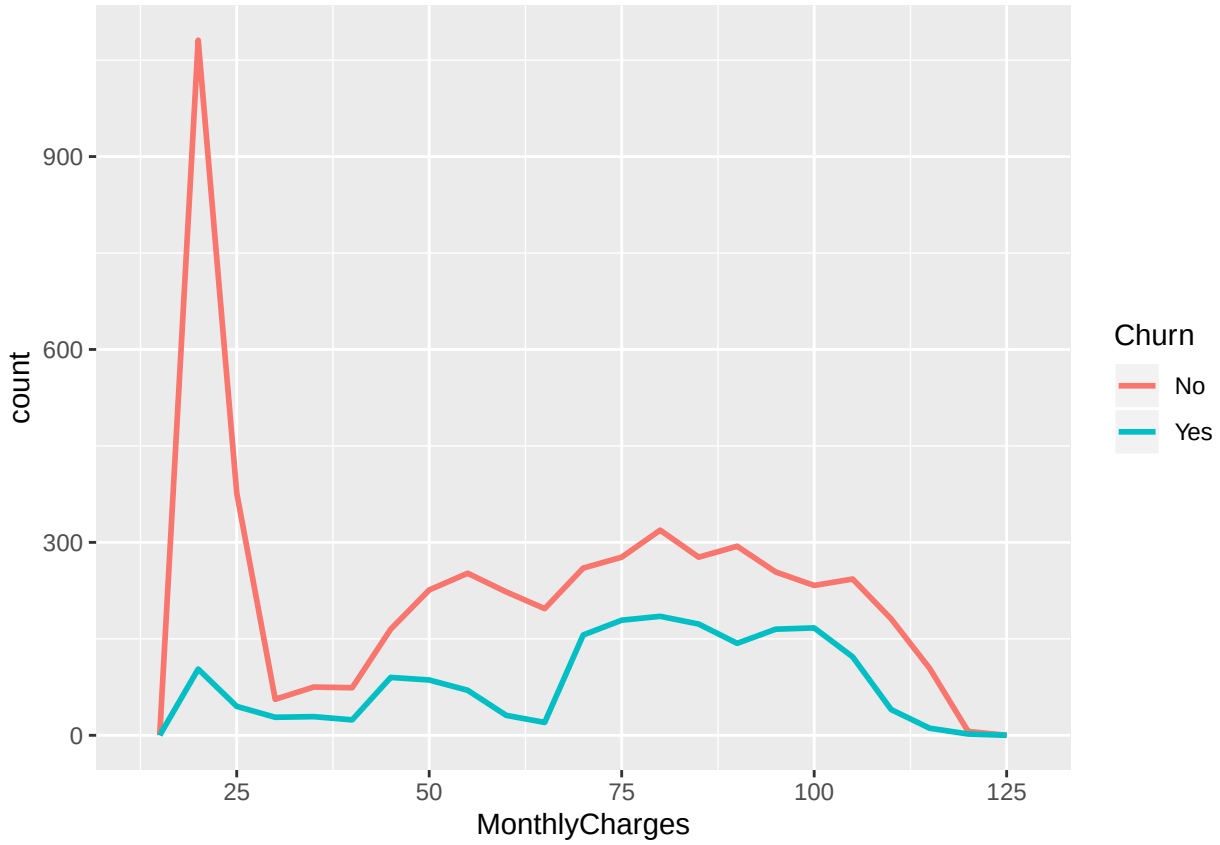
```
#To see the names of the rows in the dataset
names(customerData)

#>  [1] "customerID"       "gender"           "SeniorCitizen"    "Partner"
#>  [5] "Dependents"       "tenure"           "PhoneService"     "MultipleLines"
#>  [9] "InternetService"  "OnlineSecurity"   "OnlineBackup"     "DeviceProtection"
#> [13] "TechSupport"      "StreamingTV"      "StreamingMovies"  "Contract"
#> [17] "PaperlessBilling" "PaymentMethod"    "MonthlyCharges"   "TotalCharges"
#> [21] "Churn"

#Display the dataset structure and sumary
str(customerData)

#> 'data.frame':    7043 obs. of  21 variables:
#>  $ customerID      : Factor w/ 7043 levels "0002-ORFBO","0003-MKNFE",..: 5376 3963 2565 5536 6512 6552 100
#>  $ gender          : Factor w/ 2 levels "Female","Male": 1 2 2 2 1 1 2 1 1 2 ...
#>  $ SeniorCitizen   : int  0 0 0 0 0 0 0 0 0 0 ...
#>  $ Partner         : Factor w/ 2 levels "No","Yes": 2 1 1 1 1 1 1 1 2 1 ...
#>  $ Dependents      : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 2 1 1 2 ...
#>  $ tenure          : int  1 34 2 45 2 8 22 10 28 62 ...
#>  $ PhoneService    : Factor w/ 2 levels "No","Yes": 1 2 2 1 2 2 2 1 2 2 ...
#>  $ MultipleLines   : Factor w/ 3 levels "No","No phone service",..: 2 1 1 2 1 3 3 2 3 1 ...
#>  $ InternetService : Factor w/ 3 levels "DSL","Fiber optic",..: 1 1 1 1 2 2 2 1 2 1 ...
#>  $ OnlineSecurity  : Factor w/ 3 levels "No","No internet service",..: 1 3 3 3 1 1 1 3 1 3 ...
#>  $ OnlineBackup    : Factor w/ 3 levels "No","No internet service",..: 3 1 3 1 1 1 3 1 1 3 ...
#>  $ DeviceProtection: Factor w/ 3 levels "No","No internet service",..: 1 3 1 3 1 3 1 1 3 1 ...
#>  $ TechSupport     : Factor w/ 3 levels "No","No internet service",..: 1 1 1 3 1 1 1 1 3 1 ...
#>  $ StreamingTV     : Factor w/ 3 levels "No","No internet service",..: 1 1 1 1 1 3 3 1 3 1 ...
#>  $ StreamingMovies : Factor w/ 3 levels "No","No internet service",..: 1 1 1 1 1 3 1 1 3 1 ...
#>  $ Contract        : Factor w/ 3 levels "Month-to-month",..: 1 2 1 2 1 1 1 1 1 2 ...
#>  $ PaperlessBilling: Factor w/ 2 levels "No","Yes": 2 1 2 1 2 2 2 1 2 1 ...
#>  $ PaymentMethod   : Factor w/ 4 levels "Bank transfer (automatic)",..: 3 4 4 1 3 3 2 4 3 1 ...
#>  $ MonthlyCharges  : num  29.9 57 53.9 42.3 70.7 ...
#>  $ TotalCharges    : num  29.9 1889.5 108.2 1840.8 151.7 ...
#>  $ Churn           : Factor w/ 2 levels "No","Yes": 1 1 2 1 2 2 1 1 2 1 ...

#Display first rows of the dataset
head(customerData)

#>   customerID gender SeniorCitizen Partner Dependents tenure PhoneService
#> 1 7590-VHVEG Female             0     Yes         No      1           No
#> 2 5575-GNVDE   Male             0      No         No     34          Yes
#> 3 3668-QPYBK   Male             0      No         No      2          Yes
#> 4 7795-CFOCW   Male             0      No         No     45           No
#> 5 9237-HQITU Female             0      No         No      2          Yes
#> 6 9305-CDSKC Female             0      No         No      8          Yes
```

```
#>      MultipleLines InternetService OnlineSecurity OnlineBackup DeviceProtection
#> 1 No phone service             DSL             No          Yes               No
#> 2               No             DSL            Yes           No              Yes
#> 3               No             DSL            Yes          Yes               No
#> 4 No phone service             DSL            Yes           No              Yes
#> 5               No     Fiber optic             No           No               No
#> 6              Yes     Fiber optic             No           No              Yes
#>   TechSupport StreamingTV StreamingMovies       Contract PaperlessBilling
#> 1          No          No              No Month-to-month              Yes
#> 2          No          No              No       One year               No
#> 3          No          No              No Month-to-month              Yes
#> 4         Yes          No              No       One year               No
#> 5          No          No              No Month-to-month              Yes
#> 6          No         Yes             Yes Month-to-month              Yes
#>                PaymentMethod MonthlyCharges TotalCharges Churn
#> 1           Electronic check          29.85        29.85    No
#> 2               Mailed check          56.95      1889.50    No
#> 3               Mailed check          53.85       108.15   Yes
#> 4 Bank transfer (automatic)          42.30      1840.75    No
#> 5           Electronic check          70.70       151.65   Yes
#> 6           Electronic check          99.65       820.50   Yes

#To select just the continuous variables and summarise it
library(dplyr)
continues <- select_if(customerData, is.numeric)
#Sumarize the variables to find NA's and outliers
summary(continues)

#>  SeniorCitizen        tenure      MonthlyCharges    TotalCharges
#>  Min.   :0.0000   Min.   : 0.00   Min.   : 18.25   Min.   :  18.8
#>  1st Qu.:0.0000   1st Qu.: 9.00   1st Qu.: 35.50   1st Qu.: 401.4
#>  Median :0.0000   Median :29.00   Median : 70.35   Median :1397.5
#>  Mean   :0.1621   Mean   :32.37   Mean   : 64.76   Mean   :2283.3
#>  3rd Qu.:0.0000   3rd Qu.:55.00   3rd Qu.: 89.85   3rd Qu.:3794.7
#>  Max.   :1.0000   Max.   :72.00   Max.   :118.75   Max.   :8684.8
#>                                                    NA's   :11

#Display the factor columns and summarise it
factorColumns <- select_if(customerData, is.factor)
summary(factorColumns)

#>       customerID      gender     Partner    Dependents PhoneService
#>  0002-ORFBO:   1   Female:3488   No :3641   No :4933   No : 682
#>  0003-MKNFE:   1   Male  :3555   Yes:3402   Yes:2110   Yes:6361
#>  0004-TLHLJ:   1
#>  0011-IGKFF:   1
#>  0013-EXCHZ:   1
#>  0013-MHZWF:   1
#>  (Other)   :7037
#>           MultipleLines     InternetService            OnlineSecurity
#>  No              :3390   DSL        :2421   No                 :3498
#>  No phone service: 682   Fiber optic:3096   No internet service:1526
#>  Yes             :2971   No         :1526   Yes                :2019
#>
#>
#>
#>
#>               OnlineBackup             DeviceProtection
#>  No                 :3088   No                 :3095
#>  No internet service:1526   No internet service:1526
#>  Yes                :2429   Yes                :2422
#>
#>
#>
#>
```

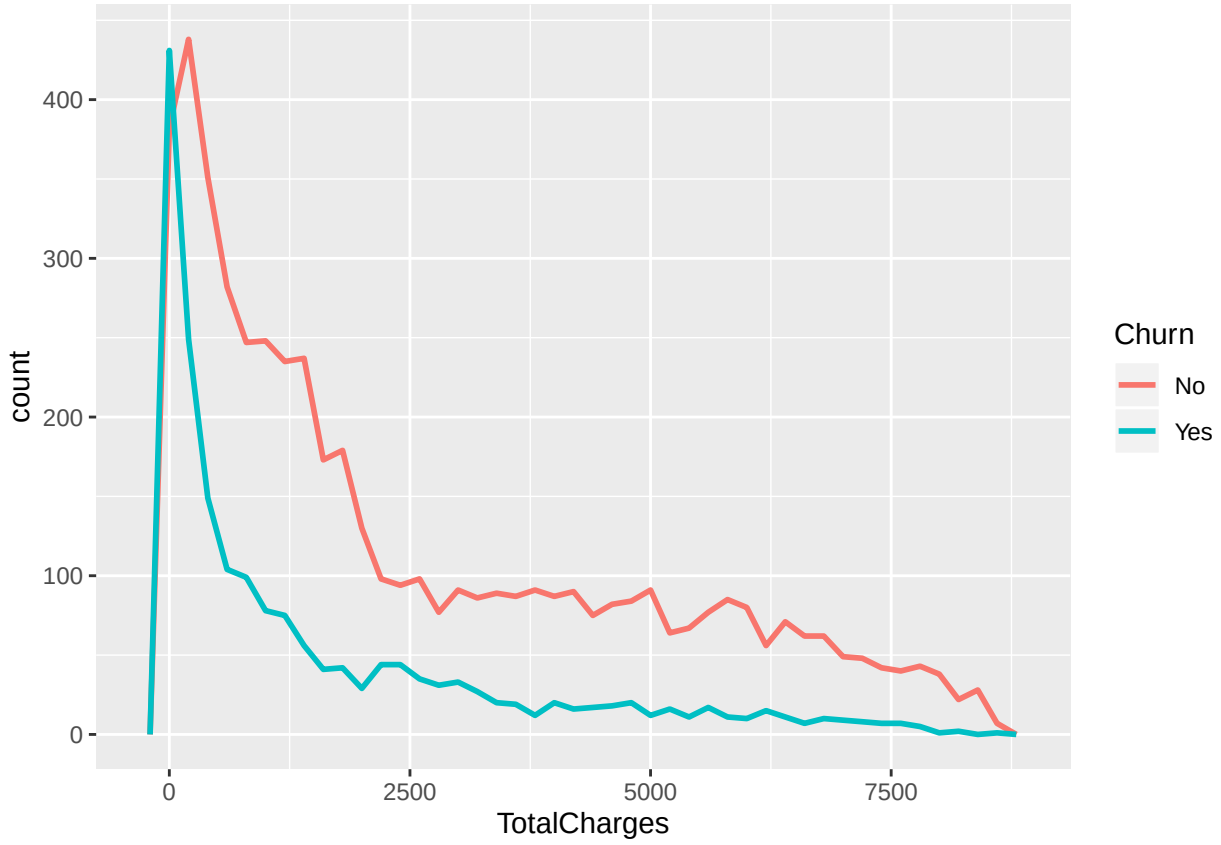
```
#>              TechSupport               StreamingTV
#>  No                 :3473   No                 :2810
#>  No internet service:1526   No internet service:1526
#>  Yes                :2044   Yes                :2707
#>
#>
#>
#>
#>            StreamingMovies           Contract    PaperlessBilling
#>  No                 :2785   Month-to-month:3875   No :2872
#>  No internet service:1526   One year      :1473   Yes:4171
#>  Yes                :2732   Two year      :1695
#>
#>
#>
#>
#>                    PaymentMethod  Churn
#>  Bank transfer (automatic):1544   No :5174
#>  Credit card (automatic)  :1522   Yes:1869
#>  Electronic check         :2365
#>  Mailed check             :1612
#>
#>
#>
```

### Continuous Variables

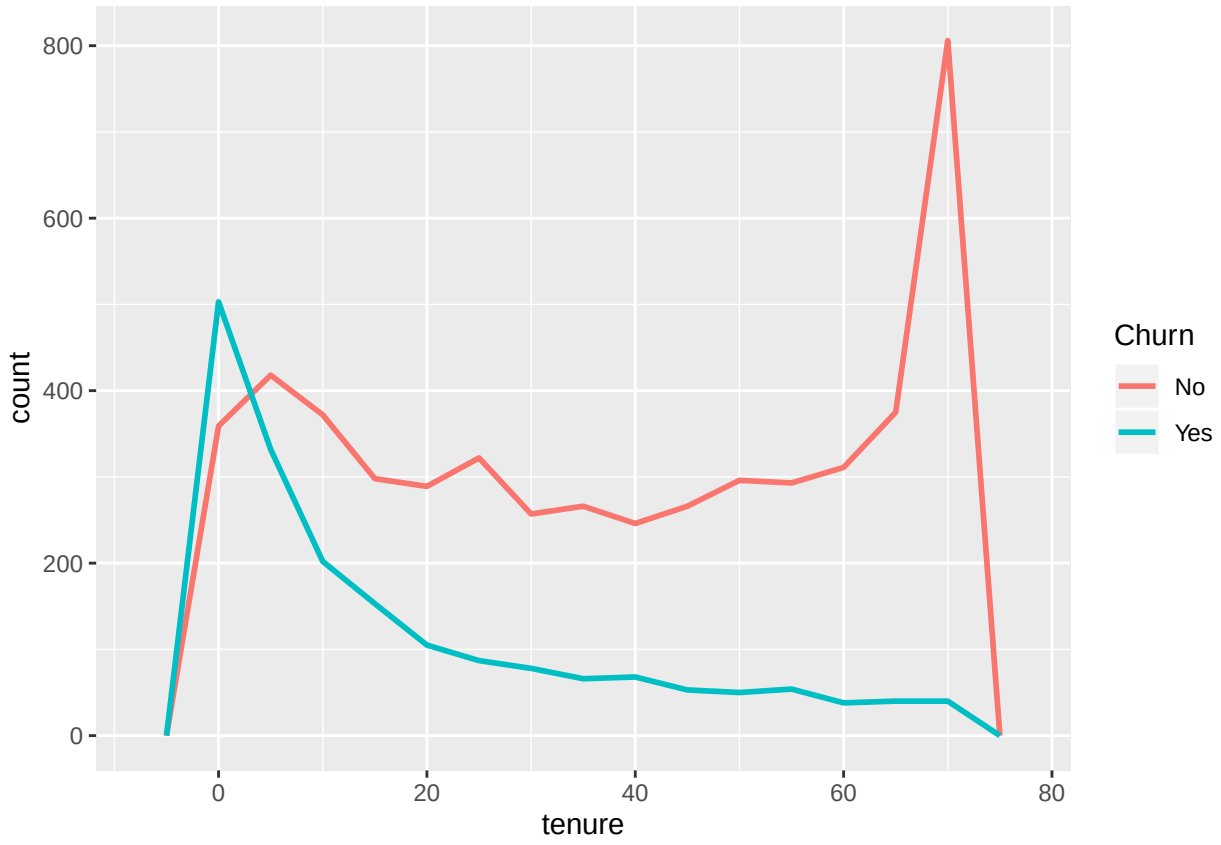
For continuous variables, let's check for their distributions.




The number of current customers with MonthlyCharges below $25 is extremly high. For the customers with Monthlycharges greater than $30, the distributions are similar between who churned and who did not churn.




The distribution of TotalCharges is highly positive skew for all customers no matter whether they churned or not.



The distributions for tenure are very different between customers who churned and who didn't churn. For customers who churned, the distribution is positve skew, which means customers who churned are more likely to cancel the service in the first couple of months. For current customers who didn't churn, there are two spikes. The second spike is much more drastic than the first one, which means a large group of current customers have been using the service more than 5 years. There is no obvious outliers for 3 numeric variables.

### Missing Data

From the above summary, we can observe that 11 TotalChargesNA. Considering the number of missing data is quite small, we can remove them directly.

### Data correlation and other observations

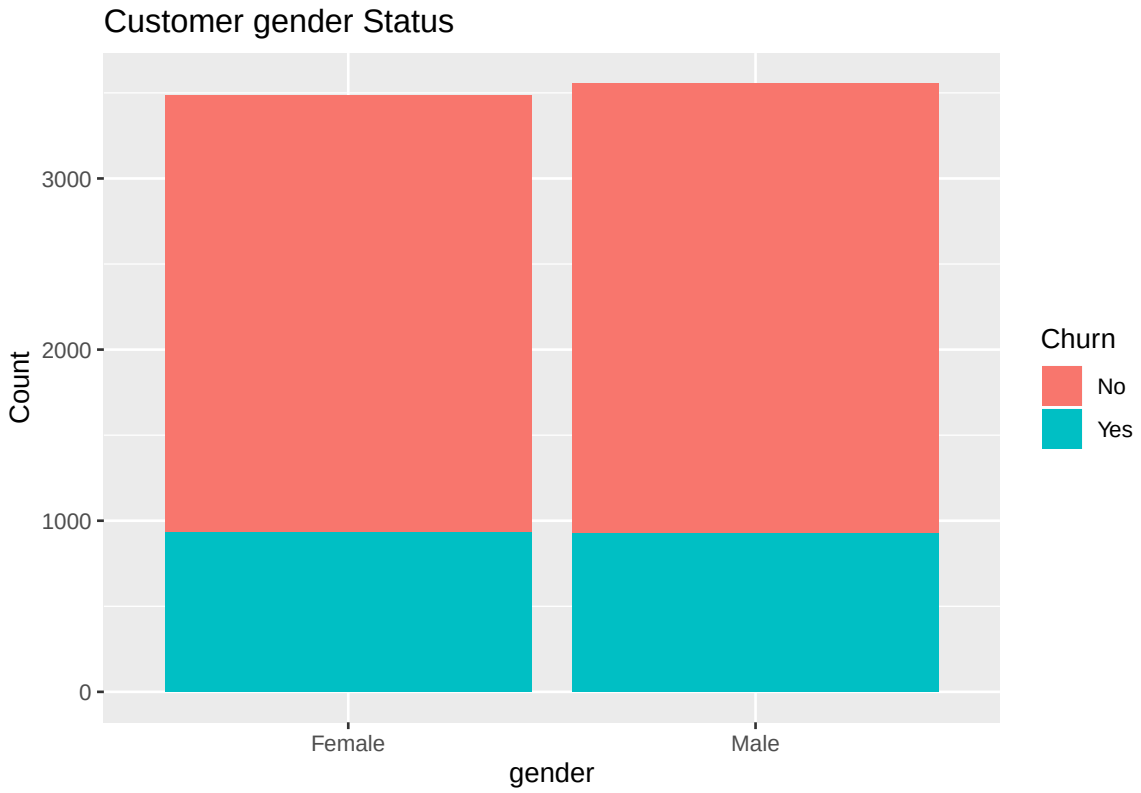



**Figure 1**

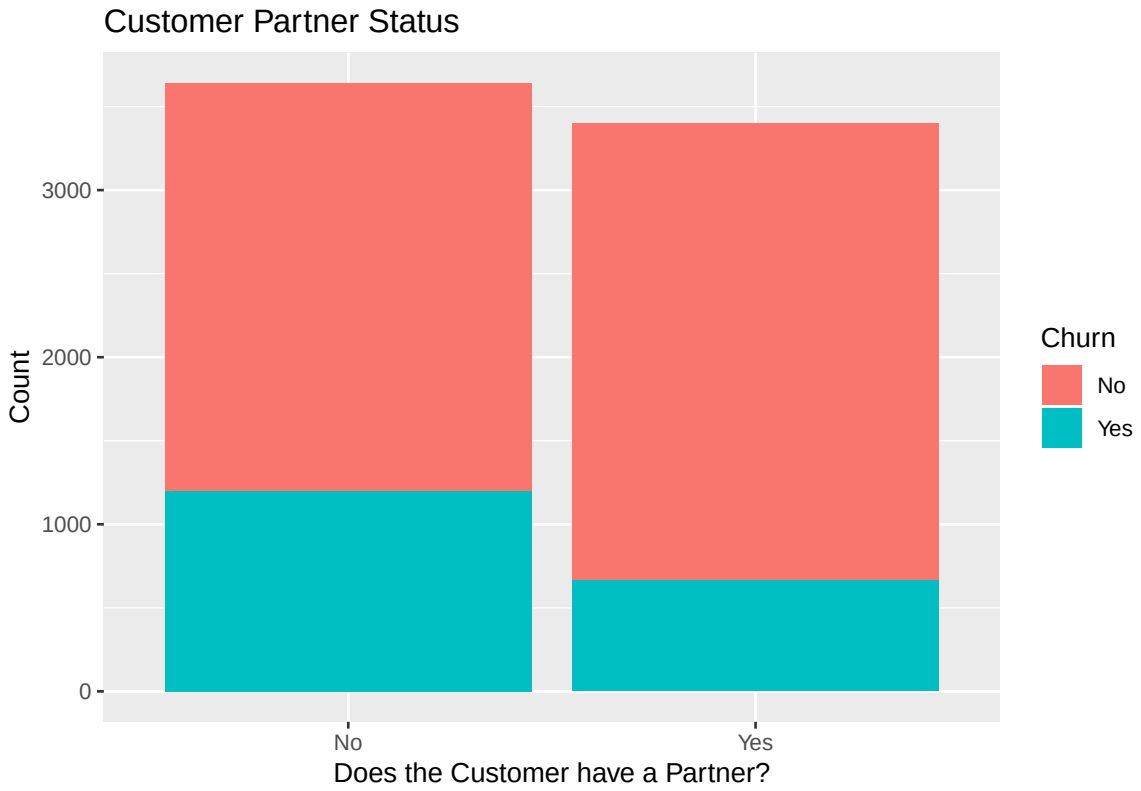



**Figure 2**

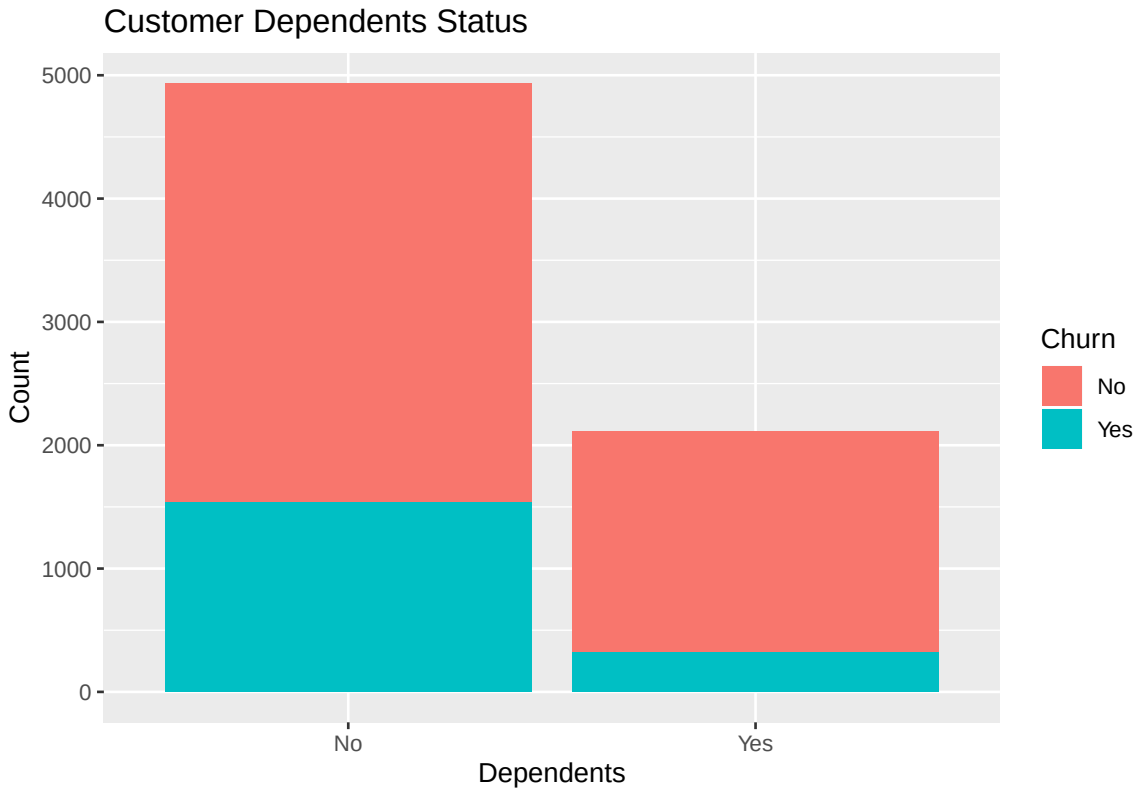



**Figure 3**

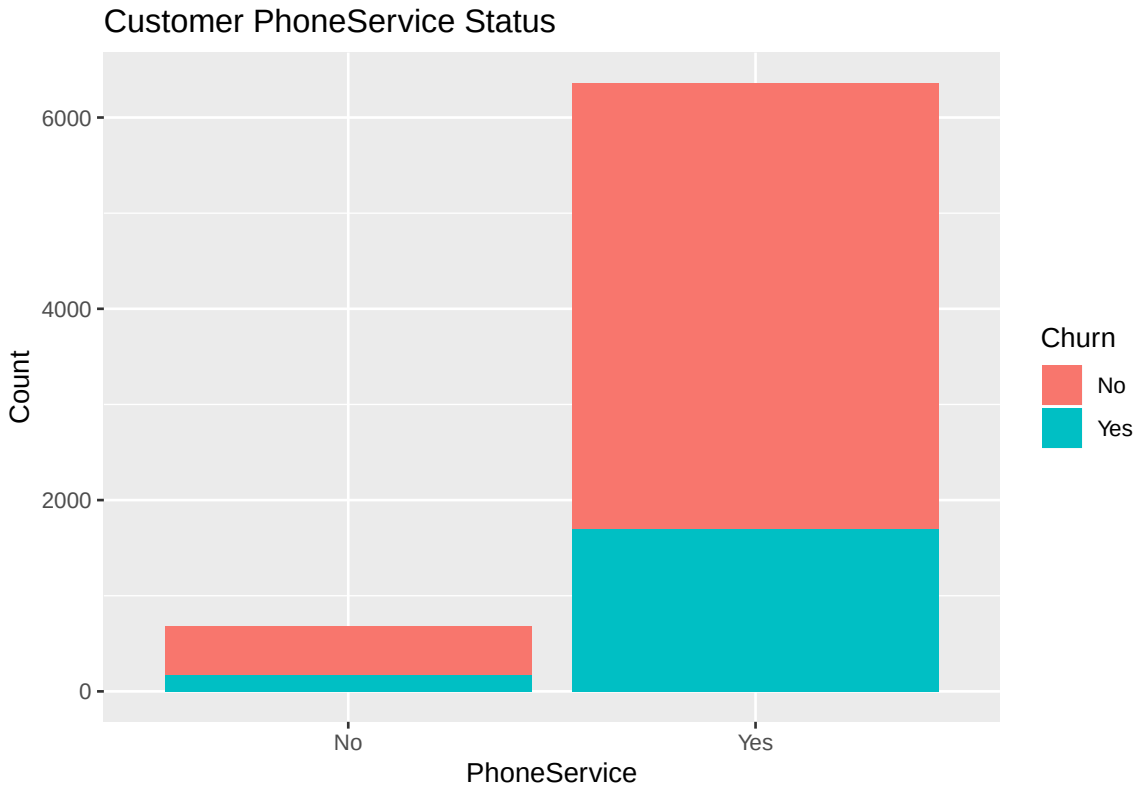



**Figure 4**

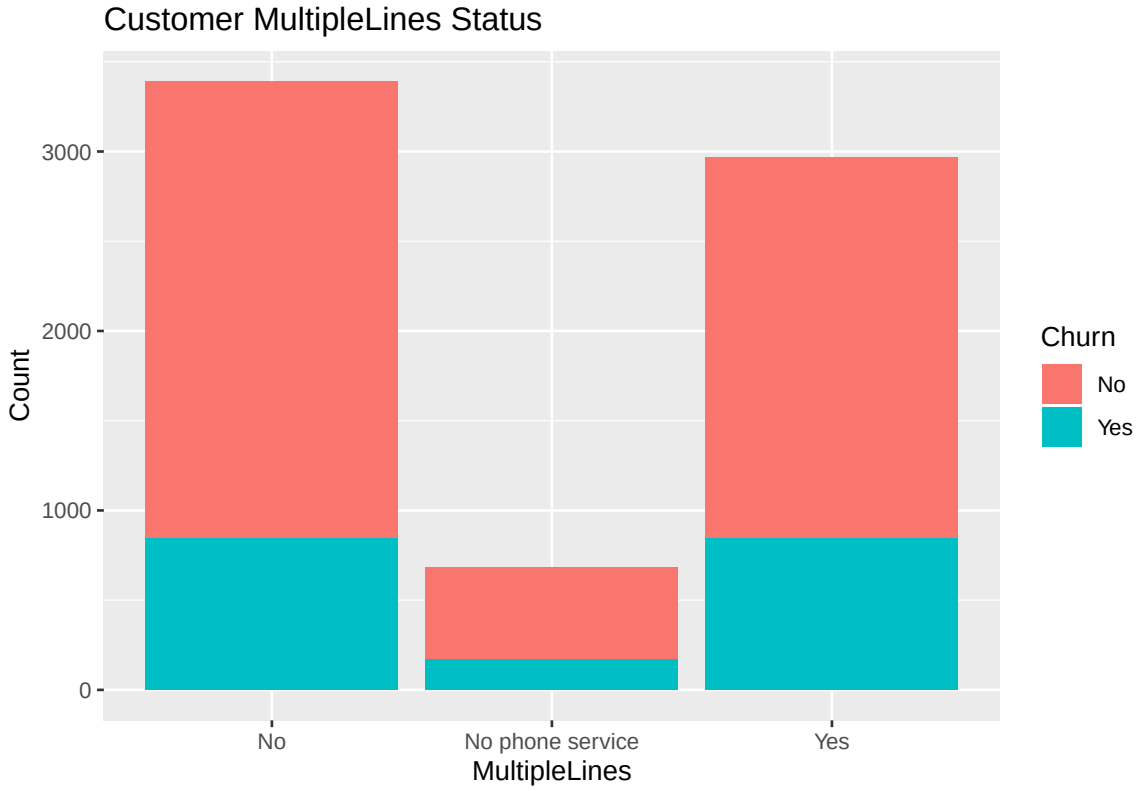



**Figure 5**

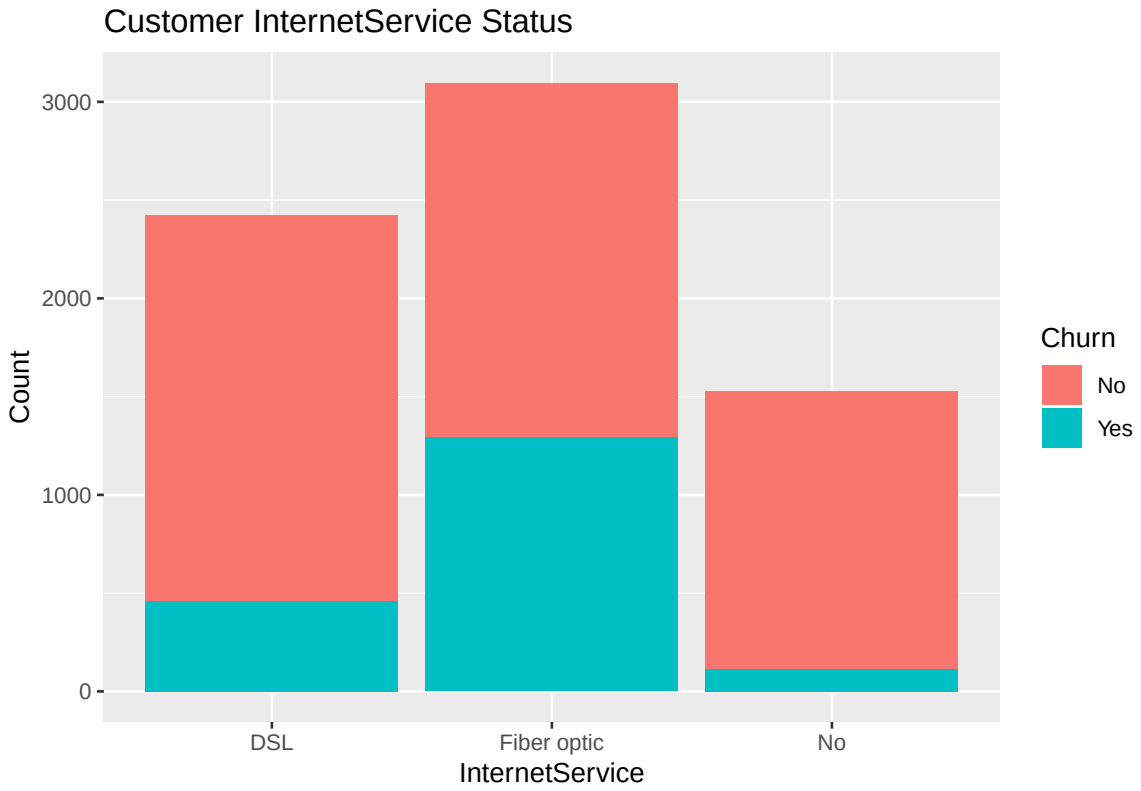



**Figure 6**

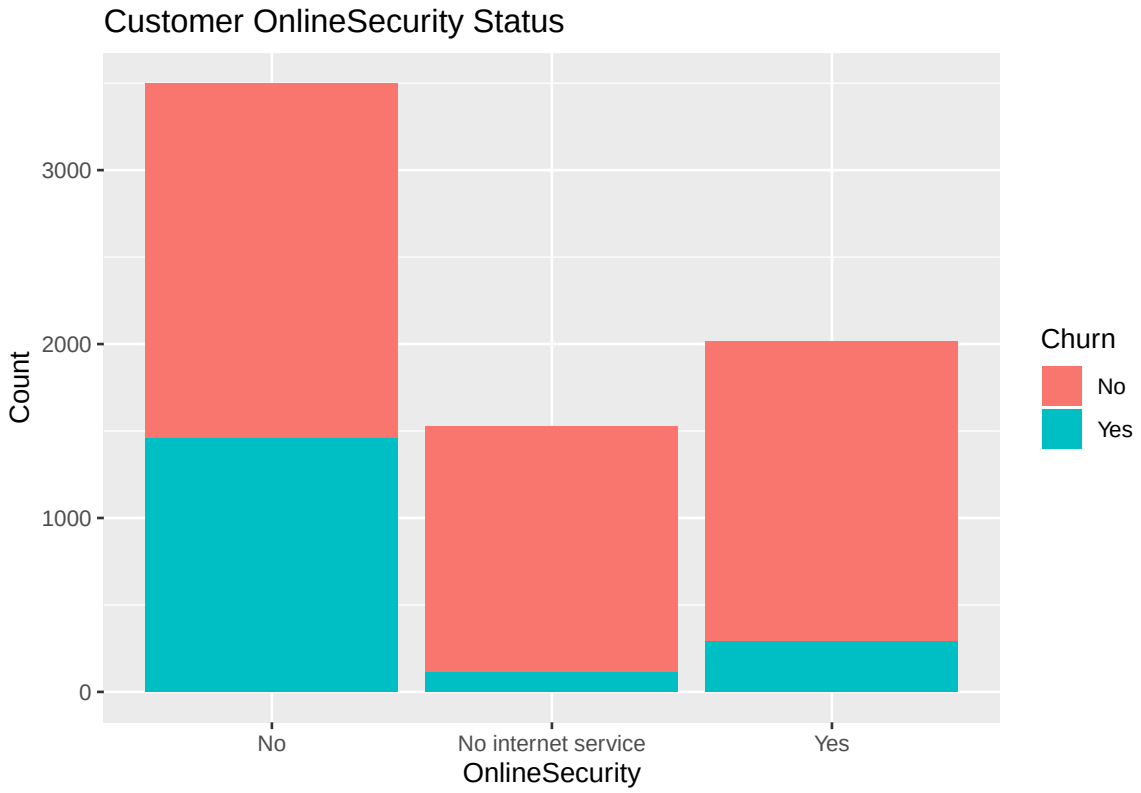



**Figure 7**

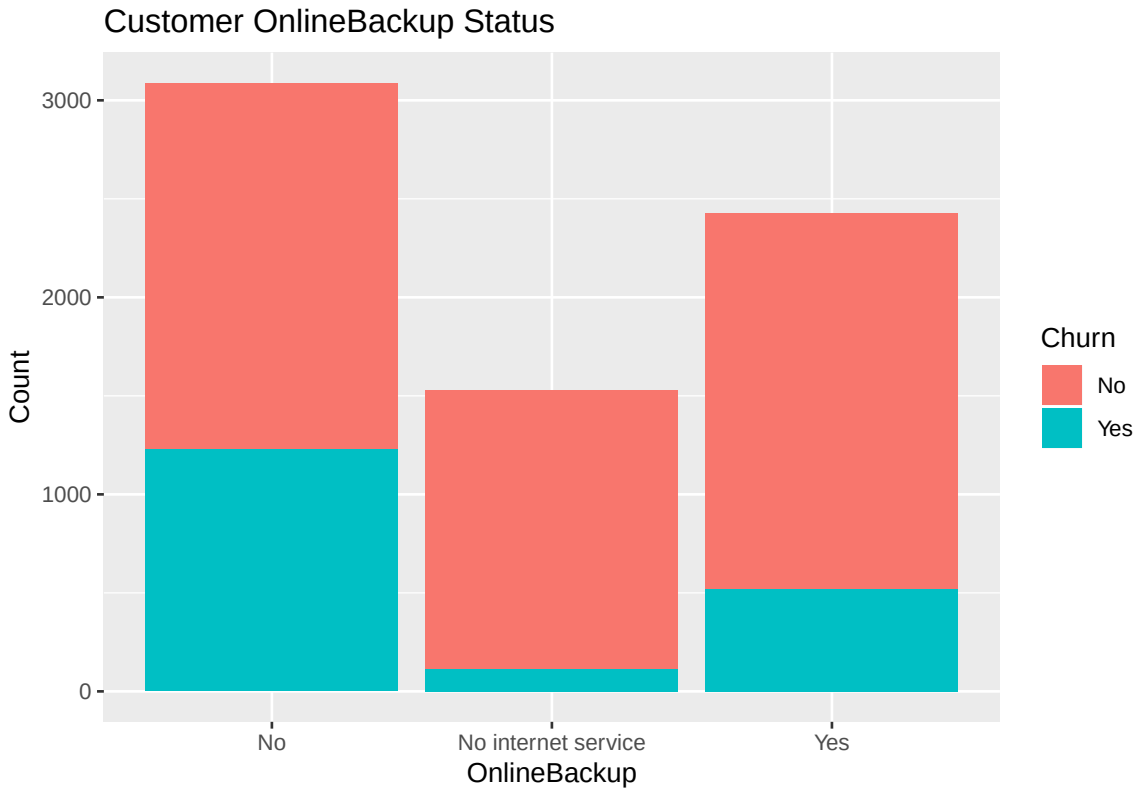



**Figure 8**

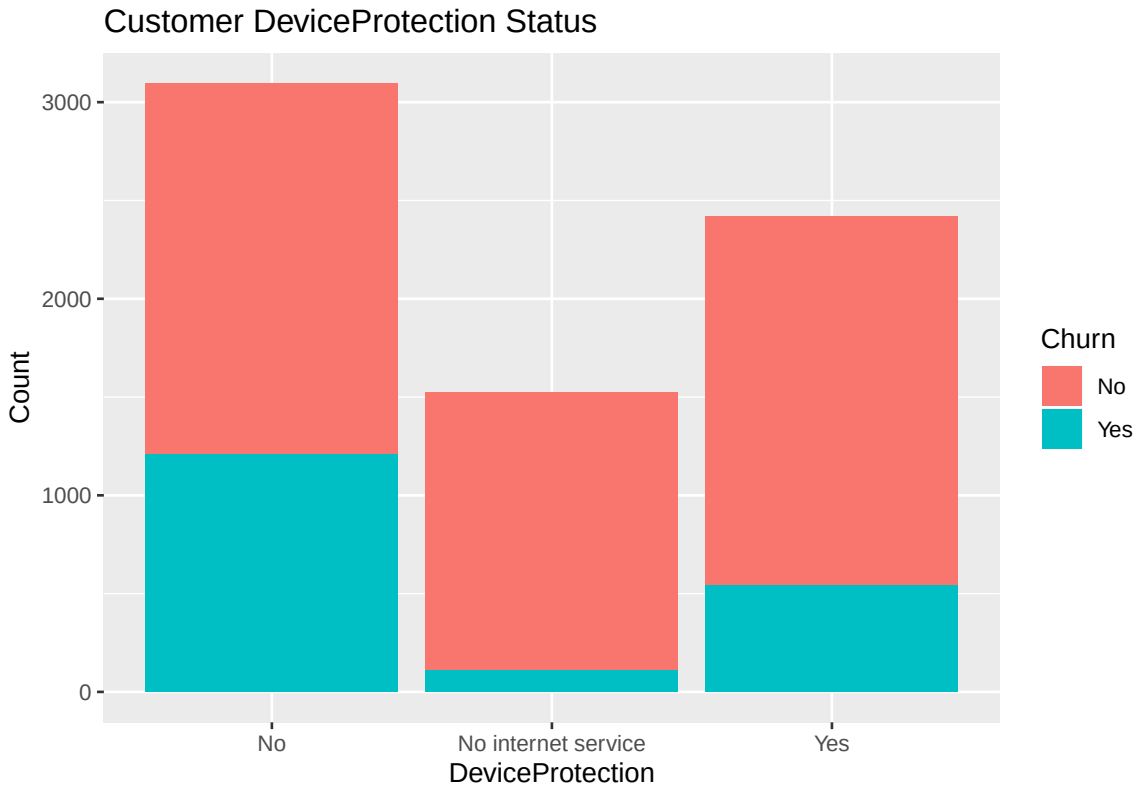



**Figure 9**

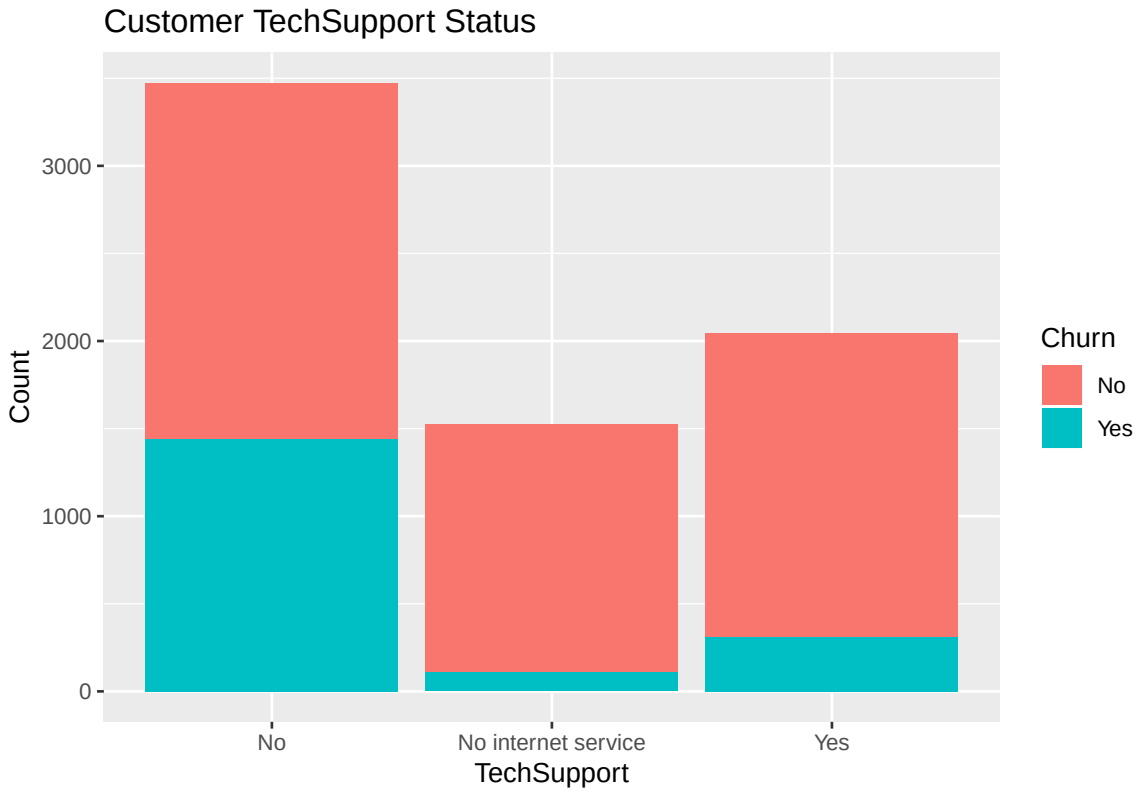



**Figure 10**

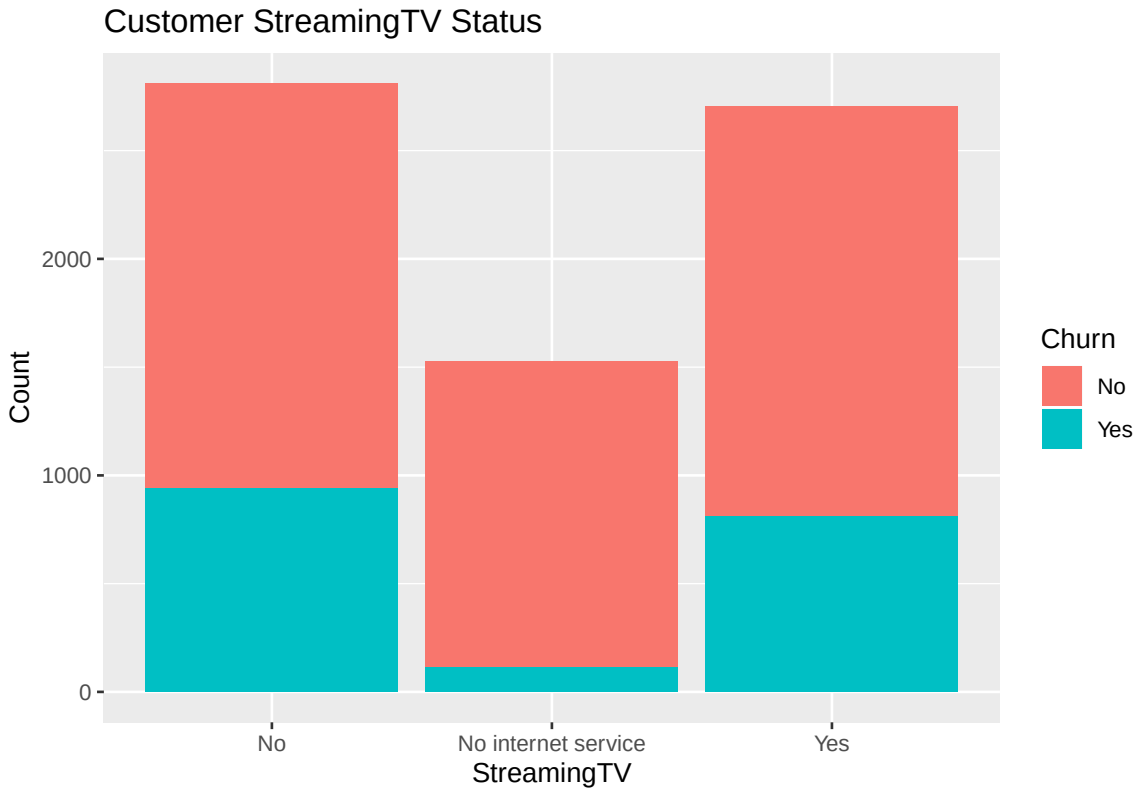



**Figure 11**

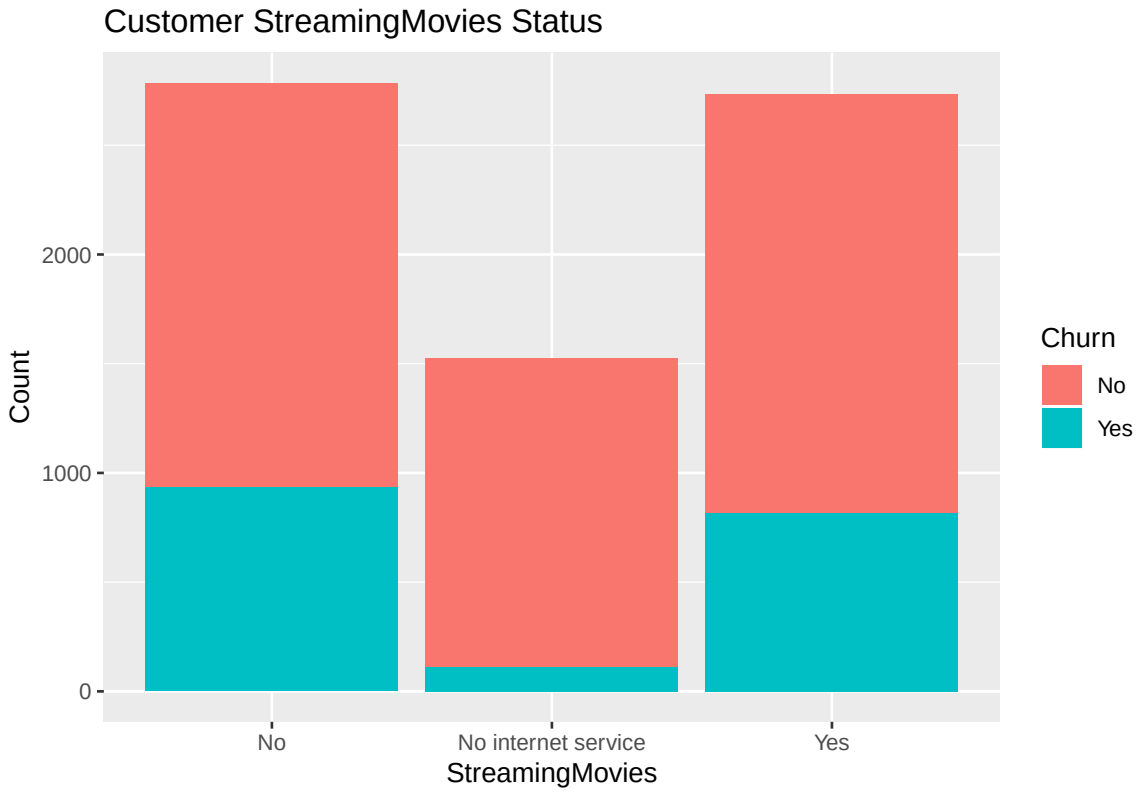



**Figure 12**

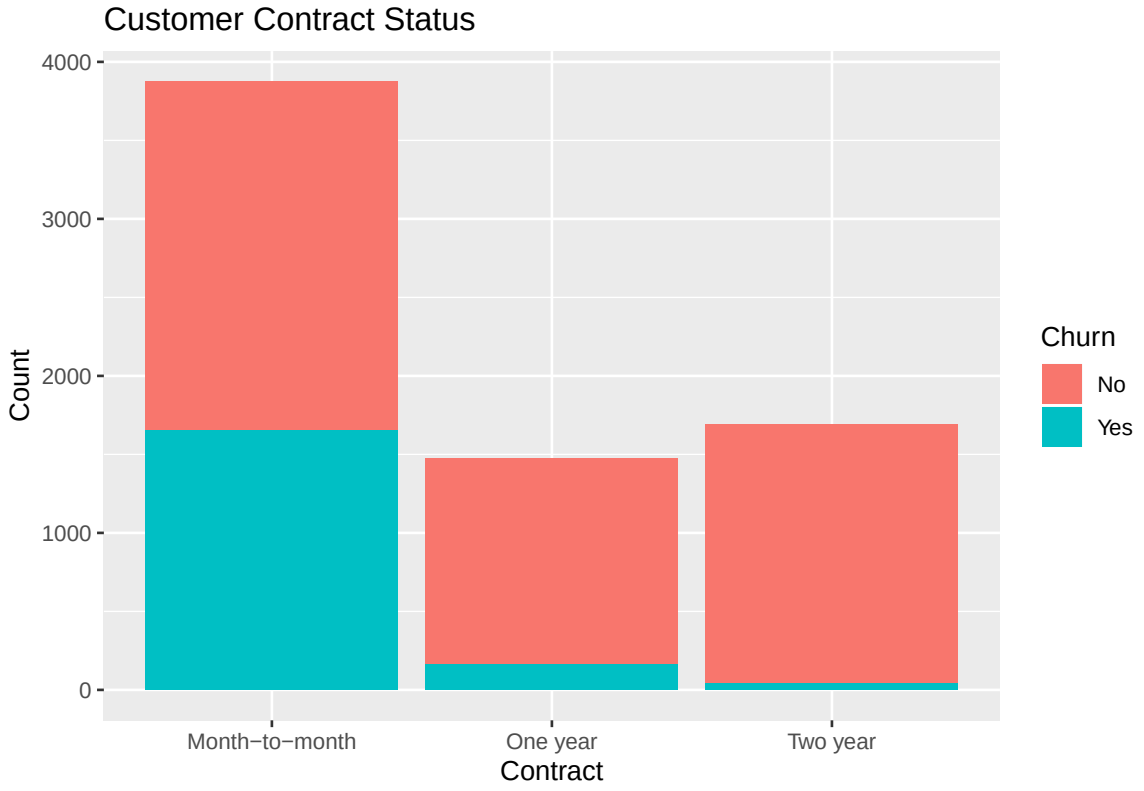



**Figure 13**

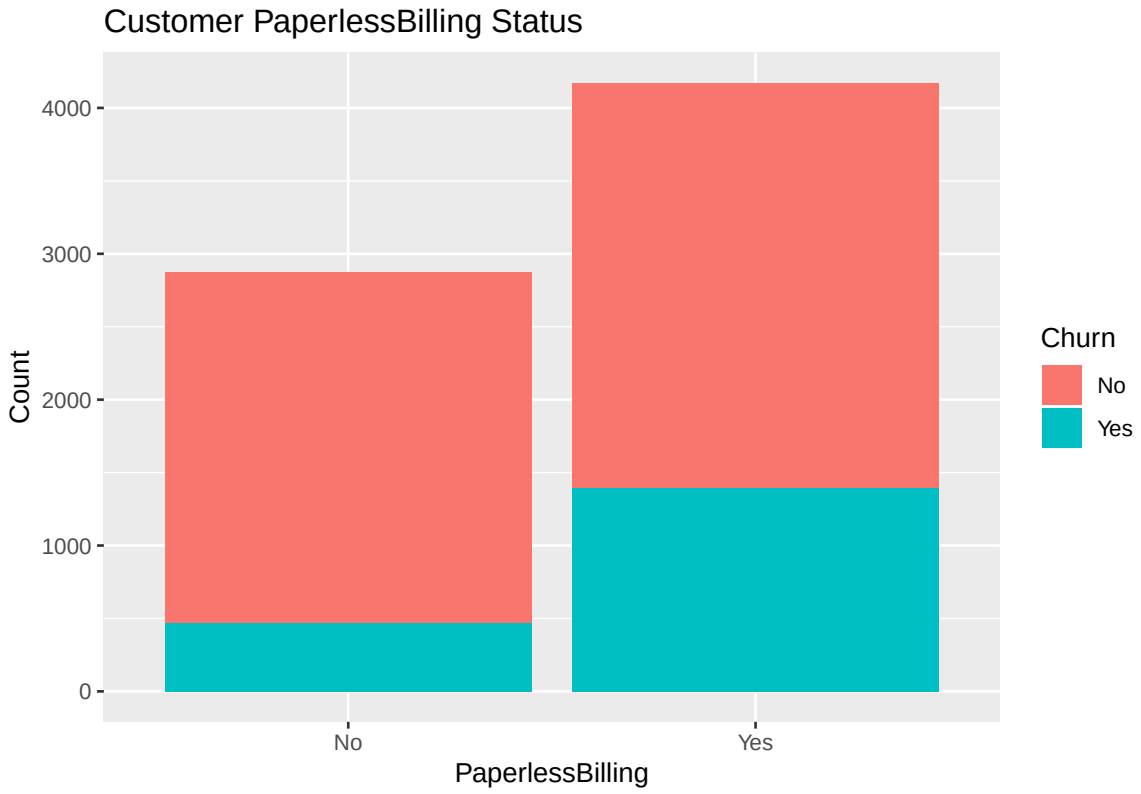



**Figure 14**

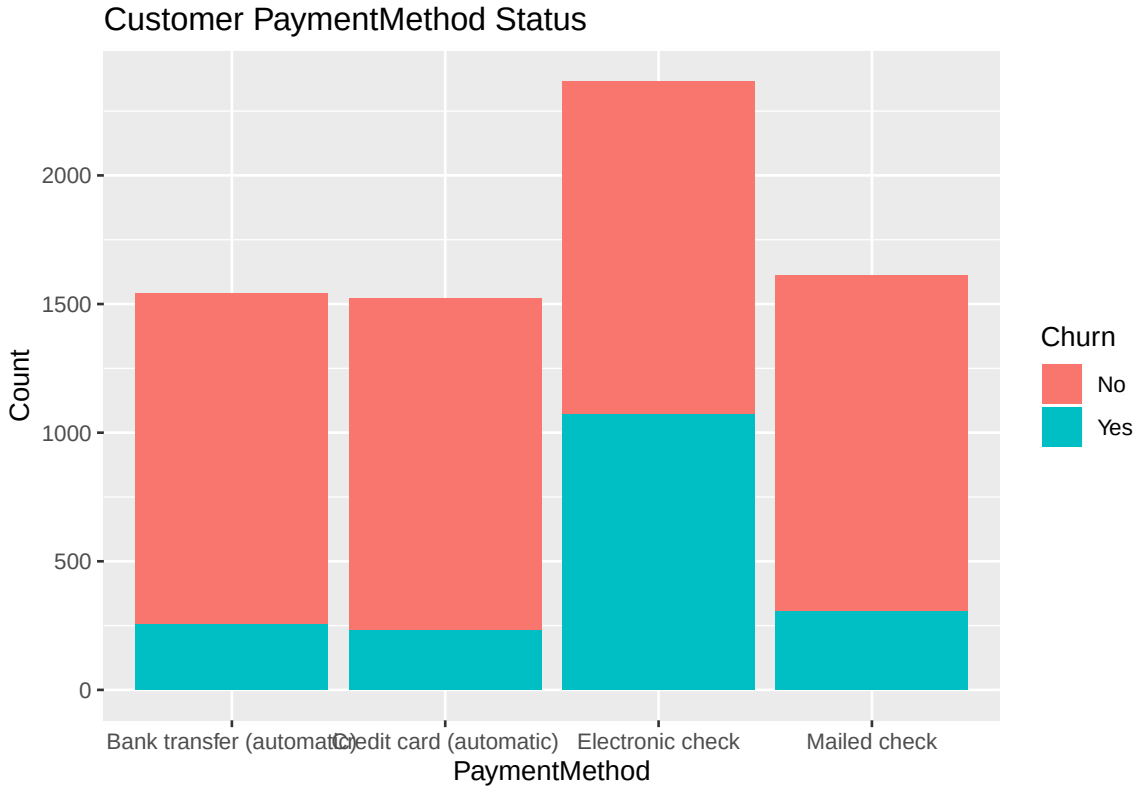



**Figure 15:** Test1

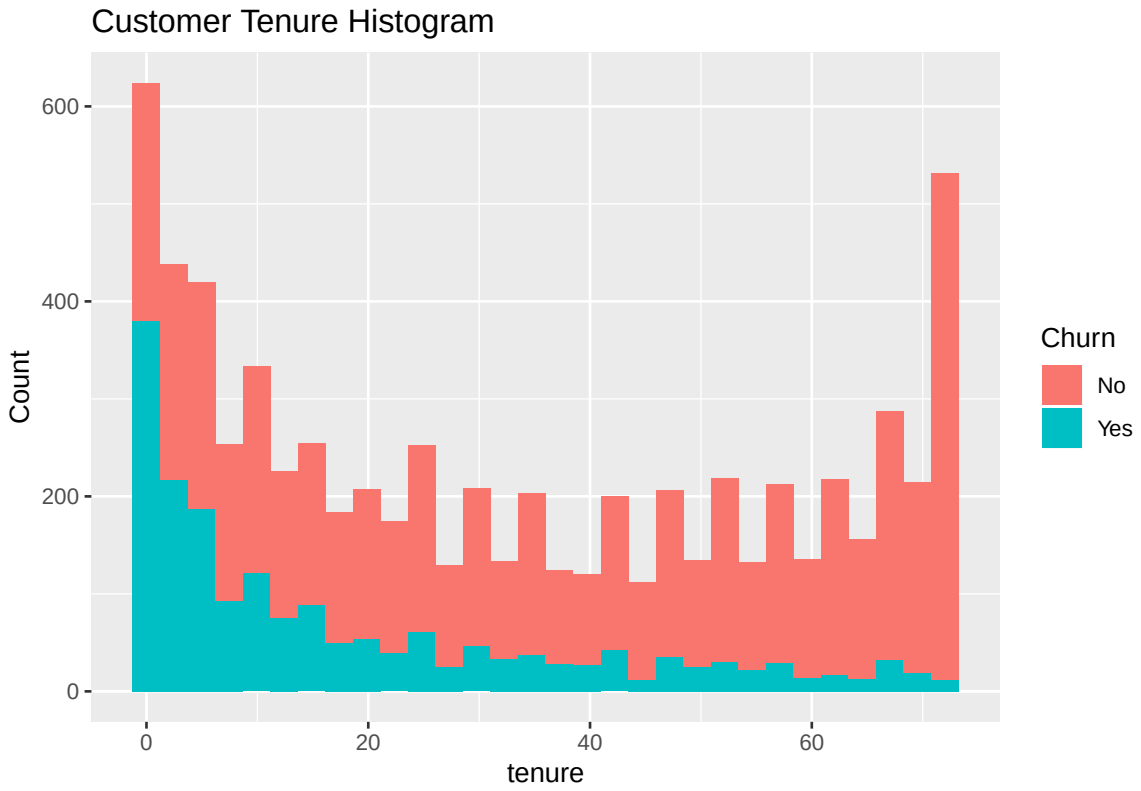



**Figure 16**

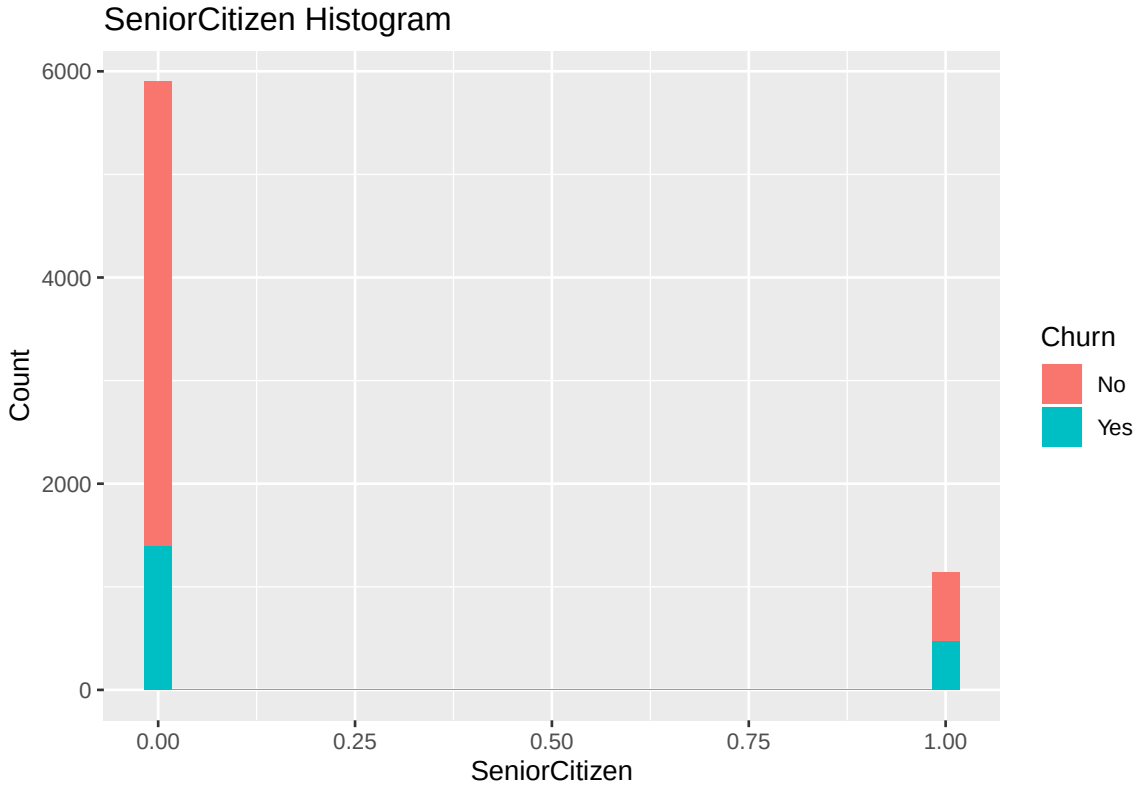



**Figure 17**

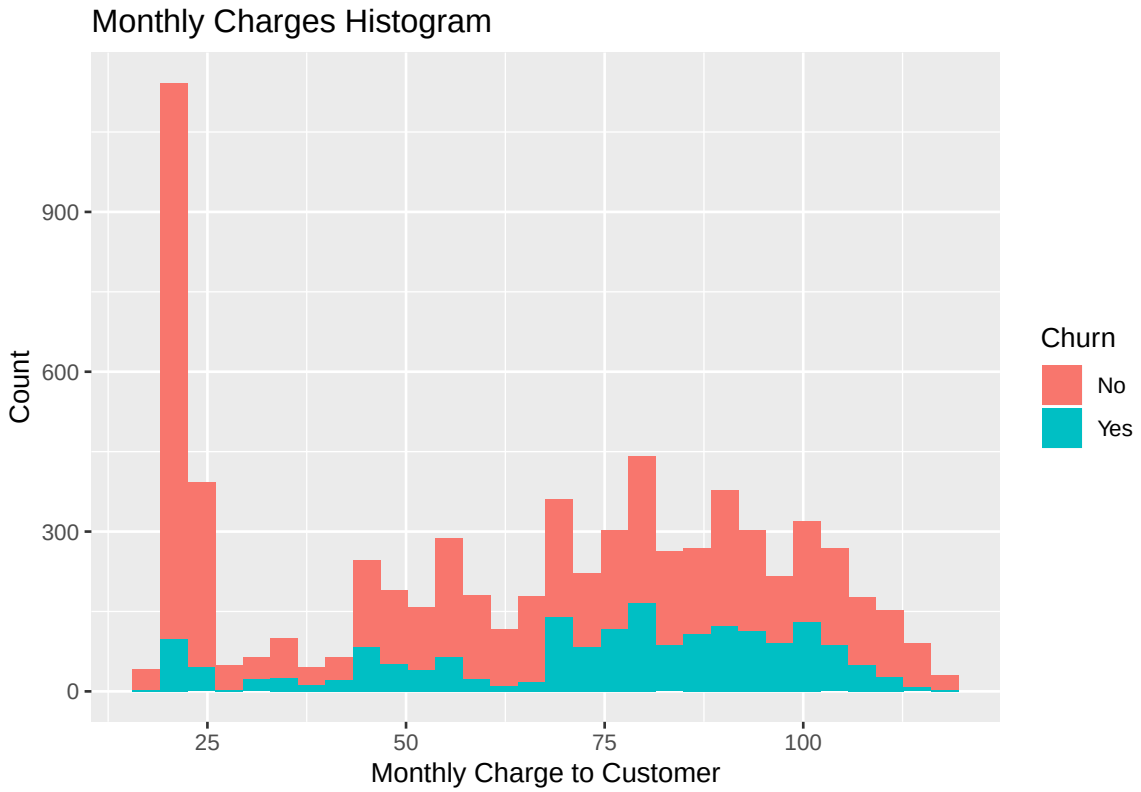



**Figure 18**

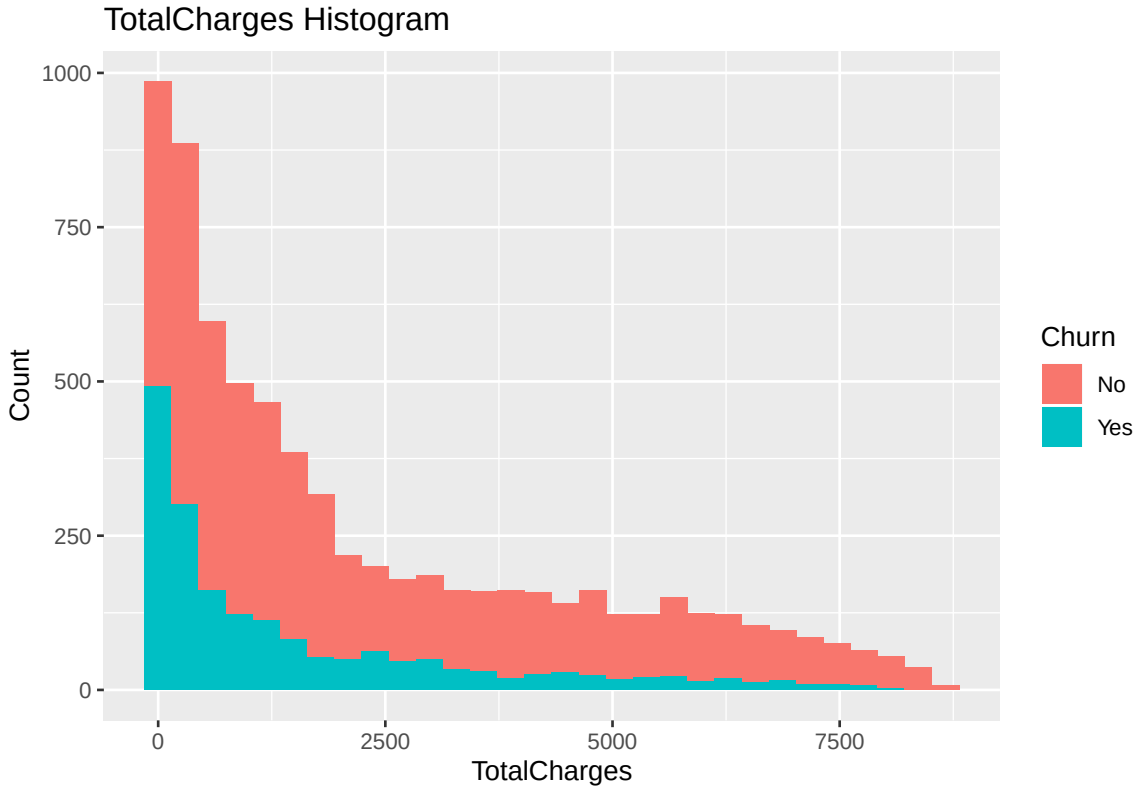



**Figure 19**

General Insights From Initial Data Exploration These are simple observations made by looking at the above charts.

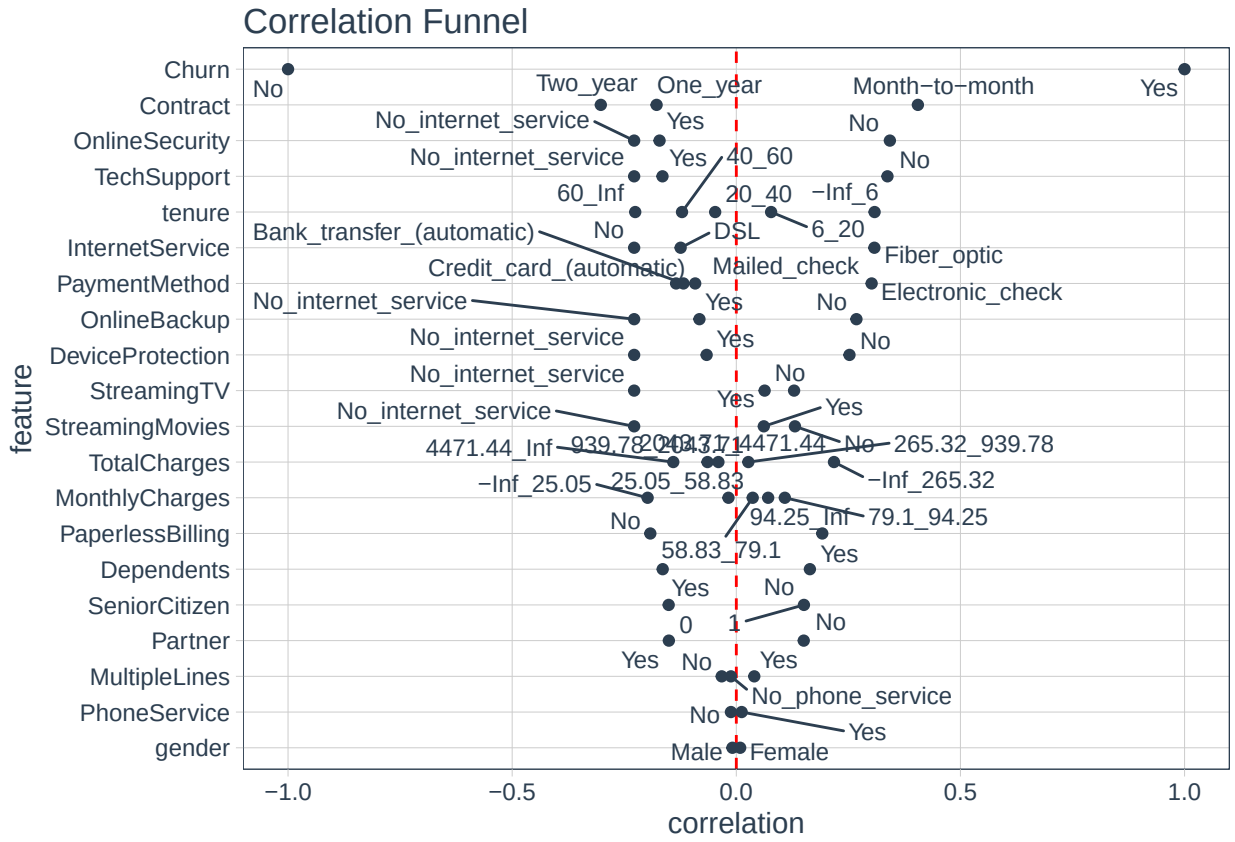
-Customers with a partner or dependents are much less likely to cancel their service -The longer a customer's tenure, the less likely they are to cancel -Customers with fiber optic internet service are especially likely to cancel -Customers on month-to-month contracts are especially likely to cancel -Customers who use paperless billing are more likely to cancel -Customers who pay by electronic check are more likely to cancel

The last step is to evaluate the correlation between predictor variables. Using a cut-off point of .6 we can say that there is a high level of correlation between the variables tenure, monthly charges, total charges and total services. These will need to be accounted before entering further modelling.

```
customer_churn_tbl = read.csv("../data/WA_Fn-UseC_-Telco-Customer-Churn.csv" )
data("customer_churn_tbl")


customer_churn_binarized_tbl <- customer_churn_tbl %>%
  dplyr::select(-customerID) %>%
  mutate(TotalCharges = ifelse(is.na(TotalCharges), MonthlyCharges, TotalCharges)) %>%
  binarize(n_bins = 5, thresh_infreq = 0.01, name_infreq = "OTHER", one_hot = TRUE)

customer_churn_corr_tbl <- customer_churn_binarized_tbl %>%
  correlate(Churn__Yes)

customer_churn_corr_tbl
```

```
#> # A tibble: 60 x 3
#>    feature         bin              correlation
#>    <fct>           <chr>                  <dbl>
#>  1 Churn           No                    -1
#>  2 Churn           Yes                    1
#>  3 Contract        Month-to-month         0.405
#>  4 OnlineSecurity  No                     0.343
#>  5 TechSupport     No                     0.337
#>  6 tenure          -Inf_6                 0.309
#>  7 InternetService Fiber_optic            0.308
#>  8 Contract        Two_year              -0.302
#>  9 PaymentMethod   Electronic_check       0.302
#> 10 OnlineBackup    No                     0.268
#> # ... with 50 more rows
```

```
customer_churn_corr_tbl %>%
  plot_correlation_funnel()
```




We can see that the following features are correlated with Churn:

"Month to Month" Contract Type No Online Security No Tech Support Customer tenure less than 6 months Fiber Optic internet service Pays with electronic check

We can also see that the following features are correlated with Staying (No Churn):

"Two Year" Contract Type Customer Purchases Online Security Customer Purchases Tech Support Customer tenure greater than 60 months (5 years) DSL internet service Pays with automatic credit card

```
customerData = customerData %>%filter(complete.cases(.))
customerData = subset(customerData,select = -customerID)
```

## Modeling and Evalutation

Finally we have reached the stage where we can start training and evaluating classification models. At this point we have clear understanding of our data. We have gotten rid of the features that did not present much value. ## Feature Selection

Generally speaking feature evaluation methods can be separated into two groups: those that use the model information and those that do not. Clearly at this stage of our research the models are not ready. Thus we will be exploring the methods that do not require model.

This group of the method could be spit further as follows:

- wrapper methods that evaluate multiple models adding and/or removing predictors. These are some examples:
  - recursive feature elimination
  - genetic algorithms
  - simulated annealing
- filter methods which evaluate the relevance of the predictors outside of the predictive models.

Before we proceed any further let's ensure that all categorical values get converted back to the factors. This is useful for dimentiality reduction algorithms and model training.

```
customerData = mutate(customerData,
          gender = as.factor(unclass(gender)),
          Partner = as.factor(unclass(Partner)),
          Dependents = as.factor(unclass(Dependents)),
          PhoneService = as.factor(unclass(PhoneService)),
          MultipleLines = as.factor(unclass(MultipleLines)),
          InternetService = as.factor(unclass(InternetService)),
          OnlineSecurity = as.factor(unclass(OnlineSecurity)),
          OnlineBackup = as.factor(unclass(OnlineBackup)),
          DeviceProtection = as.factor(unclass(DeviceProtection)),
          TechSupport = as.factor(unclass(TechSupport)),
          StreamingTV = as.factor(unclass(StreamingTV)),
          StreamingMovies = as.factor(unclass(StreamingMovies)),
          Contract = as.factor(unclass(Contract)),
          PaperlessBilling = as.factor(unclass(PaperlessBilling)),
          PaymentMethod = as.factor(unclass(PaymentMethod)),
          Churn = as.factor(unclass(Churn)))
```

It is time to run feature selection algorithm.

```
predictors = subset(customerData,select = -Churn)
label = customerData[,20]

# run the RFE algorithm
rfePrediction = rfe(predictors, label, sizes=c(1:19),
                    rfeControl = rfeControl(functions=rfFuncs, method="cv", number=3))
print(rfePrediction)

#>
#> Recursive feature selection
#>
#> Outer resampling method: Cross-Validated (3 fold)
#>
#> Resampling performance over subset size:
#>
#>  Variables Accuracy  Kappa AccuracySD  KappaSD Selected
#>          1   0.7490 0.2305  0.0017762 0.039212
#>          2   0.7759 0.3782  0.0017762 0.008282
#>          3   0.7679 0.2877  0.0071004 0.093271
#>          4   0.7760 0.3940  0.0030764 0.017467
#>          5   0.7890 0.4116  0.0038711 0.020445
#>          6   0.7949 0.4299  0.0049446 0.018672
#>          7   0.7962 0.4370  0.0028406 0.018660
#>          8   0.7984 0.4417  0.0028406 0.014292
#>          9   0.7986 0.4534  0.0008532 0.009382
#>         10   0.7989 0.4516  0.0010736 0.008845        *
#>         11   0.7961 0.4459  0.0018596 0.005075
#>         12   0.7955 0.4451  0.0030267 0.003626
#>         13   0.7985 0.4512  0.0058857 0.008299
#>         14   0.7952 0.4362  0.0029863 0.012695
#>         15   0.7944 0.4361  0.0015382 0.009314
#>         16   0.7935 0.4320  0.0059727 0.009550
#>         17   0.7929 0.4282  0.0024998 0.005910
#>         18   0.7929 0.4267  0.0036284 0.007292
#>         19   0.7952 0.4336  0.0015382 0.008146
#>
#> The top 5 variables (out of 10):
#>    tenure, TotalCharges, Contract, MonthlyCharges, TechSupport
```

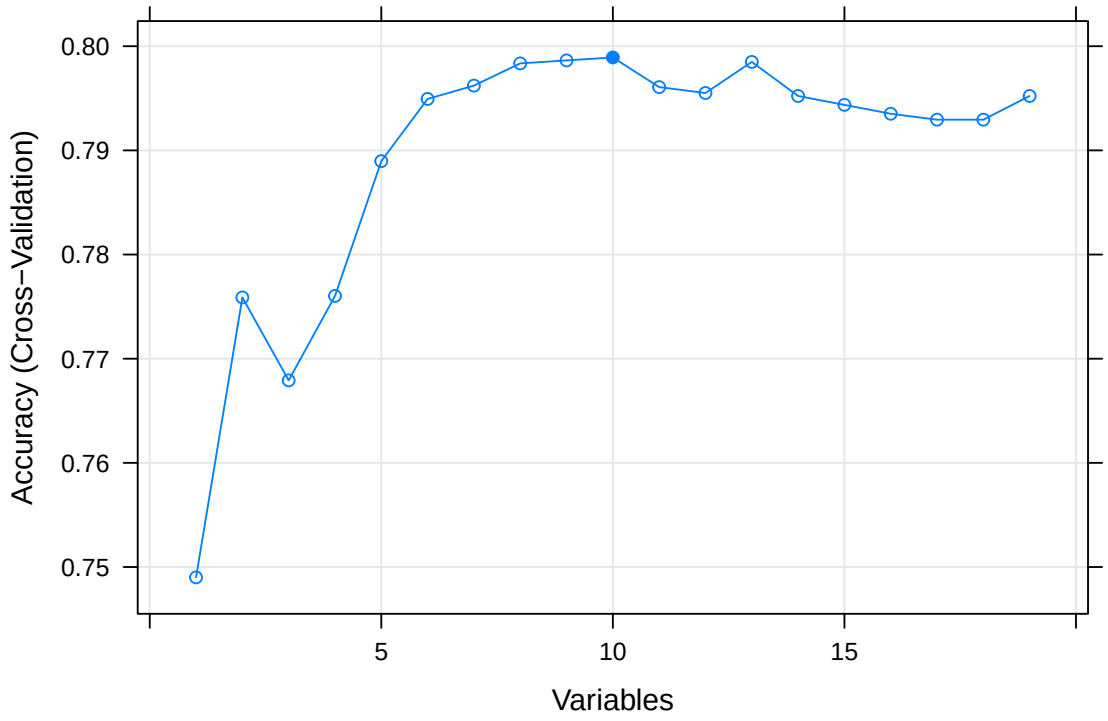



**Figure 20:** Number of Predictors vs Accuracy

Figure 20 illustrates that the accuracy practically flattens out when a number of predictors reaches 8. The accuracy improves a bit more when a number of features reaches 8 but the gain is negligible. Here is the list of features ordered by importance. We take first nine for model training.

```
#>  [1] "tenure"          "TotalCharges"    "Contract"        "MonthlyCharges"
#>  [5] "TechSupport"     "OnlineSecurity"  "InternetService" "OnlineBackup"
#>  [9] "PaymentMethod"   "MultipleLines"
```

### Data Upsampling

There is one more step to make before we get to the model training. As shown in Figure **??** our data set is unbalanced. This could cause model over-fitting. So let's split the data into the training and testing sets and up-sample the training set.

```
set.seed(1608)

# keep only the selected features
finalSample = customerData %>% dplyr::select(c(selectedPredictors,"Churn"));

splitIdx = createDataPartition(finalSample$Churn, p=0.7, list = F)  # 70% training data
trainData = finalSample[splitIdx, ]
testData = finalSample[-splitIdx, ]

set.seed(590045)
columns = colnames(trainData)
trainData = upSample(x = trainData[, columns[columns != "Churn"] ],
      y = trainData$Churn, list = F, yname = "Churn")

rm(splitIdx, columns, finalSample)
print(table(trainData$Churn))

#>
#>    1    2
#> 3615 3615
```

As we can see now the training set is balanced.

Thus we have prepared our training and test data sets. We have identified the most important features. We are ready to work on the prediction models.

### Decision Tree Model

Decision Tree algorithm is simple to understand, interpret and visualize. Effort required for data preparation is minimal. This is probably why the Decision Tree model tends to be the method of choice for predictive modeling of many.

```
#> Setting levels: control = no, case = yes

#> Setting direction: controls < cases

#> Conditional Inference Tree
#>
#> 7230 samples
#>    8 predictor
#>    2 classes: 'no', 'yes'
#>
#> No pre-processing
#> Resampling: Cross-Validated (5 fold)
#> Summary of sample sizes: 5784, 5784, 5784, 5784, 5784
#> Resampling results across tuning parameters:
#>
#>   mincriterion  ROC        Sens       Spec
#>   0.01          0.8552514  0.7125864  0.8420470
#>   0.50          0.8506961  0.7195021  0.8320885
#>   0.99          0.8392769  0.6829876  0.8406639
#>
#> ROC was used to select the optimal model using the largest value.
#> The final value used for the model was mincriterion = 0.01.

confusionMatrix(data = pred.decisionTreeModel.raw, testDataCopy$Churn)

#> Confusion Matrix and Statistics
#>
#>           Reference
#> Prediction   no  yes
#>        no  1050  107
#>        yes  498  453
#>
#>                Accuracy : 0.713
#>                  95% CI : (0.6932, 0.7322)
#>     No Information Rate : 0.7343
#>     P-Value [Acc > NIR] : 0.9871
#>
#>                   Kappa : 0.3984
#>
#>  Mcnemar's Test P-Value : <2e-16
#>
#>             Sensitivity : 0.6783
#>             Specificity : 0.8089
#>          Pos Pred Value : 0.9075
#>          Neg Pred Value : 0.4763
#>              Prevalence : 0.7343
#>          Detection Rate : 0.4981
#>    Detection Prevalence : 0.5489
#>       Balanced Accuracy : 0.7436
#>
#>        'Positive' Class : no
#>
```

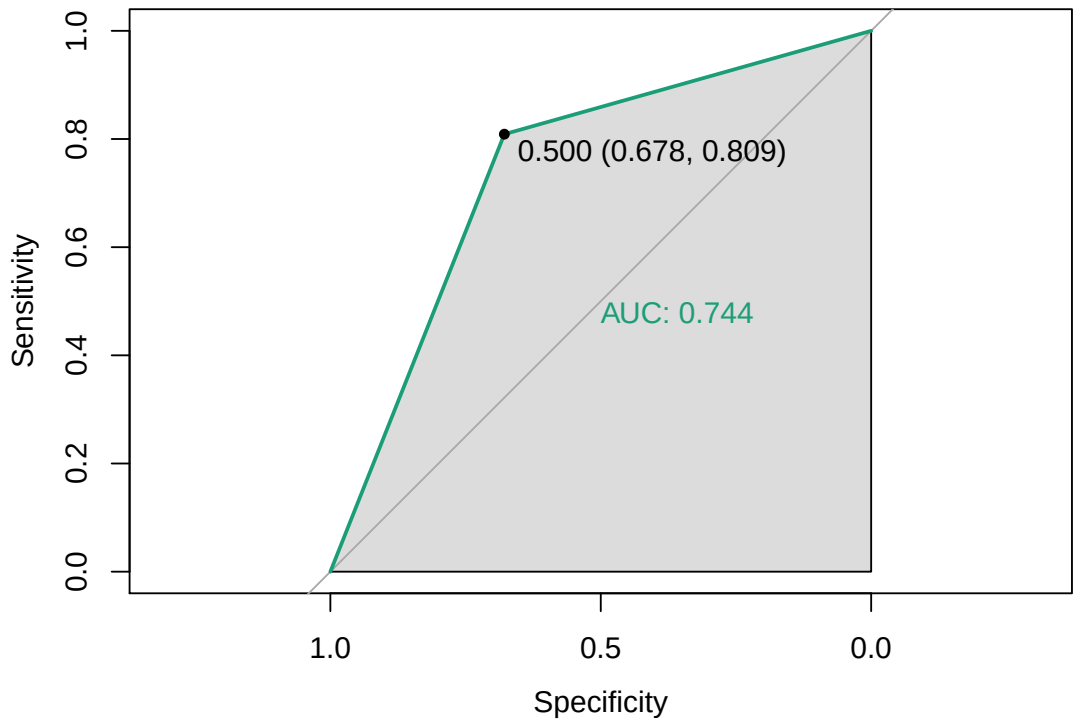



**Figure 21:** Classification Tree Model AUC and ROC Curve

### Naive Bayes Model

Naïve Bayes classification is a kind of simple probabilistic classification methods based on Bayes' theorem with the assumption of independence between features.

It is simple (both intuitively and computationally), fast, performs well with small amounts of training data, and scales well to large data sets. The greatest weakness of the naïve Bayes classifier is that it relies on an often-faulty assumption of equally important and independent features which results in biased posterior probabilities. Although this assumption is rarely met, in practice, this algorithm works surprisingly well and accurate; however, on average it rarely can compete with the accuracy of advanced tree-based methods (random forests & gradient boosting machines) but is definitely worth having in our toolkit.

```
#> Naive Bayes
#>
#> 7230 samples
#>    8 predictor
#>    2 classes: 'no', 'yes'
#>
#> No pre-processing
#> Resampling: Cross-Validated (5 fold)
#> Summary of sample sizes: 5784, 5784, 5784, 5784, 5784
#> Resampling results across tuning parameters:
#>
#>   usekernel  ROC        Sens       Spec
#>   FALSE      0.8262922  0.5836791  0.8824343
#>    TRUE      0.8297156  0.3695712  0.9380360
#>
#> Tuning parameter 'fL' was held constant at a value of 0
#> Tuning
#>  parameter 'adjust' was held constant at a value of 1
#> ROC was used to select the optimal model using the largest value.
#> The final values used for the model were fL = 0, usekernel = TRUE and adjust
#>  = 1.
```

```
confusionMatrix(data = pred.naiveBayesModel.raw, testDataCopy$Churn)

#> Confusion Matrix and Statistics
#>
#>          Reference
#> Prediction  no yes
#>        no  550  47
#>        yes 998 513
#>
#>               Accuracy : 0.5043
#>                 95% CI : (0.4827, 0.5258)
#>    No Information Rate : 0.7343
#>    P-Value [Acc > NIR] : 1
#>
#>                  Kappa : 0.176
#>
#>  Mcnemar's Test P-Value : <2e-16
#>
#>             Sensitivity : 0.3553
#>             Specificity : 0.9161
#>          Pos Pred Value : 0.9213
#>          Neg Pred Value : 0.3395
#>              Prevalence : 0.7343
#>          Detection Rate : 0.2609
#>    Detection Prevalence : 0.2832
#>       Balanced Accuracy : 0.6357
#>
#>        'Positive' Class : no
#>
```

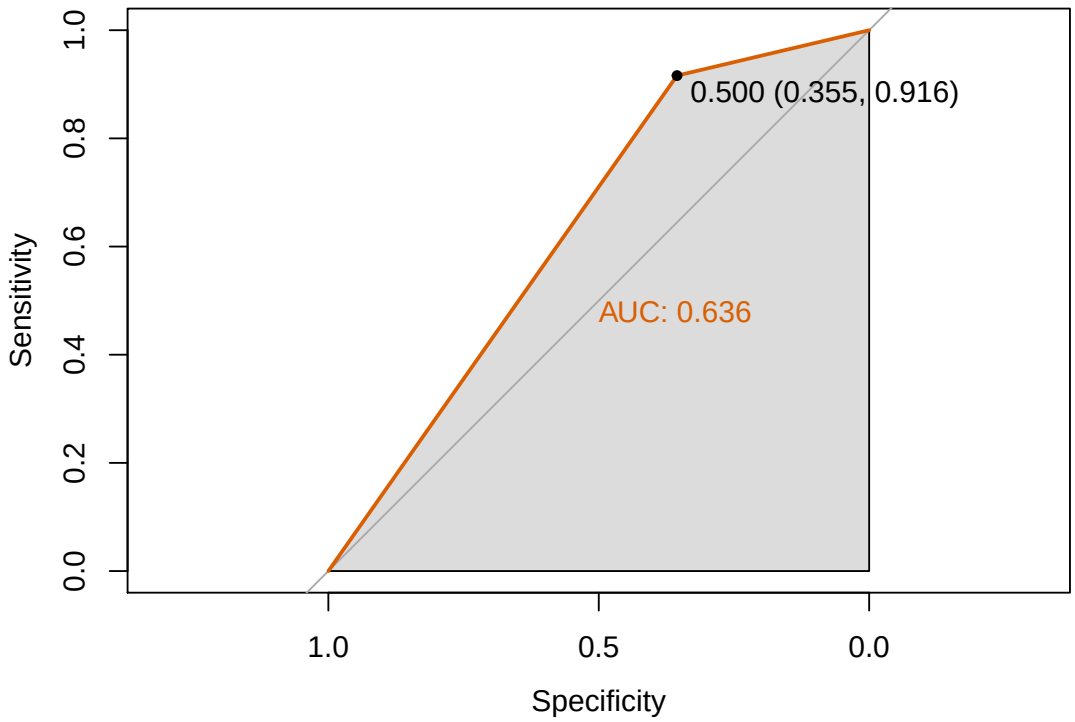



**Figure 22:** Naive Bayes Model AUC and ROC Curve

### Random Forest Model

Random Forest is also considered as a very handy and easy to use algorithm, because it's default hyperparameters often produce a good prediction result. Random Forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model. The main limitation of Random Forest is that a large number of trees can make the algorithm to slow and ineffective for real-time predictions. In general, these algorithms are fast to train, but quite slow to create predictions once they are trained.

```
#>    user  system elapsed
#>   27.96    0.43   28.41
```

```
#> Random Forest
#>
#> 7230 samples
#>    8 predictor
#>    2 classes: 'no', 'yes'
#>
#> No pre-processing
#> Resampling: Cross-Validated (3 fold)
#> Summary of sample sizes: 4820, 4820, 4820
#> Resampling results across tuning parameters:
#>
#>   mtry  ROC        Sens       Spec
#>    2    0.8549601  0.6921162  0.8511757
#>    7    0.9332195  0.7892116  0.9297372
#>   13    0.9311195  0.7869986  0.9253112
#>
#> ROC was used to select the optimal model using the largest value.
#> The final value used for the model was mtry = 7.
```

```
confusionMatrix(data = pred.randomForestModel.raw, testDataCopy$Churn)
```

```
#> Confusion Matrix and Statistics
#>
#>           Reference
#> Prediction   no  yes
#>        no  1257  213
#>        yes  291  347
#>
#>                Accuracy : 0.7609
#>                  95% CI : (0.7421, 0.779)
#>     No Information Rate : 0.7343
#>     P-Value [Acc > NIR] : 0.0028607
#>
#>                   Kappa : 0.4133
#>
#>  Mcnemar's Test P-Value : 0.0006039
#>
#>             Sensitivity : 0.8120
#>             Specificity : 0.6196
#>          Pos Pred Value : 0.8551
#>          Neg Pred Value : 0.5439
#>              Prevalence : 0.7343
#>          Detection Rate : 0.5963
#>    Detection Prevalence : 0.6973
#>       Balanced Accuracy : 0.7158
#>
#>        'Positive' Class : no
#>
```

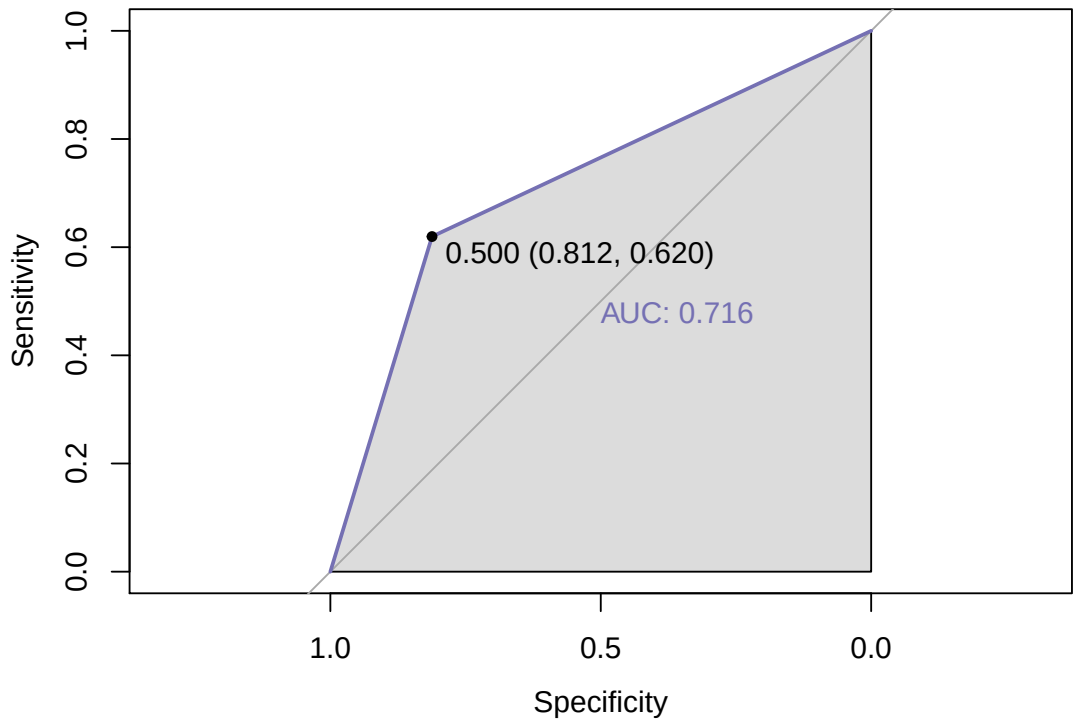



**Figure 23:** Random Forest Model AUC and ROC Curve

### Logistic Regression Model

Logistic regression is an efficient, interpretable and accurate method, which fits quickly with minimal tuning. Logistic regression prediction accuracy will benefit if the data is close to Gaussian distribution. Thus we apply addition transformation to the training data set. We will also be employing 5-fold cross-validation resampling procedure to improve the model. In addition to the above we are going to convert *Location* categorical value to numeric data type. We could have used dummy encoding but having 49 locations such approach does not seem beneficial.

```
confusionMatrix(data = pred.logRegModel.raw, testDataCopy$Churn)
```

```
#> Confusion Matrix and Statistics
#>
#>           Reference
#> Prediction    1    2
#>          1 1129  125
#>          2  419  435
#>
#>                Accuracy : 0.7419
#>                  95% CI : (0.7227, 0.7605)
#>     No Information Rate : 0.7343
#>     P-Value [Acc > NIR] : 0.2228
#>
#>                   Kappa : 0.4335
#>
#>  Mcnemar's Test P-Value : <2e-16
#>
#>             Sensitivity : 0.7293
#>             Specificity : 0.7768
#>          Pos Pred Value : 0.9003
#>          Neg Pred Value : 0.5094
#>              Prevalence : 0.7343
#>          Detection Rate : 0.5356
```

```
#>    Detection Prevalence : 0.5949
#>       Balanced Accuracy : 0.7531
#>
#>        'Positive' Class : 1
#>
```

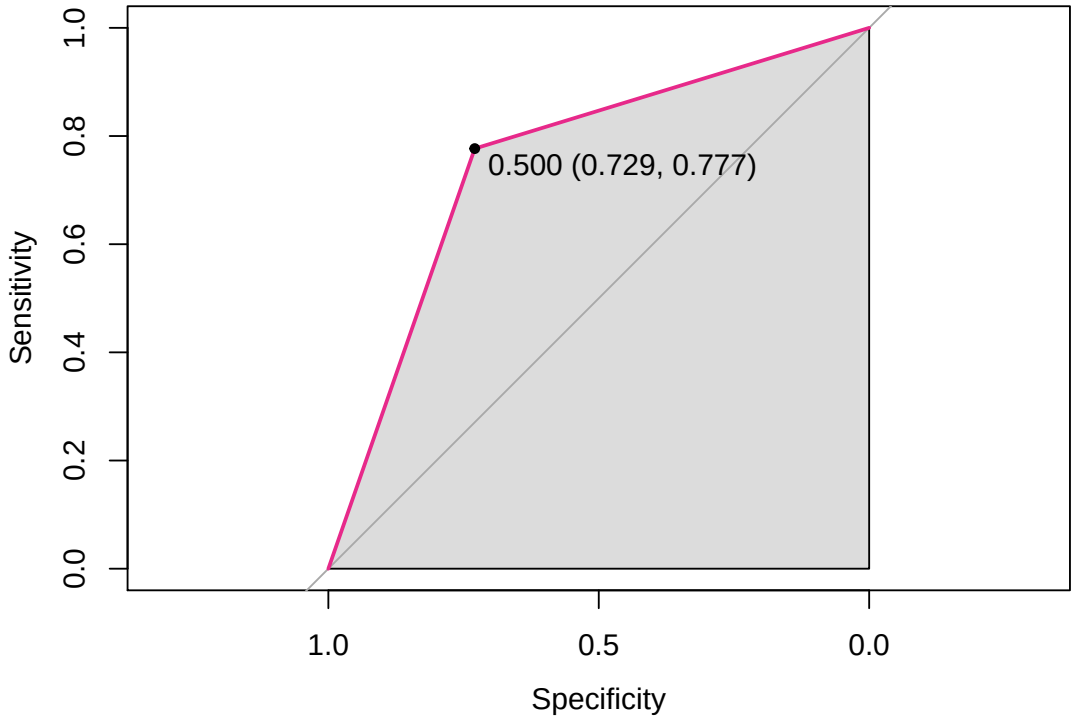



**Figure 24:** Logistic Regression Model AUC and ROC Curve

### Model Comparison

Now it is time to compare the models side by side and pick a winner.

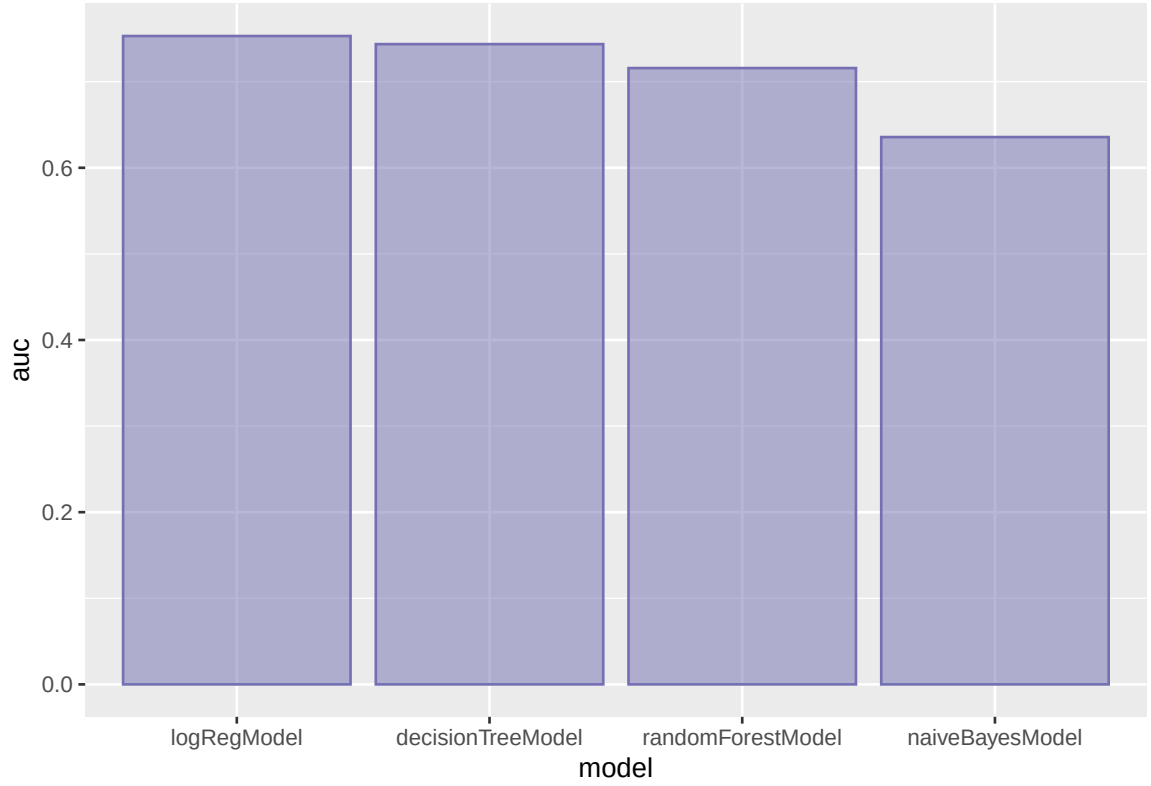



**Figure 25:** Model AUC Comparison

```
#>                model       auc
#> 1       logRegModel 0.7530569
#> 2 decisionTreeModel 0.7436116
#> 4 randomForestModel 0.7158292
#> 3   naiveBayesModel 0.6356843
```

**AUC - ROC perfomance** AUC stands for Area under the ROC Curve and ROC for Receiver operating characteristic curve. This is one of the most important KPIs of the classification algorithms. These two metrics measure how well the models distinguishing between the classes. The higher AUC the better model predicts positive and negative outcome.

Figures 21, 22, 23, 24 and accompanying data show that on the test data set all the models demonstrated very close resuts. Random Forest has the highest overall accuracy (85%) but performs poorly predicting rainy days (65%), thus the balanced accuracy is lower (about 78%).

Naive Bayes has lesser overall accuracy in comparison with the Random Forest but is more balanced, demonstrating consistent power to predict rainy and sunny days with almost equal accuracy. It scored over 78% on the balanced accuracy.

Logistic regression model scores the best having the highest AUC and all other metrics. It's balanced accuracy is 80%.

The Decision Tree performance is close to the other models with the balanced accuracy of 76%.

**Model interpretibility** Logistic Regression, Decision Tree and Naive Bayes are all highly interpreatable models. It is easy to explain to the business what impact each input parameter has. The decision tree could be visualized (provided if it is not too large).

Random Forest on the other hand is a black-box model, complex algorithm which is difficult to explain in simple terms.

## Model Deployment

The model can demonstrate how various customer elements affect the probability of the churn.

It is simple to understand and deploy.

## Conclusion

Through exploring customer churn dataset,we selected and tuned a model to predict whether one customer could churn.

We commenced our research analyzing and understanding available data . Then we identified the missing data, its distribution and feasibility of imputing it. We continued our research selecting the most impactful data attributes to use as an input for our future model. We apply the feature identification algorithm to do the job.

When the data preparation phase was finished we picked and analysed four different classification models: Decision Tree, Naive Bayes, Random Forest and Logistic Regression. We conducted comparative analysis of the models, reviewed their strength and weaknesses. We fitted each model using K-fold cross-validation technique. Subsequently we evaluated performance of each model applying them to the test data set and comparing AUC - ROC and balanced accuracy metrics.

Finally we moved to identifying a winning model. In order to so we reviewed each model from different angles namely:

- performance
- interpretability
- data quality sensitivity and data preparation effort

The winning model scored the highest in the majority of the categories. It was Logistic Regression, which we employed to build a Shiny App Web application.

We consider the project to be a success.

## Note from the Authors

This file was generated using *The R Journal* style article template, additional information on how to prepare articles for submission is here - Instructions for Authors. The article itself is an executable R Markdown file that could be downloaded from Github with all the necessary artifacts.

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