Telco Churn Rate Analysis: A Logistic Regression

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Final Project

Abstract

"This comprehensive report presents an in-depth analysis of the Telco Customer Churn dataset, containing 21 variables and 7043 observations, focusing on customer behavior within a telecommunications company. The primary aim of this study is to dissect the underlying patterns of customer churn, employing regression modeling techniques to identify influential factors contributing to service discontinuation. The report begins with an exploratory dive into the dataset, encompassing demographic details, service usage, contract specifics, and billing information. It encompasses a meticulous data preparation phase, model building, diagnostics, and insightful conclusions drawn from the analyses. The report underscores the significance of predictive modeling in understanding customer attrition dynamics, offering actionable insights for strategic decision-making within the telecommunications industry. The final model has an accuracy, sensitivity and specificity of around 75%"

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Data

The Telco Customer Churn dataset offers comprehensive insights into the telecommunications company's customer base. It has 21 variables and 7043 observations. It encompasses a wide array of data points, including demographic details, service usage, contract specifics, and billing information. The primary objective revolves around dissecting customer **churn** patterns, aiming to pinpoint the factors that influence customers to discontinue services. Moreover, the goal is to forecast potential customer attrition based on low trust ratings.

The dataset distinguishes customers who recently discontinued services, identified under the 'Churn' column. It also outlines the services each customer has subscribed to, encompassing phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies.

Additionally, the dataset provides essential customer account details, including their tenure with the company, contract specifics, preferred payment method, paperless billing preferences, as well as their monthly and total charges. Furthermore, it includes demographic information such as gender, age range, and indicators regarding partnership and dependents.

The following is the column description of the data whereas *Figure 1* shows the glimpse of the data set.

1. **customerID:** Unique identifier for each customer.
2. **gender:** Customer's gender (e.g., Male or Female).
3. **SeniorCitizen:** Binary indicator (0 or 1) for whether the customer is a senior citizen.
4. **Partner:** Binary indicator (Yes or No) for whether the customer has a partner.
5. **Dependents:** Binary indicator (Yes or No) for whether the customer has dependents.
6. **tenure:** Number of months the customer has been with the company.
7. **PhoneService:** Binary indicator (Yes or No) for whether the customer has phone service.
8. **MultipleLines:** Type of phone service (e.g., No phone service, Yes, or No).
9. **InternetService:** Type of internet service (e.g., DSL, Fiber optic).
10. **OnlineSecurity:** Binary indicator for whether the customer has online security.
11. **OnlineBackup:** Binary indicator for whether the customer has online backup.
12. **DeviceProtection:** Binary indicator for whether the customer has device protection.
13. **TechSupport:** Binary indicator for whether the customer has tech support.
14. **StreamingTV:** Binary indicator for whether the customer has streaming TV.
15. **StreamingMovies:** Binary indicator for whether the customer has streaming movies.
16. **Contract:** Type of contract (e.g., Month-to-month, One year).
17. **PaperlessBilling:** Binary indicator for whether the customer uses paperless billing.
18. **PaymentMethod:** Payment method used by the customer (e.g., Electronic check, Mailed check, Bank transfer).

19. **MonthlyCharges:** The amount charged to the customer per month.
20. **TotalCharges:** The total amount charged to the customer over the entire tenure.
21. **Churn:** Binary indicator for whether the customer has churned (left the service).

```
## Rows: 7,043
## Columns: 21
## $ customerID       <chr> "7590-VHVEG", "5575-GNVDE", "3668-QPYBK", "7795-CFOCW…
## $ gender           <chr> "Female", "Male", "Male", "Male", "Female", "Female",…
## $ SeniorCitizen    <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,…
## $ Partner          <chr> "Yes", "No", "No", "No", "No", "No", "No", "No", "Yes…
## $ Dependents       <chr> "No", "No", "No", "No", "No", "No", "Yes", "No", "No"…
## $ tenure           <dbl> 1, 34, 2, 45, 2, 8, 22, 10, 28, 62, 13, 16, 58, 49, 2…
## $ PhoneService     <chr> "No", "Yes", "Yes", "No", "Yes", "Yes", "Yes", "No", …
## $ MultipleLines    <chr> "No phone service", "No", "No", "No phone service", "…
## $ InternetService  <chr> "DSL", "DSL", "DSL", "DSL", "Fiber optic", "Fiber opt…
## $ OnlineSecurity   <chr> "No", "Yes", "Yes", "Yes", "No", "No", "No", "Yes", "…
## $ OnlineBackup     <chr> "Yes", "No", "Yes", "No", "No", "No", "Yes", "No", "N…
## $ DeviceProtection <chr> "No", "Yes", "No", "Yes", "No", "Yes", "No", "No", "Y…
## $ TechSupport      <chr> "No", "No", "No", "Yes", "No", "No", "No", "No", "Yes…
## $ StreamingTV      <chr> "No", "No", "No", "No", "No", "Yes", "Yes", "No", "Ye…
## $ StreamingMovies  <chr> "No", "No", "No", "No", "No", "Yes", "No", "No", "Yes…
## $ Contract         <chr> "Month-to-month", "One year", "Month-to-month", "One …
## $ PaperlessBilling <chr> "Yes", "No", "Yes", "No", "Yes", "Yes", "Yes", "No", …
## $ PaymentMethod    <chr> "Electronic check", "Mailed check", "Mailed check", "…
## $ MonthlyCharges   <dbl> 29.85, 56.95, 53.85, 42.30, 70.70, 99.65, 89.10, 29.7…
## $ TotalCharges     <dbl> 29.85, 1889.50, 108.15, 1840.75, 151.65, 820.50, 1949…
## $ Churn            <chr> "No", "No", "Yes", "No", "Yes", "Yes", "No", "No", "Y…
```

Figure 1

Exploratory Data Analysis (EDA)

Prior to commencing Exploratory Data Analysis (EDA), we conduct an initial review of the dataset to identify any instances of missing or incomplete data. Figure 2 illustrates the count of missing values present in each column, indicating the extent of missing data for each variable.

The sole variable containing missing values is the TotalCharges column. Considering that merely 11 instances (0.0015%) contain missing data, it is reasonable to conclude that eliminating these instances will not significantly impact our analysis.

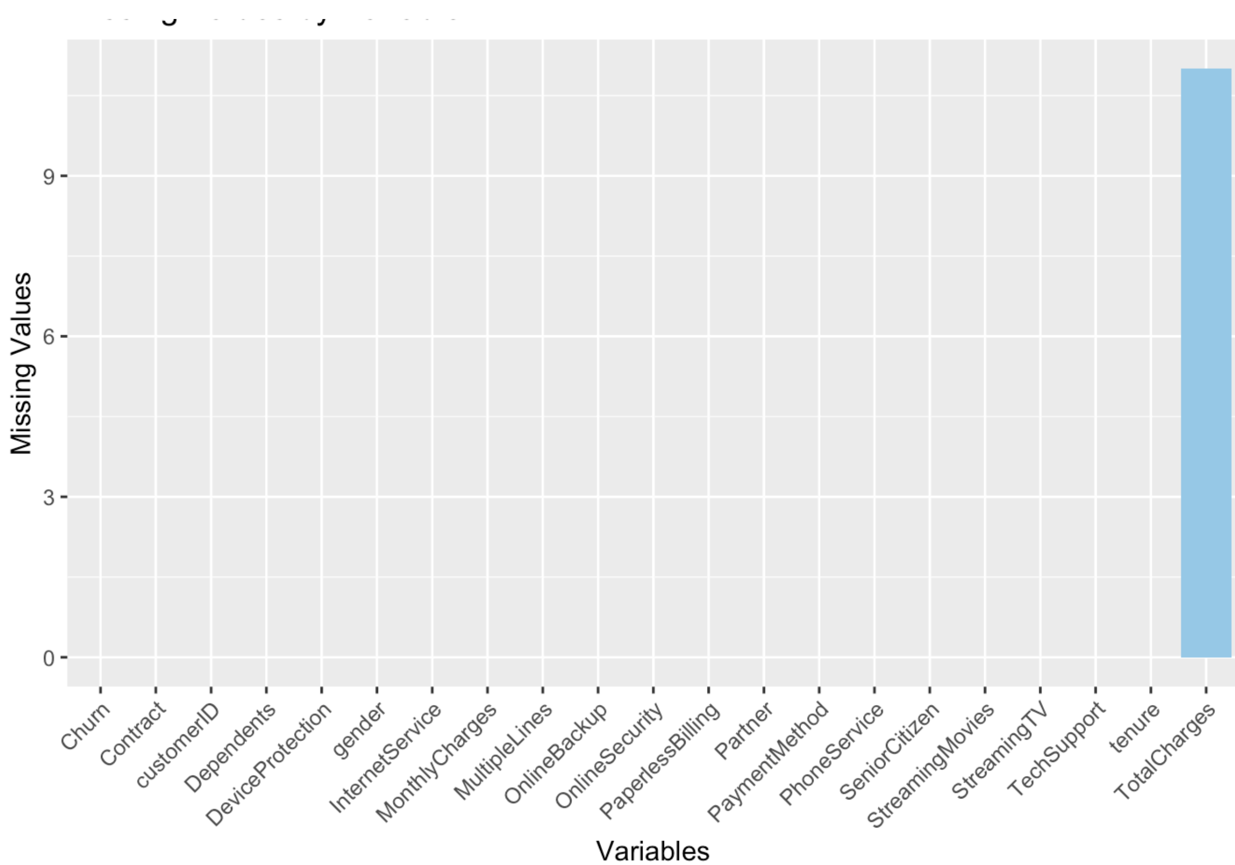

Figure 2

The key variable under consideration is Churn, indicating whether individuals have ceased the service. In Figure 3, we analyze the Churn rate, revealing that a substantial 26.58% of customers discontinued the service in the dataset's final month.

This signifies a concerning aspect as it potentially signifies a loss of 26% of revenue solely within the last month.

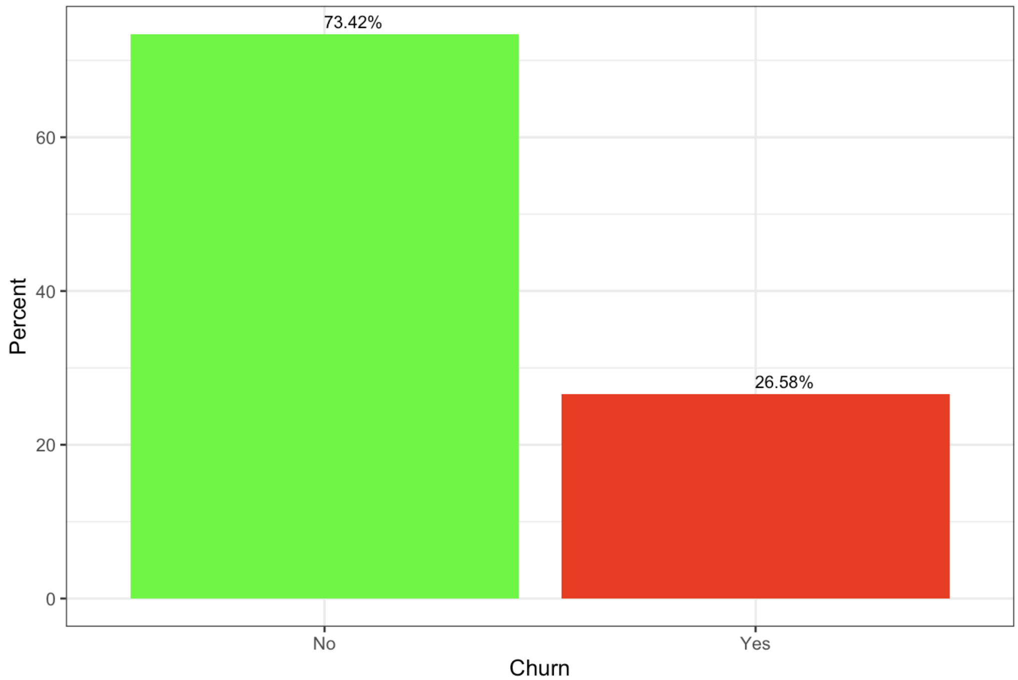

Figure 3

Categorical Variables

Next, we examine customer churn concerning specific variables such as gender, senior citizen status, having a partner, dependents, phone service, and multiple lines (Figure 4).

Our findings reveal that gender and whether customers have phone service or multiple lines do not significantly affect the churn rate. However, there is a noticeable trend where senior citizens tend to churn at a higher rate. Conversely, customers with dependents or partners tend to exhibit lower churn rates.

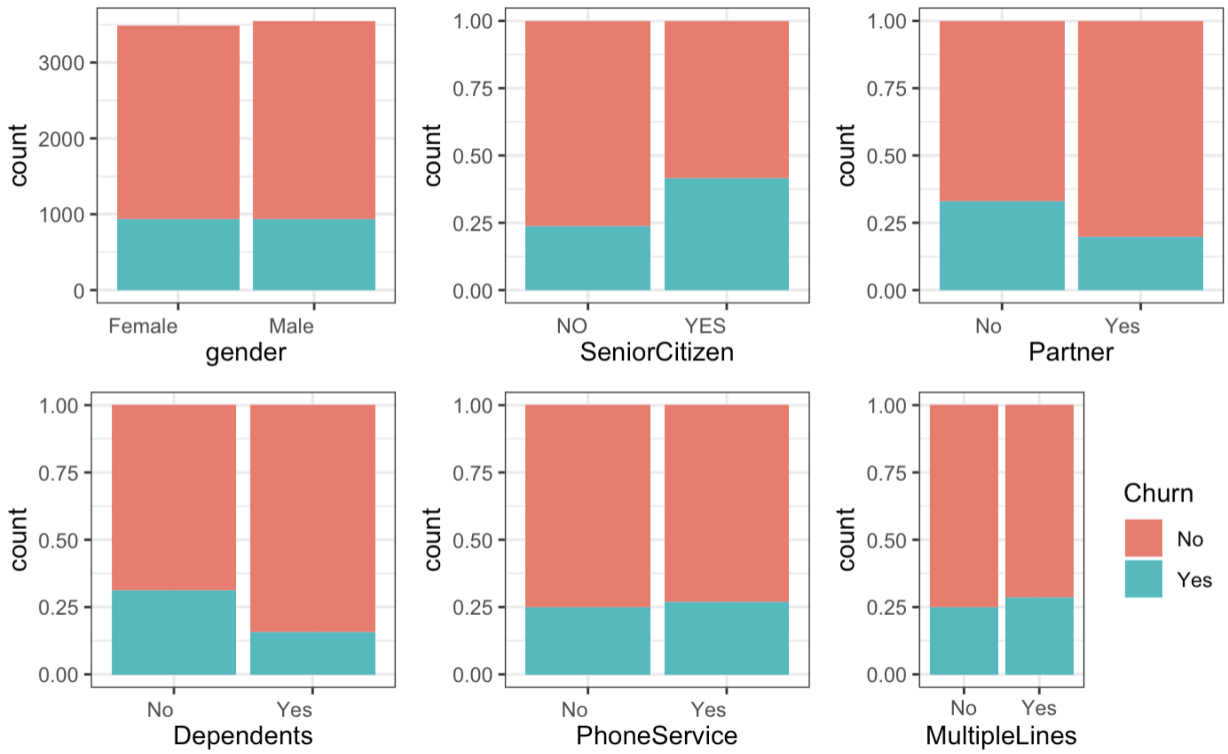

Figure 4

Next, our analysis focuses on customer churn concerning specific variables, including internet service, online security, online backup, device protection, tech support, and streaming TV (Figure 5).

Our observations indicate that customers with fiber optic tend to exhibit a higher churn rate compared to those with DSL, and notably, customers without an internet connection display the lowest churn rate. Moreover, having features such as online security, online backup, device protection, and technical support is associated with a lower churn rate. Conversely, customers with streaming TV services tend to display a higher churn rate.

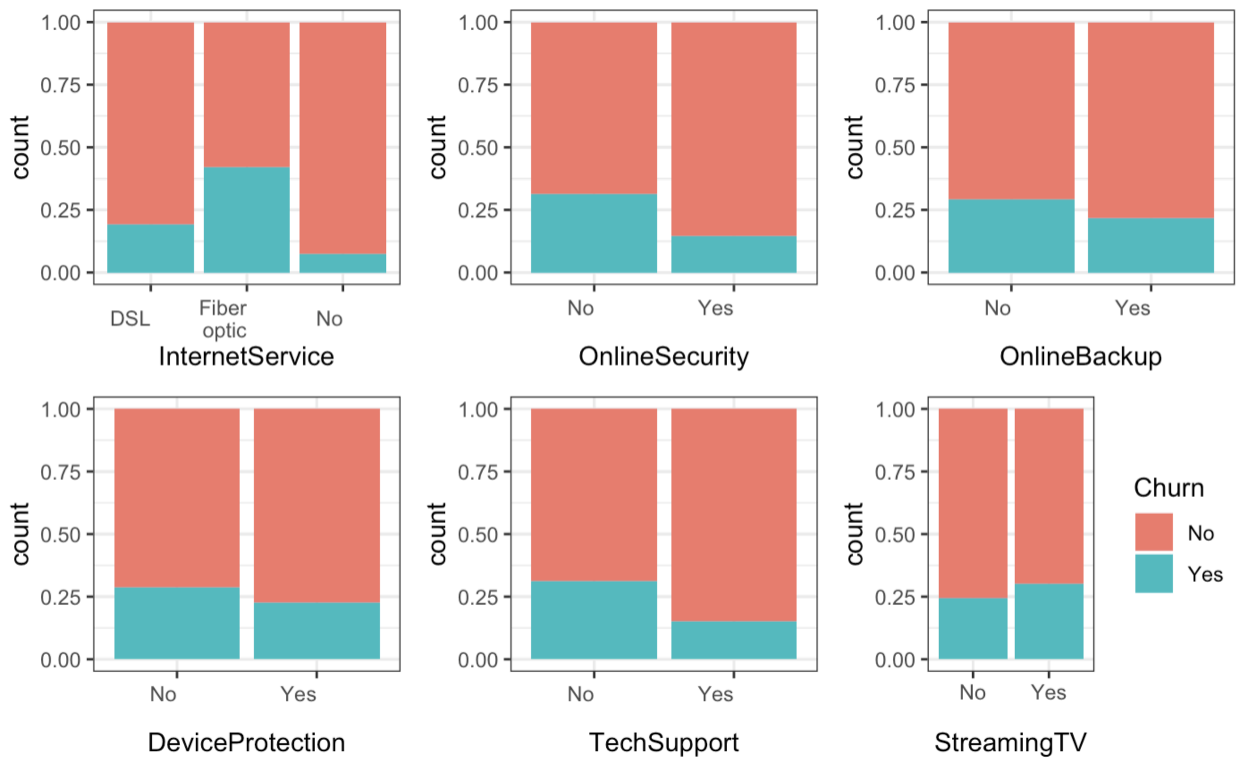

Figure 5

Next, we examine the Churn rate concerning contract type, paperless billing, and payment method in Figure 6.

Our analysis reveals distinct patterns:

- The churn rate for month-to-month contracts is notably higher compared to one-year contracts, which, in turn, demonstrate a significantly higher churn rate than two-year contracts.
- Customers using electronic check payment exhibit a considerably higher churn rate compared to those using bank transfer, credit card, or mailed check—where the rates are relatively similar.
- Furthermore, paperless billing demonstrates a substantially higher churn rate in contrast to paper billing.

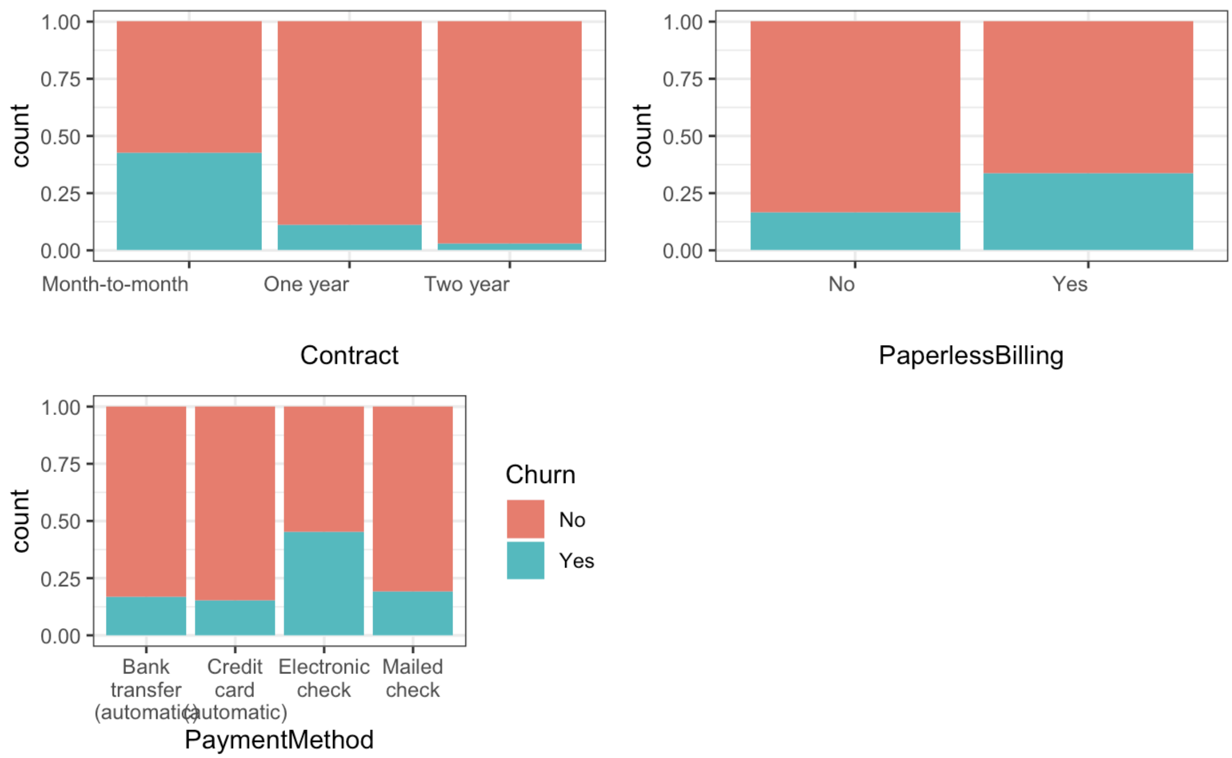

Figure 6

Based on the Exploratory Data Analysis (EDA) of categorical variables, it appears that individuals characterized as younger, possessing a month-to-month contract, showcasing higher technological engagement (such as utilizing electronic check and paperless billing), and not requiring services like tech support, device protection, and online security, tend to exhibit a higher average churn rate. Additionally, those without partners or dependents also show a tendency toward higher churn rates.

Numerical Variables

In examining the box plot of the variable "tenure" (Figure 7), a noticeable trend emerges indicating that individuals who churned are relatively new to the company's services. The median tenure for individuals who churned was around 10 months, contrasting with approximately 39 months for those who did not churn. This observation aligns with intuition, suggesting that newer customers are more prone to swiftly discontinuing their services with a company.

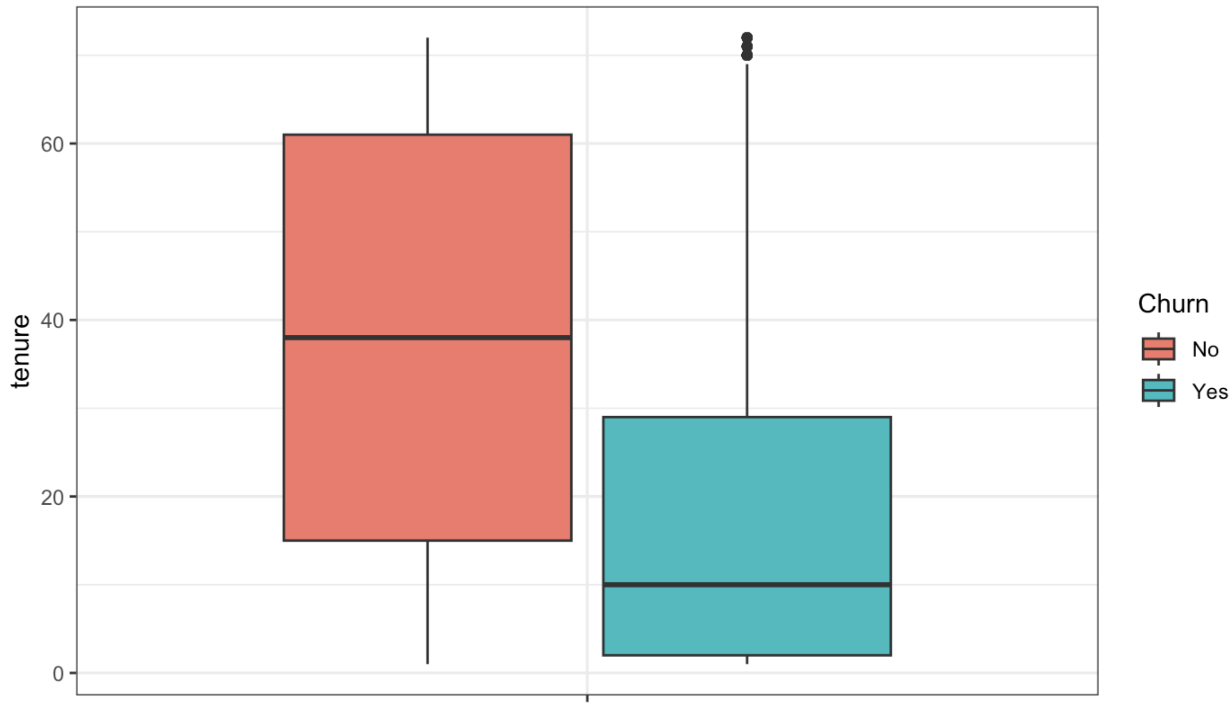

Figure 7

Upon examining the boxplot of the monthly charges variable (Figure 8), a discernible trend emerges, indicating that individuals with higher monthly payments tend to exhibit a higher churn rate compared to those with lower monthly payments. Specifically, individuals who churned displayed a median monthly payment of approximately $80, while those who did not churn had a median around $63. Additionally, it's noteworthy that individuals who churned showcased a considerably smaller interquartile range compared to those who did not churn.

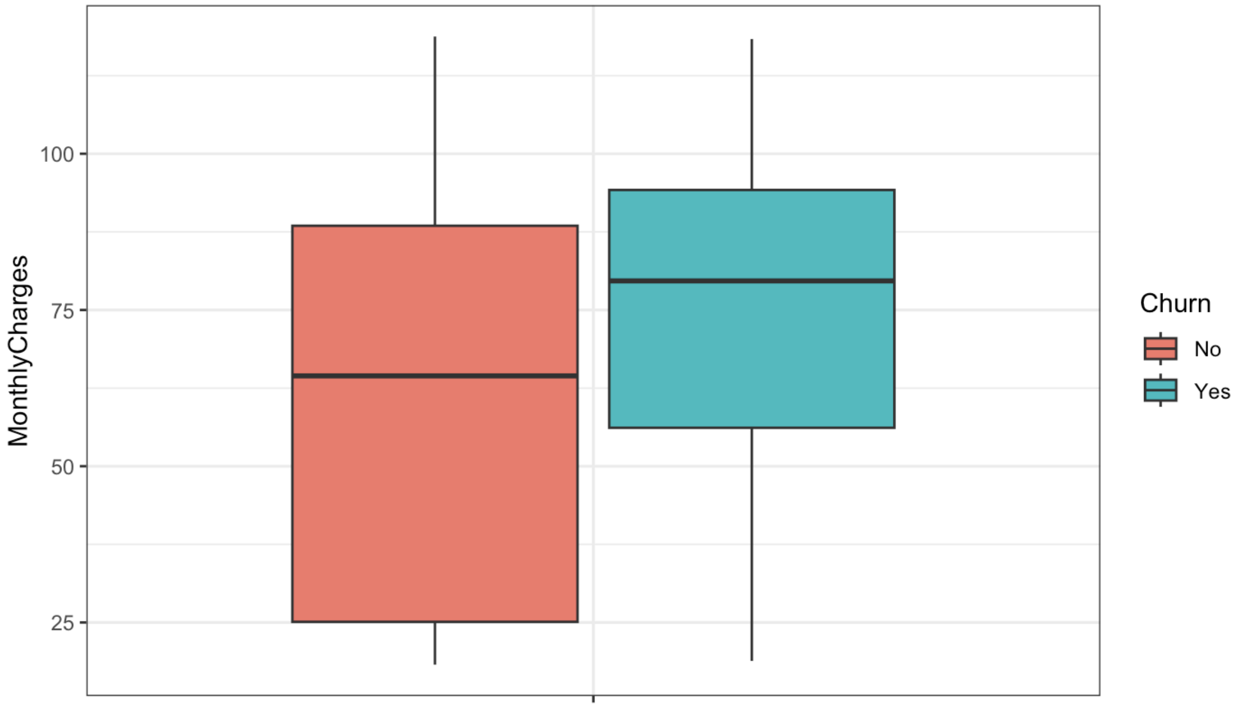

Figure 8

Upon reviewing the boxplot of the total charges variable (Figure 9), a distinct pattern emerges, indicating that individuals who churned had lower total charges compared to those who did not churn. This observation aligns with earlier findings suggesting that individuals who churned tended to be relatively new to the company, as previously observed in the dataset exploration.

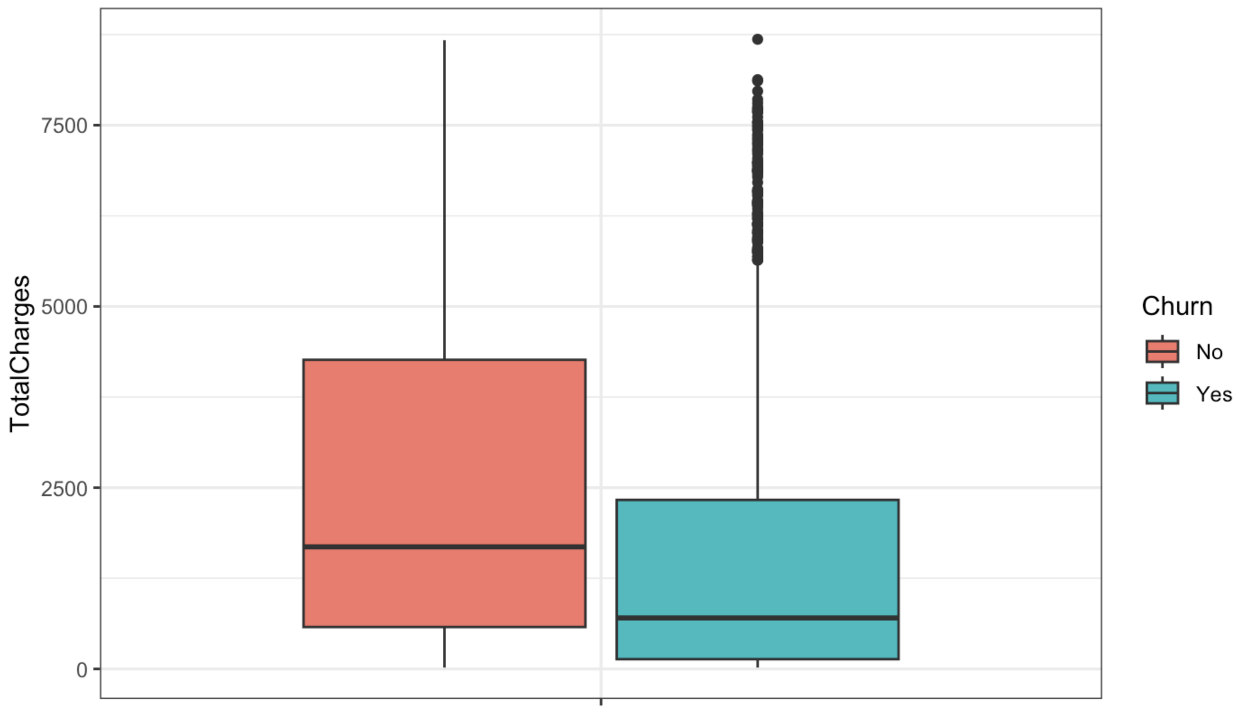

Figure 9

In Figure 10, the correlation analysis between numerical variables (tenure, monthly charges, total charges) reveals a noteworthy finding: total charges exhibit a high correlation with both monthly charges and tenure. This observation signifies a potential issue of multicollinearity if total charges are included in the model. Therefore, we need to carefully consider the inclusion of total charges in our model due to the strong correlations it shares with other variables, which might impact the model's stability and interpretation.

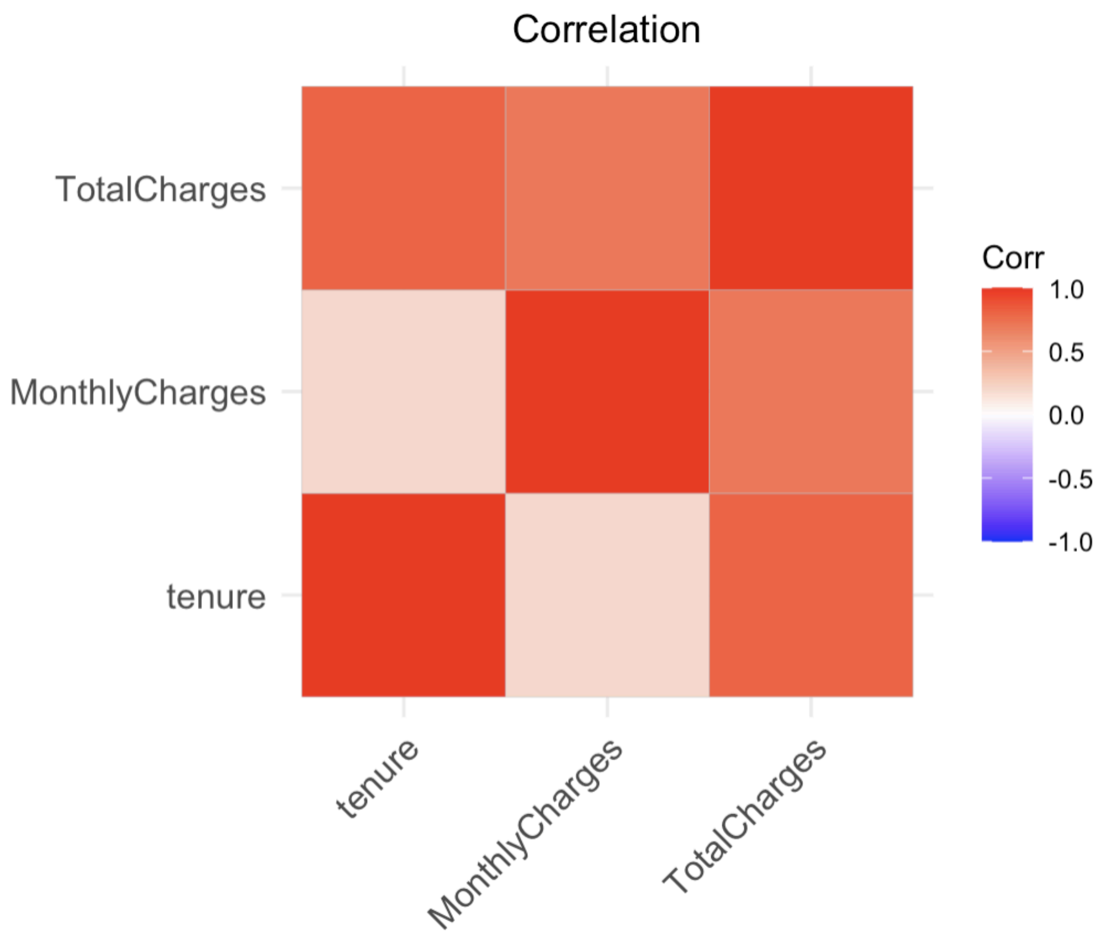

Figure 10

Outliers

In Figure 11, a box plot representation of the three numerical variables is utilized to detect potential outliers. They are tenure, monthly charges and total charges respectively.. Since no values extend beyond the whiskers of the box plots, we infer the absence of outliers within these variables.

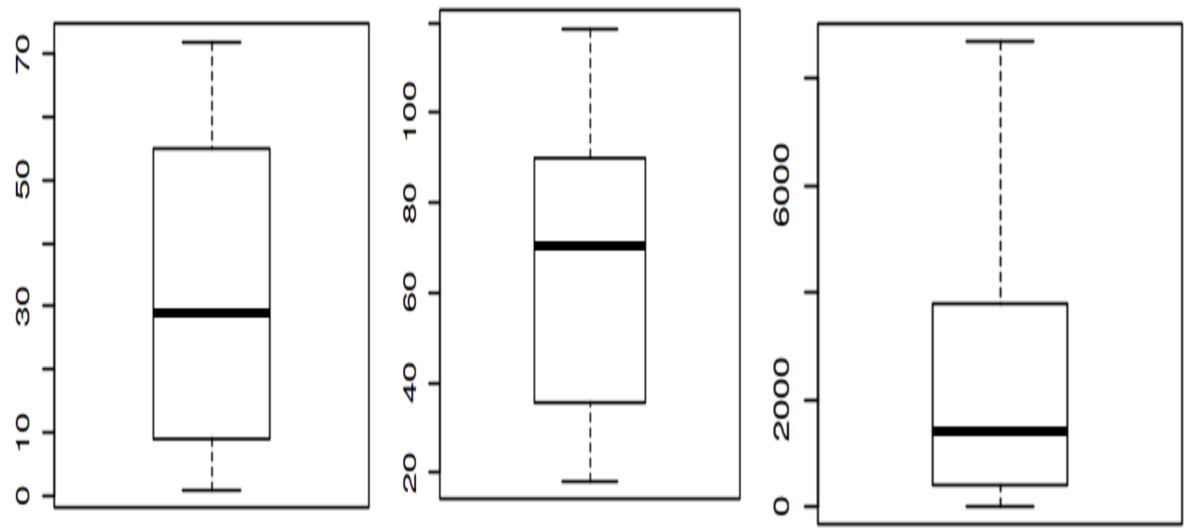

Figure 11

Data Preparation

After conducting an in-depth analysis of the data, we proceeded to refine it for modeling purposes. This involved rectifying categorical variables by addressing missing values and converting them into dummy variables, thus expanding the dataset to accommodate these transformations.

The resultant dataset, depicted in Figure 12, represents a structured collection of observations and features, meticulously cleaned and formatted for predictive modeling tasks. Additionally, we segregated the dataset into distinct training and validation subsets to ensure an effective model evaluation process."

```
Rows: 7,032
Columns: 29
$ tenure                                <dbl> 1, 34, 2, 45, 2, 8, 22, 10, 28, 62, 13, 16, 58, 49, 25, 69, 52…
$ MonthlyCharges                        <dbl> 29.85, 56.95, 53.85, 42.30, 70.70, 99.65, 89.10, 29.75, 104.80…
$ TotalCharges                          <dbl> 29.85, 1889.50, 108.15, 1840.75, 151.65, 820.50, 1949.40, 301.…
$ gender                                <dbl> 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0, 1,…
$ SeniorCitizen                         <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,…
$ Partner                               <dbl> 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0,…
$ Dependents                            <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0,…
$ PhoneService                          <dbl> 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,…
$ MultipleLines                         <dbl> 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0,…
$ InternetService.xFiber.optic          <dbl> 0, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0,…
$ InternetService.xNo                   <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0,…
$ OnlineSecurity                        <dbl> 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0,…
$ OnlineBackup                          <dbl> 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,…
$ DeviceProtection                      <dbl> 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1,…
$ TechSupport                           <dbl> 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0,…
$ StreamingTV                           <dbl> 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0,…
$ StreamingMovies                       <dbl> 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1,…
$ Contract.xOne.year                    <dbl> 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0,…
$ Contract.xTwo.year                    <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,…
$ PaperlessBilling                      <dbl> 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 1,…
$ PaymentMethod.xCredit.card..automatic. <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0,…
$ PaymentMethod.xElectronic.check       <dbl> 1, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1,…
$ PaymentMethod.xMailed.check           <dbl> 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,…
$ Churn                                 <dbl> 0, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1,…
$ tenure_bin.x1.2.years                 <dbl> 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,…
$ tenure_bin.x2.3.years                 <dbl> 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,…
$ tenure_bin.x3.4.years                 <dbl> 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,…
$ tenure_bin.x4.5.years                 <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0,…
$ tenure_bin.x5.6.years                 <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0,…
```

Figure 12

Model Building

We initiated our initial modeling by incorporating all variables into the model. The R output displayed in Figure 13 indicates that the majority of the variables exhibit insignificance, suggesting that this model does not perform well.

```
Call:
glm(formula = Churn ~ ., family = "binomial", data = train1)

Coefficients:
                                      Estimate Std. Error z value Pr(>|z|)    
(Intercept)                          1.526e+00  9.829e-01   1.552 0.120631    
tenure                              -9.856e-02  1.303e-02  -7.567 3.83e-14 ***
MonthlyCharges                      -5.062e-02  3.831e-02  -1.322 0.186321    
TotalCharges                         1.045e-04  8.833e-05   1.183 0.236699    
gender                              -4.319e-03  7.880e-02  -0.055 0.956292    
SeniorCitizen                        3.427e-01  1.020e-01   3.358 0.000784 ***
Partner                              4.964e-02  9.533e-02   0.521 0.602570    
Dependents                          -1.485e-01  1.104e-01  -1.345 0.178693    
PhoneService                         5.973e-01  7.850e-01   0.761 0.446729    
MultipleLines                        5.296e-01  2.148e-01   2.465 0.013691 *  
InternetService.xFiber.optic         2.048e+00  9.607e-01   2.132 0.033025 *  
InternetService.xNo                 -2.255e+00  9.758e-01  -2.311 0.020856 *  
OnlineSecurity                      -1.780e-01  2.155e-01  -0.826 0.408913    
OnlineBackup                         1.268e-01  2.111e-01   0.601 0.547964    
DeviceProtection                     2.556e-01  2.139e-01   1.195 0.232114    
TechSupport                         -2.607e-02  2.155e-01  -0.121 0.903713    
StreamingTV                          7.570e-01  3.935e-01   1.924 0.054396 .  
StreamingMovies                      7.109e-01  3.947e-01   1.801 0.071711 .  
Contract.xOne.year                  -6.930e-01  1.304e-01  -5.316 1.06e-07 ***
Contract.xTwo.year                  -1.658e+00  2.335e-01  -7.099 1.25e-12 ***
PaperlessBilling                     3.848e-01  9.075e-02   4.241 2.23e-05 ***
PaymentMethod.xCredit.card..automatic. -5.064e-02  1.372e-01  -0.369 0.711991    
PaymentMethod.xElectronic.check      2.492e-01  1.138e-01   2.190 0.028512 *  
PaymentMethod.xMailed.check         -7.666e-02  1.386e-01  -0.553 0.580291    
tenure_bin.x1.2.years                1.473e-01  1.910e-01   0.771 0.440556    
tenure_bin.x2.3.years                9.648e-01  3.148e-01   3.065 0.002178 ** 
tenure_bin.x3.4.years                1.955e+00  4.471e-01   4.373 1.22e-05 ***
tenure_bin.x4.5.years                2.801e+00  5.823e-01   4.811 1.50e-06 ***
tenure_bin.x5.6.years                3.599e+00  7.286e-01   4.940 7.83e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5699.5  on 4921  degrees of freedom
Residual deviance: 3983.3  on 4893  degrees of freedom
AIC: 4041.3
```

Figure 13

In our pursuit of identifying the optimal model, we employed the step AIC function to select the model exhibiting the lowest AIC. Subsequently, we excluded coefficients displaying insignificance and eliminated variables exhibiting high variance inflation factor (VIF). This process culminated in the derivation of our final model, as depicted in Figure 14.

An observation of significance reveals that all variables in this final model exhibit statistical significance, and notably, the AIC has been notably reduced from 4041 to 4027.

```
Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)    
(Intercept)                      0.616009   0.280345   2.197 0.027997 *  
tenure                          -0.085038   0.007226 -11.769  < 2e-16 ***
MonthlyCharges                  -0.021030   0.006139  -3.425 0.000614 ***
SeniorCitizen                    0.381581   0.100078   3.813 0.000137 ***
MultipleLines                    0.414859   0.105884   3.918 8.93e-05 ***
InternetService.xFiber.optic     1.412034   0.212886   6.633 3.29e-11 ***
InternetService.xNo             -1.492430   0.208176  -7.169 7.55e-13 ***
OnlineSecurity                  -0.318362   0.107497  -2.962 0.003061 ** 
StreamingTV                      0.493009   0.116951   4.216 2.49e-05 ***
StreamingMovies                  0.455224   0.114098   3.990 6.61e-05 ***
Contract.xOne.year              -0.708613   0.129001  -5.493 3.95e-08 ***
Contract.xTwo.year              -1.728080   0.229825  -7.519 5.51e-14 ***
PaperlessBilling                 0.383077   0.090414   4.237 2.27e-05 ***
PaymentMethod.xElectronic.check  0.294187   0.084368   3.487 0.000489 ***
tenure_bin.x2.3.years            0.778511   0.192789   4.038 5.39e-05 ***
tenure_bin.x3.4.years            1.725321   0.267864   6.441 1.19e-10 ***
tenure_bin.x4.5.years            2.529036   0.344165   7.348 2.01e-13 ***
tenure_bin.x5.6.years            3.314362   0.430271   7.703 1.33e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5699.5  on 4921  degrees of freedom
Residual deviance: 3991.7  on 4904  degrees of freedom
AIC: 4027.7

Number of Fisher Scoring iterations: 6
```

Figure 14

Model Diagnostic

Our model building process was executed on 70% of the dataset, designated as the training set, while the remaining 30% constituted our validation data for evaluating the model's performance.

In Table 1, our final model demonstrates a commendable level of accuracy, although it's noteworthy that the sensitivity metric falls slightly below the desired threshold.

	Predicted Churn			**Metrics**	
Actual Churn	No	Yes		Accuracy	0.8
No	1390	150		Sensitivity	0.53
Yes	263	298		Specificity	0.89

Table 1

To enhance our model's performance, we aimed to determine the optimal cutoff point that maximizes accuracy, sensitivity, and specificity. As depicted in Figure 15, the graph illustrates the search for the ideal cutoff rate for our model. Notably, we found that utilizing a cutoff of 0.305, as opposed to the standard 0.5, yields the most favorable balance among accuracy, sensitivity, and specificity.

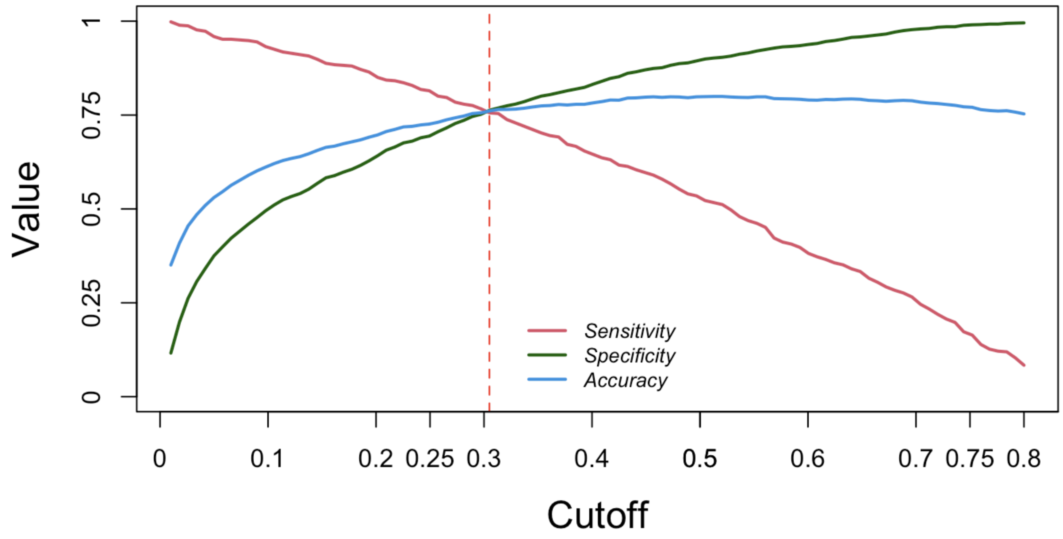

Figure 15

By opting for a cutoff value of 0.305, our revised prediction of churn versus actual churn is presented in Table 2. This table illustrates the accuracy, sensitivity, and specificity metrics associated with the 0.305 cutoff value.

	Predicted Churn			**Metrics**	
Actual Churn	No	Yes		Accuracy	0.76
No	1182	367		Sensitivity	0.75
Yes	137	424		Specificity	0.76

Table 2

Conclusion

Utilizing the results from our model, we draw conclusions regarding the dataset and the recommendations for the company. As depicted in Figure 16, the exponential values of the coefficients in our final model offer valuable insights:

- A one-month increase in service tenure corresponds to an approximate 8 percent reduction in the churn rate.
- Surprisingly, a $1 increase in monthly charges correlates with an almost 2 percent decrease in the churn rate. This outcome seemingly contradicts our initial observation during EDA, where a higher monthly service charge appeared to elevate the churn rate. However, this might be attributed to customers with higher charges also utilizing additional services or possessing certain demographics that influence the churn rate.
- Subscribing to fiber optic services significantly amplifies the churn rate (by approximately 4 times). Similarly, an increase in tenure remarkably elevates the churn rate.
- Being a senior citizen, having multiple lines, using streaming services, opting for paperless billing, and employing electronic check payment methods all contribute to an increased churn rate, consistent with our earlier EDA.
- Conversely, factors such as having no internet service, utilizing online security features, and having a one or two-year contract are associated with a reduction in the churn rate."

This interpretation of the coefficients provides valuable insights into the impact of various factors on the churn rate, corroborating or challenging earlier observations made during the exploratory analysis.

(Intercept)	tenure	MonthlyCharges
1.8515246	0.9184776	0.9791896
SeniorCitizen	MultipleLines	InternetService.xFiber.optic
1.4645980	1.5141571	4.1042951
InternetService.xNo	OnlineSecurity	StreamingTV
0.2248256	0.7273392	1.6372347
StreamingMovies	Contract.xOne.year	Contract.xTwo.year
1.5765262	0.4923268	0.1776252
PaperlessBilling	PaymentMethod.xElectronic.check	tenure_bin.x2.3.years
1.4667910	1.3420345	2.1782259
tenure_bin.x3.4.years	tenure_bin.x4.5.years	tenure_bin.x5.6.years
5.6143243	12.5414092	27.5048410

Figure 16