Mobile Service Churn Project

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Group 1

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Executive Summary

As customers with higher charges of all products are more likely to churn, better pricing strategies such as segmented usage charge or discount for excessive usage may help decrease the churn rate. Customers who use more customer service are more likely to churn, the company needs to improve customer service efficiency and solutions. Voicemail users are less likely to churn, therefore voicemail service might be an advantage and selling point of the company. International plan users are more likely to churn, the company may need to improve this product by designing differential packages for customers with different demands to choose.

Introduction

With an ultra-competitive environment, a mobile service company has a strong urge to decrease customer churn and increase customer loyalty. Analyzing customer churn data, models are built to study which factors influence customer churn, and to predict possible leaving customers so the company can attract them to stay with incentives.

Analysis and Results

PART I: Data Overview and preprocessing

1.1 Data Overview:

The dataset has 19 columns and 3332 rows in total. The 19 columns represent the 18 predictors and 1 response variable ("Churn") as table stated below. The 18 predictors can be categorized as following:

There are 3 categorical variables ("States", "IntlPlan", "VMPlan"), and the rest are continuous variables.

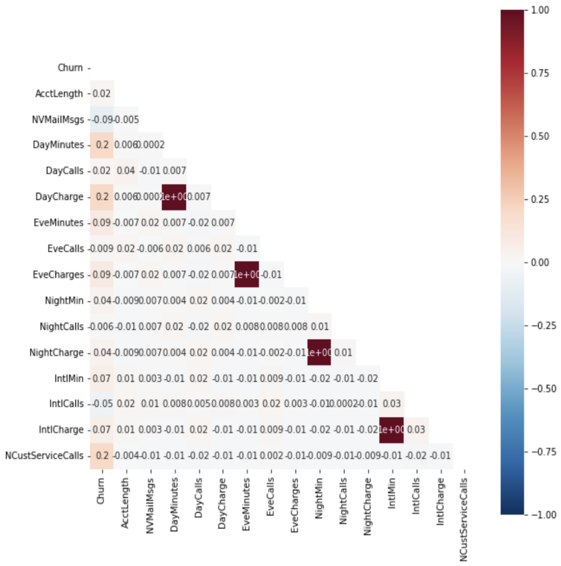
	Churn	State	AcctLength	IntlPlan	VMPlan	NVMailMsgs	DayMinutes	DayCalls	DayCharge	EveMinutes	EveCalls	EveCharges	NightMin	NightCalls	Night
0	False	OH	107	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103	
1	False	NJ	137	no	no	0	243.4	114	41.38	121.2	110	10.30	162.6	104	
2	False	OH	84	yes	no	0	299.4	71	50.90	61.9	88	5.26	196.9	89	
3	False	OK	75	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	121	
4	False	AL	118	yes	no	0	223.4	98	37.98	220.6	101	18.75	203.9	118	

1.2 Data Descriptive Analysis:

1.2.1 The dataset is unbalanced with only 14.5% of customers are churning (483 of Yes for "Churn").

1.2.2 No missing values detected.

1.2.3 Correlation matrix

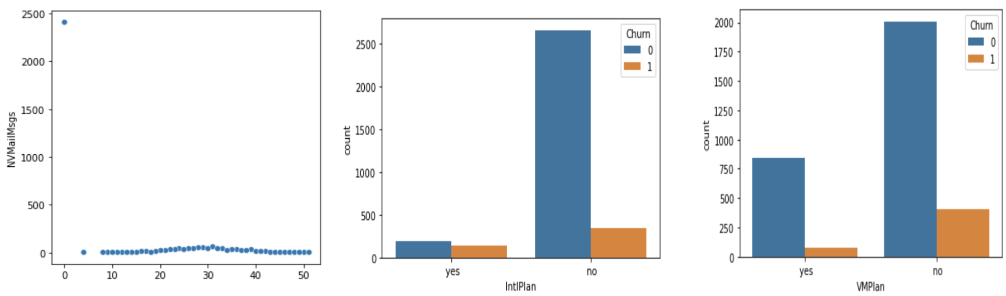


From the correlation matrix above, most predictors are not correlated with each other except some pairs with correlation coefficients of 1, which are: (1) “DayCharge” and “DayMinutes”, (2) “EveCharges” and “EveMinutes”, (3) “NightCharge” and “NightMin”, (4) “IntlCharge” and “IntlMin”.

Since charges are calculated based on the time spent in different time periods in a day, it is quite straightforward that those predictors above should have a strong linear correlation.

1.2.4 By diving into the specific predictors associated with “Churn”, several interesting points can also be found.

- Distributions of “AcctLength” for both churn and not churned groups are all centralized, meaning the length of someone has been a customer do not seem to be a determining factor in terms of churn;
- Distribution of “NVMailMsgs” is quite skewed and most average voice messages are around 0.
- In regards of two types of plans - IntlPlan and VMPlan, the graphs show that IntlPlan is more likely to churn, and without VMPlan group is also likely to churn;



PART II: Building Model

2.1 Initial Model

We start by checking the convergence problem by using the method in R to test for data separation because this problem would result in the invalid estimation of some coefficients. The result of the test shows that there is no occurrence of complete separation or Quasi-complete separation.

After preparing data sets and checking the problem, we use all variables to fit the logistic regression model and build the initial model.

Initial Model

Churn~State+AcctLength+IntlPlan+VMPlan+NVMailMsgs+DayCalls+DayCharge+EveCalls+EveCharges+NightCalls+NightCharge+IntlCalls+IntlCharge+NCustServiceCalls'

2.2 Variable Selection

Firstly, we use a stepwise selection method to select variables among all in the full model by choosing the variables in the model with the smallest AIC and constructing a reduced model with a degree of freedom equal to nine.

Secondly, we calculate the VIF values to find if multicollinearity exists. Since the VIF values of VMPlan (15.34) and NVMailMsgs (15.30) are larger than 10, we decide to drop one of them to solve the multicollinearity problem considering that the meanings of these two variables are similar.

Then, we use the Likelihood ratio test to compare the initial model and the model with the variables selected by the stepwise selection method except for NVMailMsgs(Model 3-1, Model 3), and find out that the p-value (0.078) is larger than 0.05, which means we cannot reject the null that all variables we drop have the coefficient equal to 0, thus Model 3-1 and initial model have the same explanatory power.

Model 3-1: Churn ~ IntlPlan + VMPlan + DayCharge + EveCharges + NightCharge + IntlCalls + IntlCharge + NCustServiceCalls

Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
2,656	1,712.607			
2,601	1,642.161	55	70.44593	0.0783812

Then we use the Likelihood ratio test again to compare the initial model and the model with the variables selected by the stepwise selection method except for VMPlan(Model 3-2) and find out that the p-value (0.025) is less than 0.05, showing that Model 3-2 and initial model are significantly different, we cannot use the variables in Model 3-2 to represent the whole dataset.

Model 3-2: Churn ~ IntlPlan + NVMailMsgs + DayCharge + EveCharges + NightCharge + IntlCalls + IntlCharge + NCustServiceCalls

Resid. Df	Resid. Dev	Df	Deviance	Pr(>Chi)
2,656	1,719.467			
2,601	1,642.161	55	77.30579	0.02533413

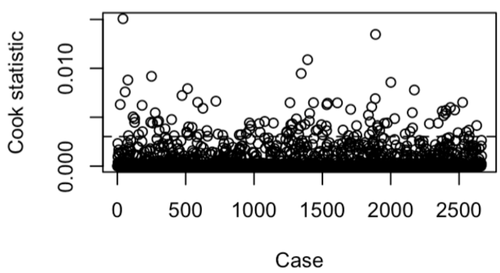
Thus, we choose Model 3-1 as the final model.

2.3 Final Model

We find that no multicollinearity problem exists by calculating the VIF values of all variables. Thus, the p-value is trustful, and all variables in the final model are significant because the p-values are all less than 0.05.

```
                 Generalized Linear Model Regression Results
==============================================================================
Dep. Variable:                  Churn   No. Observations:                 2665
Model:                            GLM   Df Residuals:                     2656
Model Family:                Binomial   Df Model:                            8
Link Function:                  logit   Scale:                          1.0000
Method:                          IRLS   Log-Likelihood:                -856.30
Date:                Fri, 09 Dec 2022   Deviance:                       1712.6
Time:                        11:33:58   Pearson chi2:                 2.69e+03
No. Iterations:                     6
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept            -7.9496      0.582    -13.652      0.000      -9.091      -6.808
IntlPlan[T. yes]      2.0472      0.162     12.656      0.000       1.730       2.364
VMPlan[T. yes]       -0.9530      0.162     -5.865      0.000      -1.271      -0.634
DayCharge             0.0742      0.007     10.306      0.000       0.060       0.088
EveCharges            0.0808      0.015      5.424      0.000       0.052       0.110
NightCharge           0.0745      0.028      2.686      0.007       0.020       0.129
IntlCalls            -0.0930      0.028     -3.302      0.001      -0.148      -0.038
IntlCharge            0.3602      0.086      4.179      0.000       0.191       0.529
NCustServiceCalls     0.5002      0.045     11.229      0.000       0.413       0.587
=====================================================================================
```

Furthermore, we discuss if the dataset has high leverage points or outliers. From the cook-distance plot, we can find that several points are regarded as high leverage points; but if we see the outlier test, the result shows that no outlier is detected. So, some points have relatively extreme x values but can still be predicted well by the model.




```
outlierTest(model3)

## No Studentized residuals with Bonferroni p < 0.05
```

PART III: Evaluation

3.1 Goodness of fit

Likelihood Ratio Test

Firstly, we do the likelihood ratio test to find out whether our final model as a whole is useful. Our null hypothesis here is that all the coefficients equal to zero. Test statistics used here is to compare the likelihood of our fitted model and the intercept only model, following a chi-squared distribution. P-value = 5.725885e-92, so we reject the null hypothesis and conclude that our final model is useful.

```
residualDeviance <- model3$deviance
nullDeviance     <- model3$null.deviance
devianceDiff     <- nullDeviance - residualDeviance
```

```
df    <- length(model3$coefficients)-1
p_val <- pchisq(devianceDiff, df=df, lower.tail=FALSE)
print(p_val)
5.725885e-92
```

Pseudo R-square

We get a Pseudo R-square = 0.2077575, that means the goodness of fitting our data is acceptable.

```
pseudoRSquared   <- 1 - (residualDeviance/nullDeviance)
print(pseudoRSquared)
0.2077575
```

Deviance test

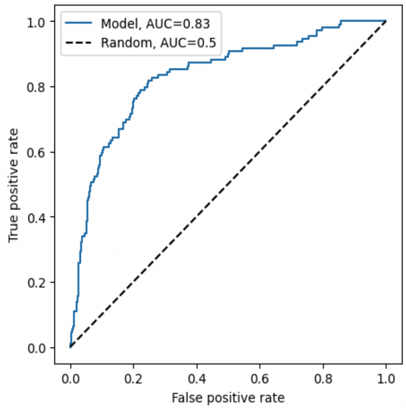
Now we use the deviance test to find out if there exists a model better than our final one. Our null hypothesis is that our fitted model is good enough. Test statistics used here is to compare the likelihood of our fitted model and a saturated model, following a chi-squared distribution. P-value = 1, so we retain the null hypothesis and conclude that our fitted model is good enough, there's no need to add interactive or higher-order terms to the model.

```
df_resi      <- model3$df.residual
p_val_devi   <- pchisq(residualDeviance, df=df_resi, lower.tail=FALSE)
print(p_val_devi)
1
```

3.2 Predictive power

AUC

The prediction performance of the model can be measured with AUC. AUC=0.83, which means the model has good predictive power to rank a random positive instance more highly than a random negative instance.



Classification Threshold

The probability threshold is needed for decision making, beyond which the instances are predicted as 1 (Churn), and below the thresholds the instances are predicted as 0 (not Churn).

If choosing 0.5 as the probability threshold, the sensitivity of the model is low (0.22) while the specificity is pretty good (0.97). This result missed the business focus on identifying as much as customer churn, even if trading off the ability to identify loyal customers. Another reason to be unsatisfied with such results is that threshold 0.5 is often used on balanced data. However, there are only around 14% of customer churn in the dataset. Therefore, the threshold at 0.5 is not enough for the business purpose or statistical inference.

One of the strategies is to choose the probability threshold where the sensitivity and specificity are the closest. In this way the threshold will be 0.15. The corresponding sensitivity is 0.77 and specificity is 0.79. Both are acceptable. Although this method still assumes the cost of false positives and false negatives are similar, threshold 0.15 will be justified to be reasonable enough in section 3.3, when we use a hypothesized profit curve to find the threshold in a reality setting.

	cutoff	sensitivity	specificity	misClassError
0	0.00	1.000000	0.000000	0.836582
1	0.05	0.917431	0.419355	0.499250
2	0.10	0.853211	0.648746	0.317841
3	0.15	0.770642	0.788530	0.214393
4	0.20	0.660550	0.845878	0.184408
5	0.25	0.614679	0.892473	0.152924
6	0.30	0.522936	0.921147	0.143928
7	0.35	0.449541	0.942652	0.137931
8	0.40	0.348624	0.953405	0.145427
9	0.45	0.302752	0.965950	0.142429
10	0.50	0.220183	0.973118	0.149925

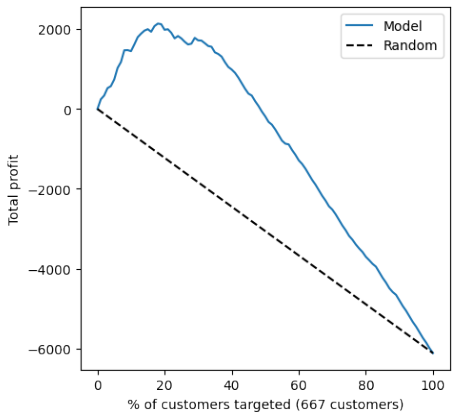
3.3 Profit Curve

Through finding the classification threshold beyond which to determine as customer churn, the issue was addressed that the cost of false positives and false negatives are not close (much more costly to lose a customer than paying extra incentives to loyal customers) under the scenario of customer churn. Accordingly, the model needs to identify as many as leaving customers in reality.

To simplify the question, it is assumed that customers will stay with incentives, but will leave without incentives. The revenue is roughly calculated as the summation of day charge, evening charge, night charge and international charge. The cost of incentive is hypothesized to be 20 dollars per month given the average revenue per customer is around 59 dollars per month. The following profit matrix can be concluded with such assumptions.

	Churn	Not Chun
Y	Revenue-cost	-cost
N	0	0

Based on the profit matrix, the profit curve can be drawn below. When the customers are ranked with their probabilities to churn, the highest profit is achieved when the top 26.44% are targeted with incentives to stay. The respective probability threshold is 0.18, which is close to the 0.15 threshold we found with the method of close sensitivity and specificity.



PART IV: Prediction and Summary

4.1 Final model

	coef	std	adj_coef	exp(coef)	exp(adj_coef)
IntlPlan	2.041353	0.295919	0.604075	7.701020	1.829558
VMPlan	−0.936289	0.447289	−0.418792	0.392080	0.657841
DayCharge	0.076539	9.257411	0.708555	1.079545	2.031054
EveCharges	0.084278	4.311311	0.363348	1.087931	1.438137
NightCharge	0.081568	2.275958	0.185646	1.084987	1.203995
IntlCalls	−0.091510	2.461450	−0.225248	0.912552	0.798318
IntlCharge	0.323891	0.753885	0.244177	1.382497	1.276570
NCustServiceCalls	0.512417	1.315652	0.674163	1.669321	1.962389

Interpret the coefficient β_i

1. A customer with an International Plan increases the odds of churn by 670.1020%; a customer with a Voicemail Plan decreases the odds of churn by 60.7920%, holding all other predictors' fixed;
2. A one-unit increase in DayCharge, EveCharge, NightCharge, International Charge, and numbers of Customer Service Calls, can separately cause an increase in the odds of churn by 7.9545%, 8.7931%, 8.4987%, 38.2497%, 66.9321%, holding all other predictors' fixed;
3. A one-unit increase in International Calls would decrease the odds of churn by 8.7448%, holding all other predictors' fixed.

Standardized coefficients

The standardized coefficients measure the relative importance of the explanatory variables in a regression model. We can see that the standardized coefficients of the variables DayCharge, Numbers of Customer Service Calls and International Plan are significantly higher than the other variables. Therefore, we can conclude that these three variables have the most important impacts on the prediction of customer churn probability.

4.2 Business Implications

Our purpose to build this model is to predict which customers are most likely to move the company's service to a competitor. This knowledge will be used to identify customers for targeted interventions, with the ultimate goal of reducing churn.

Based on the final model, we can get following insights:

1. A customer with higher day, evening, and night charge is more likely to move the company's service to a competitor. For the customers with high demand for mobile

service, they are more unsatisfied with the company's service. This might be caused by several reasons like poor communication signals or expensive costs. Customers with higher day charge have a higher churn rate compared with customers with high evening and night charge, which means the company may have no price advantage or good service quality in the daytime.

2. A customer who made a lot of customer service calls is more likely to leave the company, which is very likely caused by the bad customer service experience. For example, if the customer service is inefficient, only one call cannot help customers solve the problems. The more calls they take, the more dissatisfied they would be with the company.
3. A customer with a Voicemail Plan tends to have less probability to leave, which might indicate the company provides a relatively well-designed and attractive product or good service in this plan.
4. Although only a small percentage of users subscribed to the International Plan, those who did so have an extremely high probability to leave the company. And the more international charge they pay, the more likely they will leave. What's more, the very low percentage of subscribers of this plan might also be caused by the company's poor international service.

According to the insights above, our group can provide some suggestions for the company to retain the target customers.

1. The company can adopt a segmented charging strategy. The more the customer uses the service, the cheaper the charge. For the customers with high service demand, the company can provide a discount for the excessive usage portion.
2. To solve the customer service problem, the company should firstly retrieve customer service history data and figure out the most common problems customers usually have, finding out the pain points, especially for those who made much more calls than others. Then try to optimize the service process and service efficiency.
3. The Voicemail Plan would be the advantage of the company, which could be used as a selling point. Other products can refer to its strategy.
4. For the International Plan, the company can consider designing different kinds of preferential packages to satisfy different types of customers' demands such as international phone calls and international mobile network.

Conclusion

Feature engineering is completed through missing value detection, correlation check and variable distribution screening. After checking convergence problems, the initial model is built with all predictors. Then the model from stepwise selection beats the initial model in the likelihood ratio test. The final model arose out of the stepwise selection model after solving multicollinearity problems with VIF scores.

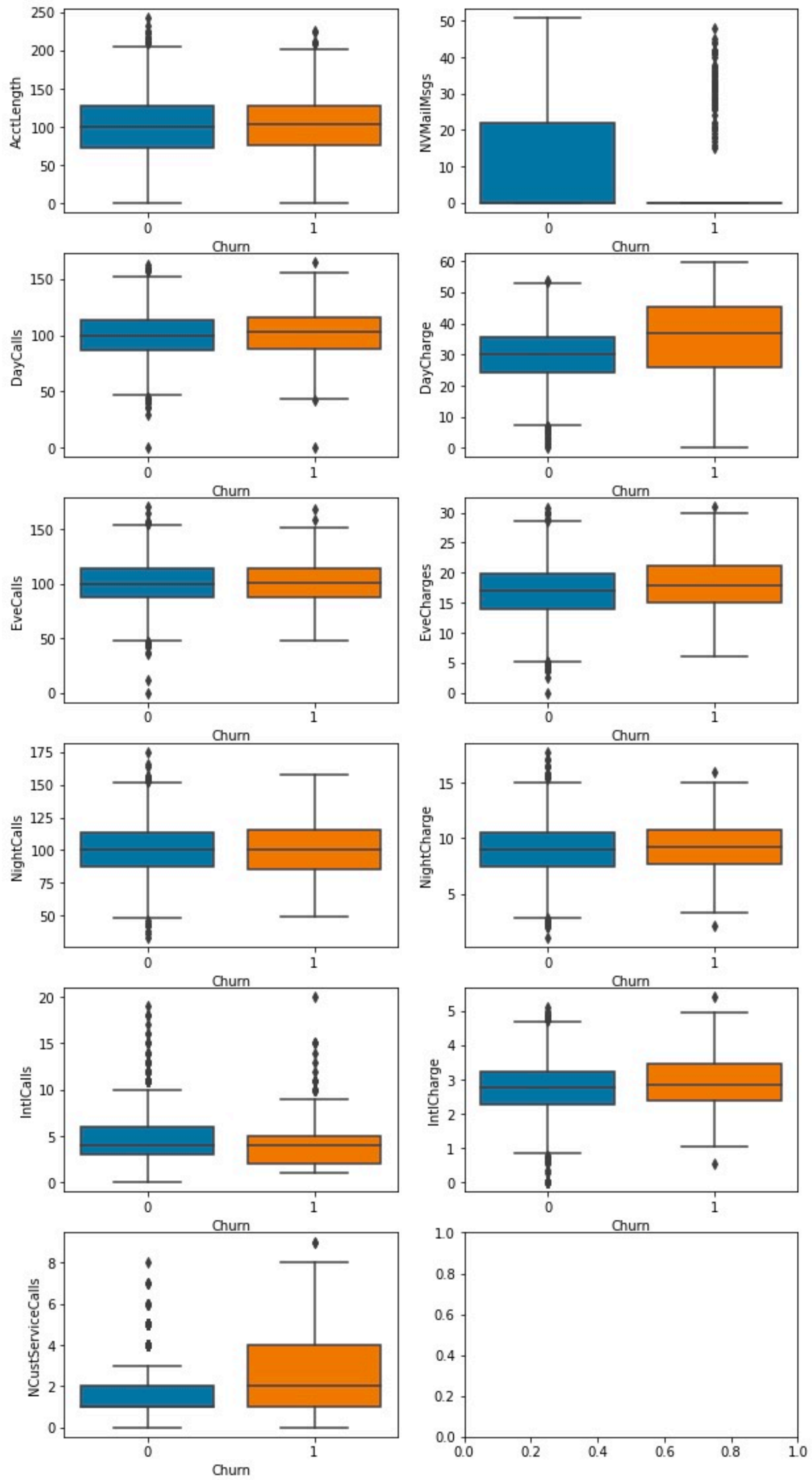
To evaluate the goodness of fit for the final model, likelihood ratio test is conducted again with the intercept only model. Together with the Pseudo R-square and deviance test, the results showed the model has acceptable ability to fit the data.

The predictive power is also acceptable as shown by AUC. To better predict churning customers in the future, we used different methods to find the classification threshold, which have consistent results.

Finally, the coefficients of the model are used to interpret business implications of customer churn behavior of the company. We came up with corresponding suggestions for the company to decrease churn rate generally such as providing better pricing strategies and improving customer service quality.

Appendix

Appendix1: Distribution of Predictors



Appendix2: The Initial Model

```
## Call:
## glm(formula = Churn ~ . - DayMinutes - EveMinutes - NightMin -
##     IntlMin, family = binomial(link = "logit"), data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.9180  -0.4969  -0.3184  -0.1714   3.1650
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -9.6268483  1.1038309  -8.721  < 2e-16 ***
## StateAL             0.4316887  0.8818298   0.490  0.62446
## StateAR             0.3022107  0.9493679   0.318  0.75024
## StateAZ             0.2022425  0.9394104   0.215  0.82954
## StateCA             1.8321929  0.9034832   2.028  0.04257 *
## StateCO             0.7228483  0.8729888   0.828  0.40766
## StateCT             0.8651320  0.8525734   1.015  0.31023
## StateDC             0.5893792  0.9394211   0.627  0.53041
## StateDE             0.9734134  0.8546189   1.139  0.25470
## StateFL             0.5940894  0.8630340   0.688  0.49122
## StateGA             0.6870917  0.8937887   0.769  0.44205
## StateHI            -1.0202541  1.2821812  -0.796  0.42620
## StateIA            -0.7137473  1.2804728  -0.557  0.57725
## StateID             0.4213372  0.9032193   0.466  0.64087
## StateIL            -0.3424257  1.0002274  -0.342  0.73209
## StateIN             0.5184612  0.8922493   0.581  0.56119
## StateKS             1.0702106  0.8502331   1.259  0.20813
## StateKY             0.9524482  0.8812643   1.081  0.27980
## StateLA             0.8757902  0.9328354   0.939  0.34781
## StateMA             1.3341104  0.8600096   1.551  0.12084
## StateMD             0.8832427  0.8420971   1.049  0.29424
## StateME             1.0909513  0.8632570   1.264  0.20632
## StateMI             1.2190829  0.8515862   1.432  0.15227
## StateMN             1.0010107  0.8405740   1.191  0.23371
## StateMO             0.6674855  0.8746177   0.763  0.44536
## StateMS             1.3207566  0.8607232   1.534  0.12491
## StateMT             1.4188686  0.8435071   1.682  0.09255 .
## StateNC             0.3535334  0.8978228   0.394  0.69375
## StateND            -0.1995773  0.9473622  -0.211  0.83315
## StateNE             0.4251506  0.9009910   0.472  0.63702
## StateNH             1.0600166  0.9049597   1.171  0.24146
## StateNJ             1.4716824  0.8275198   1.778  0.07533 .
## StateNM             0.8152689  0.8827081   0.924  0.35569
## StateNV             1.3125179  0.8373918   1.567  0.11702
## StateNY             1.2923774  0.8350277   1.548  0.12169
## StateOH             0.6200418  0.8710760   0.712  0.47658
## StateOK             0.8851817  0.8810074   1.005  0.31502
## StateOR             0.8540770  0.8592082   0.994  0.32021
```

```
## StatePA            1.1143394  0.8935179   1.247  0.21235
## StateRI           -0.2255150  0.9791848  -0.230  0.81785
## StateSC            1.9680045  0.8775647   2.243  0.02492 *
## StateSD            0.7810744  0.8934255   0.874  0.38198
## StateTN            0.4724761  0.9167053   0.515  0.60627
## StateTX            1.4229397  0.8310076   1.712  0.08684 .
## StateUT            1.1223344  0.8612049   1.303  0.19250
## StateVA           -0.2278797  0.9243469  -0.247  0.80527
## StateVT            0.1452274  0.8821927   0.165  0.86924
## StateWA            1.1197978  0.8601582   1.302  0.19297
## StateWI            0.3528822  0.8971828   0.393  0.69408
## StateWV            0.7748687  0.8620480   0.899  0.36872
## StateWY            0.0051403  0.8958747   0.006  0.99542
## AcctLength         0.0007651  0.0016482   0.464  0.64252
## IntlPlan yes       2.1846520  0.1714583  12.742  < 2e-16 ***
## VMPlan yes        -1.8921661  0.6524197  -2.900  0.00373 **
## NVMailMsgs         0.0304971  0.0205852   1.482  0.13847
## DayCalls           0.0036443  0.0032325   1.127  0.25958
## DayCharge          0.0739115  0.0073372  10.074  < 2e-16 ***
## EveCalls           0.0026838  0.0032719   0.820  0.41207
## EveCharges         0.0874690  0.0154348   5.667 1.45e-08 ***
## NightCalls        -0.0003493  0.0033326  -0.105  0.91653
## NightCharge        0.0799830  0.0289465   2.763  0.00572 **
## IntlCalls         -0.0881630  0.0289380  -3.047  0.00231 **
## IntlCharge         0.3506009  0.0896731   3.910 9.24e-05 ***
## NCustServiceCalls  0.5172816  0.0464843  11.128  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2161.7  on 2664  degrees of freedom
## Residual deviance: 1642.2  on 2601  degrees of freedom
## AIC: 1770.2
##
## Number of Fisher Scoring iterations: 6
```

Appendix3: The Reduced Model (After Stepwise Selection)

```
## Call:
## glm(formula = Churn ~ IntlPlan + VMPlan + NVMailMsgs + DayCharge +
##     EveCharges + NightCharge + IntlCalls + IntlCharge + NCustServiceCalls,
##     family = binomial(link = "logit"), data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0313  -0.5097  -0.3401  -0.2047   3.2083
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -7.950224   0.583167 -13.633  < 2e-16 ***
## IntlPlan yes       2.044968   0.161799  12.639  < 2e-16 ***
## VMPlan yes        -1.804503   0.628812  -2.870 0.004109 **
## NVMailMsgs         0.028237   0.019817   1.425 0.154204
## DayCharge          0.074205   0.007201  10.304  < 2e-16 ***
## EveCharges         0.080791   0.014920   5.415 6.13e-08 ***
## NightCharge        0.075006   0.027743   2.704 0.006859 **
## IntlCalls         -0.094260   0.028184  -3.344 0.000824 ***
## IntlCharge         0.360771   0.086239   4.183 2.87e-05 ***
## NCustServiceCalls  0.500107   0.044577  11.219  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2161.7  on 2664  degrees of freedom
## Residual deviance: 1710.6  on 2655  degrees of freedom
## AIC: 1730.6
##
## Number of Fisher Scoring iterations: 6
```

Appendix4: VIF Values of Variables in Reduced Model

```
##                      vif(model2)
## IntlPlan                1.062169
## VMPlan                 15.338609
## NVMailMsgs             15.300735
## DayCharge               1.050902
## EveCharges              1.025418
## NightCharge             1.017956
## IntlCalls               1.012512
## IntlCharge              1.017571
## NCustServiceCalls       1.082091
```

Appendix5: VIF Values of Variables in Full Model

```
##                      vif(model3)
## IntlPlan                1.062523
## VMPlan                  1.027730
## DayCharge               1.049996
## EveCharges              1.025334
## NightCharge             1.017577
## IntlCalls               1.011284
## IntlCharge              1.017260
## NCustServiceCalls       1.081643
```

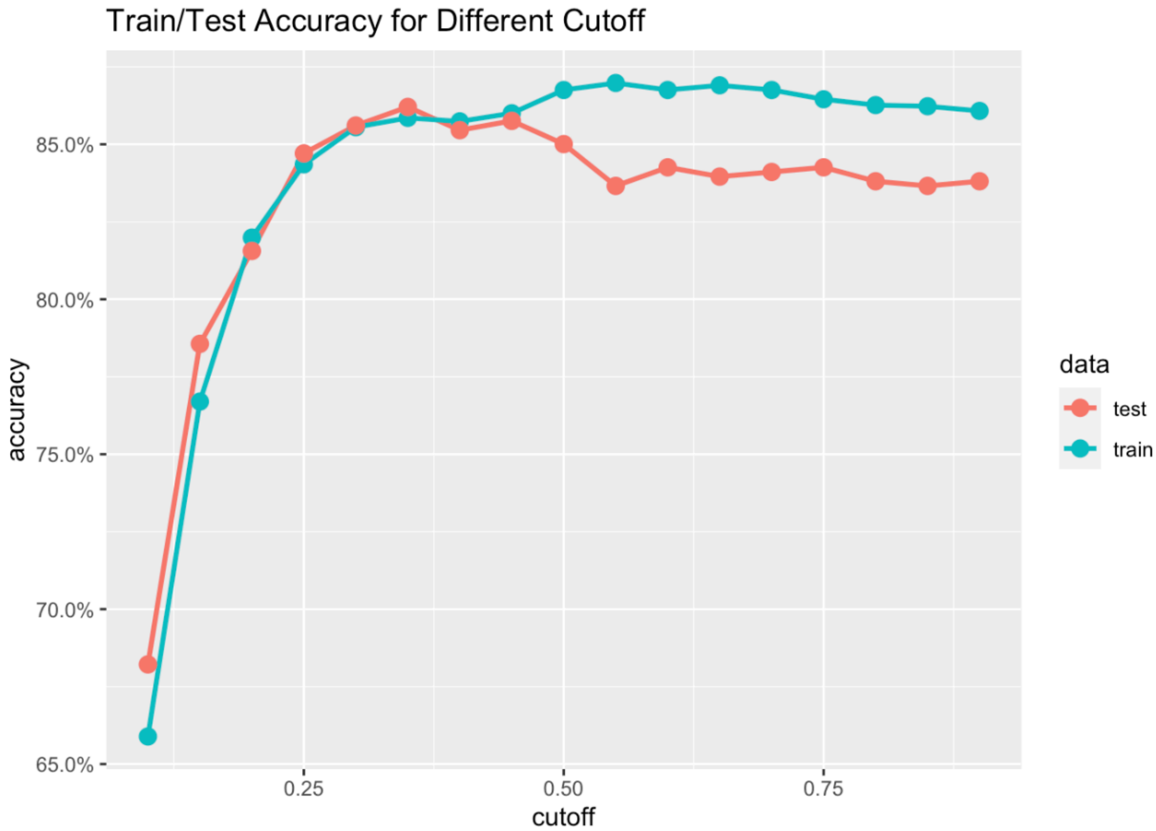
Appendix6: The Final Model

```
## Call:
## glm(formula = Churn ~ IntlPlan + NVMailMsgs + DayCharge + EveCharges +
##     NightCharge + IntlCalls + IntlCharge + NCustServiceCalls,
##     family = binomial(link = "logit"), data = train_set)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.0139  -0.5125  -0.3453  -0.2130   2.9600
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -7.942761   0.580115 -13.692  < 2e-16 ***
## IntlPlan yes       2.037839   0.161260  12.637  < 2e-16 ***
## NVMailMsgs        -0.028163   0.005290  -5.324 1.02e-07 ***
## DayCharge          0.073905   0.007182  10.290  < 2e-16 ***
## EveCharges         0.080470   0.014861   5.415 6.13e-08 ***
## NightCharge        0.073174   0.027648   2.647  0.00813 **
## IntlCalls         -0.091407   0.028103  -3.253  0.00114 **
## IntlCharge         0.357709   0.086044   4.157 3.22e-05 ***
## NCustServiceCalls  0.499271   0.044473  11.226  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2161.7  on 2664  degrees of freedom
## Residual deviance: 1719.5  on 2656  degrees of freedom
## AIC: 1737.5
##
## Number of Fisher Scoring iterations: 5
```

Appendix7: High Leverage Point

```
##        StudRes          Hat       CookD
## 3    -1.164582 0.0210035416 0.002313683
## 41    2.433809 0.0078211725 0.015071626
## 1502 -1.237075 0.0244820250 0.003199764
## 1532  3.108113 0.0004677335 0.006281064
## 1889  2.980783 0.0015297175 0.013468589
```

Appendix8: Train/Test Accuracy for Different Cutoff



Appendix9: Response curve